Linear regression and R-squared correlation analysis on major nuclear online plant cooling system

Ahmad Azhari Mohamad Nor[1], Mohd Sabri Minhat[2], Norsuzila Ya'acob[1], Murizah Kassim[1,3]
[1]School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, Shah Alam, Malaysia
[2]Reactor Technology Centre, Malaysian Nuclear Agency, Kajang, Malaysia
[3]Institute for Big Data Analytics and Artificial Intelligence, Universiti Teknologi MARA, Shah Alam, Malaysia

Article Info

Article history:

Received Nov 22, 2022
Revised Dec 14, 2022
Accepted Dec 17, 2022

Keywords:

Correlation analysis
Linear regression
Nuclear reactor
Plant cooling system
R-squared

ABSTRACT

The primary cooling system is an integral part of a nuclear reactor that maintains reactor operational safety. It is essential to investigate the effects of the cooling system parameter before implementing predictive maintenance techniques in the reactor monitoring system. This paper presents a linear regression and R-squared correlation analysis of the nuclear plant cooling system parameter in the TRIGA PUSPATI Reactor in Malaysia. This research examines the primary cooling system's temperature, conductivity, and flow rate in maintaining the nuclear reactor. Data collection on the primary coolant system has been analyzed, and correlation analysis has been derived using linear regression and R-squared analysis. The result displays the correlation matrix for all sensors in the primary cooling system. The R-squared value for TT5 versus TT2 is 89%, TT5 versus TT3 is 94%, and TT5 against TT4 is 66% which shows an excellent correlation to the linear regression. However, the conductivity sensor CT1 does not correlate with other sensors in the system. The flow rate sensor FT1 positively correlates with the temperature sensor but does not correlate with the conductivity sensor. This finding can help to better develop the predictive maintenance strategy for the reactor monitoring program.

Corresponding Author:

Murizah Kassim
Institute for Big Data Analytics and Artificial Intelligence, Universiti Teknologi MARA
Shah Alam, Selangor, Malaysia
Email: murizah@uitm.edu.my

1. INTRODUCTION

Nuclear energy is of continuing interest as a means of generating power because it can fulfil the world's expanding energy demands in an ecologically safe manner [1]. The most critical components are the fuel element, moderator, and control rods in a nuclear reactor. The reactor core creates high heat by mixing thermal neutrons with uranium, starting a fission reaction, and directing heat away from the heat exchanger to a cooling agent. The steam generated rotates the turbine, linked to the generator, generating energy. A reactant coolant pump (RCP) is an essential component. It is a single piece of equipment in a reactor's primary coolant system [2]. It is the coolant's primary source of kinetic energy. To ensure the safety of the nuclear reactor, the RCP must effectively prevent and minimize the possibility of incidents [3]. The pressurized water reactor, reactor coolant system, energy conversion system, circulation water system, turbines, transmission and distribution systems, and auxiliary system components are the primary components of nuclear power plants that use pressurized water reactors [4]. The process propagates from the primary coolant system to the nuclear research reactor digital instrumentation monitoring system. On June 28, 1982, the PUSPATI TRIGA Reactor (RTP) of the Malaysian Nuclear Agency reached criticality.

Its cooling system comprises a single shell-and-tube heat exchanger, three centrifugal pumps, and a pipe system. Then, a proposal is made to replace the heat exchanger with two 1.5 MW plate-type heat exchangers and three new centrifugal pumps and upgrade the control systems to a new single-unit integrated control system [5], [6].

Nuclear operation is a complex system and involves various numbers of systems to monitor the whole operation to ensure the safety of its operation [7]. The failure of one component is likely to trigger a chain reaction of other failures, which may have a severe effect on the nuclear reactor's ability to function [8]. The numerous sensors installed within the system can help identify the reactor's condition and allow for maintenance on any fault detected within the system [9]. It is essential to routinely check the safety of a nuclear power plant's components to discover any irregularities that might cause accidents [10]. Before evaluating raw sensor data, it must be treated to remove noise and distortion. By analyzing operation data, insight into the plant's status can be derived, helping to identify any irregularities [11]. It is essential to precisely evaluate any abnormalities in the monitoring equipment to ensure the nuclear plant's normal operation, the operators' safety, and the integrity of the reactor's components [12].

Correlation analysis is a statistical technique used to determine the linear relationships between variables. It determines the variables that are significantly and positively linked to determine how closely they are associated in magnitude and direction [13]. Correlation analysis can be utilized to investigate the connection between two or more variables. Bivariate, partial, and multiple correlation analyses are the most prevalent types of correlation analysis. It uses statistical software to compute various correlation statistics and has been used in literatures studying the relationship between various elements or variables and finds information that can be used for further studies.

This paper aims to investigate the relationship between the water temperature parameter, water conductivity parameter, and water flow rate parameter of the primary cooling system of the TRIGA PUSPATI Reactor using correlation analysis. Data collection for this paper is conducted using data collected on operation day for the year 2020. Each parameter has a daily dataset for the year 2020. The data is then transformed into an appropriate format and organized into a single dataset. The dataset is next subjected to correlation analysis, and the resulting findings will be discussed. A conclusion will be presented based on the result obtained to determine that the cooling system parameter is valuable for predictive maintenance techniques for monitoring a nuclear reactor based on its cooling system condition.

2. STATISTICAL METHOD OF ANALYSIS

An example of the application of correlation analysis is the study of the relationship between the reactor's internal and external vibration, which can be used to diagnose the condition of equipment [14]. The correlation degree between the internal and exterior vibration signals is affected by the transmission path between the two places. The frequency component is more suited for pre-processing, as determined by the correlation analysis evaluation. Correlation analysis is performed on the aspect of the Safety-II model that describes how each factor has a statistically significant relation [15]. The research results demonstrate that the model can address the limitation of the prior model and provide a more integrated perspective of the nuclear power plant's safety analysis. In solving large-scale unlabeled and multisource coupled nuclear power plant operational data, correlation analysis is typically utilized to objectively evaluate the correlation between variables [16]. A study on the recent predictive maintenance technique for nuclear reactor cooling systems using machine learning has determined the best parameters and statistical analysis method in providing the best technique in this work [17]. Regression analysis is a predictive statistical technique that describes the relationship between dependent and independent variables that can identify the connection between parameters and the decision under consideration [18]. A mathematical model with numerous independent variables to a dependent variable is known as multiple linear regression (MLR) [19]. The MLR model's advantages are its simplicity of formulation, speed of execution, and capacity to recognize the impacts of varied loads [20]. Few predictions have been done recently using machine learning techniques like used an artificial intelligence approach method known as deep neural network [21] and prediction through a web-based system [22].

Statistical analysis has been done on the surveillance test data of Korean nuclear power plants to study the fluency factor of the different model to accurately predicts the transition temperature shift (TTS) on the surveillance test data. The analysis result found that the fluence factor in the regulatory guide should be modified to accurately predict the TTS [23]. Statistical analysis is also one of the primary purposes of developing the building information modelling (BIM) operation and maintenance management system. Improving the information transmission efficiency and solving large-scale operation and maintenance data analysis will support safe operation and maintenance decision-making [24]. Correlation analysis is also used to study the effect of earthquake impacts on the nuclear power plant cluster in Fujian province [25]. The study found that nuclear power plants located in the same structural potential source area have a slight probability of exceeding their corresponding design criteria during an earthquake. Another study uses statistical analysis to develop a quantitative resilience model for power plants to identify the relations in the model using event reports from Korean nuclear power plants [26].

The best estimate plus uncertainty (BEPU) approach is used to conduct an uncertainty analysis in a pressurized water reactor on the large-break loss of coolant accidents (LBLOCA) scenario [27]. It focuses primarily on the uncertainty associated with the maximum figure of merit. Based on relevant performance indicators, the results compared alternative and traditional procedures. Another study examines LBLOCA accidents at nuclear power plants but uses classification and regression approaches [28].

Statistical analysis is also incorporated in a study comparing three severity metrics to assess risk in the nuclear energy system [29]. It uses a data set double the size of prior nuclear mishaps and accident studies. The results reveal that the rate of incidents and accidents has reduced and been relatively steady since the 1970s. Another study uses a statistical technique to develop a baseline for decommissioning nuclear projects to improve future nuclear commissioning project selection, planning, and delivery [30]. In addition, an assessment of the use of solar power plants demonstrates that, despite an increase in the relative cost of the project, it can significantly reduce air pollutants and fossil fuel use while simultaneously enhancing the efficiency of the equipment [31]. Statistical and correlation analysis has been applied in various literature studies. Table 1 shows some of the literature which presented statistical analysis in their studies and the study's objective. Although there are studies involving the analysis of a nuclear reactor, there needs to be more conducted on the cooling system of a nuclear power plant.

Table 1. Statistical analysis reviews towards objective

Research	Field of study	Objective
Kumar *et al*. [13]	Oil and Gas	Predicting the average oil rate through identifying the important element of production process
Zhang *et al*. [16]	Nuclear Engineering	Anomaly detection method for nuclear power plant using variational graph auto-encoder
Park *et al*. [15]	Nuclear Engineering	Develop a model based on safety-II for unexpected situation in nuclear power plant
Sanchez-Saez *et al*. [27]	Nuclear Engineering	Investigate the performance of alternative methods to perform uncertainty analysis of a large-break loss of coolant accident

3. METHOD

The primary cooling system of the TRIGA PUSPATI Reactor in Bangi, Selangor, was examined in 2020. Three parameters from the primary cooling system have been selected for this study. The data collected contains the parameter value from the sensor reading within the cooling system of the research reactor. This study will focus on temperature, conductivity, and water flow rate parameter reading. Figure 1 shows the overview of the research reactor cooling system. The sensors are installed and located at various stages of the cooling system. Temperature parameter data will be collected through five temperature sensors installed. Three temperature sensors are located within the cooling system's primary loop, and the other two are within the cooling system's secondary loop. TT1 and TT2 are at the reactor tank outlet, while TT5 is at the tank inlet. In the secondary loop, TT3 is located at the inlet of the cooling tower, and TT4 is at the outlet. The conductivity of water within the primary cooling system is measured using conductivity sensors that measure the water's ability to conduct electrical current. The outlet pipe of the tank is where the conductivity sensors are attached. The flow rate sensor determines the cooling system's water flow rate. It is situated at the reactor tank's input pipe.

The primary cooling system data are collected in a comma-separated values (CSV) file for each parameter. A single file stored data for a single day in 2020, and each parameter has 356 CSV files. RapidMiner Studio is used to merge all files into a single parameter file. RapidMiner Studio is a software for data science that provides the environment for data preparation, machine learning, text mining, and predictive analytics. It is a powerful statistical solution that incorporates framework architectures to improve delivery and eliminate errors by eradicating the requirement to develop code.

Multiple processes are created to process all individual dataset parameters of the primary cooling system into one single dataset. Figure 2 shows a process created in RapidMiner Studio that will read multiple files from a folder. This process will loop through the files and append all datasets into a single dataset. The new dataset created will then be saved in the repository in the RapidMiner, and a new CSV file will be written into the computer as a backup. Figure 3 shows a process created to process the raw data from the previous process and filter out any unwanted data before moving on to the next step. Next, an operation day process will filter out to only the operational day date and append it into a new dataset. The dataset is then sorted and grouped in time intervals of 30 seconds. Lastly, each parameter dataset is joined together to form a new dataset through the joined parameters process.

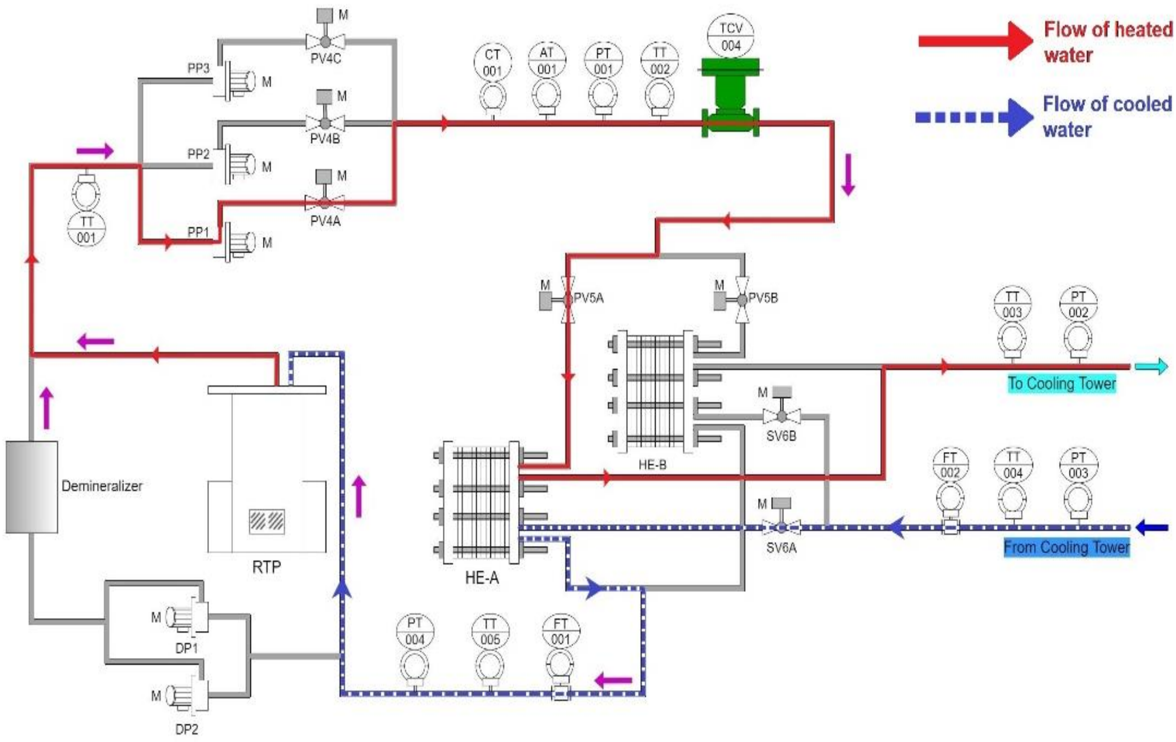

Figure 1. An overview of the cooling system in TRIGA PUSPATI Reactor

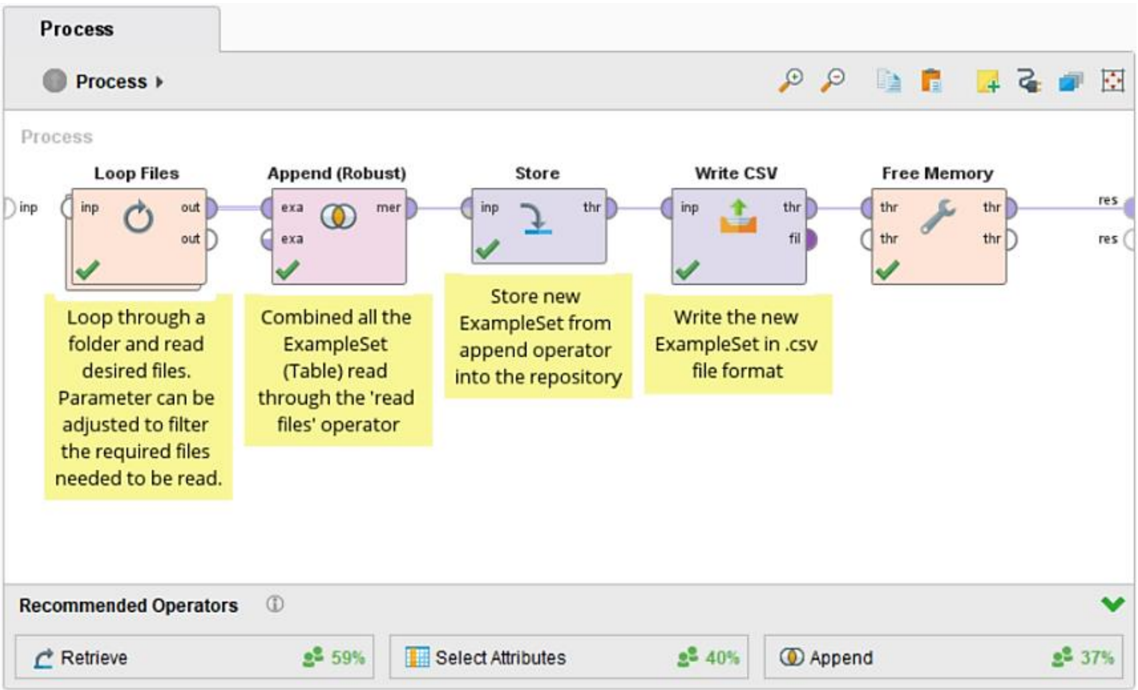

Figure 2. A read multiple files process created in the RapidMiner Studio that read all the csv files from a folder

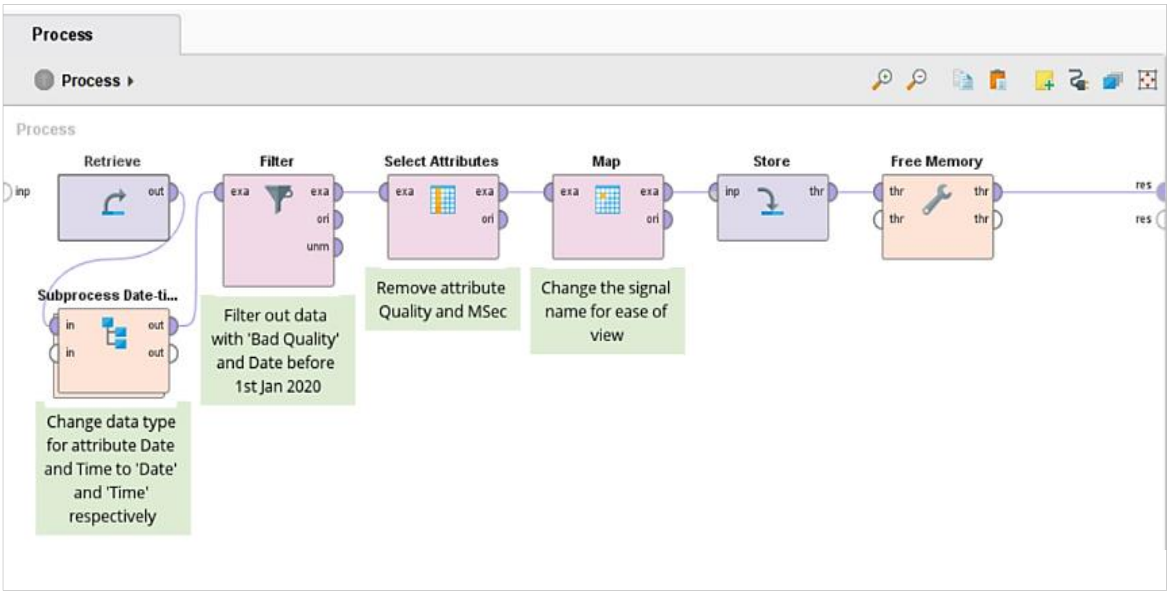

Figure 3. A data filter process created in RapidMiner Studio to pre-process data by filtering out unwanted data from the dataset

4. RESULT AND DISCUSSION

Correlation analysis is performed on the dataset of the operation day in 2020. Each parameter dataset has been filtered to only the operation day of 2020, and a correlation matrix is produced. Table 2 shows the correlation table of the primary cooling system parameter created using data collected from all sensors involved in the cooling system. In this section, the result of the correlation analysis will be discussed.

Table 2. Correlation matrix of the cooling system parameter on temperature, conductivity, and flow rate of water

	TT1	TT2	TT3	TT4	TT5	CT1	FT1
TT1	1.000						
TT2	0.998	1.000					
TT3	0.975	0.974	1.000				
TT4	0.669	0.665	0.809	1.000			
TT5	0.943	0.946	0.972	0.814	1.000		
CT1	-0.083	-0.080	-0.048	0.041	-0.036	1.000	
FT1	0.460	0.462	0.374	-0.043	0.278	-0.083	1.000

4.1. Correlation between temperature sensors

As mentioned in the previous section, there are multiple temperature sensors installed within the cooling system of the TRIGA PUSPATI Reactor. Three sensors are located before the heat exchanger, and two are after the heat exchanger. This section will discuss the correlation between the temperature sensor TT5 and other temperature sensors, as it is the final sensor before the water returns to the reactor tank.

Firstly, the correlation coefficient between water temperature at TT5, TT1 and TT2 are 0.943 and 0.946, respectively. From these correlation coefficient values, the parameter reading at TT5 strongly correlates to TT1 and TT2. Both TT1 and TT2 sensors are located closely in the primary cooling system, thus explaining that the correlation coefficient is almost similar. Figures 4 and 5 show the scatter plot analysis of TT5 against TT1 and TT2, respectively. The linear regression line is also presented in the scatter plot graph. The positive linear regression indicates there is a correlation between the parameters, and it also indicates that there is a positive relationship between the parameter variables.

The R-squared (R2) value shown on the graph is the coefficient of determination, indicating the closeness of the data point from the fitted regression line. The R-squared value for TT5 against TT1 and TT2 are 0.8884 and 0.8942, respectively. This value shows that around 88% of the data are used to explain the linear model for TT5 compared to TT1. Approximately 89% of the data points in the study are a perfect fit to the linear regression line for TT5 compared to TT2.

Next, the correlation coefficient between temperature sensor TT5 versus TT3 and TT4 are 0.972 and 0.814, respectively. This value shows that both TT3 and TT4 are strongly correlated to the water temperature at TT5. The temperature sensors TT3 and TT4 are located at the secondary loop in the cooling system. Figure 6 shows the scatter plot analysis of TT5 against TT3, and Figure 7 shows TT5 against TT4. A positive linear regression line can be seen in both analyses, indicating a positive relationship between the two variables in each regression model. The R-squared value for TT5 versus TT3 is 0.9453, indicating that approximately 94% of the obtained data can be utilized to explain the variation in the dependent variable surrounding its linear regression model. The R-squared value in the analysis of TT5 against TT4 is 66%.

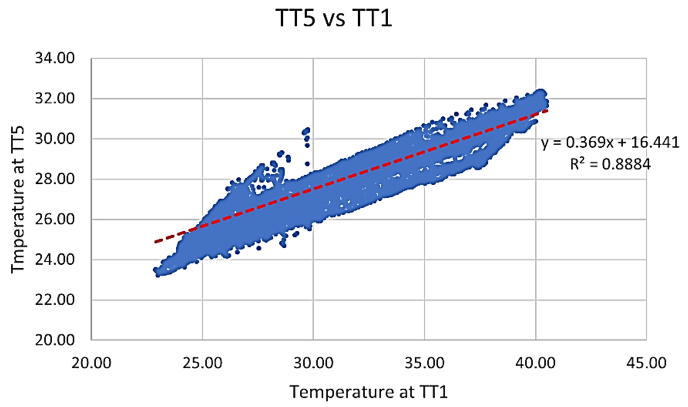

Figure 4. A scatter plot analysis of sensor TT5 against sensor TT1

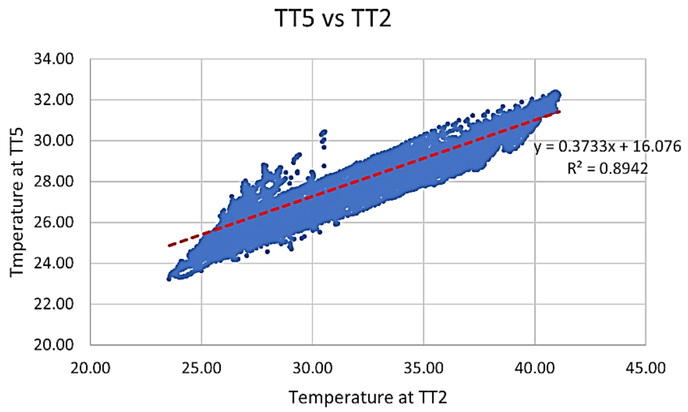

Figure 5. A scatter plot analysis of sensor TT5 against sensor TT2

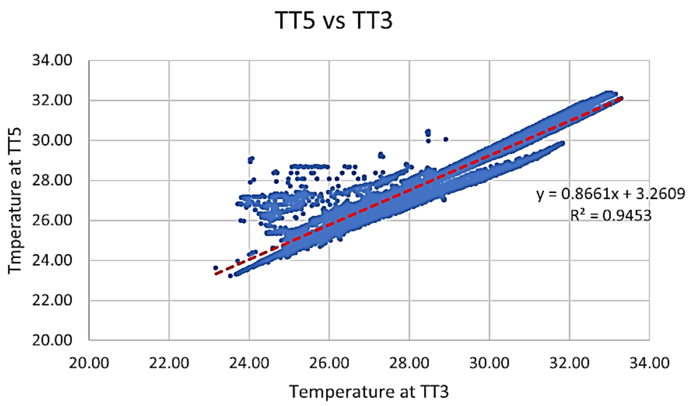

Figure 6. A scatter plot analysis of sensor TT5 against sensor TT3

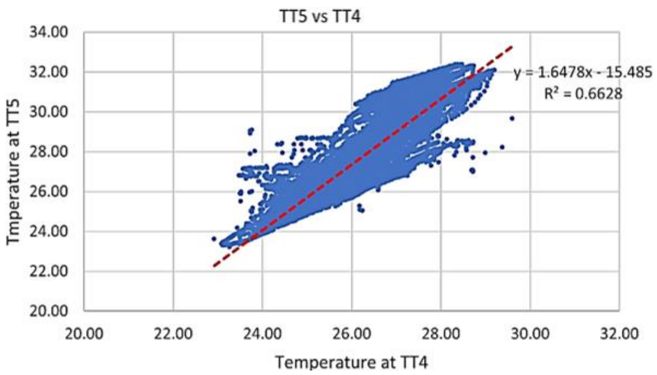

Figure 7. A scatter plot analysis of sensor TT5 against sensor TT4

4.2. Correlation between conductivity and temperature sensor

One conductivity sensor, CT1, is installed within the cooling system's primary loop. It takes the reading of the conductivity of water in the outlet pipe from the reactor tank. The correlation matrix in Table 2 shows that the correlation coefficient between CT1 with TT1 and TT2 is -0.083 and -0.080, respectively. As both values are close to 0, it is identified that water temperature at TT1 and TT2 is not correlated with water conductivity. Figure 8 presents a scatter plot analysis of CT1 against TT1, and Figure 9 shows the scatter plot analysis of CT1 against TT2. A linear regression line is presented in the graph. The horizontal regression line shows no relationship between the two parameters. This result reveals that any changes in water temperature at TT1 and TT2 do not affect water conductivity in the cooling system. The correlation coefficient value for conductivity sensors CT1 with both temperature sensors TT3 and TT4 is presented in Table 2. However, it is not considered in the analysis as both temperature sensors are in the secondary loop of the cooling system. The water inside the secondary loop does not interact directly with the conductivity sensor CT1 in the primary loop. There is also no correlation between CT1 and TT5, as the correlation coefficient value is -0.036, close to 0.

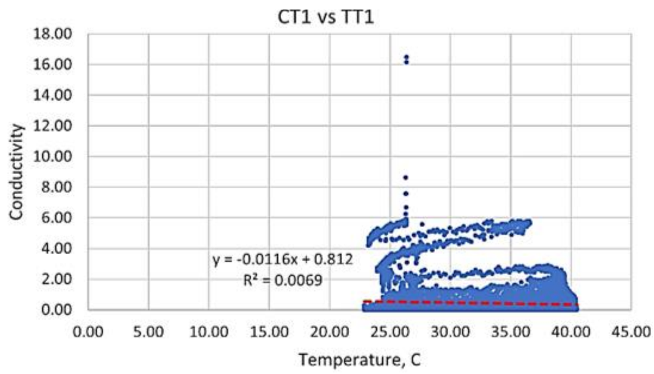

Figure 8. A scatter plot analysis of sensor CT1 against sensor TT1

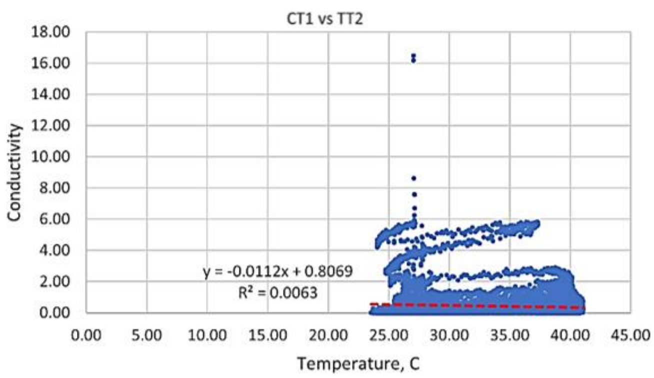

Figure 9. A scatter plot analysis of sensor CT1 against sensor TT2

4.3. Correlation between flow rate sensor and temperature sensor

A flow rate sensor, FT1, is installed at the inlet pipe into the reactor tank after the heat exchanger. The correlation coefficient of FT1 with the temperature sensors is shown in Table 2. Firstly, the correlation coefficient FT1 with temperature sensors TT1 and TT2 are 0.460 and 0.462, respectively. The correlation coefficient values show that the water flow rate at FT1 positively correlates with the water temperature at TT1 and TT2. Figure 10 shows the scatter plot graph of FT1 against TT1, and Figure 11 shows the scatter plot graph of FT1 against TT2. A positive linear regression line is plotted on the graph in both figures. It displays that any changes in the water temperature will linearly affect the water flow rate. The R-squared value for both regression model is 0.21, which indicate that only about 21% of the data point is fitted within the regression model. It is also worth noting that the temperature sensors are installed far from the water flow sensor in the cooling system.

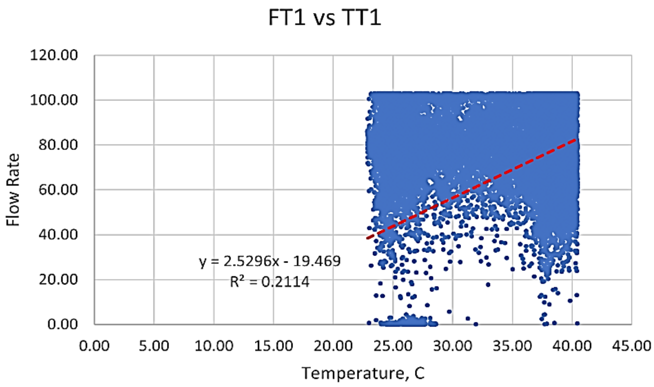

Figure 10. A scatter plot analysis of sensor FT1 against sensor TT1

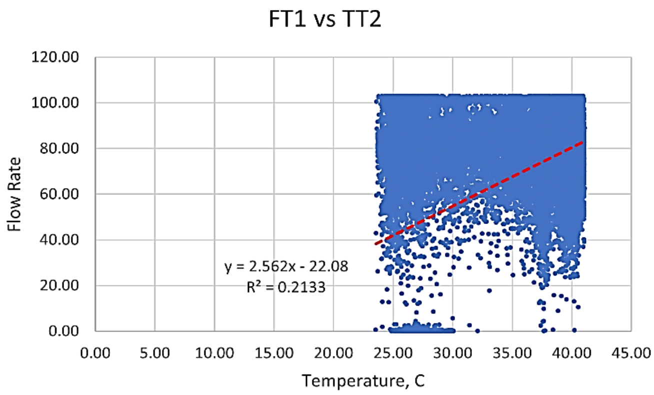

Figure 11. A scatter plot analysis of sensor FT1 against sensor TT2

The correlation matrix in Table 2 shows a correlation coefficient value for FT1 with the temperature sensor TT3 and TT4 are 0.374 and -0.043, respectively. However, these values are not considered in the analysis because the water from the secondary loop where TT3 and TT4 are installed does not directly interact with the water flow rate sensor in the primary loop. Next, the correlation coefficient of FT1 with TT5 is 0.278, showing a positive correlation between FT1 and TT5. Figure 12 shows the scatter plot analysis of the correlation, and a linear positive regression line is plotted onto the graph. It displays that any temperature changes will affect the water flow rate in the cooling system. The R-squared value for FT1 with TT5 is 0.07, which explains that the variation of TT5 can explain only about 7% of the data point variation of FT1.

4.4. Correlation between conductivity sensor and flow rate sensor

The correlation matrix in Table 2 shows that the correlation coefficient between conductivity at CT1 and water flow FT1 is -0.083. It can be determined that there is no correlation between the two parameters within the cooling system, as the correlation coefficient value is close to 0. This result denotes that any changes in the water conductivity value at sensor CT1 do not affect the water flow rate within the cooling system.

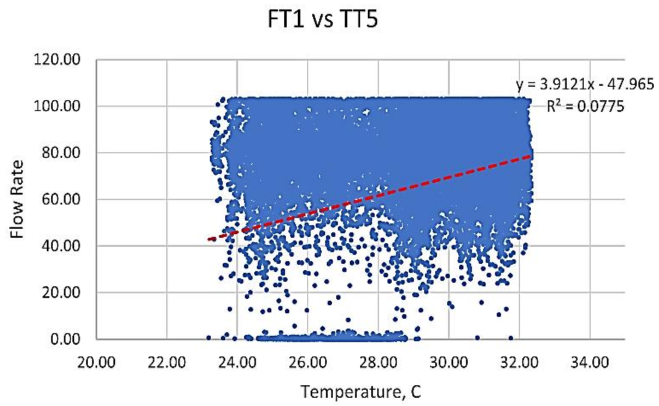

Figure 12. A scatter plot analysis of sensor FT1 against sensor TT5

5. CONCLUSION

The cooling system in a nuclear reactor is essential as it helps control the heat produced by the nuclear fission at the reactor core and transfers the heat through the coolant in the cooling system to be released into the atmosphere. Multiple sensors are installed within the reactor cooling system to monitor the cooling system's efficiency and maintain a safe nuclear operation environment. The cooling system parameters involved in this study are temperature, conductivity, and water flow. Correlation analysis is performed on the dataset of the RTP cooling system taken during the operation day in 2020. The analysis is being conducted using seven sensors. According to the correlation matrix, the water temperature at sensor TT5 correlates positively with other temperature sensors. The conductivity sensor does not correlate with the temperature of the water in the cooling system. The water flow rate at sensor FT1 in the cooling system does correlate with water temperature sensors and does not correlate with water conductivity in the cooling system. Based on the result achieved, the water temperature parameter can be valuable in developing a predictive model for a predictive maintenance program to improve the nuclear reactor monitoring and maintenance system.

ACKNOWLEDGEMENT

The authors would like to thank the Institute for Big Data Analytics and Artificial Intelligence (IBDAAI), Universiti Teknologi MARA, Kompleks Al-Khawarizmi, 40450 Shah Alam, Selangor, Malaysia, for the support fund in publishing this paper. The authors also would like to thank the Research Management Centre (RMC), Universiti Teknologi MARA, Shah Alam, for the support grant no 600-RMC/GPK5/3(006/2020) for this research.

REFERENCES

[1] G. Hu, T. Zhou, and Q. Liu, "Data driven machine learning for fault detection and diagnosis in nuclear power plants: A review," *Frontiers in Energy Research*, vol. 9, May 2021, doi: 10.3389/fenrg.2021.663296.

[2] W. Zhang, C. Wu, S. Yang, B. Huang, and D. Wu, "Study on the characteristics of the nuclear reactor coolant pump during the process-divided start-up period," *Annals of Nuclear Energy*, vol. 178, Dec. 2022, doi: 10.1016/j.anucene.2022.109381.

[3] Z. Qu *et al.*, "Study on pressure surge characteristics of reactor coolant pump shaft stuck accident condition based on wavelet analysis," *Nuclear Engineering and Design*, vol. 397, Oct. 2022, doi: 10.1016/j.nucengdes.2022.111921.

[4] Yu Da-hai, Yu Xiu-yue, Chen Feng, and Chen Chang-jian, "Modeling and parameter measurement research pressurized water reactor nuclear power generator's prime mover and governor," in *2014 International Conference on Power System Technology*, Oct. 2014, pp. 1033–1039, doi: 10.1109/POWERCON.2014.6993950.

[5] T. Lanyau, M. F. Zakaria, Z. Hashim, M. F. A. Farid, and M. S. Kassim, "Replacement of PUSPATI TRIGA reactor primary cooling system and safety considerations," *Journal of Nuclear and Related Technologies*, vol. 7, no. 2, pp. 112–124, 2010.

[6] N. A. M. Fadil, M. Kassim, A. A. M. Nor, and M. S. Minhat, "Analysis characterisation of coolant monitoring system for nuclear research reactor digital instrumentation," 2022, doi: 10.1063/5.0109320.

[7] H.-P. Nguyen, P. Baraldi, and E. Zio, "Ensemble empirical mode decomposition and long short-term memory neural network for multi-step predictions of time series signals in nuclear power plants," *Applied Energy*, vol. 283, Feb. 2021, doi: 10.1016/j.apenergy.2020.116346.

[8] B.-S. Peng, H. Xia, Y.-K. Liu, B. Yang, D. Guo, and S.-M. Zhu, "Research on intelligent fault diagnosis method for nuclear power plant based on correlation analysis and deep belief network," *Progress in Nuclear Energy*, vol. 108, pp. 419–427, Sep. 2018, doi: 10.1016/j.pnucene.2018.06.003.

[9] H. A. Gohel, H. Upadhyay, L. Lagos, K. Cooper, and A. Sanzetenea, "Predictive maintenance architecture development for nuclear infrastructure using machine learning," *Nuclear Engineering and Technology*, vol. 52, no. 7, pp. 1436–1442, Jul. 2020, doi: 10.1016/j.net.2019.12.029.

[10] D. Tian, J. Deng, G. Vinod, T. V Santhosh, and H. Tawfik, "A constraint-based genetic algorithm for optimizing neural network architectures for detection of loss of coolant accidents of nuclear power plants," *Neurocomputing*, vol. 322, pp. 102–119, Dec. 2018, doi: 10.1016/j.neucom.2018.09.014.
[11] X. Tian, V. Becerra, N. Bausch, T. V Santhosh, and G. Vinod, "A study on the robustness of neural network models for predicting the break size in LOCA," *Progress in Nuclear Energy*, vol. 109, pp. 12–28, Nov. 2018, doi: 10.1016/j.pnucene.2018.07.004.
[12] D. Ramos *et al.*, "Dynamic Bayesian networks for temporal prediction of chemical radioisotope levels in nuclear power plant reactors," *Chemometrics and Intelligent Laboratory Systems*, vol. 214, Jul. 2021, doi: 10.1016/j.chemolab.2021.104327.
[13] A. Kumar K., R. J. Ramasree, and M. Faisal, "Performing predictive analysis using machine learning on the information retrieved from production data of oil & gas upstream segment," in *2019 International Conference on Communication and Signal Processing (ICCSP)*, Apr. 2019, pp. 0385–0391, doi: 10.1109/ICCSP.2019.8698107.
[14] S. Wu and S. Tao, "Correlation analysis of reactor internal and external vibration based on Sum squared residual," in *2020 IEEE 4th Conference on Energy Internet and Energy System Integration (EI2)*, Oct. 2020, pp. 3139–3142, doi: 10.1109/EI250167.2020.9347060.
[15] J. Park, J. Kim, S. Lee, and J. Kim, "Modeling safety-II based on unexpected reactor trips," *Annals of Nuclear Energy*, vol. 115, pp. 280–293, May 2018, doi: 10.1016/j.anucene.2018.01.044.
[16] L. Zhang *et al.*, "System-level anomaly detection for nuclear power plants using variational graph auto-encoders," in *2021 IEEE International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC)*, Aug. 2021, pp. 180–185, doi: 10.1109/SDPC52933.2021.9563515.
[17] A. A. Mohamad Nor, M. Kassim, M. S. Minhat, and N. Ya'acob, "A review on predictive maintenance technique for nuclear reactor cooling system using machine learning and augmented reality," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 6, pp. 6602–6613, Dec. 2022, doi: 10.11591/ijece.v12i6.pp6602-6613.
[18] R. Rathi and D. P. Acharjya, "A framework for prediction using rough set and real coded genetic algorithm," *Arabian Journal for Science and Engineering*, vol. 43, no. 8, pp. 4215–4227, Aug. 2018, doi: 10.1007/s13369-017-2838-y.
[19] M. Goyal and M. Pandey, "A systematic analysis for energy performance predictions in residential buildings using ensemble learning," *Arabian Journal for Science and Engineering*, vol. 46, no. 4, pp. 3155–3168, Apr. 2021, doi: 10.1007/s13369-020-05069-2.
[20] F. Kang, X. Liu, and J. Li, "Concrete dam behavior prediction using multivariate adaptive regression splines with measured air temperature," *Arabian Journal for Science and Engineering*, vol. 44, no. 10, pp. 8661–8673, Oct. 2019, doi: 10.1007/s13369-019-04095-z.
[21] M. K. Alsmadi, "Modified SEIR and machine learning prediction of the trend of the epidemic of COVID-19 in Jordan under lockdowns impact," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 5, pp. 5455–5466, Oct. 2022, doi: 10.11591/ijece.v12i5.pp5455-5466.
[22] A. O. Afolabi and O. Abimbola, "Application of machine learning in cement price prediction through a web-based system," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 5, pp. 5214–5225, Oct. 2022, doi: 10.11591/ijece.v12i5.pp5214-5225.
[23] G.-G. Lee, M.-C. Kim, J.-H. Yoon, B.-S. Lee, S. Lim, and J. Kwon, "Statistical analysis on the fluence factor of surveillance test data of Korean nuclear power plants," *Nuclear Engineering and Technology*, vol. 49, no. 4, pp. 760–768, Jun. 2017, doi: 10.1016/j.net.2017.02.005.
[24] W. Liang, J. Yang, X. Liu, J. Wei, and D. Zhang, "Research and development of BIM operation and maintenance system in nuclear power plant," *IOP Conference Series: Earth and Environmental Science*, vol. 310, no. 3, Aug. 2019, doi: 10.1088/1755-1315/310/3/032051.
[25] Q. Wu, J. Wu, and M. Gao, "Correlation analysis of earthquake impacts on a nuclear power plant cluster in Fujian province, China," *Environmental Research*, vol. 187, Aug. 2020, doi: 10.1016/j.envres.2020.109689.
[26] J. T. Kim, J. Park, J. Kim, and P. H. Seong, "Development of a quantitative resilience model for nuclear power plants," *Annals of Nuclear Energy*, vol. 122, pp. 175–184, Dec. 2018, doi: 10.1016/j.anucene.2018.08.042.
[27] F. Sanchez-Saez, A. I. Sánchez, J. F. Villanueva, S. Carlos, and S. Martorell, "Uncertainty analysis of a large break loss of coolant accident in a pressurized water reactor using non-parametric methods," *Reliability Engineering & System Safety*, vol. 174, pp. 19–28, Jun. 2018, doi: 10.1016/j.ress.2018.02.005.
[28] J. F. Villanueva, A. I. Sánchez, S. Martorell, and S. Carlos, "Analysis of LBLOCA accidents in nuclear power plants using classification and regression techniques," in *Proceedings of the 30th European Safety and Reliability Conference and 15th Probabilistic Safety Assessment and Management Conference*, 2020, pp. 727–733, doi: 10.3850/978-981-14-8593-0_4428-cd.
[29] S. Wheatley, B. Sovacool, and D. Sornette, "Of disasters and dragon kings: A statistical analysis of nuclear power incidents and accidents," *Risk Analysis*, vol. 37, no. 1, pp. 99–115, Jan. 2017, doi: 10.1111/risa.12587.
[30] D. C. Invernizzi, G. Locatelli, and N. J. Brookes, "How benchmarking can support the selection, planning and delivery of nuclear decommissioning projects," *Progress in Nuclear Energy*, vol. 99, pp. 155–164, Aug. 2017, doi: 10.1016/j.pnucene.2017.05.002.
[31] M. R. Moghadam, D. Toghraie, M. Hashemian, and G. Ahmadi, "Finding susceptible areas for a 50 MW solar thermal power plant using 4E analysis and multiobjective optimization," *Journal of Thermal Analysis and Calorimetry*, vol. 144, no. 5, pp. 1761–1782, Jun. 2021, doi: 10.1007/s10973-020-10371-0.

BIOGRAPHIES OF AUTHORS

Ahmad Azhari Mohamad Nor is an M.Sc. student at Universiti Teknologi MARA (UiTM), Shah Alam, Selangor, Malaysia in Electrical Engineering Program. He received his first degree from Universiti Teknologi MARA (UiTM) Shah Alam, with Honours, in electronic engineering in 2020. He can be contacted at email: ahmadazharimohamadnor97@gmail.com.

Mohd Sabri Minhat received a B.Eng. degree in electronics engineering (majoring in robotics and automation) from Multimedia University (MMU) and an M.Eng. degree in mechatronics and automatic control from Universiti Teknologi Malaysia (UTM), Johor Bahru, Malaysia, in 2009 and 2016, respectively. He is currently pursuing a Ph.D. degree with the Department of Control and Mechatronics Engineering, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, with a specialization in the control system. He is a Research Officer on Staff with the Section of Reactor Instrumentation and Control Engineering, Reactor Technology Centre, Technical Support Division, Malaysian Nuclear Agency. His current research interests include reactor control, reactor modelling, system identification, model predictive control and fuzzy logic. He can be contacted at email: sabri@nm.gov.my

Norsuzila Ya'acob is an associate professor at the Department of Communication Engineering, Faculty of Electrical Engineering, Universiti Teknologi MARA (UiTM). In 2010, she was awarded a Ph.D. degree in Electrical, Electronics & Systems Engineering from Universiti Kebangsaan Malaysia (UKM), for a work on Modelling and Determination of Ionospheric Effects to Improve GPS System Accuracy. She is the Deputy Director for UiTM Satellite Centre at the FKE. She is also a member of the Wireless Communication Technology Group (WiCoT). She is currently on the Engineering Accreditation Council (EAC) panel for evaluating the accreditation process for an electrical engineering program. She has published more than 120 indexed journal papers including high-impact ISI journals. She is now a corporate member of IEM (Institution of Engineers Malaysia), Professional Engineer (P.Eng. Mal), Malaysia Board of Technologist (MBOT), and Institution of Geospatial and Remote Sensing Malaysia (IGRSM). She can be contacted at norsuzila@uitm.edu.my

Murizah Kassim is currently working as an associate professor at the School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, Shah Alam, Selangor. She is now joining as a senior fellow at Institute for Big Data Analytics and Artificial Intelligence (IBDAAI), Kompleks Al-Khawarizmi, Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia. She received her Ph.D. in electronic, electrical, and system engineering in 2016 from the Faculty of Built Environment and Engineering, Universiti Kebangsaan Malaysia (UKM). She has published many indexed papers related to computer network, IoT, Web, and Mobile development applications research. She experienced for 19 years in the technical team at the Centre for Integrated Information System, UiTM. She is also head of Enabling Internet of Things Technologies (ElIoTT) research group UiTM. She joined the academic in January 2009 and is currently a member of MBOT, IEEE, IET, IAENG, and IACSIT organizations. She can be contacted at email: murizah@uitm.edu.my.