Optimal efficiency on nuclear reactor secondary cooling process using machine learning model

Ibnu Hajar[1,4], Murizah Kassim[1,2], Mohd Sabri Minhat[3], Intan Nabina Azmi[1]
[1]School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, Shah Alam, Malaysia
[2]Institute for Big Data Analytics and Artificial Intelligence (IBDAAI), Universiti Teknologi MARA, Shah Alam, Malaysia
[3]Reactor Technology Centre, Malaysian Nuclear Agency, Kajang, Malaysia
[4]Department of Electrical Engineering, Faculty of Electricity and Renewable Energy, PLN Institute of Technology, Jakarta, Indonesia

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ABSTRACT

This review delves into the quest for optimal efficiency in the secondary cooling process of nuclear reactor water plant coolant systems. Modeling secondary cooling nuclear processes is hardly performed. Thus, Neural networks with traditional statistical methodologies are integrated to innovate a hybrid model to revolutionize nuclear reactor cooling systems' performance, reliability, and safety. A total of 63 indexed papers were reviewed in the nuclear field that analyzed critical research gaps, including the need for uncertainty modeling and resilience against external hazards. Insights into sensor technologies, data analytics, and real-time monitoring underscore the importance of continuous optimization and predictive maintenance were reviewed. A descriptive analysis for a month of sampling data was presented for the parameters of temperature for TT003 and TT004 and pressure for PT002 and PT003 of the secondary process. The confidence level of 95.0% is identified for the temperature and pressure parameters. The lowest standard error was recognized at 0.00032 and 0.01691, respectively. The review culminates with a forward-looking perspective, recognizing the pivotal role of hybrid machine learning models in shaping the future of secondary cooling processes for nuclear reactor water coolant plants to improve the efficiency and sustainability of nuclear reactor systems.

Corresponding Author:

Murizah Kassim
Institute for Big Data Analytics and Artificial Intelligence (IBDAAI), Universiti Teknologi MARA
40450 Shah Alam, Selangor, Malaysia
Email: murizah@uitm.edu.my

1. INTRODUCTION

Nuclear energy has become an essential role in the global energy landscape since it is a stable and sustainable source of electricity. The fission reaction between thermal neutrons and uranium produces intense heat in the reactor core, which causes heat to escape from the heat exchanger and coolant to be used. The turbine, which is connected to the generator, is then turned on by steam, producing electricity. Fuel elements, moderators, and control rods are unquestionably essential parts of a nuclear reactor. Reactor coolant pump (RCP): the only high-speed rotating device in a pressurized water reactor's primary coolant loop system and a vital component of nuclear reactors [1]. The optimization approach for the high-specific speed mixed-flow reactor coolant pump has been demonstrated by research, and it has been found that the hydraulic performance of the RCP is significantly influenced by the types of impellers used [2]. The primary components of pressurized water reactor (PWR) nuclear power plants are, in fact, the pressure water reactor, reactor coolant system in the primary circuit, steam and power conversion system in the secondary circuit, circulating water system, turbines, transmission and distribution systems, and auxiliary system components [3]. The process spreads to the nuclear research reactor digital instrumentation monitoring system through the primary and secondary coolant systems. On June 28, 1982, the Malaysian Nuclear Agency recognized the PUSPATI TRIGA reactor (RTP) as a critical achievement. The reactor comprises a single 1-MW shell-and-tube heat exchanger, three centrifugal pump units, and a piping system. The proposed changes include replacing the single 1-MW shell-and-tube heat exchanger with two 1.5-MW plate-type heat exchangers, replacing the current centrifugal pump system with three new units, and upgrading the two instrumentation and control units to a new single-unit integrated control system, also known as the supervisory control and data acquisition (SCADA) system [4].

In addition to the primary cooling system, a secondary cooling system is also necessary to maintain the coolness of the reactant process in a power plant reactor. Nevertheless, no case study employing variable modeling has been carried out up to this point. Previous research has identified three issues which are the likelihood of RTP's continued operation. The daily processes for the data on RTP are still manual operations and inspection checking nowadays. This is because there are not as many staff on duty to oversee operations around the clock, which increases the risk of an unintentional mishap. While erosion is a mechanical surface deformation by liquid at high flow velocities, typical material corrosion requires chemical and electrochemical reactions [5]. The practical application of this technology depends critically on nuclear reactor safety and efficiency. The secondary cooling process is an essential operation in the complex network of a nuclear reactor system because it directly affects the water coolant system's overall performance and thermal stability [6].

Deterministic models have historically been used to optimize cooling procedures in nuclear reactors. However, these models may find it difficult to account for these intricate systems' dynamic and nonlinear characteristics [7]. The need for novel approaches that can precisely forecast and optimize the secondary cooling process in real-time is rising as the need for greater efficiency and safety becomes more pressing. The significance of the project toward execution in certain nuclear research reactor sections is diverging according to predictive analysis data. The information indicates the need for future recommendations for potential events and scenarios. Using various pertinent techniques, some projects have been implemented in primary coolant for monitoring systems. Following the replacement of the heat exchanger in April 2010, researchers from Malaysia's nuclear research reactor suggested increasing the effectiveness of the RTP primary cooling system reconstruction. The increasing error in system stability, system indications, non-functional functions, intermittent signals in the system, increased reactor downtime, and increased maintenance time are the reasons behind the RTP's proposal to improve RTP instrumentation and control [8]. Nowadays, data analysis is crucial, particularly for projections about the future. Numerous platforms for pre-analyses and analytics have been created on occasion. These methods are applied by several tools that use historical or contemporary data to assess the information. This initial data characterization will allow modeling, simulating, and analyzing dynamical systems in a flow sheeting context. Continuous time, sampling time, or a combination of the two can describe linear and nonlinear systems [9]. Predictive maintenance estimation was done using statistically based models built from process data by fitting a probabilistic model to the data without depending on engineering or physics principles [10]. General path models (GPMs) and stochastic process models (SPMs) are two major statistically-based model types [11].

The predictive analysis strongly suggests the issue's likely remedy. Model parameter determination may benefit from the same processes that help standardize quality parameters [12]. Predictive analysis methodologies frequently employ machine learning algorithms such as fuzzy logic, decision trees, artificial neural networks, and evolutionary programming. Thus, utilizing the combination of two or more machine learning models called hybrid machine learning models, the prediction data in this study will be presented using temperature, flow, and pressure parameters from data generated in the secondary cooling system. Analysts use patterns in historical data and current events to predict future events. Even though accurate prediction does not exist, analysts stand a better chance of success if they possess thorough knowledge. Three primary data mining techniques, clustering, classification, and regression are applied in various settings. Clustering is an unsupervised learning technique in which the algorithm processes the data simultaneously. The information must be divided into data clusters by the algorithm. Most well-clustering methods are density-based spatial clustering of applications with noise (DBSCAN), hierarchical clustering, k-means clustering, and k-medoids clustering. Classification, or supervised learning, requires a subset of recorded samples called training data. A classification model is constructed and fitted to the analysis to anticipate the prospect. This model is then used for a separate set of stored records designated testing data [13]. One kind of supervised machine learning problem is regression, which predicts a continuous output variable using one or more input features. Regression aims to connect the input features and the output variable so that the model can forecast previously unobserved data [14].

The efficiency of nuclear reactor water coolant systems is critical for maintaining safe and optimal operation within nuclear power plants. This study aims to enhance the understanding and performance of the secondary cooling process through a comprehensive review and advanced analytical methods. Focusing on the secondary cooling systems, particularly the parameters influencing their efficiency, we seek to identify optimal operational practices and predictive models. Employing a combination of traditional statistical approaches and modern machine learning techniques, we aim to develop robust models that can predict and improve the efficiency of this cooling system. The manuscript is organized as follows: the method section details the review of the secondary cooling process, data collection parameters, the application of a maximum likelihood estimator for optimal efficiency, and deploying various machine learning models, including a hybrid approach and performance measurement. The results and discussion section presents findings related to the coolant system, machine learning model, time series analysis, predictive models, and critical parameters, alongside exploring research gaps and secondary data analysis. Finally, the conclusion summarizes the insights and implications of our study.

2. METHOD

The prominent publishing databases' online search tools are the most preferred method of finding review structures. The review structure for the optimal efficiency of the secondary cooling process for the nuclear reactor water plant cooling system using a hybrid machine learning model is depicted in Figure 1. Most journals and proceedings chosen for inclusion in literature reviews have been sourced from the IEEE Xplore database, which is indexed in SCOPUS and Science Direct. Google Scholar has also been used because it offers a wide variety of papers providing peer assessments of products from selected databases. The research framework served as the basis for defining the search keywords. The critical components of the following search query are the nuclear reactor, secondary cooling process, water plant cooling system, optimal efficiency, and hybrid machine learning model. Every review paper must include terms related to the nuclear reactor, such as the primary and/or secondary coolant system, machine learning, and hybrid machine learning model. All review papers were chosen during a five-year period that ran from 2019 to 2023. From 2019 to 2023, most of the journals and proceedings were selected. Papers published before years of 2019, a few journals and proceedings were selected. There are roughly 63 reviews, including 50 from journals and 12 from proceedings.

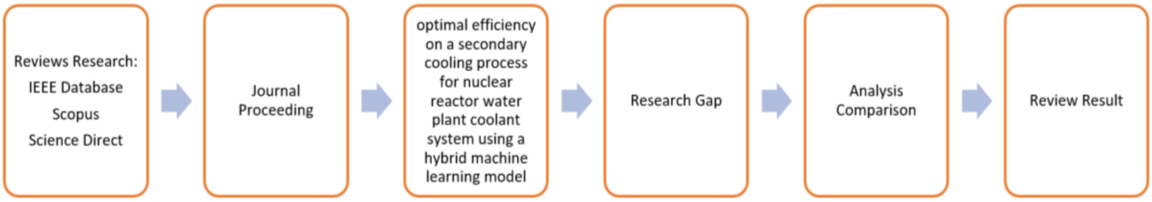

Figure 1. The review structure of optimal efficiency on a secondary cooling process for nuclear reactor water plant coolant system

2.1. Nuclear reactor water coolant plant secondary cooling process review

Preconditions are applied to specific phases of the decision tree technique, the primary experiment used in predictive analysis. This ensures that the secondary cooling system operates smoothly and provides precise data. As a result, the primary cooling system and secondary cooling system comprise the nuclear cooling system. Therefore, the secondary cooling system is only determined in this work concerning the analysis of the primary goal. The system process operating in the RTP secondary cooling system is depicted in Figure 2. The secondary water coolant plant is the red-colored substance that runs from the cooling tower to the heat exchanger and vice versa.

The parameter tools utilized in the secondary water coolant plant process are fundamental for effectively monitoring and controlling critical operational parameters. These tools include temperature sensors for real-time monitoring of coolant temperatures, pressure gauges to ensure safe operating conditions, and flow meters for accurate measurement of coolant flow rates [15]. The integration of these parameter tools enables comprehensive monitoring and control of the secondary water coolant plant process, ensuring optimal performance, reliability, and safety in power generation operations. The water coolant process is illustrated in Figure 2. Water from the reactor flows into the heat exchanger in the primary loop of the system, while water from the cooling tower flows into the heat exchanger in the secondary loop. The process begins when the cold water from the cooling tower passes via the sensors' pressure PT003, temperature TT004, and flow sensors FT002 to heat exchanger channel-A (HE-A). Subsequently, the cold water from HE-A moves to RTP by the flow FT001, temperature TT005, and pressure PT004 characteristics. After entering RTP, the chilly water became hot. After passing through the temperature TT001, pressure PT001, and temperature TT002, the hot water from RTP goes to the HE-A. At point 4, the temperature control variable is TCV004. After that, the secondary stage's temperature TT003 and pressure PT002 will return the hot water from HE-A to the cooling tower [16].

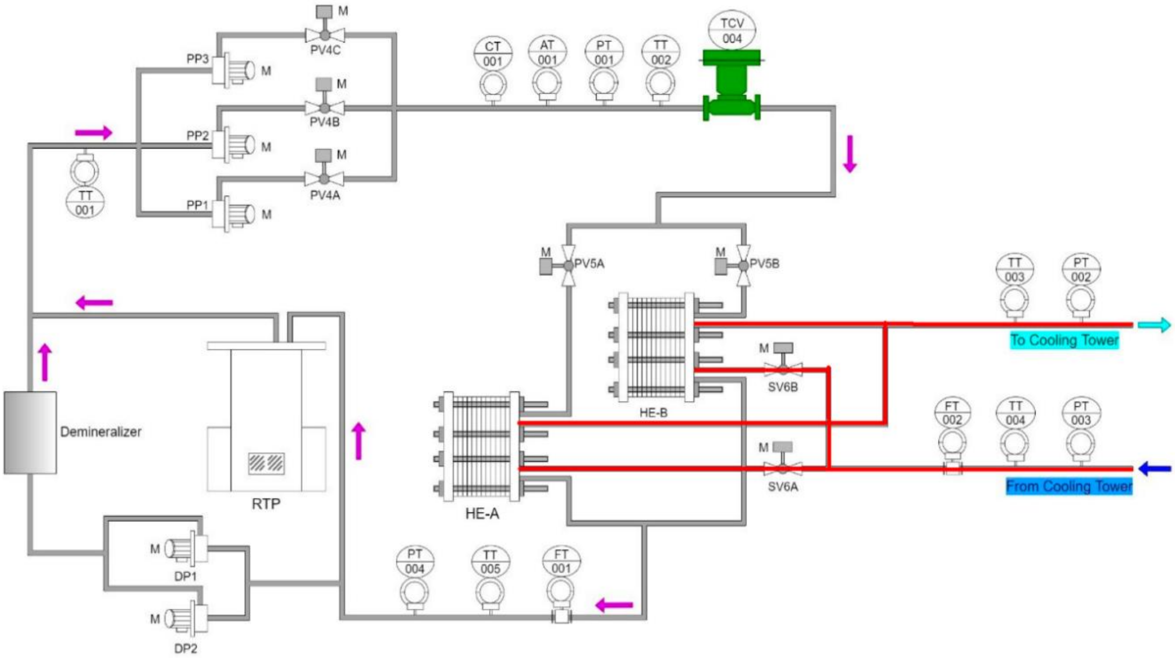

Figure 2. The secondary plant (red colored line) water coolant system at RTP

2.2. RTP cooling system parameter and data collection

The process of collecting data for real-time or live time from an interactive physical system is essential for control engineering and water cooling in nuclear reactor plants. This collection method is a key component of the predictive machine learning model, designed to optimize the secondary cooling process workflow. Figure 3 illustrates this process in detail, highlighting the integration of real-time data collection within the broader context of the machine learning model's application.

Although the nuclear plant may identify a variety of sensors, this study will gather the parameters of the water coolant, including temperature, water flow rate, and pressure, in online or offline observable systems. All sensor and quantitative data are gathered from the functioning nuclear reactor plant. An inter-arrival time number of cycles is collected to compile the data. Data collection and processing, feature extraction, error data, and model creation will all be statistically pre-analyzed to ascertain prediction maintenance. The complexity and nonlinearity of sensor signals necessitate filtering the raw data. Thus, the main objective of feature extraction is to use the patterns and trends in the sensor outputs to foresee errors in data gathering or malfunctions. Data is then abstracted to improve performance modeling. The collected data will be statistically analyzed, and critical parameters will be found. The best moment to issue an alert for decision maintenance is then determined by feeding the extracted information into the prediction model that has been constructed.

The cold-water cycles through the first three steps of the cooling system process, while channel A (HE-A) or channel B (HE-B) is used through a valve to control temperature, pressure, and flow from the cooling tower to the heat exchanger. Every day, the Heat Exchanger varies in different ways. As stated in Table 1, the preconditions are in place for the stages of counterbalancing.

The secondary cooling process involved sensor calibration and water temperature, pressure, and flow rate monitoring systems. Daily and monthly checklists will investigate safety and operational channels involving water temperature, pressure, and flow rate parameters. Table 1 presents the optimal range for the parameter operation at RTP. The data samples are about 2×1,048,575 in January and June 2023, for a total of about 2,097,150 data samples.

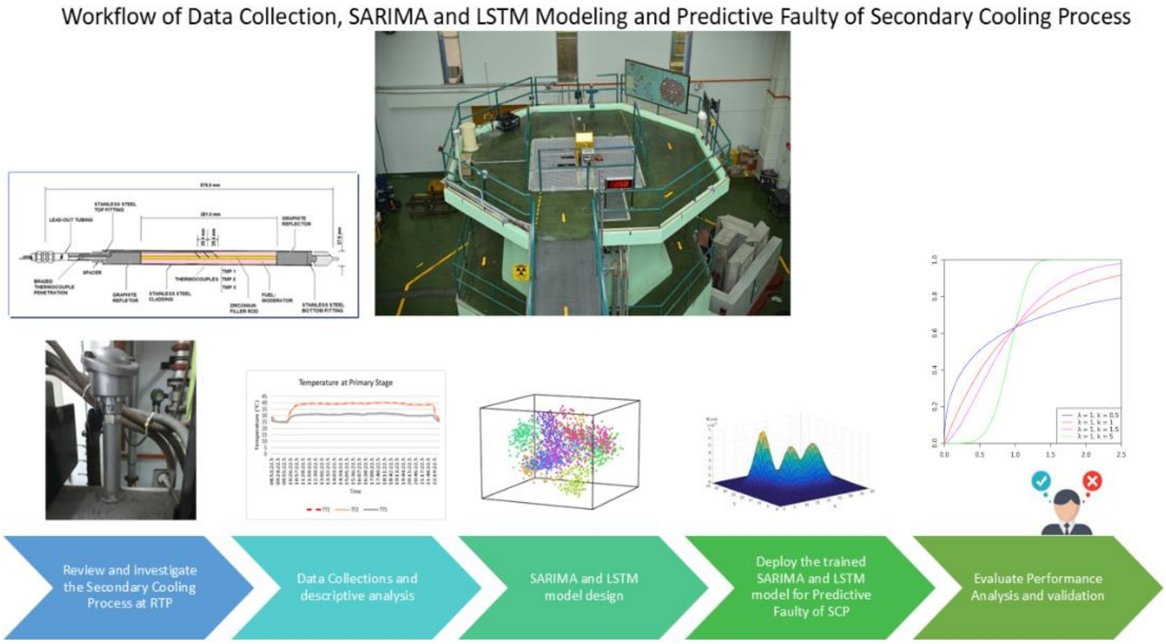

Figure 3. Workflow of a predictive machine learning model for the secondary cooling process

Table 1. Parameters with parameters under normal condition

Parameters	Preconditions
Temperature	The cold-water temperature after the heat exchanger must be less than 32 °C. The maximum hot water temperature after the tank (or before the heat exchanger) is less than 45 °C.
Flow	The measurement of the flow sensor at the primary and secondary loop is relatively equivalent to: Nominal flow primary: 80 m^3/h Nominal flow secondary: 180 m^3/h
Pressure	Different water pressures create the flow of water. Yet, the flow can regulate the pressure by controlling the pump. 80 kPa in the primary loop 180 kPa in the secondary loop

2.3. Optimal efficiency with distribution model using maximum likelihood estimator

The general path model (GPM), a unit-specific prediction model, entails choosing an acceptable degradation metric to describe the system's decline toward failure. The residual usable life of the system or component is then estimated by extrapolating a functional fit of this parameter to a pre-established failure threshold. GPM was proposed to identify a suitable parametric regression model that would capture the deterioration trend over time. The generic route model captures the unit-wise volatility in degradation data, which also permits the direct use of degradation data. The deterioration path of unit i is specified for every given time t as (1),

$$yi(t) = \eta(t, \varphi, \theta t) + \varepsilon i \tag{1}$$

The vector φ represents the fixed (population) effects for every unit, θt represents the random (individual) effects for the i^{th} unit, and the normally distributed measurement errors are represented by $\varepsilon i\ N(0, \sigma 2)$. Three primary presumptions underpin this approach. Initially, it is necessary to transfer the deterioration data to a $\eta(\cdot)$ function by capturing it using valid failure models. Furthermore, the historical data must be gathered under comparable circumstances, considering a fair variance of every element. When a component or process fails, a final, predetermined critical degree of deterioration is known as a "soft failure". Various distributions can be considered for the $\eta(\cdot)$ parameters, like Weibull, normal, log-normal, and others. Errors in data collection in time can be identified with model parameters. Prediction maintenance can be done where the parameters in the model need to be estimated at the offline stage. This research is live data collected and updated at the online stage, taken from time to time. Maximum likelihood estimation (MLE) may be used for live data parameter estimation, and the expectation-maximization (EM) approach yields accurate results. According to the review, the online parameters are best determined using the Bayesian framework, in which posterior distributions of the model parameters are produced using recently gathered data.

2.4. Machine learning deployments

A machine learning model deployment is a crucial phase in the machine learning lifecycle where a trained model is available in a production environment [17]. Deploying a machine learning model involves transitioning from a development or research setting to a practical, real-world application [18]. Deploying a machine learning model for optimizing the secondary cooling process in a nuclear reactor water coolant plant is a complex task that requires careful planning and consideration of safety, accuracy, and real-time performance. Deploying a machine learning model for optimizing the secondary cooling process in a nuclear reactor water coolant plant is a meticulous process that involves addressing the specific challenges and safety considerations inherent to nuclear facilities. The initial steps include defining the optimization goals and collecting historical data related to the secondary cooling process, which typically comprises temperature, pressure, and flow rate variables. Feature engineering becomes crucial to enhance the model's understanding, and choosing an appropriate machine learning model, such as recurrent neural networks (RNNs) or long short-term memory (LSTM) networks, is vital for capturing temporal patterns in the data. Training the model involves splitting the dataset into training and validation sets, emphasizing fine-tuning hyperparameters for improved accuracy. Evaluating the model's performance with metrics like energy efficiency and temperature stability is paramount. Safety and regulatory compliance are integral components, ensuring the model aligns with stringent standards applicable to nuclear facilities. Whether on-premises, cloud, or edge devices, the deployment environment must support real-time predictions and integrate seamlessly with the plant's control systems. The crucial aspects include scalability considerations, monitoring mechanisms for real-time performance tracking, security measures, and continuous improvement through a feedback loop. Collaboration between data scientists, engineers, and domain experts is essential for successful deployment, and regular maintenance checks, user training, and an emergency response plan contribute to the overall robustness of the deployed machine learning model.

2.5. Hybrid machine learning

Integrating a hybrid machine learning model for optimizing the secondary cooling process in a nuclear reactor water coolant plant involves a nuanced and sophisticated approach. The deployment strategy begins with a meticulous definition of the optimization objectives and the acquisition of pertinent historical data encompassing variables like temperature, pressure, and flow rates. The hybrid model which combines elements of neural networks and traditional statistical approaches is adept at capturing the intricate dynamics of the secondary cooling process. Feature engineering becomes pivotal, allowing the model to extract meaningful patterns and relationships from the data. The model's selection involves an astute fusion of supervised and unsupervised learning techniques to harness predictive capabilities and exploratory insights. Training and validation phases are dedicated to refining the model's parameters for optimal accuracy and efficiency. Key evaluation metrics, such as energy efficiency and temperature stability, guide the thorough assessment of the model's performance. Deployment considerations include seamless integration into the plant's infrastructure, whether on-premises or in the cloud, emphasizing real-time capabilities and scalability. Continuous monitoring, robust security measures, sustained collaboration across diverse expertise, and a comprehensive maintenance strategy contribute to the effectiveness of the hybrid machine learning model, ensuring optimal efficiency in the secondary cooling process of a nuclear reactor water coolant plant.

2.6. Machine learning performance measure

Designing effective performance measures for machine learning models deployed to optimize the secondary cooling process in a nuclear reactor water coolant plant is crucial for ensuring efficiency and safety in nuclear operations. One of the key metrics is energy efficiency, reflecting the model's ability to strike a balance between effective cooling and energy conservation. In a nuclear reactor, maintaining temperature stability is critical to prevent fluctuations that could compromise the reactor's safety and stability. The model's capacity to accurately predict and control temperature variations is integral to the overall success of the cooling system. Additionally, the system's responsiveness to dynamic changes in operating conditions is a crucial performance measure, ensuring that the machine learning model can adapt swiftly to varying demands. This adaptability is particularly significant in a nuclear reactor, where real-time responses to operational changes are essential for maintaining optimal efficiency and safety. The performance evaluation process involves a comprehensive analysis of these metrics, considering immediate and long-term impacts on the nuclear reactor's operational stability. Fine-tuning the machine learning model based on these performance measures becomes an iterative process, aiming to achieve an optimal equilibrium between efficiency and safety. Continuous monitoring and adaptation to evolving conditions contribute to the model's robustness in navigating the complexities of the secondary cooling process in a nuclear reactor water coolant plant. In essence, establishing and refining performance measures are fundamental to machine learning models' successful deployment and sustained effectiveness in enhancing the efficiency of the secondary cooling process in nuclear facilities.

3. RESULTS AND DISCUSSION

This section provides a detailed discussion of the nuclear coolant system parameters. The details and comparison of the machine learning model were defined and compared. Predictions using the machine learning method were examined using various parameters. Lastly, research gaps were presented in Tables in the design, and the next prediction system was deployed to identify optimal efficiency for the nuclear reactor's secondary cooling process.

3.1. Coolant system at the nuclear reactor

The primary cooling system has a pivotal role in nuclear reactors. It allows reactor coolant to circulate in a loop from the reactor core to a secondary cooling system [19]. It also ensures that the reactor core is kept cool enough to avoid damage during operation. In a PWR, the primary cooling system circulates pressurized water heated from the reactor core and transfers the heat to a secondary system in the steam generator [20]. The water in the secondary system is heated and converted to steam, which drives the turbine. Then, the steam cools down and returns to water in the condenser [21]. Different types of reactors use different coolants in their cooling systems. Table 2 shows the kind of reactor with its reactor coolant.

Table 2. Type of reactor coolants

Reactor Type	Coolant	References
Pressurized water reactor	Light water	[22]
Gas-cooled reactor	Helium gas	[23]–[25]
Liquid metal-cooled reactor	Lead-bismuth eutectic	[26], [27]
Pool-type reactor	Water	[28]

3.2. Machine learning model

Machine learning (ML) is a subset of artificial intelligence (AI) that simulates the learning process by establishing a predictive model, analyzing its output given specified parameters, and progressively updating the model to increase its accuracy [29]. A machine learning application comprises three major components: model, parameters, and learner. The process of creating analytical models is automated by machine learning. The element of the system that receives inputs and produces identifications or predictions is called the model. Parameters in machine learning are data inputs for analytical models used to process using the model. Any signal, component, or data item the model may employ for decision-making is called a parameter. The learner is the component of the system that evaluates actual results against predictions made by the model and modifies the model's parameters and, consequently, its overall structure in response to the findings. For algorithms, a variety of machine learning model types are frequently used. Machine learning algorithms differ in the issues they can solve, how they approach problems differently, and what kinds of data they need to work at their best. The three most common algorithms are supervised, unsupervised, and reinforcement learning, as in study [30]. Supervised learning algorithms are characterized using training data, a set of training examples containing several inputs and the desired output. As the training data are processed by the machine learning algorithm, a function or model is optimized that can be used to predict the output for inputs that were not present in the initial training data [31]. Classification, regression, and similarity learning are three types of supervised learning algorithms [32], while supervised learning algorithms refine a predictive model based on data with inputs and outputs, unsupervised learning algorithms are used to find structures, patterns, and relationships in cases without training data. Unsupervised algorithms such as grouping or clustering of data points are helpful in analyzing data that has not yet been categorized or labeled [33]. The algorithms used in reinforcement learning differ from those in supervised and unsupervised learning. They designate a setting where the software agent works toward a specific aim, and they optimize a model or function those aids in the software agent's achievement of the goal. In the context of an application like Google's Alpha Zero, the environment could be a chess game, and the aim could be winning the game [34].

3.3. Time series machine learning model

A time series machine learning model is designed to make predictions or classifications based on data that varies with time. Time series data consists of observations or measurements collected and recorded over regular intervals, such as hours, days, and months. The main goal of a time series machine learning model is to capture patterns, trends, and dependencies within historical time-ordered data to make informed predictions about future values [35]. Time series models explicitly consider the temporal order of observations [36]. The relationship between current and past observations is crucial for making accurate predictions. Time series data is inherently sequential, and the sequence of observations matters. This sequential nature distinguishes time series models from traditional machine learning models that assume each observation is independent [36]. Many time series models use lag features, which involve using past values of the time series as input features for predicting future values. The idea is to capture temporal patterns and trends. Time series often exhibit trends (long-term changes) and seasonality (repeating patterns). Effective models should be able to capture and account for these components. Time series models are used in various domains where observations are collected over regular intervals, such as stock prices [37], [38], weather data [39], and energy consumption [40], [41]. When working with time series data, it is essential to consider factors such as seasonality, trends, stationarity, and the specific characteristics of the data [42]. Model selection should be based on the problem's nature and the forecasting task's requirements. Experimenting with different models and tuning hyperparameters is often necessary to achieve the best performance for a particular time series dataset [43]–[45].

3.4. Predictive machine learning model for secondary cooling systems

Predictive maintenance can be defined as maintenance strategies that use the actual operating condition of an equipment to predict its future states based on its past operation. This maximizes the time interval between maintenance tasks and prevents unnecessary maintenance [46]. Predictive maintenance in the primary cooling system has been studied in several literature. Data-driven predictive maintenance models typically apply machine learning techniques to establish a model that can take operation data. This model requires a large amount of data for the prediction to be accurate [47]. Table 3 shows some of the machine learning methods applied in previous studies and the focus of the studies. The artificial neural network (ANN) is a machine learning model based on the human nervous system that can link a system's input and output. Pattern recognition, data relationships, and learning through experience are all ways in which an ANN obtains knowledge. It is a collection of computational nodes organized into various layers. The better the nodes in a network are connected, the better the prediction as an output [48]. Support vector machine (SVM) is a supervised learning algorithm that is useful for classification and regression and searches for the optimal separating hyperplane [49]. Using machine learning techniques in maintenance processes can bring several advantages to the monitoring process of a power plant.

Table 3. Machine learning techniques found in several literature

Authors	ML Techniques	Objective
Guillen *et al.* [50]	Long short-term memory (LTSM)	To assist in the detection of anomalies indicative of current or pending failure of critical process equipment in a nuclear power plant.
Santos *et al.* [51]	Deep rectifier neural network (DRNN)	Using machine learning to nuclear accident identification problem in a nuclear power plant
Ayo-Imoru and Cilliers [52]	Feed forward back propagation (FFBP)	Early detection of anomalies during transient operation of nuclear power plant
Saeed *et al.* [53]	Convolution neural network (CNN) and LTSM	A fault monitoring instance for nuclear power plant to correctly detect and classify faults at any plant state
Tian *et al.* [54]	Multilayer perceptron (MLP)	To predict the break size in loss-of-coolant accident (LOCA) in a nuclear reactor
Liu and Zio [55]	Support vector regression	Case studies used on reactor coolant pumps in nuclear power plant to predict leakage.
Ayodeji and Liu [56]	Multiclass SVM	Fault detection and diagnosis on each sub-unit of the reactor coolant system of the pressurized water reactor.

Table 4 shows some of the advantages and limitations found in the literature work. Most of the advantages of machine learning are related to the ability to predict and detect faults in plant operations. However, some limitations were found, such as the inability to get the suitable parameter to be used and the method implemented focusing on a particular component of a system when there are a lot of elements involved that make up the whole cooling system.

Table 4. Several advantages and limitations of machine learning model

Authors	Method	Advantages	Limitation
Ayodeji and Liu [56]	SVM	Able to predict faults for a different location in the plant	The sensor placement is not suitable for obtaining appropriate parameter
Guillen [50]	ANN	Enable the plant to detect an anomaly that is hidden in the process data	Only focuses on the drywall fan coil units of a power plant
Ayo-Imoru and Cilliers [52]	ANN	Detecting fault during transient	Need to meet several requirements to enable the use of dynamic reference
Santos *et al.* [51]	ANN	Able to achieve better precision results after a period of learning	Unable to provide the correct response to an untrained event

3.5. Important parameters for secondary cooling systems

The nuclear reactor is a safety-critical system that depends on sensor readings on critical parameters to maintain the safety of its operation [15]. Several parameters were found in many previous studies. Table 5 shows several past literature studies and the parameters used in the research of monitoring the cooling system. The most parameters used in the literature are temperature, flow, and pressure. This shows that these parameters are essential in nuclear reactor monitoring. The temperature dictates if the heat exchanges within the cooling system are efficient and can prevent the reactor core from meltdown. The pressure of the coolant shows if the coolant is properly distributed through the cooling system and provides good coolant flow in the system.

Thus, there is a lack of hybrid machine learning modeling, especially a combination of seasonal autoregressive integrated moving average (SARIMA) and long short-term memory (LSTM) modeling used to predict the secondary cooling process at a nuclear reactor. Implementing such a hybrid model could significantly enhance the accuracy and reliability of predictions. This approach focuses on identifying faulty processes and optimizing efficiency performance in a nuclear reactor.

Table 5. Several past literature studies and the key parameters

Authors	Title	Key parameter
Ioannou *et al.* [57]	Intelligent techniques for anomaly detection in nuclear reactor	Coolant flow, coolant temperature
Zeng *et al.* [58]	Machine learning based system performance prediction model for reactor control	Fuel temperature, coolant temperature, coolant flow
Zhang *et al.* [59]	Prediction of leak before break (LBB) leakage for various conditions by genetic neural network and genetic algorithms	Pressure, temperature, crack depth, crack length
Ayo-Imoru and Cilliers [52]	Continuous machine learning for abnormality identification to aid condition-based maintenance in nuclear power plant	Pressure, temperature, feedwater flow, pressurizer level
Wang *et al.* [25]	Influence of cooling water parameters on the thermal performance of the secondary circuit system of a modular high-temperature gas-cooled reactor nuclear power plant	Temperature and mass flow rate
Nor *et al.* [15]	Linear regression and R-squared correlation analysis on major nuclear online plant cooling system	Temperature, conductivity, flow rate

3.6. Research gaps

Identifying research gaps in the secondary cooling process of nuclear reactor water coolant plants is crucial for advancing these systems' understanding, efficiency, and safety. Table 6 shows research gaps in several studies of nuclear reactor water coolant plants using machine learning models. Addressing these research gaps will contribute to the development of more efficient, resilient, and sustainable secondary cooling systems for nuclear reactor water coolant plants, ensuring their safe and reliable operation in the long term.

3.7. Sampling reviews on secondary data analysis

Descriptive analysis for the secondary cooling process in a nuclear reactor water coolant plant involves examining and summarizing key characteristics and behaviors of the system without delving into complex statistical inferences. This analysis provides a comprehensive overview and understanding of the secondary cooling process. Table 7 and Table 8 show the temperature and pressure parameters, respectively, where the TT003 and TT04 are temperature transmitters of three (3) and four (4), and PT002 and PT003 are pressure transmitters of two (2) and three (3) which are in the secondary cooling process system and transmit the data from the field of the secondary plant to the SCADA as collected data. Descriptive analysis is a foundational step for further investigations. It can guide decision-making processes related to the operation, maintenance, and optimization of the secondary cooling system in a nuclear reactor water coolant plant. It provides valuable insights into the system's behavior and forms the basis for more advanced analytical approaches.

Table 6. Research gaps

Research	Objective	Parameter used	ML method
Support vector ensemble for incipient fault diagnosis in nuclear plant components [56]	Fault detection of reactor coolant system	Flow, temperature, pressure	Multiclass SVMs
Detecting loss-of-coolant accidents without accident-specific data [60]	Fault detection of loss-of-coolant accident	Flow, temperature	ANN
A RELAP5-3D/LSTM model for the analysis of drywell cooling fan failure [50]	Anomalies detection on drywell cooling fan	Temperature, flow	LSTM
Continuous machine learning for abnormality identification to aid condition-based maintenance in nuclear power plant [52]	Early detection of anomalies of nuclear reactor during transient operation	Pressure, temperature, flow, pressurizer level	FFBP
Prediction of LBB leakage for various conditions by genetic neural network and genetic algorithms [59]	Predict LBB leakage of the nuclear reactor at various conditions	Pressure, temperature	Genetic Neural Network and FFBP
A study on the robustness of neural network models for predicting the break size in LOCA [54]	Predict break size loss-of-coolant accident in nuclear power plant	Pressure, inlet/outlet temperature, flow	Multilayer perceptron
Predictive maintenance technique for primary cooling system using augmented reality at RTP [61]	Predict equipment failure in RTP's primary cooling system using augmented reality.	Temperature, flow, conductivity	ANN
Data driven methods for break size and location estimation in LOCA based on deep learning [62]	Predict the size and location of the break in LOCA	Temperature, pressure, flow rate, water level	CNN
Optimal efficiency on nuclear reactor secondary cooling process using machine learning model (Hajar *et al.* 2024 – this research)	Predict faulty equipment and optimize its efficiency performance in the RTP secondary cooling system using a hybrid machine learning model.	Temperature, flow, and pressure	SARIMA, LSTM, MLE, maximum likelihood estimator.

Table 7. Temperature characteristics

Characteristics key	TT003	TT004
Mean	31.70090734	31.32447777
Standard error	0.000344731	0.000294897
Median	31.7419	31.35851
Mode	31.89019	31.48871
Standard deviation	0.21802703	0.186509294
Sample variance	0.047535786	0.034785717
Kurtosis	-0.840489866	-0.87842043
Skewness	-0.312279801	-0.291424597
Range	0.81742	0.81018
Minimum	31.2283	30.83406
Maximum	32.04572	31.64424
Sum	12680362.93	12529791.11
Count	400000	400000
Largest (1)	32.04572	31.64424
Smallest (1)	31.2283	30.83406
Confidence level (95.0%)	0.000675662	0.000577989

Table 8. Pressure characteristics

Characteristic key	PT002	PT003
Mean	73.4844097	184.4566094
Standard error	0.024542091	0.009285265
Median	70.48611	186.14
Mode	71.99074	189.6267
Standard deviation	15.52178108	5.872517029
Sample variance	240.925688	34.48645626
Kurtosis	8.322640119	-0.862869228
Skewness	2.59081755	-0.650292833
Range	99.92765	20.2547
Minimum	50.86805	171.4554
Maximum	150.7957	191.7101
Sum	29393763.88	73782643.77
Count	400000	400000
Largest (1)	150.7957	191.7101
Smallest (1)	50.86805	171.4554
Confidence level (95.0%)	0.04810176	0.018198839

4. CONCLUSION

In conclusion, this review illuminates the paradigm shift towards optimal efficiency in the secondary cooling process of nuclear reactor water coolant systems by integrating hybrid machine learning models. By fusing SARIMA, LSTM, and MLE methodologies, this hybrid approach emerges as a transformative force, ushering in a new era of enhanced performance, reliability, and safety for nuclear reactor cooling systems. The review underscores the significance of dynamic modeling, and advanced control strategies in achieving heightened efficiency. Moreover, exploring research gaps, including uncertainty modeling and resilience against external hazards, sets the stage for future investigations. This paper highlights the crucial role of sensor technologies, data analytics, and real-time monitoring in ensuring continuous optimization and predictive maintenance, which are critical components for sustained efficiency gains. Looking ahead, integrating hybrid machine learning models emerges as a cornerstone shaping the future of secondary cooling processes in nuclear reactor water coolant plants to improve the efficiency and sustainability of nuclear energy systems.

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BIOGRAPHIES OF AUTHORS

Ibnu Hajar received a B.Eng. degree in electrical engineering from Hasanuddin University, Makassar, Indonesia, in 1999 and an M.Sc. degree in electrical engineering from the University of Applied Sciences (Fachhochschule Darmstadt), Germany, in 2005. Currently, he is pursuing his Ph.D. at the School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, Selangor, Malaysia. He is also a lecturer at PLN Institute of Technology, Jakarta, Indonesia. His research interests include renewable energy, power quality, power electronics, power generation, power grids, power transmission reliability, relay protection, power system stability, power transmission lines, power transmission protection, harmonic distortion, load flow control, overcurrent protection, power distribution protection, control system and its applications, and machine learning applied power system and control system. He registered as a member of the Institution of Engineers Indonesia (PII) since 2016. He can be contacted at email: ibnu.hajar@itpln.ac.id.

Murizah Kassim is currently working as the head of publications and innovation unit and senior fellow at the Institute for Big Data Analytics and Artificial Intelligence (IBDAAI), Universiti Teknologi MARA, Shah Alam, Selangor, Malaysia. She is an associate professor from the School of Electrical Engineering, College of Engineering, UiTM. She received her PhD 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 data engineering, machine learning, computer networks, IoT, and web and mobile development applications research. She has experienced for 19 years in the technical team at the Centre for Integrated Information System, UiTM. She is also an associate member of the 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 via email: murizah@uitm.edu.my.

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 modeling, system identification, model predictive control, and fuzzy logic. He can be contacted at email: sabri@nm.gov.my.

Intan Nabina Azmi received a diploma and a B. Eng. (Hons) in electrical engineering (electronics) from Universiti Teknologi MARA (UiTM), Malaysia. In 2023, she earned her master's in electrical engineering from UiTM Shah Alam, Malaysia. Currently, she is pursuing her PhD at the College of Engineering, UiTM Shah Alam, Malaysia. Her research interests are information delivery to wireless networks, mobile drone models, drone applications in disaster areas, nuclear reactor coolant systems, machine learning, and time series analysis. She can be contacted at email: hellointan.azmi@gmail.com.