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Continuous Improvement Through Knowledge-Guided Analysis in Experience Feedback

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***Abstract* - Continuous improvement in industrial processes is increasingly a key element of competitiveness for industrial systems. The management of experience feedback in this framework is designed to build, analyze and facilitate the knowledge sharing among problem solving practitioners of an organization in order to improve processes and products achievement. During Problem Solving Processes, the intellectual investment of experts is often considerable and the opportunities for expert knowledge exploitation are numerous: decision making, problem solving under uncertainty, and expert configuration. In this paper, our contribution relates to the structuring of a cognitive experience feedback framework, which allows a flexible exploitation of expert knowledge during Problem Solving Processes and a reuse such collected experience. To that purpose, the proposed approach uses the general principles of root cause analysis for identifying the root causes of problems or events, the conceptual graphs formalism for the semantic conceptualization of the domain vocabulary and the Transferable Belief Model for the fusion of information from different sources. The underlying formal reasoning mechanisms (logic-based semantics) in conceptual graphs enable intelligent information retrieval for the effective exploitation of lessons learned from past projects. An example will illustrate the application of the proposed approach of experience feedback processes formalization in the transport industry sector.**

Keywords - Continuous Improvement, Experience Feedback, Root Cause Analysis, Ontology, Transferable Belief Model.

1 INTRODUCTION

Industrial products developed nowadays are more and more complex and involve several technologies at the same time. Moreover, design time is reduced, adding new constraints during pre-industrialization phases. In this context, sharing experience feedback and lessons learned is a key issue to improve the performance of organizations over time. However, sharing this knowledge is made difficult in large organizations for two main reasons:

- the project based management which creates a partitioning of the produced knowledge,
- the distributed structure of nowadays organizations implies virtually space across geographic and temporal boundaries.

In order to overcome these difficulties, building an experience feedback and lessons learned repository can be of major interest to share knowledge through time and space. This is made all the more relevant that, during the past decades, considerable efforts have been made by industrial firms in order to standardize their products and their processes. Therefore, from a representational point of view, the knowledge acquired from previous problem solving experiences should be reused as much as possible to allow the domain experts to find appropriate solutions with minimal effort. After solving one problem (leading to an experience) of many to be solved, experts can transfer lessons learned from one context to another without having to achieve the whole problem solving process. However, in some fuzzy domains, experts may sometimes be more overconfident and they may miss very obvious features without a root cause problem analysis or with a misleading problem analysis. These new constraints are rarely taken into account in traditional problem solving methods. The concern of this work is to address the knowledge capitalization and exploitation for continuous improvement in the resolution of industrial problems. Different tools and approaches for the acquisition, representation and exploitation of knowledge have been proposed especially in knowledge engineering sciences [Hicks 04]. However, these methods dedicated to model expert knowledge modelling, show some practical difficulties: experts often lack motivation, skills and time to document their expertise, a mediator is often needed to remove semantic distance between the expert and the knowledge-based system, the regular update of the knowledge referential is difficult. Thus, experience feedback, which advocates a capitalization during the activities of experts, helps to overcome these disadvantages [Henninger 03]. Naturally, the captured knowledge remains fragmentary and requires additional efforts if it is to be generalized. Finally, a compromise appears between the quality and generality of knowledge and the effort required to acquire it. In a context of rapidly evolving knowledge (such as encountered in continuous improvement processes), it may be interesting to focus on reducing the effort to obtain knowledge allowing experience feedback [Weber et al. 01]. Besides, in many companies, quality certification requirements have led to standardized problem-solving processes in which experts investigate the causes of the problems and attempt to eradicate them.

In this context, the experience feedback approaches based on standardized problem solving methods can contribute to continuous improvement in business processes. In an experience feedback approach of this kind, the knowledge is generated, on one hand, from the capitalization of knowledge and know-how used in industrial processes and, on the other hand, formalized through the tools and methods used by actors in their work [Jacobsson et al., 10]. For example, in the Swedish Centre for Lessons Learned from Incidents and Accidents (NCO), learning from accidents is institutionalized in order to overcome various social barriers and to disseminate information so that new insights in accident prevention are as widely applied as possible [Lindberg et al., 10].

Historically, experience feedback was mainly based on statistical methods to identify some failure laws. However, this kind of feedback does not allow the extraction of expert knowledge from the technical data. This is made possible by the "cognitive approach" of experience feedback modelling. It models the expert knowledge of the organization and facilitates the enrichment of knowledge repository by using methods from artificial intelligence. The cognitive vision framework of experience feedback provides means of understanding, interpreting, storing and indexing the activities of experts [Weber and al. 03].

This work specifically focuses on issues in the "analysis" activity (mainly oriented towards the search of the root causes of a problem) of experience feedback processes. It uses semantic technologies and reasoning mechanisms to refine indexation and adaptation steps by keeping track of the analysis performed. The analysis model must incorporate the possibility for an expert to appoint the most significant descriptors necessary for the best explanation of factors affecting problem occurrence and severity [Beler 08]. The resulting analysis would correspond to a combination of relevant pieces of cognitive task analysis on which the domain expertise has associated a degree of belief that takes into account all the available evidence [Shafer 90]. Indeed, knowledge related to cognitive elements underlying the analysis generation and lessons learned can be produced by tools that enable the formal description of physical tasks and cognitive plans required from a user to accomplish a particular work goal [Militello and Hutton 98].

The paper is structured as follows. Section 2 exposes a state of the art concerning knowledge management for experience feedback and a comparison between the potentially relevant semantic technologies is discussed. Section 3 presents the three layer-model proposed for analysis improvement in experience feedback framework. An illustrative application example is exposed in section 4. Finally, section 5 concludes and discusses future challenges.

2 KNOWLEDGE MANAGEMENT FOR EXPERIENCE FEEDBACK: STATE OF THE ART

2.1 Modelling of cognitive experience feedback

Experience Feedback is a structured process of capitalization and exploitation of information extracted from the analysis of positive and / or negative events. Here, the term “event” is used to generically identify occurrences that may produce safety, health, environmental, quality, reliability or production impacts. Experience Feedback uses a set of human and technological resources that must be managed to reduce the repetition of errors and to promote effective practices [Hermosillo et al. 05]. In all cases, the Experience Feedback process reveals two phases: the capitalisation phase which allows the construction of the experience feedback repository and the exploitation phase which consists in the reuse of the capitalized experiences. In cognitive experience feedback, the capitalisation phase can rely on problem solving methods commonly used in the industrial field (such as 9S [IAQG 10], 8D [Rambaud 06], 7-Step [Shiba 97], PDCA, Six Sigma-DMAICS [Geoff 01]). The main activities in the problem solving process are [Hicks 04]

- The composition of a problem solving team;
- The description and assessment of the problem highlighted by events;
- The analysis of events to identify their root causes and the validation of this analysis;
- The formulation of the problem solutions and its application checking (corrective actions);
- The action suggestions to prevent a new occurrence of the problem (preventive actions and lessons learned).

Our work fits into the scheme of the experience feedback framework detailed in [Rakoto, 04]. [Rakoto, 04]. In this framework, a structured description of gradual transformation, by actors, of an event into knowledge is proposed. For example, this can be used in a continuous improvement process through a problem solving method use (e.g. 8D or Six Sigma-DMAICS) for the Quality Assurance department assisting a supplier in improving the quality of its products/services. Despite the seeming disparity in purpose and definition among the different problem solving methods, they have some base component features in common (figure 1). The four components ("context - analysis - solutions - lessons learned") of cognitive experience feedback process are described as follows:

- The first level leads to the event description: we call it the context level. Context provides a general picture of the problem to solve prior to in depth analysis. It contains for instance the description of a faulty product and its use conditions when the problem occurred. [Brézillon 99]. Context is useful in representing and reasoning about a restricted state space within which a problem can be solved. The identification of critical events is often made by a multidisciplinary committee. In this case, risk criteria are the terms of reference (standards, measures, or expectations) used to make a judgement or a decision on the significance of risk to be assessed [Gouriveau and Noyes 04]. Risk criteria may include: associated costs and benefits, legal and statutory requirements or stakeholders concerns. Thus, beyond a critical threshold, the experience feedback is recorded systematically.
- The second level leads to the definition and implementation of solutions for the event: we call this the case or experience level. An event must be

analyzed according to its context (search of the causes and evaluation of the effects on the system) to propose corrective actions. A Tree Analysis Diagram is often used to list the various potential causes and their weighting factor that characterizes their degree of plausibility [Smets and Kennes 94]. In a causal tree, the worst thing that happened or almost happened is placed at the top. This formalization is important, since it focuses on the most likely branches (e.g. safety nets) to validate the root causes.

- The "knowledge" level refers to the knowledge of one or several experiences, summarizing the involved analysis (knowledge brought by the domain experts), and the knowledge obtained (measurement, prediction) and / or generalized rules from this set of experiences (e.g. rules from accident investigations). For instance, some rules of design are generalized from the analysis of accidents and system failures in process industries. According to [Taylor 07] design errors can be avoided with better design techniques and better design reviews. In the same way, change programs focused on structural factors (including creating safe technological design) have better effects in safety improvements [Lund and Aarø 04].

We facilitate the development of an integrated method by establishing semantic correspondences between activities of different problem solving methods. Using the suggested meta-model ("context - analysis - solutions - lessons learned") a translation between the various underlying methods is possible even though it may lead to the loss of some semantics or information. For each activity, we seek the semantic description, which accounts for which problem solving phenomena the activity is intended to represent. The representation mapping of each activity into a common meta-model has been achieved thanks to a modelling process described in [Anaya et al. 10] which relies on the following three axes:

- Structural questions: Which class(es) of things is the activity intended to represent? Which properties is the activity intended to represent?
- Behavioural questions: Which states is the activity intended to represent? Which transformations is the activity intended to represent?
- Functional questions: Which instantiation level is the activity intended to represent? Which modality (or mode) is the activity intended to represent?

Sometimes, the method of experience feedback is applied to the process itself, and includes evaluation activities that lead to improvements in the process. For example, in the CHAIN model of experience feedback [Lindberg et al., 10], six evaluation activities have been developed to ensure that all important phases of the process are covered. These activities are as follows:

- *Initial reporting*. All plausible events for in depth accident investigation should be reported in sufficient detail for a decision and investigated.
- *Selection methodology*. Events selected for in-depth investigation should be those from which as much information as possible can be extracted for preventive work.
- *Investigation*. Procedures and methodologies of investigation are conceived to provide information that is as useful as possible for the prevention of future accidents.
- *Dissemination of results*. The investigation results are distributed and used to prevent from future accidents.
- *Preventive measures*. The information from accident investigations is used to prevent from future accidents.
- *Evaluation*. The experience feedback process is regularly evaluated, and improved through experience feedback.

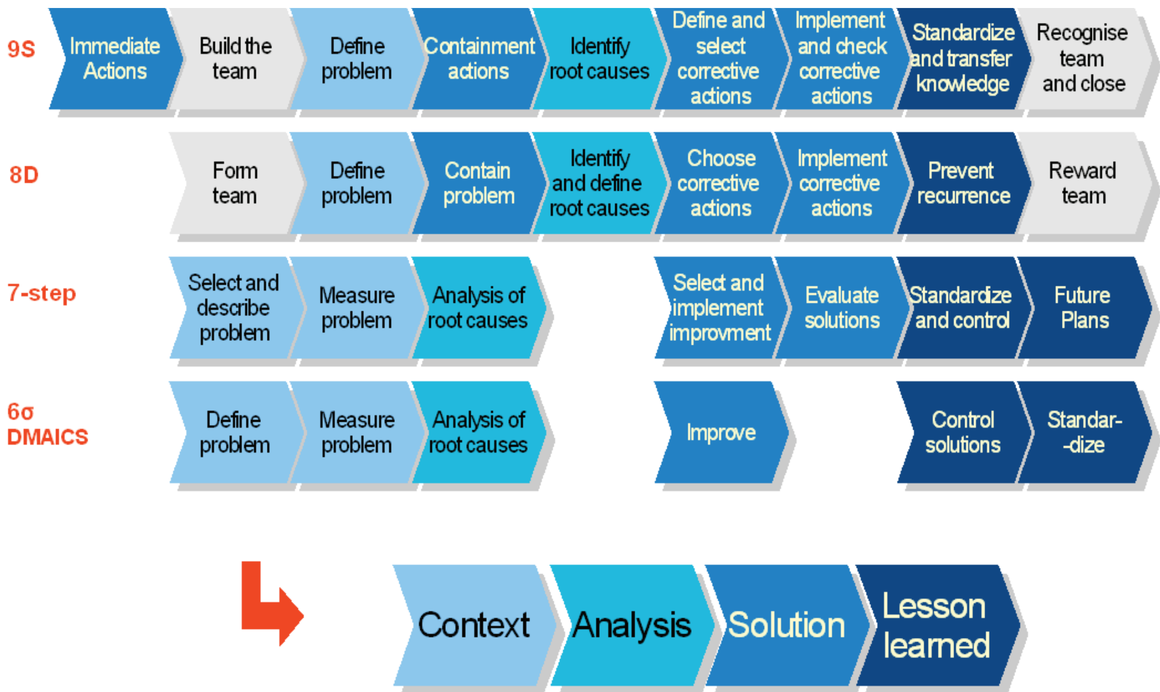

Figure 1. The cognitive experience feedback process.

2.2 Semantic technologies in experience feedback

Semantics technologies help to ensure that the information exchanged by heterogeneous and geographically distributed organizations/systems is meaningful and that all the communicating parts interpret it in the same way (e.g., [Chituc et al. 08]). They provide means to describe knowledge about an application domain, to use systematically and to share this domain knowledge in order to achieve the tasks of the problem-solving process.

The key to being able to integrate information in a reusable way is the use of semantics which describe the meaning of a word or a concept. Indeed, the semantic annotation and reconciliation using ontology is a systemic solution to solve an important conceptual barrier for interoperability, namely the semantic incompatibility [Chen et al., 08].

Semantic technologies based on ontologies enable the proper integration of knowledge in a way that is reusable by several applications across industrial processes, from design to control and execution. For instance, for process automation, semantic description of products and services allows the sharing of product definitions between companies [Zhao and Liu 08]. Ontologies are formal shared conceptualization in which the semantics are embodied in descriptions of the concepts of the application domain, the relationships between them and their properties [Gruber 93]. Decision support systems based on semantic technologies have already been applied for the optimization of industrial processes [Kamsu et al 08].

Ontologies are usually represented using knowledge representation languages (e.g. Description Logics (DLs) [Borgida 96]) or specifically developed ontology representation languages (e.g. OWL (Web Ontology Language) [Casteleiro and Diz 08]). The language semantics are commonly expressible through first order logic and may contain different features depending on what was considered important by the language developers. But it should also be chosen according to the needs of the resulting ontology-based application. At least three trends relating to ontology languages [Van Eck et al., 01] can be listed:

- the information modelling trend, where the focus is on objects and object properties (e.g. frame logics [Angele and Lausen 2004]). Here, relations and interactions are considered as secondary.
- the semantic network trend (e.g. Resource Description Framework Schema (RDFS) [Yao et Etzkorn 06]) with a less strict semantics and where the ontology is usually described like as an arbitrary graph.
- the description logics trend (e.g Description Logics (DLs)) [Borgida 96] and Conceptual Graphs (GCs) [Sowa 84]) where the focus is on concepts and their roles. It uses first order predicate logic as the underlying formalism and makes use of abstraction and refinement as structuring primitives. This trend combines well-defined logical semantics with efficient reasoning.

The information modelling and semantic network trends lack formal (logic-based) semantics or are generally undecidable, whereas the description logics trend overcomes these deficiencies [Baader et al., 07]. Besides, on the basis of several criteria (expressive power, reusability, formal precision), our work relates to the description logics trend because, it provides means to understand the application domain and to make reliable automated formal reasoning. Particularly, the ontology with conceptual graphs approach undertaken in this paper is very interesting for problem solving. Indeed, the properties (e.g. formal semantics, separation of knowledge types and possible translations into other languages [Sowa 00]) of conceptual graphs make them suitable for modelling and specifying experiences feedback processes in which reasoning plays an essential role.

2.3 Reasoning techniques in experience feedback

In our works, we have considered that an experience feedback framework should rely on the conceptualization of domain vocabulary and relevant knowledge relating to the activities of an organization. The objectives are to explicitly represent experiential knowledge in an organization, and allow its access and re-use by members. Capitalization and Exploitation are the two main sub-processes of an experience feedback process [Rakoto 04]. Capitalization is based on the industrial problem solving method as introduced in section 2.1. Each step is a capitalization sub-process (event and context description, analysis and solution determination). Exploitation is based on the following sub-processes: retrieval, adaptation and generalization. These steps are the core techniques that support the Experience Feedback problem solving cycle and have been inspired by the Case Based reasoning (CBR) cycle [Aamodt and Plaza 94]. A general CBR cycle may be described by the following four cyclical steps:

a) Retrieve the experienced cases from the case-base whose problem is most similar to the new problem.
b) Reuse the solutions from the retrieved cases to elaborate a solution for the new problem.
c) Revise (adapt) the proposed solution to take into account the problem differences between the new problem and the retrieved cases.
d) Retain the new problem and its revised solution as a new experience for the knowledge-base (case-base) if appropriate.

Case-based reasoning is - in effect - a cyclic and integrated process of problem solving, learning from this experience, and solving a new problem. However, the reuse of experiences poses multiple problems, often poorly resolved, including the reuse of analysis elements. For instance, similar cases may not have similar output/event states since problem solver may have different way to break down the problem. Therefore, some researchers previously proposed the clustered ontology approach to represent the semantic meaning of a case [Lau et al. 09]. To overcome the analysis reuse difficulty, we consider appropriate to provide key contextual information of analysis associated to experience feedback and lessons learned. This is based on semantic annotation, which enriches the unstructured or semi-structured data with a context that is further linked to the structured knowledge of a domain. More formally, semantic annotation is the act of attaching metadata information about the semantic content of a document, in such a way as to tag ontology class instance data and map it into ontology classes [Uren et al. 06]. The main requirement for appropriate analysis reuse is to provide the references from the lessons learned to a semantic repository, containing further knowledge. Such semantic annotation in a lesson learned document is built on a controlled vocabulary (ontology) and the generated additional information identifies or defines a concept in a semantic model in order to describe the analysis part of that document. Compared with traditional case representations (e.g. frame logics [Angele and Lausen 2004]), conceptual graphs formalism has the advantages of enriched semantic representation with its native ontology integration.

The conceptual graphs formalism has a set of reasoning operations using some mappings between two graphs that respect their structure. These reasoning operations rely on the mathematical field of graph theory, but keep the properties of consistency and completeness with respect to the first order predicate logic, which gives a "formal semantic" [Mugnier 95]. Some researchers have adopted Conceptual Graphs directly as a formalism for representing semantic annotations in different contexts [Dieng-Kuntz and Corby 05]. The use of conceptual graphs operations in a structured problem solving approach can help by stipulating which analytical tools (e.g. diagnostic tools) to use and when. A structured graph-based method can also offer a guide as to when a particular tool is inappropriate (e.g. poor equipment or tool placement) during experience feedback reasoning. Conceptual graph operations (projection, rules and constraints) [Baget and Mugnier 02] serve as reasoning mechanisms for experiences retrieval. Thus the matching of relevant experiences in a given context is based on semantic similarity measurement between conceptual graphs built from the same ontology [Corby et al. 06]. Ontology-guided search using similarity measurement of domain-specific ontologies, enables to judge the relevance of information dealing with the subject expressed in a request, and provides a ranking of responses [Genest and Chein, 05].

3 Improving the "analysis" activity of experience feedback processes: a three-layer model

This section focuses on the "analysis" activity of the experience feedback processes, since it influences both what is assumed to be important causal factors behind problems (e.g. accidents resulting from organizational failures) and what types of remedial actions are proposed during knowledge exploitation. Usually, case adaptation knowledge is harder to acquire and demands a significant knowledge engineering effort [Policastro et al. 04]. An alternative to overcome such difficulties in acquiring adaptation knowledge, is the improvement of the "analysis" activity, where case adaptation knowledge is extracted from previously obtained knowledge associated to underlying reasoning of analysis models. We emphasize the importance to go into "analysis" activity thoroughly with structured mechanisms to define, recognise and reuse the problem-solving trace of the experience feedback process.

Several analysis methods (e.g. Barrier analysis, Change Analysis or Root Cause Analysis) may be used to analyze and bring back knowledge on problems and near-problems [Katsakiori et al. 09]. Such analysis methods are closely associated with analysis models that reflect the different views of causality, human agency, and moral responsibility. Analytic models postulate clear cause-effect links whereas the systemic models treat problems as emergent phenomena of complex systems [Hollnagel 04]. The purpose is to provide information that is useful for correct knowledge reuse and for the prevention of future problems.

For this purpose, we propose a three layer model for the improvement of the "analysis" activity of the experience feedback process. It allows a truly semantic representation of knowledge and a more flexible reasoning about modeling expertise (including the quality of context information) (Figure 2). This model consists of an operational layer (described with Root Cause Analysis), a semantic layer (specified with conceptual graphs model) and a belief level (represented with transferable belief model).

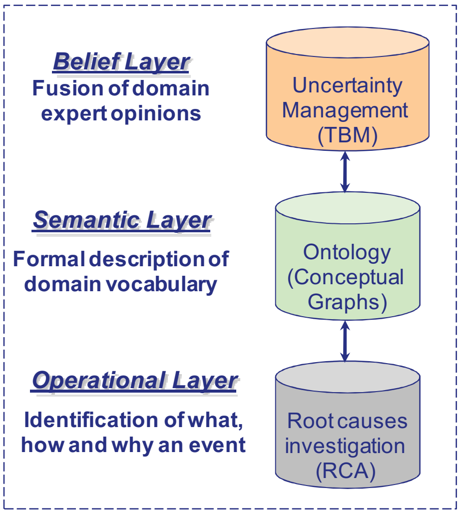

Figure 2. The model analysis layers.

3.1 Operational Layer using Root Cause Analysis

This layer corresponds to the practice of Root Cause Analysis (RCA), which aims at identifying, correcting and eliminating the root causes of problems or events. General principles of Root Cause Analysis include activities that take place before or after the occurrence of the problem, such as initial reporting for *identification* of root causes, *problem investigation* with understandable conclusions, *selection of one true* root cause, *establishment of a sequence* of events, and experience-based problem *prevention* [Wilson et al. 93]. The RCA process involves data collection, cause charting, root cause identification and recommendation generation and implementation. There are many analytical methods and tools available for determining root causes to unwanted occurrences and problems [Vanden Heuvel et al. 08]. Useful tools for Root Cause Analysis are, for example: the “5 Whys” [Ohno 88], the Ishikawa diagrams (also called Fishbone Diagrams) [Ishikawa 90] or the Failure Modes Effects Analysis (FMEA) [Stamatis 03].

For efficiency and ease of use, we emphasize the importance of the "5 Whys" that is a RCA technique for engineers or technically shrewdness individuals to help get to the true causes of problems. The method consists in constructing a representation graph of the chain of causes that led the main fault. It is used to explore the cause/effect relationships underlying a particular problem. In fact, as a question-asking method, it allows the domain experts to gradually identify the origin of a problem (root cause). The "5 Whys" technique postulates that five iterations of asking why are generally sufficient to get to a root cause. Basic categories of root causes are the following: material cause (e.g. defective raw material), equipment cause (e.g. incorrect tool selection), environment cause (e.g. forces of nature), management cause (e.g. poor management involvement), method cause (e.g. poor procedures), and management system cause (e.g. training lacking).

We define a validation process for performing the three first steps of RCA in order to understand the relationships between contributory factors, the root cause and the defined problem. This validation process displays causal factors (such as human errors and component failures) in a tree-structure and includes the following elements (figure 3):

- The description of the problematic event is expressed as contextualized hypotheses of expertise. At this step, these hypotheses are not yet verified but that if true would explain certain facts or phenomena;
- During the analysis phase, high-level hypotheses (pairs of event/condition) are partitioned into sets of sub-hypotheses (pairs of sub-event/condition) that form some hierarchical trees. The hierarchy may be several levels deep before bottoming out in questions that can be directly assessed and answered by evidence.
- The confidence level or certainty level of the expert on the specified hypotheses is modeled. Appropriate and accurate credibility assessment on all suggested hypotheses is the foundation for rigorous analysis. The assessment process would be used to reach the root causes or underlying issues which are of regulatory significance.
- Accurate assessment of hypotheses credibility helps to remove bias and provides a structure for the analyst to test the validity of the hypotheses applied to a problem. Experts should naturally seek to validate the hypotheses (potential root causes) with the highest degree of plausibility. This validation phase is to apply a filter to determine the hypothesis used as the most relevant root causes of the problem.

In the "5 whys" technique up to five rounds of asking "why something happened" is required to unearth all underlying issues. This corresponds to a practical compromise between the depth of investigation and the corresponding effort. The method proposed in this paper is not limited to this level of investigation. For general analysis of the cause of any problem, usually in a multi-disciplinary team setting, contributory factors are discussed and in-depth causal factors are written down and traced back until a clear understanding of the root cause is reached. In the proposed framework, the agreement among experts is reached according to a hierarchical fusion of expert opinion in the Transferable Belief Model (TBM) [Smets and Kennes 94], which is an elaboration on the Dempster-Shafer theory [Shafer 76]. The general idea is to merge conjunctively subgroups of expert opinions in each domain of expertise (e.g. design or production areas), before disjunctively merging the different results [Minh Ha-Duong 08]. This hierarchical fusion emphasizes the agreement and ignores conflict between the original beliefs, as far as the degree of conflict remains low between experts.

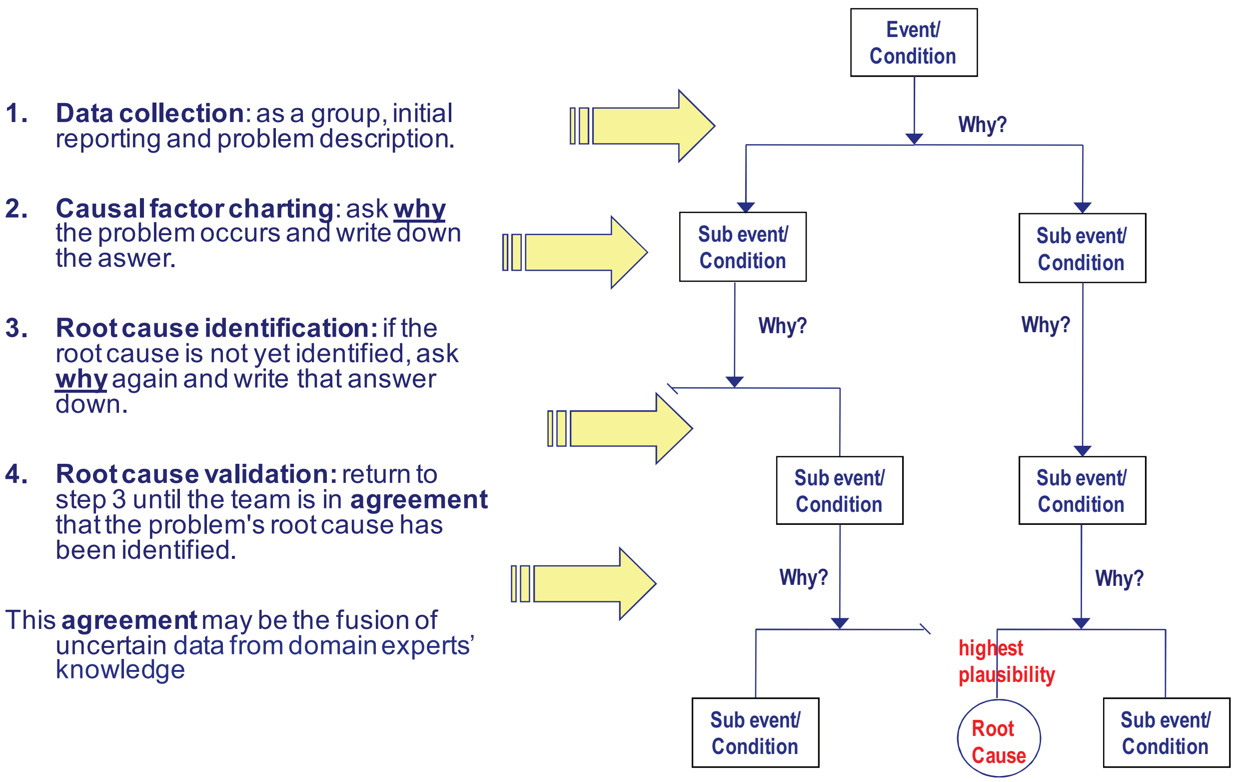

Figure 3. Using the "5 Whys" model for determining a root cause to a problem

3.2 Semantic layer using formal ontology

This layer is intended to provide an appropriate domain vocabulary with the description of a formal ontology allowing the formalization of knowledge coming from experience feedback. By providing controlled structured vocabularies for the consistent descriptions of entities of different sorts and the semantics framework for capturing the relevant relationship between these entities, ontologies support retrieval of data and semantic enhancement of a domain of knowledge or discourse [Gruber 95]. In this framework, a general description of causal factors is provided with sufficient background information about their meaning and constraints on their logically consistent application. Since synonym problems may cause the mismatching of similar cases, an ontology provides a formal semantic representation of the objects for case representation. For instance, the semantic layer is used to ensure that two concepts, which might appear in different databases in different forms with different names, can be described as truly equivalent (i.e. they describe the same object). This enables a more shareable and consistent descriptive representation of all of the available information, showing what things interact with and what role they might have in a given context [Guarino 95]. An ontology thus describes the logical structure of a domain, its concepts and the relations between them. The ontology of a problem domain specifies concepts and relations about which knowledge is to be accumulated and processed. It helps to keep the domain knowledge separate from the operational knowledge so that both can be altered without affecting the other [Uschold and Gruninger 96]. Ontology development is fundamentally a creative modelling activity of several domain experts that define the basic domain concepts and axioms for communication between software systems and interoperability between concurrent engineering teams. This in turn improves problem solving and decision making, since it permits to keep track of everyone's experiences and to provide well documented work specifications. A formal specific ontology for experience feedback processes can be a very useful tool for conveying an accurate meaning to collaborative work environment between domain experts [Dieng-Kuntz et al. 06]. As a result, it is shown that shareable ontologies are a fundamental precondition for reusing knowledge, serving as means for integrating problem-solving, domain-representation, and root cause analysis.

Conceptual graphs [Sowa 00] are clearly a relevant formalism for representing such an ontology, since it supports structuring of enterprise information and knowledge management with formal semantics allowing unambiguous understanding of the meaning of information exchanged (e.g. messages, business documents) [Khelif et al 07]. Another aspect of knowledge structuring is that semantically related pieces of information are gathered together. Hence, it is possible to really report as much as possible experiences analysis and solution(s).

As a short definition, a conceptual graph is a directed, finite, connected graph consisting of concepts and conceptual relations. Concepts and relations represent declarative knowledge. Conceptual graphs are provided with a semantics in first-order-logic, defined by a mathematical mapping classically denoted by Φ [Sowa 84]. This shows how the symbols of conceptual graphs theory map into corresponding quantities in logic theory, transforming the axioms of its domain into axioms or theorems of first-order-logic. Concept types are translated into unary predicates and relations into predicates of the same arity. Individual markers become constants. To an ontology O is assigned a set of formulas $\Phi(O)$ which translates the partial orders on concept types and relations: if t and t' are concept types, with t'< t, one has the formula $\forall x(t'(x) \rightarrow t(x))$; similarly, if r and r' are n-ary relations, with r'< r, one has the formula $\forall x_1 \ldots x_n (r'(x_1 \ldots x_n) \rightarrow r(x_1 \ldots x_n))$. This structural mapping provides a vehicle for the formalization of ontologies with mathematical rigor.

From a conceptual point of view, we choose to represent basic elements of root cause in a tree structure showing the possible hierarchical organization of an ontology. For instance, in figure 4, "Defective raw material" is a sub-concept of "Material Cause" and the others basic elements (Wrong type for job, Lack of raw material) of "Material Cause" are tree down from it.

Procedural knowledge can be attached through graph operations exploiting the graph-theoretic features of the networks during reasoning processes that preserve the mathematical semantics [Chen and Mugnier 08]:

- With respect to graph rules, semantic-based reasoning are executed for inferring new context information grounded on the defined concepts and properties, and on the individual elements retrieved from models analysis [Kamsu and Chapurlat 06]. For instance, it is possible to derive the set of individual elements that are related to a given one by a particular property (e.g., the set of activities taking place in a specific defective equipment or tool), or to calculate the most specific class an individual element belongs to (e.g., the fact that the activity performed by a given role is a planned maintenance).
- With respect to graph constraints [Baget and Mugnier 02], it is possible to make consistency checking in the definition of an ontology, as well as in its population by new instances. Consistency checking is performed to capture possible inconsistencies in the definition of the conceptual classes and properties of the ontology (e.g., a class of analysis techniques being a subclass of two disjoint classes), or in its population (e.g., a machine being in different states at the same time).

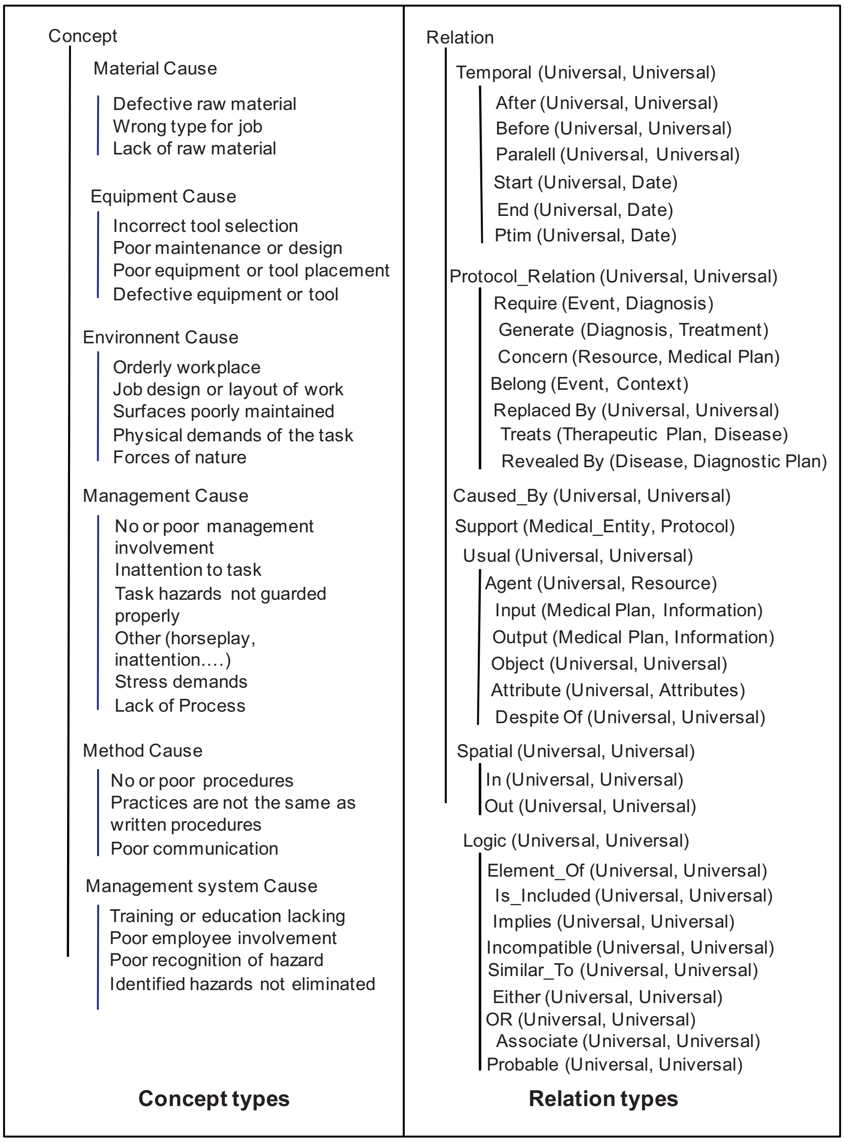

Figure 4. Partial ontology of root cause elements

3.3 Belief layer using transferable belief model

One of the key requirements of expert knowledge modelling is capturing and making sense of imprecise and sometimes conflicting data, about the physical world. This section addresses the problem of representing, reasoning about and overcoming uncertainty in experience feedback information. It aims to provide a way to manage and integrate uncertainty at different stages of the analysis phase in order to have the most suitable analysis information.

Here, we stress two main purposes for reasoning on uncertainty: improving the quality of analysis information, and inferring new kinds of analysis information [Bettini et al. 10]. Reasoning to improve the quality of analysis information typically takes the form of multi-expertise fusion where data from different expertises are used to increase confidence, resolution or accuracy. Reasoning for the purpose of inferring new analysis information typically takes the form of deducing higher-level analysis (like the Failure analysis) from lower-level analysis (like the Spectroscopic Analysis, Surface Analysis or Software Based Fault Location Techniques).

Different approaches have been used for reasoning on uncertain context information (fuzzy logic [Zadeh 99], probabilistic logic [Fagin et al. 90], Bayesian networks [Ranganathan et al. 04], Hidden Markov models [Liao et al. 07], and the Dempster–Shafer theory of evidence [Shafer 76]). In this work, the Dempster–Shafer theory is chosen to represent any form of uncertainty (full knowledge, partial or total ignorance), since it is a generalization of the Bayesian theory of subjective probability and enables the assessment of the degree of belief in a fuzzy event. Dempster–Shafer theory is a mathematical theory of evidence based on belief functions and plausible reasoning, which is used to combine separate pieces of information (evidence) to calculate the probability of an event [Shafer 90]. Specifically, we use reasoning mechanisms of the Dempster–Shafer theory for combining the independent analysis of multiple expertises each of which analyses one and the same problem. The belief in a hypothesis is constituted by the sum of the masses of all subsets of the hypothesis. In fact, the belief level is supported by the transferable belief model (TBM) [Smets and Kennes 94], which is an elaboration on the Dempster-Shafer theory. Beliefs can be held at two levels: (1) a *credal* level where beliefs are interpreted and quantified by belief functions, (2) a *pignistic* level where beliefs can be used to make decisions and are quantified by probability functions [Smets 05]. When a decision must be made, beliefs at the credal level induce a probability measure at the pignistic level, i.e. there is a pignistic transformation from belief functions to probability functions.

Some general evidence properties, such as the independence or the level of conflict, are considered in the choice of the appropriate combination rule. Therefore some authors (e.g. [Minh Ha-Duong 08], [Klein et al. 10]) have proposed a hierarchical approach with different combination rules used for different source clusters and fusion level. The general idea is to merge conjunctively coherent sources, before disjunctively merging the different results. We propose a hierarchical fusion procedure based on this idea. Experts are not combined symmetrically, but grouped into expertise domains where they share a domain specific explanation of the way the world works, including the relevant perceptual features in their domain. Within groups, beliefs are combined using the cautious conjunction rule [Denoeux 08], whereas across groups the non-interactive disjunction [Shafer 90] is used. As a way to add doubt to a Basic Belief Assignment, the *discounting* rule is useful for adding lots of doubt to experts' opinions, or saying that some experts are less qualified than others [Shafer 76]. Expert group opinions are taken as not independent information sources, the cautious conjunction operator emphasizes the agreement and ignores conflict between the original beliefs (as far as the degree of conflict remains low between experts). As shown in figure 5, a two-level fusion scheme is proposed: the first-level outputs of each group are the inputs of the fusion second-level, which are thus combined to obtain the second-level output across groups. This more comprehensive information is the basis on which a belief-based decision is made, in order to determine the most credible root cause with the paths leading to this root cause and the plausibility of their occurrence. Since root cause analysis provides accurate information for solving problem, tasks become easier.

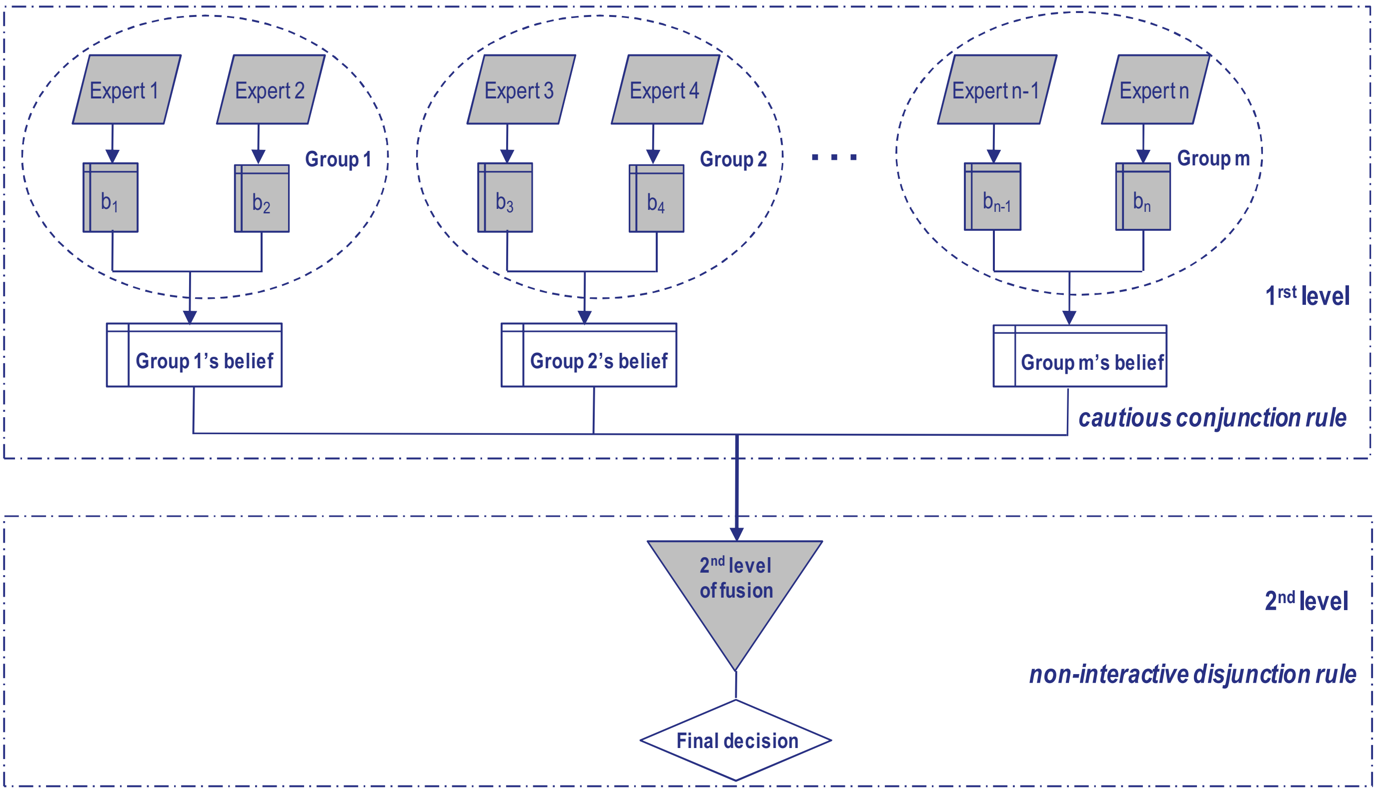

Figure 5. Scheme of the hierarchical fusion procedure

4 APPLICATION EXAMPLE

4.1 The T-REX Project

In order to foster transfer of innovation between academic and industry, the AVAMIP (regional agency for the promotion of research in Midi-Pyrénées (France)) has supported the T-REX project launched by the ENIT (National Engineering School of Tarbes, Southern France). The T-REX project aimed at offering methodological and software support for knowledge management (KM), and in particular for capitalization and exploitation phases of experience feedback processes. This project is carried out in collaboration with Alstom Transport that develops and markets the most complete range of systems, equipment and services in the railway sector (e.g. rail vehicles, rail infrastructure, and associated maintenance services). Particularly, Tarbes plant provides throughout the world electric range of products and services for traction systems (e.g. electric propulsion systems, electronic power modules and switchgears).

From a software point of view, the T-REX application is a client–server architecture in which the user interface, functional process logic ("business rules"), computer data storage and data access are developed and maintained as independent modules. This application displays information related to such services as:

- browsing the problem solving process (event, context, analysis, solutions, and lessons) with appropriate methods (e.g. 8D or Six Sigma-DMAICS)
- the manipulation of some root causes analysis tools (e.g. "5 whys", Ishikawa diagrams (also called fishbone diagrams))
- the semantic search engine that measures the relative relevance of the retrieved annotations by their similarity to the query of a user. It addresses possible mismatches between end-user and domain vocabulary concepts by approximating the query’s semantics.
As shown in figure 6, the web architecture of T-REX enables to analyse an event according to its context. The analysis level is handled for use in investigating and categorizing the root causes of events with their degree of plausibility. Following the analysis level (identification of the most plausible root cause for a major contributor to the event) and solution level (specification of workable corrective actions), achievable recommendations for preventing their recurrences are then generated (lessons level). These recommendations are implemented by the scheduling or tracking of work activities (e.g. modification of the risk assessment process, development of a preventive maintenance strategy or review of the vocational training development process). It is also possible to ensure an efficient retrieval of experience feedback elements by enabling multi-criteria search and inferences based on domain knowledge (figure 7).

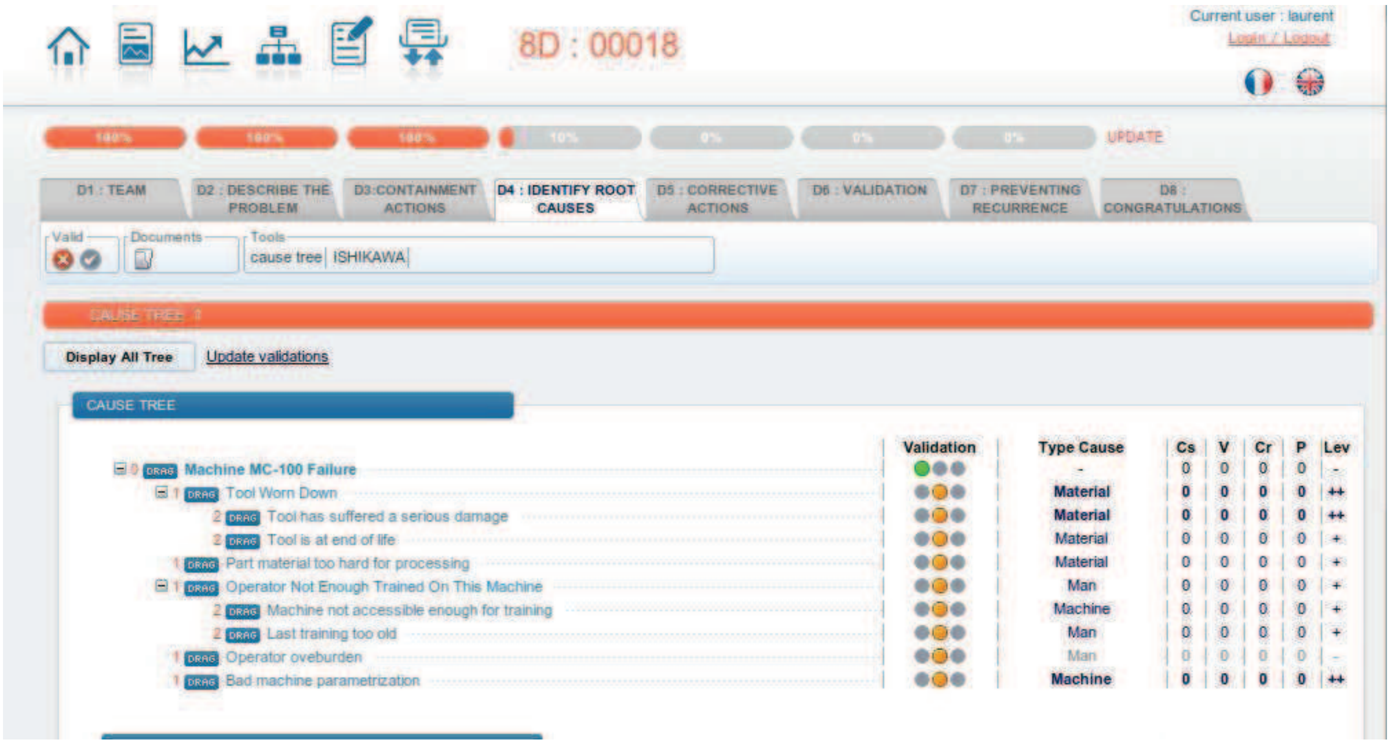

Figure 6. Root causes validation in the 8D method with T-REX

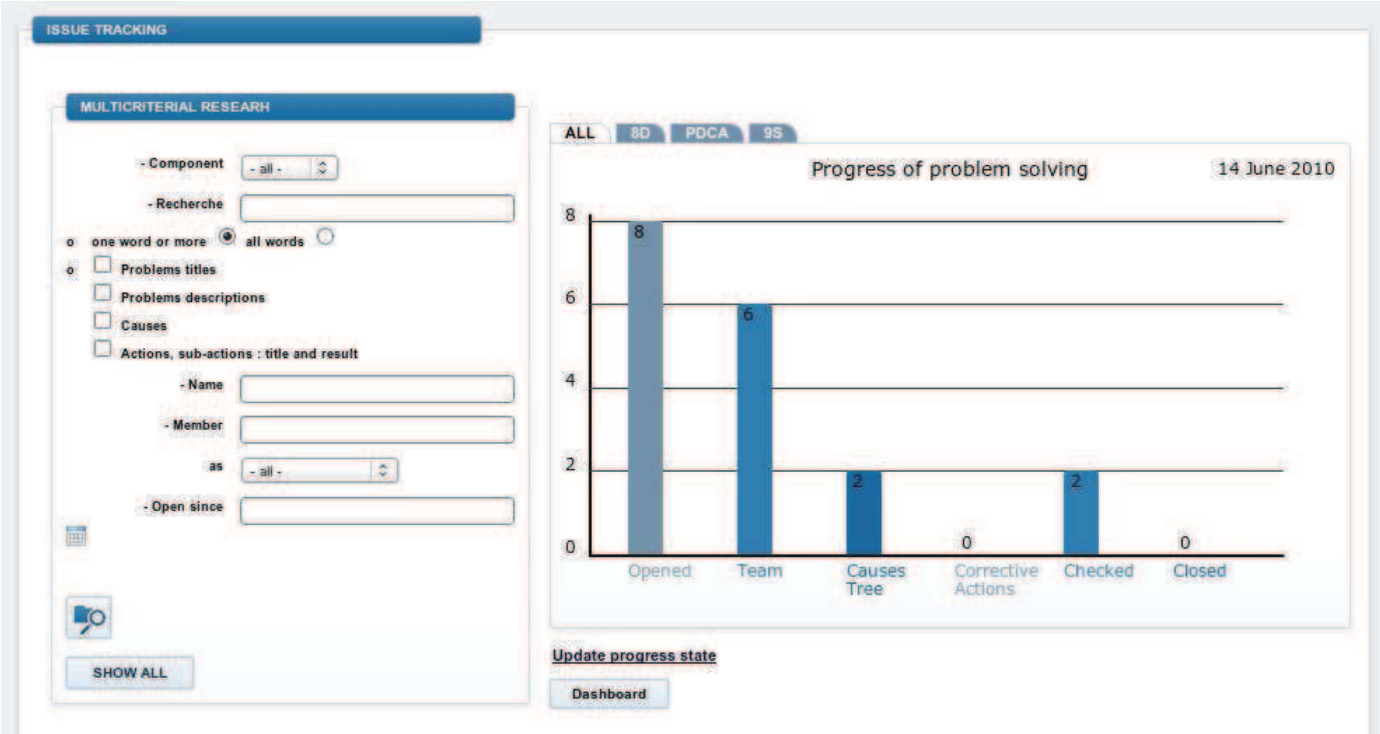

Figure 7. The T-REX multi-criteria based search engine

4.2 Case study: a breakage failure in the ignition system

In this case study from the railway industry, a concrete example is described showing, step-by-step, the three layers of the proposed model. The context description is a failure such as a breakage in the MOS driver component for an ignition card. The deterioration of the ignition system tends to restrain the performance of the traction system. To cope with such a situation it is important, as described above, to handle the problem and therefore to determine what corrective / preventive actions are appropriate.

<u>Operational layer: root causes investigation</u>

The fishbone diagram is used to identify root causes that potentially contribute to a breakage of the MOS driver component for an ignition card. Figure 8 shows Equipment, Materials and Methods factors that may cause the overall problem. Causes are traced back to root causes with the “5 Whys” technique.

<u>Semantic layer: ontology description</u>

The ontology description enables to capture the semantics of domain expertise by deploying knowledge representation primitives, allowing handling a more specific vocabulary pertaining to the case study. The domain ontology of figure 4 is enriched (from the general to the specific) in figure 9 in which the additional concepts are written in bold. If needed, further knowledge can be captured by logical rules (e.g. low magnetic noise design rules) or constraints (e.g. traction characteristics) which give deep understanding on application.

<u>Belief layer: fusion of domain expert opinions</u>

Some lessons learned are generated by domain experts during the problem solving process and they may help to prevent similar problems from occurring in the future. We now describe all the hypotheses that are specified by the three different experts involved in the problem solving process:

- *Hypothesis-A from electrical expert:* "thermal overheating resulting in short circuits (e.g. latchup)".
- *Hypothesis-B from design expert*: "incorrect design of the ignition card".
- *Hypothesis-C from electromagnetic expert:* "driver’s high sensibility to magnetic fields".

Two qualitatively different groups of distributions can be identified (a "production" group and a "design" group): Group 1= {*Electrical expert*, *Electromagnetic expert*}, Group 2= {*Design expert*}.

We use the two qualitative groups outlined above for the hierarchical approach (figure 10): (i) the beliefs of *Electrical expert* and *Electromagnetic expert* are combined using a cautious conjunction operator; (ii) the second stage combines the two groups together using the non-interactive disjunction operator.

In Table 1, each line describes aspects of the basic belief assignment using for the hierarchical fusion approach. For any subset X, the basic belief assignment with the mass m(X) represents the certain belief that the state of the world is in X. For decision-making in the Transferable Belief Model, the pignistic probability function of m, defined by [Smets 05] is used:

$$BetP(\omega) = \frac{1}{1 - m(\emptyset)} \sum_{X \ni \omega} \frac{m(X)}{|X|}$$

BetP (A) = (0 + 0.0425/2 +0.125/3)*1/0.55≈0.11

BetP (B)=(0.051+0.0425/2+0.3315/2+0.125/3)*1/0.55≈0.51

BetP (C) = (0 +0.3315/2+0.125/3)*1/0.55≈0.38

In the case study a decision-maker should select first Hypothesis-B from the design expert, because it maximizes the expected utility. In summary for the breakage failure in the ignition system, the action that provides an optimal answer is "to redesign of the ignition card without using MOSFET driver function with an alternative supplier".

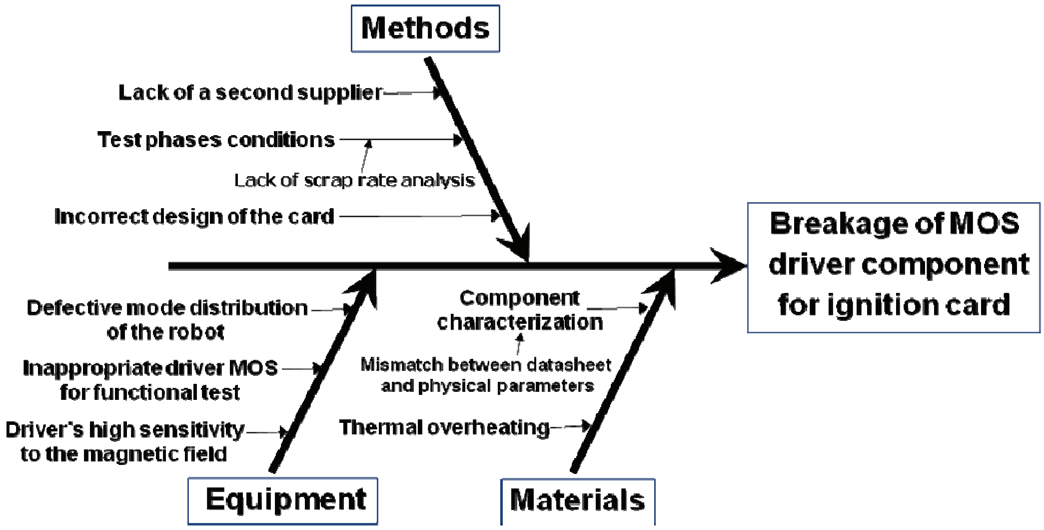

Figure 8. Ishikawa diagram for the case study

Concept

Material Cause

Defective raw material
Driver MOS Quality
Wrong type for job
Component characterization
Lack of raw material

Equipment Cause

Incorrect tool selection
Inappropriate Driver MOS for functional test
Poor maintenance or design
Poor equipment or tool placement
Driver's high sensitivity to the magnetic field
Defective equipment or tool
Defective distribution mode of robot

Environment Cause

Orderly workplace
Job design or layout of work
Surfaces poorly maintained
Physical demands of the task
Forces of nature

Management Cause

No or poor management involvement
Inattention to task
Task hazards not guarded properly
Other (horseplay, inattention....)
Stress demands
Lack of Process

Method Cause

No or poor procedures
Lack of a second supplier
Practices are not the same as written procedures
Lack of scrap product analysis
Poor communication

Management system Cause

Training or education lacking
Poor employee involvement
Poor recognition of hazard
Identified hazards not eliminated

Relation

Temporal (Universal, Universal)

After (Universal, Universal)
Before (Universal, Universal)
Paralell (Universal, Universal)
Start (Universal, Management's Cause)
End (Universal, Management's Cause)
Function (Universal, Universal)
Transformation (Universal, Universal)
Transport (Universal, Universal)
Stockage (Universal, Universal)
Uncertainty (Universal, Universal)
Credibility Of (Universal, Universal)
Plausibility of (Universal, Universal)

Usual (Universal, Universal)

Agent (Universal, Equipment's Cause)
Substitute (Equipment, Equipment's Cause)
Object (Universal, Universal)
ProprietyOf (Universal, Universal)
Variables Of(Universal, Universal)
Rules Of (Universal, Universal)
Value Of (Universal, Universal)
MesureUnit (Universal, Universal)

Spatial (Universal, Universal)

In (Universal, Universal)
Out (Universal, Universal)

Logic (Universal, Universal)

Element_Of (Universal, Universal)
Implies (Universal, Universal)
Incompatible (Universal, Universal)
Similar_To (Universal, Universal)
AND (Universal, Universal)
Conjonction (Universal, Universal)
Disjonction (Universal, Universal)

Figure 9. Domain specific ontology for the case study

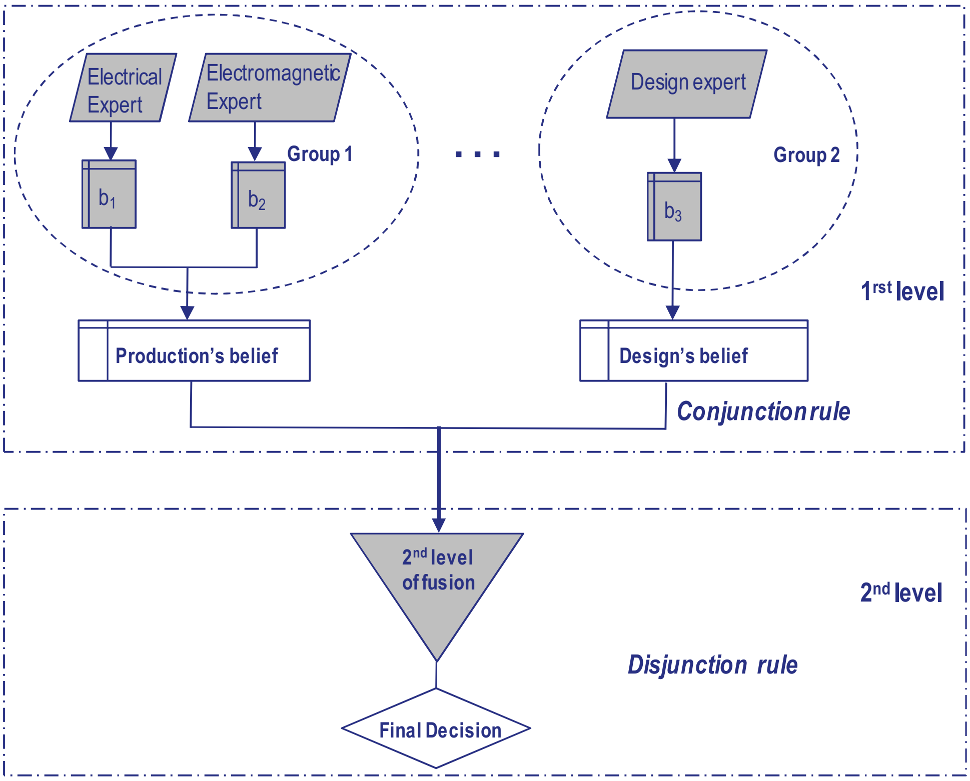

Figure 10. Hierarchical fusion procedure for the case study

Hypothesis	Expert1 Electrical expert	Expert2 Design expert	Expert3 Electromagnetic expert	Expert1∩ Expert3	(Expert1∩ Expert3) U Expert2
Ǿ	0	0	0	0.45	0.45
A	0,3	0	0	0.03	0
C	0	0	0,6	0.24	0
{A, C}	0	0	0	0	0
B	0	0,85	0	0.06	0.051
{A, B}	0,2	0	0	0.02	0.0425
{B, C}	0	0	0,3	0.15	0.3315
{A, B, C}	0,5	0,15	0,1	0.05	0.125

Table 1. The fusion of expert opinion on the case study

4.3 Evaluation of the framework

At Alstom Transport Tarbes, it was decided to implement an Action Plan Management System that would support consolidation of process solving tools according to methods adopted by the company. This software system is intended to allow users to easily define action plans, manage their progress and follow up, and monitor the results to ensure the improvement of the operational activities. The current version of this framework enables users to share actions or action plans across different sites of ALSTOM Transport, but they can only create and manage corrective, preventive or improvement actions from various sources (e.g. 8D, customer complaints, audits and board reviews). The T-REX project is specialized by studies made for the railway industry sector about the integration of a knowledge package in the Action Plan Management System. The proposed framework will be integrated into such industrial applications via a collaborative portal available throughout the ALSTOM Transport sites. At present, the analysis module of T-REX has given some satisfactions and early outcomes assessments by end-users are very encouraging. This module endeavours to provide a challenging and supportive experience feedback environment for users by enhancing the key analysis and subject knowledge appropriate to validate the most plausible root cause of an event. Such causal factor is the greatest contributor that, if eliminated, would have either prevented the occurrence or reduced its severity. A preliminary evaluation of the T-REX application has resulted in encouraging results with respect to both increasing the speed of problem solving processes by experts, compared to a previous mean (developed in Excel), and enhancing the accuracy of the analyses. Enhancing models analysis of root causes allows the development of systematic improvements and assessment of the impact of corrective programs with respect to the top management quality objectives.

The work presented in this paper has some common features with the Decisional DNA approach [Sanín et al. 09a, Sanín et al. 09b]: Experience Knowledge Structure, formal ontology and uncertainty management. However, the approach proposed by Sanin has some restrictions: (i) some formal models (such as physical equations) are needed to describe the knowledge experience of a specific domain. Such models generally do not exist for the systems and the problems tackled in our study. (ii) Given the multiple Sets of Experience, if partial knowledge is encoded by the function of certainty; their combination is not described in an explicit way. Our work complements the Decisional DNA approach with the process used to find root causes of problems and a hierarchical fusion of set of Experience Knowledge in the Transferable Belief Model. The strength of the DNA approach is that it proposes a multi-domain knowledge structure able to be adaptable and multipurpose.

5 CONCLUSION

As presented in this paper, the proposed approach relates to knowledge management in problem solving and experience feedback processes. The main contribution is the proposition of a dedicated analysis model relying on three complementary layers: operational, semantic and belief. This model helps to support experts:

- When they look for the most plausible root causes for a problem (use previous analysis),when they elaborate an action plan to solve and eradicate the problem (use previous solutions).
- More specifically, with this cognitive approach of experience feedback, root causes are reasonably identifiable and the analysis model associated to lessons learned indicates the arguments in favour of the chosen solution according to experiential knowledge exploitation.

There are several practical industrial benefits of the proposed technologies/methodologies experimented in the railway industry sector:

* The description of the basic elements of root cause at the semantic level prevents a model analysis to be misunderstood and facilitates the reasoning processes over the expert opinions. Moreover, the semantic enhancement of experience feedback modelling makes it possible to better identify major issues for industrial processes improvement.

* The knowledge exploitation is possible asynchronously and remotely throughout the organization: the expertise assets are enriched over time and shared.

* The explicit integration of the expert opinions on the plausibility of hypotheses during root cause analysis enables to better take into account this expertise for reasoning. The use of the Transferable Belief Model and related fusion mechanisms facilitates the inference. However some work still remains to make this representation more easily accessible to practitioners.

From a more global perspective, the knowledge engineering technology implemented enables to collect and exploit experiential knowledge in continuous improvement processes of any complex system in which problematic events require in depth (expert) analysis.

Several issues requiring additional efforts are currently under investigation:

- an improved support of experts when they split masses between hypotheses since the use of the TBM at an operational level may not be intuitive,
- the active dissemination (push) of experiences to the relevant actors by integrating the actor profiles (expertise domain, competences),
- the coupling of the experience feedback model with specific architectural principles [Krishnan and Bhatia 09] to foster better interoperability with business applications.

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6 REFERENCES

[Hicks 04] Hicks, M.J., Problem Solving and Decision Making, 2nd Ed., Cengage Learning Business Press, 2004.

[Henninger 03] Henninger, S. Tool Support for Experience-Based Software Development Methodologies. Advances in Computers, 59(1), pp. 29-82, 2003.

[Weber et al. 01] Weber, R.O., Aha, D.W., Becerra-Fernandez, I., (2001) Intelligent lessons learned systems. Expert Systems with Applications, 20 (1), pp. 17-34.

[Jacobsson et al., 10] Anders Jacobsson, Jaime Sales, Fesil Mushtaq. Underlying causes and level of learning from accidents reported to the MARS database. Journal of Loss Prevention in the Process Industries, Volume 23, Issue 1, January 2010, Pages 39-45.

[Lindberg et al., 10] Anna-Karin Lindberg, Sven Ove Hansson, Carl Rollenhagen. Learning from accidents – What more do we need to know? Safety Science, Volume 48, Issue 6, July 2010, Pages 714-721.

[Weber et al., 03] Rosina O. Weber, David W. Aha. Intelligent delivery of military lessons learned. Decision Support Systems, Volume 34, Issue 3, February 2003, Pages 287-304.

[Beler 08] Beler, C., Modélisation générique d'un retour d’expérience cognitif : Application à la prévention des risques. PhD thesis, National Polytechnic Institute of Toulouse, France, 2008.

[Shafer 90] G. Shafer, Perspectives on the theory and practice of belief functions, International Journal of Approximate Reasoning 4 (1990) 323–362.

[Militello and Hutton 98] Militello, L.G., Hutton, R.J.G., Applied cognitive task analysis: a practitioner's toolkit for understanding cognitive task demands. Ergonomics, vol. 41, no 11, 1618-1641, 1998.

[Hermosillo et al. 05] Hermosillo, W. J., Rakoto, H., Grabot, B., Geneste, L. A competence approach in the experience feedback process. In Integrating Human Aspects in Production Management, IFIP International Federation for Information Processing series, 160, Ed., Springer: New York, pp. 220-235, 2005.

[IAQG 10] IAQG (International Aerospace Quality Group).Supply Chain Management Handbook (SCMH), Chapter 9: Control of Non Conformities, corrective and preventive actions. Document available on-line: http://www.iaqg.sae.org/iaqg/handbook/scmhtermsofuse.htm (latest access in December 2010)

[Rambaud 06] Laurie Rambaud. 8D Structured Problem

Solving: A Guide to Creating High Quality, 148 pages, Publisher: PHRED Solutions (October 22, 2006), ISBN 0-9790553-0-X.

[Sanín et al. 09a] Cesar Sanín, Leonardo Mancilla-Amaya, Edward Szczerbicki, Paul CayfordHowell. Application of a Multi-domain Knowledge Structure: The Decisional DNA. Intelligent Systems for Knowledge Management, Springer, Berlin, 65-86 (2009).

[Sanín et al. 09b] Maldonado Sanin Cesar Augusto, Szczerbicki Edward. 'Experience-based knowledge representation: SOEKS', Cybernetics and Systems, 40 99-122 (2009).

[Shiba 97] Shoji Shiba. The 7-Step Problem-Solving Method, Center for Quality of Management, Cambridge, MA, October 1997.

[Geoff 01] Tennant, Geoff (2001). SIX SIGMA: SPC and TQM in Manufacturing and Services. Gower Publishing, Ltd.. p. 6. ISBN 0566083744, 2001.

[Rakoto 04] Rakoto, H. Integration du Retour d'Experience dans les processus industriels - Application a Alstom Transport, PhD thesis, National Polytechnic Institute of Toulouse, France, 2004.

[Brézillon 99] Brézillon, P. Context in problem solving: A survey. The Knowledge Engineering Review, 14(1), 1-34, 1999.

[Gouriveau and Noyes 04] Gouriveau, R., Noyes, D., Risk management - dependability tools and case-based reasoning integration using the object formalism. Computers in Industry, 55(3), pp. 255-267, 2004.

[Smets and Kennes 94] Smets Ph. and Kennes R. The transferable belief model. Artificial Intelligence, vol. 66, no2, pp. 191-234, 1994.

[Taylor 07] Taylor, J.R. Understanding and combating design error in process plant design. Safety Science 45 (1–2), 75–105, 2007.

[Lund and Aarø 04] Lund, J., Aarø, L.E. Accident prevention. Presentation of a model placing emphasis on human, structural and cultural factors. Safety Science 42 (4), 271–324, 2004.

[Anaya et al. 10] V. Anaya, G. Berio, M. Harzallah, P. Heymans, R. Matulevičius, A.L. Opdahl, H. Panetto, M.J. Verdecho. The Unified Enterprise Modelling Language—Overview and further work. Computers in Industry, Vol. 61, Issue 2, February 2010, Pages 99-111.

[Lindberg et al., 10] Anna-Karin Lindberg, Sven Ove Hansson, Carl Rollenhagen. Learning from accidents – What more do we need to know? Safety Science, Volume 48, Issue 6, July 2010, Pages 714-721.

[Chituc et al. 08] C.-M. Chituc, C. Toscano and A. Azevedo, Interoperability in collaborative networks: independent and industry-specific initiatives—the case of the footwear industry, Computers in Industry 59 (7) (2008), pp. 741–757.

[Chen et al. 08].Chen, D., Doumeingts, G., Vernadat, F. Architectures for enterprise integration and interoperability: Past, present and future. Computers in Industry, 59(7), pp. 647-659, 2008.

[Zhao and Liu 08] W. Zhao, J.K. Liu. OWL/SWRL representation methodology for EXPRESS-driven product information model: Part I. Implementation methodology. Computers in Industry, Volume 59, Issue 6, August 2008, Pages 580-589.

[Gruber 93] Gruber T.R. A translation approach to portable ontology specifications. Knowledge Acquisition, n°2(5), pages 199-220, 1993.

[Kamsu et al. 08] Kamsu Foguem B., Coudert, T., Béler, C., Geneste, L. Knowledge Formalization in Experience Feedback Processes: An Ontology-Based Approach. Computers in Industry, 59(7), pp. 694-710, 2008.

[Borgida 96] A. Borgida. On the relative expressiveness of description logics and predicate logics. Artificial Intelligence, 82:353-367, 1996.

[Casteleiro and Diz 08] M. Argüello Casteleiro and J.J Des Diz. Clinical practice guidelines: A case study of combining OWL-S, OWL, and SWRL. Knowledge-Based Systems, Volume 21, Issue 3, April 2008, Pages 247-255.

[Van Eck et al 01] P. Van Eck, J. Engelfriet, D. Fensel, F. van Harmelen, Y. Venema, M. Willems. A survey of languages for specifying dynamics: a knowledge engineering perspective. IEEE Transactions on Knowledge and Data Engineering 13 (3) (2001) 462–496.

[Angele and Lausen 2004] J. Angele, G. Lausen, Ontologies in f-logic, in: S. Staab, R. Studer (Eds.), Handbook on Ontologies, Springer-Verlag, Berlin, 2004, pp. 29–50.

[Yao and Etzkorn 06] Yao H., Etzkorn L., Automated conversion between different knowledge representation formats. Knowledge-Based Systems, Volume 19, Issue 6, p. 404-412, October 2006.

[Sowa 84] J.F. Sowa, Conceptual Structures: Information Processing in Mind and Machine. Addison-Wesley Publishing Company, Reading, MA, 1984.

[Baader et al 07] Franz Baader, Ian Horrocks, and Ulrike Sattler. Chapter 3: Description Logics. In Frank van Harmelen, Vladimir Lifschitz, and Bruce Porter, editors, Handbook of Knowledge Representation. Elsevier, 2007.

[Sowa 00] J.F. Sowa, Knowledge Representation: Logical, Philosophical, and computational Foundations, Brooks Cole Publishing Co., 2000.

[Aamodt and Plaza 94] Aamodt, A., Plaza, E., (1994) Case-based reasoning: foundational issues, methodological variations, and system approaches. AI Communications, 7 (1), pp. 39-59.

[Lau et al.09] Adela Lau, Eric Tsui, W.B. Lee . An ontology-based similarity measurement for problem-based case reasoning. Expert Systems with Applications, Vol 36, pp 6574–6579, 2009.

[Uren et al. 06] Victoria Uren, Philipp Cimiano, José Iria, Siegfried Handschuh, Maria Vargas-Vera, Enrico Motta, Fabio Ciravegna. Semantic annotation for knowledge management: Requirements and a survey of the state of the art Web Semantics: Science, Services and Agents on the World Wide Web, Volume 4, Issue 1, January 2006, Pages 14-28.

[Mugnier 95] M.L. Mugnier. On generalization/specialization for conceptual graphs, Journal of Experimental and Theoretical Artificial Intelligence 7 (1995) 325–344.

[Dieng-Kuntz and Corby 05] Dieng-Kuntz, R., O, Corby. Conceptual Graphs for Semantic Web Applications. International Conference on Conceptual Structures - ICCS'2005, Kassel, Germany, 17-23 July, 2005.

[Baget and Mugnier 02] Baget, J.F., Mugnier, M.L. Extensions of simple conceptual graphs: the complexity of rules and constraints. Journal of Artificial Intelligence Research, 16(1), pp. 425-465, 2002.

[Corby et al. 06] Corby, O., Dieng-Kuntz, R., Faron-Zucker C., Gandon, F., (2006) Searching the Semantic Web:

approximate query processing based on ontologies. IEEE Intelligent Systems Journal, 21 (1), pp. 20-27.

[Genest and Chein, 2005] Genest, D., Chein, M. A Content-search Information Retrieval Process Based on Conceptual Graphs. Knowledge And Information Systems, 8(3), Springer, pp. 292-309, 2005.

[Policastro et al 04] Policastro, C.A., Carvalho, A.C.P.L.F., Delbem, A.C.B. Automatic knowledge learning and case adaptation with a hybrid committee approach. Journal of Applied Logic, 4(1), pp. 26-38, 2004.

[Katsakiori et al. 09] Katsakiori, P., Sakellaropoulos, G., Manatakis, E. Towards and evaluation of accident investigation methods in terms of their alignment with accident causation models. Safety Science 47 (7), 1007–1015, 2009.

[Hollnagel 04] Hollnagel, E., 2004. Barriers and Accident Prevention. Ashgate Publishing Limited, England.

[Wilson et al. 93] Wilson, P. F., Dell, L. D., and Anderson, G. F. Root cause analysis: A tool for total quality management. ASQC Quality Press, Milwaukee, USA, 1993.

[Vanden Heuvel et al. 08] Lee N. Vanden Heuvel, Donald K. Lorenzo, Walter E. Hanson, Laura O. Jackson , James R. Rooney and David A. Walker. Root Cause Analysis Handbook: A Guide to Effective Incident Investigation. Third Edition, By ABS Consulting - Published by Rothstein Associates Inc. ISBN #1-931332-51-7 (978-1-931332-51-4), Brookfield, Connecticut, U.S.A, (July, 2008).

[Ohno 88] Taiichi Ohno, Toyota Production system: beyond large-scale production, Productivity Press, Portland OR, 1988. ISBN 0-915299-14-3.

[Ishikawa 90] Kaoru Ishikawa; (Translator: J. H. Loftus); Introduction to Quality Control; 448 p; ISBN 4-906224-61-X OCLC 61341428, 1990.

[Stamatis 03] D. H. Stamatis. Failure Mode and Effect Analysis: Fmea from Theory to Execution. ASQ Quality Press; 2nd edition, 300 pages, ISBN-10: 0873895983, November 2003.

[Gruber 95] Gruber, T. R., Toward Principles for the Design of Ontologies Used for Knowledge Sharing. International Journal Human-Computer Studies, 43(5-6):907-928, 1995.

[Guarino 95] Guarino, N. Formal Ontology, Conceptual Analysis and Knowledge Representation, International Journal of Human-Computer Studies, 43(5-6):625–640, 1995.

[Uschold and Gruninger 96] Uschold M., Gruninger M. Ontologies: Principles, Methods and Applications, Knowledge Engineering Review, vol.11:2, p. 93-136, 1996.

[Dieng-Kuntz et al. 06] Dieng-Kuntz, R., Minier, D., Ruzicka, M., Corby, F., Corby, O., Alamarguy, L., Building and using a medical ontology for knowledge management and cooperative work in a health care network. Computers in Biology and Medicine, 36 (7–8), pp. 871-892, 2006.

[Khelif et al 07] Khelif, K., Dieng-Kuntz, R., Barbry, P.: An ontology-based approach to support text mining and information retrieval in the biological domain. Journal of Universal Computer Science (JUCS) 13(12) (2007) 1881–1907.

[Chen and Mugnier 08] M. Chein and M-L. Mugnier. Graph-based Knowledge Representation: Computational Foundations of Conceptual Graphs. Series: Advanced Information and Knowledge Processing. Publisher: Springer, 445 pages, Hardcover, ISBN 978-1-84800-285-2. London (United Kingdom), 01 October 2008.

[Kamsu and Chapurlat 06] Kamsu-Foguem B. and Chapurlat V (2006). Requirements modelling and formal analysis using graph operations. International Journal of Production Research,Vol. 44, No. 17, 1 September 2006, 3451–3470.

[Bettini et al. 10] Claudio Bettini, Oliver Brdiczka, Karen Henricksen, Jadwiga Indulska, Daniela Nicklas, Anand Ranganathan, Daniele Riboni. A survey of context modelling and reasoning techniques. Pervasive and Mobile Computing, Volume 6, Issue 2, April 2010, Pages 161-180.

[Zadeh 99] L. A. Zadeh, Fuzzy sets as a basis for a theory of possibility. Fuzzy Sets and Systems, 100 (1999) 9–34.

[Fagin et al. 90] R. Fagin, J. Y. Halpern, N. Megiddo, A logic for reasoning about probabilities. Inf. Comput. 87 (1-2) (1990) 78–128.

[Ranganathan et al. 04] A. Ranganathan, J. Al-Muhtadi, R. H. Campbell, Reasoning about uncertain contexts in pervasive computing environments, IEEE Pervasive Computing 3 (2) (2004) 62–70.

[Liao et al. 07] L. Liao, D. J. Patterson, D. Fox, H. Kautz, Learning and inferring transportation routines. Artificial Intelligence. 171 (5-6) (2007) 311–331.

[Shafer 76] G. Shafer. A Mathematical Theory of Evidence, Princeton University Press, NJ (USA), 1976, ISBN: 0-691-10042-X (hardback), 0-608-02508-9 (reprint).

[Smets 05] Philippe Smets. Decision making in the tbm: the necessity of the pignistic transformation. International Journal of Approximate Reasoning, 38(2):133–147, May 2005.

[Minh Ha-Duong 08] Minh Ha-Duong. Hierarchical fusion of expert opinions in the Transferable Belief Model, application to climate Sensitivity. International Journal of Approximate Reasoning, Volume 49, Issue 3, November 2008, Pages 555-574.

[Klein et al. 10] Klein J., Lecomte C., Miché P. Hierarchical and conditional combination of belief functions induced by visual tracking,. International Journal of Approximate Reasoning, Volume 51, Issue 4, March 2010, Pages 410-428.

[Denoeux 08] Thierry Denoeux. Conjunctive and disjunctive combination of belief functions induced by non distinct bodies of evidence. Artificial Intelligence, 172(2–3):234–264, 2008.

[Krishnan and Bhatia 09] Krishnan, S., Bhatia, K., (2009) SOAs for scientific applications: Experiences and challenges. Future Generation Computer Systems, 25(4), 2009, pp 466-473.