

## Prediction of Golden Time for SIS Recovery during LOCAs via Rule-Dropout Deep Fuzzy Neural Networks

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### 1. Introduction

If a loss-of-coolant accident (LOCA) happens in nuclear power plants (NPPs), core cooling capability is maintained and abnormal states are mitigated by various safety-related systems and facilities in NPP. However, in the event that safety injection systems (SISs) among these systems do not function in time, core cooling capability can be lost on account of delayed emergency core coolant injection, and eventually the risk that reactor core is uncovered and damaged can occur. Hence, a technique to predict the time for SIS recovery is considered to be needed to prevent core uncover and reactor vessel (RV) failure in the LOCA circumstance when SISs do not normally work. In this study, the corresponding time is defined as golden time.

As a technique that predicts golden time, deep fuzzy neural networks (DFNNs) [1-3] with rule-dropout is utilized in the study. Briefly, the rule-dropout DFNN, a kind of artificial intelligence technique, is the method that syllogistic fuzzy reasoning through multi-connected fuzzy neural network (FNN) modules is simplified and the fuzzy rule number in every single FNN module is individually adjusted to efficiently improve its inference capability by its multiple modules. Simulated data on the postulated LOCAs in which safety injection does not normally actuated in optimized pressurized reactor 1000 (OPR1000) were applied to the rule-dropout DFNN.

### 2. Deep Fuzzy Neural Networks with Rule-Dropout

#### 2.1 DFNN

The DFNN, which determines an entire network structure of the rule-dropout DFNN, consists of more than two FNN modules; thus, it takes not only basic inference mechanism by FNN but also the structure that a result from the previous module is transferred into the next module as a fact for syllogistic reasoning as the main characteristics. In the DFNN, a result from the directly connected former FNN module is transmitted into the current FNN module as an additional input (refer to Eq. (1)). The DFNN can be considered as an efficient method since only one result gradually improved through all the FNN modules is utilized in the final module.

$$\begin{aligned} &\text{IF } x_1(k) \text{ is } \mu_{i1}^l(k) \text{ AND } \cdots \text{ AND } x_m(k) \text{ is } \mu_{im}^l(k), \\ &\text{AND } \hat{y}^{(l-1)}(k) \text{ is } \mu_{i(m+1)}^l(k), \end{aligned} \quad (1)$$

$$\text{THEN } \hat{y}^l(k) \text{ is } f_i(x_1(k), \cdots, x_m(k), \hat{y}^{(l-1)}(k)) \quad (l > 1)$$

where  $x_j$  ( $j=1, 2, \cdots, m$ ) is the input variable,  $\mu_{ij}$  is the membership function for the  $i$ -th fuzzy rule ( $i=1, 2, \cdots, n$ ) and the  $j$ -th input,  $\hat{y}^l$  is the output from the  $l$ -th FNN module, and  $f_i$  is the consequent part of the  $i$ -th rule, which is generally a first-order polynomial of the inputs as follows:

$$f_i(x_1(k), \cdots, x_m(k), \hat{y}^{(l-1)}(k)) = \sum_{j=1}^{m+1} q_{ij} x_j(k) + r_i \quad (l > 1) \quad (2)$$

Here,  $q_{ij}$  and  $r_i$  are the weighting value of the  $j$ -th input for the output of the  $i$ -th fuzzy rule and the bias of the  $i$ -th rule output.

As internal structure of the rule-dropout DFNN, each of the FNN module consists of typical five-layer FNN, where Takagi-Sugeno type fuzzy inference is implemented [4]. In the FNN module, the  $i$ -th rule of the  $j$ -th variable is defined using Gaussian function of Eq. (3).

$$\mu_{ij}(x_j(k)) = \exp(-(x_j(k) - c_{ij})^2 / 2s_{ij}^2) \quad (3)$$

where  $c_{ij}$  and  $s_{ij}$  are the center position and the sharpness of a Gaussian function, respectively.

#### 2.2 Rule-Dropout DFNN

The existing DFNN can induce overfitting since the FNN modules of which the number of fuzzy rules is the same are sequentially connected. Hence, the fuzzy rule number of each FNN module is individually adjusted by the rule-dropout. The rule-dropout determines the number of fuzzy rules by dropping out (or maintaining) specific fuzzy rules among the entire fuzzy rules, which are the same in all the FNN modules. The fuzzy rule number to be dropped out is selected using a genetic algorithm (GA) [5] finding which fuzzy rules are not appropriate. Once the fuzzy rules are dropped out, the nodes and connectives on them are eliminated in the FNN module.

In the rule-dropout DFNN, the number of fuzzy rules in the former part is usually less than that in the latter part. That is, the fuzzy rule number which is maintained increases as the FNN module is added. Therefore, the rule-dropout DFNN can be established as an optimal model by adding the module with proper

fuzzy rule number determined while preventing overfitting.

### 2.3 Rule-Dropout DFNN Optimization

The optimization of the overall rule-dropout DFNN is basically achieved through module optimization. GA and least-squares methods were used to optimize each module. The GA was applied to optimize for the number of fuzzy rules and the antecedent parameters. In addition, the GA used the fitness function of Eq. (4) to select the optimal fuzzy rule number and antecedent parameter values among candidate groups generated by the genetic operation.

$$F_r = \exp(\alpha E_{r_1} + \beta E_{r_2} + \alpha(E_{v_1} - E_{r_1}) + \beta(E_{v_2} - E_{r_2}))$$

$$\text{condition} \begin{cases} \alpha(E_{v_1} - E_{r_1}) = 0, E_{v_1} < E_{r_1} \\ \beta(E_{v_2} - E_{r_2}) = 0, E_{v_2} < E_{r_2} \end{cases} \quad (4)$$

where  $\alpha$  and  $\beta$  are negative coefficients.  $E_{r_1}$  and  $E_{v_1}$  are root mean square (RMS) error for training and verification data, respectively.  $E_{r_2}$  and  $E_{v_2}$  are maximum error for training and verification data. The RMS and maximum errors for training data follow Eqs. (5) and (6), and the errors for verification data are calculated in the same way.

$$E_{r_1} = \sqrt{\frac{1}{N_t} \sum_{k=1}^{N_t} \left( \frac{y(k) - \hat{y}(k)}{y(k)} \times 100 \right)^2} \quad (5)$$

$$E_{r_2} = \max_k \left| \frac{y(k) - \hat{y}(k)}{y(k)} \times 100 \right|, k = 1, 2, \dots, N_t \quad (6)$$

The least-squares method was applied to optimize the consequent parameters  $q_{ij}$  and  $r_i$  in Eq. (2).  $q_{ij}$  and  $r_i$  were determined by minimizing the following Eq. (7):

$$J = \frac{1}{2} \sum_{k=1}^{N_t} (y(k) - \hat{y}(k))^2 \quad (7)$$

After the FNN module is optimized through GA and least-squares, the module identification proceeds by the fitness function in Eq. (8). The fitness values calculated in the previous module and the current module are compared, and it is configured as a primary model only when the fitness value of the current module is higher.

$$F_{all} = \exp(-\omega_1 E_{a_1} - \omega_2 E_{a_2}) \quad (8)$$

where  $\omega_1$  and  $\omega_2$  are coefficients for RMS and maximum errors for development data, which is combining training and verification data. Likewise,  $E_{a_1}$  and  $E_{a_2}$  are calculated in the same way as Eqs. (5) and (6).

FNN module optimization and identification proceed up to the maximum number of FNN modules. The maximum number of FNN modules is 15. When the number of FNN modules reaches the maximum, the final model is determined by selecting the optimal

number of FNN modules from the primary model configured using Eq. (8).

### 3. Data Preparation

Modular accident analysis program (MAAP) [6] was used to simulate the postulated LOCA scenarios for the acquisition of the data used for developing a golden time prediction model. Specifically, LOCA location, delayed operation of high-pressure safety injection (HPSI) and low-pressure safety injection (LPSI), and pressurizer power-operated relief valve (PORV) open/close operation were involved in considered scenarios as presented in Table I. In addition, safety injection tank and containment spray system were assumed to work normally. In Table I, the reason why HPSI and LPSI operation is delayed is to find the maximum time when core uncover and RV failure do not occur even if the SISs are not functioning in time. The range of LOCA break size is from 1/10,000 of double-ended guillotine break (DEGB) to DEGB, which is divided into 270 cases. Hence, the number of 270 simulated data on each accident type was acquired using the MAAP, respectively.

To develop the golden time prediction model, 6 input variables related to core integrity and heat removal were applied. The data applied to the training were obtained by integrating 30 or 60 or 150 seconds after the reactor trip from the total data simulated according to the sequence of the accident. In order to effectively learn and test the prediction model, the data are split into training, verification, and test data.

Table I: Postulated LOCA scenarios

Accident type	1	2	3	4
LOCA location	Hot-leg		Cold-leg	
HPSI operation	Delay injection & recirculation	N/A	Delay injection & recirculation	N/A
LPSI operation	N/A	Delay injection & recirculation	N/A	Delay injection & recirculation
PORV	Close	Open	Close	Open

### 4. Prediction Results of Golden Time for SIS Recovery

#### 4.1 Prediction Results of Golden Time Using Rule-Dropout DFNN

When predicting the golden time using the developed rule-dropout DFNN model, the number of optimized fuzzy rules for each module is 2 to 4. In general, rule-dropout DFNN has improved inference performance as the number of fuzzy rules increases, but the number of fuzzy rules is relatively low when predicting golden time; it is because it is possible to accurately predict the golden time with only a small number of fuzzy rules. Rather, as the number of fuzzy rules increases, high prediction errors occurred. Fig. 1 shows the characteristic of rule-dropout DFNN, which shows improved prediction performance as the number of FNN modules increases. That is, as the FNN module increases, the RMS error decreases, and the fitness value increases.

Tables II and III show the golden time prediction performance through the developed rule-dropout DFNN model. RMS and maximum errors for test data are within about 3.6% and 15.5% in hot-leg LOCA, and about 4.2% and 13.3% in cold-leg LOCA. Most of the prediction errors are higher when performing golden time prediction to prevent RV failure. This is because the input data do not change significantly when the break size is small, but the prediction value fluctuates severely. Figs. 2 and 3 show the prediction result of the rule-dropout DFNN model.

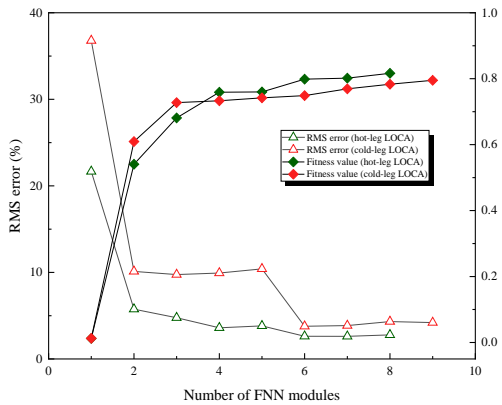


Fig. 1. RMS error and fitness value according to the number of FNN modules (in case of the golden time prediction to prevent core uncover in accident type 1 and 3).

Table II: Prediction performance of rule-dropout DFNN model (hot-leg LOCA)

SIS operation	Prevention target	Training data		Test data	
		RMS error (%)	Max. error (%)	RMS error (%)	Max. error (%)
HPSI delay	Core uncover	1.705	5.265	2.784	6.688
	RV failure	5.737	45.846	3.576	15.498
LPSI delay	Core uncover	0.827	2.093	0.950	1.959
	RV failure	1.239	6.919	3.237	14.706

Table III: Prediction performance of rule-dropout DFNN model (cold-leg LOCA)

SIS operation	Prevention target	Training data		Test data	
		RMS error (%)	Max. error (%)	RMS error (%)	Max. error (%)
HPSI delay	Core uncover	1.825	11.070	4.201	13.296
	RV failure	2.809	16.395	2.183	8.141
LPSI delay	Core uncover	0.269	1.011	0.667	1.969
	RV failure	1.221	7.001	1.856	7.334

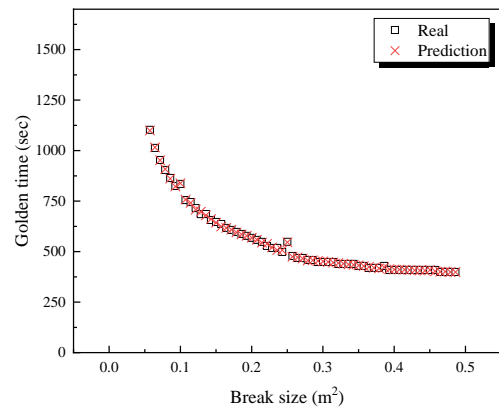


Fig. 2. Golden time prediction result to prevent core uncover (in case of accident type 2).

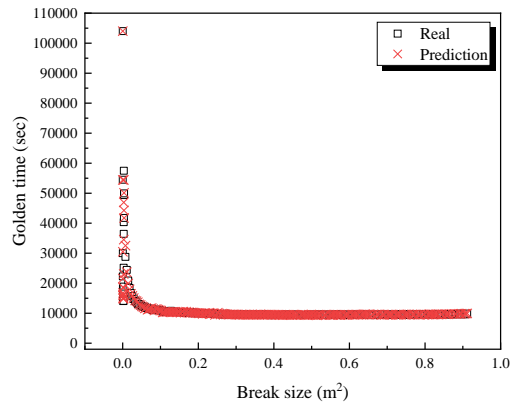


Fig. 3. Golden time prediction result to prevent RV failure (in case of accident type 3).

#### 4.2 Comparison with Prediction Results for Golden Time Using Support Vector Regression

The prediction performance of the developed rule-dropout DFNN model was compared with that of the support vector regression (SVR) model. The SVR model has the same structure and characteristics as the SVR used in the previous study [7], but the applied input variables and data are different; it is the same as those applied for the rule-dropout DFNN model

development. Tables IV and V show the prediction performance of SVR model. Overall, the prediction error of the rule-dropout DFNN model is lower than that of the SVR model. Especially, RMS and maximum errors for the case of RV failure prevention are much more reduced in the rule-dropout DFNN model.

The SVR and rule-dropout DFNN models have different learning mechanisms. The SVR model is a method of determining an optimal regression function by mapping training data to feature space of high dimension [8], whereas the rule-dropout DFNN model performs multi-level learning in which one step ahead learning is consistently added to the next learning by adding the FNN modules. The main reason why the SVR model shows higher error than the rule-dropout DFNN model with regard to the golden time prediction is considered that it originates from the difference of these learning mechanisms for both methods.

Table IV: Prediction performance of SVR model (hot-leg LOCA)

SIS operation	Prevention target	Training data		Test data	
		RMS error (%)	Max. error (%)	RMS error (%)	Max. error (%)
HPSI delay	Core uncover	0.621	2.854	2.947	4.936
	RV failure	7.336	82.357	1.957	7.137
LPSI delay	Core uncover	0.033	0.042	4.573	10.970
	RV failure	8.829	69.499	10.774	43.203

Table V: Prediction performance of SVR model (cold-leg LOCA)

SIS operation	Prevention target	Training data		Test data	
		RMS error (%)	Max. error (%)	RMS error (%)	Max. error (%)
HPSI delay	Core uncover	0.136	0.270	2.748	8.101
	RV failure	0.966	12.559	9.260	37.431
LPSI delay	Core uncover	0.235	1.355	3.000	8.566
	RV failure	1.229	15.105	8.818	43.952

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### 5. Conclusions

In this study, the golden time for SISs recovery was predicted to prevent aggravation of accidents when SISs do not operate normally in LOCA situation. Rule-dropout DFNN model was developed as a technique for predicting golden time. Specifically, the rule-dropout DFNN model predicted the golden time to prevent core uncover and RV failure. The rule-dropout DFNN model accurately predicted the golden time and showed a much lower prediction error compared to the SVR model. Therefore, the developed rule-dropout DFNN model can be utilized as a foundational technique to provide the maximum time for the operator to recover the SISs when the SISs are not working, and to help the operator take action within golden time.

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