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Use of Machine Learning with On-Line Monitoring Systems for Reprocessing

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INTRODUCTION

Nuclear fuel reprocessing plants face significant economic challenges in meeting security, safeguards, and environmental regulations. Directly addressing these problems later in the design process coupled with overly conservative designs can lead to higher operational and upfront costs. Safeguards are just one component, but future advancement of reprocessing technologies will require efficient accountancy and plant monitoring approaches. These approaches will be required for both domestic and international safeguards. On-line monitoring of bulk processing facilities is preferred as compared to grab sampling and destructive analysis which can lead to longer turn-around-times and higher costs. Many on-line measurement technologies exist, but the complex radiation environment and higher measurement uncertainties for actinides limits their effectiveness. This work is examining how machine learning techniques can be used to develop safeguards systems that operate predominantly through on-line or non-destructive measurements.

BACKGROUND

Safeguards requirements for bulk processing facilities can be difficult to meet due to the high throughput of fissionable material. A 1000 MT/yr reprocessing plant can process over 10,000 kg of Pu annually. For a one-month balance period, measurement uncertainties are needed in the <0.5% range in order to meet loss detection goals for a significant quantity. As a result, accountancy systems typically rely on sampling and destructive analysis (which must be performed in a laboratory) in order to meet the goals. This is true for both domestic and international safeguards requirements.

However, measurement technologies and data analytics approaches are constantly evolving. Recent research on spectroscopy for aqueous reprocessing facilities shows that accountancy goals can be achieved using only on-line spectroscopic probes along with bulk level measurements and flowmeters [1]. Past work has also explored the use of multi-variate data for advanced process monitoring of fuel cycle facilities [2,3,4]. These approaches need to be tied together more, and machine learning algorithms have promise in developing the work.

A difficulty with machine learning is that its implementation is not usually intuitive or transparent. This is a problem for safeguards in which transparency to the regulator is important. Data analytics cannot be overly complex in order to provide assurance that all material is accounted for and that facilities are not being misused. Inspectors and regulators need to be able to easily understand any data analytics approach.

This summary provides a methodology for how on-line monitoring technologies and machine learning can be used to develop a more efficient safeguards approach for future facilities. Particular attention is focused on how to make these systems transparent enough to be accepted by a regulator. Modeling and simulation is being used to demonstrate the concept.

OPERATOR VS. REGULATOR

While an advanced safeguards approach is feasible for a new facility, retrofits to existing facilities would be difficult. This paper assumes that the operator of a new facility will utilize as many on-line measurements as possible. The inspector goal is to verify declarations with as much reliance on unattended measurements as possible and a limited number of non-destructive verification measures.

A new aqueous reprocessing plant will likely make use of the latest precision level and flow measurements along with UV-Vis-NIR spectroscopy for on-line measurement of actinides. The use of that measurement data, though, may be problematic for the regulator due to the need for an optical probe in the hot cell, maintenance considerations, and the fact that spectroscopy to measure actinides utilizes detailed chemometric models for calibration. The international inspector may want to rely on a measurement technology that is easier to install and maintain.

The value of the machine learning approach is to help the regulator to use a great deal of operator-declared data, along with a minimal number of on-line verification measurements, to make a transparent and justified safeguards conclusion.

MODELING

The on-line measurements and data analytics approaches considered here were tested using the Separation and Safeguards Performance Model (SSPM) [5]. The SSPM uses Matlab Simulink to simulate the material flow, operations, and measurements in a bulk processing facility. Various versions of the SSPM exist to cover different types of facilities and throughputs. For this work, a 1000 MT/yr PUREX reprocessing plant model was used.

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Figure 1 shows the PUREX model in Simulink. The gray blocks represent the major unit operations. The signals connecting the blocks represent material flows—the models are designed to track all elements, bulk liquid or solid flow rates, and isotopics. The blue blocks represent operator measurement points, but the level measurements are not shown on this level. The green blocks represent verification measures that the inspector may use. Finally, the red blocks are points where diversion scenarios can be turned on to determine how the safeguards system responds. Although the SSPM contains significant detail to mimic the timing of reprocessing operations, it was designed to study safeguards systems and approaches.

Past work has set up the safeguards system to be representative of an existing facility. This allows for a baseline to compare against when investigating new approaches. Current best practices for statistical analyses are worked into the SSPM, but the machine learning techniques are currently performed outside of Matlab Simulink. Eventually, these techniques could be added to the SSPM, but for now, it is easier to use the SSPM to produce data sets that can then be examined externally using PYTHON.

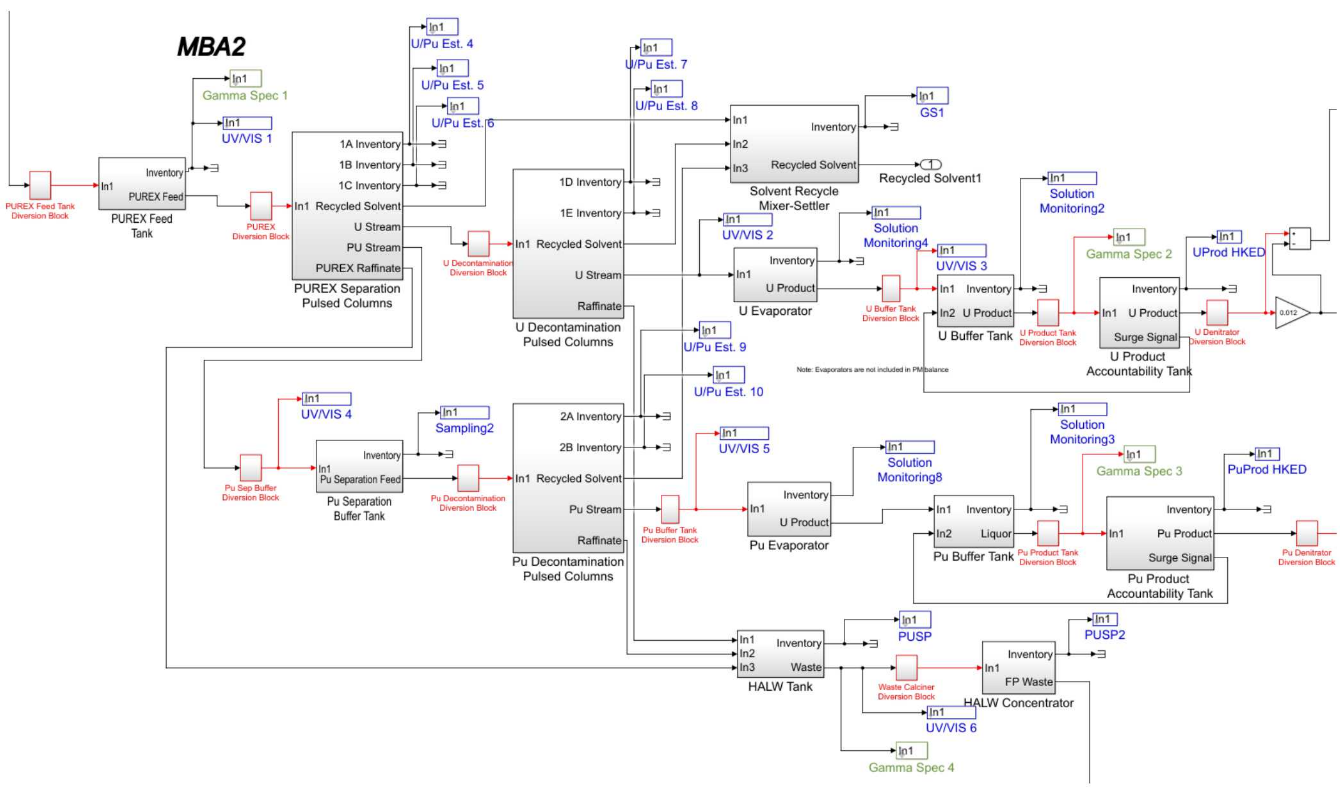

Figure 1: PUREX Safeguards Model

DATA ANALYTICS CONCEPT

The assumption behind the approach is that the operator will utilize on-line measurements for both process monitoring/control and for their declaration of the material balance. Periodic calibration will be required in which grab samples will be analyzed, but the operator will rely mainly on precision level measurements, flowmeters, and spectroscopy for materials accountancy.

The goal of the data analytics concept is to allow the inspector to verify the declaration without requiring grab samples and destructive analysis (or by significantly reducing the need for sampling). The inspector may utilize joint use level measurements on key product tanks since that has already been demonstrated as part of the Rokkasho Reprocessing Plant safeguards approach [6]. Measurements using NaI detectors are assumed for accessible pipes in a few select other locations. The machine learning algorithm will correlate all the data to determine if the declaration looks correct or falsified.

Joint use level measurements can easily be used to detect *direct* material loss since these measurements can have low uncertainty (0.1%). Additional nuclear measurements are needed to detect *substitution* loss. A substitution loss is when an insider or nation state diverts material and tries to hide it by replacing it with a surrogate. For example, Pu nitrate solution may be replaced with U nitrate in order to “beat” the bulk material balance. The nuclear measurements must be able to detect evidence of a substitution. They do not necessarily need to be able to quantify actinide loss, as long as they can indicate a problem. In this manner, the system is used to alert that sampling and detailed analysis may be needed.

As indicated in Figure 1 above, gamma spectroscopy is assumed to be used for the verification. NaI detectors are limited in the lowest measurement uncertainty that can be achieved for directly measuring U and Pu. However, the measurement uncertainty for determining if a substitution diversion has occurred could be much lower. The drop of a particular peak or change of a peak ratio may be measured with more precision than directly estimating U or Pu content. A machine learning technique should be able to be trained to pick up such an event.

Modeling gamma spectroscopy is made possible by the full isotopic tracking in the SSPM and coupling with the GADRAS (Gamma Detector Response and Analysis Software) tool [7]. GADRAS allows for the simulation of gamma spectra using a variety of standard detector types. While NaI detectors are currently being examined, portable high purity germanium detectors will also be considered in the future.

MACHINE LEARNING APPROACH

The PUREX SSPM is being used to generate a large amount of normal plant operating data. The model is set up to randomize the fuel feed going into the plant in order to provide natural variation. This data is being used to train a machine learning algorithm.

A One-Class Support Vector Machine (OCSVM) was chosen for this application [8]. The OCSVM is an unsupervised machine learning technique that can be trained with normal plant operational data only. (This is important because an actual facility will not realistically be able to provide off-normal data for training, so supervised machine learning techniques are not desirable.) The OCSVM can take any number of input data streams and generate a boundary around that normal data such that some defined percentage of points (say 95%) fits inside it. Then during operation, the OCSVM will take the measurement data and generate a classification of 1 (normal) or -1 (off-normal) at each point the calculation is applied. An alarm is reached when a certain frequency of off-normal classifications occurs.

Figure 2 illustrates how the OCSVM technique works and shows an example of results during an abrupt diversion. There will be some misclassifications during normal operation, but a material loss is indicated by a significant increase in the number of misclassifications. The bulk of the technical work is on optimizing the parameters to balance sensitivity with false alarm probability.

For the application here, the key inputs will be the level measurements from the joint use equipment and the data from the gamma spectroscopy of the inputs and outputs. This also may be coupled with the operator-declared data.

Past work has shown that the level measurements by themselves can easily detect direct loss, even for fairly protracted diversion scenarios. A machine learning algorithm is not needed for that case since the loss can be detected with a simple bulk material balance. The OCSVM is mainly there to detect the substitution diversions. The OCSVM is looking at a correlation of all the bulk data along with gamma spectra from some select locations to look for inconsistencies. Substitution diversions will alter the gamma spectra in ways that would be indistinguishable in a traditional Pu balance, but detectable using a properly trained machine learning algorithm.

DISCUSSION

This paper was focused on setting up the methodology, but much more work is needed to test the concept under a variety of conditions. Initial work on the concept was applied to a generic pyroprocessing safeguards approach. The OCSVM technique showed promise, and so was applied to aqueous as well. Further work is needed to fine tune the algorithm to optimize performance.

Of particular interest in this work is the ability to present the data and algorithm in a way that will be more transparent to an inspector or regulator. For example, the test may be set up so that in the case of an increase in misclassifications, the program will pull up the gamma spectra or bulk measurements that are most responsible for the misclassification. This would allow the inspector to rapidly determine the problem and location. Future work will present more detailed results and a comparison against current best practices.

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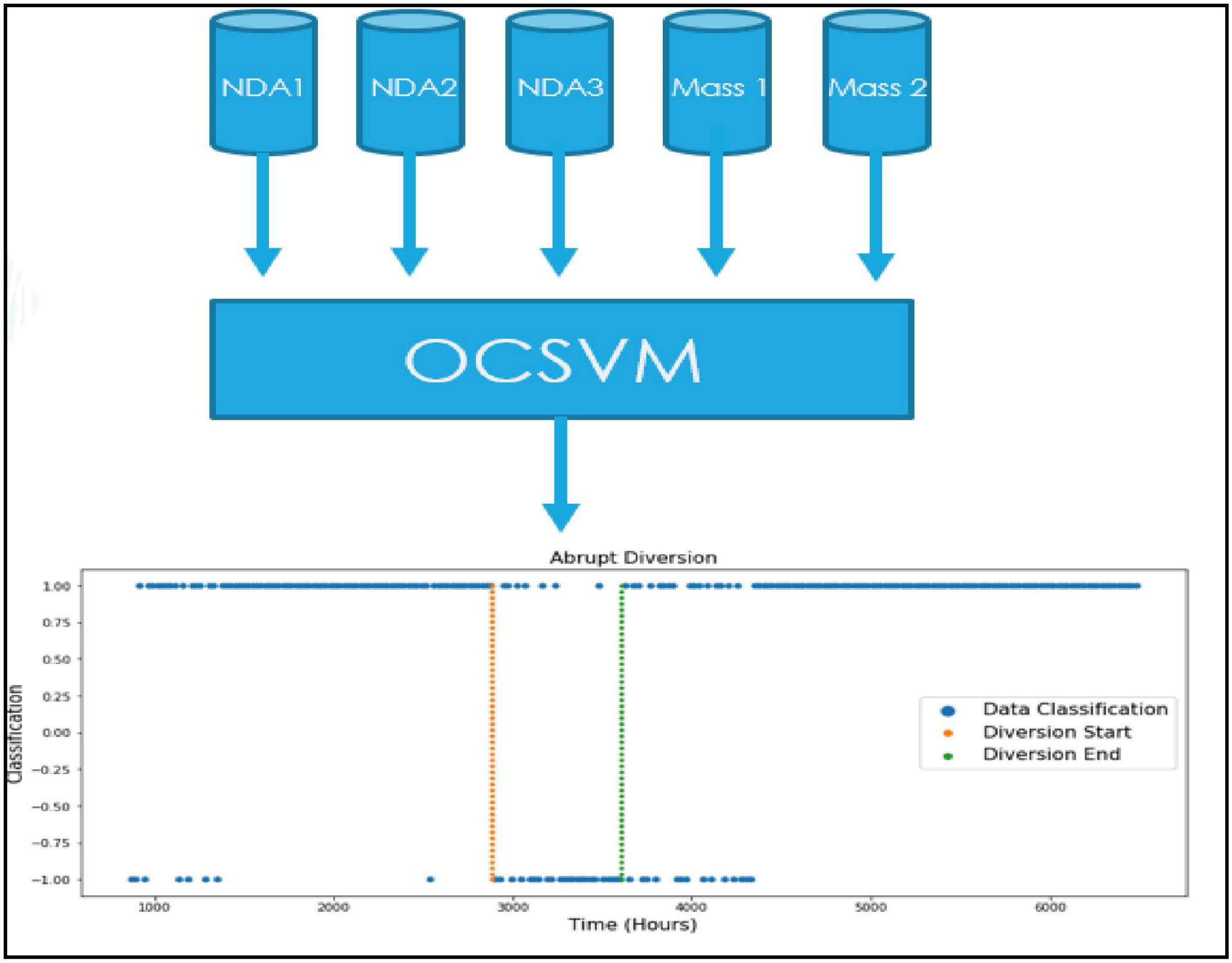

Figure 2: Illustration of the OSCVM Technique

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