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A SE Approach to Predict the Peak Cladding Temperature using Artificial Neural Network

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Abstract : Traditionally nuclear thermal hydraulic and nuclear safety has relied on numerical simulations to predict the system response of a nuclear power plant either under normal operation or accident condition. However, this approach may sometimes be rather time consuming particularly for design and optimization problems. To expedite the decision-making process data-driven models can be used to deduce the statistical relationships between inputs and outputs rather than solving physics-based models. Compared to the traditional approach, data driven models can provide a fast and cost-effective framework to predict the behavior of highly complex and non-linear systems where otherwise great computational efforts would be required.

The objective of this work is to develop an AI algorithm to predict the peak fuel cladding temperature as a metric for the successful implementation of FLEX strategies under extended station black out. To achieve this, the model requires to be conditioned using pre-existing database created using the thermal-hydraulic analysis code, MARS-KS. In the development stage, the model hyper-parameters are tuned and optimized using the talos tool.

Key Words : Systems Engineering, Artificial Intelligence, Deep Learning, Artificial Neural Network, FLEX Strategy, MARS-KS, APR1400, Station Blackout, Peak Cladding Temperature.

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1. Introduction

The operation of nuclear power plants may experience some events that if not controlled or mitigated in a timely fashion, undesired results will be incurred. If the event progresses into an accident, some instrumentation or components degradation or even failure may occur under the harsh environment of the accident. This may affect or delay the operator's response causing the situation to progress into a more complicated one.

This necessitates predicting the system response under various conditions to ensure the plant safety, soundness of emergency procedures and effectiveness of accident mitigation measures. Traditionally, nuclear thermal hydraulics and nuclear safety have relied on numerical simulations to predict the system response of a nuclear power plant either under normal operation or accident condition. However, this approach may sometimes be rather time consuming which makes it not suitable for monitoring and optimization problems, particularly under severe accident conditions where fast calculation of the performance parameters is essential to expedite the decision-making process for accident mitigation. This concern can be addressed by using artificial intelligence (AI) or data-driven approaches.

Some studies used AI to predict important monitoring variables like water reactor level, wall temperature at critical heat flux [2], flow pattern [3], fault in important systems like primary heat transfer systems (PHT) [4], nuclear power plant accident identification problem (NAIP) [5], reactor system behavior [6], and AI has also used for sever accidents to predict their major scenarios. Even though those studies show accurate results, however the use of AI in nuclear industry is still limited and therefore more studies need to be conducted to fully understand the potential and more importantly the limitations of data-driven techniques for nuclear safety.

2. Objective

In this work, an AI algorithm is developed using an artificial neural network (ANN) to accurately predict the peak cladding temperature, a performance metric to indicate the success of the diverse and flexible coping strategy (FLEX) strategy in enhancing the plant's capability to cope with a station blackout. For complex nonlinear problems, like the problem at hand, the accurate prediction of the relationship between the inputs and output necessitates an artificial network structure. To train the ANN model a thermal-hydraulic model is developed using Multi-Dimensional analysis of reactor safety (The Korea institute of nuclear safety) KINS standard (MARS-KS) [3] system code to generate a database of the system response under station blackout condition. And for efficient planning and management of this work, a Systems Engineering (SE) approach is adopted.

3. Systems Engineering Approach

For this work, the Kossiakof Systems Engineering method [4] is implemented starting with stakeholder identification and requirement analysis, functional and physical definitions, all the way to model verification and validation.

3.1 Stakeholders Identification

The stakeholders can be categorized into four main groups with economic, social, environmental and technical interests, as shown in Table 1.

<Table 1> Stakeholders categorization

Category	Stakeholders
Social	• Public • Media
Economic	• Utility • Nuclear Industry • Government • Investors • Manufacturers • Suppliers
Technical	• Regulators • Researchers and scientists • Contractors • Engineers • Technicians • Operators
Environmental	• Environmental Regulators • Neighboring Countries • Pressure Groups

3.2 Requirements Derivation

This step is needed to establish a systematic procedure for the ANN model development, while simultaneously meeting the stakeholders' needs. Table 2 summarizes these requirements which can be categorized into three main groups: mission requirements, originating requirements, and system and component requirements.

3.2.1 Mission Requirements

These requirements are derived from stakeholders needs. The model should correctly predict the peak cladding temperature with sufficient accuracy to earn the stakeholders confidence in application of AI in nuclear industry as a computationally efficient prediction tool. Hence the mission requirement is set to satisfy the regulatory requirements on the main stakeholder requirement for the society.

<Table 2> ANN Model requirements for peak cladding temperature prediction

Requirements	Description
Mission Requirements	1. The model shall be capable of correctly predicting peak cladding temperature. 2. The model should be able to predict the temperature without using a physical simulation (Code) and using independent variables.
Originating Requirements	1. The ANN model is able to predict PCT using predefined databases without overfitting or underfitting.
System Requirements	1. The predicted temperatures shall satisfy a linear correlation coefficient of at least 0.90. 2. The error shall be within 0.5 %. 3. The error of validation dataset shall be lower or equal the error of the training dataset. 4. The error of the training dataset shall not be larger than the error of the validation dataset. 5. The dataset used shall satisfy the 95/95 tolerance limit according to the UNSRC regulatory guide 1.105.[9]

3.2.2 Originating Requirements

Originating requirements should reflect statements made by the stakeholders about the system's capabilities; hence, they should define the constraints and performance parameters which should be met by the system. Specifically, the ANN model should be able to predict the PCT using predefined databases without overfitting or underfitting.

3.2.3 System Requirements

These requirements are a translation of the originating requirements into "engineering language", where it becomes much more detailed than the originating requirements. These requirements are actually related the determination coefficient (R2) that represents how the predicted values match the actual values. Additionally, it sets constraints on the model accuracy, while preventing overfitting and hence maintaining the model generalization.

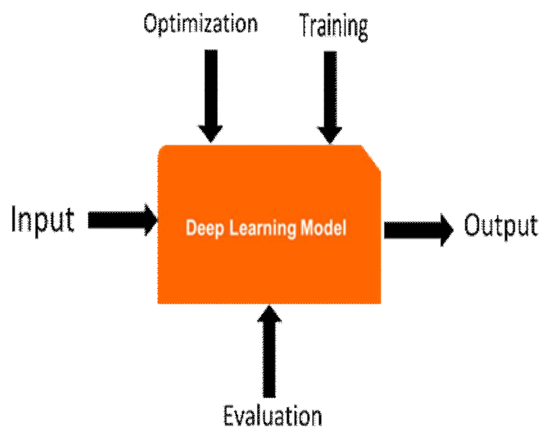
Finally, the dataset that would be used for new predictions shall fulfill the uncertainty requirement of 95% probability and 95% confidence set by the USRNC regulatory guide for best estimate analysis.[9]

3.3 Model Architecture

The model architecture discusses the organization of the model and can be split into: functional architecture and physical architecture.

3.3.1 Functional Architecture

The functional architecture of the prediction model is shown in Figure (1). The model takes in the inputs, tunes the model hyper-parameters during the optimization process on a subset of the data, uses another subset of the data during training process, and last subset of data is used during the evaluation process, at which point the model is ready to predict the output for a set of input para meters.



[Figure 1] top to bottom functional architecture

3.3.2 Physical Architecture

The physical architecture depends on the type of problem, but includes the following key items as shown in Figure (2).

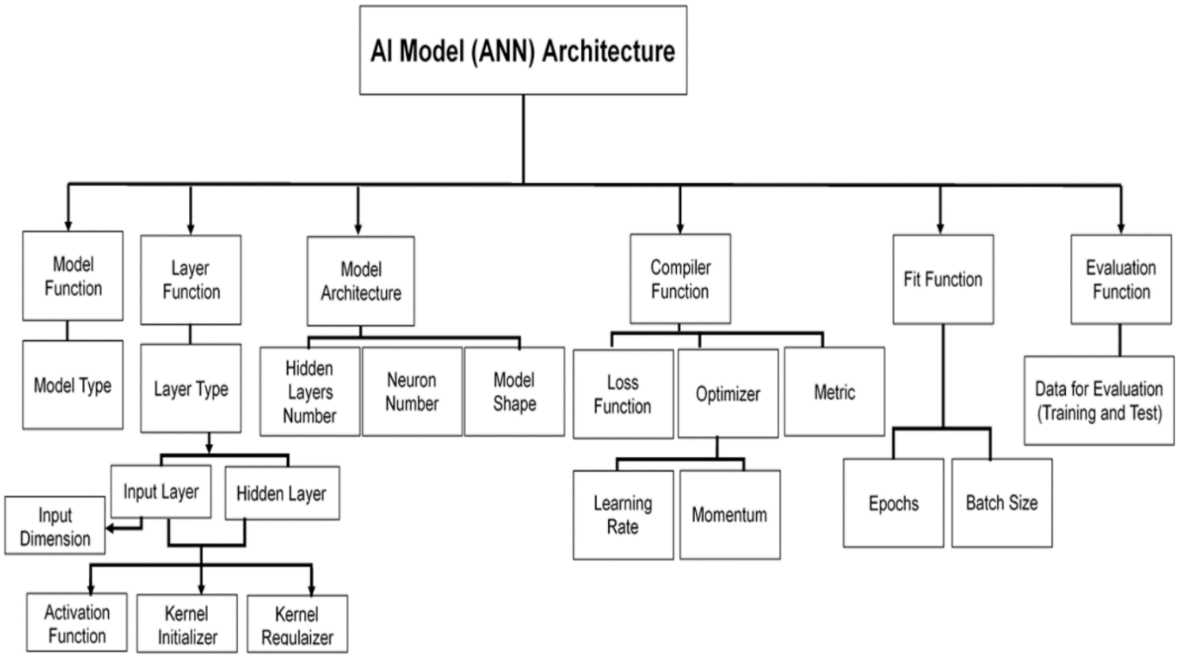
Model function determines the type of the model. The sequential model is the most suitable type for the problem at hand.

Layer function determines the layer kind which is also problem dependent. In this work a dense network is used.

Model configuration or ANN architecture can be either triangle, brick, or funnel.

Compiler function where the loss (error) function, optimizer type, and prediction metric are defined.

Fit function includes the test or/and validation datasets, batch size, and the number

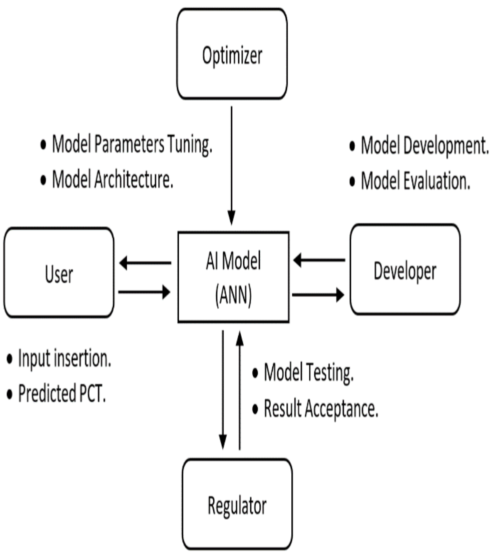


[Figure 2] ANN model architecture

of epochs are defined.

Evaluation function is used to examine the best model obtained from the optimization process.

This structure is deployed as Jason model, where it could be easily invoked for making new prediction for peak cladding temperature.

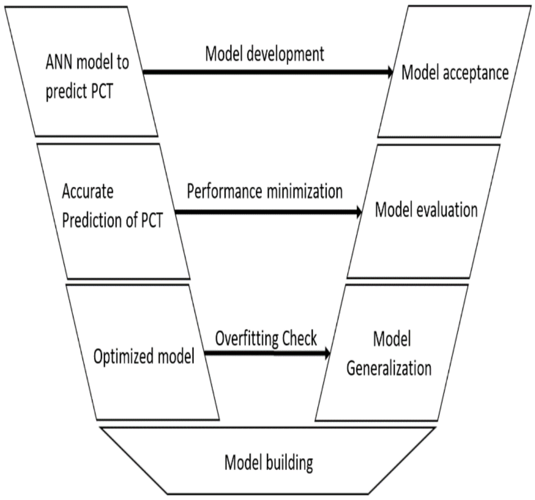


[Figure 3] ANN model context diagram

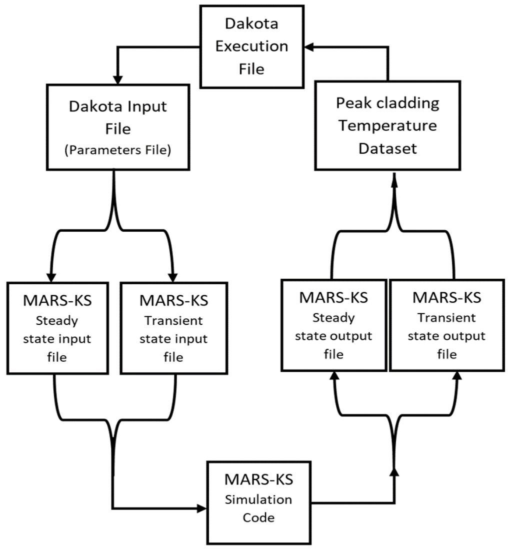
3.4 Verification and Validation

The validation process is required to prove the ability of the model to satisfy the condition of generalization. This checked by monitoring the model performance on both training and test datasets, the metric and the loss function are used to make a decision about the model performance.

During development phase, the model is usually validated by splitting the dataset into training and validation subsets. The model is evaluated at the end of each epoch using the validation subset. The evaluation model is validated using subset that is derived from the whole dataset that had been collected as shown in section (4) in this paper and according to v-model as shown Figure (4).



[Figure 4] ANN V-model



[Figure 5] Database generation using Dakota

4. Data Collection and Model Development

4.1 Data Collection

The dataset used for building the AI model had been generated from the uncertainty quantification for the SBO scenario. 16 uncertain parameters were used to express the big phenomena that occur in the accident, the impact of the various uncertain parameters, shown in tables (3) and (4), on the PCT was assessed by building a framework coupling the thermal hydraulic code, MARS-KS and the statistical tool, Dakota [6], using python programming language as shown in Figure (5).

The uncertain parameters were identified based on the phenomena identification and ranking table (PIRT) developed by Kang et al. [7] and on the uncertainty analysis performed by Kozmenkov et al. [8] and by Lee et al.[9] Next, the uncertain parameters were sampled and propagated into the developed thermal hydraulic model, using Dakota to produce the minimum number of samples that ensures the United States nuclear regulatory commission (USNRC) requirements of 95% probability and 95% confidence. The produced dataset contained 924 samples in total and included 17 variables, 16 of them are independent variables (P1 –P16) and the 17th variable is the dependent quantity that is the PCT. Those independent variables were used as an input for the artificial neural network model to predict the dependent quantity.

The accident can be divided into two main phases before and after FLEX implementation. Spearman's correlation was applied to measure the degree of correlation between the input parameters of every phase and the PCT. The Spearman's correlation was selected because of the nonlinearity of the data. It is worth noting that the sensitivity study revealed that not all of the variables of the thermal hydraulic model were strongly impacting the peak cladding temperature. Hence, to cut down the training time for the AI model, only three input features were selected for every phase, given their strong correlation with the output. For the first phase (before FLEX implementation), those features are reactor power (P1), initial pressurizer level (P8), and the multiplier for vapor Dittus-Boelter correlation (P11). This

<Table 3> SBO phenomena and uncertain parameters

Phenomenon	Uncertain parameter (symbol)
Thermal power generation in core	Initial total reactor power (P1)
	Decay heat power (P2)
Primary system energy accumulation	Fuel heat capacity (P3)
	Fuel conductivity (P4)
Primary and secondary systems pressure control	Initial pressure in pressurizer (P5)
	Set point for pressurizer relief valve (P6)
	Initial pressure in the steam generator (P7)
Heat removal (from primary and secondary systems)	Multipler for liquid Dittus-Boelter correlation (P8)
	Multipler for vapor Dittus-Boelter correlation (P9)
	Multiplier for Chen nucleate boiling model (P10)
Coolant flow (primary system)	Initial total mass flow rate (P11)
	Total moment of inertia for circulation pumps (12)
Coolant injection by emergency Core Cooling Systems ECCSs and mobile pumps (primary and secondary systems)	Initial coolant inventory in SITs (P13)
	Initial pressure in SITs (P14)
	Initial coolant temperature in SITs (P15)
	Initial temperature in the mobile pumps (P16)

work involves the development of two separate models: the ANN model and the thermal-hydraulic model. First each model is introduced followed by the work flow within each model and the interaction between the two models.

4.2 MARS-KS Simulation

A station blackout (SBO) is an accident scenario where all the plant's alternating current electric power sources are lost. This renders many of the safety systems unavailable which may lead to inventory loss, core uncover and threaten the plant's integrity. Accordingly, many utilities have adopted the diverse and flexible strategies (FLEX) to enhance the coping capability of their advanced nuclear reactors.

<Table 4> Uncertain parameters characteristics

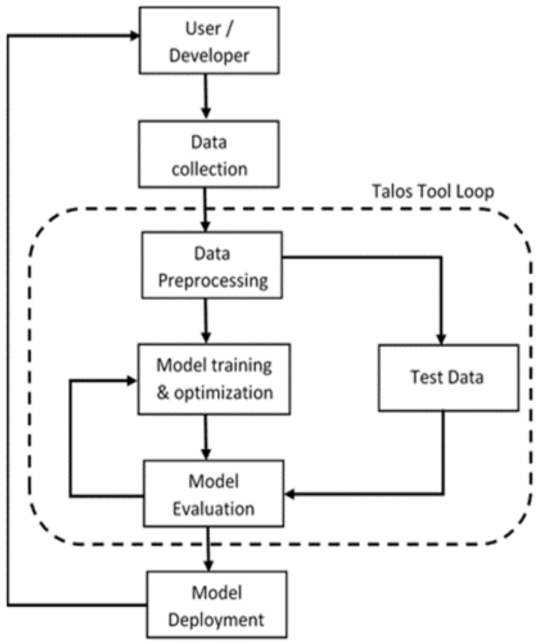
Symbol	Range	Distribution
P1	0.98-1.02	Normal
P2	0.92-1.08	Uniform
P3	0.98-1.02	Normal
P4	0.90-1.10	Normal
P5	0.974-1.026	Uniform
P6	0.982-1.017	Uniform
P7	0.974-1.026	Uniform
P8	0.85-1.15	Uniform
P9	0.8-1.2	Uniform
P10	0.8-1.2	Uniform
P11	0.95-1.05	Uniform
P12	0.8-1.2	Uniform
P13	0.88-1.12	Normal
P14	0.93-1.23	Uniform
P15	0.93-1.23	Uniform
P16	0.94-1.06	Uniform

The peak cladding temperature (PCT) is an important metric that can be used to assess the success of the FLEX strategies. Peak cladding temperature refers to the temperature of the material that surrounds the fuel, and if not maintained below 1477 K. If it is not maintained, this structure will collapse and the radioactive material will be released. So, if the PCT is maintained well below 1477K, the fuel integrity can be assured. However, the success window of FLEX implementation relies on various initial and operating conditions that may be uncertain at the time of the accident. This work builds on a previous work [6], where a best estimate plus uncertainty (BEPU) analysis was performed to analyze a station blackout for APR1400 nuclear reactor to ensure the successful implementation of the emergency operating procedures. A model of the plant is used to generate the system response using the realistic multi-dimensional thermal hydraulic system code MARS-KS V1.4. The SBO model assumptions are:

- FLEX equipment is aligned at 2 hours.
- RCP seal leakage is 21 gpm.
- Battery power is guaranteed for 8 hours.
- Feed and bleed are performed on the secondary side.
- Safety injection pump is unavailable.
- Shutdown cooling pump is unavailable.
- Auxiliary charging pump is unavailable.
- Motor driven auxiliary feed water pump is unavailable.

4.3 Model Workflow

The workflow used in this work follows the general path used for any model development regardless of the application as shown in Figure (6).



[Figure 6] ANN model building workflow

The first step is to gather data that is either produced by a physics-based simulation code or collected from measuring devices in experiments or from historical data that were measured through the operational life. For this work, the database was produced by the MARS-KS thermal hydraulic system code coupled with the statistical tool, Dakota, to propagate the uncertain parameters into the thermal hydraulic model. This is achieved by using a python script to provide a communication interface between the two codes as previously explained and shown in Figure (5).

Next, the data should be transformed into useable form in what is known as data preprocessing. Different transformations may be needed starting with data cleaning, centering and normalization. The transformation may be performed on inputs, output, or both.

Data transformation is required because the inputs have different unit, this leads to variables with different scales. These differences may make problem modeling very hard, however training of unscaled variables results in a model with large weights, thus the model performance will be poor.

In this work, the transformation technique that had been used was normalization which was only applied on the dependent variable because the inputs were normalized by Dakota. The dependent variable is a real value (PCT), so the difference in scale was large.

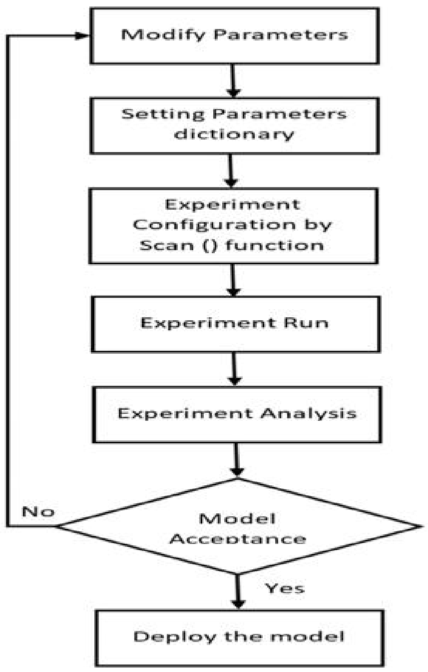
As shown in the Equation (1) below.

$$(x_{max} - x_{min}) \frac{x - x_{min}}{x_{max} - x_{min}} + x_{min} \quad (1)$$

The third step is the model optimization. This is the most challenging phase, in which the model searches for the best combination of hyper parameters that will enhance its prediction capability while avoiding both underfitting and overfitting. There are a number of optimization tools available, for example, the KERAS tuner.

In this work the talos tool [11] as shown in Figure (7), had been used to optimize hyper-parameters and network configuration using the random search method. The random search technique is recommended for models with a large number of hyper parameters.[10] This makes it a very practical and efficient tool for model tuning.

Considering the ANN structure, mainly three different shapes could be tested, these are: triangle, brick, and funnel.



[Figure 7] talos optimization work flow

Using the talos tool [11], more than 1729 models were tested with different combinations of hyper-parameters to search for the best model. In this work the best model was deployed and used for the prediction of the peak cladding temperature.

The analysis includes reporting the results and doing the prediction, and according to the prediction results the model even finalized or a second round of optimization started after parameters enhancement by increasing or decreasing their values, that depends on the result of the correlation matrix sensitivity, on the other hand, some parameters could be tested using statistical analysis to catch the best one like loss function and the optimizer type. For this work, the best model parameters are shown below in Table 5.

<Table 5> Best ANN model hyperparameters

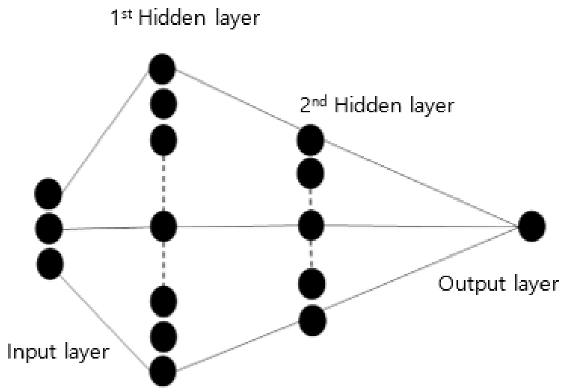
Number	Hyperparameter	Value (in this work)
1	Optimizer	Adam
2	Initializer	Normal
3	Learning rate	3.0007
4	Activation function (output layer)	Linear
5	Network shape (configuration)	Triangle
6	Epochs	1000
7	Number of neurons if the first hidden layer	32
8	Batch size	41
9	Hidden layers number	1
10	Dropout	0
11	Activation function (input layer and hidden layers)	Relu

4. Results

The developed ANN model has the structure shown in Figure (8), with an input layer, two hidden layers and an output layer.

This triangular configuration was suggested by talos tool, with 32 neurons in the first hidden layer and 16 nodes in the second one.

The model successfully predicts the peak cladding temperature with a root mean squared error of 0.77 Kelvin, mean absolute error is 0.60, and the coefficient determination (R2) is 0.93. This proves that the AI model can successfully capture the salient characteristics embedded in the database and reflect with reasonable accuracy the relationship between input and outputs.



[Figure 8] ANN prediction Model Architecture

5. Conclusion

In this work, the ability of artificial neural network to predict a key performance metric for reactor safety, specifically, the peak cladding temperature, given a set of initial and operating conditions. The model can be therefore used to monitor critical variables related to nuclear safety and help in the decision making process in a timely fashion. However, more studies are required to confirm the ability, and more importantly, the limitations of the model in handling databases resulting from different accident scenarios before any concrete conclusions can be derived in relation to the nuclear safety applications in real power plants.

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