DEVELOPMENT OF TRIGA MARK II RESEARCH REACTOR CORE MONITORING SYSTEM USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

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ABSTRACT

Most of TRIGA research reactors has successfully converted the instrumentation and control (I&C) system from analog-based to digital-based. The digital I&C system is capable to monitor and control variables and parameters as well as to react to the design safety limits and conditions. In this study, the methodology on monitoring three of the core safety-related parameters was developed using the Adaptive Neuro-Fuzzy Inference System (ANFIS) method at Reactor TRIGA PUSPATI (RTP). There were two parts involved which were parameter prediction and deviation calculation. Each parameter was generated with 12 -14 fuzzy inference system (FIS) models according to input-partitioning types. The generated model then underwent the training and testing phases to identify the good fit models which can be calculated based on three statistical calculations which are correlation coefficient (R^2), mean absolute error (MAE) and root mean square error (RMSE) to be further validated using a novel dataset. The second part of this study was carried out by constructing the algorithm to calculate the relative error between the predicted parameters and the design safety limit. For validation, the novel RTP dataset was used to select only one good fit model with an optimum input-partitioning method to represent the ANFIS model for parameter prediction in the monitoring system. In fuel temperature reactivity coefficient (FTC) validation, the results show that the Model 12 with fuzzy c-mean and the initial clusters centers of 3 had the lowest MAE and RMSE values which were 0.0110 and 0.1051 respectively however the R^2 values are poor; R^2 at 0.0795. For the fuel pin power (FPP) parameters at 12 fuel rods radial locations, Model 7 and Model 8 with subtractive clustering as the input-partitioning types and the optimal influenced radius values of 0.40 and 0.45 were selected to represent the FPP parameters at B04 and the rest of the fuel rods. The results show a good accuracy in predicting FPP parameters as the MAE and RMSE were calculated with the lowest values on each of fuel rod. The predicted FPP also shows a strong R^2 values of 94% on the average. The validation of the power peaking factor (PPF) at the hot rods determined by the TRIGLAV code also demonstrates a good ANFIS model with 0.45 as the optimal influenced radius value in subtractive clustering input-partitioning types in Model 8. The model results in the lowest MAE and RSME with the R^2 values at 0.1844, which is quite low. Although the calculated R^2 for FTC and PPF parameters have weak R^2 values, this statistical calculation was only used to present the relationship between the actual and prediction output and was not used as the primary model performance evaluation to conclude on the models' accuracy and capability to predict the parameters. Thus, from these findings, the inclusion of FTC, FPP and PPF with specific optimal input-partitioning type on each ANFIS model can be implemented in the monitoring system for enhancing the reactor safety at TRIGA research reactors.

ABSTRAK

Kebanyakkan reaktor penyelidikan TRIGA telah berjaya menukar sistem instrumentasi dan kawalan (I&C) dari pangkalan-analog ke pangkalan-digital. Sistem I&C digital mampu memantau dan mengawal pembolehubah dan parameter serta bertindak balas terhadap had dan syarat keselamatan yang telah ditetapkan. Dalam kajian ini, kaedah untuk memantau parameter teras yang berkaitan dengan keselamatan teras telah dimajukan di Reaktor TRIGA PUSPATI (RTP) dengan mengunakan teknik sistem *Inference Neuro-Fuzzy Adaptive* (ANFIS). Terdapat dua bahagian yang terlibat dalam kaedah yang dibangunkan iaitu parameter ramalan dan pengiraan sisihan. Setiap parameter telah dibina dengan 12-14 model *fuzzy inference system* (FIS) berdasarkan jenis pembahagian-input. Proses latihan dan ujian terhadap model FIS telah dijalankan untuk mengenalpasti beberapa model yang baik melalui pengiraan statistik seperti pekali korelasi (R^2), purata ralat mutlak (MAE) dan punca purata kuasa dua ralat (RMSE) untuk digunapakai dalam proses pengesahan dengan mengunakan set data yang novel. Bahagian kedua iaitu pembinaan algoritma untuk pengiraan ralat relatif diantara parameter ramalan dan had keselamatan juga telah dijalankan. Seterusnya, dalam pengesahan model ANFIS, data novel RTP telah digunakan untuk memilih hanya satu model yang sesuai dengan kaedah pembahagian-input yang optimum untuk mewakili model ANFIS untuk meramal parameter dalam sistem pemantauan teras. Pengesahan untuk parameter pekali suhu reaktif bahan api (FTC) mendapati Model 12 dengan *fuzzy c-mean* serta 3 pusat kluster mempunyai nilai MAE dan RMSE yang terendah iaitu 0.0110 dan 0.1051 tetapi mempunyai nilai R^2 yang lemah iaitu 0.0795. Untuk parameter kuasa pin bahan api (FPP) di 12 lokasi radial rod bahan api, Model 7 dan Model 8 dengan *subtractive clustering* sebagai jenis pembahagian-input dan nilai optimum pengaruh jejari iaitu 0.40 dan 0.45 telah dipilih untuk mewakili parameter FPP di B04 dan rod bahan api yang selebihnya. Hasil dapatan kajian menunjukan ramalan FPP parameter yang baik kerana MAE dan RMSE dikira dengan nilai terendah untuk setiap rod bahan api. Ramalan FPP ini juga menunjukkan nilai R^2 yang tinggi iaitu 94% secara purata. Pengesahan bagi parameter faktor memuncak kuasa (PPF) di rod bahan api yang panas yang telah ditentukan oleh kod TRIGLAV juga menunjukkan pembahagian-input *subtractive clustering* dan optimum jejari iaitu 0.45 pada Model 8 sebagai model ANFIS yang terbaik. Nilai MAE dan RMSE juga rendah tetapi mempunyai nilai R^2 yang lemah iaitu 0.1844. Walaupun R^2 untuk ramalan parameter FTC dan PPF mempunyai nilai yang lemah, pengiraan statistik ini hanya menunjukkan hubungan diantara parameter ramalan dan sebenar serta tidak digunakan sebagai penilaian prestasi model yang utama untuk membuat kesimpulan mengenai ketepatan dan keupayaan model untuk meramal parameter. Oleh itu, berdasarkan hasil kajian ini, kemasukan FTC, FPP dan PPF dengan optimum pembahagian-input yang khusus pada setiap model ANFIS boleh dilaksanakan dalam sistem pengawasan untuk meningkatkan keselamatan reaktor di reaktor penyelidikan TRIGA.

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LIST OF ABBREVIATIONS

AELB	-	Atomic Energy Licensing Board
ANN	-	Artificial Neural Network
ANFIS	-	Adaptive Neural Fuzzy Inference System
CC	-	Clusters center
DAQ	-	Data Acquisition and Signal Processing
FIS	-	Fuzzy Inference System
FCM	-	Fuzzy c-mean
FPP	-	Fuel Pin Power
FTC	-	Fuel Temperature Reactivity Coefficient
GD	-	Gradient Descent
IAEA	-	International Atomic Energy Agency
I&C	-	Instrumentation and Control
LSE	-	Least Square Estimator
MAE	-	Mean Absolute Error
MCNP	-	Monte-Carlo N-Particles Code
MF	-	Membership Function
PPF	-	Power Peaking Factor
ReDICS	-	Reactor Digital Instrumentation and Control System
REG	-	Regulator control rods
RMSE	-	Root Mean Square Error
RTP	-	Reactor TRIGA PUSPATI
SAR	-	Safety Analysis Report
SC	-	Soft Computing
SF	-	Safety control rods
SHIM	-	Shim control rods
SPNDs	-	Self-Powered Neutron Detectors
TR	-	Transient control rods
TRIGA	-	Training, Research, Isotope, General Atomic
UZrH	-	Uranium Zirconium Hydride
WR-NMS	-	Wide Range- Neutron Monitoring System

LIST OF SYMBOLS

α_f - Fuel temperature reactivity coefficient ($\$^oC^{-1}$)
σ - Standard deviation
c - Center
ρ - Reactivity ($)
T_f - Fuel temperature (^oC)
r - Influence radius value
D - Density measure
J_m - Cost function
d_{ij} - Euclidean distance
m - Fuzziness index
ϕ - Corrected neutron flux ($n.cm^{-1}s^{-1}$)
C - Normalization constant
I - SPND current signals (A)
τ - Decay time (s)
Y - Data output
μ - Membership function
P - Power (kW)
B - Boron
C - Carbon
H - Hydrogen
U - Uranium
V - Vanadium
Zr - Zirconium
wt% - Weight percentage
η - Learning rate
α - Generic parameters

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CHAPTER 1

INTRODUCTION

1.1 Research Background

A nuclear research reactor can be defined as a reactor for generating and utilization of various types of radiations for training, research, and other purposes (IAEA, 2005). The common designs of research reactors are pool-type, tank-type, and tank-in-pool type reactors. Training, Research, Isotopes, General Atomics (TRIGA) reactors are one of the pool-type design that has the unique fuel element ($UZrH_x$) and can be operated either at steady state or in a safe pulse mode to a very high power level in a fraction of second (IAEA, 2016a). According to the IAEA (2006), every research reactor should be equipped with the highest safety standards to ensure people and the environment surrounding the reactor's area are protected and safe from any radiation hazards. Most of the research reactors have small potential hazards towards the radiological consequences to the public compared with power reactors. However, the reactor may pose a greater potential hazard to the site worker and operating personnel (Adorni et al., 2007).

Therefore, research reactors should be installed with a system that is capable to monitor and record the reactor’s behavior to maintain the reactor’s safety. This can be done by monitoring the operational and safety parameters using process signals with the detection of any deviation that occurred during the reactor operations to ensure the reactor’s integrity and to protect the personnel from any radiation hazard. The system that specifically monitors the reactor core behavior continuously is the core monitoring system which is capable of providing the core status (Zagrebaev et al., 2017). Besides, the core monitoring system also helps in responding to the plant operation’s requirement and can be utilized for various purposes such as in nuclear fuel cycle strategies, fuel design, and safety analysis (Jozef & Radim, 2014).

In TRIGA reactors, the core monitoring system works by transmitting the instrumentation signals directly from the core to the Data Acquisition and Signal Processing (DAQ) System and Control Console System which are connected to the independent control system computer via high-speed ethernet link to display the real-time operational and safety parameters on the reactor data display and reactor graphic display in the control room (General Atomics, 2015). Most of the parameters that are monitored for the core status have instrumentation such as thermocouples to monitor the fuel temperature and pool temperature, wide range fission chamber for neutron flux monitoring, wide-range logarithmic instrument for continuous indication of reactor power from source level to full power, and others.

However, there are supplementary parameters that are related to the core safety which cannot be measured directly using instrumentations and require complex derived calculation. The limitation excludes these core safety-related parameters from being monitored during reactor operations. Besides, these parameters are frequently calculated using a computational method such as Monte Carlo N-particles code (MCNP), CITATION code, TRIGLAV code and others which usually consume a great amount of computational time and cost. To overcome these problems, several studies that have successfully introduced and implemented the application of the soft computing technique to estimate and predict the core safety-related parameters. Besides, the soft computing technique has also been implemented successfully in various nuclear field by using fuzzy logic, fuzzy inference system (FIS), artificial neural network (ANN) and evolutionary algorithm in reactor power control, reactor surveillance and diagnostic, fault detection system, nuclear fuel management and others that are related to reactor safety improvement for efficient reactor operations (Jayalal et al., 2014; Muzzamil & Ali, 2013). ANN is one of the soft computing types that has been reported and used widely in nuclear fields. Recently, a lot of researches have proved the ability of the ANN to estimate and predict the derived parameters such as power peaking factors, thermal margin, and effective multiplication factors (Mazrou & Hamadouche, 2004; Montes et al., 2009; Na et al., 2004; Amany et al., 2015).

Therefore, the goal of this study is to develop a new methodology on monitoring the core safety-related parameters by using the combination of two soft computing techniques (FIS and ANN) which is an Adaptive Neuro-Fuzzy Inference System (ANFIS) to upgrade the current core monitoring system for safe and efficient reactor operations in TRIGA research reactors. The developed methodology consists of two parts where the first part is for the parameter prediction using the ANFIS method and the second part is for the comparison between the predicted parameter and the established safety limit value as stated in the Safety Analysis Report (SAR). The validation will be conducted by using the novel operational reactor data while the accuracy and the performance of the method will be evaluated using statistical analysis approaches.

1.2 Problem Statement

Reactor TRIGA PUSPATI (RTP) is the only TRIGA research reactor that is available in Malaysia and has been operated safely for more than 30 years without any incident as stated in the unusual event reporting categories (Julia et al., 2011). According to Lanyau et al. (2012), the reactor was in the progress to upgrade the reactor power from low to high power due to the demand for increasing the neutron flux for diversifying the reactor utilization. In Farid et al. (2019), the RTP has been successfully upgraded to enhance the reactor’s safety based on five strategic programs. One of the five programs is the upgrading of the instrumentation and control (I&C) system at the reactor console from analog-based to digital-based. However, there are only five safety and operational parameters that are available and monitored on the digital RPS to represent the reactor status. The parameters include fuel temperature, pool water level, reactor percent power, wide range neutron monitoring system and reactor period. Besides, only reactor percent power and fuel temperature parameters are displayed directly from the instrumentation to the reactor console.

Although the reactor has been operated safely at low power with only five basic parameters being monitored as recommended in IAEA (2016a), it is necessary to include the core safety-related parameters in the core monitoring system to improve the safety of the reactor, personnel, and the environment when the reactor is ready to be operated at high power. The core safety-related parameters such as temperature reactivity coefficient, fuel pin power, and power peaking factors have high influential towards the reactor’s safety which are frequently calculated using computational code like MCNP and TRIGLAV in RTP reactor. Since these parameters require high computational cost and time, the parameters are excluded to be monitored in the RPS of RTP. In this study, the development of the new methodology to monitor these core safety-related parameters will be conducted by the prediction method by using the soft computing technique which is ANFIS.

Besides that, the application of ANFIS for parameter prediction in the nuclear research reactor is limited. Most of the previous studies used the application of ANN to estimate the core parameters as reported in Jiang et al. (2008), Hedayat et al. (2009) Schlünz et al. (2015) and Amany et al. (2015). Thus, in this study, the exploration of the ANFIS method is carried out extensively by developing the ANFIS model and the deviation algorithm construction in order to upgrade the core monitoring system in RTP.

1.3 Objectives

The main aim of this study is to develop a new methodology for the deployment of the core safety-related parameters to upgrade the current RTP core monitoring system by using the ANFIS method. To accomplish this aim, the following specific objectives will be fulfilled:

(a) To upgrade the RTP core monitoring system by using an algorithm from the ANFIS method for prediction on the core safety-related parameters.

(b) To construct the deviation algorithm between the predicted parameter developed in (a) with the design limit value stated in the Safety Analysis Report (SAR) of RTP.

(c) To verify the algorithm developed in (a) and (b) using a novel RTP dataset for the evaluation assessment of the developed model based on the performance and accuracy.

1.4 Scope of the Study

As this research was focusing on the TRIGA type of research reactors, the reactor selected in this study was the RTP that is located in Malaysia and is under planning to upgrade the current reactor power to a high power reactor for various application especially in reactor physics, thermal-hydraulic, and others (Lanyau et al., 2012). Since the RTP has been operating for more than 30 years, the improvement and replacement of various reactor components are necessary to ensure and maintain the reactor's integrity and to ensure safe reactor conditions. Thus, this study proposes to enhance the reactor's safety by upgrading the current core monitoring system by adding three important core safety parameters that typically require complex computation code to calculate.

The upgrade core monitoring system developed in this study is focusing on monitoring the parameters that are related to reactor core safety. This study is limited to three parameters that have a high influence on reactor safety and efficient reactor operation. The selected core safety-related parameters are the fuel temperature reactivity coefficient (FTC), radial fuel pin power distribution (FPP), and hot rod power peaking factor (PPF). The FTC parameter is chosen as the TRIGA reactor has the unique safety feature which allows the reactors to automatically shut down the operation even all the control rods were removed. Thus, having the FTC parameters on the monitoring system can help the reactor operators, trainees, personnel, students, and researchers to understand better about the core status and behavior as well as for better reactor performances. Besides, the FPP parameters and the PPF parameters are also listed in the core safety parameters which are important to assure the safe reactor operations (Khan et al., 2015).

These parameters (FTC, FPP, and PFF) require complex derivation calculation that is influenced and can be correlated by many factors from parameters that were measured directly. Thus, there are only three measured parameters that will be used to develop the ANFIS model which are the fuel temperature, the control rod (CR) positions, and the neutron flux. The details regarding the correlation between measured parameters with the selected core safety-related parameters are shown in Figure 1.1.

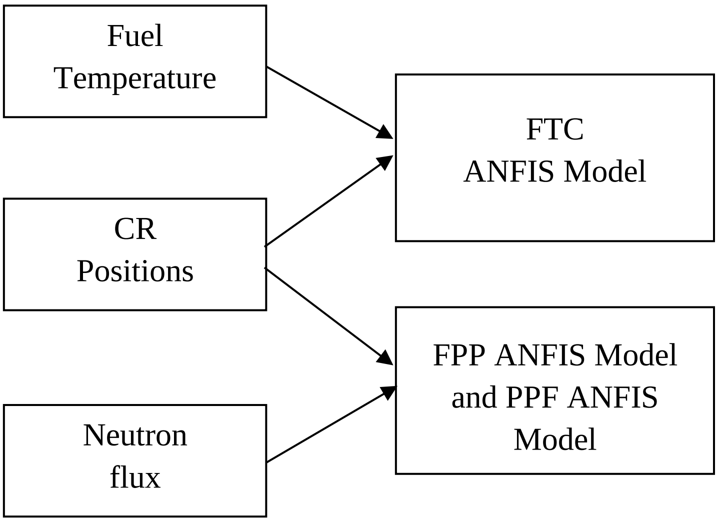

Figure 1.1 Measured parameters for ANFIS model development.

1.5 Significance of the Study

The safe and efficient operations of nuclear reactors are one of the important criteria to ensure the reactor integrity and safety of the human and environments. This study is focusing to develop a methodology based on soft computing techniques that are used to predict the proposed parameters to be implemented in the core monitoring system for upgrading the safety of RTP. Besides, the application of soft computing techniques has been widely used in the nuclear field and proven as a good functional approximation tool in the nuclear field.

In addition, the developed methodology for upgrading the core monitoring system will contribute not only to the reactor's safety but also for various purposes such as education and training as well as providing the reactor operators with the core status and knowledge regarding the reactor's behavior during reactor operation.

1.6 Organization of the Thesis

The thesis is structured as follows: the introduction of the research is presented sequentially in this chapter and the literature review of related study is presented in Chapter 2. In Chapter 3, the methodology for the ANFIS model construction, deviation algorithm and the procedure for validation, and verification of the developed methodology are presented. The results based on the model construction including the model training behavior, model performances evaluation as well as the constructed deviation algorithm followed by the validation results are documented in Chapter 4. Finally, the conclusion and recommendation for future works are presented in Chapter 5.

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