New Methodology on Combining Source Term Categories for Multi-Unit Level 3 PRA

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1. Introduction

Researches on Multi-Unit Probabilistic Risk Assessment (MUPRA) are actively performed worldwide. And, current efforts are being made to expand the scope of PRA for estimating site risk beyond single-unit. MUPRA is an essential technology to achieve this. Most inter-unit dependencies are considered in level 1 PRA. Most pressurized water reactors have very few dependencies that need to be considered in Multi-Unit level 2 PRA because containments are independent in Korea. However, many source term category (STC) combinations can occur in Multi-Unit level 3 PRA. As the number of units increases in a multi-unit accident, the number of STC combinations increases exponentially. It is maybe possible to calculate all STC combinations up to two units, but it is very difficult to calculate all STC combinations when the number of units is more than three. Therefore, new method to estimate consequences of many STC combinations was developed in this study. To solve this problem, Support Vector Regression (SVM) was utilized among Artificial Intelligence (AI) techniques. Machine learning was performed by training set based on certain criteria, and the ability of estimating consequences was tested for the model completed.

2. Methods and Results

It was needed to create an SVR model for early fatality (EF) and latent cancer fatality (LCF), respectively. This was because the tendency to EF and LCF was different even if same amount of radioactive materials were released. It was quite difficult to create an SVR model for EF where threshold doses were considered. Therefore, only SVR model for LCF would be presented in this study. SVR model for EF would be developed in the future. Additionally, two OPR1000 nuclear power reactors were selected for multi-unit accidents.

2.1 Consequence Modeling

The MACCS 3.11 version developed by the Sandia National Laboratory (SNL) was utilized for calculations of consequence [1]. The population-weighted risk which was obtainable result by the MACCS was considered as the consequence.

It was needed to complete the MACCS models for the calculations of consequence. Most domestic input parameters investigated by our research team for the MUPRA were used except for decontamination part [2]. ATMOS, EARLY, CHRONC, and COMIDA2 modules were considered for long-term effects. Intermediate phase and emergency response actions, such as evacuation, sheltering, and relocation, were not considered. It is general to consider the emergency response actions for a realistic level 3 PRA. However, the emergency response actions are the most dominant input parameters affecting consequence. Therefore, the uncertainties of the SVR model could be very large when the emergency response actions were considered. It would be needed to develop the SVR model considering the emergency response actions although those were not considered in this study.

2.2 Support Vector Machine

Support vector machine (SVM) technique was originally developed for solving classification problems. However, SVM has been extended and widely utilized to solve nonlinear regression problem along with the development of Vapnik's ε-insensitive loss function. SVR adopts the structure risk minimization (SRM) principle unlike conventional neural network adopting empirical risk minimization (ERM). The SRM principle is be superior to the ERM principle because the SRM seeks to minimize an upper bound of the generalization error consisting of both training error and confidence level [3]. Brief description of SVR model is below.

Given a set of data (x_i, y_i) (i: i-th samples) where x_i is the input vector to SVR, y_i is the true output value, SVR uses Eq.(1) for an approximation function which is

$$y = f(x) = \sum_{i=1}^{N} w_i \phi_i(x) = \boldsymbol{w^T \phi(x)} + b \qquad (1)$$

where $\phi_i(x)$ is high-dimensional feature space which is nonlinearly mapped from the input space x. Weight matrix(w) and a bias(b) are estimated by minimizing Eq. (2) which is regularized risk function.

$$\begin{aligned} R_{min} &= min\left(\frac{1}{2}\|W\|^2 + \frac{C}{N}\sum_{i=1}^{N} L_\varepsilon\big(Y_i, f(X_i)\big)\right) \\ L_\varepsilon&\big(Y_i, f(X_i)\big) \\ &= \begin{Bmatrix} 0 & |Y_i - f(X_i)| \le \varepsilon \\ |Y_i - f(X_i)| - \varepsilon & others \end{Bmatrix} \end{aligned} \qquad (2)$$

Minimizing $\|W\|^2$ which is regularized term makes a regression function as flat as possible (function capacity). Second term is empirical error estimated by the ε-insensitive loss function shown in Fig.1. This imposes zero loss for predicted values within the ε-tube and some penalties for predicted values outside the tube. Those penalties are decided by the value C. Values of ε and C

are user-specific input parameters. Values of W and b can be obtained by introducing the primal objective function Eq.(3) including slack variables ξ_i and ξ_i^* (Fig.2).

$$R_{min} = min\left(\frac{1}{2}\|W\|^2 + \frac{C}{N}\sum_{i=1}^{N}(\xi_i + \xi_i^*)\right)$$
$$\text{Subject to: } \begin{Bmatrix} Y_i - W\cdot\phi(x_i) - b \le \varepsilon + \xi_i \\ W\cdot\phi(x_i) + b - Y_i \le \varepsilon + \xi_i^* \\ \xi_i \ge 0, \xi_i^* \ge 0 \end{Bmatrix} \quad (3)$$

And, this minimization problem can be solved by dual form and kernel function. After some mathematical works, Eq.(1) would be Eq.(4) which is explicit form.

$$y = f(x) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)K(X_i, X) + b \quad (4)$$

Values of α_i and α_i^* are Lagrange multipliers and $K(X_i, X)$ is kernel function.

There are some typical kernel functions such as linear, polynomial, sigmoidal, and radial basis function (RBF). It is possible to solve nonlinear problems by using kernel function. RBF (Eq.(5)) was selected for kernel function in this study.

$$K(X_i, X_j) = \exp\left(-\frac{\|X_i - X_j\|^2}{\sigma^2}\right) \quad (5)$$

Value of σ^2 is the width parameter of RBF.

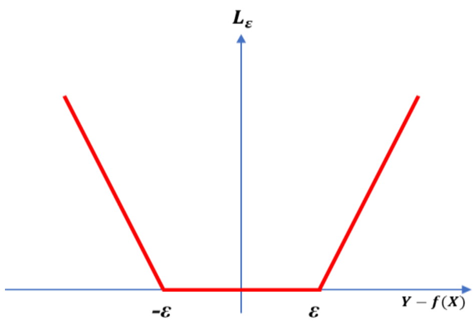

Fig.1. ε-insensitive loss function

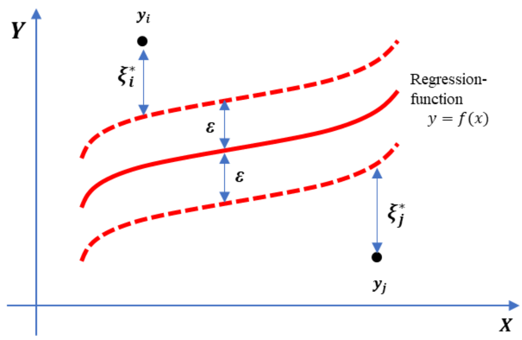

Fig.2. ε-tube and slack variables

2.3 Inputs and Outputs

It is important to select input parameters (X_i) that reflects the characteristics of output to train SVR model well. For this, temporal and radioactive characteristics were considered [4]. Firstly, release delay times (PDELAY in MACCS) from accident initiation were considered for temporal characteristic of each STC. PDELAYs of each STC and the difference between the two were selected for input parameters (X_1, X_2, X_3). These were considered to reflect the variability of weather conditions applied at the releases. Secondly, sum of release fractions (RELFRC in MACCS) for each radioactive material class (Xe, Cs, Ba, I, Te, Ru, Mo, Ce, La) were selected for input parameters (X_4~X_{12}). These were considered to reflect some linearity between the amount of radioactive material and consequence. All input parameters were normalized as Eq.(6) to have a value between zero to one.

$$X_{i,norm} = \frac{X_i - X_{min}}{X_{max} - X_{min}} \quad (6)$$

2.4 Training and Testing Set

The consequence results of single-unit level 3 PRA for the reference reactor were calculated and utilized for selecting training set. Sixteen STCs were lined up according to the LCF population-weighted risk result. And, twelve STCs were selected as evenly as possible based on the minimum and maximum results. The remaining STCs were considered as testing set. The training and testing set of this study were shown in Table I. The number of samples were counted by eliminating redundancy because the reference reactors were same nuclear power reactor types. The training set consisted of samples which were only combinations of twelve STCs. And, the testing set consisted of samples including at least one of the four STCs selected.

Table I: Training and Testing Set

	Training Set	**Testing Set**
STC #	1, 2, 3, 6, 7, 10, 13, 15, 16, 17, 18, 19	4, 8, 11, 12
Number of Samples	78	58

2.5 Training SVR Model

MATLAB 2017a version was utilized to train SVR model. MATLAB offers support vector regression by ‘fitrsvm’ which is built-in function. Therefore, if users provide only a few input parameters, such as training set, type of kernel function, epsilon, penalty coefficient, MATLAB automatically generates SVR model. By using this built-in function, it was possible to train and generate the SVR model estimating LCF population-weighted risk (consequence). Additionally, epsilon and penalty coefficient were assigned automatically by using optimization option of 'fitrsvm' built-in function.

2.6 Results.

Verification of the SVR model trained was performed by root mean square error (RMSE) and mean relative error (MRE) which are defined in Eq.(7), (8),

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{Y_P - Y_T}{Y_T}\right)^2} \quad (7)$$

$$MRE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_P - Y_T}{Y_T}\right| \quad (8)$$

where N is the number of samples, Y_P is a consequence prediction of SVR model trained, and Y_T is a true consequence calculated by MACCS.

Firstly, a few types of kernel function were considered to train the SVR model. RBF, linear, and polynomials were applied, and the results were shown in Table II. All input parameters ($X_1 \sim X_{12}$) in these calculations.

Table II: Performance Results of the SVR model according to Kernel functions

Kernel Function	RMSE	MRE
RBF	0.0736	0.0586
Linear	0.0898	0.0712
Polynomial (2nd)	0.1671	0.1373
Polynomial (3rd)	0.0787	0.0560
Polynomial (4th)	0.0725	0.0560
Polynomial (5th)	0.1050	0.0760
Polynomial (6th)	0.8035	0.7374

As expected, it was confirmed that the RBF was appropriate kernel function. Third and fourth order polynomials were also appropriate kernel functions. However, as the order of the polynomial kernel function increased, errors were increased. Based on these results, the RBF was expected to be appropriate kernel function. The values of RMSE and MRE should be decreased by continuous future research.

Secondly, SVR model was trained by using temporal input parameters ($X_1 \sim X_3$) and one out of nine radioactive material classes to investigate the effect of each radioactive material class. Based on these results, the radioactive material classes which relatively had the small RMSE and MRE were considered as input parameters at the same time. These results are shown in Table III.

Table III: Performance Results of the SVR model according to Input parameters

Considered Input Parameters	RMSE	MRE
$X_1 \sim X_3$ + **Xe** (X_4)	1.1071	0.8410
$X_1 \sim X_3$ + **Cs** (X_5)	0.1644	0.1337
$X_1 \sim X_3$ + **Ba** (X_6)	0.4653	0.3574
$X_1 \sim X_3$ + **I** (X_7)	0.2161	0.1557
$X_1 \sim X_3$ + **Te** (X_8)	0.3276	0.2630
$X_1 \sim X_3$ + **Ru** (X_9)	0.9612	0.6845
$X_1 \sim X_3$ + **Mo** (X_{10})	1.1230	0.7745
$X_1 \sim X_3$ + **Ce** (X_{11})	0.3068	0.2144
$X_1 \sim X_3$ + **La** (X_{12})	0.6131	0.4751
$X_1 \sim X_3$ + **Cs, I** (X_5, X_7)	0.5923	0.4086
$X_1 \sim X_3$ + **Cs, I, Te, Ce** (X_5, X_7)	0.6197	0.4475

The results were slightly different from the expectations. The SVR model was not trained well although only radioactive material classes with small RMSE and MRE were considered. It was judged that there were some correlations between input parameters considered. Therefore, the selection of input parameters which are appropriate to train SVR model is very important.

3. Conclusions

New methodology for estimating consequences of STC combination was developed in this study. For this, SVR was applied among AI techniques. Firstly, the appropriate input parameters were selected in the view of temporal and radioactive material classes. Secondly, the training and testing sets were set considering the single unit level 3 PRA results of the reference reactor. Finally, the SVR model was trained by using 'fitrsvm' built-in function of MATLAB. In this step, several sensitivity analyses were performed about kernel function and selection of input parameters. It was confirmed that RBF was appropriate kernel function type, and the appropriate selection of input parameters was very important.

The SVR model developed in this study only considers two unit's STC combinations. More advanced SVR model treating more units should be developed in the future research. Moreover, other AI techniques such as neural network could be applied in this study. Conclusively, this study would contribute to development of Multi-Unit level 3 PRA.

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