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Original Article

A machine learning informed prediction of severe accident progressions in nuclear power plants

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ABSTRACT

A machine learning platform is proposed for the diagnosis of a severe accident progression in a nuclear power plant. To predict the key parameters for accident management including lost signals, a long short term memory (LSTM) network is proposed, where multiple accident scenarios are used for training. Training and test data were produced by MELCOR simulation of the Fukushima Daiichi Nuclear Power Plant (FDNPP) accident at unit 3. Feature variables were selected among plant parameters, where the importance ranking was determined by a recursive feature elimination technique using RandomForestRegressor. To answer the question of whether a reduced order ML model could predict the complex transient response, we performed a systematic sensitivity study for the choices of target variables, the combination of training and test data, the number of feature variables, and the number of neurons to evaluate the performance of the proposed ML platform. The number of sensitivity cases was chosen to guarantee a 95 % tolerance limit with a 95 % confidence level based on Wilks' formula to quantify the uncertainty of predictions. The results of investigations indicate that the proposed ML platform consistently predicts the target variable. The median and mean predictions were close to the true value.

1. Introduction

Signals for important safety parameters for the nuclear power plant can be corrupted or lost due to a harsh environment of high pressure, radiation, and temperature during a severe accident progression. In the FDNPP accident, TEPCO operators had difficulties in diagnosing the possibility of core damage due to false signals for the core water level [1, 2] and the pressure signals for the reactor vessel, drywell, and suppression chamber were corrupted intermittently [2]. There are also key parameters needed for the operator to take proper mitigation actions. There was a hydrogen explosion and the release of a significant amount of radioactive materials into the atmosphere in the Fukushima accident [1]. Though there are hydrogen concentration measurements and radiation monitors in a nuclear reactor [3], they do not provide quantitative information.

If there is an aid for the operator to estimate key parameters for accident management such as the mass of hydrogen generation and mass of nuclear aerosols in the drywell and lost or corrupted signals, it will be very helpful for the operator to take proper mitigation action. In this paper, we propose a Machine Learning (ML) framework integrated with accident simulation data to help the operator overcome these situations.

Recently research efforts on utilizing Machine Learning (ML) platforms for analyzing transients in nuclear power plants continue to grow in various categories such as the design of nuclear reactor core [4], classification of accidents [5], forecasting of accident progression [6], pipe thinning detection [7], a surrogate model for thermal-hydraulic system code [8], diagnosis of sensor faults, abnormal events, and accidents [9-14], inference models for operator support systems [15], reinforcement learning for the operation of nuclear power plant [8], and modeling of severe accident scenarios [16]. An ML model for a diagnosis of severe accident progression was also proposed [17] and it was pointed out that the regression type of ML model resulted in poor performance when only available measurement signals were used.

In this investigation, important feature variables are chosen among many plant parameters where importance ranking was determined by a recursive feature elimination technique using RandonForestRegressor (https://scikit-learn.org/stable/). Then, an ML model utilizing Long Short Term Memory (LSTM) network is proposed. The LSTM recurrent neural network has been exercised in recent years for the modeling and prediction of nonlinear time-variant system dynamics [18–20]. The LSTM unit can remember values over arbitrary time intervals and the three gates control the flow of information through the cell.

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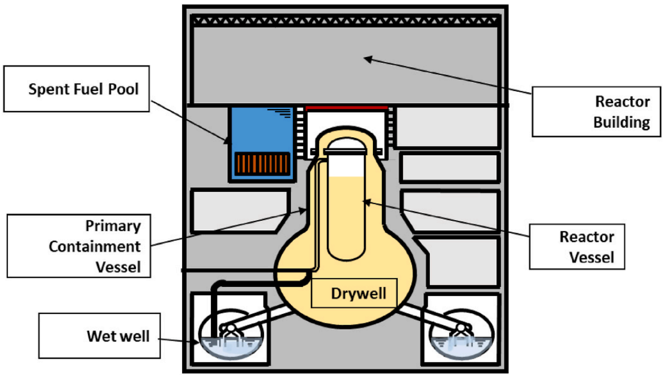

Fig. 1. A conceptual picture of FDNPP unit 3.

To train the ML model, we need training data. However, as the experimental data and/or actual plant data for the severe accident progression is scarce, we relied on MELCOR [21] computer code to simulate the severe accident progressions. MELCOR code has been widely used during the last decades. Results of a recent OECD/BSAF (Benchmark Study of the Accident at the Fukushima Daiichi Nuclear Power Station) project demonstrated that MELCOR can predict the severe accident progression in the FDNPP accident reasonably well (M. [22–24]). So, training data were obtained by multiple MELCOR simulations of the Fukushima Daiichi Nuclear Power Plant (FDNPP) accident at unit 3, where three days of accident progression is considered.

In the ML model, the accident scenarios simulated by the MELCOR code are simplified as times series data of selected feature variables, while multi-physics and multi-time scale phenomena including thermal hydraulics, fuel damage, transport of molten fuels, structural materials interaction, and generation and transport of fission product are involved in the MELCOR simulation. It is natural to ask the question of whether this reduced-order ML model could predict the complex transient response from the nuclear power plant [25].

To address this issue, we took a systematic approach. At first, we generated a wide range of training data by varying the operation of plant equipment, operator actions, and parameters for phenomenological models in the MELCOR simulation. Then, we evaluated the sensitivity of different choices of target variables, number of feature variables, and number of neurons on the accuracy of ML predictions. Finally, as we do not know the best hyper-parameters for the ML algorithm in advance, we predicted the target variable statistically. We employed Wilks' formula based on non-parametric statistics [26] to determine the required number of sensitivity cases.

2. Material and methods

We considered a situation when a loss of signal occurred or an estimation of key parameters for accident management was needed. Then we predicted the target variable of either the lost signal or key parameter using the available feature variables using the proposed ML platform.

2.1. *Preparation of training and test data*

As actual plant data for severe accidents is scarce, we relied on the simulations of the severe accident progression using the best-estimate mechanistic computer code of MELCOR [21] to generate the training and test data for the accident progression in FDNPP unit 3. We minimized the model uncertainty by using the recent MELCOR version 15254. A schematic diagram of the FDNPP unit 3 configuration is shown in Fig. 1.

A peer-reviewed MELCOR plant model and input parameters for the accident progression in FDNPP unit 3 reported in Sevon [23] are used to ensure reliability and avoid user bias. While the scenario reported in Sevon [23] is taken as the reference case, we changed the operation of plant equipment including RCIC (Reactor Core Isolation Condenser), operator actions of containment venting and spray, a rupture of the main

Table 1
Cases Considered for Training and Testing of the ML platform.

Cases	RCIC flow rate	Containment Venting	Oxide fuel rods collapse temperature, Candling melt flow rate	Main steam line failure	Spray to drywell and wetwell
Case 1	Reference value	Reference value	2800, 0.2	151,740 s	Reference value
Case 2	50 %, 50 %	Reference value	Reference value	151,740 s	Case 1
Case 3	10 %, 50 %	50 %	Reference value	151,740 s	Case 1
Case 4	Case 1	Reference value	2400, 1.0	151,740 s	Case 1
Case 5	Stop RCIC at 36,000 s	Reference value	2400, 1.0	151,740 s	Case 1
Case 6	Case 5	Turned off occasionally	Case 5	100,000 s	Turned off
Case 7	Case 5	Same as case 6	Case 5	200,000 s	Case 6
Case 8	Case 5	Same as case 6	Case 5	50,000 s	Case 6

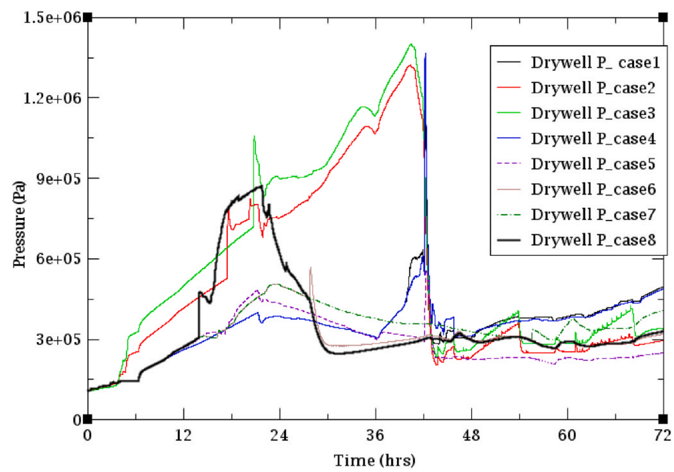

Fig. 2. Behavior of drywell pressure.

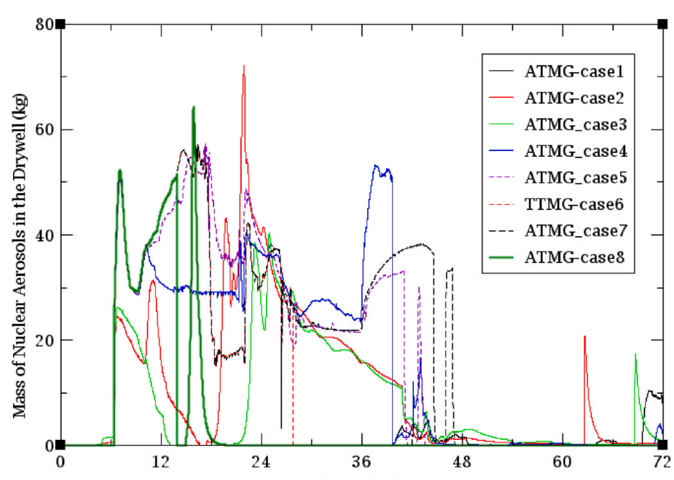

Fig. 3. Mass of nuclear aerosols in the drywell.

Table 2
Candidate feature variables.

Variables	Ranking/ (Sequential number)	Target Variable	Scaling Parameters
Lower plenum level	1 (0)	-	5.245 m
Core Water level	1 (1)	Y	3.71 m
Reactor Vessel Pressure	1 (2)	Y	7 MPa
Volumetric steam flow rate from RCIC	1 (3)	-	10.0 m^3/s
HPCI exit velocity	1 (4)	-	14.0 m/s
Amount of hydrogen generation,	1 (5)	Y	1200 kg
Mass of aerosols in drywell	1 (6)	Y	50 kg
Wetwell pressure	1 (7)	-	0.5 MPa
Drywell pressure	Target Variable	Y	0.5 MPa
Flow rate of spray from CST (Condensate Storage Tank) to wet well	4		
Open Fraction of SRV (Safety Relief Valve) -A, B, C, D, E, F, G, H	13, 10, 11, 16, 15, 9, 14, 12		
Flow rate of wet well spray	8		
Drywell spray flow rate	7		
Open fraction of steam line failure flow path	5		
Containment venting line open fraction	6		

Table 3
Exercises for the ML platform.

Exercises	Training Cases	Total Number of Training Data Points	Test Case
Model 1 (1234–8)	Cases 1, 2, 3, 4	19,992	Case 8
Model 2 (123456–8)	Cases 1, 2, 3, 4, 5, 6	29,988	Case 8
Model 3 (1234567–8)	Cases 1, 2, 3, 4, 5, 6, 7	34,986	Case 8

steam line, and parameters for phenomenological models such as fuel collapse temperature, and candling mass flow rate. The cases considered are summarized in Table I. As a representative plant response, drywell pressures and mass of nuclear aerosols in the drywell obtained from MELCOR simulation of eight cases are illustrated in Fig. 2 and Fig. 3. It can be seen that the responses from eight cases vary significantly from each other in terms of peak, timing, and overall shape. We claim that we covered a quite wide range of accident scenarios.

2.2. Selection of feature variables and training models

An ML algorithm of recursive feature elimination (RFE) wrapper and RandomForestRegressor provided in sklearn (https://scikit-learn.org/stable/) is used in evaluating the priority of feature variables. Here, we took the drywell pressure as the target variable. Twenty candidate feature variables were selected among many MELCOR variables as listed in Table II. Then, eight important parameters were selected among 20 candidate variables in terms of importance in determining the drywell pressure using RandomForestRegressor. We tagged the sequential number to each parameter for convenience, while we investigated the sensitivity of the number of feature variables. Starting from the 4 feature variables with sequential numbers from 0 to 3, we increased the number of feature variables up to 8.

The fact that each feature variable behaves quite independently and changes in feature variables in time are quite different among various scenarios as can be seen in Figs. 2 and 3 makes it difficult to find the best extraction strategy for the time series data. As a compromise, the transient data obtained from the MELCOR analyses are reformatted in a multivariate time series with 5000 data points at equal time intervals. To avoid the potential problem of numerical convergence in the ML algorithm, we scaled the feature variables so that feature variables vary between 0 and 1 during the whole transient. The responses of feature variables are quite different from each other and independent.

In this analysis, we used different combinations of training and test data to see the sensitivity of the range of training data on the prediction accuracy for the ML platform. The exercised models are described in Table III. For the model 1, we used 4 training data to predict case 8. For the models 2 and 3, we increased the range of training data. In Table III, the total number of training data points is specified for each case. It is noticed that case 8 is quite different from others. So, if the ML is trained with time series data from other cases, it will be rather difficult for the ML algorithm to predict case 8. This is the reason why we took case 8 as the test data. We tried to tackle a difficult problem.

2.3. A formulation of machine learning problem

The mathematical formulation of severe accident progression is based on the conservation of mass and energy in time and space. For example, the conservation of mass in a control volume is expressed below.

$$\partial\rho/\partial t + \nabla\bullet(\rho v) = \Gamma \quad (1)$$

where ρ is density, v is velocity vector, Γ is volumetric mass source density. The rate of change in density is governed by the other parameters at the current and previous time steps. We can approximate the above equations for the numerical solution in the computer code like MELCOR

$$\rho^t = \rho^{t-1} - \Delta t \text{ x } (\Gamma - \nabla\bullet(\rho v))^t \quad (2)$$

where the values in the parentheses at time step t can be approximated with values at t and t-1. So, the density at the current time step is a function of density in the previous time step, and the velocities and mass source at the current and previous time step

We intend to mimic this conservation law in the ML formulation. Using the values of feature variables at the previous time step and current time step, we want to predict the target variable such as dry-well pressure at the current time using the values of the other feature variables. Then, this problem can be mathematically formulated as below.

$$y_t^{ifeature+1} = \mathbf{g}\,(y^*_t, y^*_{t-1}) + w(t) \quad (3)$$

$$y^*_t = (y_t^0, y_t^1, y_t^2, .. y_t^{ifeature}) \quad (4)$$

where $y^*_t = (y_t^0, y_t^1, y_t^2, .. y_t^{ifeature})$ is a vector for feature variables at time t, and y^*_{t-1} is a vector for feature variables at time t-1, and w(t) is the noise. The index for the feature variable "ifeature" is less than 7. $y_t^{ifeature+1}$ is the target variable t time t. We can see that ML formulation in equations (3) and (4) resembles the conservation law in equations (1) and (2).

The prediction of missing information in the multivariate time series was previously investigated by recurrent neural networks [27]. However, for the formulation of conservation law, the LSTM network fists the purpose. The LSTM recurrent neural network was developed and exercised in recent years for the prediction of nonlinear transient system dynamics [18–20]. It carries time history information while avoiding the gradient vanishing or exploding problem. The basic entity called the LSTM unit consisted of a cell with neurons and three gates: an input gate, an output gate, and a forget gate. An LSTM unit can remember values over arbitrary time intervals and the three gates control the flow of information through the cell. During the training process, weights and biases for the memory cell and three gates are determined [28]. The weights and biases represent the function **g** in equation (3). The function **g** depends on the configuration of nuclear power plants and physical phenomena involved in the accident progression.

Table 4
Summary of the Model (Number of features 5, number of neurons 120).

Layer	Output Shape	Number of trainable parameters
Input	None, 4998, 5	0
RNN (LSTM)	None, 4998, 120	60480
Time distributed	None, 4998, 1	121

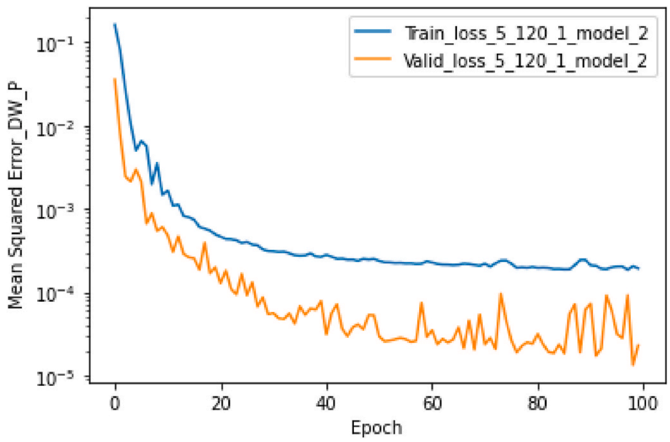

Fig. 4. Typical behavior of MSE during iteration.

2.4. Training of the machine learning model

The LSTM network implemented in Keras (https://keras.io) written in Python and running on the TensorFlow [29], is used to build an ML platform for training and testing. The model has one LSTM layer with a variable number of neurons among 30, 60, 90, 120, and 150 and a variable number of features between 4 and 8. Adams optimizer [30] with a loss represented by Mean Squared Error (MSE) was used. To see the effect of the stochastic nature of the gradient descent algorithm, each case is repeated three times. A summary of the ML model for a representative case, where the number of features is *5* and the number of neurons is 120, is shown in Table IV. The total number of *trainable* parameters is 60,480. When the target variable is changed, the same procedure applies.

The representative shape of changes in MSE during the iteration in the training and validation are shown in Fig. 4 for the case in Table IV. This is the case for Model 2 in Table III, where time series data from cases 1, 2, 3, 4, 5, and 6 are used for training, and time series data for case 7 is taken as the validation data. Here, the target variable is drywell pressure (DW_P). We do not observe noticeable underfitting or overfitting. As the behavior of train and validation losses depended on the choice of combination of training data and validation data, the number of feature variables, and the number of neurons, we used the same number of epochs for the sensitivity studies described in section 3 to follow for fair comparison.

To see the effect of changes in the target variable on the performance of ML predictions, a target variable representing a lost signal or key parameters for accident management was chosen among drywell pressure, core water level, reactor vessel pressure, amount of hydrogen generation, and mass of nuclear aerosols in the drywell. Then, the remaining variables are taken as feature variables. Starting from the case with four feature variables of the lower plenum level, the core water level, reactor vessel pressure, and volumetric steam flow rate from RCIC at the current time step, we increased the number of feature variables up to eight. With this formulation, the prediction of the target variable became a supervised learning problem.

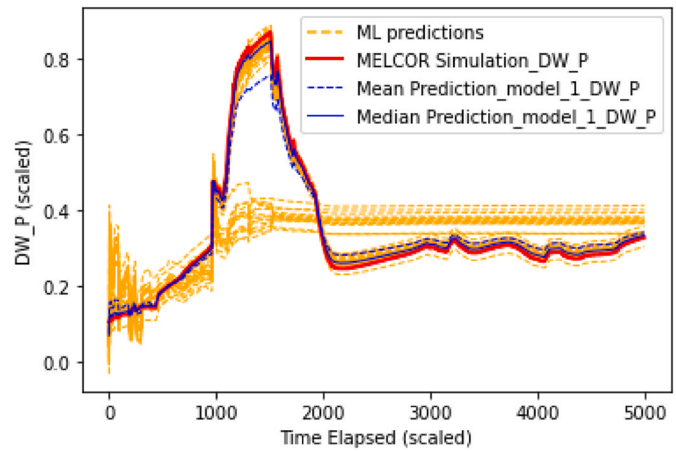

Fig. 5. ML Predicted and MELCOR Drywell pressure (Model 1).

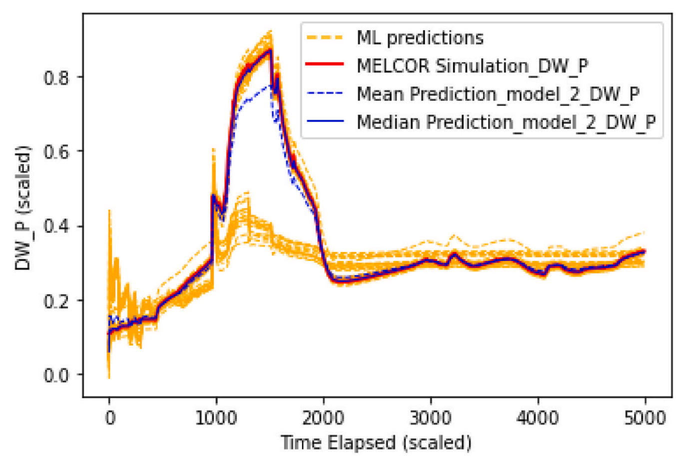

Fig. 6. ML Predicted and MELCOR Drywell pressure (model 2).

3. Results of analyses

3.1. Prediction of drywell pressure

Here, we assume a situation when the signal for the drywell pressure is lost while information for other feature variables is available. The true value of drywell pressure and values for other feature variables are taken from the results of the MELCOR simulation. It has to be noted that the MELCOR simulation results are approximations for the "true" value because the values were not obtained from real accident situations.

Fig. 5 shows a comparison of drywell pressure (DW_P) for case 8 simulated by the MELCOR and the drywell pressure predicted by the ML platform for model 1, where the ML platform is trained with MELCOR cases 1, 2, 3, and 4. The 75 redictions are indicated in orange dashed lines in Fig. 5. The total number of ML predictions for a single model is 75 (5x5x3), where 5 different numbers of neurons, 5 different numbers of feature variables, and 3 repeated cases are considered. It is shown that there are two branches of prediction. One is close to the true value approximated by the MELCOR simulation and the other quite deviated from the MELCOR simulation. Mean and median predictions were close to the true value.

Fig. 6 shows a comparison of the drywell pressure simulated by the MELCOR and the predicted pressures by the ML platform for model 2, where the ML platform is trained with MELCOR cases 1, 2, 3, 4, 5, and 6. It shows the effect of an increase in the range of data. We can see that the overall trend is in the same direction as that of model 1 in Fig. 5. We can see that the accuracy of prediction increased slightly with an increase in

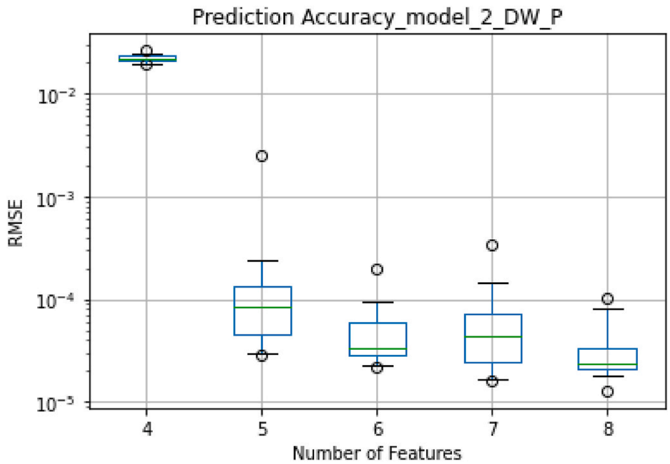

Fig. 7. RMSE at different numbers of feature variables (model 2 – drywell pressure).

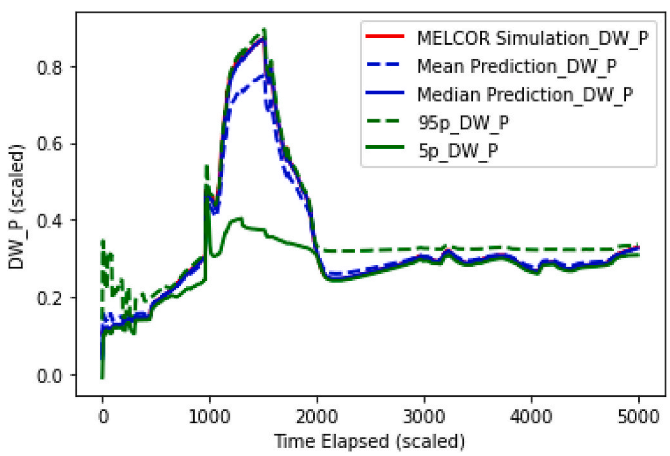

Fig. 8. ML Predicted and MELCOR Drywell pressure (All 225 cases included).

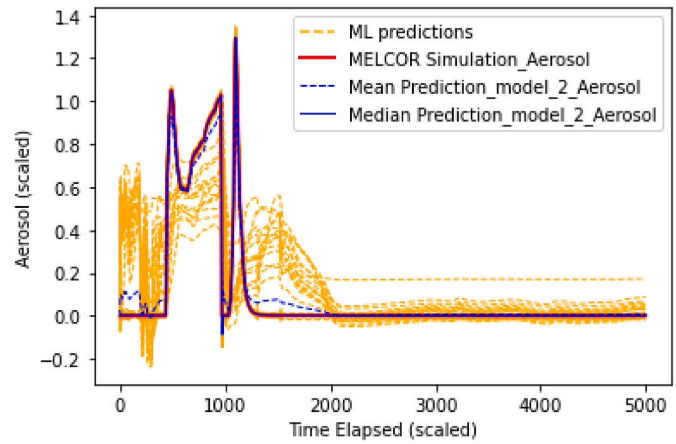

Fig. 9. ML predicted and MELCOR mass of nuclear aerosol.

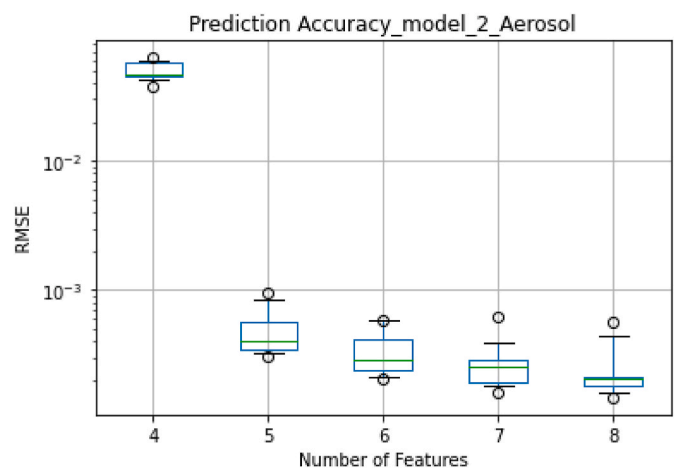

Fig. 10. RMSE with Different Numbers of Feature Variables (Model 2 – mass of aerosol).

the range of training data.

It needs to be pointed out that the drywell pressure behavior for case 8, which is the test case, is quite different from those of cases 1, 2, 3, 4, 5, and 6. So, an increase in the range of training data has positive and negative effects, since the weights and biases of the ML platform are optimized for all the data. That is why we do not see much improvement in the accuracy of the predictions between model 1 and model 2.

A boxplot for the root mean squared error (RMSE) between the MELCOR simulation and ML prediction at different numbers of feature variables for model 2 is shown in Fig. 7, where median, minimum, maximum, inter-quartile range, and outliers are indicated. For each feature variable, there are 15 cases. It is shown that there was a significant improvement in the accuracy of the predictions when we increased the number of feature variables greater than 5. MSE is less than 10^{-3} if the number of feature variables is greater than 5. The authors believe that one branch of prediction in Fig. 5 represents the cases with high accuracy with RMSE less than 10^{-3} and the other branch is the case with low accuracy. Because we do not know the best hyper-parameters for the ML algorithm, this kind of behavior has to be cautioned when we use ML algorithms in the field.

Finally, we combined all the predictions using models 1, 2, and 3 and considered the fact that we do not know the best ML model in advance. Therefore, we need to predict the target variable statistically. We combined results for models 1, 2, and 3 in Fig. 8. We can find the mean, median, 95 %, 5 % of the distributions for 225 (75x3) cases. Here, we employed Wilks' formula based on non-parametric statistics [26] to determine the minimum required number of cases to guarantee the 95 % tolerance limit with a 95 % confidence level. The required number was 59. So, the results of 225 cases provide enough tolerance and confidence level. It is seen that the median and mean of the distributions follow the true value quite closely. The 5 percent distribution was quite off from the true value.

3.2. Prediction of mass of nuclear aerosols

There are key parameters for accident management such as the amount of hydrogen generation and the mass of nuclear aerosols in the drywell. As they are not be measured directly, these values can only be estimated using sophisticated computer models. However, they are crucial information for the operator to estimate the risk of a hydrogen explosion and the risk of the release of radioactive materials into the atmosphere [1,31]. So, we were interested in the capability of the proposed ML platform to predict these key parameters for accident management.

The comparison of the mass of nuclear aerosols in the drywell predicted by the ML platform and the mass of aerosols obtained from the MELCOR simulation is shown in Fig. 9 for model 2. It is shown that the mean and median of ML predictions follow the trend and values of the true amount of aerosols in the drywell properly. Boxplot for the root mean squared error (RMSE) with different numbers of feature variables for model 2 is shown in Fig. 10. The RMSE was less than 10^{-3} when we used the number of feature variables greater than 5.

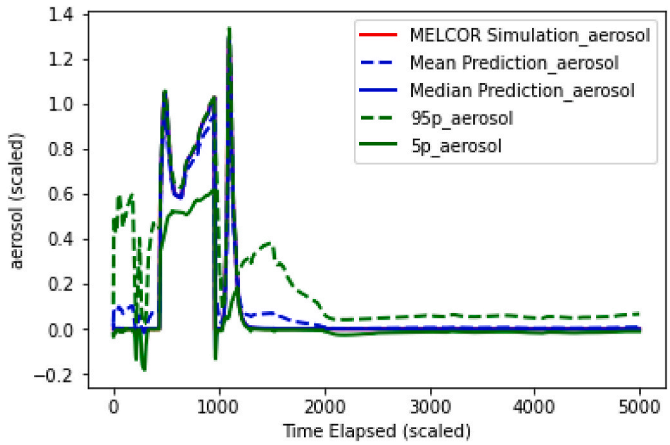

Fig. 11. ML predicted and MELCOR mass of nuclear aerosols (all predictions).

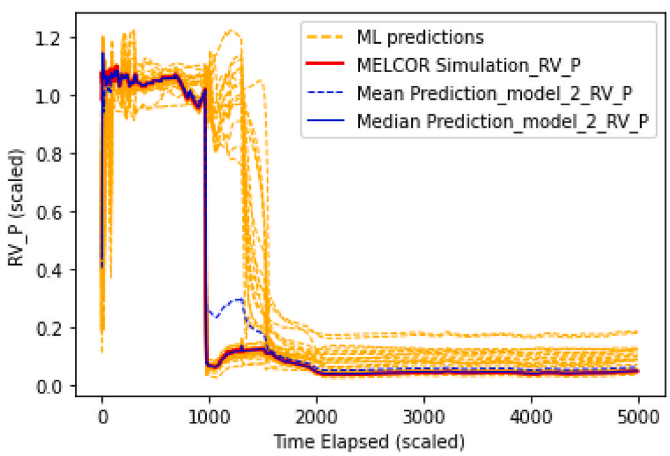

Fig. 12. ML predicted and MELCOR simulated reactor vessel pressure (model 2).

Finally, we looked at the mass of nuclear aerosols for all 225 ML predictions compiling the results of models 1, 2, and 3 in Fig. 11. We can find the mean, median, 95 %, 5 % of the distributions for 225 cases. It is seen that the median and mean of the distributions follow the true value quite closely, which is consistent with the predictions from each model of 1, 2, and 3. So, we can see that the proposed ML platform can predict not only missing signals but also key parameters for accident management.

3.3. *Prediction of other signals or key parameters*

The next question is the sensitivity of the choice of target variables on the accuracy and trends of the predictions by the proposed ML platform. During the severe accident progression, various kinds of false or corrupted signals can happen. In the FDNPP accident, TEPCO operators had difficulties in diagnosing the possibility of core damage due to false signals for the core water level [[1], TEPCO 2011]. As can be seen from the measurement for each unit of FDNPP posted on the Information Data Portal of the Fukushima Accident [2], pressure signals for the reactor vessel, drywell, and suppression chamber were also corrupted intermittently. So, we analyzed the capability of the ML platform in predicting the reactor vessel pressure (RV_P) and core water level (Core_L).

We predicted the reactor vessel pressure from the ML platform using the information from other feature variables. The comparison of the reactor pressure vessel predicted by the ML platform and the true reactor

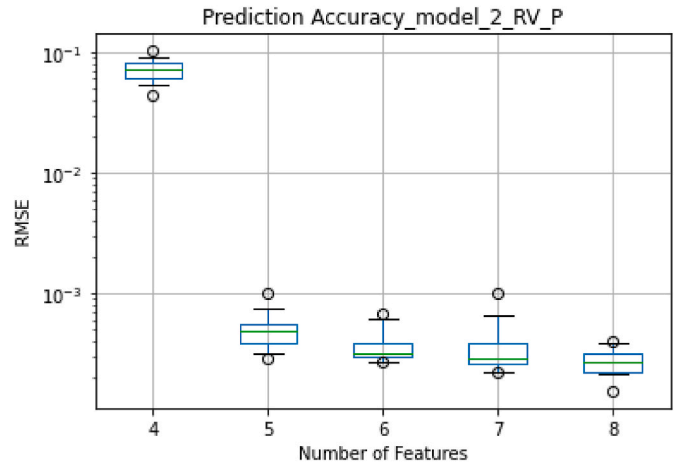

Fig. 13. RMSE with different numbers of feature variables (model 2 – reactor vessel pressure).

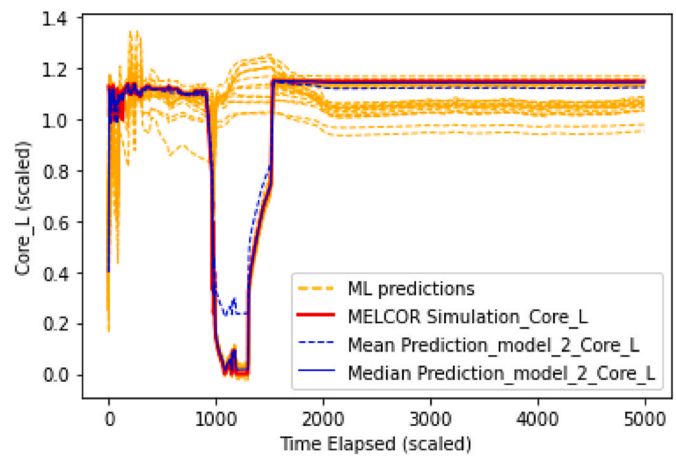

Fig. 14. ML predicted and MELCOR simulated core water Level (model 2).

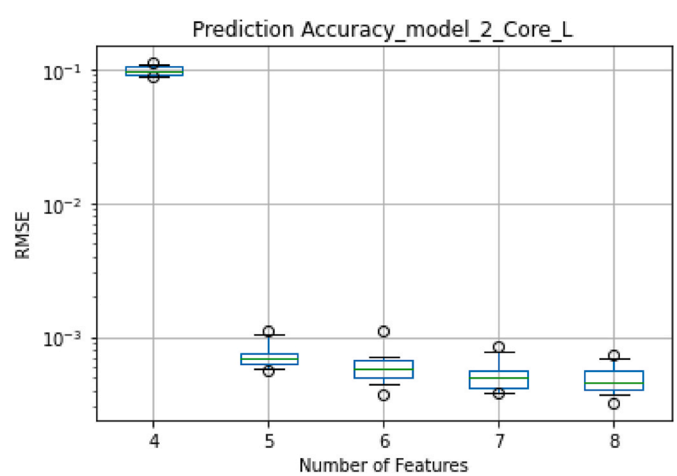

Fig. 15. RMSE with different numbers of feature variables (model 2 – core Level).

vessel pressure obtained from the MELCOR simulation is shown in Fig. 12 for model 2. There are two branches of prediction. One is close to the true value and the other is a little off from the true value. In Fig. 13, a boxplot for the root mean squared error (RMSE) with different numbers of feature variables for model 2 is shown. The RMSE was less than 10^{-3}

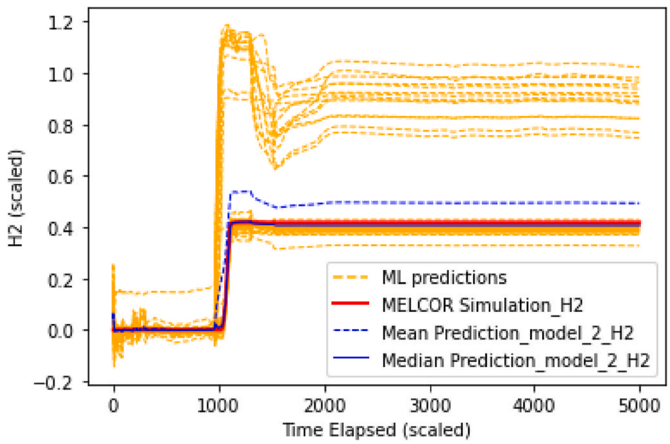

Fig. 16. ML predicted and MELCOR simulated hydrogen generation (model 2).

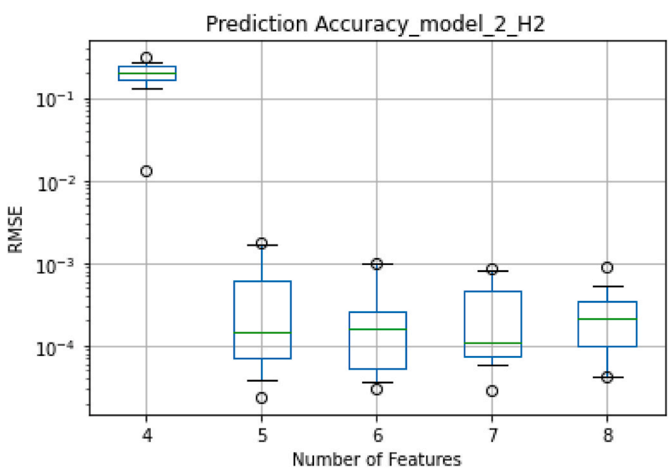

Fig. 17. RMSE with different numbers of feature variables (model 2 – hydrogen generation).

when we used the number of feature variables greater than 5.

The results of core water level prediction are shown in Fig. 14 and Fig. 15, and the results of predictions for hydrogen generation (H2) are shown in Fig. 16 and Fig. 17. We can find that the overall trend is the same as that of other target variables. There are two branches of predictions and mean and median predictions are quite close to the true value. The RMSE was less than 10^{-3} when we used the number of feature variables greater than 5.

The results of the above sensitivity studies for models 1, 2, and 3 are summarized in Table V, where averaged mean squared error at different numbers of feature variables for the predictions of different target variables are provided. We can see that the proposed ML platform can consistently predict a lost signal or key accident management parameters. The MSE was less than 10^{-3} when we used the number of feature variables greater than 5. From the comparison of results from models 1, 2, and 3, we can see that the accuracy of prediction tends to increase slightly with an increase in the range of training data. An increase in the range of training data has positive and negative effects since the weights and biases of the ML platform are optimized for all the data.

4. Concluding remark

As the proposed ML model represents the MELCOR simulated severe accident progression in a multi-variate time series of feature variables, it is a reduced-order model. We performed a systematic sensitivity study on the choice of the range of training data, target variables, number of feature variables, and number of neurons to evaluate the general applicability of the ML platform. The results discussed above demonstrate that the proposed ML platform can predict a lost signal including drywell pressure, reactor vessel pressure, and core water level and/or key accident management parameters such as the amount of hydrogen generation and mass of nuclear aerosols properly.

Since we do not know the best hyper-parameters for the ML platform in advance, we looked at the statistical distributions of the predictions. We obtained the mean, median, 95 %, 5 % of the distributions for 225 cases compiling the results of models 1, 2, and 3 for each target variable. It is seen that the median and mean of the distributions follow the true value quite closely consistently for all target variables.

Pre-trained ML model for a specific target variable such as drywell pressure exercised for all 3 models with 75 sensitivity cases took 3.2 min on a desktop computer with the specification of AMD Ryzen 7 3700X 8-Core Processor at 3.59 GHz clock speed. It is much faster than the MELCOR simulation, which would take hours for a simulation of a single case.

The above findings open a new window for the practical application of the proposed ML platform for the diagnosis and mitigation of severe accident progression. The fact that a significant portion of the test cases deviated from the MELCOR simulation results suggests that the current model needs to be improved further.

Authors contributions

JinHo Song: Conceptualization, Methodology, Software, Original Writing, **SungJoong Kim:** Reviewing and Editing, Methodology,

Table 5
Averaged mean squared error for the sensitivity study cases.

Target Variable	Models	Number of Feature Variables				
		4	5	6	7	8
Drywell Pressure	1	0.026662	0.000264	0.000176	0.000137	0.000148
	2	0.021561	0.000095	0.000528	0.000217	0.000048
	3	0.022972	0.000202	0.000060	0.000106	0.000039
Amount of Nuclear Aerosols	1	0.053313	0.000731	0.000448	0.000393	0.000363
	2	0.054761	0.000665	0.000289	0.000239	0.000220
	3	0.055287	0.000396	0.000453	0.000220	0.000199
Reactor Vessel Pressure	1	0.130440	0.000779	0.000573	0.000519	0.000368
	2	0.070159	0.000505	0.000408	0.000323	0.000270
	3	0.071431	0.000401	0.000285	0.000336	0.000251
Core Level	1	0.147953	0.001016	0.000805	0.000712	0.000629
	2	0.099299	0.000733	0.000604	0.000537	0.000499
	3	0.108546	0.000711	0.000697	0.000517	0.000419
Amount of Hydrogen Generation	1	0.400574	0.000796	0.000815	0.001128	0.000639
	2	0.198134	0.000479	0.000259	0.000285	0.000270
	3	0.223899	0.000216	0.000320	0.000248	0.000345

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Data availability

Data are available from the authors upon reasonable request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] IAEA, The Fukushima Daiichi Accident, 1 – 4, 2015.
[2] TEPCO, Information Portal for the Fukushima Daiichi Accident Analysis and Decommissioning Activities, 2022. https://fdada.info/en/home2/. (Accessed 31 August 2023).
[3] USNRC, ML11171A416 - Westinghouse AP1000 Design Control Document Rev. 19 - Tier 2, 2011 (Chapter 19) - Probabilistic Risk Assessment - Appendix 19D Equipment Survivability Assessment (36 page(s), 6/13/2011, https://www.nrc.gov/docs/ML1117/ML11171A500.html. (Accessed 31 August 2023).
[4] V. Sobes, B. Hiscox, E. Popov, et al., AI-based design of a nuclear reactor core, Sci. Rep. 11 (2021) 19646, https://doi.org/10.1038/s41598-021-98037-1.
[5] G.P. Choi, et al., Estimation of LOCA break size using cascaded fuzzy neural networks, Nucl. Eng. Technol. 49 (3) (2017) 495–503.
[6] M.I. Radaideh, et al., Neural-based time series forecasting of loss of coolant accidents in nuclear power plants, Expert Syst. Appl. 160 (2020) 113699, https://doi.org/10.1016/j.eswa.2020.113699.
[7] Y.H. Chae, S.G. Kim, H. Kim, J.T. Kim, P.H. Seong, A methodology for diagnosing FAC induced pipe thinning using accelerometers and deep learning models, Ann. Nucl. Energy 143 (2020) 107501.
[8] J. Bae, J.W. Park, S.J. Lee, Limit surface/states searching algorithm with a deep neural network and Monte Carlo dropout for nuclear power plant safety assessment, Appl. Soft Comput. 124 (2022) 109007.
[9] Y. Chae, C. Lee, S. Han, P. Seong, Graph neural network based multiple accident diagnosis in nuclear power plants: data optimization to represent the system configuration, Nucl. Eng. Technol. (2022) 54.
[10] G. Lee, S.J. Lee, C. Lee, A convolutional neural network model for abnormality diagnosis in a nuclear power plant, Appl. Soft Comput. 99 (2021).
[11] S. Ryu, B. Jeon, H. Seo, M. Lee, J.-W. Shin, Y. Yu, Development of Deep Autoencoder-Based Anomaly Detection System for HANARO, Nuclear Engineering and Technology, 2022.
[12] S. Ryu, H. Kim, S.G. Kim, K. Jin, J. Cho, J. Park, Probabilistic deep learning model as a tool for supporting the fast simulation of a thermal–hydraulic code, Expert Syst. Appl. (2022) 200.
[13] J. She, et al., Diagnosis and prediction for loss of coolant accidents in nuclear power plants using deep learning methods, Front. Energy Res. (2021), https://doi.org/10.3389/fenrg.2021.665262.
[14] J.H. Shin, J.M. Kim, S.J. Lee, Abnormal state diagnosis model tolerant to noise in plant data, Nucl. Eng. Technol. 53 (2021) 1181–1188.
[15] J.S. Kang, S.J. Lee, Concept of an intelligent operator support system for initial emergency responses in nuclear power plants, Nucl. Eng. Technol. 54 (2022) 2453–2466.
[16] K. Hossny, W. Villanueva, H.D. Wang, Distinctive physical insights driven from machine learning modelling of nuclear power plant severe accident scenario propagation, Sci. Rep. 13 (2023) 930, https://doi.org/10.1038/s41598-023-28205-y.
[17] J.H. Song, K.S. Ha, A simulation and machine learning informed diagnosis of the severe accidents, Nucl. Eng. Des. 395 (2022) 111881, https://doi.org/10.1016/j.nucengdes.2022.111881.
[18] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural Comput. 9 (8) (1997) 1735–1780.
[19] B. Lindemann, et al., A survey on long short-term memory networks for time series prediction, Procedia CIRP 99 (2021) 650–655, https://doi.org/10.1016/j.procir.2021.03.088.
[20] A. Sagheer, M. Kotb, Time series forecasting of petroleum production using deep LSTM recurrent networks, Neurocomputing 323 (2019) 203–213, https://doi.org/10.1016/j.neucom.2018.09.082.
[21] SNL, SAND2018-13560 O, MELCOR Computer Code Manuals 2 (2018). Reference Manual Version 2.2.11932.
[22] M. Pellegrini, et al., Main findings, remaining Uncertainties, and lessons learned from the OECD/NEA BSAF project, Nucl. Technol. (2020), https://doi.org/10.1080/00295450.2020.1724731.
[23] T. Sevón, A melcor model of Fukushima Daiichi unit 3 accident, Nucl. Eng. Des. 284 (2015) 80–90, https://doi.org/10.1016/j.nucengdes.2014.11.038.
[24] S.I. Kim, et al., Analysis of Fukushima unit 2 accident considering the operating conditions of RCIC system, Nucl. Eng. Des. 298 (2016) 183–191.
[25] S. He, et al., A deep-learning reduced-order model for thermal hydraulic characteristics rapid estimation of steam generators, Int. J. Heat Mass Tran. 198 (2022) 123424.
[26] N.W. Porter, Wilks' formula applied to computational tools: a practical discussion and verification, Ann. Nucl. Energy 133 (2019) 129–137.
[27] Z. Che, S. Purushotham, K. Cho, et al., Recurrent neural networks for multivariate time series with missing values, Sci. Rep. 8 (2018) 6085, https://doi.org/10.1038/s41598-018-24271-9.
[28] F. Emmert-Streib, et al., An introductory review of deep learning for prediction models with big data, Front. Artif. Intell. (2020), https://doi.org/10.3389/frai.2020.00004.
[29] M. Abadi, et al., Tensorflow: Large-Scale Machine Learning on Heterogeneous Distributed *Systems*, 2016 *arXiv preprint arXiv:1603.04467*.
[30] Diederik P. Kingma, Jimmy Ba. Adam: A Method for Stochastic Optimization, 2015. https://doi.org/10.48550/arXiv.1412.6980. Published as a conference paper at ICLR 2015.
[31] M. Hosoda, S. Tokonami, H. Tazoe, et al., Activity concentrations of environmental samples collected in Fukushima Prefecture immediately after the Fukushima nuclear accident, Sci. Rep. 3 (2013) 2283, https://doi.org/10.1038/srep02283.