The Exploration of Machine Learning Based Process Monitoring for Pyroprocessing Safeguards

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1. Introduction

Pyroprocessing has been considered as an important part of spent fuel management in the Republic of Korea. One of the major challenges in the development of pyroprocessing technology is nuclear safeguards. To augment the capability for pyroprocessing safeguards, use of Process Monitoring (PM) has been suggested [1,2]. The PM-based approach takes advantage of various process data produced during operation to detect anomalies which may be related to safeguards-significant events.

In this study, use of PM for pyroprocessing safeguards through the machine learning-based approach was investigated.

2. Process Monitoring

PM has been used to monitor the operational state and operating conditions in a variety of commercial plants. By installing different sensors in proper locations at the facility, during the operation, various signals can be produced including physical, electrochemical [3], and spectroscopic analytical signal in a pyroprocessing facility. Fig. 1 shows an example of the concept using the electrorefining (ER) process, which is one of the major unit processes in pyroprocessing. Therefore, the first step is listing available sensors and their corresponding signals.

Prior to obtaining information about process operation from signal, normal and off-normal operating conditions should be defined. In off-normal operation, diversion would be suspected through an inductive method. As a next step, process applicable signals need to be selected from among the available signals. This can be done by investigating the function and performance of each signal. As a result, the off-normal operation can be distinguished in real time, based on signal data.

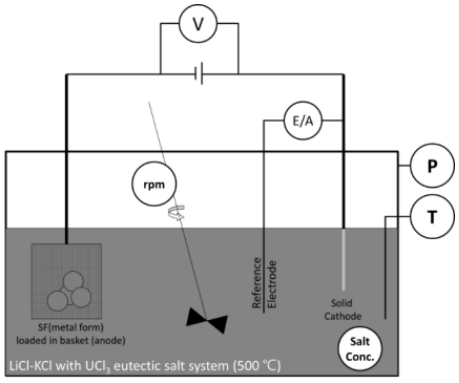

Fig. 1. Application of applicable sensors to electro-refiner.

For example, in case of ER process where uranium is selectively separated from spent fuel and deposits on a cathode, detection of an off-normal operation based on PM is describe in the following. In normal operation, the density of electrolyte, which includes special nuclear material, maintains a certain range. However, regardless of the intention, if the operating condition is shifted to a certain way, plutonium could co-deposits on a cathode with uranium. As a results, the density would be slightly decreased because of the weight difference. For the same reason, a cathode density is increased. Therefore, if the density is measured correctly and its information is provided in a timely manner, the off-normal operation would be detected [4].

3. Machine Learning

Machine Learning (ML) is an application of artificial intelligence. Using statistical inference, the computer learns without explicit programing. Based on existing data, ML can predict unseen data. Therefore, to employ this approach, sufficient quantities of data should be acquired.

3.1 Data development

ML requires extensive data, from which statistical inference can be drawn. The collected data should be produced in various operating conditions including both normal and off-normal operations. Considering efficiency and practicality, data development will be achieved through both experiments and model simulations. For these reasons, the target is limited to the ER process.

In ML, the obtained data should be categorized into three data sets: training data, validation data, and test data. In the training stage, to reduce decision error, a variety of data should be used including the data that represent normal and off-normal conditions. Data available for each of the three stages above must match the objectives. Training will use a majority of the data while rational validation requires about 20% of data. Finally, in the testing stage, the performance of the machine is examined using 20% of available data.

3.2 Algorithm study

To develop a system using provided data properly, the appropriate type of algorithm should be studied. Based on a purpose of ML, there are various applicable algorithms. Considering that the purpose of this study is predicting/estimating the operation state or operating condition of the process from data, the algorithm function is to classify anomalous data.

There are several algorithms for the classification. Depending on the characters of selected signal(s), adequate algorithm(s) will be attempted.

4. Conclusion

In this study, an approach to develop a machine learning based process monitoring method was discussed to support pyroprocessing safeguards. Necessary data development will be an important part of this effort and further research will be conducted to examine the feasibility of the proposed work.

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