Fall 2008 | Winter 2009 | Spring 2009 | Summer 2009 | Volume XXXVII, Number 3

JNMM Journal of Nuclear Materials Management

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JNMM (ISSN 0893-6188) is published four times a year by the Institute of Nuclear Materials Management Inc., a not-for-profit membership organization with the purpose of advancing and promoting efficient management of nuclear materials.

SUBSCRIPTION RATES: Annual (United States, Canada, and Mexico) $200.00; annual (other countries) $270 (shipped via air mail printed matter); single copy regular issues (United States and other countries) $55; single copy of the proceedings of the Annual Meeting (United States and other countries) $175. Mail subscription requests to *JNMM*, 111 Deer Lake Road, Suite 100, Deerfield, IL 60015 U.S.A. Make checks payable to INMM.

ADVERTISING, distribution, and delivery inquiries should be directed to *JNMM*, 111 Deer Lake Road, Suite 100, Deerfield, IL 60015 U.S.A., or contact Jill Hronek at +1-847-480-9573; fax, 847/480-9282; or E-mail, inmm@inmm.org. Allow eight weeks for a change of address to be implemented.

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JNMM Journal of Nuclear Materials Management

Spring 2009, Volume XXXVII, No. 3

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Springing Forward with INMM

By Steve Oritz
INMM President

It is with great sadness that I report the loss of a great friend and colleague. Vince DeVito, who has been the Secretary for the Institute for as long as I can remember, passed away while playing golf in Naples, Florida, in April. He has always been one of INMM's most loyal members and has been our connection to the history of the institute. He was always willing to serve wherever he could. Vince was a mentor to many of us. He will be missed greatly but remembered with honor and admiration.

Spring is a great time of year for INMM. This is the time of year when we put together the technical program for the annual meeting and we come up with a budget for the year. This year the INMM Executive Committee has also used springtime to look to the future of the Institute.

Charles Petri and his Technical Program Committee spent a full day in March laying out the technical program for this year's annual meeting. A lot of work takes place at headquarters prior to this; they make sure we have everything we need ahead of time to make this process as easy as possible. The Technical Program Committee had more than 470 papers to sort through and assemble into a program and it looks to be very exciting. I believe this is the most papers submitted for an annual meeting in many years. We were really pleasantly surprised in the response to our call for papers, especially in a down economy.

The Executive Committee (EC) worked very hard in March to come up with a budget to support the work of the institute. After a couple of iterations of the budget, we believe we have put together a plan to carry us forward for the next year and to strengthen the foundation of our organization.

In March we also spent some time on strategic planning. EC Member-at-Large Grace Thompson is facilitating this effort. It is clear from the types of papers we are receiving for the annual meeting that some technical divisions have more interest than others. We understand that the papers we receive are tied to the work that is being done in government and industry. For example, when funding was increased for implementation of technology to increase security following September 11, there was less funding appropriated by U.S. National Nuclear Security Administration for R&D in this area. As a result the Physical Protection Technical Division did not receive as many papers as it was accustomed to because most of their papers were typically centered on new technologies. At the same time the U.S. Department of Defense continued to spend R&D money in this area but they do not largely participate in our organization. Strategic planning for the institute will be a dynamic ongoing activity. We have currently established a focus group chaired by Member-at-Large Ken Sorenson to take a look at the structure of the organization. We want to make sure we continue to meet the needs of our membership and that we are all inclusive in representing the community of nuclear material management.

I would like to emphasize the importance of our student chapters. We recognize that student chapters are vital to the INMM and are a source of future professionals in nuclear material management. Understanding the needs and strengths of student chapters to us as an organization will be integral to our strategic planning.

The Institute has made a one time donation to the new "National Museum of Nuclear Science and History" located in Albuquerque, New Mexico USA. The museum is an affiliate of the Smithsonian Institution and is chartered by Congress. For our sponsorship we are recognized on the large periodic table of the elements that is prominently displayed on the entryway floor of the museum. We are proud to be part of this educational resource on nuclear history.

INMM President, Steve Ortiz can be contacted by e-mail at sortiz@sandia.gov.

An INMM Era Has Ended

By Dennis Mangan
Technical Editor

INMM lost a dear and dedicated friend on April 8, 2009, when Vince DeVito died suddenly playing golf in Naples, Florida USA. Although Vince was never president of our Institute, his wise leadership was always present, especially because he held the position of secretary since 1973. With his Italian heritage, he was affectionately referred to by many as the Godfather of the Institute. He has been recognized as the unofficial historian of our Institute. He will be definitely a hard act to follow. At all the Executive Committee Meetings that I have attended, Vince's voice was always heard. When he spoke, everyone listened. He always came from a position of past history, coupled with future vision. Vince was a very special person and he will be dearly missed.

We have plans to appropriately reflect on Vince's life and activities in our Institute in the summer issue of the *Journal*, which will be available at our Annual Meeting in Tucson, Arizona USA, in July. There is a nice brief summary of his INMM history on the INMM Web site at http://www.inmm.org. There is also a blog to share information about Vince at http://vincentdevito.blogspot.-com. This blog, which was posted by his daughter Victoria, says the following: "Anyone who knew 'Big Vince' knows that he played golf with the same passion that he lived life, and he could not have found a better way to depart from us." He contributed much to our Institute, but I believe one of his most favorites was the formulation of our INMM golf tournament at our annual meeting.

Vince DeVito with his wife Jeanne. The couple was married for 55 years until Mrs. DeVito's passing

In this issue we have two technical articles. The first is *Process Monitoring Techniques for Nuclear Material Diversion Detection,* authored by J. Wesley Hines, James Henkel, and Belle Upadhyaya, all at the University of Tennessee in Knoxville, Tennessee USA. This paper considers online monitoring models for detecting diversion of uranium from a hypothetical uranium blend-down facility having feed lines of high-enriched uranium and low-enriched uranium gaseous hexafluoride. The second paper, *Bayesian Estimation of the Source and Suppression Effects in Vehicle Radiation Signatures,* is authored by James Gattiker and Tom Burr, both of Los Alamos National Laboratory, Los Alamos, New Mexico USA. They explore the sources of the components comprising a radiation signal from scanning containers and vehicles for radiation-emitting cargo, with the intent to gain improved detectability and data anaylese.

As a final paper, Yvonne Ferris, our INMM president in 1985 and 1986, provides her thoughts on the improvements and growth of our Institute, thus adding to remembrances of our 50-years. She provides some interesting insights.

JNMM *Technical Editor Dennis Mangan can be reached by e-mail at dennismangan@comcast.net.*

Process Monitoring Techniques for Nuclear Material Diversion Detection

J. Wesley Hines, James J. Henkel, and Belle R. Upadhyaya
University of Tennessee, Knoxville, Tennessee USA

Abstract
This paper first reviews the state-of-the-art in process monitoring as applied to nuclear power, chemical industry, and other process facilities. The example application of using online process monitoring technologies for safety-related sensor calibration monitoring is presented. This application summarizes the methods, data requirements, performance measures, and uncertainty quantification techniques from the newly published report NUREG CR 6895. The methods are applied to a simulated blend-down operation similar to the fissile mass flow monitor for the HEU transparency implementation instrumentation in Russia, described by Uckan, March-Leuba, and others (INMM 2001). The conventional process monitoring methods are augmented through the development of algorithms that allow the addition of fissile flow measurement instrumentation and through data reconciliation techniques. The results of the simulation are used to quantitatively assess the ability of process monitoring techniques to detect changes in normal operations, diversion of nuclear materials, sensor calibration drift, anomalies in system devices, and nuclear material enrichment.

Introduction
Online Monitoring (OLM) techniques have been developed and applied to process applications such as safety critical sensor calibration verification in the nuclear industry.[1] The three volume NUREG/CR-6895 series[2-4] was developed for the NRC to provide background, technical guidance and explore implementation issues related to the use of Online Monitoring (OLM) for the extension of safety critical sensor calibration intervals. Additionally, a two volume IAEA series of reports[5,6] was developed to provide guidelines to member states for the use of online monitoring techniques for a variety of applications in nuclear power plants. These techniques have been approved in a general way for nuclear power plants for monitoring and calibration of safety critical components and are used extensively in the nuclear power industry.[1]

The purpose of online sensor calibration monitoring is to identify sensors that may require maintenance due to sensor drift or other malfunction. In OLM systems, data collected from plant sensors are evaluated with an auto-associative empirical model to obtain an independent estimate of the actual, un-faulted plant parameter. This estimate is compared to the sensor signal in order to determine if the sensor has faulted. With this technology, continuous or near-continuous sensor surveillance is possible. As a result, it is possible for manual sensor calibration to be performed based on the sensor's condition, rather than the time-based calibration schedule now observed. These techniques use empirical models to monitor a process for anomalous behavior that may be due to equipment malfunction, degradation, or improper operation.

Online Monitoring was developed to assist condition monitoring (CM) of plant equipment. CM is the practice of identifying the operating status of system components and using the current component condition to determine the optimal maintenance schedule. Previous maintenance strategies relied on preventive (periodic) maintenance and reactive maintenance. Preventive maintenance means performing maintenance on a set time schedule, regardless of the equipment's current condition. Preventive maintenance has two major drawbacks. First, maintenance resources are wasted on systems that do not require maintenance, leading to expensive and unnecessary maintenance schedules. In addition, performing unnecessary maintenance on healthy components can introduce failure catalysts into previously properly working systems. Conversely, reactive maintenance is performing maintenance when a system component fails. This maintenance strategy leads to unplanned and expensive system downtimes.[7]

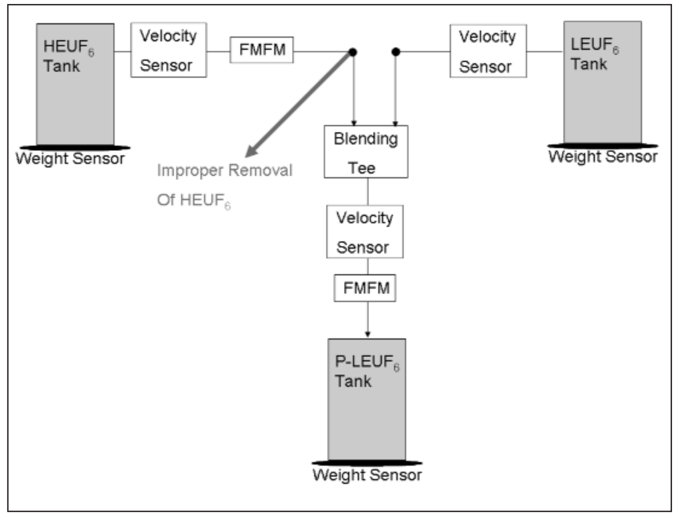
CM can be further divided into two major tasks: state estimation and state monitoring. State estimation refers to estimating the current condition, or state, of a system component. Three techniques are generally used in state estimation: redundant signal monitoring, reference signal monitoring, and diverse signal monitoring. State estimation using redundant signals takes the average sensor reading when a large number of redundant signals are available and uses that average sensor reading as an estimate of the system state. State estimation using reference signals involves comparing a sensor's response to a calibrated reference signal to distinguish between sensor drift and process drift. The third technique, state estimation using diverse signals, is useful when a large number of redundant sensors are not available. Instead of determining the system state from a set of redundant signals or a reference signal, the system state is determined from other system sensors that are correlated with the sensor being monitored. This technique is generally more practical than installing a large number of redundant sensors and relies heavily on both physical and empirical modeling. Physical modeling relies on knowledge of the physics of the system to predict system states. For instance, by measuring the temperature of a gas in a known volume, the pressure of the gas can be predicted based on established physic relations of gas pressure and temperature. While physical modeling has the advantage that it allows one to predict future system states for new process operation, it has the disadvantage that it is not easily generalized to different systems because it requires detailed knowledge of the physics particular to the system. Alternatively, empirical modeling does not require knowledge of the system's physics, and it does not provide any analyzable relationships between system parameters. Instead, empirical modeling compares current operating conditions to past operating conditions to determine the expected current condition. The disadvantage of empirical modeling is that its predictive range is limited by the past operating conditions. If a new process condition is encountered that is significantly different from the past operating history, the empirical model will be unable to predict the new operating condition. However as data exemplifying the new operating condition is appended to the known past operating condition data, model predictions become more reliable. A more complete technical review of CM and OLM techniques is available in Reference 7. Historically, these monitoring techniques have been applied specifically for condition monitoring for maintenance scheduling.[8]

Application on OLM techniques for safeguards is not a new concept. Several papers exploring OLM techniques at gaseous centrifuge enrichment plants for the detection of undeclared production by monitoring the enrichment cascade and the load cell stations are available in References 9-14. Additionally, a review of process monitoring techniques applied to safeguards is available in Reference 15. This paper explores the application of empirical monitoring techniques for safeguards monitoring of a uranium blend-down enrichment facility.

Facility and Instrumentation Description

In a hypothetical uranium blend-down facility, uranium of two different enrichments is blended into a product with a desired target enrichment. The facility is set up to run in a batch mode, where tanks of high-enriched uranium-hexafluoride (HE-UF_6) and low-enriched uranium hexafluoride (LE-UF_6) are fed through instrumented lines, blended together, and then stored as product low-enriched uranium hexafluoride (PLE-UF_6). At standard normal atmospheric pressure and temperature, uranium-hexafluoride is nominally a solid. However, for the purpose of this paper the uranium-hexafluoride was assumed gaseous. A combination of sensors is used to monitor the process, as shown in Figure 1. All three legs are instrumented with flow meters, which measure the gas flow velocity, and weight sensors that monitor the instantaneous weight of the storage tanks. In addition, the high-enriched leg and the product leg are instrumented with fissile mass flow monitors (FMFM), which measure the mass flow of fissile material and are based on principles similar to the ones developed in References 16 and 17. For this study, the facility was modeled in MATLAB's SIMULINK to generate simulation data for modeling and testing.

Figure 1. Diagram of blending facility and instrumentation points



The simulated measurements from the three flow meters, three weight sensors, and two FMFMs were used to create empirical models that encompass normal operating conditions. For the simulations, the velocities were varied to simulate actual operations, while the enrichments were held constant. A parameter was used in the model to represent a scenario where there is an unauthorized removal of the high-enriched material just prior to the blending tee. Because the simulated removal happens just prior to the blending tee, its effects should only be seen in the PLE-UF_6 sensors. Table 1 summarizes the instrumentation in the hypothetical facility.

In real-world systems, sensor measurements are contaminated by three types of noise: process noise, sensor noise, and electronic noise. Process noise is noise that is common to all redundant measurements, such as small perturbations about the true velocity due to turbulent flow. Sensor noise and electronic noise are independent noise sources, generally taken to be white, Gaussian noise.

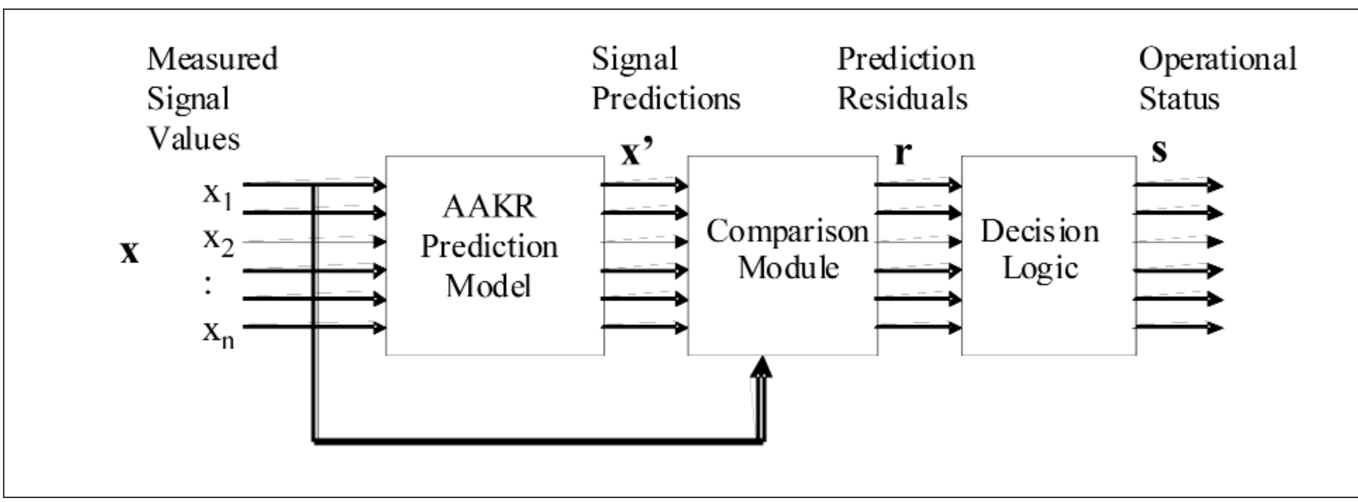
Methodology

To simulate actual measurements, 1.0 percent process noise was added to both the high- and low-enriched fluid velocities. Additionally, independent measurement noise was added to each sensor. The flow meters and weight sensors had 1.0 percent and 0.1 percent Gaussian noise of their maximum sensor reading, respectively. Uncertainty in radiation sensors is not quantified the same way as process sensors; however, for simplicity, the FMFM were assumed to have 1.0 percent Gaussian noise also. Six scenarios

Table 1. Process instrumentation

Sensor Number	Sensor Type
1	HE-UF_6 weight sensor (g)
2	LE-UF_6 weight sensor (g)
3	PLE-UF_6 weight sensor (g)
4	HE-UF_6 gas velocity (cm/s)
5	LE-UF_6 gas velocity (cm/s)
6	PLE-UF_6 gas velocity (cm/s)
7	Fissile Mass Flow Monitor on HE-UF_6 leg
8	Fissile Mass Flow Monitor on PLE-UF_6 leg

Figure 2. Anomaly detection and identification diagram



were simulated in which the magnitudes of the flow discrepancies were varied. The first scenario was considered the normal case, in which the measured and actual flows agree (no HE-UF_6 bleed-off). The normal case scenario represents unfaulted data. The remaining five scenarios consisted of discrepancies of 0.1 percent, 0.5 percent, 1.0 percent, 2.0 percent, and a 10.0 percent off-set. The flow discrepancies represent the material removal from the HE-UF_6 leg. The simulated material removal occurs at the 2000th time step just after the HE-UF_6 FMFM. Therefore the effect of the removal is only present in the product-leg flow meter, weight sensor, and the FMFM.

Four different models were created and evaluated. For each model, the autoassociative kernel regression (AAKR) architecture was used. For the first model, the AAKR model is built using only data from the flow meters and weight sensors. The second model uses the same data as the first model, with data reconciliation techniques applied to the flow and weight sensors. For the third model, no data reconciliation techniques are used but the FMFM sensors are included. Finally, in the fourth model the FMFM sensors are included and data reconciliation techniques are applied to the flow and weight sensors. The objective of this study is to quantify the sensitivity of the models to detect the differences between measured mass flow rate and the actual mass flow rate entering the blending tee. The AAKR model outputs are the corrected sensor values predicted by the empirical model.

Autoassociative Kernel Regression (AAKR)

An AAKR model is used to model the sensor relationships in the blending process. The modeling method has been used for nuclear power plant sensor calibration verification[18] and is implemented in a MATLAB Process and Equipment Monitoring Toolbox.[19] Normal operational data were used to create the non-parametric model, while the faulted data was used to simulate the anomalous behavior. The model is an error correcting technique used to produce residuals between the corrected (predicted) values and measured values. The residuals are then examined to detect anomalies and identify the cause of the anomalous operations. Figure 2 is a block diagram of the monitoring, detection and identification system.

Since descriptions of AAKR do not readily appear in the open literature, the following derivation is based upon multivariate, inferential kernel regression as derived by Wand and Jones[20] and described in Reference 21.

AAKR is a nonparametric, empirical modeling technique that uses historical, fault-free observations to correct any errors present in current observations. The exemplar or memory vectors used to develop the empirical model are stored in a matrix X, where $X_{i,j}$ is the i^{th} observation of the j^{th} variable. For n_m observations of p process variables, this matrix can be written as:

$$\mathbf{X} = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,p} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,p} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n_m,1} & X_{n_m,2} & \cdots & X_{n_m,p} \end{bmatrix}$$

Using this format, a query vector is represented by a 1xp vector of process variable measurements. This vector, x, can be written as:

$$x = [x_1 \; x_2 \ldots x_p]$$

The corrected version of the input is calculated as a weighted average of historical, error-free observations termed memory vectors (X_i). The mathematical framework of this modeling technique is composed of three basic steps. First, the Euclidean distance between a query vector and each of the memory vectors is computed. The Euclidean distance equation for the i^{th} memory vector is:

$$d_i(\mathbf{X}_i, \mathbf{x}) = \sqrt{(X_{i,1} - x_1)^2 + (X_{i,2} - x_2)^2 + \cdots + (X_{i,p} - x_p)^2} \quad (1)$$

For a single query vector, this calculation is repeated for each of the n_m memory vectors, resulting in an n_mx1 matrix of distances: d.

Next, these distances are converted into similarity measures or weights by evaluating the Gaussian kernel, expressed by:

$$\mathbf{w} = K(\mathbf{d}) = \exp\left(-\frac{\mathbf{d}^2}{h^2}\right) \quad (2)$$

Here, h is the kernel bandwidth and w are the weights for the n_m memory vectors.

Finally, these weights are used to form a weighted average of the memory vectors according to:

$$\hat{\mathbf{x}} = \frac{\sum_{i=1}^{n_m} (w_i \, \mathbf{X}_i)}{\sum_{i=1}^{n_m} w_i} \quad (3)$$

If the scalar a is defined as the sum of the weights, i.e.,

$$a = \sum_{i=1}^{n_m} w_i \,, \quad (4)$$

then Equation (3) can be represented in a more compact matrix notation as:

$$\hat{\mathbf{x}} = \frac{\mathbf{w}^{\mathrm{T}} \mathbf{X}}{a} \, . \quad (5)$$

The parameters to be optimized in an AAKR model are the memory matrix (X), the kernel bandwidth *(h)*, and in some instances the distance function.[22] The developer must decide how many and which vectors to include in the memory matrix and how large to make the bandwidth, which indirectly controls how many memory vectors are weighted heavily during prediction.

Data Reconciliation

All measurements have some measurement error. Data reconciliation attempts to reduce measurement errors in such a way to preserve the laws of conservation of mass. This technique has been used for nuclear power plant process monitoring.[23-25] The following derivation is described in References 23 and 25.

The restriction vector, $f(\bar{x})$, and the vector of measured values, $f(x)$, are related through:

$$f(\bar{x}) = f(x) + \frac{\partial f}{\partial \bar{x}} \cdot v \quad (6)$$

where v is the corrective vector to be determined. The corrective vector is applied to the measured values to force the measured values to follow conservation laws. For example, conservation of mass states that the total inflow to the blending tee must equal to the total outflow. This basic principle indicates that the sum of the HE-UF_6 leg flow and the LE-UF_6 leg flow measurements should equal the PLE-UF_6 flow measurement. However, due to measurement noise, it is highly unlikely that this exact relationship is fulfilled. Data reconciliation determines the most likely corrective vector, v, based on the known measurement standard deviations that would force the conservation principle to be true.

The solution to Equation 6 requires v to be minimized, whose solution can be shown through References 23 and 25 to be:

$$v_{\min} = -\left(\frac{\partial f}{\partial \bar{x}} S_x\right)^T \cdot \left(\frac{\partial f}{\partial \bar{x}} S_x \cdot \left(\frac{\partial f}{\partial \bar{x}}\right)^T\right)^{-1} \cdot f(x) \quad (7)$$

where S_x is a matrix of known measurement standard deviations. Equation 7 is then substituted into Equation 6, which then is the solution used to reconcile the data values.

Results of Application

A MATLAB SIMULINK model was developed to simulate the blending tee enrichment facility described. This model was used to simulate both normal plant operations and anomalous operations with HE-UF_6 bleed-off. Data collected during the simulation is used to develop an AAKR model to monitor the blend-down process. The instantaneous weight sensor does not provide useful data for the AAKR because the instantaneous weight of a tank is not correlated with any of the flow variables. Therefore, the derivative of the weight sensor data are approximated by the difference between two consecutive observations to determine the instantaneous rate of change in weight, or mass flow rate. Four different models are considered. The first and second model used only the mass flow rate data and the gas velocity data. The mass flow rate and the gas velocity should be related by the inverse of the gas density and the inverse of the pipe area. Therefore they essentially give the same information, but because the data come from independent sensors they provide a level of redundancy. Model 2 differs from model 1 because the data are preprocessed using the data reconciliation technique described previously. Model 3 uses the same sensors as model 1 with the addition of the two FMFM measurements. Model 4 uses the eight sensors from Model 3, but as in model 2 the data are preprocessed with the data reconciliation technique with the exception of the radiation sensors.

Even though the instantaneous weight sensors are not well suited for the AAKR method, they can provide useful information. A bleed-off scenario will eventually be detected by tracking the tank weight residual, i.e., the initial total weight of HE-UF_6 and LE-UF_6 less the current sum of the three weight measurements. This residual will steadily increase as more HE-UF_6 is bled off.

All four models have similar performance on the unfaulted data. The unfaulted data performance describes the ability of the model to predict, or confirm, the measured sensor values. Table 2 summarizes the average accuracy and average uncertainty of each of the four models.

Table 2. Unfaulted data performance (in percent of mean value)

	Model 1	Model 2	Model 3	Model 4
Accuracy	0.4502	0.2674	0.5762	0.4255
Uncertainty	1.5846	1.9444	2.1155	1.7315

The model is able to predict the 1 percent process noise because it is common in each sensor. However, the independent measurement noise cannot be predicted. The accuracy is less than 1 percent because the model tends to average the sensor noise through the inherent redundancy in the physical arrangement.

Model 1 – No Radiation Sensors, No Data Reconciliation

For Model 1 (three flow meters and three mass flow rate sensors) any HE-UF_6 bleed-off would only be shown in the PLE-UF_6 flow meter or mass flow rate change because the LE-UF_6 flow sensor is independent of the HE-UF_6 flow sensors and the bleed-off is assumed to occur downstream of the HE-UF_6 flow sensor but before the blending tee. Model 1 was not able to detect any of the five fault cases: 0.1 percent, 0.5 percent, 1.0 percent, 2.0 percent, and 10.0 percent bleed-off. Even the extreme 10 percent case was not identifiable through visual inspection. The pipe cross sectional area for the LE-UF_6 leg is a factor of 4 larger than the pipe cross-sectional area for the HE-UF_6 leg. In addition, the gas velocity for the LE-UF_6 leg is a factor of 8 larger than the HE-UF_6 gas velocity. This results in the LE-UF_6 leg mass flow rate being approximately a factor of 32 larger than the HE-UF_6 leg; therefore, the PLE-UF_6 flow sensor is dominated by the LE-UF_6 flow rate. Because the PLE-UF_6 flow sensor is dominated by the LE-UF_6 flow rate, even a high HE-UF_6 leg bleed-off is difficult to detect in the PLE-UF_6 sensor. Figure 3 shows the results for the PLE-UF_6 flow sensor for case 5 (10 percent bleed-off). In the top graph of Figure 3, both the predicted and measured values (solid line and dashed line respectively) lie on top of each other making

Figure 3. Detection results for PLE-UF_6 flow sensor for Model 1 (10 percent bleed-off)

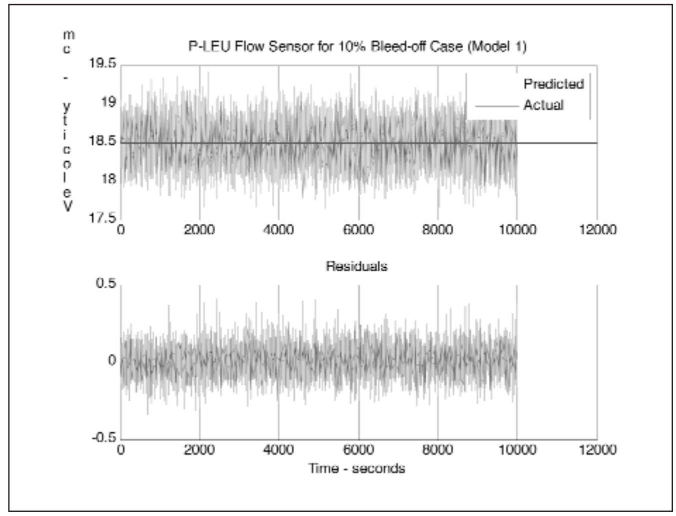
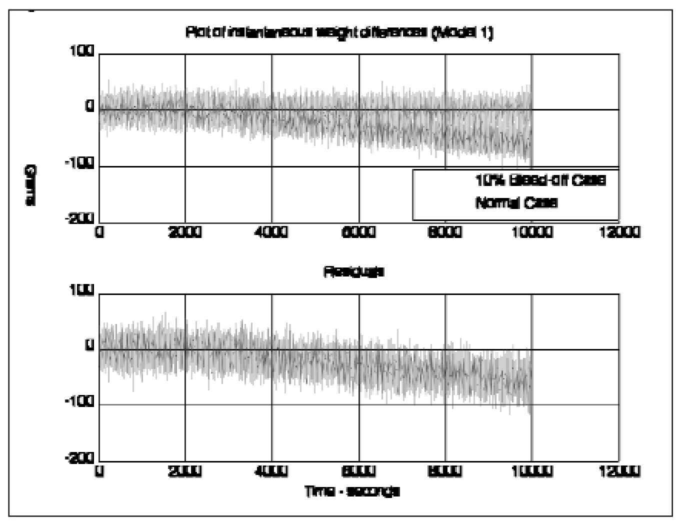


Figure 4. Tank weight residuals for Model 1 (10 percent bleed-off)



them nearly indistinguishable. The lower graph of Figure 3 plots the residual, which is the predicted minus the actual values. A fault would be seen as a step change in the residual plot at the time that the fault occurs.

Even though the AAKR model is unable to detect the change due to the HE-UF_6 bleed-off, by tracking the instantaneous weight of each tank and calculating the residual uranium mass, a gradually growing residual indicates that some material is being removed. Figure 4 shows the residuals for the normal case and the 10 percent bleed-off case. Ideally the normal case residuals would all be zero, but measurement noise introduces some uncertainty. The 10 percent bleed-off case clearly shows a growing residual, but because the flow is dominated by the LE-UF_6, it takes several hours before a significant diversion from the normal case is seen; the initial bleed-off happens at time=2,000 and then continually bleeds-off until the end of the simulation. From Figure 4 there is not a clear, instantaneous point where the residuals show a fault. However, it is clear by about the 6,000th time step that the residuals have deviated from their normal range (shown in the first 2,000 time steps).

Model 2 – No Radiation Sensors, With Data Reconciliation

For Model 2, data reconciliation techniques were used to preprocess the data, and the reconciled data were used to build an AAKR model. This model quantifies the improvement due only to data reconciliation over the base model (Model 1). Reconciling the data forces the data to follow known conservation laws. For these simulations, conservation of mass was employed, i.e., the total inlet flow into the blending tee had to equal the total outlet flow of the blending tee. Data reconciliation forces the conservation laws to hold true. An adjustment factor is calculated and applied to the sensor values to force the conservation law to be true. The adjustment factor is weighted according to each sensor's standard deviation and the gross error of the sensor values with respect to the conservation law. Therefore, sensors with smaller standard deviations are adjusted less than sensors with larger standard deviations, and the total magnitude of these adjustments is larger when the total error is larger. However, even employing data reconciliation Model 2 was also not able to detect any of the bleed-off scenarios. Figure 5 shows the results for the PLE-UF_6 flow sensor for case 5 (10 percent bleed-off). Because data reconciliation constrains the measurement values, the noise of the measurement is reduced. Comparing the lower plot of Figure 3 with the lower plot of Figure 5 shows that the range of the residuals has been reduced from ± 0.4 to about ±- 0.2. As with Figure 3, both the predicted and actual measured values (solid line and dashed line, respectively), lie on top of each other making them nearly indistinguishable

Because data reconciliation forces the conservation of mass law, the weight tank residuals are all forced to zero. However, tracking the changes in the correction factors serves the same purpose as tracking the residuals in the weight sensors before using data reconciliation. Even with data reconciliation, several hours pass before the bleed-off can be detected visually. Figure 6 shows

Figure 5. Detection results for PLE-UF_6 flow sensor for Model 2 (10 percent bleed-off)

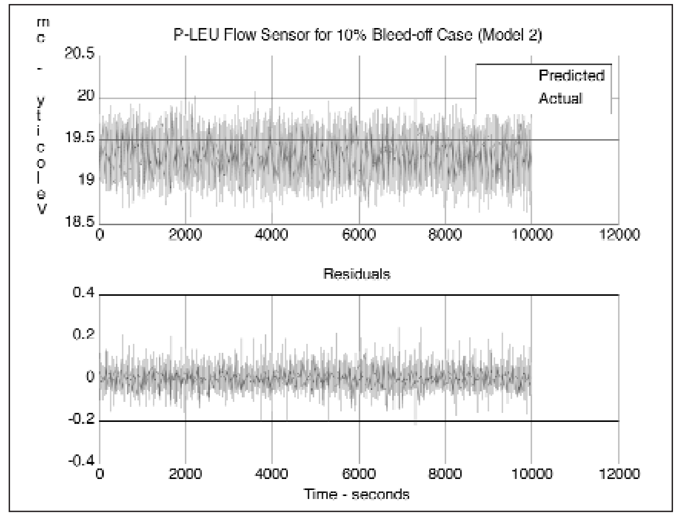
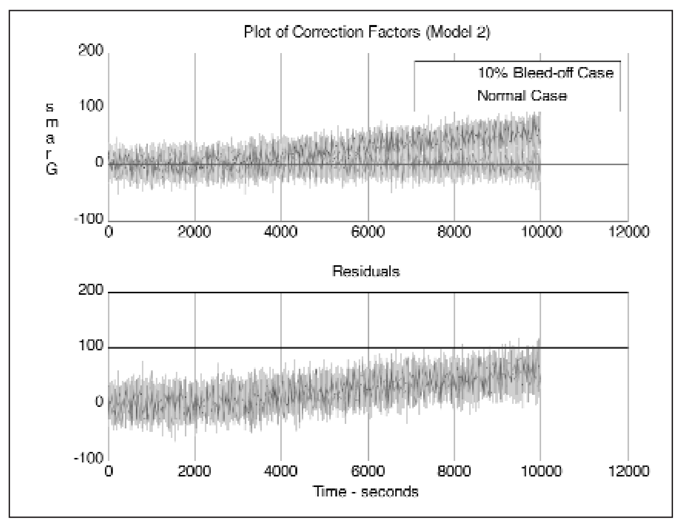


Figure 6. Correction factor residuals for Model 2 (10 percent bleed-off)



the correction factors for the normal and 10 percent bleed-off case. Comparing Figure 6 and Figure 4 shows that the deviation is slightly easier to detect when using data reconciliation (Figure 6) because of the reduced noise.

Model 3 – With Radiation Sensors, No Data Reconciliation

For Model 3, the two FMFM radiation sensors were appended to the data for Model 1. This model quantifies the improvement due to incorporation of radiation sensors over the base model (Model 1). Because the FMFMs are sensitive to the amount of Uranium-235 (^{235}U), any bleed-off from the HE-UF_6 should show a significant change in the PLE-UF_6 FMFM. However, the PLE-UF_6 also has a ^{235}U signal because of the LE-UF_6 leg. The ^{235}U content for the LE-UF_6 leg was assumed to be 0.7 percent, the composition of natural uranium. While the ^{235}U content of the LE-UF_6 leg is a smaller per-

Figure 7. Detection results for PLE-UF_6 flow sensor for Model 3 (10 percent bleed-off)

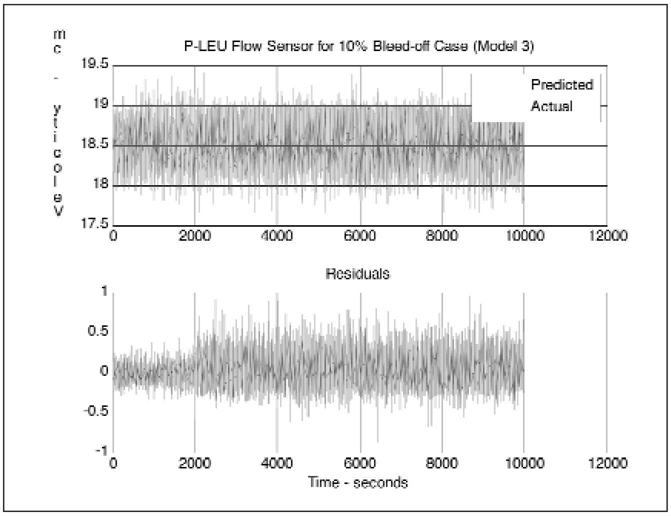
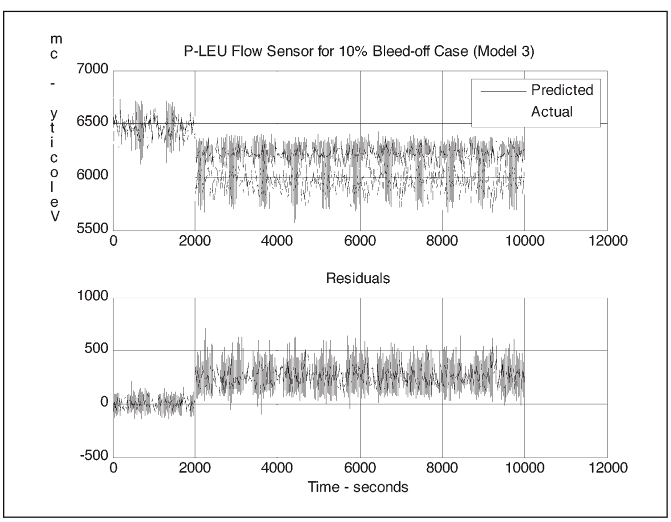


Figure 8. Detection results for PLE-UF_6 FMFM sensor for Model 3 (10 percent bleed-off)



cent, its large flow rate (compared to the HE-UF_6 flow) represents a sizable contribution. Figure 7 and Figure 8 show the monitoring results for the 10 percent bleed-off in the PLE-UF_6 flow sensor and FMFM. In each figure there is a clear change in the residuals at the 2,000th time step, indicating some type of fault. For small enough bleed-offs the change in residuals would not be significant enough to visually determine a fault.

Plotting the weight residual yields the same result as seen in Figure 4. Implementing radiation sensors into the AAKR model gives a significant improvement in detection time, allowing for near instantaneous visual detection, whereas in the previous models instantaneous detection was not possible.

Model 4 – With Radiation Sensors, With Data Reconciliation

Figure 9. Detection results for PLE-UF^6 flow sensor for Model 4 (10 percent bleed-off)

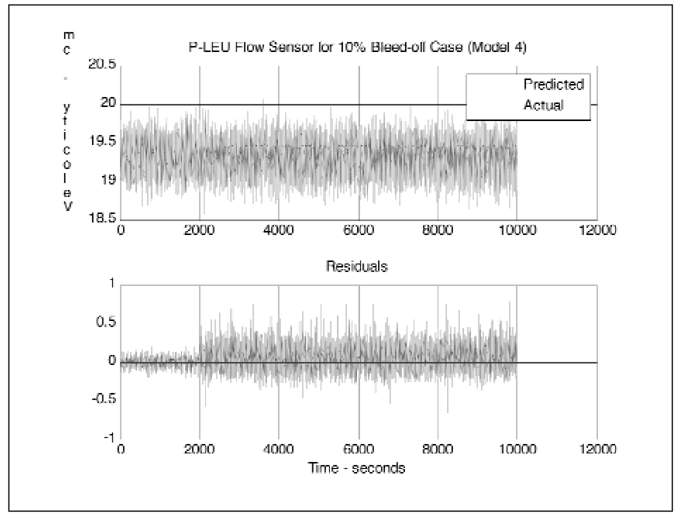
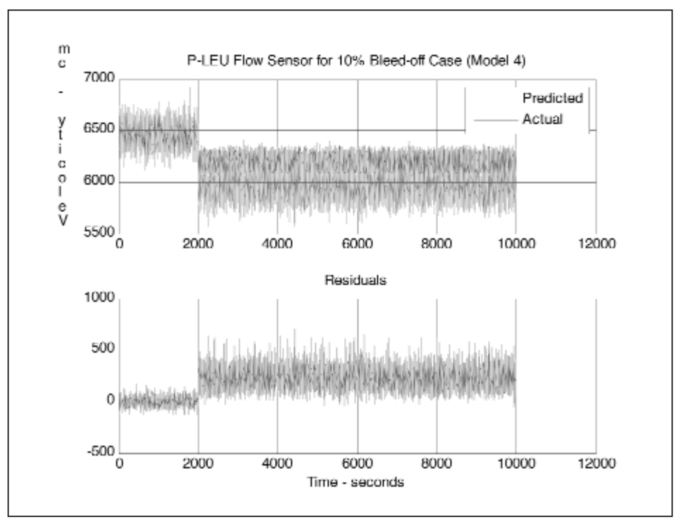


Figure 10. Detection results for PLE-UF_6 FMFM sensor for Model 4 (10 percent bleed-off)



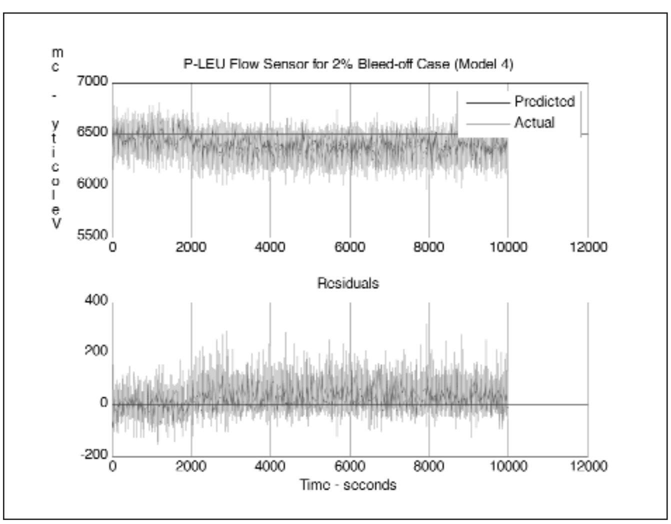
For Model 4, the data are preprocessed as in Model 2 (with the exception of the FMFMs), and all the sensors are used as in Model 3. This model quantifies the combined effect of data reconciliation and incorporating radiation sensors over the base model (model 1). Figure 9 and Figure 10 show the monitoring results for the 10 percent bleed-off in the PLE-UF_6 flow sensor and FMFM. In each figure there is clearly a change in the residuals at the 2,000th time step, indicating some type of fault. The detection characteristics between Model 3 and Model 4 are very similar. As with Figure 3, both the predicted and actual measured values (solid line and dashed line respectively), lie on top of each other making them nearly indistinguishable. However, the residuals show a clear change. The plot of residuals in Figure 9 and Figure 10 does not clearly show that incorporating radiation sensors with data reconciliation adds any benefit to only incorporating radiation sensors (Figure 7 and Figure 8). In Figure 9 the predicted and actual sensor values appear to be the same at each time step, but plotting the residuals shows a clear trend change at the 2,000th time step.

Because the improvements of Model 4 over Model 3 are not visible simply by inspecting the residual plots, Table 3 summarizes some of the model performance metrics. Two additional metrics are shown in Table 3 that are output by MATLAB and provide additional insight into the analyses of the data, the Error Uncertainty Limit Monitoring (EULM) and the Sequential Probability Ratio Test (SPRT).

Table 3. Metrics of Model 3 and Model 4

	Model 3	Model 4
Accuracy (percent)	0.5762	0.4255
Uncertainty (percent)	2.1155	1.731525
Auto-sensitivity	0.6498	0.5325
Cross-sensitivity	0.1523	0.1293
EULM Detectability	6.0722	4.3041
SPRT Detectability	1.5819	1.0946

Figure 11. Detection results for PLE-UF_6 FMFM sensor for Model 4 (2 percent bleed-off)



With each metric, a lower value is desired. The accuracy is expressed in terms of percent error, therefore a lower value indicates less error. The analytical uncertainty is also expressed as a percent, with a lower uncertainty corresponding to a higher precision. Auto-sensitivity is a measure of robustness, with a lower value indicating a higher robustness. The cross-sensitivity measures the spillover effect. The EULM Detectability indicates the smallest fault that is detectable using Error Uncertainty Limit Monitoring, which monitors the uncertainty of the prediction errors relative to some specified tolerance. Finally, the SPRT Detectability measures the smallest process parameter change that can be detected using the Sequential Probability Ratio Test. A more complete explanation of these metrics can be found in References 27, 28, and 29.

The SPRT Detectability for Model 4 is 1.0946 percent of mean value. Therefore the smallest deviation the model can detect is 1.1 percent. Because the PLE-UF_6 FMFM is dominated by the ^{235}U from the HE-UF_6 leg, a 2 percent bleed-off is detectable. Figure 11 shows the monitoring results for PLE-UF_6 for the 2 percent bleed-off case. At the 2,000th observation, there is a visible step change in the residuals, which is indicative of the fault.

Conclusion

This paper presents the application of OLM techniques for safeguards monitoring. The results show that OLM techniques developed for sensor calibration monitoring are well suited for enrichment process anomaly detection and are sensitive enough to detect subtle changes in operations when coupled with nuclear radiation measurements. Five scenarios were simulated examining the effects of a 0.1 percent, 0.5 percent, 1.0 percent, 2.0 percent, and 10.0 percent HE-UF_6-leg bleed-off. Four different AAKR models were created. The first model was a baseline model that used only process sensors. The second model incorporated data reconciliation techniques for noise reduction. The third model incorporated radiation sensors. The fourth model incorporated both radiation sensors and data reconciliation. The baseline model (Model 1) and Model 2 were unable to detect any of the simulated bleed-off scenarios. The models incorporating radiation sensors (Model 3 and Model 4) were able to instantly detect the 10 percent bleed-off scenarios. Both models were also able to detect the 2 percent bleed-off scenario, but not the 1.0 percent, 0.5 percent, or 0.1 percent scenarios. The SPRT detectability indicates that Model 3 would have been able to detect about a 1.6 percent bleed-off scenario while Model 4 would have been able to detect about a 1.1 percent bleed-off scenario. Incorporating data reconciliation techniques and radiation sensors improved the detectability substantially over the baseline model.

This work illustrated the usefulness of process monitoring techniques for monitoring critical facilities. Future work to improve anomaly detection includes optimizing model performance, developing a design for safeguards techniques that specify optimal instrument placement, and evaluation of the techniques for remote monitoring and tamper resistance. Future investigation would also incorporate non-traditional data that are indicative of movements in a facility (such as vibration and motion detection), and information pertinent to its physical characteristics and surrounding environment.

Biographies

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Bayesian Estimation of the Source and Suppression Effects in Vehicle Radiation Signatures

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Abstract

A Bayesian approach to estimate the radiation signature in vehicle profiles is presented. In the setting of interest, the background count rate, the profile length, and the background suppression due to the vehicle all vary from vehicle to vehicle. The Bayesian approach provides uncertainty estimates and an effective way to enforce constraints, such as the radiation source signature being nonnegative. Results of an experiment consisting of adding synthetic signals into real signal-free profiles are included.

Introduction

An important aspect of U.S. homeland defense is scanning vehicles for radioactive materials that could be used in a terrorist attack. Vehicles entering the United States are currently being passively screened for gamma and neutron radiation. Each vehicle slowly passes by a set of fixed radiation sensors, resulting in a profile time-series measurement from each sensor. Various upgrades to currently-deployed sensors are being considered, such as using gamma detectors that have better energy resolution. The cost/benefit of candidate upgrades should be compared to the cost/benefit of optimized existing systems. Therefore, our goal here is to consider possible improvements to current detection algorithms in current sensors. To focus the discussion, we consider only the low energy gamma detectors with attention to the fact that the vehicle suppresses the natural background. Currently implemented alarm rules ignore this background suppression.

We model the radiation measurement R of a vehicle as $R = S + U + B$, where the S is the source term that we are interested in detecting (that may be null), U is the suppression effect caused by the shielding of the background by the vehicle, and B is the radiation background, i.e., natural radiation. The goal in processing measurements is to mitigate the impact of U and B, recovering S from R with the highest possible fidelity. In the examples we consider, R is measured each 0.1 second, thus resulting in a vehicle profile to be analyzed.

The gamma radiation background signature B is noise from the radioactivity of terrestrial materials (Geelhood et. al., 2004). This leads to slow variation on a time scale much longer than the vehicle measurement time. The slow background variation can be modeled by a constant mean value, or a linear trend of small absolute slope across the vehicle profile. The background variation over the profile time scale is small compared to the magnitude of the background, amounting to only a few percent of the total.

The source effect S is a measured response due to a radiation source in the vehicle moving across the sensor's field of view. It should increase the count rate in several successive measurements due to the nature of the observations. We refer to the measured source term as the signal, i.e., the signal to be detected in the presence of these other effects.

Both the background B and the source S are counts of discrete events over a time window; they are well modeled as arising from a Poisson distribution having a time-varying mean. Our strategy for mitigating this noise is to smooth the profile, with a scheme that yields the best estimate of the underlying mean signal. Smoothing is an important issue that will be discussed below.

The suppression effect U refers to the shielding of the radiation background by the vehicle, and is a significant reduction of the natural background. Unlike the background, the suppression effect can be characterized and mitigated without hardware or shielding changes; this is our main theme here. We explore and compare methods that attempt to factor out the background signal and the suppression effect, resulting in an estimate of the signal for classification.

A complicating issue is the presence of naturally occurring radioactive materials (NORM), and their unknown source level. Most materials are radioactive to some degree. Many cargo materials are of low radioactivity compared to background radiation, and can be effectively thought of as a null signal. Other innocent cargo materials have count rates that are considerably higher than average background. Classic high-NORM sources are observed from clay-based products (i.e., cat litter), natural biological concentration (i.e., bananas, high in potassium), and people having undergone medical scans and treatments with active materials (Kouzes, et al., 2004; Nuclear Reachback Reference Manual, 2006). These sources result in measurements that are unmistakably positive. Smaller NORM sources will result in detected radiation above background, but not sufficient to alarm. The data used in this analysis are classified as "no signal," because they did not alarm in the current system; however some of these "no-alarm" profiles appear to contain a small component of NORM signal.

Because our model of the various effects involves additive effects, isolating the signal is a problem of decomposing these effects. There is not enough information to uniquely estimate model parameters in an unconstrained, purely data-driven approach. Bayesian approaches provide a natural framework in this case, allowing information to be supplied by constraining the solution with prior information known about the various components.

The following two sections include additional background regarding the data profile and smoothing the profile, our general approach to profile decomposition, including a brief description of Bayesian methods, model components, priors, and parameter estimation. The next two sections give example decomposition results and results of a simulation experiment in which synthetic signals were injected into hundreds of real profiles. The final section summarizes and describes areas for future work.

The Data Profile and Smoothing

Though multiple sensors measure the vehicle, this discussion focuses on processing data from a single arbitrarily chosen sensor. The approach applies to all sensors; however only the gamma counts exhibit significant suppression effects, and therefore, the data analyzed here are the low-energy gamma counts from one instrument panel. The raw profiles are a time series of radiation counts from 0.1 second windows. Vehicles drive slowly past the sensors, but in an unregulated manner so that the velocity is not known or indeed even necessarily constant. We are forced to assume however, that the time axis is linear; this noise source adds nonnegligible variation around the average suppression effect. Raw profiles may have quite different record sizes; the mean in our sample set is approximately 250 measurements, though this can range by approximately a factor of three in either direction, with some very short and some very long profiles that are removed for this analysis (Burr et. al., 2005 and 2006).

In this analysis, the profiles are smoothed and resampled onto a standard grid. The smoothing is done by modeling the profile with a Gaussian process model (GPM) (Jones, 1998), which is then used to interpolate onto a regular grid of 100 points. In spirit, any smoother and interpolator can fulfill this function, though the GPM is preferred to ad hoc schemes because of its proper foundations and well-characterized properties. Spline smoothers are another good choice (Burr et. al., 2005 and 2006).

The GPM method assumes a covariance of the raw profile data points x_i and x_j given by,

$$\frac{1}{\lambda_S} e^{-\beta d(x_i, x_j)} + \frac{1}{\lambda_Z} I(i = j),$$

where the distance measure d is the linear (Euclidean) distance between the measurements, and I is the indicator function valued 1 when the argument is true, zero otherwise.

This formulation allows the control of the continuous approximation. The β term scales the correlation distance; a larger β implies less correlation between neighboring measurements. The λ_z and λ_s precision terms correspond to the variability of the data around the true underlying data mean. In this application, β was selected to give a reasonable estimate, and λ_z and λ_s are set to each account for half of the variability of the data, then re-estimated from an initial model's residual and variance to produce a final answer. Once the GPM is established, the mean and variance may be estimated for any time point. Presently, we are using only the mean, though future work could take advantage of the variance as an uncertainty. Further, we anticipate choosing a degree of smoothing that leads to the variance approximately equaling the mean, which corresponds to Poisson variation around the mean.

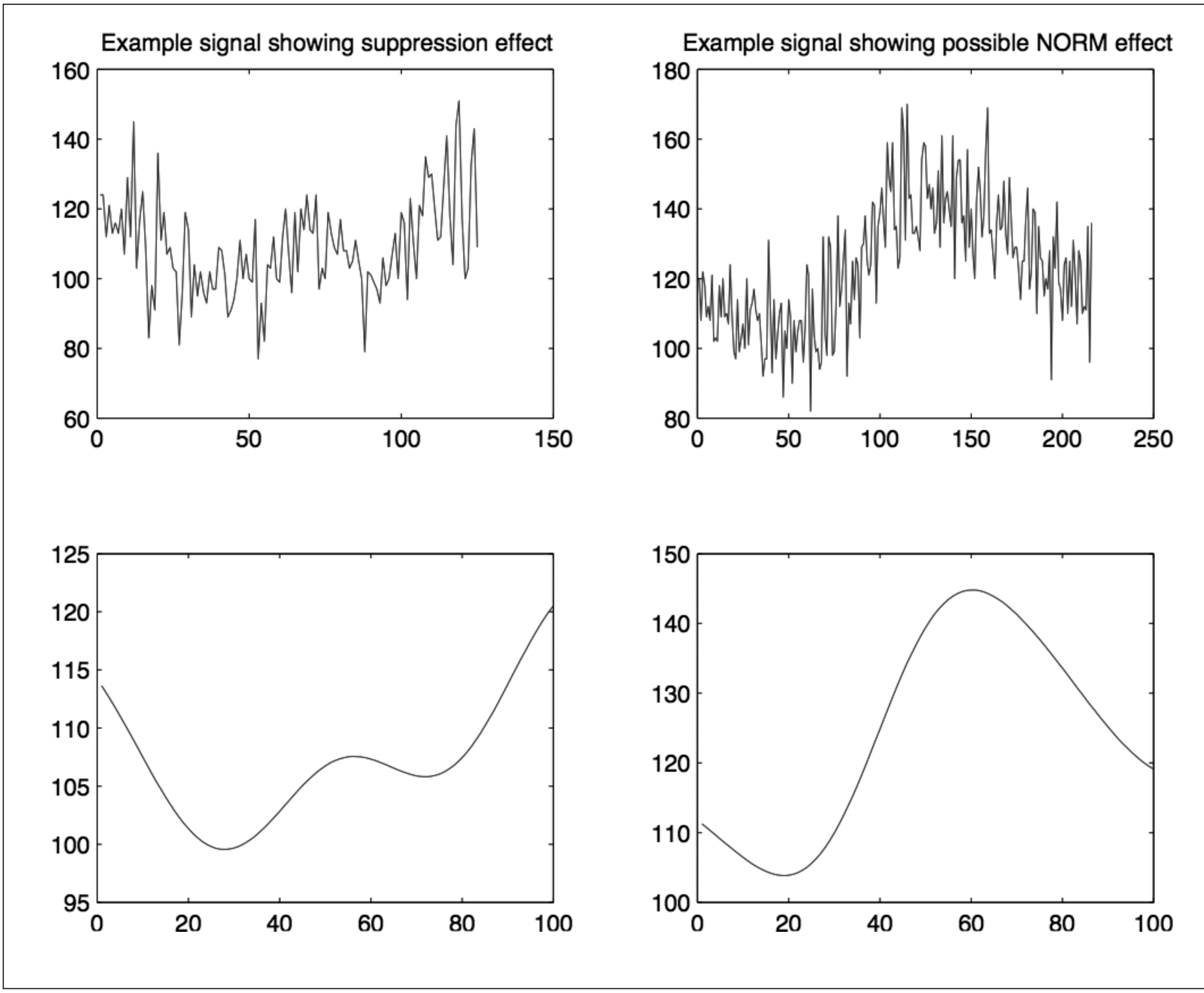
Two examples of a raw profile and a smoothed and standardized profile are given in Figure 1. The first example shows a profile with the suppression effect, the second profile shows what is likely a NORM signal superimposed on the suppression effect. The response units are intentionally omitted in all figures.

Profile Decomposition

The goal is to decompose the profile into its parts: the background and vehicle suppression effects (the null component), and the remainder that can be taken to be the radiation signature (the signal component). These effects are redundant, which raises a model identifiability issue; alternative models should be controlled with more information than simply modeling each term using a general regression model. The signal component must be represented by a very flexible model, because its behavior has very little constraint beyond nonnegativity (though any known constraints may be added with an appropriate representation). A reasonable model for this is a Gaussian mixture (kernel) model with several components with fixed centers located across the profile. The null component is taken to have a mean offset and a linear term with a small absolute slope to represent the rough characteristics of background at this time scale, and a non-zero component of suppression effect templates, which is an ad hoc basis derived from observed data.

A simple least-squares decomposition with the basis described would yield results that are unstable with respect to the desired decomposition. In the Bayesian framework, priors can inform on the constrained values of the components of the decomposition. There are various ways to generate the solution, including constrained least-squares, or a general (e.g., simplex) optimization of the likelihood formulation. We will use MCMC (Markov Chain Monte Carlo, a technique for sampling from a posterior distribution) sampling to estimate the posterior density of the parameters, producing point estimates of parameters as well as confidence bounds (Geyer, 1992).

Figure 1. Typical profiles, raw on top, smoothed and resampled on the bottom. The left shows a well-behaved suppression effect; the signal on the right is an apparent NORM. The response units are intentionally omitted in all figures.

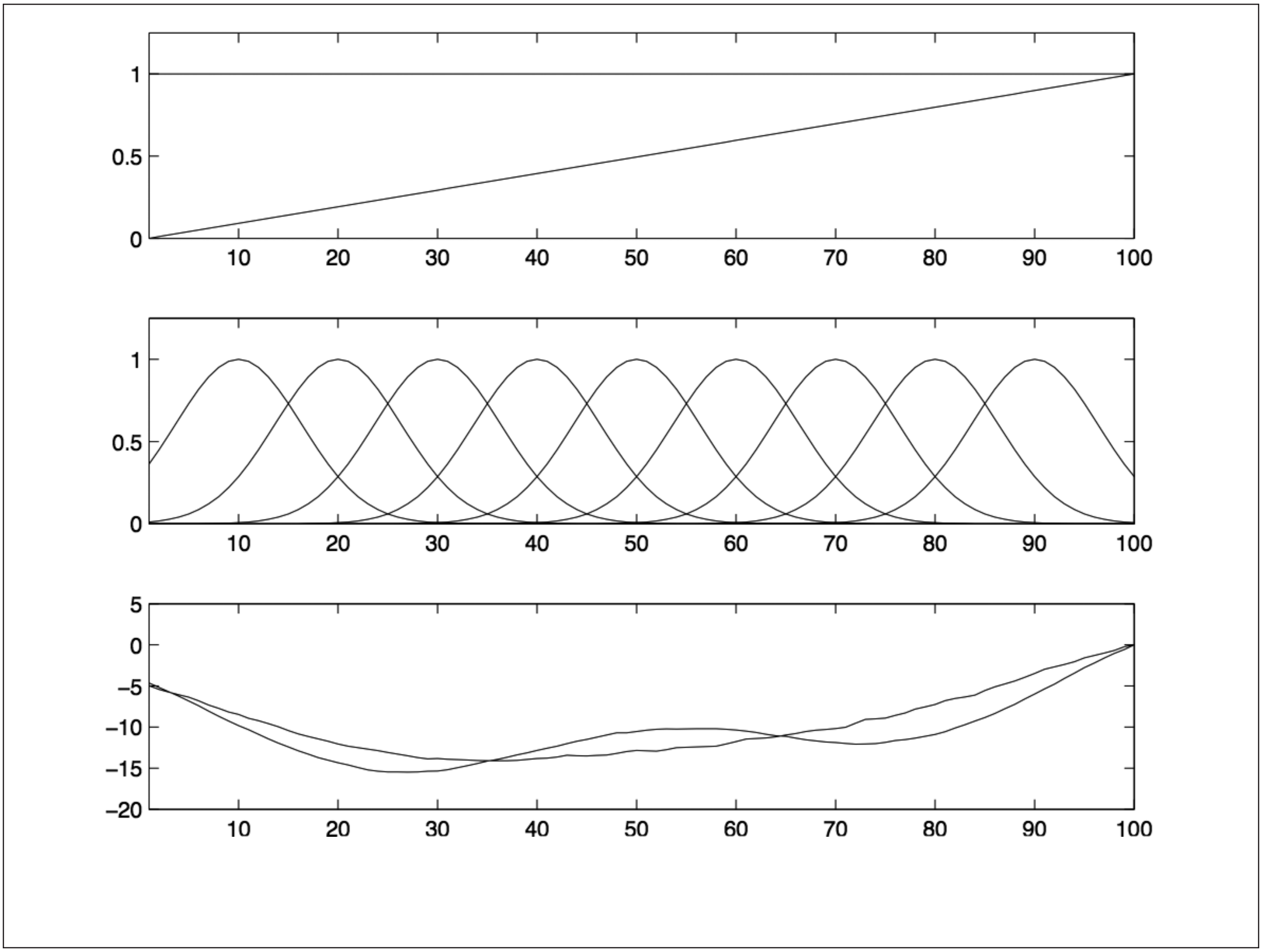


Bayesian Background

Bayes' rule follows from a simple rule of conditional probability and allows one to calculate the probability of event B given that event A has occurred, P(B|A), as P(B|A) = P(A|B) P(B)/P(A). The rule has never been controversial, although particular applications of it have led to debates regarding the relative merits of "frequentist" (nonBayesian) versus "Bayesian" approaches. The key Bayesian concept is to regard unknown parameters as random variables and then express knowledge and uncertainty about these parameters by choosing an appropriate prior probability distribution for them, Prior(parameters). Choosing a likelihood for the data given these parameters, Likelihood(data|parameters), is common to all approaches. Bayesians then apply Bayes' rule to compute the posterior probability of the parameters given the prior and the likelihood, Posterior(parameters) = Likelihood (data|parameters) x Prior(parameters)/C, where C is a normalization constant to make the posterior integrate to one.

In our context, the parameters are the coefficients for the basis decomposition to be presented below, and the Bayesian approach is useful because it allows us to impose constraints on these parameters. Of course if the constraint is not valid because it arises from bad assumptions, the approach is flawed. The sometimes subjective choice of the prior probability (perhaps allowing only nonnegative values for example) for the parameters is the source of much of the controversy. For example, a Bayesian approach to sampling in safeguards was presented by Gorbatenko et. al. (2006) in which the true defect probability p_D (an unknown parameter) among stored items was regarded as a random vari-

Figure 2. Basis components for the decomposition. The top frame shows the mean and linear components modeling the background, the middle frame shows the Gaussian kernels modeling the signal, and the bottom frame shows the two empirically derived components for the suppression effect.



able. Because the choice of prior probability for p_D is controversial in this context, safeguards specialists typically prefer a frequentist approach to sampling. It turns out in this case that, as Gorbatenko et. al. (2006) showed, if one assumes a uniform prior for p_D on [0,1] to reflect maximal ignorance prior to sampling, then the Bayesian approach is very nearly the same as the frequentist approach. In general, Bayesian approaches can be controversial, mostly arising from choice of the prior and interpretations of subjective probabilities. Our prior probabilities below reflect constraints such as certain parameters being nonnegative, and so are expected to be relatively noncontroversial.

Model Components

Figure 2 shows the components of the model. The suppression effect components were computed from the data. Inspection of the data reveals two distinct suppression effect profiles are captured by a characteristic form of "U" or "W." These are identified as profiles that have one minimum/no maxima, and two minimum/one maximum, respectively. Profiles of these types represent more than 95 percent of the 713 randomly selected non-alarming profiles analyzed here (Burr et. al., 2005 and 2006). The two components are generated by taking the median over the profiles of the two groups. It may be that these two profile suppression types represent the characteristic signatures of articulated vehicles' and solid vehicles' distinct suppression effect (Shokair et. al., 2004a and 2004b).

The decomposition is performed by estimating scalar coefficients for each component, so that the scaled components sum to the profile. The coefficients must be constrained to produce useful results.

Model Priors

The most important aspect of the priors in this study is that they constrain the component coefficients (weights) to be nonnegative for the suppression, mean, and Gaussian kernel weights. This means that only the suppression effect components can capture a negative departure from the constant plus linear terms, and only the Gaussian components can capture a generalized nonlinear positive departure. It is primarily this nonnegativity constraint that enables the simultaneous and stable estimation of the suppression and signal components, though other aspects of the priors, detailed in Table 1, are also important. For example the suppression effect coefficients should be near 1, the Gaussian basis coefficients should have a weak preference to be small, and the slope of the background should be small.

Table 1. Prior probabilities on the component weight terms. The Gamma distribution with parameters *(a,b)* is denoted $\Gamma(a,b)$ and the Gaussian distribution with mean ? and standard deviation σ is denoted $N(\mu,\sigma)$.

Constant	$\Gamma(1,10^{-3})$	Weak prior, tend toward zero
Linear	N(0,5)	Absolute slope small
Gaussian	$\Gamma(1,10^{-4})$	Weak prior, tend toward zero
Suppression	$\Gamma(1,1)$	Tends to zero, and not >> 1
Sup.,joint	$\Gamma(5,5)(x_1) \times \Gamma(5,5)(x_2)$	Tends to make one component near zero, the other near 1.

The joint prior in the last row refers to an attempt to make one suppression effect dominate. Because any given profile has a fixed number of extrema, with most having either the characteristic "U" or "W" shape, we prefer not to allow an arbitrary weighted average of the "U" and "W" shapes to help explain the profile's shape. Without this joint effect the two suppression templates tend to share the contribution; with this they tend to emphasize one or the other.

MCMC Parameter Estimation

We assume that the negative log likelihood of the data given a set of coefficients θ is approximately proportional to the mean square error of the constructed profile compared to the observed profile. That is, we assume the likelihood is approximately Gaussian; provided the Poisson mean for the detected counts is sufficiently large, this is a very good approximation. The posterior probability is proportional to the likelihood $L(D|\theta)$ times the prior for θ, $L_\theta = C \times L(D|\theta) \times \text{Prior}(\theta)$, where C is a normalization constant that makes the posterior probability integrate to one. The value of L_θ is thus computable for any proposed θ. The MCMC method is a recipe for proposing a new trial θ vector based on the previous value, which is accepted with a probability depending on its relative likelihood. The key feature of MCMC is that after a transient from the initial θ, it gives a sequence of draws from the joint probability density function of θ. These draws can then be used to locate the posterior mean or maximum value of the parameters, and to estimate confidence bounds.

Results of Decomposition

An Example Profile

MCMC is started from initial coefficients including: mean signal for the offset, zero for the Gaussian kernels and linear basis coefficients, and 0.5 for suppression coefficients. The MCMC chain stabilizes on the scale of a few hundred draws, as can be seen in Figure 3. Figure 4 shows characteristics of a decomposition.

The reconstructed data are a very good fit to the original profile, with confidence bounds tighter than can be displayed. The decomposition itself is less certain, as the redundant factors tradeoff through MCMC chain. That is, even though the profile is consistent with different combinations of model basis components that all result in good reconstruction, characterizing these trade-offs are important in the problem domain. This is the advantage of the MCMC method, as it allows reconstruction of confidence bands on the reconstructed radiation signal, as shown. The confidence bounds are the confidence in the coefficient estimates given the model, priors, and data.

Note that any mismatch between the profile and the suppression component is "explained" in the source terms. Therefore, essentially all profiles will have a positive source estimate. However, this positive source estimate can be treated empirically by selecting thresholds above which the estimated source is thought to be significant.

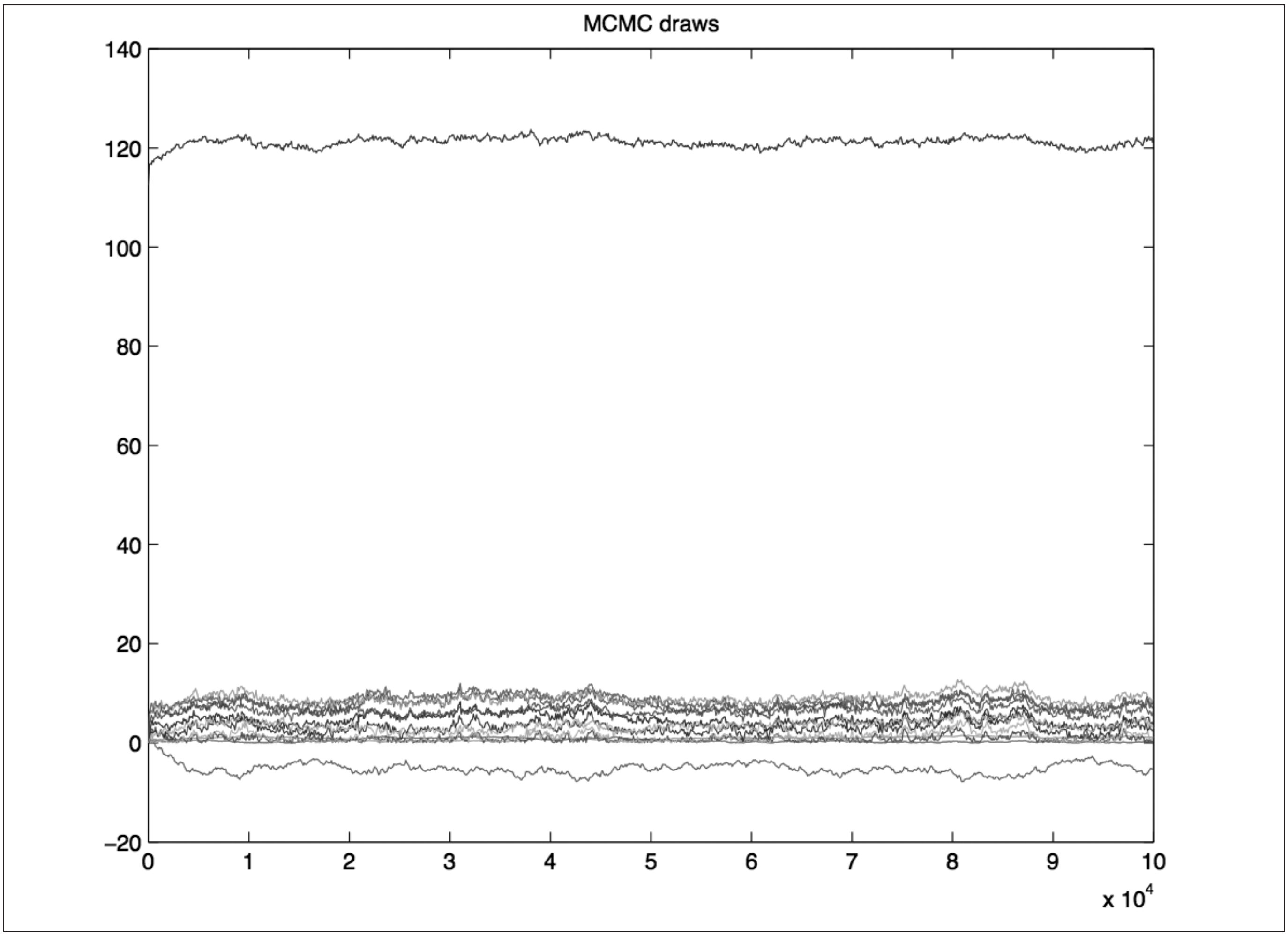
Conglomerate Results

Figure 5 shows the results of overlaid profile decompositions from vehicle traces classified as no signal. Some radiation effects are extracted, which must be taken to be NORM aspects of the signals. This is intended to show the summary results of the decomposition in a qualitative manner, showing the general characteristics of the signals and the estimated null and signal components.

Comparing to Mean Subtraction

An initial evaluation of the results is to compare the decomposition to a simple alternative. The most basic method for removing the suppression effect is to simply subtract the mean profile from each. The horizontal axis in the scatterplot in Figure 6 is the maximum value of each of the 713 profiles in that scheme; the vertical axis is the maximum value of each corresponding decomposition signal. The decomposition includes the (10,90) confidence (10 percent and 90 percent quantiles) around each. There is a clear correlation in the profiles that have a very high

Figure 3. The MCMC chain for the example in Figure 4. The upper trace is the constant offset term, the lower trace is the linear term, the other traces represent the various remaining components.



maximum value (i.e., high NORM), with basic agreement in the values, though the maximum value is consistently larger with the decomposition method.

Figure 7 shows a zoom in to the dense region of the plot in Figure 6, where the estimated signal is small. There is clearly a subset of cases where one method estimates the signal to be low and the other estimates it to be higher. One feature of interest is that the decomposition method never returns a signal less than zero.

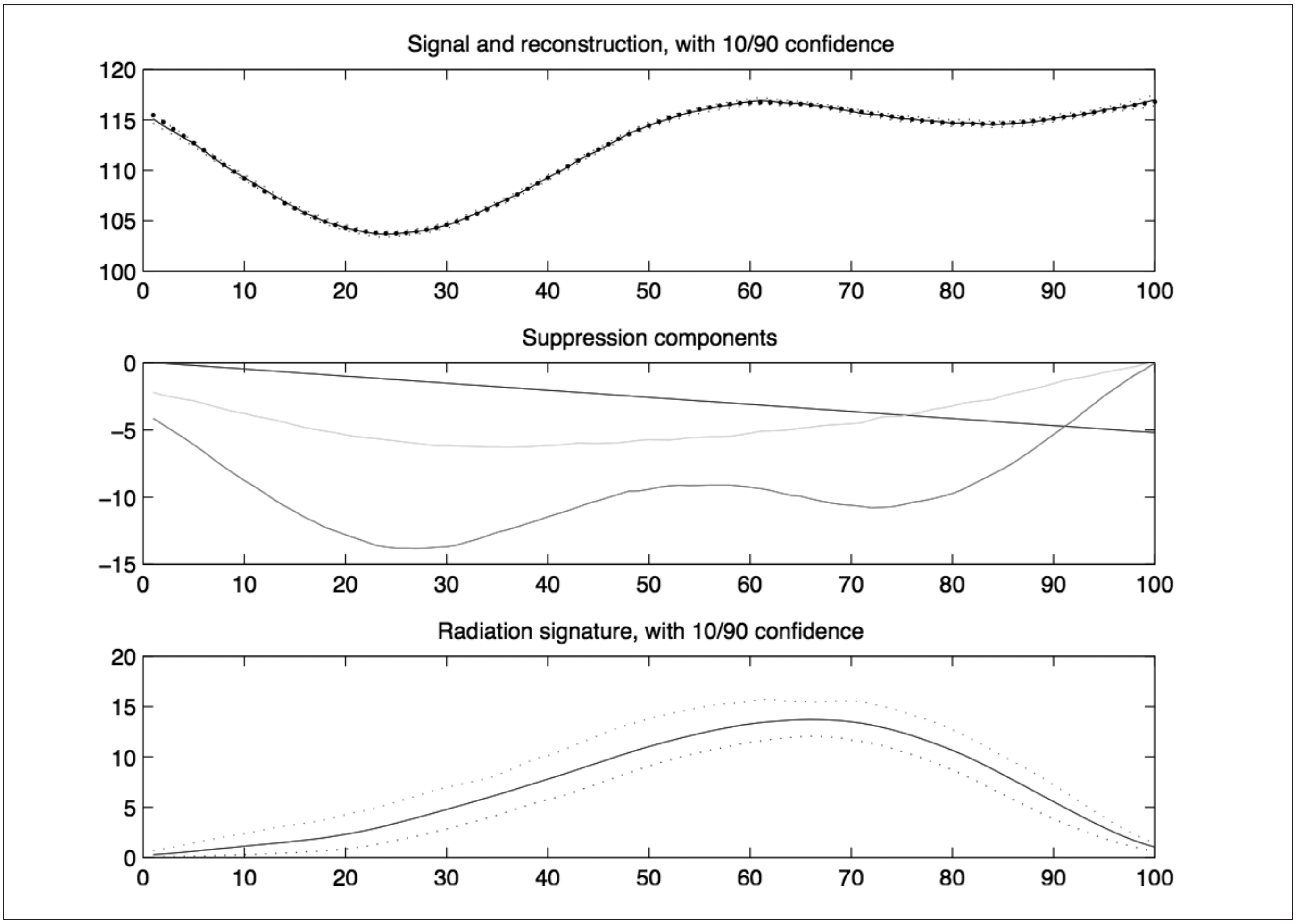
Without ground truth this is of only qualitative utility, but it shows that the results of signal estimation are not unreasonable. The next section investigates performance in a more quantitative manner by injecting synthetic radiation signals into the profiles.

Testing with Synthetic Signal Injection

This section will show a comparison of some alternative approaches, injecting a signal into the profiles to produce a positive signature. A dataset is constructed containing both the given (null) profiles and generated positive profiles. The positive profiles are the null profiles plus an injected signal term which has a normal shape centered at 60, with a standard deviation of 10, scaled to have a specified maximum value. This location would correspond roughly to the vehicle cargo area, and the smooth profile is consistent with many types of radiation signatures.

Each method's performance is computed for a selection of injected signal magnitudes. The performance is shown in Figure 8 (a typical receiver operating characteristic curve, ROC), which shows the proportion of true negatives vs. the proportion of true positives across threshold values that range from that which produces all negative classification to all positive classification. The classification is based on whether any point in the profile exceeds a given constant threshold, which is the same alarm rule that is currently being used. Sequential tests that monitor for runs of positive residuals should also be evaluated (Burr et. al., 2006) as possible alarm criteria, but this is beyond our scope here. The bet-

Figure 4. Decomposition of a vehicle signature. The top frame is the vehicle signature (dots), with the mean, and 10/90 confidence bounds superimposed (bounds are too tight to appear on this scale). Middle frame shows the mean suppression effects. The lower frame shows the radiation signature signal estimated mean and 10/90 confidence bounds.



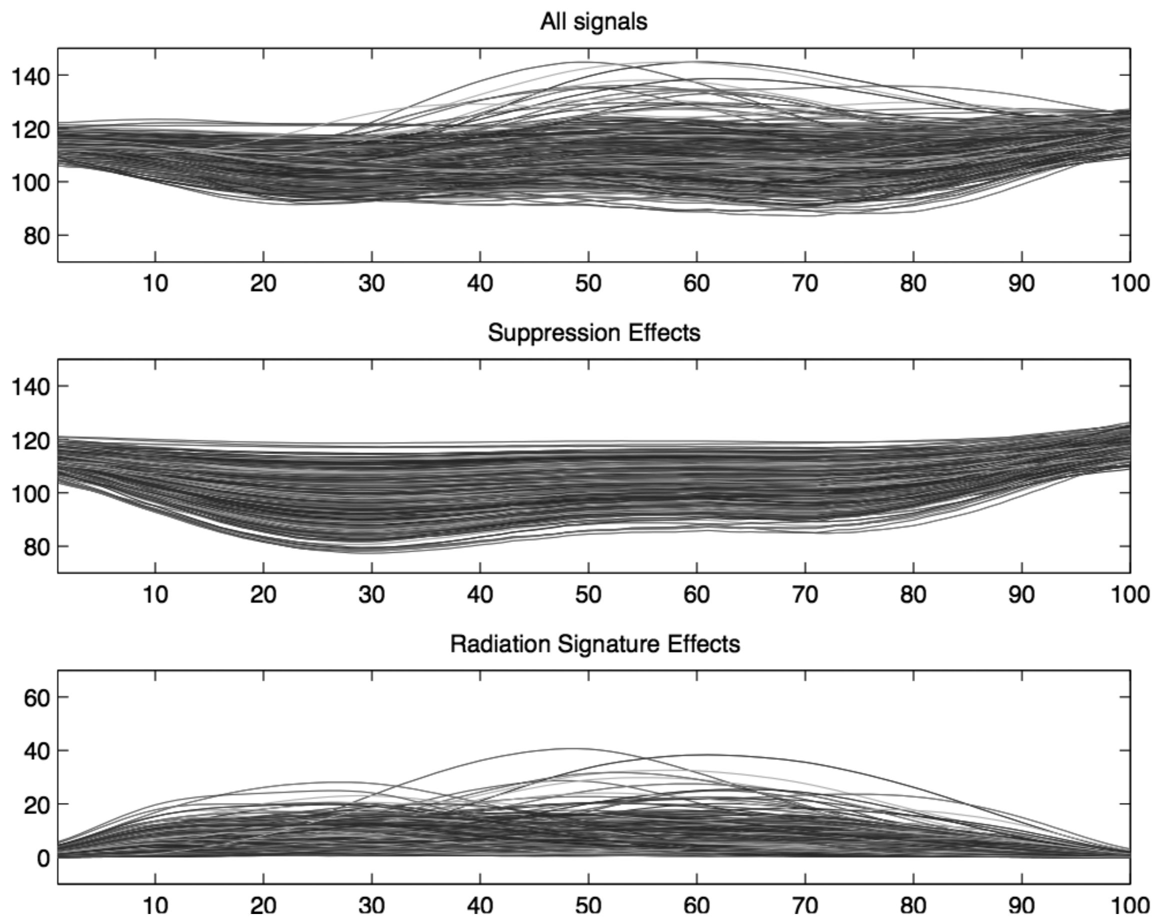
ter a method, the higher the curve at each point on the horizontal axis; that is, for a given true positive fraction, the better method has the larger true negative fraction.

The methods associated with the different curves in Figure 8 are:

- decomposition, the method we have introduced. The decomposition method is run on every positive and negative profile independently. This is a field-computable estimate of the source signal. Though the suppression profiles are drawn from the sample data, these are highly averaged and contribute little overfitting in this aspect; some additional details are below.
- mean0, a method in which the scalar mean of each negative profile is subtracted from both the negative and corresponding positive (signal injected) profile. This is a falsely optimistic and not field-computable estimate because the null mean of a positive profile is really unknown.
- mean0 and mean signal sub, the operation in mean0 augmented by subtracting the mean suppression profile of all the negatives from every profile, both negative and positive. This is falsely optimistic as above, and the suppression profile is computed from the data (as in the decomposition method).
- pre-mean sub, a short window of 10 measurements preceding each profile is used to estimate the background mean; this mean is subtracted from the profile. This is a field-computable estimate.
- pre-mean sub and mean signal sub, the pre-mean sub, with the subtraction of the null mean profile, as an estimate of the suppression effect. This is a slightly optimistic estimate because the suppression effect for the positives is taken from the pre-injection nulls.

Overall, the methods are distinguished only for very small signals, that is, where the injected signals are much less than the background measurement. For signals greater than the magnitude of the background, there is no ambiguity about positive versus negative classification in any of the methods.

Figure 5. Conglomerate decomposition results. All of the 713 signals are plotted in the top frame, the suppression effects estimated from the signal decompositions are in the second frame, and the estimated signals are shown in the bottom frame.



The best overall performer is the mean0 and mean signal sub. We call this "best possible" because, by using information from the construction of the signals that would be unknown in real estimation, it shows an upper bound on performance of this sort of model. This method pretends that we know the underlying null signal mean corresponding to the positives, though of course this is not possible. The next best performer is the decomposition method, followed by other methods.

The decomposition method here does use suppression profiles derived from the data, but this highly averaged estimate does not contain significant information relevant to the construction of the profiles. For example, in constructing alternative "U"-shaped profiles, there are 171 examples. Comparing the mean of 100 alternative draws of 80 of these profiles, the coefficient of variation, $100\sigma/\mu$ is between 0.1 percent and 0.5 percent, indicating that the calculation is not highly dependent on the specific data used for the calculation of the suppression profile.

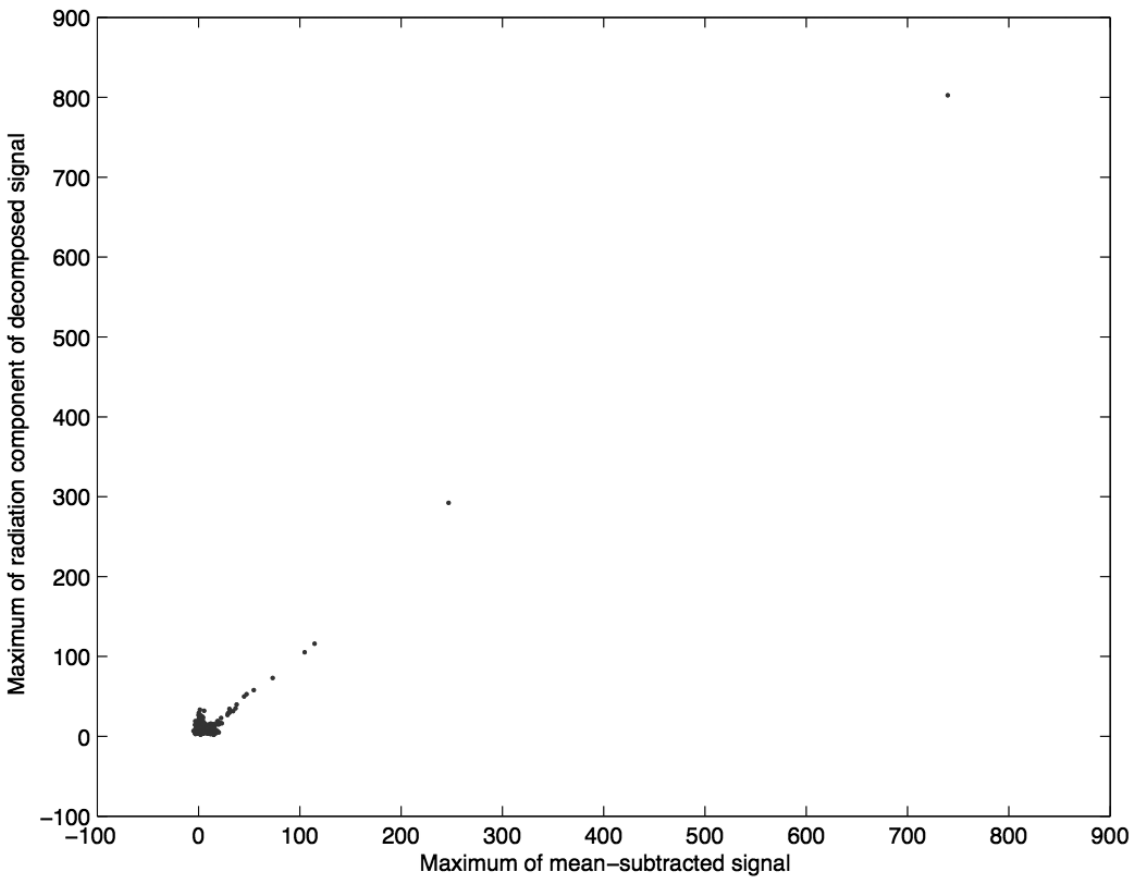
Conclusions

The decomposition of the smoothed profile method constructs a useful estimate of the radiation signature in the low energy gamma counts. This method is also computationally practical. Developing the MCMC chain displayed takes less than one minute on commodity hardware, and in an application context, a shorter chain of just a few seconds would be necessary.

In an installation, we envision a "first-cut" decision that puts vehicles into categories of: definite signal, where the radiation measurement shows an unmistakable signal, twice background or larger; definite non-signal, where a stringent threshold is not exceeded; and ambiguous signal. The decomposition approach presented here is applicable for further analysis of those profiles in the ambiguous signal category where a more refined analysis is needed to characterize the profile in detail for closer scrutiny.

We anticipate that any approach will suffer from mismatch between any given profile and the suppression component. In this approach, the mismatch is explained in the source terms.

Figure 6. Scatterplot of the maximum value of each estimated residual signal with two methods: horizontal axis is subtracting the global mean from each, vertical axis is estimating the residual (radiation effect) with the decomposition method. The decomposition method also shows (10,90) confidence region for each.

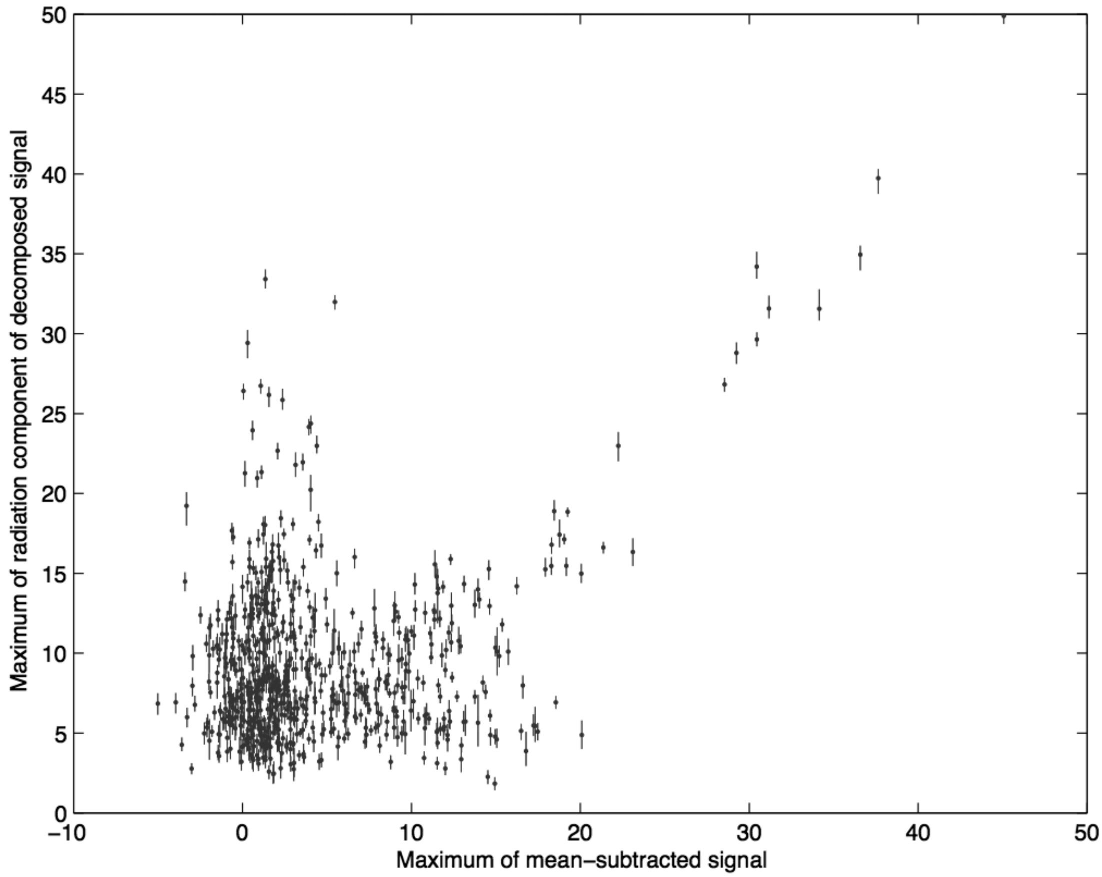


Therefore, all profiles examined to date have had a positive source estimate. However, this positive source estimate can be treated empirically by selecting thresholds above which the estimated source is thought to be significant.

Next steps include:

- Refinement of the suppression effect terms. In this preliminary analysis, the effects were derived from (imperfect) data. A more principled effect or set of effects should refine the usefulness of this approach. A parameterized treatment perhaps more consistent with the application context, as opposed to simple linear contributions of kernels could be useful. Additional information, perhaps using computer models such as MCNP (Briesmeister, 2000) to allow customization of suppression parameters observed vehicle characteristics would obviously be helpful.
- Closely related to the above, the refinement of prior distributions will increase the accuracy of the end results.
- Because the background is not highly variable over the profiles in this study, an additive suppression effect is tolerable. However, the physics of the system instead suggest that the effect should be modeled as multiplicative.
- This analysis treated a single sensor from an array that are performing simultaneous measurement. The broader analysis will treat multiple sensors as a single phenomena, as well as multiple sensor types. This will involve deconvolution of installed sensor transfer functions from an ideal signal, but will add a significant capability of noise suppression.
- Two stages were performed: smoothing and decomposition. Both of these operations could be integrated into a single method, simultaneously determining smoothing parameters and decomposition parameters with the MCMC sampling.
- Additional information can be taken from the associated uncertainty bounds, and fully exploiting the uncertainty estimates through the smoothing and decomposition procedures is a topic for further study.
- At various stages, we assume either Gaussian or Poisson likelihoods, which has been informally checked using plots and evaluation of the variance to mean ratio; however, this needs

Figure 7. Zoom in on Figure 6



further empirical evaluation (Burr et. al., 2005 and 2006).

- The injected signal had a normal shape centered at 60, with a standard deviation of 10, scaled to have a specified maximum value. Although this location corresponds roughly to the vehicle cargo area, and the smooth profile is consistent with many types of radiation signatures, clearly the signal model should be extended. This is a possible application for computer MCNP modeling (Briesmeister, 2000) to complement physical tests.

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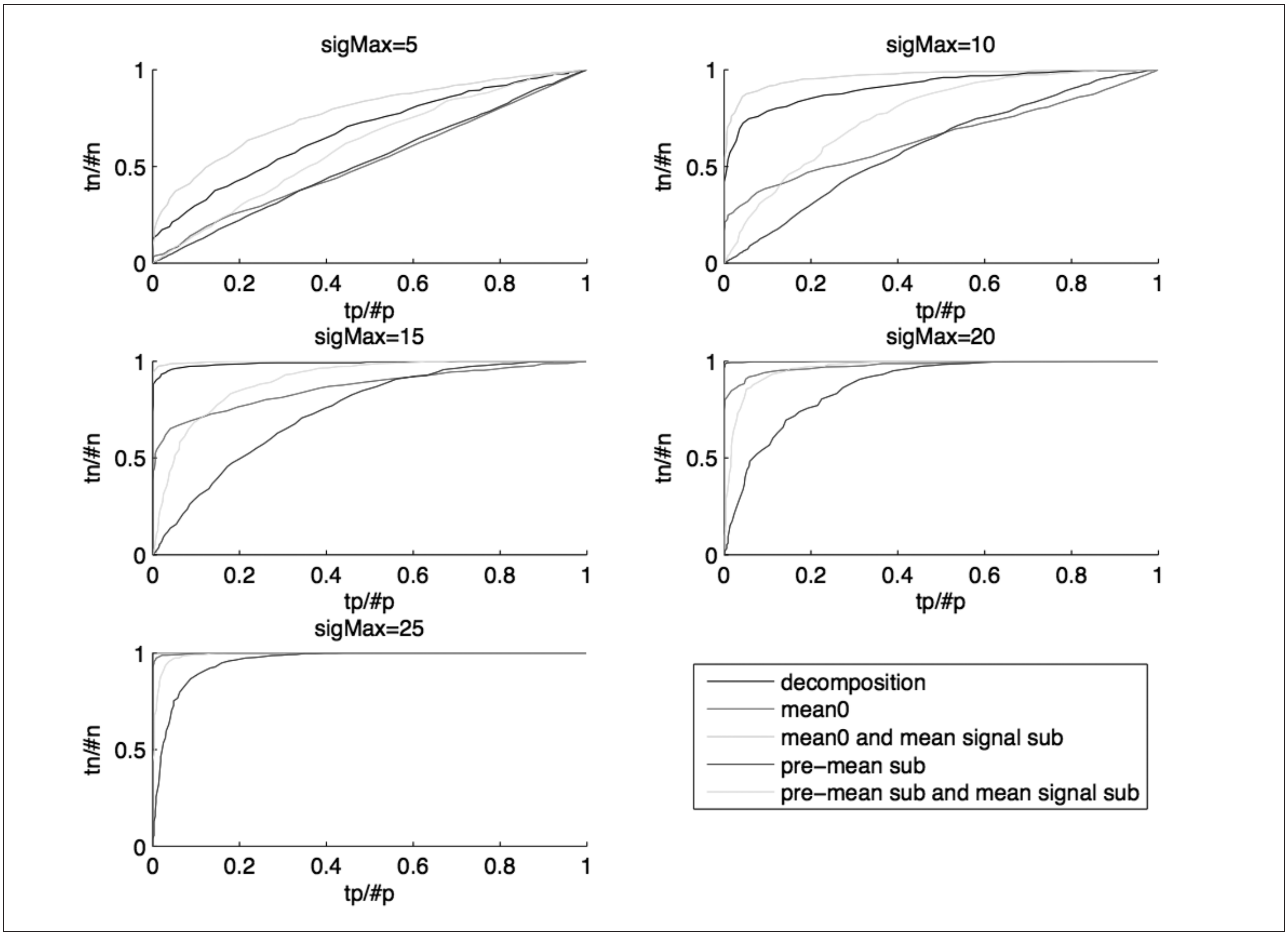
Figure 8. ROC curves for the various methods, at different levels of injected signal. The ROC plots show the fraction of true negative vs. fraction of true positive across an implicit threshold range. The different axes correspond to different magnitudes of injected signal.



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50th Anniversary Remembrances

Yvonne M. Ferris
INMM President, 1985–1986

What a privilege and honor to be asked to contribute to the *Journal of Nuclear Materials Management.* I have been a member of INMM since 1972, which makes me a newcomer by many standards, but nevertheless I have seen the Institute grow in national and international stature, in membership, in technical papers to include content and number of papers, in outreach programs, and in general nuclear materials management influence.

What amazes and delights me the most are the new and exciting directions the INMM has taken. One direction that particularly pleases me is the increased participation of women in the INMM. One reason for this growth is, of course, more women are in the work force now than there were fifty years ago. Another reason is more women are choosing careers in science, engineering, mathematics, accounting, and other disciplines pertinent to nuclear materials control than there were fifty years ago. The INMM can be proud of its early realization that this new stratum of "woman power" could and should be tapped and incorporated into the Institute. Women are now contributing in all phases of the workings of the INMM. They're officers, Executive Committee members, standing and ad hoc committee chairs, and all manner of responsibility. Their involvement is also felt in INMM's many chapters. Their talents and contributions have been and continue to be vital to the excellent management and growth of the INMM.

Another direction that is pleasantly overwhelming for me to see and experience is the increasing number of marvelous young men and women who are responding to the nuclear materials management call. For example, in the 1970s our student paper competition program was going strong, but it lacked interested students because, for the most part, their advisors did not encourage them to participate. At that time the nuclear industry was not high on the list of suitable and important topics in academia and we had difficulty in drawing student competitors. The INMM prevailed, I'm proud to say, so that to date at the INMM annual meeting, we have as many as thirty-two student papers, some of which are presented by students competing for the J. D. Williams Student Paper Award and some presented by students who have been encouraged by their advisor to participate in the INMM Technical Program. This growth in participation is due in large part to the enthusiasm and perseverance of Mark Killinger, the INMM's first recipient of a Student Paper Award in 1979 and Mark Leek, chair of the Student Activity Committee.

I could go on forever about the wonderful growth paths I have seen since 1972 such as (listed in no particular order) the student member mentor program; the formation and organization of six technical divisions; the continual improvement in the exhibits especially the superb exhibit dedicated to the students during the 2008 INMM annual meeting; the increase in the number of sustaining members; the always helpful and courteous headquarters staff; the twenty chapters, which include eight international chapters and six student chapters, and so many more.

The INMM holds a dear and warm place in my heart for assisting me to mature in my career, introducing me to many influential people in the several and diverse fields which comprise nuclear materials management, providing some beautiful and professionally friendly venues for our meetings, and always lending a helping hand when requested. As the INMM Mission Statement says, *inter alia,* "The Institute of Nuclear Materials Management was formed in 1958 to encourage: The advancement of nuclear materials management in all its aspects." The INMM does exactly that.

BNS Wins £13 million Contract for Dounreay Decommissioning

BNS Nuclear Services has won a £13 million open book contract from Dounreay Site Restoration Ltd. (DSRL) to provide maintenance and operations services in support of the decommissioning the site's two fast reactors. The contract is expected to run for three years, with an option to extend by up to two years.

Until now, four different companies have provided maintenance and operations support at the reactors. The appointment of BNS will bring together under one management the work previously done by the four companies.

Central to this challenge is the combining of the two reactor workforces who each have specialist knowledge. This means not only sharing knowledge and skills built up over the years, but also managing the inevitable culture change. At the heart of this process is the development and implementation of a common electronic works control system. The safety issues surrounding this are critical, and BNS is expected to develop an integrated planning system for the reactors' maintenance and operations activities. Once up and running, the system should be able to give performance statistics, such as how long individual maintenance tasks are likely to take, further aiding task planning. With just one contractor responsible for the planning process, it is expected that DRSL will benefit from the economies of scale that should flow when both operations and maintenance tasks are combined by the same team.

NNSA Transfers Radiation Detection System at Port of Antwerp to Belgium Customs *Partnership Aimed at Detecting Smuggled Nuclear Material*

The U.S. National Nuclear Security Administration (NNSA) joined the Federal Public Service of Finance of the Kingdom of Belgium Customs and Excise Administration (C&EA) in February to celebrate two successful years of radiation detection operations at the Port of Antwerp. In a ceremonial transfer at the Belgian Consulate, NNSA entrusted all of the Port of Antwerp's radiation detection equipment and property to the C&EA and Antwerp Port Authority.

The Port of Antwerp, located in northern Belgium on the North Sea, is one of the largest ports in Europe in terms of container traffic volume. Under NNSA's Megaports Initiative, radiation detection equipment was installed on both the right and left banks of the port at the gates to ten container terminals and other strategic exit/entry points. The equipment installed scans import, export, and rail container traffic at the port. The C&EA monitors the traffic from two central alarm stations and is responsible for radiation alarm analysis and response. Under a special cost-sharing arrangement, C&EA contributed to the detection efforts by funding the installation of the radiation detection equipment at two of the terminals.

NNSA cooperation with Belgium in radiation detection efforts at the Port of Antwerp began in 2004. The first terminals were commissioned in 2007 and the last two terminals in October 2008. NNSA continues to work with Belgium to augment the system with state-of-the-art equipment. NNSA and the government of Belgium are also working together and sharing costs on the installation of radiation detection equipment at the Port of Zeebrugge. The installation of equipment at both ports supports the U.S. Customs and Border Protection's Container Security Initiative, which targets and prescreens maritime cargo containers destined for U.S. ports.

NNSA has also partnered with Belgium on export controls, with the International Nonproliferation Export Control Program (INECP) demonstrating its Commodity Identification Training (CIT) to an EU-wide audience in Brussels in October 2007. NNSA also provided its CIT Instructor Training—a "train the trainer" course—to Belgian customs personnel. This year, Belgium will launch its own CIT program.

NRC Issues Safety Evaluation Report for Three Mile Island Nuclear Plant License Renewal Application

The U.S. Nuclear Regulatory Commission staff in March issued its safety evaluation report (SER) with open items for the proposed renewal of the operating license for the Three Mile Island Nuclear Station, Unit 1 (TMI-1), located in Middletown, Pennsylvania USA. The report documents the interim results of the NRC staff's review of the license renewal application and site audits of TMI-1's aging management programs to address the safety of plant operations during the period of extended operations. Overall, the results show that the applicant has identified actions that have been or will be taken to manage the effects of aging in the appropriate safety systems, structures and components of the plant and that their functions will be maintained during the period of extended operation.

Exelon Generation Group, LLC, owner and operator (formerly AmerGen Energy Company, LLC.), submitted an application to the NRC on January 8, 2008, to extend the TMI-1 license by twenty years. Under NRC regulations, the original operating license for a nuclear power plant has a term of forty years. The license may be renewed for up to an additional twenty years if NRC requirements are met. Therefore, if approved, the current operating license for TMI-1, which expires on April 19, 2014, would be extended until 2034.

In a letter dated March 13, Brian Holian, director of the Office of Nuclear Reactor Regulation's Division of License Renewal, provided Exelon with the SER. The SER will be available on the NRC's Web site. Issuance of a SER is a typical milestone in a license renewal review.

The NRC staff will present its final conclusions on the license renewal application in an update to this SER which is estimated to be issued in July 2009.

The SER and the license renewal application have also been provided to the NRC's Advisory Committee on Reactor Safeguards (ACRS), an independent body of experts that advises the NRC on reactor safety matters. An ACRS subcommittee is expected to discuss the SER during a meeting on April 1. The meeting, which will take place at NRC Headquarters in Rockville, Md., USA will be open to the public. The full ACRS will later issue a report discussing the results of its review.

Refurbished W76 Warhead Enters U.S. Nuclear Weapon Stockpile

The first refurbished W76 nuclear warhead has been accepted into the U.S. nuclear weapon stockpile by the Navy, according to a senior official at the Department of Energy's National Nuclear Security Administration (NNSA). This culminates a ten-year effort to ensure that the aging warhead, already years beyond its original intended life, can continue to be a reliable part of the U.S. nuclear deterrent.

Most nuclear weapons in the U.S. stockpile were produced thirty to forty years ago, and no new nuclear weapons have been produced since the end of the Cold War. Integrated into the Department of the Navy's Trident II D5 Strategic Weapon System, the first W76 entered the stockpile in 1978.

NNSA must use science-based research and development to extend the lifetime of the current weapons in the stockpile. By extending the life, or time that a weapon can safely and reliably remain in the stockpile without having to be replaced or removed, of a current weapon, NNSA is able to maintain a credible nuclear deterrent without producing new weapons or conducting new underground nuclear tests.

NNSA Ships Additional Surplus Special Nuclear Material From Livermore Shipment Reduces High-security Material Onsite by an Additional 20 Percent

The U.S. National Nuclear Security Administration (NNSA) announced in February that more than 55 percent of the plutonium and uranium materials stored at the Lawrence Livermore National Laboratory (LLNL) in California have been relocated. The material was moved to the Savannah River site in South Carolina and the Y-12 National Security Complex in Oak Ridge, Tennessee, under high security.

The shipment is part of NNSA's plan to remove high-security nuclear material from LLNL by 2012. This is the seventh shipment to leave LLNL since the de-inventory project was initiated.

As part of its Complex Transformation, NNSA plans to consolidate nuclear materials at five sites by 2012, with significantly reduced square footage at those sites by 2017. This will further improve security and reduce security costs and is part of NNSA's overall effort to transform the Cold War era nuclear weapons complex into a twenty-first century nuclear security enterprise. The latest shipment from LLNL was completed in full compliance with existing safety and environmental laws and procedures.

Materials must be processed to stable forms and repackaged to meet federal shipping and storage requirements prior to shipment. The original date to remove all high-security material from LLNL, based on equipment capability and capacity, was 2014. NNSA has developed a timeline to remove this material as early as possible, accelerating the target completion date to 2012. To reach this goal, NNSA is installing extra equipment to increase capacity.

Author Submission Guidelines

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The *Journal of Nuclear Materials Management* is an English-language publication. We encourage all authors to have their papers reviewed by editors or professional translators for proper English usage prior to submission.

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  2. Jones, F. T. 1976. *Title of Book*, New York: McMillan Publishing.
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Education (If you are applying for a student membership, indicate the year that you anticipate receiving your degree)

College/University Major/Degree Year Degree Obtained/Expected

1. ______________________________

2. ______________________________

3. ______________________________

If you are applying for a student membership, provide contact information for a faculty advisor to verify your full-time status:

Name ______________________________ Telephone ________________________ E-mail ________________________

Membership Type Desired

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❑ 0 – 19 employees $250
❑ 20 – 49 employees $500
❑ 50 or more employees $750

From the categories listed below, please indicate your top 3 areas of interest within INMM (1 being the greatest interest):

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Membership in Other Scientific and Technical Societies (Attach additional sheet if necessary)

Society Names and Membership Grades ______________________________

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Complete the application (keep a copy for your records) and mail or fax it with membership dues to:

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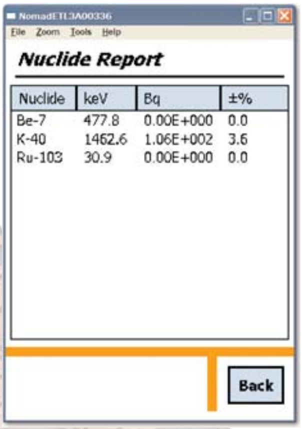

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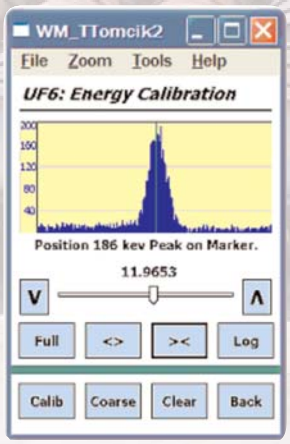

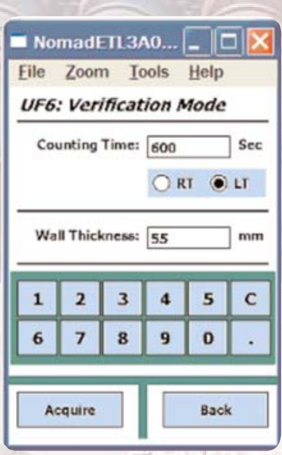

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