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"CLASCA": Learning System for Classification and Capitalization of Accident Scenarios of Railway

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ABSTRACT
In the process of analysis and assessment of the safety of a rail transportation system, one of the difficulties is to ensure the completeness of the accident scenarios taken into account by all the actors involved in the development of the system. The present work is to formalize, classify and archive the historical scenarios experienced on transportation systems in French already certified and/or approved such that the VAL, MAGGALY, TVM 430 of the TGV Nord. The goal is to develop a database of historical scenarios from the know-how of the manufacturers, masters of book and experts and researchers from the French Institute IFSTTAR to help examine the completeness of safety analyzes. The development and the operation of this basis of scenarios have need resort to the techniques of knowledge acquisition and automatic learning. The application of methods for the acquisition of knowledge has resulted essentially on the constitution of a database of historical knowledge which comprises 70 scenarios relative to the risk of "collision". The exploitation by machine learning of this basis of scenarios in order to extract the relevant knowledge in a purpose explanatory or made decision-making the object from the system "CLASCA" presented in this paper.
Keywords: Railway transport, Safety, Accident Scenarios, Risk assessment, Machine learning, Knowledge acquisition, Knowledge based system.

I. INTRODUCTION

The modes of reasoning which are used in the context of safety analysis (inductive, deductive, analogical, etc.) and the very nature of knowledge about safety (incomplete, evolving, empirical, qualitative, etc.) mean that a conventional computing solution is unsuitable and the utilization of artificial intelligence techniques would seem to be more appropriate. The aim of artificial intelligence is to study and simulate human intellectual activities. It attempts to create machines which are capable of performing intellectual tasks and has the ambition of giving computers some of the functions of the human mind - learning, recognition, reasoning or linguistic expression. Our research has involved three specific aspects of artificial intelligence: knowledge acquisition, machine learning and knowledge based systems (KBS). Development of the knowledge base in a KBS requires the use of knowledge acquisition techniques in order to collect, structure and formalizes knowledge. It has not been possible with knowledge acquisition to extract effectively some types of expert knowledge. Therefore, the use of knowledge acquisition in combination with machine learning appears to be a very promising solution. The approach which was adopted in order to design and implement an assistance tool for safety analysis involved the following two main activities [1]:

– Extracting, formalizing and storing hazardous situations to produce a library of standard cases which covers the entire problem. This is called a historical scenario knowledge base (HSKB). This process entailed the use of knowledge acquisition techniques,
– Exploiting the stored historical knowledge in order to develop safety analysis know-how which can assist experts to judge the thoroughness of the manufacturer's suggested safety analysis. This second activity involves the use of machine learning techniques.

The following section presents these two activities which are involved in the methodology of assessing the safety of rail transport.

II. KNOWLEDGE ACQUISITION AND MACHINE LEARNING: TWO APPROACHES TO IMPROVE THE PROCESS OF EXPERTISE TRANSFER

Knowledge acquisition [2] was recognized as a bottle neck from the first appearance of expert systems, or more generally knowledge based systems (KBS). It is still considered to be a crucial task in their creation. Extraction or elicitation refers to the collection of knowledge from experts in the field whereas the concepts of transfer or transmission of expertise refer to the collection and subsequent formalization of the knowledge of a human expert. The term knowledge acquisition refers to all the activities which are required in order to create the knowledge base in an expert system.

Knowledge acquisition (KA) is one of the central concerns of research into KBSs and one of the keys not only to the successful development of a system of this type but also to its integration and utilization within an operational environment. Two main participants are involved in KA: the expert, who possesses know-how of a type which is difficult to express, and the cognitive scientist who has to extract and formalize the knowledge which is related to this know-how, which as far as the expert is concerned is usually implicit rather than explicit.

This time-consuming and difficult process is nevertheless fundamental to the creation of an effective knowledge base. While KA was at the outset centered around the expert/cognitive scientist pairing it very soon raised crucial problems such as the identification of the needs of users or the selection of a means of representing knowledge. The excessive divergence between the language which the experts used in order to describe their problem and the level of abstraction used in representational formalizations of knowledge provided the motivation for a large amount of research aimed at facilitating the transfer of expertise.

The new KA approaches aim to specify more effective methodologies and to design software's which assist or partially replace the cognitive scientist. Some work suggests viewing the design of a KBS as a process of constructing a conceptual model, on the basis of all the available sources of knowledge (human or documentary) which relate to solving the problem. In this context KA is perceived as a modeling activity. Other research stresses the benefits of methods which guide the cognitive scientist in the transfer/modeling process. Tools and techniques are used to provide assistance with verbalization, interviews with experts and document analysis. Currently available KA techniques mainly originate in cognitive psychology (human reasoning models, knowledge collection techniques), ergonomics (analysis of the activities of experts and the future user), linguistics (to exploit documents more effectively or to guide the interpretation of verbal data) and software engineering (description of the life cycle of a KBS).

In summary, KA may be defined as being those activities which are necessary in order to collect, structure and formalize knowledge in the context of the design of a KBS. A survey of state of the art research in the domain of knowledge acquisition made it possible to select a method for developing a KBS for aid in the analysis of safety for automated terrestrial transport systems. This method showed itself to be useful for extracting and formalizing historical safety analysis knowledge (essentially accident scenarios) and revealed its limits in the context of the expert safety analysis, which is particularly based on intuition and imagination.

In general, current knowledge acquisition techniques have been designed for clearly structured problems. They do not tackle the specific problems associated with multiple areas of expertise and the coexistence of several types of knowledge and it is not possible to introduce the subjective and intuitive knowledge which is related to a rapidly evolving and unbounded field such as safety. Although cognitive psychology and software engineering have produced knowledge acquisition methods and tools, their utilization is still very restricted in a complex industrial context. Transcribing verbal (natural) language into a formal language which can be interpreted by a machine often distorts the knowledge of the expert.

This introduces a bias in passing from the cognitive model of the expert to the implemented model. This disparity is in part due to the fact that the representational languages which are used in AI are not sufficiently rich to explain the cognitive function of experts and in part to the subjective interpretation of the cognitive scientist.

These constraints act together to limit progress in the area of knowledge acquisition. One possible way of reducing these constraints is combined utilization of knowledge acquisition and machine learning techniques. Experts generally consider that it is simpler to describe examples or experimental situations than it is to explain decision making processes. Introducing machine learning systems which operate on the basis of examples can generate new knowledge which can assist experts in solving a specific problem. The know-how of experts depends on subjective, empirical, and occasionally implicit knowledge which may give rise to several interpretations.

There is generally speaking no scientific explanation which justifies this compiled expertise. This difficulty emanates from the complexity of expertise which naturally encourages experts to give an account of their know-how which involves significant examples or scenarios which they have experienced on automated transport systems which have already been certified or approved.

Consequently, expertise should be updated by means of examples. Machine learning can facilitate the transfer of knowledge, particularly when its basis consists of experimental examples. It contributes to the development of the knowledge bases while at the same time reducing the involvement of cognitive scientists. In our approach, learning made use of the HSKB to generate new knowledge likely to assist experts evaluates the degree of safety of a new transport system. Learning is a very general term which describes the process by which human beings or machines increase their knowledge. Learning therefore involves reasoning: discovering analogies and similarities, generalizing or particularizing an experience, making use of previous failures and errors in subsequent reasoning [3], [4] [5].

The new knowledge is used to solve new problems, to carry out a new task or improve performance of an existing task, to explain a situation or predict behavior. The design of knowledge acquisition aid tools which include learning mechanisms is essential for the production and industrial development of KBSs. This discipline is regarded as being a promising solution for knowledge acquisition aid and attempts to answer certain questions [3]: how can a mass of knowledge be expressed clearly, managed, added to and modified?

Machine learning is defined by a dual objective: a scientific objective (understanding and mechanically producing phenomena of temporal change and the adaptation of reasoning) and a practical objective (the automatic acquisition of knowledge bases from examples). Learning may be defined as the improvement of performance through experience.

Learning is intimately connected to generalization [4]: learning consists of making the transition from a succession of experienced situations to knowledge which can be re-utilized in similar situations. Expertise in a domain is not only possessed by experts but is also implicitly contained in a mass of historical data which it is very difficult for the human mind to summarize. One of the objectives of machine learning is to extract relevant knowledge from this mass of information for explanatory or decision making purposes. However, learning from examples is insufficient as a means of acquiring the totality of expert knowledge and knowledge acquisition is necessary in order to identify the problem which is to be solved and to extract and formalize the knowledge which is accessible by customary means of acquisition. In this way each of the two approaches is able to make up for the shortcomings of the other. In order to improve the process of expertise transfer, it is therefore beneficial to combine both processes in an iterative knowledge acquisition process.

Our approach has been to exploit the historical scenario knowledge base by means of learning with a view to producing knowledge which could provide assistance to experts in their task of evaluating the level of safety of a new system of transport.

III. ASSESSMENT OF RAILWAY TRANSPORT SAFETY

One of the research activities which is currently in progress at the French institute IFSTTAR relates to the certification of automated public transport systems and the safety of digital control systems. Our study took place within this context and aimed to design and create a software tool to aid safety analysis. The purpose of this tool is to evaluate the completeness and consistency of the accident scenarios which have been put forward by the manufacturers and to play a role in generating new scenarios which could be of assistance to experts who have to reach a conclusion regarding the safety. As part of its missions of expertise and technical assistance, IFSTTAR evaluates the files of safety of guided transportation systems. These files include several hierarchical analysis of safety such as the preliminary analysis of risks (PAR), the functional safety analysis (FSA), the analysis of failure modes, their effects and of their criticality (AFMEC) or analysis of the impact of the software errors. These analyses are carried out by the manufacturers. It is advisable to examine these analyses with the greatest care, so much the quality of those conditions, in fine, the safety of the users of the transport systems. Independently of the manufacturer, the experts of IFSTTAR carry out complementary analyses of safety. They are brought to imagine new scenarios of potential accidents to perfect the exhaustiveness of the safety studies. In this process, one of the difficulties then consists in finding the abnormal scenarios being able to lead to a particular potential accident. It is the fundamental point which justified this work.

The commissioning authorization for the transport system is granted by the relevant State departments on the basis of the certification dossier. Certification is the official recognition that a function, a piece of equipment or a system complies with a set of national or international regulations. State departments generally make use of external audits or expert bodies such as IFSTTAR in order to draw up certification notices. IFSTTAR has as its main objectives the examination and evaluation of the development, validation and approval methods of the system. This process consists of devising new scenarios for potential accidents to ensure that safety studies are exhaustive. One of the difficulties involved in this process is finding abnormal scenarios which are capable of generating a specific hazard. This is the fundamental issue which inspired this study. There is a hierarchy of several ranked safety processes which are accepted by INRETS and conducted by the manufacturer in order to identify hazardous situations, potential accidents, hazardous units or equipment and the severity of the consequences which would result. These processes are as follows [6]:

- Preliminary hazard analysis (PHA),
- Functional safety analysis (FSA),
- Hardware safety analysis (HSA)

– Software safety analysis (SSA)

Modes of reasoning used in security analysis (inductive, deductive, by analogy ...) and the nature of security knowledge (incomplete, evolving, empirical, qualitative ...) confirm that a conventional computer solution is inadequate and that the use of techniques of artificial intelligence (AI) seems most appropriate.

The approach which was adopted in order to design and implement an assistance tool for safety analysis involved the following two main activities:

– Extracting, formalizing and storing hazardous situations to produce a library of standard cases which covers the entire problem. This is called a historical scenario knowledge base (HSKB). This process entailed the use of knowledge acquisition techniques,
– Exploiting the stored historical knowledge in order to develop safety analysis know-how which can assist experts to judge the thoroughness of the manufacturer's suggested safety analysis. This second activity involves the use of machine learning techniques.

The next section presents the results of these research activities.

IV. RESULTS OF KNOWLEDGE ACQUISITION

The scenarios which have been collected together so far in the historical knowledge base relate to the collision problem and have been constructed on the basis of the Safety of railway transport systems French: VAL, POMA 2000, MAGGALY and TVM430 (Northern TGV). However, in spite of the large number of knowledge extraction sessions (approximately thirty) and the utilization of several knowledge collection techniques (interviews, questionnaires, protocol analysis, conceptual classification, etc.) the knowledge acquisition model did not permit the detailed identification of the mechanisms involved in the reasoning of experts, or the strategies and heuristic approach which they use in problem solving. This difficulty is essentially due to the novelty and complexity of the field and the intuitive, evolving and creative nature of the reasoning mode employed by experts [1].

We shall present below the results of knowledge acquisition as they relate to analyzing and characterizing an accident scenario.

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An accident scenario describes a combination of circumstances which can lead to an undesirable, perhaps even hazardous, situation. It is characterized by a context and a set of events and parameters. Knowledge acquisition led to the development of a model which is essentially based on the identification of the eight parameters which describe an accident scenario [1] (figure 1).

Examination of the concept of scenario revealed two fundamental aspects. The first is static and characterizes the context. The second is dynamic and shows the possibilities of change within this context, while stressing the process which leads to an unsafe situation. In the case of dynamic description we have adopted the formalism of Petri Nets. The Petri net makes it possible to focus attention onto a specific environment of the system for which there is a variety of plausible animation sequences. Each of these sequences corresponds to a scenario.

The form adopted for the static description is that of a list (figure 2) in which several essential descriptive parameters are described in attribute/value terms. Very schematically, guide way transit systems are considered as being an assembly of basic bricks and a new system possesses certain bricks which are shared by systems which are already known. In the context of this study the basic bricks which have currently been identified have been grouped together in the descriptive sheet, and the CLASCA tool finds and then exploits shared bricks in order to deduce the class to which a new scenario belongs or evaluate its completeness.

The main result of applying knowledge acquisition techniques was to develop a generic representation model for accident scenarios and create a historical scenario knowledge base which contained approximately sixty scenarios relating to the risk of a collision. Knowledge acquisition did, however, encounter the difficulty of extracting the expertise which is involved at each stage of the safety analysis process. This difficulty emanates from the complexity of expertise which naturally encourages experts to give an account of their know-how which involves significant examples or scenarios which they have experienced on automated transport systems which have already been certified or approved. Consequently, expertise should be updated by means of examples. Machine learning can facilitate the transfer of knowledge, particularly when its basis consists of experimental examples. It contributes to the development of the knowledge bases while at the same time reducing the involvement of cognitive scientists. In our approach, learning made use of the HSKB to generate new knowledge likely to assist experts evaluates the degree of safety of a new transport system.

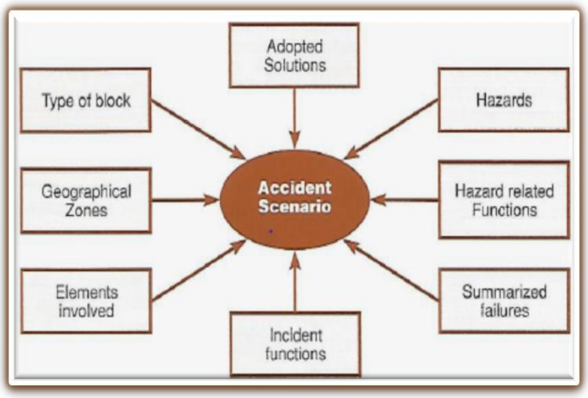

Fig.1 Parameters which describe an accident scenario

List of attributes	List of possible values
Type of block	Fixed block
	Moving block
Hazards	Collision
	Derailment
	Poorly controlled emergency evacuation
	Falling in a vehicle
	Falling onto the way
	Person dragged along the way
	Electrocution
	Shock during door closure
Hazards related functions	Management of automated driving
	Train localization
	Control of entrance and exit
	Train monitoring
	Management of direction control
	Speed instruction
	Management of train stopping
	Platform/Way Safety
	Full control/High Voltage permission
	Redundancy switching
	Initialization
	Manual driving
	Alarm management
	Evacuation
	Pushing
	Protection of routes
	Traction/braking
Geographical zones	Terminus
	Station
	Line
	Train entry
	Section limit
Elements involved	Number of trains'
	CC operator
	Mobile operator
	AD with redundancy
	AD without redundancy
Incident functions	Route management
	Traffic control
	Instructions (consistency, vigilance)
	Communication (transmission)
Summarized failures	SF52 Stationary train on way
	SF24 Permanent traction failure
	SF9 Entering occupied block
	SF11 Invisible element in the zone of completely automatic driving
	SF10 Erroneous re-establishment of Safety frequency/High voltage
Adopted solution	AS51 Check the traction current during emergency braking, open circuit breakers if necessary

Fig.2 List of the parameters which relate to an example of accident scenario

V. THE GENERAL PRINCIPLE OF THE CLASCA SYSTEM

CLASCA is a learning system which uses examples in order to find classification procedures. It is inductive, incremental and dedicated to the classification of accident scenarios. In CLASCA the learning process is no monotonic, so that it is able to deal with incomplete accident scenario data, and interactive (supervised) so that the knowledge which is produced by the system can be checked and in order to assist the expert in formulating his expertise. CLASCA incrementally develops descriptions of classes of historical scenarios with a dual purpose of characterizing a set of unsafe situations and recognizing and identifying a new scenario which is submitted to the experts for analysis. CLASCA contains five main modules (figure 3):

- A scenario input module,
- A predesign module which is used to assign values to the parameters and learning constraints which are required by the system. These parameters mainly affect the relevance and quality of the classification knowledge which is learnt and the rapidity with which the system achieves convergence,
- An induction module for learning descriptions of scenario classes,
- A classification module, the purpose of which is to deduce the class to which a new scenario belongs on the basis of descriptions of classes which have been found by induction (inferred)

previously and by referring to a similarity criterion,

– A dialogue module for the reasoning of the system and the decision of experts. In justification the system retains a result from the deduction phase in order to construct its explanation. Following this phase of justification of classification decisions the expert decides either to accept the proposed classification (in which case CLASCA will learn the scenario) or to reject this classification. In the second case it is the expert who decides what subsequent action should be taken. He may, for example, modify the learning parameters, create a new class, alter the description of the scenario or put the scenario on one side for later inspection.

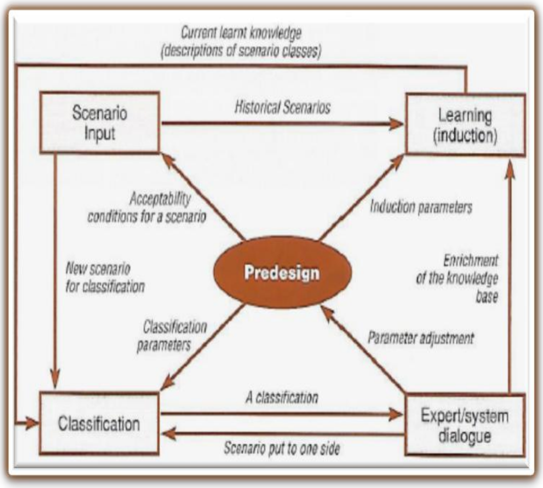

Fig.3 General Architecture of "CLASCA"

The purpose behind this is to provide the expert with historical scenarios which are partially or completely similar to the new scenario. This mode of reasoning is analogous to that which experts use when they attempt to find similarities between the situations which have been described by the manufacturer's scenarios and certain experienced or envisaged situations involving equipment which has already been certified and approved. Classification of a new scenario involves the two following stages:

– A characterization (or generalization) stage for constructing a description for each class of scenarios. This stage operates by detecting similarities within a set of historical scenarios in the HSKB which have been pre-classified by the expert in the domain,
– A deduction (or classification) stage to find the class to which a new scenario belongs by evaluating a similarity criterion. The descriptors of the new scenario (figure 2) are compared with the descriptions of the classes which were generated previously.

This level of processing not only provides assistance to the expert by suggesting scenarios which are similar to the scenario which is to be dealt with but also reduces the space required for evaluating and generating new scenarios by focusing on a single class of scenarios Ck.

CLASCA involves the collection of safety analysis knowledge with respect to automated transport systems. This knowledge is as follows:

– The HSKB which consists at present of about sixty historical scenarios which relate to a collision hazard. These scenarios have been formalized on the basis of a static description then placed in classes by the expert,
– An accident scenario description language, which consists of a set of descriptors (figure2: parameters which describe a scenario). These were collected during the knowledge acquisition phase and a type and a field are associated with them,
– Accident scenarios which are described using this language. These may be historical and pre-classified by the expert in order to add to the HSKB, or new and suggested by the manufacturer. In the second case the experts will attempt to evaluate the consistency of the scenarios,
– Learning parameters (induction, classification and convergence parameters),
– Acceptability constraints for a scenario.

1. Induction of descriptions of classes of scenarios

This stage involves generalizing the classes which have been pre-defined by the experts in order to generate a comprehension description for each class which both characterizes the division which has been conducted by the expert and makes it possible to identify to which class the new example belongs. Each description which is learnt is characterized by a combination of three elements: (<Attribute> <Value> <Frequency>). The frequency of appearance is computed for each descriptor (attribute/value) in order to limit the loss of information. As an example, figure 4 shows the characteristic description of the "initialization sequence" class which was generated by CLASCA.

The description of a class is further enriched by taking into account the associated summarized failures which are involved. These SFs will subsequently be exploited in order to develop the base of learning examples.

2. Classification of a new example of a scenario

In this stage a new example of a scenario is assigned to an existing class Ck. For this it is necessary to define a classification criterion which measures the degree of resemblance between the new example and each of the pre-existing classes. This similarity criterion is based on statistical calculations and takes account of the semantics of the domain of application. In the situation where CLASCA has assigned the new example of a scenario to a class, this class needs to be updated. The updating process generates four situations as below:

– The phenomenon of particularization of descriptors: descriptors which are considered characteristic at the instant t may lose their significance at the instant (t+1),
– The phenomenon of generalization of descriptors: descriptors which are considered not to be meaningful may become characteristic,
– Phenomena of simultaneous particularization and generalization,
– The learning of new descriptors which enrich the description of the class.

This phenomenon of descriptor changeability demonstrates the no monotonic character of learning in CLASCA.

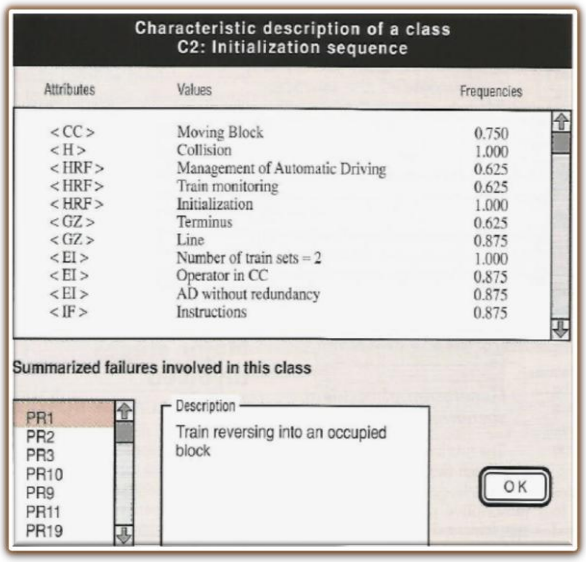

Fig.4 Example of a characteristic description of a class C2: Initialization sequence

VI. INCREMENTALITY, CIRCULARITY OR ITÉRATIVITÉ OF LEARNING

The ideal behavior of a system of learning would be the one who, looping on itself, continually improve its knowledge to the contact of the experiments in which it is confronted. This characteristic of systems who learn, adapt or evolve is qualified of "iterative dimension" or even "circularity" of knowledge [4]: a knowledge induced can be used with a view to learn new knowledge that will serve themselves to build other. For that a learning process is continuous, it must be that the bulk of the information contained in the scenarios of accidents is retained in order to ensure that the learning continues with the new scenarios. As well the notion of incrementality means not only that the system CLASCA accepts the examples of accident scenarios one after the other. Furthermore, it should be that when adding a new example scenario, the amendments to be made do not result in the complete reconstruction of the knowledge obtained from all of the scenarios in the learning base. This characteristic of the learning is often necessary to allow for the use of the information learned when the whole of learning is not yet sufficiently representative of the field of application such as the rail safety.

In summary, a system of learning is incremental said if it is endowed with the capacity to evolve the knowledge learned in the course of a previous cycle, without having to each time reprocess all of the examples collected. However, the evolution of the knowledge during the course of a learning process generates two types of incrementality: monotonous and non-monotonic.

In the monotonous incrementality (growth or decline continues of knowledge) The learning does that produce new knowledge to complement the initial knowledge without calling into question the knowledge already learned. It follows that the capacity to recognize its own errors seems to be absent. The monotonous incrementality is not adapted to the treatment of noisy data or scalable.

In learning non-monotonic, it is to integrate a new object (scenario of accident) in an existing hierarchy, while restructuring this last. The shaft is built using four operators: creation of a node, deleting a node, merger of two nodes and bursting in two of a node. In the presence of a new example to classify, the learning process can undo what it has learned in the previous step: to destroy a Node already created, burst a node previously merged. This reversibility of the process allows an evolution non-monotonic of knowledge.

Unlike the approach monotonous, learning non-monotonic is better adapted to the noisy data, however the process does not offer more guarantees of convergence and becomes theoretically capable of swinging or loop. Generally the convergence is ensured by progressively reducing the influence of the accident scenarios considered. As well, as the process of learning advance, the examples are less and less determinants. The knowledge acquired gradually takes the not on new examples 'learning. This leads inevitably to sensitivity to the order of taking into account the examples of accident scenarios.

This last point is a main objective of our research work in order to improve the update phase of the learning base in the CLASCA system.

VII. CONCLUSION

In artificial intelligence, we perceive two major independent research activities: the acquisition of knowledge which to better understand the transfer of expertise and the machine learning proposing the implementation of inductive, deductive, abductive techniques or by analogy to equip the system of learning abilities. The methodology which was adopted in order to design and implement an assistance tool for safety analysis involved these two activities. The development of system "CLASCA" for safety insisted us to use jointly and complementary both approaches. The purpose of this tool is contribute to the generation of new accident scenarios that could help experts to conclude on the safe character of a new rail transport system. CLASCA is a learning system which uses examples in order to find classification procedures.

It is inductive, incremental and dedicated to the classification of accident scenarios. In CLASCA the learning process is nonmonotonic, so that it is able to deal with incomplete accident scenario data, and interactive (supervised) so that the knowledge which is produced by the system can be checked and in order to assist the expert in formulating his expertise. CLASCA incrementally develops descriptions of classes of historical scenarios with a dual purpose of characterizing a set of unsafe situations and recognizing and identifying a new scenario which is submitted to the experts for analysis. The purpose behind this is to provide the expert with historical scenarios which are partially or completely similar to the new scenario. This mode of reasoning is analogous to that which experts use when they attempt to find similarities between the situations which have been described by the manufacturer's scenarios and certain experienced or envisaged situations involving equipment which has already been certified and approved.

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