Estimation of fuel temperature reactivity coefficient of a research reactor using ANFIS

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Abstract. Fuel Temperature reactivity coefficient is one of the important operational and safety parameters in nuclear reactors to monitor for normal operation and transient safety analysis in research as well as in power reactors. The aim of this work is to estimate the temperature reactivity coefficient by using adaptive neuro-fuzzy inference system (ANFIS) as a preliminary assessment for developing an online monitoring system in research reactors such as the Reactor TRIGA PUSPATI (RTP). The input for the learning mechanism is the fuel temperature recorded at Ch A of the instrumented fuel element (IFE) and control rod positions with the fuel temperature reactivity coefficient as the targeted output. The ANFIS model was validated using testing data that consisted of fuel temperature measured at Ch B and results on -0.00571 °C⁻¹ (-3.997 pcm °C⁻¹) of actual output and -0.00592 °C⁻¹ (4.144 pcm °C⁻¹) of predicted output. Through the developed model, it showed that the ANFIS also can be used as a tool to estimate the fuel temperature reactivity coefficient with good prediction and accuracy shown from the calculation of mean absolute error (MAE) of 0.00349.

1. Introduction
Temperature reactivity coefficient is one of the important operational and safety parameters in nuclear reactors for monitoring of normal operation and transient safety analysis in research as well as in power reactors [1]. Fuel temperature is one of the main operating parameters that affect the reactivity during reactor operation. When there are changes in the fuel temperature, the reactivity will also be affected. This affected reactivity is called the reactivity feedbacks and characterized as reactivity coefficients. The reactivity coefficient can be defined as the change of reactivity per unit change in some operating parameter of the reactor. In this work, the operating parameters chosen is fuel temperature data which measured by instrumented fuel element in Reactor TRIGA PUSPATI (RTP) core. One of the basic safety aspects for TRIGA reactor is the fuel temperature coefficient [2]. The reactors were inherently designed with negative temperature reactivity coefficient that automatically reset the reactor back to stability in any case of power excursion event.

In TRIGA reactor, the fuel element consists of uranium zirconium hydride (UZrH) which characteristically to have large negative fuel temperature coefficient. When the temperature of the hydride rises, the probability that a thermal neutron in the fuel element will gain energy from the excited state of an oscillating hydrogen atom in the lattice will also increase. As the neutrons gain energy from the ZrH, the thermal neutron spectrum in the fuel element shifts to a higher average
energy which causes the neutron spectrum to harden [3]. Besides, increases in fuel temperature will affect the Doppler broadening due to the increased resonance capture reaction rate in U-238. In TRIGA Doppler effect contributes less than half to total fuel temperature reactivity effect [4].

The fuel temperature reactivity coefficient (FTC) is one of the important safety parameters as it implies the neutron population in the reactor core during fission process to ensure safe and efficient reactor operations. As such, development of the online monitoring system at IRP-R1 TRIGA reactor that monitors the parameters such as control rod worth, reactor temperature reactivity coefficient and the loss of reactivity during reactor operation were previously initiated [5-7]. The developed monitoring system depend on the equations that were used in the data acquisition and processing system installed at one of the instrumented fuel rods in the reactor core.

In Rabir [8] works, the measurement of the fuel temperature reactivity coefficient, $\alpha_T$ at RTP has been conducted by measuring the reactor power, fuel temperature, and the control rod positions. The results were approximately $-6.925 \text{pcm} \degree\text{C}^{-1}$ of the average temperature reactivity coefficient which is 30% lower than the safety limit given in Safety Analysis Report (SAR). The method was done through offline mode by using Equation 1 where the reactivity change, $\Delta \rho$ was obtained from the calibrated control rod curve and the $\Delta T$ were measured using instrumented fuel elements. However, this method is not feasible for the online monitoring system of research reactors. Thus, in this study, the goal is to develop a new methodology to estimate the temperature reactivity coefficient by using adaptive neuro-fuzzy inference system (ANFIS) for the preliminary assessment of online monitoring system in research reactors.

$$\alpha_T = \frac{\Delta \rho}{\Delta T}$$

2. Materials and Method

2.1 ANFIS

In nuclear industries, the artificial intelligence (AI) has been used widely in the monitoring system, fault detection system, nuclear reactor safety analysis, and others [9-12]. ANFIS is one of the soft computing techniques that combine the fuzzy system and neural network method which can be effectively used due to the easy interpretability of fuzzy logic, as well as the superior learning ability and adaptive capability of neural networks [13]. ANFIS can serve as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions, $\mu_f$ to generate the stipulated input-output pairs. The integrated technique combines both methods’ advantages and also eliminates their disadvantages which then are capable to be used as a new flexible tool to predict fuel temperature reactivity coefficient.

As studied by Salman et. al in [9], the ANFIS method has proven to be an excellent function approximation tools to predict the critical heat flux with high accuracy. Besides, works done by Antio et. al in [10] showed that the ANFIS has also been used to predict the power peaking factors accurately and in real time. As studied by Man Gyun Na et. al in [11], the prediction of power peaking factor has also been estimated using the fuzzy neural network which is suitable for local power density monitoring. Similarly, this study was intended to utilize ANFIS that can predict the fuel temperature reactivity coefficient at RTP using online fuel temperature and control rod positions measurements.

2.2 ANFIS Architecture

ANFIS or Sugeno-type fuzzy inference system (FIS) is chosen in this study as it is simple in computation and easy to be combined with optimizing and self-adapting methods [13]. The Sugeno-type FIS has been proposed by Tagaki and Sugeno, and by Sugeno and Kang [15]. Initially, Tagaki and Sugeno proposed to use fuzzy IF-THEN rules as followed:

$$L^{(0)}: \text{IF } x_i \text{ is } F_i^l \text{ and } \ldots \text{ and } x_n \text{ is } F_n^l, \text{ THEN } y^l = c_0^l + c_1^l x_1 + \ldots + c_n^l x_n$$  (2)
where \( F_i \) are fuzzy, \( c_i \) are real-valued parameters, \( y^r \) is the system output due to rule \( L^{(i)} \), and \( i = 1, 2, \ldots, M \). ANFIS architecture consists of five layers as shown in Figure 1 below. A Circle and square in Figure 1 reflect the adaptive capabilities in which the circle indicates fixed node while square specifies the adaptive node that can change the parameters during training.

In Figure 1, there are two inputs labelled as \( x \) and \( y \) with the targeted output of \( z \). Each node in the first layer generates a membership grade while nodes in the second layer calculate the firing strength of the rule. Next, nodes in the third layer calculate the ratio of the 1 and 2 rule’s firing strength to the total of all firing strength. In the fourth layer, each node is an adaptive node which maps to the output membership functions. The node in the fifth layer gives the overall output [13].

Figure 1. ANFIS architecture [10].

2.3 Methodology
The data input for the training and checking procedures are the four control rod positions and fuel temperature measured from the instrumented fuel elements of Channel A and Channel B. The targeted output is calculated using Equation (1). The reactivity change is determined from the calibrated control rod curve by considering each critical rod position, before and after each step. The error of the reading is estimated in ±0.1 cents, mainly due to the uncertainty in rod position [8].

The development of the network is constructed using Neuro-Fuzzy Designer toolbox in MATLAB software. The training and checking procedure for the model are shown in the flowchart in Figure 2. In this study, there are two types of membership function that are chosen in each FIS model which are \textit{gaussmf} in Model 1 and \textit{gauss2mf} in Model 2 as stated in Table 1 below. Figure 3 shows each of the membership function shapes for all inputs and Figure 4 displays the final membership function after the training session.

The optimization method used in this training procedure is hybrid which consists of two parts of the gradient method and least square method. The gradient method is applied to the calculation of input membership function parameters whereas the least square method is applied to the calculation of output function parameters [2]. The checking data was used to validate the FIS model developed.
during the training procedure and can be loaded before starting the training session. The purpose of having checking data associated with training data is to represent the point of overfitting in the developed model. The overfitting can occur during the training procedure, when the checking error should decrease but somehow at a certain point, increase. Then, the modelled FIS can be validated when the root mean square error for checking data decreases as the training begins. Table 1 shows the details used for training and validating the FIS model. The least checking error of the model was later used for estimating the fuel temperature reactivity coefficient.

![Flowchart for training and checking session of ANFIS in Neuro-Fuzzy Designer GUI.](image)

**Figure 2.** Flowchart for training and checking session of ANFIS in Neuro-Fuzzy Designer GUI.
Table 1. ANFIS input details before training sessions.

| Model | 1 | 2 |
|-------|---|---|
| No. of $\mu_f$ | 2 2 2 2 2 2 2 2 2 2 | 2 2 2 2 2 2 2 2 2 2 |
| Input 1 | gaussmf | gauss2mf |
| Input 2 | gaussmf | gauss2mf |
| Input 3 | gaussmf | gauss2mf |
| Input 4 | gaussmf | gauss2mf |
| Input 5 | gaussmf | gauss2mf |
| Shape of $\mu_f$ | | |
| Type of $\mu_f$ | Output | Linear |
| Training method | Hybrid | Hybrid |
| Epochs | 500 | 500 |

Figure 3. FIS model with different membership functions before training session: (a) gaussmf shape (b) gauss2mf shape.
Figure 4. FIS model with different membership functions after the training session: (a) gaussmf shape (b) gauss2mf shape

3. Results
Table 2 lists the information from the ANFIS training procedures which show performance of the model on predicting the outputs. Model 2 shows the overfitting characteristic which makes the selection of membership functions not the best choice for modelling the training data. The overfitting occurs due to the sudden increases in checking error during the training session. Figure 5 shows each model's training error and checking errors. It is clear that the overfitting occurs in Model 2 while in Model 1, the training session does not exhibit any overfitting characteristics.

|          | Model 1 | Model 2 |
|----------|---------|---------|
| No. of nodes | 92      | 92      |
| No. of linear parameters | 192     | 192     |
| No. of nonlinear parameters | 20      | 40      |
| Total no. of parameters | 212     | 232     |
| No. of Fuzzy rules | 32      | 32      |
| RSME Training Error | 0.0031  | 0.0030  |
| RSME Checking Error | 0.0066  | 0.0318  |
| Overfitting    | No      | Yes     |
Figure 5. Training and checking error after training each Model; (a) Model 1, (b) Model 2.

Therefore, only Model 1 was used to test the real data as shown in Figure 6. The test data were obtained from fuel temperature measurement at Channel B. To evaluate the performance and the quality of the model, the mean absolute error (MAE) is calculated by using Equation 2 [16]. The MAE for Model 1 is 0.00349 which implies the model can predict the output accurately. In terms of fuel temperature reactivity coefficient, the average results from the actual output and predicted output of the testing data are -0.00571 $^\circ$C$^{-1}$ (-3.997 pcm $^\circ$C$^{-1}$) and -0.00592 $^\circ$C$^{-1}$ (4.144 pcm $^\circ$C$^{-1}$), both are less than the values reported in the RTP Safety Analysis Report of 0.014$^\circ$C$^{-1}$ (-10 pcm $^\circ$C$^{-1}$) [17].

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - f_i|
\]

where $y_i$ and $f_i$ are the actual outputs and predicted the output.
4. Conclusion
Estimation of the fuel temperature reactivity coefficient at RTP has been demonstrated using ANFIS techniques. The model developed by ANFIS are capable in predicting the output which results on -0.00571 °C⁻¹ (-3.997 pcm °C⁻¹) and -0.00592 °C⁻¹ (4.144 pcm °C⁻¹) of actual output and predicted output which are less than the values reported in the SAR. The performance and quality of the model are also good with 0.00349 of MAE. Thus, ANFIS can be one of the alternative methods to calculate the fuel temperature reactivity coefficient in the future. This concept also can be applied to develop real-time monitoring system.

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