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AN EXPERT SYSTEM FRAMEWORK FOR NONDESTRUCTIVE WASTE ASSAY

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ABSTRACT

The management and disposition of transuranic (TRU) waste forms necessitates a determination of entrained TRU and associated radioactive material quantities as per National TRU Waste Characterization Program requirements. The technical justification and demonstration of a given nondestructive assay (NDA) method used to determine TRU mass and uncertainty in accordance with Program quality assurance objectives is a difficult task for many waste forms. Difficulties are typically founded in waste NDA methods that employ standards compensation techniques and/or the employment of simplifying assumptions regarding waste form configurations. The capability to determine and justify TRU mass and mass uncertainty can be enhanced through appropriate integration of waste container data/information using expert system and empirical data-driven techniques in conjunction with conventional data acquisition and analysis methods. Presented is a preliminary expert system framework that integrates the waste form data base, algorithmic techniques, statistical analyses, expert domain knowledge bases, and empirical artificial intelligence modules into a cohesive system. The framework design and bases in addition to module development activities are discussed.

BACKGROUND

The ability to manage and disposition TRU waste is predicated on demonstrating compliance with applicable characterization requirements. Non-destructive waste assay methods are used in the National TRU Waste Characterization Program to determine the mass of waste-entrained radionuclides. The capability and performance of waste NDA systems employed in the Program must comply with requirements as set forth in the TRU Waste Characterization Program Quality Assurance Program Plan (QAPP).[1] Parameters for which waste NDA system performance must be demonstrated and technically justified include total bias and total uncertainty as defined per the QAPP. Within the instrument response envelope of commonly employed NDA techniques, certain standard compensation and bias quantification techniques can be derived to account for a number of prominent measurement bias sources. These techniques rely on the knowledge of the bias and precision elements and the fact that there is a unique instrument response relation for each particular bias element. In reality, the functional form of a number of bias sources and their interrelationships are not necessarily known and understood for many waste forms. Additionally, each waste NDA technique has limitations where the response is non-unique, interfered with, or there is no measure of a particular waste form attribute from which bias arises. An example of an assay modality and waste form attribute where there is no measure is active thermal neutron interrogation and fissile material clumping. This commonly employed measurement modality has no viable response indicator of the fissile material configuration for which an account can be made of the induced bias. Hence, alternate approaches to the interpretation/integration of NDA data and supportive information enhancing the characterization capability base is of interest.

In consideration of Program quality assurance objectives for total bias and total uncertainty and the reality of difficult-to-account-for waste form bias sources, it is logical to look to other mechanisms for acquiring and processing data/information to arrive at a defensible assay solution. The solution may reside in the acquisition of additional waste form configuration information and/or deducing that one or more different measurement modalities would yield necessary data. Regardless of the approach, additional or reformatted information will in all probability be of value in completing the solution in

a defensible manner. Another view to take in lieu of additional data/information is to ask if all presently available information and data confirm that the waste form configuration attributes are within the capability bounds of the employed NDA technique. This perspective or concept is most applicable in those cases for which alternate measurement modes and/or information are not available. In either case, consideration of the assay routine is required to either substantiate the implemented technique or acquire and utilize additional data/information to justify and demonstrate that a solution with known uncertainty bounds has been achieved.

For most waste characterization programs, it is not feasible to maintain technical experts in waste NDA to analyze the instrument response acquired on each waste container to conclude whether the technique is applicable or whether additional information is needed. Therefore, the ability is desired to assess instrument response and all pertinent data/information in an on-line fashion yielding a tangible assay confidence factor related to compliance criteria. A technology ideally suited to this task is that of expert systems technology. In accordance with the concept of evaluating available data/information, an expert system can be configured to classify measurement data and associated waste form configuration information as either consistent or inconsistent with respect to all available knowledge. Consistency leads to confidence in parameters of importance, i.e., fissile material mass and alpha activity and a quantifiable indicator of quality control. Inconsistency can take many forms as a function of which particular sets of information and data provide confirmatory evidence and which do not. Regardless, significantly more is known about the assay process in that the measurement results support all other knowledge and vice versa or that inconsistencies are present, prompting an investigation into technique applicability.

An expert system can be constructed with capabilities expanded beyond basic consistency testing, thereby employing additional evaluation tools and data from other measurement modalities. Relevant analysis resources include exploratory statistical routines and empirical artificial intelligence techniques such as neural networks and fuzzy logic, hypothesis testing tools, adaptive system learning routines, and waste form generation information bases. An expanded expert system of this nature will necessarily be derived from experience gained with the construction testing and validation of a system based on the simpler consistency verification concept. An interim goal of the data analysis component of the Waste Assay Measurement Information System project[2] is to develop an initial phase expert system that addresses the concept of assay consistency with quantifiable compliance capabilities.

EXPERT SYSTEM OVERVIEW

Expert systems are computer programs that emulate the reasoning process of a human expert using previously established rules for a well-defined domain. They combine knowledge bases of rules and domain-specific facts with information representing specific instances acquired from the environment of interest. Functionally expert systems infer and draw conclusions from available data and information. A particularly powerful feature is the interactive acquisition of new and relevant data/information via questions. The expert system can also tell and justify how a given conclusion has been reached via an explanation facility, potentially giving the user insight on the problem at hand. Expert systems are modular in structure, typically consisting of the following parts: (1) a knowledge base, (2) an inference engine, (3) a global or working memory, and (4) a user interface. The knowledge base contains the expert domain knowledge for use in problem solving. The working memory is used as a scratch pad and to store interim reasoning data and information provided to the system from the environment of interest. The inference engine uses the domain knowledge together with acquired information to provide an expert solution. High-level rules are implemented in the inference engine to avoid blind searches of the solution space. The user interface is the link to the outside world and provides an explanation facility to illustrate to the user how a particular decision was reached.

There are many ways to represent knowledge in an expert system. The three most popular representation schemes are rules, semantic networks, and frames. The rule scheme is the primary method used in the subject system. Rules are used to build a domain-specific knowledge base represented via domain facts and heuristics that specify a set of actions to be performed for a given situation. A rule is composed of an antecedent and a consequent of the general form: IF antecedent THEN consequent. The antecedent of a rule is a set of conditions (or conditional elements) that must be satisfied for the rule to be applicable. The consequent of a rule is the set of actions to be executed when the rule is applicable. Confidence measures are associated with the various rules to capture the probabalistic nature of the rules often called certainties. Several methods (such as tables of probability-related information) exist to define and represent rule certainties. An important advantage of expert systems is the ease with which knowledge bases can be modified as new rules and facts become known.

An inference mechanism, or engine, using logical reasoning is necessary to determine the most appropriate response when the knowledge base is consulted. The inference engine is the driver program for the expert system using the knowledge base to reach a particular conclusion. It is responsible for ensuring that questioning is done in a concise, logical manner, determining when to search the knowledge base for the information and scheduling other necessary actions. It will take action as indicated via a knowledge state found to be true based on the current facts presented to the expert system. The inference engine is, in effect, the intelligence that allows the expert system to make conclusions based on the expertise or knowledge stored in the knowledge base.

Inference engine reasoning methods primarily operate in one of two ways. They may be data-driven, known as forward chaining, or they may work backwards from conclusions or hypotheses, known as backward chaining. A forward chaining system begins with problem domain input data and moves down the inference chain until a conclusion is reached. Goal-directed reasoning is termed backward chaining where the system starts with a hypothesis or goal and works backward through the facts until it reaches a final node or conclusion. The actual reasoning process consists of constructing new rules or sentences from existing ones and ensuring that the new ones represent facts that actually follow from the facts of previous sentences represented. Hence, the inference procedure derives logical sentences from the knowledge base that represent facts, which follow from facts embodied in the knowledge base.

NONDESTRUCTIVE WASTE ASSAY FRAMEWORK

Waste NDA has many features suitable for the application of expert system technology. The measurement data set acquired from a given waste container may or may not embody information sufficient to extract the parameters of importance and the associated uncertainty. Use of an expert system allows one to utilize available knowledge concerning a given waste container in addition to the capabilities of the applied measurement technique to substantiate a viable solution. For instance, waste form generation process knowledge can bound and/or yield probable radioactive material compositions, radioactive material age, radioactive material chemical compound, probable elemental compositions, probable density distributions, waste form configuration, etc. Oftentimes, the generator has previously acquired assay data in the same or differing packaging configurations, which can be evaluated for consistency. Data bases containing previous measurement records can be consulted to see if certain statistical parameters fit historical distributions. Algorithmic assessment routines may be implemented to determine and/or evaluate specific parameter values per the acquired data and associated knowledge. Empirical artificial intelligence (AI) techniques can be utilized to look for data patterns and features that should be or not be present. Statistical hypothesis testing can be performed at various points in the problem domain to support the decision-making process of the system. The system capability of adaptive learning based on cumulative system experience could be exploited to enhance the knowledge of the system. Finally and most importantly, the expert knowledge base allows the implementation of domain expert rules based in theory as well as heuristics. This is considerably more information that can be used to define and bound a solution than can be determined from the response of an NDA instrument calibrated in accordance with a specific regimen.

An illustration of a preliminary expert system framework delineating applicable knowledge and data base components is shown in Figure 1. Each component is defined based on a particular type of knowledge or data/information source. These components or modules support the reasoning processes residing in the expert domain knowledge base. It is notable that such a modular arrangement supports the documentation, validation, and modification of the various knowledge and data modules.

NDA FRAMEWORK COMPONENTS

The following is a brief description of the function of each module in the preliminary expert system. The

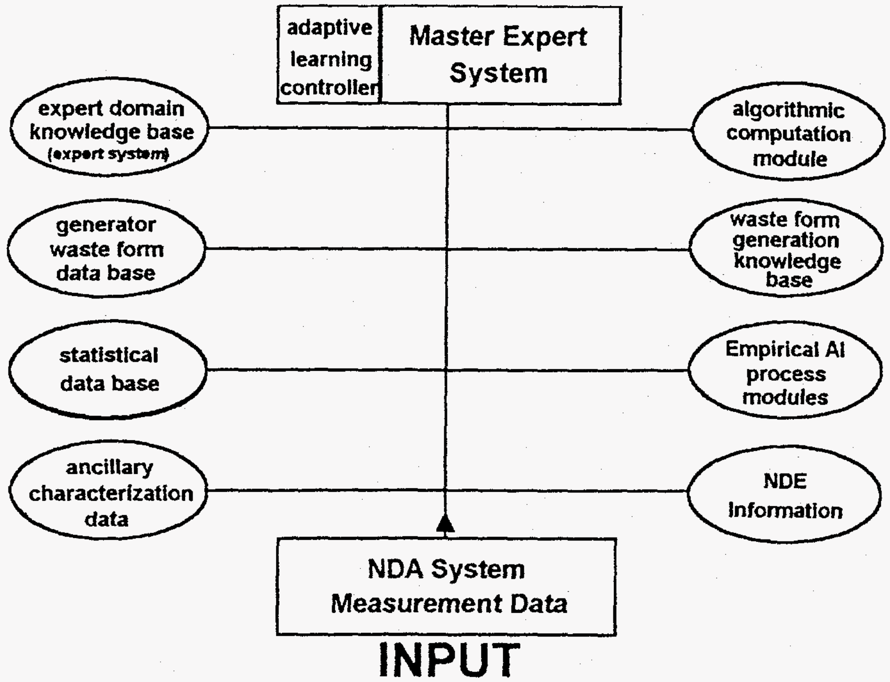

FIGURE 1. PRELIMINARY WASTE NDA EXPERT SYSTEM FRAMEWORK

modules are defined based on a logical partitioning of the knowledge and data/information space pertinent to the problem. The collective set of modules is intended to contain all available data, information, and knowledge an NDA expert would utilize to produce a best estimate on the fissile material mass and associated uncertainty for a given container. The structure of the data and information contained in the module set to be used by the expert system is that of an object-oriented database.[4]

Master Expert System - The master expert system oversees operation of the system as negotiated by the expert domain knowledge based expert system. For example, the master expert system interacts with the user, handles result conflicts, and manages the adaptive learning controller based on the accumulation of data and information in the system over time. A part of the adaptive learning component would be a statistical analysis routine that continually updates parameters and correlations of interest to the expert system.

Non-Destructive Waste Assay Measurement Data (System Input) - This input data vector contains pertinent raw acquired NDA measurement data in addition to the reduced data and associated parameters of significance. It constitutes the fundamental data source from which the forward chaining inference procedure starts. The input data set format is such that differing fields can be extracted by other modules for various operations supporting the expert system analysis, e.g., empirical AI routines looking for patterns. Data preprocessing can also be implemented at this stage, providing a format more amenable to the various components of the expert system.

Expert Domain Knowledge Base Module (Expert System) - This knowledge base contains the fundamental principles of the waste NDA problem domain in the form of rules and heuristics. This module contains the conditional questions and search direction data.

Waste Generation Process Knowledge Base (Expert System) - This knowledge base contains previously established waste form attributes by generation process. Such attributes are the waste form generation method and the resultant characteristics of the waste form. The knowledge base will be consulted in terms of the potential presence or absence of certain attributes per waste type and the associated variable range. The expert domain module will, as appropriate, consult this knowledge base regarding expected radionuclide compositions, waste form configurations, etc. Characteristics and attributes of the waste form must be consistent with measured parameters.

Statistical Module - The employment of statistical models in the context of the expert system can take the form of a classical, hypothesis-driven or confirmatory data analysis approach or a data-driven, exploratory data analysis approach. Applied statistical methods in this module range through descriptive statistics, statistical inference procedures, hypothesis testing, goodness-of-fit tests, regression and correlation analysis, analysis of variance techniques, principal component analysis, classification via cluster analysis techniques, conditional expectation evaluations, linear discriminant functions, etc., for parameters of interest per predefined populations.

Algorithmic Processing Module - This module contains first-principle algorithms for the evaluation of specific parameters. Examples include a figure of merit for quantifying the alpha,n component, the comparison of measured parameters to those predicted by MCNP models, and the execution of bounding computations to support validity determinations.

Empirical AI Module - Empirical data exploration and processing techniques generally classified as artificial intelligence techniques are addressed in this module. The focus of these techniques is to perform classification functions using pattern recognition techniques, supervised and unsupervised learning and clustering techniques, and data-driven empirical methods. Examples include the class of neural networks, learning vector quantization, genetic algorithms, K-Nearest Neighbor regression, adaptive kernel methods/local basis function methods, fuzzy inference systems, fuzzy neural systems, generalized memory-based learning, and constrained topological mapping. One implementation has been the use of the Fuzzy ARTMAP neural network for waste form matrix classification.[3]

Non-Destructive Examination Module - Important NDA parameters can be extracted from NDE data. Such parameters of use include the container fill height and the effective matrix density and its distribution. The availability of such information, appropriately formatted, is a useful input to the expert system.

Historical/Generator Data Module - Historical generator data include a great deal of information regarding the time of waste production and packaging and shipment, assay values acquired prior to shipment, waste form and configuration data, etc. All of this information can be used when bounding the uncertainty in the assay value.

Ancillary Characterization Data/Information - This module contains information and data derived from specific characterization projects. An example would be a sludge drum coring project and the debris characterization project. In these efforts, drums were opened and sampled to determine and verify their contents and radionuclidic compositions. Such data provide confirmatory evidence of actual waste form characteristics and serve as a benchmark when evaluating related containers.

It is important to note that this is a comprehensive system that may take a considerable effort to establish and validate. It is quite plausible to build the expert system in discrete subsets and apply each as developed. For example, the first stage of knowledge base development could be directed at evaluating the acquired measurement data with respect to algorithmic bounding parameters and waste form generation data. Once established, the benefits of this expert system component could be realized while other more-time-consuming components are in development and testing phases, an advantage of the modular nature of expert systems.

UNCERTAINTY IN EXPERT SYSTEMS

Human experts do not proclaim to be exact in their reasoning and will factor a measure of uncertainty into such processes and final decisions. Likewise, expert systems have mechanisms for representing and managing uncertain knowledge entailed in the set of facts and heuristics as well as environmental data input to the system. There are a number of ways to represent uncertain knowledge, the most common being the use of probabalistic techniques, certainty factors, and fuzzy logic.

Bayesian networks and fuzzy logic techniques are currently under investigation[5,6] for application in the subject waste NDA expert system. Bayesian or belief networks can be used to represent uncertainty through the production of a complete probabalistic model of a domain that is computationally sound. Fuzzy logic is currently being used as a classification tool and as a method to represent the degree of certainty in the classification. After the preliminary classification studies, investigation into the utility of a fuzzy expert system through the assignment of rules, heuristics, and system input to fuzzy sets will be undertaken. In such a system, the inference engine provides a fuzzy output, which may need to be defuzzified depending on the application domain.

The management of uncertainty may also be treated via evidential reasoning. Evidential reasoning is based on the Dempster-Shafer theory (DST) and is an effective method to represent ignorance, incomplete information, or inexact rules in expert systems. DST also provides a mechanism to handle conflicting data and rules and is ideal to integrate knowledge from different sources.

CONCLUSIONS

Waste NDA techniques in many cases do not take advantage of all available knowledge about the problem domain, which can lead to difficulty in technically justifying adherence to compliance criteria. Experts system technology has been identified and investigated as a viable means to accommodate all available domain-specific knowledge into a cohesive system. A system for the accumulation of available knowledge for use by the expert system has been developed, the Waste Assay Measurement and Integration System. The identification of waste NDA data/information sources and means to represent and evaluate such knowledge and the associated uncertainty are under study. The expert system is compatible with compliance demonstration activities, and the solution technique is tractable in that the explanation facility output details those factors used to determine the solution and how uncertainty was treated in each particular case.

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