IDENTIFICATION OF NPP TRANSIENTS USING ARTIFICIAL INTELLIGENCE

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ABSTRACT

If the accidents happen in nuclear power plants (NPPs), the NPP operators identify the transients through observing the behaviors of the major parameters. However, the integrity of the instrumentation signals is not ensured under the accident circumstances and the major parameters essential in identifying the transients can rapidly change although the instruments generate accurate signals. Thus, to successfully control the accidents by taking necessary measures relatively faster, it is very important to provide the operators with the information that can identify the transients and accidents accurately. In this study, the transients of severe accidents in NPPs are identified and classified using artificial intelligence methodologies. Several transients are identified using support vector classification (SVC) and probabilistic neural network (PNN) as artificial intelligence methodologies. The used data for the transients are the simulation data using the modular accident analysis program (MAAP) code for the optimized power reactors (OPR1000s). The time-integrated values of chosen simulated sensor signals are used as the input variables for identifying the transients. As a result of this study, the proposed models identified the transients quite precisely. Therefore, the quite accurate identification of the transients indicates the excellence of these artificial intelligence methods and they will produce useful supporting information for the operators even under extreme transient circumstances in NPPs.

Key Words: Transient Identification, Artificial Intelligence, Support Vector Classification, Probabilistic Neural Network

1 INTRODUCTION

In the event that the accidents occur in nuclear power plants (NPPs), the plant operators are aware of the transients by watching the behaviors of the major parameters of the accidents. This is to prevent the situation that eventually goes on a severe accident or to mitigate the undesired condition after the occurrence of an accident through a timely and right decision when an abnormal circumstance such as a design basis accident (DBA) or an early severe accident happens. However, a wrong decision can be made due to lack of time needed for classifying the relevant information and utilizing the expertise in an accident circumstance. In addition, the integrity of the instrumentation signals is not ensured in such circumstances. The major parameters critical in identifying the transients may rapidly change although the instruments in NPPs generate accurate signals. Therefore, to successfully control the accidents by comparatively fast implementing proper measures, it is very essential to give operators the information that can be used to identify the transients precisely. In other words, the data which quite accurately identify an accident and are provided for the operators will be helpful and important supporting information under an extreme circumstance in NPPs.

In this study, the major transients in NPPs are identified and classified by artificial intelligence methodologies using machine learning. The transients are identified by utilizing support vector classification (SVC) [1]-[2] and probabilistic neural network (PNN) [3] to apply this classification problem. Support vector machines (SVMs) are normally used for a classification and a regression analysis. In this study, since the SVM model has been used to be applied to the classification problem, the accidents are classified using this method, which is termed SVC in this case. Similarly, PNN is a general method using the supervised learning to be applied to the classification problems. The PNN model that can relatively easily and instantly learn is applied to identifying the transients by using the time-integrated values of the selected signals in specified times immediately after the reactor scram, which is the same as the SVC model.

In the past studies [4]-[6], there were plenty of efforts to identify the transients using several artificial intelligence methods. These studies identified the main initiating events such as loss of coolant accidents (LOCAs) where the break positions are hot-leg, cold-leg, and steam generator tube (SGT), total loss of feedwater (TLOFW), and station blackout (SBO) by utilizing some artificial intelligence methods. In this study, in addition to aforementioned five accidents, additional accidents such as main steam line break (MSLB) and feedwater line break (FWLB) are identified and classified and also, much more simulation data have been used. When an accident happens beginning from the steady-state operation in NPPs, the instrumentation signals show a time-dependent pattern that is distinct with regard to the type of an accident. Thus, the transients are able to be classified by properly choosing the plant process parameters [7]. Therefore, the input variables are the time-integrated values of selected simulated sensor signals which are considered highly correlative. The data for the transients are the simulation data obtained from modular accident analysis program (MAAP) [8] for optimized power reactor 1000 (OPR 1000).

2 ARTIFICIAL INTELLIGENCE TO IDENTIFY THE TRANSIENTS

In this study, the SVM and PNN as the artificial intelligence methods are applied to the classification problem. The accidents are distinguished and identified in a short time after the reactor scram using the data obtained from simulating the major accidents that may happen in NPPs. If the operators in NPPs comply with suitable management guidance through the accurate accident identification data, an initiating event will not go on a severe accident [5].

2.1 Support vector machines

The SVMs are learning systems that make use of a hypothesis space of linear functions in a high-dimensional feature space and are trained with optimization theory with a learning algorithm. The ANNs and SVMs are dissimilar in terms of risk minimization. The SVMs utilize a structural risk minimization (SRM) principle to reduce the upper bound on the expected risk as far as possible while the ANNs use a traditional empirical risk minimization (ERM) principle to find the smallest approximation errors on the learning data [9]. The SRM principle [2] is shown in Fig. 1. The bound on the risk is explained as the aggregate of the empirical risk and the confidence interval. The ERM method minimizes only the empirical risk at all costs, while the SRM method searches for the function f^* that accomplishes the smallest bound on the smallest guaranteed risk $R(f^*)$, which is for the ascribed amount of data. The empirical risk decreases as the capacity expressed as h which is the element of the structure increases, whereas the confidence interval gets bigger. The smallest bound of the risk is gained on the proper element of the structure. Consequently, the difference in risk minimization becomes a preferable generalization performance, which is the objective in statistical learning, for the SVMs than ANNs [2].

A common multi-class classification problem can be extended to consideration on the binary (two-class) classification problem. In this problem, the main purpose is to divide into two classes by a function which is called a classifier. Although there are a lot of classifiers that can separate the data, only the one classifier can maximize the distance between the classifier and the nearest data point of each class which is termed margin. Additionally, this classifier is called optimal separating hyperplane. Therefore, the binary classification methods can make a decision rule so as to sort out the data vectors into one of two classes based on a learning data set of which classification is known as a *priori*. In other words, general binary classification problems consist of N learning data indicated as $T = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N}$ in which $\mathbf{x}_i \in R^m$ means the sample data vector and y_i expresses a class $y_i \in \{+1,-1\}$, from which a link between input and output is learned. Every learning data vector $\mathbf{x}_i$ belongs to a class by $y_i \in \{+1,-1\}$.

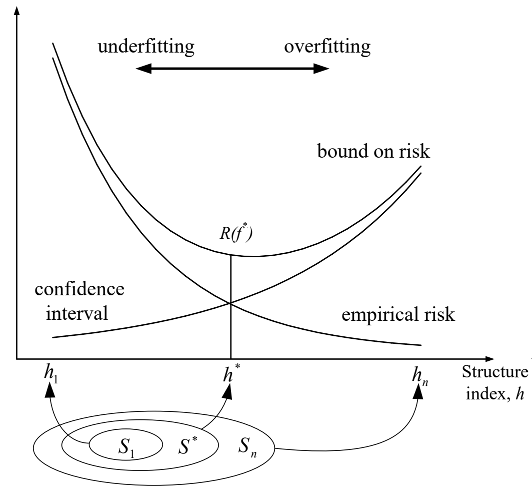

Fig. 1. An illustration of the principle of SRM.

In the event that binary class is able to be linearly separated into two sides, data classification is achieved by finding a hyperplane which divides the learning data set *T* so that the entire learning data points of the same class are on the same side of the hyperplane while maximizing the distance between the hyperplane and the data point nearest to the hyperplane [10], which is explained in Fig. 2 graphically. The optimal hyperplane bisecting both classes is able to be defined as follows:

$$\mathbf{w} \cdot \mathbf{x} + b = 0 \tag{1}$$

where the vector $\mathbf{w}$ and the bias b establish the decision boundary.

The margin which is the width between the two parallel dotted lines of $\mathbf{w} \cdot \mathbf{x} + b = 1$ and $\mathbf{w} \cdot \mathbf{x} + b = -1$ is $\frac{2}{|\mathbf{w}|}$. Thus, The magnitude of **w** has to be minimized in order to maximize $\frac{2}{|\mathbf{w}|}$. In other words, the following function has to be minimized by finding the extremum of the vector **w** to acquire the hyperplane optimally separating the data point.

$$\Phi(\mathbf{w}) = \frac{1}{2}|\mathbf{w}|^2 \tag{2}$$

where

$$\mathbf{w} = \begin{bmatrix} w_1 & w_2 & \cdots & w_m \end{bmatrix}^T$$

However, the assumption that all the learning data are precisely classified is regarded impossible. Thus, some misclassifications are allowed by using the slack variables. That is, in the case that the hyperplane can accurately divide the data points, adding a non-negative slack variable ξ_i (refer to Fig. 2) to Eq. (2) was proposed to handle the problems related to misclassification [9] so as to take the noise on the data into account. The slack variable ξ_i is the adequate misclassification error. Therefore, the generalized optimal hyperplane is acquired by **w** and *b*, which minimize the function as follows:

$$\Phi(\mathbf{w},\boldsymbol{\xi}) = \frac{1}{2}|\mathbf{w}|^2 + \lambda\sum_{i=1}^{N}\xi_i \tag{3}$$

subject to the constraints

$$\begin{cases} y_i\left(\mathbf{w}\cdot\mathbf{x}_i + b\right) \geq 1-\xi_i, \quad i=1,2,\cdots,N \\ \xi_i \geq 0, \quad i=1,2,\cdots,N \end{cases} \tag{4}$$

where

$$\boldsymbol{\xi} = \begin{bmatrix}\xi_1 & \xi_2 & \cdots & \xi_N\end{bmatrix}^T.$$

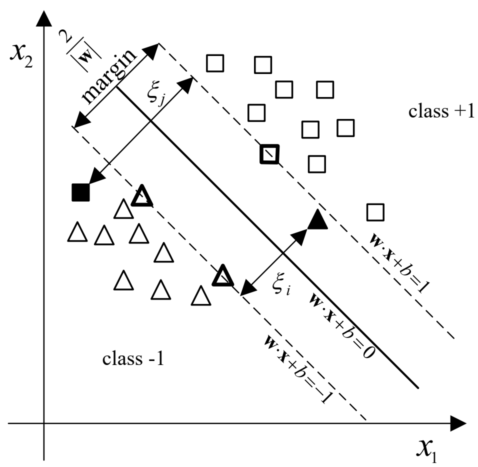

Fig. 2. Binary classification and misclassification due to the noise on measured data by a SVC model.

In the event that the linear decision boundary in input spaces is not able to divide both classes adequately, it is feasible to establish the hyperplane making a separation linearly in higher dimensional feature space. The SVC model performs the work acquiring the optimal separating hyperplane in multi-dimensional input space by transforming the learning data into a higher dimensional feature space. The hyperplane assorting the two-class data is formed in higher dimensional feature space and makes maximum the separation margin between the hyperplane and the data point placed nearest to the hyperplane. Eventually, this hyperplane as a classifier is utilized to distinguish the data of unknown classification [11]. That is to say, existing input space is converted into high-dimensional feature space by a nonlinear map $\boldsymbol{\varphi}(\mathbf{x})$. The function $\phi_i(\mathbf{x})$ is termed the feature that nonlinearly transformed from the input space $\mathbf{x}$ and $\boldsymbol{\varphi} = \begin{bmatrix}\phi_1 & \phi_2 & \cdots & \phi_N\end{bmatrix}^T$. The hyperplane is determined in high-dimensional feature space and a linear classification problem in the high-dimensional feature space substitutes for the nonlinear classification (refer to Fig. 3).

The variable termed a regularization parameter λ manages the trade-off between the complexity of the SVC model and the number of non-separable points. The Lagrange multiplier method to find the extremum of a function with constraints and standard quadratic optimization method can be used to compute $\mathbf{w}$ and b. The classifying function is expressed as below:

$$f(x) = \operatorname{sgn}\left(\sum_{i\in SVs}\alpha_i y_i K(\mathbf{x}_i,\mathbf{x}) + b\right) \tag{5}$$

where b^* is a bias term expressed as $b^* = -\frac{1}{2}\sum_{i=1}^{N}\alpha_i y_i\left[K(\mathbf{x}_i,\mathbf{x}_r)+K(\mathbf{x}_i,\mathbf{x}_s)\right]$ and $K(\mathbf{x}_i,\mathbf{x}) = \boldsymbol{\varphi}^T(\mathbf{x}_i)\boldsymbol{\varphi}(\mathbf{x})$ is termed the kernel function. In this study, a radial basis function was used as the kernel function, which is $K(\mathbf{x}_i,\mathbf{x}) = \exp\left(-\frac{(\mathbf{x}-\mathbf{x}_i)^T(\mathbf{x}-\mathbf{x}_i)}{2\sigma^2}\right)$. The best performance in simulation applications of this study appears due to using the radial basis function.

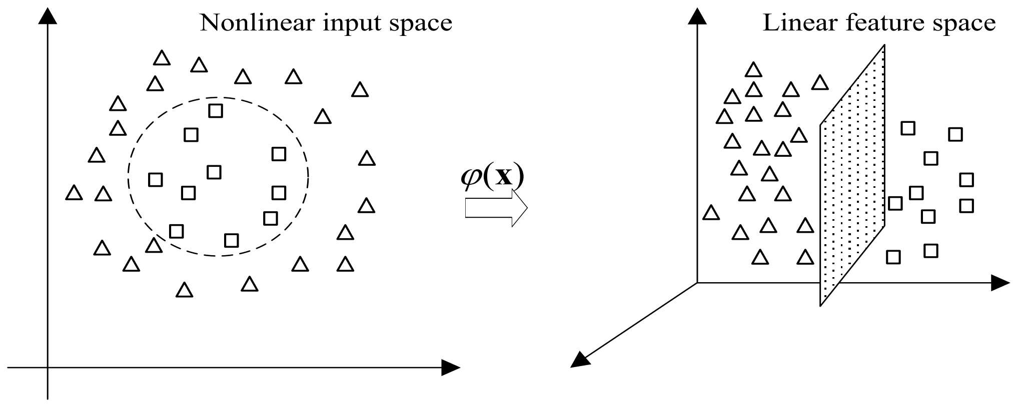

Fig. 3. Mapping to linear feature space from nonlinear input space.

2.2 Probabilistic neural network

As another artificial intelligence method in this study, the PNN [3] is a method that is generally applied to pattern classification problems and it fulfills a neural network of a Bayesian classifier. In this work, the PNN is utilized as a nonlinear pattern classifier that distinguishes the main initiating events such as LOCAs of which the break locations are hot-leg, cold-leg, and steam generator tube, TLOFW, SBO, MSLB, and FWLB by using the brief time-integrated values of some of the specified sensor signals shortly after the reactor scram, which is the same as the SVC model.

The PNN is featured by the main advantage that its learning is prompt and simple. The operational principle of the PNN is to define a probability density function (PDF) for every data class on the basis of the learning data and a smoothing parameter σ. The PDF clarifies the boundaries for every data class while the parameter σ makes a decision on the quantity of interpolation that take places between neighboring kernels. The PDF is utilized in estimation of the probability that the new pattern affiliated to every data class so as to categorize new patterns [12].

The classification of new patterns is carried out by disseminating the pattern vector via the PNN. The PNN consist of a four layers such as input units, pattern units, summation units, and output unit as shown in Fig. 4. The input units transfer the identical input values to all of the pattern units. The pattern units calculate distances from the input vector to the learning input vectors and generate a vector of which components show how near the input is to a learning input. The summation units add these works for all classes of inputs to make an output vector of probabilities. Lastly, a competitive transfer function on the output from the summation units selects the biggest value of these probabilities. A PNN is trained by first allocating every learning pattern to a pattern unit according to each corresponding class and then establishing the linking weight vectors which are the same as this learning pattern. In this paper, since the learning of the PNN is quite prompt and simple as stated above, the computational procedure for the learning of the PNN is not contained.

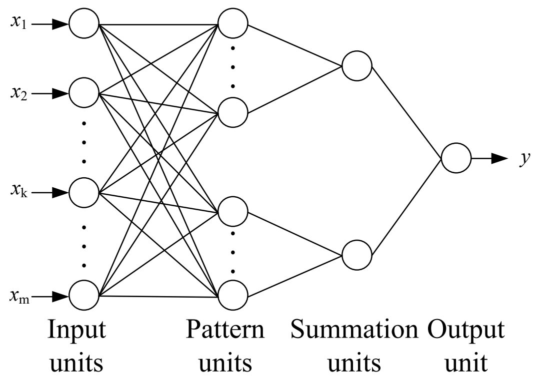

Fig. 4. Organization for pattern classification into categories of PNN.

3 PROPOSED METHODS APPLIED TO TRANSIENT IDENTIFICATION

In this paper, the SVC and PNN models as the non-linear classifiers are utilized to recognize the major transients in NPPs in a very brief time interval after the reactor scram. The simulated accidents are three LOCAs (hot-leg, cold-leg, and SGT), TLOFW, SBO, MSLB, and FWLB. All utilized simulated signals used in this study are core exit temperature, containment pressure and temperature, pressurizer pressure and water level, sump water level, reactor core water level, broken side S/G pressure and temperature, broken side S/G water level, unbroken side S/G pressure and temperature, and unbroken side S/G water level.

These simulated sensor signals are utilized in order to apply to the proposed SVC and PNN methods. The reason of using the MAAP code is because the data containing real accident circumstances rarely exists. A total of 620 simulation data comprised of 600 LOCAs (200 in each break location), 3 TLOFWs, 3 SBOs, 7 MSLBs, and 7 FWLBs are used in this work. All the accident simulation data are separated into the learning data and the validation data. There are a total number of 584 learning data which consist of each 190 LOCA at three break positions, 2 TLOFWs, 2 SBOs, 5 MSLBs, and 5 FWLBs. The validation data are comprised of the rest of the whole simulation data. The learning data have a role to train the SVC and PNN models, and the validation data are used to independently check whether the proposed models operate well [5]. Among the simulation data, each data differ from the rest of the data with regard to the break position and size in case of the LOCA, MSLB, and FWLB simulation data. In case of the TLOFW and SBO, the data differ from the others in respect to the causes of the accidents such as creep, an operator, or a sudden occurrence.

In this paper, there are three SVC models utilized to distinguish the seven types of accidents. The SVC models as the binary classifiers distinguish the data by expressing classes such as '+1' and '-1'. That is to say, The SVC models were trained in order to classify LOCAs including SGTR where break locations are hot-leg and cold-leg, TLOFW, SBO, MSLB, and FWLB such as (1, 1, 1), (1, 1, -1), (1, -1, 1), (-1, 1, 1), (1, -1, -1), (-1, 1, -1), (-1, -1, 1), respectively. Additionally, in the event that the simulation data do not belong to any type of an accident classification, the SVC models are configured to regard this case as a non-classification.

The simulated sensor signals as the inputs to the SVC and PNN models are the time-integrated values obtained by integrating the simulated measurement signals in a brief time interval after the reactor scram as below:

$$x_j = \int_{t_s}^{t_s+\Delta t} g_j(t)dt, \quad j = 1, 2, \cdots, 13 \tag{6}$$

where $g_j(t)$ is a specified signal, Δt is integration time span, and t_s is scram time. The integration time span of Eq. (6) applied to the SVC and PNN models is up to 20 seconds right after the reactor scram.

In this work, the accidents were identified according to the three types of assumptions that measurement errors exist or not (0% error), or the safety systems operate. Table I shows classification results under the assumption without a measurement error. In the case of using the SVC model, the accidents are accurately identified without a misclassification and any don't know classification. On the contrary, using the PNN model, there is 1 misclassification in every integration time interval.

Table I. Result of the classified transients using the SVC and PNN models without measurement error

Performance result	Integrating time (sec)	No. of Misclassification	No. of Don't know classification
SVC	3	0	0
	5	0	0
	10	0	0
	20	0	0
PNN	3	1	-
	5	1	-
	10	1	-
	20	1	-

Assuming measurement errors, the six types of errors such as -3%, 3%, -5%, 5%, and random errors which are below 3% and 5% are used in this study. Each minus and plus error option means under-measurement and over-measurement for the simulated signals. The random errors are assumed that the range of a measurement error value is determined from -3% to 3% or from -5% to 5%. These error types are assumed to determine the impact of the measurement errors on the SVC and PNN models. Table II and III indicate the results of accident classification results using these proposed models, respectively.

Table II. Classification results using the SVC model with measurement errors

SVC performance result	Integrating time (sec)	-3%	3%	-5%	5%	Random (below 3%)	Random (below 5%)
No. of Misclassification	3	0	1	1	2	1	1
	5	1	1	1	2	0	1
	10	2	4	4	7	0	0
	20	3	10	7	18	0	0
No. of Don't know classification	3	0	0	0	0	0	0
	5	0	0	0	0	0	0
	10	0	0	0	0	0	0
	20	0	0	0	0	0	0

Table III. Classification results using the PNN model with measurement errors

PNN performance result	Integrating time (sec)	-3%	3%	-5%	5%	Random (below 3%)	Random (below 5%)
No. of Misclassification	3	2	0	8	0	1	1
	5	1	1	1	0	1	1
	10	2	2	7	5	1	1
	20	2	1	6	6	0	0
No. of Don't know classification	3	0	0	0	0	0	0
	5	0	0	0	0	0	0
	10	0	0	0	0	0	0
	20	0	0	0	0	0	0

Table IV. Classification results using each model with safety system actuation

performance result	Integrating time (sec)	No. of Misclassification	No. of Don't know classification
SVC	3	1	0
	5	0	0
	10	0	0
	20	0	0
PNN	3	1	-
	5	1	-
	10	1	-
	20	1	-

The purpose of the consideration with the safety system actuation is to check whether there is an effect by the safety system actuation on the accident classification after the reactor scram. The classification results in case of safety system actuation are drawn on Table IV. The safety system actuation does not almost affect the classification results. This is because the proposed models use only initial information before the safety systems operate.

4 CONCLUSIONS

In this study, the transients are identified under the three types of assumptions. It is verified that the performances of the PNN method are better than the SVC method when several specific measurement errors are assumed. However, the SVC has a less misclassification number than the PNN in case that the measurement error is 0% or each random error is considered. In the event that the safety systems are actuated, the accident identification results are checked in integration time span up to 20 seconds with consideration for an effect of safety system actuation. In this case, the SVC model shows more correct classification results than the PNN model. The PNN is regarded as a slight better model than the SVC in this work.

Although each proposed model shows some misclassification results under the assumptions that several measurement errors exist or the safety systems operate, the accurate accident identification by the proposed models could be carried out since it is regarded that the number of misclassification is small particularly up to 10 seconds. All misclassified accidents are LOCAs where break positions are cold-leg and hot-leg. That is to say, the identified event is hot-leg LOCA even though the real initial event is cold-leg LOCA, and vice versa.

The SVC and PNN models can be one of the ways available in actual surveillance system in NPPs. It can be judged that the proposed SVC and PNN models have good performances on the accident recognition. In other words, supporting information for the operators can be generated by using the proposed models, which is available to early accident circumstance and can lead to effective action.

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