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Descriptive Analysis on Parameters Process of Nuclear Reactor Primary Core Coolant System

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Abstract

This study investigates the relationship between parameters in the primary coolant system of the Reactor TRIGA PUSPATI (RTP), focusing on water temperature, pressure, and flow. The objective is to enhance understanding of system dynamics for fault prediction and condition monitoring, addressing the challenge of ensuring safety and operational integrity in nuclear facilities. Utilizing real-time monitoring data from RTP, the study employs preprocessing, descriptive analysis, correlation analysis, and linear regression. Results reveal significant relationships between temperature sensors and moderate correlations with pressure and flow sensors, indicating variability in system performance over time. Specifically, temperature sensors TT1 and TT2 exhibit a very high positive correlation of 0.97, while temperature sensors TT1 against TT5 and TT2 against TT5 show strong positive correlations of 0.66 and 0.66, respectively. Moderate positive correlations are observed between temperature sensors TT1, PT4, and FT1, ranging from 0.36 to 0.32. Additionally, descriptive analysis of temperature, pressure, and flow parameters between two months indicates variability in system performance. The study's significance lies in its contribution to safety assessments and maintenance planning in nuclear power plants. It emphasizes the importance of using actual operational data for comprehensive analysis and bridging the gap between theoretical knowledge and practical applications in nuclear engineering.

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1. Introduction

Reactor TRIGA PUSPATI (RTP) has operated for more than 30 years at the Malaysian Nuclear Agency since 1982 [1]. The standard nuclear fuel used at RTP is a compound of uranium and a 1:6 ratio of zirconium hydride, [2,3]. The coolant system at RTP consists of two cooling systems named primary and secondary. The coolant system is equipped with a heat exchanger, probes, pumps, a nitrogen-16 diffuser, and an associated valve connected to the RTP tank by aluminum pipes. The primary coolant system is essential to cool the reactor core, as the high water temperature in the reactor tank is generated by nuclear fission reactions [4]. However, the secondary coolant system aims to remove heat that circulates from the reactor tank into the heat exchanger. These circulations of coolant system loops and facilities are significant in protecting the reactor core from critical conditions and shielding the workforce around the nuclear power plant from the danger of ionizing radiation. Furthermore, this coolant system is monitored remotely using a few sensors: pressure, temperature, and flow. Additionally, six sensors were facilitated in the primary coolant system to ensure comprehensive monitoring and early detection of any deviations.

The operation of nuclear facilities is complex, requiring oversight of multiple systems to ensure safety [5]. The failure of a single component may initiate a cascade of subsequent failures, potentially compromising the reactor's operational integrity [6]. The series of sensors within the system can detect the reactor's status and enable prompt maintenance in response to any identified faults [7]. Regular safety inspections of a nuclear power plant's components are vital to detect any abnormalities that potentially lead to accidents [8]. Prior to analyzing raw sensor data, preprocessing is necessary to eliminate noise and distortion. Analysis of operational data provides insight into the plant's status and aids in the identification of any deviations [9]. It is crucial to meticulously assess any anomalies in the monitoring equipment to ensure the nuclear plant's normal operation, the operators' safety, and the integrity of the reactor's components [10].

Recently, several studies have been conducted on anomaly prediction in the nuclear reactor field using three parameters that have been mentioned previously. Temperature and flow parameters have been used to record neutron flux signals within pressurized water reactors [11]. A study has been conducted on the leakage of Leak Before Break (LBB) using pressure, temperature, and crack depth and length [12]. Pressure, temperature, feedwater flow, and pressurizer level parameters were also used to eliminate unnecessary maintenance costs [13]. This study shows that these three parameters are essential in monitoring the primary cooling system of a nuclear reactor. The temperature dictates if the heat exchanges within the cooling system are efficient and can prevent the reactor core from the meltdown. The pressure of the coolant shows if the coolant is distributed adequately through the cooling system and provides good coolant flow in the system.

Descriptive analysis is a fundamental method used to summarize and understand data. It involves examining key characteristics, such as central tendency, variability, distribution, and relationships between variables, including scatterplots. This analysis method is widely used in the nuclear engineering field. Several studies employing life cycle assessment (LCA) have emphasized the potential of nuclear electricity as a low-carbon-emitting electricity source [14]. However, questions have arisen regarding the variability of results. Therefore, this study utilizes descriptive analysis to investigate this topic further. Another study was conducted using a similar analysis method in West Kalimantan in the context of GIS-based multi-criteria analysis for nuclear power plant site selection [15].

Correlation analysis, a statistical technique, is employed to identify linear relationships between variables. It assesses the variables significantly and positively linked, determining the extent of their association in magnitude and direction [16]. Correlation analysis is frequently used to objectively evaluate the relationships between variables when dealing with extensive unlabeled and multisource coupled operational data from nuclear power plants [17]. Correlation analysis is applied within the framework of the Safety-II model, revealing statistically significant relationships among various factors [18]. The research findings indicate that this model can mitigate the limitations of previous approaches and provide a more holistic perspective on safety analysis in nuclear power plants. Additionally, the correlation analysis has proven to be a relevant statistical tool in time series data analysis where it has been applied to study the correlation in primary nuclear online plant cooling systems [19]. The parameters involved are temperatures, conductivity and water flow rate. The outcome of the analysis showed that the data perfectly fit the prediction model. Another study has been conducted to evaluate the dependence of the heat transfer properties of a molten salt mixture as a coolant in a nuclear system [20]. Density, specific heat and viscosity are the parameters involved, and the calculated values stated that they are approximately 20% different from the experimental results. Another correlation between multidimensional variables and equipment status for nuclear power plant condition monitoring has been explored [21]. This method is the preliminary stage of the study, where the authors want to obtain the relationship between twenty parameters against the Squared Prediction Error (SPE) contribution rate. A research study on energy transfer and interaction between liquid metal and water has been done and found a significant correlation between different flow types against different heat transfer [22]. Another correlation observation has explored the effect of transient fission gas during a loss of coolant accident (LOCA) tested in a simulation [23]. However, the outcome of the correlation between two cladding bursts was applied for cladding failure prediction. This process is evidence that correlation analysis is essential for advanced prediction models. Additionally, an investigation was conducted on the small break loss of coolant accident (SBLOCA) scenario, considering various residual heat removal correlations [24]. It was discovered that the long-term residual heat removal capacity plays a crucial role in determining coolant loss. The specific mathematical form of the residual heat removal correlation was derived and is applicable across different scenarios. A dynamic simulation of nuclear hybrid energy system has been completed to investigate the significant impact of the coolant system [25]. The correlation of the heat transfer and pressure drop within the coolant system has been done as a reference for the model development. A nondimensionalized correlation has been developed to predict the temperature profiles in the VVER-1000 reactor [26]. Samples generated for this study are 59 and 80% of it is acquired as a training dataset. The high predictability of correlation of determination is presented with 95%. The correlation analysis is not only analyzed in numerical form but also in images. A study titled 'Hydrogen enhanced localized plasticity in zirconium as observed by digital image correlation' performed correlation using images as input [27]. The method helped the authors to gain a significant outcome where the correlation analysis highlighted substantial strain localization.

However, outside of the nuclear study context but with similar parameters such as temperature, pressure and flow, a descriptive analysis has been done to predict daily and monthly rainfall [28]. The datasets consist of six variables: temperature, pressure, dew point, humidity, visibility and wind speed, and have been split into 70% and 30% for training and validation. Then, the correlation coefficient was conducted and found that 0.8063 and 0.8012 for daily and monthly prediction, respectively. Research has been conducted on using a hybrid solar dryer for ginger drying [29]. Temperature, humidity and solar intensity parameters are considered in this study and the correlation coefficient is highly approximate to 1. Another study using descriptive analysis of stingless bee IoT application monitoring system data has been conducted [30]. Four sensors were installed at the target beehive: temperature, humidity, weight and gas. A moderate negative correlation between temperature and humidity is 0.7378, indicating that humidity tends to decrease as temperature increases. Most of the studies obtained the datasets from simulation which means there is lacked of studies tested using actual data from nuclear power plants or research centers.

This paper aims to investigate the relationship between parameters in RTP's primary coolant system, including water temperature, pressure and flow. Data collection of this paper is collected from a real-time monitoring system at the nuclear research facility, RTP. The data is collected daily from midnight to the following midnight. The dataset undergoes correlation analysis, and the subsequent findings will be examined. Based on the findings, a conclusion will be drawn to determine the effectiveness of cooling system parameters in fault predicting and monitoring the condition of a nuclear reactor's cooling system.

2. Methodology

The coolant system of the Reactor TRIGA PUSPATI (RTP) consists of two loops, primary and secondary. Fig. 1 shows two blue and red arrows indicating the water flow within the primary coolant system as cold and hot water, respectively. The coolant system initiates with the discharge of cold water from the cooling tower into the heat exchanger identified as HE-A, with monitoring conducted through sensor parameters, namely pressure (PT003), temperature (TT004), and flow (FT002). Subsequently, the cold water from HE-A is directed into the reactor tank, with its flow, temperature, and pressure monitored by sensors FT001, TT005, and PT004, respectively, as depicted in Figure 1. The cold water changes to hot water upon entering the reactor tank. The hot water from the RTP tank streams to the temperature (TT001), pressure (PT001), temperature (TT002), and flow into the HE-A. TCV4 controls the temperature at point 4. Next, the hot water from HE-A returns to the cooling tower, passing through temperature sensor TT003 and pressure sensor PT002. However, the primary core coolant system is monitored from the cold water's exit from HE-A until the hot water returns to HE-A. Six sensor parameters are involved in the primary loop: TT001, TT002, TT005, PT001, PT004, and FT001.

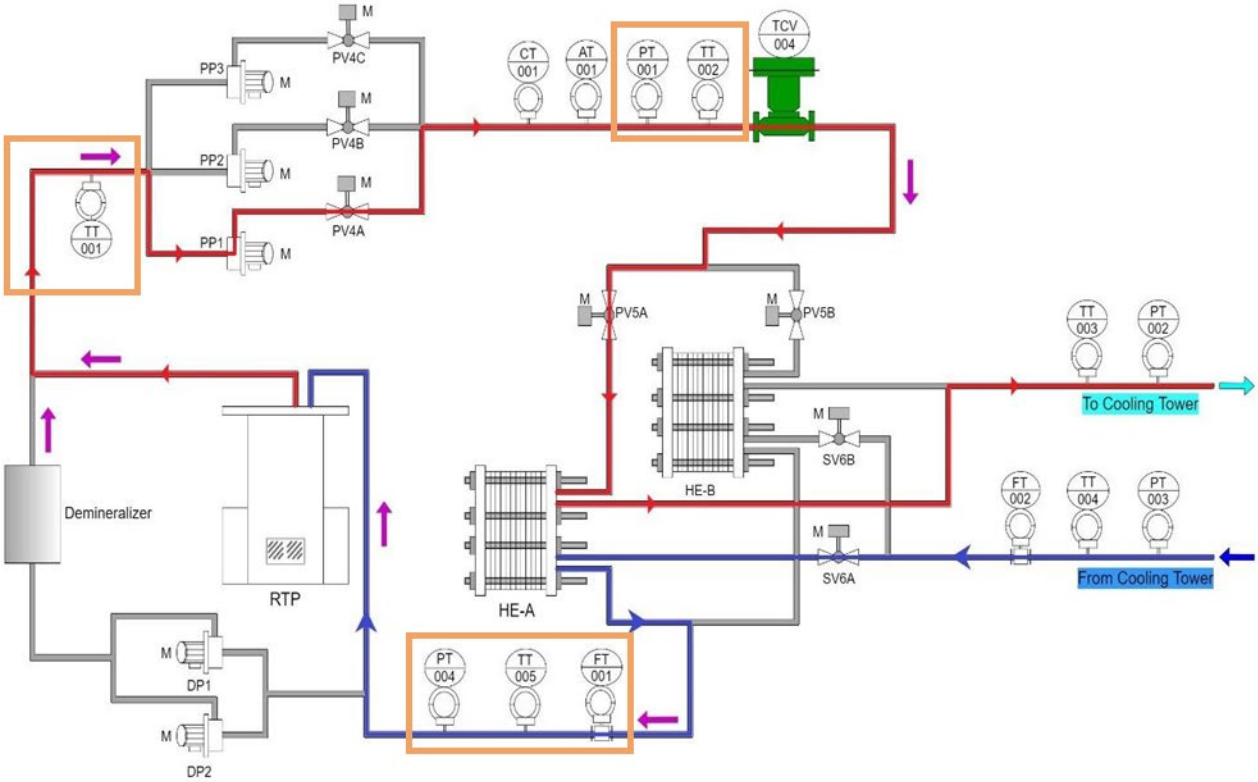

Fig. 1 *The flow of water within the primary core cooling process*

The coolant system data are collected for all parameters in comma-separated values (CSV) files from the Supervisory Control and Data Acquisition (SCADA) system. Data are collected at 0.5-second intervals and stored in CSV files monthly for 2023. All twelve CSV files will undergo data preprocessing, as depicted in Fig. 2, using the Python programming language on the Visual Studio (VS) Code platform. Since the initial CSV files contain data for all eighteen parameters, data selection for the primary core coolant system is required. Then, the datasets need to be checked to ensure completeness for each month. Subsequently, all unwanted data will be eliminated to perform descriptive analysis. Two months of the dataset with a 5-month gap, March and September, are selected for preprocessing due to having the least amount of unwanted data. The operation days in March are the third highest while in September are the lowest. This provides a significant comparison, as it allows for a deeper understanding of how the operation days contribute to the data trends. These two months of data were selected for analysis to observe the operational performance of the nuclear reactor's primary core coolant system. The total number of data varies depending on the month. The total data accumulated for each parameter in March and September is 5,356,800 and 5,184,000, respectively. However, this number will change after data preprocessing.

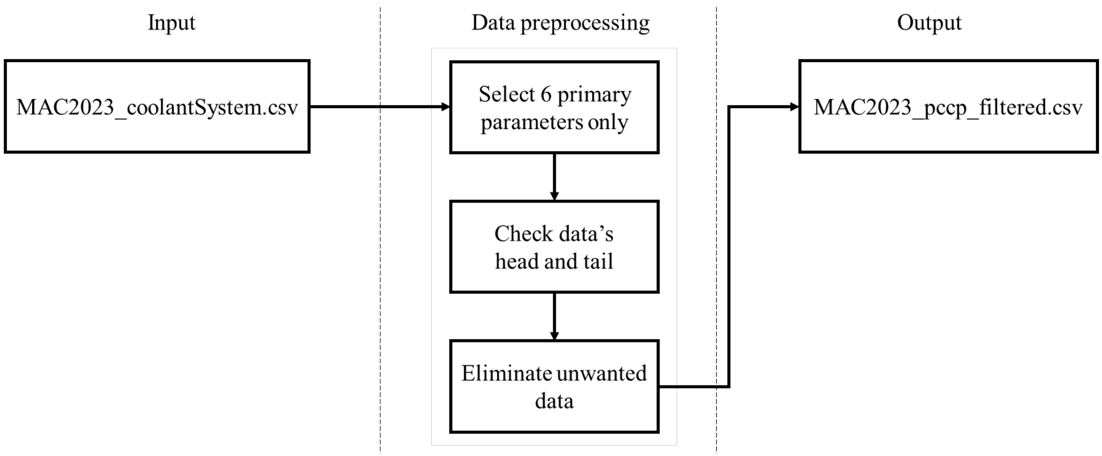

Fig. 2 *The flow of data preprocessing*

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Descriptive analysis is performed using the Python language on the VS Code platform to observe the dataset criteria. Descriptive analysis applies several parameters that have the following features to summarize and describe data. The parameters are categorized into four measure groups which are central tendency, variability, distribution shape, and statistics summary. Measures of central tendency, including the mean, median, and mode, indicate the central point of the dataset. The variability measures such as standard deviation, variance, range, minimum, and maximum, provide insights into the spread and dispersion of the data. Skewness and kurtosis refer to the shape and the distribution of the accumulated data. Statistics summaries such as the sum and count, provide a general overview of the dataset size and total values. While the standard error is the measure of the amount of variability in sample means from the true population mean. Next, the correlation matrix and linear regression are performed to obtain the correlation of each parameter. This paper used 20% of the datasets for testing and the rest for training. These results provide insights into the relationships between variables, aiding in understanding the underlying patterns within the data. Furthermore, graphical representations such as scatter plots and histograms are generated to visually explore the distribution and trends present in the dataset, enhancing the interpretation of the analytical findings.

3. Results

3.1 Descriptive Analysis

The descriptive analysis results from temperature, pressure, and flow parameters will be discussed. Data of each parameter will be observed and compared between collections from March and September of 2023. The data collected at the same point but vary in time. Temperature data will be presented from two sources which are SCADA and logbook records. The comparison between the two sources is necessary due to misaligned data.

3.1.1 Descriptive Analysis of Temperature

Table 1 shows the temperature data collected at TT01 for MAC2023 and SEP2023. SCADA data shows a consistent increase in mean temperature by 3.62% from March to September, whereas LOGBOOK data shows a smaller increase of 0.54%. Median temperatures increase by 2.91% in SCADA data and by 2.24% in LOGBOOK data. Mode temperatures decrease by 0.83% in SCADA data but increase by 6.80% in LOGBOOK data. The standard deviation in SCADA data decreases by 32.66%, reflecting more stable temperatures, while LOGBOOK data shows a 12.19% increase, which suggests greater variability. Variance decreases by 54.65% in SCADA data but increases by 25.87% in LOGBOOK data. Temperature range decreases by 14.10% in SCADA data and by 18.33% in LOGBOOK data. Minimum temperatures rise by 26.03% in SCADA data and by 0.80% in LOGBOOK data. Maximum temperatures increase by 2.46% in SCADA data but decrease by 5.41% in LOGBOOK data. Kurtosis increases by 96.07% in SCADA data, which points to a more peaked distribution, while LOGBOOK data shows a 1720.64% increase. Skewness in SCADA data increases by 35.73%, which means a more positively skewed distribution, whereas LOGBOOK data shows a 75.05% decrease, reflecting a more negatively skewed distribution. The sum of temperatures rises by 0.88% in SCADA data and by 84.50% in LOGBOOK data. The count of temperature readings decreases by 2.66% in SCADA data and by 81.67% in LOGBOOK data. Finally, the standard error decreases by 31.25% in SCADA data but increases by 161.98% in LOGBOOK data. Overall, SCADA temperatures show increased stability, while LOGBOOK temperatures display more variability and significant changes in distribution, likely due to the large difference in data count between the two sources.

Table 1 *Descriptive analysis of temperature at TT001*

Parameters	Mac2023		Sep2023	
	SCADA	LOGBOOK	SCADA	LOGBOOK
Mean	30.9362	32.6317	32.0639	32.8091
Median	30.8124	33.4500	31.7093	34.2000
Mode	30.9426	32.3000	30.6858	34.5000
Standard Deviation	3.7549	2.9991	2.5288	3.3647
Variance	14.0994	8.9944	6.3950	11.3209
Range	26.6674	12.0000	22.9022	9.8000
Minimum	18.7970	25.0000	23.68345	25.2000
Maximum	45.4644	37.0000	46.5857	35.0000
Kurtosis	3.6039	0.1241	7.0675	2.2573
Skewness	1.2850	-1.0736	1.7436	-1.8795
Sum	164761930.4895	1957.9000	166217641.8264	360.9000
Count	5325856	60.0000	5183948	11.0000
Standard Error	0.0016	0.3872	0.0011	1.0145

The comparison of SCADA and LOGBOOK data addresses misaligned between the two sources. Discussions with the RTP's research officer confirmed that temperature data slightly differs between the sensor readings and the SCADA system. Currently, the team conducts data forensics to resolve the issues. However, this analysis highlights the need for accurate data alignment to ensure consistent and reliable temperature monitoring.

3.1.2 Descriptive Analysis of Pressure

Table 2 displays the descriptive analysis of pressure data collected at PT001 for MAC2023 and SEP2023. The data shows a substantial decrease in mean pressure of 63.15% from March to September. Median pressure drops by 66.78%, while mode pressure decreases significantly by 97.39%. The standard deviation falls by 28.30%, which reflects more stable pressures. Variance decreases by 48.59%, indicating greater consistency. The pressure range falls by 40.47%. Even though the minimum pressures rise by 9613.89%, it is still a small count which indicates the valve is closed. Maximum pressures decrease by 38.78%. Kurtosis falls by 95.66%, which points to a flatter distribution. Skewness decreases by 8.56%, which suggests a more symmetrical distribution. The sum of pressures declines by 64.16%, and the count of pressure readings decreases by 2.66% due to the number of days in September. Finally, standard error falls by 27.19%. The data trend from Mac2023 shows higher average pressures, greater variability, and a broader range of pressure values compared to SEP2023. This trend is significant and influenced by the number of RTP's operational days. Since March had more operational days compared to September.

Table 2 *Descriptive analysis of pressure at PT001*

Parameters	Mac2023	Sep2023
Mean	178.8405	65.8901
Median	166.6811	55.3385
Mode	400.0	10.4456
Standard Deviation	76.3767	54.7659
Variance	5833.4019	2999.3027
Range	399.9277	237.9485
Minimum	0.0723	6.9300
Maximum	400.0	244.8785
Kurtosis	1.0413	0.0455
Skewness	1.0050	0.9644
Sum	952478696.0238	341570815.5431
Count	5325856	5183948
Standard Error	0.0331	0.0241

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3.1.3 Descriptive Analysis of Flow

Table 3 presents a descriptive analysis of flow data accumulated at FT001 for MAC2023 and SEP2023. The data shows consistent flows with a 74.86% decrease in mean from March to September. The median flow decreases slightly by 0.52%. The mode remains constant with no change. The standard deviation decreases by 48.62%, indicating more stable flows. Variance decreases by 73.62%, indicating more consistent flows. The flow range decreases by 4.63%. Minimum flows increase by 1007.50%, indicating a considerable rise from near zero to a higher minimum value. Maximum flows decrease by 4.62%. Kurtosis significantly increases by 816.77%, indicating a more peaked distribution. Skewness increases by 145.32%, indicating a more positively skewed distribution. The sum of flows decreases by 75.52%. The count of flow readings decreases by 2.66%. Finally, standard error decreases by 50.29%. The data from March to September show that both the mean flow and variability decreased significantly. This trend is significant and reflects the impact of the number of RTP's operational days, as March had a greater number of operational days compared to September.

Table 3 *Descriptive analysis of flow at FT001*

Parameters	Mac2023	Sep2023
Mean	10.7112	2.6935
Median	0.2112	0.2101
Mode	0.2101	0.2101
Standard Deviation	27.7970	14.2778
Variance	772.6730	203.8540
Range	96.2482	91.7965
Minimum	0.0004	0.0043
Maximum	96.2486	91.8009
Kurtosis	3.1686	29.0900
Skewness	2.2712	5.5742
Sum	57046539.3976	13963106.4188
Count	5325856	5183948
Standard Error	0.0121	0.0063

3.2 Correlations between Process Parameters

The matrix displays correlation coefficients ranging from -1 to 1, where -1 signifies a strong negative correlation, 0 indicates no correlation, and 1 represents a strong positive correlation. The color scale on the right visually represents these values, with red indicating positive correlations and blue indicating negative correlations.

3.2.1 Correlation Matrix of March 2023

The correlation matrix depicted in Fig. 3, collected in March 2023, reveals significant relationships between various variables. TT1 and TT2 exhibit a very high positive correlation of 0.97, along with TT1 and TT5, 0.66, and TT2 and TT5, 0.66. Moderate positive correlations are observed between TT1, PT4, and FT1, 0.36 each, and between TT2, PT1, 0.34, PT4, 0.31, and FT1, 0.32. TT5 shows moderate negative correlations with PT4, -0.37, and FT1, -0.36. PT1 displays low correlations with the TT variables, ranging from 0.16 to 0.34, while PT4 and FT1 exhibit very low negative correlations with TT1 and TT2 -0.06 -0.052, respectively. This matrix underscores strong positive relationships among the TT variables and moderate negative relationships with PT4 and FT1.

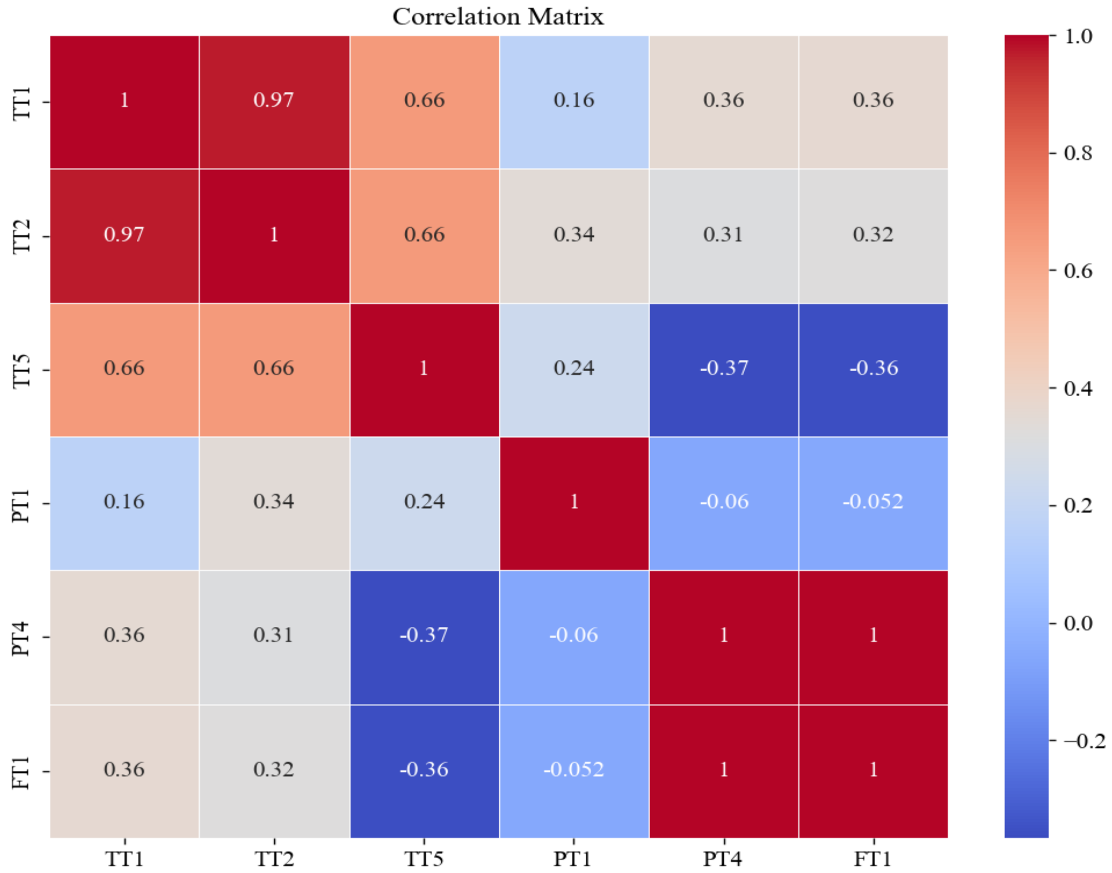


Fig. 3 *Correlation matrix collected in March 2023*

3.2.2 Correlation Matrix of September 2023

The correlation matrix depicted in Fig. 4 shows TT1 and TT2 exhibit a very high positive correlation of 0.96, along with TT1 and TT5 at 0.86 and TT2 and TT5 at 0.83. Moderate positive correlations are observed between TT1, PT4, and FT1 at 0.25 each, and between TT2, PT1 at 0.34, PT4 at 0.24, and FT1 at 0.23. TT5 shows moderate negative correlations with PT1 at -0.31, PT4 at -0.16, and FT1 at -0.19. PT1 displays low positive correlations with the temperature variables, ranging from 0.24 to 0.34, while PT4 and FT1 exhibit very low negative correlations with TT1 and TT2, around -0.098 and -0.0013, respectively. This matrix underscores strong positive relationships among the TT variables and moderate negative relationships with PT1, PT4, and FT1.

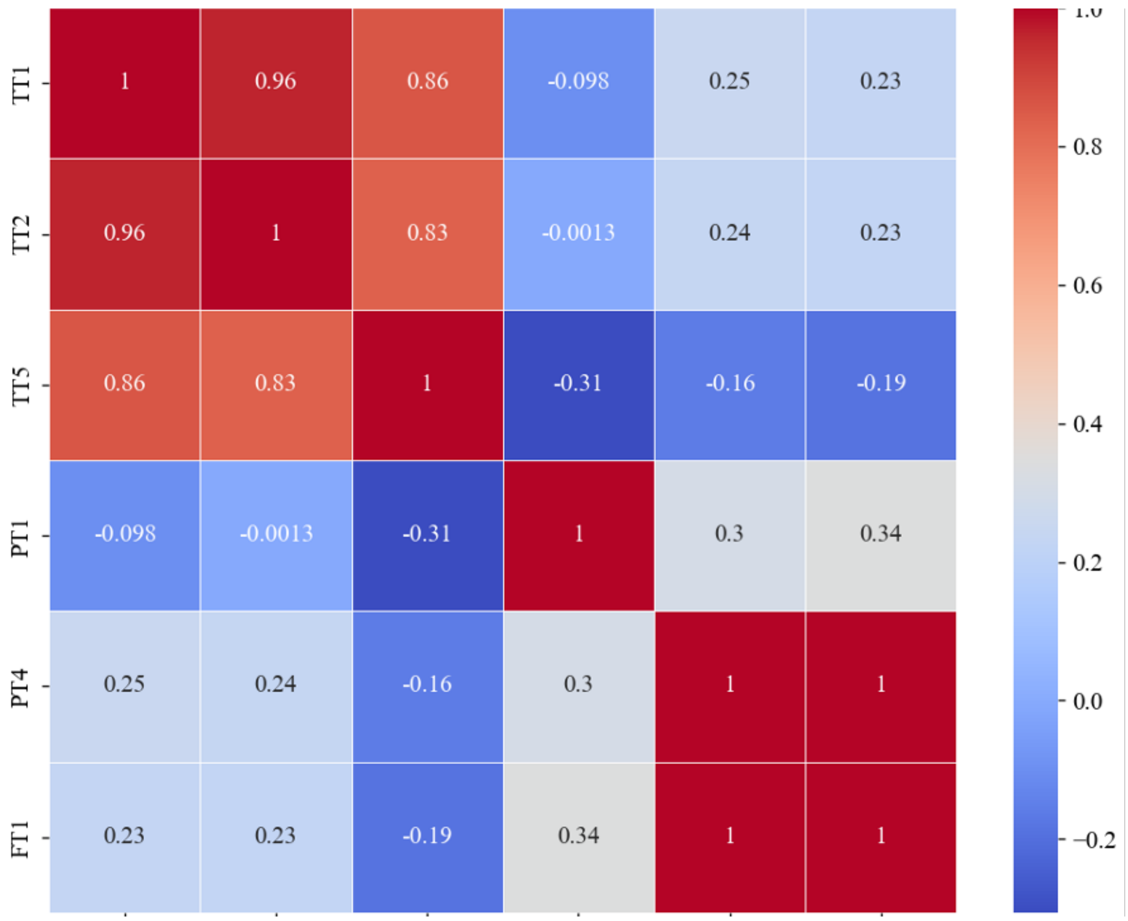


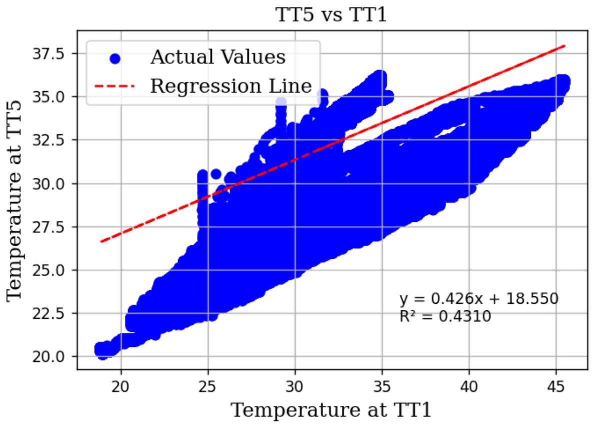
Fig. 4 *Correlation matrix collected in September 2023*

3.3 Linear Correlation between Process Parameters

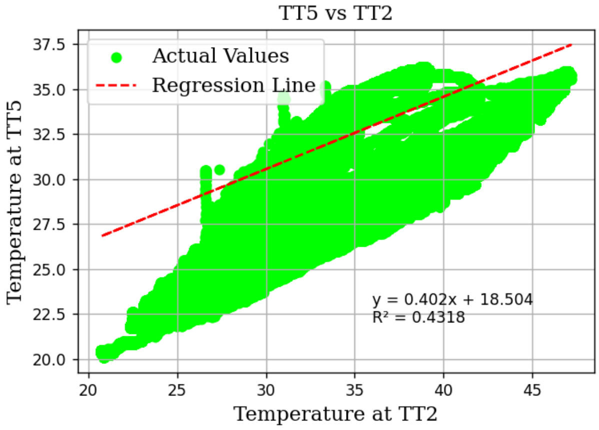
The linear correlation between process parameters is essential for optimizing and controlling various industrial processes. The outcome of the correlation matrix collected in March 2023 showed significant positive values compared to the result from September 2023. Then, the linear correlation between process parameters will be continued with the dataset from March 2023. This section will explore five key categories to understand these relationships better. The first category examines the correlation between temperatures. The second category focuses on the correlation between pressures and temperatures. The third category investigates the relationship between pressures. The fourth category studies the relationship between flow and temperatures. Finally, the fifth category analyses the correlation between flow and pressure.

3.3.1 Temperatures Correlation

Fig. 5 consists of two scatter plots illustrating the linear correlation between temperatures measured at different locations, explicitly comparing TT5 with TT1 and TT5 with TT2. Scatterplot (a), TT5 vs TT1, has a red regression line with a slope of 0.426, while scatterplot (b) has a slope of 0.402. Both results are close in value due to the proximity of the sensors in the primary core coolant system and indicate a strong linear relationship with temperature at TT5. Furthermore, an R-squared (R2) value of TT5 against TT1 is 0.7310, and TT2 is 0.7316. These values show that around 73% of the data points fit the pattern described by the relationship between TT5 against TT1 and TT5 against TT2, implying a moderate-to-strong correlation between the variables.



(a) TT5 against TT1

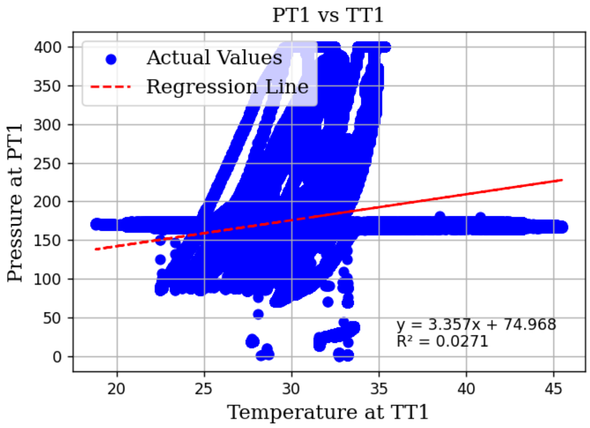


(b) TT5 against TT2

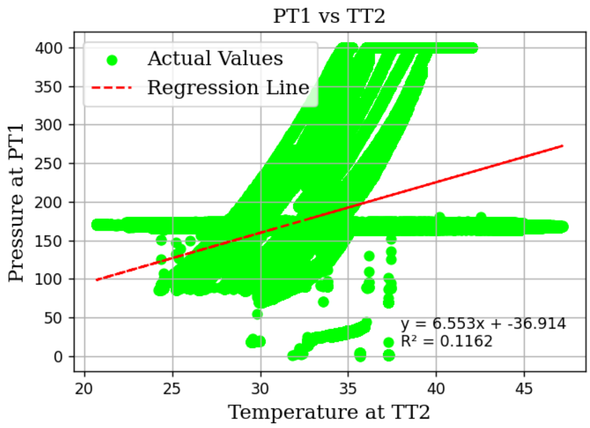
Fig. 5 *Linear correlation between temperatures*

3.3.2 Pressure Against Temperatures Correlation

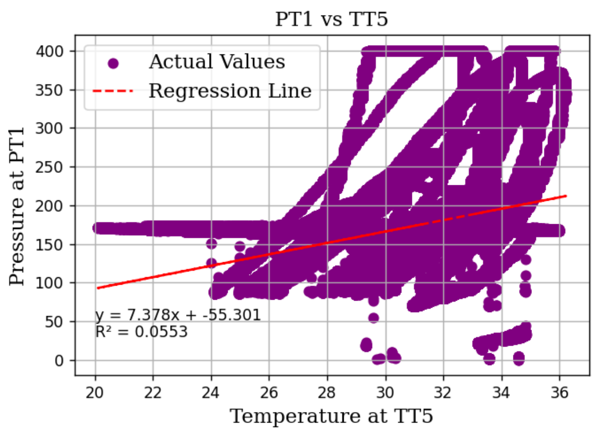
Fig. 6 consists of three scatter plots illustrating the linear correlation between pressure PT1 and temperatures measured at different locations, explicitly comparing PT1 with TT1, TT2, and TT5. Scatterplot (a), PT1 vs TT1, has a red regression line with a slope of 3.357, while scatterplot (b), PT1 vs TT2, has a slope of 6.553, and scatterplot (c), PT1 vs TT5, has a slope of 7.378. These results show an increasing trend in the strength of the linear relationship between PT1 and the temperatures at the different locations. Furthermore, an R-squared (R^2) value of PT1 against TT1 is 0.0271, PT1 against TT2 is 0.1162, and PT1 against TT5 is 0.0553. These values indicate that the linear models only explain a small to moderate proportion of the variability in the data, with the strongest correlation being between PT1 and TT2.



(a) PT1 against TT1



(b) PT1 against TT2



(b) PT1 against TT5

Fig. 6 *Linear correlation between pressure PT1 and temperatures*

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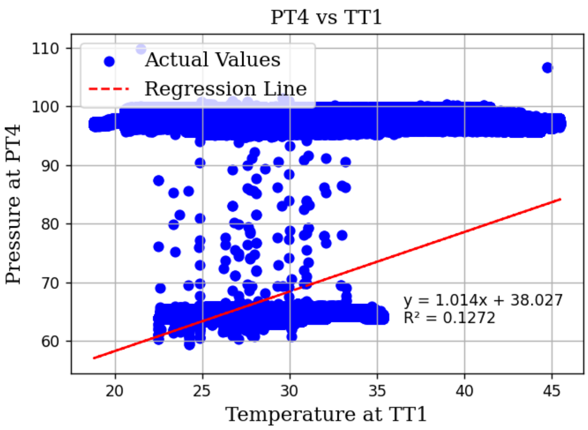
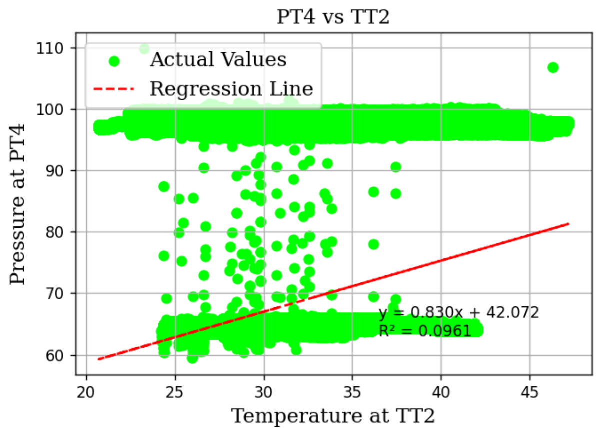
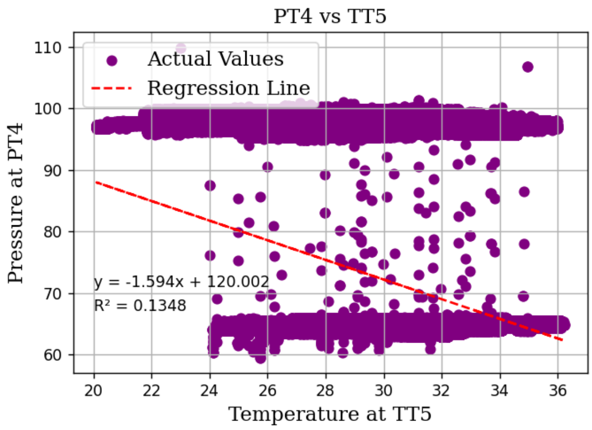
Fig. 7 consists of three scatter plots illustrating the linear correlation between pressure PT4 and temperatures measured at different locations, explicitly comparing PT4 with TT1, PT4 with TT2, and PT4 with TT5. Scatterplot (a), PT4 vs TT1, has a red regression line with a slope of 1.014. Scatterplot (b), PT4 vs TT2, has a slope of 0.830, and scatterplot (c), PT4 vs TT5, has a slope of -1.594. These results indicate varying degrees of linear relationships, with PT4 vs TT1 and PT4 vs TT2 showing positive slopes, while PT4 vs TT5 shows a negative slope. Furthermore, the R-squared (R^2) values for PT4 against TT1, TT2, and TT5 are 0.1272, 0.0961, and 0.1348, respectively. These values suggest that the linear correlation between pressure PT4 and temperature is relatively weak across all three comparisons, with the strongest relationship observed between PT4 and TT5.



(a) PT4 against TT1



(b) PT4 against TT2



(b) PT4 against TT5

Fig. 7 *Linear correlation between pressure PT4 and temperatures*

3.3.3 Pressures Correlation

Fig. 8 consists of a scatter plot illustrating the linear correlation between pressures measured at different points, explicitly comparing PT4 with PT1. The scatter plot has a red regression line with a slope of -0.008, indicating a slight negative relationship between the pressures at PT4 and PT1. Furthermore, the R-squared (R^2) value is 0.0036, showing that only 0.36% of the data points fit the pattern described by the relationship between PT4 and PT1, implying a weak correlation between the variables. Additionally, these pressure sensors are not located in the same single loop of the primary coolant system. It was separated by a cooling tower and heat exchanger.

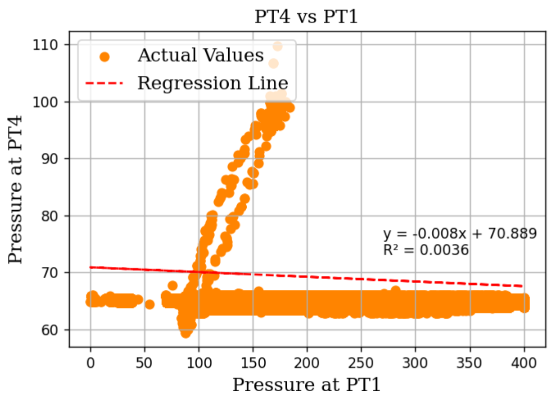
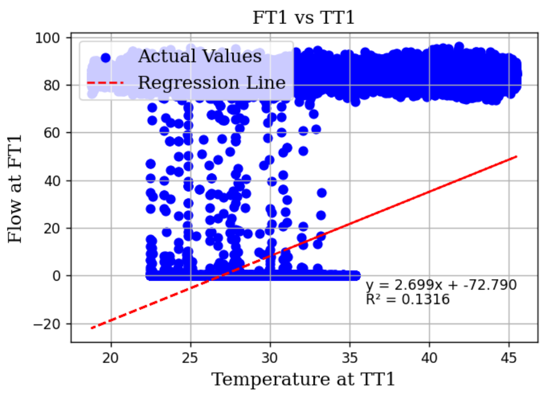


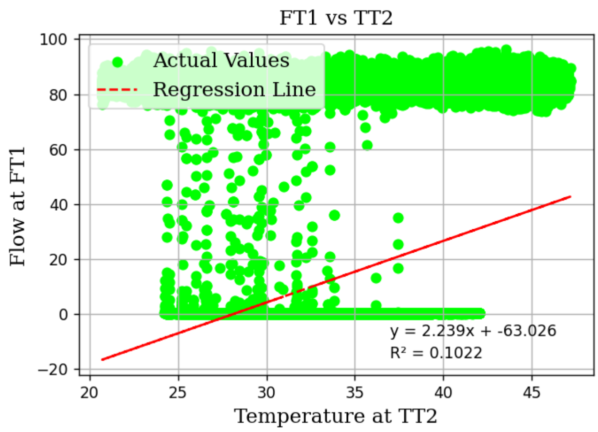
Fig. 8 *Linear regression of pressures*

3.3.4 Flow Against Temperatures Correlation

Fig. 9 consists of three scatter plots illustrating the linear correlation between flow (FT1) and temperatures measured at different locations, explicitly comparing FT1 with TT1, FT1 with TT2, and FT1 with TT5. Scatterplot (a), FT1 vs TT1, has a red regression line with a slope of 2.699 and an R-squared (R^2) value of 0.1316. This output indicates a moderate positive linear relationship between FT1 and the temperature at TT1, with around 13% of the data points fitting the regression line pattern. Scatterplot (b), FT1 vs TT2, has a red regression line with a slope of 2.239 and an R-squared (R^2) value of 0.1022. This result suggests a weaker positive linear relationship between FT1 and the temperature at TT2, with only around 10% of the data points following the regression line pattern. Scatterplot (c), FT1 vs TT5, has a red regression line with a slope of -4.076 and an R-squared (R^2) value of 0.1289. This outcome indicates a moderate negative linear relationship between FT1 and the temperature at TT5, with around 13% of the data points fitting the regression line pattern. In summary, the regression line slopes for FT1 against TT1, TT2, and TT5 are 2.699, 2.239, and -4.076, respectively, showing varying degrees of positive and negative linear relationships. The R-squared values for these comparisons are 0.1316, 0.1022, and 0.1289, respectively, indicating that the strength of the linear relationships is relatively weak to moderate across all three comparisons.



(a) FT1 against TT1



(b) FT1 against TT2

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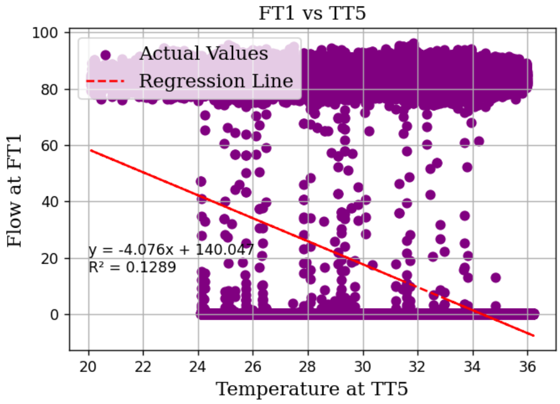

(b) FT1 against TT5

Fig. 9 *Linear correlation between flow and temperatures*

3.3.5 Flow Against Pressure Correlation

Fig. 10 consists of a scatter plot illustrating the linear correlation between the flow at FT1 and the pressure at PT1. The scatter plot has a red regression line with a slope of -0.019. The R-squared (R^2) value for the plot is 0.0028. These results indicate a weak linear relationship between the flow at FT1 and the pressure at PT1, as the slope is close to zero and the R^2 value is extremely low, suggesting that only 0.28% of the variation in the data is explained by the linear model. This implies that there is no linear correlation between the variables. Additionally, these sensors are not located in the same single loop of the primary coolant system. It was separated with the cooling tower and heat exchanger.

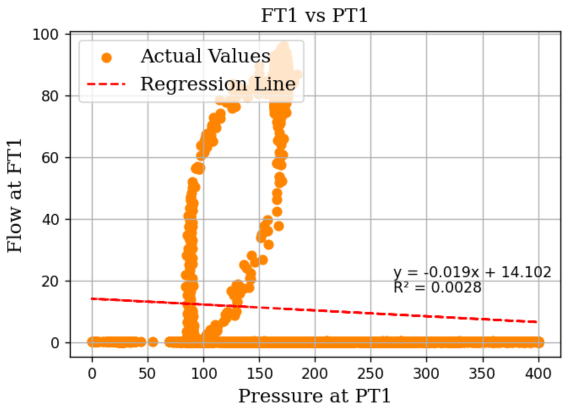

Fig. 10 *Linear correlation between pressures*

4. Conclusion

In summary, this study analyzes the primary coolant system of Reactor TRIGA PUSPATI (RTP) by examining water temperature, pressure, and flow parameters. The findings highlight the importance of real-time monitoring data for safety assessments in nuclear power plants. This is demonstrated through descriptive analysis, which reveals performance variations over different months, while correlation analysis identifies significant relationships between temperature sensors and moderate correlations with pressure and flow sensors. Furthermore, linear regression enhances understanding of linear relationships between process parameters for better control. Each method, including preprocessing, descriptive analysis, correlation analysis, and linear regression, contributes to a comprehensive understanding of the system dynamics. Additionally, based on data collected at RTP, this research offers insights applicable to larger nuclear power plants, highlighting its significance in enhancing safety and efficiency in nuclear energy production for daily usage.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***Conceptualized the research study, data collection and graphical representation of data:*** *Intan Nabina Azmi;* ***designed the descriptive analysis framework and coordinated the overall research process:*** *Murizah Kassim;* ***Led the technical parameters identification and expertise on nuclear reactor systems:*** *Mohd Sabri Minhat;* ***Advise on experimental design and computational modeling:*** *Wan Fairos Wan Yaacob.* ***Contributed significantly to the data collection****: Ibnu Hajar. All authors reviewed the results and approved the final version of the manuscript.*

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