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Identification of NPP accidents using support vector classification

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1. Introduction

If accidents happen in nuclear power plants, plant operators will try to find out abnormal plant states by observing the temporal trends of some important parameters. However, operators are provided with a part of information and also, there is not enough time to analyze the information. So, it is very difficult for operators to predict the progression of the events by staring at temporal trends of some parameters on large display panels in the main control room. In addition, during a series of accident progression, the operators will face hundreds of instrument readings that show some typical patterns of that accident.

In case of the accidents that happens in a nuclear power plants (NPPs), it is very important to identify its accidents for the operator. Therefore, in order to effectively manage the accidents, the initial short time trends of major parameters have to be observed and NPP accidents have to accurately be identified to provide its information to operators and technicians.

In this regard, the objective of this study is to identify the accidents when the accidents happen in NPPs. In this study, we applied the support vector classification (SVC) model to classify the initiating events of critical accidents such as loss of coolant accidents (LOCA), total loss of feedwater (TLOFW), station blackout (SBO), and steam generator tube rupture (SGTR). Input variables were used as the initial integral value of the signal measured in the reactor coolant system (RCS), steam generator, and containment vessel after reactor trip. The proposed SVC model is verified by using the simulation data of the modular accident analysis program (MAAP4) code [1].

2. Methods and Results

2.1 Support Vector Machines (SVM)

Support vector machines (SVM) is based on statistical learning theory that uses the obtained probability distribution in the process that targets a learning diagnosis of category information and training data to estimate the decision making function. SVM is a kind of the empirical data modeling method that is divided into an empirical risk minimization (ERM) method and a structural risk minimization (SRM) method. ERM minimizes learning error by using the learning diagnosis. SRM selects the decision making function that minimizes the empirical risk for the subgroup after subdividing a whole group into subgroups. SVM can be applied to classification and regression problems [2].

2.2 Support Vector Classification (SVC)

A support vector classification (SVC) model is used as a classifier to classify the data of a non-linear form. It makes the decision principle to classify a data vector into a binary form such as $(\mathbf{x},y),\ldots,(\mathbf{x},y),\ \mathbf{x}\in R,\ y\in\{-1,+1\}$. Optimal separating hyperplane maximizes the distance between the boundary surface and the closest data without an error. Fig. 1 shows the optimal separating hyperplane.

Fig. 2 shows an example of a binary classification by SVC model. A variety of decision boundary exists if there is a dataset as shown in the figure. Fig. 2 shows the most stable and balanced decision boundary. There is a certain distance between the decision boundary and the actual dataset and this gap is called margin.

A boundary surface in the SVC is expressed as $\mathbf{w}\cdot\mathbf{x}+b=0$. The boundary surface to accurately classify the data is a boundary surface that minimizes Eq. (1) [3].

$$\begin{aligned}&\Phi(\mathbf{w})=\frac{1}{2}\mathbf{w}\,\mathbf{w}\\&y\left(\mathbf{w}\cdot\mathbf{x}+b\right)\geq 1\end{aligned}\qquad(1)$$

Lagrange function should be minimized with respect to $\mathbf{w}$ and b, and should be maximized with respect to $\alpha\geq 0$. Eq. (3) shows the minimum with respect to $\mathbf{w}$ and b. Eq. (4) shows the maximum with respect to $\alpha\geq 0$.

$$\Phi(\mathbf{w},b,\alpha)=\frac{1}{2}\mathbf{w}\,\mathbf{w}-\alpha\left[y\left(\mathbf{w}\cdot\mathbf{x}+b\right)-1\right]\qquad(2)$$

$$\begin{aligned}&\frac{\partial\Phi}{\partial\mathbf{w}}=\mathbf{0}\quad\Rightarrow\quad\mathbf{w}=\sum_{i=1}^{N}\alpha_i y_i\mathbf{x}_i\\&\frac{\partial\Phi}{\partial b}=0\quad\Rightarrow\quad\sum_{i=1}^{N}\alpha_i y_i=0\end{aligned}\qquad(3)$$

$$\begin{aligned}&\max_{\alpha}\left(-\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j\mathbf{x}_i\cdot\mathbf{x}_j+\sum_{i=1}^{N}\alpha_i\right)\\&\min_{\alpha}\left(\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j\mathbf{x}_i\cdot\mathbf{x}_j-\sum_{i=1}^{N}\alpha_i\right)\end{aligned}\qquad(4)$$

Subject to the constraints

$$\begin{cases} \alpha_i \geq 0, \ i = 1, \cdots, N \\ \sum_{i=1}^{N} \alpha_i y_i = 0 \end{cases}$$

Minimizing with respect to $\mathbf{w}$ and b, and maximizing with respect to $\alpha \geq 0$, an optimal separating hyperplane can be expressed as Eq. (5).

$$\begin{aligned} &\mathbf{w} \cdot \mathbf{x} + b = 0, \\ &\mathbf{w} = \sum_{i=1}^{N} \alpha_i y_i \mathbf{x}_i, \quad b = -\frac{1}{2} \mathbf{w}^T (\mathbf{x}_r + \mathbf{x}_s) \end{aligned} \tag{5}$$

$\mathbf{w}^T \mathbf{w}$ should be minimized to maximize the distance between the two parallel dotted lines shown in Fig. 2. The generalized optimal separating hyperplane is determined by minimizing the following functional as follows:

$$\Phi(\mathbf{w}, \boldsymbol{\xi}) = \frac{1}{2} \mathbf{w}^T \mathbf{w} + \lambda \sum_{i=1}^{N} \xi_i \tag{6}$$

subject to the constraints

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

where

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

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

The non-negative parameter ξ_i in the second term of Eq. (6) was used to deal with the problems associated with a misclassification due to the noise on the data. In Fig. 3, the filled triangle and rectangle indicate the data with measurement noise. The parameter ξ_i is a measure of the misclassification.

In the case where the linear boundary in the input spaces cannot separate the two classes properly, it is possible to create a hyperplane that allows a linear separation in higher dimensional feature space. The SVC models carry out this task by implicitly mapping the training data into higher dimensional feature space. A hyperplane is then constructed in this feature space that bisects the two categories and maximizes the margin of separation between itself and those points lying closest to it. Specifically, the primal space is transformed into high dimensional feature space by a nonlinear map $\boldsymbol{\varphi}(\mathbf{x})$, as shown in Fig. 4. The function, $\phi_i(\mathbf{x})$, is called the feature that is nonlinearly mapped from the input space $\mathbf{x}$, and $\boldsymbol{\varphi} = \begin{bmatrix} \phi_1 & \phi_2 & \cdots & \phi_N \end{bmatrix}^T$. Fig. 4 shows the hyperplane established in high dimensional feature space and the nonlinear classification is replaced by a linear classification problem in high dimensional feature space. The parameter, λ, in Eq. (6) controls the trade-off between the complexity of the SVC model and the number of non-separable points, and is referred to as a regularization parameter. The Lagrange multiplier technique and standard quadratic optimization technique can be used to solve the vector $\mathbf{w}$ and the bias b, and the solution to the convex optimization problem can be expressed as follows:

$$f(x) = \operatorname{sgn}\left(\sum_{i \in SVs} \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + b \right) \tag{7}$$

where

$$b^* = -\frac{1}{2} \sum_{i=1}^{N} \alpha_i y_i \left[K(\mathbf{x}_i, \mathbf{x}_r) + K(\mathbf{x}_i, \mathbf{x}_s) \right]$$

$$K(\mathbf{x}_i, \mathbf{x}) = \boldsymbol{\varphi}^T(\mathbf{x}_i) \boldsymbol{\varphi}(\mathbf{x})$$

$$K(\mathbf{x}_i, \mathbf{x}) = \exp\left(-\frac{(\mathbf{x} - \mathbf{x}_i)^T (\mathbf{x} - \mathbf{x}_i)}{2\sigma^2} \right)$$

2.3 Application to NPP accident identification

SVC model is used as a classifier for classifying the data of the non-linear form. Input variable of the SVC model is composed of the signal measured at RCS, steam generator, and containment vessel. After reactor trip, major accidents is classified by using a very short time integral value of the measured signal.

The data was obtained using MAAP4 code. Input variables of SVC model are integral value of the simulated sensor signals 13. The data were divided into training data and test data. The training data consist of 190 hot-leg LOCAs, 190 cold-leg LOCAs, 190 SGTR, 2 SBO, and 2 TLOFW. The test data consist of 10 hot-leg LOCAs, 10 cold-leg LOCAs, 10 SGTR, 1 SBO, and 1 TLOFW.

In this paper, since the SVC model is a binary classification model, three SVC models were used to classify five types of events according to NPP accidents. The three SVC models were trained so that they categorize the hot-leg LOCA, the cold-leg LOCA, the SGTR, the SBO, and the TLOFW as (1, 1, 1), (1, 1, -1), (1, -1, 1), (1, -1, -1), and (-1, 1, 1) respectively as shown in Table I.

NPP accidents are identified by the trained SVC model as shown in Fig. 5. As a result, perfectly identifying accidents without errors is shown in table 2 irrespective of the integral time. That is, perfect identification was accomplished even though pretty short time measurement values were used.

Since the aforementioned results were generated from simulated data, it was assumed that there were no measurement errors in the input signals. Now, three types of measurement errors are assumed to determine the effect of the measurement error on the proposed algorithm: +5% error, -5% error, and random error. Table 3 shows each measurement error. The +5% error option assumes a 5% over-measurement for all input signals. The random error option assumes that the measurement errors of the input signals have a normal distribution with zero mean and 5% standard deviation. The SVC models classify NPP accidents with a few misclassification despite these measurement errors as shown in table 4.

Table 5 shows the results of the case when the safety system works. Each of the safety systems was operated with delay.

Table I: Event identification using the SVC model

SVC Mode	Hot-leg LOCA	Cold-leg LOCA	SGTR	SBO	TLOFW
SVC1	1	1	1	1	-1
SVC2	1	1	-1	-1	1
SVC3	1	-1	1	-1	1

Table II: Transient identification

Integrating Time	Misclassification No.	Don't Know Classification No.
3	0	0
5	0	0
10	0	0
20	0	0
30	0	0
40	0	0
50	0	0
60	0	0
90	0	0

Table III: Assuming measurement errors

Signals	Random errors (%)	5% Under error	5% Over error
Core exit temperature	-1.30	5	-5
Containment pressure	-5.00	5	-5
Containment temperature	0.38	5	-5
Pressurizer pressure	0.86	5	-5
Pressurizer water level	-3.44	5	-5
Sump water level	3.58	5	-5
Reactor core water level	3.57	5	-5
Broken side S/G pressure	-0.11	5	-5
Broken side S/G temperature	0.98	5	-5
Broken side S/G water level	0.52	5	-5
Unbroken side S/G pressure	-0.56	5	-5
Unbroken side S/G temperature	2.18	5	-5
Unbroken side S/G water level	-1.77	5	-5

Table IV: Transient identification under measurement errors

Integrating Time	Misclassification No.			Don't Know Classification No.		
	random	5%	-5%	random	5%	-5%
3	0	0	0	0	0	0
5	0	1	1	0	0	0
10	0	0	0	0	0	0
20	0	0	0	0	0	0
30	0	0	0	0	0	0
40	0	0	0	0	0	0
50	0	0	1	0	0	0
60	0	0	1	0	0	0
90	0	0	0	0	0	0

Table V: Transient identification (safety system actuation)

Integrating Time	Misclassification No.	Don't Know Classification No.
3	1	0
5	5	0
10	6	0
20	5	0
30	5	0
40	3	0
50	2	0
60	0	2
90	2	1

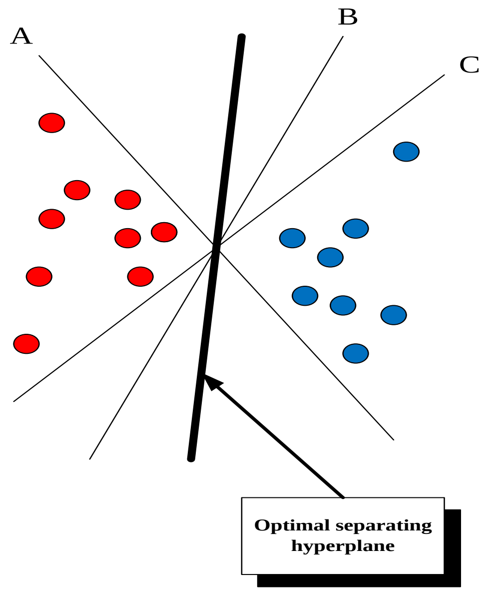

Fig. 1. Optimal separating hyperplane

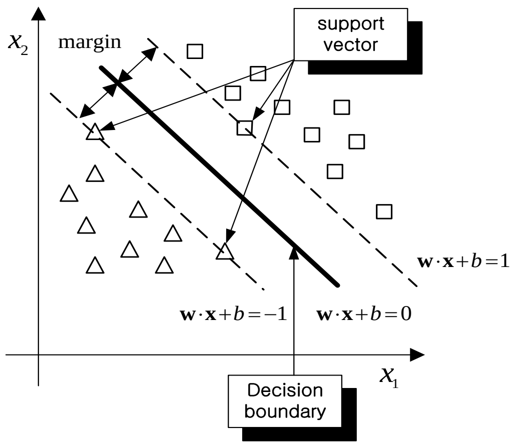

Fig. 2. An example of a binary classification using the SVC model

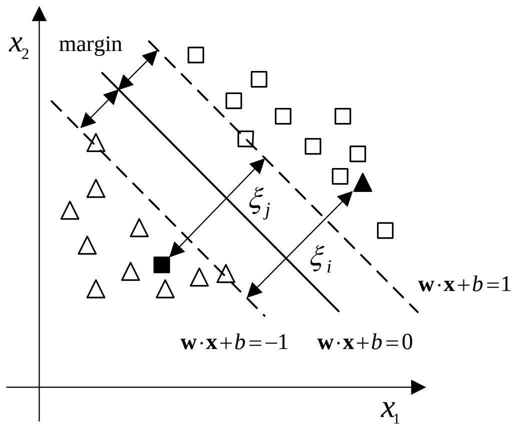

Fig. 3. An example of a misclassification due to noise in the measured data

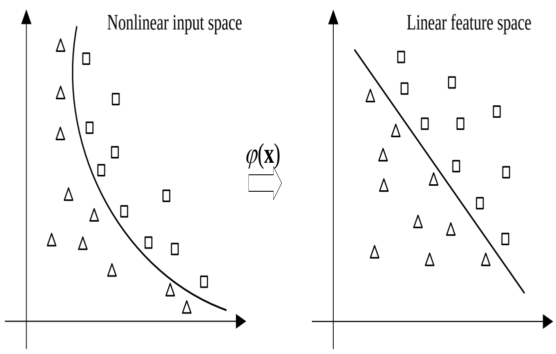

Fig. 4. An example of a misclassification due to noise in the measured data

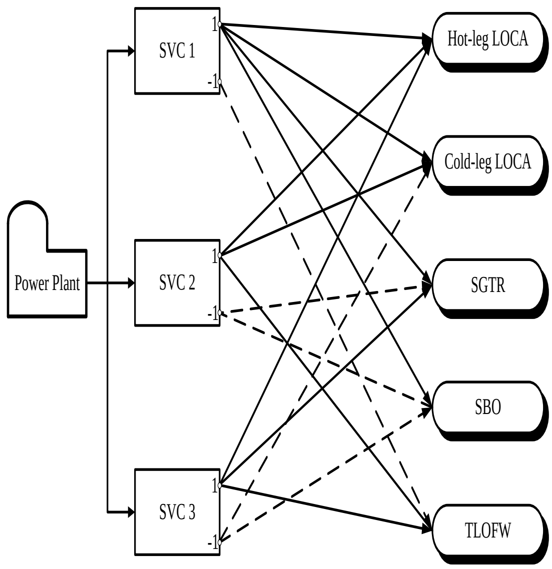

Fig. 5. Event identification using the SVC model

3. Conclusions

In this study, the proposed SVC model is verified by using the simulation data of the modular accident analysis program (MAAP4) code. We used an initial integral value of the simulated sensor signals to identify the NPP accidents. The training data was used to train the SVC model. And, the trained model was confirmed using the test data. As a result, it was known that it can accurately classify five events. Since the proposed algorithm uses initial data after reactor trip although the accident simulation data are deficient and the initial simulation data was known to be accurate, it can be effectively used in an actual NPPs as well.

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