International Advance Journal of Engineering Research (IAJER)
Volume 6, Issue 12 (December- 2023), PP 05-10
ISSN: 2360-819X
www.iajer.com

Research Paper **Open Access**

Development of Fault Detection and Diagnosis for Reactor Cooling System by Using Artificial Intelligent Techniques

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ABSTRACT: Reactor Cooling System (RCS) equipped with a safety system that will trigger when the reading from the sensor exceeds the threshold of normal operation. Fault Detection and Diagnosis (FDD) system is one of the safety measures that have been in ensuring the safety of the reactor. Act in giving immediate response when the faults occur and have the capability to identify the faults location. This allows the operator to react swift and according if any disturbance were to happen. In realizing this, a model-based FDD system, a system modelling and fault diagnosis algorithm need to be studied. For this study, two artificial intelligence techniques have been applied which are Adaptive Neuro Fuzzy Inference System (ANFIS) for system modelling and Artificial Neural Network (ANN) to diagnose the fault on a reactor cooling system. The ability of neural networks to learn from experience or previous data has demonstrated a significant improvement in fault detection efficiency. Additionally, a history-based strategy that is based on historical data has been shown to improve the accuracy of fault identification. As a result, complete FDD systems that successfully detect and classify 8 fault classes with performance of 96% accuracy have been developed.

Keywords - Fault Detection, ANFIS modelling, ANN classification

I. INTRODUCTION

Emergence of the artificial intelligence (AI) along the Industry 4.0 have opened a path in nuclear industry sector in investing in this technology. AI implementation in the nuclear reactor can boost its safety features. Reactor TRIGA Puspati or RTP for short is the research reactor in Malaysia that have been operated for 41 years. Thus it is essential for the reactor to be equipped with current technology especially with AI. Nevertheless, with the rise of AI technology, it is crucial to investigate technique and method that can be applied to improve the safety features of the reactor. From worldwide perspective ANN have the capability to be integrated into the reactor system, for example a study by M. El-Sefy et al. The author predict nuclear power plant dynamic behaviours by using ANN [1]. O. Akay and M. Das also applied ANN for modelling total heat transfer coefficient of the reactor cooling system [2]. This study emphasize on the reactor cooling system, in maintaining the normal temperature of the reactor. Therefore, this study is to simulate fault detection and diagnosis (FDD) on the cooling system through the implementation of neural network. FDD have a very significant role in critical and high-cost processes and operation. Early identification of process defects can help control abnormal event and prevent damages. There is the need to design a model that can identify and diagnose the fault type such that the consistent mechanism can be preserved [3][4]. To achieved that, a model-based FDD system is being developed using Artificial Intelligence (AI) technique.

II. LITERATURE REVIEW

Rahman, R. Z. A., et al. [3] discussed about the use of genetic algorithm and recursive least square in Takagi Sugeno Fuzzy model to model the non-fault and fault model for process control rig. The model is used to identify faults, potential faults, and faults that are already present. These residual signals are used ANN to identify the respective faults and decide whether the process is faulty.

2.1 MODEL BASED APPROACH

A model-based FDD system requires the users to understand the process model since it has relations on a lot of process variables. It is to obtain information on changes according to certain faults. Takagi-Sugeno-Kang (TSK) model are the most common architecture of ANFIS [5] Razavi-Far et al. [6] present a combination of neuro network and fuzzy logic method as an FDD method called neuro-fuzzy (NF) for a steam generator. The NF learning and adaptation of Takagi-Sugeno fuzzy models is being used for residual generation while Mamdani model is used for residual evaluation. NF schemes combine the ability of fuzzy reasoning in evaluating unsure data from the helps of ANN such as learning, optimisation and generalisation capabilities. As an outcome, NF model-based methods produce an excellent diagnostic result.

2.2 ADAPTIVE NETWORK BASED FUZZY INFERENCE SYSTEM

The size of the input–output data set is critical when data is limited, and data production is expensive [7]. This can be said that if the data is little, ANFIS may not be the best method to model the system. Despite the drawbacks, what make ANFIS are exceptional for modelling is that it is easy to applied, less time-consuming and have good generalization abilities [8]. Iphar [9] had presented an ANFIS model for hydraulic impact hammers. From the result, ANFIS model outperforms the ANN and classical multiple regression models in terms of prediction performance. Additionally, the ANFIS model has a smaller standard error of estimation and a larger correlation coefficient, r than the ANN or classical multiple regression models. As a result, ANFIS is the most accurate prediction method for estimating the net breaking rate of hydraulic impact hammers. ANFIS are suit to model the system due to its nature to take into account the non-linearity, noise, uncertainty effect, disturbance by preparing error models by using the network [5].

III. METHODOLOGY

In this study 2 different neural network model are develop. ANFIS model was developed for cooling system modelling while the feedforward neural network are used for classify the fault based on the residual generated. The first step is to study the existing method used that related to the project. The research is a survey stage where many methods with different approaches were being discovered and compared. It also reveals the FDD system that have been implemented in the industries and which method suits the project the most.

3.1 NONLINEAR DYNAMIC MODEL

Figure 1 shows the input and output of three sub model of the system which can be classified as multiple input single output MISO system. This project implemented model-based FDD methods which makes the system modelling extremely crucial. To construct the model for the system, a clear understanding on the nonlinear dynamic model need to be achieved.

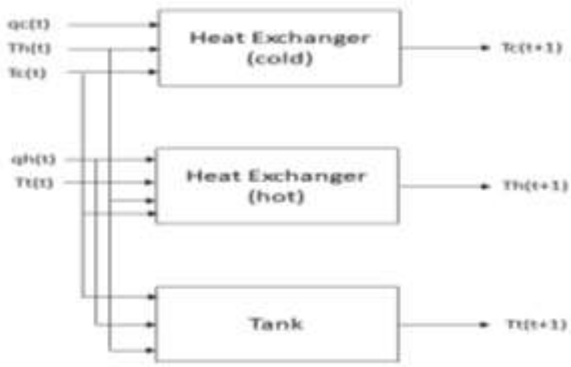

Figure 1: MISO sub system for the Reactor Cooling System

3.2 SUB SYSTEM MATHEMATICAL MODEL

The different between a process control rig from the previous research [4] and the RCS is the source of the heat from the process control rig come from a controlled heating element while the source of the heat from RCS is the nuclear element which is Uranium fuel. The model of the subsystems Tank (Tt), Heat Exchanger (Hot) (HEh), and Heat Exchanger (Cold) (HEc), can be written as in the following form:

$$\frac{dT_t}{dt} = \frac{q_h}{V_t}(T_h - T_t) + \frac{Q}{C_p \rho V_h} - \frac{UA}{C_p \rho V_h}(T_t - 300) \tag{1}$$

$$\frac{dT_h}{dt} = \frac{q_h}{V_h}(T_t - T_h) - \frac{U_h A_h}{C_{ph} \rho_h V_h}(T_h - T_c) \tag{2}$$

$$\frac{dT_c}{dt} = \frac{q_c}{V_c}(T_{ci} - T_c) - \frac{U_c A_c}{C_{pc} \rho_c V_c}(T_c - T_h) \tag{3}$$

3.3 ADAPTIVE NEURO FUZZY INFERENCE SYSTEM MODEL

The ANFIS model structure consist of 1 input layer, 3 hidden layer, and 1 output layer. Figure 2 shows the structure of ANFIS model for Heat Exchanger (Cold) sub system. The crisp input is represented in gaussian membership function at fuzzification layer. Layer 2 is fixed nodes which representing fuzzy if…then rules. Layer 3 is fixed node representing normalized firing. Layer 4 is adaptive node with linear function or defuzzification layer. The last layer is a summation layer or the output layer which will give the last predicted value for the model.

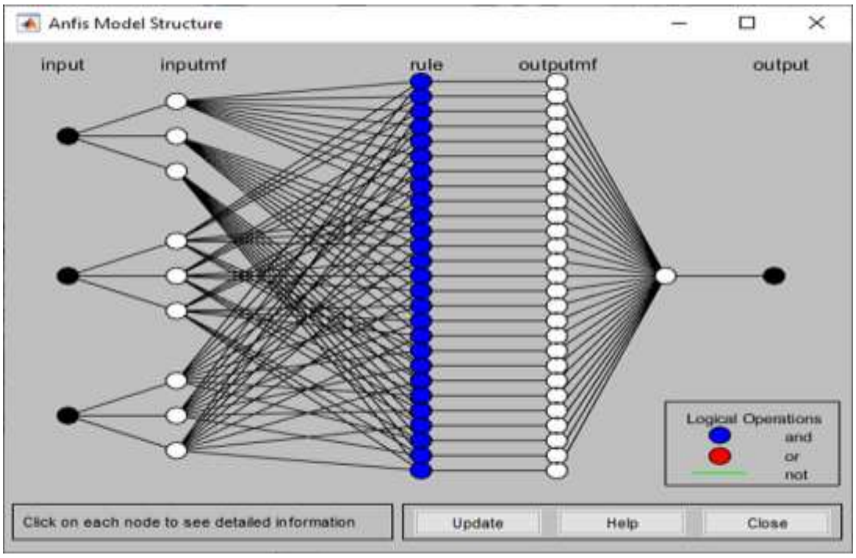

Figure 2: ANFIS Modelling System

3.4 ARTIFICIAL NEURAL NETWORK FOR FAULT CLASSIFICATION MODEL

The algorithm of ANN is based of feedforward neural network being develop using ANN toolbox application in MATLAB. One of the mostly used neural network architecture is the multi layer perceptron (MLP) with feed forward [10]. The algorithm of the Feedforward neural network are as follows:

$$a_j = \sum_i^m w_{ji} x_i \tag{4}$$

$$z_j = f(a_j) \tag{5}$$

$$y_j = \sum_i^m w_{kj} z_j \tag{6}$$

A total of 554 residual data from each fault class bring fed into the ANN model which 388 data to train the model and 166 data to test the model. The structure of ANN model for fault classification is as in figure 3. There are three layers which are one input layer, one hidden layer with 10 nodes and one output layer with 8 outputs as corresponding to 8 fault classes. The residuals are being fed into ANN model as input, which will classify it into fault class based on which fault residual is being fed as input. The outcome of a fault diagnostic can be read in such a way that the output of a particular output node is close to 1, indicating that the associated fault happened, while the output of a particular output node is close to 0, indicating that the corresponding fault did not occur.

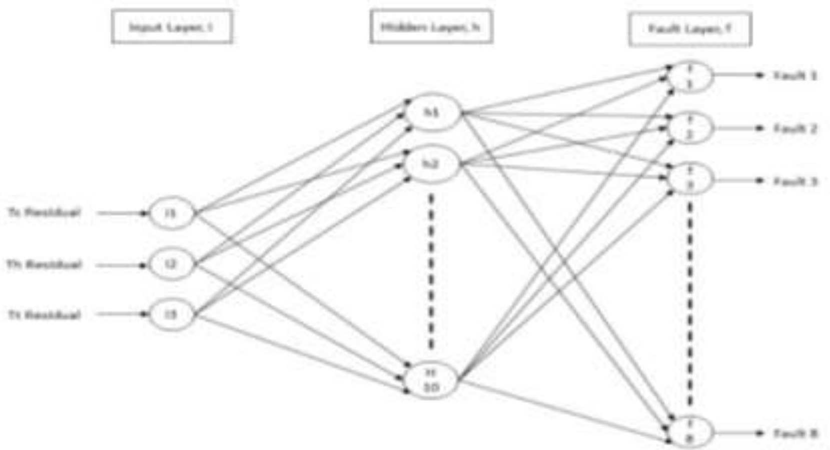

Figure 3: ANN Fault Classification Structure

VII. RESULT AND DISCUSSIONS

As the performance from completed model is good, the parameters that was set to build the model is fixed. This is because the data between normal and faulty condition is similar. Table 1 show the value of RMSE from each subsystem model.

Table 2 shows the final result with fixed parameter on learning rate, momentum rate, number of nodes at hidden layer. From the result, at epoch of 10000, it delivers the most optimum performance which is at 96.31% with MSE of 0.0055 which also the best compared to the others epoch. Despite having the most optimum performance, accuracy for fault number 4 only able to produce an overall accuracy of 77.1% for its class.

The system model performance is excellent while the overall accuracy for ANN fault classification model is good. To improve the accuracy of fault classification, the fault with low accuracy such as fault 4 need to be improve. This can be done by taking more data in order for the ANN to train better. Train more data can help the algorithm to classify the residual better. Having more data is a way to increase the accuracy of the model.

Table 1: Healthy and Faulty ANFIS Model Performance

Model	Sub model	RMSE
No Fault	HEc	0.1034
	HEh	0.47056
	Tt	0.1329
Tc Fault	HEc	0.0005
	HEh	0.5142
	Tt	0.1277
Priservalve 1 Fault	HEc	0.1059
	HEh	0.272
	Tt	0.1249
Priservalve 2 Fault	HEc	0.096
	HEh	0.2942
	Tt	0.1146
qc Fault	HEc	0.1272
	HEh	0.4973
	Tt	0.1297
qh Fault	HEc	0.1028
	HEh	0.5989

	Tt	0.1531
Th Fault	HEc	0.186
	HEh	0.006
	Tt	0.2401
The Fault	HEc	0.1164
	HEh	0.5441
	Tt	1.39E-06

Table 2: ANN Classification Overall Accuracy

EPOCH	**10000**
Learning rate	0.5
Momentum rate	0.7
Node hidden layer	10
Training MSE	0.0055
Overall Accuracy	96.3102
Class 1	100
Class 2	98.7951
Class 3	100
Class 4	77.1084
Class 5	97.5903
Class 6	96.9879
Class 7	100
Class 8	100

VIII. CONCLUSION

The fault detection and diagnosis system are successfully being developed using Artificial Intelligence technique which are ANFIS to model the healthy and faulty system and ANN for fault classification. Furthermore, the GUI for FDD platform to be implemented is also being design successfully. The consistency of the ANFIS system model performance play an important role in project's result. A total of 8 models with 24 sub system (Heat Exchanger (Cold), Heat Exchanger (Hot), Tank) shows good result with RMSE of lower than 1. The performance of the FDD system developed on this project deliver 96.31% overall accuracy which considered as acceptable performance. The accuracy of FDD system is critical as it serve as the first layer of process plant safety that cannot afford a failure and give a false alarm to the operator.

ACKNOWLEDGEMENTS

This research was supported by the International Atomic Energy (IAEA) Research Grant and Universiti Putra Malaysia Grant.

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