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Original Article

PREDICTION OF SEVERE ACCIDENT OCCURRENCE TIME USING SUPPORT VECTOR MACHINES

SEUNG GEUN KIM, YOUNG GYU NO, and POONG HYUN SEONG *

Department of Nuclear and Quantum Engineering, Korea Advanced Institute of Science and Technology, Number 373-1, Guseong-dong, Yuseong-gu, Daejeon 305-701, Republic of Korea

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ABSTRACT

If a transient occurs in a nuclear power plant (NPP), operators will try to protect the NPP by estimating the kind of abnormality and mitigating it based on recommended procedures. Similarly, operators take actions based on severe accident management guidelines when there is the possibility of a severe accident occurrence in an NPP. In any such situation, information about the occurrence time of severe accident-related events can be very important to operators to set up severe accident management strategies. Therefore, support systems that can quickly provide this kind of information will be very useful when operators try to manage severe accidents. In this research, the occurrence times of several events that could happen during a severe accident were predicted using support vector machines with short time variations of plant status variables inputs. For the preliminary step, the break location and size of a loss of coolant accident (LOCA) were identified. Training and testing data sets were obtained using the MAAP5 code. The results show that the proposed algorithm can correctly classify the break location of the LOCA and can estimate the break size of the LOCA very accurately. In addition, the occurrence times of severe accident major events were predicted under various severe accident paths, with reasonable error. With these results, it is expected that it will be possible to apply the proposed algorithm to real NPPs because the algorithm uses only the early phase data after the reactor SCRAM, which can be obtained accurately for accident simulations.

1. Introduction

Because both size and complexity of nuclear power plants (NPPs) are increasing, understanding system problems and their mitigation poses significant challenges to operators [1]. If a transient occurs in an NPP, operators will try to predict which kind of abnormality has occurred by checking various plant status variables to protect the NPP from hazardous situations such as severe accidents. Because the operator's actions are heavily affected by the instructions written in the procedures, it is very important for operators to determine the initiating events. However, due to the many complicating factors, such as overload of information, high workload in urgent situations, and the short time available

* *Corresponding author.*
E-mail address: phseong@kaist.ac.kr (P.H. Seong).

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for diagnosis, operators can become confused and make wrong decisions, thereby leading to dangerous situations. To help operators mitigate abnormalities of NPPs properly and effectively, various operation support systems with artificial intelligences (AIs) have been developed. For example, AI techniques were applied to signal validation systems [2–4], fault diagnosis systems [5,6], and many other support systems.

Similarly, operators take actions based on severe accident management guidelines (SAMGs) when there is the possibility of a severe accident occurrence in an NPP. In such a situation, information about the occurrence times of severe accident-related events is very important to operators so that they can set up severe accident management strategies. Currently, there are many computer codes that can perform severe accident-related analyses, but because they require a long time for both the simulation and the setting of parameters, it is hard to apply such codes in real-time support systems. Therefore, support systems that can quickly provide this kind of information to operators would be very useful when they try to manage severe accidents.

A previously conducted study that dealt with severe accident monitoring using several AI techniques [7] successfully predicted the occurrence times of several severe accident-related events, including core exposure time, time when core exit temperature exceeds 1,200°F, and reactor vessel (RV) failure time. However, the study was only conducted for a case in which no action was taken for mitigation of the accident. In a real situation, however, operators would take certain mitigation actions before a severe accident happens, and these cases also need to be considered. Therefore, various paths to severe accidents should be considered to develop more realistic support systems.

To monitor and predict severe accidents, diagnosis of initiating events should be the first step. In this research, fault diagnosis using support vector classification (SVC) and support vector regression (SVR) algorithms that were suggested by Na et al. [8] were applied with some modifications. The similarity between this study and the reference comes from the use of the same algorithms, that is, SVC and SVR. However, the main difference is that the reference trained two SVRs for break size estimation in the loss of coolant accident (LOCA) case, with consideration of the hot leg LOCA and cold leg LOCA, whereas there were six SVRs for break size estimation with consideration not only of the hot leg and cold leg but also of small break (SB), medium break (MB), and large break (LB) LOCAs. Because of this major difference, two SVCs were applied to classify the SB, MB, and LB LOCAs before the detailed break size estimation was conducted by the trained SVR.

SVC and SVR are included in support vector machines (SVMs); an SVM is a machine-learning algorithm that has been successfully used in pattern recognition for cluster analysis [9]. SVM is applied in many fields of research because of its high performance in finding global optimums, and high performance in real applications as well as in artificial neural networks, which have been applied for a comparatively long time.

This research also proposes an algorithm based on SVR that predicts the occurrence time of major events of severe accidents, such as maximum core temperature exceeding 1,200°C, RV failure, and containment (CTMT) failure when operators fail to mitigate transient. By using event-tree (ET) analysis, which is widely used in the field of probabilistic risk assessment, our method is able to classify various paths that lead to core damage; in addition, severe accident scenario occurrence times can be predicted for each major path.

Because there are many kinds of initiating events and severe accident paths, considering all of them is very labor intensive. However, if it is possible to show that these methodologies can predict the occurrence time successfully, expanding the coverage of the research will be much easier. In this regard, only an LOCA transient was considered as an initiating event and eight severe accident paths under this LOCA situation were selected as parts of a case study. The eight severe accident paths contain four severe accident paths from the SB LOCA, and two paths each from the MB and LB LOCAs, according to probabilistic priority. In addition, for further simplification, conservative assumptions (i.e., assuming the worst cases) were made for each path. For example, severe accidents can occur when three or all four safety injection lines fail to inject water in an LB LOCA condition. In this regard, it is assumed that all four safety injection lines failed to inject water in the safety injection failure-related paths, because this is the most serious case.

The proposed algorithms were trained and validated using data obtained from the MAAP5 (modular accident analysis program) code simulations. The reference plant for this research is the Advanced Power Reactor 1400 (APR1400).

2. LOCA identifications

Prior to the prediction of occurrence time under LOCA cases, it is necessary to identify the break location because the occurrence time differs according to the break location. In this regard, hot leg LOCA and cold leg LOCA were identified using SVC in this study. Similarly, because the severe accident path and occurrence time differ according to the break size, SB LOCA, MB LOCA, and LB LOCA were classified using multiple SVCs and SVRs. In addition, the detailed break size was estimated to verify the accuracy of the suggested methodology, although the results were not used for occurrence time prediction.

2.1. *Data acquisition*

To estimate the break location and break size of an LOCA, it is necessary to collect data sets that indicate how plant status variables will change when an LOCA occurs. Because there are only a few sets of accident data, data should be obtained from computational simulations.

Data sets obtained from the simulation were used for training the SVC and SVR algorithms; properly trained SVC and SVR algorithms have the capability to classify break locations and estimate break sizes with the inputs of the plant status variables. In addition, the trained algorithms are able to perform such classification or estimation in a short time after transient occurrence, so that operators can start the mitigation process as quickly as possible.

Table 1 – List of training data sets and testing data sets.

Training data break size (ft^2)	Testing data break size (ft^2)
0.005, 0.006, 0.007, 0.008, 0.009, 0.010, 0.011, 0.012, 0.013, 0.014, 0.015, 0.016, 0.017, 0.018, 0.019, 0.02, 0.025, 0.03, 0.04, 0.05, 0.06, 0.07,	0.004, 0.0055, 0.0075, 0.0095, 0.0105, 0.0115, 0.0135, 0.0155, 0.0175, 0.0195, 0.0225, 0.035, 0.055, 0.075, 0.095, 0.175, 0.225, 0.325, 0.375,
0.08, 0.09, 0.10, 0.15, 0.20, 0.25, 0.30, 0.35,	0.475, 0.525, 0.575, 0.625, 0.675, 0.725,
0.40, 0.45, 0.50, 0.55, 0.60, 0.65, 0.70, 0.75,	0.775, 0.825, 0.875, 0.925, 1.1
0.80, 0.85, 0.90, 0.95, 1.00	
(Cold leg, hot leg each: total 86 data sets)	(Cold leg, hot leg each: total 60 data sets)

Because the quality of training data heavily affects the quality of the trained algorithm, acquisition of reliable training data is necessary. In this study, training data were acquired using the MAAP5 code, developed by Fauske & Associates (Nuclear Applications), located in Illinois, U.S.; this code is used worldwide for severe accident analysis and has been provisionally proven as a reliable simulation code. Data were acquired based on the APR1400 reactor parameters, developed by Korea Hydro & Nuclear Power (Central Research Institute), located in Daejeon, Korea.

Moreover, Lindholm et al. [10] and Allison [11] performed research using the MAAP4, MELCOR, and SCDAP/RELAP5 computer codes; both reported that the three listed codes predicted similar trends in the early phase. Because the MAAP5 code is an upgraded version of MAAP4 and only early phase data (from SCRAM to 60 seconds after SCRAM) were used for the break location and size estimation, data acquisition using the MAAP5 code in this research is reasonable.

2.2. Break location identification

2.2.1. Methodology

To identify the break location of an LOCA, SVC was trained to differentiate between a cold leg LOCA and hot leg LOCA using 13 plant status variables that are observable in main control rooms. The variables used are as follows: broken side steam generator (S/G) pressure, level, and temperature; unbroken side S/G pressure, level, and temperature; pressurizer (PRZ) pressure and level; core water temperature and level; sump water level; and CTMT pressure and temperature.

During the training process, time derivatives of each variable were used. In detail, time derivatives from an emergency shutdown (i.e., SCRAM) to 60 seconds after shutdown were used.

Eighty-six training data sets consisting of 43 cold leg data sets and 43 hot leg data sets were used for training of the SVC. The break sizes of the training data sets varied from 0.005 ft^2 to 1.0 ft^2. For validation, the trained SVC was applied to 60 testing data sets consisting of 30 cold leg data sets and 30 hot leg data sets. The break sizes of the testing data sets varied from 0.004 ft^2 to 1.1 ft^2. Because the range of the break size is broader in the testing data sets, it is possible to check the extrapolation performance of the trained SVC. Table 1 shows the break sizes of each training and testing data set.

The parameters for SVC were optimized using the grid-search method. The radial-basis function (RBF; Fig. 1), which is generally selected for mapping real-world data, was used as the "kernel function". The general shape of the RBF is as follows:

$$K(x, x') = \exp\left(-\frac{\|x, x'\|^2}{2\sigma^2}\right) \quad (1)$$

2.2.2. Results of break location identification

Because the optimized hyperplane of SVC should be able to classify all the training data sets correctly, the trained SVC accurately classified the break locations of all 86 training data sets. The trained SVC was also found to have correctly identified the break locations of all 60 testing data sets. There were no classification errors among the total of 146 data sets and, hence, strict accuracy analysis using type I error (false positive) and type II error (false negative) could not be conducted. However, because there were a large number of testing data sets with various break sizes, it is expected that it will be possible to perform correct classification of the break location for most LOCA cases.

2.3. Break size estimation

2.3.1. Methodology

LOCAs can be classified according to break size into three categories, namely, SB LOCA, MB LOCA, and LB LOCA. When the break size is smaller than 0.02 ft^2, it is classified as an *SB LOCA*. Break sizes between 0.02 ft^2 and 0.5 ft^2 are classified as an *MB LOCA*, and those bigger than 0.5 ft^2 are classified as a *LB LOCA*.

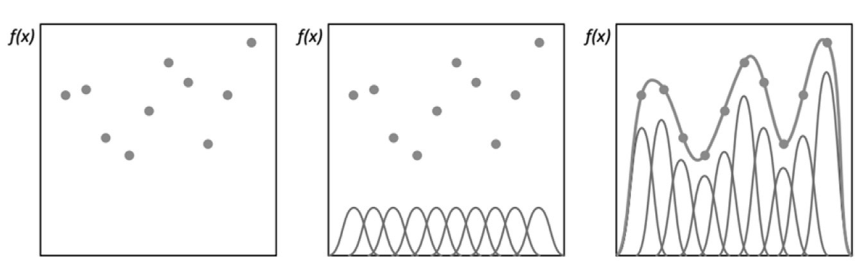

Fig. 1 – Representation of function by summation of radial basis function [12].

As the progress levels are different for these three types of LOCA, the classifications of SB LOCA, MB LOCA, and LB LOCA are helpful for more accurate break size estimation. To identify these three types of LOCA, two SVCs were trained to classify the three classes of data set. For the training, time derivatives of the same 13 plant status variables were used.

After the rough break size estimation of the SVCs, SVRs were applied to estimate break size more accurately. Because there are two kinds of break location (cold leg and hot leg) and three classifications of break size (SB LOCA, MB LOCA, and LB LOCA), six SVRs were trained for each LOCA scenarios. With the classification results of the previous SVCs, the corresponding SVR was applied and the break size was estimated.

Because the antecedent SVCs roughly classify the break location and the break size using the 13 plant status variables, it is not necessary to conduct regression analysis using all 13 plant status variables. Besides, training the SVRs using all 13 plant status variables takes a very long time. Instead, considering some important variables, which are the parameters that are closely related to break size, such as PRZ pressure, is sufficient to train the SVRs for break size estimation. As a result, six SVRs were trained only using the time derivatives of the PRZ pressure data.

The same 86 training data sets consisting of 43 cold leg data sets and 43 hot leg data sets were used for training the SVCs and SVRs; to validate the trained SVCs and SVRs, the same 60 testing data sets consisting of 30 cold leg data sets and 30 hot leg data sets were applied.

The parameters were optimized using the grid-search method, and RBF was used as the kernel function for all SVCs and SVRs.

The methodology for estimating break location and size using SVC and SVR was based on the research performed by Na et al. [8], but with some modifications for break size estimation and optimization.

2.3.2. *Results of break size estimation*

Because the optimized hyperplane of SVC should be able to classify all training data sets correctly, trained SVCs accurately classified all 86 training data sets into SB LOCA, MB LOCA, and LB LOCA. The trained SVCs also correctly classified all 60 testing data sets. There were no classification errors among the total of 146 data sets; therefore, the strict accuracy analyses that accompany type I errors and type II errors could not be conducted. However, because there were large numbers of testing data sets with various break sizes, it is expected that it will be possible to perform correct classification of the break size for most LOCA cases.

Six SVRs were applied to estimate the break size of the training data sets and the testing data sets using SVR's own regression functions. Root-mean-square (RMS) estimation errors for all 86 training data sets were calculated and found to be 4.02% and 3.66% for the 43 cold leg data sets and the 43 hot leg data sets, respectively. For the testing data sets, RMS estimation errors were calculated and found to be 5.70% and 3.92% for the 30 cold leg data sets and the 30 hot leg data sets, respectively (Figs. 2 and 3). However, break size was not properly estimated for the data sets that had actual break sizes of 0.004 ft^2 and 1.1 ft^2. From these results, it can be seen that the trained SVRs did not show good results at

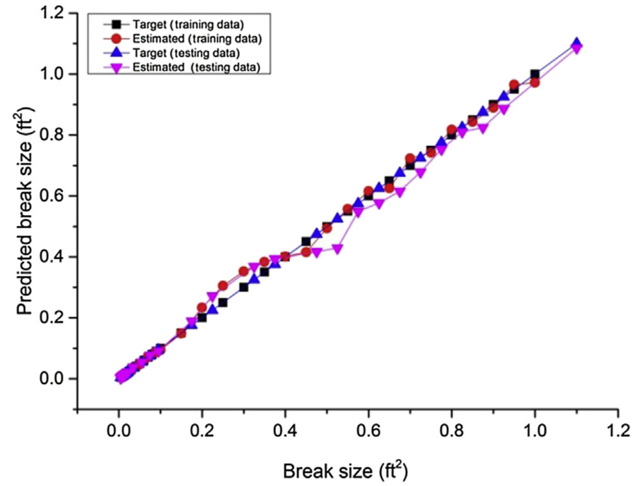

Fig. 2 – Predicted break size (cold leg loss of coolant accident).

extrapolation, meaning that the SVRs are valid within the range of break size from 0.005 ft^2 to 1.0 ft^2.

Because the previous mean errors were calculated by including all testing data sets, RMS error will decrease when the data sets for extreme actual break size (0.004 ft^2 and 1.1 ft^2) are neglected. Therefore, the results are sufficient to prove that the break size estimation performances of the six SVRs are within acceptable levels. Table 2 shows the RMS error of break size estimation.

3. Severe accident occurrence time predictions

After identifying the break location and break size of an LOCA, the occurrence time of important severe accident-related events, such as maximum core temperature exceeding 1,200°C (temperature at which zircaloy starts to rapidly react

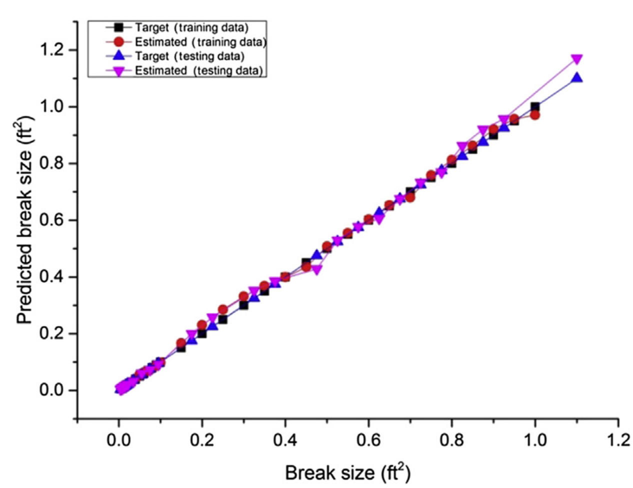

Fig. 3 – Predicted break size (hot leg loss of coolant accident).

Table 2 – RMS and maximum estimation errors of break size.

Data type	RMS error	Maximum error
Training data, cold leg	4.02	21.96
Training data, hot leg	3.55	15.20
Testing data, cold leg	5.70	27.50
Testing data, hot leg	3.92	14.71

Data are presented as %.
RMS, root mean square.

with oxygen), RV failure, and CTMT failure, were predicted using multiple SVRs. Although ET analyses from the preliminary safety analysis report were referenced to reduce the number of severe accident paths to be considered, there are still many paths that lead to severe accidents and it is very labor intensive to consider all of them. Instead, four severe accident paths from the SB LOCA and two paths each from the MB LOCA and the LB LOCA were selected as case studies according to probabilistic priority. ET analyses for SB, MB, and LB LOCA cases are shown in Figs. 4–6, whereas the considered paths are represented in Table 3. In addition, conservative assumptions, which mean a consideration of the worst case for each path, were made in this study. For example, severe accidents can occur when three or all four safety injection lines fail to inject water in the LB LOCA condition. In this regard, it is assumed that all four safety injection lines failed to inject water in the safety injection failure-related paths, as this is the most serious case.

3.1. *Data acquisition*

Similar to the cases of break location and size estimation, the MAAP5 code was used to acquire data sets because the quantity of real accident data is very low. Even though there is real accident data, it is hard to use because the accident data were not acquired under controlled conditions, which means that the data cannot be included in the domain of interest. Trends of 13 plant status variables for times when maximum core temperature exceeded 1,200°C, RV failure times, and CTMT failure times were obtained by simulation. As is documented in the "Data Acquisition" section, accident simulation data are accurate in early accident phases; the proposed algorithm will be applicable for real NPPs because the SVRs were trained using these data.

Actual time data for validation of the suggested methodology were obtained using the same code with the assumption that the data sets from the MAAP5 code simulations

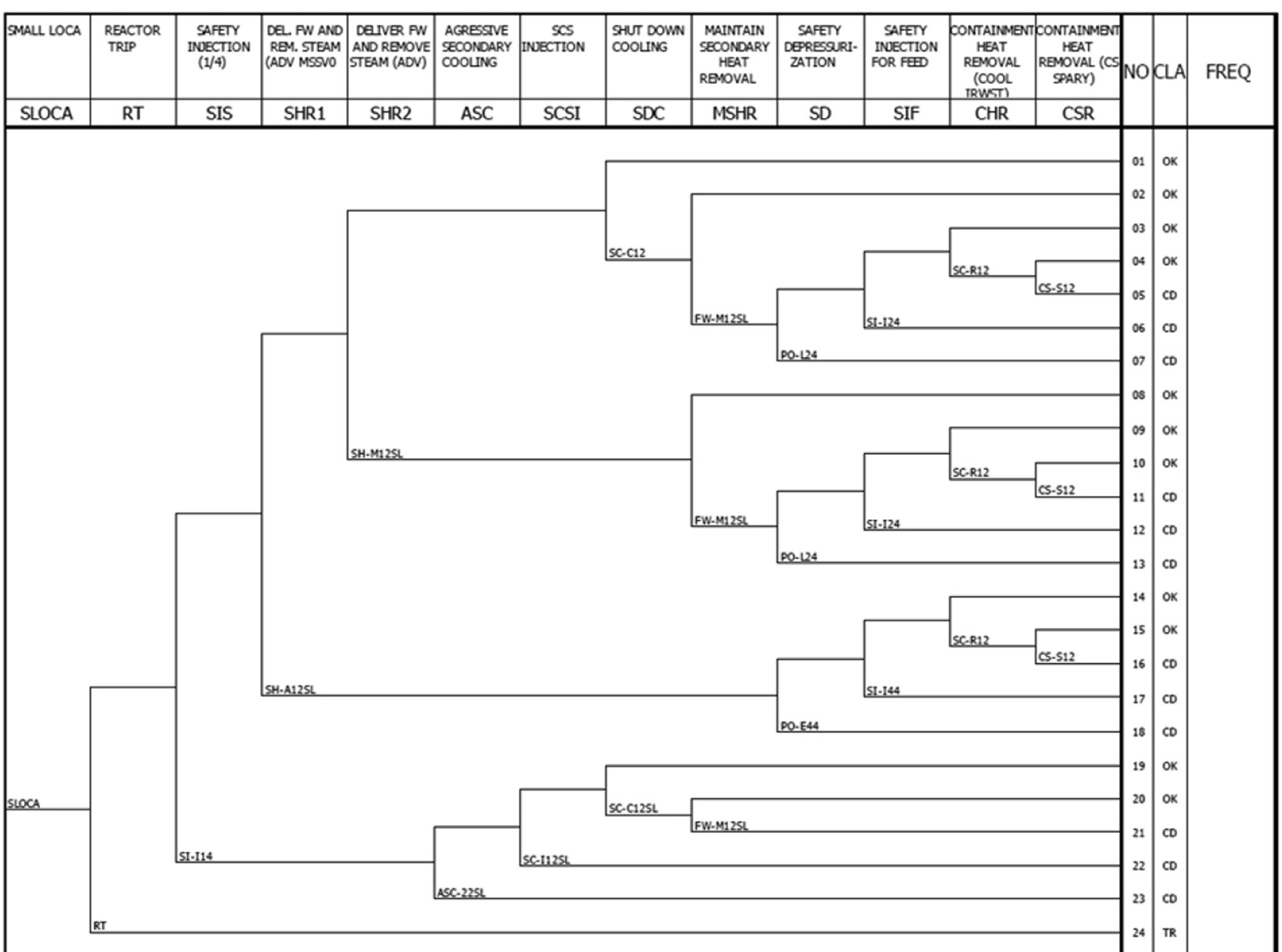

Fig. 4 – Event-tree analysis for small break loss of coolant accident.

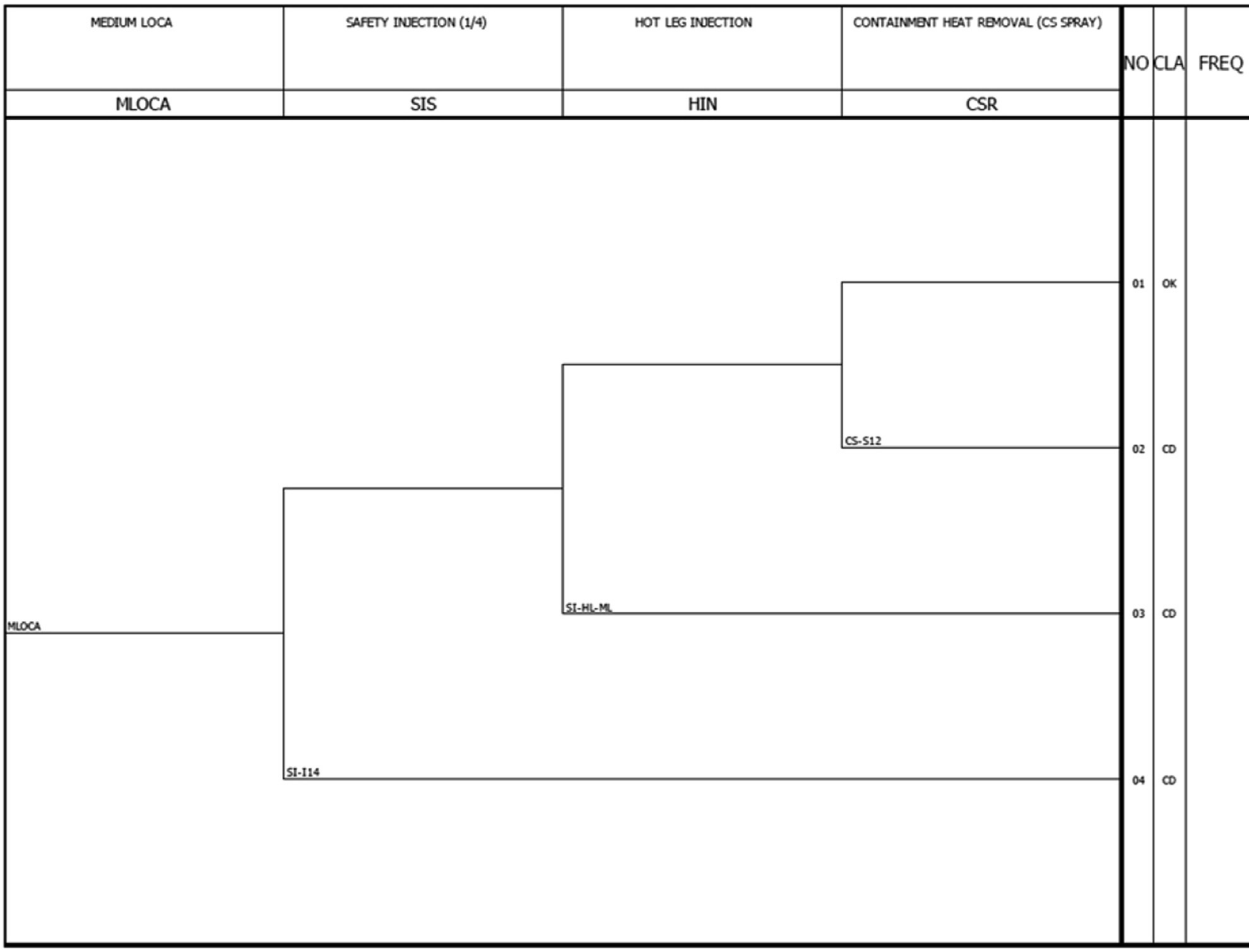

Fig. 5 – Event-tree analysis for medium break loss of coolant accident.

accurately describe the severe accident situations because MAAP was mainly developed for analyses of severe accident situations of NPPs.

The data sets from simulation were used for the training of the SVRs for each severe accident path and for the validation of the proposed algorithm.

3.2. *Severe accident occurrence time predictions*

3.2.1. *General methodology*

Because accident progress is different for each severe accident path, it is obvious that the relation between the plant status variables and the occurrence times will be different from path to path. Furthermore, the hot leg LOCA cases and the cold leg LOCA cases should be considered separately because the trends of plant status variables in the early phase are different for these two cases. As a result, 16 SVRs should be trained to find the relations between the plant status variables and the occurrence times of one kind of event for each of the selected paths (as there are three kinds of event, 48 SVRs are required). However, for SB LOCAs Numbers 21–23, MB LOCA Number 04, and LB LOCA Number 04 sequences, CTMT failure times were not considered because two other events were considered to be more important events. By contrast, for SB LOCA Number 07, MB LOCA Number 02, and LB LOCA Number 02 sequences, only the CTMT failure time was considered because radioactive material will be released to the environment when CTMT fails, even when the RV does not fail. Therefore, 26 SVRs were actually needed to be trained (20 SVRs for maximum core temperature exceeding 1,200°C and RV failure, and 6 SVRs for CTMT failure). Based on the results of break location and break size estimation, it was determined which kind of trained SVR among the 26 SVRs should be applied for occurrence time prediction.

For the SB LOCA cases, 16 cold leg data sets and 16 hot leg data sets were used to train the corresponding SVRs. Seventeen cold leg data sets and 17 hot leg data sets were used for the MB LOCA cases; 10 cold leg data sets and 10 hot leg data sets were used for the LB LOCA cases. Similarly, 10 cold leg data sets and 10 hot leg data sets were applied as testing data for each case.

For each case, regression functions that define the relations between the occurrence time and certain plant status variables were obtained by training the SVR algorithms with the training data sets. After this, the parameters for each SVR were optimized using the grid-search method, and RBF was

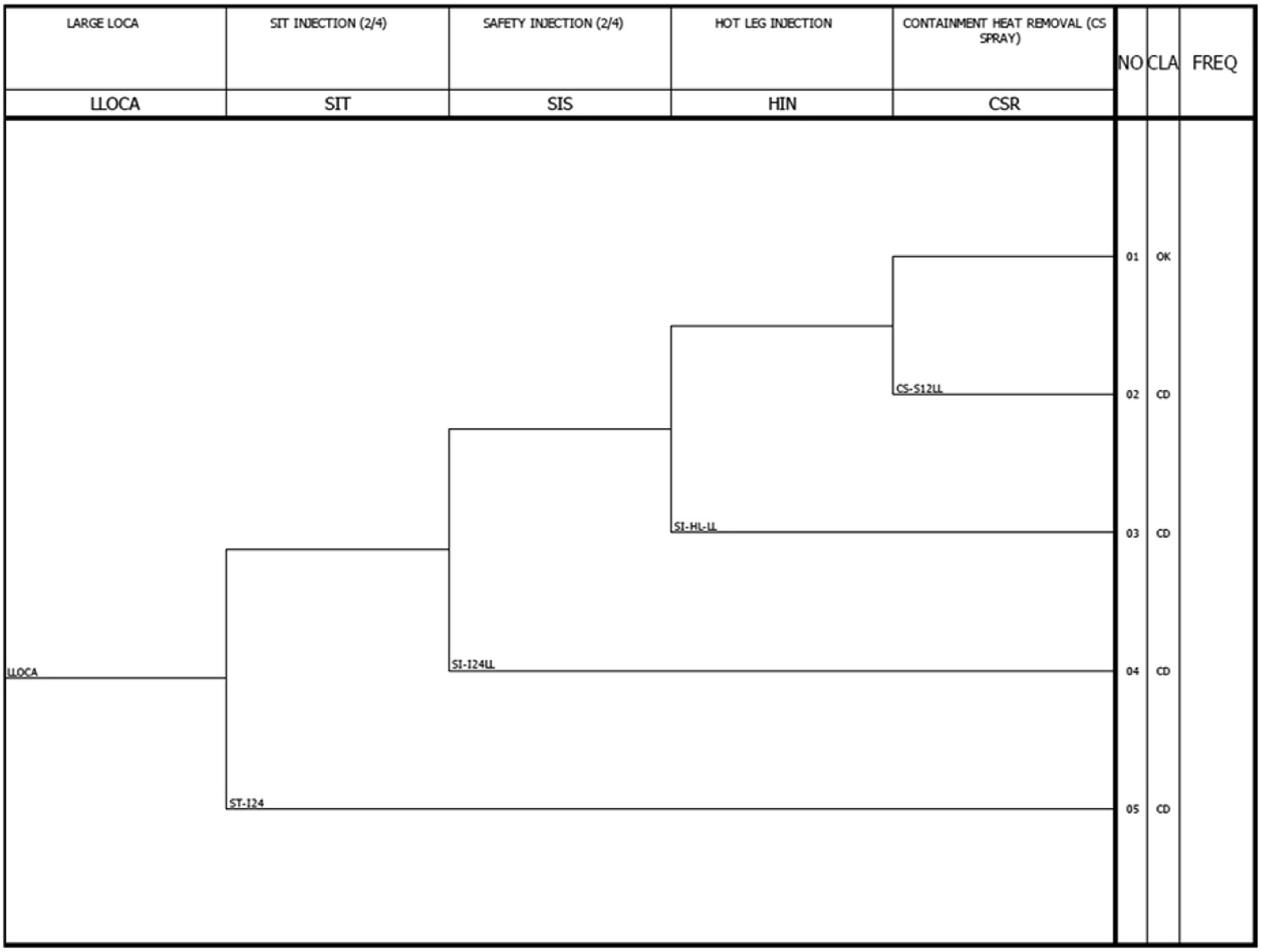

Fig. 6 – Event-tree analysis for large break loss of coolant accident.

used as the kernel function for all the SVRs. Table 4 presents the selected plant status variables for each severe accident-related event. Variable selection was conducted with a consideration of the physical relations.

First, the core temperature can rise to 1,200°C only when the amount of decay heat is larger than the amount of heat transfer from the primary system to other systems. Because the amount of decay heat can be considered a function of time, it is not related to the 13 variables. Instead, variables related to heat loss were selected. In the case of a LOCA, the heat of the primary side can be transferred into the unbroken

Table 3 – Considered sequences in severe accident occurrence time prediction.

Transient type	Considered sequences (numbering)
SB LOCA	Number 07 (#1)
	Number 21 (#2)
	Number 22 (#3)
	Number 23 (#4)
MB LOCA	Number 02 (#1)
	Number 04 (#2)
LB LOCA	Number 02 (#1)
	Number 04 (#2)

LB, large break; LOCA, loss of coolant accident; MB, medium break; SB, small break.

Table 4 – Selected variables for each severe accident-related event for training SVRs.

Event type	Selected variables
Time when maximum core temperature exceeds 1,200°C	Unbroken side S/G temperature
	CTMT pressure
	CTMT temperature
	Collapsed water level
RV failure time	Unbroken side S/G temperature
	CTMT pressure
	CTMT temperature
	Collapsed water level
CTMT failure time (time when CTMT pressure exceeds 4 atm)	PRZ pressure
	CTMT pressure
	CTMT temperature
	Collapsed water level

CTMT, containment; PRZ, pressurizer; RV, reactor vessel; SVR, support vector regression.

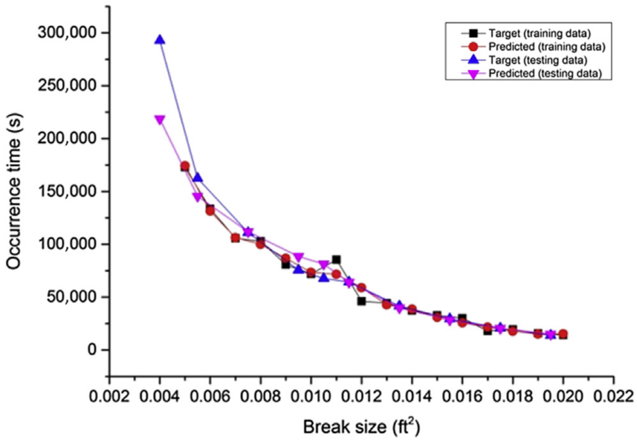

Fig. 7 – Prediction results of time when maximum core temperature exceeds 1,200°C (small break Number 2, cold leg).

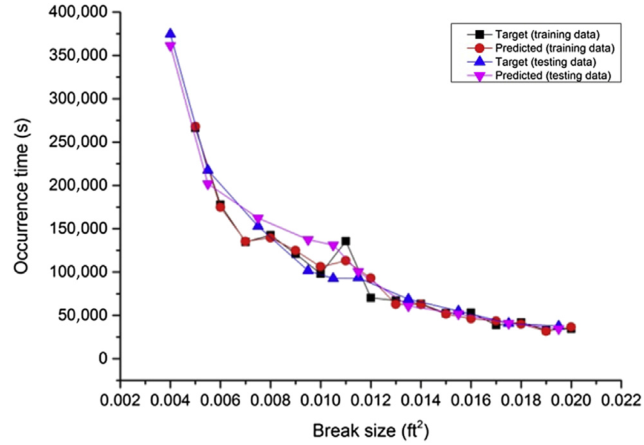

Fig. 9 – Prediction results of reactor vessel failure time (small break Number 2, cold leg).

secondary side or into the CTMT. Therefore, an unbroken S/G temperature was selected to consider the heat transfer to the secondary side; to consider the heat transfer to the CTMT, CTMT pressure, CTMT temperature, and collapsed water level were selected.

Similarly, RV failure can be regarded as an extension of the core temperature rise. Therefore, the same variables that were selected for the prediction of the time at which the maximum core temperature will exceed 1,200°C were selected.

For CTMT failure, it was assumed that the CTMT will fail if the CTMT pressure exceeds 4 bars. CTMT pressure rapidly increases at first when a LOCA happens due to leakage and vaporization of the primary side coolant; it then increases almost linearly during the decay heat removal processes. Because the rise of CTMT pressure is almost entirely caused by steam, the overall amount of water should be considered. In this regard, PRZ pressure was selected to consider the amount of water in the primary side. The CTMT pressure and CTMT temperature were selected to consider the amount of vaporized steam. Finally, the collapsed water level was selected to consider the amount of unvaporized leaked water.

3.2.2. *Results of severe accident occurrence time prediction*

In five cases (SB LOCA Numbers 21–23, MB LOCA Number 04, and LB LOCA Number 04 sequences), the time at which the maximum core temperature exceeds 1,200°C and the RV failure time were predicted using the trained SVRs. The results are shown in Figs. 7–10. The RMS errors are presented in Tables 5–7. Except for the SB LOCA Number 2 hot leg scenario, the RMS prediction errors for the time at which the maximum core temperature exceeds 1,200°C and for the RV failure time were < 10% for all cases.

In three cases (SB LOCA Number 07, MB LOCA Number 02, and LB LOCA Number 02 sequences), CTMT failure times were predicted. The results are shown in Fig. 11 and 12. The LB LOCA Number 1 case was not considered because the break size did not affect the CTMT failure time significantly. As in

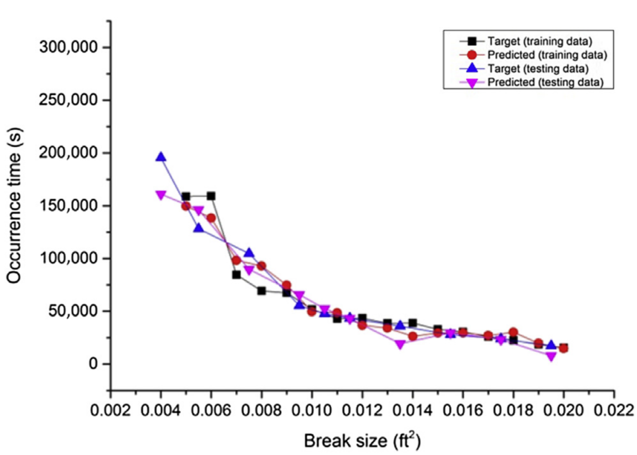

Fig. 8 – Prediction results of time when maximum core temperature exceeds 1,200°C (small break Number 2, hot leg).

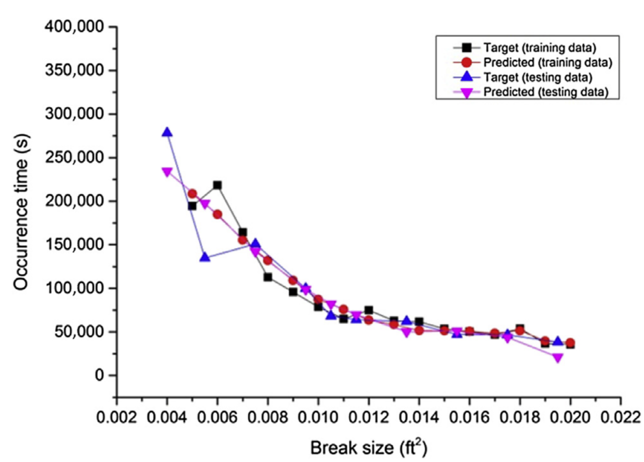

Fig. 10 – Prediction results of reactor vessel failure time (small break Number 2, hot leg).

Table 5 – RMS and maximum errors for time when maximum core temperature exceeds 1,200°C prediction.

Scenario	RMS error (cold leg)	RMS error (hot leg)	Maximum error (cold leg)	Maximum error (hot leg)
SB LOCA Number 1	—	—	—	—
SB LOCA Number 2	5.35	15.50	28.00	33.98
SB LOCA Number 3	4.40	5.30	14.30	18.14
SB LOCA Number 4	8.41	2.06	33.04	6.03
MB LOCA Number 1	—	—	—	—
MB LOCA Number 2	3.86	3.88	10.30	12.88
LB LOCA Number 1	—	—	—	—
LB LOCA Number 2	8.09	3.48	22.98	8.70

Data are presented as %.
LB, large break; LOCA, loss of coolant accident; MB, medium break; RMS, root mean square; SB, small break.

Table 6 – RMS and maximum errors for reactor vessel failure time prediction.

Scenario	RMS error (cold leg)	RMS error (hot leg)	Maximum error (cold leg)	Maximum error (hot leg)
SB LOCA Number 1	—	—	—	—
SB LOCA Number 2	2.59	12.52	35.07	46.46
SB LOCA Number 3	2.74	3.59	7.16	12.68
SB LOCA Number 4	9.22	3.36	6.55	10.17
MB LOCA Number 1	—	—	—	—
MB LOCA Number 2	1.72	1.51	11.85	6.69
LB LOCA Number 1	—	—	—	—
LB LOCA Number 2	1.65	1.29	4.28	3.22

Data are presented as %.
LB, large break; LOCA, loss of coolant accident; MB, medium break; RMS, root mean square; SB, small break.

the previous cases, RMS prediction errors for CTMT failure times were < 10% for all four scenarios.

From these results, it can be seen that the predictions of the time at which the maximum core temperature exceeds 1,200°C, the RV failure time, and the CTMT failure time were accurate for most selected scenarios.

4. Discussion

In this research, occurrence times of three kinds of major severe accident events, including the time at which the maximum core temperature exceeds 1,200°C, RV failure time, and CTMT failure time, were predicted using the SVR algorithm. For simplicity, ET analyses of SB LOCA, MB LOCA, and LB LOCA were referred to and severe accident paths with high probabilities were selected for case studies; conservative assumptions were made. In addition, for the preliminary step, SVCs and SVRs were applied to identify the break location and the break size of the various LOCA scenarios. Integrated values for all of the 13 kinds of plant status variables from reactor SCRAM to 60 seconds after SCRAM, or some of these variables were used for estimation and prediction. The RBF was used as the kernel function for all SVCs and SVRs; optimization of the SVCs and SVRs was conducted using the grid-search method. Algorithms for the break location and size

Table 7 – RMS and maximum errors for CTMT failure time prediction.

Scenario	RMS error (cold leg)	RMS error (hot leg)	Maximum error (cold leg)	Maximum error (hot leg)
SB LOCA Number 1	3.39	9.69	52.43	29.13
SB LOCA Number 2	—	—	—	—
SB LOCA Number 3	—	—	—	—
SB LOCA Number 4	—	—	—	—
MB LOCA Number 1	2.01	1.60	10.64	8.51
MB LOCA Number 2	—	—	—	—
LB LOCA Number 1	Not considered [a]	Not considered [a]	Not considered [a]	Not considered [a]
LB LOCA Number 2	—	—	—	—

Data are presented as %.
CTMT, containment; LB, large break; LOCA, loss of coolant accident; MB, medium break; RMS, root mean square; SB, small break.
[a] The LB LOCA Number 1 case was not considered because the break size does not significantly affect CTMT failure time.

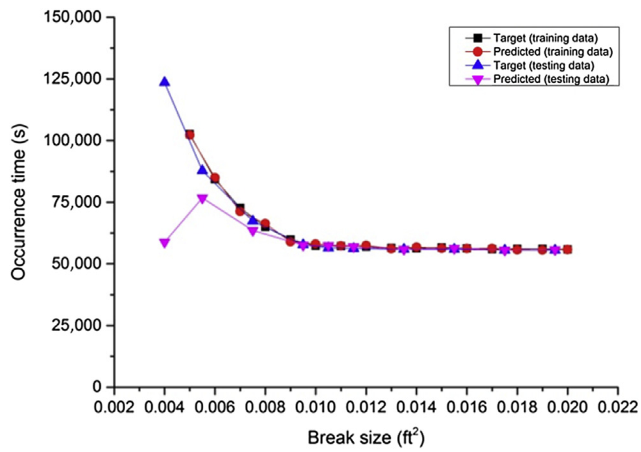

Fig. 11 – Prediction results of CTMT failure time (small break Number 1, cold leg).

estimation of LOCA using SVC and SVR, developed by Na et al. [8], were referred to in this research.

The algorithm for break location and size estimation of an LOCA was successfully applied and the identification results of the LOCA were found to be reasonable. Break locations of the training data sets and the testing data sets were successfully classified into categories of cold leg LOCA and hot leg LOCA using the SVC. In addition, using two SVCs, the training data sets and testing data sets were correctly classified into categories of SB LOCA, MB LOCA, and LB LOCA according to the break size. Detailed break size estimation was conducted using multiple SVRs; the RMS error of estimation was approximately 3–6%.

The times when maximum core temperature exceeds 1,200°C, RV failure time, and CTMT failure time were predicted with reasonable levels of error. Except for severe cases, the RMS errors of prediction were < 10% for all three kinds of events. The possibility of severe accident occurrence time prediction using SVC and SVR algorithms was verified in this research. Furthermore, it is expected that it will be possible to apply the proposed algorithm to real NPPs because the algorithm uses only the early phase data after the reactor SCRAM, which can be obtained accurately for accident simulations.

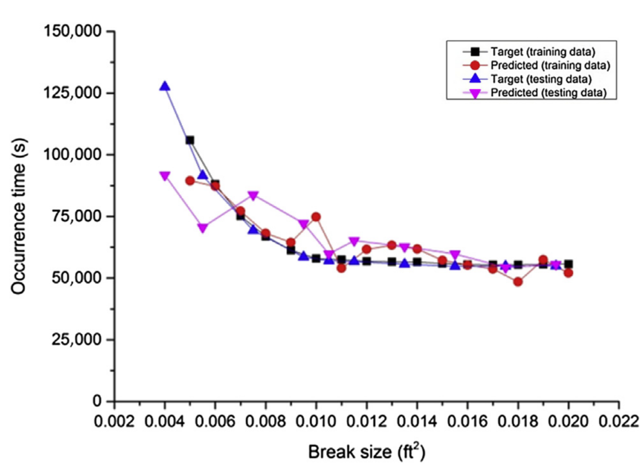

Fig. 12 – Prediction results of containment failure time (small break Number 1, hot leg).

Further work to lower the prediction error should be conducted. More delicate optimization of the SVC and SVR algorithms by adjusting various parameters should produce better results than those of the current research. In some studies, optimization problems have been solved by applying other algorithms, such as genetic algorithms to search for appropriate parameter values [13,14]. If this kind of methodology is applied for the selection of the appropriate parameter values, overall estimation quality is expected to be enhanced.

Moreover, to check the performance of the proposed algorithm more precisely, a validation method such as *k*-fold cross validation could be applied.

Finally, because the MAAP code was developed mainly to simulate severe accident scenarios, the use of the RELAP or MARS code for break location and size estimation, instead of the MAAP code, could lead to more accurate results, even though the performance of the MAAP code is almost identical to those other codes for short-time simulation. Therefore, it will be very meaningful to conduct research that compares results that can be obtained using these three, or even more, codes.

Conflicts of interest

The authors have no conflicts of interest to declare.

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REFERENCES

[1] Z. Yangping, Z. Bingquan, W. Dongxin, Application of genetic algorithms to fault diagnosis in nuclear power plants, Reliab. Eng.Syst. Safe. 67 (2000) 153–160.
[2] J.W. Hines, D.J. Wrest, R.E. Uhrig, Signal validation using an adaptive neural fuzzy inference system, Nucl. Technol. 199 (1997) 181–193.
[3] M.G. Na, A neuro-fuzzy inference system for sensor failure detection using wavelet denoising, PCA and SPRT, J. Korean Nucl. Soc. 33 (2001) 483–497.
[4] J. Garvey, D. Garvey, R. Seibert, J.W. Hines, Validation of on-line monitoring techniques to nuclear plant data, Nucl. Eng. Technol. 39 (2007) 149–158.
[5] E.B. Bartlett, R.E. Uhrig, Nuclear power plant diagnostics using an artificial neural network, Nucl. Technol. 97 (1992) 272–281.
[6] M. Marseguerra, E. Zio, Fault diagnosis via neural networks: the Boltzmann machine, Nucl. Sci. Eng. 117 (1994) 194–200.
[7] Y.G. No, J.H. Kim, M.G. Na, D.H. Lim, K.I. Ahn, Monitoring severe accidents using AI techniques, Nucl. Eng. Technol. 44 (2012) 393–404.

[8] M.G. Na, W.S. Park, D.H. Lim, Detection and diagnostics of loss of coolant accident using support vector machines, IEEE Trans. Nucl. Sci. 55 (2008) 628–636.
[9] M Claudia, S. Rocco, E. Zio, A support vector machine integrated system for the classification of operation anomalies in nuclear components and systems, Reliab. Eng. Sys. Safe. 92 (2007) 593–600.
[10] I. Lindholm, E. Pekkarinen, H. Sjovall, Evaluation of reflooding effects on an overheated boiling water reactor core in a small steam-line break accident using MAAP, MELCOR, and SCDAP/RELAP5 computer codes, Nucl. Technol. 112 (1995) 42–57.
[11] C. Allison, Comparison between MAAP, MELCOR, and SCDAP/RELAP5, Proceedings of the Workshop on Severe Accident Research in Japan (SARJ-97), JAERI (Japan atomic energy research institute), Yokohama, Japan, 1998 Oct 6–8, pp. 396–401.
[12] R. Gutierrez-Osuna, CSCE666: Pattern Analysis, Radial basis functions lecture notes [PowerPoint slides], Dept. of Computer Science & Engineering, Texas A&M University, Texas, U.S., 2011. Retrieved from http://research.cs.tamu.edu/prism/lectures/pr/pr_l19.pdf.
[13] N. Xin, X. Gu, H. Wu, Y. Hu, Z. Yang, Application of genetic algorithm-support vector regression (GA-SVR) for quantitative analysis of herbal medicines, J.Chemometr. 26 (2012) 353–360.
[14] K. Chen, C. Wang, Support vector regression with genetic algorithms in forecasting tourism demand, Tourism Manage. 28 (2007) 215–226.