FURTHER DEVELOPMENT OF NPP SURVEILLANCE AND DIAGNOSTIC SYSTEMS BY USE OF INTELLIGENT TECHNOLOGIES

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Abstract

Recent development work at ISTec/GRS has been directed to more automation of surveillance techniques by utilization of the technological progress and existing tools. Neural nets, fuzzy techniques and rule-based methods were investigated for application in feature classification and automized identification of anomalies. First applications were aimed at classification of useful patterns and suppression of non-relevant signal components in order to avoid false alarms (e.g. in acoustic monitoring) and at signal validation under normal and disturbed plant conditions. Other on-going projects are aimed at the application of the successful methods to other surveillance tasks such as on-line assessment of sensor behaviour and ageing phenomena of instrumentation. The paper gives an insight in the intelligent analysis techniques and highlights their potential use for other surveillance tasks in nuclear power plants.

INTRODUCTION

On-line component and process monitoring as well as incipient fault detection systems have been developed and applied successfully during the last two and a half decades /BOS93/, /WAC95/. Useful on-line information on component conditions, degradations, or other anomalies is provided to the operator in a way that at any time during operation the actual status can be assessed and – if there are first indications or incipient anomalies - contermeasures can be planned carefully in due time without stress. As an additional layer in the defense-in-depth concept diagnostic systems play an important role for improving the safety and availability of NPPs.

The measurement and analysis principles of the systems dealt in sequel are based on signature analysis of dynamic signals, on feature selection, and - for the time being - on assessment of deviations/trends of features (or feature sets/feature vectors) by human experts using model knowledge and/or long-term operational experiences. The extensive implementation of the human experts in the diagnostic process – as usual up to now – is rather time-consuming and costly. Therefore, in future work emphasis should be placed on the reduction of costs created by human evolvement where reasonably possible. Basic investigations how to substitute the human assessment at least partly and to promote from feature monitoring/trending systems to real diagnostic systems have been performed by ISTec within the last years.

The progress in computer technology in particular with respect to performance and cost/benefits and the availability of new developments in computer science providing software tools for intelligent signal analyses are excellent prerequisites for further developments and applications towards more advanced on-line systems with automized reasoning and diagnostic capabilities.

Recent development work at ISTec/GRS has been directed to improve existing surveillance techniques by utilization of the technological progress and existing tools. Neural nets, fuzzy techniques and rule-based methods were investigated with respect to their potential for application in feature classification and automized identification of anomalies. First goals were aimed at classification of useful patterns and suppression of non-relevant signal components in order to avoid false alarms (e. g. in acoustic monitoring) and at signal validation under normal and disturbed plant conditions. Other on-going projects are aimed at the application of the successful methods to non-mechanical surveillance tasks such as on-line assessment of sensor behavior and aging phenomena of instrumentation. The paper gives an insight in the intelligent analysis techniques and highlights their potential use for other surveillance tasks in nuclear power plants.

1. AUTOMIZED DIAGNOSIS BASED ON NEURAL NETS

Advanced burst signal processing in loose parts monitoring (LPM) has been a first application towards more automized diagnosis. Classification module has been developed by our institute and applied for the Siemens LPMS KÜS'95 /BEC 95/. The motivation of this development was enforced by the fact, that more and more German utilities are replacing their old analogue systems by a new generation of digital LPMS. With the help of modern hardware and software technologies new possibilities are available for digital data acquisition, storage, userfriendly interfaces and implementation of improved false alarm reduction strategies.

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The classification module is based on an multi-layer feed forward artificial neural network with five input nodes (x1 to x5), two hidden layers with five nodes each, and two output nodes (y1 and y2), Figure 1a.

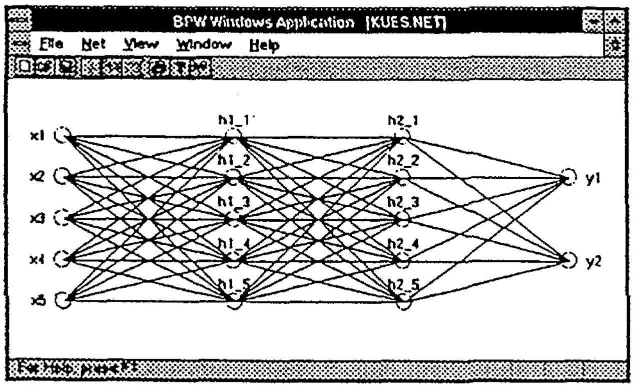

Fig. 1a: Structure of the neural network

Five parameters which characterize the burst form adequately, are determined automatically: the local maximum time (=Tlm), the global maximum time (=Tam), the normalized area (=Fläche), the intensity ration (=Intens) and the fine structure (=Feinst.) /OS 87/. They are used as inputs of the neural network and the output values y1 determines the class value. y2 is a sensor identification value. Each event is classified as one of the five possible classes (or an unknown class): electrical/thermal disturbance signal, burst signal, flow induced noise, calibration signal and background signal. The software has a single event user interface and a user dialogue for the classification of burst ensembles. The later is demonstrated in figure 1b.

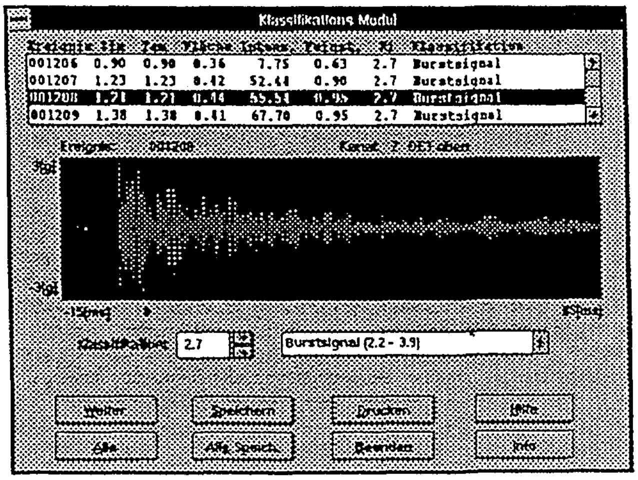

Fig. 1b: User dialogue for the burst ensemble classification

The list above the signal graphs contains: the event number, five calculated feature values, the class value and class type in full text. Below the signal graph are: the edit button for the class a value of the selected acoustic event, other control buttons for save, list printing, etc.

In this way the digitally stored signal patterns can be classified into the pre-defined classes automatically. Test results in the ISTec acoustic Lab using digital or tape-recorded plant signals achieved a correct classification rate of ca. 90 %. The supervisor in the plant can extend the user training set and retrain the network for adaption of the diagnostic capability to special signal paths in his plant without any change of the software.

The classification module and another acoustic module are programmed as MS-Windows 3.1 dynamic link library (DLL) add-ons and already installed in German PWR and a Russian plant of VVER-1000-type /DIN 96/.
Other research activities at ISTec are dealing with the fuzzy logic application in LPMS /DW 97/ and the combination of both technologies which leads to a neuro-fuzzy classification systems /DIN 98/.

2. AUTOMIZED DIAGNOSIS BASED ON FUZZY LOGIC

The theory of fuzzy sets and fuzzy logic /ZAD 65/, /ZAD 75/ are widely used in the automatic decision making /ZIM 87/, fuzzy control /PRE 92/ and also – more and more – in fuzzy diagnosis systems /FRA 94/, /ISE 95/.

Fig. 2 shows the basic concept of a fuzzy logic based classification/diagnosis system with the main steps: fuzzification, rule inference and defuzzification. Its structure is comparable to the fuzzy control systems (in special cases where fuzzy diagnosis results are desired the defuzzification step can even be omitted). Mathematically the classification/diagnosis process can be described as a mapping of a feature vector into a class/fault vector.

2.1 Definition of Fuzzy variables

For designing of a fuzzy logic based system the five signal parameters (Tlmax, Tgmax, Area, Intens. and FeinStr.) can be used as fuzzy input variables directly and the system output is a fuzzy class value. The class value has to make four possible linguistic values according to the four possible class types. Each input variable was assigned with three possible linguistic values "small", "medium" and "big" at the beginning (can be increased to *very* big, *very* small, etc. , if necessary). Figure 3 shows an example for a feature value x.

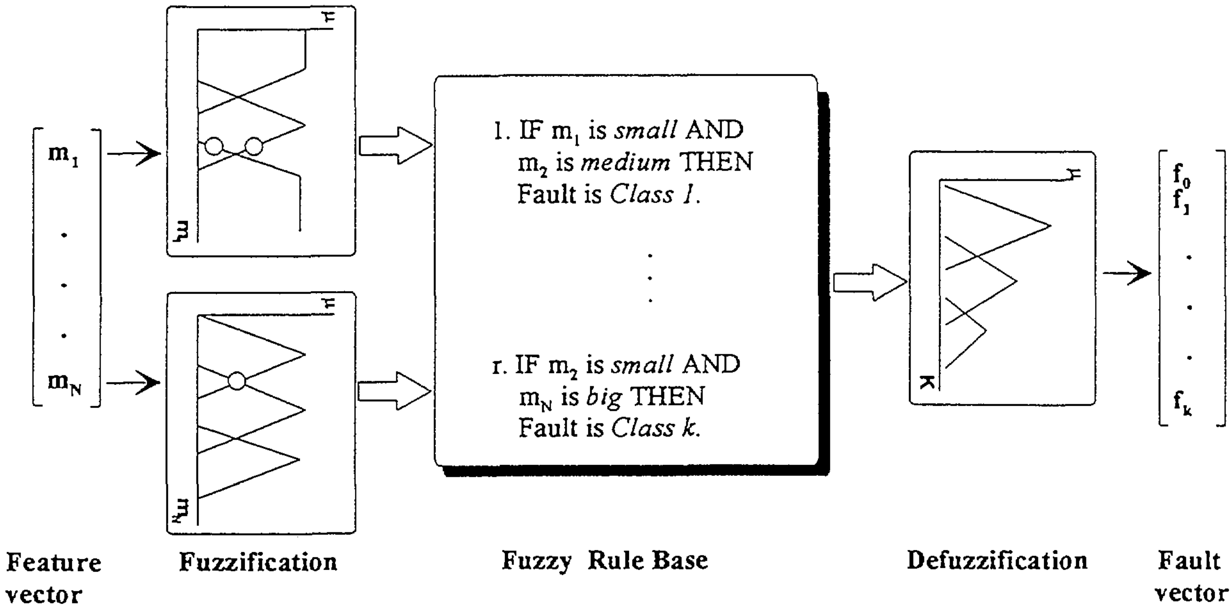

Fig. 2. Basic concept of a fuzzy diagnosis system

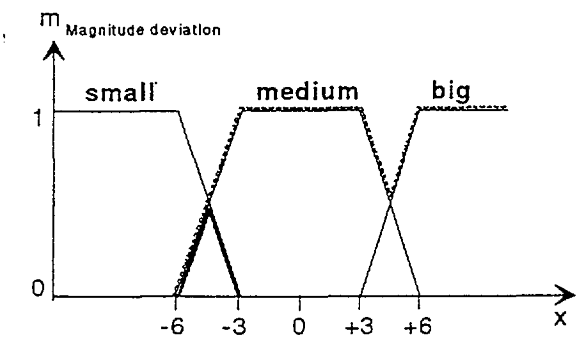

Fig. 3. Fuzzification of a feature value x

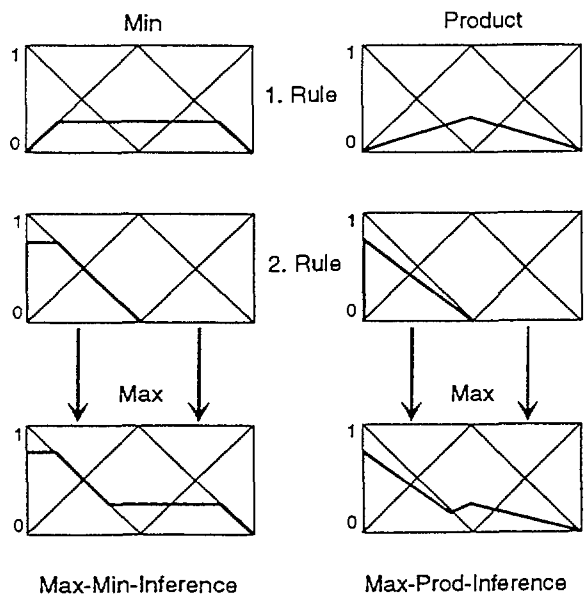

Fig. 4. Max-Min- and Max-Prod-Inference (Preuß, 1992)

2.2 The Fuzzy Inference

From the two inference methods well-known in the literature (Fig. 4) the Max-Prod-Method is used. It keeps the shape of the membership functions and is easier to be implemented.

3. SYSTEM OPTIMISATION BASED ON STATISTICAL ANALYSIS

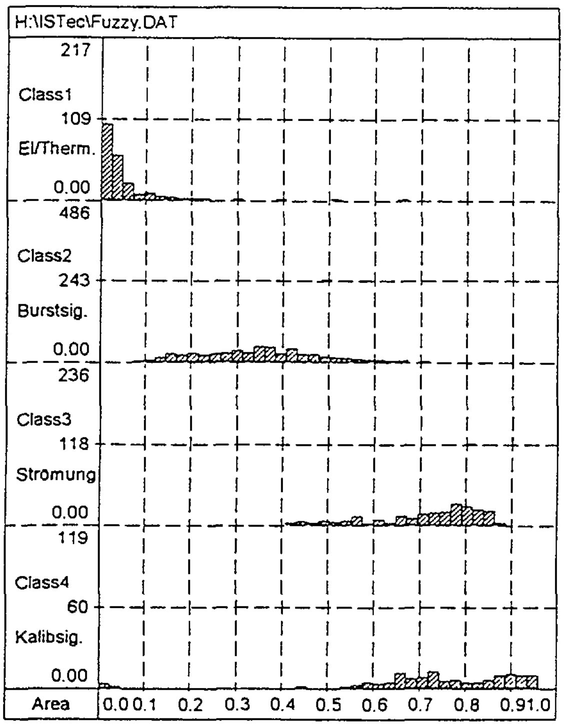

Fig. 5. Histogram of the parameter "Area"

3.1 Generation of Membership Functions and the Fuzzy Rule Base

The membership functions are generated and optimised after intensive statistical data analysis (1058 data records of four known classes classified by human experts are used). The well-known statistical histograms were used to get the shape of membership functions. Fig. 5 gives an example of the distribution of the fuzzy variable "Area" according to different classes (the x axis is normalised). Other graphical representations of the data set like the distributions of different parameters versus one special class are also helpful. Based on these analysis results the fuzzy rule base can be generated (Table 1) and the membership functions optimised interactively for achieving the best diagnosis results (Fig. 6).

Table 1 The generated rule matrix

Features/ Class	El./Therm. Signal	Burst Signal	Ström. Signal	Kalib. Signal
TLmax	*very small*	*small*	*big*	
TGmax				*small*
Area	*small*	*medium*	*big*	*very big*
Intens.			*small*	
FeinStr.	*small*	*medium*		*small or big*

3.2 The Operator-Mix

Because the signal transfer path of the acoustic signals are rather complex in the nuclear power plants and the signal/noise ratio is sometimes low, the calculated feature values are uncertain. The described fuzzy system achieved a correct reclassification rate of ca. 91.7% using the 1058 data set. A neural network solution (trained with the same data set) with a reclassification rate of 95.3% is only a little bit better. Table 2 shows the judgement matrix of the reclassification results of the fuzzy system. The diagonal elements are correct classifications and the c0 class represent possible rejections (no classification).

Table 2 Judgement Matrix

	c1	c2	c3	c4	c0
c1	87%	12.4%	0.5%	0.0%	0.0%
c2	0.8%	98%	0.6%	0.4%	0.0%
c3	0.0%	18.6%	81%	0.0%	0.0%
c4	5.9%	0.0%	0.0%	94%	0.0%

For safety related applications like the nuclear power plant it could be desirable to achieve 100% for the critical class c2 (= no missing alarm). This requirement couldn't be achieved by tuning membership functions using the rule base in table 1.

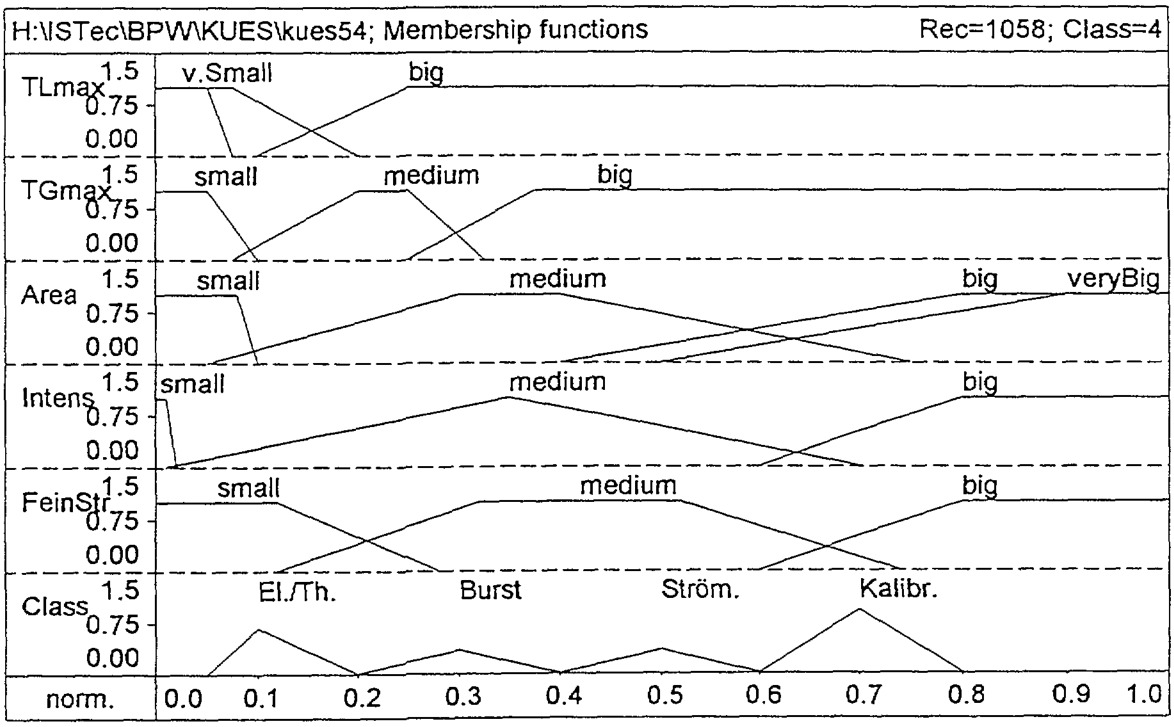

Fig. 6. Optimised membership functions

Better results became possible by the mixed use of the AND-operators. For the non critical classes (c1, c3 and c4) the normal Min-operator is used for the logical AND-Operation:

$m(A \text{ and } B) = \min(m_a, m_b)$(1)

Whereas for the critical class c2 the Average-operator is used instead:

$m(A \text{ and } B) = (m_a + m_b) / 2$ (2)

Formula (2) is comparable with the fuzzy distance measure. It takes the averaged fullfilment of different fuzzy variables and has no so strong excluding property as the Min-operator. It could be expected that the c2 class patterns are easier to pass the classifier. Table 3 shows the new results.

Table 3 Judgement matrix using mixed AND-operators

	c1	c2	c3	c4	c0
c1	**82%**	17.1%	0.5%	0.0%	0.0%
c2	0.0%	**100%**	0.0%	0.0%	0.0%
c3	0.0%	33.5%	**66%**	0.4%	0.0%
c4	0.0%	9.2%	0.0%	**88%**	2.5%

The total performance goes down to 87.5% which can be interpreted as the costs for getting 100% correct classification for class 2 (no missing alarm).

4. AUTOMIZED DIAGNOSIS WITH KNOWLEDGE-BASED SYSTEMS

Since nearly three decades of method development and application of surveillance and diagnostic techniques in nuclear power plants ISTec (formerly GRS and LRA of Technical University Munich) has collected comprehensive operational experiences and built up databanks for signatures and long-term trends in the different diagnosis domains. All analysis results gained from two third of the German NPPs are available including such before the time when the automated data acquisition with the condition monitoring system COMOS was established (i. e. before 1987). The databanks and the teams of experts for the particular diagnosis domains form an excellent platform for the ISTec Diagnosis Center in Garching.

Besides reliable and short-term support to the plant operator and maintenance personal for interpretation of observed signature deviations (in vibration) or burst patterns (in acoustics), an important objective of the Center is the collection of knowledge and maintaining it for future applications or further system/method developments. Therefore, with the collected data material and operational experiences a broad basis and best prerequisites are given for further improvement by introducing rule-based methods, systems with learning capabilities, or knowledge-based systems.

In a first step a knowledge-based diagnosis system has been developed for primary circuit components /BD 93/. Hereby an industry expert shell was used used together with the comprehensive knowledge of the vibration signature databank as well as calculations with a structure model by which parameter sensitivity studies and fault simulations were performed.

In an other project the basic structure of a knowledge-based fault diagnosis system for rotating machineries system was developed for monitoring the condition of an emergency and residual heat removal pump during monthly repetitive tests of this stand-by safety system /SDW 92/. The results were encouraging and showed that for more-dimensional feature vectors an automized reasoning for the identification of the causes of anomalies is not only beneficial, but also feasible with reasonable effort.

An interesting application is assumed in the field of signal validation especially for cases when redundany or analytical diversity (on-line model calculation) is not possible, but self-validation from the sensor signal itself is needed. Since knowledge about characteristic feature behavior caused by incipient failures in measuring channels is available and also knowledge about the dependency of these features on time, an approach with a rule-based diagnostic systems is supposed to be feasible and can solve problems raising up during accident situations in NPPs. A comparison and evaluation of existing concepts and national approaches has been performed recently within an common European project /WAD 95/, /WEU 96/. Also methods based on neural net application have been investigated in this project.

5. CONCLUCIONS

Several intelligent technologies have been investigated with respect to their potential, feasibility of realization, and benefits in operational use for different tasks in online surveillance and diagnostics of safety relevant components. Neural nets, fuzzy techniques, and knowledge-based systems as well as combinations of these techniques were applied to actual diagnostic tasks.

A fuzzy logic based classification/diagnosis system for automatic classification of acoustic burst events of the loose parts monitoring system (LPMS) in nuclear power plants has been developed. The performance is comparable to a neural network solution. The advantages of the fuzzy system are on the one side a better understanding of the diagnosis results and on the other side demonstrated by the ability to achieve 100% correct classification for the critical class which is difficult to be guaranteed by the neural network solution.

A further progress can be achieved by the combination of both methods /DIN 97/. The expected high reduction rate of false alarms will be proved in future practical use and make the LPMS-system and also other comparable information systems e.g. the vibration monitoring system /BOS 93/ more reliable so that the plant operator will get more precise information about the plant conditions. Also the combination of these methods with a rule-based diagnosis is seen to be a way for more automation. The measurements and analysis principles shown in the paper are applicable for other surveillance tasks based on feature classification such as leak monitoring, aging detection and signal validation.

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