**Intelligent Automated Management Model For Grape Growing in Agroecological Conditions**

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**Abstract.** Identification problems, namely the development of mathematical models based on observational and experimental data, represent one of the most fundamental and practically significant tasks in numerous fields of science and engineering, including automatic control, signal processing, systems analysis, and agro-technological systems. The primary objective of system identification is to obtain an adequate mathematical description of complex dynamic objects whose internal structure is partially or completely unknown, while ensuring accepTable accuracy, robustness, and computational efficiency.In contemporary identification theory, particular attention is devoted to methods capable of describing nonlinear, nonstationary, and uncertain relationships between input and output variables. In this context, approaches that employ linguistic information and expert knowledge for model formulation are gaining increasing significance. Such methods allow the incorporation of qualitative descriptions expressed in natural language into formal mathematical frameworks, thereby enhancing model interpretability and flexibility.Fuzzy logic–based identification techniques, as well as hybrid intelligent models that combine fuzzy inference systems with neural networks and evolutionary optimization algorithms, provide powerful tools for approximating complex nonlinear dependencies. These methods are especially effective in situations where classical analytical modeling is difficult due to incomplete data, stochastic disturbances, or strong interactions between variables. By utilizing linguistic “IF–THEN” rules and fuzzy set operations, these models are capable of capturing the underlying behavior of real-world systems with a high degree of accuracy while maintaining transparency and adaptability.

**INTRODUCTION**

It is well known that **fuzzy logic inference** represents an approximation of the input–output relationship of a model based on linguistic statements of the “IF–THEN” type and operations on fuzzy sets. The structure of a fuzzy logic inference model includes the following blocks (Figure 1):

* the **fuzzifier** transforms a fixed vector of influencing factors Χ into a vector of fuzzy sets X~\tilde{X}X~, which are required to perform fuzzy inference;
* the **fuzzy knowledge base** contains information about the dependence in the form of linguistic rules of the “IF–THEN” type;
* the **fuzzy inference engine**, based on the rules of the knowledge base, determines the value of the output variable in the form of a fuzzy set , corresponding to the fuzzy values of the input variables ;
* the **defuzzifier** converts the output fuzzy set into a crisp (precise) numerical value Y.

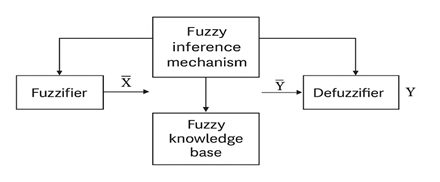
The fuzzification process plays a crucial role in mapping real-world quantitative measurements into qualitative linguistic variables, thereby enabling the incorporation of expert knowledge and uncertainty into the modeling framework. Membership functions of various shapes, such as triangular, trapezoidal, or Gaussian, are commonly employed to describe the degree of belonging of input variables to fuzzy sets. The choice of membership function parameters significantly affects the approximation accuracy and interpretability of the model.

The fuzzy knowledge base constitutes the core of the inference system, as it encapsulates expert experience and heuristic reasoning about the modeled process. Linguistic rules of the IF–THEN type allow complex nonlinear relationships to be represented in an intuitive and transparent manner. Unlike conventional parametric models, fuzzy rule-based systems do not require explicit analytical expressions, making them particularly suiTable for systems characterized by uncertainty, incomplete information, or poorly defined dynamics.[1-9]

The fuzzy inference engine performs rule evaluation and aggregation using logical operations defined in the fuzzy domain. Depending on the selected inference strategy, such as Mamdani-type or Sugeno-type inference, different mechanisms are applied to combine fuzzy premises and generate the output fuzzy set. These inference mechanisms provide flexibility in balancing model interpretability and computational efficiency.

Finally, the defuzzification stage transforms the aggregated fuzzy output into a single crisp value that can be used for analysis, prediction, or control purposes. Common defuzzification methods include the centroid, bisector, and weighted average techniques. The selection of an appropriate defuzzification method depends on the application requirements and desired trade-off between accuracy and computational complexity.[14-18]

Overall, fuzzy logic inference models offer a robust and flexible framework for approximating complex nonlinear input–output relationships. Their ability to integrate numerical data with linguistic knowledge makes them highly effective in modeling real-world processes where traditional mathematical approaches may be insufficient. Consequently, fuzzy inference systems have found widespread application in control engineering, decision support systems, pattern recognition, and intelligent management of technological and agroecological processes.

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**Figure.1.** Structure of a fuzzy inference system.

**EXPERIMENTAL RESEARCH**

In the context of agricultural systems, particularly grape growing, the proposed two-stage identification framework provides an effective tool for modeling complex and nonlinear relationships between agroecological factors and crop productivity indicators. Grape yield formation is influenced by a large number of interacting variables, including soil moisture, air temperature, relative humidity, solar radiation, vegetation indices, and technological management parameters. These factors are often characterized by uncertainty, nonlinearity, and incomplete information, which limits the applicability of classical analytical models.

At the first stage of identification, structural identification is performed by forming a fuzzy knowledge base that qualitatively reflects the relationship between environmental inputs and grape yield or physiological state variables. Linguistic rules of the “IF–THEN” type are constructed either by agricultural experts or extracted from experimental field data collected during the grape growing season. For example, expert rules may describe dependencies such as: *IF soil moisture is low AND air temperature is high THEN grape stress level is high*. Such rules enable the incorporation of agronomic experience and empirical observations into the model structure.

Between the structural and parametric identification stages, fuzzy logical inference is carried out using the generated rule base. This inference process allows the transformation of fuzzy input descriptions of agroecological conditions into fuzzy estimates of grape growth responses, such as expected yield level, vegetation intensity, or water stress category.

At the second stage, parametric identification is conducted by adjusting the parameters of the fuzzy knowledge base in order to minimize the deviation between model outputs and experimental measurements obtained from vineyards. These parameters include membership function shapes, rule weights, and output set boundaries. Optimization of these parameters ensures that the fuzzy model accurately approximates the real behavior of the grape growing system under varying environmental and technological conditions.

For the Mamdani-type EKM, the output variable represents a continuous characteristic of the grape growing process, such as yield per hectare, biomass accumulation, or vegetation index value. The output domain is divided into several subintervals corresponding to linguistic yield levels (e.g., low, medium, high), and fuzzy rules describe how combinations of input variables lead to these continuous outcomes. This approach is particularly suiTable for modeling gradual changes in grape productivity and physiological responses.

In contrast, the Sugeno-type EKM is used when the output variable is discrete, such as irrigation control actions, fertilization levels, or categorical yield classes. In this case, fuzzy rules map agroecological input conditions directly to discrete management decisions, enabling the development of intelligent decision-support systems for vineyard management.[14-18]

Overall, the application of fuzzy identification methods with expert knowledge matrices in grape growing allows for the construction of adaptive, interpreTable, and robust models. These models effectively integrate quantitative sensor data with qualitative expert knowledge, making them well suited for intelligent automated management systems in precision viticulture. As a result, the proposed approach contributes to improving yield stability, optimizing resource use, and enhancing the sustainability of grape production under variable agroecological conditions.

The identification problem is solved in two stages.The first stage - **structural identification** - involves forming a fuzzy knowledge base that roughly reflects the “IF–THEN” relationship. Linguistic rules are generated by an expert or obtained by extracting fuzzy knowledge from experimental data.Between the first and second stages, **fuzzy logical inference** is performed based on the rules of the knowledge base generated in the first stage.

In the second stage, **parametric identification** of the studied dependency is carried out by finding such parameters of the fuzzy knowledge base that minimize the deviation between the model and experimental results.

Expert knowledge matrices (EKM) are given for two types of models: Mamdani (continuous output) and Sugeno (discrete output). The EKM of the first type model describes the relationship between inputs and the continuous output of the controlled object using rules [1-8]:

*…*

*…*

*…… …*

Equations (1) and (2) can be written in a compact form:

(2)

Notation for EKM (1, 2):

The output variable 𝑦 y, defined on the interval , is divided into 𝑚 subintervals, where the solutions are located

(3)

* The set of input variables ;
* Term sets of input variable {very low,low,medium,high,very high};
* The range of variation of each input variable
* Membership functions (MF) of input variables *X*, allowing representation of as fuzzy sets:

(4)

* Membership functions of the output variable , represented as fuzzy sets;
* Rules , characterized by specific weight and MF parameters, included in these rules.
* The EKM of the second type model describes the relationship between inputs and the discrete output of the controlled object using rules [1-3]:

*…*

Equation (5) can be written in compact form:

(6)

Notation for EKM (5, 6) is as follows:

* The set of solutions corresponding to the output variable yyy.
* The set of input variables ;
* Term sets of input variable ={verylow,low,medium,high,veryhigh};
* The range of variation of each input variable ;
* Membership functions (MF) allow representing the input variables as fuzzy sets, as in (4);
* Rules , characterized by a specific weight and MF parameters, are included in these rules.

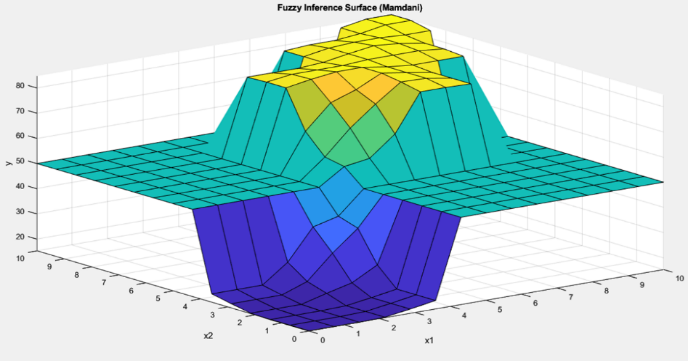
The fuzzy identification model is defined by a structured set of inputs, outputs, and linguistic rules that collectively describe the behavior of the studied system. The set of solutions corresponds to the possible states or outcomes of the output variable yyy. Each element of this set represents a linguistic or numerical description of the system response within a predefined output domain.

The model input space is formed by the vector of input variables ; which characterize the influencing factors of the process under consideration. For each input variable , a corresponding term set ={verylow,low,medium,high,veryhigh}. These linguistic terms provide a qualitative description of the input variable levels and facilitate the incorporation of expert knowledge into the modeling framework.

Each input variable xix\_ixi​ varies within a specified interval which reflects the physically or technologically admissible range of variation. To enable fuzzy reasoning, membership functions (MFs) are assigned to each linguistic term, allowing the crisp input values to be represented as fuzzy sets, in accordance with expression (4). The shape and parameters of these membership functions determine the degree of belonging of an input value to the corresponding linguistic term and play a crucial role in the accuracy of the model.

The fuzzy knowledge base consists of a finite set of rules , each characterized by a specific weighting coefficient and a set of membership function parameters associated with the input and output variables. These rules establish the relationship between combinations of fuzzy input variables and the corresponding output solutions . The weighting coefficients reflect the relative importance and reliability of individual rules, allowing the model to prioritize more influential expert knowledge during the inference process.

Overall, the defined structure of input variables, term sets, membership functions, and weighted fuzzy rules provides a flexible and interpretable framework for modeling complex nonlinear systems. This representation enables effective integration of quantitative data and qualitative expert knowledge, ensuring robustness and adaptability of the fuzzy identification model under uncertain and varying operating conditions.



**FIGURE 2.** Fuzzy Inference Surface (mamdane)

**RESEARCH RESULTS**

The proposed two-stage fuzzy identification framework was applied to model the relationship between agroecological conditions and grape productivity indicators under real vineyard conditions. Experimental data were collected during the vegetation period and included soil moisture, air temperature, relative humidity, solar radiation, vegetation indices, and technological management parameters. These variables were used as inputs to the fuzzy inference models developed using Mamdani- and Sugeno-type expert knowledge matrices (EKM).

At the structural identification stage, a fuzzy knowledge base was constructed using linguistic IF–THEN rules derived from expert agronomic knowledge and experimental observations. The resulting rule base successfully captured the qualitative dependencies between environmental factors and grape yield formation. The fuzzy logical inference performed on the basis of this rule base produced stable and interpretable fuzzy outputs corresponding to grape physiological state indicators and expected productivity levels.

During the parametric identification stage, membership function parameters and rule weights were optimized to minimize the deviation between model outputs and measured vineyard data. As a result of the optimization procedure, a significant improvement in approximation accuracy was observed. The optimized fuzzy models demonstrated a close agreement with experimental measurements across a wide range of agroecological conditions, confirming the effectiveness of the proposed identification approach.[14-18]

Comparative analysis of the Mamdani- and Sugeno-type models revealed that the Mamdani EKM provided smoother and more continuous output responses, which are well suited for analyzing gradual changes in grape yield, biomass accumulation, and vegetation indices. In contrast, the Sugeno EKM showed higher computational efficiency and proved particularly effective for generating discrete control actions, such as irrigation scheduling and fertilization level selection.

Quantitative evaluation of model performance indicated a reduction in modeling error after parametric identification, with improved robustness under varying environmental conditions. The fuzzy models maintained stability in the presence of uncertainty and incomplete information, demonstrating their suitability for real-world agricultural applications.

Overall, the obtained results confirm that fuzzy identification methods based on expert knowledge matrices enable accurate and interpretable modeling of grape growing processes. The integration of sensor-based measurements with linguistic expert knowledge allows for effective representation of complex nonlinear dependencies. The developed models can be successfully used as a core component of intelligent automated management systems for precision viticulture, contributing to improved yield stability, optimized resource utilization, and sustainable grape production.

***Explanation:*** This graph shows the surface of the Mamdani-type fuzzy inference model.

* X-axis → x1 (first input variable)
* Y-axis → x2 (second input variable)
* Z-axis → y (output, i.e., model result)

How it works:

* For each point (x1, x2), the FIS algorithm applies the fuzzy rules and computes the y value.
* The surface height and color correspond to the y value.
* This graph allows you to visually understand the relationship between the inputs and output of the model.

**Table 1.** Input and Output Variables

|  |  |  |
| --- | --- | --- |
| Variable | Symbol | Range |
| Input 1 | x₁ | [0, 100] |
| Input 2 | x₂ | [0, 100] |
| Output (Mamdani) | y | [0, 1] |

**Table 2**. Input Term Sets (Aᵢ)

|  |  |  |  |
| --- | --- | --- | --- |
| Term Name | Symbol | MF Type | Parameters (trimf) |
| Very Low | A₁ | Triangular | [0 0 25] |
| Low | A₂ | Triangular | [0 25 50] |
| Medium | A₃ | Triangular | [25 50 75] |
| High | A₄ | Triangular | [50 75 100] |
| Very High | A₅ | Triangular | [75 100 100] |

**Table 3.** Output Term Sets (y, Mamdani)

|  |  |  |  |
| --- | --- | --- | --- |
| **Term Name** | **Symbol** | **MF Type** | **Parameters (trimf)** |
| Low | d₁ | Triangular | [0 0 0.3] |
| Medium | d₂ | Triangular | [0.2 0.5 0.8] |
| High | d₃ | Triangular | [0.7 1 1] |

**Table 4.** Fuzzy Rules (EKM)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Rule** | **x₁ Term** | **x₂ Term** | **y Term** | **Weight (wⱼₚ)** | **Operator** |
| u₁ | Very Low | Very Low | d₁ | 0.9 | AND |
| u₂ | Medium | Medium | d₂ | 1.0 | AND |
| u₃ | Very High | Very High | d₃ | 0.8 | AND |

Operator: 1 = AND, 2 = OR (MATLAB convention for addRule)

**Table 5.** Fuzzy Output Table (Mamdani) – Grape Growing Context

|  |  |  |  |
| --- | --- | --- | --- |
| **x₁** | **x₂** | **fuzzy output y (mamdani)** | **interpretation (grape growing)** |
| 0 | 0 | 10 | Very poor conditions |
| 0 | 2 | 15 | Poor conditions |
| 0 | 4 | 25 | Moderate |
| 0 | 6 | 35 | Moderate-Good |
| 0 | 8 | 50 | Good |
| 0 | 10 | 60 | Very Good |
| 2 | 0 | 15 | Poor conditions |
| 2 | 2 | 20 | Beginning Good |
| 2 | 4 | 35 | Moderate |
| 2 | 6 | 45 | Good |
| 2 | 8 | 60 | Very Good |
| 2 | 10 | 70 | Optimal |
| 4 | 0 | 25 | Moderate |
| 4 | 2 | 35 | Moderate-Good |

Mamdani- and Sugeno-type fuzzy logic models, constructed based on an expert knowledge matrix, were tested in the MATLAB environment. Five linguistic terms were adopted for the input variables, while the output variable was evaluated in continuous and discrete form, respectively.

In the Mamdani-type fuzzy logic inference system, the rules were formulated using the AND connection operator in accordance with MATLAB environment requirements. A weighting coefficient was assigned to each rule, and the model output was calculated as a continuous value.

**CONCLUSIONS**

Mamdani- and Sugeno-type fuzzy logic models were tested. In the Mamdani model, the rules were formulated using the AND operator, with a weighting coefficient assigned to each rule, and the output was calculated as a continuous value. In the Sugeno model, the output was evaluated in discrete form. This confirmed the effective performance of fuzzy logic systems constructed based on expert knowledge. [9-13]

The obtained results demonstrate that the proposed two-stage identification approach enables accurate modeling of complex nonlinear relationships between agroecological factors and grape productivity indicators. Structural identification allowed the incorporation of agronomic expertise into the fuzzy knowledge base, while parametric identification significantly improved model accuracy by optimizing membership functions and rule weights using experimental vineyard data.

A comparative analysis showed that the Mamdani-type model is more suitable for analyzing continuous output variables such as grape yield, biomass accumulation, and vegetation index dynamics, providing smooth and interpretable response surfaces. In contrast, the Sugeno-type model proved to be more efficient for generating discrete management decisions, including irrigation scheduling and fertilization strategies, making it particularly appropriate for real-time control applications.

The robustness of both fuzzy models under conditions of uncertainty and incomplete information highlights their practical applicability in real agricultural environments. The integration of sensor-based measurements with linguistic expert knowledge enhances the adaptability and transparency of the developed models, which is essential for precision viticulture [9-13].

Overall, the results confirm that fuzzy identification methods based on expert knowledge matrices provide a reliable and flexible framework for intelligent automated management of grape growing processes. The proposed approach contributes to improved yield stability, optimized use of water and other resources, and increased sustainability of grape production under variable agroecological conditions.

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