# OPTIMIZATION OF FUZZY MEMBERSHIP FUNCTION-BASED ABNORMAL EVENT DIAGNOSIS MODEL IN NUCLEAR POWER PLANTS

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## ABSTRACT

Abnormal event diagnosis models for nuclear power plants have been extensively studied using plant simulators. However, discrepancies exist between real plant data and simulator-generated data due to factors such as the simplification of thermal-hydraulic codes in simulators and sensor noise in actual plants. These discrepancies can reduce the effectiveness of artificial intelligence-based diagnosis models and limit real-plant applicability. To solve this problem, we propose an abnormal event diagnosis model incorporating an optimized fuzzy membership function-based feature extraction method to represent trend features from simulator-generated data. By optimizing fuzzy membership functions, the model improves the extracting performance of trend features and this method can make abnormal event diagnosis model more representative of actual plant behavior. A membership function optimization algorithm is employed to systematically adjust membership function parameters and ensures more effective trend extraction from the data. This approach enhances the diagnostic performance of the deep neural network-based diagnosis model by providing optimally extracted data trends that adjust more robust for real plant conditions. Experimental results demonstrate that the optimized fuzzy membership function-based feature extraction method effectively captures data trends while mitigating discrepancies between simulated and synthetic data designed to mimic real plant characteristics. The findings suggest that the proposed method can improve the robustness and reliability of abnormal event diagnosis models by facilitating applicability in real plant environments. This study contributes to developing a more robust and reliable artificial intelligence-based abnormal event diagnosis model and ultimately supporting safer and more efficient plant operations.

Keywords: Nuclear power plant, Deep neural network, Abnormal event, Diagnosis, Fuzzy membership function

## I. INTRODUCTION

An abnormal event diagnosis in nuclear power plants remains a crucial safety task because operators must recognize changes in plant behavior quickly and decide on corrective actions under severe time pressure. Most artificial-intelligence diagnosis models are trained almost exclusively on data generated by high-fidelity plant simulators, because such simulators can reproduce a wide range of events without endangering actual equipment. Unfortunately, when these same models are deployed in actual control rooms, we cannot expect the same level of performance they demonstrated in the simulator. One root cause is that the thermal-hydraulic codes embedded in simulators, although detailed, still simplify or omit secondary phenomena, for example three-dimensional mixing, sub-cooled boiling in complex geometries. At the same time, real instruments in an operating plant introduce additional uncertainties: sensor drift accumulates over months, calibration bias shifts set-points, electromagnetic interference injects random noise, and control-system delays distort time stamps. The combined effect is a systematic distribution shift: statistical properties such as mean, variance, and cross-correlation of simulator signals differ from those of real-plant signals, as shown in Fig. 1 [1]. Models that learned fine-grained decision boundaries in the simulator domain therefore encounter unfamiliar patterns in real plants, leading to reduced diagnostic accuracy in the transient [1].

To solve the discrepancies between simulator data and real-plant data, we propose an abnormal event diagnosis framework that converts each plant variable into fuzzy membership functions capturing long-term trends—decrease, stay equal, or increase—through a fuzzy-based feature extraction method (FFEM) [2]. In addition, the membership functions for key variables are optimized via gradient descent to maximize inter-class separation, and the resulting optimized membership functions are fed into a neural classifier, enabling the extracted features to reproduce real-plant behavior with much higher fidelity. Supplying these optimized fuzzy features to a simple one-dimensional convolutional neural network (CNN) greatly improves robustness: accuracy stays above 95 percent even when synthetic plant data emulates harsh plant conditions, whereas a conventional CNN model without FFEM degrades sharply. The remainder of this paper details the data preparation pipeline, the FFEM design, the membership-function optimization algorithm, and the diagnosis network architecture.

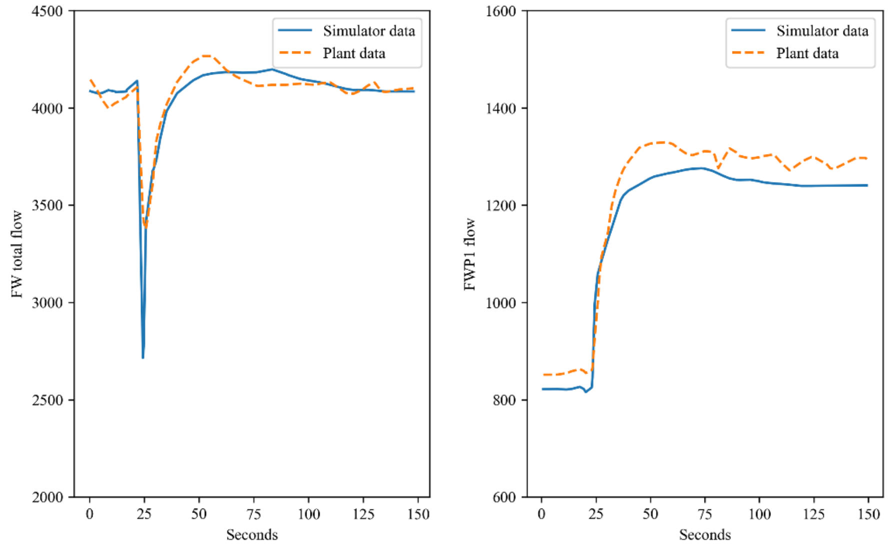


**FIGURE 1. Data discrepancies between simulator and plant data for feedwater total flow (left) and feedwater pump 1 flow (right).**

## II. METHOD

### I.A. Fuzzy-based Feature Extraction Method

Fuzzy logic was proposed to describe ambiguous or uncertain situations that ordinary binary logic cannot handle. Instead of assigning a crisp "true" or "false" value, fuzzy logic expresses how strongly a numerical input belongs to intuitive linguistic concepts such as low, normal, or high. This graded approach helps machines interpret real-world sensor signals that include noise and drift [3]. Our abnormal event diagnosis framework applies fuzzy logic at the feature level and a neural network at the decision level. Every process variable is first converted to a long-term trend value that compares the current reading with two earlier points. The trend enters a set of membership functions that assign fuzzy grades for decrease, stay equal, and increase, as shown as Fig. 2. The resulting fuzzification represents plant behavior in a form that is less sensitive to short-term fluctuations than raw data. A simple one-dimensional convolutional classifier then maps the fuzzy features to an event label.

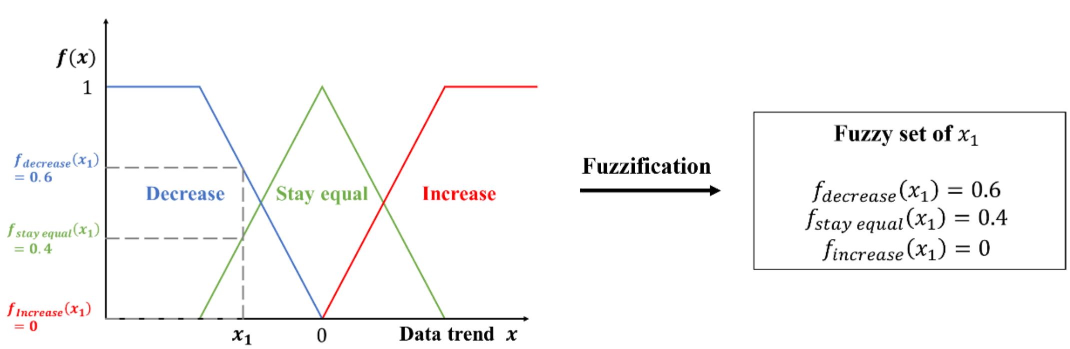


**FIGURE 2. Fuzzification process of a data trend.**

Fig 3. Overall architecture that connects a conventional fuzzy-inference system (top) with the proposed abnormal event diagnosis framework (bottom). In the classical scheme, crisp sensor measurements are first fuzzified, evaluated against rules stored in the knowledge base by the inference engine, and finally defuzzified into crisp control actions. The lower panel shows how the same three-step logic is embedded in our pipeline: simulator variables pass through the optimized FFEM to create fuzzy inputs; a neural-network classifier learns an abnormal event diagnosis model during the training phase (black arrows); and, during deployment (orange arrows), real-plant measurements flow through the optimized FFEM and the trained model to support operator judgment.

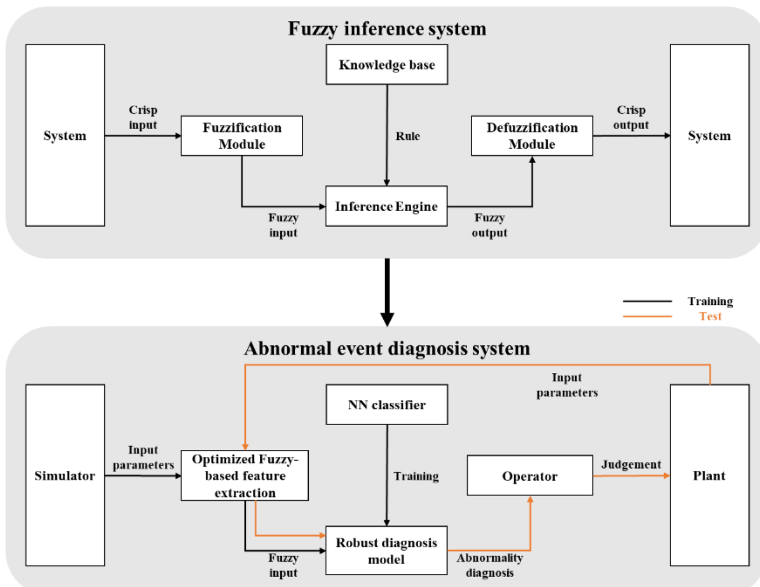


**FIGURE 3. Schematic frameworks of a fuzzy inference system and the abnormal event diagnosis system**

Fig. 4 illustrates the two-step Fuzzy-based Feature Extraction Method (FFEM) described. For each selected time-series variable $x(t)$, the long-term trend is computed. The three black traces show typical sensor histories; the red markers denote the start and end points used to evaluate $\Delta x$. A positive $\Delta x$ (red arrow) indicates a sustained increase, a negative value (blue arrow) indicates a sustained decrease, and values near zero (green arrow) correspond to a steady condition.

$$\Delta x = x(t) - x(t - 120s) \tag{1}$$

First, the long-term trend $\Delta x$ is obtained from the time series by Eq. (1). The normalized trend is then evaluated by seven triangular membership functions, $\mu_1$ through $\mu_7$, displayed in the center of Fig. 4 and labeled "high decrease," "intermediate decrease," "low decrease," "stay equal," "low increase," "intermediate increase," and "high increase." Each function returns a grade between 0 and 1, and the seven grades collectively form the fuzzy-value vector defined in Eq. (2),

$$f(\Delta x) = [\mu_1(\Delta x), \mu_2(\Delta x), \ldots, \mu_7(\Delta x)] \tag{1}$$

The right-hand bar charts in Figure 4 visualize this fuzzy set: for a moderate decrease (green path), the "low decrease" and "intermediate decrease" grades dominate; for a pronounced drop (blue path), only "high decrease" is active; and for a sharp rise (red path), "intermediate increase" dominates with a smaller contribution from "high increase."

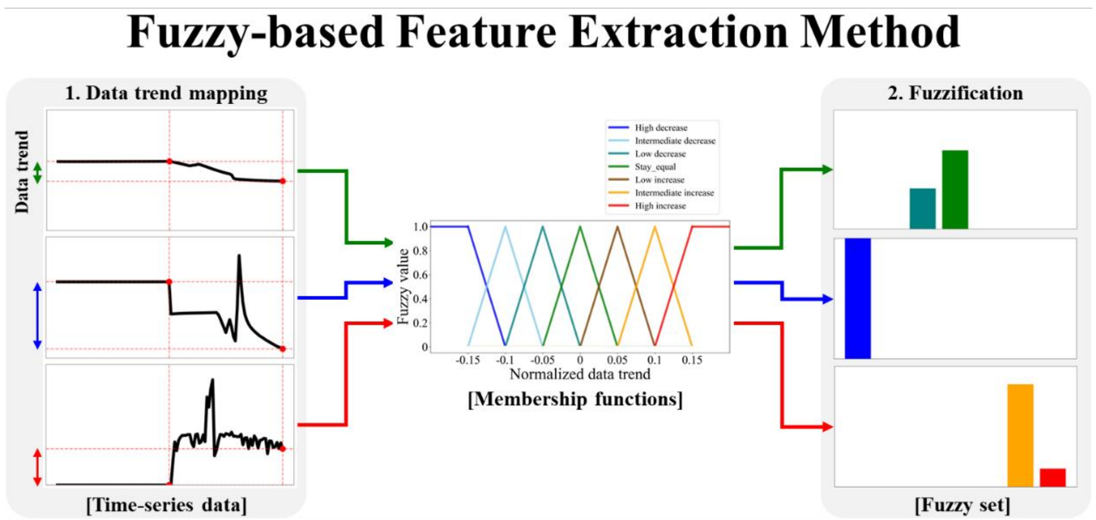


**FIGURE 4. Fuzzy-based feature extraction method (FFEM)**

### I.B. Optimized Fuzzy-based Feature Extraction Method

Before launching the gradient-descent procedure, we compute gain-based feature-importance scores for the entire set of process variables using light gradient boosting machine (LGBM). The scores are sorted in descending order, and we keep only those variables whose cumulative importance exceeds 95 percent of the total. Membership functions associated with this 95 percent subset are updated by gradient descent, while the remaining variables retain their default membership functions and are excluded from tuning. This filter ensures that optimization targets the most diagnostically relevant variables without being distracted by low-information channels.

To sharpen the discriminative power of the seven membership functions $\mu_1, \ldots, \mu_7$, we adjust their break-point parameters $\theta$ by gradient descent. The update is driven by a inter-class separation loss that enlarges the distance between every in-class sample and every out-of-class sample in fuzzy space. where $C$ is the number of classes, $D_c$ and $D_{\bar{c}}$ denote the index sets of samples with label $c$ and "not $c$", and $n_c$ and $n_{\bar{c}}$ are their sizes. The loss is negative because we maximize inter-class separation; minimizing $\mathcal{L}_{separ}$ therefore pushes the squared distance term upward. In practice we implement Eq. (5).

$$\mathcal{L}_{separ}(\theta) = -\sum_{c=0}^{C-1} \frac{1}{n_c n_{\bar{c}}} \sum_{k \in D_c} \sum_{l \in D_{\bar{c}}} \left|\left| f_\theta(x_k) - f_\theta(x_l) \right|\right|_2^2 \qquad (5)$$

### III. EXPERIMENTAL SETTINGS

The complete workflow for data generation, feature selection, fuzzy feature extraction, and model evaluation is shown in Fig. 5. A simulator is used as the common data source, but the datasets for the training environment (left, green) and the test environment (right, blue) are generated independently. For training, baseline runs are collected, passed through feature selection, the Optimized Fuzzy-based Feature Extraction Method (FFEM), and a CNN classifier that is trained on the resulting fuzzy features. For testing, the simulator is re-run under diversified operating conditions and sensor-noise injection to create synthetic plant data. The same feature-selection rules and the optimized FFEM are applied, and the pretrained CNN classifier is copied into the test pipeline to produce abnormal-event diagnoses. Dashed arrows highlight the noise-injection step (upper right) and the internal operation of FFEM (lower right).

We created the entire data set with a 1 400 MWe two-loop Barakah pressurized-water-reactor simulator. One "normal" condition and 52 distinct abnormal events were simulated. Each record spans 240 s; the abnormal event is injected exactly at $t = 120\,s$. The raw log contains about 14,000 variables. We trained an LGBM model on the changeable variable set and ranked the gain-based feature-importance scores. Only the 785 variables whose importance is positive were retained. Among those 785 variables, we applied membership-function optimization only to the 99 variables whose cumulative importance accounted for 95 percent of the total. The remaining variables retained the default membership functions shown in Fig. 4.

Normalization relies on physical units: Boolean or categorical variables are left unchanged; level signals expressed in percent are divided by 120 % of the design span; all other variables are divided by 120 % of their maximum observed value. This unit-aware scaling keeps numeric inputs in a consistent range without distorting engineering meaning.

We adopted a simple one-dimensional CNN consisting of a single Conv1D layer (128 filters, kernel size = 3) followed by ReLU activation, max-pooling, 20 % dropout, flattening, and a soft-max output layer. The model is optimized with Adam (learning rate = 0.001); training uses a batch size of 64 and early stopping with a patience of 30 epochs. The same architecture is applied to both the baseline FFEM and the optimized FFEM so that performance improvements can be attributed solely to membership-function optimization.

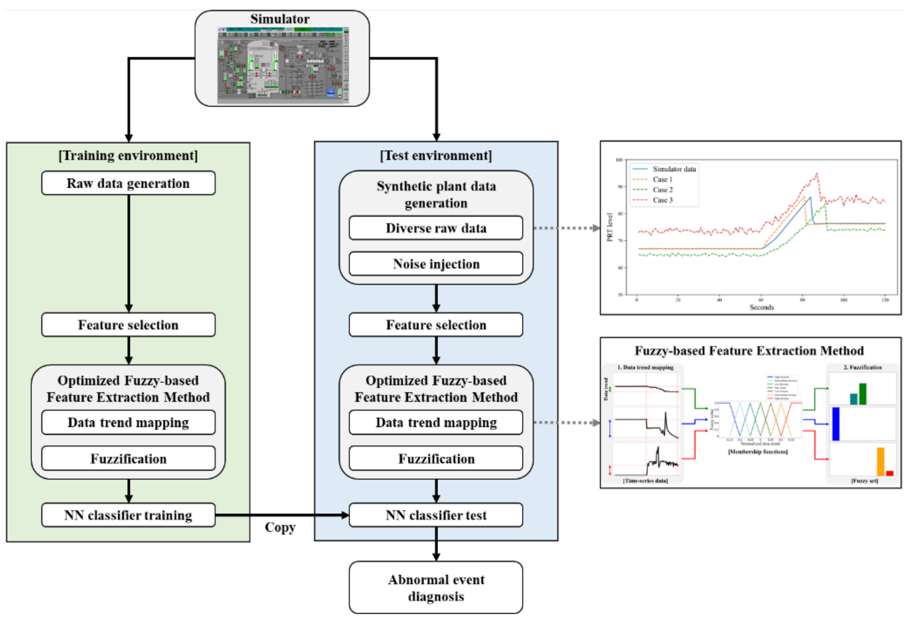


**FIGURE 5. Abnormal event diagnosis training and test process.**

## IV. RESULTS

Table 1 compares the diagnostic accuracy of the baseline model ("Not optimized") and the proposed model with optimized FFEM under four test conditions. When no synthetic noise is added ("None"), the accuracy increases from 97.0 % to 97.9 %, which is a modest yet measurable improvement. Under progressively harsher noise (Case 1 to Case 3), the optimized model consistently outperforms the baseline by 1.0 to 1.4 percentage points and never drops below 95 %. Averaged over the four test sets, membership-function optimization delivers a mean improvement of 1.2 percent point.

These findings follow the trend reported by Cho et al. [2]. In their study, removing the FFEM stage caused a clear accuracy collapse whenever sensor noise was present, whereas including fuzzy-trend features kept accuracy in the mid-90 % range. Our results show the same pattern: the optimized FFEM preserves high accuracy under all three noise cases, confirming that (i) fuzzy features shield the classifier from distribution shift and (ii) further tuning of membership functions adds an extra margin of robustness.

Fig. 6 shows the seven optimized membership functions for pressurizer pressure control system variable. After gradient descent, the triangles are evenly spaced and symmetric, fully covering the observed trend range while maximizing separation between adjacent grades. This reshaping explains the systematic accuracy gains observed in Table 1.

**TABLE I. Abnormal event diagnosis results.**

| | | Diagnostic accuracy (%) | |
|---|---|---|---|
| | | Not optimized model | Optimized model |
| Test dataset | None | 97 | 97.9 |
| | Case 1 | 96.4 | 97.4 |
| | Case 2 | 95.9 | 97 |
| | Case 3 | 94.5 | 95.9 |

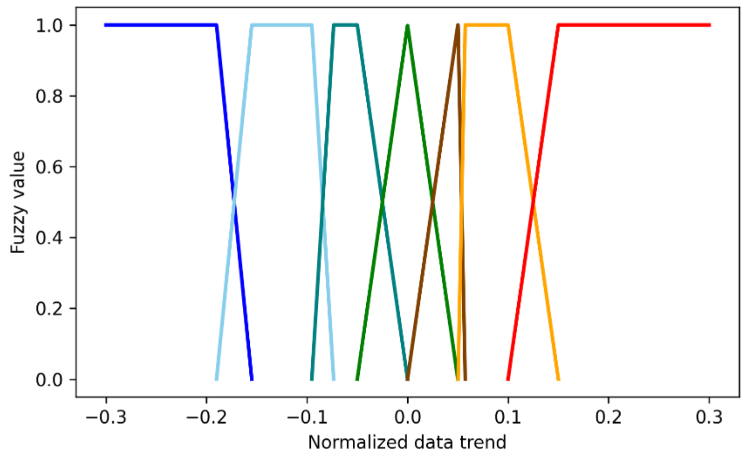


**FIGURE 6. Optimized membership function of pressurizer pressure control system.**

## V. CONCLUSIONS

This work proposed an abnormal event diagnosis framework that combines (i) LightGBM-based feature selection, (ii) the Fuzzy-based Feature Extraction Method (FFEM), and (iii) gradient-descent optimization of membership functions. Only variables whose cumulative importance exceeds 95 % are tuned, focusing computational effort on diagnostically relevant channels. Experiments with a Barakah 1 400 MWe two-loop PWR simulator demonstrate that the optimized FFEM raises average accuracy by 1.2 percent points and maintains over 95 % accuracy even under severe synthetic noise. These outcomes confirm that optimizing membership functions to maximize inter-class separation is an effective strategy for bridging the simulator-to-plant distribution discrepancies.

Future research will (a) validate the method against actual plant variables, (b) extend the optimizer to Gaussian membership shapes, and (c) integrate uncertainty quantification to provide confidence levels alongside diagnostic decisions.

## ACKNOWLEDGMENTS

This work was supported by Korea Institute of Energy Technology Evaluation and Planning(KETEP) grant funded by the Korea government(MOTIE)(RS-2024-00403194, Next-Generation Nuclear Technology Creation IP-R&D Talent (Human Resources) Development Project)

This work was supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT) (No. RS-2022-00144042)

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