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A review on predictive maintenance technique for nuclear reactor cooling system using machine learning and augmented reality

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ABSTRACT

Reactor TRIGA PUSPATI (RTP) is the only research nuclear reactor in Malaysia. Maintenance of RTP is crucial which affects its safety and reliability. Currently, RTP maintenance strategies used corrective and preventative which involved many sensors and equipment conditions. The existing preventive maintenance method takes a longer time to complete the entire system's maintenance inspection. This study has investigated new predictive maintenance techniques for developing RTP predictive maintenance for primary cooling systems using machine learning (ML) and augmented reality (AR). Fifty papers from recent referred publications in the nuclear areas were reviewed and compared. Detailed comparison of ML techniques, parameters involved in the coolant system and AR design techniques were done. Multiclass support vector machines (SVMs), artificial neural network (ANN), long short-term memory (LSTM), feed forward back propagation (FFBP), graph neural networks-feed forward back propagation (GNN-FFBP) and ANN were used for the machine learning techniques for the nuclear reactor. Temperature, water flow, and water pressure were crucial parameters used in monitoring a nuclear reactor. Image marker-based techniques were mainly used by smart glass view and handheld devices. A switch knob with handle switch, pipe valve and machine feature were used for object detection in AR markerless technique. This study is significant and found seven recent papers closely related to the development of predictive maintenance for a research nuclear reactor in Malaysia.

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1. INTRODUCTION

The introduction of the fourth industrial revolution, also known as Industry 4.0, has led to the rise of the smart factory through the implementation of technologies such as cyber-physical systems and the internet of things into conventional factories. These changes the focus of the manufacturing industry to set up intelligent products and processes, which include automation, digitalization and integration of information and communication technologies in production processes, to increase flexibility and performance of the production [1]. However, the implementation of the technologies has increased the complexity of the processes, maintenance, and services, which demand the operator to have the necessary skills to oversee the production [2].

The Malaysian Nuclear Agency has operated Reactor TRIGA PUSPATI (RTP), one megawatt (MW) thermal power TRIGA MARK II research reactor model that provides isotope production, neutron activation analysis, and training. It dissipates heat from the reactor into the cooling system. It discharges it into the atmosphere using demineralized light water as its primary coolant [3]. Since its inception in 1982, the most significant change in the RTP system has been the conversion of its instrumentation and control console system (ICCS) from analog to digital in 2013. It implements a means of controlling the power reactor through control rod movement and monitoring and displays for all reactor parameters to protect the reactor from abnormal conditions [4].

Nuclear power plants rely heavily on maintenance to ensure their operation's reliability, availability, and safety. Due to prolonged usage, power plant equipment will inevitably degrade and become less dependable over time. Due to equipment deterioration, it is crucial to estimate its future state and plan a maintenance schedule to maximize its use and effectiveness while avoiding catastrophic failures in the core system. The evolution of information technologies and the increase in data availability become an advantage due to the component's accessible data, which can discover early-stage irregularities, diagnose the source, and forecast its remaining useful life (RUL). Its precise and dependable forecasting has enabled more effective maintenance planning and implementation at the most convenient times [5]. As a result, a predictive maintenance strategy was developed, which uses actual data collected from the equipment to forecast its future condition, effectively schedule maintenance tasks, and reduce unnecessary maintenance. Machine learning (ML) is a low-cost tool that can learn from large amounts of data and find patterns, allowing it to build a model that accurately predicts when anomalies will affect the entire system. A predictive maintenance model is usually combined with a machine-learning algorithm to maximize its effectiveness.

This research aims to review the predictive maintenance technique for the primary cooling system in a nuclear reactor and identify the important parameter involved in maintaining and monitoring the cooling system operation. Then, we identify the application of augmented reality (AR) in maintenance management and its model design. This research will help nuclear reactor operators effectively identify and act on early faults detected within the primary cooling system in nuclear power plants. A focus on the type of cooling system used in a nuclear power plant is presented in section 2, different predictive models, and tools available are shown in section 3, and various ML and AR technology are presented in section 4. Section 5 presents the result of the overall review by presenting the research gaps for ML and AR. Lastly, the conclusion of the review study and future research directions is indicated in the conclusions.

2. MATERIAL AND METHOD

2.1. Nuclear reactor cooling system

Any nuclear reactor must have a primary cooling system. It lets coolant from the reactor core circulate in a loop to a secondary cooling system [6]. The fission reaction of the fuel produces an infinite amount of heat in reactor cores during regular operation. The heat generated must be transmitted to the environment to maintain a steady temperature following the reactor design temperature. The primary cooling system takes heat from the reactor core and passes it through a heat exchanger to the secondary cooling system [7]. The heat is then delivered from the secondary cooling system to the cooling tower, which is released into the atmosphere [8].

Figure 1 shows an overview of the cooling system at RTP, consisting of the primary and secondary cooling systems. The primary cooling system takes water from the reactor, pumps it through the heat exchanger, and then pumped back into the reactor. The secondary cooling system brings water from the cooling tower to the heat exchanger and back to the tower. Hot water from the reactor is pumped to the heat exchanger, passing through several sensors. The parameter monitored through the sensor is temperature, pressure, flow rate, and conductivity. Water is cooled down in the heat exchanger by the water from the secondary cooling system. Then the cooled water from the heat exchanger is pumped back to the reactor, passing through several sensors that monitor the parameter.

Table 1 shows several reactor type classifications by their coolant found in the literature. Several types of reactors use different coolants in their cooling system. The coolant used can be light water, heavy water, gas, or liquid metal. For example, in pressurized water reactor (PWR), the light water in the primary cooling system is kept under pressure to prevent it from boiling and flowing through the reactor core [9]. While most reactor uses water in their cooling system, some reactors use other alternative such as gas and liquid metal as their primary coolant.

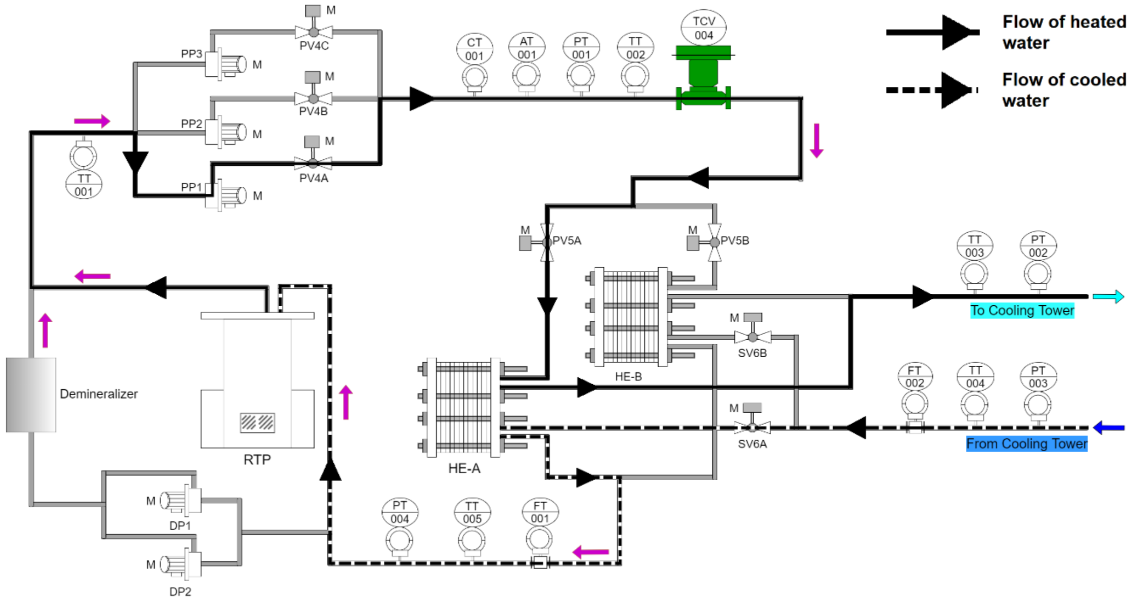

Figure 1. An overview of the primary cooling system at RTP. The solid line arrow indicates heated water while the dashed line arrow indicates cooled water

Table 1. Existing reactor type and its coolant

Reactor Type	Description	Coolant Used
Pressurized water reactor [9]	A reactor fills its core with cooling water that is kept under pressure to prevent it from boiling	Light water
Pool-type reactor [10]	A reactor with a cylindrical shaped tank that immerses its core in an open pool of water	Water
Gas-cooled reactor [11]	A reactor that uses graphite as moderator and gas as its coolant	Helium gas
Liquid metal cooled reactor [12]	A reactor that uses liquid metal as primary coolant	lead-bismuth eutectic

3. RESULT AND DISCUSSION

3.1. Predictive maintenance tools

This section describes the tools utilized to focus on building a predictive maintenance model for this research on the nuclear reactor in Malaysia. RapidMiner software is used extensively in this study to analyze the data collected from the reactor's cooling system and build a predictive model for the system. This software has a feature that uses a block-like operator to build the predictive model using several available machine learning models within it.

3.1.2. Predictive maintenance

Predictive maintenance is a maintenance management strategy that uses an equipment's current condition to identify abnormalities early and recognize the signs of impending machine failure. It analyses and measures data obtained to predict the future condition of an essential part of a machine to maximize the usage of component services life [13]. There are several approaches to using all available data to make a prediction. It could be a model-driven or data-driven approach [14]. The model-driven technique comprises creating a mathematical model of the machine that can accurately explain the degradation of a machine with high reliability. The latter method uses the massive amount of data collected and ML and statistical analysis to create a model that generates results based on historical operating data trends [15]. Predictive maintenance policies are often used together with other monitoring approaches like prognostic and health management (PHM) and condition-based maintenance (CBM). These approaches shared the same goals of detecting anomalies, fault diagnosing, and predicting equipment's RUL. The typical step for implementing these methods involve data collection, data manipulation, state detection, health assessment, prognostic assessment, and maintenance action. Figure 2 explains each step in predictive maintenance architecture [16].

3.1.2. Predictive maintenance for primary cooling system

Predictive maintenance is a type of maintenance that uses an equipment’s current operating condition to predict its future states based on its previous operation. As a result, the time interval between maintenance jobs is maximized, and unnecessary maintenance is avoided. Several studies have been done on predictive maintenance in primary cooling systems. ML is commonly used in data-driven predictive maintenance to create a model that can accept operating data. For this predictive model to be accurate, a vast amount of data is required.

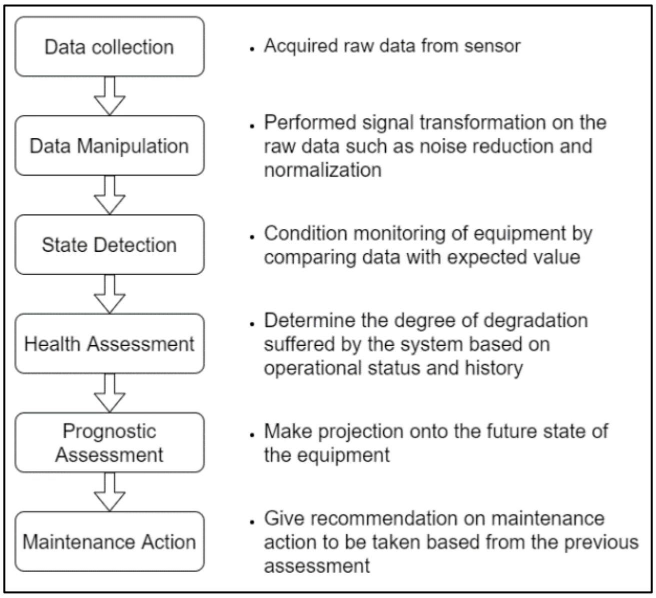

Figure 2. Steps in predictive maintenance architecture

The artificial neural network (ANN) is an ML model that can link a system's input and output. It is based on the human nervous system. An ANN acquires information in various ways, including pattern detection, data correlations, and learning via experience. It is a collection of computational nodes that are organized into layers. The more a network's nodes are connected, the better the output prediction it produces [17]. ANN models are built-in layers, as shown in Figure 3, consisting of an input layer, output layer, and hidden layers. The hidden layer can be one or more layers. The support vector machine (SVM) is a supervised learning technique that finds the best separating hyperplane for classification and regression [18]. It can map input data to output data using its training dataset and then generate labels for data with a certain level of precision. SVM can learn data classification patterns with a balance of accuracy and reproducibility, and it is a valuable tool [19].

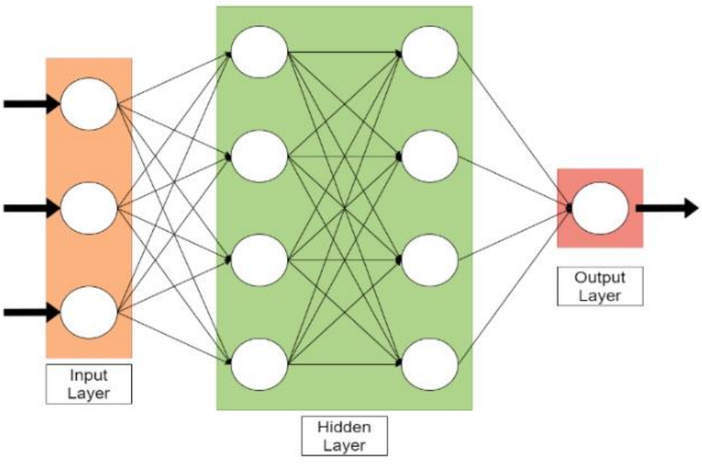

Figure 3. The general structure of the artificial neural network model

A Bayesian network (BN) represents information about an uncertain domain in which each node represents a variable, and each edge represents a probability for that variable. It is a probabilistic graphical model represented in a directed acyclic graph with no loops or self-connections. BN has a wide range of applications and is essential to modern data mining and ML techniques [20]. A genetic algorithm (GA) is a population-based search algorithm inspired by natural selection that utilizes the concept of survival of the fittest. It is an optimization algorithm that explores multiple search points to find optimal solutions simultaneously and independently. It changes the search process through the probabilities of crossover and mutation, modifying encoded genes, evaluating multiple individuals and producing multiple solutions [21].

3.1.3. Predictive analysis modelling using RapidMiner

RapidMiner is an open-source data science software program that can be used for many data and text mining projects and is compatible with various operating systems [22]. It is a platform for ML, data mining, image processing, and business analytics tools that include an extraction operator for determining the project's characteristics and performing specific operations [23]. Using techniques like predictive data analysis and descriptive data analysis can provide information that will help the user make more informed decisions [24]. The application of this tool can be found in various fields such as education, medical, oil, and gas. Table 2 shows several past literatures that is found to have used RapidMiner in its research. In RapidMiner Studios, various algorithms and modelling can be used to build the predictive model. Figure 4 shows the interface of RapidMiner Studio with several views' tabs. A model like decision tree (DT), neural network (NN), logistic regression (LR), and many more are available in the operator panel, as shown in Figure 5. Data to be used needs to be imported into the repository before it can be further processed in the process panel with another operator to produce the desired result. The drag-and-drop feature in this tool allows for a more straightforward modelling build without coding the processes.

Table 2. RapidMiner application found in the literature

Author	Brief description
Poucke *et al.* [25]	Integrating the MIMIC-II database in RapidMiner for data manipulation, pre-processing, and predictive analytics without the requirement to write code which enables scalable predictive analysis of clinical data
Kumar *et al.* [26]	Applying regression model in RapidMiner to predict the average oil rate using one month's worth of data collected from an oil well.
Rosado *et al.* [27]	Using the naïve Bayes classification technique in RapidMiner to predict the performance improvement of junior high school students based on certain criteria.
Samant *et al.* [23]	Discussing the details of several tools available for data mining and machine learning
Madyatmadja *et al.* [24]	Presenting the results of using big data to predict student learning effectiveness in educational institutions

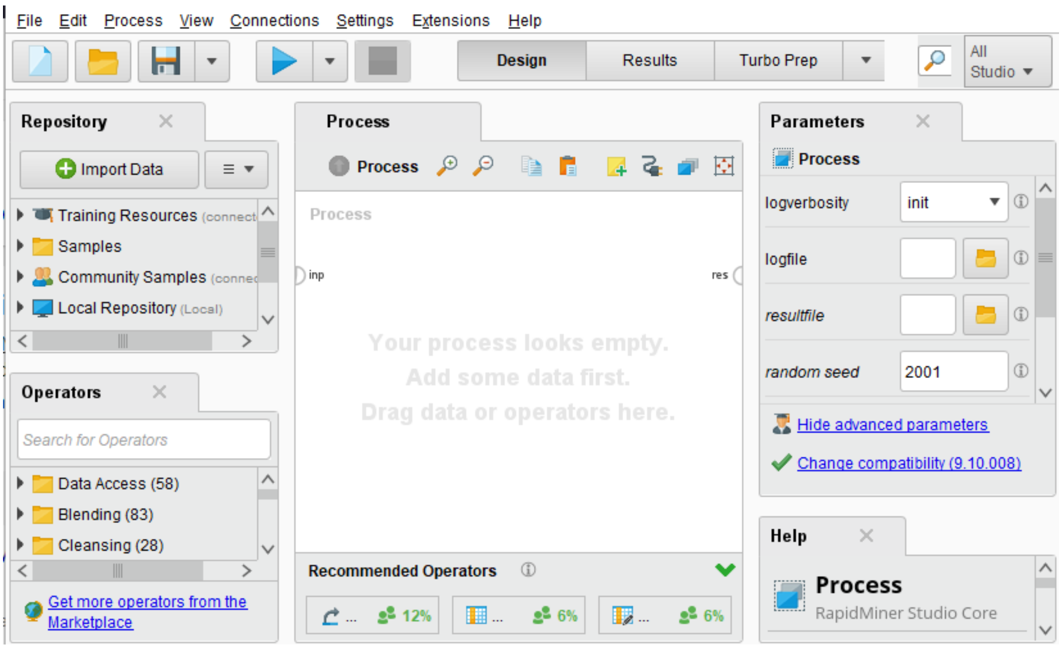

Figure 4. RapidMiner Studio main interface

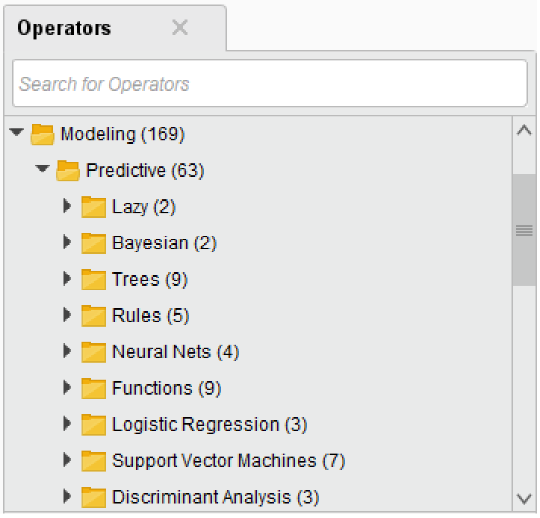

Figure 5. Selection of predictive modelling algorithm available on the operator panel in RapidMiner

3.2. Machine learning and augmented reality

This section presents the reviewed study which research has been identified based on technology, parameters used, ML techniques, and AR model. Detail comparison has been done on the four (4) main factors. This identified factors are important to develop the new predictive maintenance technique for nuclear reactor cooling system using machine learning and augmented reality in Malaysia.

3.2.1. Machine learning technique

Table 3 show some application of ML in previous studies and the focus of each study. This study will use the ANN model to develop the predictive maintenance model. The model will be built using the RapidMiner software. The data collected from the RTP will be split into several sets for training, testing, and validating the trained model.

Table 3. Machine learning technique that has been applied in previous literature

Model	Technique Applied	Research Focus	Year
ANN	LSTM	Detection of anomalies indicative of current critical process equipment in nuclear power plant	2020 [28]
	Deep rectifier neural network	Nuclear accident identification problem	2019 [29]
	FFBP	Early detection of anomalies during transient operation of nuclear reactor	2018 [30]
	Convolution neural network (CNN) & LTSM	Fault monitoring to detect and classify fault at any plant state	2020 [31]
	Multilayer perceptron	Predict the break size in a Loss-of-coolant accident in a nuclear reactor	2018 [32]
SVM	Support vector regression	Predict leakage on reactor coolant pump	2017 [33]
	Multiclass SVM	Fault detection on sub-unit of the reactor coolant system	2018 [34]
BN		Predict the concentration of radioisotopes in the primary circuit of the nuclear reactor	2021 [35]
GA		Detection of loss-of-coolant accidents of nuclear power plant	2018 [36]

3.2.2. Important parameter for primary cooling system

A nuclear reactor relies on sensor readings on vital parameters to keep it running safely. Sensors such as in Figure 6(a) conductivity transmitter sensor and Figure 6(b) temperature transmitter sensor are installed within the cooling system to get the parameter reading. Several parameters have been discovered in past research used for monitoring purposes. Table 4 lists some previous literature studies and the research parameter used in each study. Based on the finding in the table, temperature, water flow, and water pressure are the most utilized parameters in the literature. It demonstrates the importance of these parameters in nuclear reactor monitoring. This study will use the primary cooling system parameter on the coolant's temperature, flow rate, and conductivity. The temperature will determine whether the cooling system's heat exchanges are efficient and prevent the reactor core from meltdown. The coolant pressure in the cooling system indicates if the coolant is evenly distributed throughout the cooling system and can provide adequate coolant flow. The cooling system's temperature should be kept at 45 °C, the coolant flow rate at 80 m^3/s, and the coolant's conductivity at less than 2 μS/m.

(a) (b)

Figure 6. Transmitter sensors are installed in the primary cooling system; (a) conductivity transmitter and (b) temperature transmitter

Table 4. Parameter used in literature studies

Author	Description	Parameter used
Ioannou *et al.* [37]	A novel methodology for detecting an anomaly in a nuclear reactor	Fuel assembly vibration, coolant flow, coolant temperature
Zeng *et al.* [38]	System performance prediction model that supports the development of autonomous control for small reactor	Fuel temperature, coolant temperature, coolant flow
Zhang *et al.* [39]	Predicting the leakage of leak before break in various conditions	Pressure, temperature, crack depth, crack length
Ayo-Imoru *et al.* [30]	Detect fault in the transient of nuclear power plant	Reactor coolant system (RCS) pressure, RCS average temperature, SG feedwater flow, pressurizer level, charging flow, pressurizer heater power
Chung [40]	Machine learning to support real-time assessment of accident conditions in nuclear power plant	Core exit temperature, pressurizer pressure, auxiliary feedwater flow, safety injection water flow

3.2.3. Augmented reality

One of the advanced technologies that stem from the industry 4.0 concept is AR. It allows a digital object to be exhibited in a real-world setting via smart devices. Thus bringing computer-generated elements into the real-world view [41]. It supplements the real world with a virtual object by superimposing virtual objects aligned with a real object in the real environment, which can be interacted with in real-time [42]. This technology enables the presentation of real-time information in specific areas. Integration with other technology will expand its potential applications and improve its performance, resulting in a better outcome [43]. For example, an AR application prototype has been developed to study the responsiveness to changes in bus schedules in smart bus transportation systems [44]. It can also be seen as a tool in education settings that increases learning experiences and acts as a support tool for online learning activities [45]. Because of its ability to merge real and virtual things in the real world through its computational and visualization capabilities, AR has been utilized to aid maintenance operations in industrial settings. This study will try to implement an AR application with predictive maintenance techniques. The application for this study will be developed using Unity 3D software and the Vuforia engine.

3.2.4. Augmented reality to support nuclear reactor

In the literature, AR has been utilized to assist with the operation of a nuclear reactor. It can assist in identifying the apparatus to be inspected and recognizing its condition using a handheld device that can run an AR application [46]. AR is used to design a scanning support system for a 3D reconstruction model of a nuclear power facility using an RGB-D camera that scans the surrounding [47]. It can also be used to recognize and visualize a 3D model of crucial nuclear reactor equipment [48]. There is also a study on employing AR as a maintenance guidance system, which aids in the maintenance and training of complex equipment [49].

3.3. Augmented reality design model

AR applications can be designed in two ways which are a marker-based application or a markerless application. An AR application must be designed in a suitable design model based on how it is implemented with another system. Each of the design models has its characteristics and requirement for them to be able to carry out their purpose. Both design model-specific is further discussed in the next section.

3.3.1. AR marker-based model

The 3D marker-based AR application uses an image target as a visual cue to start the display of virtual content via an AR application. After that, the digital content is anchored to the marker, which is then augmented in the real world. It helps the app recognize the device's position and associate it with an AR object. Table 5 shows past research that has used 3D marker-based images in an AR application.

Table 5. Literature on the marker-based AR system

Author	Description	Device used
Havard *et al.* [50]	AR system as maintenance demonstrator and training during a maintenance operation	Smart glass
Cachada *et al.* [51]	Prototype AR application for maintenance support to train and guide personnel during maintenance	Tablet & Head-mounted device
Wang *et al.* [48]	AR used in recognition and visualization of key equipment in nuclear power plant	Handheld device
Oshima *et al.* [46]	AR as a maintenance support tool to identify apparatus to be inspected	Handheld device

3.3.2 AR markerless model

A markerless AR application does not rely on a target image. Instead, the AR system recognizes a piece of equipment's inherent feature as a region of interest (ROI). A pre-processed image of the equipment is used to extract an object's feature. After the minimum boundary of a point is determined, that point is chosen as the object's reference point. Table 6 lists past publications that have used markerless AR in their research.

Table 6. Literature on markerless AR system

Author	Description	Object detection
Qian *et al.* [52]	Wearable Assistive System with maintenance and assembly guidance function	Switch knob & handle switch
Lima *et al.* [53]	AR application on automotive sector	Car
Park *et al.* [54]	Wearable AR for smart task assistance to provide visual guidance	Various object
Diao *et al.* [55]	BARMS smartphone-based platform for cooling tower and in-wall pipe mapping maintenance assistance	Pipe & Valve
Sabarinathan *et al.* [56]	AR system for maintenance operation of a machine	Machine feature
Valognes *et al.* [57]	A markerless AR system that applies virtual data onto track object	Graffiti & facial feature

3.4 Machine learning and augmented reality analysis

Overall, 56 referred publications have been reviewed to find the research gaps in predictive maintenance techniques for nuclear reactor cooling systems using machine learning and augmented reality. The closest study has been found in papers between 2018 and 2020 which six research papers related to the nuclear reactor field have been discovered. The research gap comparison in the literature is provided in Table 7 in terms of the technology employed, the parameter used, and the ML method used. Most research has been done through experiments and utilizes simulated data based on earlier research. Based on this review study, the next data collection on an actual nuclear reactor's primary cooling system will be taken and analyzed. In comparison to earlier studies and literature evaluations, it has been discovered that no AR research has been conducted. It was, on the other hand, solely based on ML.

A new monitoring system incorporating modern technologies such as ML and AR is required. An ML algorithm is used to develop a predictive maintenance model. Based on the review done in this paper, a few algorithms are more prominently used than others. ANN models are the most used technique to detect any anomalies during the operation of a nuclear reactor. It suggests that the algorithm has clear advantages over other algorithms that can create a good result for detecting anomalies in the monitoring system of a nuclear power plant. There are numerous sensors involved in monitoring the operation of a nuclear reactor, which takes a reading of a parameter in the system. The most prominent parameter used for monitoring based on the reviewed studies is the temperature reading of the cooling system. It is followed by water pressure and the water flow rate within the cooling system. Implementing AR with the predictive maintenance model can bring an innovative approach to the reactor maintenance program. Using a marker-based AR model with the marker installed near the sensor or cabinet panel allows the on-site inspection officer to get the information of the predictive analysis of the cooling system through a handheld device. The availability of information on the predictive analysis through devices other than the control panel allows for better decision-making regarding future maintenance planning and scheduling.

Table 7. Research gap on technology, parameters, and ML method used

Author	Technology used	Parameter used	ML method
Ayodeji and Liu [34]	ML	Flow, temperature, pressure	Multiclass SVMs
Farber and Cole [58]	ML	Flow, temperature	ANN
Guillen [28]	ML	Flow, temperature	LTSM
Ayo-Imoru *et al.* [30]	ML	Pressure, temperature, flow, pressurizer level	FFBP
Kassim *et al.* [39]	ML	Pressure, temperature	GNN & FFBP
Tian *et al.* [32]	ML	Pressure, temperature, flow	Multilayer perceptron (MLP)
Azhari, This research	ML & AR	Temperature, flow, conductivity	ANN

4. CONCLUSION

Currently, preventive maintenance and corrective maintenance are still being used in the RTP maintenance program. This maintenance method is not very effective and could lead to unnecessary maintenance. The implementation of predictive maintenance and AR in the maintenance operation of a nuclear reactor will improve the performance, reliability, and safety of its operation. A good maintenance program would reduce maintenance costs, prevent unnecessary maintenance, maximize production, and increase equipment lifetime. The future direction of this study is to model one ML technique based on water coolant system data collection to predict better predictive maintenance of nuclear reactor systems. Through a smart device, AR allows a virtual object to exist in the real-world environment, which can be used to display the maintenance of machine status information in the industrial sector. Further study also will develop a new predictive maintenance technique using AR for the primary cooling system at RTP. Integrating AR systems with predictive maintenance will bring new meaning and experience to the monitoring process. It will also enhance human-machine interaction and improve the execution of maintenance interventions. Since this study mainly focuses on the primary cooling system, future recommended improvements to the predictive maintenance model may be applied to other parts of the nuclear reactor system.

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