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SUPERVISORY MONITORING SYSTEM IN NUCLEAR POWER PLANTS

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ABSTRACT

Monitoring of a power plant is one of the essential tasks during operation and the computer-based implementations are nowadays seemingly quite mature. However, presently these are still not satisfactory enough to meet the high standards of the licensing requirements and they are mostly not truly integrated to the plant's design-based monitoring system. This is basically due to the robustness problem as the majority of the methods are not robust enough for the monitoring of the safety parameter set in a plant or intelligent supervision. Therefore, a supervisory monitoring system (SMS) in a plant is necessary to supervise the monitoring tasks: determining the objectives to be obtained and finding the means to support and fulfill them. SMS deals with the changing plant status and the coordination of the information flow among the monitoring subunits. By means of these the robustness and consistency in monitoring is achieved. The paper will give the guidelines of knowledge and data management techniques in a framework of robust comprehensive and coordinated monitoring which is presented as supervisory monitoring. Such a high level monitoring serves for consistent and immediate actions in fault situations while this particularly has vital importance in preventing imminent severe accidents next to the issues of recognition of the monitoring procedures for licensing and enhanced plant safety.

1. INTRODUCTION

The goal of monitoring is to detect process changes and faults during normal operations and to take actions to avoid damage to the process or injury to human operators. Process supervision or monitoring in an operating power plant is essential in two main aspects. These are in the first place, to avoid the accidents and in the second place system availability. Monitoring contains the following tasks. Fault detection and diagnosis; fault evaluation; decision on operating state; fault evaluation. To enhance the monitoring activities early process fault detection and localization is required such that sufficient time is provided for fault elimination and prevention of further fault development. Fault diagnosis is a major part of a monitoring task. From this viewpoint many fault detection methods have been developed [Willsky 1976], [Pau 1981], [Iserman 1984], [Gertler and Singer 1985].

The implemented methods use deterministic as well as stochastic signals. However, these methods are still rather simple and consist of mainly limit value checking of some available single signals or derived statistical quantities. The most important monitoring functions are the alarm handling and protection. These are achieved by means of conventional instrumentation which are foreseen for licensing. In parallel with the technological developments new instrumentation's and methodologies are endeavored to be integrated to the monitoring systems for enhanced safety and cost effective operations. In this respect, computer technology and its derivative artificial intelligence (AI) can be referred in the first place. Due to this, a number of parametric, non-parametric methods and AI implementations are developed for fault diagnosis the outcomes of which are used in various ways. Among these methods and implementations mention may be made to fast Fourier transform (FFT) techniques, time-series analysis , hypothesis testing methodologies. Also, new information processing technologies may be mentioned along this line [Türkcan et al. 1996; Ciftcioglu and Türkcan , 1996]. Although all these implementations are nowadays seemingly quite mature, presently these are still not satisfactory enough to meet the high standards of the licensing requirements and they are mostly not truly integrated to the existing monitoring system so that they remain often as the secondary systems for operator's aid and are articulated as 'decision support systems'. This is basically due to the robustness problem as the majority of the methods are not robust enough for the monitoring of the safety parameter set in a plant or intelligent supervision. For instance, majority of time-series methodologies make use of residuals for fault diagnosis where reference residuals are defined precisely for each normal operational status and normal operational changes e.g., power level change, require re-calibration. In a sensor-failure scheme, a failed sensor is assumed to have no effect on the computation by analytical redundancy although to some degree it effects the accurate status determination. In AI category, similar problems are involved in the majority of the neural network (NN) approaches, for instance.

2. SUPERVISORY MONITORING TASKS

Referring to above mentioned shortcomings, a supervisory monitoring system (SMS) in a plant is necessary to supervise the monitoring tasks: determining the objectives to be obtained and finding the means to support and fulfill them. SMS tasks is quite different from the conventional monitoring processes since the adaptation of the SMS behavior or structure to deal with the changing plant status and the coordination of the information flow among the units are essential. By means of these the robustness and consistency in monitoring is achieved. The supervisory monitoring is performed through an accurate system model in multilevel form and it addresses higher level monitoring aspects. Modeling can be constituted by several components like static modeling, dynamic modeling and computational modeling.

Operating in real-time, the tasks of a SMS can be divided into two major categories:

1. Fault detection and diagnosis which includes optimal state estimation
2. Model management which includes simulation and learning

Fault detection and diagnosis performs the detection of incipient failures and causes of the failures. It should also report the failures to the operator. This pass of information should be done intelligently so as to help the operator focus on the current part of interest. Fault detection can be carried out by means of several ways; namely, by processing received alarms, by model referenced process verification, and by data and trend analysis. In each case, the diagnosis has to be done as fast as possible to avoid the obscurity of the real cause of the fault.

For *alarm handling*, an essential problem the alarm overwhelming, that is a situation when too many alarms are generated. This should be carefully considered by alarm gradation. For the *process verification* of the operation by the measurements at hand, the measured quantities should be compared regularly against the values from the models based on the first principles. Also it should include a reference model to predict the future operational values and verify if these predicted values match the actual measurements. When a difference is detected, a potential fault is detected and it should be possible to infer some prognostic information. In case of a model fault, an error is found in the model description which is subject to improvement. For the *data and trend analysis* sensory data from the plant should be validated prior to their use. Should there may be discrepancies between the incoming data and the model-based counterparts consistency and valid operational status must be established.

Model management maintains and exploits a process model reflecting the current state of the process. Measurement values, trends, failures and structural changes are recorded in a data base so that topological and behaviorally correct process model is always available for the other tasks of the SMS such as prognosis tasks. Hence the model management acts as a data base as well as it identifies current and future states and trends of the plant and evaluates the model. This is achieved by model and parameter updating and learning.

For *model and parameter updating*, all sensory data should be stored into the model so as to keep the model as accurate as possible. Any change in the plant dynamics should be reflected into the model. Also the model must be regularly aligned to the measured process state. This is because in case a discrepancy, to distinguish between model fault and operational fault is rather difficult. This process is called model alignment. As the plant model is in the form of several layer corresponding to shallow-knowledge and deep knowledge, there should be a systematic transfer of behavior of the lower layer to a higher level. This is called abstraction. Generally the lowest level is fed with the plant's sensory data. The higher levels should stay tuned to plant data by evaluating the abstraction relations.

For *learning* one can distinguish two modes: supervised and unsupervised. Supervised learning is initiated and coordinated by the predetermined means and it is performed in adaptive form. In contrast with this the unsupervised learning is executed automatically and autonomously by the system in an intelligent way.

Learning addresses quantitative values of the system parameters, validity of existing concepts or creation of new concepts. Learning of quantitative values is concerned with numerical aspects, like parameter estimation to update current parameter values or backpropagation for weight adjustments in neural networks. Learning with respect to existing concepts deals with updating current structure of process models with known modeling elements. It applies process identification techniques to determine the current structural properties of the process in terms of known concepts and updates the model if necessary. Leaning new concepts is necessary when certain process phenomena cannot be described with available concepts.

Learning some inherent features of the process can require unsupervised learning. It requires parameter estimation to adjust initial parameter estimation errors and to deal with parameter variations due to process aging (e.g. burn-up).

Learning should be performed on every layer of the hierarchical monitoring system. Once the model is constructed and put to operation, learning must be performed on-line fully automatically. The gained experiences by learning can be used for derivation of heuristic rules or cases to speed up future search for solutions. For example, symptoms could be stored together with the actually observed fault, as a new case in a case-based fault diagnosis system.

Learning is a necessary ingredient of intelligence and it is one of the main characteristics of the SMS. Learning can also address the improved use of solution procedures and of combinations of task methods. By analyzing the effectiveness of current combinations, new rules can be created for composing improved combinations for future use. Such a learning process benefits the monitoring process with its advanced inference mechanism called supervisory inference. This is depicted in Fig.1.

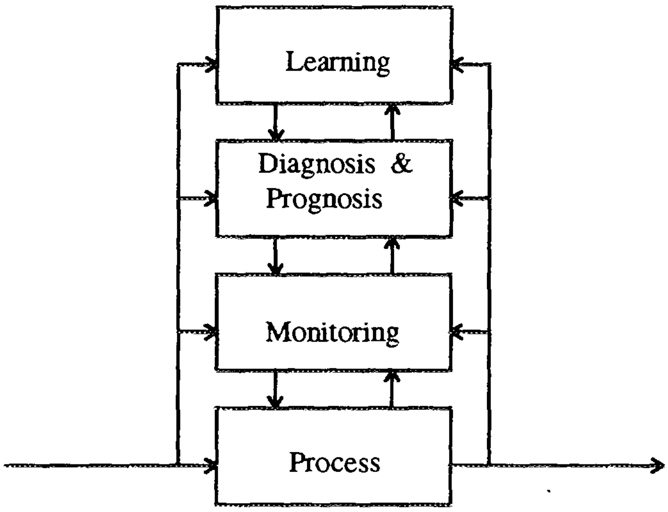


Fig.1. Supervisory inference

3. MAN-MACHINE SUPERVISORY MONITORING INTERFACE

The more powerful and flexible man-machine interface hardware and articial intelligence (AI)-based support tools become, the more emphasis needs to be put on the cognitive demands posed to a human operator. Since the operator is assumed to sustain the overall decision-making task in the supervisory monitoring loop, this imposes criteria with respect to the maximum cognitive load an operator can deal with properly. Human errors may be of different types. These are broadly categorized as *detection errors, cognitive errors and execution errors.* Therefore, taking an operator perspective while designing the man-machine interface is imperative.

From the above discussions, it is clear that the complexity of the supervisory monitoring systems should be hidden behind a simple, easy to understand interface. It is important to recognize that humans do not think numerically. When building operator interfaces for supervisory monitoring systems, this implies that data should be presented conceptually, that is symbolically or linguistically. The vast pattern recognition capabilities of humans should be exploited by applying new display techniques to create enhanced, data rich pictures. Linguistic labeling of data could be applied, using fuzzy classifications, to generate a natural language interface for better understanding of system messages.

The operator thinks on several levels of abstraction, from detailed low-level monitoring to aggregated overviews. The operator zooms into or out of a part of the operation to switch to a more specialized or higher category of decisions. Orthogonal to that, the operator is able to perceive multiple information flows in parallel, like a single screen containing several trends or momentary operational status values is viewed and interpreted at once.

4. KNOWLEDGE MANAGEMENT AND DATA HANDLING

4.1. Knowledge management

In the supervisory monitoring system, knowledge-based expert systems play the essential role. For knowledge representation the computational effectiveness is required. Solutions to problems in knowledge representation and inference should satisfy the real-time constraint. Also, it is necessary to identify and formalize inference structures appropriate for dealing with incompleteness and uncertainty. An AI system must be able of reasoning with incomplete and uncertain information. The current status of the expert systems are briefly described below.

A first generation expert system is a shallow expert system which consists of a knowledge processing unit and a heuristic knowledge base. An expert shell contains no a priory knowledge. It has to be filled with domain knowledge prior to its use. Domain knowledge is captured in production rules. The production rule paradigm is a model for human reasoning. It captures an expert's experience and casual reasoning strategy. It is a representation paradigm where knowledge can be captured in the form of rules. The rules consists of compiled associations of facts and phenomena with solutions and actions. The knowledge base containing these rules is a large set of recompiled chunks of deep knowledge ready to use rather than a collection of shallow knowledge in the form of if-then rules.

In the first generation expert systems, two fundamental forms of reasoning process is involved. These are forward chaining and backward chaining. Both strategies work on production rules, but complementary. Forward chaining works from antecedent to conclusion, while backward chaining works from conclusion to antecedent. There are several ways for the improvements to increase search speed, performance. However first generation expert systems contain shallow knowledge. Expert systems based on purely shallow knowledge cannot give satisfactory explanations about their behavior and show abrupt degradation at the edge of their knowledge domain, since no compiled knowledge about cases that never have occurred before is available. Moreover, since knowledge elicitation depends on subjective human experts addressing only a limited number of cases, the expert system's knowledge domain is incomplete and possibly inconsistent of format and meaning. The disadvantages and limitations of first generation expert systems are summarized below in three categories, namely concerning human-computer interactions, problem-solving flexibility and extendibility-maintainability [Keravnou, 1990].

- Incoherent sequences of questions
- Redundant questions
- Historical information on a case is not maintained, requiring the user to enter it again for each consultation on that case.
- Inflexible user interface where information is required to be entered in very specific terminology's and formats, otherwise information is ignored.
- User is neither allowed to revoke an answer nor to pursue the effects of an alternative answer.
- Explanations do not cover al the explanation needs of the user.
- Performance degrades dramatically when dealing with rare case.
- Inability to recognize that a problem case is at the periphery or outside of its area of expertise.
- Difficult to modify the system's knowledge. Consistency checks are not facilitated
- Inability of the system to evolve on the basis of its experiences in problem solving

Causes of disadvantages and limitations above are explained as follows.
- Shortcomings of reasoning knowledge that it is not complete. The generic tasks and strategies are implicit,

- Shortcomings of domain-factual knowledge due to its structure which is not compatible to the way human experts model their knowledge.

The causes all originate from the differences and incompatibilities between human and expert systems knowledge representation and processing.

Referring to the shortcomings of the first generation expert systems, the second generation solutions are summarized below.

In second generation expert systems, knowledge is derived from the first principles introducing generality. However this does not imply that the resulting model precisely describe the physical model because the first principles are not detailed enough for the complexity of the real world.

Designing a second generation expert system with the objective to overcome a specific first generation limitation without solving this limitation in the context of others, is prone generating local, non-robust solutions (Keravnou, 1990). For sound improvements in second generation expert systems, the limitations in the first generation counterpart must be well understood. Hence, the architecture should then be designed from the perspective of the root causes and not of their effects. Then, the architecture will provide a global and thus effective solution.

Integrating first and second generation expert systems should make it possible to use heuristic knowledge to decide when to carry reasoning back and forth from heuristics to first principles. This is important when experience fails or is lacking or when the domain model is incomplete.

Efficiency and the ability to reason progressively ensure that model-based reasoning is performed in time. This is very important for critical situations where response time should be small to avoid imminent accidents. A progressive reasoning mechanism generates a preliminary answer using only a very small knowledge base. While time is available , gradually larger knowledge bases are accessed to refine this answer step by step. After some time, the current inference takes the precedence. This way, a subsequently more accurate answer is always available at any point in time.

4.2. Data Handling

To process the massive amount of low-level data from the plant, two approaches can be used. These are parallelism and hierarchy. For parallel data handling neural networks for solving pattern recognition and minimization problems is of particular interest. Here simple procedures are carried out on all data items concurrently by means of simple processors. There are many such processors and there is no need for complex data structures. In contrast with parallelism, in the hierarchical approach the data are structured as efficiently as possible in order to concentrate processing where it is needed. The two approaches are not mutually exclusive as they are approaches for the same problem. However hierarchical approach is more systematic where the data items are grouped into higher level categories. By varying the category level data may be viewed at various levels of detail.

With respect to supervisory monitoring, two aspects of data manipulation are of importance. These are trends and uncertainty processing which are described in the followings.

4.2.1. Trend analysis

Trends of process measurements are an important source of information. They indicate behavioral properties, such as oscillations and monotonic increase. By analyzing trends, it is possible to quickly extrapolate future events, crossing alarm boundaries for example. Several trend representations are available. Each of them has its own expressive power. Among the simplest methods are linear and non-linear regression analysis, least squares, exponential smoothing or moving average. These methods all process raw history data of limited time window length, generating mean behavior.

To represent oscillations as well, Fourier analysis is used, expressing signals as a sum of sine waves. In principle, the signal should be of infinite length for the Fourier analysis to work well. Therefore Fourier analysis methods produce results under the assumption that a signal will behave in the future as it has done in the past. An adaptation is the short-time Fourier transform, used to transform a fixed length part of a signal. A disadvantage of this method is its sensitivity to noise.

On the highest level of expressive power are wavelets, representing a signal as a series of predefined, scaleable wave shapes [Daubechis, 1992]. Wavelets allow for scaling of detail over time, because they are self-similar representations that compress or expand in time as frequencies of the original signal increase or decrease, respectively. Gabor type representations retain the shape of the envelope, while the frequency is changed. In wavelet representations the frequency is retained, while expanding or compressing the shape of the envelope. This allows to preserve all information contained in the original signal, in contrast with Gabor type representations where these are of fixed duration, forcing information to be thrown away when they are scaled. These are represented in Fig.2.

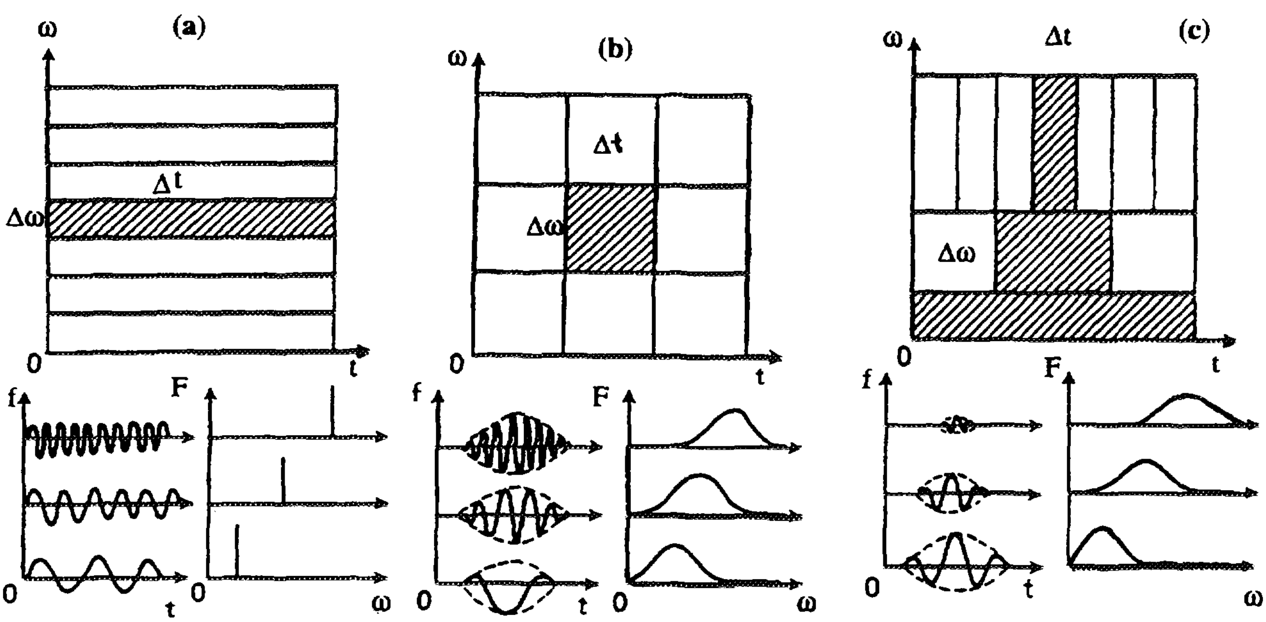
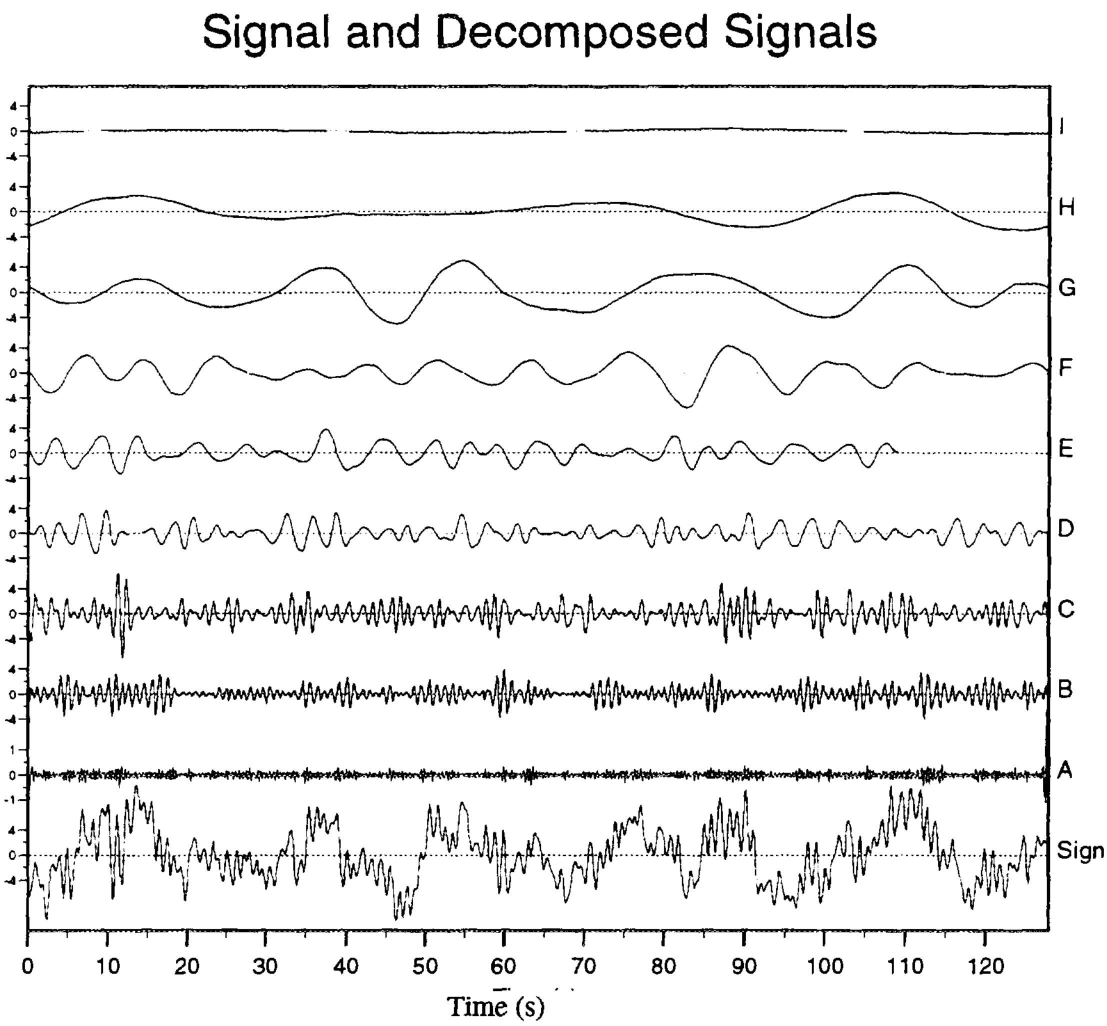


Fig.2 : Fourier (a), Gabor (b) and wavelet (c) representation where $\Delta\omega$ is frequency resolution, Δt time resolution. Note that each level of representation is orthogonal to each other, so that summation of the represented variations yield the variation from the sensor, i.e. perfect reconstruction *Such a representation does not assume periodicity of the data so that it is superior to FFT type analyses.*

The multi-resolution representation capability of wavelet analysis is represented in Fig.3.



Signal: AC signal ; sampling rate 8 samples/second

A: decomposed signal for 4.	to 8.	Hz
B: decomposed signal for 2.	to 4.	Hz
C: decomposed signal for 1.	to 2.	Hz
D: decomposed signal for 0.5	to 1.	Hz
E: decomposed signal for 0.25	to 0.5	Hz
F: decomposed signal for 0.125	to 0.25	Hz
G: decomposed signal for 0.0625	to 0.125	Hz
H: decomposed signal for 0.03125	to 0.0625	Hz
I: decomposed signal for 0.015625	to 0.03125	Hz

Fig.3 : Multiresolution signal decomposition by wavelet transformation
"Transient Detection by Wavelet Transform", Ö Ciftcioglu and E. Türkcan, SMORN VII, 19-23 June 1995, Avignon, France

When informative power of a trend representation technique is plotted against the scale of representation, each of the techniques takes a position in this space. The more a technique is situated in the upper right part of the figure, the more it is apt for supervisory monitoring as depicted in Fig.4.

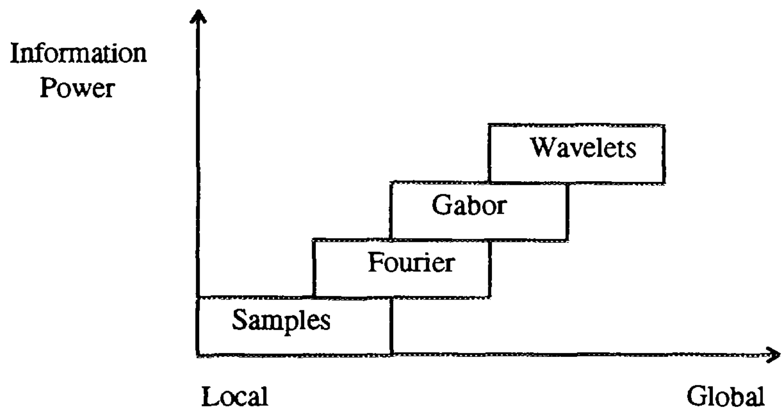


Fig.4 : Informative power of data representation

4.2.2. Uncertainty

Uncertainties can be handled by means of two different paradigms. These are analytical paradigm and rule-based paradigm. The analytical paradigm concerns the probability density of the uncertain quantity and the associated confidence levels. This type of treatment is rather conventional and well known. It operates on the measured values from the sensors the probability density being in most cases gaussian.

The rule based paradigm concerns the fuzzy sets and associated logic where fuzzy set theory was first introduced by Zadeh [1965]. A concept that plays a central role in fuzzy logic is the concept of a linguistic variable. The concept of a linguistic variable enters in the characterization of dependencies through the use of fuzzy 'if-then' rules. With fuzzy sets, a numerical value is classified into one or more linguistic labels, each with an associated membership value. This results in a multi-value representation since the membership functions, representing the numerical strength of linguistic labels for the domain of classification, overlap. An input value intersects with one or more membership functions of the input classification and it is classified by as many linguistic labels. Before entering a fuzzy system, numerical values are fuzzified. This is usually done by an input classification, matching input values against a chosen set of linguistic labels. These labels partly overlap so that a numerical value can be classified into more than one label, each with an associated membership value. Inference is performed by evaluating fuzzy production rules. Propagation of fuzziness is linear with respect to arithmetic operations. Logical combinations are performed by T- and S-norms for conjunctions and disjunctions, respectively. T- and S-norms have to fulfill four criteria, namely, they should be non-decreasing functions in each argument, be commutative, be associative and they should have an identity value.

Since a numerical value can be classified into more than one linguistic value, more than one rule might be triggered, producing several answers. This multiple answer is defuzzified to obtain a crisp numerical value.

The fuzzy approach can be supported by neural network approach as well. The relation between these two approaches referring to the supervisory monitoring is depicted in Fig.5.

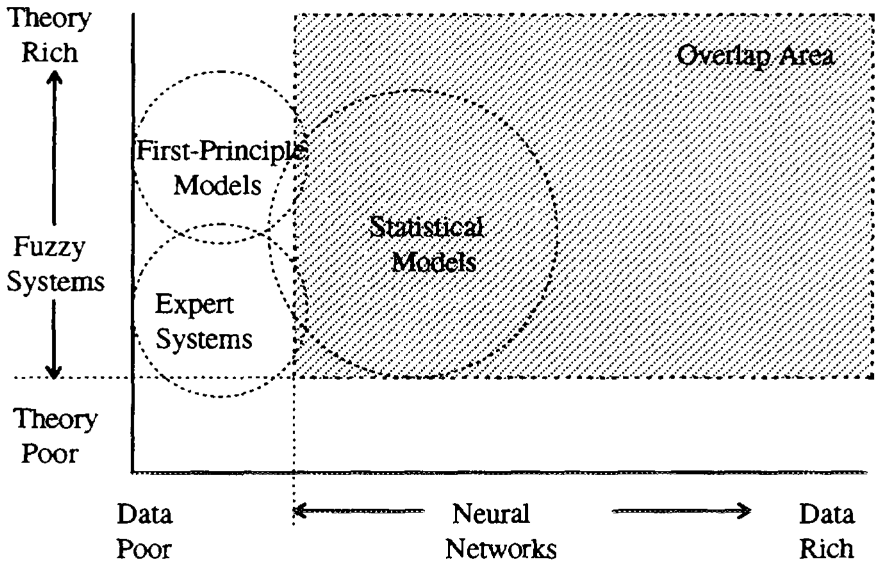


Fig.5 : Fuzzy versus neural networks in supervisory monitoring

5. CONCLUSIONS

The paper shows that supervisory monitoring requires high-level programming approaches to manage the increased problem complexity of large-scale, plantwide process monitoring applications. Modularity and symbolic processing are key issues for solving problems associated with supervisory monitoring. Modularity is needed in a hierarchical approach to deal with the high degree of large scale process complexity. Symbolic processing offers improved reasoning flexibility needed to handle a large variety of expected and unexpected situations.

Improved data representations are needed to effectively represent trends and anomalies of process signals. The detected and isolated trends are the source of motivation supplying information to higher layers of the supervising system. Not all signal analysis techniques are able to do this in sufficient detail, because they assume a certain structure of the signal, which is seldomly present in all signals of a process. Therefore, more expressive representation and analysis techniques should be used, which are general enough to capture the diversity of shapes and preserve the main signal characteristics in higher decision levels.

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