Aquaculture monitoring system using multi-layer perceptron neural network and adaptive neuro fuzzy inference system

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ABSTRACT

The water quality is the most important parameter for aquatic species health and growth. The condition is very critical and is essential to monitor continuously. Poor water quality will affect health, growth and ability of the animal to survive. These also affected their harvesting yields based on the amount and size of the animal. The main water parameters such dissolved oxygen (DO), pH, temperature, salinity and turbidity are monitored and control for good water quality. The data were acquired by the developed instrument and send wirelessly through GPRS/GSM module to cloud-based database. The data were retrieved and the water quality is predicted using fuzzy logic and multi-layer perceptron. MATLAB software was used for the model which is developed based on Mamdani fuzzy interface system. The membership functions of fuzzy were generated, as well as the simulation and analysis of the water quality system. Results show that the performance of fuzzy method can improve system performance in monitoring the water quality. This system also provides alert signals to farmers based on specific limit value for the water quality parameters. This will help the breeders to make certain adjustment to ensure suitable water quality for the aquaculture system.

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1. INTRODUCTION

The system tank or pond water quality monitoring is an important element in the viability of aquaculture industry [1]. The animal urine and poop will increase in ammonia, salinity, electrical conductivity (EC), turbidity, pH and temperature of the water [1]. Dissolved oxygen (DO), ammonia (NH_3, NH_4+), nitrite (NO_2-), salinity, EC, potential hydrogen (pH), temperature, and turbidity are the primary factors that determine a healthy environment for freshwater aquaculture [2].

Traditionally the measurements of water multi-parametric quality are done manually. If contamination is suspected or detected, a sample of water is sent to laboratory for analysing the harmful substances [3]. The monitoring should be done regularly if possible daily to ensure good water quality. It also ensures that there is adequate oxygen to create a secure and favorable environment for the animal's maximum growth. Low water quality will reduce the animal growth and sometime increase number of demise, where low yields will treat the breeder survival in the industry.

Constructing an affordable and reliable water quality monitoring system is urgently needed. It will allow the industry to improve environmental control, reduce losses and improve product quality and consistency [4]. The aquaculture quality index is comprised of several factors such as DO, pH value, temperature, and ammonia nitrogen content [5]. In a study conducted by Zhang *et al*. [6] in the Zhuanghe River of China, the most significant indicators affecting water quality were found to be DO, water temperature, and pH value. Akyol *et al*. [7] studied fish farm species richness in the Aegean Sea and determined that water temperature, pH value, and DO content were the three primary factors influencing fish richness. Jafari and Khayamian [8] employed corona discharge ion mobility spectrometry (CD-IMS) in their research. An improved fuzzy comprehensive evaluation method for aquaculture water quality measurement was proposed by You [9] by creating new membership function and DO, pH, temperature and ammonia content as water quality indicator. The incorporation of internet of things (IoT) devices is useful for monitoring the requirement of aquaculture and facilitating the provision of necessary resources for fisheries as proposed by Tamim *et al*. [10] and Prasuna *et al.* [11] but they did not perform any data analysis for their system. To make the water quality measuring system portable, Putra *et al.* [12] proposed the device is incorporated into an Android-based mobile application. Their system which includes a turbidity sensor, red, green, and blue (RGB) sensor, light emitting diode (LED) light source, and electronics components is handheld but only collects data on turbidity. Based on previous studies, most are either focused on the lab-based analysis system or only focused on certain parameters. The collected data still needed to be send to the lab for analysis [12]. This paper presents the multisensory system for aquaculture water quality monitoring. It will discuss the system architecture, multi-layer perceptron (MLP) and adaptive neuro-fuzzy inference system (ANFIS). The data are being retrieved from cloud-based system and the water quality will be predicted to determine it suitability. These thus offers in situ data collection and would allow immediate corrective action to sustain good water quality.

The use of multi-layer perceptron neural network (MLPNN) and ANFIS for the prediction of water quality is proposed. Neural network and fuzzy logic are two popular artificial intelligent (AI) prediction techniques. While neural networks are replicated models of biological networks made up of neurons [6], fuzzy systems are built on linguistic concepts that resemble human behaviour or reflection [13]. Particularly in weather forecasting, fuzzing and neural network prediction concepts are frequently combined [14]–[16]. An adaptive neuro-fuzzy inference system that functions in both language and learning choice capabilities is created using a hybrid predictor that blends fuzzy and neural networks.

Nowadays, the MLP is frequently used in soft real-time applications as an control mechanism based on AI or in order to make decision on the system. MLP prediction model is illustrated in Figure 1. In time series application, the input will be fed into a model in a serial pattern whereby input yt-1 on node one will be fed as input to node two as soon as node one receives new input yt and this input feeding pattern will carry on until all input nodes are covered [17]. In MLP as a predictor, it is restrained to be used in stationary time-series condition which its statistics do not change with time [18].

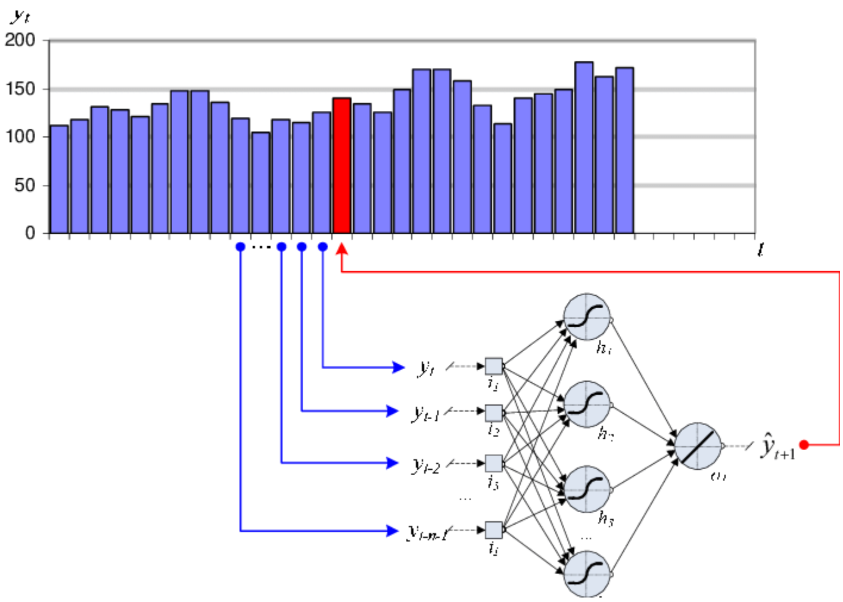


Figure 1. Time-series MLP prediction model [17]

The fuzzy logic theory and foundation, created by Zadeh, served as the basis for the fuzzy system’s implementation. The human ability to respond quickly and mentally to respond quickly and mentally to solve problems with a high degree of uncertainty without the need for intricate measurement or computation served as the original inspiration for the fuzzy logic theory [19]–[21]. By employing sets of fuzzy IF-THEN rules, fuzzy logic functions as mapping process from given input(s) to the output(s) [22]. Figure 2 shows the the basic architecture of fuzzy inference system (FIS), which consists of four major functional blocks. The rule base in this basic FIS structure is composed of the rule base, which is made up of multiple fuzzy IF-THEN rules, and the database that describes the membership function of the fuzzy sets that are used in fuzzy rules. While a defuzzification process turns fuzzy results into a crisp output, a fuzzification process transforms crisp input into degrees of matches with linguistic value. FIS executes the inference operation on the pre-defined rules in the decision-making block [23], [24].

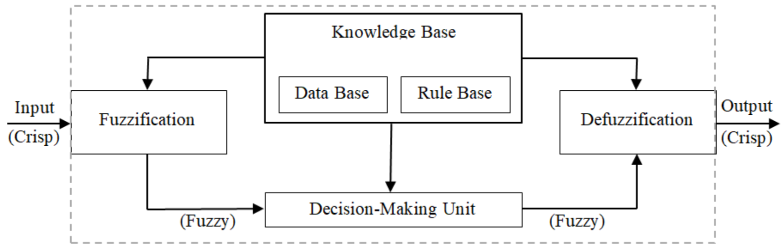


Figure 2. Structure of fuzzy inference system [25]

An artificial neural network (ANN) and a FIS are combined to create the ANFIS. By using a multi-value logical system, such as fuzzy logic, to extract hidden imprecise data, the ANFIS improves the mapping function's accuracy. The ANFIS converts the input space to an output space by means of a neural network's multilayer feedforward learning process and fuzzy reasoning [14], [26].

A reliable and effective modelling system for prediction and computation processes is produced by combining an adaptive neural network system with a fuzzy verbal decision process. Figure 3 illustrates the five layers that make up the basic structure of ANFIS which goes from the input layer to the output layer. ANFIS have the advantage of being able to gather numerical data from the expert system and fuzzy rule and use it to adaptively build a rule base. The function of the ANFIS layer was described as follows by Chang and Chang [14] and Zounemat-Kermani and Teshnehlab [26]:

Layer 1: this is the input layer where the appropriate membership function in the fuzzy set was used to generate membership grades. The definition of the layer 1 output is:

$$\mathrm{OP}_i^1 = \mu_{Ai}(x) \text{ for } i = 1{,}2 \text{ or} \tag{1}$$

$$\mathrm{OP}_i^1 = \mu_{Bi-2}(y) \text{ for } i = 3{,}4 \tag{2}$$

where x, y are the crisp input to the node I and Ai, Bi are the linguistic fuzzy set defined by the shape of the membership function µAi and µBi. The shape of the membership function can be Gaussian, generalized bell-shaped, trapezoidal, or triangular.

Layer 2: the second layer, also referred to as the rule nodes layer, applies an AND operation to the signals that are received. This second layer output OPi2 represents the firing strength of a rule and it is computed as:

$$\mathrm{OP}_i^2 = w_i = \mu_{Ai}(x) \text{ x } \mu_{Bi}(y)\ , i = 1{,}2 \tag{3}$$

Layer 3: the third layer, referred to as the average nodes layer and labeled N, is responsible for calculating the ratio and adding up the firing strengths of all the rules. The calculation of normalized firing strength will be as:

$$\mathrm{OP}_i^3 = \overline{w_i} = \frac{w_i}{\sum_1^i w_i}\ , i = 1{,}2 \tag{4}$$

Layer 4: The fourth layer served as a consequent nodes layer, using the subsequent node function to calculate each rule's contribution to the model's output:

$$\mathrm{OP}_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i) \quad (5)$$

where pi, qi, and ri are the parameters set in the consequent part of Sugeno fuzzy model and the coefficient of linear combination in (5).

Layer 5: the output layer, also known as the final layer, is the fifth layer. There is only one node in this layer, and it computes and adds up every incoming signal to the output. In this layer, the ANFIS defuzzification procedure is calculated as:

$$\mathrm{OP}_i^5 = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (6)$$

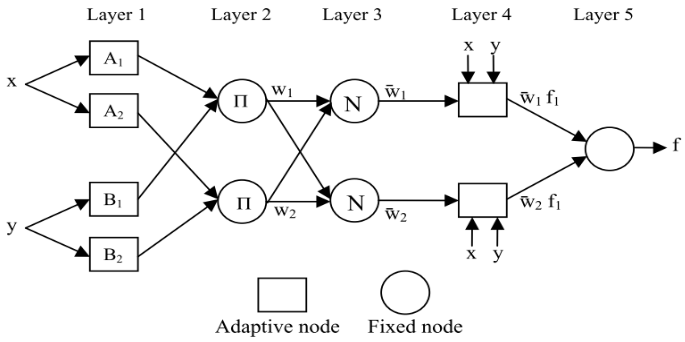


Figure 3. ANFIS basic architecture

2. METHOD

An experiment was carried out to validate the developed instrument's sensitivity and detection limit in relation to the fish tank water sample. The samples were collected from Institute Sustainable Agrotechnology (INSAT) aquaculture centre in University Malaysia Perlis. The aquaculture tanks are approximately 6.77×6.55×0.55 m and using recycling aquaculture system (RAS). The tanks are regularly clean and water is keep changing twice a week to maintain its quality. The instrument was dipped into the tanks while performing the measurement. Then the equipment was dipped into distilled water to clean its sensors. The measurement process was repeated for ten time to ensure its repeatability. Next, using a general packet radio service (GPRS)/global systems for mobile (GSM) module, the device will wirelessly transmit the average of the ten measured data points to a cloud-based database.

2.1. System architecture

A multisensory system is part of the system architecture depicted in Figure 4 and is being developed to measure water quality parameters from ponds or aquaculture tanks. The way the sensors react is similar to how our taste receptors work, sending signals from the nerves to the brain. The signal that is generated will correlate with the concentration of the water parameter. Selected water parameter sensors, an embedded controller, a signal conditioning circuit, a GSM/GPRS communication module, and a system embedded program make up the instrument.

The selected multi-sensory are DO, pH, temperature, EC and turbidity which will be generated electric signals which based on the parameter’s concentration. To improve data acquisition, the multisensory are positioned inside a close-fitting sensing chamber. The most crucial factor in the metabolic processes and breeding processes of aquatic species is DO. that, due to the oxygen's dissolved state, controls the growth rate and output yield. Depending on the species, size, temperature, diet, and movement of the animal, oxygen is needed for respiration. The level of DO can be increased through plants such as floating tree and mechanical devices e.g. paddle wheel. Lower and higher DO will reduce the growth and responsible for animal death [27]. The DO level is the main parameter to control in aquaculture system [28]. Temperature and salinity level have an impact on the amount of oxygen that can dissolve or become saturated in water [29]. The DO is measured in milligram per liter (mg/L) or parts per million (ppm). Normally the animal is comfortable with DO value around 5 to 6 ppm [30]. The system is developed using the DO Galvanic probe sensor from DFRobot which ranges from 0 to 20 ppm.

The measure of acidity or alkalinity of tank water is pH which range from 0 to 14 where 7 is considered neutral. In aquaculture farms, the pH of the water is lowered by acid formation caused by bacterial nitrification and the metabolism of aquatic organisms. The pH value also dependent on the temperature and DO [1]. A large number of animals can tolerate pH between 5 to 10, but for most of aquatic species the range is from 6.5 to 8.5 [29]. This pH range will ensure the animal health and good growth [31]. The developed system is using a pH sensor from DFRobot and the range is from 0 to 14 with 0.1 accuracy.

The water temperature affects the chemical and biological reactions of cold-blooded aquatic species. Therefore, it is important to regulate and maintain the water's temperature at a level that is healthy for the animals and promotes their optimal growth. The temperature of the water affects the animal's breathing, feeding, metabolism, growth, behavior, reproduction, detoxification rate, and bioaccumulation [10]. Most of the suitable temperature for the animal is between 20 to 35°C. To measure the water's temperature, DFRobot's DS18B20 temperature sensor is utilized. The sensor operating range is from -10°C to +85°C with ±0.5°C accuracy.

The EC sensor is used to gauge an ion's capacity to conduct electricity in water. The presence of impurities in the water tank will raise the EC value, signaling a shift in the water's salinity. Osmotic water is used to reduce the EC value if it is higher than the suitable range, and calcium carbonate solutions or salt are used to raise it if the value is lower than the range [11].

The turbidity is an indicator of environmental condition of the water. It's amount of suspended particles present in the water. This vary from silt where it is difficult to see through the water (high turbidity), to clear (low turbidity). Generally, it can be classify as classified as clear or low (turbidity less than 25 mg/l), intermediate (between 25 and 100 mg/l) and high or muddy (over 100 mg/l) [32]. Some fish species need high turbidity environment to live while some live in low turbidity. The water turbidity is measured by a DFRobot sensor.

The multi-sensory output signal of the instrument is regulated by a signal conditioning circuit before it is received by the embedded controller. The voltage follower in the circuit acts as an amplifier with a high input impedance and a low output impedance, along with a biasing network. The measurement range of the sensor output response will depend on the amplifier's impedance matching. To remove undesirable frequencies from the multisensory output signal, apply a low pass filter (LPF). A ESP32 microcontroller is used as the instrument embedded controller. The instrument multi-sensory responses profiles are called 'fingerprints' and corresponds to the water quality parameter. The onboard analog to digital converter (ADC) of the microcontroller will transform the multisensory output response into a digital signal. Data acquisition, transmission, utility, and instrument operating status are all shown on an alphanumeric liquid crystal display (LCD). A regulated 12-volt DC power supply powers the developed instrument. The data are being acquired by the instrument at periodic time-frame and send to a cloud-based database by using a GPRS/GSM module. The data being analyse using MLP and ANFIS to predict the water quality parameter value. The system will display the values of predicted water quality parameters by using tables.

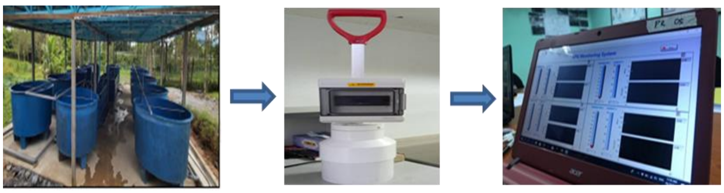


Figure 4. The system architecture

2.2. Data analytic system

The system that was based on ANFIS and MLP was used to conduct the experimental tests. Based on training, the MLP-based prediction system that is appropriate for current state classification functions. Regarding future output prediction and classification, the FIS-based system—later dubbed the ANFIS-based system—gains an adaptive neural network to aid in the learning process and provide feedback for improving the membership function and rules.

2.2.1. MLPNN system

The proposed structure of MLP predictor is shown in Figure 5, in which the body temperature, heart rate and speed are fed to the input nodes. Before feeding in the raw input, the normalisation of all input data is necessary. It is to ensure the input data has been standardised for better activation distribution. Ten hidden nodes have been selected for this model using brute force searching technique. Brute force technique is one of the simple technique to find the optimal hidden node but exhausting because of the need to going through all possible options and seeing which works the best [33].

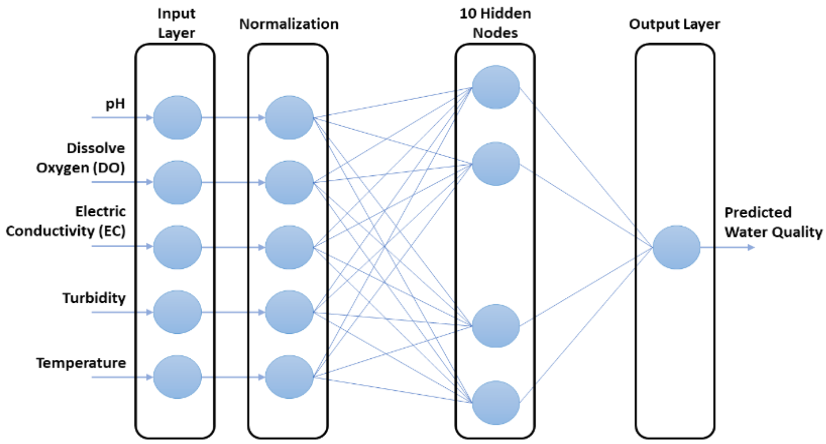


Figure 5. The MLP predictor structure

2.2.2. ANFIS system

Figure 6 uses a Sugeno-type fuzzy system to illustrate the proposed ANFIS predictor system. Using historical input data, the ANN back propagation method selected the rules as training output. The amount of data input is categorized based on the information gathered from the cloud. In order to produce a high accuracy prediction, adaptive feedback from ANN will influence the input membership function, rules selection, and subsequent parameter in the decision-making process. This system's output is used to predict the water quality, and the output from the water quality index table is used to calculate the error rate. Five distinct tanks have undergone two different test scenarios. In the first case, an additional 20% of data output was predicted using 80% of the collected data. In contrast, the second scenario forecast the 40% data output using 60% of the data that was gathered.

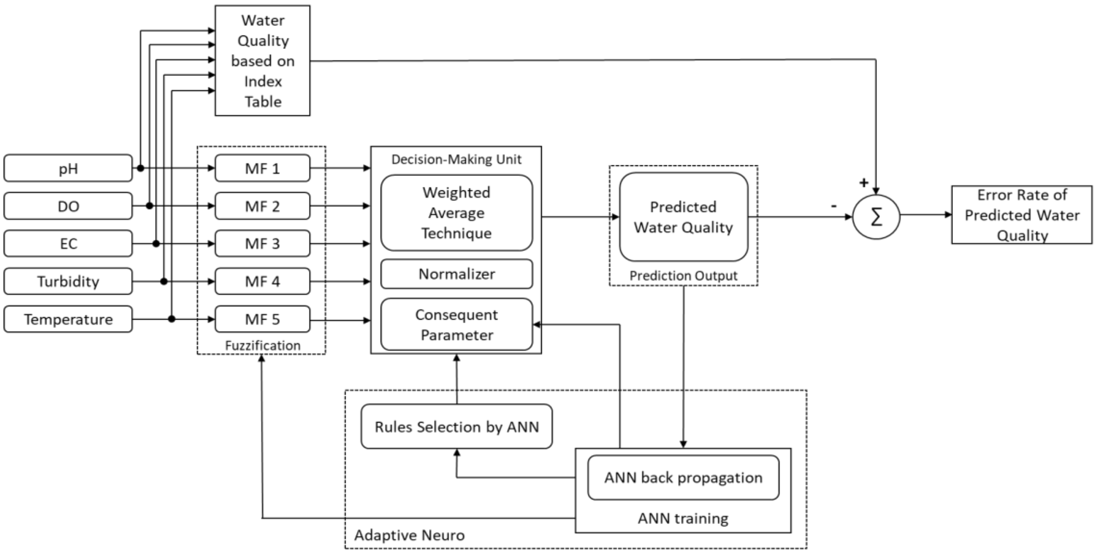


Figure 6. ANFIS-based predictor system diagram

3. RESULTS AND DISCUSSION

Tanks 1 through 5 have tested the proposed prediction system using the MLPNN and ANFIS system in an outdoor testbed. The tanks placed at Institute Sustainable Agrotechnology (INSAT) aquaculture centre in University Malaysia Perlis. The tanks are regularly clean and water is keep changing twice a week to maintain its quality. The instrument was dipped into the tanks while performing the measurement. Then the equipment was dipped into distilled water to clean its sensors. The measurement process was repeated for ten time to ensure its repeatability.

3.1. MLPNN prediction

This MLP predictor algorithm was run using matrix laboratory (MATLAB) software. Maximum iteration for each training session was set to 100 times, but with this less complexity and low historical data, since it runs in real-time condition, the epoch never hit maximum iteration for this application. The longest time taken to train data was recorded as 6 seconds for this application. The MLP predictor performance evaluation as illustrated in Figure 7 show that the epoch stop after 13 iterations and the best validation performance was recorded at 7 epoch iteration with 37.4825 MSE value.

The scatter diagram of the relationship between the predicted output and the actual output is illustrated in Figure 8. The correlation coefficient (R) was calculated to evaluate the predictor performance other than using the mean squared error (MSE) and the root mean square error (RMSE). The r=0.99633 considered a strong positive linear relationship which makes MLP predictor significant to this study.

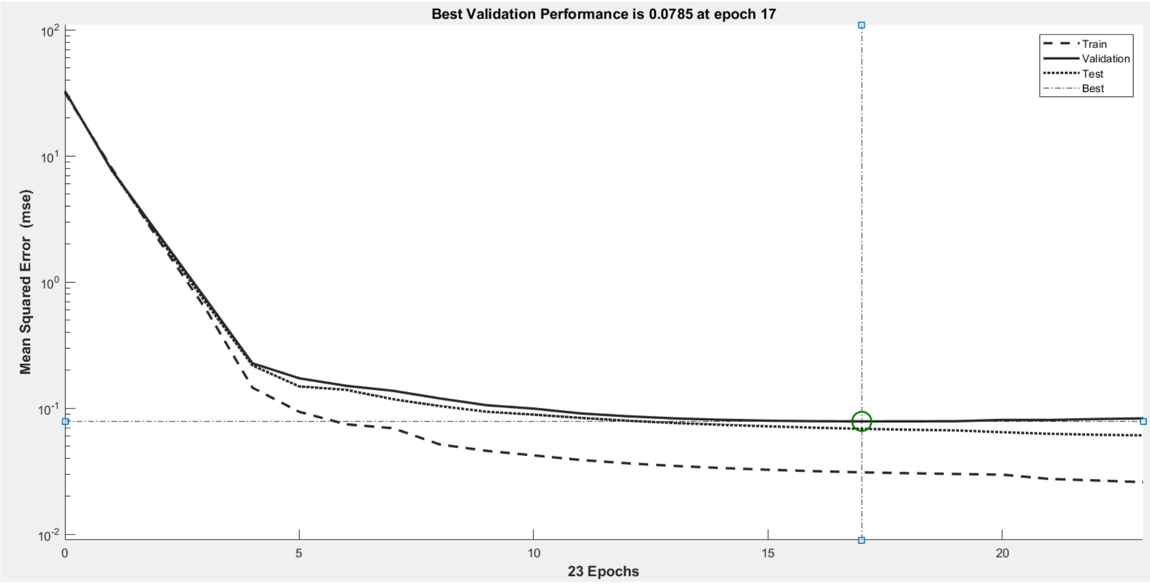


Figure 7. MLP predictor performance evaluation

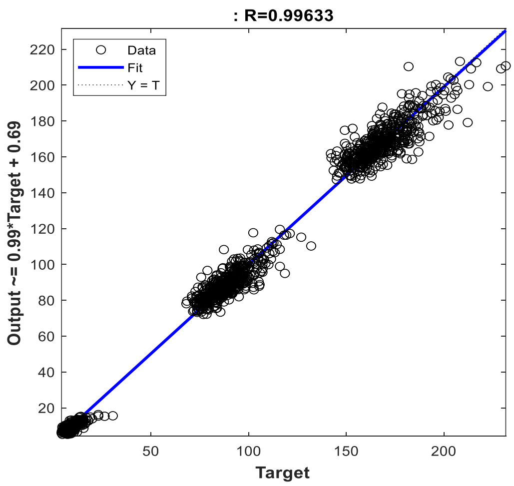
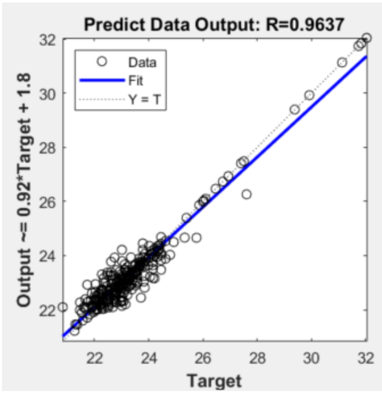


Figure 8. Relationship between predicted output and actual data using MLP predictor model

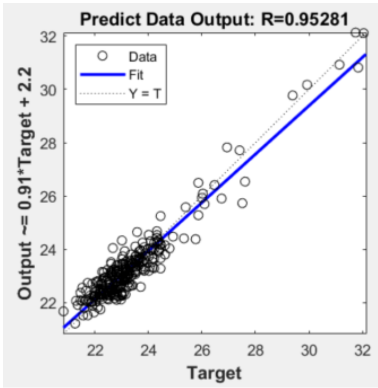
3.2. ANFIS prediction

MATLAB software was used to generate the two FIS generation methods (grid partitioning and fuzzy c-means) for all experimental test. The fuzzy c-means and grid partitioning are used because the application in this research does not need to handle large number of input parameters. The comparison between actual and target data can be view in Figure 9, where the FIS generated using grid partitioning provide a better regression with a correlation of coefficient, r=0.9637 as depicted in Figure 9(a) in comparison to the fuzzy c-means with a correlation of coefficient, r=0.9528 as shown in Figure 9(b). The regression analysis for both fuzzy c-means and grid partitioning were obtained from the comparison between ANFIS prediction output with actual cloud data.

Collected data from several laps are used as historical data to train the ANFIS system and then perform a prediction. The results from the ANFIS prediction model were shown in Figure 10. As can be seen in Figure 10(a), there is a slight difference between the target (collected historical data) and prediction output with 0.0022 MSE value and 0.047 as RMSE value as depicted in Figure 10(b). It will be a slightly higher MSE and RMSE with lower R-value for predicting output data compared to train data while developing the ANFIS predicting model due to its process and amount of historical data. For MSE, RMSE and R-value produced by this ANFIS predicting model show that it is reliable and suitable to use for this application.

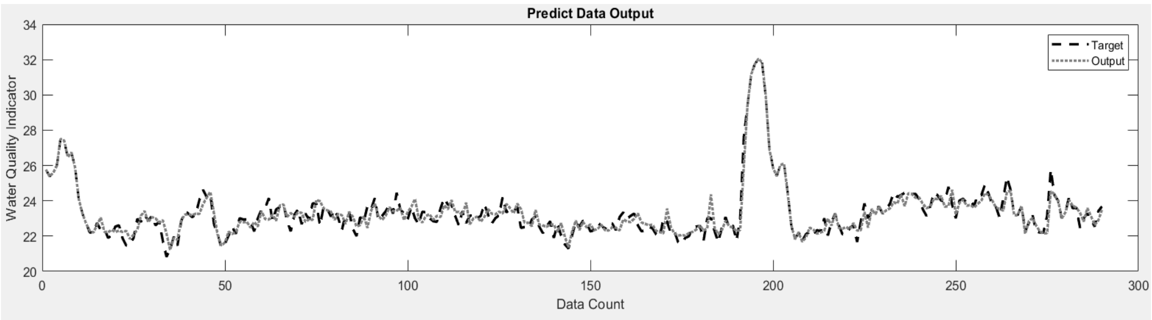


(a)

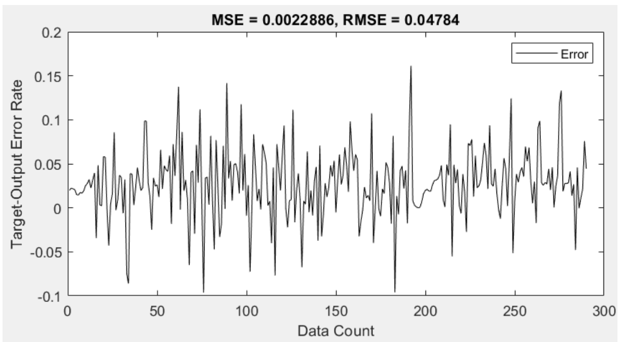


(b)

Figure 9. Comparison between actual target data and ANFIS predictor output data, (a) ANFIS using grid partioning FIS generator and (b) ANFIS using fuzzy c-means, and (FCM) FIS generator



(a)



(b)

Figure 10. Water quality data using ANFIS model (a) target (collected historical data) vs prediction output data and (b) MSE and RMSE value between the target and prediction output data

4. CONCLUSION

The current real-time input variables can be used to predict the output using MLPNN and ANFIS. The prediction process is extended in MLPNN and ANFIS to predict multiple steps ahead of the output that was learned from the preceding input. Prediction accuracy rises when a large amount of historical data is made available during the learning process. In this paper, we have successfully implemented the predictor system using the MLPNN and ANFIS model to predict the water quality. Hence the MLPNN predictor provide a better accuracy with correlation of coefficient, r=0.9963 compared to ANFIS with grid partioning FIS correlation of coefficient, r=0.9637, ANFIS predictor still reliable to use as water quality predictor since ANFIS provide less computational time compare to MLPNN.

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REFERENCES

[1] A. Masek, M. A. Rudi, and S. Sekeri, "Water quality monitoring for goldfish aquarium using IoT," *International Journal of Recent Technology and Engineering (IJRTE)*, vol. 8, no. 6, pp. 1177–1180, Mar. 2020, doi: 10.35940/ijrte.f7605.038620.

[2] V. Vishwakarma, A. Gurav, H. Patel, and S. Sahasrabudhe, "Acqua culture monitoring system," in *2018 International Conference on Smart City and Emerging Technology, ICSCET 2018*, Jan. 2018, pp. 1–4, doi: 10.1109/ICSCET.2018.8537345.

[3] F. Torán, D. Ramírez, A. E. Navarro, S. Casans, J. Pelegrí, and J. M. Espí, "Design of a virtual instrument for water quality monitoring across the Internet," *Sensors and Actuators, B: Chemical*, vol. 76, no. 1–3, pp. 281–285, Jun. 2001, doi: 10.1016/S0925-4005(01)00584-6.

[4] D. E. Helbling and J. M. VanBriesen, "Continuous monitoring of residual chlorine concentrations in response to controlled microbial intrusions in a laboratory-scale distribution system," *Water Research*, vol. 42, no. 12, pp. 3162–3172, Jun. 2008, doi: 10.1016/j.watres.2008.03.009.

[5] Y. Ma and W. Ding, "Design of intelligent monitoring system for aquaculture water dissolved oxygen," in *Proceedings of 2018 IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference, IAEAC 2018*, Oct. 2018, pp. 414–418, doi: 10.1109/IAEAC.2018.8577649.

[6] X. Zhang *et al.*, "Evaluation and analysis of water quality of marine aquaculture area," *International Journal of Environmental Research and Public Health*, vol. 17, no. 4, p. 1446, Feb. 2020, doi: 10.3390/ijerph17041446.

[7] O. Akyol, A. Özgül, F. O. Düzbastllar, H. Şen, J. M. O. De Urbina, and T. Ceyhan, "Influence of some physico-chemical variables on wild fish richness beneath sea-cage fish farms in the Aegean Sea, Turkey," *Journal of the Marine Biological Association of the United Kingdom*, vol. 100, no. 7, pp. 1171–1179, Nov. 2020, doi: 10.1017/S0025315420001034.

[8] M. T. Jafari and T. Khayamian, "Direct determination of ammoniacal nitrogen in water samples using corona discharge ion mobility spectrometry," *Talanta*, vol. 76, no. 5, pp. 1189–1193, Sep. 2008, doi: 10.1016/j.talanta.2008.05.028.

[9] G. You *et al.*, "Evaluation of aquaculture water quality based on improved fuzzy comprehensive evaluation method," *Water (Switzerland)*, vol. 13, no. 8, p. 1019, Apr. 2021, doi: 10.3390/w13081019.

[10] A. T. Tamim *et al.*, "Development of IoT based fish monitoring system for aquaculture," *Intelligent Automation and Soft Computing*, vol. 32, no. 1, pp. 55–71, 2022, doi: 10.32604/IASC.2022.021559.

[11] Y. G. Prasuna, U. N. Devi, R. Krishnaprasanna, and V. Vijayabaskar, "Development of IoT based fish monitoring system for aquaculture," *International Research Journal of Modernization in Engineering Technology and Science*, Mar. 2023, doi: 10.56726/irjmets34574.

[12] B. T. W. Putra, L. A. Rocelline, and W. N. H. Syahputra, "Embedded system in handheld water turbidity meter for smallholders," *Microprocessors and Microsystems*, vol. 93, p. 104603, Sep. 2022, doi: 10.1016/j.micpro.2022.104603.

[13] M. Blej and M. Azizi, "Comparison of Mamdani-type and Sugeno-type fuzzy inference systems for fuzzy real time scheduling," *International Journal of Applied Engineering Research*, vol. 11, no. 22, pp. 11071–11075, 2016.

[14] F. J. Chang and Y. T. Chang, "Adaptive neuro-fuzzy inference system for prediction of water level in reservoir," *Advances in Water Resources*, vol. 29, no. 1, pp. 1–10, Jan. 2006, doi: 10.1016/j.advwatres.2005.04.015.

[15] M. H. Kazeminezhad, A. Etemad-Shahidi, and S. J. Mousavi, "Application of fuzzy inference system in the prediction of wave parameters," *Ocean Engineering*, vol. 32, no. 14–15, pp. 1709–1725, Oct. 2005, doi: 10.1016/j.oceaneng.2005.02.001.

[16] H. A. Majdar and M. Vafakhah, "Monthly river flow prediction using adaptive neuro-fuzzy inference system (a case study : Gharasu watershed , Ardabil Province-Iran)," *Ecopersia*, vol. 3, no. 4, pp. 1175–1188, 2016.

[17] S. F. Crone and N. Kourentzes, "Naive support vector regression and multilayer perceptron benchmarks for the 2010 Neural Network Grand Competition (NNGC) on time series prediction," in *Proceedings of the International Joint Conference on Neural Networks*, Jul. 2010, pp. 1–8, doi: 10.1109/IJCNN.2010.5596636.

[18] T. Koskela, M. Lehtokangas, J. Saarinen, and K. Kaski, "Time series prediction with multilayer perceptron , FIR and Elman neural networks," in *In Proceedings of the World Congress on Neural Networks*, 1996, pp. 491–496.

[19] J. M. Andrić and D.-G. Lu, "Fuzzy methods for prediction of seismic resilience of bridges," *International Journal of Disaster Risk Reduction*, vol. 22, pp. 458–468, Jun. 2017, doi: 10.1016/j.ijdrr.2017.01.001.

[20] M. Neshat and A. Adeli, "A comparative study on ANFIS and fuzzy expert system models for concrete mix design," *International Journal of Computer Science*, vol. 8, no. 3, pp. 196–210, 2011.

[21] L. A. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, no. 3, pp. 338–353, Jun. 1965, doi: 10.1016/s0019-9958(65)90241-x.

[22] T. J. Ross, *Fuzzy logic with engineering applications: third edition*. Wiley, 2010.

[23] A. A. Shleeg and I. M. Ellabib, "Comparison of Mamdani and Sugeno fuzzy interference systems for the breast cancer risk," *International Journal of Computer, Electrical, Automation, Control and Information Engineering*, vol. 7, no. 10, pp. 1343–1347, 2013.
[24] M. A. Salman and N. I. Seno, "A comparison of Mamdani and Sugeno inference systems for a satellite image classification," *Anbar Journal for Engineering Sciences*, pp. 296–306, 2010.
[25] S. Sudin *et al.*, "Real-time track cycling performance prediction using ANFIS system," *International Journal of Performance Analysis in Sport*, vol. 18, no. 5, pp. 806–822, Sep. 2018, doi: 10.1080/24748668.2018.1523520.
[26] M. Zounemat-Kermani and M. Teshnehlab, "Using adaptive neuro-fuzzy inference system for hydrological time series prediction," *Applied Soft Computing Journal*, vol. 8, no. 2, pp. 928–936, Mar. 2008, doi: 10.1016/j.asoc.2007.07.011.
[27] W. Boonsong *et al.*, "Real-time water quality monitoring of aquaculture pond using wireless sensor network and internet of things," *Journal of Theoretical and Applied Information Technology*, vol. 98, no. 22, pp. 3573–3582, 2020.
[28] M. A. Romli, S. Daud, S. M. Zainol, P. L. E. Kan, and Z. A. Ahmad, "Automatic RAS data acquisition and processing system using fog computing," in *2017 IEEE 13th Malaysia International Conference on Communications, MICC 2017*, Nov. 2018, vol. 2017-November, pp. 229–234, doi: 10.1109/MICC.2017.8311764.
[29] S. R. J. Ramson, D. Bhavanam, S. Draksharam, A. Kumar, D. J. Moni, and A. A. Kirubaraj, "Sensor networks based water quality monitoring systems for intensive fish culture -a review," in *Proceedings of the 4th International Conference on Devices, Circuits and Systems, ICDCS 2018*, Mar. 2019, pp. 54–57, doi: 10.1109/ICDCSyst.2018.8605146.
[30] M. Ahmed, M. O. Rahaman, M. Rahman, and M. A. Kashem, "Analyzing the quality of water and predicting the suitability for fish farming based on IoT in the context of Bangladesh," in *2019 International Conference on Sustainable Technologies for Industry 4.0, STI 2019*, Dec. 2019, pp. 1–5, doi: 10.1109/STI47673.2019.9068050.
[31] S. Ion, V. Cristea, E. Bocioc, T. I. Ionescu, M. T. Coada, and I. Enache, "Monitoring the water quality in the aquaculture recirculating systems," *Journal of Environmental Protection and Ecology*, vol. 12, no. 4, pp. 1656–1660, 2011.
[32] M. W. Dewan, D. J. Huggett, T. W. Liao, M. A. Wahab, and A. M. Okeil, "Prediction of tensile strength of friction stir weld joints with adaptive neuro-fuzzy inference system (ANFIS) and neural network," *Materials and Design*, vol. 92, pp. 288–299, Feb. 2016, doi: 10.1016/j.matdes.2015.12.005.
[33] L. Mao and L. Jackson, "Selection of optimal sensors for predicting performance of polymer electrolyte membrane fuel cell," *Journal of Power Sources*, vol. 328, pp. 151–160, Oct. 2016, doi: 10.1016/j.jpowsour.2016.08.021.

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