Facility On/Off Inference by Fusing Multiple Effluence Measurements

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I. Introduction

Inferring the operational status of a reactor facility using measurements from an independent in-situ monitoring system is critical to the assessment of its compliance to agreements. In particular, such a monitoring system could assist in identifying activities beyond the agreed upon ones, for instance, longer operational periods. In this paper, we consider the problem of inferring the on/off status of a reactor facility by using effluence measurements of three gases, namely, Ar-41, Cs-138, and Xe-138, which are collected on its stack.

We implement and study classifiers to infer the on/off status using ground truth measurements collected over a period of one year. We first present classifiers based on thresholding the measurements of individual effluence types, and then present methods that combine their outputs or measurements. We develop sample-based implementations of four fusers based on a simple majority rule, Chow's recognition function [1], physics-based radiation counts model [2], and correlation-coefficient (closely related to the sum of squared difference) method [3]. We apply the latter three fusers to pairs and all three gas effluence types. Our results show that: (i) these gas effluence measurements are effective in inferring the on/off status of a reactor facility, for example, best fusers achieve 97% detection at 1% false alarm rate, and (ii) the performance depends on the data and classification method, and in particular, fusers that combine three effluence types based on physics-based models and correlation-coefficients outperform the majority rule and Chow's fusers as well as individual and pairs of effluence types.

II. Effluence Measurements of Reactor Facilities

Effluence measurements of Ar-41, Cs-138, and Xe-138 gases are collected on the ventilation off-gas stack of the High Flux Isotope Reactor (HFIR) in Oak Ridge National Laboratory (ORNL). These gases are continuously monitored using a feeding tube in the stack as shown in Figure 1, and the measurements are statistically analyzed and provided every four hours. The stack itself is shared by another reprocessing facility at ORNL, which complicates the on/off classification task for HFIR. The Figures 2(b), 2(c), and 2(d) show scatter plots of the ground truth data for on/off periods of HFIR from January 2015 to January 2016 shown in Figure 2(a).

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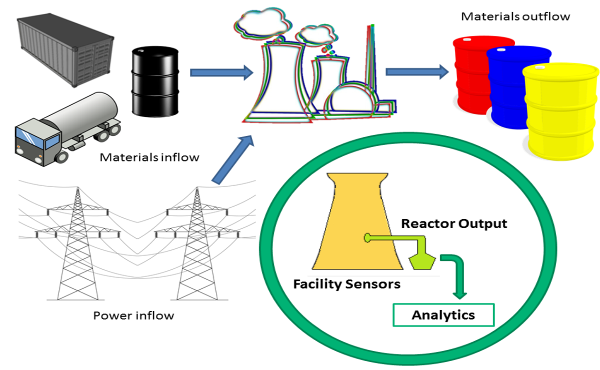
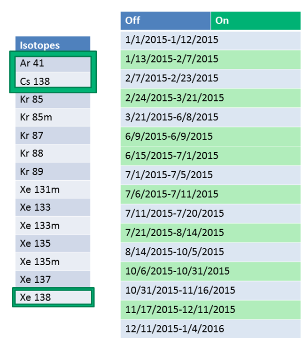
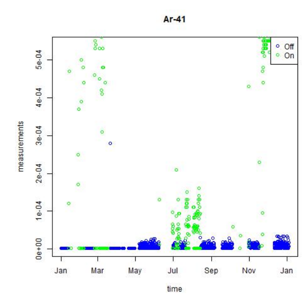


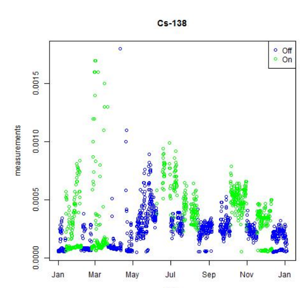
Figure 1. Stack instrumentation of reactor facility.



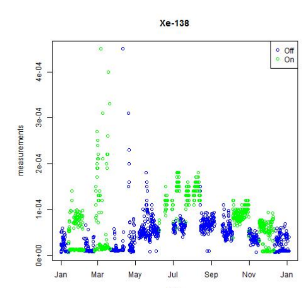
(a) Isotopes and operational timeline of facility.



(b) Ar-41 on/off measurements.



(c) Cs-138 on/off measurements.



(d) Xe-138 on/off measurements.

Figure 2. Effluence Measurements.

III. Classifiers Design and Performance

We train the individual classifiers with four different thresholds for each set of Ar-41, Cs-138, and Xe-138 ground truth measurements, and combine their outputs using four types of fusers.

A. Classifier Thresholds and Majority Fuser

To infer on/off status of the facility, we train individual classifiers using the ground truth data, and combine their outputs using a simple majority rule. Using half of the data when the facility is off, we identify 3%, 5%, 7%, and 10% top and bottom measurements, and set the threshold $\tau_{i,j}$ to be the maximum of remaining measurements, where $i \in \{Ar41, Cs138, Xe138\}$ and $j \in \{3\%, 5\%, 7\%, 10\%\}$. We then compare the rest of the *off-periods* data as well as all *on-periods* data (that is, when the facility is on) to the individual threshold $\tau_{i,j}$: the decision is *on* if the measurements are above the threshold, and *off* otherwise. Using these testing datasets, we estimate the false alarm and positive detection rates for individual classifiers. For each percentage j, we combine the individual classifiers' decisions for all i, corresponding to Ar-41, Cs-138, and Xe-138, using a simple majority rule.

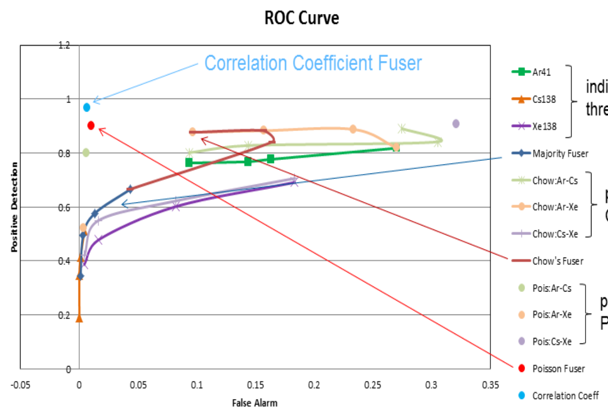


Figure 3. Summary ROC curve.

B. Chow's Fuser

For the second fuser, we make use of the statistical independence of measurements, which are radiation counts. We adapt Chow's recognition function for binary recognition problem to thresholding classifiers in the previous subsection. In this Chow's fuser, we utilize a threshold weighted-majority decision (derived under statistically independent decisions) for all three gas types as well as considering them in pairs. Let $a_{i,1} = \{\textit{on-data}\}$ and $a_{i,2} = \{\textit{off-data}\}$, for $i \in \{Ar41, Cs138, Xe138\}$. The individual threshold classifier decisions $x_{i,l}$, for $l \in \{Date : Time\}$ are assigned the weights given by the logarithmic ratio $w_i = \log \frac{(1-\beta_{i,1})\beta_{i,2}}{\beta_{i,1}(1-\beta_{i,2})}$ where $\beta_{i,k} = \mathbb{P}(x_{i,l} = 0 | a_{i,k})$. These weighted decisions $\{w_i x_{i,l}\}$ are used to compare their total or pairwise sum to the threshold $\tau = \sum_{i=1}^{n} \log \frac{\beta_{i,1}}{\beta_{i,2}}$ to make fused on/off decision.

C. Physics-Based Fuser

We now exploit the fact that measurements follow a Poisson distribution, for which the Sequential Probability Ratio Test (SPRT) is given by $0 < \sum_{i=1}^{n} w_i(m_{S_i} - m_{B_i})$ for $i \in \{Ar41, Cs138, Xe138\}$. Based on this equation, these exist weights $\{w_i\}$ such that the sum of the weighted differences between the *on* measurements and *off* measurements is positive. Using ground truth data, we divide the sets of measurements into a training set and a test set. We use the training set to maximize the sum of differences in measurements, where the weights are $w_i \in \{-1, 1\}$. We then use these weights to define a threshold $\tau = \frac{1}{4}\sum_{i=1}^{n} w_i(m_{S_i} - m_{B_i})$ and use the test measurements to estimate the false alarm and positive detection rates. We do this by maximizing the sum $\sum_{i=1}^{n} w_i m_i$ with $w_i \in \{-1, 1\}$ and comparing it against the threshold τ. We call this fuser Poisson's fuser and as with Chow's fuser, we test it pairwise and for all gas effluence types.

D. Correlation-Coefficient Fuser

The last fuser is based on fixing a window of background measurements, say $\{\vec{m}^0_{B_i}\}$ for $i \in \{Ar41, Cs138, Xe138\}$, and computing its correlation coefficient for both *on* and *off* measurements. Let $w \in \mathbb{N}$ be the window size and assume $\vec{m}_{T_i}$ is either an *on* or *off* training measurement, we define the correlation coefficient to be $\vec{m}^0_{B_i}\vec{m}_{T_i} = \sum_{j=1}^{w} m^j_{B_i} m^j_{T_i}$. Using the correlated training set, we maximize the sum of weighted differences between the *on-data* measurements and the *off-data* measurements, that is $\max \sum_{i=1}^{3} w_i(\vec{m}^0_{B_i}\vec{m}_{S_i} - \vec{m}^0_{B_i}\vec{m}_{B_i})$ with $w_i \in \{-1, 1\}$. As with the Poisson fuser, we then use these weights to define a threshold $\tau = \frac{1}{4}\sum_{i=1}^{n} w_i(\vec{m}^0_{B_i}\vec{m}_{S_i} - \vec{m}^0_{B_i}\vec{m}_{B_i})$ and use the test measurements to estimate the false alarm and positive detection rates. We do this by maximizing the sum $\sum_{i=1}^{3} w_i \vec{m}^0_{B_i}\vec{m}_i$ with $w_i \in \{-1, 1\}$ and comparing it against the threshold τ.

IV. Performance Comparison

We estimate the false alarm and detection rates of various classifiers, and the results are summarized in Figure 3, wherein the false alarm and detection rates are shown on X and Y axes, respectively. In general for a classifier, lowering of the threshold parameter leads to higher detection rate but also increases the false alarm rate. The desired performance of a classifier is a high detection rate at a low false alarm rate, as indicated for physics-based and correlation-coefficient fusers applied to all three effluence types. Our results lead to the following conclusions: (i) These gas effluence types are effective in inferring the on/off status of a facility. However, the best case with 97% detection at 1% false alarms required fusing all three effluence types using the physics-based or correlation-coefficient method. (ii) Overall, the fusion of multiple gas effluences provides better performance compared to those based on individual and pair-wise effluence types. (iii) Fusers based on physics-based models and correlation-coefficient outperform the simple majority and Chow's fusers, thereby illustrating the importance of the fuser choice.

References

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