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Fuzzy MIMO model for efficient control of complex processes with uncertainties and nonlinearities

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Abstract. This paper shows the impact of the MIMO model on control system solutions for efficient control of complex nonlinear processes (multiple input, multiple output model) in terms of efficiency, product quality and energy efficiency. In modern automatic control systems, there is a need for increased capacity in long-distance data transmission, high-speed local area networks, etc. Capacity can be increased by extending the frequency range. However, the application of these techniques is limited by biosafety requirements, limited power supply (in mobile devices), and electromagnetic compatibility. Therefore, if these approaches to communication systems do not ensure the speed of transmission of information about technological processes, a weak correlation will appear. The values of indicators for the construction and use of fuzzy MIMO models of control decisions are expressed in the form of linguistic variables. The fuzzy MIMO model makes qualitative decisions in the control of complex processes. This includes uncertainty and nonlinearity problems, which are used to optimize complex systems.

1 Introduction

A Fuzzy MIMO model (model with multiple inputs and multiple outputs) used in process control is characterized by the fact that it combines fuzzy logic and the concept of multicomponent systems (MIMO) to create a model that can effectively control complex processes with uncertainty and nonlinearity. The main characteristics of the fuzzy MIMO model are:

1. multiple inputs and outputs: the model considers multiple inputs and multiple outputs of the system, which allows controlling several parameters simultaneously.
2. fuzzy logic: the model uses fuzzy rules to describe the behavior of the system, which allows taking into account different scenarios and inputs.
3. adaptability: the fuzzy MIMO model is able to adapt to changing conditions and process requirements.

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The fuzzy inference method using the fuzzy MIMO model is based on:

1. fuzzy rule computation: fuzzy rules are first formulated to describe the relationships between input and output variables of the system;
2. uncertain output set: go through a fuzzy inference process, where, based on fuzzy rules, the original input values are transformed into a fuzzy output set;
3. defuzzification of the output: defuzzification converts the fuzzy output set into specific values of the output variables of the system;
4. control and adaptation: the values obtained are used to control the process, and the model itself can be tuned and adapted based on feedback to improve the results.

The advantages of the fuzzy MIMO model in process control are manifested in:

1. Ability to handle fuzzy data: the model is able to control the process even in the presence of uncertainty and fuzziness in the data;
2. Versatility: the model can be applied to different systems given their multiple inputs and outputs;
3. Flexibility and adaptability: the fuzzy MIMO model is flexible and adaptive, which allows it to effectively manage a variety of processes.

The use of the fuzzy MIMO model in process control allows for more efficient and flexible control systems that can adapt to complex and variable production conditions [1].

2 Materials and methods

To understand the use of the fuzzy MIMO model with the interdependence of output variables in the example of the control decision selection model, let us consider a decision making situation in a complex system where several inputs (parameters) affect several outputs (results).

Suppose we have a manufacturing process control system where various factors affect productivity, product quality, and energy efficiency. Let us consider an example of using a fuzzy MIMO model in the control decision selection model:

1. Input variables: temperature, pressure, raw material flow rate, concentration
2. Output variables: productivity, product quality, energy efficiency.

The following requirements are imposed on the fuzzy MIMO model:

1. Adaptability and flexibility: the model should be able to adapt to changing process conditions and requirements without the need for redesign.
2. Interdependency: the model should take into account the interdependency of variables and provide correct control with respect to these interdependencies.
3. Accuracy and reliability: the model should provide accurate and reliable control decisions based on input data and specified objectives.
4. Resource efficiency: the model should utilize resources (time, computing power) efficiently for fast and accurate decision making.

To apply the fuzzy MIMO model, it is necessary to formulate fuzzy rules describing the relationships between input and output variables; evaluate the importance of each input parameter to the output variables and their mutual influence; uncertain output set, i.e., to carry out the setup and definition of the fuzzy output set based on the input data and fuzzy rules; defuzzification and transformation of the fuzzy output into specific control actions taking into account the given objectives and constraints, continuous monitoring and cor.

It is extremely important that the fuzzy MIMO model in the control decision selection model satisfy the above requirements to provide an effective control of the production process adapted to the complex and interdependent variables of the system. Proper tuning and implementation of the model contribute to the optimization of production processes and to the improvement of plant efficiency [2,3].

At such a statement of the problem, the fuzzy MIMO - model of the choice of control decisions is built in the following sequence: setting input and output indicators; formation of logical and linguistic scales of input and output indicators.

To build and use a fuzzy MIMO-model of choice of control decisions, the values of indicators should be represented in the form of linguistic variables. Linguistic variables allow describing fuzzy concepts such as "high", "low", "fast", "slow", etc., which better correspond to human intuition and natural language [4-5].

Representation of indicator values in a fuzzy MIMO model:

1. "Linguistic Terms": The value of indicators values such as temperature, pressure, raw material flow rate, productivity and others should be represented as linguistic terms. For example, temperature can be described as "low", "medium", "high".
2. "Affiliation": Each indicator value belongs to a specific linguistic term with a certain degree of affiliation. For example, the value "25 degrees" may be partly "high temperature".
3. "Fuzzy Rules": Indicator values are used in fuzzy rules to determine the logic of control decisions. For example, if "temperature is high" and "raw material consumption is medium", then "increase productivity".
4. "Fuzzy Sets: Indicator values are converted into fuzzy sets with defined membership functions to allow fuzzy logic and inference.

Example representation of indicator values:

- “Temperature”:

- Low: \(\mu_{low}(x) = \begin{cases} 1, & \text{if} x \leq 20 \\ (30 - x)/(30 - 20), & \text{if} 20 < x < 30 \\ 0, & \text{if} x \geq 30 \end{cases} \)

- Meduim: \(\mu_{medium}(x) = \begin{cases} 0, & \text{if} x \leq 20 \text{or} x \geq 40 \\ (x - 20)/(30 - 20), & \text{if} 20 < x < 30 \\ (40 - x)/(40 - 30), & \text{if} 30 < x < 40 \end{cases} \)

- High: \(\mu_{high}(x) = \begin{cases} 0, & \text{if} x \leq 30 \\ (x - 30)/(40 - 30), & \text{if} 30 < x < 40 \\ 1, & \text{if} x \geq 40 \end{cases} \)

This representation of indicator values as linguistic variables allows the fuzzy MIMO model to effectively describe and utilize the data for making control decisions based on fuzzy logic. This approach makes the model more flexible and able to accommodate different management scenarios in the decision-making process.

The terms for different indicators that match in name may have different parameters. To set the term-multiplicities of input and output indicators and build their logical-linguistic scales in fuzzy logic, it is required to perform the following points:

Setting the term-multiples of input and output indicators:

S.1. "Identification of variables": identify input and output variables that characterize the control system.

S.2. "Definition of term-multiplicities": for each variable, term-multiplicities are created that describe its values.

Construction of logical-linguistic scales:

1. "Definition of belonging functions": for each term, its belonging function is defined, which indicates how much the value of the variable belongs to a certain term. This can be a triangular, trapezoidal or other function.

2. "Composition of linguistic variables": the ranges of values to which each term belongs are specified. For example, for temperature: "low" could be 0°C to 20°C, etc.

The construction of such logical-linguistic scales makes it possible to effectively describe and use the values of indicators based on fuzzy logic for making control decisions.

Let us consider an example in which three terms {Low, Medium, High} each are used to evaluate input and output values: R_{in1} - L_{in1}, M_{in1}, H_{in1}; R_{in2} - L_{in2}, M_{in2}, H_{in2}; R_{in3} - L_{in3}, M_{in3}, H_{in3}; R_{out1} – L_{out1}, M_{out1}, H_{out1}; R_{out2} - L_{out2}, M_{out2}, H_{out2}.

To describe the linguistic variables, to set the term-multiples of input and output indicators, and to build their logical-linguistic scales in fuzzy systems, the typical L-R-functions are often used. Typical L-R-functions (L-R functions) are membership functions, which are used in fuzzy logic to describe fuzzy sets. They are a special class of functions that determine how much an element (value) belongs to a given fuzzy set. These functions provide a mathematical basis for dealing with fuzzy data and allow expressing uncertainty and fuzziness in information. L-R functions can have triangular, trapezoidal, bell-shaped [1] and other shapes.

3 Results and discussion

When solving control problems in fuzzy logic, L-R functions are used to determine what weight or importance is given to each rule of the rule base of an artificial system based on fuzzy inputs, and when making decisions to control systems, L-R functions help to determine what actions will be taken based on fuzzy rules and inputs [6,7,8].

Example of using L-R functions:

Suppose we have a term "temperature" and three terms for it: "cold", "warm", "hot". L-R-functions can determine to which range of values these terms correspond, e.g.:

- "cold" - the L-R function may have a peak around 0°C and decline as the temperature increases.
- "warm" - the function has a peak around 20°C, etc.

This representation using L-R functions allows for effective modeling and use of fuzzy variables in the control decision making process.

When using the bell-shaped type of L-R-functions presented in Figure 1 for the output variable R_{out1}, the value of L_{out1} is given in the following form:

$$L_{out1}(R_{out1}) = exp\left[-\frac{1}{2}\left(\frac{R_{out1}-a_1}{b_1}\right)^2\right], \quad (1)$$

where a_1, b_1 are the parameters of the membership function.

During the process of modeling the values a_i and b_i related to the belonging function can be corrected.

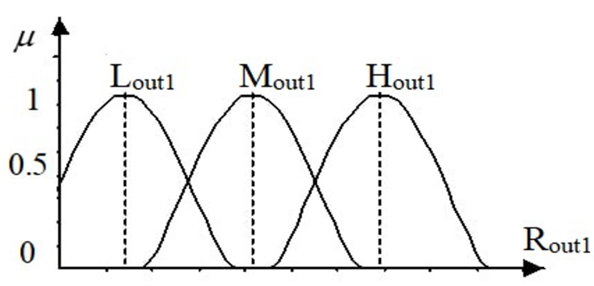

Fig. 1. Logico-linguistic scale.

S.3 When performing this item, it is necessary to:

1. correlate the values of output indicators with control decisions:
   - This step involves analyzing the actual output data of the system (e.g., productivity, product quality, etc.) in order to make control decisions.
   - Fuzzy logic allows expressing the relationship between data and control decisions in the form of fuzzy rules.
2. Identify groups of control decisions:

- After correlating the values of output indicators with the corresponding decisions, the task of grouping these decisions arises for the effective management of the system.
- The grouping of control decisions allows to optimization of the decision-making process, reduces complexity, and increases the efficiency of the control system.

The above can be explained by the following example:

1. Correlation: By analyzing the data of temperature, pressure and raw material consumption in the production process, the system correlates them with the corresponding control decisions, for example, increasing raw material consumption by increasing temperature to increase productivity.
2. Allocation of decision groups: The system can allocate groups of control decisions, such as a decision group for productivity improvement, a group for product quality improvement, etc., which helps in optimizing process control.

When the input measures R_{in1}, R_{in2}, R_{in3} affect the output measures R_{out1}, R_{out2} in a complex way, in some cases, a fuzzy model with MIMO structure may be more suitable for modeling such complex relationships than a set of fuzzy models with an MISO structure. This is explained by the fact that the fuzzy model of the MIMO structure takes into account many connections (allowing one to take into account the relationship between several input and output variables simultaneously, which is important when analyzing complex systems), allowing complex modeling (allowing one to take into account the relationship between several input and output variables simultaneously), the, use One MIMO model can reduce modeling error, since all information about the relationships between variables is taken into account in one model, allowing interrelated fuzzy logic rules to be combined, which can improve the accuracy and predictability of the model [9-10].

Although a set of fuzzy models with MISO structure can also be applied for such modeling, this approach may lead to a more complex model system needing additional coordination and management compared to a single MIMO model.

Thus, when the interaction between input and output indicators is complex, the application of a single fuzzy MIMO model instead of multiple fuzzy models with MISO structure may be preferable in terms of modeling and prediction convenience.

In order to systematize and describe the results of analysis or decision making based on the data obtained from the fuzzy MIMO model or other similar methods, the classification definitions of joint evaluation of output indicators R_{out1} and R_{out2} are formed (Table 1).

Table 1. Consistency of output indicators with controls.

The value of the indicator R_{out1}	**Indicator values R_{out2}**	**administrations**						
		U_1	**U_2**	**U_3**	**U_4**	**U_5**	**U_6**	**U_7**
L_{out1}	L_{out2}	+	-	-	-	-	-	-
L_{out1}	M_{out2}	+	-	-	-	-	-	-
$L_{out}1$	H_{out2}	-	+	-	-	-	-	+
M_{out1}	L_{out2}	-	+	-	-	+	-	-
M_{out1}	M_{out2}	-	-	+	-	+	-	-
M_{out1}	D_{out2}	-	-	+	-	-	-	+
H_{out1}	L_{out2}	-	-	-	+	-	+	-
H_{out1}	M_{out2}	-	-	-	+	-	+	-
H_{out1}	H_{out2}	-	-	-	+	-	-	+

Based on the data in Table 1, we can identify certain groups of controls used by the selection model: Gr_1 - U_1; Gr_2 - U_2 & U_7; Gr_3 - U_2 & U_5; Gr_4 - U_3 & U_5; Gr_5 - U_3 & U_7; Gr_6 - U_4 & U_6; Gr_7 - U_4 & U_7.

Classification definitions have some purposes and advantages:

- Classification definitions help to interpret and understand the results of output evaluation.
- The formation of classification definitions helps to standardize the process of estimation and classification of output indicators, which makes the information more understandable and easier to use.
- Definitions help to systematize data and results related to the evaluation of output indicators, which simplifies subsequent analysis and management decision-making.

On the basis of classification definitions, conclusions and recommendations for further process management can be drawn on the basis of the evaluated output indicators.

Example of application of classification definitions:

1. Output indicators R_{out1} and R_{out2}:

- Classification definitions may indicate, for example, that a joint high score of R_{out1} and R_{out2} indicates high efficiency or quality of process execution.
- Definitions can categorize output indicators into levels, e.g. "low", "medium", "high", which helps to draw conclusions more quickly and accurately.
- Based on the classification definitions, it is possible to determine what steps or corrective actions need to be taken in the case of certain combinations of output indicator scores.

Thus, classification definitions of the joint estimation of output indicators Rv1 and Rv2 serve as an important tool for analysis and interpretation of the results, allowing us to the information more effectively for making managerial decisions and optimizing processes.

S.4. At this stage, the initial base for fuzzy rules of the model is formed.

Let us consider an example of the structure of the initial rule base for the fuzzy model on the basis of preformulated classification definitions of qualitative assessments of output indicators.

Example of classification definitions of output indicators:

1. R_{out1}:

- High efficiency: [70, 100]
- Medium efficiency: [40, 70]
- Low efficiency: [0, 40]

2. R_{out2}:

- High quality: [80, 100]
- Medium quality: [50, 80]
- Low quality: [0, 50]

Initial rule base structure and fuzzy rules:

1. Structure of initial rule base:

- Definition of input variables: R_{in1}, R_{in2}
- Definition of output variables: R_{out1}, R_{out2}

2. Fuzzy rules:

Let there be an initial rule base with several rules based on pre-formulated classification definitions:

- Rule 1: If R_{in1} is "high" and R_{in2} is "high", then R_{in1} is "high" and R_{in2} is "high quality".
- Rule 2: If R_{in1} is "medium" and R_{in2} is "medium", then R_{out1} is "medium" and R_{out2} is "medium quality".
- Rule 3: If R_{in1} is "low" and R_{in2} is "low", then R_{in1} is "low" and R_{out2} is "low quality".

3. Rule Structure:

- A rule is formulated based on the condition (IF) of input variables and the conclusion (THEN) of output variables.
- Each rule consists of a fuzzy condition and a corresponding fuzzy inference.

This structure of the rule base and fuzzy rules allows modeling and analyzing the behavior of the system on the basis of qualitative evaluations of output indicators defined in advance.

By adapting and augmenting the rule base with feedback, the accuracy and efficiency of the model can be improved.

The proposed model combines the properties of a neuro-fuzzy classifier (when selecting a group of control decisions) and a fuzzy production model (when assessing the feasibility of choosing this selected group of control decisions).

Let us consider a simplified example of creating a structural diagram for a fuzzy model with a neuro-fuzzy classifier and a set of a fuzzy rule. The neuro-fuzzy classifier helps in classifying the input data, and groups of fuzzy rules subsets determine specific control decisions depending on the input parameters.

Structure diagram of fuzzy model with a neuro-fuzzy classifier:

1. Input data:

- R_{in1}, R_{in2} - input variables.

2. Neuro-fuzzy classifier:

- Fuzzy neural network: applied to input data classification and decision making.
- Neural elements: process input data and predict appropriate categories of control decisions.

3. A set of subsets of fuzzy rules:

- Group 1:
- Rule 1: R_{in1} "high" и R_{in2} "high" -> Group decision 1
- Rule 2: R_{in1} "medium" и R_{in2} "medium" -> Group decision 2
- Group 2:
- Rule 3: R_{in1} "low" и R_{in2} "high" -> Group decision 3
- Rule 4: R_{in1} "high" и R_{in2} "low" -> Group decision 4

Example of a model structure of algorithm:

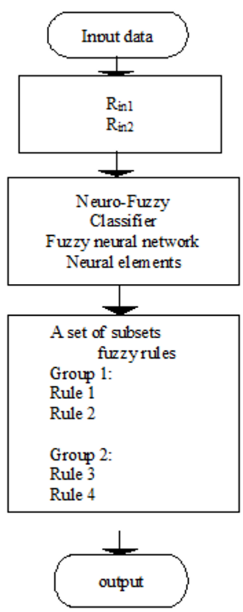

Fig. 2. Structure of algorithm of fuzzy model.

Based on the above, it can be concluded that the fuzzy MIMO model provides valuable tools and advantages for controlling complex processes, especially where uncertainties and nonlinearities are present. The main advantages of the fuzzy MIMO model are:

- Consideration of multiple inputs and outputs:

  - MIMO (Multiple Inputs, Multiple Outputs) allows multiple inputs and outputs to be considered rather than just one as in conventional models, which significantly increases its adaptability.
- Uncertainty Management:
  - The ability to handle fuzzy data allows the model to adapt to uncertainty and fuzziness of input data, which is important for real-world processes.
- Flexibility and adaptability:
  - Fuzzy logic and MIMO structure make the model flexible and adaptive to changing conditions, which is important for processes with variable parameters.
- Complex Relationship Modeling:
  - Allows complex relationships between multiple parameters to be taken into account, which is usually not possible with classical models.
- Qualitative decision making:
  - Based on fuzzy rules and inference, the model is capable of qualitative and intuitive decision making similar to human learning from experience.
- Resilience to noise:
  - Due to fuzzy logic, the model is resilient to noise and changes in data, which enhances its performance in real-world environments.
- Management Optimization:
  - Allows optimization of control processes by considering multiple inputs and outputs, which can lead to better results and efficiency.

4 Conclusion

Thus, the fuzzy MIMO model is a powerful tool for controlling complex processes where uncertainties and nonlinearities are present. Its flexibility, adaptability, and quality decision making make it an effective choice for optimization and control of complex systems. MIMO models are used in predictive control (or Model Predictive Control, MPC) and is a control method that is based on predicting the behaviour of the system and making control decisions based on these predictions. Advantages of using a MIMO model in a control system:

- MIMO models allow multiple inputs and outputs of a system to be controlled simultaneously, which is particularly useful in complex systems where there is interconnectivity between different variables;
- MIMO systems typically provide better performance and control accuracy by accounting for the interrelationship between different variables;
- By being able to control multiple variables simultaneously, MIMO systems are usually more stable and resilient to external disturbances.

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