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Identification of Cold-Leg Break Size in LOCA Accident Using Artificial Neural Networks and Simulation Database

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Abstract: The most widely studied LOCA (Loss of Coolant Accidents) is a rupture of a cold leg pipe causing the Reactor Cooling System to depressurize first, with different break sizes corresponding to the change in trigger signal from the Instrument and Control System (I&C System) such as pressure, temperature, power, pressure vessel water level, etc. is different. Therefore, the response of nuclear power plant varies considerably with the size of break. To mitigate the consequence of LOCA with a given break size, it is necessary to design the emergency core coolant systems so that the fuel is cooled efficiently during all phases of the accident. Therefore, the size of rupture needs to be detected and identified as soon as possible right after reactor scram. To achieve this goal, this study is conducted to investigate the applicability of artificial neural networks (ANN) for recognizing LOCAs, especially identifying the rupture sizes of the LOCAs according to the changes of operational parameters of VVER-1000 nuclear power plant. This study mainly focuses on building, training, and optimizing the artificial neural networks using simulation databases obtained from the RELAP5 simulation program for VVER-1000 reactor technology. Results clearly showed the potential application of ANN-based model for detecting the break size even with uncertainty of input parameters added.

Keywords: *LOCA, Artificial Neural Networks, RELAP5, VVER-1000.*

I. INTRODUCTION

The events related to the Loss of Coolant Accidents (LOCA) in the nuclear power plant are evaluated as one of the incidents causing serious consequences. The LOCA scenario is also considered to be one of the prominent scenarios that safety and operational systems are designed to respond to. Corrective actions must be applied whenever potentially unsafe conditions occur. The diagnosis of a potentially unsafe plant condition should be quick and accurate. The objective of the plant diagnostic system is any potentially unsafe operating scenario is to give plant operators and engineers sufficient time to formulate, confirm, initiate, and perform the appropriate corrective actions [1][2]. Therefore, the study of identification methods is very necessary.

Nuclear power plants are higgly complex systems that are operated and monitored by human operators. When faces with an unplanned transient, such as a plant accident scenario, equipment failure or an external disturbanceto the system, the operator has to carry out the diagnostic and corrective actions based on the process instrument readings [3]. Depending upon the severity of an accident, instrument’s readings might not give a clear indication of an anormaly at its incipient stage. In addition, difficulties encountered in analyzing nuclear power plant operational data are uncertainty, incomplete,

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intermittent, and noisy [1]. Therefore, it necessitates developing an intelligent system that will assist the operator to identifysuch transients at the earliest stages of their developments. The artificial neural network (ANN) is a powerful machine learning tool for solving complicated problems and improving the ability to identify problems in the operation of nuclear power plants. Recently, many studies aimed at applying ANN in diagnosis and fault identification in nuclear power plants have been conducted. Bartlett and Uhrig (1991) [1] trained the ANN to classify selected nuclear power plant accident conditions. A real-time ANN learning methodology with an adaptive real-time monitoring capability is descrived for plant-wide data from an operationg nuclear power plant by Nabeshima et al., 1994 [4]. Fernandez et al., 2017 [5] created neural networks topologies to use Multi-Application Small Light Water Reactor integrated test facility's data and evaluate its capability of predicting the systems behavior during various core power inputs and a loss of flow accident.

To mitigate the consequence of LOCA with a given break size, it is necessary to design the emergency core coolant systems so that the fuel is cooled efficiently during all phases of the accident. Therefore, the size of rupture needs to be detected and identified as soon as possible right after reactor scram.

To achieve this goal, in this study, the authors will proceed to construct the LOCA accident simulation database with small break size (SB-LOCA) at the cold-leg of the VVER-1000 nuclear power plant on the RELAP5 program. Using simulation database to build ANN-based model to identify the break size. Results clearly showed the potential application of ANN-based model for detecting the break size even with uncertainty of input parameters added. Its ability to provide technical data can help decision makers to take actions more rapidly, identify safety issues, or provide an intelligent system with the potential of using pattern recognition for reactor identification and classification.

II. THE SIMULATION DATABASE

In this report, the VVER-1000 nuclear reactor technology is performed to construct the simulation model in RELAP5 program. The VVER-1000 reactor technology is widely used in Russia with a horizontal stream generator design. The reactor coolant system including two loops, reactor vessel, steam generator is modeled. The entire operation of the reactor as well as thermal hydraulics phenomenon with different failure scenarios is simulated by the RELAP5 program. The system nodeification diagram is presented in Fig.1.

The LOCA scenario was developed to simulate a nuclear power plant state of loss of coolant flow due to the presence of a break at the cool-leg location with small size (SB- LOCA). After calculating by RELAP5 program with the change of 39 different break sizes, a set of data about the change of 34 parameters indicating the operational characteristics of the nuclear power plant over time as follows: pressure, temperature, mass flow rate, water level, power, etc. The changes of the parameters were monitored both before and after the *scram* time with time steps of three seconds and one second, respectively. The database is normalized and used for analysis, determining parameters that have little or no change over time for different break sizes, to select key parameters that are useful in determining detect the break size. Fig. 2 shows the change of some key parameters over time with different break sizes such as CL25, CL28, CL30 corresponds to the size is 25 mm, 28 mm and 30 mm, respectively. There are 12 most important key parameters were selected, which were significantly influenced in the evolution of LOCAs, detailed in Table I.

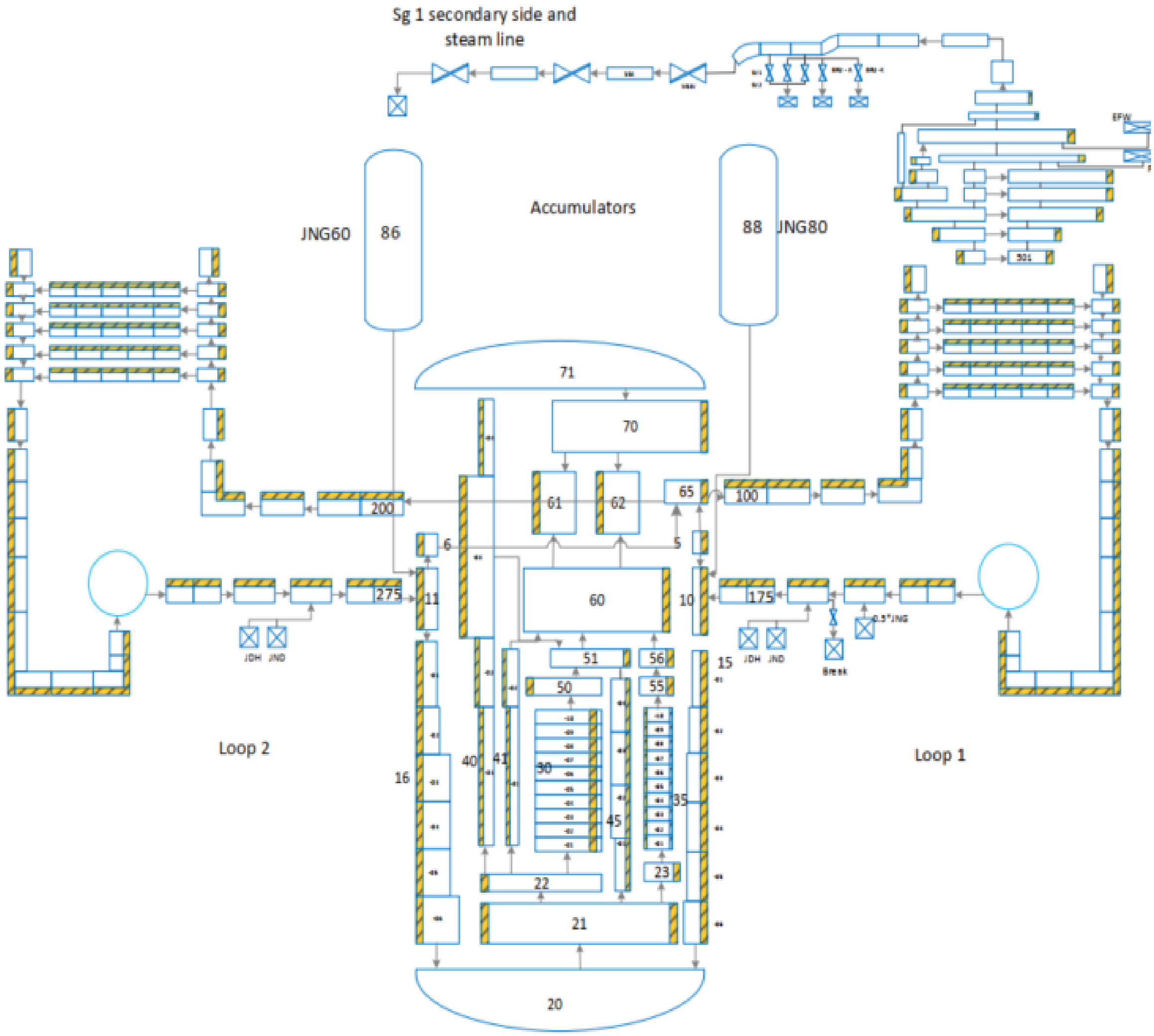

Fig. 1. The diagram of system nodeification in RELAP5 program

Table I. Twelfth key parameters of simulation database

No.	Nomenclature	Name
1	p	Lower Plenum bot.
2	p	Upper Plenum mid
3	p	SG per Plate-S Dryer
4	mflowj	CL Junction
5	tempf	Fluid temperature at Hot Leg
6	rktpow	Kinetic Power
7	mflowj	SG-BRU-K valve
8	cntrlvar	PRZ Collapsed Level
9	cntrlvar	SG-Level
10	mflowj	HL Junction
11	p	HL-Upper Plenum
12	p	CL-pump connect

Additionally, eight cases with break sizes varying from 30mm to 100mm, in which were 100 random cases with different changes of key parameters. This is to consider the uncertainty factor of the phenomenon, which improves the predictive power of the ANN-based model of the uncertainty input parameters.

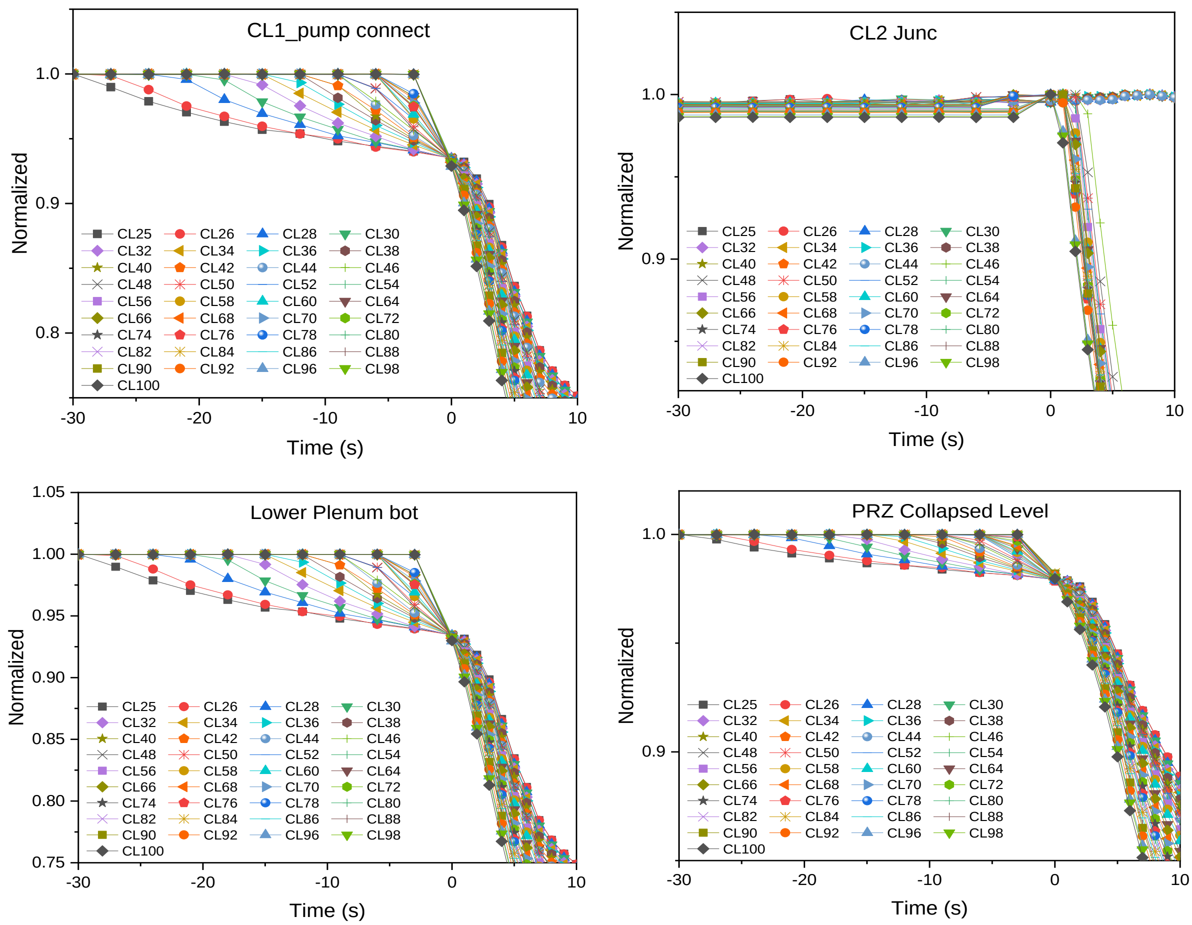

Fig. 2. The change of some key parameters

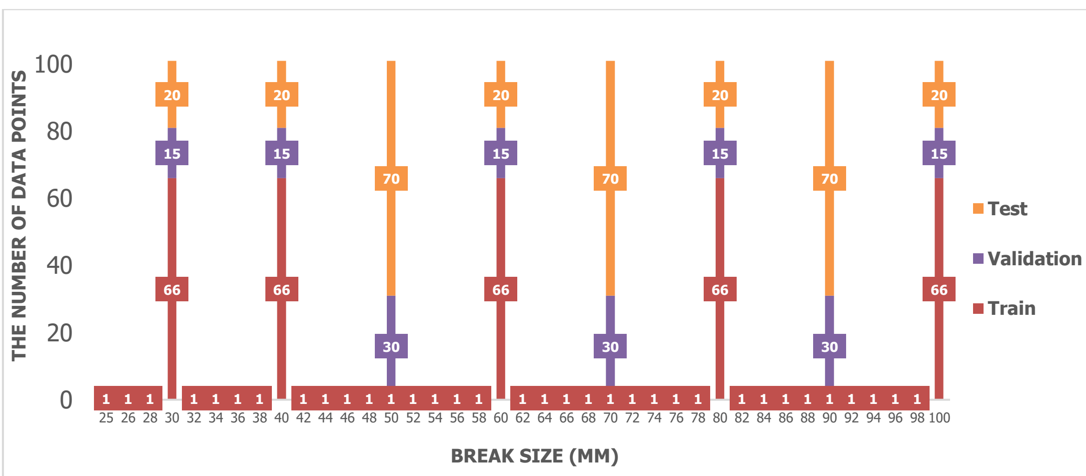

Fig. 3. The data division for ANN training

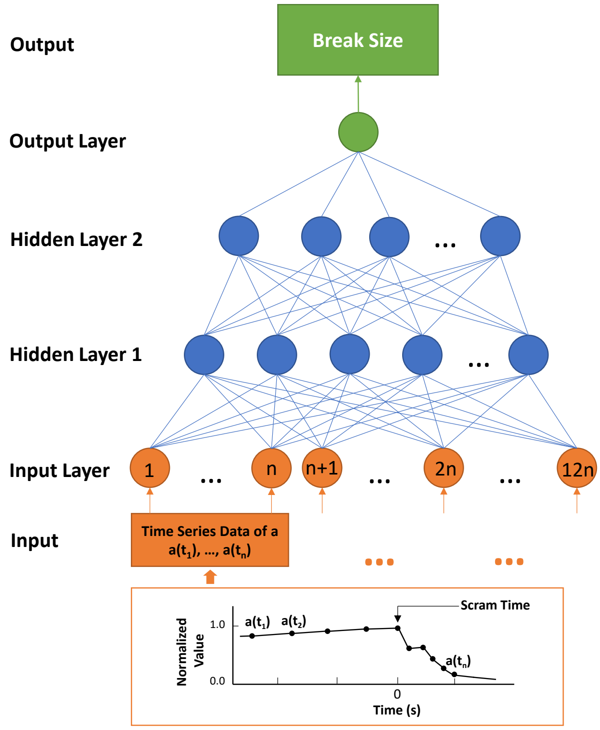

Fig. 4. Structure of ANN-based model

III. INDENTIFICATION METHOD USING ANN-BASED MODEL

The simulation data including the change of 12 key parameters obtained through the RELAP5 program is used in the training process in which the weights and biases are modified to attain better approximation of desired output. The output target values correspond to the break size in each case. The simulation database consists of 839 data points corresponding to different cases of 39 break sizes varying from 25mm to 100mm. The input of each data point is a collection of *Time Series Data*, each time series data describing the change over time of a corresponding key parameter. Fig. 3 presents the structure of the ANN-based model to detect the break size using the collection of time series data as the ANN input.

The type of ANN used in this work is the *multilayer feedforward net*, including one input layer, one output layer, and two hidden layers. The transfer function in input and output layer is linear transfer function (*purelin*), while the functions of log-sigmoid (*logsig*). The number of neurons in input and output layer are determined based on the number of key parameter and one predicted result (break size). To determine the number of neurons in each hidden layer, the traditional *Trial-and-Error* method was utilized by changing the number of neurons in the hidden layer and checking the values of the mean square error (MSE) and the coefficient of determination (R^2) as defined below:

$$MSE = \frac{\sum_i (y_{i,target} - y_{i,pred})^2}{n} \quad (1)$$

$$R^2 = 1 - \frac{\sum_i \left(y_{i,target} - y_{i,pred}\right)^2}{\sum_i \left(y_{i,target} - y_{mean}\right)^2} \, \epsilon[0,1] \quad (2)$$

The database including 839 data points, after pre-processing is divided into three parts for training, testing and validation. The data division should ensure that all instances of different break sizes are included in the training data. Fig. 4 depicts the division of the data into three separate parts. In the cases with break sizes of 50, 70, and 90 mm, the training data consists of only one point, the rest of the data corresponding to other uncertainties is divided into test and validation data. In this way, it is possible to check the interpolation and predictive ability of the ANN for uncertain cases. Each ANN configuration has it weights, and biases initialized using the *Nguyen-Widrow* method. To avoid overfitting, the ANN is trained with the *Levenberg-Marquardt* algorithm along with early stopping.

IV. RESULTS AND DISCUSSION

Table II. Comparison of different structures of hidden layers

Structure of hidden layers	Test data (R)	Performance (MSE)	Total number of weights and biases
10-10	0.96221	1.24E-8	2541
15-15	0.99237	3.89E-9	3886
20-10	0.99485	4.34E-9	5061
20-20	0.99560	7.81E-10	5281
25-25	0.99141	9.84E-9	6726
30-10	0.99278	6.75E-9	7581
30-20	**0.99672**	**2.15E-10**	**7901**
30-30	0.99386	4.89E-10	8221
40-10	0.99424	2.32E-10	10101
40-30	0.99347	8.74E-11	10941
40-40	0.98972	5.93E-11	11361
45-45	0.99065	8.89E-11	13006
50-30	0.99265	5.67E-11	13661

To find the optimal number of neurons in the hidden layers, each ANN structure is trained 10 times with random initiated weights and biases, and then the averaged values of training performance and coefficient of determination of test data were obtained. Table II shown the comparison of different structures ANN. Three criteria are considered for choosing the optimal ANN structure: the training performance, the test error and the total number of weights and biases, which is used to evaluate the ANN size. Therefore, the structure (30-20) is chosen as the optimal structure, because it has the best accuracy at the test data as well as training performance and ANN size are also good.

Fig. 5 shown a comparison of predicted results with target values, with the coefficients $R_{train} = 1$, $R_{test} = 0.99918$, $R_{val} = 0.99941$ and $R_{all} = 0.99966$. Most of the data points are in the 1:1 linear regression line, showing good capability to accurately predict by the ANN-based model.

In the cases where there is no uncertainty in the training data (data points are 50, 70 and 90 mm), the prediction results are slightly biased, indicating that the ANN-based model capable of relatively accurate identification even with uncertainty of input parameters added.

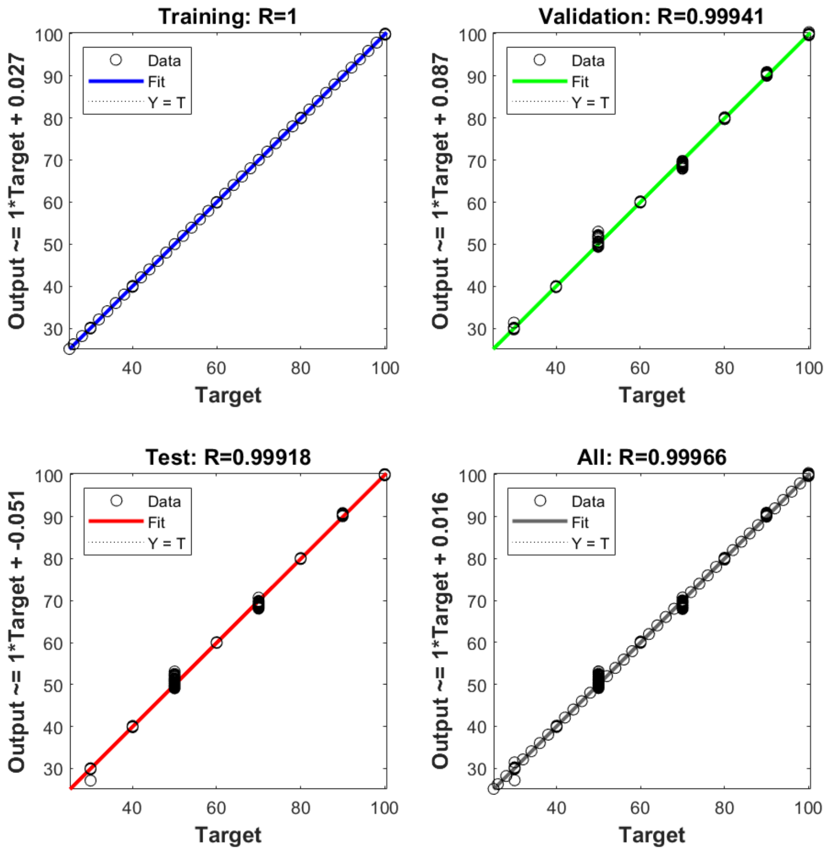

Fig. 5. Compare predictive and target results

V. CONCLUSIONS

This study has performed the construction of SB-LOCA fault simulation data with different break sizes at the cold-leg in a nuclear power plant using VVER-1000 technology. With simulated database, the authors have built an ANN-based model to identify the corresponding break size. The results showed that the accuracy of the ANN-based model, even when considering the uncertainty of the input data. This proves the great potential of the application of ANN in quickly identifying the break size in the LOCA.

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