Knowledge Engineering and Data Science (KEDS)
Vol 5, No 2, December 2022, pp. 122–128

pISSN 2597-4602
eISSN 2597-4637

Adaptive Neuro-Fuzzy Inference System for Waste Prediction

Haviluddin[a,1,*], Herman Santoso Pakpahan [a,2], Novianti Puspitasari [a,3], Gubtha Mahendra Putra [a,4], Rima Yustika Hasnida [a,5], Rayner Alfred [b,6]

[a] *Informatics Engineering, Faculty of Engineering, Universitas Mulawarman, Jalan Sambaliung No.9 Gunung Kelua Campus, Samarinda 75119, Indonesia*
[b] *Knowledge Technology Research Unit, Universiti Malaysia Sabah, Jalan UMS, Kota Kinabalu, Sabah 88400, Malaysia*
[1] *haviluddin@unmul.ac.id;* [2] *pakpahan.herman891@gmail.com;* [3] *novianti_miechan@yahoo.com;* [4] *gubthamp@fkti.unmul.ac.id;* [5] *ryustica@yahoo.com;* [6] *ralfred@ums.edu.my*
* *corresponding author*

ARTICLE INFO

Article history:
Received 3 October 2022
Revised 29 October 2022
Accepted 30 October 2022
Published online 30 December 2022

Keywords:
Waste
Prediction
ANFIS
Samarinda

ABSTRACT

The volume of landfills that are increasingly piled up and not handled properly will have a negative impact, such as a decrease in public health. Therefore, predicting the volume of landfills with a high degree of accuracy is needed as a reference for government agencies and the community in making future policies. This study aims to analyze the accuracy of the Adaptive Neuro-Fuzzy Inference System (ANFIS) method. The prediction results' accuracy level is measured by the value of the Mean Absolute Percentage Error (MAPE). The final results of this study were obtained from the best MAPE test results. The best predictive results for the ANFIS method were obtained by MAPE of 3.36% with a data ratio of 6:1 in the North Samarinda District. The study results show that the ANFIS algorithm can be used as an alternative forecasting method.

I. Introduction

The ever-increasing volume of waste produced due to human activity poses a massive threat to both the environment and public health. Waste management has emerged as one of the most pressing concerns for governments and communities worldwide due to the ongoing rise in the global population and the acceleration of urbanization [1]. In recent years, there has been an increasing awareness of the detrimental effects of waste on the environment, such as contamination of the air and water [2], deterioration of the land [3], and emissions of greenhouse gases [4]. Ineffective waste management procedures have also been linked to various health issues, such as respiratory disorders, infectious infections, and malignancies [5]. As a direct consequence of this, waste management has risen to the top of the agenda for decision-makers in government, those in charge of waste management, and other stakeholders [6]. They are actively looking for ways to manage waste sustainably, cut down on the amount of waste generated, and lessen the adverse effects of waste on the environment and public health. The difficulty of accurately predicting the amount of waste produced in a particular location is one of the obstacles faced in waste management.

Prediction is a process that involves certain behaviors or phenomena that will occur in the future. Predictions can be made quantitatively or qualitatively. The quantitative measurement uses statistical methods, while the qualitative measurement is based on the opinion (judgment) of those who make predictions. Based on the time horizon, predictions can be grouped into three parts: long-term, medium-term, and short-term [7]. Predictions can be qualitative (not in the form of numbers) or quantitative (in the form of numbers). Qualitative predictions are difficult to do to obtain good results because the variables are very relative. Quantitative prediction is divided into two, namely: single prediction (point prediction) and interval prediction (interval prediction). A single prediction consists of one value, while an interval prediction consists of several values in the form of an interval (interval) bounded by lower limit values (lower limit prediction) and upper limit (high prediction) [8]. Prediction of the volume of landfill waste is carried out to assist related parties in making policies on the growth

https://doi.org/10.17977/um018v5i22022p122-128

of the volume of waste increasing daily. Making predictions makes it possible to make earlier preparations and considerations to anticipate if the volume of waste piles increases, which can cause environmental pollution and make residents uncomfortable.

Various analysis of waste handling management and municipal solid waste (MSW) continues to be carried out by researchers with a predictive approach using artificial intelligence. A study in Brisbane, Australia, found that the long short-term memory (LSTM) model outperformed traditional statistical models in forecasting MSW generation, particularly when capturing long-term trends [9]. The LSTM, the ARIMA model, and traditional artificial neural networks (ANN) accuracy reach 0.92, 0.10, and 0.74. The study also found that incorporating demographic data and economic indicators into the LSTM model improved the accuracy of the forecasts. The use of ANN and support vector machines (SVM) in forecasting MSW quantity can potentially improve the efficiency and effectiveness of waste management systems in Johannesburg, South Africa, as well as other urban areas worldwide [10]. In the ANN models, the ten-neuron structure (ANN10) performed best with a determination coefficient (R2) of 99.9%, while in the SVM models, the linear model performed best with an R2 of 98.6%. From the results obtained from the ANN10 model, the total amount of MSW generated per year in the City of Johannesburg is envisaged to get to 1.95 × 106 tonnes in 2050 with an average annual waste of 1.78 x 106 tonnes.

The study analyzes various scenarios and uses a fuzzy technique for order of preference by similarity to the ideal solution (TOPSIS) to forecast MSW generation and evaluate the effectiveness of different waste management strategies to improve municipal MSW planning and forecasting in the Canary archipelago [11]. A modeling study that uses multiple models to forecast MSW generation in China uses multiple regression analysis. The result predicts that MSW generation in China will continue to increase, with an annual growth rate of approximately 3% [12]. The study uses a system dynamics model to simulate plastic waste generation in India over a 50-year period [13]. The model incorporates population growth, economic development, plastic consumption, and waste management practices. The results suggest that without intervention, the amount of plastic waste generated in India will continue to increase rapidly, leading to environmental hazards such as pollution and public health risks. Another study in India uses four different AI models, including ANN, decision trees (DT), random forests (RF), and support vector regression (SVR), to develop a forecast model for MSW generation [14]. The study evaluates the performance of each model and compares their accuracy in forecasting MSW generation. The study results suggest that the ANN model is the most accurate in forecasting MSW generation, followed by the SVR, RF, and DT models.

Waste can be said to be one of the problems faced by many cities around the world, including Indonesia. In Indonesia, according to law number 18 of 2008 concerning waste management, waste is the residue of daily human activities and natural processes in the solid form [15]. Increasing population can cause activities in urban areas to increase, as well as the waste produced. This makes it difficult for the Department of the Environment (DLH) to manage waste, so a predictive study is needed to be appropriately managed. This is crucial for the proper planning and management of waste disposal systems. One method that has shown promise in waste prediction is the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS is a hybrid artificial intelligence technique that combines the advantages of fuzzy logic and neural networks. ANFIS has been successfully used in various applications, including waste prediction, because this method is adaptive, which means that if there is a change in parameter values, it will be connected to existing neurons in getting accurate prediction results [16]. In this context, ANFIS can be used to develop accurate models for waste prediction by analyzing various factors influencing a waste generation, such as population growth, economic development, and waste management practices.

The use of ANFIS in waste prediction can help waste management authorities make informed decisions regarding the design and operation of waste disposal systems, thereby minimizing the impact of waste on the environment and public health. This paper will review the application of ANFIS in waste prediction and its potential for improving waste management practices to assist DLH Samarinda City, East Kalimantan, in adequately organizing the volume of landfill waste. This article consists of the motivation for writing articles in the first part. Second, it describes the working model of the ANFIS method. Third, analysis of the experimental results. The conclusion of the research is at the end.

II. Method

A. Data Collection

The data used in this study is data on the volume of waste dumps in Samarinda City. Samarinda City is the capital of East Kalimantan, with an area of 718 km2. The period of the waste collection dataset used was from January 2012 - December 2018, with a total of 840 data. The dataset consists of 10 Samarinda City sub-districts, as seen in Table 1.

Table 1. 10 Samarinda city sub-districts

Subdistrict	An Area (km^2)
Palaran	182.53
Samarinda Seberang	12.49
Samarinda Ulu	22.12
Samarinda Ilir	17.18
North Samarinda	229.52
Sungai Kunjang	69.23
Sambutan	100.95
Sungai Pinang	34.16
Samarinda City	23.69
Loa Janan Ilir	26.13

Meanwhile, population growth continues to increase every year. According to the Central Statistics Agency for Samarinda City, in 2018, the population reached 858,931 people. From 2012-2019 the volume of waste piles in Samarinda City experienced fluctuating changes along with population and industry growth. There are 5:2 and 6:1 data usage ratio scenarios.

B. Data Normalization

Based on the principle of an intelligent system, the data on landfills' volume is first normalized [17]. Data normalization is changing the scale of data within a specific range so that the data has a more balanced distribution and can be processed more effectively by machine learning algorithms. Data normalization helps fix scale issues in data, where some features/variables can have an extensive range of values compared to others, thereby affecting machine learning models' analysis and prediction results. Data normalization can also help speed up the model training process, reducing the number of iterations required and increasing prediction accuracy. The normalization used in this study is min-max normalization. Meanwhile, the normalization formula as in (1) with a range of values [0–1]. After obtaining the predicted results, the data will be denormalized to return the initial values [18].

$$X_{norm} = \frac{x' - \min(x)}{\max(x) - \min(x)} \tag{1}$$

where, X_{norm} are the results of normalization, x' the data to be normalized, $\min(x)$ and $\max(x)$ are the minimum and maximum values for all data.

C. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is an adaptive network based on the Fuzzy Inference System (FIS), using a hybrid learning algorithm procedure. ANFIS can build an input-output based on human knowledge (IF-THEN fuzzy rules) with the proper membership function. In principle, ANFIS parameters can be separated into the premise and consequence parameters that can be adapted to hybrid training. Hybrid learning is carried out in two steps, a forward step and a backward step [19]. The following is the pseudocode for the steps in the ANFIS method.

```
Inputs: Monthly Input Data
Output: Monthly Dataset Predictions

// Begin
Initialize the antecedent parameters and consequent parameters
Define the input data and output data
Determine the number of membership functions and their parameters for each
input variable
```

```
5  Calculate the degree of membership for each input variable and membership
   function
6  Calculate the firing strength of each rule based on the degree of
   membership of each input variable
7  Normalize the firing strength of each rule
8  Calculate the weighted average of the consequent parameters for each rule
9  Calculate the output of the system by summing the weighted averages of the
   consequent parameters for each rule
10 Use a training algorithm to adjust the antecedent and consequent parameters
   to minimize the error between the predicted output and the actual output
11 Repeat steps 4-9 for each input-output pair in the training data
12 Test the trained model on new input-output pairs and evaluate its
   performance.
13 // End
```

The network to be implemented uses ANFIS with the Sugeno model. In the Sugeno model, each fuzzy rule predicts the output as a linear function of the input variables. In this experiment, the test parameters used can be seen in Table 2.

Table 2. Variable test parameter value

Parameter	Mark
Number of MFs	2, 3
MF type	trapmf, trimf, gbellmf
Learning Rate	0.2; 0.4; 0.6
Epoch	100
Error Rate	0.01
Step size decreases the rate	0.9
Step size increase rate	1.1

D. Predictive Accuracy

MAPE was chosen to measure forecasting accuracy. MAPE is an error measurement that calculates the size of the percentage deviation between actual data and forecast data [20]. The forecasting model will be perfect if it produces a MAPE value that is less than 10% and will be bad if it is above 50%. This study's MAPE score criteria were <10% very good, 10%-20 % good, 20%-50% good enough, and > 50% bad [21]. Meanwhile, the formula for calculating MAPE accuracy measurements can be seen in (2).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{Xt - Ft}{Xt}\right| \text{ x } 100\% \tag{2}$$

where n is the amount of data; $Xt$is the actual data for the period - t; $Ft$is the prediction of the -th period t.

III. Results and Discussion

In this part, the experimental findings of the ANFIS approach that has been employed in the process of forecasting the amount of landfill data are described. In order to make an accurate forecast of the findings based on the phases of the experiment, setting the test parameters is crucial. Following that, the testing procedure that was based on data ratios of 5:2 and 6:1 was carried out so that the outcomes of the predictions could be compared, as shown in Table 3.

Table 3 demonstrates that virtually all of the MAPE provided by the sub-districts were acceptable because their values were below 50%, with the exception of Samarinda Ulu (K3), which had a value of 56.15%. The MAPE for each individual subdistrict is represented by a separate number in each of the two current ratios. The MAPE in the Sambutan District (K7) is 4.01%, whereas the MAPE in the Sungai Kunjang District (K6) is 31.79%. This represents a ratio of 5:2 between the two districts. The MAPE in North Samarinda (K5) is the lowest, coming in at 3.37%, while the MAPE at K3, which comes in at 56.15%, is the highest. As compared to the 6:1 ratio, the overall findings indicate that the 5:2 ratio has a better average MAPE value (14.61%) than the 6:1 ratio (22.36%). Predictions of waste volume for 2019 have been established based on the findings of the most accurate ratio that is currently available; these forecasts are provided in Table 4.

Table 3. MAPE testing 10 districts in Samarinda City

Subdistrict	Code	Ratio 5:2	Ratio 6:1
Palaran	K1	10.35%	9.95%
Samarinda Seberang	K2	9.61%	9.23%
Samarinda Ulu	K3	19.37%	56.15%
Samarinda Ilir	K4	6.62%	3.37%
North Samarinda	K5	6.62%	3.36%
Sungai Kunjang	K6	31.79%	45.24%
Sambutan	K7	4.01%	4.00%
Sungai Pinang	K8	24.88%	44.25%
Samarinda City	K9	15.22%	4.62%
Loa Janan Ilir	K10	17.60%	43.41%

Table 4. Prediction results for the volume of landfills for ten districts in Samarinda City in 2019

Month	Prediction of Waste Stockpiles Volume (m^3) in 2019									
	K1	K2	K3	K4	K5	K6	K7	K8	K9	K10
January	5198	7157	10445	6176	10993	10269	5723	8928	6449	3047
February	5131	7505	10345	6124	11115	10269	5943	8874	6472	3047
March	5092	7824	10292	6090	11242	10269	6138	8851	6492	3047
April	5068	8092	10265	6067	11375	10269	6316	8842	6507	3047
May	5055	8305	10252	6053	11511	10269	6398	8838	6520	3047
June	5048	8468	10244	6044	11647	10269	6436	8836	6529	3047
July	5044	8589	10241	6038	11779	10269	6453	8835	6537	3047
August	5041	8678	10239	6034	11905	10269	6461	8835	6544	3047
September	5040	8743	10238	6032	12019	10269	6464	8835	6549	3047
October	5039	8789	10238	6030	12119	10269	6466	8835	6553	3047
November	5039	8822	10237	6029	12204	10269	6467	8835	6556	3047
December	5039	8846	10237	6029	12273	10269	6467	8835	6559	3047
Total	**60834**	**99818**	**123273**	**72746**	**140182**	**123228**	**75732**	**106179**	**78267**	**36564**

According to Table 4, it is known that there is a monthly variation in the total volume of garbage heaps across all of the subdistricts. Both the Sungai Kunjang Subdistrict (K6) and the Loa Janan Ilir Subdistrict (K10) have the same amount of expected monthly volumes over a period of one year, which comes out to 10,269 m3 and 3,047 m3, respectively. The most major garbage mounds, totaling 140,182 m3, are located in the North Samarinda Subdistrict (K5) after one year. In the meanwhile, the Loa Janan Ilir District (K10) has a limited number of garbage heaps that are less than 36,564 m^3.

From the prediction results using ANFIS for the volume of landfills in 10 sub-districts in Samarinda City in 2019 in Table 3, several suggestions can be submitted to deal with waste problems. (1) Evaluate the waste management system in each sub-district to reduce the volume of waste heaps produced. This can be done by improving the waste collection, sorting, and processing systems to make them more efficient. (2) Campaign to reduce waste at the source at the individual and community levels. This can be done by educating about good and correct waste management and promoting using recycled products. (3) Improvement of waste management infrastructure in each sub-district, such as constructing appropriate final disposal sites and constructing more effective and efficient waste processing facilities. Thus, it is expected to reduce the volume of landfill waste generated and reduce the negative impact of waste disposal that is not appropriately managed.

IV. Conclusion

Predictions using ANFIS for the volume of landfill waste in 10 sub-districts in Samarinda City, East Kalimantan Province, generally have MAPE that is not bad. The average MAPE for 2018 at a data ratio of 5:2 is 14.61 %, and a data ratio of 6:1 is 22.36 %. The 5:2 data ratio is then used to predict the volume of waste in 2019. From the results of the predictions, each sub-district experienced an increase in the volume of landfills in 2019 because the population and industry have increased. This shows that each sub-district produces predictive values for the volume of waste piles that are not much different. Some suggestions that can be submitted to deal with waste problems in each sub-district are evaluating the waste management system, carrying out waste reduction campaigns, and improving waste management infrastructure. The study's results stated that the ANFIS method was good enough to be used as a predictive method. Future research compares and optimizes the ANFIS method to produce various prediction accuracies.

Declarations

Author contribution

All authors contributed equally as the main contributor of this paper. All authors read and approved the final paper.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflict of interest

The authors declare no known conflict of financial interest or personal relationships that could have appeared to influence the work reported in this paper.

Additional information

Reprints and permission information are available at http://journal2.um.ac.id/index.php/keds.

Publisher’s Note: Department of Electrical Engineering - Universitas Negeri Malang remains neutral with regard to jurisdictional claims and institutional affiliations.

References

[1] S. Dos Santos et al., “Urban growth and water access in sub-Saharan Africa: Progress, challenges, and emerging research directions,” Sci. Total Environ., vol. 607–608, pp. 497–508, Dec. 2017.
[2] P. O. Ukaogo, U. Ewuzie, and C. V. Onwuka, “Environmental pollution: causes, effects, and the remedies,” in Microorganisms for Sustainable Environment and Health, Elsevier, 2020, pp. 419–429.
[3] J. Jambeck et al., “Challenges and emerging solutions to the land-based plastic waste issue in Africa,” Mar. Policy, vol. 96, pp. 256–263, Oct. 2018.
[4] K. O. Yoro and M. O. Daramola, “CO2 emission sources, greenhouse gases, and the global warming effect,” in Advances in Carbon Capture, Elsevier, 2020, pp. 3–28.
[5] S. M. Simkovich et al., “The health and social implications of household air pollution and respiratory diseases,” npj Prim. Care Respir. Med., vol. 29, no. 1, p. 12, Apr. 2019.
[6] J. M. Chisholm et al., “Sustainable waste management of medical waste in African developing countries: A narrative review,” Waste Manag. Res., vol. 39, no. 9, pp. 1149–1163, 2021.
[7] K. G. Boroojeni, M. H. Amini, S. Bahrami, S. S. Iyengar, A. I. Sarwat, and O. Karabasoglu, “A novel multi-time-scale modeling for electric power demand forecasting: From short-term to medium-term horizon,” *Electr. Power Syst. Res.*, vol. 142, pp. 58–73, Jan. 2017.
[8] H. Haviluddin and R. Alfred, “Performance of Modeling Time Series Using Nonlinear Autoregressive with eXogenous input (NARX) in the Network Traffic Forecasting,” Proceeding IEEE, pp. 164–168, 2016.
[9] D. Niu, F. Wu, S. Dai, S. He, and B. Wu, “Detection of long-term effect in forecasting municipal solid waste using a long short-term memory neural network,” J. Clean. Prod., vol. 290, p. 125187, Mar. 2021.
[10] O. O. Ayeleru, L. I. Fajimi, B. O. Oboirien, and P. A. Olubambi, “Forecasting municipal solid waste quantity using artificial neural network and supported vector machine techniques: A case study of Johannesburg, South Africa,” J. Clean. Prod., vol. 289, p. 125671, Mar. 2021.
[11] C. Estay-Ossandon, A. Mena-Nieto, and N. Harsch, “Using a fuzzy TOPSIS-based scenario analysis to improve municipal solid waste planning and forecasting: A case study of Canary archipelago (1999–2030),” J. Clean. Prod., vol. 176, pp. 1198–1212, Mar. 2018.
[12] L. Chhay, M. A. H. Reyad, R. Suy, M. R. Islam, and M. M. Mian, “Municipal solid waste generation in China: influencing factor analysis and multi-model forecasting,” J. Mater. Cycles Waste Manag., vol. 20, no. 3, pp. 1761–1770, Jul. 2018.
[13] Y. Van Fan et al., “Forecasting plastic waste generation and interventions for environmental hazard mitigation,” J. Hazard. Mater., vol. 424, p. 127330, Feb. 2022.
[14] U. Soni, A. Roy, A. Verma, and V. Jain, “Forecasting municipal solid waste generation using artificial intelligence models—a case study in India,” SN Appl. Sci., vol. 1, no. 2, p. 162, Feb. 2019.
[15] L. A. H. Purba and A. Erliyana, “Legal Framework of Waste Management in Indonesia,” 2020.
[16] H. Haviluddin and A. Jawahir, “Comparing of ARIMA and RBFNN for short-term forecasting,” Int. J. Adv. Intell. Informatics, vol. 1, no. 1, pp. 15–22, 2015.
[17] Haviluddin and R. Alfred, “Performance of modeling time series using nonlinear autoregressive with eXogenous input (NARX) in the network traffic forecasting,” 2016.
[18] Mislan, H. Haviluddin, S. Hardwinarto, and M. Aipassa, “Rainfall Monthly Prediction Based on Artificial Neural Network: A Case Study in Tenggarong Station, East Kalimantan - Indonesia,” Procedia - Procedia Comput. Sci., vol. 59, pp. 142–151, 2015.

[19] S. Kusumadewi and I. Guswaludin, "Fuzzy Multi-Criteria Decision Making," Media Inform., 2017.
[20] A. Pranolo, Y. Mao, A. P. Wibawa, A. B. P. Utama, and F. A. Dwiyanto, "Robust LSTM With Tuned-PSO and Bifold-Attention Mechanism for Analyzing Multivariate Time-Series," IEEE Access, vol. 10, pp. 78423–78434, 2022.
[21] A. P. Wibawa, Z. N. Izdihar, A. B. P. Utama, L. Hernandez, and Haviluddin, "Min-Max Backpropagation Neural Network to Forecast e-Journal Visitors," in 2021 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), Apr. 2021, pp. 052–058.