Development of machine learning methodology to diagnose the important factors on the severe accident conditions.

Yongju Cho, Sunhong Yoon *
KEPCO-E&C, Nuclear Technology Research Dept, 269 Hyeoksin-ro, Gimcheon-si, 39660
**Corresponding author: rty1474@kepco-enc.com*

1. Introduction

We have developed a diagnostic methodology using machine learning (ML) technology to figure out the important information including the break size, location, other remarkable events such as core uncover, relocation, reactor vessel failure and so on.

Regarding the diagnosis methodology on the prediction of the LBLOCA break size, our study is focusing on the relation between the measurement parameters and the accuracy of prediction. The prediction of important information using ML method is based on the big data made by MAAP version 5.03 analyses on the LBLOCA-induced severe accidents in APR1400.

When predicting the important facts, we found the fact that a more accurate prediction is possible if more parameters are taken into accounts. If all the plant's measurement parameters are used, the results of the prediction can be more accurate, but it seems not reasonable in ML because such an approaching method requires huge big data and very high capacity-level hardware system. So It is not economical.

The measurement parameters in the power plant are expressed in our ML model as features, and we developed the diagnosis ML model to optimize the number of the features and applied it to predict the break sizes of LBLOCA accidents.

2. Assessment of the importance of features

The LBLOCA diagnostic model presented in this paper is a random forest based model, and random forest is an important algorithm in our ML model for predicting the break sizes of LBLOCA accidents.

The importance level of the features is expressed as the ranks of MDI (Mean Decrease Impurity) in terms that how much each feature affects the accuracy of the prediction.

2.1 Random forest

As an ensemble method synthesizing predictions by multiple decision tree models, it is widely known as analysis technique in high dimensional data of many variables compared to the number of observations and higher prediction accuracy than a single decision tree model in general. The model is modeled through a random subspace that randomly selects the variables of the decision tree model.

As a result, randomness is maximized, which lowers the correlation between decision trees, thereby reducing prediction errors. Through this principle, random forest is claimed to be more robust to noise, more stable, faster and more accurate than other boosting classifiers in the ensemble method**[1].**

2.2 MDI(Mean Decrease Impurity) Importance

Commonly used importance measure is the Mean Decrease Impurity (MDI). The impurity-based feature importance ranks the numerical features to be the most important features**[2].**

When the ML model works as a regressor, the node is cut in the direction of reducing variance by using MSE (Mean Square Error). In this process, the variables that reduce the impurity the most are of the greatest importance. The process of quantifying the reduction of this variable is called MDI.

3. Application of the ML methodology

In this study, the goal is to develop the diagnostic model in order to optimize the number of the measurement parameters, so called features in our ML model.

As mentioned in the introduction, since it is not economical to use all the parameters presented in SAMG (Severe Accident Management Guidance), we developed the ML model to rank the importance of the parameters and applied it to optimize the importance ranks of the features in terms of the prediction of LBLOCA break sizes using MDI method.

3.1 Training data

The features to be used in machine learning were selected by considering the measurement parameters related to SAMG. So we extracted 30 parameters (in ML, called features). The break sizes of the LBLOCA ranged from 6 inches to 16 inches with a spacing of 0.01 inch. Thereby, we had the dig data from the analyses of 1,400 cases, each feature (j) of each case was integrated over 60 seconds after scram using the following equation of **(1) [3]**. Then, we made **Table 1** data set for ML in integrated 1400 cases and 30 parameters.

$$x_j = \int_{\Delta t}^{t_s+\Delta t} g_j(t)\, dt \qquad \text{j} = 1,2,3 \ldots\ldots 30 \qquad \textbf{(1)}$$

*where $g_j(t)$ is a simulated signal, Δt is an integrating time span, and t_s is reactor scram time**[3].***

Table 1 : Data set for ML(1401rows × 32columns)

case	LOCA SIZE (Inch)	Pressure in pressurizer	Pressure in primary system	Temp in pressurizer compt	Temp in annular compt #4	Temp in annular compt #3
0	6.00	5.440798 e+08	5.440798e+ 08	20148.7761	20219.2849	20265.3181
1	6.01	5.439511 e+08	5.439511e+ 08	20150.2994	20220.8184	20267.0001
2	6.02	5.448275 e+08	5.448275e+ 08	20151.1197	20221.8602	20267.7797
1399	15.99	3.803337 e+08	3.803337e+ 08	23027.0653	23514.4052	23356.4910
1400	16.00	3.804734 e+08	3.804734e+ 08	23034.2771	23520.0511	23364.1599

3.2 Machine learning

Shown in **Fig. 1** the number of leaf nodes of the random forest tree was 2 and the features of the split node were randomly configured. We combined these models and trained them. This algorithm was considering uncertainty of data.

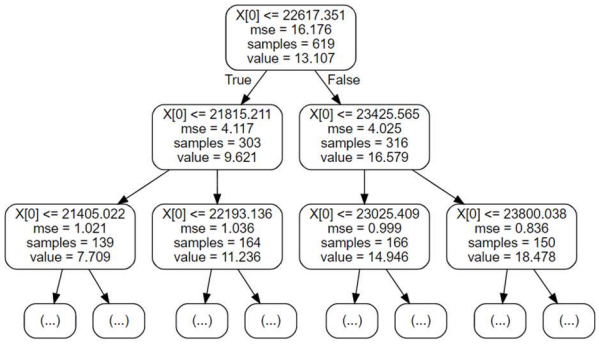


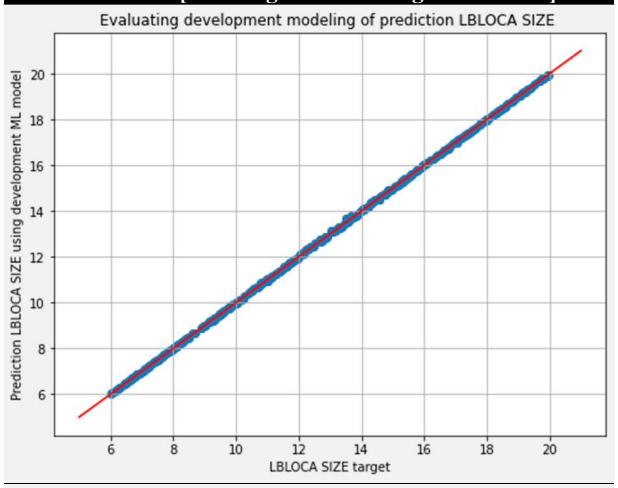
Fig. 1 – Random forest tree for data set

70% of the existing data was used for training and the rest was used for evaluation. The evaluation criteria is MSE(Mean Squared Error), RMSE(Root Mean Squared Error), MAPE(Mean Absolute Percentage Error), R^2 $score$. There are no absolute evaluation criteria for modeling evaluation indicators. In general, a good ML model has smaller MSE, RMSE, and MAPE values while larger R^2 $scores$.

As a result, it was concluded that the model trained by 30 input features is reasonable model for LBLOCA size diagnosis **(Table 2).**

Table 2 shows that the performance development modeling of prediction LBLOCA break sizes and the values of MSE, RMSE, MAPE, and R^2 scores. X-axis is test target which is 30% remaining data except using ML training data. Y-axis is prediction LBLOCA size using our modeling. The performance values show an well-trained ML model.

Table 2 : Performance development modeling when using 30 features [Training data set using 30 Features]



Model Performance	
MSE	0.0008
RMSE	0.0284
MAPE	0.1745
R^2 score	0.9999

3.3 Important features extraction methodology

The optimization in this paper was optimized by indexing the importance of features when developing an LBLOCA size prediction model through a data set using 30 features, and by the evaluation values (MSE, RMSE, MAPE, R^2 $score$) when training on the same model algorithms by creating a data set for each feature.

First, the MDI method was used to evaluate the previously presented development model. The next thing to do was making data set for each feature (Pressure in pressurizer, Pressure in primary system, Temp in pressurizer compt etc.…). Then, train the algorithm in the same way as before using the data set for each feature. **Table 3** showed the MDI rank of a model trained with 30 features as a data set, and MSE, RMSE, MAPE and R^2 $score$ were modeling values trained with each feature as data set.

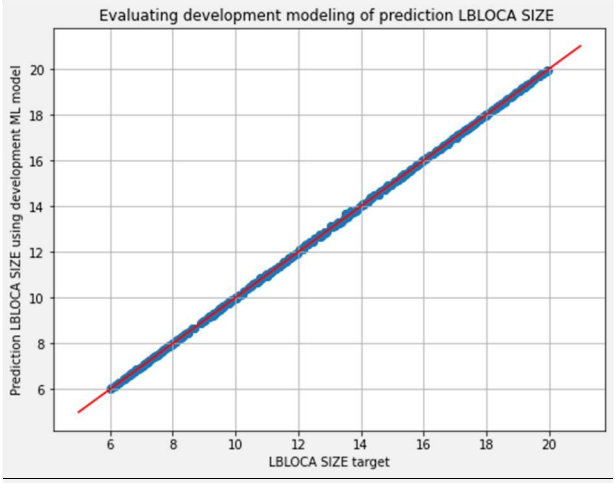
After 15 MDI rank features, one or more of the MSE, RMSE, MAPE, R^2 scores differed by at least several times. We found out that the features with low MDI rank are mostly poor MSE, RMSE, MAPE, R^2 scores. In summary, it was necessary to look at MDI MSE, RMSE, MAPE and R^2 score. In this model We removed 14 features in order to optimize the number of the features. They were marked in red in the **Table 3.**

Table 3 : Evaluate each feature using developing modeling [Training data set using each Feature]

MDI rank	Feature	MSE	RMSE	MAPE	R^2 score
1	Water level in Cavity	0.0274	0.1654	0.2852	0.9983
2	P in pressurizer	0.0689	0.2625	0.9957	0.9957
3	Core Exit T	1.9449	1.3946	8.0565	0.8797
4	Core collapsed water level	0.0093	0.0967	0.6781	0.9994
5	Pressure in CTMT dome	0.0016	0.0405	0.2338	0.9999
….	…..	…..	…..	…..	…..
15	T of gas in annular Compt SW-#1 El.100'	0.00264	0.0514	0.2585	0.9998
16	Water Temp in loop 4 cold leg	3.8151	1.9532	12.3814	0.7640
17	Water Temp in loop 2 cold leg	3.8030	1.9501	12.4084	0.7647
…..	….	….	….	….	….
20	Water Temp in loop 3 cold leg	2.1814	1.4770	8.4166	0.8650
21	Water Temp in loop 1 cold leg	2.0795	1.4426	8.4743	0.8713
22	Flow rate of ESF	10.4055	3.2258	25.8784	0.3562
…..	….	….	….	….	….

Table 4 is LBLOCA Size Prediction And Performance using machine learning through 16 features extracted by excluding those with lower MDI ranking or poor $R^2\ score$, MSE, RMSE and MAPE values. After extracting them, the machine learning model was trained using this Training data. The results were similar to those of the model with 30 input features shown in **Table 2.**

Table 4 : LBLOCA Size Prediction And Performance using machine learning through optimizing the features [Training data set using 16 Features]



Model Performance	
MSE	0.0010
RMSE	0.0329
MAPE	0.1910
R^2 score	0.9999

4. Conclusions

The purpose of this study was to optimize by reducing the number of the measurement parameters (or features) required for machine learning without compromising accuracy. We found that the random forest sampling method and the evaluation criteria such as MSE, RMSE, MAPE, $R^2\ score$ are useful to figure out the important ones out of all the considerable features. In the future, the optimized features will be derived by extending the prediction of another scenario shown in the progresses of severe accident.

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[3] Geon Pil Choi, Kwae Hwan Yoo, Estimate of LOCA Break Size Using Cascaded Fuzzy Neutral Networks, Nug. Eng. Technol. 49 (2017) 495-503