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Reliability and Safety Assessment of a Passive Containment Cooling System in Advanced Heavy Water Reactors

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Passive Safety Systems (PSSs), which rely on natural forces and processes, such as natural circulation, gravity, internal stored energy, etc., are increasingly utilized in generation 3+ and generation 4 advanced nuclear power plants to increase inherent safety features of the nuclear reactor design. Although PSSs should considerably increase the safety of nuclear power plants, it is still challenging to systematically assess the reliability of passive systems because of the lack of data and uncertainties associated with phenomenon involving natural forces that underlies their safety functions. In this study, the Fault Tree Analysis (FTA) was used to assess the reliability and safety of the Passive Containment Cooling System (PCCS) in Advanced Heavy Water Reactor (AHWR). The failure probability of PCCS was calculated from the failure probabilities of Basic Events (BEs). Using the data for the failure probabilities of Top Event (TE) and BE from the FTA model, two Artificial Neural Network (ANN) models were proposed for the reliability analysis of PCCS to supplement the FTA model. Rectified Linear Unit (ReLU) and Sigmoid activation functions were utilized to build ANN models, and an Adaptive moment estimation (Adam) optimizer was used to train the ANN models to make these models computationally efficient. The results of the FTA model were compared with the predictions of the ANN models to find out the ANN model performance.

Keywords: Reliability, Passive Safety Systems, Passive Containment Cooling System, Fault Tree Analysis, Artificial Neural Networks

1. Introduction

Passive Safety Systems (PSSs) received a renewal of interest following the significant nuclear accidents at Three Mile Island (1979), Chernobyl (1986), and Fukushima (2011). A PSS is a type of safety system used in nuclear power plants that relies on natural forces and processes, such as natural circulation, internal stored energy, gravity, etc., without the need for active intervention or control, to maintain the safety of the plant (Solanki et al. 2020). The goal of PSSs is to provide a high level of safety and security in the event of a Loss-of-Coolant Accident (LOCA) or other emergency situations by relying on inherent design features and the behavior of materials rather than relying on active control systems or human intervention. PSSs are typically designed to provide a large margin of safety and to be highly reliable and resistant to failure in order to ensure that a nuclear power plant remains safe even in the most severe accidents or emergencies (Bae et al. 2021). They offer advantages over active systems, such as reduced dependence on external energy sources, no requirement for operator intervention to activate them, and lower costs, including easier maintenance (J. Lee et al. 2023). Despite the fact that PSSs play a vital role in the safety of nuclear power plants, assessing their reliability can be challenging due to insufficient data and a limited understanding of the underlying safety functions of the natural driving forces (Jin et al. 2022).

The application of the Probabilistic Safety Assessment (PSA) methodology to advanced reactor designs has proven useful in demonstrating their safety and identifying potential vulnerabilities. This approach allows for the evaluation of alternative design features and potential improvements to the original design (Iwamura, Araya, and Murao 2012). The PSA results may suggest or recommend the replacement of components with more reliable ones. However, there are technical challenges in applying PSA to evaluate nuclear power plants (NPPs) due to insufficient empirical data, diverse failure scenarios, and different phenomenology. These difficulties can influence decisions regarding plant safety levels and defense-in-depth evaluations. A crucial aspect of PSA is the appropriate handling of uncertainties associated with data utilized for quantitative analysis, which must be adequately represented, propagated, and interpreted (Y. H. Lee, Jang, and Lee 2011).

A typical PSA model comprises of interlinked Fault Tree (FT) and Event Tree (ET) models, represented in Boolean logics (Khakzad, Khan, and Amyotte 2013). The FT models system failures, which may result from different combinations of component failures, in parallel or sequentially. ETs are used to evaluate the likelihood of specific outcomes based on a sequence of events or scenarios. They typically start with a specific initiating event, and the branches represent the possible subsequent events and their probabilities. In the PSA model, ET headings are typically linked to individual FTs with mitigating systems of ET. By utilizing Fault Tree Analysis (FTA), it becomes possible to evaluate the failure probability of each mitigating system connected to the ET heading, thereby providing a quantitative estimation of the overall probability of the Top Event (TE) (Purba et al. 2020). To reduce the computational time of FTA, the Artificial Neural Network (ANN) model can be used (Bolbot, Gkerekos, and Theotokatos 2021).

An ANN is a computational model inspired by the structure and function of the human brain, used for pattern recognition, classification, and prediction tasks (Agatonovic-Kustrin and Beresford 2000). ANNs are a type of self-learning models that can be effectively employed to represent complex systems, particularly when the underlying relationships between input and output data are not fully understood, and can identify and learn correlations between inputs and target values (Solanki et al.

2020). In reliability and safety assessment, they can be used to predict the failure probability of a component or system. They can also be used to perform sensitivity analysis, which can assist in detecting the most critical parameters affecting reliability. They can be trained using historical data, such as maintenance records, and can also incorporate expert knowledge (Sarker 2021). They can manage large amounts of data and can model complex, non-linear relationships between variables.

In this paper, the FTA was used to assess the reliability and safety of the Passive Containment Cooling System (PCCS) in Advanced Heavy Water Reactor (AHWR). After that, using failure probability data obtained from the FTA model, two ANN models are proposed for the reliability analysis of PCCS. The number of hidden layers and nodes per hidden layer for the ANN model was selected by hyperparameter tuning technique, and activation functions, Rectified Linear Unit (ReLU) and Sigmoid were utilized to build ANN models. An adaptive moment estimation (Adam) optimizer was utilized for training the ANN models to make the model computationally efficient. Finally, the results of FTA were compared with the predictions of the ANN models to find out ANN model performance.

2. Passive Containment Cooling System (PCCS) and Failure Probabilities of its Components

In the event of a severe accident, the nuclear reactor containment system serves as the top defense against the release of radioactive fission products into the environment. To maintain containment integrity during such an event, either energy management features that can act as long-term heat sinks or pressure relief systems like the containment filtered venting system are provided. Fig. 1 illustrates a schematic diagram of the containment system in AHWR (Kumar et al. 2014). Many generation 3+ and generation 4 advanced nuclear reactors utilize PCCS to safeguard the containment during severe accidents. The primary goal of PCCS is to keep the pressure of the primary containment below the design limit without the requirement for operator intervention and to maintain its integrity in the event that active containment cooling is not feasible or available during an accident scenario (Adinarayana and Ali 2021).

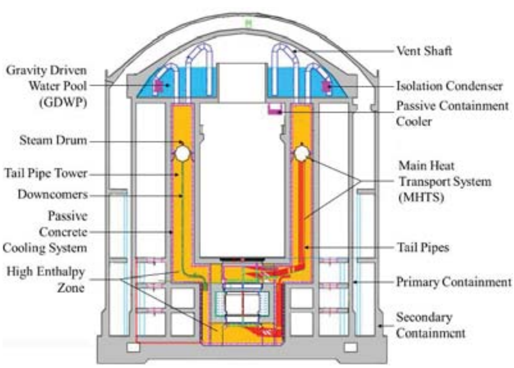


Fig. 1. Schematic diagram of containment system in AHWR (Kumar et al. 2014).

To control the pressure of primary containment after a LOCA and consequently maintain the containment integrity, the PCCS is used to attain post-accident primary containment cooling through the natural circulation. Main Heat Transport System (MHTS) and reactor core are enclosed in the high enthalpy zone of the Primary Containment, while the remaining primary containment is surrounded by the low enthalpy zone. Gravity Driven Water Pool (GDWP), a spherical water tank serving as the suppression pool, is part of the low enthalpy zone. Maintaining the GDWP water level is essential to ensure adequate submergence of the vent shafts in the pool, enabling sufficient suppression in the initial stages after an accident. Increasing water temperature reduces the suppression capability of the GDWP, resulting in reduced energy absorption and higher containment pressure (Kumar et al. 2014).

Passive systems typically fail to function properly not because of problems with their driving mechanism but because of deviations in critical parameters. These deviations can be caused by the failure of active components, such as valves, pumps, and electric signals, or passive components, such as passive valves and relief valves. If The PCCS fails to keep the system operating within design limits, it may be due to intermediate events such as the high water temperature of the GDWP or low water level in the GDWP. FT was developed for each case until the root cause, or Basic Event (BE), was identified. High water temperature in the GDWP can be caused by failures in the header to pool valves, recirculation loop, and pool to header valves to remain open. The recirculation loop can fail if at least three or more of the four recirculation loops failure occur. The low water level in the GDWP can be caused by failure in the header to pool valves and failure in the make up circuit (Kumar et al. 2014).

The components that were identified as BEs for the failure of PCCS have their failure probabilities obtained from plant operating experience data and generic data (IAEA 1988; Kumar et al. 2014), as depicted in Table 1. The failure probability of these components was used to evaluate the reliability and safety assessment of PCCS.

Table 1. Failure probabilities of Basic Events (BEs) for the failure of PCCS.

Basic Events	Failure Probability
Valve 1 fails to remain open (pump loop 1)	1.0×10^{-4}
Valve 2 fails to remain open (pump loop 1)	1.0×10^{-4}
Pump failure (pump loop 1)	3.2×10^{-2}
Check valve fails to function (pump loop 2)	1.0×10^{-4}
Valve 1 fails to remain open (pump loop 2)	1.0×10^{-4}
Valve 2 fails to remain open (pump loop 2)	1.0×10^{-4}
Pump failure (pump loop 2)	3.2×10^{-2}
Check valve fails to function (pump loop 2)	1.0×10^{-4}
Recirculation loop 1-4 failure	3.3×10^{-2}
GWDP pool to GDWP header valve 1-8 fails to remain open	1.0×10^{-4}
Header to pool valve failure	1.0×10^{-5}
Valve fails to remain open	1.0×10^{-4}
Maintenance valves fails to remain close	8.0×10^{-4}

3. Methodology

In this paper, we built a FT to identify the failure probability of the TE using the failure probabilities of the BEs. Assuming 10% standard deviations (SD) associated with BEs, 2000 data points of failure probability for every BE were generated. Using these failure probabilities of BE, we calculated the corresponding failure probability of TE. Afterward, we trained two ANN models using the failure probability of BE and TE for different activation functions, ReLU and Sigmoid and validated the ANN models. Once the ANN model was validated, we used it to predict the failure probability of TE and compared it with the results from FTA. By doing so, we determined the effectiveness of using the ANN model for predicting the failure probability of TE compared to FTA. Fig. 2 represents the methodology of this work.

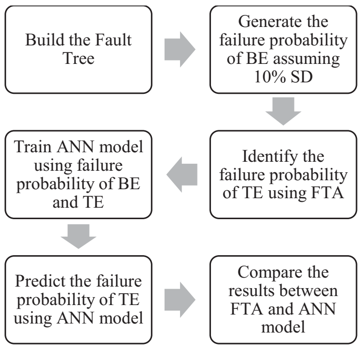


Fig. 2. Methodology overview.

4. Fault Tree Analysis (FTA)

A FT is a diagram that shows all possible events leading to system failure, their logical combinations, and how they relate to each other (Hong, Lee, and Cheng 2006). FTA is a commonly used tool for PSA in nuclear power plants, but it requires quantitative failure rates or probabilities for all BEs in the system FT (Purba 2014). The application of this technique involves the identification and classification of hazards, as well as the estimation of the probability of an undesired failure or accident, referred to as a TE. BEs are the components and subsystems that trigger the occurrence of a TE (Ferdous et al. 2007). In this study, AND, OR, and Voting gates were employed to construct the FT. An OR gate is used when only one event is required, but an AND gate requires each input event must occur in order for the output event to occur. A Voting gate (i/n gate or i-out-of-n gate) is a gate with n input events, where the output event is triggered if i or more of the input events occur (Xiang et al. 2011). Eq. (1), Eq. (2), and Eq. (3) show the mathematical formula to calculate the failure probability using AND, OR and Voting gate, respectively.

$$P_{AND} = \prod_{i=1}^{n} P_i \tag{1}$$

$$P_{OR} = 1 - \prod_{i=1}^{n} (1 - P_i) \tag{2}$$

$$P_{Voting} = \binom{n}{i} P^i (1 - P)^{n-i} \tag{3}$$

Fig. 3 shows the FT for the failure of PCCS and that FT was built using CAFTA 5.3 Educational version software. Voting gates were used to calculate the intermediate event, recirculation loop (3/4) failure, and pool to header valves (2/8) fail to open.

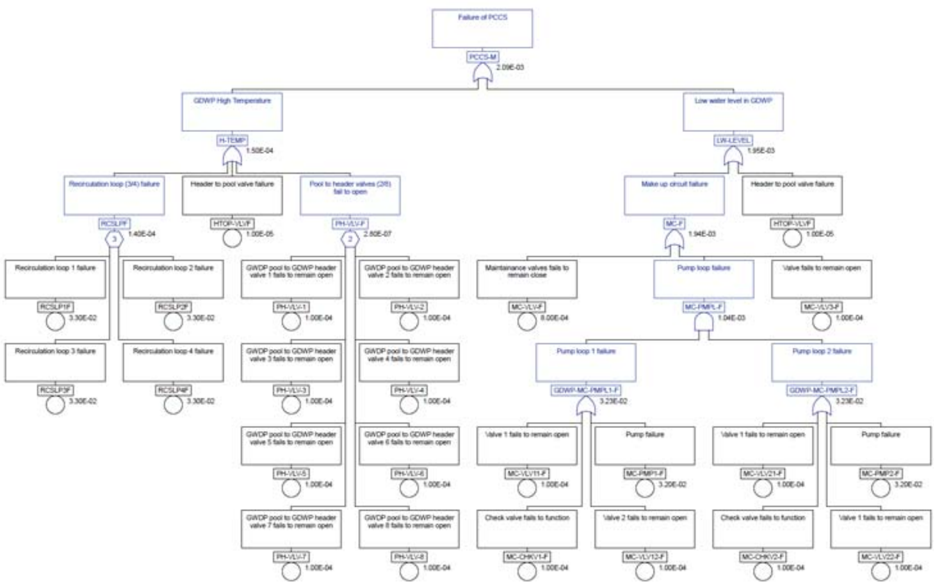


Fig. 3. Fault tree for the failure of PCCS.

5. Artificial Neural Network (ANN) Models

The fundamental structure of an ANN comprises nodes and connections that interconnect them. Each node and connection have associated weight and bias properties, respectively, which constitute the primary mechanism for information storage in a network. To approximate complex entities, a neural network must undergo training for a specific problem by adjusting these weights and biases. The feedforward multi-layer Perceptron (MLP) is a widely used network type for approximation, which is trained using the back-propagation algorithm (Vazirizade, Nozhati, and Zadeh 2017). In this study, we employed the schematic network type illustrated in Fig. 4, which comprises an input layer, two hidden layers, and an output layer. Each ANN model consists of an input layer with thirteen neurons for input data of failure probabilities of BEs and an output layer with one neuron for output data of failure probability of TE. There are two hidden layers; layer-1 contains eight neurons, and layer-2 contains two neurons, as shown in Fig. 4. The best number of hidden layers and neurons per hidden layer for the ANN models was chosen using the hyperparameter tuning technique.

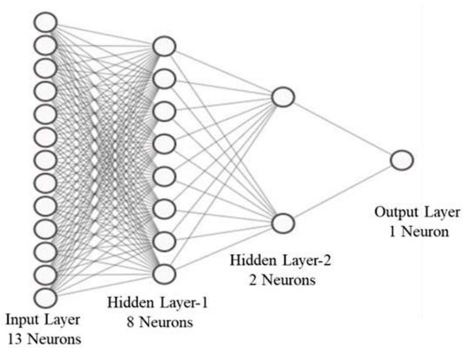


Fig. 4. Structure of proposed ANN model.

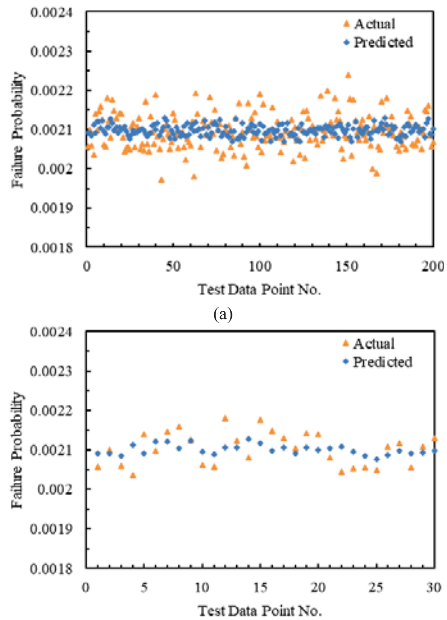
Two ANN models were constructed using ReLU and Sigmoid activation functions. The mathematical expressions of these functions are represented by Eq. (4) and Eq. (5), respectively. To ensure computational efficiency, the Adam optimizer was used to train the models. The models were trained on 70% of the data (1,400 data points), while 20% of the data (400 data points) was utilized for model validation, and 10% of the data (200 data points) was reserved for evaluating the model performance.

$$R(z) = \begin{cases} z & if\ z > 0 \\ 0 & otherwise \end{cases} \quad (4)$$

$$\sigma(z) = \frac{1}{1+e^{-z}} \quad (5)$$

6. Results and Discussions

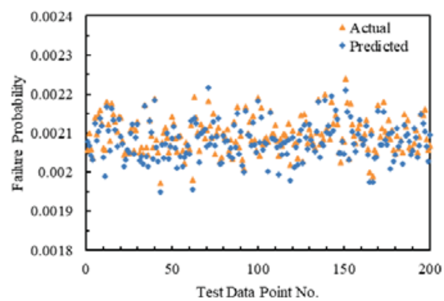
The predicted failure probability of the TE for the ANN model using the ReLU activation function and the actual failure probability of TE for the test set data points are shown in Fig. 5. Fig. 5(a) displays all 200 test data points, while Fig. 5(b) presents only 30 test data points for better visualization.



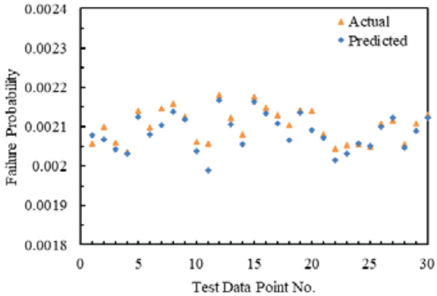
(b)

Fig. 5. Comparison between actual test set data and predicted data of ANN model using ReLU activation function.

Fig. 6 depicts the predicted and actual failure probabilities of TE for the test set data points using the Sigmoid activation function. Fig. 6(a) shows all 200 test data points, while Fig. 6(b) presents a closer look at only 30 test data points.



(a)



(b)

Fig. 6. Comparison between actual test set data and predicted data of ANN model using Sigmoid activation function.

In terms of Mean Absolute Error (MSE), Fig. 7 illustrates the performance of each ANN model. The Sigmoid-trained model has an MSE value that is approximately 66% lower than the ReLU-trained model.

From Fig. 5, Fig. 6 and Fig. 7, it was observed that the ANN model trained using the Sigmoid activation function performed better than the model trained using the ReLU activation function for this work. However, the ANN model with the Sigmoid activation function requires more computational time than the one with the ReLU activation function. Although there may be no significant difference in computational time for small ANN models, it could be a crucial factor for more complex models.

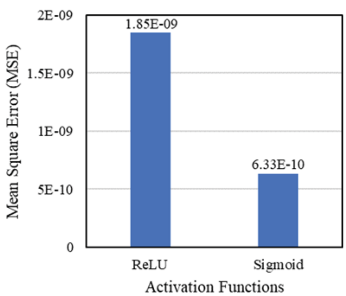


Fig. 7. Comparison of ANN models in terms of Mean Square Error (MSE).

7. Conclusions

This paper demonstrates that the ANN model as a supplement of FTA model can be used to evaluate the reliability and safety assessment of a system. However, there still exists very small errors between the actual and predicted data of the failure probability of TE. For small FT, there will be no significant difference between the computational time of ANN and FTA model. For FT with large number of basic events and dependent events, the ANN model can be more computationally efficient than the FTA model. In future work, a more developed ANN model could be built to maximize the robustness and efficiency of the model, and incorporate the time dependency of the events in the model.

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