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**FAULT DETECTION AND
DIAGNOSIS IN INDUSTRIAL
SYSTEMS, BASED ON FUZZY
LOGIC – A SHORT REVIEW**

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Abstract

The paper presents a fuzzy method in fault detection and diagnosis. This method provides a systematic framework to process vague variables and vague knowledge. The supervision of the process requires the treatment of quantitative and qualitative knowledge. Here fuzzy logic approaches are especially attractive for symptom generation with fuzzy thresholds, linguistically described observed symptoms and the approximate reasoning with multi level fuzzy rule based systems for fault symptom tree structures.

Keywords: *process monitoring, fuzzy logic, fault detection, diagnosis*

1. INTRODUCTION

1.1. General Things

In the field of control engineering new topics continue to flourish and develop. In common with general scientific investigations the new concept of fault detection and process monitoring emerge as a new growth area in process control. This innovative concept coalesces into a new sub-discipline. A little maturity has been acquired by the new concept. Archival publications and monographs may be study in the international scientifically literature. The reason of developing fault detection and diagnosis is based on new real time instrumentation technologies in manufacturing plant installations. Process operators are using process data to minimize plant downtime and optimize plant operations. The traditional routes to fault detection were model based and them the process has to be well understood. An alternative group of methods has emerged which do not require the use of an explicit model. Model-free and non-parametric methods for fault detection, process optimization and control design are in current development.

Many technical processes are operating now under automatic control based on the progress of control theory. A general scheme for the organization of process automation tasks in several levels is presented in fig. 1 [Ise95].

The measurement and manipulation takes place at in the lowest level. The next level contains feedforward and feedback control. Here some variables u , y are adjusted according to conditions v or reference variables w . The second level contains supervision; it is the monitoring level, which serves to indicate undesired or unpermitted process (fault detection) states and to take appropriate actions (based on fault identification and diagnosis) as process recovery, fail-safe, shut-down, triggering of redundance systems or reconfiguration schemes. The higher

levels may perform tasks such as optimization, coordination or general management in order to meet economic demands or

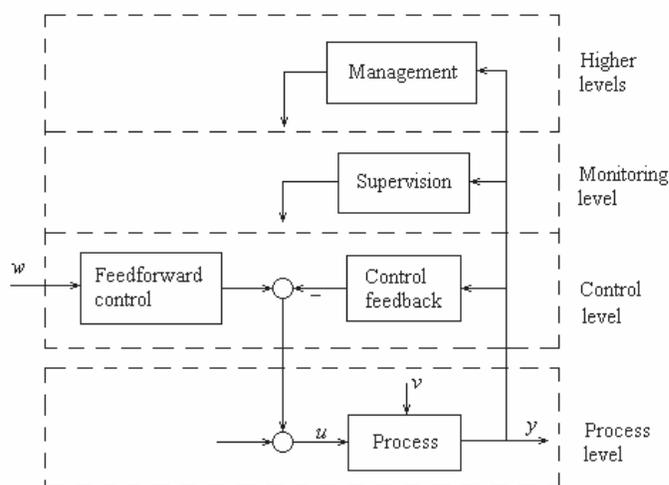


Fig. 1. The block diagram of multilevel process automation

scheduling. The lower levels need a fast reaction and act locally and the higher levels are dedicated to tasks that act globally. Modern manufacturing facilities are large scale, highly complex and operate with a large number of variables under closed-loop control. An early accurate fault detection and diagnosis for these plants can minimize downtime, increase safety of plant operations and reduce manufacturing costs. Plants are becoming more heavily instrumented, resulting in more data becoming available for use in detecting and diagnosing faults. Classical methods have a limited ability to detect and diagnose faults in such multivariable processes. This has led to a surge of scientific effort to develop more effective process monitoring methods. To apply these methods in the real industrial systems a large amount of research must be done.

The domain of control of electrical drives is a large field of application for the fault detection and diagnosis techniques. This domain is appropriate for practicing engineering in process monitoring. Numerous and ample simulators for a large scale

electrical drives applications may be developed. Data from the process – electrical drive – may be collect and applied to the monitoring techniques to detect, isolate and diagnose various fault. The process monitoring techniques can be modeled, simulated and implemented using commercial software as Matlab and Simulink [Bea94, Che92, Lot93, Vol2'0/1, 2].

These researches are focused on the approach based on fuzzy logic and neural networks, as new concepts developed versus the conventional concepts as statistical quality control, analytical methods, knowledge base methods, canonical variant analysis or Fisher discriminate analysis.

In the control of the electrical drives there is a large push to assure higher security of the electrical drive, to reduce electrical machine rejection rates and to satisfy the increasing stringent safety of the entire process controlled by the electrical drives and its environment. To meet the higher standards, the electrical drives contain a large number of variables operating under closed-loop control. The standard process controllers, for example PID controllers, are designed to maintain satisfactory operations by compensating for the effects of disturbances and changes occurring in the process. While these controllers can compensate for many types of disturbances, there are changes in occurring in the electrical drives that the controllers cannot handle adequately. These changes are called *faults*. More precisely, a fault is defined as a no permitted deviation of at least one characteristic property or variable of the system (resistance, inductance, moment of inertia, friction coefficient, voltage, flux or current, or quality criteria, as for example the overshoot).

The types of faults occurring in industrial systems include process parameter changes, disturbance parameter changes, actuator problems and sensor problems. Short circuit of the motor resistance or friction coefficient rising are examples of process parameter changes. A disturbance parameter change can be an extreme change of in the load torque or in the ambient temperature. An example of an actuator problem is a destroyed transistor in the power converter, and a sensor producing biased

measurements is an example of a sensor problem. To ensure that the process operations satisfy the performance specifications, the faults in the process need to be detected, diagnosed and removed. These tasks are associated with *process monitoring*. Different methods were developed for process monitoring.

The goal of process monitoring is to ensure the success of the planned operations by recognizing anomalies of the behavior. The information not only keeps the plant operator and maintenance personnel better informed of the status of the process, but also assists them to make appropriate remedial actions to remove the abnormal behavior from the process. As a result proper process monitoring, downtime is minimized, safety of plant operations is improved and manufacturing costs are reduced. As industrial systems have become more highly integrated and complex, the faults occurring in modern processes present monitoring challenges that cannot be treated with conventional methods. The weakness of the linear methods of detection and diagnosis have led to a surge of research concentrated to the methods of the artificial intelligence as fuzzy logic and neural networks. The growth of the research activity can also be explained by the fact that industrial systems are becoming more heavily instrumented, resulting in larger quantities of data available for use in process monitoring and that modern computers are becoming more powerful. The availability of data collected during various operating fault conditions is essential to process monitoring. The storage capacity and computational speed of modern computers enable process monitoring algorithms to be computed when applied to large quantities of data [Chi01].

The electrical drives, controlled in real time with digital equipments and software of high performances, are at this moment suitable for the implementation of such monitoring algorithms [Har94].

1.2. Process Monitoring Procedures

The four procedures associated with process monitoring are [Chi01]: *fault detection*, *fault identification*, *fault diagnosis* and *process recovery*.

Fault detection is determining whether a fault occurred. Early detection may provide invaluable warning on emerging problems, with appropriate actions taken to avoid serious process upsets.

Fault identification is identifying the observation variables most relevant to diagnosing the fault. The purpose of this procedure is to focus the plant operator's and engineer's attention on the subsystems most pertinent to the diagnosis of the fault, so that the effect of the fault can be eliminated in a more efficient manner.

Fault diagnosis is determining which fault occurred, in other words, determining the cause of the observed out-of-control status. It can be more specifically defined as determining the type, location, magnitude and time of the fault. The fault diagnosis procedure is essential to the counteraction or elimination of the fault.

Process recovery, also called *intervention*, is removing the effect of the fault and it is the procedure needed to close the *process monitoring loop*. Whenever a fault is detected, the fault identification, fault diagnosis and process recovery procedures are employed in the respective sequence, otherwise, only the fault detection procedure is repeated.

The schema of the process monitoring is presented in fig. 2. Whenever a fault is detected, the fault identification, fault diagnosis and process recovery procedures are employed in the respective sequence, otherwise only the fault detection procedure is repeated.

It is not necessary to implement all four procedures in a process monitoring. For example, a fault may be diagnosed (the procedures of fault diagnosis) without identifying the variables

immediately affected by the fault (the procedure of fault identification) and recover the normal operation. Often, the goal of process monitoring is to incorporate the plant operators and engineers into the process monitoring loop efficiently rather than to develop an entire automat monitoring scheme.

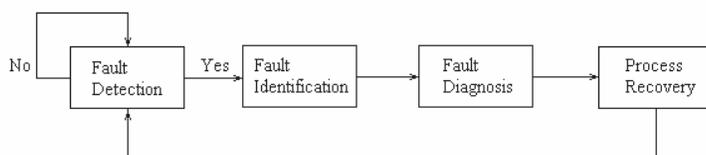


Fig. 2. The schema of the process monitoring loop

After a fault occurs, the process may be recovered, reconfigured or repaired and returning to the control strategy. Once a fault has been properly diagnosed the optimal approach to counteract the fault may not be obvious. A feasible approach may be the return to the standard process control strategy. Several methods were developed to evaluate the controller performance and these can be used to determine to which control strategy need to be returned to restore the satisfactory performances. For example, in the case of a sensor problem, a sensor reconstruction technique can be applied to the process to restore the control operations. Even the process recovery is an important and necessary part of the process monitoring loop, it is not the focus of this approach. All the phases presented in the above scheme may be implemented on the control systems of the electrical drives.

1.3. Process Monitoring Measures

The process surveillance contains one or more measures, based on different theories, as: statistics, pattern classification and system theory. These measures represent the behavior of the process. The idea is to convert on-line data collected from the process into a few measures and to assist the operators in determining the status of the operations and diagnosing the

faults. For fault detection limits must be placed on the measures. A fault is detected whenever one of the evaluated measures is outside the imposed limits. In this way, a measure is able to define a wrong behavior of the process accordingly the out of control status. In these measures the values of the variables can be compared with the values of other variables to determine the variable most affected by the fault. Developing and comparing measures that accurately represent the different faults of the process can also diagnose faults.

The goal of process monitoring is to develop measures that are maximally *sensitive* and *robust* to all possible faults. Faults are manifested in several ways and not all faults may be detected and diagnosed with only a few measures. Each measure characterizes a fault in different manner; one measure will be more sensitive to certain faults and less sensitive to other faults relative to other measures. This motivates using multiple process monitoring measures, with the proficiency of each measure determined for the particular process and the possible faults.

Possible monitoring measures can be classified as being associated with one or more of approaches [Chi01]: *data driven*, *analytical* and *knowledge-based*. The data driven measures are derived directly from process data. Modern industrial systems as the electrical drives are large-scale systems. They are equipped with a lot of instruments, which produce large amount of data. Too much information is beyond the capability of an operator to assess the process operations from observing the data. The data driven techniques have the ability to transform the high-dimensional data into a lower dimension, in which the important information is captured. The improvement of a large-scale process monitoring scheme may be done using statistical techniques. The disadvantage of the data driven techniques is that their proficiency is highly dependent on the quantity and quality of the process data.

The analytical approach uses mathematical models often constructed from the primary mathematical and physical laws of the processes. The analytical approach is applicable to

information rich systems, with available satisfactory models and enough sensors. Most analytical measures are based on parameter estimation, observer based design and parity relations. The applications of the analytical approach are made on systems with a small number of inputs and outputs and states. Because the analytical approaches need detailed models in order to be effective it is difficult to apply these measures to large-scale systems. Whenever, the analytical measure may be apply to the electrical drives, because they have a small number of inputs and outputs and also they have good state space models. The main advantage of the analytical approach is the ability to incorporate physical understanding of the process into the monitoring strategy. In other words, when detailed models are available, the analytical measures have good performances. The electrical drives are systems suitable for application of the analytical measures. Models of the electrical are developed.

The knowledge-based approach uses qualitative models to develop process monitoring measures. The knowledge-based approach is well suited for systems with non-available detailed models, with complex and nonlinear models. The knowledge-based measures are based on causal analysis, expert systems or pattern recognition. Like the analytical approach the applications of the knowledge-based measures are on system with a small number of inputs, outputs and states. The electrical drives are non-linear systems with complex models. For an easier application of the knowledge-based measures software packages must be developed.

1.4. Process Monitoring Methods

1.4.1. Fault Detection Methods

Different *model based fault detection methods* were developed in the last 25 years, by using mathematical model. The tasks consist in the detection of faults in the technical process, actuators and sensors by measuring the available input and output variables u and y . Fig. 3 presents the scheme of such a detection in a control system.

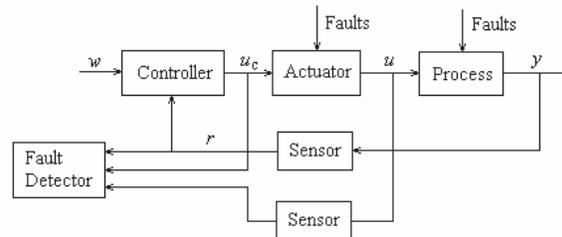


Fig. 3. The scheme of fault detection in a control system

The process is considered to operate in an open loop. A distinction can be made between static and dynamic, linear and nonlinear process models.

Several important model based fault detection methods are used. *Parameter estimation* presents changes of parameter estimates. *State estimation* presents the changes of states estimates or output errors. *Parity equations* offer the output error or polynomial error.

The measured or estimated quantities like signals, parameters, state variables, or residuals are usually stochastic variables with mean value and variance, as normal values for the non-faulty process. Analytical symptoms are obtained as changes with reference to the normal values. If a fixed threshold is used, a compromise has always to be made between the detection of small faults and false alarms because of short term exceeding. Methods of change detection, which estimated the change of the

mean, value and relate it to the standard deviation may improve the decision. Membership fuzzy logic functions may be used to specify the universe of discourse for a such approach.

1.4.2. Fault Diagnosis Methods

The task of fault diagnosis consists of determining the type of fault with as much possible such as the fault size, location and time of detection. The diagnosis procedure is based on the observed symptoms of the process.

Based on heuristic knowledge and inference mechanism for diagnosis *expert systems* are used to imitate the reasoning of human experts when diagnosing faults. The experience from a domain can be formulated in terms of rules, which can be combined with the knowledge from the physical-mathematical laws that are ruling the process or with a structural description of the system. Expert systems are able to capture human diagnostic reasoning that are not expressed into mathematical models.

Pattern recognition techniques use associations between data patterns and fault classes without an explicit modeling of internal process states or structures. Examples are *artificial neural networks* and *self organizing maps*. These techniques are related to the data driven techniques in terms of modeling the relation between data pattern and fault classes. Neural networks are black boxes that learn the pattern entirely from the training sessions [Chi01].

All methods based on data-driven, analytical and knowledge based approaches have their advantages and disadvantages, so that no single approach is best for all applications. Usually the best process monitoring scheme uses multiple statistics or methods for fault detection, identification and diagnosis. A good approach is to incorporate several techniques for process monitoring as neural network with fuzzy logic and expert systems. This can be beneficial also in the application of the electrical drives.

2. FUZZY LOGIC APPLICATIONS FOR PROCESS MONITORING

2.1. General Things

Many control systems are based today on fuzzy logic. The development of the fuzzy control theory offers alternative techniques for process monitoring strategies, which describes human reasoning in linguistic form. The fuzzy supervision knowledge-based may replace a human operator. Fuzzy logic provides a systematic framework to process vague variables and knowledge. There are some automation functions for which the fuzzy logic may offer attractive possibilities and advantages.

The main elements in the process information, as: input variables, the process classes, the automation functions and the output variables have different degrees of vagueness. The crisp information may be treated with fuzzy logic.

With regard to the *input signals* usual measurement equipment is designed to deliver signals with precise mean values and low standard deviations. *Low cost sensors* may have imprecise outputs with biased values and large standard deviations. *Non directly measurable variables* can only be calculated or estimated based on other measurement variables and analytical models and therefore imprecise to some extent. Also *linguistic values* of a human operator may be processes. Hence, the degree of precision and imprecision of the input variables may vary within fairly broad ranges.

The description of the static and dynamic behavior in form of a mathematical models plays a crucial role as well for the design of the technical processes as for a systematic design of high performance control systems. Processes from different process classes (mechanical, electrical, thermal, chemical and biological) may be described using basic physical- mathematical principles. Theoretical modeling can be applied using energy balance equations, state equations and phenomenological laws. The

structure of the mathematical model is obtained with lumped parameter or distributed parameter (ordinary or partial differential equations). By this way quantitative models based on physical laws result and one can distinguish the following cases [Ise95]. *Analytical process models*, they are quantitative models. If the structure is known, the parameters can be determined experimentally by parameter estimation and identification methods. Quantitative process models result from proper combination of theoretical and experimental modeling. If physical laws in the form of equations cannot express the internal behavior, as for not well-defined process, some qualitative information on the causalities may be expressed as rules: *If <condition> then <conclusion>*. The condition part contains as inputs the memberships of facts to the premise and possibility their logical connection by *AND*, *OR* and *NOT*. The conclusion part describes the logical consequence on the output. Then one can distinguish *heuristic process models* (qualitative models) [Ise95].

The functions of the process automation (control, supervision, management, man-machine interface) are usually organized according to the levels shown in fig. 1. For *supervision* the basic task is to check if variables exceed tolerances. These tolerances are usually a compromise between small values to early detect faulty behavior and large values to avoid false alarms subject to normal process fluctuations. In reality these tolerances are not crisp but fuzzy variables. Moreover, in many cases fault diagnosis means to treat vague process knowledge and therefore to apply rules [Chi01, Ise95].

The man-machine interface is designed for human interaction. Basic tasks of the human operator are higher-level tasks as supervision, management and redundancy for all control functions. The actions of human operators are based on qualitative knowledge and many be better describes by rules than by precise algorithms. The information in process automation generally changes from using precise algorithms at the lower levels to using more rules at the higher levels.

Actuators with electrical, pneumatic or hydraulic drives need crisp inputs. *Output variables* to the human operators through the man-machine interface can be either crisp.

2.2. Knowledge based fault detection

Within automatic control of technical systems supervisory functions serve to indicate undesired or unpermitted process states and to take appropriate actions in order to maintain the operation and to avoid damages or accidents. Following functions can be distinguished [Ise95]:

Monitoring: measurable variables are checked with regard to tolerances and alarms are generated for the operator;

Automatic protection: in the case of dangerous process state, the monitoring function initiates automatically an appropriate counteraction;

Supervision with fault diagnosis: based on measured variables features are calculated, symptoms are generated via change

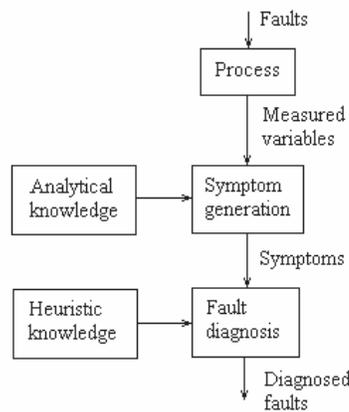


Fig. 3. Scheme of knowledge-based fault detection and diagnosis

detection, a fault diagnosis is performed and decisions are made for counteractions.

The diagram of knowledge based fault detection and diagnosis is presented in fig. 4. The main tasks can be subdivided in fault detection by symptom generation and fault diagnosis. The symptom generation can be *analytic* or *heuristic*.

Analytical symptom generation is based on analytical knowledge on the process, used to produce quantitative analytical information. Based on measured process variables a data processing has to be performed to generate first characteristic values by: *-Limit value* checking of directly measurable signals. Characteristic values are exceeding signal tolerances. *-Signal analysis* of directly measurable signals by use of signal models like correlation functions, frequency spectra, autoregressive moving average models. Characteristic values are amplitudes, frequencies or model parameters. *-Process analysis* by using mathematical process together with parameter estimation, state estimation and parity equation methods. Characteristic values are parameters, state variables or residuals. These features are compared with the normal features of the non-faulty process and *methods of change detection and classification* are applied. The resulting changes of the described direct measured signals, signal models or process models are then *analytical symptoms* of faults.

Heuristic symptom generation is in addition to the symptom generation with quantifiable information and they can be produce by using *qualitative information* from human operators. Through human observation and inspection heuristic characteristic values in form of special noise, colour, smell, vibration, wear and tear etc. are obtained. The process history in form of performed maintenance, repair, former faults and lifetime, load measures constitute a further source of heuristic information. Statistical data achieved from experience with the same or similar processes can be added. By this way *heuristic symptoms* can be represented as linguistic variables (small, medium, large) or as vague numbers (around a certain value).

An example for a stochastic symptom treated with fuzzy logic is presented in fig. 5.

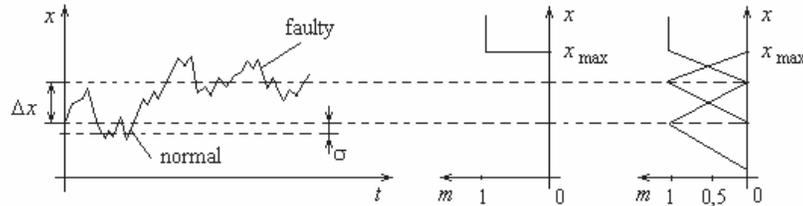


Figure 5. Fuzzy membership approach for a stochastic variable $x(t)$

A fixed threshold x_{\max} is used and a compromise between the detection of small faults and false alarms must be made. A triangle membership function $m(x)$ is specified with the center as the mean and the lower width due to a Gaussian distribution 68% or 95% of all values lie within those intervals. A combined symptom representation of the mean and the standard deviation is obtained. By matching the current value $m(x)$ with the symptom's membership function we obtain a gradual measure for exceeding a *fuzzy threshold*.

For the processing of all symptoms in the inference engine it is advantageous to use a unified representation. One possibility is to present the analytic and heuristic symptoms with confidence numbers $c(x) \in [0, 1]$ and treatment in the sense of probabilistic approaches known from reliability theory [...]. Another possibility is the representation as membership function $m(x) \in [0, 1]$ of fuzzy sets (fig. 6).

By these fuzzy sets and corresponding membership functions all analytic and heuristic symptoms can be represented in a unified manner within the range $[0, 1]$. These integrated symptoms are the inputs for the inference mechanism, presented in the following chapter.

For establish heuristic knowledge bases for diagnosis there are several approaches. In general specific rules are applied in order to set up logical interactions between observed symptoms (effects) and unknown faults (causes). The propagation from appearing faults to observable symptoms in general follows physical cause-effect relationships where physical properties and

variables are connected to each other quantitatively and also as functions of time. The underlying physical laws are frequently not known in analytical form or too complicated for calculations. Therefore heuristic knowledge in form of qualitative process models can be expressed in form of IF-THEN rules: *IF (premise) THEN (conclusion)*.

The condition part (premise) contains facts in the form of observed symptoms Δx as input and the conclusion part includes events and faults as a logical cause of the facts. This procedure results in fault symptom trees, relating symptoms to events and faults. Then symptoms or events are associated by AND and OR operators.

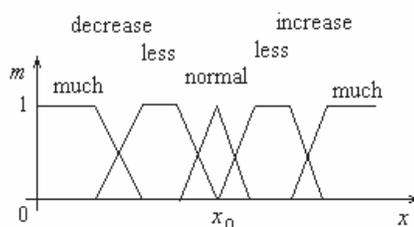


Fig. 6. Examples of membership functions for symptoms

Based on the available heuristic knowledge in form of heuristic process models and weighting of effects different diagnosis forward and backward reasoning strategies can be applied. Finally the diagnosis goal is achieved by a fault decision, which specifies the type, size and location of the fault as well as its time detection. By using the strategy of forward chaining a rule, the facts are matched with the premise and the conclusion is drawn based on the logical consequence. Therefore with the symptoms Δx as inputs the possible faults are determined using the heuristic causalities. In general the symptoms have to be considered as uncertain facts. Therefore a representation of all observed symptoms as membership function $m(x)$ of fuzzy sets in the interval $[0, 1]$ is feasible, especially in unified form.

3. THE BASIC STRUCTURE OF A FUZZY ENGINES FOR FAULT DIAGNOSIS

A *fuzzy inference engine* has the basic structure from fig. 7. It contains the *fuzzification* and *defuzzification* interfaces and the inference based on *fuzzy rules*. The input u and output y information is crisp. The fuzzification interface offers a fuzzy information A of the inputs u . The inference offers also a fuzzy information B for the outputs y . The inputs u are symptoms and the outputs y are diagnosis of faults.

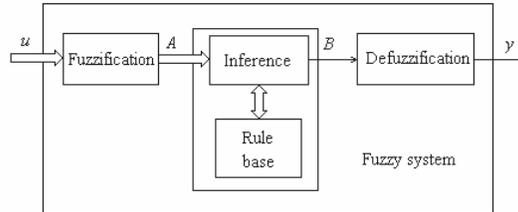


Fig. 7. The structure of a fuzzy system for fault diagnosis

An example of an *inference* based on *min-max method* is presented in fig. 8.

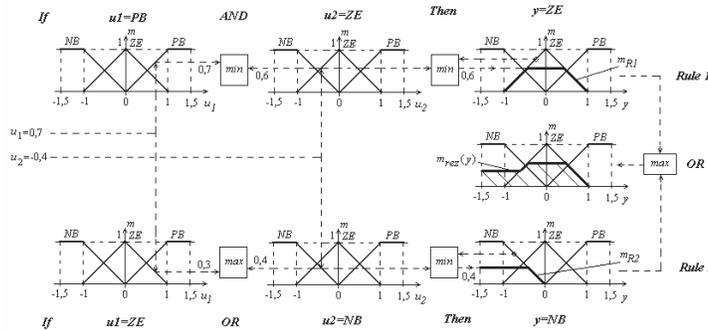


Fig. 8. The min-max inference

The most used defuzzification is based on the *center of gravity method*, presented in fig. 9.

Approximate reasoning with fuzzy logic is made with the structure from fig. 7 of a fault symptom tree. A fuzzy rule based

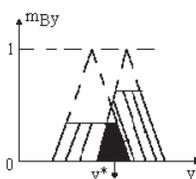


Fig. 9. Defuzzification

system with multiple levels of rules can be established. The symptoms $u=\Delta x$ are represented by fuzzy sets A , with linguistic meanings like “normal N ”, “less increased LP ”, “much increase MP ” etc.

In contrast with fuzzy control *fuzzy fault diagnosis* differs by:

- inputs are mostly no crisp measurements, but detected symptoms represented as fuzzy sets;
- not only one level or rules does exist, but mostly several levels;
- frequently it is difficult to specify the membership functions of the intermediate events because of very vague knowledge.

The approximate reasoning follows the steps describe in fig. 7: fuzzyfication, rule activation with evaluation by the compositional rule of inference and defuzzification.

The dimension of the fuzzy rule base is given by: number of symptoms, number of rules per level, number of levels and number of faults.

The overall dimension may therefore blow up strongly even for small componets or processes. Therefore the software implementation is important. Mainly two procedures to perform the reasoning are known: *sequential rule of activation* and *multiple rule activation* [Ise95].

Top reduce the computation effort simplifying assumptions may help.

4. CONCLUSION

In the fault detection and diagnosis fuzzy logic provide a systematic framework to process vague variables and vague knowledge. As the vagueness in fault detection is high the potential of fuzzy logic grow to higher levels.

The supervision of the process requires the treatment of quantitative and qualitative knowledge. Here fuzzy logic approaches are especially attractive for symptom generation with fuzzy thresholds, linguistically described observed symptoms and the approximate reasoning with multi levele fuzzy rule based systems fro fault symptom tree structures.

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