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Fully Integrated Safeguards and Security for Reprocessing Plant Monitoring

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Abstract

Nuclear fuel reprocessing plants contain a wealth of plant monitoring data including material measurements, process monitoring, administrative procedures, and physical protection elements. Future facilities are moving in the direction of highly-integrated plant monitoring systems that make efficient use of the plant data to improve monitoring and reduce costs. The Separations and Safeguards Performance Model (SSPM) is an analysis tool that is used for modeling advanced monitoring systems and to determine system response under diversion scenarios. This report both describes the architecture for such a future monitoring system and present results under various diversion scenarios. Improvements made in the past year include the development of statistical tests for detecting material loss, the integration of material balance alarms to improve physical protection, and the integration of administrative procedures. The SSPM has been used to demonstrate how advanced instrumentation (as developed in the Material Protection, Accounting, and Control Technologies campaign) can benefit the overall safeguards system as well as how all instrumentation is tied into the physical protection system. This concept has the potential to greatly improve the probability of detection for both abrupt and protracted diversion of nuclear material.

Acknowledgement

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Acronyms

ASD	Adversary Sequence Diagram
AMUSE	Argonne Model for Universal Solvent Extraction
ATLAS	Adversary Time-Line Analysis System
BHEP	Baseline Human Error Probabilities
BPL	Bulk Process Line
CuSum ID	Cumulative Sum of the Inventory Difference
DAC	Daily Administrative Check
GWD	Gigawatt Days
HRA	Human Reliability Analysis
ID	Inventory Difference
IPL	Item Process Line
LA	Limited Area
LSDS	Lead Slowing Down Spectroscopy
MBA	Material Balance Area
MC&A	Material Control & Accountability
MCMC	Markov Chain Monte Carlo
MIP	Multi-Isotope Process
MPACT	Material Protection Accounting and Control Technologies
MT	Metric Tons
NDA	Non-Destructive Analysis
NRTA	Near Real Time Accountability
PA	Protected Area
PIDAS	Perimeter Intrusion Detection and Assessment System
PPS	Physical Protection System
PUREX	Plutonium Extraction
SEID	Standard Error of the Inventory Difference
SEPHIS	Solvent Extraction Process Having Interaction Solutes
SNF	Spent Nuclear Fuel
SNM	Special Nuclear Material
SQ	Significant Quantity
SSPM	Separations and Safeguards Performance Model
TALSPEAK	Rare Earth Extraction
TRU	Transuranics
TRUEX	Transuranics Extraction
UREX	Uranium Extraction
UV-Vis-NIR	Ultraviolet-Visible-Near Infrared

1.0 Introduction

Future nuclear fuel cycle facilities face challenging economics and concerns over proliferation. Strengthening proliferation resistance through more advanced materials accountability and thicker layers of physical security can easily lead to even higher costs. Modeling and simulation provides a way to design advanced plant monitoring systems that can both improve accounting and security while optimizing costs to the operator. Cost savings can be realized if these advanced designs are worked in early in the design process.

The Separations and Safeguards Performance Model (SSPM) has been developed over the past several years to meet this modeling and simulation need [1,2,3]. The goal was to create a plant-level model of reprocessing for testing newly-developed measurement instrumentation, unique data correlation strategies, the integration of differing types of plant data, and the evaluation of diversion scenarios—all for the purpose of designing the architecture for an advanced, integrated plant monitoring system.

Existing reprocessing plants process a wealth of information including measurements for traditional materials accountancy, measurements for process monitoring and control, administrative checks, and sensors for physical security. While some of this data is integrated, these systems are traditionally separate. Part of this work involves evaluating how these monitoring systems can be integrated to make more efficient use of all the plant data to strengthen the safeguards and security of the plant.

In the past year, various statistical tests and pattern recognition options were evaluated for use in setting alarm conditions for diversion scenarios. These statistical tests allow the designer to put in alarm conditions below an appropriate false alarm probability. Since much of the performance of the plant is dependent on these material balance alarms, this modification to the model was a key improvement upon which all the results are based.

With the improved statistical tests, new instrumentation that is being developed to improve safeguards has been evaluated in the model to determine overall effectiveness. Improvements to measurements of used fuel at the front end, as well as improvements to measurement of plant inventories has been examined to improve the timeliness of detection of material loss.

Lastly, the SSPM has been modified to include a physical protection system design for the two key mass balance areas (MBAs). This builds on previous work [2]. These systems include the protection barriers and physical protection elements. Another subsystem to represent administrative checks and procedures at the plant was also added, and includes the incorporation of human reliability data. The plant monitoring system was designed to fully integrate the material balance alarms with these systems. The response under diversion scenarios is described.

2.0 Separations and Safeguards Performance Model (SSPM) Capabilities

The Separations and Safeguards Performance Model (SSPM) [3] is a transient model of a UREX+ reprocessing plant. A PUREX version has also been developed, and either of these models can be easily modified to include additional extraction steps. The SSPM is constructed in Matlab Simulink and tracks cold chemicals, bulk fluid flow, solids, and mass flow rates of elements 1-99 on the periodic table. In addition, the radioactivity, thermal power, and neutron emission rates can be determined for any stream or vessel in the plant [4]. Considerable detail has been added to the model to adequately model tank filling and emptying, plant transients, and separation chemistry [5]. However, one of the main uses of the model is to test advanced plant monitoring concepts. The SSPM contains models for a large number of materials accountancy and process monitoring measurements and material balance calculations.

Figure 1 shows the front end of the SSPM in the Simulink environment for a UREX+ plant, which makes up MBA1. The processing stages are shown as black rectangles and contain subsystems which model their operation. Each signal connecting the blocks contains a 101-element array that keeps track of the mass flow rates of elements 1-99, the total liquid flow rate, and the total solids flow rate.

The blue blocks, which may be connected to either process streams or vessel inventories, are used to simulate accountancy measurements. For example, the "Acc MS" block above the accountability tank simulates a plutonium concentration measurement from a sample taken once every 8 hours. Each measurement block is customized for the particular measurement. Random and systematic errors are customizable for each measurement block to reflect different measurement techniques.

The red blocks are diversion blocks that are used optionally to divert material throughout the model in order to determine the instrumentation response to material loss. Diversion scenarios are set up with a startup M-file script which allows the user to choose from a large number of diversion locations.

Figure 2 shows the separations portion (MBA2) of the model. MBA2 is much larger than MBA1, so it contains many more measurement points. Many of the blue measurement blocks represent plutonium measurements that are not currently installed in existing plants—these are modeled to examine future strategies. For both MBA1 and MBA2, the process monitoring measurements are shown one level down in the details of each individual process unit. This was mainly done in an effort to keep the top level model from getting too cluttered.

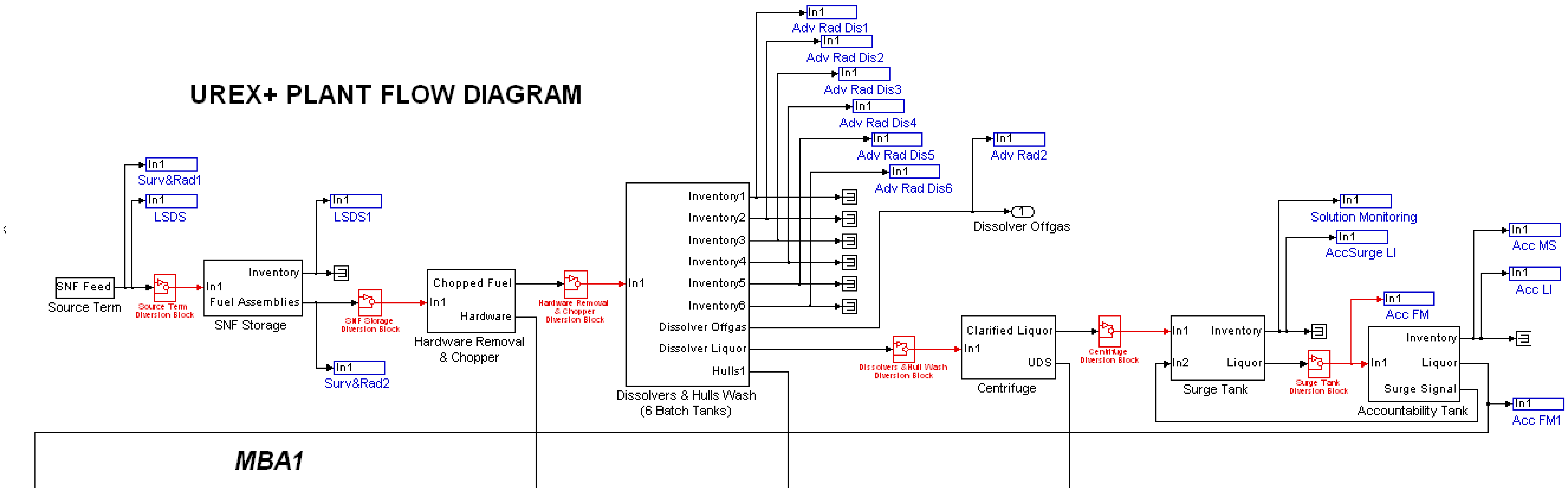

Figure 1: Front end (MBA1) of the SSPM in Simulink

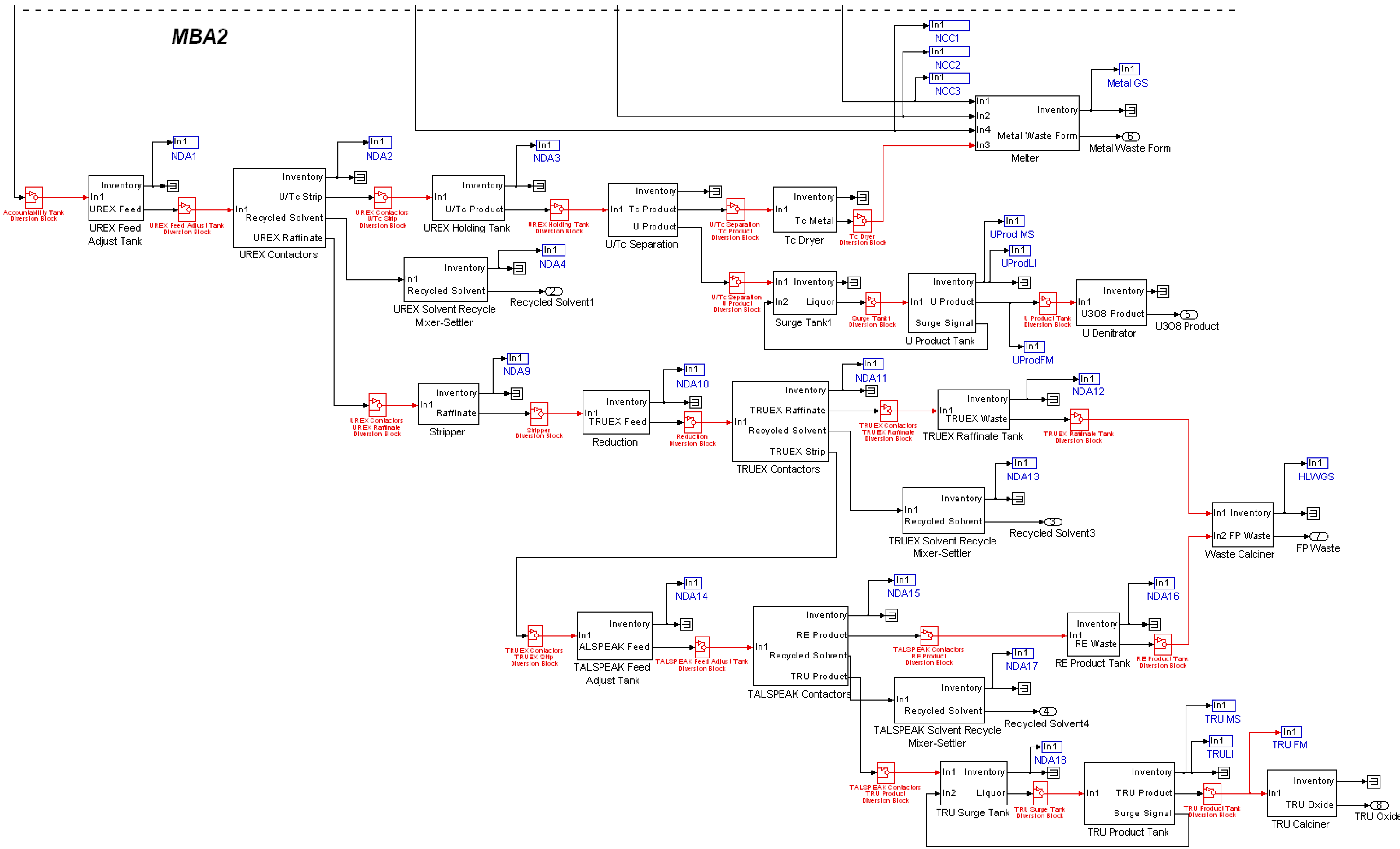

Figure 2: Separations (MBA2) portion of the SSPM in Simulink

Source Term

A user of the model is able to choose the source term that will be used for a run. Nine different source terms were generated using ORIGEN to provide input data for the model that covers a range of pressurized water reactor fuels. Additional fuel types could be added as needed (such as mixed oxide fuel). The user can choose a burnup of 33, 45, or 60 GWD/MT using a startup script before the model runs. Three enrichments can also be chosen (appropriate to each burnup value). Finally, the user can specify the cooling time of the fuel (1, 5, 10, 25, or 50 years). These choices are used to load the correct source into the model.

Heat Load and Radioactivity Tracking

The ORIGEN data that is used for the source term also includes elemental heat load, radioactivity, alpha radioactivity, and neutron emission rates for the fuel. An algorithm was developed in the model to determine these values for any stream or vessel at any point in the plant. The algorithm uses the fraction of that material left in a stream and links back to the original ORIGEN data. This feature may be useful for plant designers that need to know expected heating rates or radiation fields.

Chemical Separations

The current model used for this work treats a bank of centrifugal contactors as a black box with a set separations fraction for each element. This simplification is adequate for most analyses, but will not model certain plant transients correctly. Parallel work has examined the integration of either the SEPHIS (Solvent Extraction Process Having Interaction Solutes) code, developed at Oak Ridge National Laboratory [6], or the AMUSE (Argonne Model for Universal Solvent Extraction) code, developed at Argonne National Laboratory [7]. A parallel report describes the progress being made in that area [5]. Recent results have shown the AMUSE code to be more useful and applicable for a plant with centrifugal contactors, and this code is expected to be completely integrated into the SSPM in the next year. This improvement will allow changes in the model flow streams to directly affect the separations rates through the plant.

Materials Accountancy and Process Monitoring

The measurement blocks throughout the plant can be setup to simulate any type of material measurement of interest. Bulk process monitoring measurements may produce data continuously, while sampling and analytical measurements may produce concentration measurements once per batch. The SSPM contains over a hundred various measurements that are all used to calculate overall material balances. Particular attention has focused on maintaining continuity of the timeline and matching up continuous and batch measurements properly.

All measurement blocks allow the user to change the random and systematic errors (as one standard deviation). At each measurement point while the model runs, a random number generator is used to simulate a random error (around a normal distribution) that is added to the actual value—this random error changes on each measurement. The systematic error uses a random number generator to simulate a systematic error once at the beginning of the run, and then that value is held constant over the run—this simulates the systematic bias that occurs in measurements. Currently, measurement drift and recalibration are not accounted for. The measurement data is pulled into a different part of the model to perform the material balance calculations.

Diversion Scenarios

The startup script also allows the user to specify a diversion scenario. Material can be diverted from a total of 26 different locations, between each of the major process steps. The user must input the starting time and ending time of the diversion (in hours) as well as the fraction of material diverted. The diversion scenario is setup to remove material directly at a constant rate during that time. However, modifications can be made in the model to divert material in pulses or to simulate material loss and replacement with a cold chemical.

Material Balances

The simulated process monitoring and materials accountancy measurements are used in an extensive monitoring subsystem to calculate inventory differences (ID). Two types of calculations occur. The bulk process monitoring data is used to calculate an ID across each processing unit. This simply balances the inflows, outflows, and the change of the inventory, but only balances bulk measurements such as a bulk volume or bulk mass balance. The second type of calculation determines the plutonium ID across the two MBAs in the plant model. This calculation is more extensive because it requires many measurements and a combination of analytical and process monitoring measurements.

In addition to the ID, the cumulative sum of the inventory difference (CuSum ID) is also tracked. All of the errors are propagated to determine the overall standard error of the inventory difference (SEID) for each ID and CuSum ID calculation. The CuSum ID, along with the SEID is the best way to visually track the processes in the plant. The monitoring subsystem also contains a large number of scopes that plot all this data. The user can open the scopes at any time during the model run to track specific areas in the plant.

3.0 Statistical Tests

Although the CuSum ID calculations in the SSPM can be monitored to look for anomalies, the error grows with time. Statistically, diversions that occur early in a run are more likely to be detected than late in a run. Various statistical tests are used to set alarm conditions that make detection equally probable at any point in time. An accepted statistical approach is to use Page's Test to set alarm conditions. Various pattern recognition techniques may also be used to look for anomalies, but this area has not been explored as much in the past. Bayesian statistics are another approach to predict plant behavior and look for off-normal events. This section describes the recent work on finding an acceptable statistical test to use in the SSPM. The alarms generated by the test are an important element both for testing new instrumentation and for evaluating the integration with physical security.

3.1 Page's Test

The standard Page's Test assumes statistical independence of each value in a series of ID measurements. However, all ID measurements are correlated since the ending inventory of one balance period is equal to the beginning inventory of the subsequent balance period. Proper implementation of the Page's Test will account for all correlations, but this calculation is based on a particular plant design. Also, the matrix algebra becomes computationally intensive as the number of IDs increases. As a result, Page's Test is difficult to implement in the SSPM in a way that can be calculated as the model runs. Since this work is pushing toward more frequent inventory balances, the calculation time would make its use unfeasible.

Fortunately, a method was used to simplify the implementation of the Page's Test and to allow the test to be calculated as the model runs. The covariance between different ID measurements is due to the systematic errors of all the measurements that are used. Based on the current model setup, the systematic errors are held constant for each run (or for each calibration period). These systematic errors lead to a bias in the ID series, and this bias can be learned and corrected. By making the assumption that the bias correction accounts for all systematic errors, and by assuming that different measurements are independent (different pieces of equipment), a simplified version of Page's Test can be used. The following equations were modified from references 8-11.

The ID series must first be transformed into an independent series V:

$$V_1 = ID_1$$

$$V_i = a_i ID_{i-1} + ID_i \text{ , } i = 2,3,\dots \qquad \text{(Eq. 1)}$$

The coefficient a depends on the inventory and total measurement variances as follows:

$$a_1 = 0$$

$$a_i = \frac{\sigma_{inv}^2}{\sigma_{ID}^2 - a_i \sigma_{inv}^2} \text{ , } i = 1,2,\dots \qquad \text{(Eq. 2)}$$

The σ_{inv}^2 is the variance on the inventory measurement, and the σ_{ID}^2 is the variance on the total measurement which includes the inventory and flow rate measurements. These values are calculated in the SSPM.

The Page's Test can be set up to look for both high and low alarm cases, but since material loss is the main concern, only the high alarm was used. (Material loss shows up as a positive deviation in the standard convention for inventory difference calculations.) The Page's Test is given as:

$$S_1 = V_1$$
$$S_i = \max\{S_{i-1} + V_i a_i - k\sigma_{V,i_{i-1}}\}, i = 2,3,\ldots \qquad \text{(Eq. 3)}$$

where

$$\sigma_{V,1}^2 = \sigma_{ID,1}^2$$
$$\sigma_{V,i}^2 = \sigma_{ID,i}^2 - \frac{\sigma_{inv}^4}{\sigma_{V,i-1}^2}, i = 2,3,\ldots \qquad \text{(Eq. 4)}$$

An alarm is indicated if:

$$S_i > h\sigma_{V,i} \qquad \text{(Eq. 5)}$$

Page's Test requires choosing an h and k value to meet the test requirements. In this case h and k are chosen to set the false alarm probability to an acceptable value while achieving an adequate level of sensitivity. A great deal of work can go into setting the appropriate h,k values, but for this work, h=6 and k=0.02 was found to provide reasonable results.

Each area in the SSPM that was setup to calculate the ID and CuSum ID also included a calculation for both the inventory variance and total measurement variance. These values are fed into a block that performs the statistical tests (see Figure 3). This custom block first performs the bias correction of the CuSum ID signal. This requires a learning period during which the bias can be calculated.

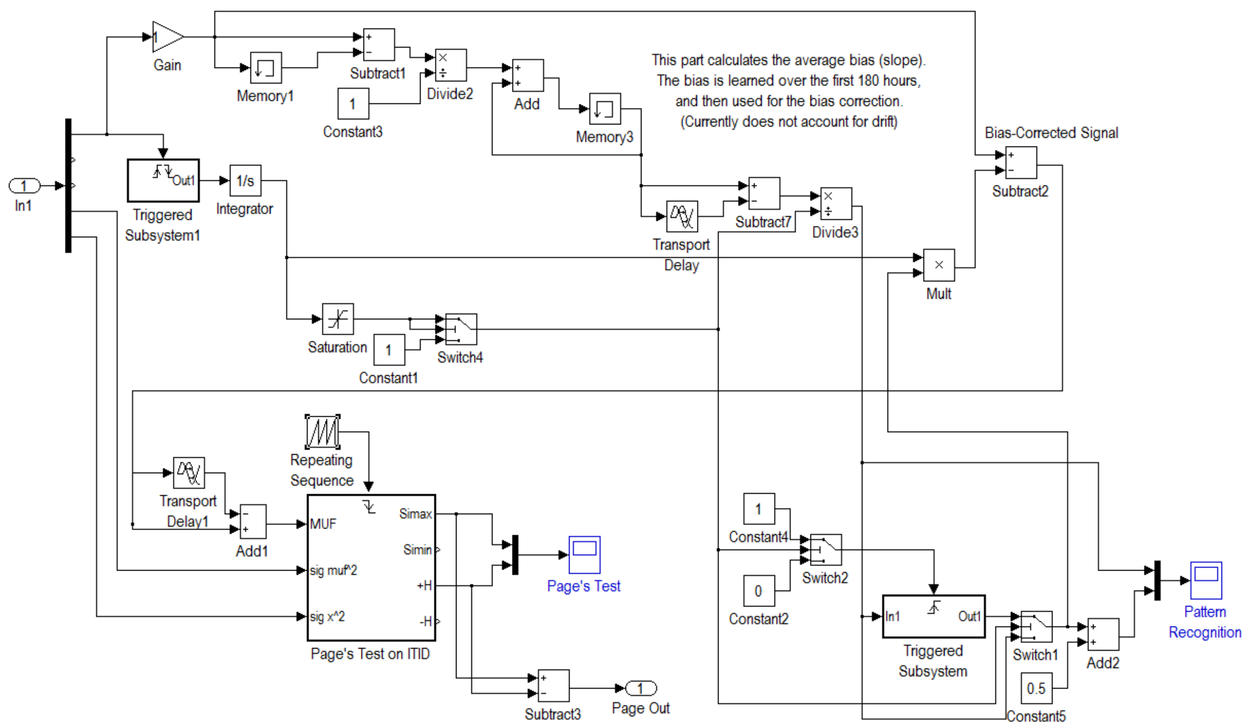

Figure 3: Bias correction and alarm subsystem

Then the bias corrected ID signal and the variances are fed into another subsystem that performs the Page's Test. Figure 4 shows the Page's Test subsystem. This calculation uses Simulink memory blocks to perform the recursive series as described in the equations above. If any value in the S series surpasses the alarm condition, a message block will pop up to indicate the time and location.

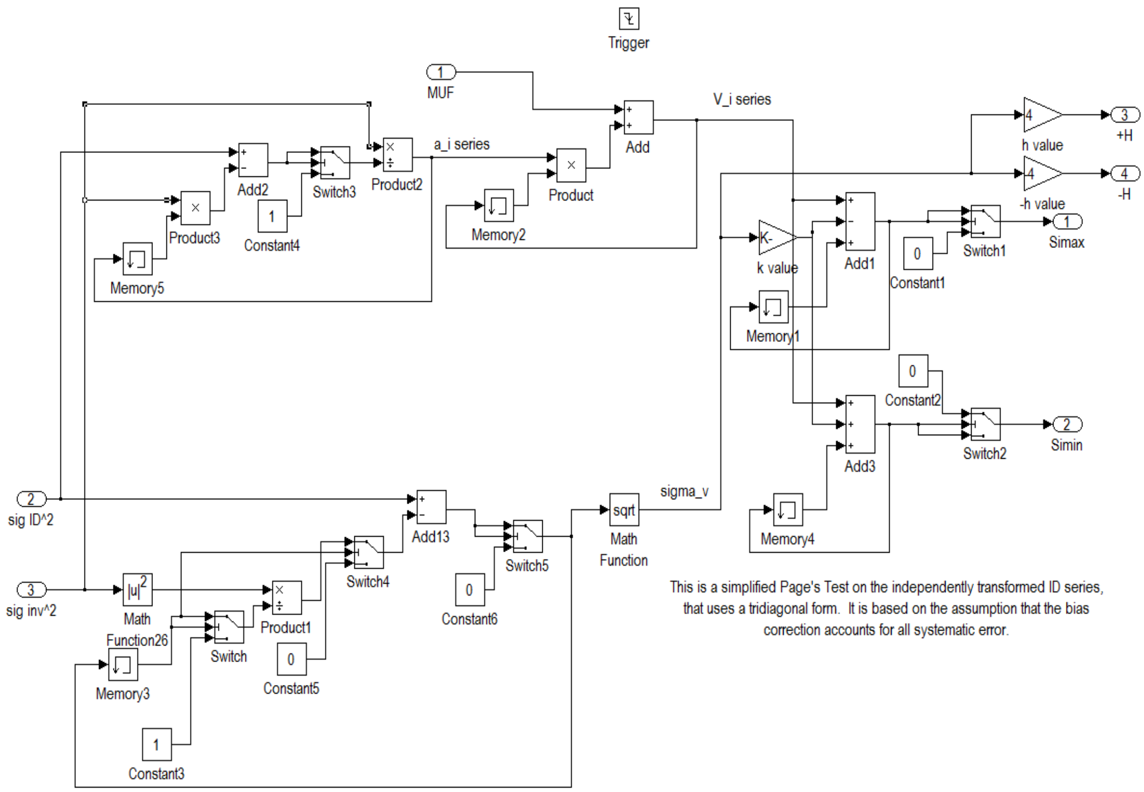

Figure 4: Simplified Page's Test subsystem

The bias correction and Page's Test calculation is somewhat of a drain on the overall model performance. Repeating this test a number of times on different areas in the plant was found to slow the model down too much. To remedy this situation, the calculation is only performed on areas for which a diversion has been programmed. This may appear to defeat the purpose of the test since obviously in a real plant there would be no knowledge of a diversion, but it is set up this way to make the analysis easier. In an actual plant in real time, the calculation could be performed numerous times with ease.

3.2 Pattern Recognition Test

In addition to the Page's Test, an alternative pattern recognition test was developed to look for plant anomalies. The motivation for this test was the fact that often diversion scenarios can be visually recognized in a CuSum ID plot. The goal of pattern recognition is to recognize when such deviations occur and set up appropriate alarm conditions. This particular test was not based on past work, but rather designed specifically for this application.

The pattern recognition test was based on the bias correction calculation as described in the previous section. Bias correction uses a learning period to determine the slope of a CuSum ID plot. During normal operation, this slope is due solely to the systematic errors of all the measurements that are used. A material loss is indicated by a change in the slope. Thus the pattern recognition calculation learns the slope and then looks for significant increases (or decreases) in the slope. Similar to the Page's Test, the alarm condition can be tuned to make it sensitive enough to detect protracted diversions while maintaining an acceptable false alarm probability. The pattern recognition test is shown in the lower right hand corner of Figure 3 above.

3.3 Bayesian Statistics

Bayesian time-series analysis was also examined to develop distribution parameters for measurement values, followed by using Bayesian forecasting to predict a range of expected values for future times. This analysis initially used one tank from the SSPM as an example that included two input flows, an inventory measurement, and one output flow rate (the UREX Adjustment Tank). The method of doing this is based on Bayes' Theorem. Bayesian time-series analysis and Bayesian forecasting are described below.

3.3.1 Bayesian Time-Series Analysis

All Bayesian analysis utilizes Bayes' theorem, which is represented in Equation 6.

$$P(\theta|X) \times P(X) = P(X|\theta) \times P(\theta) \qquad \text{(Eq. 6)}$$

In Equation 6, X represents anything that can be understood as evidence. In this work, X represents a data point, specifically a measured value of one of the four tank variables (feed input, acid input, tank inventory, and output). The simulated data comes directly from the SSPM. Table 1 presents ten sets of measurements that are used in the model.

Time[]	Mfeed[]	Macid[]	Minv[]	Mout[]
196.689	0.00000	0.00000	1982.14	1452.93
196.706	0.00000	0.00000	1953.94	1453.08
196.723	0.00000	0.00000	1930.04	1454.96
196.739	0.00000	0.00000	1909.47	1456.61
196.756	0.00000	0.00000	1884.52	1456.62
196.773	2420.97	1453.66	1905.49	1454.76
196.789	2419.31	1450.41	1945.40	1455.60
196.806	2415.50	1453.76	1979.55	1454.22
196.823	2417.52	1453.66	2029.12	1454.51
196.839	2418.12	1450.30	2066.55	1455.20

Table 1: Simulated data for Bayesian time-series analysis

A more descriptive form of Bayes' theorem for use in the work reported here is presented in Equation 7.

$$P''(\theta = \theta_i \mid X) = \frac{P(X \mid \theta = \theta_i) \times P'(\theta = \theta_i)}{P(X)}$$

$$\equiv \frac{P(X \mid \theta = \theta_i) \times P'(\theta = \theta_i)}{\sum_{i=1}^{n} \left(P(X \mid \theta = \theta_i) \times P'(\theta = \theta_i) \right)} \quad \text{(Eq. 7)}$$

The reason for rearranging Bayes' theorem into Equation 7 is that Bayesian analysis is a form of parametric statistical analysis. That is, the model used to describe the variables of interest assumes a form for each distribution (e.g., normal, gamma, etc.). Parameter estimation is then performed using Bayes' theorem in the form presented in Equation 7. Once the parameters are estimated to the point that the analysis is complete, distributions for the variables of interest are fully determined (to the level of fidelity of the parameter estimation process *and to the level to which the form of the assumed distribution can be trusted*). The single-primed values in Equation 7 are the prior values of the distribution describing the parameter of interest. For a normal distribution, θ is a vector composed of the mean and variance of the distribution. The double-primed values are the posterior values for the parameters.

Bayesian time-series analysis begins with assuming a form for the distributions of each of the variables of interest. This assumed distribution includes assumed parameters for the distribution. These assumed parameter values are the prior values. In the work reported here, the variables of interest are actually the measured values. This is true because these values are not truly ever known. Only the measured values for these variables can be known.

The measured values of the variables are normally distributed with a mean that is equal to the true values of the variables plus a systematic error term. The systematic error term is sometimes called the bias, or the drift, of the measurement. The bias is not known and is modeled as being normally distributed with a mean of zero and an unknown variance. The variance of the bias is modeled by defining the precision as the inverse of the variance, then assuming a gamma distribution with a mean of one and a variance of one for the precision. This is equivalent to an inverse gamma distribution for the variance; however, the software that is used (WinBUGS) defines the normal distribution in terms of the precision. The prior distributions for the variances of the measured quantities correspond to the random errors associated with the measurements. Thus, two separate error terms for each measurement are accounted for in the model – the bias and the random error.

The software used in this work is WinBUGS Version 1.4.3 [12]. The 'BUGS' in WinBUGS is an acronym for 'Bayesian inference Using Gibbs Sampling'. The Gibbs sampler is an algorithm that is used to generate a sequence of samples from the joint probability distribution of two or more random variables. The joint distribution of interest is the distribution determined by the parameter vector θ – in the case of a normal distribution, $\theta=(\mu,\sigma^2)$. This is accomplished via a method termed Markov Chain Monte Carlo (MCMC) sampling [13].

WinBUGS allows a user to develop complex models and update the parameters based on the latest data without limiting the results to any particular type of distribution. The numerical simulation techniques that are used are imperative as most realistic systems do not conform to mathematical techniques that can be solved analytically. As the name implies, this is specialized software that is intended for Bayesian inference. Users of other software packages have developed packages that allow WinBUGS to be integrated into them. Some examples are R2WinBUGS, which allows WinBUGS to be opened and run from the R statistical environment and MATBUGS, which allows a user to operate WinBUGS from the MATLAB environment.

In statistical modeling, many forms of uncertainty are introduced. In this particular work, the goal is to find a way of determining whether a given measurement is outside the values that are acceptable in assuming no diversion of nuclear material has taken place. Therefore, a prediction of the acceptable values for a future measurement must be made. However, the ***actual*** values of the variables for which measurements are made (flow rates and inventory level) are not known either. Since the true values are not known, they must also be modeled as random variables. (It should be noted that the immediately following discussion applies only to the flow rates as the inventory level is determined by the initial value and the flow rates. Therefore, it is necessary to search for only the initial value of the inventory, NOT subsequent values.) This introduces a dilemma in modeling. The measurements are assumed to be dependent upon the true values of the variables. The true values are therefore assumed to be correlated with the measurements. However, this produces a loop that is not compatible with the software being used. To work around this problem, distributions for the variables are assumed. The greater the precision – or smaller the variances – of these variables, the less flexibility the model has in selecting a value. In other words, if a small precision is chosen, then the model is more highly restricted in selecting a value for the variables.

Using a broad distribution with information that is known *a priori* allows one to choose different, widely-spaced values for the mean estimate of the given variable. As the number of samples increases, the posterior distributions for the different initial values should converge to the true values of the variables. Thus, with simulated data, one can check the model to ensure that the different initial values lead to convergence as expected.

One complication with the model that was developed in this work is that the flow rates are binary. Any of the flow rates can be either the zero or the value that is designated by the simulator. Therefore, a valid parameter estimation process for the actual flow rate in the “on” position must have a means of disregarding instances when the flow rate is zero. This is accomplished by defining a Bernoulli variable – P – that takes on a value of unity if the measured flow rate is greater than zero and a value of zero if the measured flow rate is equal to zero. This creates two distributions that must be mixed to create a bimodal distribution for flow rate. However, each of the two separate distributions can be utilized in other parts of the model, as will be necessary in the forecasting process.

3.3.2 Bayesian Forecasting

In principle, Bayesian forecasting is relatively simple once the time-series history has been analyzed. In the software used in this work, the analyst simply appends rows to the end of the data (shown in Table 1) to be used for forecasting. The distributions that have been developed for the various parameters during the time-series analysis phase projects into the future based on the resulting distributions.

The variable of most interest in material accountability studies is the CuSum ID. In the model developed for this work, the CuSum ID is defined in terms of the (incremental) inventory difference. The ID at any time a measurement is taken is defined as the difference in the actual inventory and the measured inventory. Since the actual inventory is never truly known, this is a random variable at each time step. The CuSum ID is the sum over all measurements of the ID.

Since the ID and the CuSum ID both depend on the measured value for the inventory, one way of testing the validity of the model with simulated data is to use a portion of the data for historical time-series analysis, then predict into the future and compare these results to the portion of the data that corresponds to the times for which the results were projected. Table 2 presents the actual simulated data that were used in the model. The rows that are in black font are used in the time-series analysis portion of the analysis. The rows in blue were compared to the predictions of the model.

As stated in the previous sub-section, the system under study can have any number of the flow rates equal to zero or equal to a pre-determined value at any time step. The number of configurations for a system with a total of ‘m’ flow paths and ‘n’ of these flow paths open is determined by Equation 8.

$$\binom{m}{n} \equiv \frac{m!}{n!(m-n)!} \qquad \text{(Eq. 8)}$$

Since the number of open flow paths, ‘m’, can range from zero to the total number of flow paths in the system under study in the work reported here, the total number of configurations is given by Equation 9.

$$\sum_{n=0}^{m}\binom{m}{n} \equiv \sum_{n=0}^{m}\frac{m!}{n!(m-n)!} \qquad \text{(Eq. 9)}$$

With m=3, this implies that eight equations – that is, eight different models – are needed for forecasting purposes.

Time[]	Mfeed[]	Macid[]	Minv[]	Mout[]
196.689	0	0	1982.14	1452.93
196.706	0	0	1953.94	1453.08
196.723	0	0	1930.04	1454.96
196.739	0	0	1909.47	1456.61
196.756	0	0	1884.52	1456.62
196.773	2420.97	1453.66	1905.49	1454.76
196.789	2419.31	1450.41	1945.4	1455.6
196.806	2415.5	1453.76	1979.55	1454.22
196.823	2417.52	1453.66	2029.12	1454.51
196.839	2418.12	1450.3	2066.55	1455.2
196.856	2416.367	1451.493	196.856	1454.543
196.873	2421.752	1452.687	196.873	1455.601
196.889	2417.204	1451.611	196.889	1454.923
196.906	2417.306	1455.625	196.906	1454.288
196.923	2418.888	1452.557	196.923	1455.793
196.939	2421.454	1451.309	196.939	1451.412
196.956	2414.880	1451.741	196.956	1457.139
196.973	2418.872	1453.154	196.973	1454.050
196.989	2417.310	1454.273	196.989	1456.586
197.006	2416.298	1455.002	197.006	1456.584
197.023	2419.658	1454.128	197.023	1452.306
197.039	2419.808	1451.889	197.039	1453.327
197.056	2415.932	1452.256	197.056	1453.218
197.073	2420.198	1454.295	197.073	1454.915
197.089	2415.500	1451.827	197.089	1454.476
197.106	2416.649	1451.030	197.106	1455.106
197.123	2419.639	1452.365	197.123	1452.216
197.139	2417.712	1454.854	197.139	1456.692
197.156	2415.734	1451.953	197.156	1454.710
197.173	2418.863	1452.566	197.173	1454.419
197.189	2419.550	1452.442	197.189	1457.572
197.206	2415.562	1452.784	197.206	1455.743
197.223	2418.761	1452.105	197.223	1456.597
197.239	2419.831	1453.219	197.239	1455.775
197.256	2420.176	1454.709	197.256	1453.939

Table 2: Simulated data used for time-series analysis and forecasting. The blue portion was used to validate the forecasting results of the model.

3.4 Test Results under Diversion Scenarios

The Page's and Pattern Recognition Tests were both set up in the SSPM, so these two tests could be compared against each other under the same diversion scenarios. The goal was to determine if the tests could respond rapidly enough to detect material loss. In general, a good goal is to indicate an alarm before one half of a significant quantity of plutonium can be removed (in this case, 4 kg of plutonium). Numerous diversion scenarios were evaluated, but two results are shown here. In all cases, process monitoring measurements were used to detect bulk material loss. The Bayesian approach was examined separately and was not examined under a diversion scenario for this work.

3.4.1 Abrupt Diversion using Page's Test and Pattern Recognition

The first test was an abrupt material loss using the SSPM from the UREX Feed Adjust Tank over 300 hours. This diversion started at hour 300 and ended at hour 600, and 0.5% of the tank solution was removed during that time (enough for 8 kg of plutonium over 300 hours). Figure 5 shows the results of both of the tests.

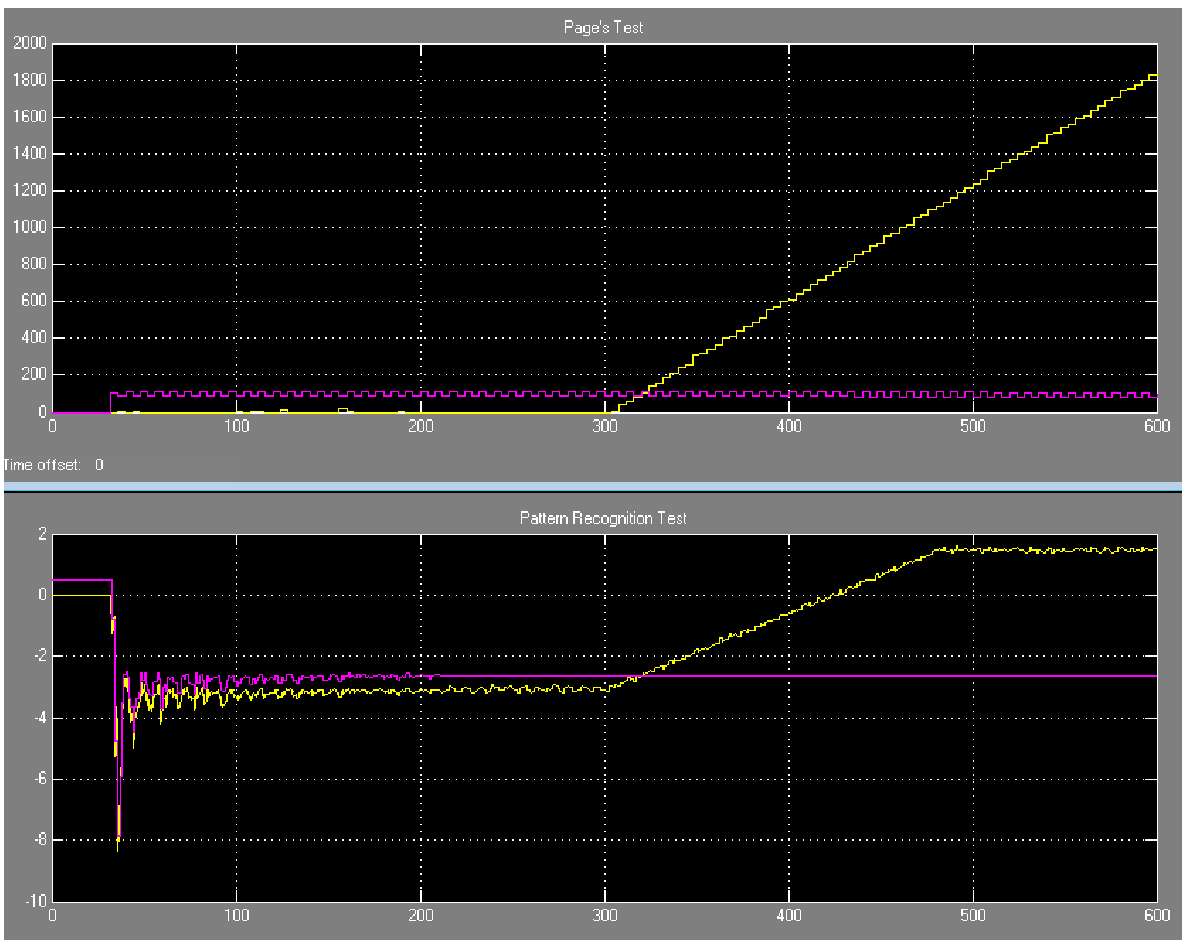

Figure 5: Abrupt diversion response, Page's Test (top), pattern recognition (bottom)

In both graphs, the signal is the yellow line, while the test condition is the magenta line. Surpassing the test condition indicates an alarm. Both tests were able to respond to the diversion and indicate an alarm near hour 325. Since the tests were able to respond well before half of a significant quantity was removed, they were both successful. This scenario shows little difference between the two techniques.

3.4.2 Protracted Diversion using Page's Test and Pattern Recognition

The second diversion scenario was a protracted diversion over 1600 hours from the Stripper Tank, which is before the TRUEX extraction. This diversion started at hour 400 and ended at hour 2000, and 0.1% of the solution was removed during this time. Figure 6 shows the test results.

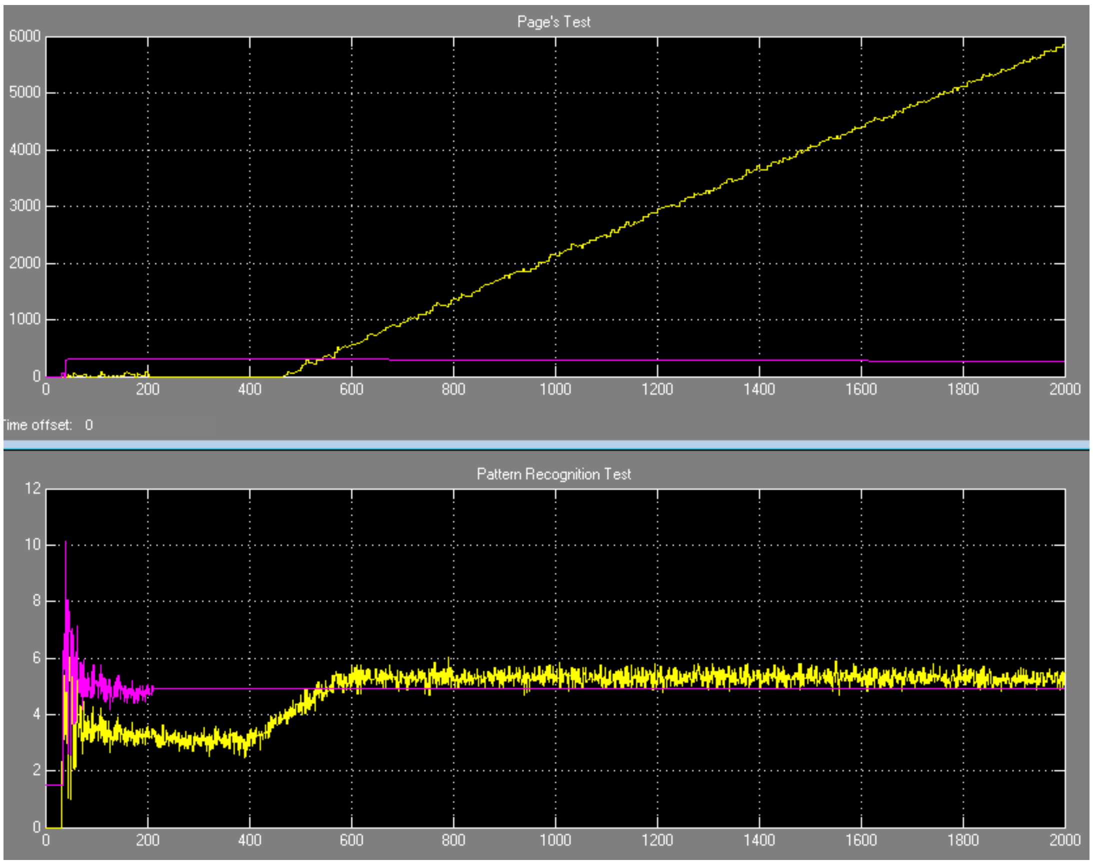

Figure 6: Protracted diversion response, Page's Test (top), pattern recognition (bottom)

It should be noted that the h,k values of the Page's Test and the alarm condition of the pattern recognition were modified for this area of the plant. In an actual plant these values would need to be tuned to each area to optimize the test. Again, both tests were able to respond to the diversion and indicate an alarm near hour 550. Since the tests were able to respond well before half of a significant quantity was removed, they were both successful. The pattern recognition test only just passed the threshold condition, but that is expected for such a small fraction of material removed.

3.4.3 Bayesian Approach Results

The Bayesian approach examined the predictability of measurements in the UREX feed adjustment tank during normal operation. Figures 7 through 10 present results for the forecasting of measurements. The four figures show the forecast compared to the simulated values for the inventory measurement, feed flow, acid flow, and outflow respectively. The median predictions are all very close to the simulated data, and the 95% credibility intervals are very tight. Since the true flow rate and inventory values can never be truly known, the best one can hope for without experimental verification is the ability to predict the simulated measurements that have been provided. This method can be extended to use the predicted values to set alarm conditions for material loss. An actual plant can use past results or results from cold startup for verification.

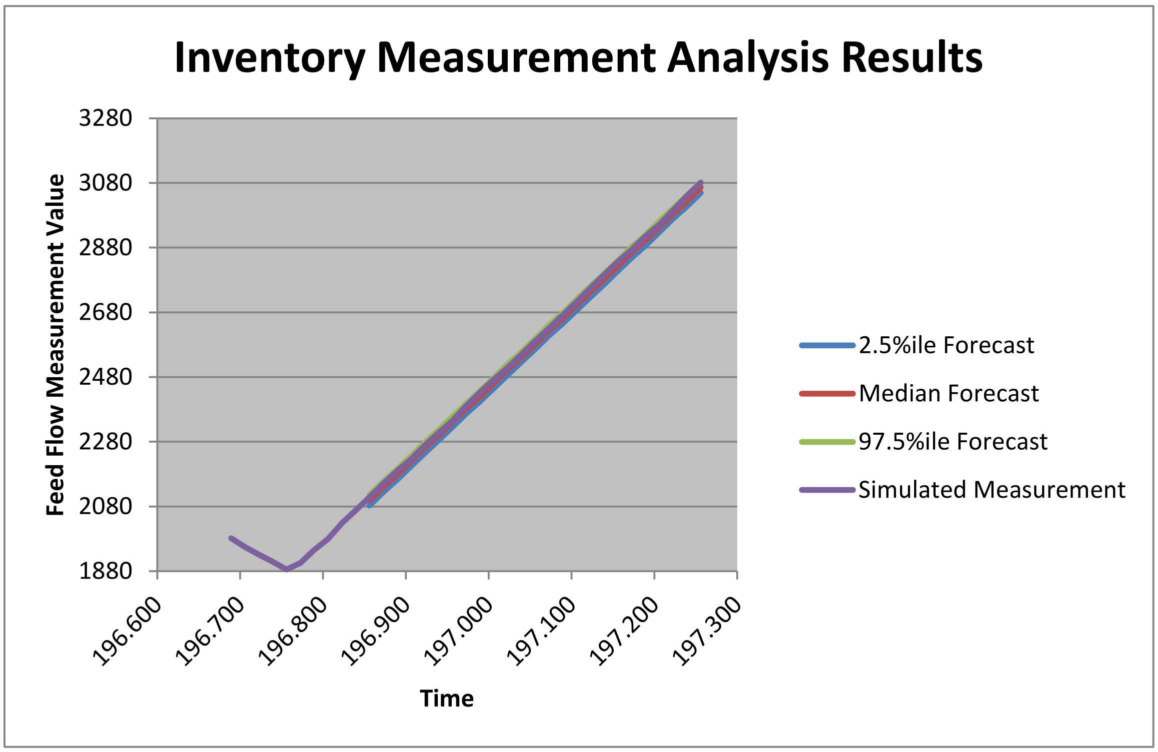

Figure 7: Bayesian approach, simulated inventory measurement data and forecasting

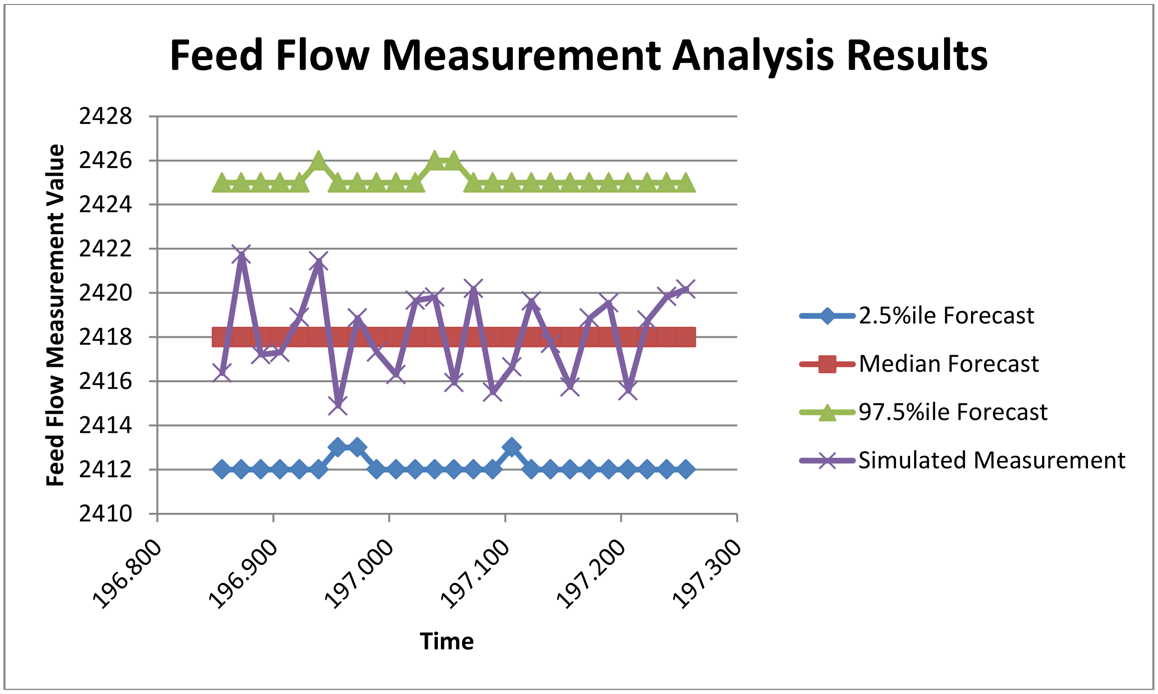

Figure 8: Bayesian approach, simulated feed flow measurement data and forecasting

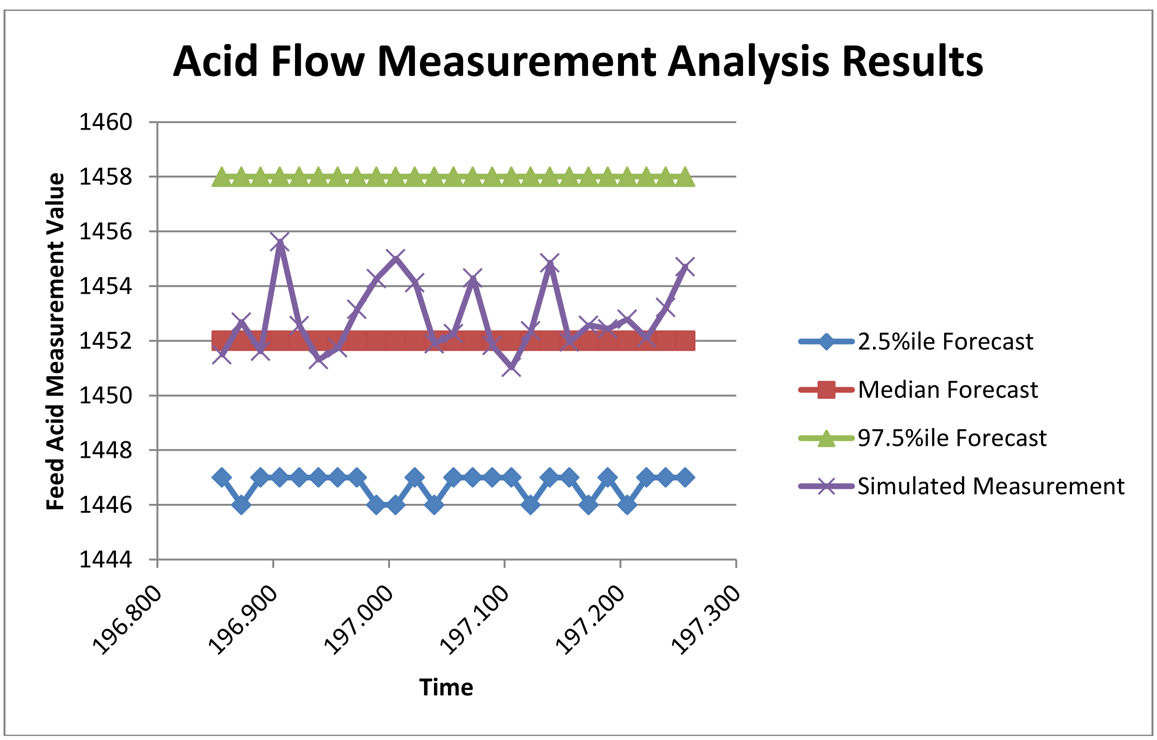

Figure 9: Bayesian approach, simulated acid flow measurement data and forecasting

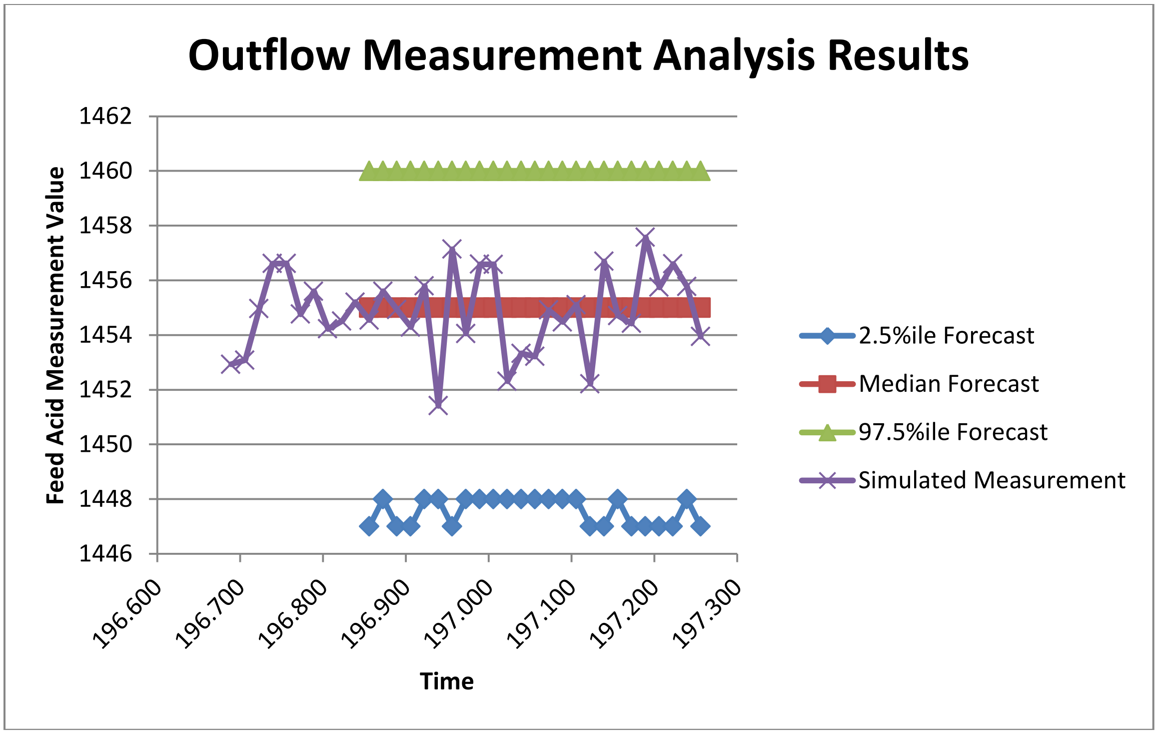

Figure 10: Bayesian approach, simulated outflow measurement data and forecasting

3.5 Discussion of Statistical Tests

Both the simplified Page's Test and pattern recognition methods provided similar probability of detecting material loss. They both utilized about the same amount of computational time. However, since the Page's Test is a more accepted method for setting alarm conditions, this test was chosen for use throughout the model. The pattern recognition test will be retained for additional study, but does not appear to provide any advantage. The analyses shown in the remainder of this report all use this simplified Page's Test to evaluate response to diversion scenarios under different instrumentation.

One considerable drawback to using bias correction to simplify the Page's Test is that it requires a learning period. Multiple runs have shown that sometimes the learning period is not completely representative—this will lead to false alarms during normal operation. The total measurement uncertainty plays an important role. In general as the uncertainty of the measurement increases, there is more scatter in the data, and the bias correction is more likely to be slightly off. Future work will need to examine this issue in more detail.

The results of the Bayesian forecasting appear promising, but the time required to perform the calculations was lengthy. Incorporation into the SSPM will not be possible unless the calculation time can be decreased significantly. However, it should be noted that this is simply a limitation of the way the SSPM is used for rapid diversion scenario analyses—in an actual plant the calculation times would not be a problem.

There are a few options for improving the calculation time of the Bayesian approach. The current algorithm could be programmed directly in Simulink, or a compatible programming language could be used. Also, the calculation should only focus on predicting the CuSum ID as opposed to individual flow rate measurements. Future work should examine these methods of optimization as well as how the Bayesian approach will respond in various diversion scenarios.

4.0 Analysis of New Measurement Technologies

As new measurement technologies are developed or as existing technologies improve, plant monitoring may improve. Assessment of these technologies requires a systems study since a large number of measurements typically come together to calculate an ID—an improvement in one area may not necessarily improve the overall calculation if the weakest areas of the plant are not addressed.

The SSPM was used to evaluate the impact that these new technologies can have on safeguards. Part of the purpose of this analysis is to help guide the development of new technologies in the Fuel Cycle Technologies program. The following sections describe the new technologies currently being developed and show an analysis of their impact on plant monitoring. The sections are broken down by type of measurement.

4.1 Used Nuclear Fuel Measurements

Past work [14,15] has consistently found that the absence of precision measurements of actinides in used fuel is one of the current weaknesses of materials accountability. Precision measurements cannot be taken until the fuel is dissolved and reaches the accountability tank. As a result, an ID cannot be calculated with much precision on the front end of the plant. For this reason operators rely on item accounting, containment, and surveillance of fuel at the front end.

Actinide measurements are particularly difficult on used fuel due to the high radiation background and self-shielding of the material. Past and current work is examining a number of non-destructive measurement techniques for potential use in improving the measurement of actinides in used fuel [15]. Four such techniques are being supported by the MPACT working group: Lead Slowing Down Spectroscopy (LSDS), Noble Gas Detectors, Fast Neutron Multiplicity, and Compton Veto.

For this work, the individual technologies were not the focus, rather the modeling focused on looking at the effects of improving the uncertainty of the measurement. This parametric study shows the goals that the new technologies should attempt to meet. Experimental results of the four technologies can be used to determine which have the best chance of reaching the goal.

A factor complicating this analysis is that an ID calculation requires the used fuel input measurement, the accountability tank and other output measurements, and the inventory measurements of all vessels in the front end. The inventory is not measured in existing plants, so it would either need to be estimated or measured as well. Measurement of actinides while undergoing dissolution would be extremely difficult due to the inability to sample and the difficult geometry. Therefore, this inventory measurement can only feasibly be estimated from the original used fuel measurement. Batch processing will be easier for accounting in this manner than continuous dissolution, so a series of batch dissolver tanks were used in the model. For this analysis, it was assumed that the inventory measurements could be estimated with the same random and systematic error as the used fuel measurement.

A number of runs were completed with a diversion of material from the surge tank right before the accountability tank in MBA1. The goal was to determine the detection limits for protracted diversions. In all cases, a total of 8 kg of plutonium was removed. In parallel, the process monitoring bulk material balances were used to determine how they may fill in gaps in anomaly detection. Table 3 shows the result of the analysis for various measurement uncertainties.

Used Fuel Measurement	Longest Protracted Diversion Detected
σ_r=10%, σ_s=10%	~4 h
σ_r=5%, σ_s=5%	~8 h
σ_r=1%, σ_s=1%	~320 h
σ_r=0.5%, σ_s=0.5%	~640 h

Table 3: Used nuclear fuel measurement analysis

At the 10% and 5% error levels for the used fuel measurement, the uncertainty was so large that only very abrupt diversions could be detected. At the 1% error level, a 320 hour diversion of 1 significant quantity (SQ) could be detected, and at the 0.5% error level, a 640 hour protracted diversion of 1 SQ could be detected. The significant improvement for the bottom two (beyond the ratio of the errors) is due to the fact that the measurement of Pu in used fuel storage is driving the overall uncertainty. For large errors, the uncertainty of the Pu measurement in storage is equal to or greater than the amount of Pu diverted. As the error comes down and the inventory uncertainty is well below the amount of Pu diverted, detection sensitivity increases. This non-linear relationship is part of the reason why systems studies like this are required.

Based on these results, a used fuel measurement must reach 1% in order to be able to provide protection against protracted diversions, but even at these levels, longer protracted diversions would not be detected. However, the results in Table 3 do not show the use of process monitoring data. If mass or volume balances are taken using the bulk process monitoring data with uncertainties near 0.1%, the longest diversion detected is near 4000 hours, which is equal to about 8 months of plant operations (taking into account down time).

Bulk measurements do not provide complete protection since it is possible for material to be diverted and replaced with surrogates. Process monitoring provides a significant advantage for monitoring direct material loss only. If it is not possible to reduce the used fuel plutonium measurement significantly, plants will likely need to continue to rely on containment and surveillance to ensure the area has not been tampered with.

4.2 Precision NDA Measurements

Completing a plutonium mass balance requires knowledge of the inventory of material within an MBA. For a more complex plant like UREX+ with multiple extraction steps, the internal plant can contain many processing vessels. Sampling of every area is impractical, and it is very difficult to get a representative sample is some locations. New non destructive analysis (NDA) measurements that can estimate plutonium content without disturbing operations could be valuable.

The MPACT campaign is investigating three new measurement technologies that may be useful for this goal: microcalorimetry, Compton veto, and the multi-isotope process (MIP) monitor. In addition, the Separations campaign is evaluating the UV-VIS technique for on-line process monitoring. The following outlines the uncertainty goals for these technologies to provide a benefit to the safeguards system.

For the front end of the plant (MBA1), the previous section already described the goals for improvement. The assumption was made that the measurement uncertainty on the used fuel would be equal to the uncertainty of the inventory of the dissolver tanks. Therefore, measurement uncertainty of plutonium in the dissolver tanks should achieve 1% or better to provide any value to the system. Because the amount of plutonium in the dissolver tanks is so large, this measurement drives the overall mass balance just as much as the used fuel measurement.

For MBA2, previous work determined that a number of locations process small or trace amounts of plutonium [1], and these areas can have large measurement uncertainties without affecting the overall measurement error. In order to test this more formally, the model was used to parametrically change the measurement errors and look at the effect on the CuSum ID error bars. To start, all of the tanks processing large amounts of plutonium were assumed to be sampled and measured at low uncertainty (at 0.2% random and systematic error). The plutonium in all remaining processing units, contactor banks, and tanks in MBA2 was assumed to be measured to 2%, 5%, 10%, and 20% over the same diversion scenario. Figure 11 shows the areas that were varied in this study.

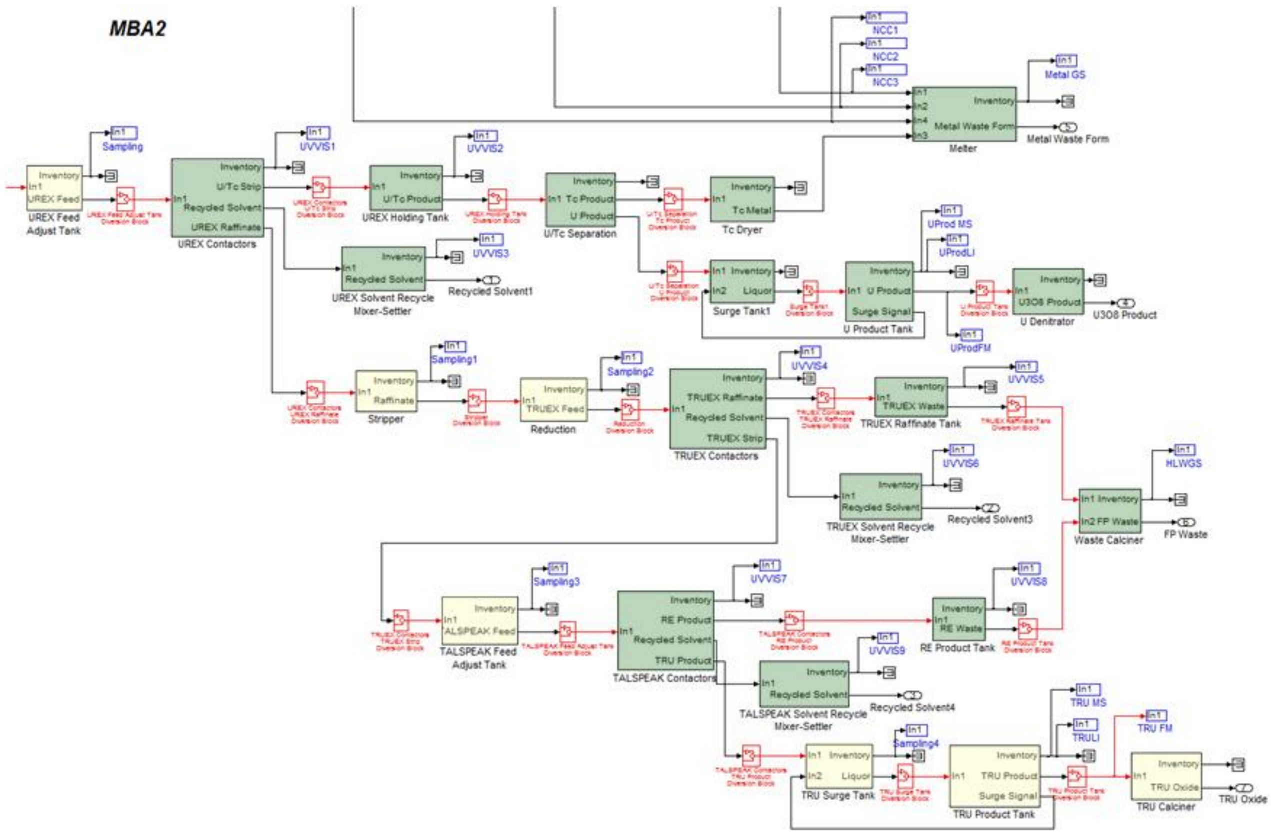

Figure 11: MBA2 with areas processing small (green) and large (yellow) quantities of plutonium

Figure 12 shows the CuSum ID plots from the analyses assuming the small inventory measurements are at 2%, 5%, 10%, and 20%. The fact that the magnitude of the error bars does not change show that increasing the measurement uncertainty has almost no effect on the overall uncertainty. Also, the random scatter in the data does not increase visually. Therefore, these locations in MBA2 only require a plutonium measurement at 20% or better in order to achieve near real time accountability (NRTA). A number of simpler technologies can easily achieve this level of uncertainty.

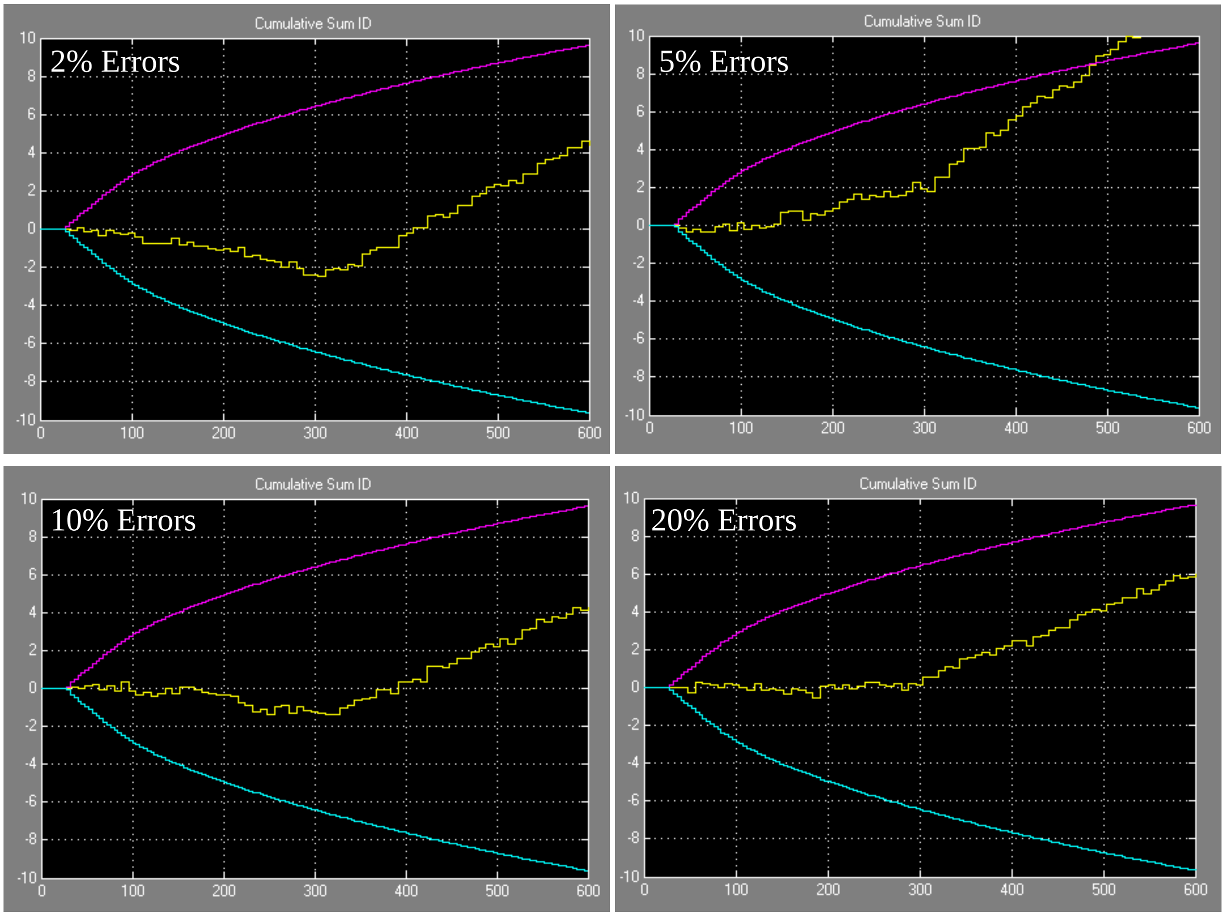

Figure 12: Parametric analysis results showing little difference in error bars as the uncertainty increases for areas processing small quantities of plutonium

4.3 Sampling Points

Traditional accounting from sampling at key tanks can be a lengthy process for a few reasons: First, the tanks need to be mixed thoroughly to get representative samples. Second, the measurement requires chemical separations first before running through a mass spectrometer. Third, the use of mL-sized samples poses radiation hazards that may slow down the progress. For all of these reasons, traditional sampling requires a lot of time for analytical staff.

Proposing more sampling points will require improvements in all three areas. Methods for getting representative samples in shorter times or through well-designed pauses in operation will be required. Measurement technologies that do not need to do chemical separations or techniques for automating the separations will help to speed the processing time. Finally, the use of mL sampling will help to reduce radiation hazards and reduce waste from the analytical lab.

These techniques are outside the scope of this report but are investigated in a parallel project (reference 5) and in references 16 and 17. Such advanced sampling technologies will play an important role in developing a near real time plant monitoring system.

4.4 Discussion

Any potential improvements to the front end of reprocessing depend on improving the used fuel measurement. Bulk mass measurements are useful in the absence of a better used fuel measurement, but they will still rely on containment and physical protection on the front end.

Optimization of MBA2 can allow for a near real time system without requiring expensive equipment throughout the plant. A majority of the areas in MBA2 require a plutonium measurement with uncertainty of 20%, and many simple technologies can be used. In many cases, process monitoring measurements coupled with a simple spectroscopic technique will be adequate. A relatively small number of additional tanks will need to be sampled, but current work should allow for additional sampling without increased cost.

5.0 Safeguards and Security Integration

The previous sections describe materials accountancy, but material measurements are only one part of a plant's defense against material loss. Reprocessing plants also contain extensive physical protection barriers and administrative procedures to protect against loss. True diversion scenario analyses must look at how the material, once removed, will make it off-site. Existing plants do not integrate these various systems extensively.

The SSPM has been used to setup a physical protection system (PPS) to examine how material balances and administrative procedures can be better integrated into the overall plant monitoring system. The following sections describe the setup for the PPS, administrative procedures, the model setup in the SSPM, and results under various diversion scenarios. ATLAS [18] (Adversary Time-Line Analysis System) was used to design a hypothetical PPS for both MBAs in the SSPM.

The modeling for this work focused on theft or diversion of material by an insider adversary during normal facility operations. The insider adversary has access to and knowledge of the plant's operations and is assumed to be a passive, non-violent insider who will undertake diversion activities without the use of any tools. For each security layer, descriptions of the protection elements and associated hypothetical performance values for delay times and detection probabilities were developed for the ATLAS model. Delay times and detection probabilities were tailored specifically for the insider, leading to two key assumptions: (1) the delay times are analogous to adversary task times for an insider; and (2) traditional detection methods would not be effective against a knowledgeable insider, so detection is based primarily on observations of unauthorized activities and attempts at unauthorized access. Performance values for the model are given in a limited release appendix.

5.1 MBA1 ATLAS Model

The front end includes fuel receipt through the accountability tank, and is contained entirely in the fuel building. Fuel is received and stored on-site in the fuel building to maintain continuous operation. Fuel chopping, dissolution, and accountability would occur in a hot cell or canyon. A surge tank regulates batch flow into the accountability tank where samples can be taken for precise analytical measurements. The feed out of the accountability tank leaves the fuel building to go to a different building where separation occurs.

Figure 13 is the adversary sequence diagram (ASD) for the front end of the facility. An ASD is a two-dimensional graphical representation of all PPS layers and protection elements defined for a facility, as well as all possible adversary paths through the facility. The target material is chopped, used fuel pieces containing uranium and plutonium oxide. This target is indicated at the bottom of the ASD in Figure 13. The type of target is an item process line (IPL) and the primary safeguard for detection is input verification of the target material (by bulk mass balance).

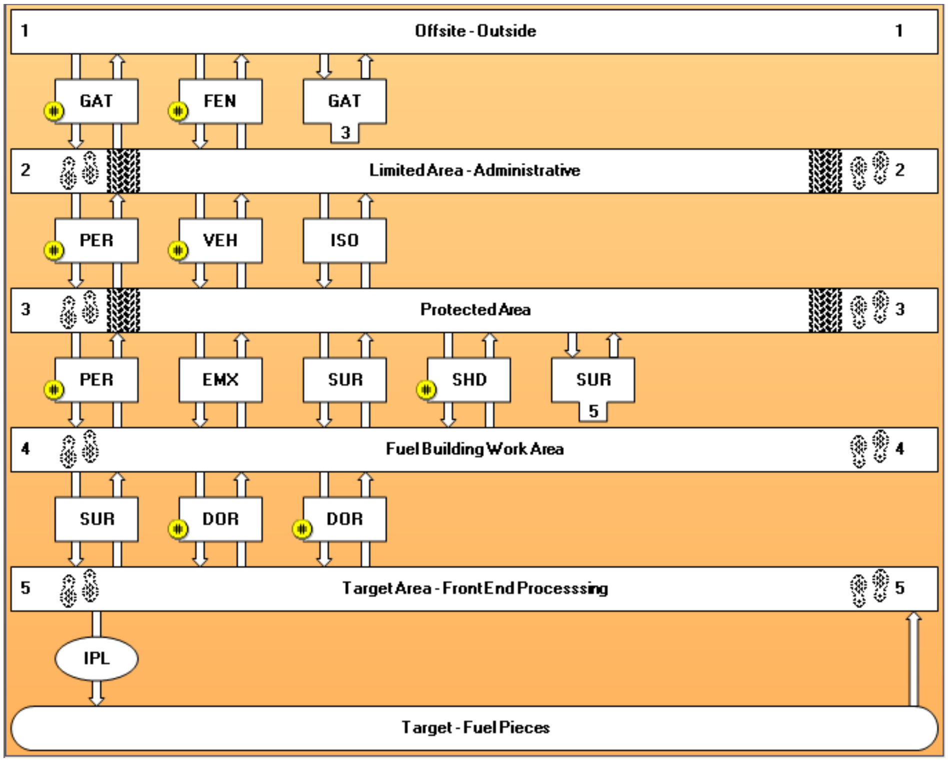

Figure 13: Adversary sequence diagram for the front end

Security Layers and Physical Protection System Elements- MBA1

The protection elements between the target area and the fuel building work area include the following:

- Surface (SUR)- Hot cell wall
  The insider adversary cannot penetrate this barrier because he has no tools.

- Door (DOR)- Hot cell door:
  The adversary has authorized access and can open an electronically coded lock on the vault-type door. The door position monitor may alarm or may be disabled, but assessment of unauthorized activity is needed. General observation and a portal SNM monitor on exit may provide detection of unauthorized activity.

- Door (DOR)- Canyon ceiling access:
  The adversary may have authorized access and can attempt to obtain the padlock key for the ceiling access. The door position monitor may alarm or may be disabled, but the assessment of unauthorized activity is needed. No general observation is available to provide detection of unauthorized activity.

The protection elements between the fuel building work area and the protected area (PA) include the following:

- Personnel Portal (PER)- Into fuel building work area:
  The insider adversary has authorized access from the PA to the fuel building and enters following normal procedures. An SNM monitor and metal detector are present on exit to detect unauthorized activity.

- Emergency Exit (EMX):
  The insider adversary can exit, but not enter, the fuel building through the emergency exit. An activated door position monitor may detect unauthorized activity.

- Surface (SUR)- Exterior fuel building wall:
  The insider adversary cannot penetrate this barrier because he has no tools.

- Shipping/Receiving Doorway (SHD)- Fuel cask shipping/receiving:
  Fuel casks are shipped in by rail through this doorway and unloaded for chopping. When the fuel casks are being unloaded, the insider adversary may take the opportunity to move material through the doorway, or may piggyback material on the railcar to remove it from the fuel building.

- Surface (SUR)- Fuel building wall in target area:
  This surface leads directly from the protected area to the target. The insider adversary cannot penetrate this barrier because he has no tools.

The protection elements between the protected area and the limited area (LA) are:

- Personnel Portal (PER)- Pedestrian portal into the PA:
  The insider adversary has authorized access from the LA to the PA following normal procedures. An SNM monitor and metal detector are present on exit to detect unauthorized activity.

- Vehicle Portal (VEH)- Commercial service vehicles into the PA:
  The insider adversary may piggyback material onto a commercial vehicle.

- Isolation Zone (ISO)- Perimeter Intrusion Detection and Assessment System (PIDAS) around the PA:
  The insider adversary cannot penetrate this barrier because he has no tools, and throwing material over the zone was determined to be not feasible.

The protection elements between the limited area and offsite include the following:

- Gate (GAT)- Site entrance for vehicle traffic:
  The insider adversary may take material out in a personal vehicle.

- Fence (FEN)- Fence around site:
  The insider adversary cannot penetrate this barrier because he has no tools, but can move the material past this barrier. He may be detected by a security officer on patrol.

- Gate (GAT)- Rail gate for shipping casks:
  Fuel casks are shipped in and out through this gate. The insider adversary may take the opportunity to move material through the doorway or piggyback material on a railcar.

5.2 MBA2 ATLAS Model

The separations portion of the plant includes all of the chemical processes to separate out the uranium and transuranics (TRU). The separations are undertaken in the extraction building, with product and waste streams sent via tunnel to other buildings for additional processing. UREX feed enters the separations building through a tunnel from the fuel building. After entering the separation building, it is passed through a series of contactors and strippers to successively separate out different species. The first separation step co-extracts U and Tc, which are then sent to waste processing. The raffinate is then sent through a TRUEX extraction process, which co-extracts the TRU and lanthanides. The final separation step is a TALSPEAK process, where the lanthanides are separated out, leaving a TRU product. The TRU product tank is contained within a hot cell or canyon. Figure 14 is the ASD for the separations portion of the facility. The target material is TRU solution in a product tank, as shown at the bottom of the figure. The type of target is a bulk process line (BPL).

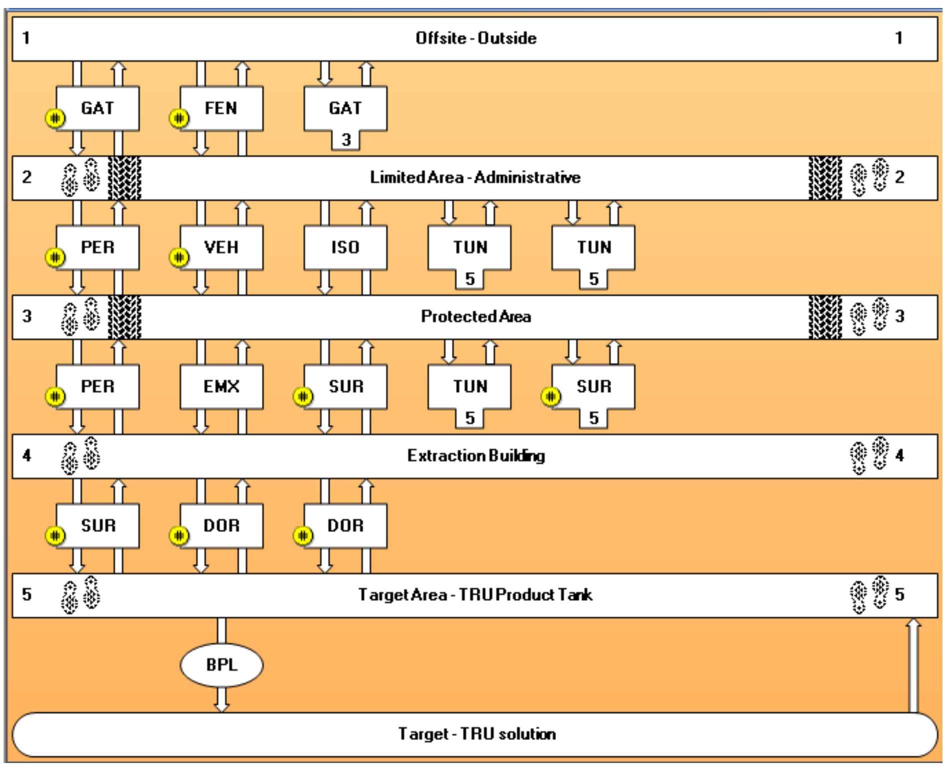

Figure 14: Adversary sequence diagram for separations

Security Layers and Physical Protection System Elements- MBA2

The protection elements between the target area and the extraction building include the following:

- Surface (SUR)- Hot cell wall
  The insider adversary cannot penetrate this barrier because he has no tools.

- Door (DOR)- Hot cell door:
  The adversary has authorized access and can open an electronically coded lock on the vault-type door. The door position monitor may alarm or may be disabled, but assessment of unauthorized activity is needed. General observation and a portal SNM monitor on exit may provide detection of unauthorized activity.

- Door (DOR)- Canyon ceiling access:
  The adversary may have authorized access and can attempt to obtain the padlock key for the vault-type door. The door position monitor may alarm or may be disabled, but the assessment of unauthorized activity is needed. No general observation is available to provide detection of unauthorized activity.

The protection elements between the extraction building and the protected area include the following:

- Personnel Portal (PER)- Into extraction building:
  The insider adversary has authorized access from the PA into the extraction building and enters following normal procedures. An SNM monitor and metal detector are present on exit to detect unauthorized activity.

- Emergency Exit (EMX):
  The insider adversary can exit, but not enter, the extraction building through the emergency exit. An activated door position monitor may detect unauthorized activity.

- Surface (SUR)- Exterior fuel building wall:
  The insider adversary cannot penetrate this barrier because he has no tools.

- Tunnel (TUN)- Tunnel to U/TRU solidification and repackaging:
  The insider adversary could send material through a tunnel from the extraction building to another building in the protected area. This tunnel leads directly from the target area into the protected area. It is not man-passable. No detection systems exist in the tunnel.

- Surface (SUR)- Extraction building wall in target area:
  This surface leads directly from the protected area to the target. The insider adversary cannot penetrate this barrier because he has no tools.

The protection elements between the protected area and the limited area are:

- Personnel Portal (PER)- Pedestrian portal into the PA:
  The insider adversary has authorized access into the PA following normal procedures. An SNM monitor and metal detector are present on exit to detect unauthorized activity.

- Vehicle Portal (VEH)- Commercial service vehicles into the PA:
  The insider adversary may piggyback material onto a commercial vehicle.

- Isolation Zone (ISO)- Perimeter Intrusion Detection and Assessment System (PIDAS) around the PA:
  The insider adversary cannot penetrate this barrier because he has no tools.

- Tunnel (TUN)- Liquid waste and U/Tc tunnels
  The insider adversary could send material through either of the two tunnels from the extraction building to a building in the limited area. These tunnels lead directly from the target area into the limited area. They are not man-passable. No detection systems exist in these tunnels.

The protection elements between the limited area and offsite include the following:

- Gate (GAT)- Site entrance for vehicle traffic
  The insider adversary may take material out in a personal vehicle.

- Fence (FEN)- Fence around site
  The insider adversary cannot penetrate this barrier because he has no tools, but can move the material past this barrier. He may be detected by a security officer on patrol.

- Gate (GAT)- Rail gate for shipping casks
  Fuel casks are shipped in and out through this gate. The insider adversary may take the opportunity to move material through the doorway or piggyback material on a railcar.

5.3 MC&A Procedures & Human Reliability

Traditional physical security measures are largely ineffective against an insider adversary; however, MC&A procedures can serve as a type of sensor to bolster both delay and detection against the insider threat. To assess the added value of MC&A procedures for material protection, these procedures were integrated into the SSPM. A human reliability analysis (HRA) model was used for this integration. HRA has been used to characterize procedures at nuclear power plants [19], and recent work has extended this method to MC&A procedures at nuclear facilities [20]. This method is useful for procedures that require a person to check the status of a critical asset. For nuclear power plant procedures, baseline human error probabilities (BHEP) have been established for several different checking procedures. Many of these activities are analogous to MC&A activities, and as such, BHEPs have been assigned to a variety of administrative MC&A activities that may occur at nuclear facilities. A daily administrative check (DAC) with a BHEP of 0.10 was integrated into the SSPM. This means that the baseline probability of detecting an anomaly with a DAC is 0.90, assuming there is enough data present to show the anomaly.

HRA prescribes a positive dependence relationship between checking activities, meaning the success of one activity depends on the success of the activity immediately preceding it. In the context of a DAC, the failure to detect an anomaly one day increases the probability that the anomaly will not be detected the next day. The strength of this dependence relationship is described by the dependency factor. Equation 10 has been adapted from the general failure equation and gives the mathematical formulation for this positive dependence relationship. It describes the probability that an anomaly will not be detected on day n, given that the anomaly was not detected the previous day.

$$P(ND_n|ND_{n-1}) = \frac{1+aP_{ND_{n-1}}}{a+1} \qquad \text{(Eq. 10)}$$

where a is the dependency factor, with values of 19, 6, and 1, corresponding to low, moderate and high dependency, respectively. This equation was used to calculate daily probabilities of MC&A detection for the duration of the simulation in the SSPM.

The complication is that the calculation for HRA cannot be applied until there is enough data present to detect the anomaly. In the case of a protracted diversion, many inventory balances may be required until there is enough confidence that the diversion should be detected. In order to model this, an additional factor must be used that represents the detection probability as a function of time, based on the diversion fraction.

While the probability of detection decreases for each MC&A instance according to the positive dependence relationship given in Equation 10, the cumulative detection probability increases according to Equation 11,

$$P_{D,cumulative} = 1 - \prod_{i=1}^{n} P_{ND_i} \qquad \text{(Eq. 11)}$$

where P_{ND_i} is the probability of non-detection for each MC&A event, or the complement of the detection probability. Thus as the length of the scenario timeline increases, the cumulative probability of detecting the theft also increases, despite the drop in detection probability for each MC&A event, because the adversary is subjected to additional MC&A checks.

5.4 Integration in the SSPM

The primary goal of the integration is to determine how additional plant data can improve the overall plant monitoring system. This was accomplished by creating PPS subsystems whose state would change if an alarm occurred in any material balance calculation or in the administrative procedures. The following two sections describe how these subsystems were setup in the model.

5.4.1 MC&A Administrative Procedures & Human Reliability

Only one example of an administrative procedure at a reprocessing plant was modeled in the SSPM, the daily administrative check (DAC). This check was assumed to occur once every 24 hours. The assumption is that a plant administrator is reviewing the plant data once daily, and this data comes from a variety of sources. The administrator may directly monitor the CuSum ID of various areas in the plant, shipper-receiver data, material movements, cold chemical supply, etc. This administrator is likely to have intimate knowledge of the plant which may allow him to identify an anomaly before the material balance system can automatically produce an alarm.

The DAC subsystem is shown in Figure 15. This calculation only starts when an actual diversion begins in the model. The probability of detection is 0.9 multiplied by a value that depends on the diversion fraction and the amount of time that has passed. Examination of numerous diversion scenarios has shown that the diversion fraction, multiplied by 10, multiplied by the time since the diversion started (in hours) is an appropriate multiplier (but it must saturate out at 1.0). The goal is to simulate how additional mass balance periods during a diversion make it increasingly likely to visually detect the event. The HRA calculations are used in the triggered subsystems to calculate a detection probability once every 24 hours. The dependency is currently set up as a constant, but could be changed for each procedure. If an alarm occurs, the output signal changes from zero to one.

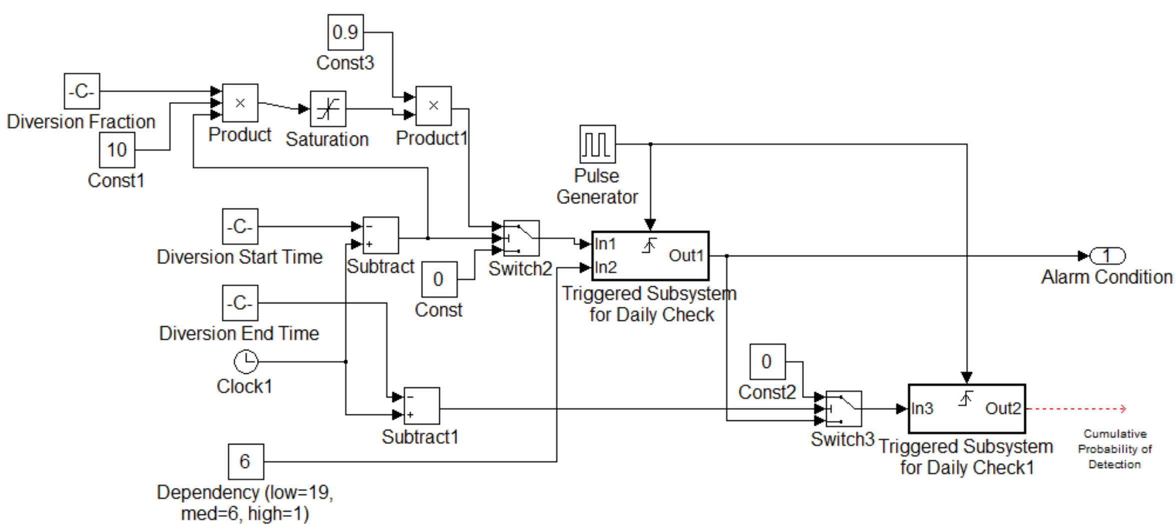

Figure 15: Daily administrative check subsystem

When the alarm condition signal changes, the model is programmed to generate a popup window that tells what the alarm is (Daily Administrative Check) and when it occurred. The alarm condition is one of the input feeds into the PPS system that can change the state of the system. Although this is just one example, this template can be copied and modified for other types of administrative procedures that may occur at different time intervals. The alarm conditions from each can be used to influence the PPS system state.

5.4.2 PPS System

The SSPM includes a number of locations from which material can be diverted. The diversion scenario is defined by the user at the start of a run. Depending on where the diverted material is coming from, the architecture for the PPS subsystems routes the diverted material through the appropriate PPS system elements.

Figure 16 shows the PPS system subsystems for MBA1 and MBA2. The inputs into each subsystem are the diverted material and three potential alarm signals: MBA alarm (plutonium balance), process monitoring alarm (bulk balance), and the MC&A administrative procedures alarm. These three alarms can all change the state of the PPS system. The window shown on the right in figure 16 allows the user to define the particular diversion path through the PPS elements. This window shows the options for MBA1. In addition to defining the path, the user can also define if the material is held up in any one barrier to find a more optimal time to divert.

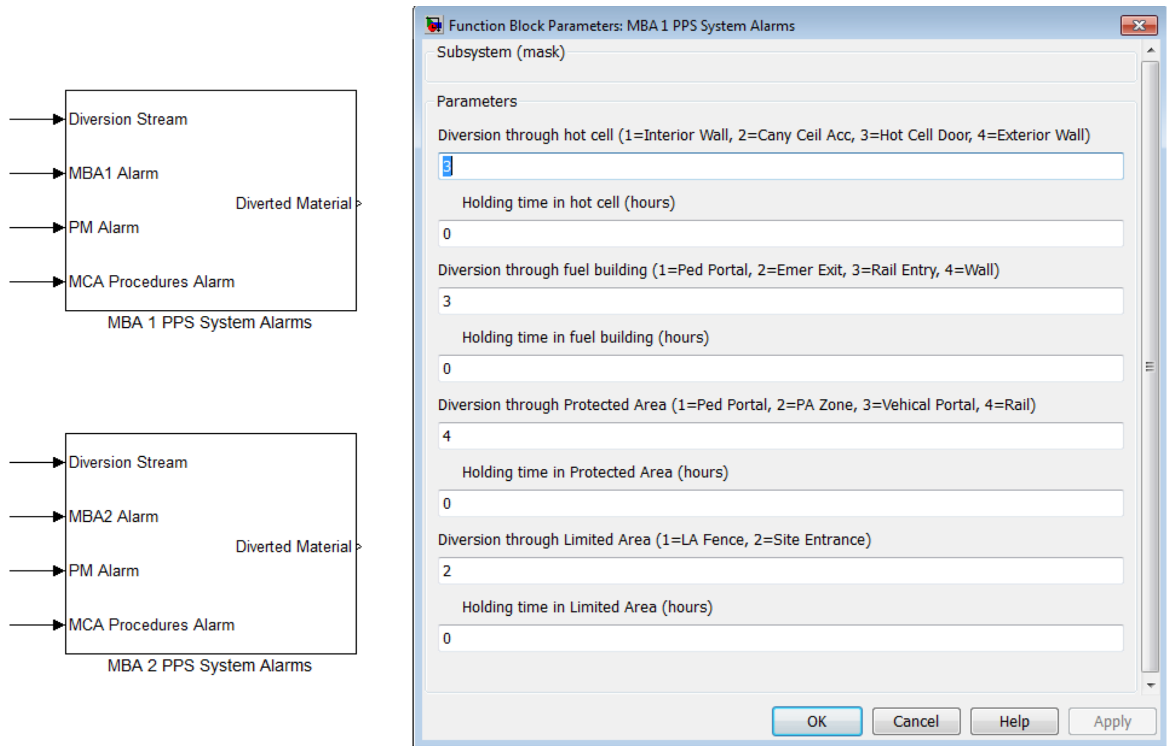

Figure 16: PPS subsystem inputs

The actual PPS for MBA1 and MBA2 (one level down in the model) are shown in Figures 17 and 18. These figures show the multiple pathways through which material can travel to get off-site, all based on the ATLAS models described previously. The particular target is chopped fuel in the process cell (hot cell) for MBA1 and the TRU product solution for MBA2.

Each particular barrier has a number of possible paths to get material out—based on the user inputs, diverted material will only travel through one pathway. In some cases, the pathways can go through multiple barriers. A delay block was used to represent the combination of penetration time and delay time for that pathway. The delay times as shown later in the example diversion scenarios are all hypothetical, but performance data from ATLAS is included in the limited release appendix. In this manner the diverted material is routed through the diversion path chosen by the user.

Each pathway has an alarm probability associated with it, although in some cases the probability may be 0%. An embedded Matlab code (labeled 'MBA PPS Alarm Messages' in the upper right hand corner of the figures) contains all of the alarm probabilities for each pathway. If material is traveling through that path, there is a finite chance of the alarm going off (as long as the probability is greater than 0%). A random number generator is used to determine if an alarm is indicated based on the associated alarm probability. An alarm is indicated with a message popup window that gives the PPS element location and the alarm time. The embedded Matlab code is shown in the limited release appendix.

The goal of this work is to examine how the integration of material balance data and administrative procedures may improve the PPS by increasing the probability of timely detection through tighter integration. Any potential alarms in the plutonium balance, the process monitoring balance, or the administrative procedures subsystems will place the PPS system into an alert state. Under an alert state, the detection probabilities of the PPS elements may increase significantly. For example, the area of the plant may undergo scrutiny, guard rounds may increase, or door combination codes may rotate. The alert state makes it more likely to detect the particular diversion pathway so that the event can be stopped. This improvement extends beyond security. If a vessel leak causes an alarm to go off, more intense scrutiny of the area will show the problem and allow the operator to fix the vessel as soon as possible.

While the diversion pathways and detection probabilities for a particular adversary were modeled in the SSPM, it is not currently setup to run an automated path analysis. The user defines the path, but the current work has not attempted any down-select to determine credible diversion scenarios. Future work can examine the path analysis to determine groups of diversion scenarios that are of concern.

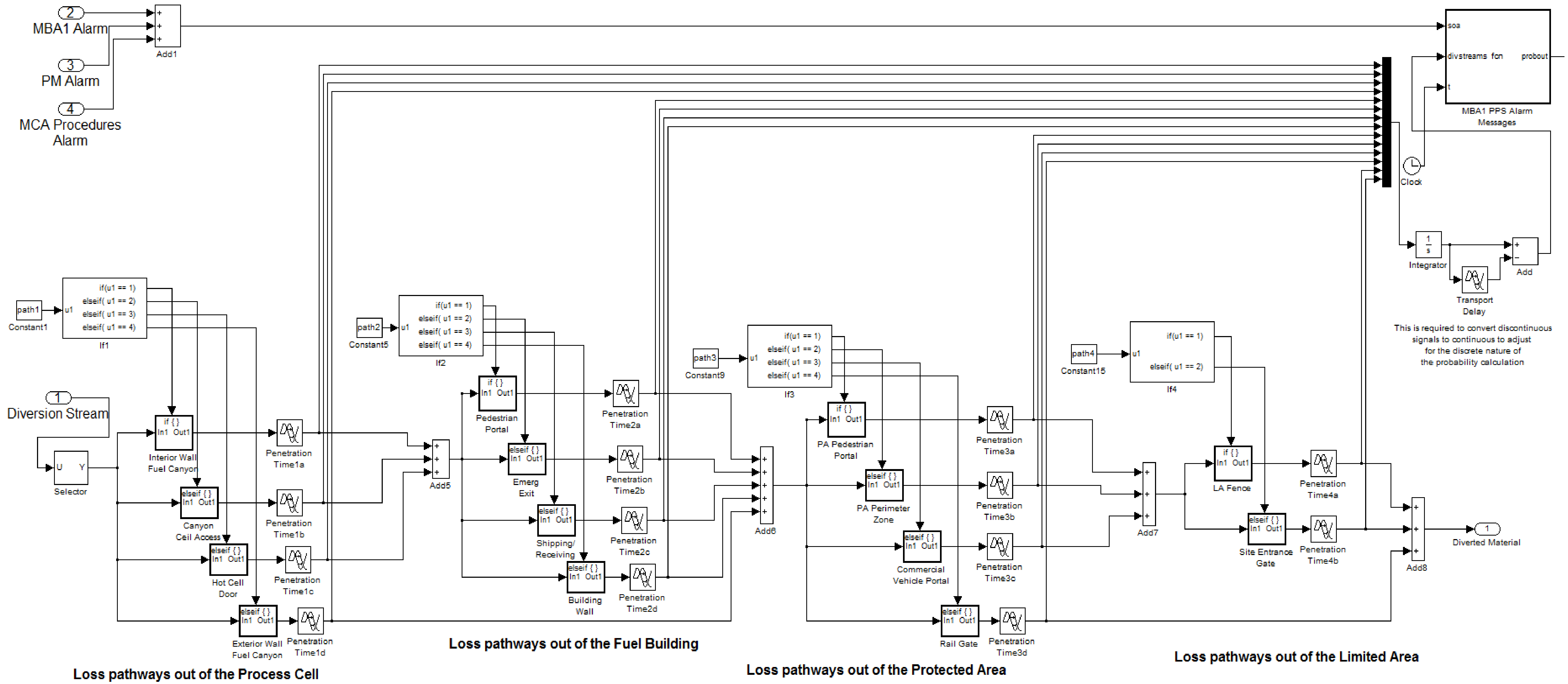

Figure 17: PPS for MBA1

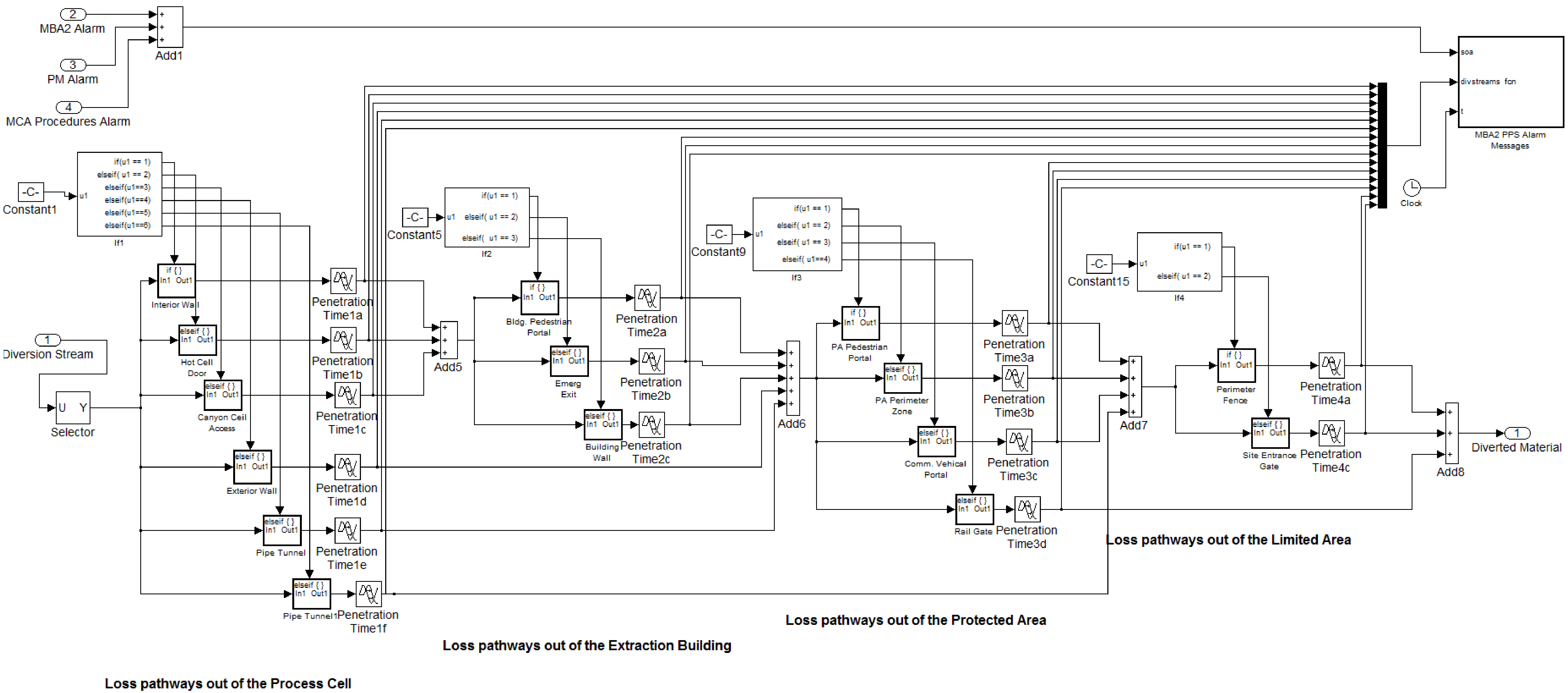

Figure 18: PPS for MBA2

5.5 Diversion Scenarios

A number of diversion scenarios were run to test the concept of the integrated systems. These runs included the culmination of all work previously described in the report, so the Page's Test was used for the plutonium balance and bulk material balance alarms. A future plant design with NRTA was also assumed. The diversion scenarios described looked at the effects of the alarms on the PPS system.

5.5.1 Effect of Plutonium and Bulk Material Balance Alarms

Initially, only the process monitoring and plutonium balance system alarms were integrated into the PPS. An abrupt diversion was set up for the MBA1 assuming that chopped fuel pieces were removed from the hot cell. This diversion occurred over 24 hours (starting at hour 300) for a total of 8 kg of plutonium. The material was assumed to be removed through the hot cell door, then smuggled out on a rail car through shipping/receiving, and then out the rail gate. The detection probabilities were arbitrarily assumed to be 25% for the hot cell door, 10% at shipping/receiving, and 10% at the rail gate. Also it was assumed that two trips would be required to get all the material out, so the probabilities were calculated every 10 hours.

Figure 19 shows the baseline results without integration of the material balance data. The left graph shows the bulk CuSum ID for the Chopper location, and the right graph shows the plutonium balance CuSum ID across MBA1. In this scenario, none of the PPS system elements alarmed. The lower probabilities coupled with only two detection opportunities limited their response.

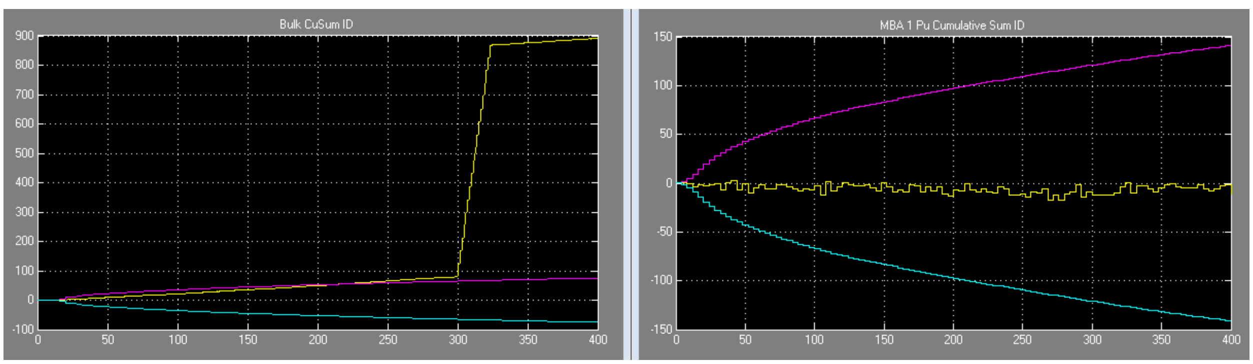

Figure 19: Abrupt diversion from MBA1 without integrated systems—no PPS alarm blocks were indicated during the diversion

The same diversion scenario was run but with the integrated system that allowed for a alert state to be reached. If an alarm signaled an alert state, the three PPS elements' detection probabilities increase to 50%. Figure 20 shows these results. In this case, the process monitoring alarm triggered an alert state 4 hours after the diversion started, and the plutonium balance was able to signal an alarm after 24 hours. The increased detection probabilities led to 2 PPS alarms. Shipping and receiving was able to detect the material diversion after 30 hours, and the site rail gate detected the material transfer after 50 hours. Note that a lag time was programmed into the model to simulate a delay time before a rail car would leave the facility.

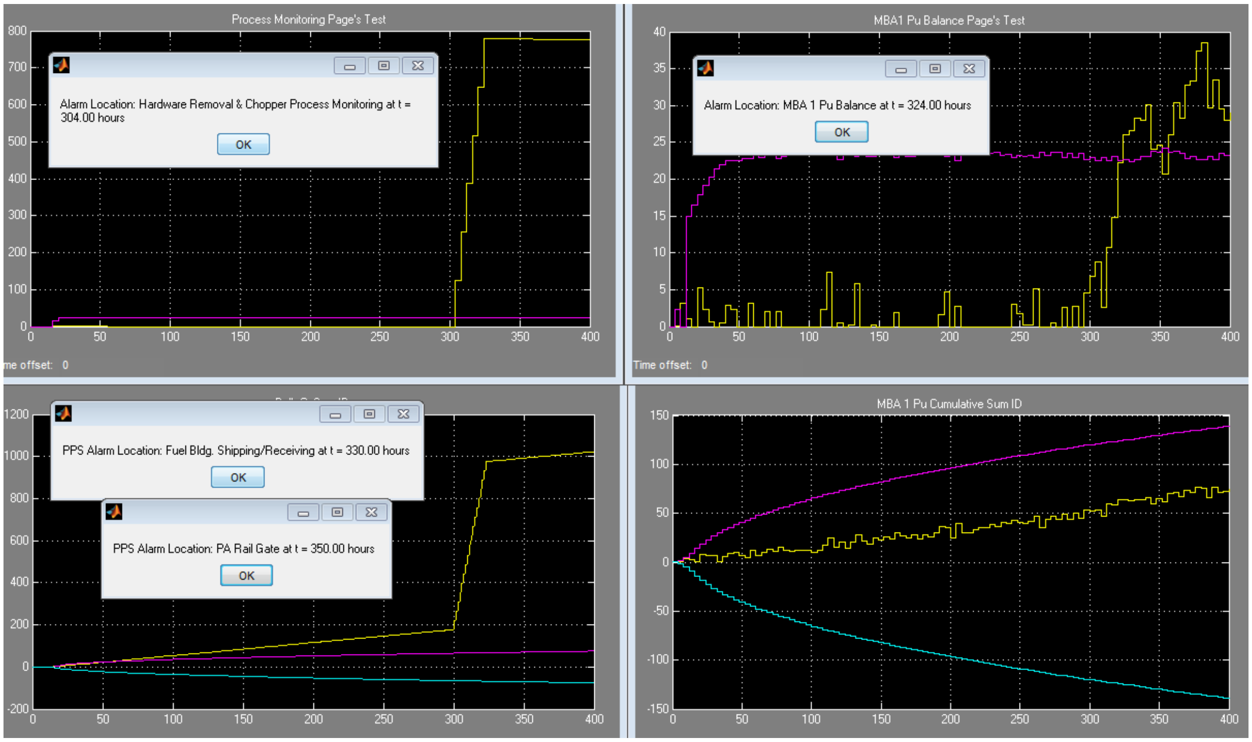

Figure 20: Abrupt diversion from MBA1 with integrated systems—the process monitoring alarm triggers an alert state causing two PPS alarms

A protracted diversion scenario was examined to look at response times when material is removed little by little over long periods of time. Due to the large volumes of liquid that must be removed for one significant quantity of plutonium, it is very possible that many trips would be needed for an adversary to remove the material. In this diversion scenario, 0.1% of the flow into the stripper tank was diverted over 1600 hours (starting at hour 300). The material was assumed to be removed from the process cell by the canyon ceiling access, then removed through the emergency exit, and then smuggled onto a rail car to leave the facility. The detection probabilities were arbitrarily assumed to be 5% for the ceiling access, 10% for the emergency exit, and 5% for the rail car exit. The alert state was designed to increase these probabilities to 50% for all three. It was assumed that there would only be one chance per day to remove material in this manner, so the detection probabilities were only calculated once every 24 hours.

Figure 21 shows the monitoring screen assuming that the materials accountancy and process monitoring data is not linked to the PPS system. The detection probabilities for a knowledgeable insider are low and remain low throughout the diversion. In fact, existing reprocessing plants that cannot achieve low uncertainty for NRTA would probably not detect this material loss until many months later at a plant flushout. Therefore, this could be representative of an existing plant. However, due to the increased number of opportunities, all three PPS elements were able to alarm. The ceiling access alarm was seen 180 hours after the start of the diversion, followed by the rail gate alarm after 276 hours, and lastly the building emergency exit after 324 hours. The PPS system was able to respond to this material diversion before half of a significant quantity was removed.

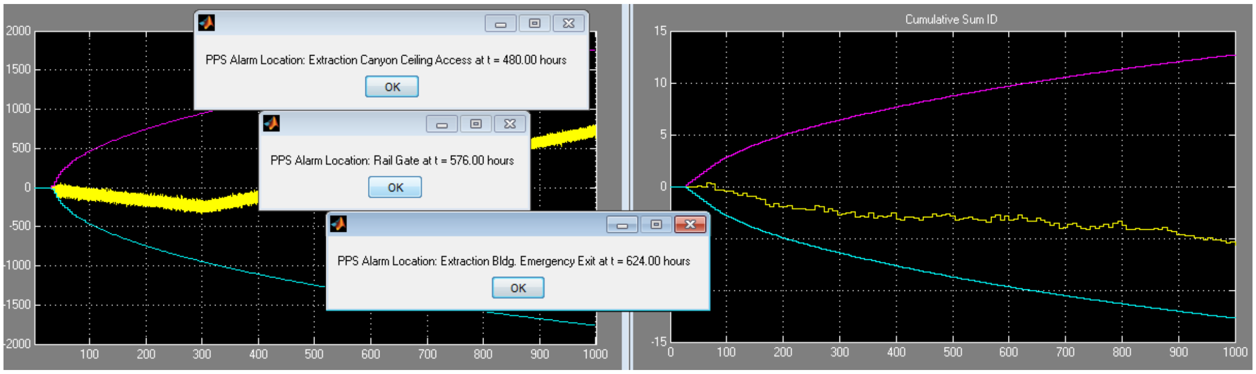

Figure 21: Protracted diversion from MBA2 without integrated systems—PPS alarm blocks were indicated due to multiple detection opportunities

In comparison to the above results, the same diversion scenario was run assuming the integrated system. Figure 22 shows the result. The process monitoring system alarmed 108 hours after the diversion started, and the plutonium balance alarmed after 124 hours. The increased detection probabilities (due to the alert state) led to an alarm at the Extraction Building emergency exit immediately, and alarms at the canyon ceiling access and rail gate shortly thereafter. Note that the diversion started at hour 300, but the PPS elements did not alarm until the alert state was achieved.

The protracted diversion scenarios show that the integration of the materials accountancy alarms can significantly speed up detection time in the PPS system elements. This example simply highlights the idea, but actual results will be highly dependent on the facility design and actual detection probabilities. These results also point out why an adversary would want to remove material all at once as opposed to over multiple days. Although the probability of detecting removal of a small quantity might be lower, repeatedly removing small amounts of material over time eventually raises the cumulative probability of detection above the probability of detecting an abrupt removal of a single larger quantity.

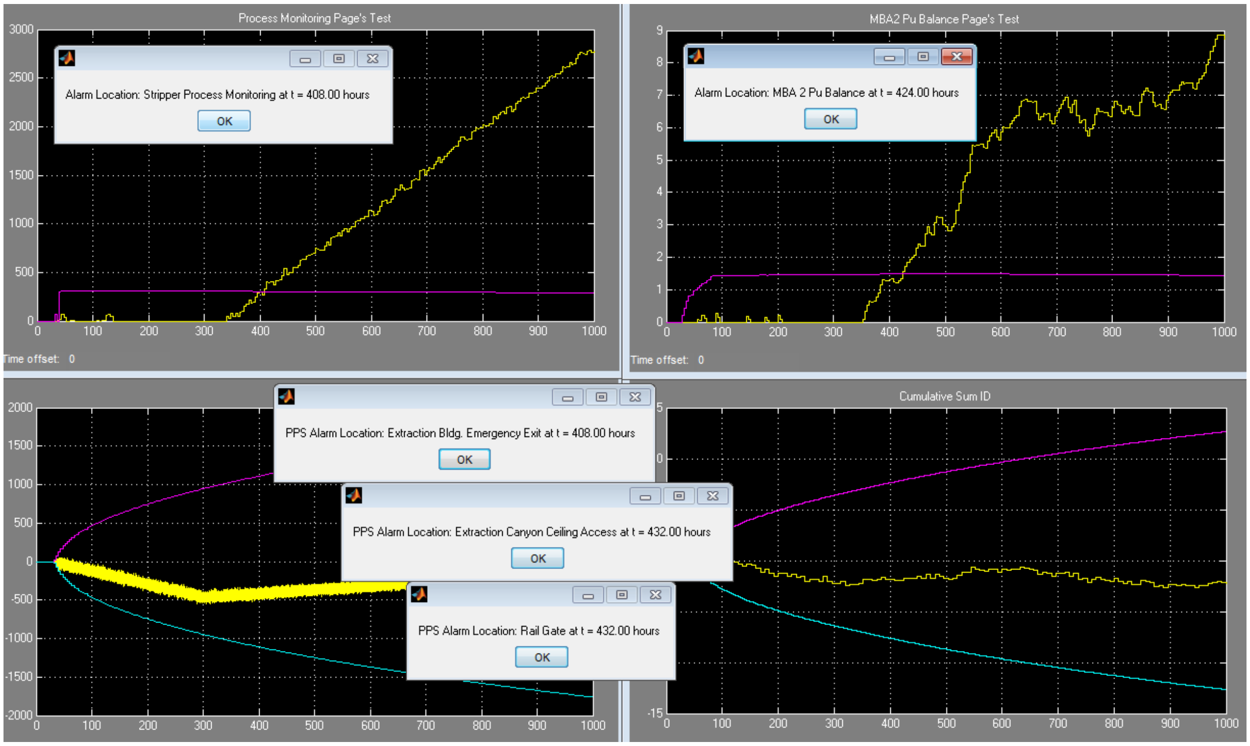

Figure 22: Protracted diversion from MBA2 with integrated systems— PPS alarm blocks were indicated earlier sue to the alert state

5.5.2 Effect of MC&A Administrative Procedures Alarms

The previous diversion scenarios did not take into account administrative procedures that may indicate process discrepancies. The administrative procedures example that was put into the model was a daily administrative check, so it will only occur once every 24 hours. Two diversion scenarios were examined to determine if an administrative procedures alarm will trigger an alert state. In both cases, the material balance alarms were disabled in the model.

The first scenario was an abrupt diversion of fuel pieces from MBA1 over 24 hours, for a total diversion of 8 kg of plutonium (the same abrupt diversion as shown earlier). It was assumed that material was removed twice during this diversion. Figure 23 shows the result from the run. During this run, the daily administrative check signaled an alarm in the middle of the diversion. This in turn triggered an alert state that indicated alarms in two of the PPS elements. A 24 hour delay time was built into this run, which is why the PPS system elements alarmed after the material was initially diverted. This result shows that the administrative procedures can enhance the plant monitoring system by improving the detection timeliness.

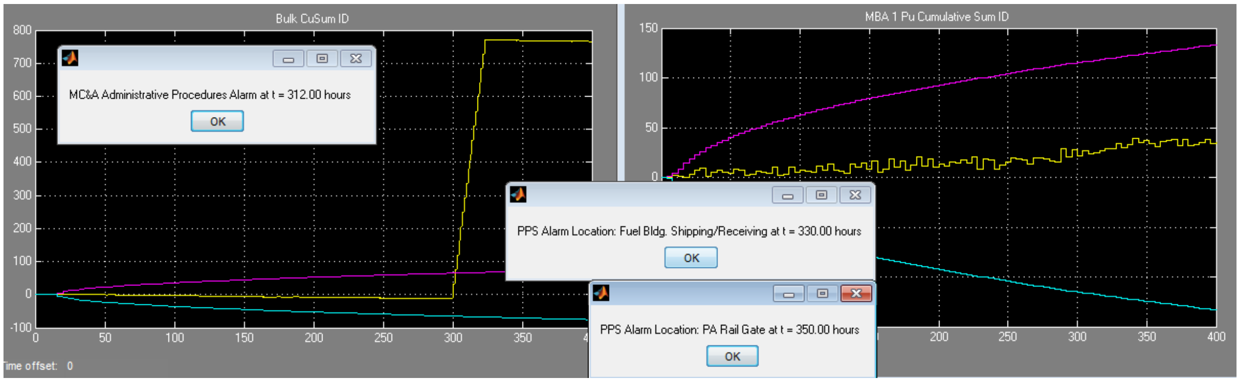

Figure 23: Abrupt diversion from MBA1 with integrated systems—the administrative procedures alarm triggers an alert state causing two PPS alarms

The second scenario was a protracted diversion of the TRU surge tank solution over 1900 hours, for a total of 8 kg of plutonium. Figure 24 shows the results from this run for the first 1000 hours. The administrative procedures signaled an alarm after 128 hours, but interestingly, one of the PPS elements alarmed before that. The two other PPS elements appear to have been helped by the alert state. Because of the large number of detection opportunities with this diversion scenario, it is unclear how much the administrative procedures helped. However, there may be examples of protracted material loss with abrupt removal from the facility that might benefit more from the administrative procedures.

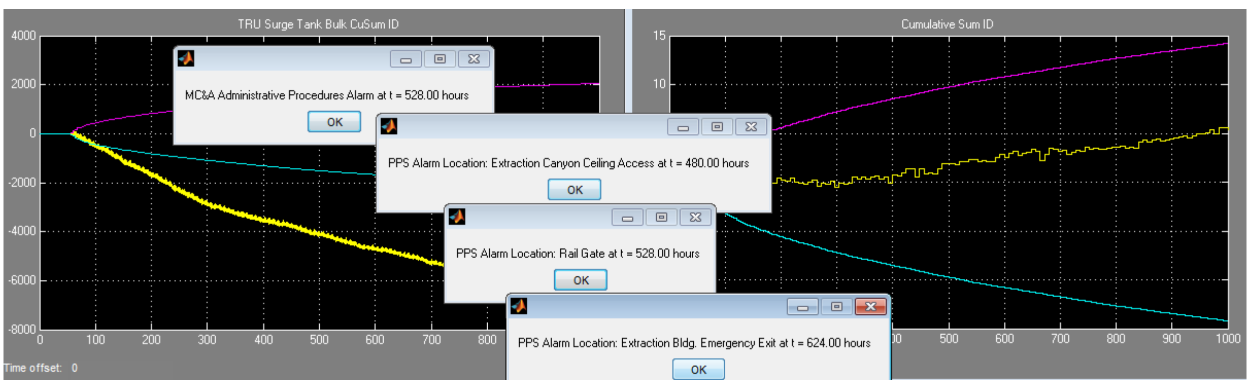

Figure 24: Protracted diversion from MBA2 with integrated systems—the administrative procedures alarm triggers an alert state causing three PPS alarms

Both of the administrative procedures scenarios examined were the same scenarios as those examined using the material balance alarms. In both cases, the process monitoring system was able to signal an alarm first, but the administrative procedures were typically able to detect an alarm before the plutonium balance. The case of a substitution diversion could be hidden from the process monitoring system, so reliance on administrative procedures and plutonium balances will still be required.

For the administrative procedures, the results are completely dependent on the detection probabilities. As described earlier, these probabilities were linked to the fraction of material diverted and based on an assumption that the probabilities grow with time as the diversion becomes more visually evident. Other administrative checks may work differently and may occur at different time periods.

5.5.3 Diversion Scenario Discussion

Combining both the use of material balances and administrative procedures, another way to show the benefit is to graph the cumulative probability that any one PPS element will alarm. Figure 25 shows a comparison of the cumulative probability without and with integrated systems. For the abrupt diversion without integration (upper left), the entire PPS has only about a 50% chance of alarming by the end of the diversion. With integration (upper right), the abrupt case has a 100% chance of alarming by the end of the diversion. For the protracted diversion case without integration (lower left), the probability surpasses 95% about 350 hours after the diversion started. With integration (lower right), the probability surpasses 95% about 100 hours after the diversion started.

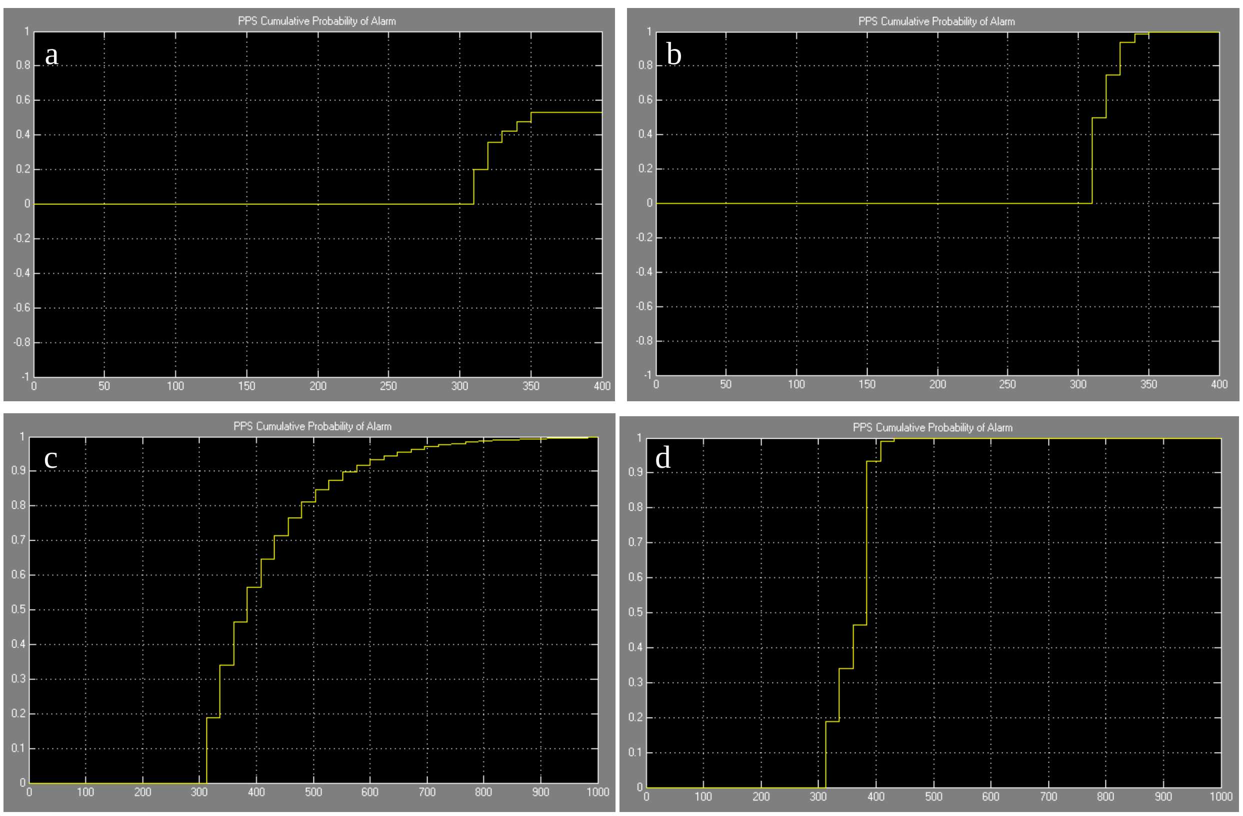

Figure 25: Cumulative probability of detection in the PPS elements for (a) abrupt diversion without integrated systems, (b) abrupt diversion with integration, (c) protracted diversion without integration, (d) protracted diversion with integration.

The diversion scenarios presented here support the use of an alert state to improve detection timeliness in a reprocessing facility. Every additional hour makes it more likely that a response force can deal with the situation before a significant quantity of material is removed. A near real time bulk and plutonium balance at low uncertainty provides a clear advantage as compared to existing plants that do not have such timely data.

The administrative procedures provide a timeliness advantage in the absence of near real time material balances. The process monitoring system appears to provide the most timely information and alarms. However, bulk material balances cannot detect a substitution diversion. For that case, the administrative procedures may be the first to alarm.

6.0 Conclusions

A number of modifications to the SSPM were made in order to provide the analyses shown here. Three statistical techniques were evaluated for setting alarm conditions for material loss. The pattern recognition and Bayesian approaches show promise, but both will require more testing under diversion scenarios. It is unclear if both approaches will hold up under the diverse conditions in a reprocessing plant. The Bayesian approach suffered from a longer computational time that can be addressed. Since there is much more rigor behind the Page's Test, this test was used throughout the model for setting alarm conditions. The simplified version of Page's Test does lead to some limitations in the model, but it has been useful for diversion scenarios analyses.

The SSPM was used to determine the design requirements for achieving NRTA in reprocessing to low uncertainty. A used fuel measurement will be required to allow NRTA on the front end, but the measurement uncertainty for plutonium must be at or below 1% in order to provide protection against protracted diversions. If this goal cannot be achieved, it will be better to rely only on process monitoring balances, containment, and surveillance of the front end.

For the rest of the separations portion of a plant, achieving NRTA requires inventory measurements throughout. Fortunately, a vast majority of the processing units (including all contactors, non-plutonium bearing product and waste tanks, and recycle tanks) only require a plutonium measurement with uncertainty near 20%. These areas are less statistically significant since they process only small quantities of plutonium. The coupling of process monitoring measurement along with a simple and inexpensive NDA technique can work in these locations. Techniques like gamma spectroscopy or UV-Vis-NIR spectroscopy may be useful here. Only a relatively small number of tanks are processing large enough quantities of plutonium to need sampling and precision analytical measurements.

The SSPM was also modified to model PPS and administrative procedures that are also used to protect reprocessing plants from material loss. A PPS system is now included that shows pathways through which material may follow to exit both MBAs. An example administrative procedure was modeled to demonstrate the additional safeguard that is provided in plants. The material balances from the process monitoring system and plutonium accountability system were used with the administrative procedures to improve the overall PPS. Material balance or administrative procedure alarms trigger an alert state in the plant which increases the probability of the detection of material loss through the various PPS elements.

Diversion scenario testing showed that without the integration of the material balance and administrative procedures, the PPS elements were much less likely to alarm. Abrupt diversions in particular could occur without detection, but protracted diversions were usually detected due to multiple detection opportunities. With integrated systems, the PPS elements in all scenarios alarmed earlier. It should be noted that the process monitoring system was the most timely for generating alarms, but in cases of substitution diversions, the plutonium balance or administrative procedures would be required to trigger an alert state.

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