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ORIGINAL ARTICLE

Preliminary study on fault detection using artificial neural network for water-cooled reactors

J.A Karim[1], T. Lanyau[1], M.Maskin[1], M.A.S Anuar[2], A.Che Soh[2] and R.Z.A Rahman[2]

[1] Reactor Technology Centre, Technical Support Division, Malaysian Nuclear Agency, 43000 Kajang, Selangor
Phone: +60389112000; Fax: +60389250755
[2] Control System and Signal Processing (CSSP) Research Centre, Department of Electrical and Electronic Engineering, Universiti Putra Malaysia, 43400 UPM, Serdang, Selangor

ABSTRACT – In the PUSPATI TRIGA reactor (RTP), many variables and instruments need to be monitored to make sure it is functioning and running accordingly. The late detection of faults may result in accidents and affect workers' safety and health. Therefore, an intelligent fault detection system is needed to detect faults in the process plant and alert for any safe point breach. This work was carried out to discover the use of an artificial neural network (ANN) to model and develop a fault detection programme in the RTP cooling system. Using actual data from the reactor to train the multilayer network model with backpropagation algorithm. Referring to the real data from the reactor, the simulation results demonstrate a good correlation between the proposed model using ANN and the real plants with a residual mean of below 1%. The preliminary results for fault detection show that ANN was able to predict the value of failure in residual factor by comparing the normal state and fault state of the plant. The proposed model using ANN method proofed that it could quickly diagnose the single fault and perform for any given failure. The research outcome could contribute to the improvement in frontier technologies and advanced manufacturing in Malaysia.

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INTRODUCTION

The operating organisation is responsible for the safety of a nuclear research facility. For more than 35 years, with a proper maintenance program, the RTP was able to operate safely. Nonetheless, the accident in Fukushima changed the whole scenario. Since then, there were deep concerns regarding the safety of ageing nuclear facilities that come with imposed by the International Atomic Energy Agency (IAEA), existing safety assessment method had to be revised [1].

Nominal incidental or accidental modes are the nuclear processes that may develop if subjected to different operational modes. The nuclear plant has parameters that should be within the scope of the operation and conditions for startup, operation, core configuration and shutdown, when in normal modes. However, unexpected incidents might happen in accidental modes but without affecting many of the components at the plant. Worse, if increased uncontrollably, the reactor can result in failing to cool down the outflow and a lot of radioactive elements may be at large. In order to prevent human injury, damage to the installation and pollution, there is a real need to diagnose the malfunctions of the reactor [2].

New safety requirements that emphasise safety fundamental principles have been introduced. The principles were adopted to improvise the safety assessment of the RTP to the highest level. Since after the programme upgrade, some subsystems at RTP have been upgraded. The analog control system has been substituted by a new digital control and the primary and secondary cooling systems have also been replaced. In this case, the overall control systems have performed differently and the cooling system has been unable to achieve the expected heat. Thus, a more detailed RTP operation study is necessary because the overall dynamic behaviour of the RTP has changed. At the same time, various parts of the RTP may deviate or fail at any juncture, hence a comprehensive intelligent fault detection and diagnosis (FDD) system would be critical [3,4].

Compared to the possible hazard produced by nuclear power reactors, research reactors pose much less threat to the public. However, this might not be the case for the operators who are more exposed and at risk. The interest in FDD methods are increasing among nuclear power industries compared to research reactors [5-9]. However, incidents also happen in nuclear research reactors as reported in [10]. The incidents have been classified according to the four major groups of initiating events: (1) the insertion of excess reactivity (Group 1), (2) the loss of flow (Group 2), (3) the loss of coolant (Group 3), and (4) human error, equipment and component failures (Group 4). Based on the operational experience presented, it is clear that uncontrolled reactivity changes and coolant channel blockages are the most serious events to be considered [10].

A nuclear reactor is a complex nonlinear, large scale and time-varying system. It becomes more challenging to build a mathematical model that is able to successfully capture the dynamic behaviour of the system as the complexity of

*CORRESPONDING AUTHOR | J.A. Karim | julia@nuclearmalaysia.gov.my

nuclear reactor processes increases. Thus, the data driven method is getting more attention because it relies on the data acquired from the processes. The method can obtain useful information by data mining technologies and have become a practical FDD technology at present. In recent years, neural networks (NNs) have grown rapidly in academia and industry as one of thedata-driven methods [5]. The NN was successfully utilised in the FDD method for nuclear power reactors [5-9] and nuclear research reactors [2,11]. However, the FDD system introduced in [2,5-9,11] did not involve the overall nuclear reactor and only involve specific cases.

The loss of coolant activities (LOCA) in boiling water reactor (BWR) is due to degradation mechanisms such as mechanical fatigue, stress accelerated corrosion (SAC) and flow accelerated corrosion (FAC) [12]. Apart from that, LOCA can also be caused by fault, like pipe rupture [13]. In order to diagnose the events and prediction, three methodologies could be implemented: quantitative mathematical model, qualitative empirical model or data-driven model [14].

The choice of which methodology to be implemented depends on the needs of each fault occurrence in the system. The justification of the best methodology to be used can be obtained based on the collected operational history data. It is important to choose the best methodology for specific fault occurrence as each methodology has its advantages and disadvantages, and can be interpreted differently when used to solve a particular nuclear power plant fault issues [15].

In [16] the temperature parameters of the inlet and outlet, and their failures are monitored using analytical redundancy methods. The work in [17] described the application of ANN in nuclear thermal-hydraulics. Sensor fault detection, isolation and reading estimate (SFDIRE) algorithm in particular was used for for the core cooling system process of this plant. The behaviour of installation caused by accidents was simulated using ANN based classification techniques [2].

In Malaysian Nuclear Agency (MNA), a lot of work and research have been done regarding safety issues of RTP [11,18,19]. However, specific method to predict system failures at the RTP is still unavailable. Therefore, a preliminary study on fault detection system was carried out at the RTP. The project was divided to the subsystems, which were integrated to develop a complete intelligent FDD for the RTP. Firstly, the project has started to model the cooling system of RTP. The aim of the project is to investigate the potential of ANN approach to model the cooling system in normal state and fault state. ANN has been selected as a tool to be exploited, mainly because of its inability to formulate a mathematical relationship between input-output system. This is caused by the non-linearity of the inputs and the outputs. On top of that, the ability to generalise well, work fast in real-time and execute complicated mapping without using functional relationship are also the justification of this choice. In order to eliminate the tedious work of fault detection in the RTP and to monitor the RTP's health relating to safety issues, the ANN approach is very promising.

DESCRIPTION OF THE RTP

The RTP was primarily designed to analyse nuetron activities, small angle neutron scattering, radioisotope production, neutron radiography, training and education purposes. It is described as a pool-like light water moderated research reactor. It has the capacity of 1MW maximum thermal power and has reach power since decades ago. TRIGA fuel was used. Enriched uranium (19.9%) is homogenously combined with zirconium hydride moderator. The configuration of the RTP core is cylindric, encircled with an annular graphite relector and enclosed in aluminium casing tank. The diameter is approximately 3.65 cm and the length is 38.10 cm. It contains 8.5% to 20% uranium 235. The ration of hydrogen to zirconium atom is 1.6 [20]. Table 1 shows the exact specification of RTP:

Table 1. Specification of the RTP

Items	Specification
Name	Reaktor TRIGA PUSPATI (RTP)
Type	TRIGA MARK II; pool-type reactor
First Criticality	28 June 1982
Max. Thermal Power	1 MW
Av. Power Density	22.8 W/cm^3
Typical Max. Thermal Neutron Flux	1×10^{13} n/cm^2/s
Shape & Size of Reactor Core	Cylindrical,55 cm in diameter × 59cm in height
Coolant	Light water
Moderator	Light water
Control Rod	B_4C
Reflector	High Purity Graphite
Fuel Element shape	Rod Type
Enrichment of U-235	Approximately 20%

Operational Cooling System of the RTP

The diameter of the cylindrical reactor core is 1.09 m. Its height is 0.89 m. Its core contains graphite dummy elements, lattice fuel moderator elements and control rods, encircled by graphite reflector. This assembly stays at the bottom of the reactor tank. It is held by the reactor's support structure. Radiation shielding is prepared by filling it up with water about 5.18m above the core, while the reactor is in operation. The pool water natural convection that circulates through the core provides the cooling effect. There are two cooling loops: primary loop (80 m^3/h flow rate) and secondary loop (160 m^3/h) that allow for heat rejection. The generated heat from the fuel is transferred to the fuel cladding surface through thermal conductivity, and the coolant inside the core helps to remove the heat. RTP operates in steady state and square wave modes. The flow rate of the core coolant is calculated using the bouyancy force balance to the friction proessure obtained across the core to achieve the steady state natural convection.

To control the reactor's power level, four rods are used. These control rods contain boron carbide, which is an absorbing material. The cooling system is made up of a water surface skimmer, filter, pump, demineraliser, associated valves and piping, head exchange unit and diverse instrumentation. This system is only needed during the operation of the reactor. The water purification and cooling systems preserve the low water conductivity, the optical clarity of the water, remove impurities and allow for reactor heat dissipation. Should one of the two cooling systems fail, automatic shutdown of the reactor will be in place. All these control rods will be inserted inside the core of the reactor. Rotating equipment such as pumps and cooling towers are numerous in order to minimise reactor operation disruption [21].

The schematic diagram of the cooling systems is given in Figure 1. During usual operation, the bulk water temperature in the reactor tank is kept below 49°C. The temperature limit ensures the resin granules work efficiently because at high temperatures, the resin may damage and reduce the ability to filter the impurities in the cooling systems. The water chemistry of the RTP is tightly bound to the purification system that flows between the primary and secondary cooling loops. Structures, systems, and components (SSCs) mainly made from stainless steel and aluminium are installed inside the cylindrical reactor core that can hold up to 22,000 l of purified water. The water interact directly with SSCs, including the fuel elements that aligned vertically to the reactor core. During the operation of the reactor, activation products are formed, and a high radiation field is produced. The purified water flows back and forth from the primary to the secondary cooling loops through a resin bed installed at the demineralised system, which can trap the impurities and activation products. Good water quality will ensure all SSCs are intact without significant degradation and maintain its optical clarity inside the reactor core. The RTP has been serving for almost 40 years; therefore, it is essential to ensure its safety for another decade.

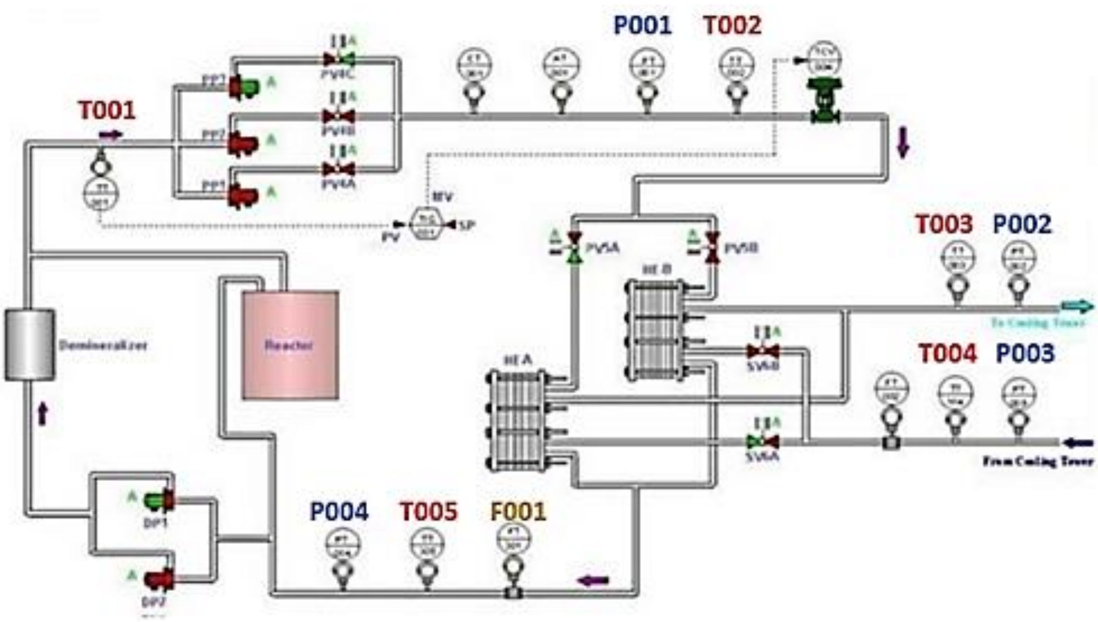


Figure 1. SCADA of the primary and secondary cooling system for RTP

Simulated Experimental Test Rig of RTP Cooling System

The fault detection system was simulated by using a test rig of the RTP cooling system. A study was conducted usint this simulated test rig to predict and to assess the detection of fault in RTP. This is due to the fact that there can be potential accidents initiated from unreliable pipe integrity, failure in electronic, actuator, sensor and associated components. This test rig, although is an experimental one, can be used comprehensively to create a database that is useful to evaluate the estimated models. Figure 2 illustrates the schematic diagram of this test rig. Water flows from the primary into the secondary system. Therefore the heat from the primary loop can be transferred in between both systems with the help of a heat exchanger. The heating rods from inside the water tank provide the heat effect. This represents the nuclear fuel in the actual reactore core. Using the operation history, several cases were extracted to simulate the faults.

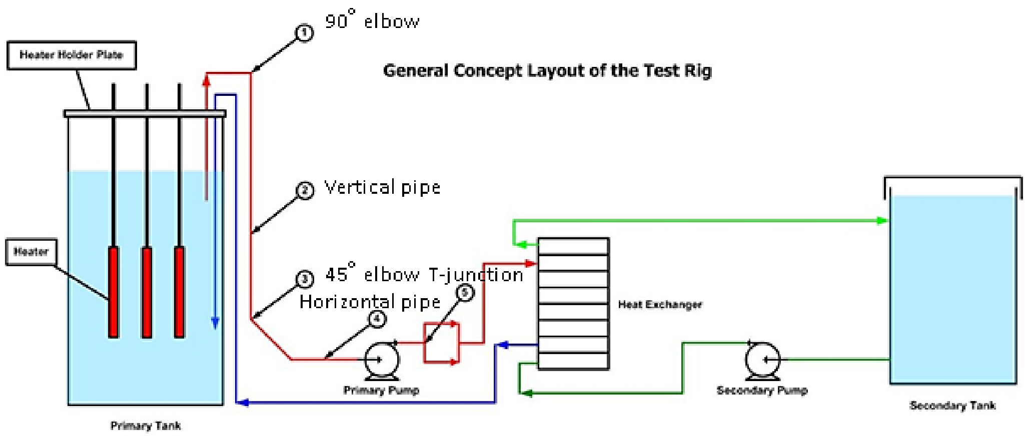


Figure 2. The schematic diagram for the simulated experimental test rig

METHODOLOGY

RTP Cooling System Modelling using Artificial Neural Network

An intelligent fault detection system was developed to overcome the tedious process of detecting fault in the RTP cooling system. The ANN-based simulation of cooling system was implemnted in the plant model as shown in Figure 3. The dataset used in this work includes water temperature, pressure, and flow rate of the RTP cooling system collected during the normal reactor operation. The model is normal when the value of residual is zero and the model is faulty when the value of residual is nonzero. Based on the normal dataset, the ANN model structure was developed for each RTP cooling subsystem as shown in Figure 4.

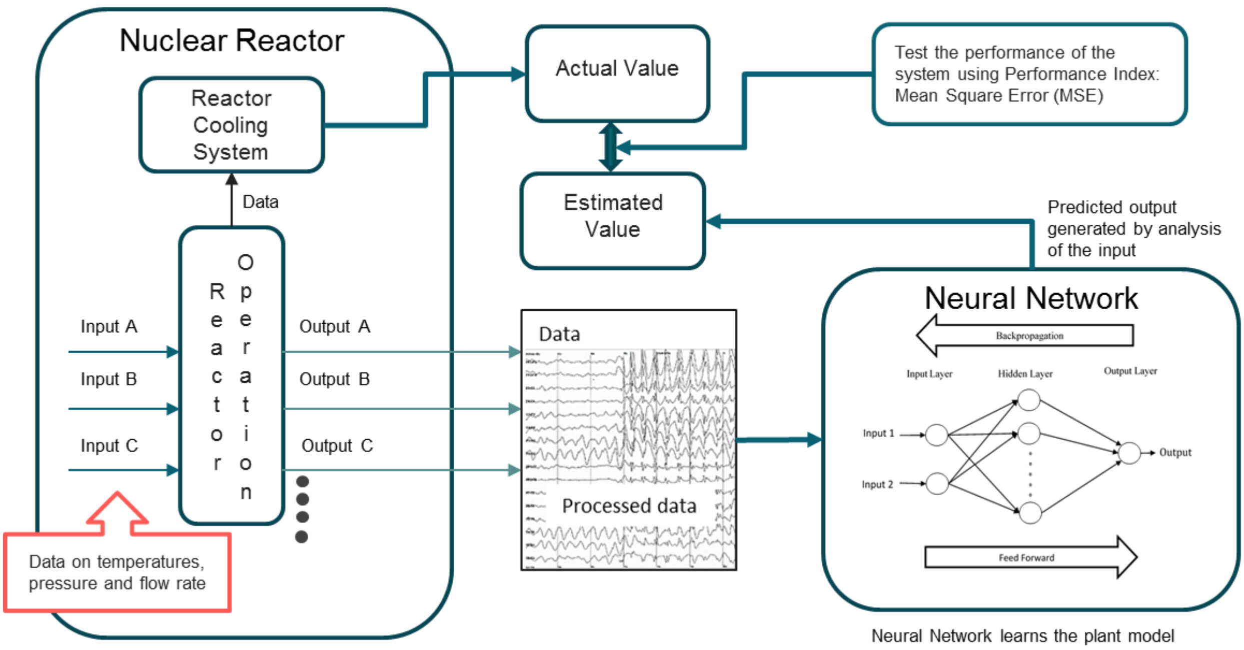


Figure 3. Plant model with a neural network

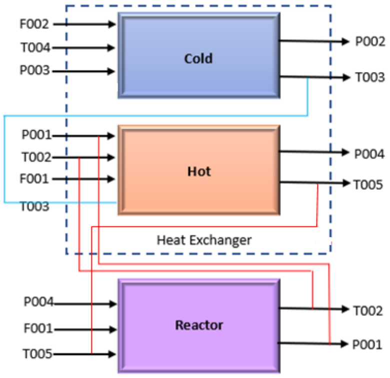


Figure 4. Block diagram of RTP cooling system

Multilayer ANN with backpropagation training has a tremendous capacity to estimate and simplify the given model. The simplest networks with concealed layers comparable to a linear regression were adopted in the model. The backpropagation algorithm solves problems in the ANN faster. For the error δ_j^l of neuron j in layer, l is given by:

$$\delta_j^l = \frac{\partial C}{\partial z_j^l} \tag{1}$$

The computation of δ^l for every layer is explored in the backpropagation and the errors are related to the quantities of real interest.

The neural network approach is by training and testing activities. Training means that a neural network is taught to seize the essential link between the selected inputs and outputs. A test database consists of a dataset that has not been used for training. The networks will be tested using this database. The model with low mean squared error (*MSE*) is a good model,while the regression (*R*) value of close to 1 shows that the outputs and the targets have a close relationship. The workflow of the proposed model is shown in Figure 5. Using the real data, the best combinations of parameters for the configuration of ANN model structure with low *MSE* and *R* close to 1 is given in Table 2.

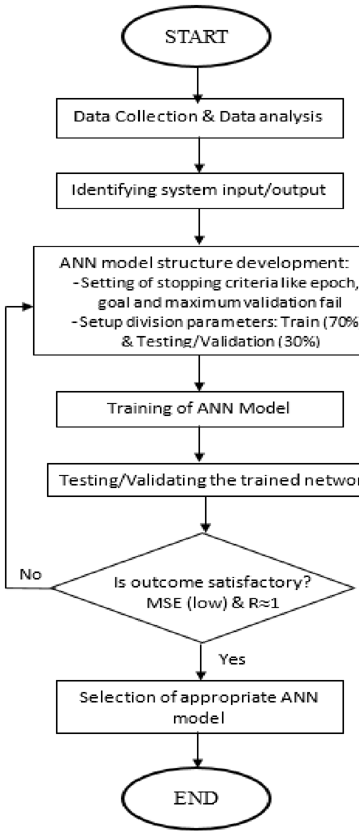


Figure 5. Worflow of the proposed model

Table 2. The structure of ANN model for RTP cooling system

Structure of ANN Model	
Subsystem 1: Cold-Heat Exchanger	3-10-2
Subsystem 2: Hot-Heat Exchanger	4-10-2
Subsystem 3: Reactor	3-10-2
Input layer	
Subsystem 1: Cold-Heat Exchanger	F002, P003, T004
Subsystem 2: Hot-Heat Exchanger	F001, P001, T002,T003
Subsystem 3: Reactor	F001, P004, T005
Output layer	
Subsystem 1: Cold-Heat Exchanger	P002, T003
Subsystem 2: Hot-Heat Exchanger	P004, T005
Subsystem 3: Reactor	P001, T002
Number of Hidden Neurons	10
Train function for Network	Levenberg-Marquadt Algorithm
Learning rate	0.001

Artificial Neural Network Modelling for Fault Detection in RTP Cooling System

The FDD define the fault occurrences in the system consisting of the available information gathered and processed to spot any deflection from nominal behaviour and categorize faults in order to conduct further sensitivity analysis. The ANN method can approximate the real system and detect faults if the model is very accurate. The ANN model for fault detection was developed using the same structure model as shown in Table 2. The time varying residual presentation is used to diagnose the model and served as a fault detector. The residuals are obtained from the command values of the controlled inputs and outputs observed from the monitored plant [22]. The preferred residuals are those that are affected by the faults only. Unfortunately, there are noise, disturbances and modelling errors. They resulted in the residuals to be nonzero and this will interfere with the fault detection process. The residual generation for a particular fault is shown in Figure 6. The design of the residual generator catered to be robust to exasperation inputs, so that each residual will respond differently to the subset of faults. At the same time, they are not affected at all by the others. Hence, the response set pattern and the fault signal become the faults' characteristics.

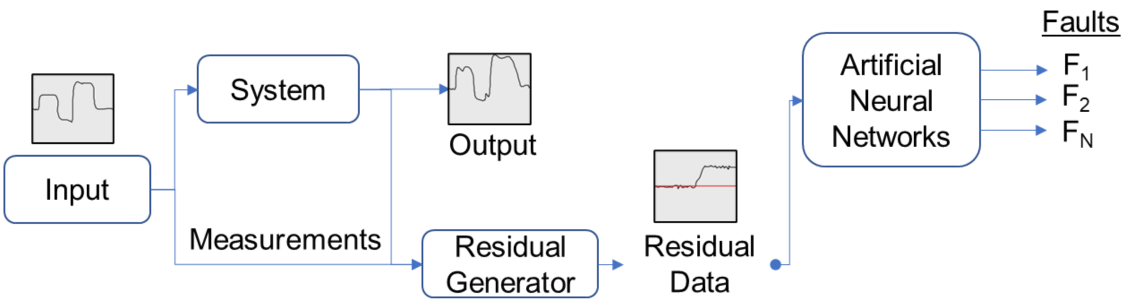


Figure 6. Residual generation using ANN

Five potential fault types generated from the process rig are shown in Table 3, together with the injection methods used.

Table 3. The simulated situation of normal and fault case for ANN training model

Fault	Fault Type	Fault Injection Method
1	75% restricted flowrate of the water in Hot-Heat Exchanger & Reactor	Making the opening of the valve F001 to be 25%
2	50% restricted flowrate of the water in Hot-Heat Exchanger & Reactor	Making the opening of the valve F001to be 50%
3	25% restricted flowrate of the water in Hot-Heat Exchanger & Reactor	Making the opening of the valve F001 to be 75%
4	75% restricted flowrate of the water in Cold-Heat Exchanger	Making the opening of the valve F002 to be 25%
5	75% restricted flowrate of the water in Cold-Heat Exchanger	Making the opening of the valve F002 to be 50%

RESULTS AND DISCUSSIONS

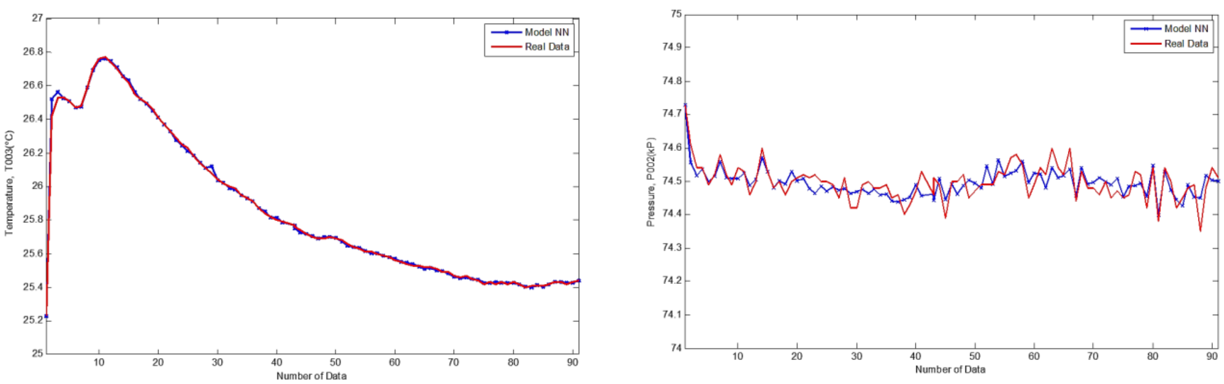
This section illustrated the ANN modelling for developing a model and fault detection for RTP cooling system. In ANN modelling, the system model representing the normal and faulty conditions are developed. The residual is generated based on the differences of the two models. If the value of residual is not zero, it is indicate that the system in the faulty condition. In order to detect the faulty condition, the best model with the high accuracy is needed to represent the real RTP cooling system with the normal condition. The modelling of subsystem is as shown in Figure 4 has been done using multilayer ANN with backpropagation method.

Based on the real data collected, the proposed ANN structure shows the best fit model for three subsystems of RTP cooling system. Table 4 shows that the *MSE* for all subsystems was the lowest and the *R* values was almost 1. The lower values of *MSE* indicate that the model is good and best fits the real model of the RTP cooling system. Meanwhile, an *R* value of 1 shows that the outputs and the targets have a close relationship.

Table 4. The performance of the RTP cooling system model using ANN modelling

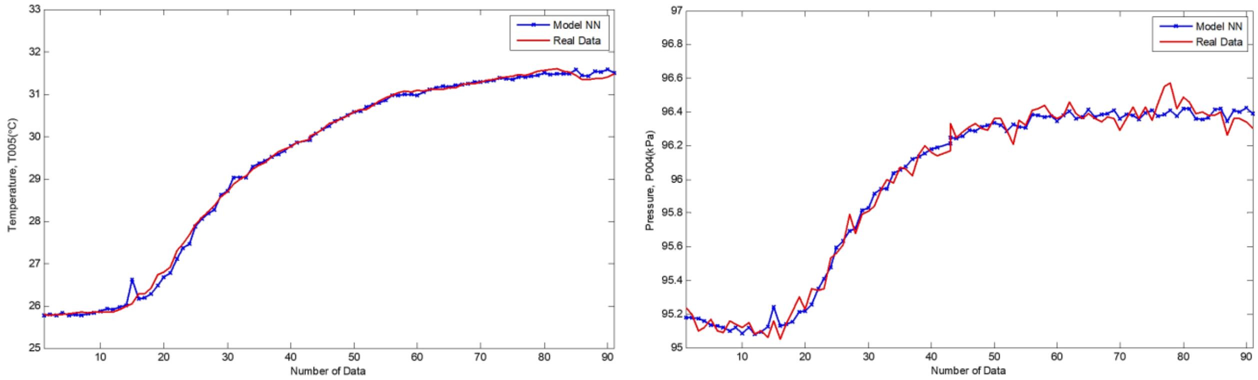
Subsystem	MSE	R value
Cold-Heat Exchanger	0.0006	0.8991
Hot-Heat Exchanger	0.0061	0.9967
Reactor	0.0543	0.9880

The simulation output for each subsystem is shown in Figures 7 to 9. Only a small fluctuation of error was shown in the output response of pressure for each subsystem. However, the overall performance of the model for the three subsystems shows an excellent fit towards the target real data, which proves that the model accuracy is high.



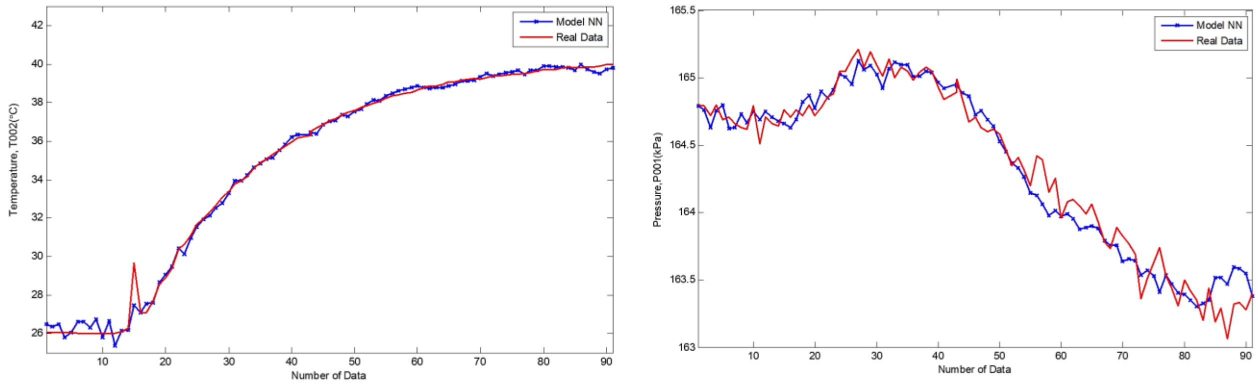
(a) (b)

Figure 7. ANN modelling for cold-heat exchanger: (a) output T003 and (b) output P002



(a) (b)

Figure 8. ANN modelling for hot-heat exchanger: (a) output T005 and (b) output P004



(a) (b)

Figure 9. ANN modelling for reactor: (a) output T002 and (b) output P001

In the model accuracy assessment, a model with residual mean of less than 10% is a good model rated as A. Then, a model with residual mean raging from 20% to 30% is considered as an acceptable model and rated as B. Meanwhile, a model with residual mean of more than 50% is a poor model rated as D and a model with the rest of the residual percentage is referred as a marginal model and rated as C [23]. Table 5 shows that all the subsystems ranked A, indicating good performance with the residual mean of below 1%.

Table 5. Summary of RTP cooling system model performance

Subsystem	Output	Mean Residual(%)	Ranking
Cold-Heat Exchanger	T003	0.0047	A
	P002	0.0025	A
Hot-Heat Exchanger	T005	0.0342	A
	P004	0.0029	A
Reactor	T002	0.0296	A
	P001	0.0037	A

A=good, B=acceptable, C=marginal, D=poor

The residuals obtained by comparing the differences between the system and fault models are used for detecting fault. The fault model also used the proposed ANN structure is given in Table 2. The residual also known as the fault symptom should predict future occurrence of fault. Zero or near to zero fault symptom is considered a no fault condition, while nonzero fault symptom is considered a faulty condition.

Since the fault was injected on the valve of the input system, only five possible errors of fault that can occur on the valve: clogged valve (75% valve F001 open), valve positioning error (50% valve F001 & F002 open) and broken valve (25% valve F001 & F002 open). Each type of faults was observed in terms of temperature and pressure because both parameters are the output for the system model. When normal condition data and fault data were trained with the suitable number of hidden neuron, the observation for all data was compared.

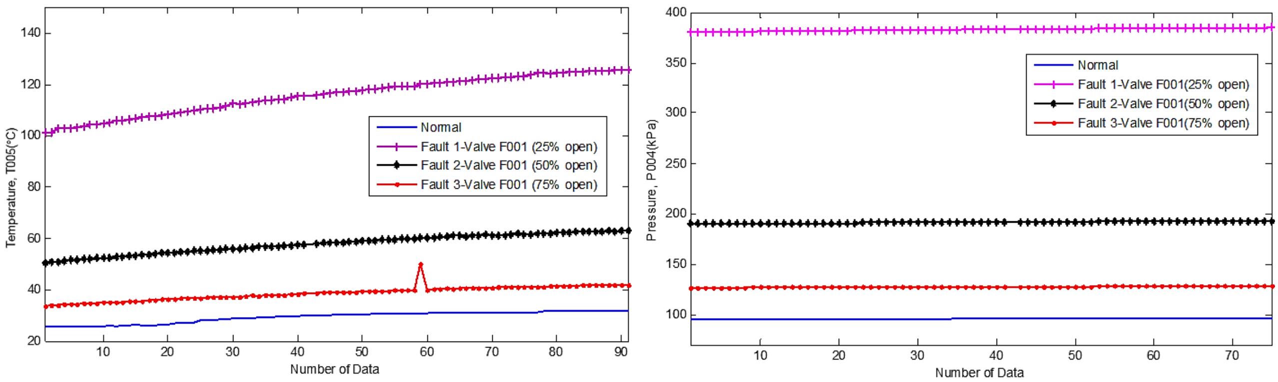
Figures 10 to 12 show the comparison of normal condition and fault condition at 750 kW reactor operation. Based on the graphs, the temperature and pressure were inversely proportional to the opening valve. As shown in the figures, the smaller the opening of the valve, the higher the reading for pressure and temperature. According to Layman's theory [24], the pressure will increase as the flow is reduced and the temperature is directly proportional to the pressure. From the data obtained in the neural network, residual data are measured by calculating the difference between the normal data and each fault as tabulated in Table 6.

Table 6 shows the residual pattern for temperature and pressure when the system experienced fault with 75% valve opening. The residual for temperature was ranging from 9.32 to 10.08°C, while the residual for pressure was approximately 31.84 to 32.55 kPa. The nominal water temperature was within the range of 20 to 33 °C during the reactor operation. Based on the results, the temperature is still low and within the range of during reactor operation and it can be considered as a small fault or small error in the system. This is because, when the opening valve is 75%, the flow of water is decreased by only 25%. This type of fault is classified as valve clogging. The valve clogging error need to solved early to prevent the fault from becoming a major serious fault. Therefore, the fault was set to be detected when the flow of water reduced by 25% as Fault 3.

The residual pattern for temperature and pressure when the system experienced fault with 50% valve were higher than those of when the system experinced fault with 75% valve opening. The residual for temperature and pressure were higher especially in the reactor subsystem. It shows that for valve F001 opening 50%, the temperature was ranging from 28.55 to 34°C, while for valve F002 opening 50% at cold-head exchanger temperature was approximately 39.35°C. As mentioned in [24], the pressure in all subsystems increased when the temperature increased. In this condition, the flow of water is decreased to 50% from the normal state. Valves F001 and F002 were 50% opened and the failure of the valves was injected to the system as fault 2 (F001) and fault 5(F002), respectively. This condition fault is considered as valve positioning error.

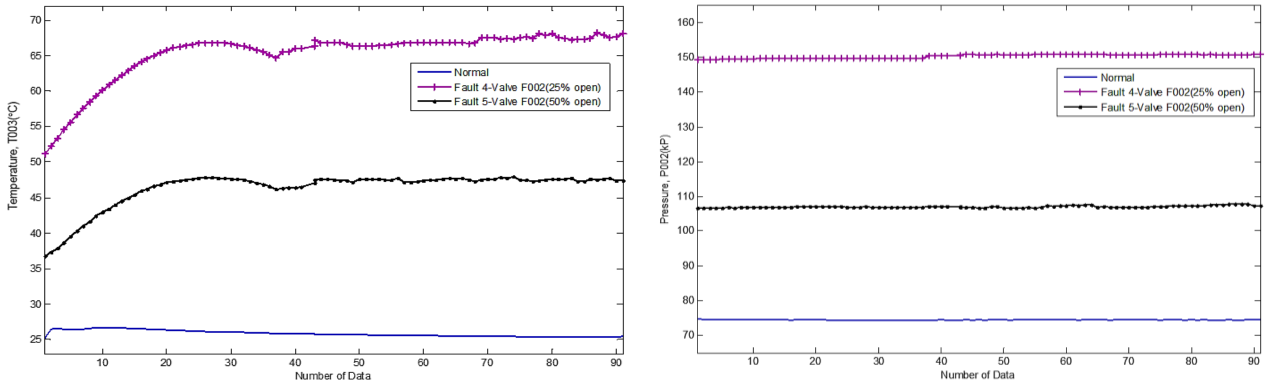
When the valves are 25% opened, the condition is considered as a critical fault because the flow of water drop is very high which is reduced by 75% compared to the normal condition. The fault is classified as damaged valve and the output shows that both temperature and pressure in all subsystems were increased.

Since this is a preliminary FDD performed on the cooling system for the RTP, the results show that the developed model could predict a single fault at a given data using the backpropagation training model. In the future, suitable selection of the filter method would be necessary to improve the fault data.



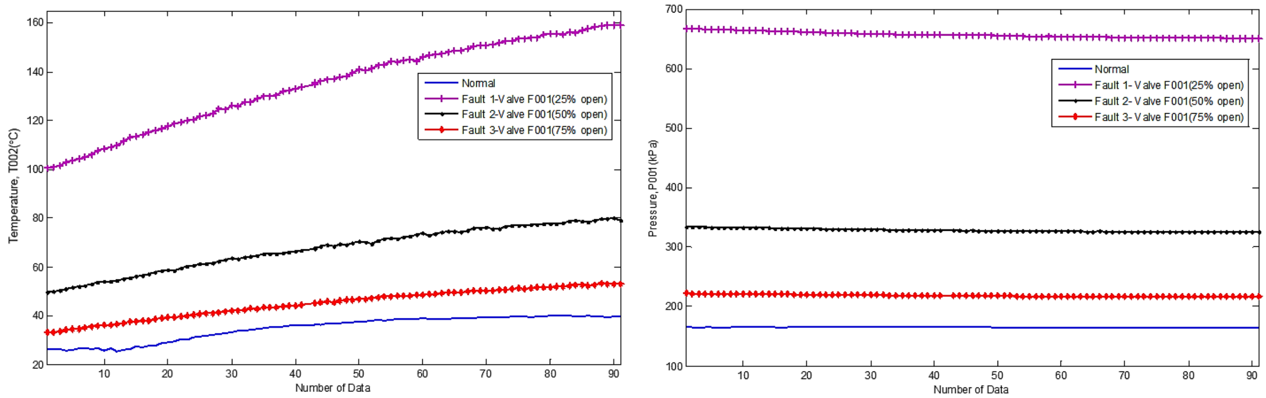
(a) (b)

Figure 10. Fault model for hot-heat exchanger: (a) output T005 and (b) output P004



(a) (b)

Figure 11. Fault model for cold-heat exchanger: (a) output T003 and (b) output P002



(a) (b)

Figure 12. Fault model for reactor: (a) output T002 and (b) output P001

Table 6. Summary of RTP cooling system for fault model

Subsystem	Output	Fault	Residual
Hot-Heat Exchanger	T005	Fault 1	86.39
		Fault 2	28.55
		Fault 3	9.32
	P004	Fault 1	287.42
		Fault 2	95.74
		Fault 3	31.84
Cold-Heat Exchanger	T003	Fault 4	39.38
		Fault 5	20.50
	P002	Fault 4	75.82
		Fault 5	32.55
Reactor	T002	Fault 1	99.77
		Fault 2	32.47
		Fault 3	10.08
	P001	Fault 1	492.27
		Fault 2	163.94
		Fault 3	54.55

CONCLUSION

The preliminary study of fault detection was done using ANN and the set of operational data from the RTP was used as a training model. In this work, the residual generator was used to obtain the residual value from the actual and measurement data. Hypothetical data show that the ANN is capable of representing the fault detection of the cooling system. Therefore, the approach of using ANN to provide the failure symptoms was clearly defined. The results show encouraging progress, but further investigation is still required by adding other parameters, such as the material integrity in the system design, to gain confidence in the decision-making process. The simulation data proved that, under the normal operating condition of the RTP, the fault can be diagnosed accurately to provide credible and real-time data. In future work, several methods will be employed to have a better understanding of the failure related to the RTP operation. The radiation effect will be considered in the model to simulate the consequences of high dose exposure to the system in faults prediction and diagnosis of the RTP.

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