# Analyzing Operation Logs of Nuclear Power Plants for Safety and Efficiency Diagnosis of Real-Time Operations

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**Abstract.** Operators' lack of understanding of the plant's operation state significantly contributes to human errors in Nuclear Power Plant (NPP) control room operations. The state of an NPP at a particular time is represented by values of analog (e.g., measurements of flow properties) and switch parameters (e.g., the status of a valve). Previous studies focused on analyzing analog parameters rarely considered the switch parameters. Estimating the plant state without considering the timings of switches can be inaccurate. This paper utilizes analog parameters to infer the timing of switches. Two main challenges of establishing a reliable prediction model are 1) high dimensional analog parameters and 2) an imbalanced switch parameter dataset with few control actions. This paper uses PCA to reduce the dimensions and SMOTE to generate more samples capturing the impacts of various control actions. Then the pre-processed data was used to train variants of KNN classifiers. Testing results show that the KNN with SMOTE oversampling but without PCA best predicts switches' timing.

## 1. Introduction

Human error is a significant contributor to the efficiency and safety issues in Nuclear Power Plant (NPP) operations (Preischl & Hellmic, 2016). Industry reports show that more than 60% of the reported events are related to human errors, among which nearly 30% of events are attributed to operation errors (IAEA, 2020). Human errors in NPP control room operations include pushing the wrong button, operating too late, controlling deviation reduced too slowly, etc. (Preischl et al., 2013). These human errors can make operators miss control goals and targets, thus leading to uncontrolled release of energy or hazardous substances. Hence, it is essential to reduce human error in NPP control room operations.

Operators' lack of understanding of the plant's real-time state and their inaccurate predictions about future plant states are the primary causes of human errors in control room operations (NRC Web, 2011). As shown in Figure 1, the operating state of NPP at a particular time is represented by two types of parameters – 1) switch parameter, which reflects the NPP component state (e.g., Valve A, valve B), and 2) analog parameter, which shows the value of process variables captured by sensor measurements (Wang et al., 2022). The analog and switch parameters within a plant have complex physical and functional interactions. Nevertheless, NPP consists of thousands of components and instruments. The large size of the plant and the many relationships within NPP systems control make it challenging for operators to maintain a holistic understanding of the plant's state and correctly predict the future states.

Many studies utilized NPP operation data to provide faster and more accurate plant behavior predictions, thus reducing human errors in control room operations. These studies used machine learning algorithms such as artificial neural networks to predict NPP behavior under different transients, monitor NPP parameter trends, and detect anomalies (Chen et al., 2018; El-Sefy et

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al., 2021). However, many studies only considered analog parameters. Discrete switch parameters containing information about plant components' states are rarely considered.

Recently, Wang et al. (2022) proposed a method to fill missing operation data of an NPP by searching the similar system operation states in control histories. In this study, the operation state of NPP is represented by a combination of analog and switch parameters. Nevertheless, few studies explored the relationship between analog and switch parameters. Joint consideration of analog and switch parameters for monitoring NPP operation is critical. Different combinations of switch parameter values can share the same analog parameter values. Relying on analog parameters alone can hardly distinguish if an anomaly is caused by the failure of process variable sensors or process fault. Thus, analog parameter-based diagnostic systems require extra human efforts to investigate the root causes of anomalies. Therefore, relying solely on analog parameters can provide human operators limited or even unreliable operation support.

This paper presents a model that maps the relationship between analog and switch parameters. The proposed model can mimic the human decision-making process in NPP control room operations. The model takes time series of analog parameter values as inputs, and operation decisions, such as whether to manipulate a component or not, at what times, as outputs (Figure 1). The key contributions are: 1) revealing the necessity of understanding the interwoven relationship between analog and switch parameters. Such understanding can lay a foundation for developing intelligent operation support tools that imitate human operators to generate control decisions. 2) proposing a modeling framework based on k Nearest Neighbours that predict the switch parameters using time series of analog parameters as inputs. We tested and validated the proposed framework through pseudo-operators' control histories collected in a human-in-the-loop NPP operation experiment.

## 2. Problem Formulation

The problem tackled in this paper is to map a set of analog parameter values to control actions based on control histories. The data structure of control histories and the problem formulation are introduced below.

All NPP operators must follow strict technical standards (Medema et al., 2012). These technical standards, also known as NPP operation procedures, provide step-by-step directions on observing real-time NPP sensors alarms and manipulating NPP control objects (e.g., turn-on valves). Stepwise instructions define the operational processes and control actions. However, the task guidance provided by these procedures is static. Operators must rely on their experiences and knowledge to estimate the "waiting" time between different steps to avoid missing the control targets.

Control actions defined in the procedures trigger changes in switch parameters. This paper uses switch parameters to infer the control action and the corresponding wait time before performing that control action. Eq. (1) illustrates if a component's state $c_t$ at time t is different from its state at time $t-1$ indicates the occurrence of a control action $CtrlA_t$. For example, Figure 1 shows three plant components' states. Valve A and valve B have discrete states, and Rod has a continuous state. According to Eq. (1), when $t = 1$, the operator did not perform any control action; therefore, the algorithm will label the work status as {wait}, the operator turned on valve A at time 2s and then manipulated Rod 1 at time 3s.

$$CtrlA_t = \begin{cases} 0, & c_t = c_{(t-1)} \\ 1 & c_t \neq c_{(t-1)} \end{cases} \tag{1}$$

Switch parameters

Analog parameters

| Time (s) | Valve A | Valve B | Rod 1 | Work status (control action/wait) | Core temperature (DEG F) | Cooling flow (KPPH) |
|---|---|---|---|---|---|---|
| 1 | OFF | OFF | 0 | Wait | 181.16 | 20.45 |
| 2 | ON | OFF | 0 | Valve A ON | 182.50 | 20.22 |
| 3 | ON | OFF | 11 | Rod 1 | 184.03 | 20.12 |
| 4 | ON | OFF | 11 | Wait | 185.60 | 20.11 |
| 5 | ON | ON | 11 | Valve B ON | 187.40 | 20.09 |
| 6 | ON | ON | 12 | Rod 1 | 189.23 | 20.08 |

**Model input:** Time series of analog parameters in the last three seconds

**Model output:** Work status at the fourth second

Operator's control decision

Figure 1: The operating state of NPP at a specific time is represented by a set of analog parameters and switch parameters (Wang et al., 2022). The changes in switch parameters reflect the operator's control decision.

A combination of plant analog and switch parameters can describe the operational state of the NPP. Similarly, the analog parameters and control action represent the operator's control decision at a particular time. Each control action corresponds to a specific range of analog parameter values (also called "operation context"). In other words, when one or multiple analog parameter values reach a certain degree, the operator in charge should manipulate the corresponding control object to ensure plant safety. NPP control room operators need to observe tens of analog parameters, indicators, and alarms to monitor plant operation. In the monitoring process, operators need to closely follow the trending of analog parameters to avoid missing the optimal contextual timing for performing each control action. Thus, the operators spent most of the time monitoring the analog parameters and little time performing control actions in an operation task. Therefore, two main challenges associated with NPP operations are: 1) the high dimension analog parameters make it challenging for operators to gain a comprehensive understanding of analog parameters' trends; 2) the control histories are imbalanced datasets because of the less frequent work status of control actions compared to {wait} class. As a result, operators are likely to miss the optimal operation context.

## 3. The Proposed Methodology

This paper aims to develop models to predict the most likely control actions based on control histories while overcoming the two challenges mentioned above: 1) high dimensional data and 2) imbalanced data samples for control actions and waiting times. The proposed framework consists of three steps (Figure 2 ): data pre-processing, model training, and model testing. The data pre-processing step employed dimension reduction and oversampling techniques to resolve the challenges brought by high dimensional analog parameters and imbalanced control histories. The model training step carefully selected the hyperparameters of the k Nearest Neighbour (KNN) classifiers. The testing step assessed the performance of the variant of KNN classifiers for predicting the control actions based on similar contextual analog parameters' values.

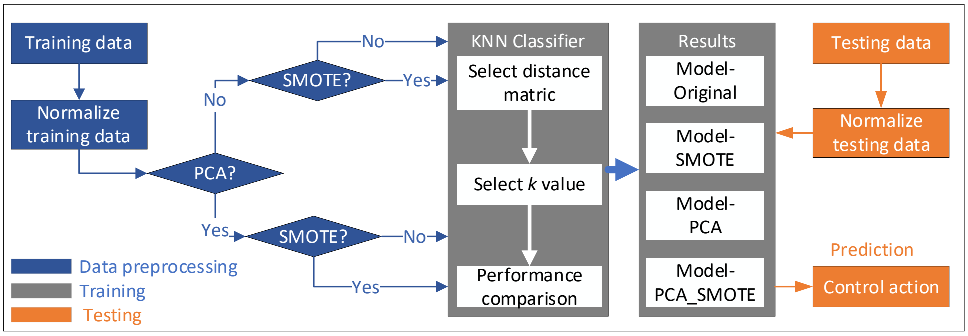


Figure 2: The framework of the proposed method for predicting switch parameters.

### 3.1 Principal Component Analysis (PCA)

Principal component analysis (PCA) has been proven very powerful in extracting critical information within process data, and it is widely applied for data-driven process monitoring (Shi et al., 2018). In PCA, let $X \in R^{m \times N}$ denote a set of normalized data with m process variables and N samples. The principal component of the data is determined by performing singular value decomposition on the covariance matrix Σ of $X$ derives:

$$\Sigma = \frac{1}{N-1} X X^T = P \Lambda P^T \tag{2}$$

Where $\Lambda = \mathrm{diag}(\lambda_1, \cdots, \lambda_m)$ $and$ $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m \geq 0$. In PCA, the load matrix $P \in \mathbb{R}^{m \times m}$ is divided as $P = [P_{pc}, P_{res}]$ and Λ is divided as $\Lambda = \begin{bmatrix} \Lambda_{pc} & 0 \\ 0 & \Lambda_{res} \end{bmatrix}$.

### 3.2 Synthetic Minority Oversampling Technique (SMOTE)

Oversampling techniques in the pre-processing step are necessary for enabling the proposed model to learn patterns from the minority class, namely control actions. This paper use SMOTE to oversample the minority class (control actions). Figure 1 shows, at time 1s, the label of the work status is {wait}. "Wait" means that the operator didn't perform any control action. NPP control histories are imbalanced since the frequency of control actions is considerably fewer than the number of {wait} status. This paper proposes SMOTE to augment the operating history. SMOTE creates synthetic samples for over-sampling the minority classes. SMOTE firstly selects several neighbors specified by the over-sampling rate. Synthetic operation states (set of analog parameters and switch parameters) are created somewhere between the original operating context and its neighbors. SMOTE is easy to implement and avoids overfitting because the synthetic samples are randomly created and prevent information loss (de Andrade Lopes et al., 2021).

### 3.3 K-nearest-neighbours (KNN)

KNN classifier is one of the most widely applied classifiers in process control research. KNN is performed by 'searching' for the nearest distance and selecting the class with the majority number among the k training data as the resulting class. In KNN, the k indicates the number of nearest neighbors to be considered in decision-making. The distance between the data is calculated by applying the distance metric. This paper adopts KNN to identify a similar operation context for performing each control action.

The classification performance of KNN is affected by the choice of distance metric and the value of k. Appropriate selection of the distance metric and value of k is important for ensuring good model performance. The pre-processed data were trained using several distance metrics and k values to select the suitable distance metric and k value. In this paper, the minimum k is set as 0, and the maximum k is determined by the minimum count of the control action classes. The paper adopted different distance metrics for the KNN classifiers and used five-fold cross-validation to evaluate and compare the performance of these classifiers.

Table 1: Distance metrics applied in KNN.

| Distance metrics | Definition | Distance function |
|---|---|---|
| Euclidean distance | The Euclidean distance is the length of a line segment between two points. | $\sqrt[2]{\sum (X-Y)^2}$ |
| Manhattan distance | The Manhattan distance between two vectors (city blocks) equals the one-norm of the distance between the vectors (Szabo, 2015). | $\sum \lvert X-Y \rvert$ |
| Chebyshev distance | The Chebyshev distance between two vectors is the greatest of their differences along any coordinate dimension (Abello et al., 2013). | $\mathrm{Max}\lvert X-Y \rvert$ |

## 4. Case Study

The authors used a gamified microworld to collect NPP control histories for testing the proposed framework of mapping time series of analog parameters to control actions. The gamified microworld reactor-Rancor was developed by Idaho National Laboratory (Ulrich et al., 2017). The Rancor simulator models five typical NPP systems: the cooling system, the reactor core, the steam generator, the feedwater system, and the turbine. As shown in Figure 3 (a), Rancor's user interface allows the experiment participants to experience NPP operation via interacting with these simulated systems of an NPP. The following introduces the experiment setup and model performance evaluations.

### 4.1 Experiment Setup

This paper selected the reactor start-up procedure as the operation task. The reactor start-up procedure is a typical NPP operation process involving various actions requiring NPP operators' attention to ensure power supplies (Boring et al., 2018). Figure 3 (b) shows the operation steps included in the start-up procedure.

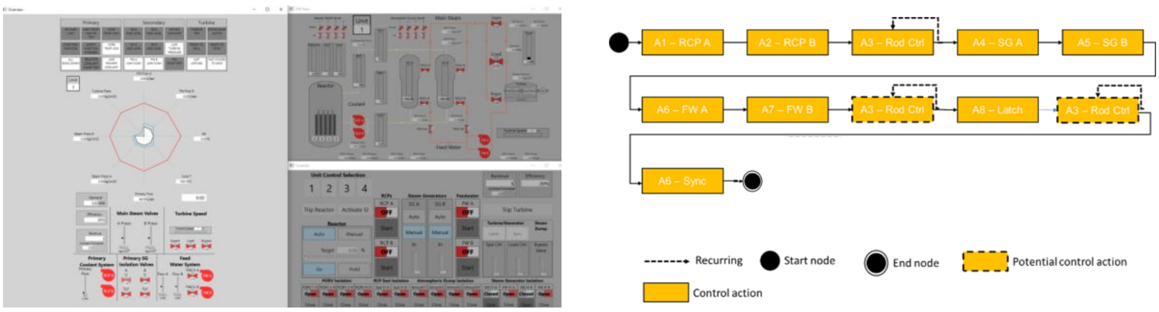


Figure 3: (a) Rancor Reactor simulator user interface; (b) Operation step in the start-up procedure.

The reactor start-up tasks involve 15 analog parameters and 10 switch parameters. The Rancor simulator updates the plant operation state each second. This paper assumes that each control action occurs at different times and that there are no concurrent control actions. The authors recruited ten student operators to perform the reactor start-up task on the Rancor simulator. Experiment participants were asked to follow the start-up procedure to start the reactor two times, and twenty control histories were collected. The experiment collected twenty control logs. As shown in Table 2, this paper used 12 logs for training and 8 logs for testing. The model input is time series of analog parameter values in the last three seconds. The model output is the work status at the fourth second. In each control log, {wait} class occupies most of the count. The training and testing set's control action ratios are 0.197 and 0.172, respectively.

Table 2: Statistics of the training set and testing set.

| | NO. of logs | Analog parameter and switch parameter pairs | Control action ratios |
|---|---|---|---|
| Training set | 12 | 1143 | 0.197 |
| Testing set | 8 | 964 | 0.172 |

### 4.2 Performance Metrics

The goal of the model is to predict control action using time series of analog parameters as input. Whether the proposed model has good prediction accuracy on the {wait} class is not the focus of this paper. This paper only considered the model's prediction accuracy on control actions. To ensure the proposed model is robust against the minority class ({wait} class) and focus on the prediction performance of the control action, this paper uses the minority classes to evaluate the model performance (Table 3).

Table 3: Confusion matrix used for calculation of performance metrics.

| Predicted | Actual | |
|---|---|---|
| | **Target control action (P)** | **Other control actions (N)** |
| Target control action (PP) | True Positive (TP) | False Positive (FP) |
| Other control actions and wait (PN) | False Negative (FN) | True Negative (TN) |

Precision, recall, F1 score, and the area under the precision-recall curve (AUC-PR) are popular performance evaluation metrics, particularly for imbalanced datasets. This paper calculated the F1 score, AUC-PR, using the confusion matrix presented in Table 3. The accuracy rate represents the percentage of correctly classified control actions and is calculated through the following equation:

$$Accuracy = \frac{number\ of\ correctly\ predicted\ control\ actions}{P+N} \quad (3)$$

## 5. Results and Discussions

### 5.1 KNN Parameter Selection

KNN algorithm has two essential parameters: the distance function and the number of K. The optimal parameters of the KNN models are decided by the best results on the training set via five-fold cross-validation. This paper use KNN to predict the correct control action by calculating the distance between the input analog parameter values and all the analog parameter values sets in the training data. Figure 4 shows the effect of the distance function and value of k. The optimal parameters k value and distance function for each model suggested in Figure 4 are shown in Table 4.

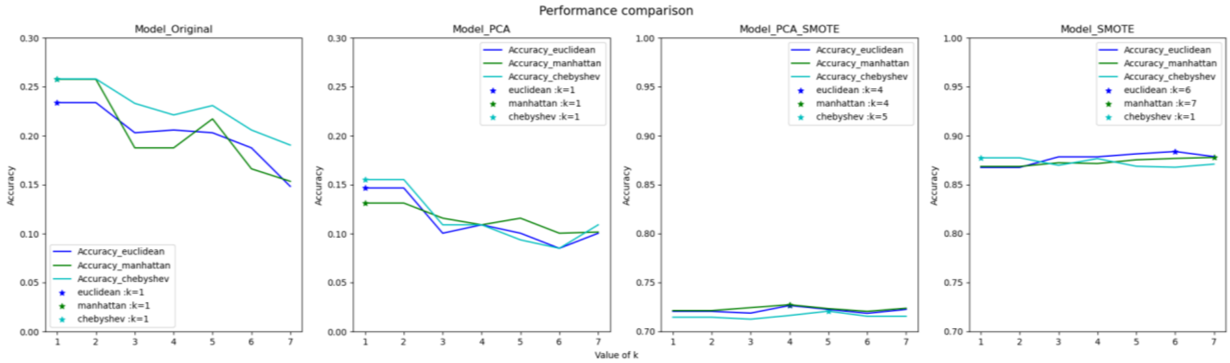


Figure 4: KNN parameter selection. Models with SMOTE oversampling have better prediction performance compared to models without oversampling.

Table 4: Parameter selection results on the four models.

| Model | Distance function | K-value | Highest Accuracy |
|---|---|---|---|
| Model-Original | Chebyshev distance | 1 | 0.258 |
| Model-PCA | Chebyshev distance | 1 | 0.155 |
| Model-PCA_SMOTE | Manhattan distance | 4 | 0.727 |
| Model-SMOTE | Euclidean distance | 6 | 0.883 |

### 5.2 Model Performance Evaluation

This section aims to compare the performance of models with different pre-processing methods. Such comparison can help identify which model can provide a more reliable mapping from the operation context to control actions. Table 5 shows the classification results of different models. The best classification results are indicated in bold. Model-SMOTE significantly outperforms the rest of the models. There are two possible reasons. Firstly, a distance-based classifier such as KNN for imbalanced datasets is always biased towards the majority classes because of its large number of samples (Prusty et al., 2017). SMOTE technique arbitrarily interpolates new minority samples in between several samples of a minority group can help counteract the imbalanced dataset problem. Secondly, PCA projects the high dimensional analog parameters to a new subspace to get a low-dimension representation of the original dataset by retaining some variance, causing information loss. Even though many studies showed PCA does not involve significant information loss, in the experiment, Model-PCA and Model-PCA_SMOTE have lower f1 scores compared to the model without PCA.

Table 5: Compare classification results of different pre-processing approaches.

| | Accuracy | Precision | Recall | F1 score |
|---|---|---|---|---|
| Model-Original | 0.247 | 0.29 | 0.369 | 0.263 |
| Model-PCA | 0 | 0.075 | 0.091 | 0.082 |
| Model-PCA_SMOTE | 0.084 | 0.082 | 0.087 | 0.084 |
| **Model-SMOTE** | **0.223** | **0.316** | **0.441** | **0.323** |

The count of control action is significantly less than the {wait} class. This paper use precision-recall curves (PR curve) to further compare the performance of Model-Original and Model-Smote. Figure 5 displays the PR curves of the two model variants. The Area Under Curve (AUC) for different control actions varies significantly. Notably, some PR curves have extremely low AUC (below 0.1), indicating that the classifiers perform even worse than random classifiers. One reason for the low AUC is the small testing sample size. Although the total number of testing samples is high, the control action ratio in the testing sample is low (0.172). The other reason is due to the nature of NPP operations. An accurate prediction in the proposed model indicates that the occurrence timing of the predicted control action is the same as the testing data. However, different operators rarely perform the same control action exactly at the same value set of analog parameters in practice. Instead, it's more reasonable to perform each control action in a set of analog parameters with similar values.

The confusion matrix shows the potential of this classifier. In Figure 6, all the diagonal elements denote correctly classified control actions. The off diagonals of the confusion matrix display the misclassified outcomes. Hence, the higher the values in the diagonal, the better the classifier. Model-SMOTE shows decent performance in predicting the majority of the control actions. Rod control action can repeat multiple times under different operation contexts. Thus, the KNN algorithm can hardly find a similar pattern for the operational contexts of rod control action. Therefore, the Rod control action has the lowest prediction accuracy.

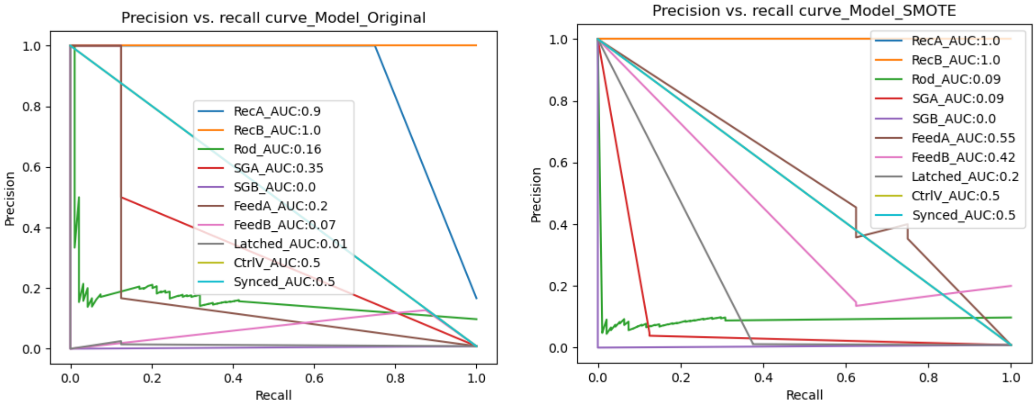


Figure 5: Precision-Recall curves.

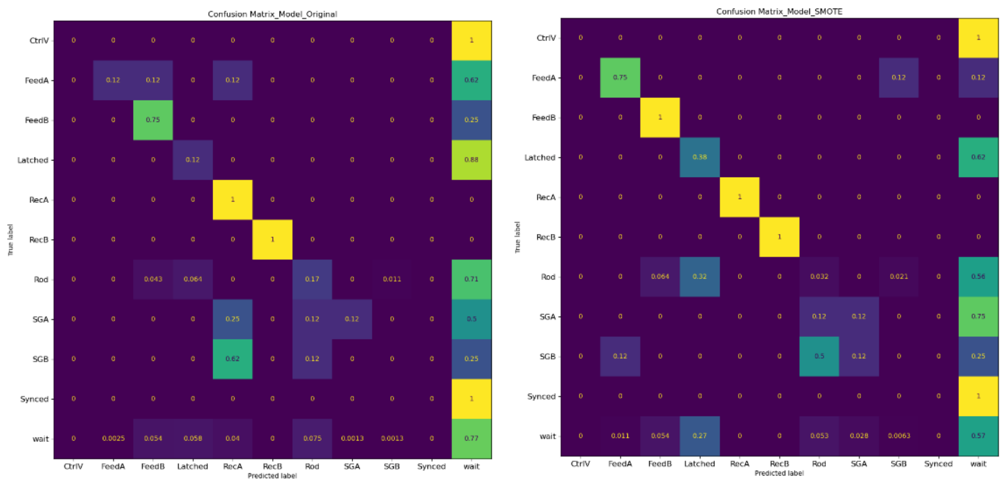


Figure 6: Confusion matrix of Model-Original and Model-SMOTE.

## 6. Conclusion

This paper proposed a variant of models based on KNN classifiers that uses analog parameters to infer the timing of the most suitable control actions. The proposed model employed PCA to compress the analog parameters to lower dimensions and SMOTE to help augment the less frequent control actions in the collected control histories. Additionally, hyperparameters of the KNN classifiers are carefully selected using 5-fold cross-validation. The authors also designed a human-in-the-loop experiment of reactor start-up to collect NPP control histories for validating the proposed control action prediction framework. The testing results indicate that the model with SMOTE data augmentation has better prediction performance than the models without SMOTE. Models with PCA have lower prediction accuracy compared to models without PCA.

Two limitations of this paper are the small data size and model performance evaluation metrics. The KNN classifier is an instance-based learning method that can make a prediction for new observations based on a few data samples. This paper used 20 logs, and the number of control actions in these logs is relatively small. In addition, an accurate prediction in the proposed model indicates that the occurrence timing of the predicted control action is the same as the testing data. In practice, the occurrence timing of control action is more likely to concentrate in operational contexts with similar analog parameter values rather than the same analog parameter values. The authors will improve the model performance evaluation method by defining a suitable time window for each control action in future work. Specifically, the authors will estimate the distribution of individual control actions in the operation process by considering analog parameter values and time.


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