

Application of the ANFIS Method to Predict Satisfaction with Facilities and Infrastructure

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Abstract

Facilities and infrastructure are all movable or immovable objects or objects that are used to support every aspect of human life. Students, lecturers and office workers at least spend about half of their active hours at work. Therefore it is very important to pay attention to the high level of comfort, security, completeness in a building. There fore we need a way to predict satisfaction with facilities and infrastructure. To provide solutions to existing problems, the authors create applications that can predict the satisfaction of facilities and infrastructure. In this article, a satisfaction prediction approach based on a data-driven technique, representing system behavior using the Takagi-Sugeno model is developed. The Adaptive Neuro Fuzzy Inference System method is used to build a predictive model. The research was conducted by interview, observation and literature study. Data were taken from 92 respondents consisting of lecturers, students, and staff/employees in the research area. The test results using this method showed satisfactory results, indicating a success rate with an accuracy of 97.2%.

Keywords: ANFIS; Application; Facilities and Infrastructure; Satisfaction

1. Introduction

In supporting an activity process, both educational and performance activities in companies, management of facilities and infrastructure is needed so that these activities run well. However, there are still many facilities and infrastructure that are not suitable and insufficient to meet existing needs. Thus, management of facilities and infrastructure is needed so that educational or performance activities in companies will be able to manage facilities and infrastructure in a more conceptual and directed manner. Facilities and infrastructure have a significant influence which is one of the foundations for carrying out an activity so that it can run optimally. To find out how this influence, it is necessary to know based on the level of satisfaction. Therefore, it is necessary to have a level of satisfaction with the facilities and infrastructure by users.

Several previous studies have concluded that the role of the quality of service facilities/infrastructure and curriculum relevance variables do not meet the requirements to be a predictor of alumni satisfaction based on data [1-2]. there is research dedicated to predicting the usage patterns of one of the most prominent categories of energy-intensive establishments in Saudi Arabia, namely schools. This particular study introduces a prediction model based on linear regression, aimed at estimating the energy consumption of school buildings. Notably, this model showcases an accuracy level exceeding 95% [3]. Additionally, research findings highlight the insufficiency of sanitary facilities in the majority of schools to cater to the requirements of young girls. The inadequacy of sanitation amenities, unreliable access to water, absence of proper disposal and drying mechanisms for menstrual materials, substandard hygiene conditions, coupled with privacy deficiencies and insufficient lighting, collectively constitute the primary deficiencies observed in school sanitation provisions [4]. Subsequent to this, the research outcomes are acquired through a sequential set of stages. In order to comprehend the management of a culture centered around literacy, the researcher examined the execution of each managerial principle. These stages encompass planning, organization, execution, and oversight [5]. There are also articles proposing a methodology based on a survey of stated and stated preferences that aims to estimate the importance of different variables on the mobility of preferred users to simulate their reactions to policies such as the introduction of a new mode of transport or charging parking fees on campus. The optimization model is oriented towards two case objects, namely maximizing the number of occupied parking spaces or minimizing the amount of free space and maximizing revenue per parking space [6].

In this study, developing a prediction model for satisfaction with facilities and infrastructure. In data processing, method was performed using the Adaptive Neuro-Fuzzy Inference System (ANFIS).

2. Research Methods

2.1. Data Collection Methods

Data collection is conducted with the aim of acquiring essential information to meet the research objectives, this study employs a questionnaire as the chosen method for gathering data. The questionnaire in this study is carried out by giving a set of written the questions by the internet to respondents the answer. In this study the sampling technique is used the population-wide, by dividing the data into training data and test data. The test size is derived from comparing the mean errors for different membership types. If it is proven that ANFIS can be used to process work transcripts [7-9].

2.2. Data Processing Methods

The data processing method is carried out starting from Problem, Approach, Implementation, Development, Measurement and Result. The first stage is the Problem, determine the problems that will be discussed in this study with solutions to make prediction models for the need renewal of facilities and infrastructure. The next stage is the Approach, collecting data for data testing with the ANFIS method. The next stage is Implementation,

The factors influence facilities and infrastructure and perform sampling techniques for training data and testing. The next stage is Measurement, making a comparison of the results of different types of membership functions. In the final stage, namely Result, make conclusions from the results of the data that has been processed for satisfaction in the use of facilities and infrastructure in the future.

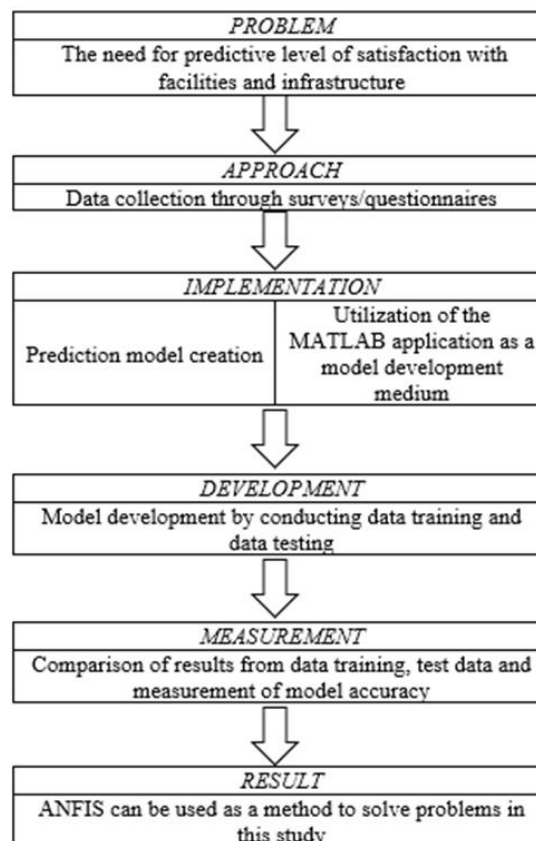


Fig. 1: Stages of the ANFIS Method

2.3. ANFIS Method

ANFIS, a neuro-fuzzy approach rooted in system input/output data, operates based on the fundamental principles of both fuzzy systems and artificial neural networks. ANFIS amalgamates a neural network and a fuzzy inference system, harnessing the complementary nature of these two algorithms to mitigate the limitations inherent in each [10-12]. Neuro-fuzzy methodology comprises the convergence of two distinct systems: a fuzzy logic system and an artificial neural network. The neuro-fuzzy system is founded upon a fuzzy inference mechanism, which is trained using a learning algorithm derived from the framework of artificial neural networks. Consequently, the neuro-fuzzy system encompasses the advantageous features present in both fuzzy inference systems and artificial neural networks. Due to its capacity to learn, this neuro-fuzzy system is often denoted as ANFIS [13-15]. The ANFIS model proves exceedingly beneficial in diverse engineering contexts, particularly when addressing incongruities or non-linearities in data, situations where traditional approaches falter or become excessively intricate. Various adaptations are introduced to optimize its functionality.

Leveraging fuzzy rule performance aids in selecting the optimal rule within the rule base, thereby reducing its size. However, the rule base generation technique employed in this study often results in a sizable rule base, particularly when dealing with high-dimensional

datasets, which subsequently diminishes the effectiveness of the reduced rule base employed following rule base induction [16-17]. The ANFIS model is configured to minimize error magnitudes.

ANFIS incorporates five significant adjustments, encompassing factors like the quantity and type of input Membership Functions (MFs), MF output, optimization strategies, and the number of epochs. The ANFIS model architecture encompasses five layers, incorporating multiple input variables, rules, and fuzzy clusters for each input variable, outlining their interconnectedness within the model. Each layer serves distinct functions in relation to the others, and this dynamic is detailed as follows:

Layer 1, often termed the fuzzification layer, ensues. This stratum encompasses a diverse array of Membership Functions (MFs) associated with each input and labeled as 'input mf'. Moreover, within this layer, the foundational fuzzy rule base is established. The essential attributes, such as the MF pertaining to each "to-i" node, are delineated within this layer as demonstrated in equation (1). In this context, 'i' represents the count of input variables, while 'A' stands for the MF that corresponds to input 'x' [18-19].

$$O_i^1 = \mu_{A_i}(x) \quad (1)$$

Layer 2 constitutes the rules layer, where every node represents distinct rules. Within this stratum, the signal received from the preceding layer undergoes multiplication, and the resultant product is transmitted, as depicted in Equation (2). Here, 'A' and 'B' represent the Membership Functions (MFs) corresponding to inputs 'x' and 'y'.

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y) \quad i = 1, 2, \dots, m \quad (2)$$

Layer 3, alternatively referred to as the normalization layer, serves the purpose of standardizing the outcomes derived from the second layer. This stage involves the normalization process for the 'i' node, as illustrated in Equation (3).

$$w_i = \frac{w_i}{w_1 + w_2 + \dots} \quad i = 1, 2, \dots, m \quad (3)$$

Layer 4 is designated as the Defuzzification layer, responsible for extracting information based on a segment of the fuzzy rules during the establishment of the connection between input and output values. This correlation is represented in Equation (4), where 'w_i' denotes the outputs originating from the third layer, and 'p', 'q', and 'r' symbolize the parameter sets associated with the inputs 'x', 'y', and 'z', correspondingly.

$$O_i^4 = w_i (p_i x + q_i y + r_i z) \quad (4)$$

Layer 5 is also known as summation layer which is referred to as 'output mf'. This layer encompasses a solitary node responsible for generating the cumulative total of all signals received from the preceding stratum. The operation of this layer is elucidated through Equation (5).

$$O_i^5 = \sum_i w_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (5)$$

3. Experimental Results

For the purpose of modeling, the selected approach within machine learning is the ANFIS technique. The training process involves a bifurcation into two distinct phases: the forward step and the backward step. In the forward step, parameter values are generated with the intent of enhancing the consequent parameters in layer four. This is achieved through the utilization of the Least Square Estimator. Conversely, during the backward step, the preceding forward step is evaluated once again, employing backpropagation and gradient descent. This process aims to refine the existing premise parameters in layer one. Processing is done by conducting training with using data train, using a grid partition with a 3 3 3 3 3 formation, data training is carried out 3 times with the first and second epochs being 200 and the third training using epoch 100, produces an error of 0.345. The initial phase of model development involves the segmentation of the dataset., then a classification is carried out where as much as 54.3% training data (50 data) and 45.7% testing data (42 data). Then upload and assign input data to the respective input arguments including: training data and test data are carried out.

Within this management approach, the training of the FIS (Fuzzy Inference System) is executed through the implementation of a grid partition, wherein the predetermined number and type of input/output Membership Functions (MFs) are employed. During the subsequent step, training is carried out using a hybrid optimization method, utilizing 50 data points. This involves employing three input membership functions with triangular shapes and linear output curves, all while maintaining a fault tolerance level of zero. The training procedure spans across 500 epochs, encompassing a total of three rounds of data training. Following the training phase, the dataset is subjected to testing, and the resultant outputs are juxtaposed to discern a comparison between the outcomes obtained from the training and testing data.

Regenerate. A comparison of the distance between the training data (blue) and the test data (red) can be seen as shown in Figure 3.



Fig. 2: Data Testing Results

The structure consists of 5 layers. The first layer has 5 inputs. The second layer is Fuzzy or the process of mapping crisp (numeric) values into fuzzy sets and determining the degree of membership in the fuzzy sets, in processing this data every single input has three membership functions. The third layer is the determination of weights. The fourth layer is the normalization of the weights. The fifth layer is the calculation of the fuzzy output level, and the last is Defuzzification. After the training is complete, the model will show an error in the training. If the training error is unacceptable, then the process is repeated by changing the MF and epoch.

The prediction model to determine the level of satisfaction with facilities and infrastructure is built using ANFIS, built with 5 inputs (PB is Planning and Budgeting, PDN is Procurement, INV is Inventory, PHN is maintenance, PHS is Elimination) with each variable having 3 neuros and one output in the form of satisfaction with the facilities and infrastructure on the fuzzy interface.

There is a combination of five inputs for each input variable with an output of 243 rules. In the experiments that have been carried out, the developed structure of the ANFIS model is 5 15 243 243 1.

Number 5 as the number of input variables, 15 as the sum of each member function, 243 as the number of rules obtained from the input, 243 as the number of rules obtained from the output, and 1 as the output.

The rule viewer shows the results of the planning and budgeting parameter with a value of 36.5, Procurement parameter with a value of 39.5,

Inventory parameter with a value of 27.5, maintenance parameters with a value of 44.5, usage parameters with a value of 25 and control parameters of 35.9. After the ANFIS model is trained, model optimization continued to be validated with 45.7% of the test dataset. The value generated by ANFIS is extracted and then compared with the output results or those that become the dependent variable using a comparison chart, from the prediction comparison graph between actual data and ANFIS test results, it can be seen that in general the results of ANFIS determination are close to the actual values. These results indicate the test results are of very good value and the comparison of actual data with predictive data.

The result of the average output is 30.45 while the average result of ANFIS is 32.8. The average results are then used to find absolute results to determine the accuracy of the data between the ANFIS results and the questionnaire. The results of this accuracy show a value of 97,2% which can be concluded that the data obtained is good enough as a basis for predicting or knowing the results of satisfaction of facilities and infrastructure.

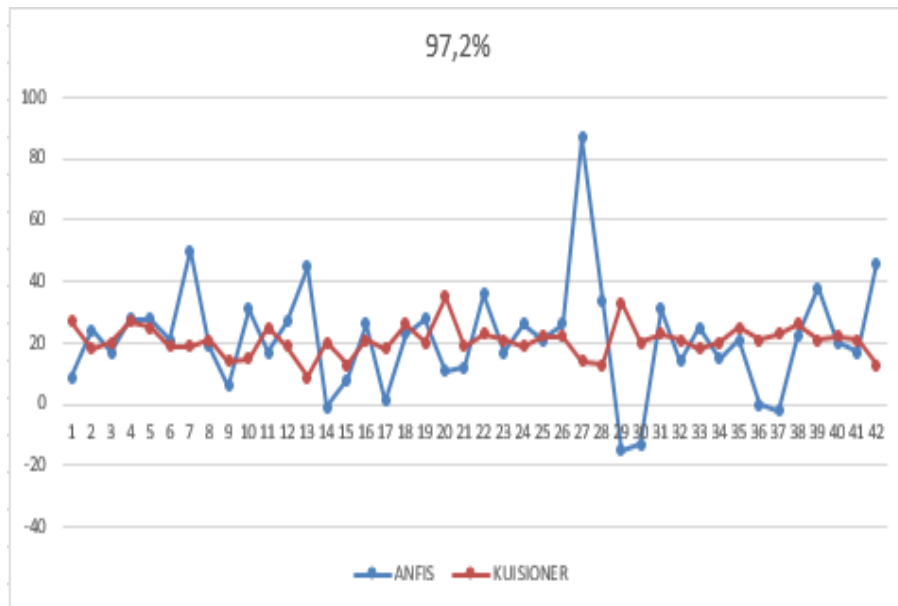


Fig. 3: Comparison Of ANFIS results with a questionnaire

The view surface shows a comparison between the two inputs to one output based on data on the assessment of the satisfaction level of facility and infrastructure management. The view surface shows the planning and budgeting variables at coordinates (27.5) and the procurement variable at coordinates (25) compared to the output of the usage variable (output).

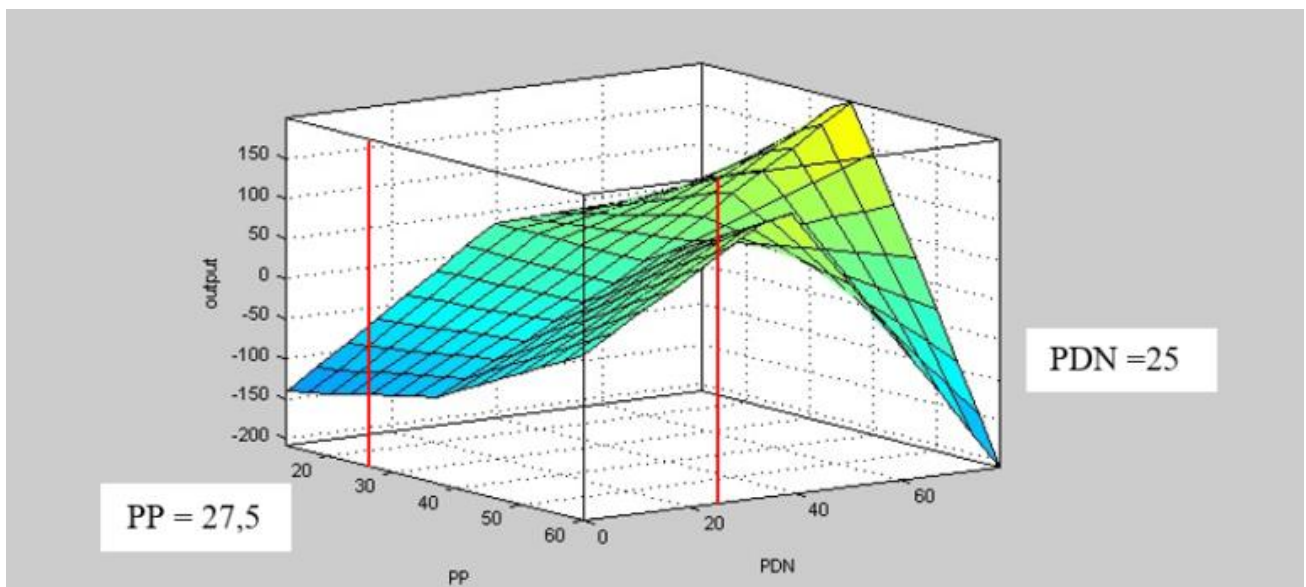


Fig. 4: View Surface Effect of Input on Output

4. Conclusion

Based on the study results from the data that has been tested using the ANFIS method, the data accuracy rate is 97,2%. For each variable, comparison of planning and budgeting to use = Good, procurement against use = Good, inventory against use = Good, maintenance of use = Good, removal against use = Good. From the results of the accumulation of all input variables to output it produces a value of 36.9 which means good.

References

- [1] R. Wiranto and S. Slameto, "Alumni satisfaction in terms of classroom infrastructure, lecturer professionalism, and curriculum," *Heliyon*, 7(6), e06679, 2021.
- [2] K. Hamdi, "Analysis of Student Satisfaction with School Infrastructure Using Fuzzy Logic. *Journal of Applied Science and Technology*," 11(3), 208-219, 2017.
- [3] A. Mohammed, et al, "A regression-based model for estimating the energy consumption of school facilities in Saudi Arabia," *Energy and Buildings*, 237, 110809, 2021.
- [4] J. Mchenga, E. Phuma-Ngaiyaye, and V. Kasulo, "Do sanitation facilities in primary and secondary schools address Menstrual Hygiene needs? A study from Mzuzu City, Malawi," *Physics and Chemistry of the Earth, Parts A/B/C*, 115, 102842, 2020.

- [5] S. Marmoah and S. Jenny Indrastoeti Siti Poerwanti, "Literacy culture management of elementary school in Indonesia," *Heliyon*, 8(4), e09315, 2022.
- [6] L. dell'Olio, et al, "A methodology based on parking policy to promote sustainable mobility in college campuses," *Transport Policy*, 80, 148-156, 2019.
- [7] M. Turnip, A. Dharma, HH. Pasaribu, M. Harahap, MF. Amri, MA. Suhendra, and A. Turnip, "An application of online ANFIS classifier for wheelchair based brain computer interface," In 2015 International Conference on Automation, Cognitive Science, Optics, Micro Electro-Mechanical Systems, and Information Technology (ICACOMIT) (pp. 134-137). IEEE, October 2015.
- [8] A. Turnip, D. Soetraprawata, M. Turnip, and E. Joelianto, "EEG-based brain-controlled wheelchair with four different stimuli frequencies," *Internetworking Indonesia Journal*, 2016.
- [9] VC. Dewi, V. Amrizal, FEM. Agustin, "The use of the anfis method (adaptive neuro fuzzy inference system) in paper age prediction applications," 2015.
- [10] SA. Andayani, S. Umyati, GM. Tampubolon, AY. Ismail, U. Dani, and A. Turnip, "Prediction model for agro-tourism development using adaptive neuro-fuzzy inference system method," *Open Agriculture*, 7(1), 644-655, 2022.
- [11] S. Jaypuria, TR. Mahapatra, and O. Jaypuria, "Metaheuristic tuned ANFIS model for input-output modeling of friction stir welding," *Materials Today: Proceedings*, 18, 3922-3930, 2019.
- [12] M. Turnip, et al, "Medical Robot Covid Orientation using IMU with PID Controller," *Internetworking Indonesia Journal Vol.13/No.1*, 2021.
- [13] D. Frayuda, et al, "Development of a Decision Support Management System for the Assessment of Personnel Quality in the Rembang Education Office Using the ANFIS Algorithm," *Journal of Science and Informatics Engineering Applications*. 6-17, 2020.
- [14] Firdusi, et al, "Policy analysis and management of basic education related to standard facilities and infrastructure policies in elementary schools," *Journal of Educational Sciences Vol 2 No 2* of 2020.
- [15] T. Rohana "Study of the Adaptive Neuro-Fuzzy Interface System (ANFIS) in Predicting New Student Admissions at Buana Perjuangan University, Karawang," *Journal of Computer Science and Information Technology Vol 6 No 1 Year 2021*
- [16] J. El-bakkouri, H. Ouadi, and A. Saad, "Adaptive Neuro Fuzzy Inference System Based controller for Electric Vehicle's hybrid ABS braking," *IFAC-PapersOnLine*, 55(12), 371-376, 2022
- [17] S. Rajab, "Handling interpretability issues in ANFIS using rule base simplification and constrained learning," *Fuzzy Sets and Systems*, 368, 36-58, 2019
- [18] DS. Balaji and T. Jeyapooan, "Development of fuzzy model in Aqua jet peening on AL 6063-T6 alloy," *Materials Today: Proceedings*, 46, 3334-3340, 2021.
- [19] M. Ahmad, K, Rashid, Z. Tariq, M. Ju "Utilization of a novel artificial intelligence technique (ANFIS) to predict the compressive strength of fly ash-based geopolymer," *Construction and Building Materials*, 301, 124251, 2021.