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Original article

Power peaking factor prediction using ANFIS method

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A B S T R A C T

Power peaking factors (PPF) is an important parameter for safe and efficient reactor operation. There are several methods to calculate the PPF at TRIGA research reactors such as MCNP and TRIGLAV codes. However, these methods are time-consuming and required high specifications of a computer system. To overcome these limitations, artificial intelligence was introduced for parameter prediction. Previous studies applied the neural network method to predict the PPF, but the publications using the ANFIS method are not well developed yet. In this paper, the prediction of PPF using the ANFIS was conducted. Two input variables, control rod position, and neutron flux were collected while the PPF was calculated using TRIGLAV code as the data output. These input-output datasets were used for ANFIS model generation, training, and testing. In this study, four ANFIS model with two types of input space partitioning methods shows good predictive performances with R^2 values in the range of 96%–97%, reveals the strong relationship between the predicted and actual PPF values. The RMSE calculated also near zero. From this statistical analysis, it is proven that the ANFIS could predict the PPF accurately and can be used as an alternative method to develop a real-time monitoring system at TRIGA research reactors.

1. Introduction

A fuel element is one of the core components in a nuclear reactor. It consists of a tube, called cladding that houses a fuel pellet. The fission reaction is occurred in the fuel pellets and releases a large amount of energy and fission neutrons. These fission neutrons will generate another fission reaction when interacting with other fuel elements in the core. This process is known as chain fission reactions. The fission neutron born from this reactions is required to be monitored for safe reactor operation. This can be done by measuring the neutron flux for determining the number of fission neutrons born by using external detectors or through the calculation of power peaking factor (PPF) [1,2]. The PPF calculation is carried out to identify the power of every fuel element in the reactor core by using computational code such as MCNP, TRIGLAV code, SRAC-CITATION code, and COBRA-EN code.

To maintain the reactor integrity, the fuel element with the highest power is necessary to be known to prevent the fuel pellets from melting [3]. Besides, the PPF also is important for reactor safety and efficient operations. However, there are no direct instrumentations available to measure this parameter and can only be calculated using computational methods such as System Analysis Module (SAM), NODAL3 code, GETERA code, TRIGLAV and MCNP code. In Ref. [4] work, both TRIGLAV and MCNP codes were applied to calculate the PPF at the TRIGA research reactor however, TRIGLAV code calculation assumes the core as a homogeneous core while MCNP required long simulations time and sophisticated computer specifications. In Ref. [5], the PPF at the hot rod of Reactor TRIGA PUSPATI (RTP) core was determined using the MCNP code through F7 tally card to calculate the power inside the fuel element which later will be used to determine the PPF using the ratio between maximum power released by the hot rod and the average power of the fuel element in the core.

Since the computational method has several limitations such as required another calculation step to determine the PPF, long simulation time, and high computational cost, thus, it is important to develop another alternative method that is fast, reliable, and efficient so that the PPF can be included in the real-time monitoring system. Due to that, the artificial intelligence (AI) methods were

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introduced by correlating several reactor variables to estimate the PPF. AI methods such as fuzzy neural network (FNN), support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS), and artificial neural network (ANN) have been applied extensively to predict the PPF. The FNN and SVM were successfully applied to predict the PPF at the hottest part of the fuel rods with 7 reactor parameters as the input variables and resulted in good prediction accuracy [6,7]. The ANFIS method also resulted with accurate PPF prediction in real-time as demonstrated in Ref. [8] however this study was the only one that applied this AI method but the training and testing methodology were not described in detail.

Other than that, most of the previous studies used ANN method to estimate the PPF. In Ref. [9] work, the application of ANN with various fuel element positions and enrichment percentages as the data input resulted in low accuracy of the predicted PPF. While in Ref. [10], the input variables including the fuel element's location and the percentage enrichment with gadolinium oxide were able to predict the local PPF with small relative error. Besides, the ANN application also works well and resulted in good predictive performances when using axial and quadrant power from the external detectors signal and the control rod positions [11–14]. Since, PPF is classified as safety core parameters, hence the inclusion of PPF in the monitoring system is desirable during reactor operation. As stated in Ref. [15], the ANN method has proven its capabilities in estimating the PPF in real-time at the Chashma Nuclear Power Plant core monitoring system.

From the literature, the application of the ANFIS for PPF prediction is limited and still not well developed yet. As the ANFIS is developed based on two types of AI, hence it has more advantages than the stand-alone AI methods. Several previous studies had shown the superiority of ANFIS on prediction study than ANN and SVM. In Ref. [16] work, the ANFIS and ANN were developed to predict the fluctuation of groundwater level in India and concluded that the ANFIS methods were better and have a good potential to model complex and multivariate problems. Comparison researches on ANFIS and SVM also prove that the ANFIS has the best performances in prediction study in Refs. [17–19] works. Hence, this study chooses to develop the ANFIS methods for PPF prediction methodology using AI in the TRIGA MARK II research reactor. The only type of research reactor that is available in Malaysia is Reactor TRIGA PUSPATI, known as RTP which has been operated since 1982 and reached its first criticality on June 28, 1982. RTP is a pool-type reactor and uses uranium zirconium hydride as the fuel-moderator element with 1 MW thermal power. The core configuration of the RTP is Core-15 as shown in Fig. 1. In this study, the dataset has been recovered from RTP to develop input-output data to train and validate the ANFIS for analyzing the prediction capability on PPF. Besides, the inclusion of grid, subtractive clustering, and fuzzy c-mean as the input partitioning method to generate the initial ANFIS model will be discussed in this paper. The developed ANFIS model will be characterized based on its performances using a statistical approach and to identify the ability of the model when dealing with unseen datasets.

2. Materials and methods

2.1. ANFIS

ANFIS method is form based on the knowledge combination of fuzzy inference system (FIS) and ANN. The FIS can create the IF-THEN fuzzy rules from fuzzy sets with an appropriate membership function (MF) to represent the way of human thinking but is limited to adaptive learning capabilities. While ANN has the adaptive learning capabilities for decision-making but could not be able to explain how the decision has been made. Hence, employing the adaptive learning capabilities from ANN into the IF-THEN fuzzy rules in FIS structures makes it more powerful and can be used for various applications to solve complex engineering or non-engineering problems.

To develop the ANFIS for PPF prediction, the model based on the ANFIS method is generated by constructing a series of fuzzy IF-THEN rules based on the MF types and layers to produce the stipulated input-output datasets [20]. These are set by the user to generate initial fuzzy rules. Then, the hybrid learning from ANN is applied to modify and update the antecedent and consequent parameters in the fuzzy rules to minimize the output error between predicted and actual output. This learning process is repeated and stops until reached the epoch number or error threshold set by the user. To explain the relationship between the input-output dataset of a complex system and the ANFIS method, the ANFIS architecture is depicted in Fig. 2.

From Fig. 2, the square box in Layer 2 and 5 are adaptive. An unknown parameters inside this layer are required to be tuned using the hybrid learning method during a training session. The ANFIS training session is carried out through forward and backward pass. In the forward pass, the neuron in Layer 1 will be moved and complete the calculation up to Layer 5. In this layer, the consequent parameters are tuned and updated using the least square estimation method (LSE). Then, proceed to calculate the output in Layer 6. The backward pass is performed to calculate the antecedent parameter using the gradient descent method (GD). The forward and backward pass process is repeated until reached the number of iterations (epoch) or error threshold specified by human expertise to stop the training session. The node in each layer in Fig. 2 is connected to other nodes with a neuron signal. This neuron is not similar to NN. The neuron just works as the connector between each node function. The detail regarding each layer and their functions based on Fig. 2 are as followed:

Layer 1:	Defined the input variables.
$O_i^{(1)} = x1,\ O_i^{(1)} = x2$, where $i = 1, 2$	
Layer 2:	The output of this layer is the multiplication of output in Layer 1 and the type of MF selected by the user. A_i and B_i are the fuzzy set. This layer is adaptive, usually known as the 'fuzzification layer'.
$O_i^{(2)} = \mu_{A_i}(x1),\ O_i^{(2)} = \mu_{B_i}(x2)$, where μ_{A_i}, μ_{B_i} = types of MF	
Layer 3:	The firing strength, $\prod_j^{(3)}$ is calculated in this layer.
$\prod_j^{(3)} = \mu_{A_i}(x1) \times \mu_{B_i}(x2)$, where $j = 1, 2, 3$ *and* 4	
Layer 4:	The normalized firing strength is calculated in this layer.
$N_j^{(4)} = \frac{\prod_j^{(3)}}{\sum_{j=1}^{4} \prod_j^{(3)}}$	
	The consequent parameters are calculated using LSE together with input $x1$ and $x2$. This layer is adaptive, known as the 'defuzzification layer'.

(continued on next page)

(*continued*)

Layer 5:	
$\text{Layer } 5_j^{(5)} = N_j f_j = N_j(p_j x1 + q_j x2 + r_j)$	
Layer 6:	ANFIS output is calculated in this layer.
$y^{(6)} = \sum_{j=1}^{4} \text{Layer } 5_j^{(5)}$	

Examples of initial IF-THEN fuzzy rules generated according to Fig. 2 are depicted in Equations (1)–(4). The x1 and x2 are the input variables, A1, A2, B1, and B2 are the fuzzy set in Layer 2 while $f_1 f_2 f_3 f_4$ are the first-order function that consists of the consequent parameter in Layer 5.

$$\text{IF x1 is A1 and x2 is B1 THEN } f_1 = (p_1 x1 + q_1 x2 + r_1) \quad (1)$$

$$\text{IF x1 is A2 and x2 is B2 THEN } f_2 = (p_2 x1 + q_2 x2 + r_2) \quad (2)$$

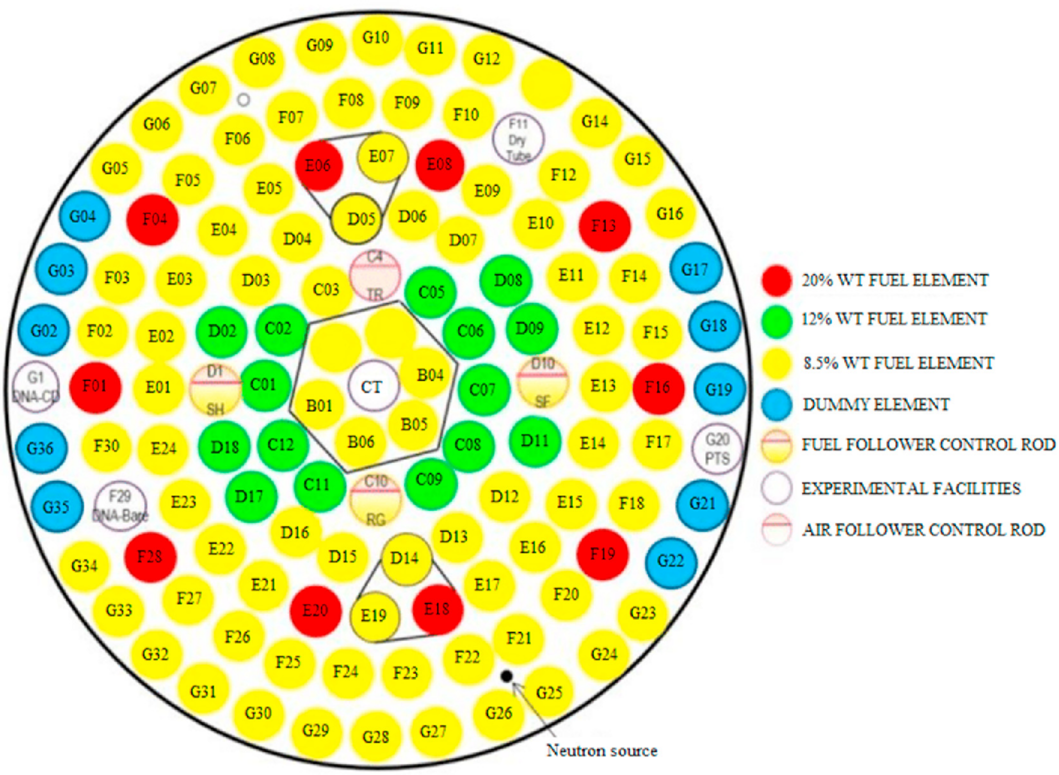

Fig. 1. Core-15 configuration of RTP [5].

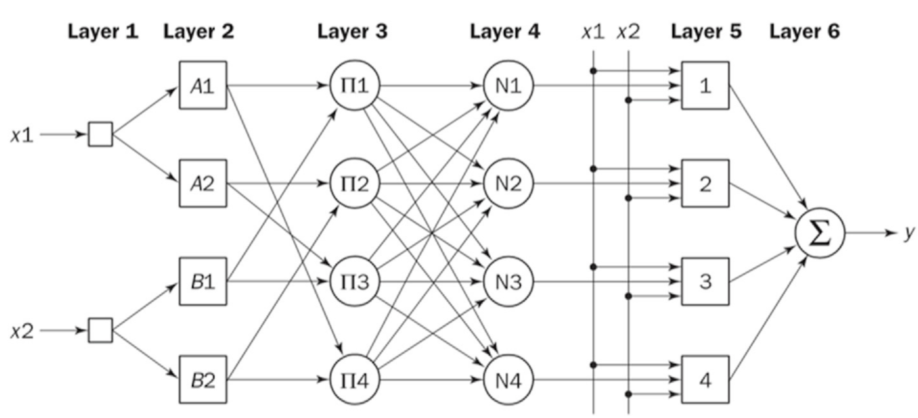

Fig. 2. ANFIS architecture with two input variables.

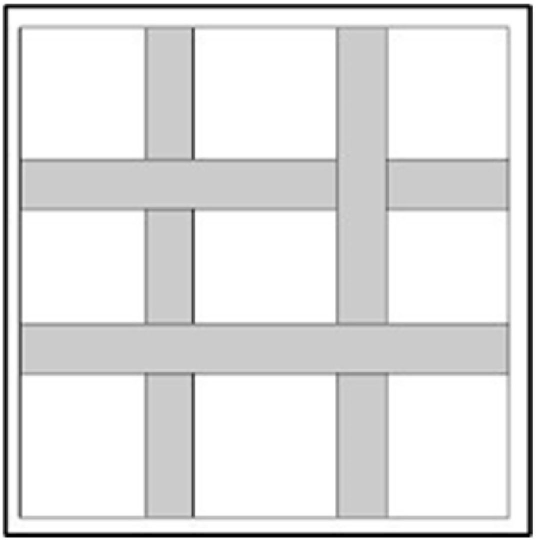

Fig. 3. GP method.

$$\text{IF x1 is A2 and x2 is B1 THEN } f_3 = (p_3 x1 + q_3 x2 + r_3) \tag{3}$$

$$\text{IF x1 is A1 and x2 is B2 THEN } f_4 = (p_4 x1 + q_4 x2 + r_4) \tag{4}$$

2.2. Input partitioning method

ANFIS method can solve any non-linear and complex relationship between input and output datasets with high precision performances. Besides having the knowledge between two AI methods, the ANFIS model with an appropriate input partitioning method could result in better model performances [21]. The number of fuzzy rules generated is also influenced by the type of input space partitioning methods. In general, there are two types of input partitioning methods which are grid partitioning (GP) and scattering partitioning (SP) methods. GP works by diving the input data space into a grid-like structure and the size of the grids are adjusted and updated during model training as shown in Fig. 3. The numbers of fuzzy rules generated under the GP method are depending on the number of input variables and the MF types and layers. For instance, if the number of the input variable is 4 and the defined MF layers is 2, then the number of fuzzy rules generated using the GP method is 2^4 = 16. Hence, if the number of the input variable is increasing then the number of fuzzy rules generated will also be increasing exponentially. Due to that, the GP method is effective when the number of inputs less than 6 to prevent the drawback known as the ‘curse of dimensionality [22].

The SP method works through the clustering method by dividing the input data space into clusters where the data in the cluster have the biggest similarities and generates a fewer number of fuzzy rules. There are three clustering methods such as subtractive clustering (SC), fuzzy c-mean (FCM), and conditional fuzzy c-mean (CFCM). The SC method is applied when the user does not have any idea about the number of clusters center based on the input data space. According to Long and Binh in Ref. [23], the SC method considers only the data point in the input data space, which technically reduces the computational calculation time and gives better distribution about the cluster centers. The number of fuzzy rules generated is depending on the number of cluster centers calculated using SC methods. The steps to calculate the number of clusters center are as followed [24]:

Step 1:	Defined the data point, x_j with highest density value, D_i using the Equation 5 below where x_i is the potential cluster's center and r_a is an influenced radius value.
$D_i = \sum_{j=1}^{n} exp\left(-\frac{x_i - x_j{}^2}{\left(\frac{r_a}{2}\right)^2}\right)$	(5)
Step 2:	Define the next cluster centers with density value, D_{i^*} using Equation 6 and the influenced radius value, $r_b = 1.5r_a$ where the D_{c1} and x_{c1} are the potential density value of the first cluster center and the selected data point as the first cluster center [19].
$D_{i^*} = D_i - D_{c1} exp\left(-\frac{x_i - x_{c1}{}^2}{\left(\frac{r_b}{2}\right)^2}\right)$	(6)

While the FCM method works by randomly determine the number of clusters at first and allowing the data point, x_i to belong to the clusters of the center, c_j. Then, the calculation of cost function, J_m is calculated iteratively to update the MF, μ_{ij}, and stop when the cost functions converge to a local minimum point with termination criteria between 0 and 1. The calculation of cost function and MF are depicted in Equations (7) and (8) while the termination criteria can be calculated using Equation (9).

$$J_m = \sum_{i=1}^{X} \sum_{j=1}^{C} \mu_{ij}^{m} x_i - c_j{}^2 \tag{7}$$

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{x_i - c_j}{x_i - c_k}\right)^{\frac{2}{m-1}}} \qquad c_j = \frac{\sum_{i=1}^{N} \mu_{ij}^{m} x_i}{\sum_{i=1}^{N} \mu_{ij}^{m}} \tag{8}$$

$$max_{ij}\left\{\left|\mu_{ij}^{k+1} - \mu_{ij}^{k}\right|\right\} < \varepsilon \tag{9}$$

2.3. Power peaking factors

From the literature, the PPF can be calculated using various computational codes and estimation methods using AI. At the RTP research reactor, the PPF is determined before re-shuffling the fuel rods to change the core configuration using TRIGLAV and MCNP codes. The best core configuration is essential to ensure the reactor operates within the safety limit as mentioned in the RTP Safety Analysis report [25]. The determination of PPF using MCNP code at RTP was calculated using the F7 tally to identify the total power produced by each of the fuel rods. Equations (10) and (11) were used to calculate the PPF after completed the MCNP simulation. The $(P_{rod})_{max}$ is the maximum power released by the hot rod, $(P_{rod})_{ave}$ is the average rod power in the core, P is the reactor power and N is the number of fuel elements in the core [26].

$$PPF_{@hot\ rod}\frac{(P_{rod})_{max}}{(P_{rod})_{ave}} \tag{10}$$

$$(P_{rod})_{ave} = \frac{P}{N} \tag{11}$$

2.4. Data description

In this paper, 6704 of the data input variables were collected at the RTP core-15 configuration with 7 critical core were adopted to conduct this prediction study. The data input consists of neutron flux and control rod positions. These two reactor variables were chosen to correlate with PPF because, during the reactor operations, the control rods were moved out from the core to allow the fission reaction to occur and the neutron flux were changed in both axial and radial directions. The movement of the control rods is independent to neutron flux, hence only the radial neutron flux measurement were conducted and used as the data input. The neutron flux measurement were done manually since the self-powered neutron detectors (SPNDs) has not yet been implemented permanently at the RTP core. The details on the experimental procedures were illustrated in Fig. 4. While Fig. 5 depicts the SPNDs locations during measurement. As for the control rod position, these data were obtained directly from the digital instrumentation and control system (I&C).

The PPF and the determination of the hot rod were carried out using the TRIGLAV code. Since there are significant range differences between neutron flux and control rod positions, thus, the min-max normalization was applied to normalize these two variables on a scale of 0–1. Then, the normalized data input-output were segregated into three different classes of the dataset where 81.4% of the dataset was separated for training data, 15.7% were reserved as checking data and the rest of the dataset was the testing

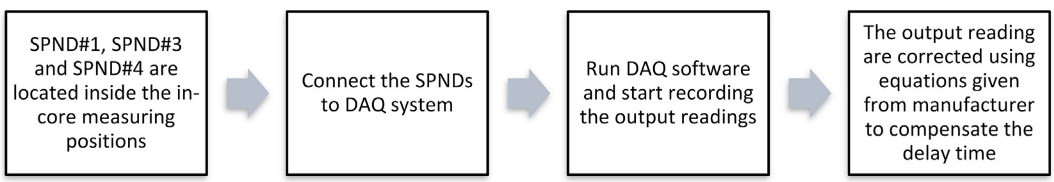

Fig. 4. Experimental procedure of SPNDs for measuring the neutron flux.

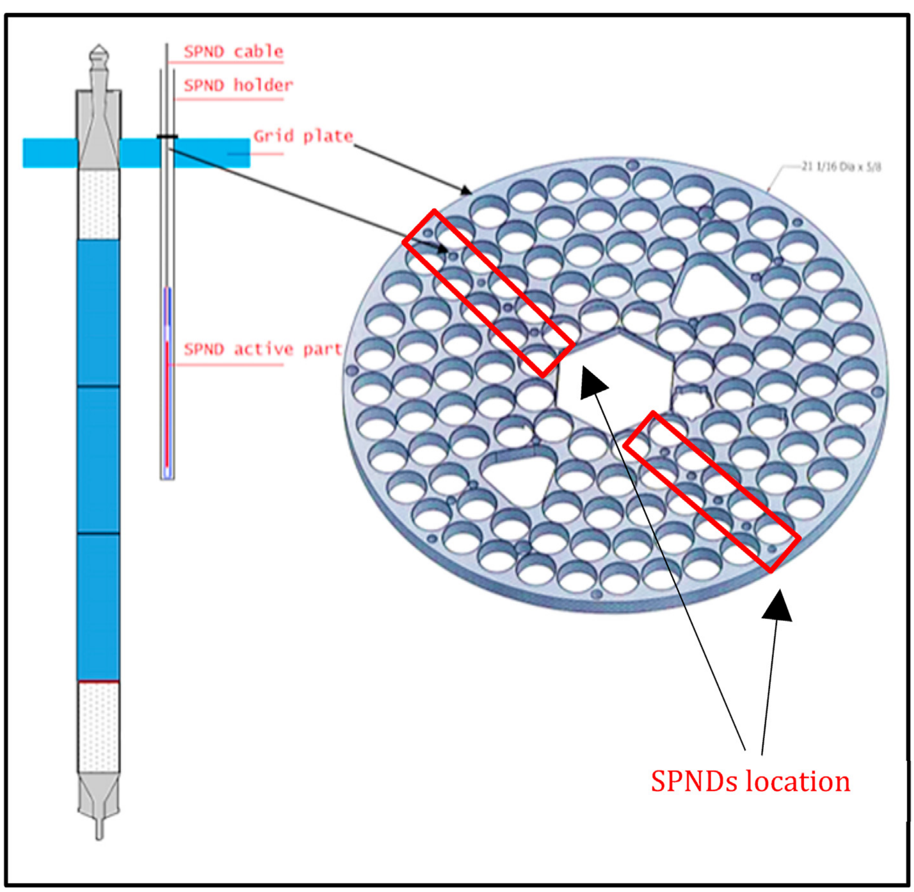

Fig. 5. SPNDs location during measurement.

Table 1
Percentages on sorting the input-output data.

Types of data	Core −15 Critical Core	Percentages (%)	Input-Output Datasets
Training data	6	81.4	5459
Checking data		15.7	1050
Testing data	1	2.9	195
Total	7	100.0	6704

data. Table 1 list the segregation percentages for each of the datasets.

2.5. ANFIS for PPF prediction

To develop the ANFIS models for PPF prediction at the hot rod of the RTP core, the training and checking data with the appropriate input partitioning methods were used to initiate the models. In this prediction study, GP and two SP methods which are SC and FCM were applied. Fourteen ANFIS models were generated and the detail regarding the type of input partitioning methods was tabulated in Table 2. The models were then undergoing the training session where the tuning and adjusting of the antecedent and consequent parameters were conducted and stops at 1000 iterations. Then, the status of the trained models was identified by calculating the error gap between the training and checking errors obtained during the training session. The model with overfitting criteria during the training session was eliminated. Only the good fit models were characterized using a statistical approach. Two statistical calculations were carried out to evaluate the model performances which are the correlation coefficient (R^2) and the root means square error (RMSE). The equation of R^2 and RMSE are shown in Equations (12) and (13). The flowchart of ANFIS models training and testing are shown in Fig. 6.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_{act_i} - Y_{ANFIS_i}\right)^2}{\sum_{i=1}^{n}\left(Y_{act_i} - \overline{Y}_{act}\right)^2} \quad (12)$$

$$RMSE = \frac{1}{n}\sum_{i-1}^{n}\left|Y_{act_i} - Y_{ANFIS_i}\right| \quad (13)$$

Table 2
Details of ANFIS models.

Model	Input-partitioning methods	MF/Radius value/CC
1	GP	*gaussmf*
2		*gauss2mf*
3	SP (SC)	0.20
4		0.25
5		0.30
6		0.35
7		0.40
8		0.45
9		0.50
10	SP (FCM)	10
11		7
12		6
13		5
14		4

3. Results and discussion

Based on the TRIGLAV code calculation, the fuel rod with the highest power at RTP core-15 configuration was identified at E20 fuel rods and the PPF calculated was 1.87 at 1 MW reactor power. The trained ANFIS models were evaluated to determine the model status and the results are tabulated in Table 3. From the table, the GP partitioning method with *gauss2mf* as the MF types is experiencing overfitting characteristics as the sudden fluctuation were observed during training session. Whereas the SC method with 0.20–0.35 influenced radius values showing the overfitting criteria. All models from the FCM partitioning method are classified as stopped as the training session resulted in undefined numerical values. Hence, models 2, 3, 4, 5, 6, and 10 to 14 are eliminated and were not included in model performance evaluation.

The model performance evaluation is carried out through statistical calculation to determine the model behavior when dealing with the dataset that is not available during the training session to identify the generalization capabilities of the model. Table 4 summarizes the result calculation of R^2 and RMSE values. Fig. 7 shows the actual and predicted values based on the testing data. From the table, the predicted PPF has a strong relationship between predicted and actual PPF with the R^2 values in the range of 96%–97% and can be observed in Fig. 7. Besides, the generalization capabilities of these four ANFIS models are excellent as the models able to predict the PPF even the testing data were not included during the training session. The RMSE calculated were also closed to 0 with Model 1 is the lowest at 1.5144×10^{-4} and Model 9 is the highest at 2.0459×10^{-4}. This result shows that the ANFIS method has good predictive performances and can be applied as the alternative method for the PPF estimation tool at TRIGA research reactors. Moreover, the ANFIS method also can be used to develop the real-time monitoring system to monitor the PPF during reactor operation for education, operator training as well as for efficient reactor operations.

4. Conclusion

PPF parameter is classified as one of the most crucial parameters to be known for preventing the fuel rods from melting and violating the safety limit values. Various computational codes have been developed to calculate the PPF however having several limitations such as long computational time and required high-cost computational tools. Due to that, the introduction of AI for estimating this parameter were applied extensively. However, the application of a hybrid AI such as ANFIS is not well developed in current research publications. Thus, in this paper, the application of the ANFIS for PPF prediction at the RTP research reactor has been conducted in detail. Two variables, neutron flux and CR position from the reactor core were used to develop the ANFIS model for PPF prediction at RTP. After the training and testing session, the results from the good fit ANFIS models showed excellent predictive performances. This can be reflected with the R^2 in the range of 0.96–0.97 which near to

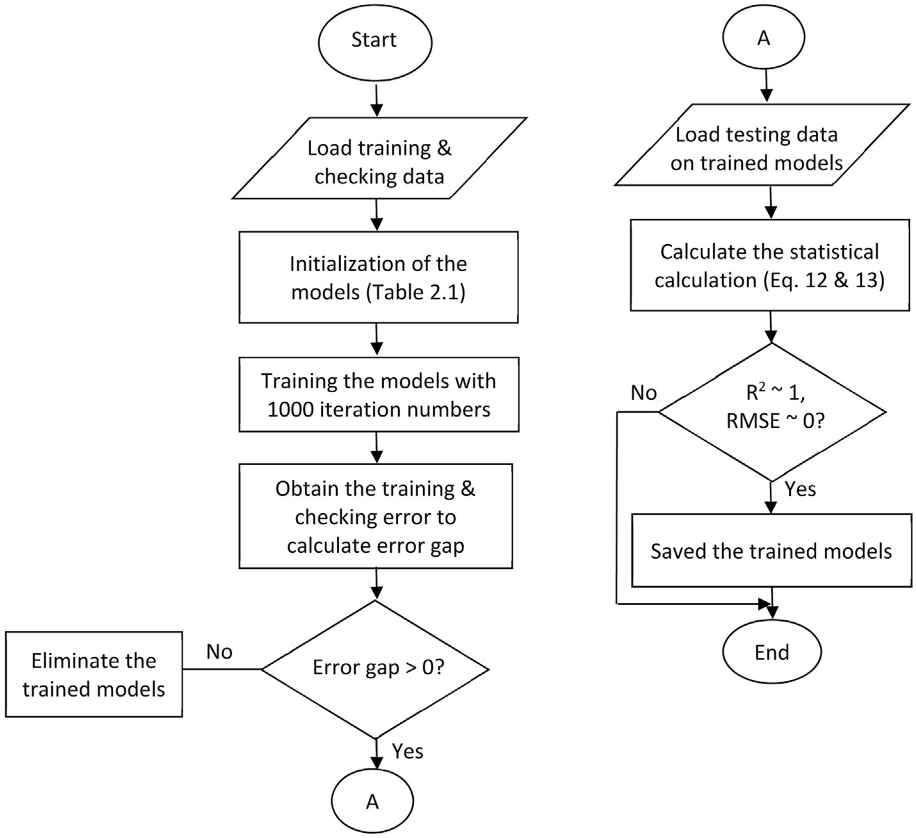

Fig. 6. Flowchart for PPF prediction using ANFIS method.

Table 3
Training and checking error at E20 fuel rods.

Model	Input-partitioning type	MF/Radius value/CC	RMSE (10^{-4})			Model Status
			Training data	Checking data	Error Gap	
1	GP	*gaussmf*	1.0928	1.1787	0.0859	Good fit
2		*gauss2mf*	1.1454	1.2678	0.1224	Overfitting
3	SP (SC)	0.20	0.9930	0.9813	−0.0117	Overfitting
4		0.25	1.2766	1.2413	−0.0353	Overfitting
5		0.30	1.5375	1.5483	0.0108	Overfitting
6		0.35	1.5964	1.5873	−0.0091	Overfitting
7		0.40	1.5729	1.5632	−0.0097	Good fit
8		0.45	1.6224	1.6262	0.0038	Good fit
9		0.50	1.8721	1.9166	0.0445	Good fit
10	SP (FCM)	8	2.0781	2.0742	−0.0039	Stopped
11		6	3.0693	2.9145	−0.1548	Stopped
12		5	3.3963	3.2772	−0.1191	Stopped
13		4	4.1101	4.0344	−0.0757	Stopped
14		3	3.6606	3.4715	−0.1891	Stopped

Table 4
Trained model performances evaluations.

Models	Partitioning types	MF/radius/cluster center	R^2	RMSE (10^{-4})
1	GP	*gaussmf*	0.9781	1.5144
7	SP (SC)	0.40	0.9653	1.9042
8		0.45	0.9600	2.0445
9		0.50	0.9600	2.0459

1 and reveals the strong relationship between the predicted and actual PPF values. Besides, the RMSE calculated also near zero in the range of 1.5144×10^{-4} to 2.0459×10^{-4}. This statistical analysis proves that the ANFIS method has good prediction capabilities and can be used as an alternative PPF prediction tool. The ANFIS method can also be applied to develop the real-time monitoring system at TRIGA research reactors.

Recommendation

As for future work, this study recommended to increase the number of input variables with other reactor parameters such as fuel burnup and thermal-hydraulic feedbacks effects which will represent the PPF more in detail. Besides, this study also recommends collecting the data for multiple core configurations so that the ANFIS model developed can be utilized for various configurations without the need to retrained and revalidate the model. In

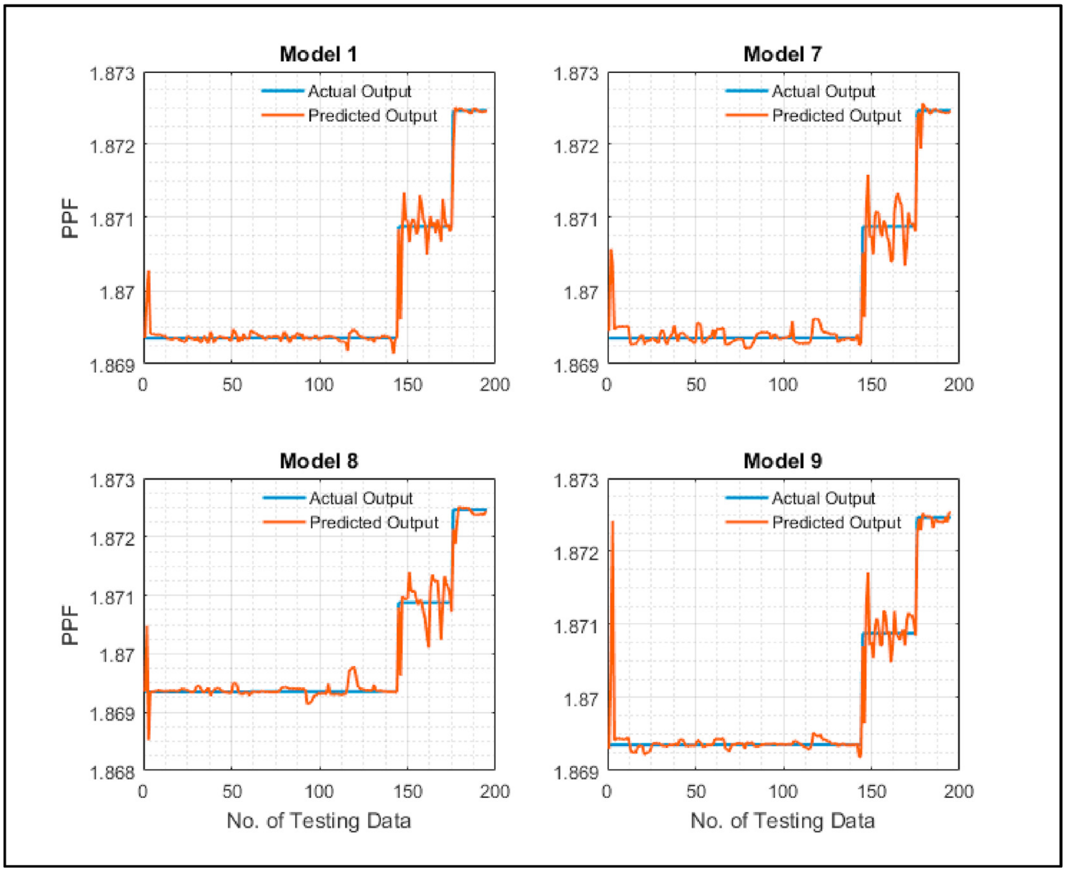

Fig. 7. Predicted PFF from ANFIS method and actual PPF values.

addition, comparison studies between ANFIS and others AI's method is also recommended to be conducted by using the same input-output dataset to identify the excellent AI methods on predicting PPF in nuclear reactors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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