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Development of an Origin Trace Method based on Bayesian Inference and Artificial Neural Network for Missing or Stolen Nuclear Materials

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1. Introduction

Nuclear energy has two faces like Janus in ancient Roman myth: One as a massive energy source, and the other as a fearful weapon. The problem is that the consequences of the weapon side are much more horrific than those of the peaceful energy source when misused or miscontrolled. For example, direct casualties by the Chernobyl accident were officially 56 [1], whereas those who directly killed by the atomic bomb ‘Little Boy’ dropped on Hiroshima were over 80,000 [2]. Thus, “to put nuclear materials under control” is an important issue for prosperity mankind. Unfortunately, numbers of illicit trafficking of nuclear materials have been increased for decades [3]. Consequently, security of nuclear materials is recently spotlighted. After the 2nd Nuclear Security Summit in Seoul in 2012, the president of Korea had showed his devotion to nuclear security. One of the main responses for nuclear security related interest of Korea was to develop a national nuclear forensic support system.

International Atomic Energy Agency (IAEA) published the document of Nuclear Security Series No.2 “Nuclear Forensics Support” in 2006 to encourage international cooperation of all IAEA member states for tracking nuclear attributions [4]. There are two main questions related to nuclear forensics to answer in the document. The first question is “what type of material is it?”, and the second one is “where did the material come from?” Korea Nuclear Forensic Library (K-NFL) and mathematical methods to trace origins of missing or stolen nuclear materials (MSNMs) are being developed by Korea Institute of Nuclear Non-proliferation and Control (KINAC) to answer those questions.

2. Nuclear Forensic Library

Setting up a database is one of the essential steps for knowledge based estimation. In addition, quality and quantity of contents in the database are so important for the resolution of results. The structure of the database and a means of data collection are briefly explained in this section.

2.1 System Overview

A term “library” is use for a kind of well-organized and linked database in this study. The library has master and slave data servers for safety of collected data. An input process of data is designed to keep integrity of data by putting a temporary storage in an administrator’s terminal. Once checked, data in the temporary storage go to the master data server under administrator’s authority as shown in Fig. 1.

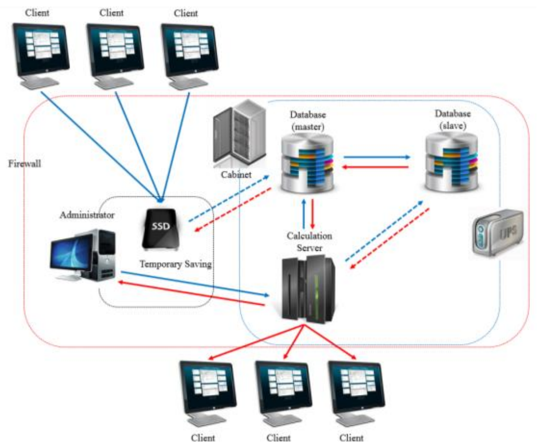

Fig. 1. Overview of K-NFL

2.2 Data Collection

The ideal nuclear forensic library would include [5]:

- Fissile materials characteristics
- Other nuclear material information that may be relevant to tracing fissile materials
- Fissile materials production and processing information
- Information on fissile materials storage sites, including types and quantities of materials and site security measures.

Practically, some technical problems exist when collecting information from companies or institutes such as confidentiality. So, minimally required data sets for nuclear forensics were determined as follow [6]:

- Radioactive decay chain parent/daughter isotopes and radioactive properties
- Actinide measurement test results.
- Uranium Oxide Quality Control (QC) data set.
- Simulated Data Sets

3. Trace Methods

One common way of classifying nuclear material is to divide nuclear fuels before and after the irradiation: new fuels and spent fuels. Two different approaches were taken for each class because of data attributes: measureable and calculable.

3.1 Bayesian Inference

Physical and chemical characteristics data of new fuels can be produced from every steps of the manufacturing process. Detailed values to measure are written in the technical specification. QC data in the check-sheet include pass/fail results of measured values. With these values and status, the origin of MSNMs can be expressed in a probabilistic manner. The Bayes' rule provides an expression for the conditional probability, for any probability distribution *P*, of *A* given *B*, which equals to

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)}$$

where,
P(*A*): a priori belief in *A*
P(*A*|*B*): a posteriori belief in *A* given evidence *B*
P(*B*|*A*): a likelihood of *A*. a belief in *B* if *A* is assumed

A method to adopt Bayesian Inference to nuclear attribution in this paper is as follows:
X indicates the possible origins of MSNMs, a set of Y_i ($i=1,2,\ldots,n$) indicates various characteristics of materials, such as indicators and annunciators. X and Y_i are defined as,

$X = \{x_1, x_2,\ldots,x_l\}$

$Y_i = \{y_{i1}, y_{i2},\ldots,y_{ini}\}$ where, $i = 1, 2,\ldots, m$.

A deterministic rule of "IF-THEN" can be described mathematically by conditional probabilities as follows:

$$\mathrm{P}(y_{ij}|x_k) = \begin{cases} 1, & if\ y_{ij} is\ expected\ on\ x_k \\ 0, & if\ y_{ij} is\ not\ expected\ on\ x_k \end{cases}$$

y_{ij} in a set of parameters Y_i is considered if any, and the probability of the origin of MSNMs x_k is revised according to Eq. 3-1.

$$\mathrm{P}(x_k|y_{ij}) = \frac{P(y_{ij}|x_k)P(x_k)}{\sum_{h=1}^{l} P(y_{ij}|x_h)P(x_h)} \quad \text{…(Eq. 3-1)}$$

Physical meaning of the result based on Bayesian Inference represents estimator's level of confidence in the origin of MSNMs.

3.2 Artificial Neural Network (ANN)

For spent fuels, a direct measure is impossible because of strong radioactivity. In this case, simulated data sets are required as mentioned in section 2.2. ORIGEN-ARP was used to calculate isotopic depletion and decay of spent fuels [7]. The advantage of simulation is abundance of data sets, and Machine Learning is an effective method to find optimal solutions in such circumstances. In an ANN (one of the machine learning methods), simple artificial nodes, called "neurons", "neurodes", "processing elements" or "units", are connected together to form a network which mimics a biological neural network. An ANN is typically defined by three types of parameters [8]:

1. The interconnection pattern between the different layers of neurons
2. The learning process for updating the weights of the interconnections
3. The activation function that converts a neuron's weighted input to its output activation.

Mathematically, a neuron's network function *f(x)* is defined as a composition of other functions $g_i(x)$, which can further be defined as a composition of other functions. This can be easily represented as a network structure, with arrows depicting the dependencies between variables. A widely used type of composition is the nonlinear weighted sum as shown in Eq. 3-2,

$$f(x)=K\left(\sum_i w_i g_i(x)\right) \quad \text{…(Eq. 3-2)}$$

where, *K* refers to as the activation function.

4. Conclusions

Although the K-NFL has been designed to perform many functions, K-NFL is being developed to effectively trace the origin of MSNMs and tested to validate suitability of trace methods. New fuels and spent fuels need each trace method because of the different nature of data acquisition. An inductive logic was found to be appropriate for new fuels, which had values as well as a bistable property. On the other hand, machine learning was suitable for spent fuels, which were unable to measure, and thus needed simulation. We strongly believe that the K-NFL contributes much to the international cooperation of nuclear forensics, and more accurate nuclear attribution can be fulfilled when development is completed.

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