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# Stochastic Model Simulation for Evaluation Of Spent Fuel Pond Inventory Verification Sampling Plans

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## Abstract

The IAEA employs statistical methods to calculate the probability of detecting diversion from each nuclear material stratum in a facility. These detection probabilities (DPs) are used for both inspection planning and effectiveness evaluation. The DPs can be calculated using a deterministic or a stochastic approach. This paper describes the benchmark calculation performed using the stochastic model for spent fuel physical inventory verification (PIV). The IAEA performs PIV inspections for spent fuel pools using several different nondestructive measurement techniques. Each instrument has a varying precision and measurement time. The inspection plan, i.e., the total number and type of measurements, is designed to achieve a desired probability of detection (DP) by considering the strengths and efficiency of each measurement type. For example, a goal amount of one significant quantity (SQ) can be achieved for spent fuel inspection plan by taking many pins from few assemblies or by taking few pins from many assemblies. Varying the number of pins taken from each assembly impacts the achieved DPs. The sampling plan must take these variations into account when determining the number and type of measurements. When the material taken from each tampered assembly is equal, the deterministic solution is a hypergeometric distribution function, but when different numbers of pins are taken from various assemblies the solution is a multivariate hypergeometric function. The stochastic approach simply simulates an inspection given the parameters of the diversion and measurements and averages over many trials. The paper will present the results from the stochastic and deterministic approach. The stochastic model results further showed that the order in which you take measurements (high precision to low precision, etc.) does not impact the achieved DPs in the sampling plan.

## Introduction

Most commercial nuclear power plants are classified as light water reactors (LWRs). Once the fuel of an LWR is spent, it is placed in a spent fuel pool as a spent fuel assembly (SFA) where it stays until enough of the fission product radioisotopes decay to the point where the SFA can be transported to long term storage. These SFAs contain plutonium that if reprocessed can be used to make a nuclear weapon. Due to the possibility of using these SFAs to make a weapon, the IAEA and other organizations that perform safeguards inspect these spent fuel pools to ensure that the SFAs have not been tampered with or removed.

Inspections are performed regularly in non-weapon states that have signed the NPT. The operators of the nuclear facility being inspected must provide the inspectors with the inventory of nuclear material on site so that the inspectors can plan to verify the declared inventory by measuring the material. Several different devices are used to measure nuclear material, but all are classified into three types of measurements. Devices that can verify that there is nuclear material in the item being measured can identify if there has been a gross defect of the item, meaning that all or nearly all the nuclear material was taken, and are called gross measurement devices. Devices that can identify if part or parts of the nuclear material in an item is missing are called partial measurement devices. When a device can identify a small defect of material from an item (a bias defect) it is called a bias measurement device. Inspectors plan to make a number of each type of measurement when inspecting a facility to ensure a desired probability of detecting a material diversion is achieved. An ongoing project at UMass Lowell has been to determine achieved detection probability based on measurements, declared inventory, and possible diversion scenarios for post-inspection analysis.

## Overview of Krieger et al.[1]

Krieger et al. explores several scenarios and problems similar to those that have been explored and will be explored in the project at UMass Lowell. The paper explores non-equal diversion, which the UMass Lowell project has already explored to an extent, and it uses a step function for its identification probability for item verification which is a different approach than what the UMass Lowell project has used.

The IAEA has historically made the assumption of equal diversion, meaning that the diverter has taken an equal amount of material from each diverted item. This assumption is used to keep the math involved in the problem simple and the justification is that there will not be a drastic difference in detection probability should the diverter decide to take different amounts of material from diverted items. An investigation to challenge this assumption was performed in [1] using a deterministic approach. For equal diversion, the probability that a diverted item will be selected can be represented by the hypergeometric distribution function, but for non-equal diversion there are more than two choices for item selection, so the selection probability is instead a multivariate hypergeometric function. Deriving the correct formula for the selection probability can be challenging but it is even more so challenging to incorporate the probability that the defected item will be identified after it is selected. A convenient solution to the latter challenge is to use a step function for identification probability.

The probability that a device will identify an item as defective can be modeled in several ways. If it is to be assumed that the measurements made by the device follow a normal distribution, then that cumulative distribution function can be used to model the identification probability of the device. Another approach is to specify a certain percent of material defected where the device will identify a diversion with the behavior of a step function in which after a certain percentage of the material is diverted, the device always identifies the diversion. In reality the ability for the inspector to identify a diversion with a device can depend on the judgement of the inspector and can follow a logistic shape.

The specific devices examined in the paper are the PGET, DCVD, and ICVD. These measurements are of the type bias, partial, and gross respectively. The step function cutoffs for each device are based on the percentage of remaining material in the SFA. The PGET can identify a single pin diversion when 0.38% of the pins or more of the material in the item (an SFA) is missing. The DCVD can identify a diversion when about 30% of the pins or more have been removed while the ICVD can only identify when there are no pins remaining in the SFA.

Both equal and non-equal diversion scenarios are considered in [1]. For the equal diversion scenario, the assemblies that are diverted from have the same number of pins taken from them (equal diversion assumption). Due to the difference in the identification cutoffs (0.38%, 30% and 100%), three regions of numbers $r_{pin}$ of removed pins must be considered: $r_{min} \leq r_{pin} \leq \lceil 0.3\, L \rceil - 1$, $\lceil 0.3\, L \rceil \leq r_{pin} \leq L - 1$, and $r_{pin} = L$, where $r_{min} = \lceil SQ \times L/(N\bar{x}_{Pu}) \rceil$ and $N$ is the number of SFAs in the spent fuel pool, $L$ is the number of fuel pins per SFA, $\bar{x}_{Pu}$ is the average amount of plutonium (Pu) per SFA, and $SQ$ is the significant quantity ($SQ$=8 [kg] for Pu). Because the DP is a monotone decreasing function in all three regions, the minimum of the DP curve is attained at $r_{pin} \in \{\lceil 0.3\, L \rceil - 1, L - 1, L\}$. Thus, a sampling plan achieves a required DP $1 - \beta_{req}$ if and only if the DP at the three values $r_{pin} \in \{\lceil 0.3\, L \rceil - 1, L - 1, L\}$ is at least $1 - \beta_{req}$.

In the non-equal diversion scenario, there are several pins taken from one set of SFAs and a different number of pins taken from another set. This example in [1] was chosen such that one set can be identified by both the PGET and DCVD while the other can only be identified by the PGET. Because of how specific this scenario is there is only one detection probability evaluated. The order of measurements, i.e., PGET > DCVD > ICVD or DCVD > PGET > ICVD, is suggested to have an impact on the final detection probability, although this is not the case.

## Equal Diversion Scenario with Step Function

In the equal diversion scenario, a hypothetical BWR spent fuel pond with 2500 SFAs is considered. Each SFA contains 96 fuel pins and an average amount of 2kg of plutonium. The sampling plan, 25 PGET, 65 DCVD, and 10 ICVD, that is chosen achieves the detection probability 0.1315. Several detection probabilities are then calculated by varying the number of pins taken from diverted assemblies.

The number of assemblies diverted from is dependent on the number of pins taken from each diverted assembly. About 384 pins, four assembly's worth, would have to be taken from the pool to reach a significant quantity of plutonium. These pins can be diverted by taking every pin in just four assemblies, taking one pin each from 384 assemblies, or any combination of pins taken from assemblies that adds to the goal amount. In general, when more pins are taken from each diverted assembly, there is less of a chance that a diverted assembly will be chosen but a higher chance that the diverted assembly will be identified as tampered should it be chosen. Conversely, if less pins are taken from each diverted assembly, then there will be a higher chance that a diverted assembly is chosen for inspection but a lower chance that it is identified as defective. It is important to note that although the extreme cases (taking 384 pins from four assemblies or from each of 384 assemblies) can sometimes represent a lowest or highest detection probability case, this is not a general rule.

Using deterministic methods, the hypergeometric distribution function is used for the selection probability of the assemblies. Because a step function is used for the identification probability, the detection probability is simply the probability that an SFA is not selected by a measurement device that can identify the SFA as tampered. For example, if the number of pins removed from each diverted assembly is 20 pins, then the detection probability simplifies to the probability that a tampered assembly is chosen to be measured by the PGET device, because neither the DCVD nor ICVD could identify an assembly as tampered with when only 20 pins are removed. The results from the scenario discussed are presented in [1] in Figure 1.

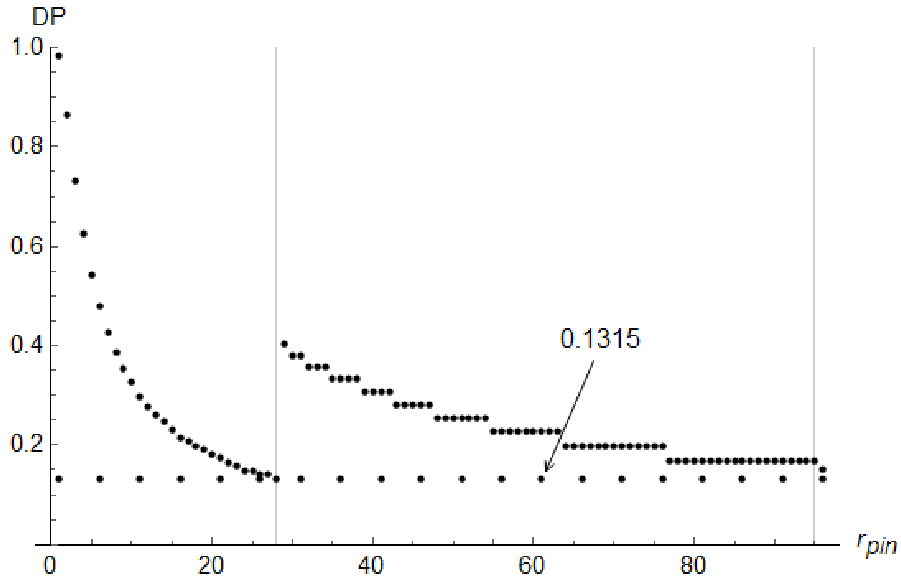


*Figure 1 - Achieved detection probability for various numbers of pins diverted with deterministic method.*

In the stochastic case, the selection probability is determined by running many simulations of the inspection. The pool is defined for each scenario of unique number of pins removed from each diverted assembly and assemblies are randomly selected from the pool. Each measurement type is performed in sequence (PGET to DCVD to ICVD). If a diverted assembly is selected and the measurement device would identify it as tampered, then the detection for that trial of the simulation is one. When all measurements are performed and none of the diverted assemblies have been detected then the detection for that trial is zero. After running thousands of trials (10000 trials were enough for this problem), the trial detection results are averaged to find the probability of detection. Running more trials causes the average detection probability to be more precise. Further reading on stochastic methods can be found in [2]. The same sampling plan and diversion scenario used in the deterministic solution was simulated and produced the results seen in Figure 2.

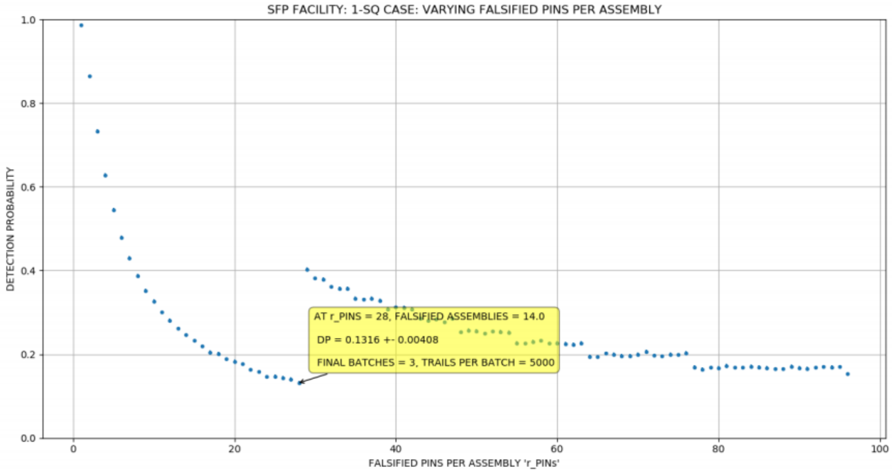


*Figure 2 - Achieved detection probability for various numbers of pins diverted with stochastic method.*

Both methods produce the same result, however the stochastic result has a small uncertainty associated with it. In both cases the minimum detection probability occurs when 28 pins are taken from 14 assemblies as this is the highest number of pins that can be taken from few assemblies before the DCVD instrument can start to identify diversions.

## Non-equal Diversion and Significance of Measurement Order

In a hypothetical spent fuel pool with 2000 SFAs, 4 pins are removed from 21 SFAs and 30 pins from 10 SFAs to reach a goal amount of 8kg of plutonium. This is an unequal diversion scenario. Because there are no gross defects in this scenario, the ICVD measurements are not impactful on the achieved detection probability. Under the equal diversion assumption, the sampling plan 97 PGET, 162 DCVD, and 59 ICVD measurements achieves a desired detection probability of 0.5.

This kind of diversion scenario is not considered by the current model of the IAEA which assumes equal diversion. In this scenario the diverter attempts to minimize the probability that a PGET will select a defective SFA by minimizing the total number of diverted SFAs. At the same time the diverter attempts to minimize the selection probability from the DCVD by minimizing the number of diverted SFAs with more than 30% of the pins missing. The strategy is a compromise of the two strategies.

As seen in [1], the mathematical complexity of the selection probability increases for non-equal diversion due to the number of types of items that can be selected exceeding two. The multivariate hypergeometric function can be used to determine the selection probability of the diverted items. Using a step function to evaluate the probability of identifying a diverted item means that if the diverted item is chosen and it has had enough material diverted to be identified by the instrument then it will be detected, so the identification probability is simplified. Even with this simplification the deterministic approach is still difficult, but a stochastic simulation is rather easy to develop.

The stochastic approach was used to calculate the DP of the diversion scenario with both a step function and with a normal distribution. The step function found the DP of the scenario to be ~91%

while the normal distribution had a slightly higher answer of ~92%. The relative standard deviation used for the PGET was 0.1%, for the DCVD was 3%, and for the ICVD was 15% (which is a common approximation). The slightly higher DP is likely due to the possibility for ICVD to catch a diversion with a 15% relative standard deviation.

In [1], an argument was made that changing the order of the measurements may affect the achieved detection probability and that taking less precise measurements first would lower the achieved detection probability. Upon running stochastic simulations of both orders of measurement, the same detection probability of 91% was calculated which agrees with the first deterministic result but not the second.

We first assume that sampling is performed in the order $n_3 \to n_2 \to n_1$, i.e., we sample first the SFAs verified by the PGET, then – from the remaining $N - n_3$ SFAs – the SFAs verified by the DCVD, and finally – from the remaining $N - n_3 - n_2$ SFAs – the SFAs verified by the ICVD. Then non-detection event occurs if for the PGET measurements none of the $21 + 10 = 31$ SFAs are in the sample, and for the subsequent DCVD measurements none of the 10 SFAs with 30 missing pins are in the sample. Thus, the DP is, with $N = 2000$, $n_3 = 97$ and $n_2 = 162$,

$$1 - \frac{\binom{31}{0}\binom{N-31}{n_3}}{\binom{N}{n_3}} \frac{\binom{10}{0}\binom{N-n_3-10}{n_2}}{\binom{N-n_3}{n_2}} \approx 0.91\,. \tag{1}$$

The term for the selection probability for the PGET is the first fraction while the selection probability for the DCVD is the second fraction. The ICVD can only identify fully emptied items as falsified, so it is not considered for this diversion scenario.

Now, consider the case the sampling is done in the order $n_2 \to n_3 \to n_1$. Then, the non-detection event occurs if for the DCVD measurements none of the 10 SFAs with 30 missing pins but $i$ SFAs out of the 21 SFAs with 4 missing pins (which can only be identified with PGET) are sampled, and for the subsequent PGET measurements none of $21 - i$ remaining SFAs with 4 missing pins and none of the 10 SFAs with 30 missing pins, are sampled. Using the multivariate hypergeometric distribution [3], we get, with $N = 2000$, $n_3 = 97$ and $n_2 = 162$, for the DP

$$1 - \sum_{i=0}^{21} \frac{\binom{21}{i}\binom{10}{0}\binom{N-31}{n_2-i}}{\binom{N}{n_2}} \frac{\binom{31-i}{0}\binom{N-n_2-(31-i)}{n_3}}{\binom{N-n_2}{n_3}} \approx 0.91\,. \tag{2}$$

The above-mentioned discrepancy in [1] is because the number of falsified SFAs that can be identified with the PGET measurements in the second step is not just $21 - i$ (as claimed in [1]) but $21 - i + 10$. This is now corrected in Eq. (2). Thus, Eqs. (1) and (2) illustrate that the DP does not depend on the order of sampling. Note that the complexity of the DP calculation in Eq. (2) greatly increases due to the fact the PGET can identify both types of diverted items as defective while the DCVD can only identify the 10 SFAs with 30 missing pins as falsified.

That the order of sampling does not play any role has been shown above for the specific scenario. But is this true in general, i.e., for any $N$, $n_3$, $n_2$ and the type of scenario considered? The answer is yes. To prove this statement let $r_3$ resp. $r_2$ be the number of SFAs from which $r_{3,pin}$ resp. $r_{2,pin}$ are assumed to be removed. Because $L = 96$, $\bar{x}_{Pu} = 2$ [kg], and $SQ = 8$ [kg] we must have

$$\frac{2\ [kg]}{96} \times \left(r_{3,pin} \times r_3 + r_{2,pin} \times r_2\right) = 8\ [kg]. \tag{3}$$

We further assume that $1 \le r_{3,pin} \le 28$ and $29 \le r_{2,pin} \le 95$ which models the situation that the PGET can identify the $r_3 + r_2$ SFAs as falsified, while the DCVD can only identify the $r_2$ SFAs as falsified. Examples are given Table 1.

| $r_3$ | $r_{3,pin}$ | $r_2$ | $r_{2,pin}$ |
|---|---|---|---|
| 21 | 4 | 10 | 30 |
| 18 | 8 | 4 | 60 |
| 34 | 10 | 1 | 44 |
| 12 | 12 | 6 | 40 |
| 21 | 14 | 3 | 30 |

*Table 1: Examples of $r_3$, $r_{3,pin}$, $r_2$ and $r_{2,pin}$ that fulfill Eq. (3). The second line presents the example used in [1] and in the calculations in Eqs. (1) and (2).*

If the sampling is done in the order $n_3 \to n_2 \to n_1$, then the DP, abbreviated by $DP_{321}$, is, see the derivation of Eq. (1), given by

$$DP_{321} = 1 - \frac{\binom{r_3+r_2}{0}\binom{N-(r_3+r_2)}{n_3}}{\binom{N}{n_3}} \frac{\binom{r_2}{0}\binom{N-n_3-r_2}{n_2}}{\binom{N-n_3}{n_2}}, \tag{4}$$

while in the case the sampling is done in the order $n_2 \to n_3 \to n_1$, the DP, abbreviate by $DP_{231}$, is, see the derivation of Eq. (2), given by

$$\begin{aligned} DP_{231} = 1 - &\sum_{i=Max(0,n_3+n_2-(N-(r_3+r_2)))}^{Min(r_3,n_2)} \frac{\binom{r_3}{i}\binom{r_2}{0}\binom{N-(r_3+r_2)}{n_2-i}}{\binom{N}{n_2}} \frac{\binom{r_3+r_2-i}{0}\binom{N-n_2-(r_3+r_2-i)}{n_3}}{\binom{N-n_2}{n_3}} \\ = 1 - &\sum_{i=Max(0,n_3+n_2-(N-(r_3+r_2)))}^{Min(r_3,n_2)} \frac{\binom{r_3}{i}\binom{N-(r_3+r_2)}{n_2-i}}{\binom{N}{n_2}} \frac{\binom{N-n_2-(r_3+r_2-i)}{n_3}}{\binom{N-n_2}{n_3}}. \end{aligned} \tag{5}$$

We now prove that $DP_{321} = DP_{231}$, i.e., the order in which the items are measured resp. sampled does not affect the DP. Using the identity

$$\sum_{i=Max(0,m-b)}^{Min\,(m,a)} \binom{a}{i}\binom{b}{m-i} = \binom{a+b}{m}$$

for any positive integers $a, b$ and $m$, see [2], and the fact that

$$\binom{N-(r_3+r_2)}{n_2-i}\binom{N-n_2-(r_3+r_2-i)}{n_3} = \binom{N-n_3-(r_3+r_2)}{n_2-i}\binom{N-(r_3+r_2)}{n_3}\,,$$

we obtain by identifying $a \to r_3$, $b \to N-n_3-(r_3+r_2)$ and $m \to n_2$,

$$\begin{aligned} &\sum_{i=Max(0,n_3+n_2-(N-(r_3+r_2)))}^{Min(r_3,n_2)} \binom{r_3}{i}\binom{N-(r_3+r_2)}{n_2-i}\binom{N-n_2-(r_3+r_2-i)}{n_3} \\ =\ &\binom{N-(r_3+r_2)}{n_3}\sum_{i=Max(0,n_3+n_2-(N-(r_3+r_2)))}^{Min(r_3,n_2)} \binom{r_3}{i}\binom{N-n_3-(r_3+r_2)}{n_2-i} \\ =\ &\binom{N-(r_3+r_2)}{n_3}\binom{N-n_3-r_2}{n_2}\,, \end{aligned}$$

i.e., by Eq. (5)

$$DP_{231} = 1 - \frac{\binom{N-n_3-r_2}{n_2}}{\binom{N}{n_2}}\frac{\binom{N-(r_3+r_2)}{n_3}}{\binom{N-n_2}{n_3}}\,. \tag{6}$$

Because

$$\binom{N}{n_2}\binom{N-n_2}{n_3} = \frac{N!}{n_3!\,(N-n_3)!}\frac{(N-n_3)!}{n_2!\,(N-n_2-n_3)!} = \binom{N}{n_3}\binom{N-n_3}{n_2}\,,$$

Eqs. (6) and (4) yield

$$DP_{231} = 1 - \frac{\binom{N-n_3-r_2}{n_2}}{\binom{N-n_3}{n_2}}\frac{\binom{N-(r_3+r_2)}{n_3}}{\binom{N}{n_3}} = DP_{321},$$

which had to be shown.

# Advantages/Disadvantages to Stochastic Method

There are many ways in which a stochastic approach to these diversion scenarios and evaluations of achieved detection probability can offer advantages over the tradition deterministic approach.

The most important advantage of utilizing a stochastic approach is that it is an alternative method that can capture discrepancies between models and highlight oversights or mathematical errors.

When both methods agree, there is more certainty that both have arrived at the correct answer instead of the less likely possibility that both methods have arrived at the same, incorrect answer. When the answers are different then it is clear that at least one is incorrect. The time to develop a stochastic approach is worth the increased certainty it provides.

Due to the intuitive nature of running simulations of an event, the stochastic approach is more straightforward. When tackling a new problem or scenario, the stochastic approach can take less time to develop because a mathematical derivation of the formula is not needed. A quick solution or estimation can be reached with the stochastic approach, before delving deep with a deterministic solution.

The selection probability in the stochastic approach is simple enough that using different kinds of approaches to identification probability is easily achieved. In the past the measurement devices used by the IAEA are assumed to have uncertainties based around the normal distribution. This has been criticized, and both step functions and logistic functions are suggested as alternatives. In a stochastic simulation of an inspection, any desired cumulative distribution function can be used as the identification probability. As long as there exists an equation or fine enough discrete values for identification probability the simulation can be performed. The most realistic option is the logistic function, as instruments have been shown to follow this trend in actual experiments with MTR assemblies at the UMass Lowell Research Reactor with an HM-5 and similarly with assemblies from the Medical Research Reactor at BNL.

In some cases, a stochastic approach can be faster at arriving at the solution. When the problem is complex enough, the deterministic solution requires more computational power than the stochastic solution. For example, when the deterministic solution utilizes a tree diagram to determine selection probability, large numbers of measurements or types of diverted items/batches will cause the deterministic calculation to take quite some time as the total number of possibilities increases dramatically. In most simple cases the deterministic solution is faster as many trials must be performed to get a precise solution with the stochastic method.

When extreme precision is required and a low uncertainty is desired, the stochastic method can take some time to get to the required solution. A larger number of trials is required for lower uncertainties, and more trials means that that the simulation takes longer.

Additionally, it is possible to develop a simulation that is not correct. In other words, the simulation performed in the code developed for the problem is not representative of the scenario. The approach is simple and not as rigorous, so it is important to make sure that the simulation is performing the scenario presented. Just as deterministic solutions can be accompanied with a proof, stochastic simulations must be evaluated to ensure that the approach does indeed solve the original problem.

# Conclusions

Stochastic simulations like the one used to verify the example from [1] are useful for a variety of reasons including the ability to provide another method to arrive at the same answer. Stochastic simulations are often less complex than deterministic solutions and this proves true for the problem presented in the paper. A simple trial simulation and average is not at all complex when compared to the multivariate hypergeometric distribution function. For this reason, stochastic solutions can serve as a check for deterministic solutions before a proof can be developed and to verify that both solutions are correct. Whenever there is doubt that the deterministic solution is correct, an easy way to verify that it is correct is to run a stochastic simulation. The impact that the order of measurements had on the detection probability in the spent fuel scenario was found to be none at all by the stochastic approach and this confirmed the suspected mistake in the deterministic equation that was developed.

## Recommendations and Future Work

There are countless areas for investigation regarding non-equal diversion strategies and the effect on DP. Changing the number of types of items in the scenario – partially diverted, bias diverted, fully diverted, and non-diverted items – offers the ability to cover a wide range of detection probabilities based on how many items are in each diverted group and how much material is diverted from each item in a group. Increasing the number of item groups increases the complexity of the deterministic solution to the selection probability with the multivariate hypergeometric distribution function. Exploring these scenarios with the stochastic method may be quickest and easiest, and any interesting scenarios can be confirmed with a deterministic approach.

The stochastic approach allows for the introduction of a more complex identification probability than the step function. The normal distribution was used to demonstrate this trait. Another alternative for identification probability is a logistic function.

Developing a way to examine many non-equal diversion scenarios systematically will help future explorations into non-equal diversion looking for specific diversion scenarios that may point out ways in which IAEA inspection plans can improve. In the equal diversion scenario, the independent variable is the number of defected items / batches, and a plot is generated with the DP as the dependent variable. In this way, a range of possible diversion scenarios is presented on one graph and the worst cases can be spotted by looking at the minimum DP values on the graph. The variables in non-equal diversion cannot be presented in the same way as with equal diversion. In equal diversion and a fixed goal amount of one SQ, the amount of material taken from each item diverted decreases as the number of diverted items increases, but with several diverted groups of different diversion amounts in non-equal diversion, the incremental change from one scenario to another is not as clear. A method to sweep through different diversion scenarios much be developed for non-equal diversion to be thoroughly investigated.

## References

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