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Current practices and future trends in expert system developments for use in the nuclear industry

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FOREWORD

One important aspect contributing to the enhancement of nuclear safety in recent years is the increasing use of computer technology. Introducing computer capabilities into the control rooms resulted in the development of computerized operator support systems. With time, these systems evolved into decision making aids with capabilities for diagnosis, trend analysis and assessment of recovery actions. A further step is the introduction of expert systems where large knowledge bases are utilized to give advice to operators when faced with difficult situations.

The International Atomic Energy Agency has sponsored a number of meetings which have explored the application of expert systems technology for use by the nuclear industry. Reports produced from these meetings have examined expert systems in terms of their technical foundation, the current state of their use and their future potential. The purpose of this report is to review the current trends in this area.

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1. INTRODUCTION

The International Atomic Energy Agency has sponsored a number of meetings which have explored the application of expert systems technology for use by the nuclear industry. Reports produced from these meetings have examined expert systems in terms of their technical foundation (October 1988 [1]), the current state of their use (October 1991 [2]) and their future potential (September 1992 [3]). The purpose of this report is not to repeat what has already been accomplished in the area of expert system evaluation, but to establish the framework for an IAEA specialists meeting, which will examine the current trends in this area.

In general, conclusions from previous IAEA studies of expert systems suggest that the field is developing rapidly and that measures should be taken to ensure that their future development addresses several important technical and implementation issues. This is especially important within the nuclear industry, where the use of expert systems has been shown to be a critical asset in the management of nuclear facilities. Previous IAEA reports have concluded that, now that this technology is maturing, it is time to pursue the use of standardized tools so that development time and cost can be reduced. Additional areas of emphasis need to be applied to the process of expert system validation and verification, the use of sound ergonomics in the development of the user interface, and improvements made in the way this technology is introduced to plant management.

Over 300 expert systems have been developed corresponding to 60 distinct fields of applications within the nuclear industry [4]. Many of these systems are now commercially available, although the majority remain in the prototype stage of development. The rapid progress in this field has been brought about through advances in computer processing speed, the commercial availability of rapid prototyping software, and improvements in techniques of building knowledge bases, to name a few. This trend will continue to the extent that preparations need to be made for ensuring that the necessary supporting resources are provided by the industry as the technology is integrated into plant operations. This will become a more critical requirement as new expert system applications are fielded.

There are three major objectives of this report. Each relates to the development of expert systems which improve the safety and efficiency of nuclear facility operations. The first objective is to identify the major distinct applications of expert systems as they relate to nuclear safety. The second objective is to identify future expert system development trends in order to help anticipate emerging tools which may spark rapid development or identify trends which may hinder its growth. The third objective is to identify development challenges.

2. NUCLEAR SAFETY APPLICATIONS

One of the key reasons why expert systems have demonstrated such great potential within the nuclear industry is due to their ability to assist in the management, diagnosis, and formulation of decisions [5]. Not as a substitute, but rather as an assistant, expert systems can be used to improve plant safety by increasing the operator's comprehension and efficiency. This is especially the case in areas where plant safety is directly affected.

2.1. PLANT SAFETY APPLICATIONS

Previous IAEA reports have identified a large number of both on- and off-line expert system applications under development throughout the world. Although one can argue that any application can be related to improving safe plant operations, it may be more relevant for this report to discuss applications which are directly related to plant safety on a day-to-day basis. Areas not directly related to plant safety are subject to the same conclusions relative to future development trends as those which are safety related.

Safety applications include those related to component condition assessment and safety system monitoring, alarm and post trip analysis, emergency planning and response, risk assessment and accident diagnosis. There are a number of expert systems which can also be classified as general operator advisors. These systems integrate databases, such as technical specifications and plant procedures, into near real-time plant operations. Table I summarizes the general expert system fields.

2.2. IMPLEMENTATION CHALLENGES

As expert systems development moves from concept through prototype into commercialization and implementation, many of the key success factors begin to emerge. These success factors can also be represented as obstacles to their successful use by the industry. Often, it is only through a technology's use that actual performance benefits can be realized. This is especially the case with expert systems. Listed below are many of the more recent issues which must be addressed if one expects this field to mature to a point where their potential benefit can be fully realized.

1. How can user requirements be better defined within the system specification?

Often the design and early development of an expert system is launched without the direct involvement of facility personnel. When the system is prepared for plant testing, significant modifications may be expected because of unacceptable performance features identified by plant personnel. This is a problem more related to the organizational split between those individuals developing the expert system code (typically the research and development department or the engineering department) and plant operations personnel. Improvements in the manner in which the expert system subject matter experts are involved in the system's development need to be made.

2. What role can (or should) the nuclear facility play in the development of the expert system?

This issue relates to the more global involvement of the facility. Whereas user needs can be addressed through the early involvement of plant experts, the plants' involvement at all levels - both technical and management - needs to be examined. The management of the Nuclear Power Plants has to be adjusted to satisfy the requirements of the future expert system advisors. The final goal of the plant operation should not be forgotten at any stage of expert system development: efficient and safe electricity production.

3. What measures are in place that ensure the quality of the system? How can this quality be tested?

Few, if any, quality standards are available for those developing expert systems. Since these systems are being developed for use in the design, operation, administration, and

TABLE I. GENERAL NUCLEAR INDUSTRY EXPERT SYSTEM APPLICATION AREAS

PLANT OPERATIONS

- Plant status monitoring
- Alarm diagnosis and filtering
- Sensor validation
- Procedure tracking
- Maintenance planning and scheduling
- Technical specification conformance
- Risk monitoring
- Maintenance risk assessment
- Plant thermal performance
- Support system monitoring and analysis
  - Chemical and volume control system
  - Diesel generator servicing
  - Water treatment analysis
  - Radiation protection
  - Xenon oscillations
- Loose parts detection
- Noise analysis
- Steam generator leak detection
- Causal analysis of plant behavior
- Outage planning
- Refuelling optimization and management

EMERGENCY PLANNING AND RESPONSE

- Emergency preparedness and response
  - On-site emergency response
  - Off-site emergency response
- Design basis accident management
- Severe accident management
- Plant security monitoring
- Fire protection
- Transient analysis and safety calculations

maintenance of facilities - all areas controlled by quality standards - it is reasonable to expect that such controls be made available specifically for expert systems. Existing software configuration management standards, although developed in response to quality requirements, are not necessarily relevant to the design and testing of expert system software. The standards for expert system shells and knowledge bases should be developed separately.

4. Have appropriate validation and verification (V&V) procedures been established?

Related to the area of quality control is that of expert system software V&V. Although guidelines have been developed for the design and development of expert systems [6], the content validity of a complex knowledge base can never be fully determined. As a result, future developers need to take into consideration site specific V&V procedures when evaluating the accuracy and completeness of their knowledge bases regardless of how the knowledge base is represented.

5. What organizational issues need to be resolved in order to ensure that the expert systems can be successfully integrated into the facility?

In some instances, expert systems will find their way into plant operations which involve personnel who are responsible for managing severe plant upset conditions (i.e. accident managers) and licensed personnel in the control room who are directly responsible for plant control decisions. Conflicts may emerge which may result in contradictions in plant control recommendations due to conflicting advice from within the control room and adjacent technical support centres or nearby emergency support facilities. The users must be defined early in the system development process. The hierarchy and responsibilities of each subject involved in management of severe situations should be clearly defined in advance.

6. What training resources are available to prepare and qualify expert system users?

The user of the expert system is typically not the developer. As a consequence, a significant amount of preparation needs to be made toward the development of training materials (manuals, training software, accident scenarios, etc.) for the end user. Indeed, the development of the software, from the user interface to the maintenance and evolution of the software, should incorporate realistic training requirements. Guidelines for the development of computer aided training software are available; however, little is available specific to expert systems. As a consequence, specific expert system training guidelines may be necessary as prototype systems are commercialized for plant use. Since expert systems are generally not safety grade equipment and their operation in emergency cases is therefore not guaranteed, the training of the users should emphasize the solely advisory role of such tools.

7. What role should the licensing play in the selection, installation, and verification of the system?

In general, if realistic studies of expert system effectiveness and reliability are performed, then some degree of regulatory approval may be realized. To date, however, reliance on computer-aided support is discouraged unless information is received in an advisory capacity in parallel with plant instrument information displays. As a consequence, plant licensing personnel need to be aware of any software, especially software used for operations advisement, that directly or indirectly affects safe plant operation and maintenance. The development of expert systems has not yet reached the point where it may replace any part of plant operation subject to regulatory body licensing.

8. What limitations need to be placed over the 'levels of assistance' provided by the expert system?

The greater the degree of modelling accuracy of an expert system and the more realistic it can display this information, the greater becomes the degree of operator acceptance. It is likely that some degree of "perceptual capture" may result from high fidelity systems. Consequently, a system designed as an advisor may become too close to an assistant to the extent that the technical foundation of the advisory support is not questioned by the user. This is also an issue related to system failure. Future systems must provide obvious indications to the user if any failures in logic occur, regardless of how subtle.

9. What criteria should be used for defining an acceptable or optimum user interface?

There are a number of man-machine interface guidelines in print which provide some degree of guidance for the design of computer generated information displays. Little guidance, however, is available for the design of expert system user interfaces. Although work in this area is progressing, it is important for the ultimate users to ensure that their requirements are compatible with good practices of display design. Independent assessments of information display effectiveness need to be provided at all stages of the expert system user interface design. With the advancement of graphical user interfaces, which utilize simple icon point and click tasks, the simplicity of the interface should become more common.

10. What measures have been implemented to ensure that future system changes can be conveniently made?

The art of expert systems resides in the way human experience is encoded in various knowledge representation schemes within a computer. Humans build on previous knowledge in complex and unique ways. Building upon previous knowledge within the structure of software code is not as obvious and elegant as human learning. This represents a major challenge for expert system developers. How can knowledge representation schemes (inference engine) and content (knowledge base) change as system modifications are made?

Ideally, the inference engine is designed with the need for future changes in mind. However, this is not always the case. It is usually the case that the knowledge base will change and, therefore, provisions must be made for this requirement. This represents a significant expert system maintenance issue and cost element.

11. What plant modifications need to be made in order to fully integrate an expert system into the facility?

In addition to the organizational and procedural issues which need to be addressed as expert systems are integrated into a facility, what are the plant hardware and software interface modifications required of on-line, near real-time systems? This is a system implementation element which is often overlooked until the later stages of the system's development. Early on in the design process special preparations need to be made to ensure that the physical interface between the data acquisition component of the expert system can "talk" to the plant computer. This interface usually consists of software modules, or "client servers", data format protocols and transmission standards. Defining the communication interface with the plant's computer early in the design process helps to bridge the gap between the facility and the development team. It also provides additional assurance that the system is compatible with plant dynamics.

Each of the issues cited above represents design and implementation issues which contribute to the overall success of an expert system development project. Whereas early development issues focused on identifying and refining technical solutions, new challenges are emerging which deal with the implementation and management of this technology. Successful programs in the future will demonstrate a balance among all of these variables.

3. FUTURE TRENDS

Improvements in expert system development tools are expected to be realized over the next few years. Improvements in computing speed and reductions in hardware costs are expected to continue throughout the next decade. The development of expert systems will become more affordable. As a result, additional applications can be expected to emerge which will broaden the usefulness and appeal of this technology. The following discussions summarize the basic areas of anticipated future change.

3.1. EXPERT SYSTEM DEVELOPMENT TOOLS

Early commercial expert system shells dominated the expert system market for a number of years. Although their use is widespread, there is a trend toward the use of object-oriented languages which can be more specifically tailored to solve logical problems independent of large shells. Commercial software packages in the future will allow the user to develop relationships without the overhead associated with generic artificial intelligence (AI) programming languages.

New, more efficient schemes for knowledge representation are emerging in the form of adaptive software, where the logic rules are self-organizing and reflect the ability of software to mirror events which it monitors in the real world. Adaptive software development tools are becoming commercially available to the non-expert programmer, such that decision support system concepts can be practically implemented without extensive knowledge of inference engine mechanics. Prototype tools are also becoming available for various types of personal computers and workstations.

3.2. SOFTWARE INTEGRATION

Expert systems which provide decision support at various levels of facility operation will require access to a wider variety of information sources. Consequently, core expert system programs will tap databases and communicate with a number of operator interfaces. For instance, in the case where an on-line advisor provides recommendations for maintenance priority, information must be accessed relative to the current state of particular plant components, previous maintenance records, pipe and instrumentation drawings, planning documentation and technical manuals. This information integration requirement will necessitate unique network design and traffic management techniques.

How all of this information is integrated will depend on information management schemes which will combine traditional logic structure, encoded as rules, with perhaps artificial neural networks - all accessing knowledge retained within a relational database. In order to provide a greater source of information support to the user, more data integration can be anticipated. In order to achieve this, more standardized programming tools will be required. Standard operating systems such as UNIX and DOS, standard communication protocols, and standard object oriented programming languages will be required in order to fully realize the potential of these hybrid expert systems.

3.3. GRAPHICAL USER INTERFACE

Two major system design issues will play an important role in the speed with which expert systems are developed and introduced to industry. First is the manner in which information is accessed and displayed to the user. Given the complexity of large on-line expert systems, unique methods must be used to provide the user with all levels of information understanding. Future user interfaces will be graphical in nature. Icons and windows will replace menu options and decision trees. Drawings will replace or augment textual information displays. Multi-dimensional graphics will represent flat surface displays and new techniques in data visualization and user tailored adaptive interfaces will emerge.

The control over the expert system will be achieved through point and click tasks, and word processing skill requirements will be kept to a minimum. Interface software will most probably be developed under X-Windows and Motif (UNIX) and Windows-3 (PC). A second design issue relates to the speed with which concepts are formalized and tested. Rapid prototyping software will become available that will allow the development and testing of user interfaces quickly, through the use of macro graphics codes. The ergonomics of information displays, as well as the quality of expert system logic can be assessed more rapidly and more thoroughly.

3.4. REAL-TIME PLANT INTERFACE

As the value of on-line expert systems is demonstrated, special requirements will surface relative to sensor health or validation. Basic questions regarding the validity of the monitored process must be assessed prior to, or in parallel with, the display of information to the user. Condition monitoring of the sensors must be distinguished from the condition of the system. As a consequence, there will be a greater use of sensor validation programs providing information on both component and system status. Therefore, conclusions regarding system performance can be made with some degree of confidence of parameter performance.

3.5. HYBRID SYSTEMS

The trend toward information integration was cited earlier in this report. As we learn to better match the problem with the solution, it is becoming clear that more than one solution may be required to solve a particular problem. In certain cases, complex non-deterministic problems will require access to simple information sources. Therefore, look-up tables may serve as information sources for logic driven programs, the output of which may serve an adaptive algorithm. All of the data traffic will be controlled by an information network manager. An example of such a circumstance is discussed below.

Expert systems which are designed for process monitoring must manipulate data in a variety of ways. This includes some form of data acquisition and quality verification, limit checking, pattern detection and matching, decision making, and user communication. The flow of data and program control commands can be complex. Although statistical methods are available to test data integrity and sensor validity, expert systems are being developed which apply rules to determine data quality. In cases where a rule-based approach may not be fast enough to keep up with high data rates, other less computationally intensive approaches may be more appropriate. This may take the form of an artificial neural network, a fuzzy logic approach, or related adaptive or probabilistic method. Regardless of how data are acquired or checked, the hybrid nature of the system becomes obvious as one moves into the processing of the data. Pattern matching logic may be conducted with the use of logical rules or, in the case of a very complex non-deterministic problem, an adaptive approach may be more appropriate. Perhaps more than one approach may be applied, in a serial fashion, to solve one problem. For instance, a set of rules may help structure data into distinct classes prior to being processed by an adaptive algorithm.

Finally, as data become sources of information, decisions need to be made relevant to the needs of the user. The expert system developer may find it appropriate to derive decisions from known rules, from most probable relationships, from best fit patterns or from simple look-up tables. Additionally, all of the data and information will have to be managed efficiently, so that the system can respond to the demands of the environment. The final expert real-time process monitoring and pattern recognition system will demonstrate a variety of approaches to information acquisition and reasoning. Clearly, a variety of methods may have to be implemented in order to provide the flexibility necessary for solving particular problems. Such hybrid systems will become typical of future expert systems.

4. DEVELOPMENT CHALLENGES

The excitement over the usefulness of expert system technology to improve nuclear plant safety is well founded. The development of effective software development tools and the availability of inexpensive computer platforms are all contributing to the rapid maturity of the field. The issues which may be standing in the way of the technology's practical application to the nuclear industry are broad in nature. Several of these key issues are discussed in the following paragraphs.

4.1. VERIFICATION AND VALIDATION

What constitutes a properly functioning expert system that fully meets the predefined objectives is a question which can never be answered beyond any reasonable doubt. However, measures can be taken to demonstrate that the developers have taken the necessary precaution to ensure the system's reliability. There is a need for the development of specific performance criteria for evaluating the effectiveness of an expert system. These criteria relate to speed of inference processing, repeatability, consistency under various degrees of uncertainty, completeness, accuracy and other performance dimensions which are related to process quality.

There are existing standards for safety related software, but there are few, if any, quality standards available for expert systems. Nuclear operators and nuclear facility staff are not necessarily prepared to develop software systems. The challenge is to organize a verification and validation (V&V) team that includes software experts and nuclear operations test specialists.

The V&V team must operate as an independent organization with the developing team from the beginning of the project.. The V&V team contributes to the software, hardware and integration requirement specifications describing minimal requirements, but must be independent from the beginning of the project.

The first verification task for the V&V team is the system design verification. In this phase a number of documents are used by the V&V team which were produced by the software developing team:

- Concept documentation
- System requirements specification
- Development schedules

The V&V team prepares a formal software verification and validation plan which guides the application of V&V to the software products to achieve the highest quality standards. Generally the V&V process by phase can be described as follows:

1. System design verification
2. Software specification verification

3. Software design verification
4. Software code verification
5. System Hardware and Software Integration Verification
6. System validation
7. Post-certification software change verification and validation

This process is not different from the handling of safety critical or related software. Standard verification and validation processes apply well to the procedural parts of an expert system, the control components and the inference engine, as furnished in an expert system "shell". Guidelines for verification and validation are available describing the minimum tasks phase by phase, and listing the documents required as input, or produced as output by the developing team and the V&V team.

Expert systems may not have a well-defined requirements specification, at least not early in the system development. One cannot handle expert systems following a typically procedural logic. They do not fit into the standard development sequence. The challenge expert systems represent is a need for quality control methods suited to an iterative development process and tests that are able to detect the kinds of errors occurring in expert systems.

The validity of a complex knowledge base requires a totally new approach. This problem seems to be similar to the problem of system specification verification. In the past, cognitive and intuitive tasks were very difficult to formalize. Today there are techniques available to prepare a system specification by using formal languages, for example PDL (program design language). Structures described by formal language can also be analyzed with computer-aided tools and their consistency and consequent behaviour can be verified. The challenge is to link such a formal language to the software to be able to (1) verify its completeness and accuracy and (2) automatically generate the system code from the formal design language.

Standard benchmarking methods are available to compare the performance of one system against another. This may include a series of realistic tests including evaluations of the user interface by experts in the area of display quality and operator surveys. Performance measurements include items such as cost, system size (number of rules), average time to examine or execute a rule, or any of the so-called metrics. These are evaluation methods, but are not related to validation unless they are implied or expressed in the system requirements. Finally, the procedures developed for the V&V of expert system software need to be integrated into the organization's quality assurance program.

For purposes of the nuclear industry it is strongly recommended that validated and codified knowledge be used for preparing the base of rules for an application. Knowledge refreshing sub-process should not be used in the development since the handling of this area requires added verification efforts.

Additionally, one should separate knowledge refreshing into another developing procedure. This way, the new version of the knowledge base or rule base following validation and confirmation can be encoded into the new version of the global expert system. After the knowledge or rule base is validated, the following steps of the development and V&V are followed:

1. Concept creation
2. Requirements analysis - Review knowledge and requirements

3. Requirements specification	-	Validate requirement specification, rough-out system validation test
4. Design prototype system	-	Review design against requirement Specification, evaluate knowledge rep.
5. Code prototype system	-	Verify correct coding against design spec.
6. Test prototype	-	Device test procedure test against requirements.
7. Validate and evaluate system	-	Device validation procedures Acceptance tests Training of users
8. Use and maintain the system	-	User evaluation

4.2. USER ACCEPTANCE

There are a number of unique tools being developed which are designed to evaluate the useability of development software and software systems. These tools will be invaluable assets as expert system developers look at ways to simplify the use of the system without sacrificing performance. When combined with the philosophy of early user involvement in the design process, and when accompanied with feedback from prototype tests, these useability evaluation tools will remove the acceptance barriers that exists in the field. The allocation of tasks between man and computer, redundancy and mutual control must be determined taking into account user acceptance. An expert system should be transparent for the end user.

4.3. KNOWLEDGE ENGINEERING

One of the most costly elements of the expert system development process is the transition from knowledge in the human domain to the domain of the computer. Current practices require direct interviews and extensive surveys. Knowledge representation schemes have to be developed, tested by subject matter experts and further verified and validated. It is a time consuming process which often serves as a barrier for the initiation of many projects. Although automatic learning methods, with the use of artificial neural networks, inductive learning, and case-based reasoning can obviate the need for knowledge engineering, such methods may not be appropriate for certain expert system applications. Knowledge acquisition time and expense remains as a significant barrier for certain expert system applications.

4.4. KNOWLEDGE REPRESENTATION STRUCTURE

The manner in which knowledge is represented within an expert system is dependent on the nature of the problem and the proposed solution. Especially in the area of process monitoring and diagnosis there is a trend toward the use of adaptive software where the scheme of knowledge representation is in the form of relationships among variables that organize themselves in a fashion that is unique to the pattern of activity being evaluated. The efficiency of this approach to knowledge representation results in a system which, in most instances, is less costly to develop. However, the availability of a plant's operating history or the use of high fidelity simulations, restricts the use of such knowledge representation to a limited number of applications. Regardless, future expert systems in the nuclear industry will use representation schemes that bear no resemblance to the logic structures of traditional knowledge bases.

Expert systems use the knowledge of the state and the components of the plant. Consequently, they need precise and up to date information. They must maintain a highly detailed computerized representation of a nuclear plant in its initial state and throughout its in-service life. This information can be shared by other software and expert systems. This information can also be used in the control room to maintain the plant or for CAD applications. The representation schemes of future expert systems must be compatible with such a system.

4.5. PLANT INTERFACE PROTOCOLS

Although most plant process computers are being linked to mainframes and peripheral computer monitors through standard communication networks, significant work remains in the development of expert system protocols. Currently, most expert system programs must be uniquely tailored to the network in place. The client-server must be developed to provide data to the expert system in a way which satisfies the unique data quality and processing requirements of the system. Although the development of a single standard protocol is not feasible due to the variety of applications, there is a need for guidelines in the general area of protocol development.

4.6. REGULATORY ACCEPTANCE

It is unclear if and when approval from a regulatory body will ever be granted for the use of an expert system as a stand-alone tool. However, given the acknowledgement from various regulatory bodies around the world that solutions are needed in the area of information management and display in the nuclear industry, it is likely that the use of such solutions may be approved outside of the control room and only on an advisory basis. The primary concern for any approval is the independence of any expert system from plant safety systems. This will be true in terms of physical plant isolation and in terms of operator decision-making without a high degree of confirmation. To ensure regulatory support (not only for solutions outside of the control room) on an advisory basis, the licensing organization must be directly involved in the V&V process from the beginning of the project. Their contribution would be in the area of supervising and evaluating the V&V plan and the process itself.

4.7. PEER REVIEW

As expert systems are developed and implemented at nuclear facilities it is important to consider the value of the peer review process as a means of guiding the system's development. Future systems will be developed with the advice of a task force, whose job it is to review the progress of the system's development, and provide constructive criticism during all development phases. Such a task force would accommodate outside, independent experts to review the progress of the project and evaluate its quality within the domain of expert systems technology.

5. CONCLUSIONS AND RECOMMENDATIONS

Expert systems have the potential to significantly contribute to the enhancement of safety and reliability at nuclear facilities. Although early systems focused on decision support tools related to plant information management, there is a trend toward the implementation of on-line systems designed for monitoring and diagnosis. The success of these systems depends to a great extent on the manner in which the users are integrated into each phase of design and testing. Additionally, realistic testing scenarios need to be developed which emphasize initial small scale demonstrations followed by full scale tests under realistic conditions. This structured approach will contribute to the technologies acceptance within the user organization and within regulatory agencies. The following discussion summarizes the recommendations which have emerged from this evaluation of the current practices and future trends of expert systems within the nuclear industry.

1. User involvement

A key factor for the successful implementation of an expert system within a nuclear facility is the involvement of the user. It is important to recognize the fact that developers of expert systems are not necessarily qualified in the area of plant operations. This gap needs to be filled by the project manager in such a way that both the developers and users respect the contributions to be made by each. Facility personnel need to become familiarized with the technical foundations of expert systems and expert system developers need to understand the practical needs of the facility.

2. Development of quality standards

The nuclear industry should take the lead in ensuring that the standards with which expert systems are developed are equal in quality to those standards used in plant design, operation, maintenance and administration.

3. Adoption of a formal V&V program

Software configuration management and structured testing programs need to guide the development of the expert system project. Performance criteria need to be established as part of the overall system specification and tests defined which will be used to assess the performance of the system. Wherever possible, independent means should be used to evaluate the performance of the software against a known benchmark. The program needs to be checked for consistency in expression of logical arguments and the matching of arguments with parameters. Program documentation within the source code should be provided, and testing of various decision paths within the code should be conducted.

4. Incremental approach to system development and testing

Start the project with a narrow, well defined application. Include the use of a pilot test program and increase the scope of the expert system once its feasibility is demonstrated. The incremental approach provides the opportunity for the user interface to be designed, tested and modified as required.

5. Organizational preparation

Ensure that representatives from various levels of plant management are kept informed of the progress of the project. Incorporate these individuals during the planning stage and throughout the development process. Establish the use of project reviews to help guide the program along a path that will satisfy the needs of the facility.

6. Early training program development

Training time and costs can be reduced through the development of a training program at the outset of the project. Training objectives can be defined and material developed as the project matures. Additionally, imbedded training capabilities may become part of the system design specification, thereby increasing the usefulness of the expert system software.

7. Regulatory communications

In situations where the expert system is used in safety related areas, then the early involvement of regulatory agencies is advisable. This involvement can be in the form of routine meetings, submittal of progress report and formal communiques regarding project status.

8. Knowledge base content and flexibility

The value of an expert system is in direct proportion to the content quality of the knowledge base and the manner in which the content is structured. Given the volume of material and complexity for typical nuclear installations, significant attention should be given to the quality of information and the manner in which information is organized in the knowledge base. Since relationships and interactions represent the major characteristics of a knowledge base, it is essential that heuristics (operator reasoning and experience) need to be merged with available models or algorithms. Redundant methods of knowledge representation are recommended wherever possible. The result is a system that is more reliable and defensible from the regulatory perspective. Finally, the knowledge base needs to be structured so that modifications in plant design or changes in operating procedures can be easily implemented.

9. Hybrid system architecture

Consider the benefits of combining more than one type of expert system to solve a particular problem. Rather than burden a single approach with peripheral tasks for which it was not designed, consider the use of different information processing schemes that can be combined without adding complexity to the system or affecting its reliability.

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Annex

PAPERS PRESENTED AT THE MEETING

USING KNOWLEDGE BASED SYSTEMS FOR RAMS ANALYSIS AND ON-LINE OPERATOR SUPPORT OF NUCLEAR POWER PLANTS

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Abstract

With the growing complexity of safety-critical industrial systems there is a need for computer-based tools which integrate different activities related to the layout of such systems and focussing on risk assessment in general. These activities should not only be applicable for early decision taking during the design phase but also allow an advanced maintenance over the whole life of an industrial system and even support on-line operator decision making. Thus such intended activities are embedded in an overall domain description flexible to adapt itself to different situations and extendible for any kind of additional information to attach to. On the other side, however, special applications running in the given domain should react to very specific contexts given by the user and keep their knowledge for themselves.

Current research resulted in the development of a methodology (STARS) and an off-line tool (Plant Editor) with which advanced layout techniques, domain administration and extension, and an evaluation of a layout topology are combined. In particular, when using this tool one has a powerful expert system for the design and maintenance of nuclear power plants.

In the second part of this paper a tool and methodology (FORMENTOR) for providing on-line decision support to operators is described.

1. Analysis of the current situation

Safety analysis - as it is done with the PSA (Probability Safety Analysis) method - shows some promising results. PSA is a good tool to collect, structure, and interpret safety-related information, and to identify and analyze strong and weak points in plant design and operation. As industrial installations are becoming more and more complex, and managing and evaluating a proper design and maintenance will be a problem of quantity, not mentioning quality aspects. In addition, safety aspects, especially for NPPs, have still to be refined, so that computerizing the task itself will not be that huge advantage as it was. Focus will therefore lie on a better use of the hardware provided: giving the programs a better quality, using advanced programming techniques, realizing a better data organization, etc. Concerning the design and licensing process - for which most PSA applications were made - any new method and tool will have to be based on that aspect.

Another requirement for changing the current situation comes from maintenance aspects and reviews of operating plants: each PSA represents a static picture - a snapshot - of the safety of a plant at a fixed moment of the plant's life cycle; performing a PSA now, however, puts some limits to its pervasion as a true risk management tool because maintaining a PSA up-to-date is cumbersome and costly and demands a lot of manpower; in most cases PSA models suffer from transparency and traceability. Even a minor change in, e.g., the plant layout, requires a lot of analysis to be repeated and, because of the many interrelationships, it is very difficult to guarantee consistency across the whole PSA model. Moreover, feedback from experience (date on failure events, initiating events, near-misses, precursors), from the plant itself or from other similar plants, has to be incorporated in the model.

A natural extension to try to use PSA in a more dynamic way caused the introduction of time as a variable for PSA which led to the so-called "Living PSA" model which can be regarded as a model for RAMS (Reliability, Availability, Maintenance, and Safety) analysis in the widest sense. Basic requirements for RAMS analysis are the following:

- possibility to represent and structure widely different kinds of information, i.e., all the information items considered in safety assessment;
- possibility to trace the analysis;

- possibility for incremental analyses, for updating the analyses without loosing consistency;
- possibility to collect and structure *all safety-related* expertise and experience in a re-usable form.

One major function of RAMS analysis is to support decision making in case of modifications to design or operation. For that reason there is a certain demand to predict future behavior of a plant system before the actual modification is done. This requires a simulator tool to prove a hypothetic situation to get predictions based on probabilistic calculations.

Concerning the RAMS analysis input it turned out that not all information and assumptions that go into a RAMS analysis are explicitly and systematically reported. Some of them remain in the heads of the analyst and are therefore sometimes difficult to backtrack. The same is true for some safety rationales underlying the design, too: some of those remain in the heads of the designers and there is a risk that might get overlooked in later design modifications.

Having this situation the most innovative points for a new approach of safety analysis were to

- collect safety-related information in a systematic way over the whole plant life-cycle: The aspect of covering all relevant information means to know location and time for occurrence of information.
- structure all available information: Classification means to define a logical structure and put the information in logical containers where appropriate. This is the point where information is becoming knowledge.
- gather knowledge: The integration of diverse types of knowledge within one system requires the syntactic acceptance and, semantically, the right use of "foreign" knowledge.
- provide the user with knowledge: Views at a-priori and derived knowledge make the whole system more transparent, and - as the results of a safety analysis should be treated as knowledge as well - a traceability of an analysis may be guaranteed by this.
- let the user put his own knowledge to the system: This requires the incorporation of user-dependent knowledge to the system. A proper working of the system has to be guaranteed.

From a user's point of view the requirements were

- immediate risk assessment of a certain layout topology
- monitoring safety evolution over a plant life-cycle
- having a robust and comprehensive system behavior.

To achieve all these points we had to go beyond the current capabilities of PSA or living PSA systems.

2. New approaches for RAMS analysis

Major solutions for new approaches came from the programming side:

- with advanced user interfaces powerful information systems can be built
- using knowledge-based systems (KBS) powerful expert systems can be performed.

The classification and the syntactic integration requirement (from above) are fulfilled by the use of KBSs. KBSs can be viewed and extended in an excellent way also.

The crucial point of decision was to bring different tasks together with one basic storing mechanism working in background. Thus knowledge about diverse aspects of a plant is kept together, and - as a consequence of the information system - viewable, accessible, modifiable, etc. Now knowledge is either derived automatically, or it is given manually to the system which means that it is entirely controlled by the user both in its logical dependency and temporal validity.

One aspect of the new methodology was to pre-elicitate a-priori knowledge in order to not to write large amounts of invariant knowledge each time the system is used. Such knowledge is surely representing plant hardware (components, units, etc.) but may describe functions and experiences, too. Similar knowledge is grouped within one knowledge base, while semantically different knowledge should be split into different knowledge bases. Generally spoken, the quality of a system is based on a proper user of a well-developed (external) knowledge base or - internally - on the grade of collaboration of knowledge bases.

Technically a knowledge base is a set of object-attribute-value triples; all triples with the same object identifier form a knowledge base entry. Knowledge base entries may semantically be classified thus forming a hierarchy of abstractions with special attributes describing the hierarchy connections.

3. The construction of an off-line tool for RAMS analysis

3.1 The aim

The Joint Research Centre is involved in several projects in which knowledge-based systems, information technology, and risk management methods within the context of safety-critical complex industrial systems are brought together. One major methodology developed was used to construct an expert system tool. With it promissing results were achieved in supporting industrial organizations managing their resources.

Starting with safety aspects it is in complex industrial installations highly desirable to develop a fast layout of an industrial system in order to predict as early as possible what might be the reason of a malfunctioning of some component. Being a certain kind of diagnostics process the looking up for reasons results in following more and more branches of a so-called fault tree. The complexity of a fault tree is proportional to the complexity of the underlying topology which the diagnostics process is based on. Therefore the fault tree construction should be directly connected to a given layout topology. The topology itself might have been developed according to some global semantic layout principles: horizontally seen there may be a distinction between a functional or a structural view of a plant system; vertically seen it is the abstraction that may alter: a plant system can be viewed as one single black-box, or as consisting of diverse sub-systems, etc. To know this abstraction level is important both for viewing (displaying) and storing aspects. In any case the system needs some external domain and expert knowledge as input to become an expert system. When this works the user should still be able to manipulate the derived knowledge; he should be able to monitor knowledge whenever a layout or fault tree construction is done. In particular the results of an assessment should be kept and traceable.

The domain knowledge is called generic because of its invariant character whereas a special plant system that has been created by the user forms some kind of specific knowledge established under a certain name (plant layout description). Knowledge put and/or retracted by the user is called temporary knowledge.

3.2 The STARS kernel

3.2.1 Introduction

Concerning off-line tool development major effort has been put to develop a methodology which was taken as basis within the STARS[1] (Software Tools for Analysis of Reliability and Safety) project. The objective was to provide knowledge-based support to all phases of design, maintenance, reliability, and safety assessment. Domains for which the STARS methodology has been developed so far are those of NPPs and chemical plants, describing their systems, sub-systems, components, their functional behavior and structural relations.

In the STARS project a number of tools has been developed (see Fig. 1) guaranteeing their collaboration [Poucet 90]; among these tools the so-called kernel (mainly consisting of the Plant Editor) and its underlying methodology is described.

3.2.2 Methodology

The main decisions made for this methodology are:

1. Use of an object-oriented database system as basic storing mechanism:
The introduction of an object-oriented database system (OODBS) substitutes previously made research which stored all relevant knowledge on Ascii files. Working with object-oriented methods [Meyer 88] also automatically provides inheritance mechanisms (within an hierarchically organized taxonomy tree), and allows the user to implement complex relational structures between different database entries.

2. Development of a CAD tool for design and risk assessment purposes:
It was decided to have as kernel tool a CAD tool (Plant Editor) with which a layout of a plant system can be developed. Basicly drawable objects can be chosen from a catalogue and placed

[1] STARS is a collaborative project with four partners contributing to it: Commission of the EC, Joint Research Centre Ispra; RISOE National Laboratory (DK); Tecsa SpA (I); VTT Technical Research Centre (SF). See also [HePoSu 92].

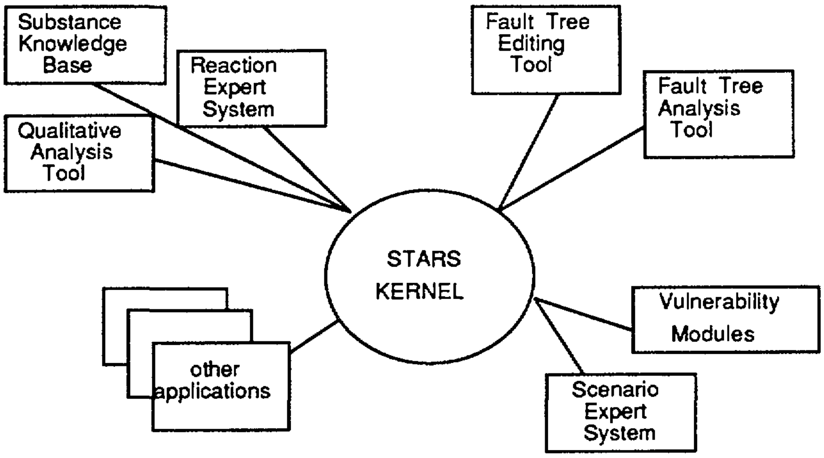

Fig. 1: The STARS project

on the screen. A layout becomes meaningful when objects drawn are connected each other appropiately thus creating a topology. Once having created a topology an immediate assessment may be done in terms of risks creating a so-called fault tree. All results - either from topology data or from risk assessment - are stored in the OODBS in appropriate structures and may be re-used later or in another STARS tool.

3. Use of generic knowledge to construct various specific applications:
The catalogue mentioned above offers drawable objects that come from a so-called generic knowledge base representing a domain taxonomy tree. Choosing one of these objects creates an instance of it (a copy) copying also all its generic knowledge into that instance. A topology created in this way contains specific knowledge of an application made by the user. There even user-dependent (i.e., not directly used for layout or risk purposes) knowledge may be incorporated.

4. System views and system extendability for user purposes:
The user should be able to view any objects selected in his layout. A view should contain all the knowledge attached to that object - either generic or specific knowledge. With a special mechanism an overwriting of already known specific knowledge and the attachment of new knowledge should be allowed by the user. A special point concerns the risk assessment part where rules are used for execution: there - in a step-wise mode - the user may write his own rules being valid only for the next step (in creating the fault tree).

3.2.3 Domain Description and Generic Knowledge

Any use of the Plant Editor is based on a certain domain. Viewing industrial installations normally two generic knowledge bases (GKBs) are supported by the tool: they represent taxonomy knowledge of structures and functions, respectively. One GKB might be empty, of course. The usage of further knowledge bases must be managed by the tool itself[2].

The generation of generic knowledge is fully supported by graphical interfaces[3].

An attribute of a knowledge base object is allowed to have more than one value (multi-valued). A value may have any representation; of course, semantically the values must be understood when used. For example, each value of the attribute "MacroFaultTree_Rules" stands for a rule which must follow a special pre-defined syntax. Along special "is_a" attributes more general knowledge may be inherited by more specific knowledge.

The usage of a GKB manifests itself in the availability of drawable objects which can be chosen to create instances of them. The drawables are organized in a menu catalogue.

[2]Theoretically there is no limitation; for very practical reasons, however, a third GKB could not be justified for this application area.

[3] This is now done by features within the OODBS.

3.2.4 Plant Layout and Specific Knowledge

The user may create the layout of his plant system by 1. choosing a drawable object, giving it a name thus creating an instance of that object, 2. connecting already displayed instances by special pre-defined connections, 3. augmenting a layout by a variety of auxiliary objects like (poly-)lines and texts, 4. selecting, moving, deleting, mirroring, and/or turning (as far it is allowed) of all created instances and auxiliary objects as he wants. The layout generation is fully managed by diverse control mechanisms and even semantic checks (which again use generic knowledge, e.g. for connections) [SchPo 92].

One particular topology layout is based on one particular GKB. It is, however, possible to switch between semantically different layouts, e.g. between structural and functional description. This functionality requires a very exact and strict management of what is possible and what is prohibited; normally such knowledge is stored in both (the developer has to foresee it) GKBs, too.

In the same way how the usage of different GKBs may contribute to a horizontal diversification, a vertical diversification is KB-driven, too. This normally quite simply-structured KB describes the different levels of abstraction that might be allowed when a plant layout is created and then saved. The tool manages switches between different abstraction levels.

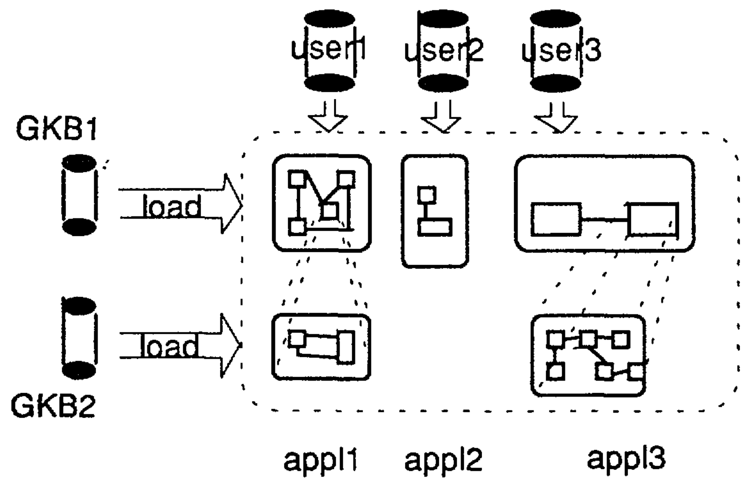

Fig. 2: Three system users using two GKBs and producing three applications

Using a matrix (Fig. 2) different applications may be developed which can be saved and re-loaded again. An application consists of specific knowledge (with pointers to generic knowledge) which is generated automatically. In addition, a viewing mechanism (Fig. 3) allows the user to edit the specific knowledge of a previously selected object out of the topology giving him the possibility to add edit more specific knowledge for that instance for private purposes or as input to subsequent STARS tools.

3.2.5 Topology Evaluation and Temporary Knowledge

Risk assessment on top of a topology is fully graphically supported and semantically checked. The system is a diagnostics system and it looks "backwards" for the causes of a misbehavior. In terms of the overall methodology a fault tree is constructed[4]. The risk assessment is explained by rules that are taken by a special inference engine working in a backward-chaining mode [HaWaLe 83]. The results of a risk assessment session are made nicely visible and, in addition, count again as new specific knowledge which might be re-used.

A special step mechanism allows a "debug"-like intervening by the user. In this particular case the actual valid rules (those which fire in the next step) are displayed. The user might augment this list of rules by temporarily valid rules for the next step only (Fig. 4). Thus his possibilities of evaluating his previous made layout are enormously extended.

[4]The contrary activity is known as failure mode and effect analysis (FMEA) which, however, is actually not part of the methodology.

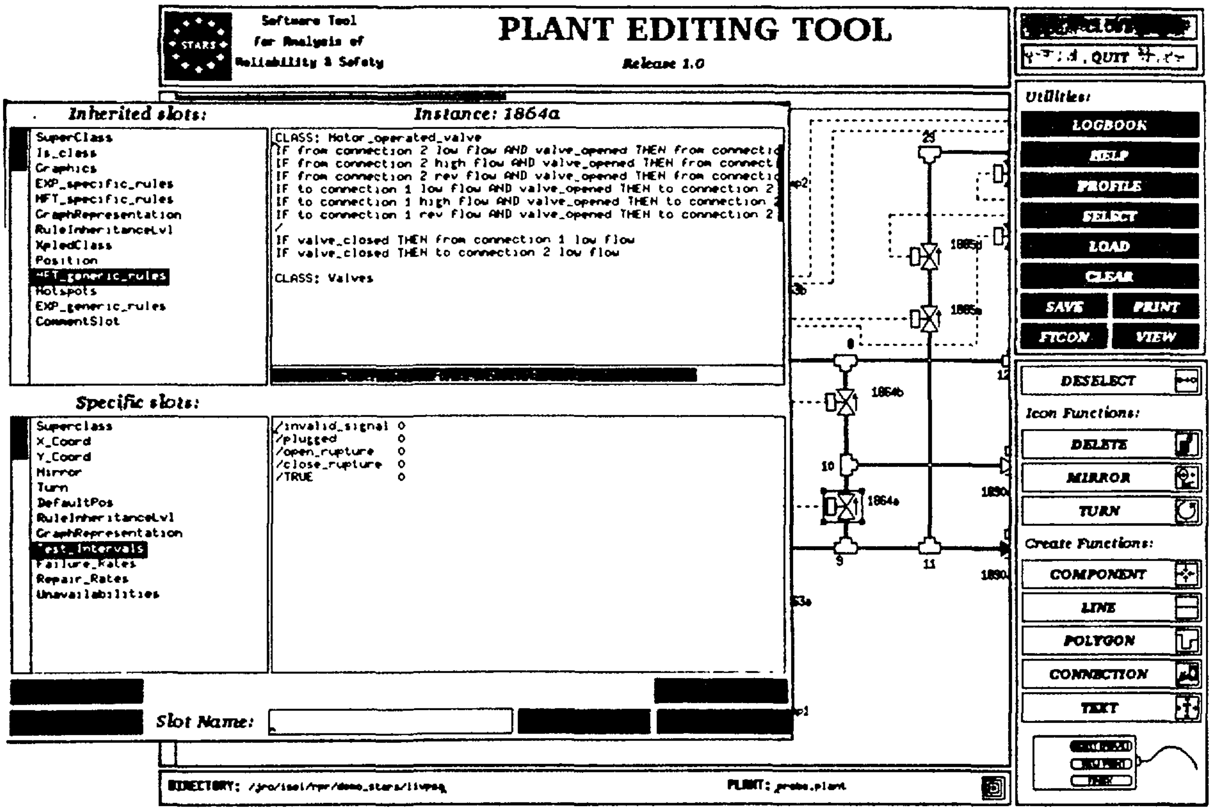

Fig. 3: Viewing the generic and specific knowledge for the component "1864a" which is selected (rectangle around it) on the canvas window. For the generic (inherited) knowledge the "MFT generic rules" slot is viewed, for the specific part the slot "Test intervals".

4. The use of safety analysis results within on-line operator advisors

4.1 Background

Classical safety analysis is a matter of studies, performed mostly during the design and development stages of hazardous systems, which then results in the the most relevant choices to be made between design alternatives. The previous chapter described a methodology and an associated computerised tool (STARS) to perform these studies and to keep them up-to-date with subsequent plant modifications. However, the tool remains an off-line tool to be used mainly by plant engineers.

Two major observations can be made about this approach when related to hazardous plants operated by human operators:

- on the one hand, safety and reliability studies try to assess values of probabilities or rates, or to identify critical paths in terms of events sequences; on the other hand, operators require a support to detect and diagnose symptoms of anomaly early, to assess potential threats on production and safety objectives, and to help them build a suitable recovery action plan. *Post hoc* analysis of major accidents in the chemical industry has shown that most of them had precursor signs, which were ignored or misinterpreted at the time [Dr91]. The systematic integration of all the available information offers the possibility for operators to have such precursor signs, and their implications, brought to their attention in time to prevent serious consequences.
- the safety expertise gained during preliminary studies is only transferred to the operators, who will have to manage safety problems in real-time, through a set of operating instructions and the installation of alarm management systems.

The first observation addresses the problem of support functions really needed for safety management during operation, and the necessary compromise, in abnormal situations, between antagonistic production and safety objectives: a responsibility given to the operator who is generally not trained to it. The second raises the question of how to integrate the knowledge, gained during safety analyses, into on-line decision support tools, and how to adapt general safety considerations to a known and specific situation.

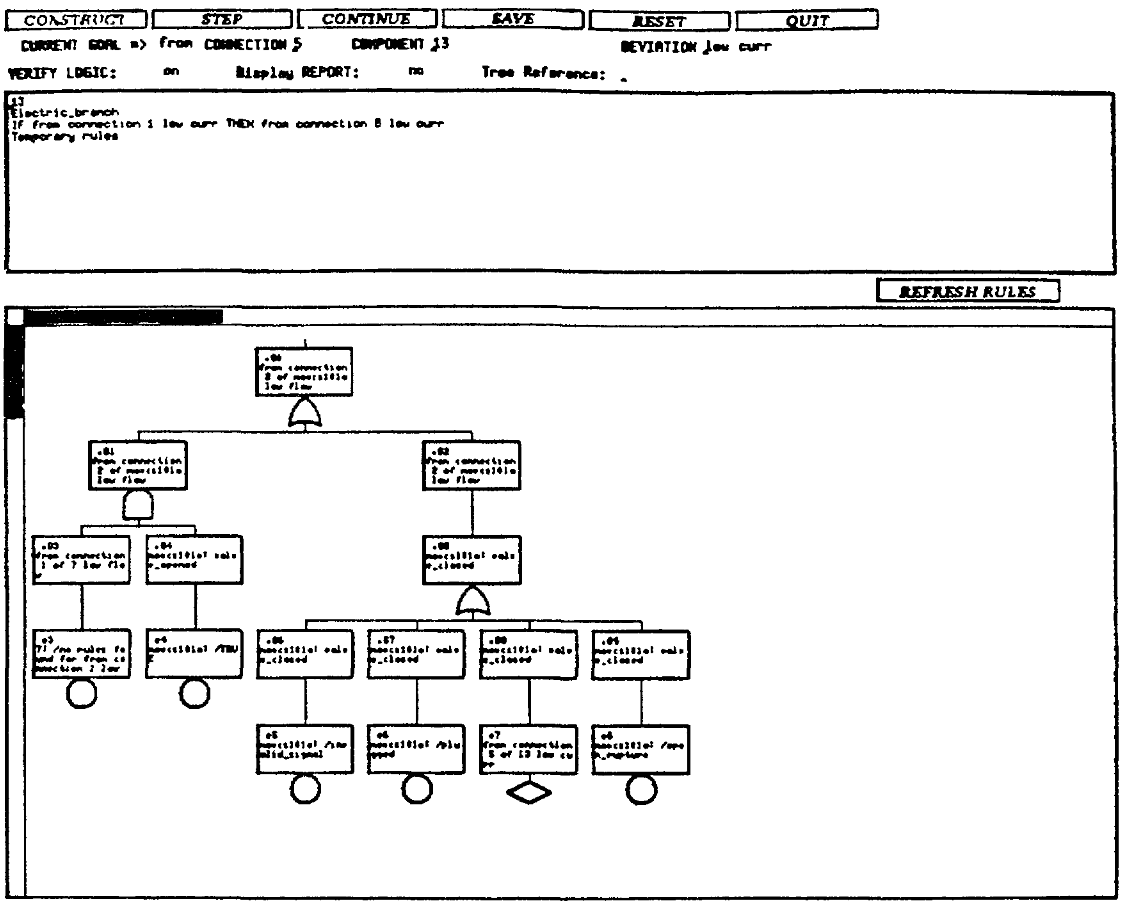

Fig. 4: A fault tree during development: one rule displayed, no temporary rules written.

FORMENTOR[5] provides a convenient solution to the problem of reusing and applying safety expertise in real-time. The FORMENTOR project [WiNoPo93] eventually resulted in the development of a safety-oriented real-time knowledge based system that supports operators of complex installations in managing potentially hazardous situations. The technical approach adopted is generic to the many industries whose operators could benefit from such systems. These include Nuclear Power Plants. The ultimate objective of FORMENTOR is to avoid major disturbances in a plant or at least to keep it in a safe state. The rationale and usefulness of operator support systems of this kind have been recognized and described elsewhere [NoMiWi93], [Lo84].

4.2 Approach

The approach taken to define the FORMENTOR functionalties has been a task-based one. Discussions with plant managers and the experience of the applications developed so far [WiNoPo93], [WiNoMi93], enabled the generic operator tasks defined in particular for the nuclear industry [Lo84] to be confirmed and generalized. The following breakdown into five tasks appears to be common across different industries (see Fig. 5):

Monitoring - detection of pre-cursor signs and symptoms of abnormal or unsafe behaviour, checking the instruments and validating their results.

Assessing the current situation - based on the results of the monitoring activity above, deciding what is the current underlying state of the plant.

Diagnosis - having worked out what the state is and discovered an anomaly, deciding how this anomaly or "symptom" has arisen and where. Typically this involves tracing mechanisms from

[5]FORMENTOR is a project in the EUREKA program of co-operative international R&D projects. The partners in the FORMENTOR consortium are: Aérospatiale Protection Systèmes (F), Cap Gemini Innovation (F), Det Norske Veritas (N) and the Institute for Systems Engineering and Informatics of the Joint Research Centre of the Commission of the European Communities, based at Ispra (I).

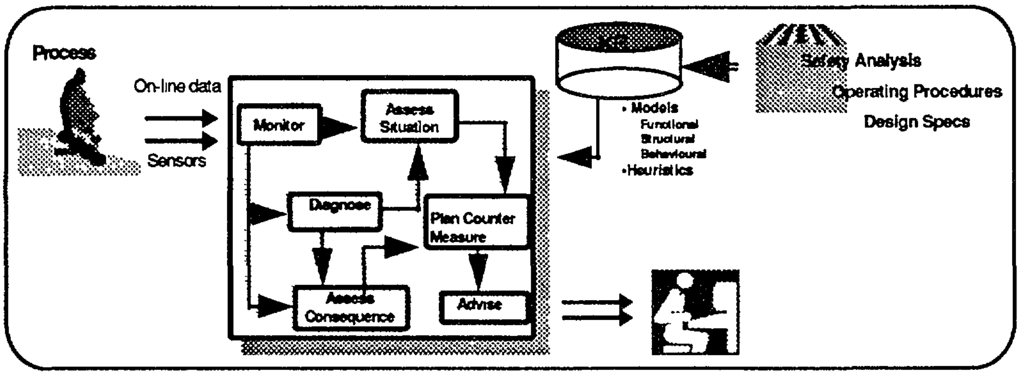

Fig. 5: FORMENTOR functional architecture

effect to cause, and often involves combining symptoms from separate parts of the plant which stem from a common cause. In many cases diagnosis of a symptom results in identification of a faulty component or subsystem.

Assessing the consequences of the current situation - deciding whether the current plant state is one which may or will evolve into a dangerous or otherwise undesirable condition.

Countermeasure planning - if the current state is dangerous, or has the potential to evolve in a dangerous manner, deciding what should be done about it. In particular, there are often a lot of possible operator interventions which might cure the immediate problem, but which have side effects on other aspects of the plant; then the most appropriate sequence of actions has to be found.

Computer systems such as those discussed here limit themselves to offering advice, with the operator retaining responsibility, rather than the computer system taking action itself. In the end it is up to the operators whether or not they use the system. To ensure user acceptance, a good Man Machine Interface design is necessary [CaCz92], leaving the user the maximum of control over the presentation and substance of the information supplied. Beyond this experience about acceptance implies to provide a system "belonging" to an operator, i.e., mirroring his experience and view on the plant.

4.3 Knowledge Bases and Models

The capability of FORMENTOR to perform many of the required tasks relies upon the choice of a set of dedicated models and operational knowledge of the plant to be supervised.

Functional model, the GTST

The Goal Tree Success Tree (GTST) model is one major knowledge representation scheme which is well suited to describe complex plant [KiMoNiHu90] [KiMo87].

The GTST model is a safety-oriented functional model of a system in the large sense, relating high-level goals to low-level hardware functionalities of the system. Applied to industrial plant, it relates high-level safety and process objectives to the functions carried out by components of the plant. See [NoMiWi93] for a more extensive description of the use of the GTST within Formentor.

Structural and Behavioural model

An industrial system, from a structural viewpoint, can be seen as a set of components bound together in order to interact. A component is another system, etc. The recursion stops when a system is considered as being atomic. A structural model then provides a structural decomposition of the plant into components and in addition embodies the interrelations (physical or logical) of the components of which it is composed.

Part of the knowledge base in this Formentor application is the Multi Layer Model (MLM) defining the plant as a hierarchy of components and their relationships to each other. The MLM is used as a coherent framework for various forms of knowledge and reasoning. In particular, behavioural knowledge can be associated to its components.

4.4 Link off-line on-line

Several attempts made convinced us that standard models built during safety analyses (Fault/event trees, Markov chains, Petri nets,...) were inadequate for a direct application in an evolving context, mainly for the following reasons: impossibility to react dynamically to incoming information (plant data and operator actions), difficulty to ensure reality matching of the models, impossibility to derive countermeasures from an exploitation of the models. However, and even if it is not possible to automatize the transfer, an extensive re-use of the results of safety studies has proven to be possible.

As such, logical links have been established between classical safety analyis methodologies and the development of a FORMENTOR application. It is obvious that for a new FORMENTOR system, all the knowledge covered by safety and risk analysis of a plant is of primary relevance.

In any case, it should be noted that a FORMENTOR system can always incorporate the experience gained in safely operating a process, either from safety/risk studies or from the expertise not put on documents but apparent in the way operators and engineers manage the plant (heuristics). At the same time, a FORMENTOR system would be easily modifiable, due to its structured design and the supporting development and KB maintenance tools: in that way it can adapt to changes in the plant hardware and variations in the process conditions.

In the following points, we will outline how results of classical safety analysis methods have an impact within each basic FORMENTOR functionality.

Monitoring:

The definition of the symptoms that could indicate abnormalities, and the way in which they should be classified, are closely related with safety analysis. The main safety parameters, which have an incidence on the safety level of the system when they are not maintained, are natural candidates for symptoms. They can be observables or computed parameters, and are associated with thresholds that are eventually used for classifying the symptoms. Minor symptoms can correspond either to relatively slow fluctuations near the operational limits or to abnormal variations with a certain frequency. Major symptoms can correspond to faster variations or to greater value shifts. Critical symptoms can correspond to fluctuations or shifts arriving to safety limits.

Assessing the current situation:

The situation assessment function is performed over the GTST model. Goals are states expressed in a positive way which can be related to the negation of unwanted events. Process goals correspond to the achievement of certain production objectives, as safety goals correspond to the avoidance of dangerous situations. The construction of the GTST is based on a functional decomposition of the target system. Information in Fault-trees can highlight the conditions needed for developing the Success Tree logic. Fault trees can indicate the relationship between top goals in the Goal Tree and support its further refinement.

Diagnosing:

Both, heuristics or model-based diagnostics systems, should be based on safety knowledge. Diagnosis is workable when there is a strong knowledge on what can go wrong in a plant and why. The heuristics causal model can use indications from Fault-trees, FMEA, etc., and from the operability instructions handbook. The definition of undesirable plant states, the use of supporting

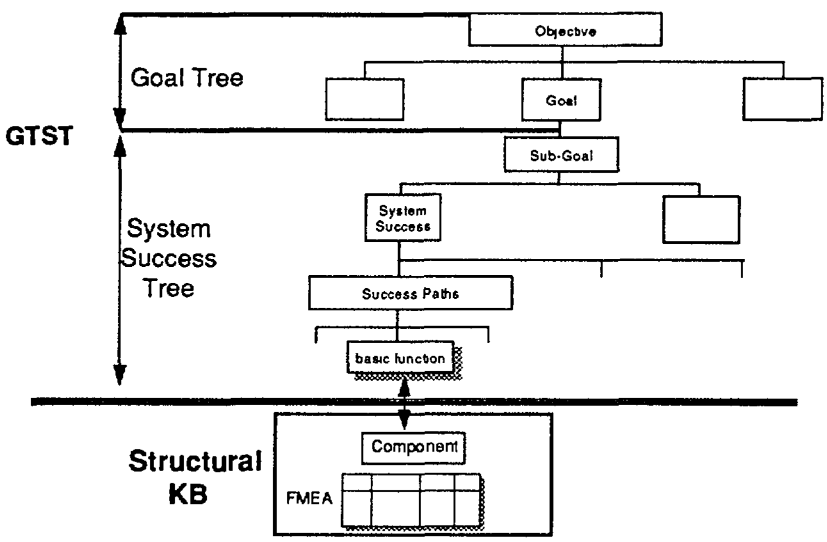

Fig. 6: One possible link between Functional and structural KB

evidence for their confirmation, the links to potential remedies, the refinement of these remedies, and the verification of their applicability against constraints, can not only be best guesses by the operators, but heuristics supported by specific studies. On the other hand, a model-based diagnosis system should necessarily use information from FMEA about the possible component failures.

Assessing the consequences of the current situation:
Consequences are obviously implied in the contents of several safety-related analyses. They cover the evolution of a process in abnormal conditions, the time period before the occurrence of certain events, and the period needed for recovering normal conditions after the application of counter-actions. What is critical when dealing with an abnormal situation is mainly how bad the state can worsen, and how much time there is for reacting.

Countermeasure planning and advice generation:
Safety analysis can give the applicability conditions for the diverse possible remedy actions. The information on consequences, on urgency of the current condition, and on what can be expected after the application of each countermeasure, can be supported by safety and risk studies. Also the probability of success of each possible action line, based for example on event trees, can be used to determine priorities. The specification of a concrete action plan should take into account the physical limits of the handle and its reliability.

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THE STATUS OF APPLICATION OF NEURAL NETWORKS IN THE NUCLEAR INDUSTRY

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Abstract

Artificial neural networks (ANN) are now accepted as a very practical AI technique, used for many applications in various fields. The nuclear industry, although aware of the potential benefits of the application of ANN, is slow in accepting this technique in nuclear power plants (NPP) control rooms, even for operator advisory roles. However, the technique is now being considered for predictive maintenance systems of NPP components, and for support roles in non-safety related systems, such as load forecasting, water chemistry, fuel management and safeguards systems. Active research on the properties and possible applications of ANN in NPP's is carried out in universities and national laboratories in several countries. Training data is supplied by the nuclear industry, either as real NPP operating data or from full scale simulators. The ability to train large scale ANN is crucial to their successful implementation in real-life situations, enabling also the development of auto-associative ANN for real-time fault diagnostics. In a demonstration example of a simulated material transfer system with 50 components, an auto-associative ANN was able to sense immediately the presence of a fault during an operation, and diagnose correctly the faulty component.

INTRODUCTION

On-line applications of intelligent computation techniques, such as Expert Systems (ES), Fuzzy Logic (FL) and Neural Networks (NN) are regarded as means to increase the safety and reliability of nuclear power plant (NPP), and other nuclear installations. The need to analyze the detailed behavior of the plant slows the implementation of some of these systems, and the derivation of the Expert Rules can be difficult in complex systems. In parallel with the growing interest in NN as viable artificial intelligence technique for complex system modeling, several applications of the NN techniques to NPP operation were reported during the years 1989 - 1991, summarized in three reviews (Uhrig, 1990, 1991, Boger, 1992). Many NN applications in industrial and other areas are now reported, recent extensive work in the nuclear industry is summarized in six reviews. (Uhrig, 1992a, 1992b, 1992c, 1993, Boger, 1993a, 1993b).

Some of these applications are aimed at the development of "on-line" operator support systems, or even closed loop controllers, as the superior execution speed of a trained NN is very attractive for these applications, and most of the effort is directed to this area. Yet, the implementation of useful NPP operator aids is hampered by two obstacles - the large number of sensors and alarms patterns that have to be recognized, which are difficult to train with the current NN techniques, and the need to pass a verification and validation (V & V) process, a vital requirement by the licensing authorities. Another growing field is the on-line monitoring of NPP components, as part of a predictive maintenance system that should replace the costly preventive maintenance scheme currently employed. This paper is the third review presented to an IAEA Workshop on the use of expert systems in the nuclear industry. It describes recent advances in the training and applications of NN in the nuclear industries, comments on the status of NN in the nuclear industry and suggests possible future roles of large scale neural networks in nuclear power plant systems.

NEURAL NETWORKS LEARNING

A detailed description of the NN theory and learning techniques may be found in the many books and papers, some of which are covered by the referred reviews, and will not be repeated here. Briefly, it refers to implementing in the computer, by software or special hardware, processing nodes (neurodes) are linked to each other by variable strength connections. The sum of all inputs to a neurode, if larger then a bias, activates the neurode. The neurode output, multiplied by the connection weights is transferred to all neurodes receiving inputs from this neurode. The training of NN is done by starting with random connection weights, presenting a known set of inputs and outputs of a system to the NN, and adjusting the connection weights to decrease the error between the NN outputs and the known system outputs. The general delta rule or the conjugate gradient variants of the error back propagation (BP) algorithms are usually used. When the error is small enough, the generalization capacity of the NN is tested by it's ability to predict correctly unknown outputs from known inputs of a test set not used in the training process.

The learning process may slow even on fast computers, especially when the NN contains many inputs and outputs. It is because of this slow learning that NN applications papers for nuclear power plants researchers are testing new architectures or learning algorithms to overcome the limitation of small to medium-size systems, with few inputs. Some researchers try to decrease the heuristic aspects of the neural network training by more rigorous statistical methods such as data pre-processing (Giraud, and Liu-Lon-Chang, 1991) computed or dynamic NN structure, (Basu, 1992, Ciftcioglu and Turkcan, 1992b), modular NN (Guo and Uhrig, 1992a), elimination of non-relevant inputs (Guo and Uhrig, 1992b, Reifman *et. al.*, 1993), the use of non-random initial connection weights (Boger, 1990), or accelerating the learning algorithms (Bartlett and Uhrig, 1992a, Javier and Reifman, 1992, Parlos *et. al.*, 1992b). A new approach to increase the confidence in the NN results is made by training another NN to estimate the error of the first one (Kim *et. al.*, 1992). An attempt to automate feature extraction and compress the number of inputs is done by a recirculation NN. (Alguindigue *et. al.*, 1991). Others try to use different concepts, such as the ART-2 algorithm (Keyvan and Rabelo, 1991), recurrent NN (Ishii, 1993), or combinations with other AI techniques (discussed in the next section).

Another obstacle to using large scale NN is the belief that many examples are needed to get robust, reliable NN. The conventional rule of thumb requires the number of examples to be at least equal to the number of connections in the NN, preferably ten time as much. As large number of examples, especially of fault situations, is usually hard to collect or generate, there is a tendency to avoid and distrust large-scale NN. The way most researchers try to overcome this obstacle is the use of full scale nuclear power plant simulators to generate data of plant responses in different abnormal or accident scenarios. Others use real plant data to train the NN to distinguish between normal and abnormal states, or use expert judgment to create probable accident scenarios (Keter and Boger, 1993). There is some evidence, mainly from spectra analysis results, that because of the interrelation between inputs, a much smaller number of examples is sufficient to train a NN to generalize correctly (Boger, 1990, Karpas and Boger, 1992, Alguindigue *et. al.*, 1993), thus decreasing the training data generation and learning requirements.

SYNERGISM WITH OTHER ARTIFICIAL INTELLIGENCE TECHNIQUES

The slow implementation of Expert System techniques in large scale systems, mainly because of the problems in knowledge acquisition, programming and verification, led to the rise of hybrid systems. This approach tries to incorporate other AI techniques such as Neural Networks and Fuzzy Logic with ES, to get a synergistic effect, utilizing the best features of each technique.

Combinations of NN and FL were used to identify reactor transients (Ikonomopoulos *et. al.*, 1991a, 1991b), perform pump diagnostics (Ikonomopoulos *et. al.*, 1992a), monitor the state of a system (Berkan *et. al.*, 1992), create models of hard-to-measure properties, "virtual instruments" (Tsoukalas *et. al.*, 1992, Ikonomopoulos *et. al.*, 1992c, Keyvan *et. al.*, 1993), and to create robust sensor network for alarm identification (Abbott and Clark, 1993). The combination of NN and ES was used to develop a robot for hazardous environments, the processing of radioactive isotopes (Spelt, 1992, 1993). Expert knowledge-based logic pre-processing of LOCA test-bench inputs is also proposed (Prock, 1992, Prock *et. al.*, 1992).

The most promising synergistic combinations of different AI techniques are in the V & V area. The use of totally different concepts, software and technologies that arrive to the same conclusions should increase the confidence of the operators in the advice given by the diagnostics and monitoring systems. However, although the concept of "diversity" is referred to in private communications, nothing was published yet on NPP diagnostics. However, parallel control scheme, in which several different algorithms are used, is already described (Eryurek *et. al.*, 1993).

AREAS OF NEURAL NETWORKS RESEARCH AND APPLICATIONS

The "traditional" aim of NN research for NPP applications is the development of a quick and reliable operator support system that would identify abnormal situations, and their causes, distinguished from "normal" transients. Thus, many researchers are active in this field (Horiguchi *et. al.*, 1991, Bartlett and Uhrig, 1991, 1992b, Watanabe *et. al.*, 1991, Tramer *et. al.*, 1991, 1992, Ciftcioglu and Turkcan, 1992a, Turkan *et. al.*, 1992, Dhanwada and Bartlett, 1992, Basu, 1992, Cheon *et. al.*, 1993, Thompson *et. al.*, 1993, Bartlett *et. al.*, 1993, Elias *et. al.*, 1993). The number of signals used to diagnose the plant state vary between two to several tens, or a time history of one or more inputs, depending on the data source and the NN learning algorithm. The scope of generality of the diagnostic capability is decreasing somewhat recently, with more realistic aims of sensor validation and "virtual instrument" generation, (Eryurek and Turkcan, 1991a, 1991b, Ikehara, 1991, Cahyono *et. al.*, 1991, De Viron and De Vlaminck, 1992), modeling of specific phenomena of the NPP or a component (Miller, 1991, Korash et. al., 1992, Welstead, 1992, Chambers *et. al.*, 1992, Parlos *et. al.*, 1992). The modest scope of these NN's allows quick implementation of useful models, and do not need much V & V to be accepted as it is more related to maintenance activities.

Closed-loop control of specific components is researched, both with "classic" NN approach (Sakai *et. al.*, 1990, Eduards *et. al.*, 1993) or in combination with fuzzy logic techniques (Cordes *et. al.*, 1991, 1992, Eryurek *et. al.*, 1993).

One of the emerging fields of interest is the on-line diagnostics of machinery, especially rotating machinery. There are two reasons for this - the aging of NPP requires more attention to the state of the equipment, and the licensing authorities sometime mandate this attention when extending operating licenses over the original predicted NPP lifetime. The second reason is that the scheduled maintenance costs are rising, skilled maintenance workers are retiring, and utilities realize that the nominal maintenance periods may be too conservative and maybe even reducing the equipment life by excessive dismanteling and re-assembling. Thus, a monitoring system that will predict incipient faults in time to take it out of service for maintenance will be much appreciated. NN are ideal for this type of "predictive maintenance", as accurate mathematical models of rotating equipment are hard or impossible to construct. The NN is taught from past history of fault patterns, or when these are not available, at least it can learn the normal behavior and alert the operators or maintenance personnel to possible faults. Another consideration was mentioned in the previous section is that these systems are considered non-safety related, so no formal software licensing or V & V effort is required. The importance of this application was recognized quite early and a special Preventive Maintenance Laboratory was created in the University of Tennessee in 1989. Now NN are included in the techniques employed to monitor deterioration of instruments and rotating equipment in the TVA NPP's (Upadhyaya, 1992). The most easy way to monitor rotating equipment is by vibration or noise spectra analysis (Alguindigue and Uhrig 1991, Alguindigue *et. al.*, 1991, 1992a, 1992b, 1993, Miller 1991, Boger, 1993c), although other available measurements are used, such as electrical current (Parlos *et. al.*, 1992), or with external values such as flow and pressure in a pump (Keyvan and Rabelo, 1991, Keyvan *et. al.*, 1993). A NN A comprehensive NPP maintenance system was recently proposed, using NN and FL concepts to track on-line the condition of every piece of equipment, based on past history records, adjusting the maintenance schedules accordingly (Simon and Raghavan, 1993).

NN are now proposed for various NPP activities, ranging from severe accident management (Silverman, 1991), electrical load demand forecasting and balancing

(Wang *et. al.*, 1992, Lu *et. al.*, 1993, Zhang *et. al.*, 1993), water chemistry monitoring and control (Sakai *et. al.*, 1990), to investigating the effect of NPP operation on the fish in Lake Ontario (Ramani *et. al.*, 1991).

The application of NN techniques to the nuclear fuel cycle activities is growing. Safeguards monitoring of nuclear material transfer and spent fuel discharge is proposed (Whiteson and Howell, 1992, Larson *et. al.*, 1993). NN are also mentioned for managing the operation of a mixed waste incinerator (Rivera *et. al.*, 1992).

THE FUTURE OF NN APPLICATIONS IN THE NUCLEAR INDUSTRY

Up to now most of the NN research in the US was carried out at universities and government funded research laboratories. For instance, the most active group in this field is Professor Uhrig's students at the University of Tennessee at Knoxville and his colleagues in the Oak Ridge National Laboratory. They mostly use data from the TVA reactors and full scale simulators. Another is active at the Idaho National Engineering Laboratory, where the source of data is the EBR-II reactor which is also used by researchers at Argonne National Laboratory and ORNL. A new project for identifying NPP transients by NN has been started at Ames Laboratory, and the Los Alamos National Laboratory is engaged in the safeguards applications of NN. Research is also carried out in Pennsylvania State University, A & M University of Texas, and other universities. The electrical utilities in the US do not appear to be confident of the applicability of NN techniques in NPP, although the attitude may be changing. The Electric Power Research Institute is sponsoring now some NN projects (EPRI, 1992), and the NN-based maintenance system proposal was prepared by General Electric, albeit for Japanese, and possibly Taiwanese, utilities (Simon and Raghavan, 1993). In Europe the situation is similar, with the most active group in the Energy Research Foundation at Petten, Holland, and some utility interest by Tractebel in Belgium. In Canada and in Japan the reverse is true. Most of the NN research is carried out by the utilities, Ontario Hydro and Toshiba for example. There is a nuclear plant integrated monitoring and diagnostic system that is approaching implementation in Point Lepreau Generating Station, which includes NN-based diagnostics (Thompson *et. al.*, 1993).

As noted above, one of the main reasons of the utilities distrust of the NN technique for on-line operator advice is the dependence on simulated data for generating the training patterns for abnormal state classification, and the V & V requirements. The first step in the training of a NN is the creation of an adequate data base. Although aided by the data collecting and processing systems installed in NPP's, this is a difficult task; especially for fault situations. One way is to use mathematical models for the creation of fault database is using a full scale reactor simulator. The responses of the sensor readings and alarm blocks to a deliberate component failure would serve as inputs for teaching the NN to distinguish between the different faults. As simulator generated databases would be suspected of lack of accuracy or realism, and plant generated databases would be accused of incompleteness of fault situations. Thus, the V & V process would not be possible. A compromise approach may be taken, in which only normal plant data, available in much quantity or detail, will be used for classifying the plant behavior.

A possible way to alley this distrust is the use of large scale auto-associative NN. Auto-associative NN is a net with identical input and output set. These nets can be taught different cases of normal plant behavior, in different situations (start-up, power level changes etc.), thus creating a model of normal situations. If this NN will be monitoring the plant, an abnormal situation will manifest itself as a large deviation between one or more NN input, and the corresponding model output, and thus alert the operator of some possible fault. If only one data-point is flagged, it may be an indication of a sensor drift or failure. However, several such flags would suggest an abnormal situation (Boger, 1993b, 1993d).

AUTO-ASSOCIATIVE NN EXAMPLES

Auto-associative NN has been already proposed for monitoring the normal behavior of a NPP (Turkan *et. al.* 1992, Kavaklioglu *et. al.*, 1992). The first study used 26 real-time sensor signals from Borssele PWR, and no deviations from normal operation were found in a test. The second study used 16 steady-state signals of a PWR, and an anomaly was detected. The extrapolation capability of a trained NN was tested using the Borssele plant data, and it was found that correct sensor readings were predicted in a situation different from the one used for training (Eryurek and Turkan, 1992). Two large-scale examples, one from actual operating data from a wastewater treatment plant, and the second from simulated material transfer system demonstrate the possible benefits of this approach in NPP's.

The first example is based on two years of operation of the Soreq Wastewater Treatment Plant in the Tel-Aviv metropolitan region, deals with the identification of the causes of high turbidity plant effluent. Two 110 input-output auto-associative NN were trained, one with normal behavior data-set (450 days), the other with high turbidity data-set (152 days). 20% of the data were not used in the NN training, to serve as test data for estimating the NN error. After 20 epochs of training both data sets mean error was about 7% in the two NN. The data of the 108 days in which the plant produced intermediate effluent turbidity were presented to both NN's, in order to identify possible causes and distinctive patterns of abnormal behavior. The inputs having large prediction errors were analyzed and several plant variables were identified as connected with the high plant turbidity (Boger, 1993b).

In the second example, a hypothetical material transfer system was simulated. Liquid may be pumped from one of ten source tanks, via one of five pumps, into one of ten receiving tanks. There are isolating valves for each tank and pump, so the system consists of 50 pieces of equipment. A 50-16-50 auto-associative NN was trained with 500 examples of all legitimate transfers, using the non-random initial weight software package, (TURBO-NEURON, 1992). The training time on a 486/33 machine in less than an hour, to an average error of 0.01. It was tested with transfer data containing single fault and double faults. In all cases was the NN able to recognize "immediately" an abnormal situation. In addition the NN was able to identify the cause of the abnormality in 99% of the single fault test cases, and in 95% of the double fault test cases (Boger, 1993d).

CONCLUSIONS

The nuclear power industry, while recognizing the NN potential for inclusion in intelligent displays and instrumentation systems, is hesitating to apply it in safety related systems, no doubt because of NN teaching problems, verification and validation issues. However, the number of non-safety applications for NPP and related fuel cycle is growing, with the maintenance related applications having the best potential for actual plant use. As the V & V issues are also difficult to solve in any type of operator support systems, the advantages of the quick setup and fast execution time of NN, combined synergisticly with fuzzy logic techniques, should overcome this hesitation. The research leading to the availability of fast learning algorithms should enable researchers and developers to apply the auto-associative technique for large-scale systems. Once experience is gained in the forthcoming monitoring and diagnostic systems in NPP's outside the US, the nuclear power industry will get more confidence in the neural networks capabilities.

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APPLICATION OF NEURAL NETWORKS IN NUCLEAR SAFETY ANALYSIS

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Abstract

Two applications of the neural network methodology in the field of nuclear safety analysis are described. The first one is the 3-D response surface generation by the Back Propagation Method. The results were not satisfactory. The second is the application of the Optimal Statistical Estimator methodology for the generation of 8-D response surface. It was used as a statistical part of the Code, Scaling, Applicability and Uncertainty (CSAU) methodology for the evaluation of Large Break Loss of Coolant Accident. The result was comparable to the one obtained by the ordinary method.

1 INTRODUCTION

A survey of the bibliographic data base shows us a considerable number of neural network applications in nuclear industry in recent years. Most developments are oriented towards some kind of on-line plant diagnostics [1,2,3,4,5,6,7,8,9,10] and [11], while much fewer deal with the some analytical applications [12,13] and [14]. During our work with the thermal-hydraulic safety analysis of Large Break Loss of Coolant Accident (LB LOCA) for the NPP Krško in Slovenia [15,16] several problems were encountered, which could be solved by the use of the artificial neural network method. Two such applications are presented here, one less and the other much more successful.

2 APPLICATION OF THE NEURAL NETWORK FOR THE RESPONSE SURFACE GENERATION IN 3-D SPACE

2.1 Definition of the Problem

In our study, referenced in [15], the final result of the analytical thermal-hydraulic simulation of LB LOCA was the Peak Clad Temperature (PCT) during the accident. This is a single value representing the temperature of the hottest spot in the whole core during the entire transient. The influence of the steam generator plugging level and of the initial break size to PCT was sought. There were altogether 35 computer runs performed using 5 different values for the break size and 7 for the plugging level. 35 calculated PCTs are shown in Table I. The PCT may be regarded as a function of two independent variables-plugging level and break size. This would produce a 3-D surface, so called response surface. If one makes a simple linear interpolation between calculated points, this surface would look like the one at the Figure 1. It was our desire to draw that surface somewhat smoothed, because it was clear to us, that uncertainty of each individual solution is quite high. A general impression about the influence of both parameters to the final result could better be understood by

Table I: Set of Peak Clad Temperatures in the first study

Break size	Plugging level						
	0	10	14	16	17	18	22
25	1343	1366	1346	1359	1369	1371	1340
30	1388	1438	1438	1424	1441	1423	1386
35	1374	1460	1460	1409	1452	1419	1428
40	1381	1412	1412	1414	1415	1432	1426
45	1316	1329	1329	1322	1369	1338	1359

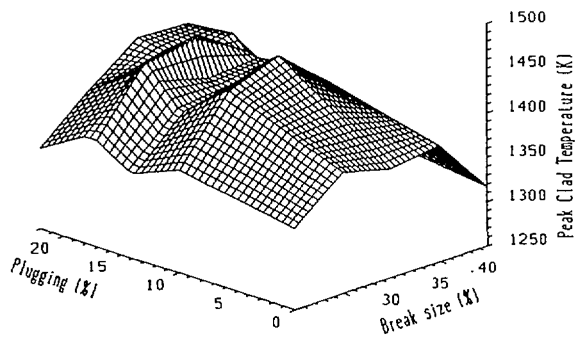

Figure 1: PCT Response Surface by linear interpolation

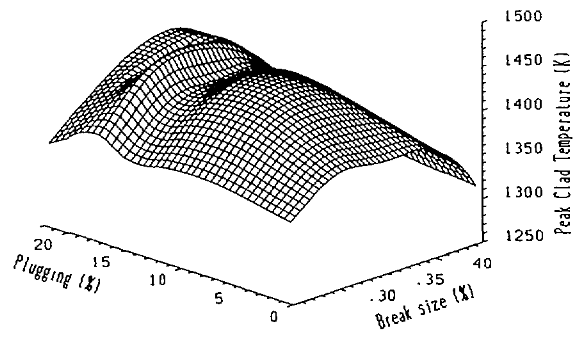

Figure 2: Spline interpolation of input data

preparing a smoothed surface. After the linear interpolation the surface was approximated by applying spline curves through, or better close to the calculated points. The result is shown on Figure 2. It later proved to be the best surface representation we could produce.

2.2 Solution by the Back Propagation Neural Network

The construction of the response surface through the points in Table I was tried also by the multilayer neural network and Back Propagation learning method [17,18]. This was more of the academic interest and was primarily intended as our initial training in neural networks. The back propagation method proved to be very slow. Considerable amount of time was spent trying to find optimal number of hidden neurons and network parameters. The best result was obtained after some 70000 learning steps and around 7 hours of computing on a 80386, 25 MHz personal computer with the 80387 numeric coprocessor. It is shown on Figure 3.

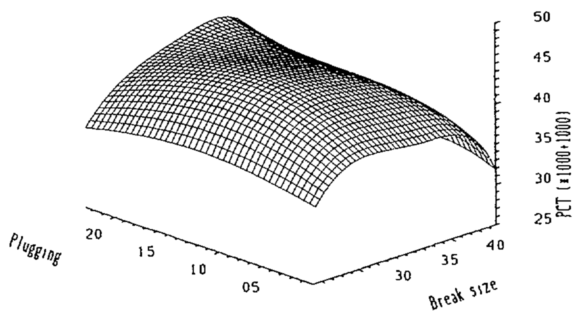

Figure 3: Neural network interpolation in a dense grid

2.3 Conclusion

Since for that particular case the response surface was not needed for any further analytical purpose and having in mind extremely cumbersome calculational process for obtaining its neural network generated version, application of back propagation for this purpose was considered unsuitable.

3 APPLICATION OF THE NEURAL NETWORK FOR THE RESPONSE SURFACE GENERATION IN 8-D SPACE

3.1 Definition of the Problem

Safety analysis of the LB LOCA by another methodology, so called Code Scaling, Applicability and Uncertainty (CSAU) evaluation [19] has also a step, that can be solved by the use of neural network. We have performed LB LOCA analysis by that methodology [20], [21]. As in the previous case the parameter we were looking for was Peak Clad Temperature. There were 7 independent variables chosen: fuel peaking factor, gap conductance, fuel conductivity, break size, pump degradation, plugging level and safety injection flow rate. For each independent variable two to three different input values were selected based on its uncertainty. Altogether 128 computer runs, giving 128 different PCT results, were performed with different combinations of input variables. The PCT values are presented in Table II.

From these results the probability density curve should be obtained. For that purpose the response surface in 8 dimensional space (7 independent and 1 dependent variable) must be generated. The probability density curve can be calculated by the random selection of input variable sets and reading the corresponding PCT values from the response surface.

The neural network may be used in the process of the response surface creation. Original method of response surface creation is described first.

3.2 Solution by the Regression Analysis

The third order response surface was used to obtain the following function for Peak Clad Temperature ,

$$PCT = \sum_{i,\,j,\,k=0}^{I,\,J,\,K} a_{i,\,j,\,k}\, X_i\, X_j\, X_k \ ,$$

where $I=J=K=7$, $X_0=0$ and X_i,X_j,X_k are the combinations of input parameters. Higher order terms are redefined as auxiliary terms to perform linear regression analysis. The regression function of the standard personal computer spreadsheet program LOTUS 1-2-3 [22] was used.

This function was then used in a Monte Carlo sampling program. 100,000 samples were collected with random variations of input parameters. For most of input parameters the uniform probability distribution has been assumed, except for the peaking factor and fuel thermal conductivity (normal distribution).

Results of Monte Carlo sampling are frequency histograms on Figure 4, which are representing probability distribution function. Final result of the analysis is the mean value of the Peak Clad Temperature after the LB LOCA 1137 K and 95% upper bound ≤1268 K.

Table II: Peak Clad Temperatures in Kelvins for the second case

	break size 0.4	break size 0.3	SI flow -20%	SI flow +20%	plug.g level 10%	plug. level 18%	pump level 1	pump level 2
nominal	1092	1087	1104	1093	1104	1100	1091	1100
F_q=-5.6%	1066	1033	1080	1062	1055	1061	1089	1080
F_q=+5.6%	1128	1087	1138	1126	1122	1131	1146	1137
F_c=-10%	1116	1099	1134	1132	1110	1136	1137	1128
F_c=-5%	1101	1096	1095	1094	1106	1112	1117	1117
F_c=+10%	1074	1061	1092	1088	1066	1081	1086	1075
G_c=-80%	1284	1225	1261	1288	1264	1287	1294	1292
G_c=-46%	1147	1120	1131	1149	1139	1154	1154	1157
G_c=+35%	1098	1065	1083	1072	1084	1072	1075	1113
F_q=+5.6%,G_c=-80%	1318	1263	1297	1299	1316	1328	1323	1325
F_q=+5.6%,F_c=-10%	1159	1128	1146	1153	1160	1152	1167	1170
F_q=+5.6%,F_c=+10%	1097	1095	1088	1090	1103	1106	1115	1110
G_c=-80%,F_c=-10%	1299	1250	1282	1312	1302	1329	1308	1313
G_c=-46%,F_c=-10%	1185	1147	1167	1166	1174	1175	1169	1193
G_c=+35%,F_c=+10%	1073	1062	1061	1063	1065	1075	1087	1090
F_q=+5.6%,F_c=-10%,	1342	1285	1336	1342	1316	1347	1316	1324

F_q - power peaking factor, F_c - thermal fuel conductivity, G_c - gap conductance

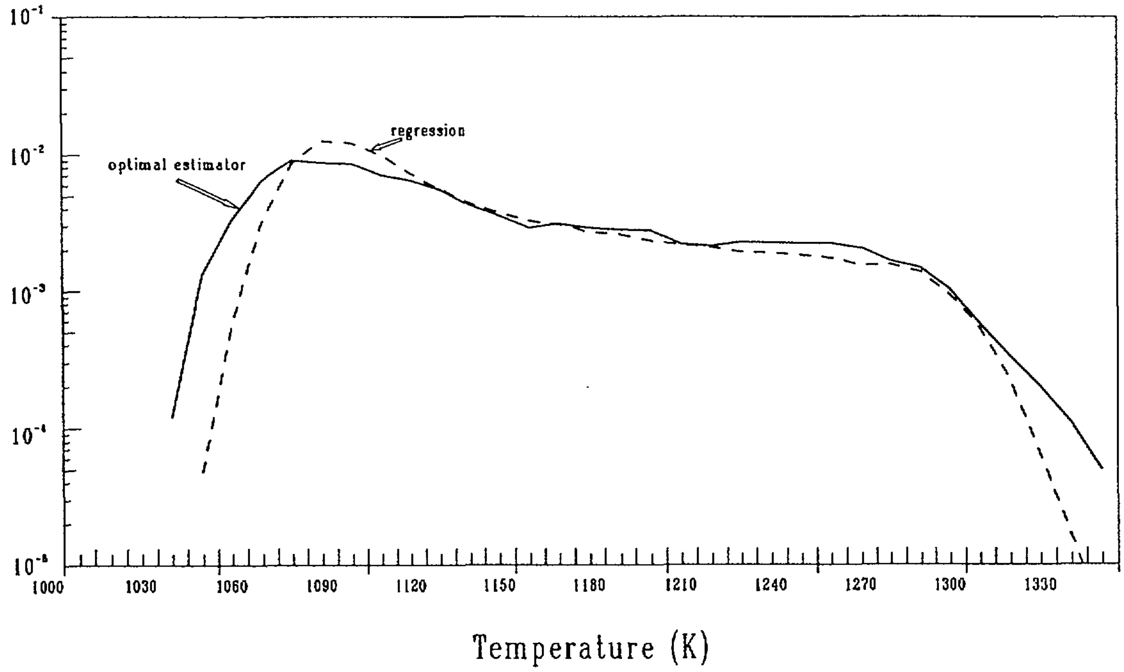

Figure 4: Comparison of Optimal Estimator and Regression Probability Density

3.3 Solution by the artificial neural network: Optimal Estimator Method

The neural network was constructed based on the Optimal Statistical Estimator, described in Grabec, [23] and Grabec, [24]. Monte-Carlo sampling was then used for the probability density calculation.

3.3.1 Description of the Optimal Estimator Method

Results from Table II were used as inputs. Each result represented one point for the response surface generation in eight dimensional space. Each input variable represented one dimension.

For the calculated input data the value

$$\sigma = \frac{S_G}{f_c\, N^{1/I}} \tag{2}$$

was calculated, where S_G is estimated standard deviation of the calculated input data, N is total number of calculated input data and I is number of input dimensions. The corrective factor f_c is to be selected by the user. The contribution of each data point to the final result estimation can be adjusted by it.

Every original data point is contributing to the estimate of the output variable value at the response surface. The Gaussian function is used for the calculation of the average weight of each input data to the final result. It is calculated by the equation:

$$\delta_a(G-G_n) = \frac{1}{(2\pi)^{I/2}\sigma^I}\, e^{-\frac{\|G-G_n\|^2}{2\sigma^2}} \tag{3}$$

where

$$\|G\|^2 = \sum_{i=1}^{I} x_i^2 \tag{4}$$

x_i is input data value, G is input vector and subscript n corresponds to the calculated input data. The optimal estimator of the value at the response surface H_0 can be calculated by the conditional average:

$$f_a(H|G) = \frac{\sum_{n=1}^{N} \delta_a(H-H_n)\ \ \delta_a(G-G_n)}{\sum_{n=1}^{N} \delta_a(G-G_n)} \tag{5}$$

where H is output vector. The optimal estimator is represented by the integral:

$$\hat{H}_0(G) = \int H\, f(H|G)\, dH \tag{6}$$

Inserting function from equation (3) into equation (5) and integrating over the vector H yields for each term in the summation of Gaussian functions its mean value H_n according to the simple expression:

$$\hat{H}_0(G) = \sum_{n=1}^{N} C_n H_n \tag{7}$$

where

$$C_n = \frac{\delta_a(G-G_n)}{\sum_{n=1}^{N} \delta_a(G-G_n)} \tag{8}$$

3.3.2 Results

All 128 peak clad temperatures were used as input data for the response surface generation by the optimal estimator program. Monte-Carlo analysis was performed by random variation of input parameters. For each point at the response surface complete calculations from equations (2) to (8) have been done. The normal (Gaussian) distribution has been used for *Peaking factor* and *Fuel conductivity* and uniform distribution for other five input parameters. The Monte-Carlo sampling required about 1 minute of CPU time for 1000 samples at the 25 MHz 80386 personal computer with 80387 numeric coprocessor. The results are shown on Figure 4. The calculated probability density function is compared with the one obtained by the regression analysis in section 3.2.

Probability distribution functions peaks are shown at Figure 5 and are also compared with those from regression analysis. The difference in 95 percentile is rather small (5 K). The 95 percentile calculated by the optimal statistical estimator method is higher then the one obtained by the regression analysis, which is conservative.

Results are summarized and compared with the results of the regression analysis in Table III.

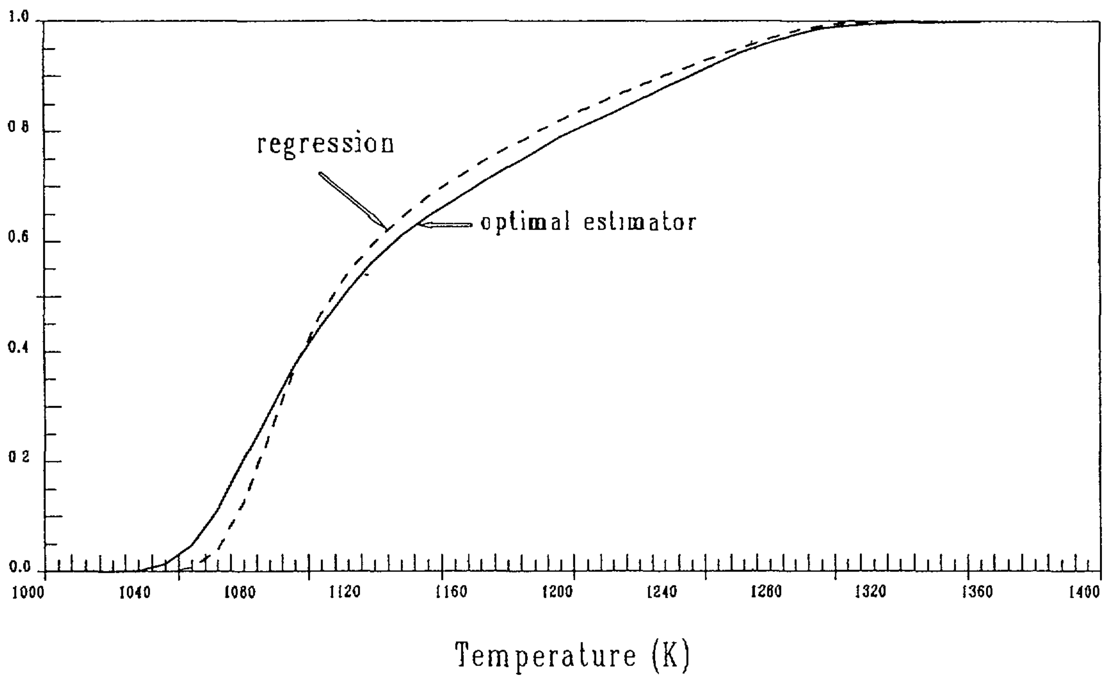

Figure 5: Comparison of Optimal Estimator and Regression Probability Distributions for the blowdown peak

Table III: Comparison of Neural Network and Regression analysis results

	Peak Clad Temperature		
	Mean PCT (K)	95% upper bound (K)	T_{95}-T_{mean} (K)
Optimal statistical estimator	1140	1268	128
Regression	1137	1264	127

4 CONCLUSIONS

The back propagation neural network method proved to be quite ineffective for the purpose of the response surface generation in 3-D space. Ordinary methods for graphical presentation of 3-D objects are much more practical.

For the statistical evaluation of the large set of computational results, which can be organized in the multidimensional response surface, the Optimal Statistical Estimator method is very useful. The final result and the speed of the method is comparable to the usually used regression analysis.

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QUALITATIVE PROCESSING OF UNCERTAINTY, CONFLICTS AND REDUNDANCY IN KNOWLEDGE BASES

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Abstract

This paper describes two techniques, created and implemented in the course of development of the real-time on-line expert system Recon at the Nuclear Research Institute at Řež, Czech Republic.

The first of them is the qualitative processing of uncertainty, which is based on the introduction of the third logic value to logic data objects, and the credibility flag to arithmetic data objects. The treatment of the third value and credibility flags during the inference, the explanation method based on the graphic representation and the uncertainty processing during the explanation are also mentioned.

The second technique, is a semantic checking of knowledge bases, which enables us to recover parts of the bases, that are meaningless, either because of an error during their implementation into a base, or because they are redundant. The paper includes the explanation of basic terms of this method, such as so called conflicts, K-group and K-situation. The two types of the conflict (dead-end and bubble) are also discussed. The paper also offers the complete mathematical apparatus, which the checking method is based on.

1) Introduction

The main result of the development project on the diagnostic technological expert system (ES) for operator support TEEX [1] was creation of rule based real-time on-line ES Recon. Since 1992 after the termination of project TEEX the development of RECON has continued independently. In this period the integrated sheel ERB [2] for creating and editing of knowledge bases was developed. The inference engine (IE) and the explanation mechanism were complemented by qualitative ucertainty processing, which is the subject of the first part of this paper.

The second part presents our approach to the detection of conflicts in knowledge bases [4], which was developed and implemented within the framework of TEEX project, and which is prepared for implementation into Recon.

2) Qualitative processing of uncertainty

2.1) Problem background

In the early stages of the TEEX project the possibility of the representation of uncertanty was considered. In order to process uncertainty correctly, the area of uncertainty in AI was reviewed. The conclusion was not to use Mycin-like IM, which process the uncertainty extensionally, because of the possibility to obtain results, which are in contradiction with knowledge from KB.

On the other hand the intentional methods such as Shachter's probabilistic inference [3], are true consistent with the theory of mathemathics. This method was implemented in ES SHAT (interactive ES) and DIAG (automatic module). Also this approach was not successful, because of high memory costs and problems with understanding of numeric results (probabilities) by users (NPP's operators).

The experience obtained creating KB for real applications show us, that uncertainty in area of NPP technology diagnostics, concerns the lack and wrong quality of input data and not the technolgy itself. The main problem was to treat data failures. Considered numerical (quantitative) methods were not suitable to solve this problem and thus - the new qualitative method of uncertainty processing was developed and implemented.

Basic framework for this method was that operator wants to see only unambiguous conclusions, based on unambiguous knowledge and on potentionally non-credible input data. The outputs of diagnostic ES are logic statemens which have Boolean values true or false (YES or NO respectively) when system is capable to give answer, or UNKNOWN value, instead of numeric measure of uncertainty, when input uncertainty obstruct the unambiguous conclusion. This new logic value enhanced Boolean sample space bool={YES,NO} to the three value sample space 3bool={YES, UNKNOWN,NO}, which is the new base for so called "three value logic" (3VL).

To be able to compute logic expressions in 3VL the data objects (log, float and int variables and constants), logic operations (NOT, AND, OR), relational operations (>,

>=,=,...) and arithmetic operations (+,-,*,/) and functions were redefined.

2.2) Application for IM

The original idea was to assign UNKNOWN value to every statement based on uncertain information. In this way one non-credible input could block a relatively considerable part of KB by UNKNOWN value, even if other, credible data, are sufficient to obtain unambiguous result. Since the special properties of Boolean logic can be used to define result, knowing only one of two operands, it is possible to obtain certain results from partially uncertain data. In standard algebraic expressions there are in principle three types of operations:

```
arithmetic:    arit X arit -> arit
relational:    arit X arit -> bool
logic:         bool X bool -> bool
```

where arit=R U Z.

The above mentioned modification of data objects means to assign to every arit object a Boolean credibility flag, and to use 3bool sample space instead of bool. The operations and functions are then redefined in the following way:

Arithmetic operations

As mentioned above an arit data object in 3VL is represented by pair <value, credibility flag>, where value$\in$arit and credibility flag$\in\{0,1\}$. Zero value of the flag means that the value is credible, if flag is 1 it means the opposite.

Redefinition:

```
arit X bool X arit X bool -> arit X bool
op1 aop op2 -> res
is computed as:
op1.value aop  op2.value -> res.value
op1.flag  U    op2.flag  -> res.flag
```

The resulting value is obtained as usual in normal arithmetic, the resulting flag is disjunction of flags of operands. Therefore even one non-credible data object in arithmetic expression leads to non-credibility of the result.

Relational operations

Redefinition:

arit X bool X arit X bool -> 3bool

op1 rop op2 -> res

is computed as:

op1.value rop op2.value -> res, if dis_flag=0,
UNKNOWN -> res, if dis_flag=1,

where dis_flag= op1.flag U op2.flag.

Similarly to the arithmetic operations, the result is UNKNOWN whenever at least one operand is non-credible, else the result is the same as in the normal algebra.

Logic operations

As the basis to operate with the third logic value so called absorption effect of Boolean logic was used. This effect can be described by following equations:

Z AND 1 = Z

Z AND 0 = 0

Z OR 1 = 1

Z OR 0 = Z, where $Z \in \{1,0\}$.

These equations tell us, that very often (in 50% of all combinations) it is sufficient to know only one operand to determine the result. Owing to this effect in real KB the non-credible input values can be absorbed, and ES gives credible results even if some of input data are not credible.

Redefinition:

3bool X 3bool -> 3bool

op1	op2	AND	OR	NOT op1
1	1	1	1	0
1	X	X	1	0
1	0	0	1	0
X	1	X	1	X
X	X	X	X	X
X	0	0	X	X
0	1	0	1	1
0	X	0	X	1
0	0	0	0	1

where 1 is YES, X is UNKNOWN and 0 is NO.

For computer processing the folowing representation of values was used:

YES = 2
UNKNOWN = 1
NO = 0.

In this representation the following equivalences are valid:

A AND B <=> min(A,B),
A OR B <=> max(A,B),
NOT A <=> 2 - A,

and implementation by classic programming languages is then trivial.

Functions

We consider functions of the following shape:

$$\text{FuncName}(par_1, par_2, \ldots, par_n).$$

Parameters are logic or arithmetic expressions, which are used like inputs and function returns arit or log data object. The value of returned object is calculated according to the function's algorithm and its credibility is disjunction of parameters' credibilities. In ES Recon is also possible to override this default credibility inside function's algorithm.

2.3) Explanation of expressions

The problem of the explanation of expressions is to determine, for each logic data object appearing in the expression, the projection of its value to the resulting value of the whole expression. The table definitions of explanation function for basic logic operations are following:

Y = op1 AND op2

op1	op2	Y	Importancy op1	op2
1	1	1	+	+
1	X	X	-	+
1	0	0	-	+
X	1	X	+	-
X	X	X	+	+
X	0	0	-	+
0	1	0	+	-
0	X	0	+	-
0	0	0	+	-

Y = op1 OR op2

op1	op2	Y	Importancy op1	op2
1	1	1	+	+
1	X	1	+	-
1	0	1	+	-
X	1	1	-	+
X	X	X	+	+
X	0	X	+	-
0	1	1	-	+
0	X	X	-	+
0	0	0	+	+

Analysing these tables we can see that in fact an operand is important if its value is equal to the value of the result.

Every logical expression can be replaced by hierarchy of basic logical operations AND, OR and NOT. The explanation of such structures can be performed in two ways.

The easier way is to take the value of an oprand, negate it so many times how many NOT operations is on path between operand and result, and so negated value compare with the result of the expression. In this case the result is a list of potentionally important operands, but their contribution could be absorbed by other operands. This fact could not be discovered by this method.

The more difficult way is to analyze the tree of the expression with regard to absorption of values of potentionally important operands.

ES Recon uses the more difficult method to analyse expressions containing only logic operations. In expressions, where logic and other operations and operands are mixed, Recon automatically chooses the simple method of explanation.

3) Semantic checking of KB

The necessity to detect conflicts and redundancies in KB arose in the course of TEEX project. For these reasons a special theory was constructed, which was also implemented in program package ZPRA1.

3.1) Basic conceptions

KB is for reasons of the semantic control represented in form of a special graph, which is a discrete analogy of so called influence diagram (ID), used in probabilistic approaches to uncertainty [3]. ID is a finite directed acyclic graph, in which every node $\underline{x}$ has its value $\underline{<x>}$ from sample space $\underline{\Omega(x)}$ (finite set of symbols) and a table of a transfer function $\underline{Tab(x)}$, which assignes to every combination of values of node $\underline{x}$ direct predecessors one value $\underline{<x>}$.

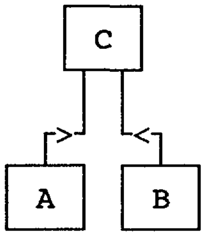
Definition 1: Node $\underline{A}$ is a *direct predecessor* of node $\underline{B}$ if in ID exists an edge A->B. Node $\underline{B}$ is a *direct successor* of node $\underline{A}$.

Definition 2: Node $\underline{A}$ is a *weak predecessor* of node $\underline{B}$ if in ID exist a path from $\underline{A}$ to $\underline{B}$.

Example 1:

This example, like all examples in the paper, is made for binary sample spaces. But all theory is valid for arbitrary dicsrete sample spaces of nodes, and therefore also for 3bool used by Recon. In this example we have three Boolean statements: A, B, C and we have a rule how to obtain value of C: C = A AND B. Representation of such a small diagnostic KB is following:

Ω(C)={1,0}



Ω(A)={1,0} Ω(B)={1,0}

Tab(C)

AB	C
11	1
10	0
01	0
00	0

Tab(A)

A	A
1	1
0	0

Tab(B)

B	B
1	1
0	0

As you can see, the leaves of graph (input nodes, evidence) have purely formal tables, because they have no predecessors and their values are input data of inference.

End of example 1.

Definition 3: A *conflict* is an unconsistency of KB with testing set of metaknowledge.

Metaknowledge mentioned in def.3 can be related to the problem area, but more often it follows from common logic, e.g. one variable can not have at the same time more than one value.

Later we will use so called *types of conflictness* (e.g. dead-end) describing types of unconsistency, and *types of conflicts* (eg. bubble) describing the semantic of metaknowledge. In this work we discuss only conflictness related to the unpossibility for a node (statement) to attain some values from sample space.

3.2 Metaknowledge

Metaknowledge is knowledge about knowledge. Since we represent knowledge in form of ID, the metaknowlege are represented by terms of ID.

Definition 4: *K-group* is a set of ID nodes, what is the metaknowledge about.

Definition 5: *K-situation* is a combination of values of nodes from K-group, which is not allowed.

In other words, metaknowledge, used to determine conflictness of nodes of ID (base) is knowledge about allowed and unallowed combinations of a set of nodes (group).

Example 2:

Let us have two binary nodes A and B ($\Omega(A)=\Omega(B)=\{1,0\}$) with following semantic:

$$A \approx x \geq y,$$
$$B \approx x < y,$$

where e.g. $x, y \in R$, i.e. real numbers. It is obvious, that truth values of these nodes can not be equal, i.e.

<A> != <B>,

what is a consequention of knowledge, that variable can not have at the same time two different values.

Using above defined def. 4 and 5 we express described knowldge in the following way:

K-group: $G=\{A,B\}$,

K-situation: $S=\{\{1,1\},\{0,0\}\}$.

End of example 2.

3.3 Conflicts

Now we can define terms related to the conflictness of nodes.

Definition 6: *Node* X of ID *is conflicting*, if K-situation is a necessary condition to attain one or more value from $\Omega(X)$.

Definition 7: Node X of ID is called dead-end, if K-situation is necessary to attain any value from $\Omega(X)$, except one.

Consequence 1: Sets of dead-ends are subsets of conflicting nodes.

Definition 8: The type of conflict called *bubble* takes a place, if a node (bubble top) exists, which requires situation, in that another node (bubble source) has at the same time two or more different values.

Example 3: How to express bubble-conflict for binary bubble source node A:

$G=\{A,A\}.$

$S=\{S_1,S_2\}=\{1,0\},\{0,1\}\}.$

$S_1=\{1,0\},\ S_2=\{0,1\}.$

As you can see it is possible to do it using K-groups and K-situations. This type of conflict is general and undesirable in most of KB.

End of example 3.

Definitions 6 and 7 define two types of conflictness, like property of node of ID. Def.6 defines a general case of conflictnes, which is a *redundancy of sample space* which has a relation to KB redundancy (see 3.6).

3.4 Detection of conflicts

From def.6 it is obvious, that apperance of all members of K-group in set of weak predecessors of node X is a necessary condition for conflictness of X.

Definition 9: *Potentionally conflicting node* (PCN) is every node, the set of weak predecesors of which contains all members of K-group.

The base for detection of conflictness of PCN X is a dividing of rows of Tab(X) into two sets, set of available and set of unavailable rows. If all members of the K-group are also direct predecessors of PCN X, then combinations of K-group members, divided to available and unavailable (K-situatons), divide rows of Tab(X) in the same manner. If one or more values from $\Omega(X)$ do not appear in set of available rows, then according to def.6 is node X conflicting (maybe dead-end).

Example 4: Dead-end node.

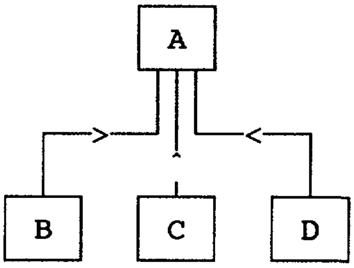
K-group: $G=\{B,C\}$.

K-situation: $S=\{\{0,1\},\{1,0\}\}$.

$\Omega(A)=\Omega(B)=\Omega(C)=\Omega(D)=\{0,1\}$.

Tab(A)

B	C	D	A
0	0	0	0 ■
0	0	1	0 ■
0	1	0	0
0	1	1	1
1	0	0	0
1	0	1	1
1	1	0	0 ■
1	1	1	0 ■



K-situations in the table are underlined and available rows (situations) are marked by "■". According to def.7 node A is a dead-end, because its value is in available situations constant.

End of example 4.

3.5) Blocking effect and its propagation

If some members of the K-group are not direct predecessors of PCN, it is necessary to investigate, wheather the K-situations will propagate to the predecessors and thus divide the rows of Tab(PCN).

Assumption : Let us suppose, that node H has n direct predecessors $E_1,\ldots,E_n$.

Definition 10: Direct predecessor E_j blocks node H, if the following expression is true:

EXIST $C_1 \in \Omega(E_j)$,

EXIST $C_2 \in \Omega(H)$: $(\langle E_j\rangle = C_1) \Rightarrow (\langle H\rangle = C_2)$.

We say, that there is so called AS-dependence between nodes E_j and H. This fact can be written as a function:

$$as(E_j,C_1,H,C_2).$$

Definition 11: A *path* is set of nodes $P=\{N_1,\ldots N_m\}$ if:
FOR $i \in [1, m-1]$,
FOR $N_i \in P$: N_i is a direct predecessor of N_{i+1}.

Definition 12: A *path* $P=\{N_1,\ldots N_m\}$ is an *AS path*, if:
FOR $i \in [2,m-1]$,
EXIST $C_i \in \Omega(N_i)$: $as(N_{i-1},C_{i-1},N_i,C_i) \cap as(N_i,C_i,N_{i+1},C_{i+1})$.
This fact will be expressed as:

$$AS(P,C_1).$$

It is obvious from def.12, that in AS path is the blocking effect propagated from the first to the last node, and then it is true that:

$$<N_1>=C_1 \Rightarrow <N_m>=C_m.$$

Owing to this property of AS paths only, it is possible, that the K-situation can be transported by AS paths from members of K-group to the direct predecessors of PCN, and rows of Tab(PCN) will be then divided. Only by AS paths it is guaranteed, that K-situation will be not absorbed between N_1 (member of K-group) and N_m (direct predecessor of PCN).

Definition 13: K-situation S_x will be transported by ID from K-group G to the direct predecessors E_i only if:
FOR $x \in G$
EXIST $P_x=\{x,\ldots,E_i\}$: $<x> \in S_x \cap AS(P_x,<x>)$.

I.e. for every node x from K-group exist an AS path P_x which transports dependence on value <x> to the direct predecessor of PKU E_i. But value of E_i need not be equal to value of x.

3.6) Redundancy

As redundant elements we call parts of ID, retrieving of which will not affect the work of ES with this KB. Such elements in KB often tell us more frequently rather about error in course of expression of knowledge by KB formalizm than about redundancy of expert's knowledge. Therefore before retrieving redundant elements from KB it is necessary to do a detailed revision of related knowledge.

The first candidates for redundant elements are nodes, conflicting according to def.6 and 7. If a node X is conflicting, it means, that it can not attain one or more values from its sample space. In this case the number of possible rows of transfer functions of successors of X will decrease. In this way the conflictness of node X (redundancy of sample space) causes redundancy of transfer functions of its successors, particulary rows corresponding to unattainable values of X.

The special case - dead-end is an extreme of conflictness, because such a node Y has no influence on its successors. Therefore all edges starting in Y are redundant and then also Y is redundant (similarly to def. 15).

Except redundancy caused by conflictness of nodes, there can also appear so called structural redundancy.

Definition 14: *Edge* A->B is *structurally redundant* (SR), if any alteration of <A> for any fixed combination of values of the other direct predessors of B will not affect <B>.

Definition 15: *Node* is *structurally redundant*, if all edges starting in it are structurally redundant.

SR nodes and edges (SR elements) are esentially also a kind of conflict according to def.3, but description of correspondent metaknowledge using K-groups and K-situations would be extremly akward. Therefore for their detection we use a special algorithm, based on the detection of redundant edges A->B:

1) In table Tab(B) we mark rows with available situations. If there is no testing metaknowledge, we will, of course, mark all rows.

2) We divide Tab(B) into several tables, one for every fixed <A> from $\Omega(A)$.

3) If the marked lines from all tables are equal, then edge A->B is structurally redundant.

Then we can cancel edge A->B and replace Tab(B) by any table created in step 2).

Example 5: Testing of the edge A->B for SR.

Tab(B)

A	C	D	B
0	0	0	1
0	0	1	1
0	1	0	1
0	1	1	0
1	0	0	0
1	0	1	1
1	1	0	1
1	1	1	0

A=0

C	D	B
0	0	1
0	1	1
1	0	1
1	1	0

A=1

C	D	B
0	0	0
0	1	1
1	0	1
1	1	0

As we can see, values of B in both small tables differ only in the first row, but both these combinations are unavailable (not marked). In the marked rows both tables are identical and edge A->B is then redundant. As a new Tab(B) we can use arbitrary one of the small tables.

End of example 5.

4) Conclusions

The solutions of all presented problems are obviously based on the absorption effect of Boolean operations.

In the area of qualitative processing of uncertainty this approach enables us to achieve a significiant increasing of capabilities of ES with minium increasing of time of processing (no difficult or floating point operations). This is valuable, esspecialy for real time ES, which must be fast and need automatic treatment of data failures. For instance ES Recon, which uses 3VL for the inference and explanation, achieves on IBM PC 486 50 MHz an average speed of 0.0063 sec/rule in compiled regime (for on-line application) and 0.13 sec/rule in interpreting regime (for off-line testing). These tests have been made using real KB prepared for a real NPP.

The application of the semantic control methods makes it possible to improve quality of KB represented by wide variety of formal methods. To do this it is sufficient to create a relatively small program converting a particular formalism, used for knowledge representation, into form of

ID, and then - use presented methods. From this point of view these methods are also a contribution to the problem of verification and validation of KB.

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APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR MODELING LOCALIZED CORROSION

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Abstract

Artificial neural networks (ANN) were applied to modeling localized corrosion of Incoloy Alloy 825 in simulated J - 13 well water. ANN as a non linear models can represent accurately localized corrosion phenomena caused by an environment containing chlorides, nitrates, fluorides and sulfates at various temperature ranges. Although the nature of the dependent variable of the ANN models, the visual rating of the localized corrosion is qualitative, a good correspondence between the output of the model and the actual indications is determined. Accurate ANN modeling has been carried out by using the visual inspection of the specimen surface, in contrast to linear modeling where in order to get a sound correlation between the system variables, a complex dependent parameter, having no clear physical meaning has been chosen. It has also been found that one can extrapolate to a certain extent, beyond the ability to interpolate (as with linear models). The ANN model predicted with a low relative error the visual rating of the corrosion rate of records which where part of the testing set of the ANN and belonging to the original full factorial design experiment. Thus, such models can be used for detailed analysis procedures as sensitivity, knowledge acquisition and optimization.

INTRODUCTION

Artificial intelligence techniques such as expert systems and artificial neural networks are being used for a wide variety of problems and analysis. Artificial neural networks have been suggested for use in problems typically solved by regression techniques. Moreover, by utilizing non linear transfer functions, the artificial neural networks are not limited to linear cases, thus, complex electrochemical systems characterizing localized corrosion and passivity can be modeled.

Passive metals such as stainless steels, nickel and aluminum alloys usually resist a wide variety of corrosive media and perform well over extended periods. In certain cases, the surface remains actually inert, but, if for any reason corrosion eventually starts, rapid penetration of the construction material takes place at very small parts of it, inducing a localized corrosion phenomena.

This phenomenon in general, and pitting and crevice corrosion in particular, is known to be one of the most severe degradation mechanisms by which containers of high level nuclear waste (HLNW) are liable to fail. Thus, modeling localized corrosion, in order to predict candidate materials performance as containers for HLNW, is vital for understanding the effect of environmental factors on pitting and crevice corrosion and the electrochemical parameters characterizing it.

Numerous analytical models for crevice and pitting corrosion phenomena were published, enabling simulation systems to be set up. Once the simulation program is operating, one would expect to acquire specific knowledge affecting the phenomena as how the process would respond if, for instance, the chemical composition or other variables of the corrosive environment would change. Some of the required knowledge can be learned by analyzing the mathematical equations governing the localized corrosion model. Another source of knowledge is laboratory experiments. These methods are easy to implement in simple systems, but not in multi - parameter processes, characterized by non - linear behavior.

This work will demonstrates the feasibility of using artificial neural networks for modeling, knowledge acquisition and learning some of the rules controlling a localized corrosion phenomenon; Incoloy Alloy 825 exposed a corrosive medium containing elements characterizing J-13 well water. Results are compared to predictions derived from linear models.

APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR MODELING

The actual potential of artificial neural networks for engineering applications became evident in the mid nineteen eighties. The rigorous name of the ANN is "artificial neural networks", showing the similarity of concepts to the neural cell networks in the brain. Processing elements are linked to each other by variable strength connections. The sum of all the inputs to such an element, activates it and produces an output. The node outputs, multiplied by connection weights are transferred to all processing elements receiving inputs from this node. Apparently, an analogous situation, though much more complex, is present in neural brain cells, whose axons and dendrites are connected to each other through synapses that modify the connection resistance during the learning process. Although many ANN architectures are possible, the most common one is presented in Figure 1. It consists of one input and two processing layers; one of which is called the "hidden layer", the other

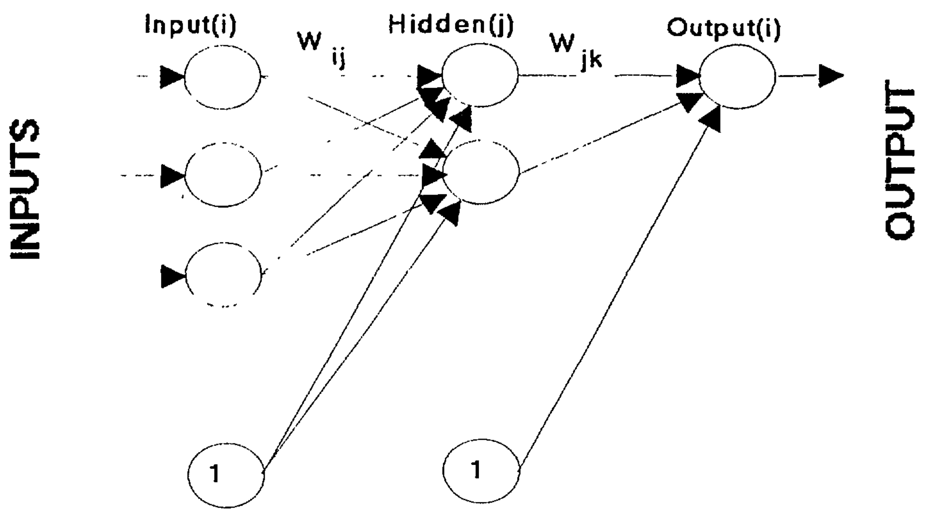

Figure 1: Basic neural network architecture

one is the "output layer". The input layer functions as a fan-out of the input variables to the second, "hidden layer". After performing the non-linear transfer function, the results are connected to the third, output layer, which also executes similar non - linear transformation.

An artificial neural node used in this study operates according to a simple mathematical transfer function; sigmoidal - shaped equations:

$$f(z) = (1 + e^{-z})^{-1}; \quad z = \Sigma W_{ij}.x_i$$

where f(z) is the node output, x_i are the outputs of the previous layer nodes, W are the connection weights leading to a node (including the bias).

The most common learning algorithm is the supervised back propagation algorithm, in which a data set of system inputs and outputs ("training set") are presented to a neural network having
initial connection weights. An error is calculated by comparing the actual outputs to those calculated by the network; the connection weights and bias are modified to decrease the sum of
squared error. This training procedure is carried out repeatedly, until the error converges to a small value. The network is tested by presenting another set of inputs and outputs ("test set"), and comparing the network outputs to the those of the test set. If the resulting error is small enough,
the network is considered trained and it may be used for predicting outputs. Thus, a system model has been created, not by programming equations but by teaching from examples. For more information, the reader is referred to two comprehensive books in this domain [(1)(2)] and several papers in recent issues of the Computers in Chemical Engineering journal.

For constructing a ANN model, two essential elements are needed: a database of the system inputs and outputs, covering the approximate range of values, and an efficient ANN training algorithm. It was the lack of the second requirement that hindered the application of ANN to non-trivial systems, as the learning rate was slow, and convergence may take days, even on powerful computers. The reason for this was the fact that random values had to be chosen as the initial connection weights, and the problem was equivalent to n-dimensional optimization, with n rising fast as the number of connections between inputs and hidden nodes increases. Even when converged, several repeat runs were needed to prove that a global minimal error was reached. Similarly, the number of hidden neurons, chosen heuristically by the network designer, had to be checked by repeat training with different hidden neuron numbers for optimal network performance.

In this study, a commercial software shell has been used[(3)]. It is based on an algorithm which performs statistical analysis of the training data set, calculates meaningful initial connection weights and estimates the number of neurons in the hidden layer. This procedure reduces the training time by a factor of 20 - 50 compared to the existing algorithms, and allows the user to build effective ANN in a matter of hours, even on personal computers. Once an ANN is trained,

its statistical validity and ability to generalize may be further increased by another algorithm which identifies non - significant inputs by statistical analysis of the hidden node behavior. Thus, allowing
re-training with reduced input set to produce a more robust and dependable ANN model.

Extraction of knowledge from a trained artificial neural network can be performed by applying the "causal index" analysis (4). Although it reflects only an average tendency for the total input range of parameters, when backed by common sensitivity analysis techniques, it can provides useful global characteristics of the investigated system. The causal index is determined by multiplying all connections weights from a specific input to a specific output and the results summed over all hidden neurons;

$$C_{l.m} = \Sigma\, W_{l.n} \cdot W_{n.m}$$

$C_{l.m}$ is proportional to $\partial B_l / \partial A_m$, where B_l and A_m are representing l-th output and m-th input respectively, and n is the hidden neuron index. Thus, it represents qualitatively the global relationships between each output and input in the system, and is easily calculated by the weights derived from the trained artificial neural network.

LOCALIZED CORROSION OF INCOLOY ALLOY 825 EXPOSED TO ELEMENTS PRESENT IN J-13 WELL WATER.

The corrosion behavior of Incoloy Alloy 825 in environments containing elements present in J-13 well water was studied extensively, examining the effects of chlorides, sulfates, nitrates fluorides and the temperature (5),(6).

Pairs of these parameters can in certain circumstances affect the localized corrosion phenomena synergistically. The effects of these factors on electrochemical parameters were investigated as well, by applying cyclic potentiodynamic polarization tests for determining susceptibility to localized corrosion.

Generally, chloride ions are promoting localized corrosion. The fact that metal halides are more stable than oxides at higher anodic potentials is responsible for the breakdown of passive films on austenitic alloys, thus, initiation and propagation of various localized corrosion forms may result. Chloride ions are liable to induce localized attack as pitting and crevice corrosion; at concentrations beyond 20 ppm, it might cause crevice corrosion of Incoloy Alloy 825, and at concentrations of 200 ppm and beyond, it might promote both pitting and crevice corrosion (7). Nitrate ions are known as inhibitors of localized corrosion, especially in the presence of aggressive ions as chlorides. The reason is attributed to the competition between these ions and chlorides for available adsorption sites on the metal surface. A synergistic inhibitive effect between chlorides and nitrates has been reported as well (7); at chloride ion concentrations beyond 100 ppm, nitrates inhibit the localized corrosion phenomena of Incoloy Alloy 825.

Fluorides and sulfates have opposite effects on localized corrosion. Fluoride ions inhibit localized corrosion (though promoting uniform attack), especially at low chloride ion concentrations, due to their strong complexing capability. On the other hand, sulfates slightly promote localized corrosion[7]. As far as the effect of temperature on localized corrosion is concerned, a minor influence is reported [7].

Localized corrosion has been investigated electrochemically, measuring pitting, corrosion and repassivation potentials, (E_D, E_{corr} and E_{rD} respectively) by applying the cyclic polarization technique. The values of E_D and E_{rD} relative to E_{corr} are indicative of the pitting susceptibility. The closer E_D is to E_{corr}, the greater susceptibility to pitting is observed. As far as the repassivation potential is concerned, the value of E_D - E_{rD} is adversely proportional to crevice corrosion resistance.

SETTING UP THE DATABASE FOR ANN SIMULATION

The basic requirement for simulating localized corrosion phenomena by the ANN technique, is the acquisition of a comprehensive database. It has to includes most of the normal and abnormal situations, covering the approximate range of values, thus, the ANN can generalize the global process behavior.
In this study, the database (set of vectors), for the ANN analysis was taken from experimental results, documented in the literature [7]. These experiments were carried out by following a two level full factorial design methodology using five factors. Thus, one can determine the effect of the variation of the independent variables on the localized corrosion rate; the dependent variable. The components of the vectors composing the ANN database, are the environmental variables characterizing the corrosive medium (concentrations of the various ions and temperature) and the measured electrochemical parameters.
The factor representing the visual rating (VR) of the localized corrosion has been chosen as the dependent variable. It varies from 1 to 4; where 4 is the most severe localized corrosion. The following components were selected as independent variables:

1. Temperature, T (^{o}C)
2. Concentrations of chloride ions, ppm
3. Concentrations of nitrate ions, ppm
4. Concentrations of fluoride ions, ppm
5. Concentrations of sulfate ions, ppm
6. Corrosion potential, E_{corr}, mV
7. Pitting potential, E_D, mV
8. Repassivation potential, E_{rD}, mV
9. The difference, E_D- E_{rD}, mV

In order to predict the extent of the localized corrosion rate, two networks were set up; one with parameters characterizing the chemical nature of the corrosive medium, 1 to 5, and the other with the electrochemical variables; 6 to 9.

The database contains 37 records (vectors). 32 records are originated from the factorial design nature of the experiment, defining the ranges with respect to each of the variables characterizing the corrosive environment and representing the extremes of the matrix. The other five records represent intermediate values of the matrix. Twenty seven records were chosen randomly as the learn set and the remainder ten records were selected as the test set.

NEURAL NETWORK MODELING

In order to model and correlate the localized corrosion phenomenon with respect to the various inputs imposed, two artificial neural networks were tested; one with temperature and chemical compositions as independent variables; the "environment variables based neural network", and the other with the electrochemical parameters as independent variables; the "electrochemical variables based neural network". Each neural network is composed of three layers, as presented schematically in Figure 1. As far as the environment variables based neural network is concerned, its input layer contains five fan out elements; scaled concentrations of chloride, nitrate fluoride and sulfate ions (in ppm units) and scaled temperature (^{o}C).

As far as the electrochemical variables based neural network is concerned, its input layer contains four fan out elements; scaled values of E_{corr}, E_p, E_{rp} and E_p- E_{rp} .

A basic feature of a neural network is its inherent ability to generalize, namely, to avoid memorization of the training set. Thus, accurate modeling, constrained by a network composed of a minimal number of processing elements has to be performed, implying the use of a the least possible number of processing elements in the input and hidden layers.

The optimal size of the neural network has been determined by the Turbo Neuron [3] shell. For the environment variables based neural network, it has been found that the sulfate ion concentration has a negligible influence on the visual rating of the localized corrosion. As far as the electrochemical variables based artificial neural networks concerned, all inputs have a meaningful influence. Consequently, for both artificial neural networks, four processing elements were used in the input layer. Two processing elements for both artificial neural networks were used in the hidden layer. The output layer for each of the two artificial neural networks contain one processing element, corresponding for VR. All inputs were properly scaled, between +1 and -1. The output has been normalized within the range of 0.1 to 0.9.

The schematic representation of the two artificial neural networks with their corresponding weights are displayed in Figures 2 and 3.

The networks were trained on an IBM compatible 486 33MHz personal computer.

The final mean square error of the environment variables based neural network was 8% for the learning set and 6% for the testing set. The final mean square error of the electrochemical variables based neural network was 9% for the learning set and 5% for the testing set.

The comparison of the VR as calculated by the environmental variables based neural network to the actual experimental observation is presented in Figure 4.

The comparison of the visual rating of the localized corrosion rate as calculated by the electrochemical variables based neural network, to the actual experimental observation is presented in Figure 5.

It should be noted that in both these cases, only data from the training set was used in the learning phase; the results include also the test set results. As good correspondence is shown, it can be concluded that both artificial neural networks adequately model the localized corrosion phenomenon.

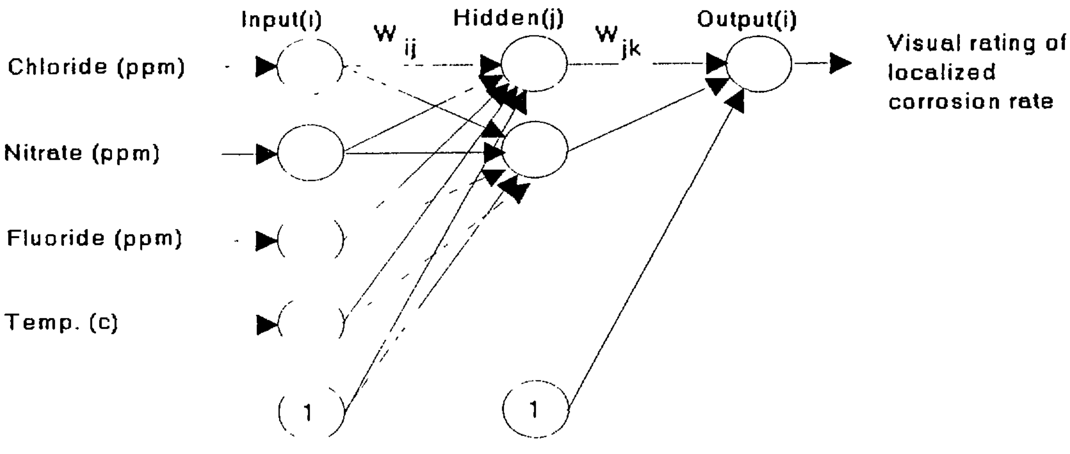

Figure 2: Neural network based on environmental variables

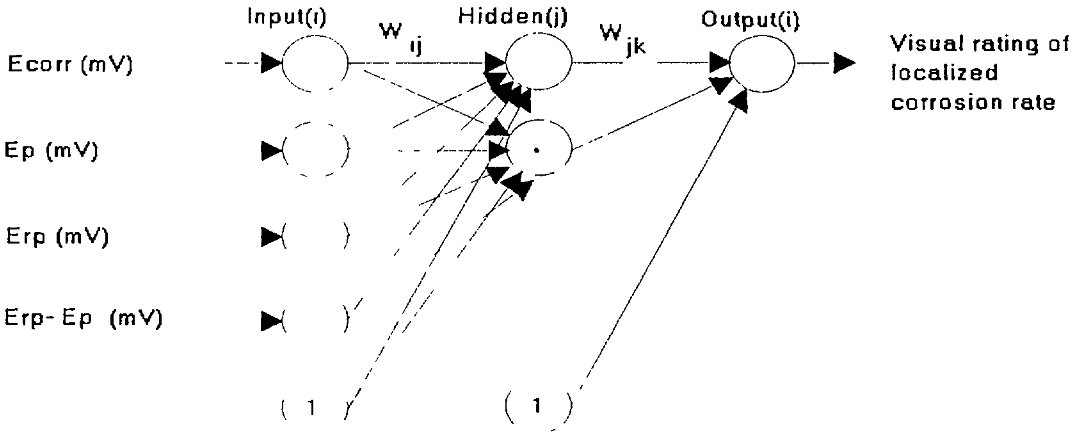

Figure 3: Neural network based on electrochemical variables

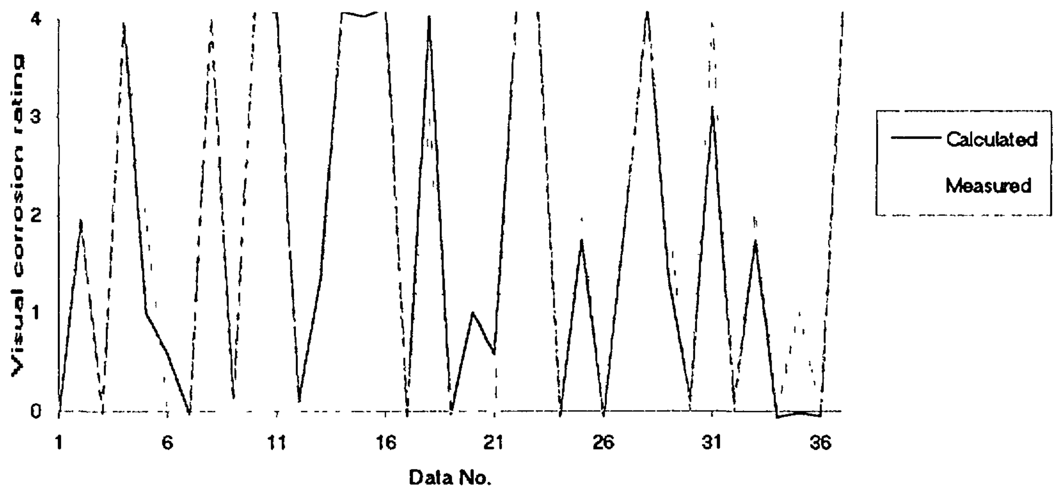

Figure 4: Calculated vs. measured results
(Neural net originated from environmental factors)

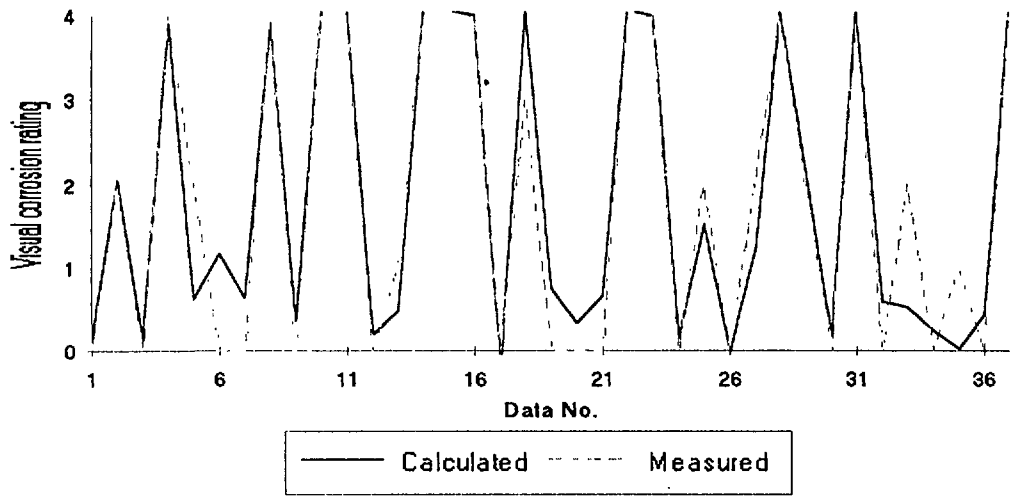

Figure 5: Calculated vs. measured results
(Neural net originated from electrochemical parameters)

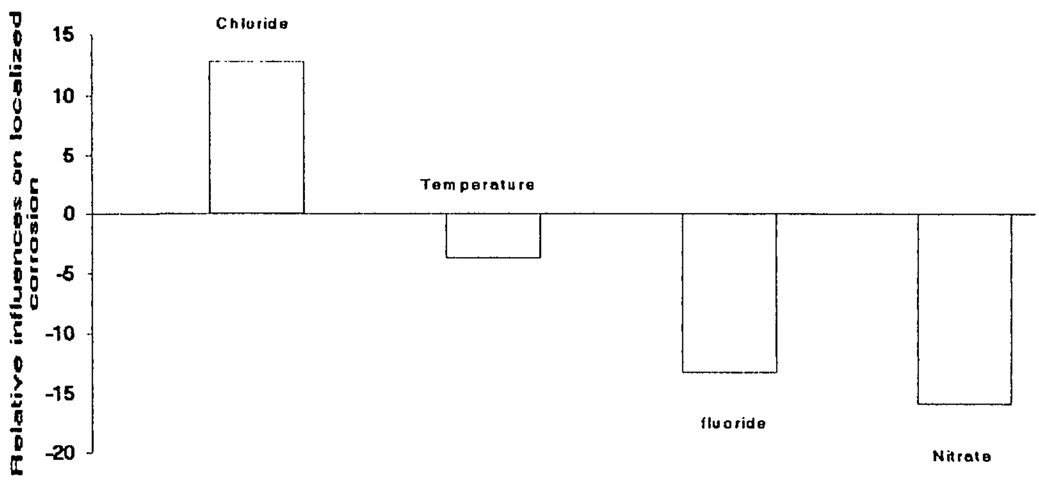

Figure 6: Causal indexes; neural net originated from environmental parameters

ACQUIRING EXPLICIT KNOWLEDGE FROM THE TRAINED ARTIFICIAL NEURAL NETWORKS.

Neural nets enclose implied knowledge which can be derived explicitly, leading to a better understanding of the effect of the parameters on the analyzed system. Graphical sensitivity analysis along with the application of the "causal index" technique can be used for efficiently analyzing complex systems such as localized corrosion phenomenon, in which the relative influence of each independent variable is not always evident.

Figure 6 summarizes global effects of each individual environmental parameters on the localized corrosion rate as reflected by the causal index of the system. The most significant parameters effecting VR are the chloride and nitrate ion concentrations. Chloride appears as a promoter of localized corrosion attack, while nitrate acts as an inhibitor. The fluoride ion is an inhibitor, though to a lower extent than the nitrate. Temperature has a minor influence on VR.

Graphical sensitivity analysis based on the ANN model of three parameters having the most substantial effect on VR; chloride, nitrate and fluoride, has been performed. According to the ANN model, negligible influence of the temperature and actually no effect of sulfate ions have been determined, thus, these variables were not analyzed.

The analysis was performed by plotting contour 3-D images of the VR based on the neural network model. The X and Y axis are the chloride and nitrate ion concentrations respectively, while the Z axis is the VR. The concentration of the fluoride ions was chosen as a parameters, thus, several contour 3-D plots were made, each one representing a specific concentration of these ions.

Typically, each 3-D image has a spherical S shape. The concentrations of the fluoride ions are determining the specific geometry of each plot. According to the relation between concentrations of chloride and nitrate ions, one can determine some general features characterizing the analyzed system. VR is directly proportional to the chloride and adversely proportional to the nitrate ion concentrations. Moreover, as the concentration of the nitrate ion rises, the effect of chloride on VR diminishes, and beyond a specific threshold it has no influence on VR, even at high chloride concentrations. On the other hand, at low nitrate concentrations, VR is sensitive to the chloride contents.

In Figures 7a to 7e, contour 3-D images of VR - chloride - nitrate, with fluoride ions as a parameter are displayed. From these images, one can examine quantitatively the effect of the environmental variables on the VR. Fluoride ions, as slightly inhibitive elements, moderately enlarges the ranges were localized corrosion is less detrimental. At concentrations over 200 ppm, no VR beyond a degree of 2 is determined.

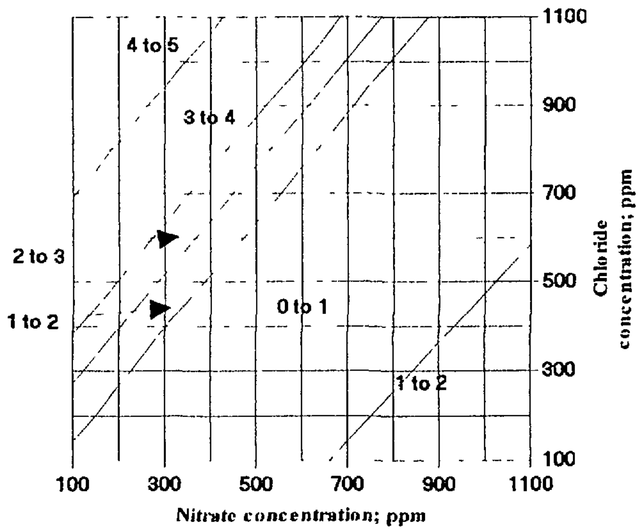

Figure 7a: Visual corrosion rating; Fluoride = 0 ppm

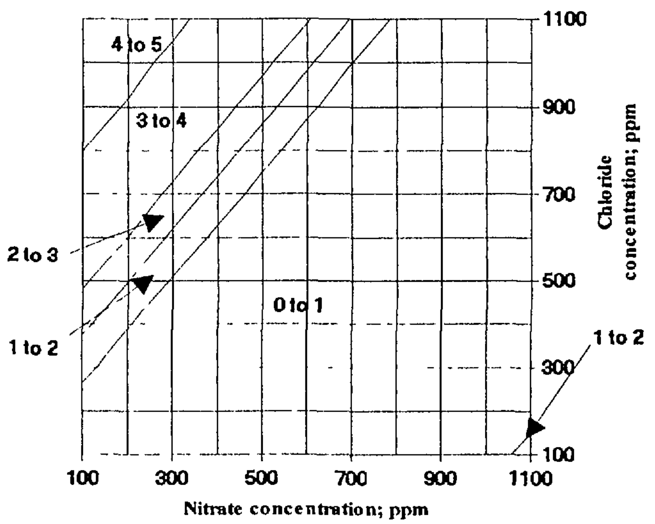

Figure 7b: Visual corrosion rating; Fluoride = 50 ppm

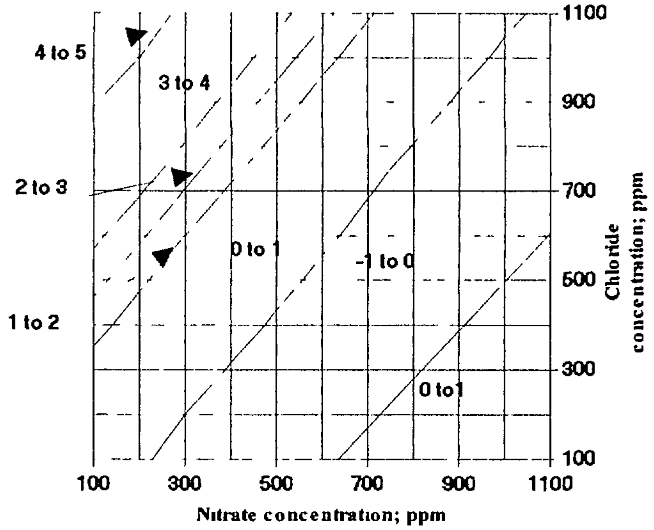

Figure 7c: Visual corrosion rating; Fluoride = 100 ppm

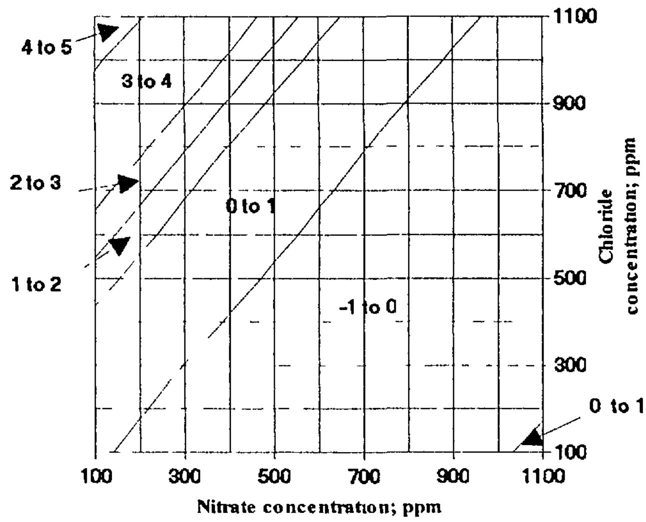

Figure 7d. Visual corrosion rating. Fluoride = 150 ppm

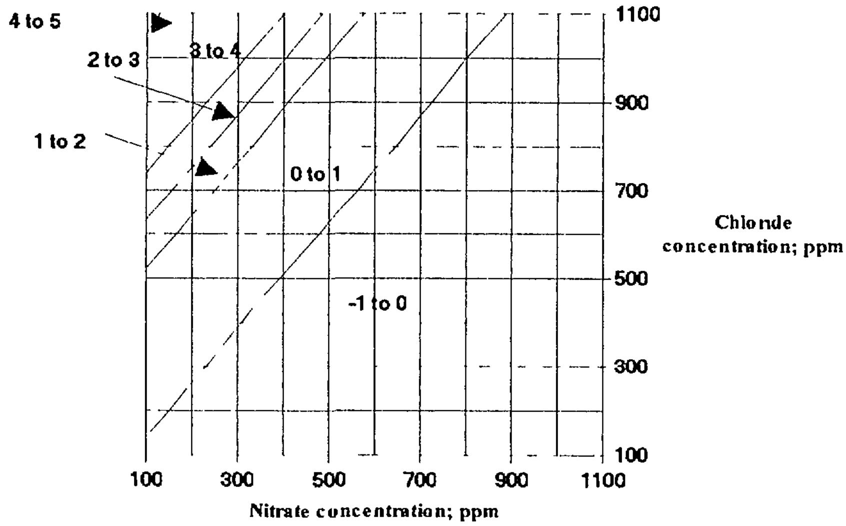

Figure 7e: Visual corrosion rating; Fluoride = 200 ppm

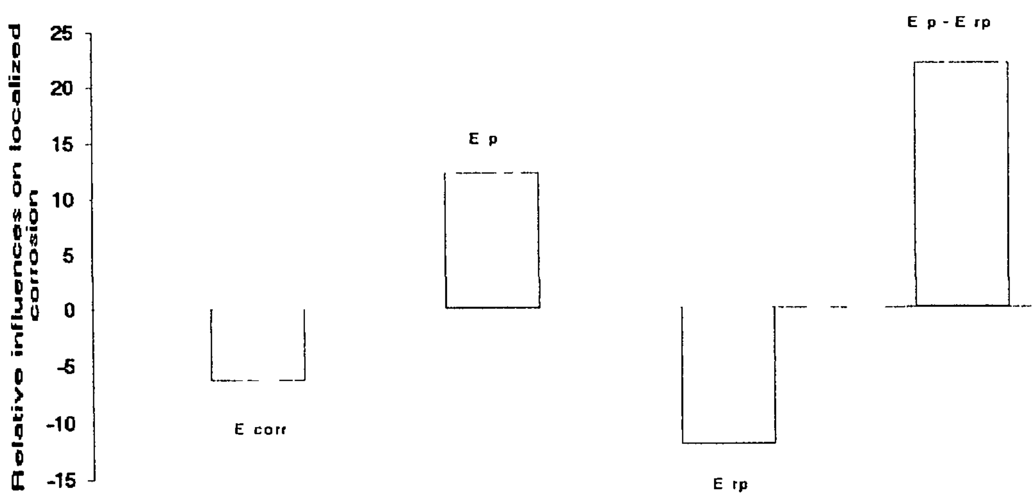

Figure 8: Causal indexes; neural net from electrochemical parameters

Electrochemical parameters can be used as indicators of localizes corrosion. In order to determine the global correlations between these variables and localized corrosion rate, a causal index has been performed; Figure 8. The most significant indicators for VR are observed by the linear modeling technique.

The causal index has an inherent limitation, as a result of the fact that it provides only global information concerning the influences of each parameter on the modeled dependent variable. Thus, it reflects only an mean tendency of the input variables. If for example, an input has a dominant effect on the output in a certain part of the input range and a negligible or even opposite in other regions, this might not be reflected by the causal index. Consequently, the causal index technique has been used in this report only as a complementary technique for investigating the relative influence of the various inputs; the detailed information concerning the effects of the various inputs has been derived from the graphical sensitivity analysis as displayed in Figures 7 and 9. It can be concluded qualitatively that the modeled output is a monotomic function of each input over the whole range of the others, and although its gradient is not constant, it reflects the influences of the input variables.

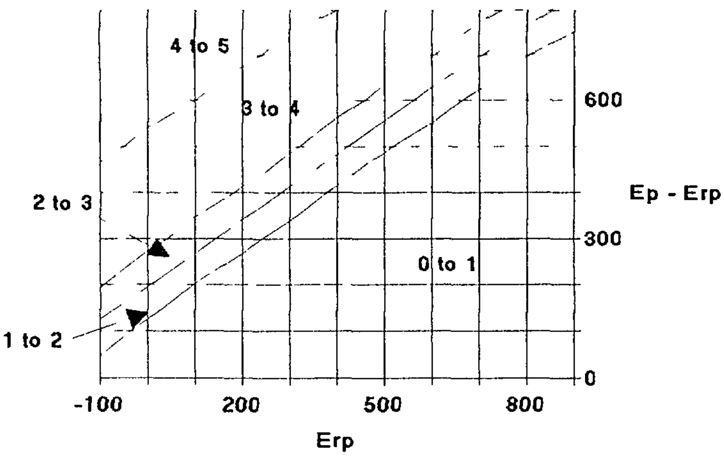

Figure 9a Visual corrosion rating, Ep = 600 MV

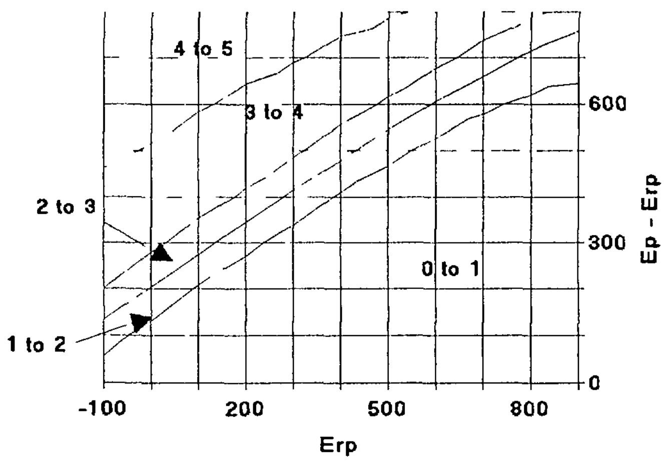

Figure 9b Visual corrosion rating, Ep = 700 MV

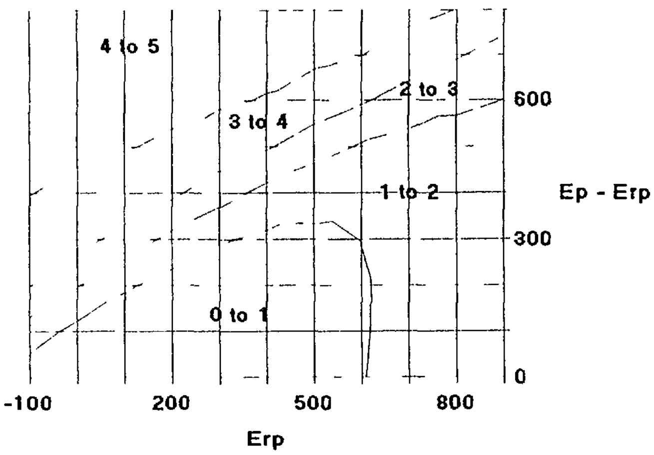

Figure 9c Visual corrosion rating; Ep = 800 MV

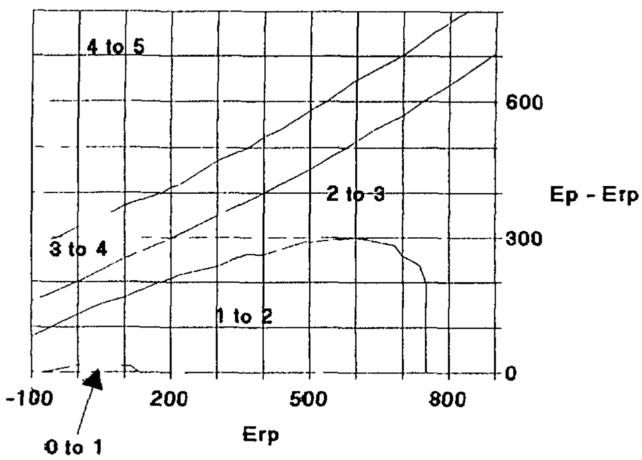

Figure 9d: Visual corrosion rating, Ep = 900 MV

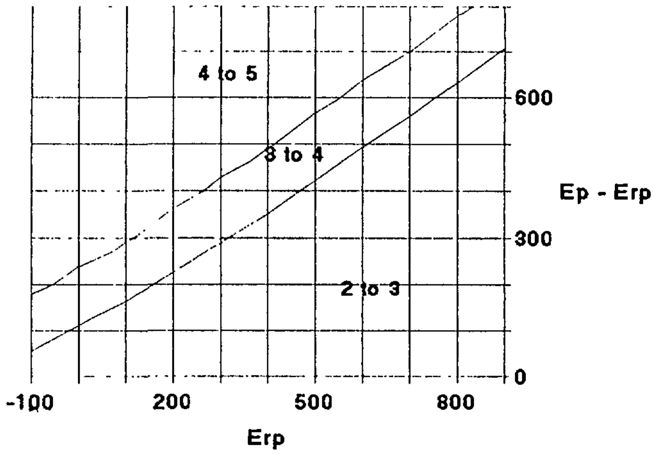

Figure 9e: Visual corrosion rating; Ep = 1000 MV

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SAMSON: SEVERE ACCIDENT MANAGEMENT SYSTEM ON-LINE NETWORK

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Abstract

SAMSON is a computational tool used by accident managers in the Technical Support Centers (TSC) and Emergency Operations Facilities (EOF) in the event of a nuclear power plant accident. SAMSON examines over 150 status points monitored by nuclear power plant process computers during a severe accident and makes predictions about when core damage, support plate failure, and reactor vessel failure will occur. These predictions are based on the current state of the plant assuming that all safety equipment not already operating will fail. SAMSON uses expert systems, as well as neural networks trained with the back propagation learning algorithms to make predictions. Training on data from an accident analysis code (MAAP - Modular Accident Analysis Program) allows SAMSON to associate different states in the plant with different times to critical failures. The accidents currently recognized by SAMSON include steam generator tube ruptures (SGTRs), with breaks ranging from one tube to eight tubes, and loss of coolant accidents (LOCAs), with breaks ranging from 0.0014 square feet (1.30 cm^2) in size to breaks 3.0 square feet in size (2800 cm^2).

1.0 NORMAL OPERATION OF SAMSON

SAMSON operates on a Sun Micro Systems 40 MHz SPARCstation 2GX UNIX machine running Sun Operating System 4.1.2 (Solaris 1.0.1). SAMSON was developed in the Motif™ window environment with MITs X11R5. A 19 inch, 256 color monitor is required to display SAMSON's windows.

1.1 Pre-Accident Operation

Data are collected via a client-server from the plant process computer via a modem and ethernet connection. In the 'normal' mode, SAMSON operates in the background, collecting data, searching the data for an initiation signal, and archiving the data. In addition, SAMSON displays five hours of data in scrollable sensor graphs to allow a user to examine data during normal operation.

When an initiation signal is received, SAMSON automatically switches to 'accident' mode, activating the five default windows and begins making predictions. The initiation signals recognized by SAMSON include a closure of a main steam isolation valve, a feedwater pump trip, a turbine trip, a safety injection actuation signal, or a reactor trip.

1.2 Accident Classification

Once an initiation signal is received, the accident must be classified into an accident type recognized by SAMSON before failure predictions can be made. A rule-based expert system classifies accidents using data collected during the first four minutes of an accident. SAMSON currently recognizes LOCAs and SGTRs. Work continues on expanding the accident types recognized. Since LOCAs and SGTRs are the most likely accidents to lead to core damage and support plate failure based on the Zion IPE, emphasis was placed on recognizing these two accident types. Once the accident is classified, the appropriate neural networks are called to begin making predictions about the failure times.

1.3 Failure Predictions

As data are received, SAMSON processes the data through the appropriate neural networks to make failure predictions. Although data is received only once per minute from Zion's PRIME computer, SAMSON processes all data in under one second, freeing the computer for other calculations as required by plant engineers. Failure predictions are displayed in the 'System Status' window (Figure 1). Three predictions are shown in both an analog and digital form; the time until the onset of core damage (CD), the time until support plate failure (SPF), and the time until reactor vessel failure. Neural networks predict the time until CD and SPF. The time until reactor vessel failure is fixed at one minute after SPF since the accident analysis code used to train the neural networks could not model reactor vessel failure. The pointer on the bar graphs moves up and down as predicted failure times change. The bar graph automatically scales if predicted failure times go off-scale or the selected scale is too large for the current predictions. Once a failure has been predicted, the portion of the window dedicated to that prediction grays, displaying instead that failure has occurred and the time the failure occurred.

Also shown in this window is the time since the start of the accident, the accident classification, and a rate meter. In Figure 1, the accident has been classified as a 0.5 square feet break LOCA. This does not mean that the break is exactly 0.5 square feet in size, but rather that it is from 0.1 square feet in size to 1 square foot in size. The networks that make the predictions were trained on a range of accident sizes, centered around the listed break size, to ensure that predictions would be accurate when the exact break size is unknown.

The rate meter, located to the right of the analog failure meter, displays the instantaneous rate of change in time until the predicted failure, indicating whether the plant is improving or degrading according to the neural networks. Negative rates, shown in red, correspond to a degrading plant state while positive rates, shown in green, indicate that the plant state is improving. The size of the bar indicates the magnitude of change.

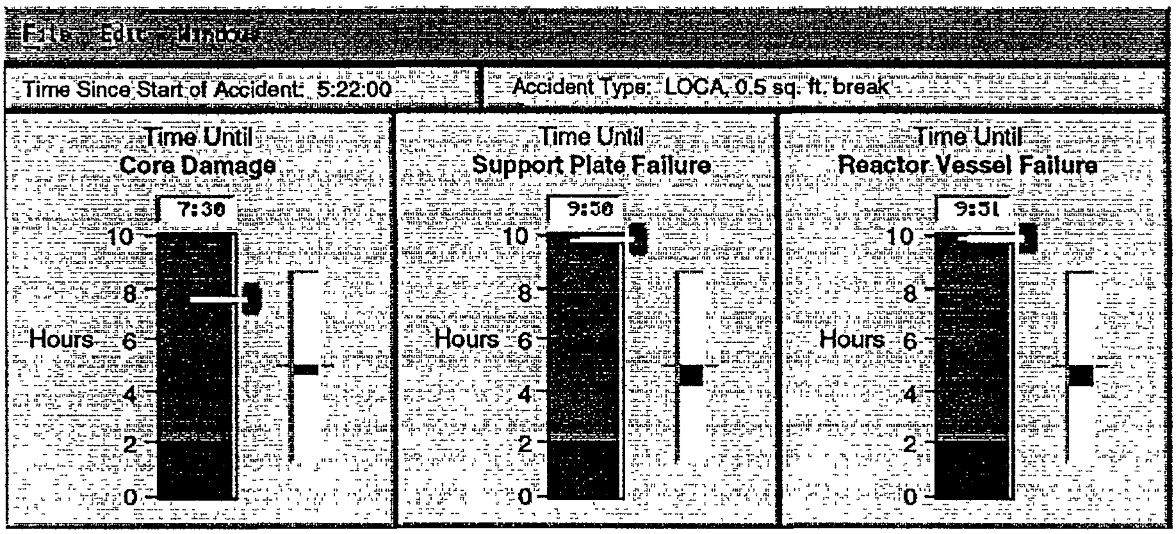

Figure 1: Zion System Status Window

1.4 Displays

When SAMSON activates due to an initiation signal, five windows are opened or activated; 'Zion System Status,' 'Predicted TTF History Graphs' (TTF stands for 'Time To Failure'), ' Events Log,' 'Sensor History Graphs,' and 'Sensor Summaries.' The user can reconfigure SAMSON, specifying which windows will open when SAMSON is launched. The 'Zion System Status' window must always be displayed since closing this window stops SAMSON. If SAMSON is used to display data during normal operations, this window is greyed out since the predictions from the neural networks, trained to recognize accident conditions, would be meaningless.

The 'Predicted TTF History Graphs' is a scrollable window showing the history of network predictions for each failure type. The graphs show the predicted time to failure on the vertical axis and the time into the accident on the horizontal axis. Once failure occurs, a message stating that failure has occurred is displayed on the graph.

The 'Events Log' records when key events occur during an accident. Initiation signals are first recorded and displayed, followed by accident classification information. Other information displayed includes:

- When failures occurred
- User actions to override decisions made by SAMSON
- When the break location was determined by SAMSON
- When recirculation of cooling water has been established
- Which sensors have failed based on SAMSON's redundancy checking
- When the network predictions were inaccurate (SPF time to failure (TTF) less than CD TTF. This could occur if bad data is received).

A 'Sensor History' window displays the historical values for any parameter monitored by the plant's process computer. The order of the graphs is user configurable since only three graphs are visible in the scrollable window at one time. If the user wants to view pressurizer pressure, cooling water flow into the reactor and containment pressure simultaneously, the user can order the graphs so those three are grouped together. As the accident progresses or as the displayed values go off-scale, the graphs will automatically adjust scales to accommodate the data.

The 'Sensor History' window can display up to five hours of data during normal operations to allow the user to perform trend analysis. SAMSON can monitor and display data for over 1000 different parameters. For accident conditions, only 27 parameters are monitored and displayed. Once an initiation signal is received, the window 'resets,' displaying data since the initiation signal was received.

The 'Sensor Summaries' window displays information about the same parameters displayed on a 'Sensor History' window. In addition to the current sensor value, the 'Sensor Summaries' also displays which sensors have failed. SAMSON uses information from the plant process computer in addition to redundancy checking to determine if a sensor has failed. If the sensor has failed, the value will not be used in the neural networks to make prediction. If no sensors are considered accurate, the neural networks will use a default value. Since this default value may not be close to the real value, the network predictions will have some additional error. However, the default values were determined so the smallest error results (not sending a value when required will cause the network to fail). Each circle next to a sensor name corresponds to an individual sensor.

2.0 Special Operation Of SAMSON

There are several other windows that perform specialized functions. Since these functions are not normally used, the windows are generally closed, but can be called when desired. Certain events can force the user or SAMSON to open these windows.

2.1 Manual Start

SAMSON continually receives data from the plant's process computers, but it is possible that the initiation signal will not be received. If this occurs, the user can manually start SAMSON. During a manual start, the 'Manual Start' window opens prior to the default windows opening. Using this window, the user has two options; to direct SAMSON to reexamine archived data over a specified time for an initiation signal or to start SAMSON assuming an initiation signal was received at a specified time. If the user directs SAMSON to reexamine archived data and an initiation signal is found, SAMSON will process all archived data since the initiation signal and then process new data as it is received. If SAMSON can not find an initiation signal within the specified time, the user is forced to specify a start time for the accident and also classify the accident.

2.2 Accident Classification Override

Since the precise starting time of the accident may not be known if the initiation signal is missed, the accident classification could be wrong. The rule based system used by SAMSON to classify accidents can also fail if data is not received during the first few minutes of the accident or if the first few minutes of data fluctuates too wildly to allow for proper classification. An 'Accident Override' window allows the user to change the accident classification at any time during the accident. Under the 'edit' menu in the 'System Status' window the user can open the accident override window. This window displays the accident type as classified by SAMSON, as well as the other accidents recognized by SAMSON. If the user selects a different accident type, SAMSON is forced to use neural networks for that accident to make failure predictions. The predictions in the 'System Status' window will be the predictions using networks designed for the user-chosen accident. For each graph in the 'Predicted TTF History Graph' window, two lines will be shown; one for the user specified accident type and one for the SAMSON classified accident type. This allows the user to compare network behavior between two accident types. The failure predictions for both accidents will continually be displayed in the history graphs, even though the 'System Status' window displays the current prediction for only the user-chosen accident type. If the user wishes to chose another accident type via the 'Accident Override' window, SAMSON will update both the 'System Status' and 'Predicted TTF History Graphs' windows with the most recent user-chosen accident type. SAMSON will also display the history predictions based on the original classification.

If SAMSON does not recognize the accident type during the first four minutes of an accident, the 'Accident Override' window is automatically opened to force the user to manually classify the accident so SAMSON can begin making predictions. The user can change the classification later in the accident as described above.

2.3 Core Thermocouple Map

A 'Core Exit Thermocouple Map' displays the temperature of the 65 core exit thermocouples. The map is color coded according to the temperature received. If a thermocouple is sending bad data, the sensor will be displayed in black. This map will give the user some indication of flow exiting the core during an accident and help to identify 'hot spots' in the core.

2.4 Recirculation Detection

A recirculation detection module was incorporated specifically for Zion Nuclear Generating Station. The Zion IPE determined that once recirculation of cooling water was established, no additional failures would occur. Once a ruled based system determined that one train of recirculation is established, network predictions are no longer necessary and are terminated. No provision is made if recirculation of cooling water is later terminated since the neural networks have not been trained on data where recirculation fails after it has been established.

2.5 Recovery Strategies

A list of recovery strategies was developed to respond to various accident conditions. The user can open the 'Recovery Strategy' window and query a database for possible recovery actions to prevent further damage from occurring. When strategies are requested, SAMSON sends the current predicted failure time along with several plant parameter values to the database, informing the database of the plant state. If matching strategies are found, SAMSON will display what equipment must be operational or what actions must be taken along with the approximate time to complete the action.

3.0 FUTURE DEVELOPMENTS

Work continues on SAMSON to make it even more capable. Future changes include:

- Creating analysis tools to explain network prediction changes
- Training new neural networks for failure detection
- Forcing SAMSON to continue predictions after predicted failure has occurred
- Training neural networks for sensor validation
- Sensor Validation override
- Integrating normal operation monitoring with accident management operation
- Comparing MAAP runs with the current accident for validation during an accident
- Using additional accident analysis codes for training the neural networks

DEVELOPMENT OF A NUCLEAR FUEL RELOAD PATTERN DESIGN SYSTEM BASED ON HEURISTIC SEARCH METHODS

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Abstract

The design of nuclear reactor fuel reload patterns involves a great amount of data, calculations, safety criteria and restrictions to be observed, as well as the knowledge of experts working in this field. Many reload patterns can be generated but only a few are optimal. In this paper the current development stage of a system based on heuristic search methods to generate and optimize fuel reload patterns using engineers is presented. The main components of the system are the knowledge base, the inference engine, the 3D Boiling Water Reactor (BWR) simulator PRESTO[1] and the user interface. The system has already developed and evaluated fuel reload patterns for the Laguna Verde Nuclear Power Plant, achieving similar patterns to those generated by the fuel supplier. Further work on optimization of patterns is about to be started. In the near future this system will be integrated in an overall system based on graphics environment to perform in-core fuel management analysis for BWR nuclear reactors.

1 INTRODUCTION

The design of nuclear fuel reload patterns is a complex task, which requires manipulation of a large number of data and parameters. Satisfaction of constraints related to safety and energy requirements has to be achieved as well. Basically, the required amount of fresh fuel assemblies and used fuel assemblies have to be shuffled in such way that requirements and constraints are satisfied. Exhaustive analysis of position combinations is prohibitive due to the explosively growth of the search space. Nuclear engineers have tackled this task using heuristics which prune the search space. However, no guaranteed heuristics has been produced, and tests of alternative configurations require neutronic models to be used for verifying them. The whole design of fuel reload patterns task is knowledge intensive, though it also involves numeric simulation, in a trial and error iterative loop.

We are developing a computer system for designing fuel reload patterns for the Laguna Verde BWR nuclear power plant. The main development tool is Nexpert Object [2]. The current capabilities of our system are generation of initial patterns generated according to several heuristics, and partial evaluation of the patterns by the PRESTO-B code. We describe below the main characteristics, development and future work on our system.

2 AN APPROACH TO DESIGN FUEL RELOAD PATTERNS

A brief description of the fuel reload patterns design and evaluation requirements is presented here, according to knowledge and experience of the expert nuclear engineers involved in this project. The main goal pursued by the whole design task is to maximize the generated energy in an operation cycle, while satisfying safety restrictions concerning the fuel integrity, and the plant operation.

2.1 The Fuel Reload Patterns Design Task

The initial requirements for designing fuel reload patterns are the final operation conditions in the previous cycle, and the desired conditions for the operation cycle being designed (i.e. operation time, capacity factor). The operations which can be carried out using these data are:

- Determination of the amount, enrichment and type of fresh fuel.
- Determination of lowest reactivity or highest exposure fuel to be removed from the reactor.
- Design of the fuel reload pattern, loading fresh fuel, and reshuffling the fuel staying in the reactor after being there during other cycles. Criteria for selecting fuel positions are consistent with the Maximum Reactivity/Minimum Peaking Principle, the Low Leakage Pattern and Control Cell Core Strategy.

The following restrictions apply:

- 1/8 core simetry.
- Assemblies from the pool are reinserted.
- Hand discharge of assemblies whose integrity appear to be damaged, and some special cases (i.e. an assembly cannot be positioned beside a control cell if the assembly has already been beside a control cell.

2.2 The Fuel Reload Patterns Evaluation Task

The fuel reload patterns are evaluated using the PRESTO-B code. This is a 3D simulator of the reactor's core, which solves the diffusion equation bared on an approximation to two group diffusion theory using a special coarse-mesh algorithm for a core representation.

- The fuel reload pattern,
- The final conditions of operation of the previous cycle,
- Nuclear data banks for the fuel types used in the fuel reloading,
- The reactor's core characteristics (i.e. core geometry, number of fuel assemblies, number of control rods),
- The operation conditions for the cycle (i.e. thermal power, feed water enthalpy, cycle exposure)

Evaluations of fuel reload paterns are carried out in four stages, and six executions of PRESTO-B are required.

- At the beginning of cycle, radial reactivity profile, and power per channel.

  At the end of cycle Haling calculations, for analizing generated energy so that it is maintained inside specified operation conditions; also, the Minimum Critical Power Ratio and the Maximum Linear Heat Generation Rate thermal limits are verified so that they are maintained inside safety margins. Radial and axial average power distributions must not exceed the design limit.

- Evaluations are done at the beginning of cycle, when conditions are cold, power is null and free of xenon. The shutdown margin must satisfy the design criteria.

- The shutdown margin is evaluated on several burning steps so that the plant's safety criteria is satisfied.

3 DEVELOPMENT OF THE FUEL RELOAD PATTERNS DESIGN SYSTEM

The current stage of development of our system shows two main subsystems

The Fuel Reload Patterns Generator

The Fuel Reload Patterns Evaluator

They really work as different modules. Fuel reload patterns are generated by the generator, and are analysed by the evaluator so that working or promising patterns are detected and selected. Additional modules will carry out optimization of promising patterns, as described in Section 4. General characteristics of the working modules are described below.

3.1 Heuristic Generation of Fuel Reload Patterns

A fuel reload pattern is generated by modifying the old fuel pattern, the one used in the previous operation stage of the analized nuclear reactor. Heuristic rules for positioning fuel assemblies were acquired from expert nuclear engineers, exploiting their knowledge and experience in the task of design of working fuel reload patterns. In order to apply such rules, once the amount of fresh fuel to be added to the reactor is determined, two work phases are required to define the new positions of all the fuel assemblies:

- Used fuel assemblies are assigned a position in the new pattern.

- Fresh fuel assemblies are positioned in the new pattern.

General guidelines are established by the expert rules. They constrain the shuffling of assemblies so that restrictions are obbeyed, and convenient sites are chosen. This set of guidelines is presented in [1]. Eight different, mutually exclusive strategies for positioning a given set of assemblies are generated following our heuristic rules.

Our implementation of the Fuel reload Patterns Generator requires two aspects of information processing to be used. First, preparation of nuclear data is accomplished so that the amounts of fresh and old fuel to be used are determined. Then the heuristic rules are used to select positions of fuel assemblies. The final result of these processing stages are eight different fuel assemblies patterns, for the same specification of fresh and recycled fuel (i.e eight different patterns for the specified amount of fresh and recycled fuel). These patterns are then tested by the Fuel reload Patterns Evaluator module.

3.2 Evaluation of Fuel Reload Patterns

The fuel reload patterns created by the Generator module are evaluated in order to select the appropriate ones according to specified requirements and restrictions. As previously stated, the evaluation is performed using the PRESTO-B code to simulate neutronic and thermohidraulic behaviour of the reactor, for stable operation and xenon transients conditions. Power distribution, fuel burnup, thermal limits and fuel reactivity are evaluated in this way.

Six executions of the PRESTO-B code have to be carried out in order to fully accomplish the evaluation of fuel reload patterns. Additionally, preparation of input data for each execution, and analysis of PRESTO-B results are the complementary tasks performed by our system in this stage.

Preparation of input data for PRESTO-B, and its execution are tasks which require extensive manipulation of information, which is done according to established procedures. However, analysis of the simulator results is one more knowledge-based decision making process. Heuristic rules are used for selecting promisory fuel reload patterns, and making suggestions for modifying the fuel reload patterns so that their performances are improved.

Modification of fuel reload patterns in order to improve its performance is actually the third processing stage of our system, and the one which will set conditions for starting the next iteration in the fuel reload patterns design task. Other aspects of the current implementation are presented in subsection 3.3

3.3 Implementation of the Fuel Reload Patterns Design System

The main physical characteristics of our system are:

- The main development environment is the NEXPERT Object shell.
- It is composed by 489 heuristic and control rules.
- A backward chaining is carried out, in order to reach a satisfactory fuel reload pattern design goal.
- Two operational Classes are defined, and their instantiation generate assemblies and fuel reload patterns.
- External support programs are written in the C programming language.
- The system is being developed in a DEC Risc machine, running Ultrix.
- The user interface works under MOTIF, using an X terminal.

4 PARTIAL RESULTS AND FUTURE WORK ON THE FUEL RELOAD PATTERNS DESIGN SYSTEM

The fuel reload patterns design system has the capability to produce fuel reload patterns already, according to the heuristic rules added up to this time. Full evaluation of the fuel reload patterns is not complete yet, as evaluation of some operative limits has not been implemented. Nevertheless, the system is now feedbacking the expert nuclear engineers which defined the heuristic rules. The experts are analysing the effects of their assumptions as used by the system. New conclusions have already been reached, and refinements to the knowledge inside the system have also be carried out.

According to the requirements specification of the fuel reload patterns design, the aspects which still require intense work are the module for modifying promisory fuel reload patterns, and the user interface. The Fuel reload Patterns Generator will be modified in order to add several new considerations and constraints to the heuristic rules for positioning fuel assemblies. The Fuel Reload Patterns Evaluator requires also further additions in order to fully carry out evaluation of the specified parameters.

Local and total validations have also to be performed. These shall be continuous tasks, as the incremental development of the system requires that a working complete prototype be produced, and successive refinements of it will be done until the achievement of requirements.

5 CONCLUSIONS

The initial stages and results of the development of a fuel reload patterns design system have been described. Tests using real data have produced results very close to those obtained by the fuel supplier. Fuel reload patterns have been obtained which are close to meet the requirements; however, no pattern generated by the system is satisfactory yet. Therefore refinements to the system's knowledge are being carried out, trying to find better ways to shuffle fuel, and get better performance. The system has allowed the expert nuclear engineers to explore new design approaches, and is also feedbacking them and validating their own knowledge.

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AN EXPERT SYSTEM FOR DIAGNOSING FAILURES IN THE CONDENSATE SYSTEM OF THE LAGUNA VERDE NUCLEAR POWER PLANT

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Abstract

An expert system for diagnosing faults and processing alarms during operation of the Condensate System of a boiling water reactor nuclear power plant is presented here. The main features of this system are its systematic knowledge acquisition methodology, based on Probabilistic Risk Analysis techniques, and an intelligent alarm prioritising mechanism for generating optimal, very fast inference strategies. The main developing tool for was the GENESIS shell, a specific use tool developed by the authors of this paper.

Introduction

The operation of nuclear power plants (NPP) during transients, when many alarms and process indicators might require the attention of the operators, can become very critical. In these cases the most relevant occurring indicators have to be recognized in order to detect possible failures, and the cause of them. Vast knowledge of the process is required to carry out such task. As a way for mitigating this problem it has been proposed that expert systems for detecting and diagnosing failures during operation of nuclear power plants could be a valuable help for increasing process reliability.

A prototype expert system for performing both process symptoms pattern recognition, and failure diagnosis of the Condensate System of the Laguna Verde BWR nuclear power plant, is presented here. In building such a system an innovative methodology based on Probabilistic Risk Analysis (PRA) techniques for capturing and representing the required knowledge was used, as well as a directed inference mechanism. An expert system shell developed for building this sort of applications, GENESIS [1], was the main development tool.

The current version of our system - CONDE - interacts with human users receiving as input data values of process variables, and generating as output the diagnosis of failures, whenever a pattern is recognized. Extending the expert system to incorporate communication links with a data acquisition system (what should ease implementing a real time expert system) will be enabled by the simple representation and inference approaches used.

Description of the Condensate System

The Condensate System of the Laguna Verde NPP is composed by the equipment included after the discharge of the main condenser's hot.well, up to the discharge of the low pressure

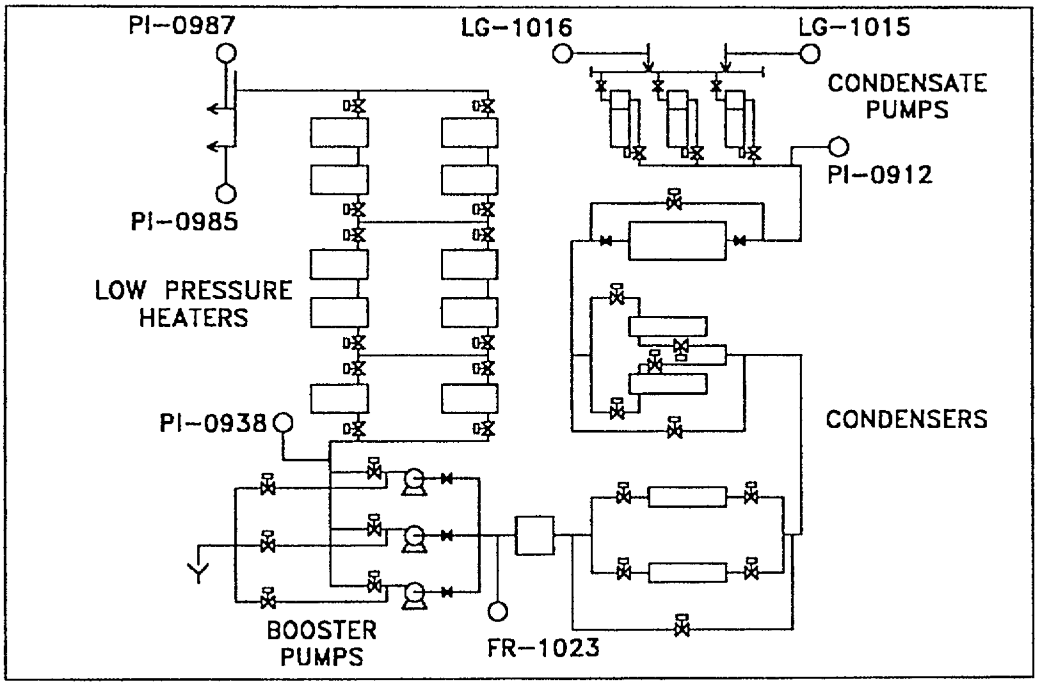

Figure 1. Simplified Diagram of the Laguna Verde NPP Condensate System

heaters (see Figure 1). The fluid there discharged is the feed water which is to be sent to the reactor, after receiving further heating in the feed water system.

The functions of the Condensate System are those shown below:

- To continuously supply water to the reactor feed water system.
- To preheat the pool reactor feed water.
- To keep the feed water quality inside purity specifications.
- To guarantee the equipment reliability so that water can be supplied to the reactor during transients.

The borders of the Condensate System are the following points:

- The input point of the Condensate System is the main condenser discharge head, which is also the suction head of the condensate pumps.
- The output point of the Condensate System is the discharge head of the low pressure heaters, which is also the suction head of the feed water pumps.
- In this prototype system the equipment used to purify the fluid were not considered as part of the Condensate System, and their associated failures were not included while building this prototype.

Development of the CONDE Expert System

The methodology used for developing CONDE is based on an original application of Probabilistic Risk Analysis techniques [2]. A description of how this methodology was used is presented below, as well as a description of the architecture and modules of our system.

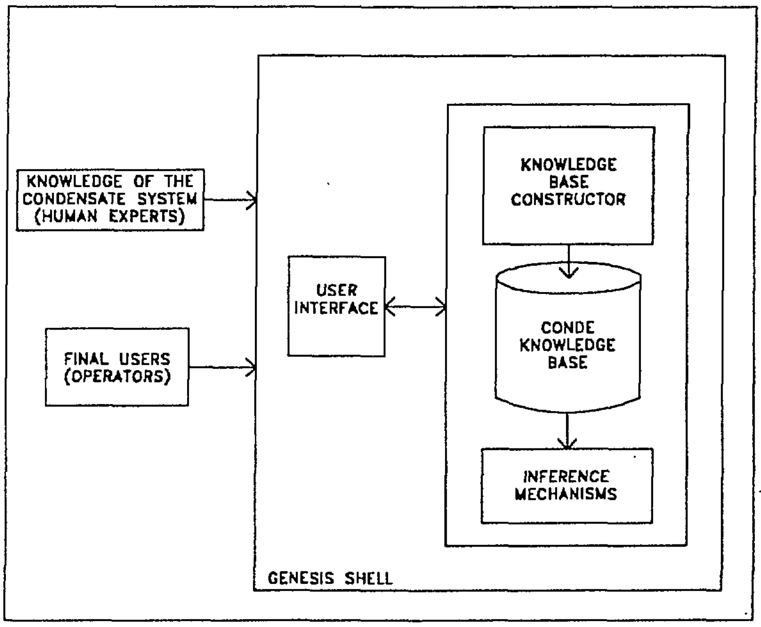

Figure 2. Architecture of the CONDE Expert System

Architecture of CONDE

The main components of CONDE are GENESIS - a shell for development of diagnosis expert systems [1], and a knowledge base containing relevant information of the Condensate System of the Laguna Verde nuclear power plant. The architecture of CONDE is shown in Figure 2.

According to the methodology proposed in [1], the knowledge base for the Condensate System was integrated by carrying out the following stages of processing:

1. A fault tree [2] was constructed, in which the top event is the failure of the Condensate System to supply the required amount of fluid at its output point (i.e. there is no flow at the discharge head of the low pressure heaters).
2. A set of symptoms was associated to each basic event in the fault tree. Detection of one of these symptoms sets is assumed to mean the occurrence of its associated basic event.
3. The probability of occurrence of every basic event was included in the information supplied as input data for the creation of the knowledge base.

GENESIS processes the information just mentioned, in order to generate a set of optimal strategies for recognizing the symptoms patterns associated to failures of complex systems. Also, an environment is provided for executing the search strategies, once they have been constructed.

The steps followed to construct the knowledge base of CONDE, and the development of the system itself are presented below.

Knowledge Elicitation

The first stage carried out in the construction of CONDE was the elicitation of knowledge concerning the Condensate System. According to the methodology suggested in [1], the following tasks were carried out:

- Construction of the appropriate fault trees for the Condensate System.
- Association of symptoms to the basic events in the fault trees.

Both tasks were performed by the developers, and they were assisted by human experts.

Construction of the Condensate System Fault Trees. Fault tree [2] is the generic name for a kind of logic-graphic model of physical systems, and are used for describing the ways in which different simple (basic) events are combined for making an undesired event to occur. The undesired event, known as *top event*, is usually a dangerous situation, a failure of the analyzed system to operate properly, etc. Immediately related, simpler events which cause the occurrence of the *top event* are connected to it by means of **AND** or **OR** logic gates, depending on their interrelationships. Each second level event is further developed in the same way up to the point where the required level of detail is reached.

When constructing fault trees the knowledge elicitation is carried out in a systematic way, according to the well-established PRA methodology for doing so [2]. The information is neatly structured, and can easily be reviewed and updated by human experts, due to the graphic representation of the fault trees. Concerning the basic events, the information contained in the fault trees includes both the specification of every basic event at the appropriate level of detail, and the probability of occurrence of the same basic event.

The top event examined for the Condensate System fault tree is: "Insufficient Flow of Condensate Fluid at the Discharge Head of the Low Pressure Heaters". This refers to cases when the output flow of the Condensate System is 50 % or less than the normal flow.

Inclusion of Symptoms. Every basic event in the fault tree was associated to a specific set of symptoms, which can be alarms, measurements, and indicators of process parameters. This task was also performed by the human experts, having in mind the mentioned basic assumption which states: if a specific set of symptoms is occurring then its associated basic event is occurring as well.

Integration of the Knowledge Base

The integration of the knowledge base was performed using the GENESIS shell, by carrying out further processing of the input knowledge as described below.

First, in order to identify all the possible modes in which the top event could occur, the fault tree was processed to find every minimal combination of basic events which can make the top event occur. Each of these sets of events is known as a *Minimal Cut Set* (MCS). The FTAP code [3] was used to generate the MCSs of the Condensate System.

The immediate step was the construction of a reduced, equivalent tree, a task carried out by GENESIS. This was done by representing the original tree in terms of an OR relation

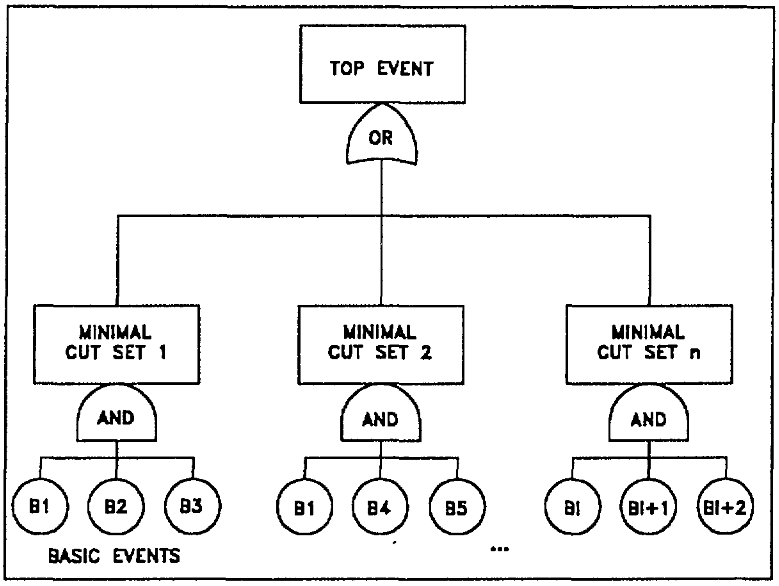

Figure 3. A Fault Tree Represented in Terms of its *Minimal Cut Sets*

between the top event and all the MCSs. This representation is shown in Figure 3, where the equivalent tree in two levels is presented. This structure largely reduced the size of the search space in the sense of deepness. It can be easily understood as the OR relationship in which the top event occurs if any of the MCSs occurs.

For the faut tree of the Condensate System 1579 MCSs were identified, taking into account only the MCSs composed by the combination of 1, 2, or 3 basic events each.

In the next processing stage the sets of symptoms associated to the detected basic events were included. An extended tree was generated in which the sets of symptoms were explicitly represented, connected to their associated basic events. The purpose for doing this was to express the tree's MCSs in terms of symptoms only (taking care of carrying out boolean reductions to avoid expressions like **A˙A**, which is reduced to **A**). An example of the inclusion of symptoms as described is presented in Figure 4.

The basic assumption for integrating the knowledge base rules in [1] is as follows. The relationship between an MCS and its associated symptoms pattern is an implication:

MCS ---> symptoms pattern

In order to carry out diagnosis, abduction on groups of symptoms is carried out. If a symptoms pattern is recognized then the MCS which it is associated to could be occurring as well. In this way, for every MCS considered for the analysis, its associated symptoms pattern was used as the conditions part of a production rule, and the basic events which integrate the MCS were taken to be the conclusions part of such a rule. An example of one of these rules is shown below.

RULE No. 1
IF
LG-1015 LOW and
LG-1016 LOW
THEN
INSUFFICIENT FLOW IN THE CONDENSER HOT WELL

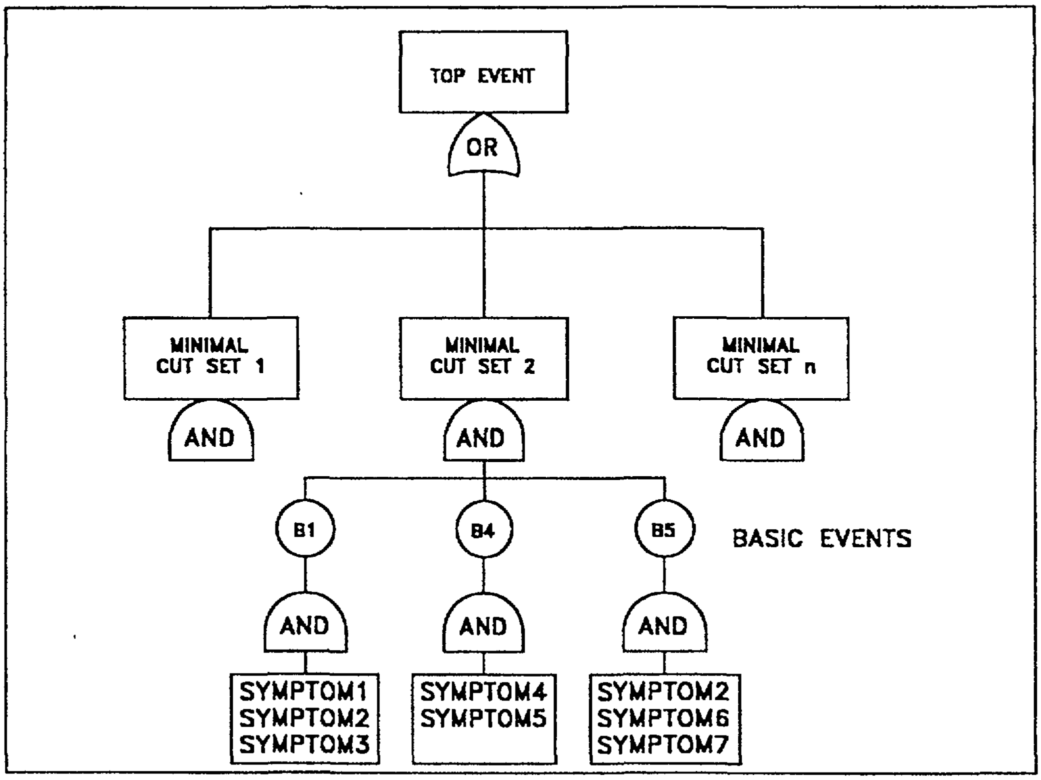

Figure 4. An Extended Tree Including Symptoms

According to this methodology, GENESIS generated 1579 production rules for the CONDE expert system.

Inference Mechanism

The number of symptoms occurring during a transient in a power plant can be very large. Furthermore, since an even larger quantity of symptoms patterns (i.e. MCS) can be originated after processing the fault tree, the search space can grow as much as the involved basic events combinations allow. In these conditions, recognizing the pattern(s) occurring during a failure can be an extremely expensive task, in terms of time. In CONDE this problem was tackled by using a directed search algorithm implemented in GENESIS [1]. In this way optimal search strategies were generated off-line, and used to carry out failures diagnosis in the Condensate System.

The search strategies generated by GENESIS are said to be directed because they "prefer" certain symptoms when starting the search. This behaviour is obtained by arranging the symptoms review order according to their probabilistic importance [2]. The most important symptoms are those whose probability of occurrence is higher, and those which are included in more patterns [1]. Attending to this aspect, two important steps were carried out by the algorithm used to construct the search strategies:

- Symptoms patterns were arranged in such a way that the most important symptoms point to the patterns they are contained in.
- The most important symptoms are positioned in an agenda, in descending importance sequence.

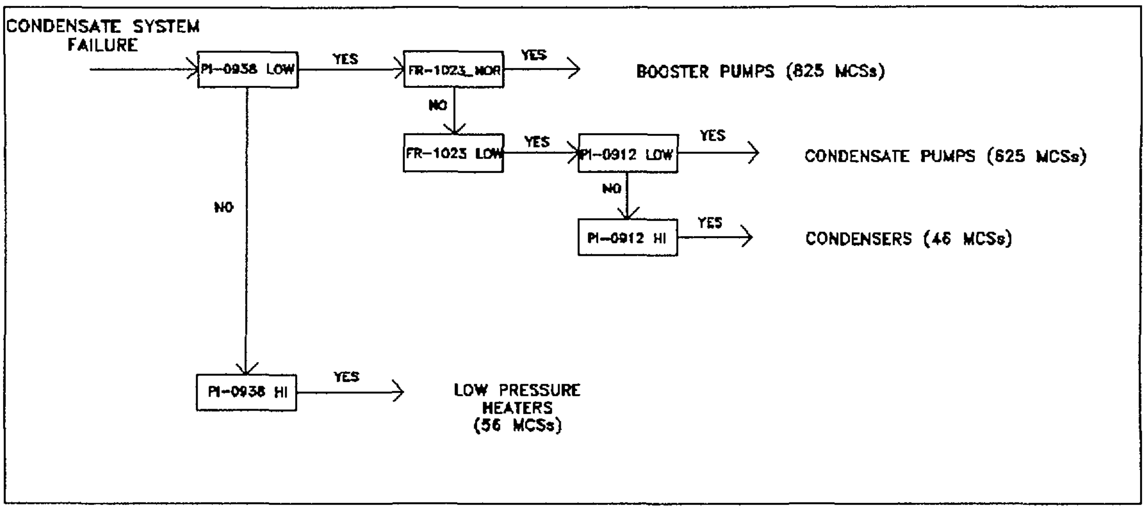

Figure 5. Search Strategy Generated Off-Line for CONDE

The effect achieved by doing this is that patterns associated to an important symptom do not have to be considered if the symptom is not detected when it is checked (i.e. part of the search space is pruned).

The search strategies used by CONDE are shown in Figure 5. The interpretation for that diagram is as follows: The symptom PI-0938 is checked to find out whether there is a problem in the low pressure heaters section or not (see Figure 1). Behind this is the fact that, if there is a problem in that section (e.g. PI-0938 is high), then a big branch of the search space can be pruned, since the rest of the system is assumed not to be in trouble (i.e. there are 1523 out of 1579 patterns which do not have to be checked). On the other hand, if the symptom PI-0938 low is detected, then the search is directed towards the booster pumps, the condensers, and the condensate pumps sections, and the most important symptoms in turn are checked (e.g. FR-1023, PI-0912), following the alternative branch of the global strategy, and pruning from the search space the low pressure heaters section.

It can be appreciated that this global strategy generated is in fact a classification of the Condensate System into simpler subsystems, resembling the way an expert operator would carry out a quick diagnosis inspection of the same system. A forward chaining mechanism is used in GENESIS for carrying out this search task.

User Interface

At this stage of development, the CONDE expert system has the capability for interacting with human experts and final users. There are two basic aspects of the communication between the expert system and its users which the user interface takes care of:

- A series of conventional menus, text and graphic display of conclusions (i.e. using screen mimics), and explanations for the results reached are available during the normal diagnosis sessions. In the current version of CONDE it asks the user for the symptoms which are present in the diagnosis session. Nevertheless, the input format for the symptoms is prepared for a future extension, to make CONDE able to cope with inputs from data acquisition systems.

- The task of updating CONDE's knowledge base can be carried out by modifying the input fault tree, the associated symptoms, or both. This information has to be supplied in simple text files, according to formats used for constructing fault trees [1].

Current Status of the CONDE Expert System

The inference mechanism supplied by GENESIS has been extensively tested in previous developments [1]. The tests carried out have shown an excellent performance of the mechanism, though further testing periods shall be done, as CONDE itself is still being enhanced. One of the most important aspects of expert systems interfaces is their ability to guarantee accessibility to relevant information which can be useful to users and developers. These aspects of CONDE's performance were tested and validated by human experts.

The current status of the CONDE expert system is that of a working prototype, for which further validations should be carried out against simulators of the Condensate System of the Laguna Verde NPP. CONDE is now a self-contained system which appears to be ready for the extensions which shall make it able to cope with real diagnosis problems.

The knowledge representation used, based on fault trees of the Condensate System, has proven to be very convenient, mostly due to the fact that the knowledge can be systematically captured. Also, accessing the knowledge is an easy task both when performing inferences and diagnosis, and when working on the maintenance of the knowledge base.

Future Work on CONDE

Some aspects in the performance of our expert system have to be enhanced, in order to make it capable to work under real conditions. They are shown below:

- The user interface should be able to read symptoms patterns from a data acquisition system, apart from the current form of the interaction (in which it is completely based on dialogues maintained between the user and CONDE). This is actually an implementation task, which shall be addressed once tests in a real environment get started.
- The knowledge elicitation task depends on the construction of fault trees for the system analyzed. A further step towards the automation of this stage has just been done [4]. After integrating a tool for systematically constructing fault trees, the resulting system will provide a powerful environment for the development and maintenance of this kind of expert systems.
- Further testing of the knowledge contained in CONDE has to be performed using a simulator of the Condensate System. The whole expert system should be able to work under this conditions, in order to make of it a really useful tool. This is the main task to be carried out in order to achieve the complete development of CONDE.

Conclusions

A prototype expert system for recognizing symptoms patterns, and diagnosing failures of the Condensate System of the Laguna Verde BWR nuclear power plant, was developed. The kind of symptoms processed by the CONDE expert system, are those which are available to operators of a real nuclear power plant (i.e. alarms, measurements, and indicators of process variables).

CONDE uses a strategy for executing directed search of the symptoms patterns space. The strategy classifies the whole condensate fluid system into several sections, resembling the behaviour of expert operators. This strategy is generated prior to the execution of the expert system itself, so that the actual diagnosis task can be carried out in a very fast execution of such strategy.

The current implementation of CONDE requires further work to be carried out on its interface. In order to make the expert system capable to work in a real environment the main requirements to satisfy are: communication between CONDE and a data acquisition system has to be implemented, as well as communication between CONDE and an automated knowledge elicitation tool. Our current work is focused in those topics. Also, extensive validations of the knowledge base are to be carried out in a simulator of the nuclear power plant analyzed.

The knowledge representation used, based on fault trees of the system analyzed, is very convenient because it provides efficient accessibility over the expert system knowledge. Also, by applying the fault trees techniques for process analysis, the development of this kind of diagnosis expert systems can be carried out in a systematic way when using the development environment supplied by GENESIS [1].

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APPLICATION OF ARTIFICIAL NEURAL NETWORKS IN ESTIMATION OF PROBABLE ACCIDENT CAUSES IN NUCLEAR POWER PLANTS

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Abstract

The concept of a Nuclear Power Plant (NPP) control room advisor, applying quick estimation of the probable accident causes, is recently a subject of growing interest. The purpose of such a tool is to assist plant operators to evaluate the situation and forecast the consequences of an accident. Several expert systems have been developed for such a task, most of them using the traditional approach of a "rule-base", where the potential accident causes are encoded in a "knowledge base" list. The main problem of such systems lies in creating and using the knowledge base which is inherently limited and unable to deal with uncertainties.

A way to use a knowledge base with treatment of uncertainties is the calculation of Bayesian probabilities of the accident cause from the time behavior of selected signals, based on NPP expert knowledge. However, this method is sensitive to errors in the instrumentation readings. Artificial neural networks (ANN) were already used to predict fault probabilities, and are known to show robustness against erroneous or incomplete input data.

An exploratory study was made to train an ANN to predict the probabilities of four causes of accidents (loss of coolant accident types), based on the time behavior of three selected parameters (pressurizer pressure and level and containment humidity). 316 time scenarios have been generated, with the cause probabilities calculated by Bayesian procedures. Four ANN models were trained by the TURBO-NEURON 1.1 software package on a basis of 251 cases to predict the cause probabilities of a particular accident scenario. The generalization capacity of the models was tested by comparing the results of the remaining 65 cases.

It was found that the ANN models were able to classify correctly the original cause in 88% of the test cases, while the probability of correct prediction by random guess is 25% . This result is considered quite encouraging for further work, in view of the possibility to increase easily the number of training cases, with a consequent increase in the generalization capability.

1. Introduction

The ability to quickly diagnose the cause of an abnormal situation in a nuclear power plant (NPP) is, obviously, an important operator aid with major safety implications. Thus, there is an ongoing effort in many companies and organizations to develop such an ability, using a variety of software tools. The main thrust is in using Expert System technology, based on "deep knowledge" of the system components behavior and interactions, using expert rules and detailed engineering models.

In recent years came, however, the realization that the common Expert System approach may not be the best available for implementation in NPP's. This is because detailed rules are hard to formulate, code, debug and maintain. The speed of diagnosis in real situations may not be fast enough, the possibility
that sensors malfunction, which may mislead "if/then" rules or models, will not indicate the right cause in time. There are also the verification and validation (V&V) requirements of the safety authorities, which are hard to meet.

One alternative approach is the artificial neural networks (ANN) approach, which depends on "learning" typical patterns of behavior in accidents in NPP, identifying the probable cause of an abnormal situation by the time response of a small number of sensors. The advantages of this approach are the fast recognition, the ability to diagnose correctly even when some of the sensors are faulty, and the compact easy to verify computer code. The main disadvantages are the limited availability of real NPP data to learn from, the lack of explanation facilities, and the distrust of experts in "machine" learning, which depends on "shallow knowledge".

Despite these objections, there are many references to attempts of using ANN for this purpose. One of the most advanced is a project by Silverman (1) to predict the probable evolution of a severe accident in a NPP, based on several sensor readings. The data for teaching the ANN is generated by a full-scale simulator of the Zion NPP.

The current view of ANN implementation is to use it in a synergistic way with other methods, each contributing it's special strength (2). In this work we test the possibility to generate the training data by probabilistic methods, based on expert knowledge of the system behavior in a small number of initiating events. If successful, this approach may be further developed into a full scale operator aid.

2. The Need for Expert-System Diagnostics in NPP

After the Three-Mile-Island accident it has been widely recognized that an onsite advisor at nuclear power plants might serve as a useful diagnostic tool for abnormal situations. Since a human expert is not always available in the control room, a computerized system with a capability to reflect the expert knowledge, can offer diagnostic and decision assistance to plant operators and managers when emergency conditions develop.

While in emergency conditions, or even in abnormal situations that might lead to emergency conditions, response time is of crucial importance to the plant. A wide and comprehensive knowledge base is necessary to evaluate many possible causes of abnormal events. These characteristics are typical to a computerized expert system.

Consequently, considerable effort has been invested in developing various computerized systems for NPP diagnostics (3-7). Most of them use the traditional approach of a "rule-base", where the potential accident causes are encoded in a "knowledge base" list. The main problem of such systems lies in creating and using the knowledge base which is inherently limited and unable to deal with uncertainties. Another way to use a knowledge base with treatment of uncertainties is the calculation of Bayesian probabilities of the accident cause from the time behavior of selected signals, based on NPP expert knowledge (8). However, this method is sensitive to errors in the instrumentation readings. Artificial neural networks (ANN) were already used to predict fault probabilities (9), and are known to show robustness against erroneous or incomplete input data.

One of the main advantages of ANN systems is the potential of learning not only from expert knowledge base, but also from actual events and transients in many NPPs and simulators. As shown in this paper, the prediction ability improves as a result of knowledge-base extension. Therefore, it can be expected that ANN can be a suitable and efficient tool for diagnostics of NPP abnormal events.

3. Neural Networks as Diagnostic Tools

The subject of ANN theory and practice is well discussed in recent years, and only a very brief description will be given here. A network of nodes ("neurons") are created by software, arranged in layers. Each node is connected to all nodes in the next layer by variable strength coefficients. The node behavior is sigmoidal, its input being the sum of the products of each preceding layer nodes output with it's connection strength. The networks are trained by presenting a set of inputs/outputs of the desired system to the first and last layers, respectively. The network error is the difference between the values of the output layer nodes and the system's known output values. The connection coefficients are then adjusted to decrease the error. This process is repeated as long as necessary, until an acceptable small training error is achieved.

ANN have been used extensively in diagnostics of complex systems, when exact models are hard to build. One type of diagnosis, much in demand, is in predictive maintenance of rotating machinery, when on-line diagnosis of impending problems can be made by ANN trained to classify normal transients from real faults. If reliable, these diagnostics can replace costly scheduled maintenance. Several papers have been published on diagnostics of particular pieces of equipment, and a plan for complete NPP system maintenance is proposed (10).

The topic of NPP state diagnostic is being studied in several places. AT an ANS meeting in November 1992, no less than four papers were presented on these topics (11 - 14). There is research going on also at the University of Tennessee / Oak Ridge National Laboratory (15). All methods use the same type of data source, namely, reactor simulators which give the sensor response to an assumed or incipient fault. The difference between the various groups is in the way the data are preprocessed, the structure of the ANN and the training algorithms. These techniques are important in achieving practical applications, as large networks usually require a lot of training effort (48,000 presentations of the training set to a rather small network were necessary for achieving 98% accuracy in one of these papers).

One way of reducing the training effort is by starting with non-random connection weights, instead of random connection weights as usual. This leads to a quick convergence of the network to the desired accuracy, and was demonstrated in several papers describing the creation of large-scale models of industrial plants (9,16,17). This algorithm is embedded in the TURBO-NEURON software package (18), which was used previously for fault diagnosis. In these works, time stationary data was used to classify faults of a rotating machinery (19), or a fault in a material transfer operation (2). In this paper, time dependent data of three sensors in a NPP was used to classify the scope of a Loss Of Cooling Accident (LOCA), by learning from simulated data generated by an expert program (8).

4. The Expert Knowledge-Base for Abnormal Events

The knowledge-base used for ANN training and testing was generated by a different expert-system concept, using the Bayesian algorithm (8). A pilot accident- scenario data-base was constructed by using basic reactor safety expertise and straightforward logic. The data base consists of four accident causes :

* very large loss of coolant accident (LOCA)

* large loss of coolant accident
* medium loss of coolant accident
* small loss of coolant accident

For each of those causes, three symptoms were considered :

* the pressure in the primary circuit
* the water level in the pressurizer
* the humidity in the containment

The value of the first symptom (primary circuit pressure) is expected to decrease rapidly in large LOCA scenarios while in small LOCA scenarios it is expected to decrease slowly. Pressurizer water level will drop immediately with a slow recovery (if any) in large LOCAs while it will hardly drop in small LOCA (assuming, of course, proper functioning of emergency systems). Containment humidity will increase in all kinds of LOCA, but it will be faster and to a higher extent for large LOCAs.

The four accident causes and the three symptoms, define an array of 12 (3 by 4) "curve families", each curve describing how the specific symptom develops in time. Each such curve is a possible scenario with a certain likelihood, assessed by the human expert. A schematic presentation of this data-base is given in figure 1.

After preparing the data-base, diagnosis can take place. Given the abnormal conditions (in our case: pressure, water level and humidity), a Bayesian algorithm is used to assign probabilities to each one of the accident causes (the 4 kinds of LOCA). So, for each set of abnormal conditions used as input, a set of four probability values (one for each LOCA type) is generated. These sets of "abnormal conditions" (input) and "probability values" (output) are actually the knowledge-base used by the ANN for training and testing.

5. Training Neural Networks for Classification of Abnormal Events

The data-base generated by the expert consists of five time snapshots of three sensors - pressure and water level in the pressurizer of a PWR, and the humidity sensor in the reactor containment. The time increments were unequal, the first one immediately following the initiating event, and 1, 5, 10, 20 seconds afterwards. The sensor values were represented by class, 1 to 4, unevenly spaced across the sensor measurement span.

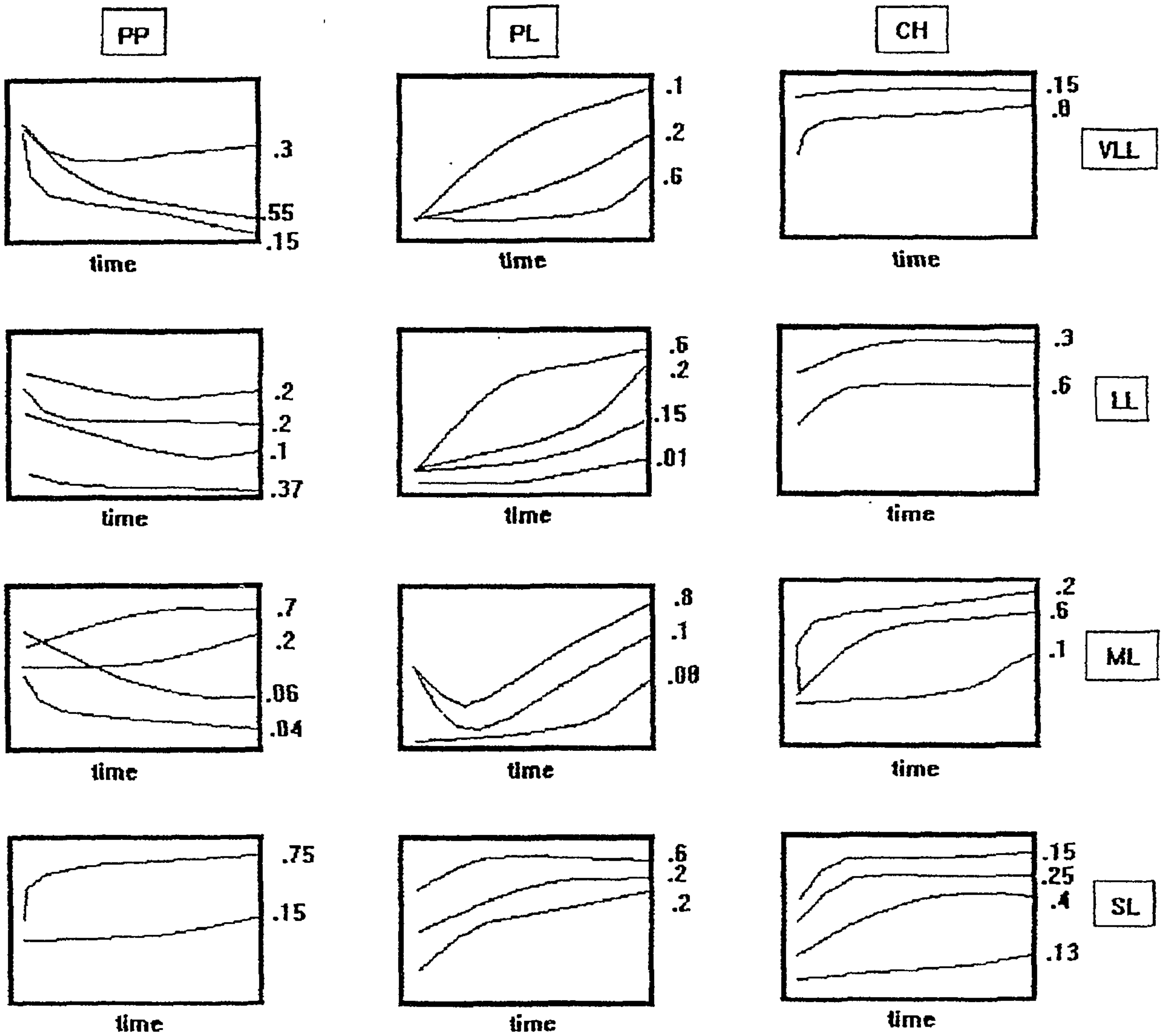

fig. 1 : data base scheme

The data-base consisted also of the estimated probabilities of each type of four LOCA's, ranging from small to very large. To convert the data-base values into input/output of a neural network, each input class was converted to binary input, 1 or 0. Thus, a class of sensor reading of 3 would be represented by 0 0 1 0. this gave 3 x 5 x 4 = 60 binary inputs to the ANN. Missing information was represented by 0 0 0 0. The outputs were first taken as the estimated probabilities. However, initial trials indicated that the dynamic range was too large, spanning the range between 10e-18 to 1.00 . Thus, the output probability of each LOCA type was grouped into 4 classes, the first between 0 - .001, the second 0.001 - 0.1, the third 0.1 - 0.5, and the fourth 0.5 - 1.0 .

The ANN was trained using the TURBO-NEURON software package, version 1.1 (18), which starts the training with non-random connection weights, calculated from statistical analysis of the training data. 16 hidden nodes were selected by the software, to use 80% of information content in the data-base. The 60 x 16 x 4 ANN took about 18 minutes to train, using the delta back-propagation algorithm option, on a 486/33 PC machine with 251 training examples. The training error was about 6%, corresponding to a correct classification in about 85% of the cases. The test data consisted of 65 examples, out of which the ANN correctly classified about 67% .

6. Discussion and Recommendations

The following table shows the first run of 40 test cases, after training the ANN with 151 known cases. the results are grouped in 4 probability categories :

case	expert	ANN	case	expert	ANN
1	4	3	21	2	2
2	3	4	22	2	2
3	3	3	23	2	2
4	4	3	24	3	2
5	4	3	25	3	3
6	4	4	26	4	4
7	1	1	27	4	4
8	2	2	28	4	4
9	4	4	29	3	3
10	4	4	30	2	1
11	2	2	31	3	3
12	2	2	32	2	2
13	4	2	33	3	2
14	4	4	34	2	3
15	4	4	35	3	2
16	1	2	36	2	2
17	3	4	37	2	2
18	4	4	38	1	1
19	2	2	39	2	1
20	3	3	40	4	4

total matching cases : 27 (67.5%)

As stated above, this work was carried out as a "pilot" study, to see if the combination of ANN with expert generated data-base could preform well enough. The correct classification rate, of 85% in the training data and 67% of the test data is quite satisfactory for a first try.

Afterwards, 100 additional cases were introduced to the ANN for more training, followed by 25 more test cases :

case	expert	ANN	case	expert	ANN
41	4	4	53	2	2
42	1	1	54	2	2
43	4	4	55	2	2
44	2	2	56	4	4
45	4	4	57	4	4
46	4	3	58	4	4
47	4	4	59	4	4
48	4	3	60	4	4
49	4	4	61	4	4
50	4	4	62	2	2
51	2	2	63	2	2
52	2	2	64	2	4
			65	2	2

total matching cases : 22 (88%)

These results are encouraging, as prediction improves after adding training data. More training data could be made available, with a projected improvement in both the training and test classifications. It is interesting to notice that the performance of the first run (training and test data alike) also improved after introducing to the ANN the second data set.

More experimenting could be done with the TURBO-NEURON 1.1 training options. The outputs could be also changed into binary coded classifications, increasing the correct classification of the arbitrary groupings of the LOCA probabilities.

In the main study, if carried out, the number of different faults will be increased to test the fast classification capabilities of the ANN. Only then will this method be considered ready for evaluation in an NPP simulator.

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REX: A METHODOLOGY USED FOR THE STRUCTURED PROCESSING OF NUCLEAR POWER PLANT OPERATION EXPERIENCE FEEDBACK. PRINCIPLES AND EXTENSION TO CASE BASED REASONING

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Abstract

Rex is a knowledge management method that was initiated and developped by the CEA in order to preserve and make use of its experience. From this objective outcame a method and a computerized tool which constitute a solution available to any company that considers knowledge acquired throughout its activities as a valuable asset and therefore is willing to capitalize it. In particular several systems prototypes have been developped to manage experience feedback issued from NPP operation.

Such a solution is worked out in terms of a cycle aimed at ensuring that, at each step of a company's activity, experience feed-back is taken into account. This cycle is activated by a computer system which inputs experience as it occurs, stores it, then allows its pertinent retrieval at the moment it is needed to help tackling new situations. Integrated within a company's organisation, a Rex system thus provides a means of permanently up-grading corporate know-how.

Carrying out a Rex project involves:

- A method for analysing needs and identifying sources of experience.
- Procedures for constructing elementary pieces of experience from documents, data bases, or interviews.
- Procedures for building up a computer representation of the knowledge domain at stake.
- A software package which includes a multimedia interface, and a retrieval engine that produces information files on the basis of questions in natural language.

An extension to a Case Based Reasoning system oriented toward operation diagnostic is presented.

Rex is an experience management method that was initiated and developped by the CEA in order to preserve and make use of the experience gathered during nuclear reactors design and start-up phases. The objective of the initial application was to preserve the knowledge feedback on the start-up of the european fast reactor Super-Phenix.

Recent studies point out that an increasing number of companies consider the management of their experience as a strategic concern. Capitalizing experience concerning NPP's operation becomes a key-factor in companies' competitiveness and in NPP's safety.

After raising the problem of experience management, we describe the principle of an Experience Feed-back Cycle. Then the Rex approach is introduced as an organic answer to the functionnal requirements of the cycle. Finally, an extension to a Case Based Reasoning system oriented toward operation diagnostic is presented.

1. The problem of experience management

Experience can be considered as an information flux generated by all the activities, from the most elementary to the most global ones, which combine themselves to attain the company's objective [1-3]. Carrying out any activity is possible only because some know-how is made available. (figure 1).

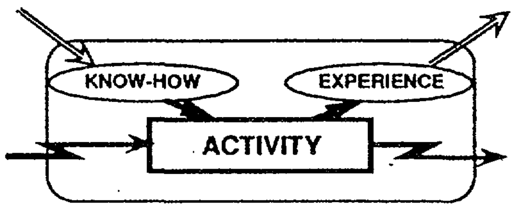

figure 1 : Carrying out an activity requires some know-how and produces experience.

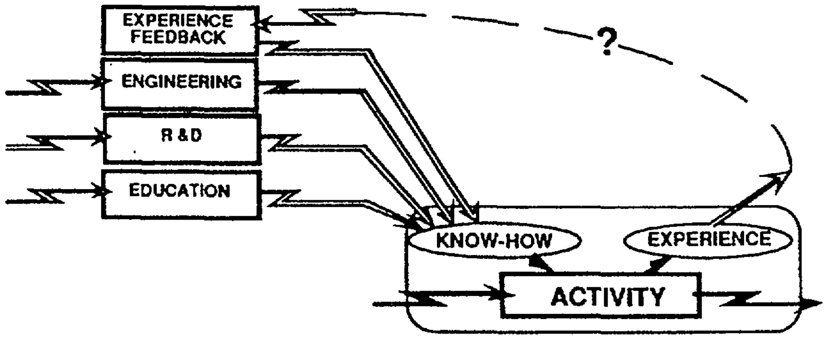

figure 2 : know-how supplying activities

As an essential resources, know-how can be improved by different means (figure 2):

- Education : hiring young graduates makes the most recent scholar knowledge at hand, and training employees keeps their skills up to date.
- R&D results: as a source of new technology.
- Engineering : to update procedures and master current techniques.
- Experience Feedback : so that any activity may benefit from past experience (to avoid redoing things, draw inspiration from similar cases, take errings into account, renew good choices).

Education, R&D, engineering have always attracted a good part of corporate investment. But, it is a paradox that most of the companies do not invest to develop their own founts of experience, although these are what makes them different from otherwise equal competitors.

With respect to these considerations, one may rightfully ask: What proportion of experience is dissipated by an activity without ever being used? What is the value of consequently lost know-how ? This value can be derived from the resulting loss of productivity, the costs induced by redoing tasks , renewing mistakes,...

Answering to these questions requires a thorough diagnostic which will often prescribe investments as necessary in order to set up some form of experience management. We think that experience management can be addressed by controlling the Experience Feed-back Cycle presented hereafter.

2. The Experience Feed-back Cycle

Capitalizing experience on an activity is done through a cycle that covers all the steps from the moment experience outcomes; up to the moment it is considered as part of some available improved know-how.

2.1. The "non-assisted" cycle

In order to get a thorough comprehension and justification of the cycle, let's examine the most elementary activity of interest to our investigation: the case of an individual carrying out a specific task at a given time. In this case, the intrinsic intelligence of the individual ensures that the experience that he may draw from his performance is turned into know-how of his own. The reliability of this natural mechanism is unfortunately very dependent on the individual's memorization capability.

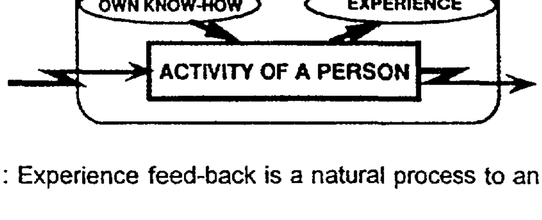

figure 3 : Experience feed-back is a natural process to an individual.

Within a group, communication between people creates a shared know-how which adds up onto each individual's own know-how.

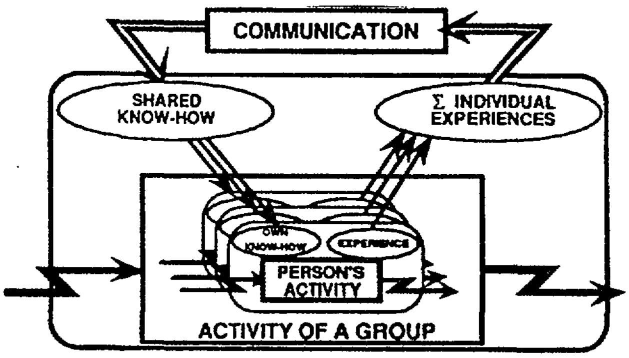

figure 4 : shared know-how results from people being part of a group and adds-up to everyone's own know-how.

As long as a group remains small enough, informal communication is sufficient to produce shared know-how. But once it comes to larger teams, informal communication still operates, but

For instance:
- when operating some industrial process, experience is collected by fact-sheets, reports...
- when performing some engineering task, designers will commit their experience in the form of application papers.
- maintenance of a plant yields results which are consigned into failure modes and effects description sheets.

It can be generally observed that, within a company, an activity will, at best, organize itself to put its formalized pieces of experience into exploitation for its own sake. But cases where this experience is put at the disposal of other activities are seldom encountered.

2.2. Mastering the Cycle

Three steps are to be distinguished in the Experience Feed-back Cycle (figure 5): first, the activity from which experience outcomes, second, the delivery function whose aim is to put experience at disposal, third, the valorization function which turns experience into know-how (i.e. value).

The first step of the the cycle pertains to the activity itself. Experience arises as a result or as a side effect to the processes which people execute within this activity:

- "as a result...", this relates to intellectual activities whose own purpose is to produce knowledge (research, studies, tests, experiments). In this category what can be labelled as experience is :

  - the straight outcome of the activity,
  - track keeping of all the choices, options, configurations that were investigated or tried, and why they were abandonned or rejected.

- "as a side effect..." : this is true for all kinds activities, including the above ones. Whilst the outcome of some experiment is labelled as experience, what happened during the experiment (tricks, short-cuts) is also to be valued as experience. Reminding of anomalies or incidents and their associated diagnostic also belongs to this category of experience, as well as knowing the explanation of discrepancies between how procedures are prescribed and how they are actually applied.

The second step of the cycle pertains to experience delivery. Experience to be collected may be "stored" in the memory of individuals, or may be already formalized in an existing system (computerized or not) in terms of synthesis reports, fact sheets, database records,... From these sources, elementary pieces of experience can be constituted and memorized. Then they must be delivered in a relevant way as requested by the next step.

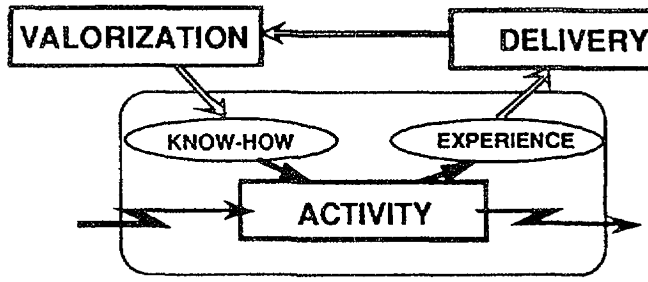

figure 5 : The Experience Feedback Cycle.

The third step of the cycle pertains to know-how valorization. This is a value-adding process that takes place at two levels: on one hand, when an individual takes into account shared experience which is put at his disposal, turns it into new know-how of his own, and then applies it to his current tasks; on the other hand, when dedicated services purposely perform the transformation of experience into know-how and distribute it so that it can be shared by all.

2.3. The Rex Method : Delivering Experience.

The purpose of a Rex Application within a company is to set up an organisation and its associated tools so that the Experience Feedback Cycle can be mastered.

Within the cycle, the valorization step is essentially a human process (relying on natural intelligence) that must be fueled with proper data in a convenient way. Such a delivery function is fulfilled by the **CEMS** (Corporate Experience Management System) whose construction is the very aim of the Rex Method. This system is made of two particular processes: one *constitutes* pieces of experience arising from an activity; the other *restitutes* those pieces to the user that has to valorize them. Between their constitution and restitution, pieces of experience are kept inside a storage element that we name the "Corporate Experience Memory" (CEMem) (figure 6).

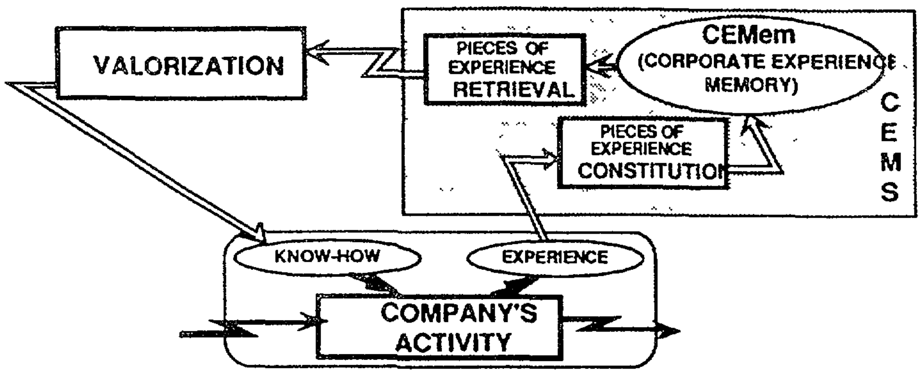

figure 6 : The purpose of the Rex Method is to build a Corporate Experience Management System which combines procedures and computerized tools, in order to "constitute", "memorize", and "restitute" experience.

3. Functional requirements of the cycle

The CEMS, as it is envisaged, must be able to tackle the issues raised in the following points.

Different sources of experience

As we said previously, corporate experience is largely held by the human brain, but is also disseminated throughout a large amount of hard copy documents or data bases (which may be made of computerized records or mere paper forms). In all the documentation, we can furthermore isolate a category of documents, in small number, which contain a high density of knowledge deriving from the company's experience. These are all synthesis reports which describe the state of the art, or the current situation of the activity. All these essential knowledge sources are to be exploited.

Different levels of aggregation

One will therefore encounter experience at all levels of aggregation: from "raw" facts worded in a straightforward way, to already mind-processed information corresponding to synthesized experience. It is important to keep track of how the latter were derived, by allowing reference to the former ones.

One experience archetype

Two requirements can be drawn from the exploration of existing types of document (like synthesis reports) or data bases whose purpose is to gather experience:

- An "atomic" form is to be used to verbalize experience. We speak therefrom of "pieces of experience". :
- The constitution of a piece of experience is to abide by a stable archetype made of three parts: a context describing header, a textual body, a list of references.The body comprises itself three parts which must be short texts (typically the size of a paragraph [4] , rarely more than a page). The first part of the body is a neutral description of the experienced fact with its ins and outs; the second part holds the issuer's own opinion or commentary; in the last part (optional), the issuer's expresses recommendations, which may whereby participate in know-how improvement. Filling this last part presupposes that the piece of experience has already been through some thinking process.

Various vocabularies and standpoints

Within the cycle, experience can be valorized either by dedicated services whose point is to transform experience into corporate know-how, or directly by any individual who would need it in his everyday tasks. People to whom experience is delivered may be of a different specialty or a different culture (technical, managerial,...) from those who issued the experience. They will generally have a different activity, use a different vocabulary: their standpoints are dissimilar. This is the main factor that impedes appropriate information retrieval in this context. Building the CEMem hence implies to address this problem. In a classical approach, data bases contain document summaries and other descriptors. These documents can be searched out by key-words which may be linked together by logical operators. As the use of these data bases requires a good knowledge of their contents, the help of a record research assistant is generally needed. It has been noted that this creates a barrier that holds back the user from gaining access to the information. We then assert that the utilization of the CEMem calls for a computerized go-between that would allow the user to direct his resarch himself and would mimic the expertise of a research assistant. This expertise is made up of:

- searching strategies,
- knowledge of thesauruses,
- knowledge of the database scope (domain coverage),
- ability to understand the user's vocabulary,
- ability to comprehend the user's standpoint .

Limitations of available text retrieval systems

The effectiveness of text retrieval systems is generallly assessed by means of two main parameters named *recall* and *precision* ([5]) which characterize the quality of search results. *Recall* is the proportion of relevant material retrieved (i.e. the ratio of the number of relevant items retrieved to the total number of relevant items in the parsed collection). *Precision* is the proportion of retrieved material that is relevant (i.e. the ratio of the number of relevant items retrieved to the total number of items retrieved). Most text retrieval systems are tuned in such a way that queries will either produce high precision, but low recall (only a few easily examined items are retrieved, but many useful items are overlooked), or, conversely, produce high recall but low precision (large piles of materials are retrieved containing a good portion of the relevant items but with a burdening number of extraneous ones). We consider that an effective retrieval system dedicated to the CEMem must achieve simultaneously high recall and good precision.

4. Principles of the Rex Method

To address the above outlined functional specifications, the Rex method [6] proposes procedures to constitute **PExes** (Pieces of Experience) and procedures to structure the **CEMem** (Corporate Experience Memory). From the application of these procedures outcomes a computer system that can be queried in natural language and displays retrieved PExes as an ordered file of information (figure 7). Each PEx can be examined together with associated documentation obtained via a connection with any existing document storage system.

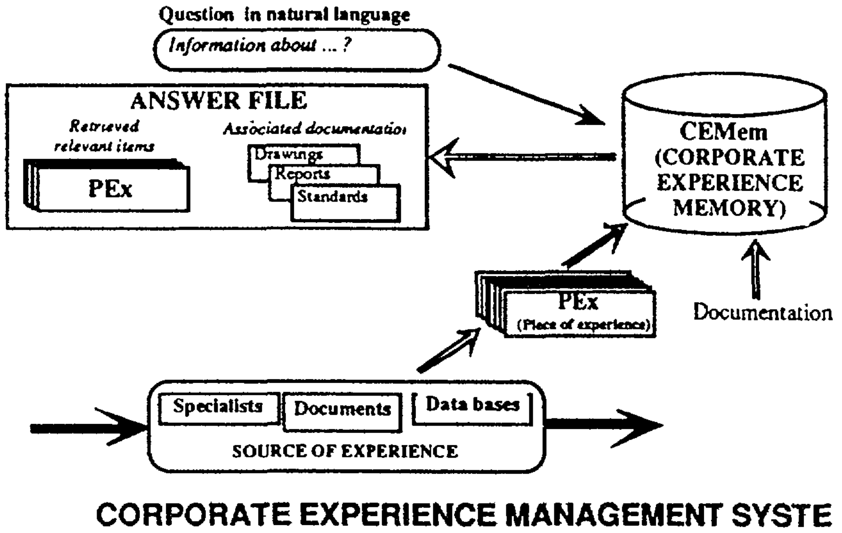

Figure 7 : Principle of Rex CEMS

4.1. Pieces of experience : constitution procedure

The constitution of PExes (Pieces of Experience) is a key point to experience management with the Rex method. PExes allow the materialization of experience whatever its origin. They are the smallest units of knowledge handled by REX and determine the resolution of an application. Whilst PExes may be of different types, which do not depend on the experience sources.but on the system's objective, they all belong to a common archetype [context + short text + references] as defined in §3.

The various experience sources condition the PEx constitution procedure:

- Information may be contained in one or more manuals used by the organization and which represents an established, clearly structured know-how: this may correspond to regulations, a calculation code, a technical reference document, a set of standards, procedures, etc.; the REX method will consider, for example, each paragraph in such documents as a PEx. Similarly, a "one record / one PEx" process applies when tackling already existing textual data bases.
- Information may represent the substance experience cumulated by the organization in the course of its activity and that this organization is endeavouring to formalize and to organize; at this level, there is no or little generalization effort for these knowledge elements: one tries to organize in a consistent manner the memorising of the facts which will be reusable at a later date, for a reasoning process by analogy; this can typically be comprised of shèets established for memorising the ins and outs or events of interest (experiment sheets, discrepancy sheets, experience feedback notes, jurisprudencial decisions, medical or technical diagnoses, exceptional procedures, etc.).

Information may correspond to the experience cumulated by the individuals in the course of their activity within the organization; the nature of such information is similar to the previous one, but it is not expressed in the same manner since, in the best possible case, it is contained in personal notebooks (whereas in the worst possible case, it is only "stored" in the memory of the individuals). The REX method proposes an interview technique to construct PExes from the know-how of these individuals This "information-taking" procedure consists in a session of three half-day interviews with a given person on a given theme. The first interview is non-directive and aims at covering the scope of all the person's recollections about the theme. The text of the interview is then broken down into PExes. In the second interview, a provisional set of PExes is presented to the interviewed person who may introduce complements and modify the contents. The purpose of the third interview is to check that these modifications have been taken into consideration. Ultimate corrections are possibly introduced.

4.2. CEMem structure : build-up procedure

A structured modelization of the domain is performed in order to meet the points stated in §3 which specified that the diversity of vocabularies and stand-points of various users had to be taken into account, and that, some expertise on the experience producing activities had to be put into the system. The modelization process comprises two facets: the descriptive model of the standpoints and the lexical items network.

4.2.1. The descriptive model

The descriptive model is built based on the various standpoints identified and selected in an initial step. Several different specialities can use the same break-down structure to organize their standpoint. These structures (often tree structures) are representative of the way in which the complete field of knowledge can be broken down into elements. Each standpoint is thus represented by a separate network of descriptive objects connected together. It is not necessary to have an exhaustive model, which covers all identified standpoints as at any time the field modeling can be enriched. This representation technique thus permits an application to be started up with only a few incomplete descriptive networks and enables the networks to be increased according to needs. The number of possible standpoints is not unlimited: a dozen seems a reasonable maximum for an industrial activity. Moreover, one hardly ever has to break down over more than five or six levels. For example, the "geographic" standpoint (or "topologic" standpoint) will be adopted whenever one wishes to locate a given field of activity in space. The "process" standpoint is used to break down a functional system into its various sub-systems.

To build up the descriptive network of a standpoint, concepts of the domain are contemplated through the standpoint "prism". Interrelations between the concepts are represented by semantic links belonging to a few well known categories: "set - element", "general - specific", "proximity", "self evolution". It should be noted that the so-called "proximity" link accounts in fact for a variety of context dependent relationships like "client - server", "in/out flux" "same function as", "next to", etc...

4.2.2. The lexical items network

The rigidity of the descriptive model does not enable the system to behave correctly with respect to requests worded in natural language To fulfill this requirement, a lexical items network is constructed. It is made of objects which are words and nominal phrases belonging to the vocabulary of the field considered. These objects are the textual symbols which form the legible aspect of the concepts used to define the standpoints. The network is weakly structurated by means of syntactic relations of the type: "kind-of" and "pertains to".

4.3. Activating the CEMem

A dual PEx integration principle

Rex proposes two complementary integration processes:

- "knowledge-oriented" positionning : A PEx, considered as an elementary knowledge item, is integrated in the CEMem model by attaching it to relevant objects in each standpoint descriptive network, in order to identify it as a vector in a multidimensional space. This operation can be aided by the system which is able to propose descriptive objects based on the recognition of lexical items in the PEx text. The final choice of relevant objects remains a manned process.
- "Text-oriented" positionning : The textual representation of a PEx can be automatically indexed on the lexical items network.

These two integration principles may be applied with variable respective proportions which condition the overall quality-to-cost ratio of the application. Figure 8 gives an overall representation of the CEMem conceptual model.

System query in natural language

The flexibility of the lexical items network associated with the domain modelization enclosed in the descriptive networks enable the system to react correctly to a question worded in natural language. REX proposes an interface which permits a request to be freely expressed. This request is analyzed by the system which, in reply, proposes candidate descriptive objects related to the lexical items that it has identified in the request. A subset of objects may then be selected if needed. A default mode also permits to skip this step.

Starting from the underlying descriptive objects of the question, the searching process propagates along the semantic links featured in the standpoints, thereby making use of the modeled knowledge of the domain. Thanks to this process, a wider set of induced PExes can be retrieved and restituted as a weighed list to the operator.

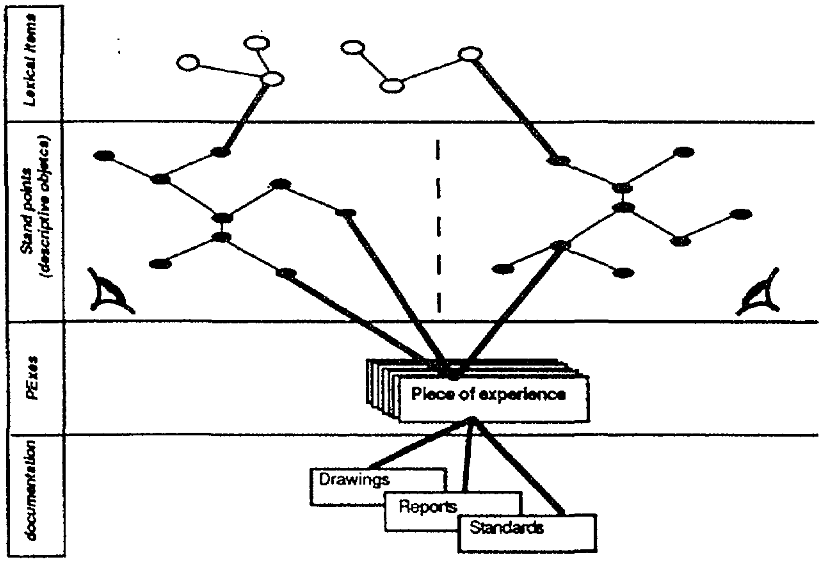

Figure 8 : conceptual model of Rex CEMem

5. Extension to Case Based Reasoning

Several system prototypes, using Rex method, have been developped in France to manage experience feedback issued from NPP operation. Presently, we are investigating how a Rex system concerning NPP's operation experience feedback can be extended to a Case Based Reasoning system oriented toward operation diagnostic.

In short a Rex system is able to collect and memorize elementary pieces of experience and it can determine among them which are the closest ones to a given question. The analogy between experience ffedback and Case Based Reasoning can be easily found : each "pieces of experience" can be concidered as a case, their collection therefore constitutes a Case Base, a "question" is a given problem and a set of closest experiences to the question is a suggested diagnostic (figure 9).

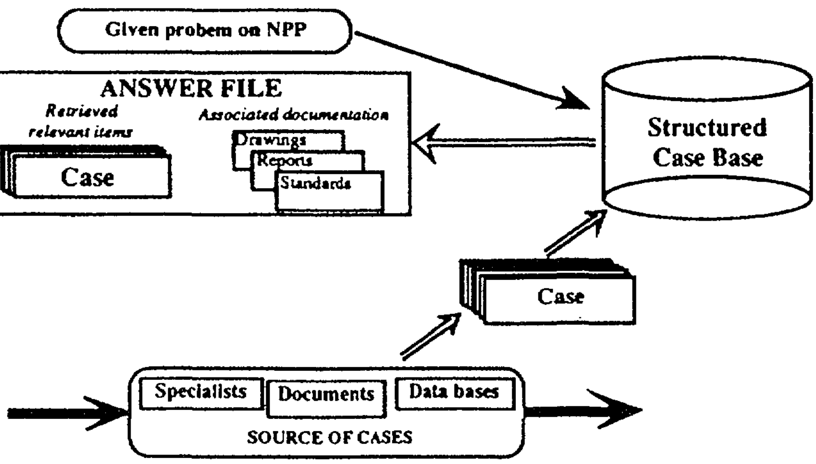

Figure 9 Analogy with Case Based Reasoning

The main application is to make use "on line" of the large NPP's event databases to improve operation diagnostic.

The most important contribution of the Rex approach is to take into account the textual field describing a case (i.e. an event) and to be able to calculate a similarity between this field and a given problem formulated in natural language.

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REPRESENTATION OF TOPOLOGICAL AND FUNCTIONAL-LOGICAL KNOWLEDGE IN AN EXPERT SYSTEM FOR PROBABILISTIC SAFETY ANALYSIS

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Abstract

This paper is devoted to the representation of knowledge in an expert system REPSA1ES (Reliability Evaluation and Probabilistic Safety Analysis - level 1 - Expert System). The prototype system has been designed to facilitate the probabilistic safety analysis (PSA) of complex hazardous industrial systems and to support safety oriented decision making during the design phase and operation of process systems. Taking into account known difficulties to manage complexity of logical and probabilistic modelling of nuclear power plants using the conventional PSA software packages we decided to represent information in a graphical form, whenever it is justified, and to automate the process of coding of objects to avoid errors. The software system consists of a CAD package, data bases, a shell for building expert system and several software modules to enable: the effective communication with the user, data and knowledge acquisition, the initiation of inferring to support logical modelling of the plant, selection of reliability models with input parameters as well as the quantitative probabilistic evaluation of accident scenarios.

1. Introduction

Two approaches are usually used to support the decision making related to the reliability and safety of nuclear installations, namely: the failure mode and effects analysis (FMEA) and the fault tree analysis (FTA). Both FMEA and FTA are systems approaches. FMEA starts with the primal precursor events and works forward to detect possible failures while FTA identifies a specific failure and works backward to identify the precursor events that could cause the failure to occur. For the probabilistic analysis of more complex systems, such as engineering safety features of nuclear power plants, FTA is combined with the event tree analysis (ETA), working forward to identify possible accident scenarios for potential initiating events (IEs). ETA and FTA are basic elements of the probabilistic safety analysis (PSA) methodology adapted in most safety studies of nuclear power plants.

The first step of successful PSA is to define the analysed systems adequately. Although this may seem elementary it is for more complex systems one of the most difficult part of the analysis (Lynch 1980). To handle the topological and functional complexity of such systems it is necessary to decompose the problem. In the current version of REPSA1ES the logical modelling of the plant is performed using the event trees and fault trees, and an approach called as "large event trees - small fault trees" was adapted. However, the object oriented probabilistic modelling methodology proposed is quite general enabling the flexible decomposing of the problem and to develop also larger fault trees.

Different decomposing approaches of a complex system make that modified topological and functional dependencies between objects should be taken into account. An object is understood very widely as an element (a single equipment component or human induced event) or as a defined collection of components belonging to engineering safety features. It was decided to apply an intermediate step before the fault tree construction, namely to define the functional-reliability properties of the object using a digraph or digraphs (in the case of a multi-phased mission of the system). It enables to extend the conventional reliability analyses to systems containing the feedback or feedforward control closed-loops as well as the sequential systems (Lynch 1980).

Three phases of the software system development have been distinguished, related to the PSA methodology proposed and scopes of the analyses, ranging from a comparatively simple system for simplified logical and probabilistic modelling to a complex software system with various modelling techniques and AI methods applied. The proposed strategy of the gradual, incremental system development corresponds with the research and software designing resources planned to be involved in the project. It is also related to new methodological challenges concerning PSA and foreseen gradually emerging possibilities to cope with. These challenges include more adequate treating of uncertainties associated with probabilistic modelling of complex hazardous technological systems including the human factor and organisational factors (Bley et al. 1992, Fujita 1992).

2. Some methodological issues of computer aided probabilistic safety analysis

2.1. Uncertainty representation and treating

Despite growing maturity in probabilistic safety analysis (PSA) methods, there are several issues that create discomfort among decision makers. These issues include the use of expert opinions (Mosleh et al. 1988), the assessment of human reliability, and the impact of organisational factors. These problems are all manifestations of the larger problem of uncertainty in the real world and consequently how that uncertainty is presented within the context of the PSA. The expert opinions issue is associated with a representation of the gathering and evaluating of expert evidence (Bley et al. 1992). There are psychological aspects and influences on the reliability and validity of expert judgements and, in particular, on probability judgements (Bolger & Wright 1992).

On the other hand the PSA methodology might provide a framework to deal with uncertainty issues in a more systematic way. Current PSA studies which include the human reliability analysis (HRA) are, to a significant extent, computer aided. So the question can be raised how to develop the computer programming tools to manage more effectively the complexity of modelling and to document the analyses with inherent assumptions and expert opinions. Identifying and treating uncertainty explicitly is the key to win among decision makers the confidence in PSA results (Bley et al. 1992).

Current PSA/HRA methodologies have been developed adapting the Bayesian subjective probability framework (Apostolakis 1989, Wu 1990) which requires precise defining of events. On the other hand there are encountered cases of events in HRA/PSA practice which can not be straightforwardly quantitatively assessed, due to insufficient knowledge (e.g. concerning the progression of physical processes for some accident conditions or dominant failure phenomena) or imprecision of propositions (using often by experts in evaluations some linguistic statements).

For dealing with cases of approximated evaluations other theoretical frameworks can be considered, e.g. the theory of possibility based on the fuzzy set theory or Shafer's theory of evidence (Zadeh 1978, Dubois & Prade 1986, 1988). The problem of uncertainty is also an important topic of artificial intelligence (AI). For representing and treating of uncertainty the Bayesian and non-Bayesian methods can be proposed (Lemmer and Kanal 1988). Some researchers are sceptical as regards applying these new theories for representing and combining information under uncertainties in PSA (Wu 1990). We share this opinion when combining of information from non-equivalent or contradictory sources, including experts, is of interest. In such cases much more attractive is the Bayesian probability framework (Wu 1990). On the other hand there are known some drawbacks of the Bayesian framework which can lead, in more complex cases, to violating its basic principles (Lee 1987).

2.2. Modelling the human factor reliability

It is known that one of the most significant contributor to risk associated with operation of industrial hazardous systems is so called human factor. There are several taxonomies of human actions/errors. Human actions/errors can be classified to be related to the phases of an accident into three categories (Dougherty 1988, IAEA 1992): (A) actions/errors in planned activities, so-called pre-initiator events, that cause equipment (systems) to be unavailable when required post initiator; (B) errors in planned activities that lead directly, either by themselves or in combination with equipment failures, to initiating events/faults and (C) actions/errors in event-driven (off-normal) activities, i.e. post-initiator events; these can be either safety actions or errors that aggravate the fault sequence. Interactions of the last category can be further subdivided into three different types for incorporation into PSA, namely: (C1) procedural safety actions, (C2) actions/errors aggravating the accident progression and (C3) improvising recovery/repair actions.

Described above behaviour types seem to involve different error mechanisms, which may mean radically different reliability characteristics. Human errors are often classified to be one of two kinds (Reason 1990): I. slip - (1) an error in implementing a plan, decision or intention (the plan is correct, its executing is not), or (2) an unintended action; a type of slip is lapse, an error in recall, e.g. of a step in a task; II. mistake - an error in establishing a course of actions, e.g. an error in diagnosis, planning or decision making. Errors are also classified as errors of commission or errors of omission. Error of commission is often understood as incorrect performance of a system-required task or action, or the performance of an extraneous action that is not required by the system and which has the potential for contributing to some system-defined failure. Error of omission is a failure to perform a task or action (Dougherty 1988).

For quantifying human actions/errors various methods/techniques are available which were described synthetically e.g. in non-source publications/reports (Humphreys 1988, Cacciabue 1988, IAEA 1992, Kosmowski 1992). There are expressed opinions that some existing HRA methods are adequate for modelling slips, especially in planned activities. For quantifying the human reliability in such cases the THERP technique is usually applied. More challenging issue is modelling of mistakes, especially in event driven situations. Mistakes, errors of omission are usually quantitatively evaluated using TRC or HRC methods (Dougherty 1988, Humphreys 1988). Much more difficult is quantifying mistakes, errors of commissions. In such situations other methods can be applied, e.g. the confusion matrix (CM) method (Dougherty 1988) or proposed recently a method for estimating probability of human based errors INTENT (Gertman 1992). Conventional HRA techniques are criticised recently (Dougherty 1990). The multi-expert SLIM method is often used to extrapolate probabilistic results, obtained from single-expert techniques or experiments on simulators, with regard to some additional Performing Shaping Factors (PSFs) which are important for a specific situation analysed.

There are also expressed opinions that the development of new human reliability models is needed (Dougherty 1990), especially for modelling operator errors of commission in event-driven situations. Two general premises for developing relevant techniques are formulated, namely: they should be based on recent trends in error psychology and that AI technology offers reach computer environments to model humans (Fujita 1992). There are already some proposals to employ AI methods to create a cognitive environment simulation (Woods and Roth 1987). Some other techniques published, related to psychological theories and AI technology are described in a non-source report (Kosmowski 1992). Unfortunately, these techniques do not offer new methods for quantifying human error probability (HEP).

2.3. Development of computerised PSA tools based on the expert system technology

PSA studies are time consuming, prone to make mistakes and very costly. There is also evidence that results of HRA and PSA assessed by different groups can give discrepancy as high as orders of magnitude. Therefore, an understandable tendency can be noticed to computerise and standardise these analyses. The expert system technology offers potentially such possibilities. There are already some examples to use this technology to support PSA (Wang & Modarres 1988, 1990, Ancelin 1990, Poucet 1990). Most of these knowledge based systems can be characterised as prototypes aimed at automation of some parts of the probabilistic safety analyses of level 1.

3. The REPSA1ES project

3.1. Features of the software system

As it was mentioned three levels of the effort to carry out the PSA/HRA have been distinguished: I, II and III which correspond to the PSA/HRA methodological issues (methods applied, details of modelling, the contribution of experts required) and relevant scopes of the computer aided analyses. Assumed features of the software system supporting PSA of level 1 and HRA using the expert system technology are presented in Table 1. The software system development has been scheduled to enable gradual and balanced realisation of designing works with regard to research resources available. In Fig. 1 a classification tree of human event-driven errors (the category C) is proposed which enables to select the appropriate technique for the human reliability modelling. Another tree was proposed for pre-initiating (latent) actions/errors (Kosmowski 1992).

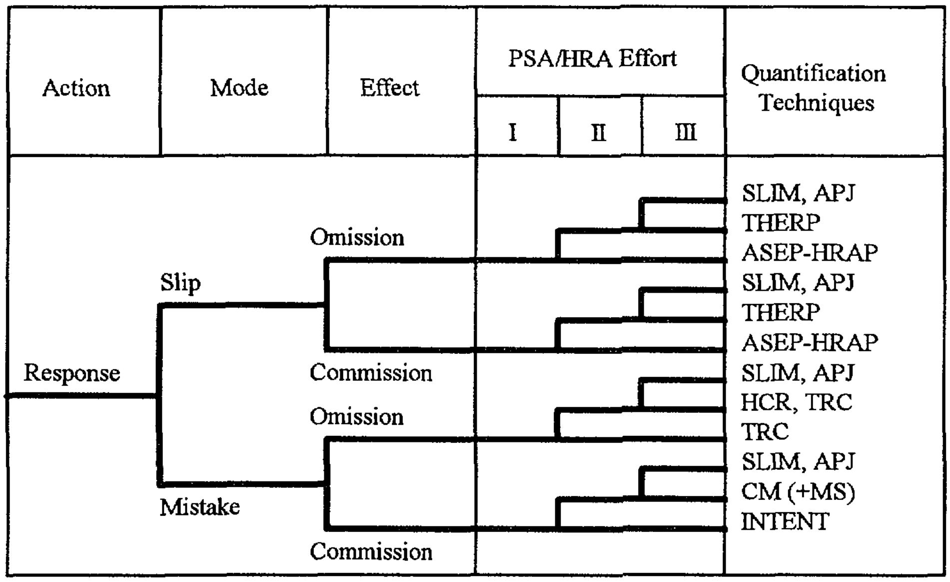
Mistakes, especially errors of commission due to misdiagnosis are considered as most difficult to model and quantify. The assessed probabilities of misdiagnosis errors of accident situations in a short period after initiating events are usually placed as elements of so called confusion matrix (CM). They represent the probability of confusing a transient j with another transient k, possibly leading to erroneous actions (Hannaman and Spurgin 1984, Wakefield 1988). The probabilities p_{jk} of such confusion depend on the similarity of symptoms such as alarms, enunciators, values of various process variables or directions and rates of their changes (IAEA 1992).

Table 1. Assumed features of the computer aided PSA1/HRA of different scopes using the expert system technology

Features of analyses and software	Scope I	Scope II	Scope III
Exhaustiveness of analyses	Rather low	Moderate	High
Cost of assessments	Relatively low	Moderate	High
Minimum users (Us)/ experts (Es) involved	Single U/E	Single E/U	Several Es/Us
Menu-driven help and explanation	Extensive	Moderate	Moderate
Heuristics	Simple	Detailed	Consensus
Simulation codes	Indirect access	Simplified models	Direct access
Object oriented modelling	Some	Limited	Advanced
Dependent failure analyses	Simplified	Limited	Exhaustive
HRA models or techniques used	Simplified (Fig.1/I)	More detailed (Fig.1/II)	Multiple experts (Fig.1/III)
Uncertainty treating frameworks	Fuzzy or Bayesian probability	Fuzzy or Bayesian probability	Bayesian or fuzzy probability
Topological and functional-logical data	Simplified	Detailed	Detailed
CAD graphical representation	Simplified	Detailed	Detailed
Semi-automatic event/fault trees construction	Some	Most	Most
Using for HRA/PSA training	Initial training	Detailed training	Research/ advanced training
Using for safety related decision making	Initial decisions	Preliminary decisions	Particular issues and final decisions
Hardware required	PC-386 RAM min. 8 MB	PC-486 RAM min. 16 MB	Work-station

These probabilities are usually subjectively assessed by experts. A method was proposed (Kosmowski & Duzinkiewicz 1993) to reduce subjectivity of assessments and to support judgements by the evaluation of some similarity measures of symptoms based on the simulated responses of the plant for initiating events considered. The calculated distance or similarity measures form the basis for creating distance or similarity tables for all pairs (j,k) of accident situations Depending on the obtained values of distance or similarity measures, the probability of confusion is then assessed by experts, e.g. using SLIM or APJ techniques. Linguistic statements concerning confusion based on similarity measure can be also proposed, e.g. high, medium, low or insignificant which can be then a basis for evaluation of probability (Wakefield 1988).

Taking into account some drawbacks of the Bayesian approach we propose to apply alternatively another framework for representing uncertainties in PSA, based on the possibility theory, in which values of probability will be represented as fuzzy numbers (Kosmowski and Duzinkiewicz 1993). Such framework seems to be justified especially in cases when the PSA/HRA studies can not be supported, for some important issues analysed, including the key cases of HRA, by high quality opinions obtained from domain experts (Table 1, scope I and II).



Abbreviations of the Human Reliability Analysis (HRA) techniques:
APJ - Absolute Probability Judgment
ASEP-HRAP - Accident Sequence Evaluation Procedure, Human Reliability Analysis Procedure (NUREG/CR-4772, 1987)
CM (+MS) - Confusion Matrix (with Modelling Support)
HCR - Human Cognitive Reliability
INTENT - A method for estimating HEP for decisionbased errors (Gertman 1992)
SLIM - Success Likelihood Index Method
THERP - Technique for Human Error Rate Predictions
TRC - Time Reliability Correlation
Remarks on applications some of these techniques from the PSA perspective can be found in (Cacciabue 1988, Humphreys 1988); CM (+MS) method outlined in the paper (Kosmowski & Duzinkiewicz 1993).

Fig. 1. Classification of human event-driven errors and some related quantifying techniques for different HRA/PSA effort

3.2. Data/knowledge bases and functions of the system

Designing works and tests of the REPSA1ES prototype modules concentrate at present on the scope II (Table 1). Functions and processing phases of the software system are presented in Fig. 2. The concept of the system (Kosmowski et al. 1991) differs in some respects to other PSA expert systems by the user friendly graphical interface with advanced CAD functions and a certain level of automation in creating of the declarative part of components/systems knowledge bases.

Data bases are important elements of the REPSA1ES system. Three groups of data bases are distinguished:
(1) External data bases which are independent from the project. There can be one or more data bases containing the reliability data of technical components (installations) and/or a data base associated with the human reliability. These data bases are available for the user as read only. They can be helpful for the creation and filling up the project data bases. The access to a new external data base is to be made through a proper configuration file. In the prototype REPSA1ES system these data bases are designed in the dBase IV format.
(2) Project data bases which belong to a group of relational data bases in the dBase IV format. They serve within the project for the collection of information with a fixed structure. Fields of records of these data bases can be filled up with the contents of information found in external data bases. Filling up of the fields can be made in an editor mode or in an interaction mode

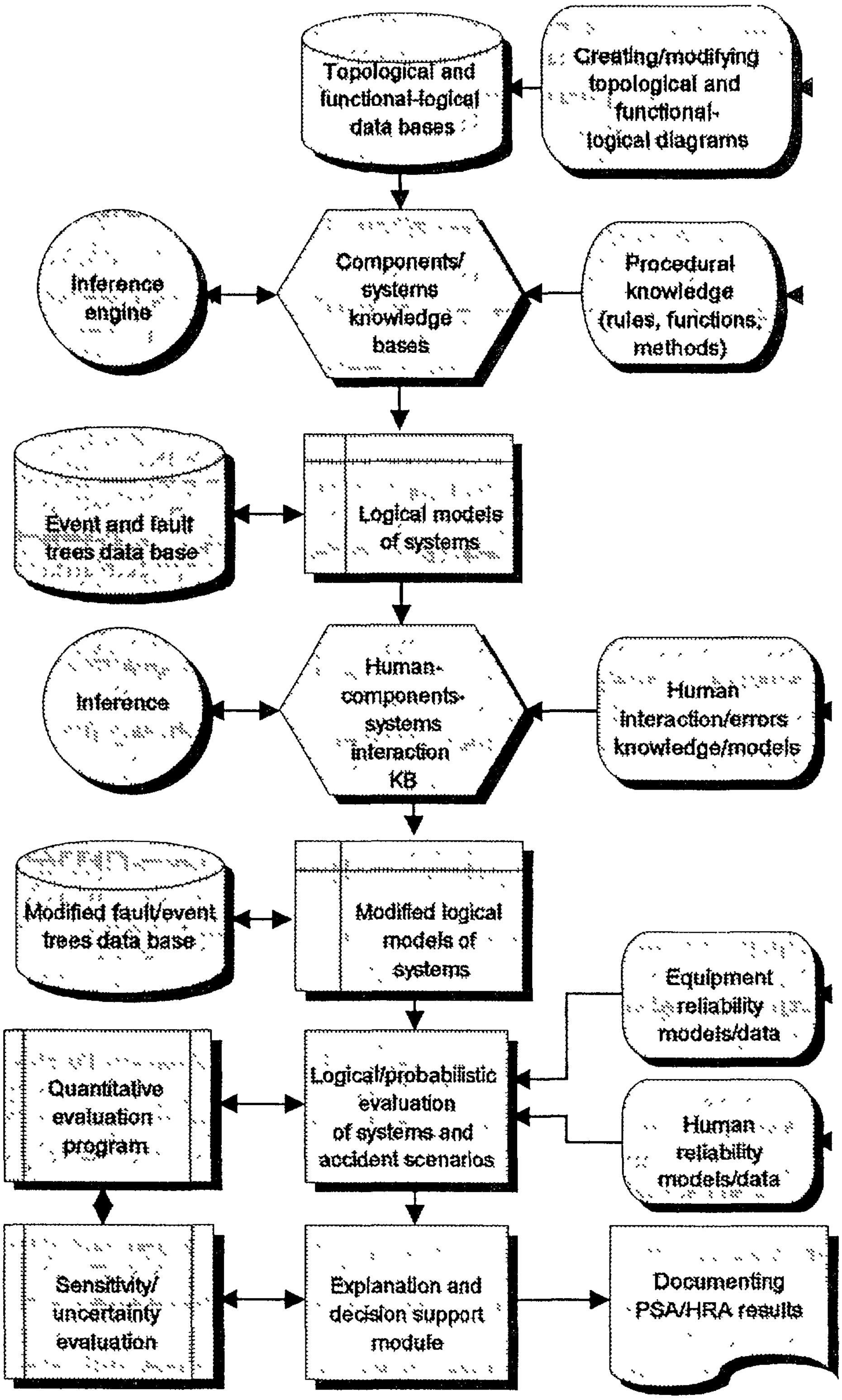


Fig 2 Functions and processing phases of a HRA/PSA software system

through a CAD support of the system. Four basic structures of these data bases have been distinguished in the prototype system:

- CTDB - components' technical data base - contains a list of the technical data for typical arrangements of components. Within these arrangements several categories of components are distinguished: mechanical, electrical, instrumentation and control equipment. The description of components consist of the category, the catalogue type, basic technical data, etc. This data base has a supporting character.

- CRDB - components' reliability data base - contains the basic reliability data of components required for the calculation of reliability indices. Each component is identified with a topological code and symbols. Fields of records of this data base can be filled up from external data bases (optionally through a correction module).
- HRDB - human reliability data base - contains the human reliability data for various situations analysed in the project. These data are obtained from different sources: an external human reliability data base (optionally through an interpolation/extrapolation module), the human reliability models/techniques (e.g. THERP) or assessments given by experts.
- IEDB - initiating event data base - contains a list of accident initiating events with comments. Its creation is related to the construction of the functional-logical diagram.

(3) Variable structure data bases - a group of data bases related to the graphical representation of information created using the CAD support system. This information is stored in ASCII files or binary files. There are five basic structures of these data bases:

- TDB - topological data bases - contain the information about topology of systems. Data bases of this type are created for each group of diagrams (mechanical, electrical, ...).
- FLDB - functional-logical data bases - contain functional and logical relations between defined objects selected from the front-line and supporting systems. Data bases of this type are created for each initiating event. The information contained in relevant ASCII file is then read by a program to fill up the structure of the declarative part of the systems knowledge base created for semi-automatic event tree construction.
- TRDB - topological-reliability data bases - contain the topological information (connections of components) for defined objects and functional-reliability information, concerning these objects, represented using digraphs. TRDB is created programmatically by marking an object on the selected system diagram and defining of a digraph for this object. The information contained in relevant ASCII file is then read by a program to fill up the structure of the declarative part of the components knowledge base created for the semi-automatic fault tree construction.
- ETDB - event tree data bases - contain symbolic information about event trees for each initiating event which is used for their graphical presentation.
- FTDB - fault tree data bases - contains symbolic information about fault trees for each defined object which is used for their graphical presentation.

The schematic interdependence of described above data bases within the REPSA1ES system are shown in Fig. 3. Data bases are filled up step by step. The system leads the user in a proper order through an active menu. The user fills up some data in the interactive mode and/or initiate some procedures. The transition into next stage is possible after filling up a minimum required information in the previous stage. Modifications of the contents of some data bases can be made. In the case of a data base related to the graphical representation of information the changes are made using a relevant program for the graphical edition which generates at the end of the edition a modified ASCII file. However, such graphical modifications will require some consecutive changes in other files, what will be manifested to the user, that some next stage files are irrelevant and must be also modified. The scheme of information handling in the prototype REPSA1ES system is shown in Fig. 4.

3.3. Examples of graphically represented information/knowledge

The functional-logical knowledge of the process system analysed is primarily represented in a graphical form, acquired from an expert or user who uses a CAD computer program. Special

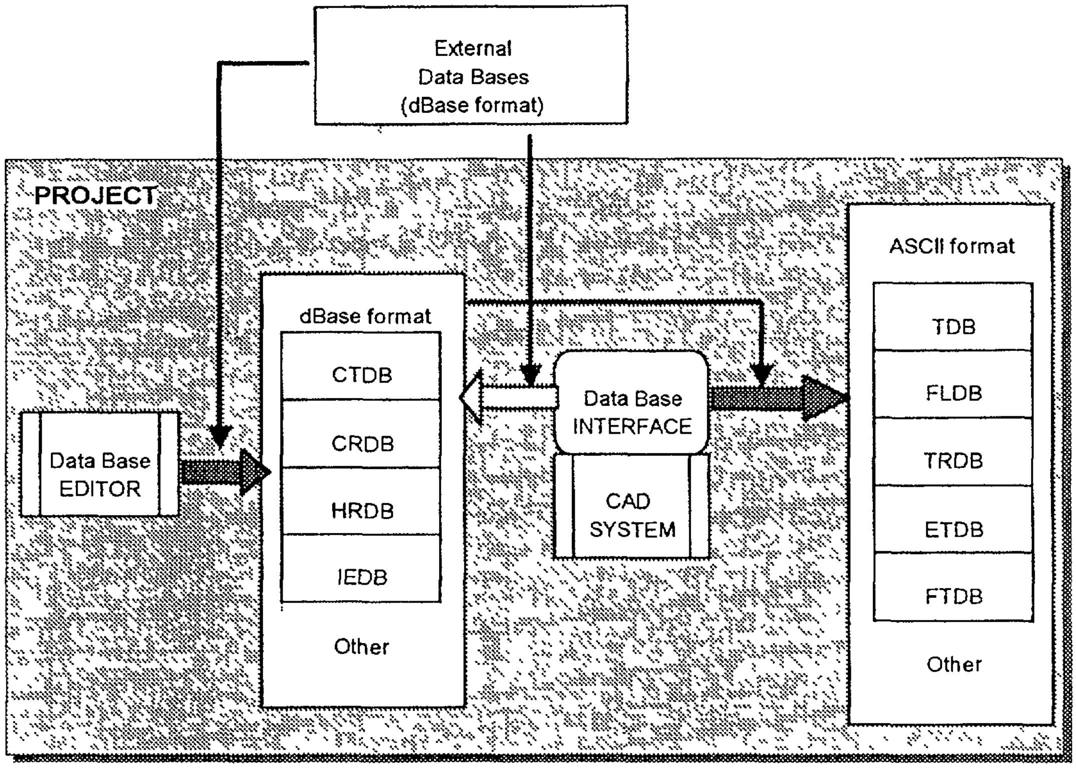


Fig.3. Schematic interdependence of data bases in the REPSA1ES system

logical diagrams are constructed for each initiating event taking into account several types of dependency between objects defined within the front line and supporting systems. Previously constructed logical diagrams can be modified. An example of the screen of the functional-logical diagram is shown in Fig. 5. At the end of the edition an ASCII file is created, as a part of FLDB, containing information about mentioned objects and types of dependency between them.

The topology of the systems is also represented in a graphical form, similarly as the design engineering diagrams. The topology of the front-line and supporting systems, including cross-connections between them, is presented on diagrams in special arrangements using a set of icons and CAD mechanisms. The diagrams are drawn using a step by step procedure starting from front-line systems. An example of the topological diagram is shown in Fig. 6. Each active component on these diagrams can be additionally described using an interface module with marking the input/output connections, e.g. the power supply and input/output control signals (when more detailed information concerning the supporting systems is available). Previously constructed topological diagrams can be modified. At the end of edition the binary and ASCII files are created as parts of TDB.

In the next phase some objects, e.g. lines within the front-line or supporting systems are marked by the user. It is possible to define for each active component its functional-reliability state which corresponds with functions of given system for initiating event analysed. For given object a digraph is then constructed with regard to defined by the user the process variables and boundary influences (i.e. external disturbances, human errors). The process of the digraph construction is partly automated. At the end of defining an ASCII file is created, as a part of TRDB, containing information about its topology and functional-reliability properties. This file form a basis for creation of the components object specific knowledge base. An example of the components general knowledge base is shown in Fig. 7.

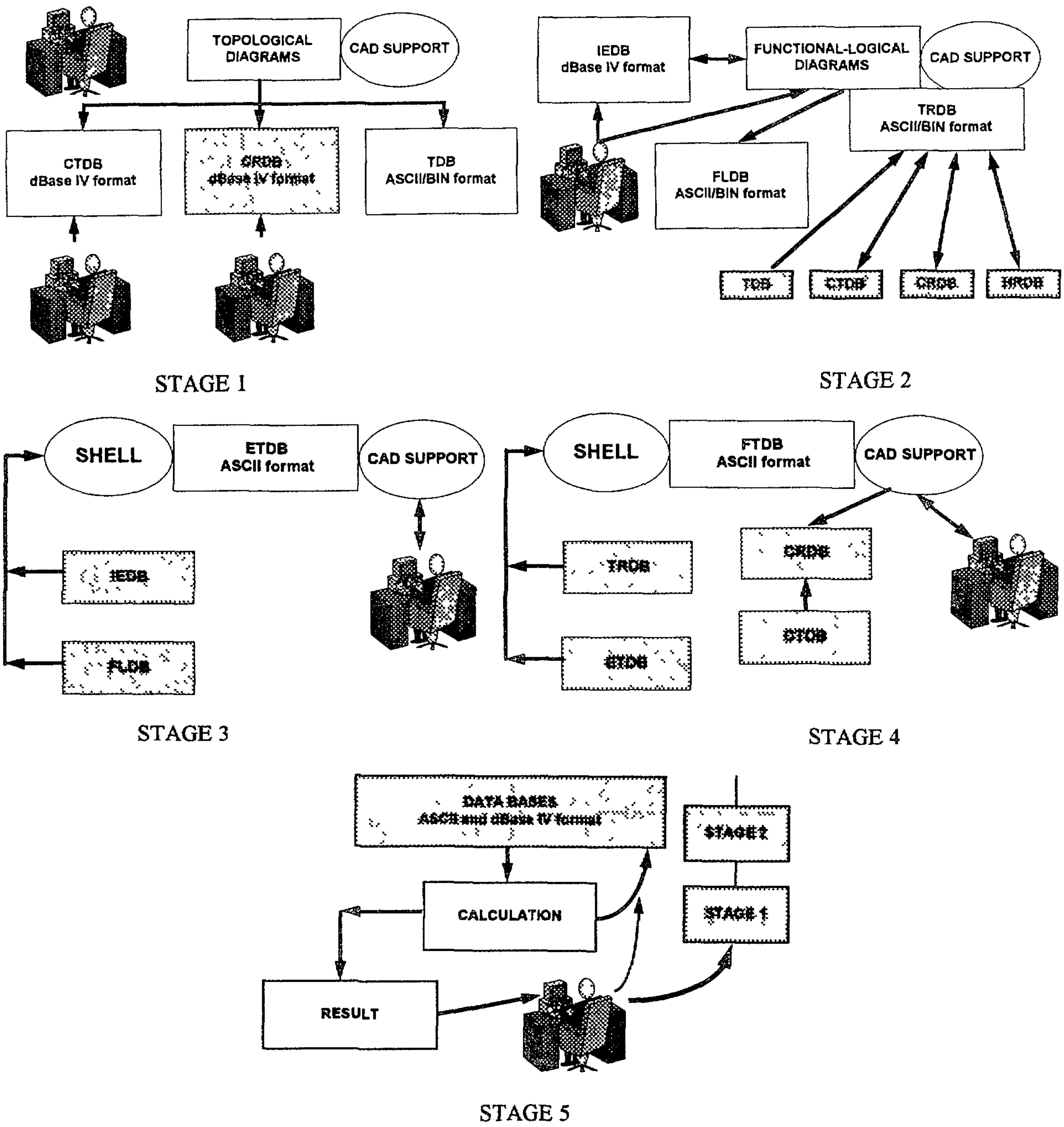


Fig. 4. Diagram of information handling in prototype REPSA1ES system

3.4. Description of the software system and its design

The REPSA1ES software system is designed to guide the analyst to follow consecutive steps of the data/knowledge acquisition and the analysis. Some functions, e.g. the event and fault trees construction and evaluation are automated. The entire modelling process is fully documented enabling easy scrutinising. The system uses the Microsoft Windows 3 1 environment For the creation of the application following programming tools have been used:

- Microsoft Visual C++ v. 1.0,
- CodeBase v. 5.0 library in C/C++ language - for the data base service in dBase IV format,
- AutoCAD for Windows, v.12 - for creating the CAD support programs (applications written in AutoLISP and C languages),
- KAPPA-PC v. 2.0.7 - a shell for building expert systems with an internal KAL language for creating KAL files and C language for creating the DLL library using KAPPA-PC's 'C' interface.

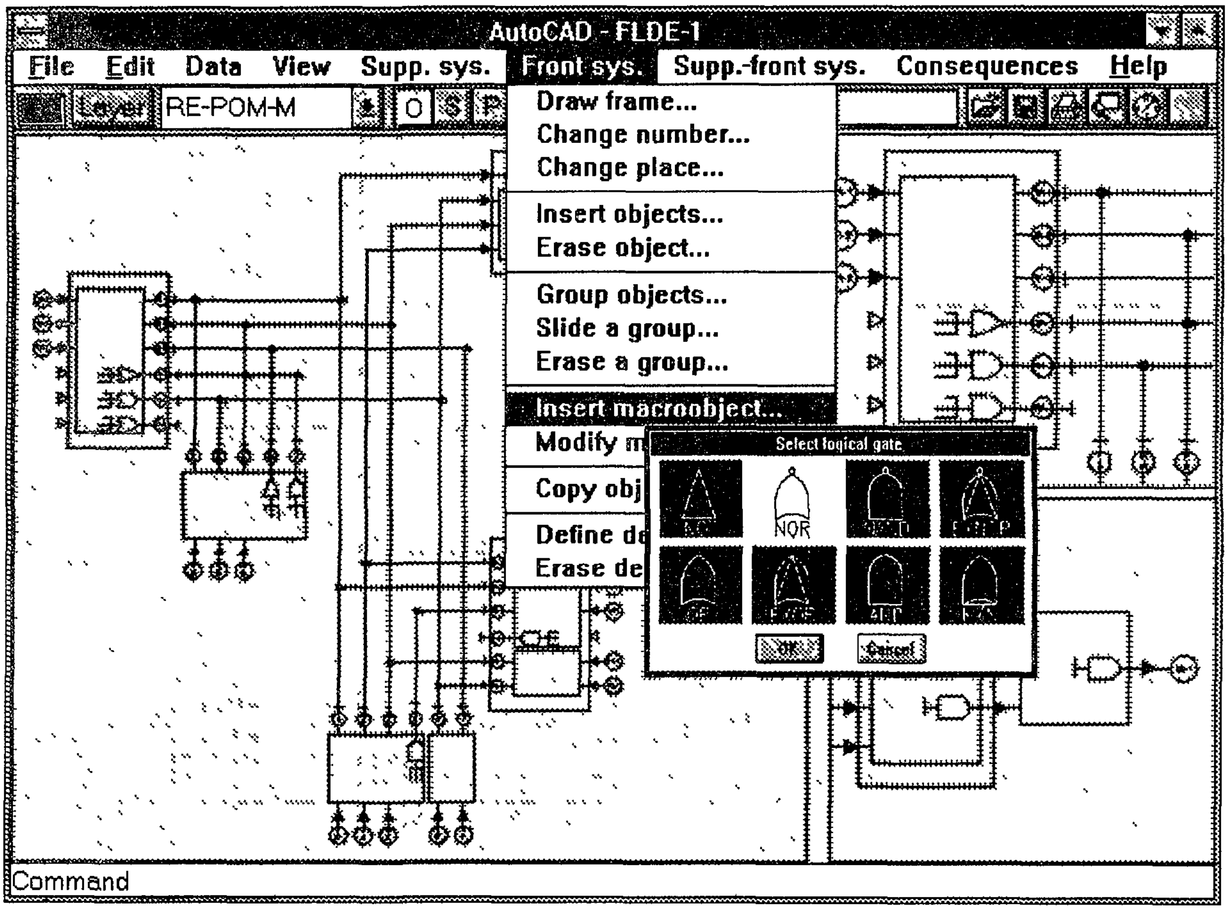


Fig. 5. Example of the functional-logical diagram screen

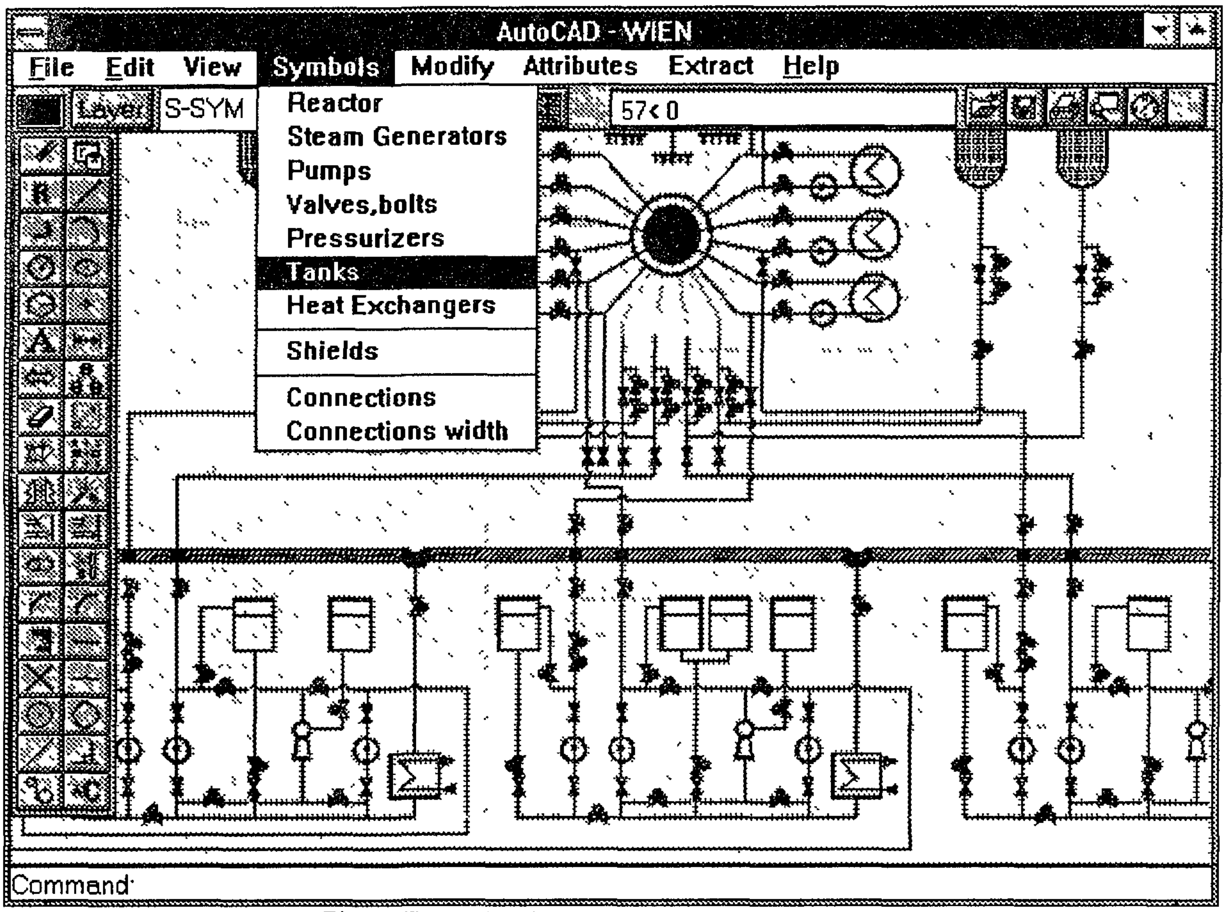


Fig 6. Example of the topological diagram screen

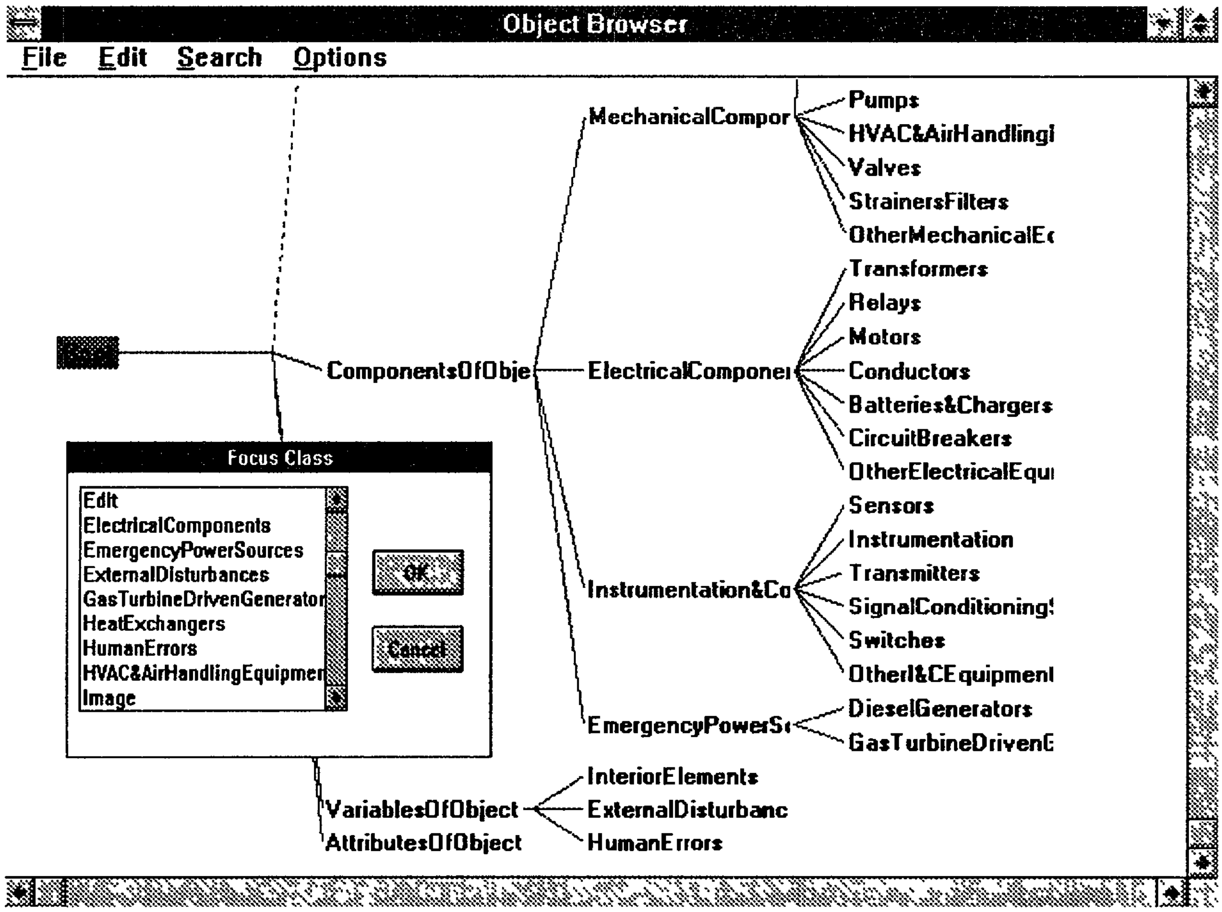


Fig. 7 Example of the components general knowledge base

The prototype REPSA1ES application requires the installation on the computer of the software system itself as well as AutoCAD and KAPPA-PC. The hardware configuration used at present is as follows: processor 486/66 MHz, 16 MB RAM, a colour monitor 17" - SVGA (1025x768, 1MB) and a laser printer.

4. Concluding remarks

The development and practical use the knowledge based software systems is a promising way to overcome some difficulties in performing and detailed documenting of PSA. The methodology proposed enables to automate some parts of analyses releasing experts from tedious, errors prone tasks (e.g fault tree construction), who can concentrate on more intellectual tasks and on supervising the entire modelling process. Such approach should gain the confidence of decision makers in PSA results The knowledge base proposed and logical models generated can be useful during the plant design and its operation, also for the probabilistic oriented after fault diagnosis Due to complexity of PSA it is proposed to develop the related software system gradually in three phases

Additional research effort is required related mainly to PSA/HRA of the scope II and III It should include such topics as·

- object oriented deterministic modelling of the plant to support the logical modelling and probabilistic evaluation,

- an advanced framework for representing and treating of imprecision and uncertainties at different levels of the model hierarchy,
- more adequate modelling of dependent failures, including common mode failures,
- combining the quantitative information from different quality sources including experts,
- effective probabilistic evaluation of accident scenarios under uncertainties with regard to the equipment oriented logic models, human induced failure events and recovery events,
- applying new psychological theories and AI methods for the analysis of man-machine interface reliability including possibilities of human intention failures in event-driven situations.

The expert systems technology and AI methods offer a promising platform for dealing more systematically with some challenging issues of PSA to support more adequately the reliability and safety related decision making.

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NUCLEAR POWER PLANT DIAGNOSTICS USING ARTIFICIAL NEURAL NETWORKS

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Abstract

Enhanced safety, reliability and operability of nuclear power plants may be achieved by the application of neural networks as a diagnostic tool to define the state of the plant at any given time. The paper presents a new neural network methodology, based on the backpropagation learning algorithm, for malfunctions management in nuclear power plants. It is shown that neural networks can be used for identifying the nonlinear dynamic behavior of nuclear power plant components, and for isolating the origin and extent of a failure, when occurring, using consecutive samplings of sensors readings.

Introduction

Among the wide spectrum of tasks involved in plant diagnostics, the *detection and isolation* of incipient failures, which is concerned with identifying the malfunctioning sub-unit or sensor is exceptionally important. Several approaches to malfunction detection and isolation exist, ranging from simple upper and lower bounds techniques [1], frequency domain techniques [2–4] through expert–system methods [5–7] to algorithms based on a state–space formulation [8–10]. Recently an artificial neural network (ANN) methods have been suggested as a diagnostic tool. The potential applications of ANN to the operation and safety of nuclear power plants are reviewed in [11–13]. A new neural network methodology, based on the backpropagation learning algorithm [14–16], has been demonstrated by the present authors for malfunctions management of a nuclear power plant [17–19]. This methodology has been developed for identifying the nonlinear dynamic behavior of nuclear power plant components, using consecutive samplings of sensors readings, and for isolating the origin and extent of a failure, when occurring. The present paper summarizes and reviews the main findings of this methodology.

Multilayered ANNs are considered a promising alternative to existing pattern recognition and signal processing techniques. This is mainly because of their prospective short execution time and their ability to learn from examples and build unique structures, for particular problems, without requiring explicit rules. These characteristics makes ANNs superior over competitive expert–system methods. It is especially true in practical engineering systems where physical rules are too complex to define, and signals corruption by noise are unavoidable. The inherent parallelism structure of the ANNs allows very rapid parallel search and best–match computations, alleviating much of the computational overhead incurred when applying traditional non–parametric techniques to signal interpretation problems.

The performance of the ANN algorithm developed in the present work has been studied and evaluated using benchmark problems related to the dynamic behavior of the High Temperature Gas Cooled Reactor (HTGR, THTR–300). The test problems consist of several possible malfunctions and Anticipated Transients Without Scram (ATWS) as well as several possible normal operational transients that the ANN is trained to identify. The input patterns which represent these scenarios are generated numerically by an originally developed simulation code HTGRSS [20, 21]. The trained ANN was tested for its ability to detect and isolate failures in the presence of noise. It was found that an ANN algorithm can be derived to detect failures and locate their origin in more than 90% of the cases studied when the noise–to–signal ratio is below 0.5 db.

The Test Problem

The computer simulation program HTGRSS [20, 21] has been formulated to predict transient behavior of an HTGR during normal operation and hypothetical accident conditions. The program is written as a package system code describing the coupled thermal, fluid-flow and neutronic (including decay heat) behavior of the nuclear fuel and coolant in the reactor core primary circuit components and the steam generators. To simplify the analysis, only two variables (sensor readings) were utilize in this work to characterize the transient behavior of the power plan: (1) the in–core neutron flux and (2) the core outlet coolant temperature. Noisy values of these two variables were introduced to the trained ANN, to deduce the state of the plant.

The ANN was trained to identify eight operation scenarios, for which a set of state variables was generated numerically as a function of time by the HTGRSS code. These test scenarios are:

1. +1% positive reactivity jump.
2. -1% negative reactivity drop.
3. +5% positive reactivity jump.
4. -5% negative reactivity drop.
5. 20% power drop in the primary coolant blower.
6. 60% power drop in the primary coolant blower.
7. 5% increase in the Steam Generator (SG) inlet water temperature.
8. 5% decrease in the SG inlet water temperature.

ANN Training Procedure

We have applied a feedforward neural network algorithm, based on a backpropagation learning [14], to analyze the simulated HTGR data. The goal of this study was to train the network to discriminate among time dependent data patterns that describe different operational states of the plant, and to eventually enhance the system's capability to handle failures when occur.

The HTGRSS code was used to generate, as a function of time, the average neutron flux and core coolant exit temperature. Noise was added to the simulated signals assuming an independent, uniformly distributed, zero mean process with different levels of amplitude. In practice, the simulated data–base may be eventually replaced by archive's measured plant data.

There is, one major difficulty in using a feedforward network along with backpropagation learning for dynamic system identification. Backpropagation learning has been used and proven to work for static pattern identification. In order to apply the back propagation method as a dynamic diagnostic tool, a basically quasi-steady process of High Rate Pattern Recognition (HRPR) has been utilized. In this method the transient analog signal of each sensor is divided into consecutive digital reading samples of time intervals τ. In the learning phase, the first n samples ($n \approx 3to5$), from a transient inception, are used as a learning vectors set which characterizes the initial stage of the scenario. The learning set is then used as a standard against which measured digital samples of similar duration are compared. In the pattern recognition execution phase, measured signal samples of this duration are recorded continuously at time steps of $\Delta t \ll \tau$. When a set of measured samples is found to be similar to a known malfunction pattern the ANN identifies it and provides information on its origin.

The network is trained to identify a measured vector (pattern), out of a total number of k learning vectors (patterns);

$$k = m \times n \tag{1}$$

where, m is the number of scenarios investigated. The first time interval initiated at the beginning of the transient.

Each learning (or measured) vector, is made of a concatenation of l vectors of simultaneous output signals samplings from l different sensors which are connected to the malfunction identification system. Each individual sensor vector consists of s entries of discreet digital signals,

$$s = \tau/\Delta t \tag{2}$$

where, τ is the sensor samplings time interval and Δt is the measurement time step over which the sensor analog signal is digitized. All the signals are normalized to have values in the closed range $[0,1]$. The magnitude of τ, Δt and n are selected according to the system time constants, input patterns, decision regions complexity and required early warning of the specific system under investigation. The dimension of the network input vector is therefore,

$$I = s \times l \tag{3}$$

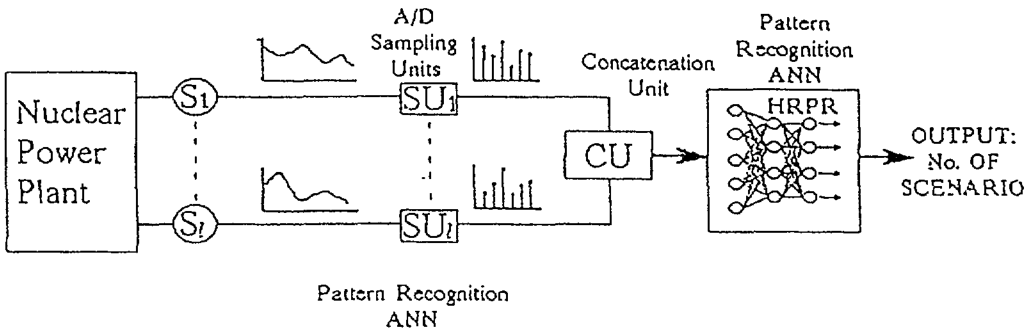

Figure 1: Failure Identification and Isolation High Rate Pattern Recognition (HRPR) System.

The pattern recognition process is described schematically in Fig. 1. A sampling-unit is attached to each of the sensors connected to the network. This unit generates a new measured vector (pattern) of s components for each individual sensor at every time step Δt. The first $(s-1)$ entries of the new vector are obtained from the translation of the previous vector entries by one location backwards, while the last entry is occupied with the most recent measured digital signal. These new vectors are then concatenated to a single measured vector and introduced to the network, as input for pattern recognition. This approach is amenable to on-line operations of continuous sampling and examining plant variable patterns at consecutive time steps of high frequency. The main assumption underlining this method is that the network execution time, t_p, is much smaller than the sampling time step Δt; i.e., $t_p \ll \Delta t$. The theoretical earliest alarm time of an incipient failure in this method is τ. However, the verification criterion for a failure occurrence which is usually defined as several subsequent identifications of the same failure, occurs some time later.

Results and Discussion

We report here the effect of the selected isolation time interval, τ, on the system performance in the presence of noise. Networks designed with various signal sampling time interval of duration τ are evaluated. The digitization time step was, $\Delta t = 2sec$.

The networks have been trained to identify and isolate eight failure scenarios ($m = 8$) using two sensors readings ($l = 2$) as described in the previous section. The learning vector set of each network consists of $k = 8$ patterns. The number of entries in each input layer of the network depends on τ. All networks consist of one hidden layer of 10 neurons and 4 neurons in the output layer. The desired output is coded as a 4-bit binary word which designates the scenario's identification number (1-8). All the neurons outputs are continuous-valued signals. In the output layer the signals values are converted to binary values using a threshold of 0.5. Sigmoidal activation functions were used for all the neurons with gain coefficient values of one for the neurons in the hidden layer, and gain coefficient values of two for the neurons in the output layer. The network weights were initialized with randomly selected values in the range of $[-0.1, 0.1]$. The networks were able to study their learning vectors set with a 100% success.

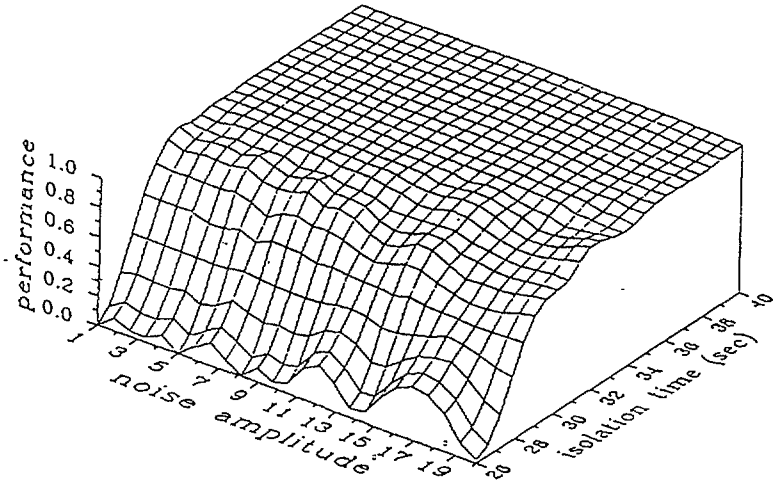

Figure 2: Network identification performance versus noise level and τ for scenario 2.

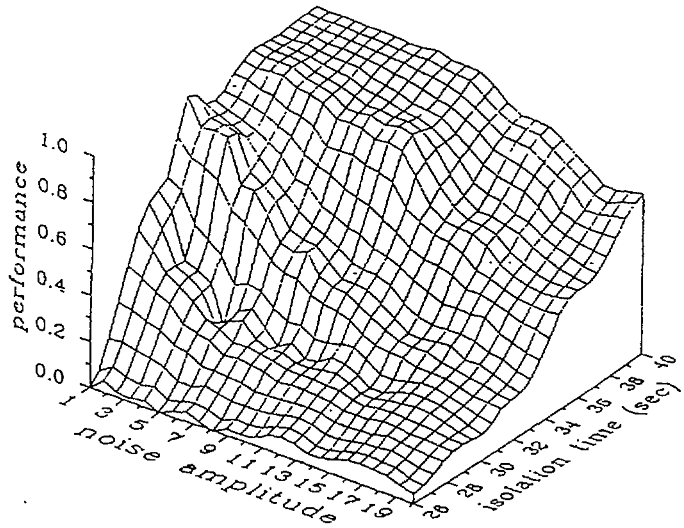

Figure 3: Network identification performance versus noise level and τ for scenario 3.

Figures 2 to 5 depict, for several representative scenarios, the network performance in terms of the fraction of the correct identification versus the level (in percent) of noise in the measured vectors and the isolation time τ. Each point on the surface represents the fraction of correct identification obtained from a series of 500 runs of pattern recognition. Each run of this series had the same nominal measured vector corrupted by a uniformly distributed, zero mean, noise with a given amplitude. The results show that for relative noise levels of up to about 2% and isolation time above 30 sec the ANN identifies all the scenarios perfectly. Using $\tau > 35sec$, a perfect correct identification can be achieved with even higher noise levels of up to 3% in almost all scenarios. A 90% correct identification, for instance, can be achieved with noise levels of up to 3% when $30 < \tau < 36sec$ compared to the same success level which can be obtained with noise level of over 5% with $\tau > 36sec$. Not all the scenarios can be identified at the same success rate. It can be seen, for instance, that the surface corresponding to scenario 5 (declines at lower level of noise relative to

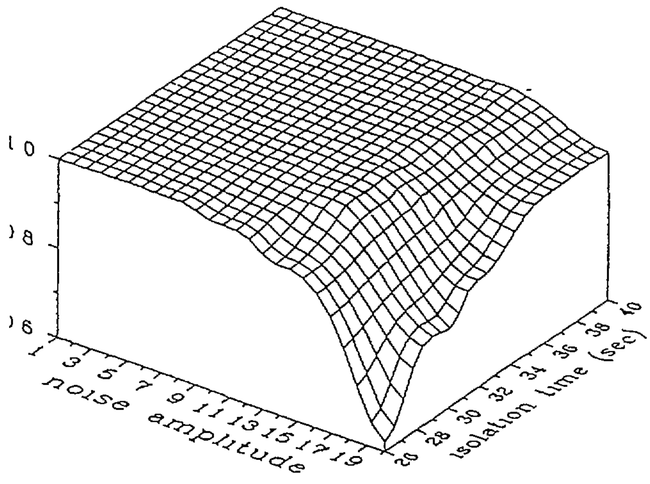

Figure 4: Network identification performance versus noise level and τ for scenario 4.

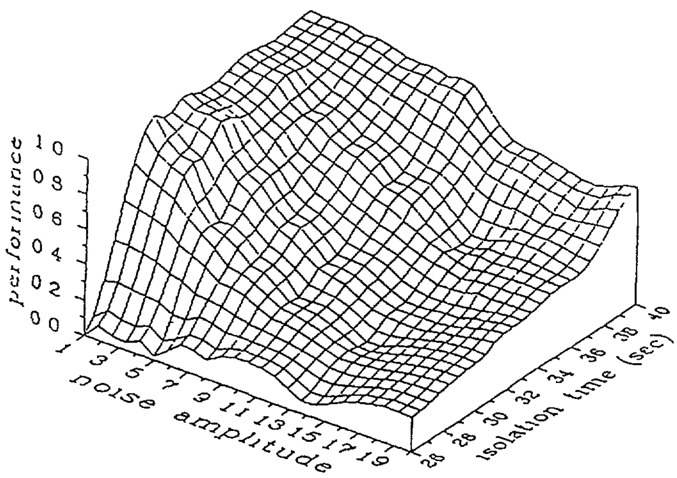

Figure 5: Network identification performance versus noise level and τ for scenario 5.

other scenarios. This is explained by the relatively large similarity between this scenario and the other. As a rule, better performance of correct identification for wider noise levels can be expected with a larger number of sensors connected to the pattern recognition system, as this provides better separability between the measured vectors.

Conclusions

A new neural network methodology, based on the backpropagation learning algorithm, is presented for malfunctions management in nuclear power plants. It is shown that neural networks can be used for identifying the nonlinear dynamic behavior of nuclear power plant components, and for isolating the origin and extent of a failure, when occurring, using consecutive samplings of sensors readings.

The results of this study provide encouraging preliminary evidence to support the feasibility of ANN based failure identification and isolation techniques. Even for a simple system which include only two sensors readings the identification of different dynamic scenarios was quite distinctive.

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