The 28th North American Fuzzy Information Processing Society Annual Conference (NAFIPS2009)
Cincinnati, Ohio, USA - June 14 - 17, 2009

Belief Rule-Based Inference Methodology to Improve Nuclear Safeguards Information Evaluation

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Abstract—**A framework for modeling, analyzing and synthesizing nuclear safeguards information with various uncertainties is proposed by using a newly developed belief rule-base inference methodology (*RIMER*). After a hierarchical analysis of States´ nuclear activities on the basis of the International Atomic Energy Agency (IAEA) Physical Model, the multi-layer structure of the evaluation model for States' nuclear activities is outlined. The special emphasis is given to the synthesis and evaluation analysis of the Physical Model indicator information by *RIMER*, which handles hybrid uncertain information in nuclear safeguards evaluation process. The proposed framework illustrates and clarifies the inference and synthesis formalism from a case study of nuclear safeguards information evaluation.**

Keywords- nuclear safeguards, physical model, decision making, belief rule-base, fuzzy logic, Dempster-Shafer theory of evidence, evidential reasoning

I. INTRODUCTION

Assurance of non-diversion of nuclear materials is the ultimate goal of safeguards. Many countries, concluding comprehensive safeguards agreements (INFCIRC/153 type) with the International Atomic Energy Agency (IAEA), are currently discussing the new additional protocol (INFCIRC/540). The protocol will make them to provide more information to the IAEA. Compared to the traditional regime, additional measures are taken into consideration in this strengthened safeguards regime, which is essentially based on additional information that can originate from different sources: information provided by the State, information collected by the IAEA, and information from open sources (e.g., media, studies). Obviously, the amount of data is enormous and not all information contributes to a better knowledge or understanding of the situation in a particular State. This information can be of very different nature: it can be relevant, but it can also be uncertain, incomplete, imprecise, not fully reliable, conflicting, overloaded, and can be quantitative or qualitative. So there is a need to establish for a sound mathematical framework that provides a basis for synthesis across multidimensional information of varying quality and an evaluation method that enables IAEA to derive a final assessment on the assurance that there has been no diversion of nuclear material and that there are no undeclared nuclear activities.

The IAEA Physical Model [1] of the nuclear fuel cycle can be taken as a systematic and comprehensive indicator system, which includes all the main activities that may be involved in the nuclear fuel cycle from source materials acquisition to the production of weapons-usable materials. Hence, it provides a convenient structure for organizing the safeguard relevant information, and can be used by IAEA analysts and inspectors to better evaluate the safeguards-related significance of information on State´s activities.

In the strengthened safeguards regime intrinsically vague information may coexist with conditions of ‘‘lack of specificity’’ originating from evidence not strong enough to completely support a hypothesis but only with degrees of belief or credibility. Several researchers have investigated how to deal with both uncertainties (e.g., different ways of integrating fuzzy sets [2, 3] and Dempster-Shafer theory [4, 5]). Recently, a generic rule-base inference methodology using the evidential reasoning (ER) approach – RIMER has been proposed [6, 7] using fuzzy logic, decision theory, and the ER approach [8]. Compared to some relevant evaluation methods on the integrated safeguards [9-12], one of the unique features of the RIMER methodology is that it provides a flexible and effective framework to represent not only precise data but also vagueness and ignorance in knowledge, as well as a rigorous inference procedure to deal with such hybrid uncertain information. In this paper, we propose a framework for modeling, analyzing and synthesizing safeguards information based on the RIMER approach as follows:

(1) Synthesis and evaluation of the Physical Model indicator information using the RIMER approach [6, 7]. In this framework, indicators are described using fuzzy linguistic variables with belief, and a fuzzy rule base with a belief structure is to capture uncertain causal relationships between these indicators and the special process estimate. Moreover, the antecedent of each IF-THEN rule is considered as an overall attribute, which is assessed to an output term in the consequent of a rule with a belief degree. Actual input can be transformed into a distributed representation for a linguistic term of an individual antecedent indicator. Finally, the inference of the rule-base is implemented using the ER algorithm.

(2) Multi-expert synthesis using the ER approach. The input information for each indicator can be provided from different sources which are normally managed by different

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experts. Once given an input, RIMER can be used to inference and generate an output. Then, the modeling framework of multi-experts synthesis is provided based on the ER approach, i.e., a combination of evidences from different sources.

(3) Multi-layer synthesis and evaluation based on the hierarchy structure. The hierarchy structure of the evaluation, based on the IAEA Physical Model, is a multi-layer comprehensive structure. It generally follows the steps that would be involved in the nuclear fuel cycle from source material acquisition to the production of weapons-usable material. Hence, in this part, the modeling framework of multi-layer synthesis is provided based on the ER approach.

II. Structure of Evaluation Model

To provide an effective evaluation, the hierarchy structure of the evaluation model of States' nuclear activities can be established based on the Physical Model.

A. The structure of States' nuclear activities

The IAEA Physical Model [1] of the nuclear fuel cycle will be taken as the basis (as a case study) for this task. It includes all the main activities that may be involved in the nuclear fuel cycle from source materials acquisition to the production of weapons-usable materials. It contains detailed narratives describing every known process for accomplishing each given nuclear activity represented in the fuel cycle and the links among them, i.e., it takes into account all the possible technological chains of production of Pu and HEU (highly enriched uranium). It also identifies and describes indicators of the existence or development of a particular process. The indicators include especially designed and dual-use equipments, nuclear and non-nuclear materials, technology/training R&D, and many others. The hierarchy structure of the Physical Model is illustrated in Figure 1, which is a multi-layer comprehensive structure.

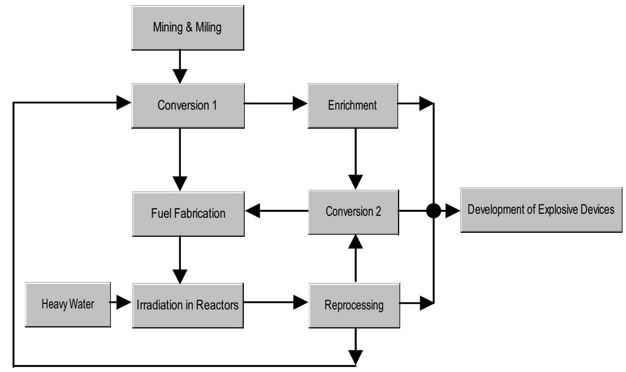

Figure 1. Hierarchy structure of the Physical Model

B. Analysis of the Physical Model indicator information

The Physical Model identifies and describes indicators for a particular process that already exists or that is under development. Up to 914 indicators, identified within the IAEA study throughout the whole fuel cycle, from mining to reprocessing, can have a different strength, but they are in one way or another signs for on-going activities. The specificity of each indicator has been designated to a given nuclear activity and is used to determine the strength of an indicator. An indicator that is present only if the nuclear process exists or is under development, or whose presence is almost always accompanied by a nuclear activity is a strong indicator of that activity. Conversely, an indicator that is present for many other reasons, or is associated with many other activities, is a weak indicator. In between are medium indicators.

The relationship between an indicator and a specific nuclear activity can be regarded as a rule. Given a particular indicator and its strength, a rule makes one infers the possible presence of an activity or not. In other words, the indicators associated with each process are placed in a quasi-logical structure along the following lines (the medium indicator has two structures because it is in between strong and weak indicators).

- If process P implies an indicator x definitely and is implied by the indicator x definitely, then x is a strong indicator.

- If process P implies an indicator y definitely (and it is unsure the indicator y implies process P), then y is a medium indicator; or
- If it is unsure that process P implies an indicator y (and the indicator y implies process P definitely), then y is a medium indicator.
- If process P may imply an indicator z or not (and the indicator z may imply process P or not), then z is a weak indicator.

The quasi-logical structure can be considered into a rule-based system detailed in next section.

C. Make a unified representation of information with different nature

The information collected by the IAEA comes from mainly three different sources, which does not directly contribute to a better knowledge of the facts, nor does it facilitate decision making. Hence it is desirable to make a unified representation of information with different nature, like the assurance degree.

The objective of evaluation on States´ nuclear activities is to get an assurance of “non-manufacture of nuclear explosive devices.” At the lowest evaluation level (i.e., indicator), the value of assurance which reflects the capacity of “no conducting a specific process at a given nuclear facility” should be evaluated. It will be determined by the assessment of “no presence of indicators" respectively which is observed or determined by experts. Usually, the assessment values are not limited to Yes or No, since experts cannot always detect the indicators arising from the process, instead they may only get certain assurance or possibility of the existence of the indicator, which is characterized by the fuzzy linguistic variable, for example, the possibility is very low, low, or high.

As an extension of the above representation, in the ER approach in [8], a belief decision matrix for problem modeling is introduced and applied so that different formats of available data and uncertain knowledge can be incorporated into assessment processes. In a belief decision matrix, the performance of an assessed option on a criterion is represented by a distribution instead of a single value. That is, it is described by a distributed assessment using a two-dimensional variable: possible referential values (assessment grades) and their associated degrees of belief. For example, suppose we use the following three linguistic grades to assess the assurance degree of existence or under development of a nuclear activity: (High, Medium, Low), and 70% of the responses are High and 30% Medium, then the assessment (or a piece of evidence) should be expressed as {(High, 0.7), (Medium, 0.3), (Low, 0)}. This is referred to as a distributed assessment. 0.7 represents the belief degree that the assessment on an indicator to the grade High. The evaluation grade can be different based on the nature of the indicator and experts' preference.

The advantages of using a distributed assessment include that it can model precise data and meanwhile capture various types of uncertainties such as probabilities and vagueness in subjective judgments. For example, in an indicator evaluation, if 20% of the information evaluates its existence to be high possibility, 30% low possibility and 50% medium possibility, one is not required to aggregate the information before using it. The distributed assessment accepts the raw information as it is.

Furthermore, if there is missing information in data, it can be represented by a distribution without either adding new or taking away existing information from the data. For example, suppose the response in the above example is 5% High, 65% Medium, 25% Low and 5% no answer given. Normally, either the missing answers need to be replaced by some estimates or the responses with missing answers are discarded, including the answers to other questions. Either way, information in data may have been distorted. Using a distribution, the information in data can be maintained by expressing the assessment as it is, e.g., the assessment of an assurance degree of "conducting a specific process at a given facility" could be {(High, 5%), (Medium, 65%), (Low, 25%)}, which is an incomplete belief distribution and the missing belief degree of 5% (=100%-5%-65%-25%) is called ignorance.

D. General evaluation structure of information on States' nuclear activities

Based on the IAEA Physical Model, the resultant evaluation structure generally follows the steps in the nuclear fuel cycle from source material acquisition to the production of weapons-usable material. Accordingly we can assess, with some uncertainty or in a qualitative level, the States´ capabilities on processing nuclear materials, like a special nuclear technology or process, e.g., enrichment of HEU under consideration of different levels, importance of different factors in a level, the reliability of information, and the strength of every indicator. The overall evaluation should be a multi-layer comprehensive evaluation (see Figure 2).

Level 1: It is the stage of processing of nuclear materials, i.e., the technologies are considered. It contains all the main activities that may be involved in proliferation, which are linked. They are generalized and little suited for performing a specific analysis. This level intends to represent the general performance of nuclear activity of a State: the level of technology development, directions of possible production of Pu and HEU, and an overall evaluation of nuclear activities.

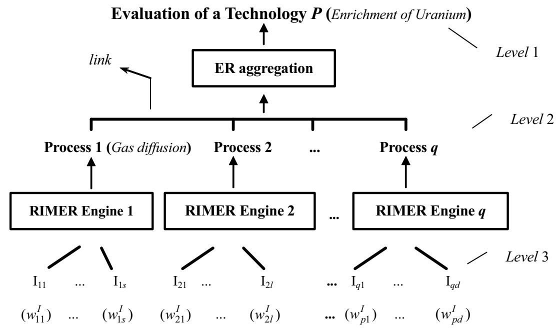

Figure 2. The evaluation structure for the special technology *P*

It is the first level of elements of the evaluation model reflects the possible presence in a country of a specific technology. The evaluation of any element of this level is expressed by a distributed assessment with a pair of linguistic grade and its belief. The evaluation of this level will be obtained from Level 2 by using the ER algorithm aggregation [8], which will be also detailed in Section 4.

Level 2: Separate processes. At this level the links between the different technologies for processing nuclear materials are clearly seen. Each activity at the top level is broken down into more specific routes or processes in this level. The evaluation of any element of this level reflects the States' capability to conduct a specific process at the qualitative and is expressed by the distributed assessment with a pair of linguistic grade and its belief. The evaluation of this level will be obtained from Level 3 by using the RIMER approach [6] firstly for each input provided by each expert, then using the multi-expert synthesis based on the ER approach [8], which will be detailed in next section.

Level 3: This is a detailed description of Level 2 and reflects the existence of specific capacity for processing nuclear materials, i.e., an indicator level. The evaluation of this level qualitatively reflects the potential of the specific facilities used by a country to conduct a specific process for treating nuclear materials. The evaluation of any element of this level reflects the possible presence or underdevelopment in a country of a specific indicator and is expressed by the distributed assessment with a pair of linguistic grade and its belief, which is described and provided by inspectors.

III. OUTLINE OF THE RIMER APPROACH FOR INFERENCE AND SYNTHESIS

This section consists of the following steps for knowledge representation and inference.

A. Belief rule-base

As discussed previously, the relationship between an indicator and a specific nuclear activity is called a rule. Given a particular indicator and its strength, a rule makes one infers the possible presence of an activity. Assume one is interested in assurance that an undeclared activity A is not taking place. These rules help match input information with associated nuclear activities. Accordingly, the following formal extended rule-based system provides a better way used to characterize the indicator strength in a more rational and realistic way.

> R_k: *IF* evidence shows that indicator I is *likely THEN the* process estimate *is* {(*definite*, 0), (*high*, 0.2), (*medium*, 0.5), (*low*, 0.3), (*none*, 0)}

where {(*definite*, 0), (*high*, 0.2), (*medium*, 0.5), (*low*, 0.3), (*none*, 0)} is a belief distribution representation for the process estimate. The beliefs in the rule-base are used to characterize the indicator strength in a more rational and realistic way.

In general, assume that the indicator, I_i can be described by J_i linguistic terms $\{A_{ij}, j=1,\ldots, J_i\}$, $i=1, 2,\ldots, d$, respectively, and one consequent variable *process estimates* can be described by N linguistic terms, i.e., $D_1, D_2,\ldots, D_N$. Let A_i^k be a linguistic term corresponding to the i^{th} indicator in the k^{th} rule, with $i=1, 2,\ldots, d$. Thus the k^{th} rule in a rule base can be written as follows:

R_k: IF $\mathbf{I_i}$ is A_i^k THEN ***process estimates*** is $\{(D_1, \overline{\beta}_{1k}),\ldots, (D_N, \overline{\beta}_{Nk})\}$, $(\sum_{t=1}^{N}\overline{\beta}_{tk} \le 1)$, with the rule weight θ_k (1)

where $\overline{\beta}_{ik}$ ($i\in\{1,\ldots, N\}$; $k\in\{1,\ldots, L\}$, with L being the total number of the rules in the rule-base) is a belief degree measuring the subjective uncertainty of the consequent "***process estimates*** is D_i" drawn due to the antecedent "$\mathbf{I_i}$ is A_i^k" in the k^{th} rule, this is referred to as *a belief rule-base*.

If $\sum_{t=1}^{N}\overline{\beta}_{tk}=1$, the output assessment or the k^{th} rule is said to be complete; if $\sum_{t=1}^{N}\overline{\beta}_{tk}=1$ for all $k=1,\ldots, L$, then the rule base is a complete rule base; otherwise, it is incomplete. Note that $(\sum_{t=1}^{N}\overline{\beta}_{tk}=0)$ denotes total ignorance about the output given the input. For example, IF an assurance degree of "exists or under development of a *weak* indicator" is *High* THEN an assurance degree of "conducting a specific process at a given facility" is {(*Good*, 5%), (*Average*, 65%), (*Poor*, 25%)}, which is an incomplete belief rule and the missing belief degree 5% (=100%-5%-65%-25%) is called ignorance.

B. Input transformation and activation weight

Considering an input corresponding to the k^{th} rule defined as in (1), $\boldsymbol{I_i}$ is (A_i^k, α_i^k), where α_i^k is the individual matching belief degree that the input belongs to A_i^k of the individual antecedent I_i appearing in the kth rule. The global matching weight w_k of the antecedent A_i^k in the k^{th} rule is generated by weighting and normalizing the α_i^k as follows:

$$w_k = (\theta_k \cdot \alpha_k)/(\textstyle\sum_{j=1}^{L}\theta_j\alpha_j) \qquad (2)$$

where θ_k ($\in\mathbf{R}^+$, $k=1,\ldots, L$) is the relative weight of the k^{th} rule, L is the number of rules in the rule base. Note that $0\le w_k\le 1$ ($k=1,\ldots, L$) and $\sum_{i=1}^{L} w_i = 1$.

C. Rule combination using the ER approach

Having determined the activation weight of each rule in the rule base, the ER approach [8] can be directly applied to

Distribution assessment framework for each attribute (**rule**)
e.g., {(H, 0.7), (M, 0.3), (L, 0)}
Distribution for R_1, Distribution for R_2, …, Distribution for R_L
($\boldsymbol{w_1}$) ($\boldsymbol{w_2}$) … ($\boldsymbol{w_L}$)
⇓ ⇓ … ⇓
Evidential Reasoning (ER) Algorithm
⬇
Distribution assessment for the output
e.g., {(H, 0.0057), (M, 0.3735), (L, 0.6208)}

Figure 3. ER algorithm used in the rule combination

combine the rules and generate final conclusions. The final conclusion generated by aggregating all activated rules by the actual input vector $\boldsymbol{I}=\{I_i;\ i=1, 2,\ldots, d\}$ can be represented as follows:

$$S(I)=\{(D_j,\ \beta_j),\ j=1,\ldots, N\} \qquad (3)$$

The ER Recursive Algorithm used in [8, 6] has been equivalently transformed into the analytical ER algorithm [7]. Using this analytical ER algorithm, the overall combined degree of belief β_j in D_j is generated as follows:

$$\beta_j = \frac{\mu\times\left[\prod_{k=1}^{L}(w_k\beta_{j,k}+1-w_k\sum_{i=1}^{N}\beta_{i,k})-\prod_{k=1}^{L}(1-w_k\sum_{i=1}^{N}\beta_{i,k})\right]}{1-\mu\times\left[\prod_{k=1}^{L}(1-w_k)\right]}, \qquad (4)$$

where $j=1,\ldots, N$, w_k is as given in (2), and

$$\mu=\left[\sum_{j=1}^{N}\prod_{k=1}^{L}(w_k\beta_{j,k}+1-w_k\sum_{i=1}^{N}\beta_{i,k})-(N-1)\prod_{k=1}^{L}(1-w_k\sum_{i=1}^{N}\beta_{i,k})\right]^{-1}.$$

The rule combination procedure using the ER algorithm is illustrated in Figure 3.

D. Multi-expert synthesis framework using the Evidential Reasoning approach

If we consider several particular indicators $I=\{I_1,\ldots, I_d\}$ to a specific process. For each particular indicator I_j ($j\in\{1,\ldots, d\}$), its description in the evaluation rule can be derived from different sources or evaluated by different experts. Assume that there are several sources (including experts) S_i ($i=1,\ldots, K$). Without lost of generality, suppose input comes from different sources evaluated by different experts.

We may assume that different sources have different reliability weights, w_{si} ($i=1,\ldots, K$). Suppose $A_{ei}(j)$ is an input vector derived from e_i for an indicator I_j. For each input, we may get a corresponding process estimate D_{ei} using the above RIMER approach, which can be formulated as follows:

IF I_j is $A_{e1}(j)$ THEN $P_{e1}(j)$ is $\{(D_1, \eta_{11}),\ldots, (D_N, \eta_{N1})\}$
…
IF I_j is $A_{ei}(j)$ THEN $P_{ei}(j)$ is $\{(D_1, \eta_{1i}),\ldots, (D_N, \eta_{Ni})\}$
…
IF I_j is $A_{eK}(j)$ THEN $P_{eK}(j)$ is $\{(D_1, \eta_{1K}),\ldots, (D_N, \eta_{NK})\}$

where $\{(D_1, \eta_{1i}),\ldots, (D_N, \eta_{Ni})\}$ results from Eq. (3) obtained using the RIMER approach. Then the actual estimates of a specific process $P(j)$ from the indicator I_j can be generated by synthesizing multi-expert assessments, i.e., by aggregating $\{P_{e1},\ldots, P_{eK}\}$ using the ER algorithm, which is represented as

$$S(P(j))=\{(D_i,\ \eta_i^j\ );\ i=1,\ldots,N\},\quad j=1,\ldots,d \qquad (5)$$

Due to several particular indicators to a specific process, the final estimate of a specific process P is the synthesis of all the assessments $S(P(j))$ (j=1,…, d) for each particular indicator using the ER algorithm again. The ER algorithm is also used to perform multi-layer synthesis at different levels of an evaluation model with a structure.

IV. Case study for the evaluation of safeguards information based on the Physical Model

Evaluation of the nuclear process is to estimate a possibility degree to what extent the objective is attained. At the lowest level, the value of possibility degrees, which reflects the capacity of "no conducting a specific process at a given nuclear facility", should be firstly evaluated. It depends on the possibility degree of "no abnormal indicator exists," which is observed or determined by inspectors. As an example we consider a specific evaluation to illustrate our method. Let it be required to evaluate the possibility degree of "No conducting specific process Gaseous diffusion enrichment" within the evaluation of production of (HEU).

For simplicity but without lose of generality, we suppose the evaluation linguistic grade involved in the case study are {*High*, *Medium*, *Low*}. Each indicator and the process are assessed into a belief distribution representation of these three values. For example if the assessment of an indicator A is:

$$\{(High,\ \beta_1),\ (Medium,\ \beta_2),\ (Low,\ \beta_3)\}$$

implies the possibility of A being exist and the confidence level, where β_i (i=1,…, 3) represents the degree of confidence in a particular belief.

A. Defining the rule base

Space constraints do not allow us to give a full account of all the rules of all knowledge bases; instead we focus on how to attach the representation of uncertainty to a rule related to the detection of our reference scenario. Suppose that F_s corresponds to the set of strong indicators, F_m corresponds to the set of medium indicators, and F_w corresponds to the set of weak indicators. Accordingly, w_s, w_m, w_w corresponds to the strength weights, respectively. There are a total of 22 indicators. If each indicator is described by three grades, then there should be a total of 3× 22=66 rules. For example, the rule can be:

IF Compressor for pure UF6 exists with High confidence THEN *process estimates* with (H_1, *1*), (*M*, *0*), (*L*, *0*) confidence

That is, 100% sure that process estimate is with High confidence.

B. Belief rule inference using the evidential reasoning (ER) approach

To illustrate how the RIMER system works in this framework, the definitions of the belief rules using linguistic terms with the consequents having the dedicated belief degrees considering only three indicators are given in TABLE I. Using the rule-base and the RIMER inference scheme, the consequent estimate is generated. In the following, we explore two scenarios on some possible combinations of values to see how the system reacts. In this case study, we set w_s=3 w_m=2, and w_w=1 numerically for the illustration purpose.

Scenario 1: The input for "Compressor for pure UF6" is given by experts with a belief distribution, for example: {(H, 0.9), (M, 0.1), (L, 0)} which means that experts are 90% sure that "Compressor for pure UF6" exists with high confidence, 10% that "Compressor for pure UF6" exists with medium confidence. In summary, it is represented as:

IF Compressor for pure UF6 exists with {(H, 0.9); (M, 0.1); (L, 0)} confidence

IF Rotary shaft seal exist with {(H, 0); (M, 0.1); (L, 0.9)} confidence

IF Header piping system exist with {(H, 0); (M, 0); (L, 1)} confidence
THEN ....

The output is implemented as in the following steps:

Step 1: *Transform the input*. Here the input is given as a distribution using linguistic terms with the belief degrees based on subjective judgments. Each belief is the individual matching degree of the input to the linguistic value. For example, the matching degree of the input to the linguistic value "High" of "Compressor for pure UF6 exists" is 0.9, and 0.8 for "Medium," etc.

Step 2: *Calculate the rule activation weight*. The activation weights w_k for all the 9 rules $R_k(k = 1,\ldots, 9)$ are generated using (2) (see [6] for details) by w_1 =0.45, w_2 = 0.05, w_3 = 0, w_4 = 0, w_5 = 0, w_6 = 0.03, w_7 = 0, w_8 = 0, w_9 = 0.17, respectively.

Step 3: *Combine activated rules*. The ER approach [8] is employed to combine the activated rules (4). The activated rules can be combined to yield the following outcome:

$O(P)$= {(H, 0.5194); (M, 0.2672); (L, 0.2134)}

where β_j is given by (1), which means that we are 51.94% sure that process P exists with high confidence, 26.72% sure that process P exists with medium confidence, 21.34% sure that process P exists with low confidence.

Scenario 2:

IF Compressor for pure UF6 exists with {(H, 0); (M, 0); (L, 1)} confidence

IF Rotary shaft seal exists with {(H, 0); (M, 0); (L, 0)} confidence

IF Header piping system exists with {(H, 1); (M, 0); (L, 0)} confidence
THEN ...

Following similar steps in Scenario 1, the system output is:

$O(P)$ = {(H, 0); (M, 0.0639); (L, 0.9361)}

TABLE I. DEDICATED RULES FOR EVALUATION OF THE PROCESS P (GASEOUS DIFFUSION ENRICHMENT)

Types	IF part	THEN part
F_s (w_s)	Compressor for pure UF6 (H)	(H_1, *1*), (*M*, *0*), (*L*, *0*)
	Compressor for pure UF6 (M)	(H_1, *0*), (*M*, *1*), (*L*, *0*)
	Compressor for pure UF6 (L)	(H_1, *0*), (*M*, *0*), (*L*, *1*)
F_m (w_m)	Rotary shaft seal (H)	(H_1, *0.7*), (*M*, *0.3*), (*L*, *0*)
	Rotary shaft seal (M)	(H_1, *0.2*), (*M*, 0.7), (*L*, *0.3*)
	Rotary shaft seal (L)	(H_1, *0*), (*M*, *0.7*), (*L*, *0.3*)
F_w (w_w)	Header piping system (H)	(H_1, *0*), (*M*, *0.6*), (*L*, *0.4*)
	Header piping system (M)	(H_1, *0*), (*M*, *0.4*), (*L*, *0.6*)
	Header piping system (L)	(H_1, *0*), (*M*, *0.1*), (*L*, *0.9*)

which means that we are 93.61% sure that process P exists with low confidence, 6.39% sure that process P exists with medium confidence, 0% sure that process P exists with high confidence. Compared with Scenario 2, we may notice that the result reflects well the real case because a strong indicator plays a more important role in the evaluation than the weak indicator, even if we are 100% sure that Header piping system exists with H, confidence, because we are 100% sure that Compressor for pure UF6 exists with low confidence, hence, the overall aggregation result is still close to process P exists with low confidence.

Considering both Scenario 1 and Scenario 2, we may notice that firstly, if the activation weight of a rule is equal to 0 (e.g., $w_3 = 0$), then the weight and the belief degree of this rule will have no influence on the final output; If the activation weight of a rule is not equal to 0, then the weight and the belief degrees of this rule will affect the final output. The degree to which the final output can be affected is determined by the magnitude of the activation weight and the belief degrees. The logic behind the approach is that if the consequent in the *kth* rule includes D_i and the *kth* rule is activated, then the overall output must be D_i to a certain degree. The distribution assessment provides a panoramic view about the output status, from which one can see the variation between the original output and the revised output on each linguistic term.

Scenario 3 (handling incomplete input information)

Assume the assessment for an indicator in the antecedent of our IF-THEN rule is not known completely. For example, we only have partial evidence that an indicator exists, i.e., we are not 100% sure, say the belief distribution is {(H, 0.7); (M, 0); (L, 0)}. This could be due to the lack of information, or experts' inability to provide precise judgments. We can still infer the result based on the RIMER method. To illustrate it, in the above case study we use the following input information:

IF Compressor for pure UF6 exists with {(H, 0.8); (M, 0); (L, 0)} confidence

IF Rotary shaft seal exist with {(H, 0); (M, 1); (L, 0)} confidence

IF Header piping system exists with {(H, 0); (M, 1); (L, 0)} confidence

THEN ...

Notice that experts are only 80% certain that Compressor for pure UF6 exists with *High* confidence. In other words, the degree of ignorance is 0.2. If we apply the RIMER methodology as in the previous section then the conclusion from the system will be:

$$O(P)=\{(\mathrm{H}, 0.449), (\mathrm{M}, 0.337), (\mathrm{L}, 0.128), (\mathrm{unknown}, 0.086)\}$$

where "Unknown" in the above result means that the output is also incomplete due to the incomplete input.

V. CONCLUSIONS

With a hierarchical analysis of the IAEA Physical Model, the multi-layer structure of the evaluation model for State´s nuclear activities was outlined. The special emphasis has been given to the synthesis and evaluation analysis of the Physical Model indicator information by using a newly developed belief rule-base inference methodology (*RIMER*). The whole framework aims at modeling, analyzing and synthesizing safeguards information that may be of very different nature under uncertainties for which the traditional quantitative approach does not give an adequate answer. The presented work is still a kind of frameworks, and the detailed real case study with comprehensive belief rule base will be further investigated for real world safeguards applications.

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