Sensitivity Evaluation of WH-type Reactor Steel Plate Failure Probability using Advanced PROFAS-RV PFM Code with Machine Learning Irradiation Embrittlement Models

Jongmin Kim [a*], Gyeongguen Lee, Minchul Kim, Bongsang Lee [a]
[a]*Material Safety Technology Develpoment Division, Korea Atomic Energy Research Institute, Yuseong-gu, Daejeon, Korea*
[*]*Corresponding author: jmkim@kaeri.re.kr*

1. Introduction

The Korea Atomic Energy Research Institute has developed PROFAS-RV, a PRObabilistic Failure Analysis System for Reactor Vessel. PROFAS-RV is continuously updated with the latest irradiation embrittlement model, stress intensity factor calculation method, crack geometries, evaluation logic and etc. In this study, an irradiation embrittlement model (IEM) incorporating a machine learning (ML) method was developed by utilizing the latest global irradiation embrittlement database, and this was embedded in PROFAS-RV [1] with recent IEM such as ASTM E900-15 [2] and WRC [3] to perform probabilistic failure evaluation of plate steel reactor vessel steel. PTS (pressurized thermal shock) evaluation for WH (westinghouse) type reactor vessel steel plate was performed, and differences for each IEM were analyzed.

2. ML Models and PFM Results

2.1 ML Model

The data used in this study were 1878 data points provided by the ASTM E900-15 supplement. There are various ML methods according to regression strategies. Among the ML methods, we first considered XGBoost [4] and Cubist (CBT) [5]. These two methods discretely segment and predict the data trends. A support vector machine (SVM), which can smoothly interpolate the data trend, was also considered [6].

The root mean square deviation (RMSD) was used to evaluate the performance of each model. The RMSD of the ASTM E900-15 was 13.3. Cubist and XGB methods showed a significant decrease compared to E900-15 with RMSD of 11.7 to 11.9, and SVM showed RMSD almost similar to that of E900-15. As a result of comparing the RMSD of the four methods, it was reconfirmed that Cubist and XGB showed excellent predictive performance. What is noteworthy about SVM is that machine learning methods showed lower RMSD than E900-15, a nonlinear regression method, even for simple modeling of explanatory variables. This is because machine learning derives the best prediction value by properly learning the complex interactions between each explanatory variable. As the number of explanatory variables to be considered increases, the ease of the machine learning technique becomes evident. The RMSD results were depicted in Fig. 1 [7].

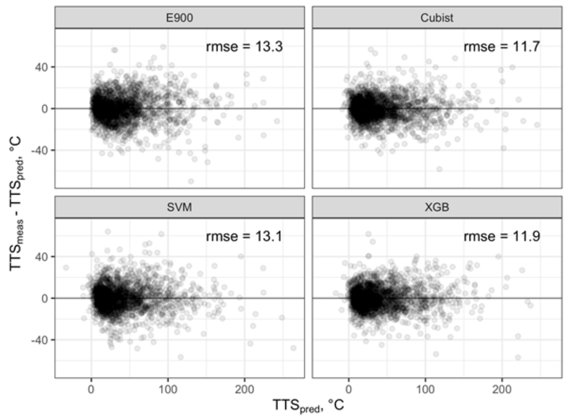

Fig. 1. Residuals of ML models

2.2 Definition of PFM Problem

Recent irradiation embrittlement models (ASTM E900-15, WRC) and ML models (Cubist, SVM, XGB) are embedded to PROFAS-RV PFM code. PTS evaluation for WH type reactor vessel steel plate was performed using updated PROFAS-RV code with recent IEM models and ML models.

A probabilistic PTS evaluation was performed for four transient states (SBLOCA, MSLB, SGTR, A014) and beltline axial weld on RPV. The reactor vessel considered has an inner radius of 66 inches, the thickness of the base metal is 6.5 inches, and the thickness of the clad is 0.125 inches. Chemical composition of Cu, Ni, P and Mn is 0.03, 0.07, 0.01, 1.7 wt%, respectively. The standard deviations are 0.006, 0.012, 0.0012 and 0.17 wt%, respectively. The crack length to depth ratio is 6, and the ASME code and K_{IC}/K_{IA} lower bound curves were used for stress intensity factor (K) calculation. For the material properties of RPV, the properties of SA533B plate obtained from the international joint research were used. The initial RT_{NDT} was set to 1.4F, and the RT_{NDT} standard deviation was 28F. The change in $\triangle RT_{NDT}$ is applied by ± 5 times the variance, and both ends are truncated. The fluence was changed to 2, 4, 6, 8 and 10 $\times$ 10^{19}, and the characteristics of each irradiation embrittlement model according to the fluences were examined. For each analysis, 2 million Monte Carlo simulations were performed using the Marshall flaw distribution.

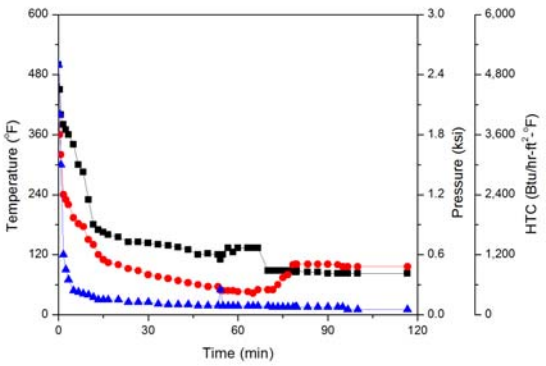

Fig. 2. Time dependent temperature, pressure and film coefficient profile (SBLOCA)

2.3 PFM Results

R.G. 1.99 showed the lowest failure probability. The probability of failure was predicted in the order of R.G. 1.99<10CFR50.61a<WRC<E900=CBT=SVM=XGB. Because an axial weld was considered in this study, it showed a high probability of failure compared to that of a circumferential weld or the base metal. The machine learning irradiation embrittlement models use the same database as ASTM E900-15, as a result, they all showed similar failure probability to ASTM E900-15. However, the failure probability of ML IEMs decreased or increased rapidly above 5 × 10^{19} of fluence due to the characteristics of ML IEMs. This result is similar to the TTS (transition temperature shift) calculation result, and among the IEMs, the SVM model and ASTM E900-15 are the most suitable model. To analyze the cause of the difference in the prediction trends of the ML IEMs, the TTS calculation results for each ML IEM were reviewed.

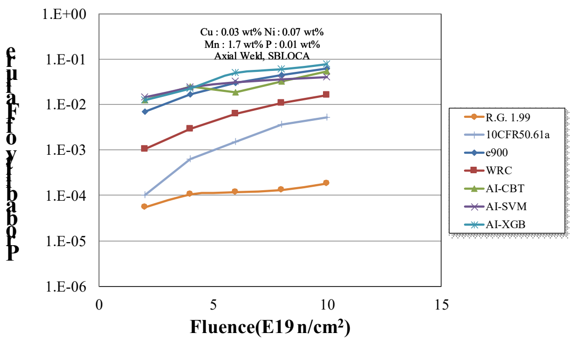

Fig. 3. Comparison of failure probability (SBLOCA)

The ML IEM showed clear differences between models. In the CBT model, Fluence increased again after a sharp drop from 5.0e+19 or higher, and XGB increased monotonically again after a sharp increase or maintained. This shows the limitations of the database used to develop the ML IEMs. Fluence shows different trends depending on data of 5 × 10^{19} or higher fluence level, or shows the predictive characteristics of CBT and XGB models in the absence of data. On the other hand, the SVM model showed a relatively smooth trend considering the absence of data and the correlation of other data, and was analyzed to predict the trend to some extent even under the extrapolation condition with high fluence level.

3. Conclusions

Recent irradiation embrittlement models and ML models are embedded to advanced PROFAS-RV PFM code. PTS evaluation for WH type reactor vessel steel plate was performed, and differences for each IEM were analyzed. The ML IEM tends to depends on the database used in developing ML models. PTS simulation evaluation results for WH type reactor vessel steel plate, R.G. 1.99 showed the lowest failure probability, and the failure probability was predicted in the order of R.G. 1.99 < 10CFR50.61a < WRC < ASTM E900 = CBT = SVM = XGB. The results of this study can be used as PFM analysis method in the life evaluation of nuclear power plants. In order to increase the usability of the results of this study, it is necessary to carry out continuous technical update in the future.

REFERENCES

[1] J. M. Kim, B. S. Lee, T. H. Kim, and Y. S. Chang, Development of probabilistic fracture mechanics analysis codes for reactor pressure vessels considering recent embrittlement model and calculation method of SIF – progress of the work, Proceeding of ASME 2016 pressure vessels & piping division conference, PVP2016-63128.
[2] ASTM International, E900-15e2 standard guide for predicting radiation induced transition temperature shift in reactor vessel materials. https://doi.org/10.1520/E0900-15E02, 2015.
[3] M. Kirk, A wide-range embrittlement trend curve for western reactor pressure vessel steels, in: ASTM Special Technical Publication, 2013, https://doi.org/10.1520/STP103999.
[4] T. Chen, C. Guestrin, XGBoost, proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining. https://doi.org/10.1145/2939672.2939785, 2016.
[5] J.R. Quinlan, Combining instance-based and model-based learning. Machine Learning Proceedings 1993, Morgan Kaufmann, San Francisco (CA), 1993, pp. 236-243, https://doi.org/10.1016/B978-1-55860-307-3.50037-X.
[6] C. Cortes, V. Vapnik, Support-vector networks, Mach. Learn, 20, 1995, pp. 273-297, https://doi.org/10.1007/BF00994018.
[7] G. G. Lee, M. C. Kim and B. S. Lee, Machine learning modeling of irradiation embrittlement in low alloy steel of nuclear power plants, Nuclear Engineering and Technology, 53, 2021, pp. 4022-4032.