FUZZY LOGIC IN CONTROLLING FLEXIBLE MANUFACTURING CELL

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Summary

In the present work a controlling method based on fuzzy rule base is proposed. Practical approaches are developed and focused on real time problems related to flexible manufacturing cell. Techniques for design and implementation of fuzzy systems in the framework of control production and quality states are presented.

Keywords: controlling, manufacturing system, fuzzy logic, turning, burnishing

Logika rozmyta w kontroli procesu wytwarzania w elastycznym gnieździe obróbkowym

Streszczenie

W artykule przedstawiono propozycję sposobu kontroli procesu obróbki uwzględniającej metody logiki rozmytej. Zastosowanie praktyczne dotyczy zagadnień funkcjonowania elastycznego gniazda obróbkowego, w szczególności mechanizmów i zasad kontroli procesu i jakości wytwarzanych wyrobów.

Słowa kluczowe: kontrola, system wytwarzania, logika rozmyta, toczenie, nagniatanie

1. Introduction

In control architecture of a Flexible Manufacturing Cell, the monitoring aims to identify the state of a system at any instant of time [1]. It is a function which supplies data decision modules within the functions of supervision and maintenance. Generally, the monitoring consists of two distinct tasks: detection and diagnosis. The role of detection is to determine any failure of the supervised system.

In this general outline of survey a reaction depends on the techniques of monitoring used. We can classify these techniques in two groups called direct and indirect.

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Direct technique is based on monitoring sensors. It requires a specific instrumentation of the plant to allow detection and the diagnosis. However, the indirect techniques use “logical” sensors which are designed from algorithms of data fusion or events correlation. The principal advantage of the direct techniques is that they generate a strong reactivity. On the other hand, the monitoring decreases clearly the reliability of the system. This justifies the interest of indirect approaches.

The computer has numerous capabilities which are not normally found in conventional measuring and test systems. This is due to its inherent speed and memory capacity. And for this reason quality assurance systems, designed with the computer usage are considerably different from those used up to the present day. Typical advantages of using the computer are:

- increasing up to 100% testing performance, rather than just testing based on a sample taking,
- automatically operating test stands which do not depend on loading conditions,
- testing of product variants,
- online quality control,
- storing and analyzing of a large amount of test data,
- integration of quality data from various test stations and over sources.

In order to utilize computer to its full extent one should design a quality control based on good knowledge of computer techniques.

Quality control planning, measurement and data evaluation require designing and using control algorithms based on probability theory and other statistical tools [2]. These algorithms need the intensive use of computers which can speed up their work out.

Nowadays computers are used as a tool for setting quality control operations, for analyzing the tests’ results and, naturally, for collecting and evaluating data and for issuing quality reports as well. One of the supreme factures of using the computer is its ability for integrating the quality assurance activities into the entire manufacturing system. For doing that, a system approach has to be taken into quality planning in order to understand the complexity and interaction among the basic manufacturing functions. This enables to design a comprehensive quality control order of operations.

Typically, a quality control system is designed in a hierarchical way and implemented on different levels of a distributed computer system for manufacturing process control. Usually, the lowest level is the test stations. On the second level the results of the quality of the produced parts tests are collected and compared with quality standards. If any deviations of quality are observed corrective action is taken. This may involve changes in a designed product, improvement in a production process, or changes in a test procedure.

In the contemporary literature corresponding with problems and ideas of AI (Artificial Intelligence), especially in the polish literature, mostly theoretical divagations are dominant. The lack of proper literature may have influence on poor popularity of AI methods implementation into fields of technological preparations of manufacturing or manufacturing management [1, 3].

Combining modern production and manufacturing methods in industry connected with the growing demands have increased the performance requirements expected from the control systems. These demands concern product life, quality, flexibility of production and safety. Contemporary production can be described by frequent changes in product throughput, product mix, operating points and operating conditions. Processes mostly exhibit strongly nonlinear behaviour and can not be approximately described using conventional linear methods. If we try to make the system knowledge adequate for building reliable models it will become a complicated and problematic task. Also, plant-wide control strategies integrating low-level control, supervision, planning and diagnostic over several levels of the plant hierarchy impose new requirements on the modelling task and chosen methods. Moreover, at lower levels only precise information is needed for proper control but the behaviour of a complete system is often determined by the increasing qualitative interaction of its components than by their quantitative behaviour. Therefore, a mathematical approach is required to facilitate coherent integration of qualitative and quantitative information, containing symbolic and numeric data, and combining computation with reasoning.

Different techniques for modelling and control based on fuzzy sets allow combining numerical and symbolic processing into one framework. Firstly, fuzzy systems are knowledge-based systems consisting of linguistic If-Then rules and may be constructed by using the knowledge of experts in the specified field of interest. Secondly, fuzzy systems are also universal approximations which are able to realize nonlinear mappings.

The knowledge involved in the building of a fuzzy system depends on several different aspects. A lot of fuzzy systems' applications relate to fuzzy control. Their goal is to model a human operator but when modelling a complex dynamic process, also physical insight, intuitive qualitative knowledge and numerical data have to be the primary sources of information. Until now, many knowledge-based fuzzy controls have been described. This paper focuses on the fuzzy modelling of systems and on the techniques for constructing fuzzy models from measured data.

2. Idea of controlling the manufacturing cell

In the design of model-based control systems, modelling and identification of the process in nonlinear system, a mathematically tractable model structure and robust parameter estimation techniques are needed. This model predicts the system outputs with a sufficient accuracy and also provides some insights into the working of the system. Model-based control system can be also easily adapted to changing working conditions.

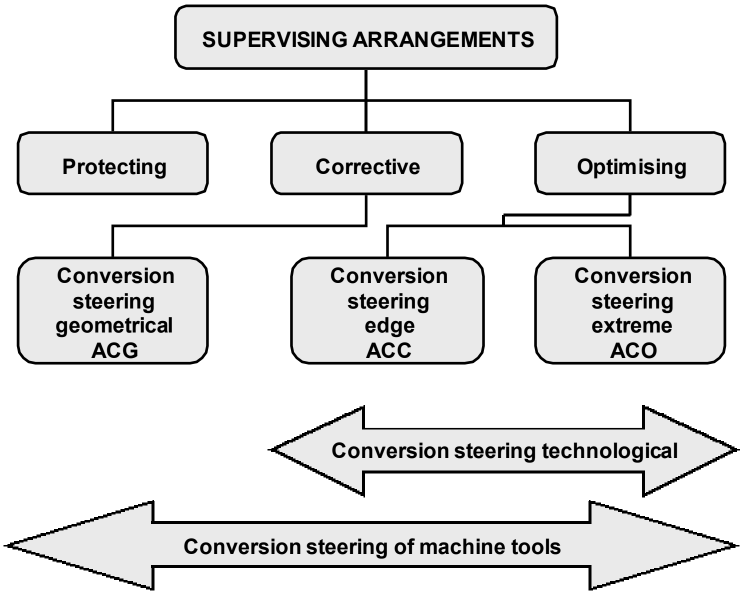

Fig. 1. Types of supervising arrangements

Fuzzy sets type modelling allows handling a system's nonlinearity by decomposing the domains of interest for the problem into fuzzy regions, and using a simple model for each of them. We can also establish a direct link from the individual regions in the model input domains to the corresponding regions in the output domains. This is an essential aspect for the validation of the model.

Providing rules as a qualitative description of the system may have a more general scope of validity, e.g. when changing the scale of the process or its parameters (Fig. 1). The membership functions serve as a numeric-to-symbolic interface. They may depend on the particular process scale changes. The fuzzy model is a flexible and transparent mathematical structure that enables describing the physical relationships in the process.

3. System model in matlab-simulink

There is a number of ways in which the concepts of fuzzy-set theory can be employed in the modelling of systems [4-7]. This paper deals only with rule-based fuzzy systems where input-output mapping is determined by a collection of fuzzy If-Then rules and an associated fuzzy inference mechanism. That is why several types of rule-based fuzzy models can be distinguished: linguistic fuzzy models, fuzzy relational models.

The fuzzy model rule base corresponds to a static regression model $y = f(x)$ for all the structures. Dynamic systems often are modelled by means of static regression structures, using the concept of the state of the system. Depending on the regression vector x chosen, we can distinguish mainly between state-space model, input-output models and hybrid approaches.

State-space model uses a state-transition function, which maps the current state and the current input of the dynamic system into the change of the state, or into the state at the next sampling instant (discrete-time case). The state transition function is static mapping that is represented by a fuzzy model, e.g. discrete-time Takagi-Sugeno model [8]:

$$\text{If} \quad \xi(k) \text{ is } A_i \text{ and } u(k) \text{ is } B_i$$

$$\text{then} \quad \begin{cases} \xi_i(k+1) = A_i \xi(k) + B_i u(k) \\ y_i(k) = C_i \xi(k) \end{cases} \tag{1}$$

where A_i and B_i, C_i, ξ_i, y_i are the state of system and corresponding signals represented by matrix.

The advantage of this model is that its structure can be related to the structure of the real system and the model rules and parameters are physically relevant.

For building fuzzy models from data generated by dynamic systems, the input-output representation can be usually applied. The state of the system is represented by a finite number of past inputs and outputs of the system, the model is given by [8]

$$\text{If} \quad y(k) \text{ is } A_{i,1} \text{ and } \ldots\ y(k-n+1) \text{ is } A_{i,n}$$

$$\text{and} \quad u(k) \text{ is } B_{i,1} \text{ and } \ldots\ u(k-m+1) \text{ is } B_{i,m} \tag{2}$$

then $\hat{y}(k+1) = \sum_{j=1}^{n} a_{i,j} y(k-j+1) + \sum_{j=1}^{m} b_{i,j} u(k-j+1) + c_i$

where $a_{i,j}$, $b_{i,j}$ and c_i are the consequent parameters. Computer programs allow carrying out these rules automatically. These statements were used for modelling rule base describing processes and material flow in flexible manufacturing cell. They were also used for obtaining the sets of input data which were taken into account and the sets of the all possible and most needed responses of the system.

The use of purely mathematical and analytical models seems to be impractical to detailed system analysis of an operating FMS. Existing literature [4-11] provides a lot of methods for fuzzy logic and genetic algorithms implementation into the FMS's control and managing systems.

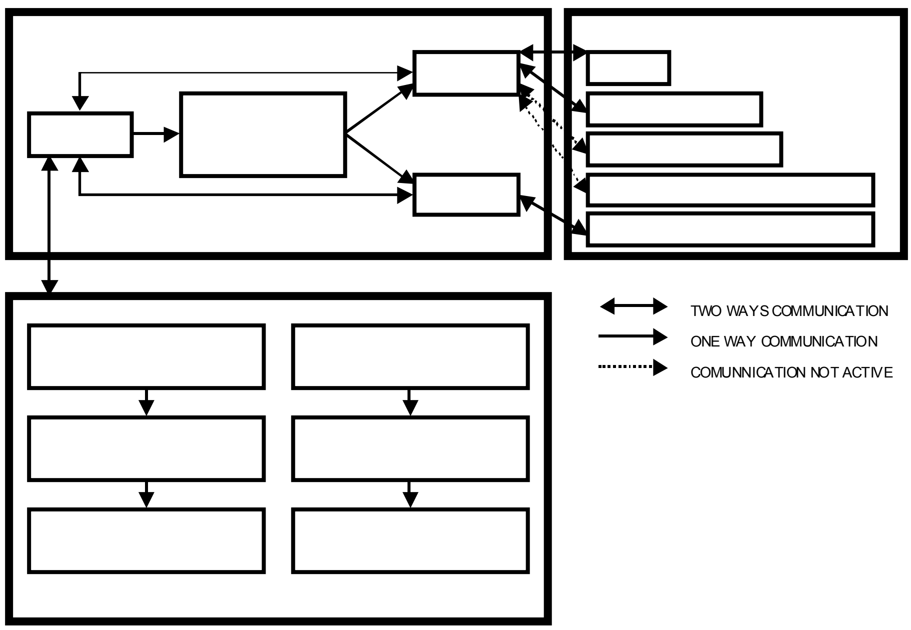

Fig. 2. Structure of Fuzzy Logic Failure Recovery System

The most important techniques of AI are quantitative reasoning and simulation, and the use of deep models. Each operation of manufacturing systems is based on human decisions. The problem with human decisions is the fact that many manufacturing activities become routine work after a long time of repetitive and boring planning and control jobs. That is the reason why it is not surprising that the decision and control systems based on AI are often implemented into manufacturing systems (Fig. 2). The AI based system has to be developed for many manufacturing activities: machine diagnosis, machine layout, system configuration, task-oriented programming, man/machine communication, vision and sensor data interruption etc.

In exemplary model (Fig. 2) we can see proposed ways of communication between elements of Flexible Manufacturing Cell and the module called Data Base. The Data Base module integrates Fuzzy Logic Failures Recovery System with Flexible Manufacturing Cell in order to enable the exchange of information between them and information transfer which is suitable and readable for each of them.

There are also numerous reasons for not implementing an AI based system into the manufacturing area. Firstly the tools for building data base for control and decision systems are difficult to apply. Secondly the methods for acquiring knowledge are not well understood yet. Afterwards control and decision systems usually contain several thousand rules and are difficult to use on conventional computer systems. In spite of these facts, AI- based systems have a major impact on manufacturing planning and control.

The builder of an AI-based system has to have a model of the system for which analyses and solutions have to be prepared. The model describes the properties of the manufacturing system all connections between them and characteristic of its behaviour. The model must be simple and include only the most important features of processes. The various models used for knowledge base creating are:

- Informal symbolic model which consists of an informal textual description of the process.
- Diagram which shows the flow of information or material through a process.
- Formal mathematical model with a set of equations that describes the behaviour of the process.
- Heuristic model with a set of rules describing the process.
- Pictorial model which allows describing the process with symbols or pictures.

4. Modelling of system work with the use of fuzzy logic reasoning

The rule of a linguistic fuzzy model has the general form:

$$\text{If } x \text{ is } A \text{ then } y \text{ is } B \tag{3}$$

and was used for the partition of the analysed data in order to get the most suitable response of the FLFRS system.

The fuzzy proposition "x is A" is the antecedent of the rule, and the proposition "y is B" is the consequent. x and y are describing linguistic variables describing values, defined as fuzzy sets on domains $X \subset R^n$ (state vector) and $Y \subset R^m$ (input vector) respectively. A and B are linguistic variables which are constant. Such fuzzy sets define certain "reference points" in the given spaces and they are also called references fuzzy sets. The membership functions for the reference fuzzy sets have to be defined in a data-based which is a part of the fuzzy system. Usually several linguistic terms A_i are defined on the domain of one variable, and the collection of these fuzzy sets [A_1, A_2... A_M] is called a fuzzy partition.

The knowledge base of the fuzzy system is formed by the rule base together with the database of process information. The input-output mapping is described and developed by the fuzzy inference mechanism. This mechanism derives an output fuzzy set from an input fuzzy set. It uses the rules together with the reference fuzzy sets and its dynamic behaviour provided by means of external dynamic filters.

Numerous programs and programming packages have been developed to solve manufacturing problems. The heart of a program consists of the rules database. The execution of a program is done by the rules of the algorithm. The rule can represents one or several results on output. It is called Fuzzy Logic Lathe (Fig. 3) and includes three stages of functioning. The first one, called fuzzyfication is responsible for changing information incoming from Data Base module (information collected and measurements taken from Flexible Manufacturing Cell) into the information which can be read by Fuzzy Logic module in Matlab. The second stage, called Rule Base is responsible for the interpretation of the fuzzyfied information. The last stage, called defuzzyfication is responsible for preparation of the information gathered from Rule Base into the way in which they can be analysed by the Simulink for Fuzzy Logic Lathe module.

It is obvious that fuzzy logic goes into a quality procedure and can be helpful in improving a quality control operation. It can help to improve data evaluation and interpretation. We can obtain from the test data the information about manufacturing of a product. Sometimes in order to diagnose the problem Fuzzy Logic Failure Recovery System must be able to find the cause of the malfunction. Complex flexible manufacturing systems are usually designed in a hierarchical fashion and for such system a large amount of knowledge has to be gathered, structured, stored, analyzed and upgraded.

For each level of production system a specific type of knowledge must be stored and processed in a comprehensive AI-based system. We can find three basic types of knowledge which are:

- functional knowledge to obtain a workable solution,
- quality knowledge to assure the integrity of the solution,
- procedural knowledge to select the optimal solution.

There is a flurry of knowledge-based system activities in nowadays manufacturing systems. It has become important to tie various knowledge-based systems together and operate them in real time. It is well known that all manufacturing operations are time dependent and many applications can not be handled well without a time scale.

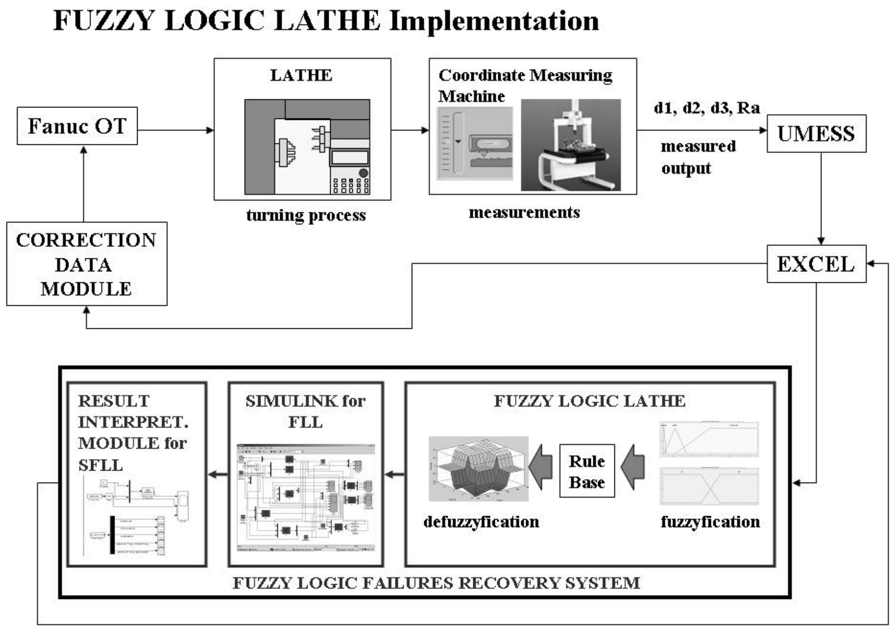

Fig. 3. Fuzzy Logic Failure Recovery System model – diagnosis module for turning

The main part of Fuzzy Logic Lathe (Fig. 3) module for analysing the turning operation is a rule base. And the execution of a program is done similarly by the rules of the algorithm. The rule can represent one or several results on output, depending on the interpretation of constructor. It is functioning in the same way by analysing the incoming information in three stages: fuzzyfication, Rule Base and defuzzyfication. The information outcoming from Fuzzy Logic Lathe is sent for analysis into the Simulink for Fuzzy Logic Lathe Centre module. The analysed information is interpreted in order to make decision which will help to control and optimise functioning of Flexible Manufacturing Cell. Then the results are sent to the Data Base where they are translated to be useful for implementation into the procedures of functioning of the elements of Flexible Manufacturing Cell.

Simulation were carried out in order to establish the model of the decision-making system designed for the chosen object of examinations (laboratory of flexible manufacturing system [12]. Objects used in the preliminary examinations were then subjected to the turning processes. The values of geometrical parameters (diameter and the roughness of the surface of processed objects) were collected.

Data subjected to processing in spreadsheets of the Excel were sent to create decision-making models. As a result of analysis a decision was received, from processed objects not-fulfilling established quality requirements to subject the part to processing at corrected putting of the blade of the machining tool, whereas to subject the part to processing with burnishing.

After applying a corrective action objects with of proper dimensions and surface quality were received. Analysis and the dataflow were established according to the scheme from Fig. 3. The scheme shows not functioning connections which can be an object of further research apart from connections carried out in another project, but they were not an object of examinations carried out as a part of this project.

After sending data to Fuzzy Logic Lathe different times of sampling for received data were set and a graphic reply being a result of the work of the decision-making model put on was obtained.

Simulation examinations were carried out for the model applied for the decision-making system designed for the below of the object of examinations (laboratory of elastic production systems at the Department) [12, 13]. Objects worked in preliminary examinations were used for examinations subjecting them to processes of accurate turning. As a result of carrying out the test measurements after the process of turning, data concerning value of geometrical parameters were received – of the diameter and the roughness of the surface of worked objects. The data subjected to processing in spreadsheets the Excel were sent to create decision-making models. As a result of analysis a decision from worked subjects not meeting assumed quality requirements was received whether a part should be processing at corrected putting the blade of the machining tile or should be subjected to processing with burnishing.

To verify the examinations two series of investigations were made for the diameter 34 mm on the Cyclone lathe applying the tile of the Sandvik Coromant company of the type DCGT 11 T3 04-UM 2035 and grinded tiles of the type DCGT 11 T3 04-UM H13A.

As a result of processing value of diameters of worked objects and the roughness of their surface included in the board were achieved. They made measurements at using Coordinate Measuring Machine Zeiss and Hommel tester together with the appropriate software. The results were analyzed using spreadsheets of the program Excel, where combinations of changes in worked diameters of objects and combinations of variation of surface roughness of surfaces of the worked object were made.

Table 1. Decisions containing cases examined during tests for the subsystem of managing the quality of the object machined on lath – Fuzzy Logic Lathe

Part No	Parameters required	Routing no	CMM after turning (d)	Hommel tester After turning (Ra)	FLL	S for FLL for d (indicator level)	S for FLL for Ra	CMM after verification (d)	Hommel tester after verification (Ra)
Part no 1	d = 34 7 prec.class Ra less than 0.63	1	34.45	0.87	d not good Ra not good	Turning 0.6052 burnishing 0.3948	Turning	34.01	0.34
Part no 2	d = 34 7 prec.class Ra less than 0.63	1	34.10	0.68	d not good Ra not good	Turning 0.2537 burnishing 0.7463	Burnishing	34.02	0.15
Part no 3	d = 34 7 prec.class Ra less than 0.63	2	34.27	0.30	d not good Ra good	Turning 0.5634 burnishing 0.4366	Turning	34.015	0.27
Part no 4	d = 34 7 prec.class Ra less than 0.63	2	34.40	0.27	d not good Ra good	Turning 0.6052 burnishing 0.3948	Turning	34.05	0.30
Part no 5	d = 34 7 prec.class Ra less than 0.63	3	34.29	0.64	d not good Ra not good	Turning 0.7496 burnishing 0.2514	Turning	34.06	0.42
Part no 6	d = 34 7 prec.class Ra less than 0.63	3	34.02	0.65	d not good Ra not good	Turning 0.3452 Burnishing 0.6548	Burnishing	34.01	0.12
Part no 7	d = 34 7 prec.class Ra less than 0.63	4	34.16	0.25	d not good Ra good	Turning 0.4189 Burnishing 0.5811	Burnishing	34.05	0.15

After the data handling and the message given to the defuzzyfication module, the data were analyzed with one-criterion method (min, max). Results were received in the form of the table of available decisions together with determining the degree of meeting the established decision-making criteria.

Applying the Fuzzy Logic Failures Recovery System brought results in the form of increasing the automation to the Flexible Manufacturing Cell work through the automation of decision-making feature as well as it influenced considerably the improvement in the quality of objects worked in EGO by applying processing with burnishing as alternative to turning (Table 1).

The possibility of the corrections of mistakes of the cells not-fulfilling their tasks and the possibility of repairing the part is also an essential matter of technological, determined as recoverable gaps requirements. In the case of the part determined as recoverable gaps after applying decisions from ordering subsystems with quality of worked objects a considerable improvement in parameters of geometrical objects was noticed – the possibility of change up the diameter of a few millimeters and the improvement in the roughness of the surface several dozen μm.

In the result of the examinations and the simulation it was proved that the model applied for steering the elastic machining nest would cause increasing the degree of the automation and the quality of executed subjects. It confirms, that applying processing with pressing enabled the improvement in the dimension of the worked subject and coarsenesses of its surface to value from the scope of the seventh class of the accuracy and the coarseness R_a = 0,32 – 0,63 μm.

5. Research, results, conclusions

Fuzzy modelling is a framework combining different modelling and identification methods, providing a transparent user interface and a flexible tool for nonlinear system modelling and control which is also comparable with other nonlinear black-box techniques.

The rule-base character of fuzzy models allows interpreting events in a way similar to the human way of describing reality. In many real applications, the manufacturers face on regular basis the problem of simultaneous optimisation of several objectives. Those objectives are often conflicted and incomparable. Also the diversity of product mix and the uncertainty of market value make interactive approaches to machining process planning inefficient owing to the extensive and frequent interactions with manufacturers for planning machining process. An AI-based system has to be created as a system which will be based on a preference model such as multi-attribute value function that represents a manufacturer overall preference.

Implementation of mathematical techniques based on linear matrix inequalities and supported by powerful software tools allow to design and analyse control systems based on the local modelling approaches. AI-based system is a much more often implemented solution for production process in mechanical engineering industry. However, effective control and supervision of production process in flexible manufacturing system always demand integration with master computer system. The idea of working of implemented supervision Fuzzy Logic Failure Recovery System is to reach required manufacturing quality.

Although many successful applications are known, fuzzy modelling is still in development.

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