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IMPROVING THE READINESS OF ENTERPRISES TO DEVELOP SUSTAINABLE INNOVATION STRATEGIES THROUGH FUZZY LOGIC MODELS⁶

The article is aimed at enhancing the strategic readiness of enterprises to adopt sustainable innovation strategies by implementing fuzzy logic-based expert systems. These systems focus on evaluating an enterprise's preparedness for innovation by using a structured assessment framework. The study seeks to establish a comprehensive indicator for gauging the readiness of innovation-active enterprises, integrating financial health indicators and strategic opportunity utilization. Methodologically, the study applies fuzzy logic inference, utilizing the Mamdani approach for defuzzification to measure the "degree of readiness to implement an innovation strategy." Two key variables – "level of crisis state of enterprise" and "use of strategic opportunities" – are derived from financial assessments and strategic analysis tools like SWOT and the ADL/LC model. A key finding of the study is the formulation of a readiness index that can assist enterprises in identifying their current capabilities and readiness level for sustainable innovation adoption. The fuzzy expert system provides a structured approach to support management decision-making, offering a strategic tool that aligns with the need for innovation in modern enterprises. Ultimately, the study underscores the importance of preparing enterprises to navigate the complex demands of innovation by fostering a systematic, adaptable approach that supports strategic development and sustainable growth in dynamic markets.

Keywords: finance; modelling; latest technologies; mathematical statistics; management decision-making

JEL: F65; G17; L26

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1. Introduction

The relevance of this study lies in the growing need for companies operating in all sectors of the economy to constantly adapt to change and innovate in order to remain competitive in the face of rapid technological advances. Rapid technological advances are changing not only the market but also the very nature of business, requiring companies to be able to respond quickly to new challenges. In addition, market dynamics are also undergoing significant changes, which is leading to an escalation of competition and challenging businesses not only to maintain their positions but also to ensure the company's sustainable development. This is compounded by the growing environmental issues that are becoming increasingly relevant, affecting the regulatory environment and public sentiment. In today's competitive global environment, the ability to implement and sustain innovative strategies is not just a way to gain a competitive advantage, but a necessity for survival and growth.

The significance of this study is that traditional models previously used to assess the readiness of companies to adopt innovation are often unable to effectively address the complexities and uncertainties that characterize today's dynamic business environment. These models usually do not take into account the multidimensionality and complexity of the factors that affect a company's ability to adapt to change and adopt new technologies. In this context, the introduction of a fuzzy expert system becomes necessary, as it offers a much more nuanced approach. This approach is able to cope with the ambiguity, subjectivity, and ambiguity associated with the assessment of the multifaceted aspects of companies' innovation readiness. This enables companies to better understand their strengths and weaknesses, and to consider the impact of external factors such as market trends or environmental requirements. This study is timely as it addresses the urgent need for more sophisticated, adaptive tools that can provide a deeper, more accurate assessment of an agricultural enterprise's innovation capabilities and readiness to innovate. Tools such as fuzzy expert systems can be used to support strategic planning, more rational resource allocation, and policy development that promotes sustainable development. Through such approaches, enterprises can be better equipped to develop and implement effective innovation strategies that not only deliver short-term results, but also contribute to long-term success and sustainability in an ever-changing external environment (Peckol, 2021).

The general trends in the development of innovations in Ukraine, in particular, in the context of globalization, were discussed in the work by Ludvik (2022). According to the scientists, it makes it possible to overcome the technological gap that exists in the context of the introduction of innovative technologies to increase the country's competitiveness. Trends in the innovative development of the Ukrainian economy were also considered by Kovalchuk (2023). The scientist noted that innovations are an integral part of the development of society, and the sustainable development of the latest economic technologies requires a comprehensive analysis, taking into account many global factors. The possibilities of Ukraine's innovative development for the prospect of post-war reconstruction were considered by Bila et al. (2023). The scientists drew attention to the need to attract investment in the country for the future in order to ensure more rapid and rational use of the latest technologies in the post-war period. Currently, studies aimed at developing fuzzy logic models are quite common in the economic literature. Thus, Khudik (2023) described a fuzzy

logic model for representing the data of a recommendation system in the field of education. For this purpose, content-oriented models, models with collaborative filtering, sequential recommendation models, session-based models, hybrid models, etc. were considered.

Kuzmenko & Vitkin (2024) developed a mathematical model based on fuzzy logic to determine the risk in the activities of a testing laboratory. Based on the principle of model building, the scientists concluded that their use could allow for a more efficient and detailed description of the linguistic components of uncertainty. In their turn, Murodian et al. (2023) built a model to optimize the selection of suppliers by an enterprise. They noted that the stability and development of the enterprise's logistics activities ensures a reasonable choice of optimal suppliers of raw materials, and therefore the formation of this kind of model is crucial. They built a model for assessing the performance of suppliers based on their competitiveness. This made it possible to formalize certain diverse indicators and systematize them on a single scale, which expanded the possibilities of practical use of the model.

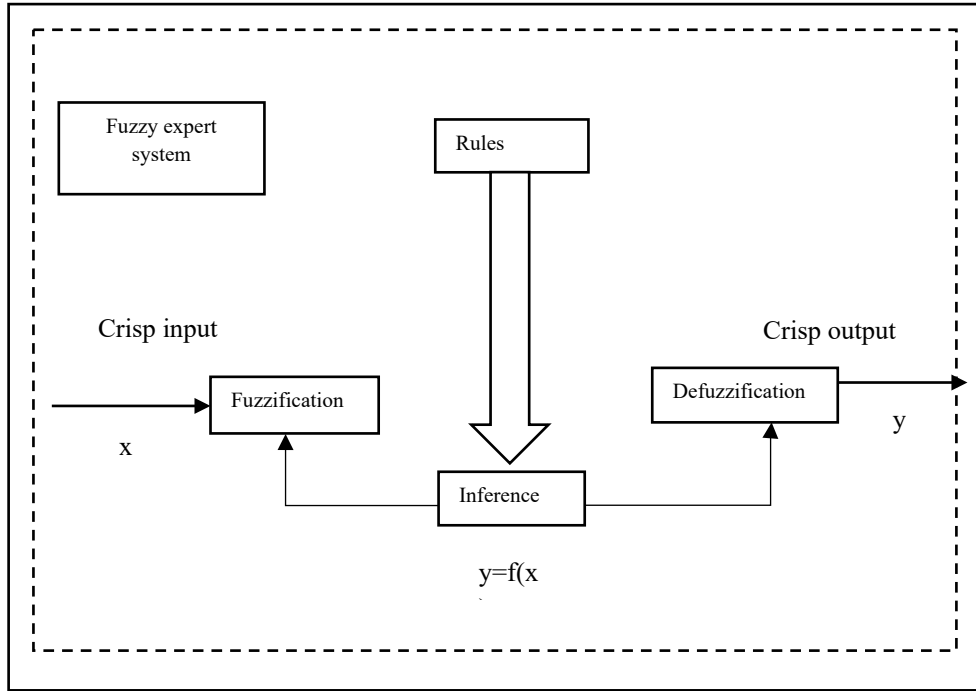
Thus, the study of the possibilities of using fuzzy logic methods is quite common in the modern economic literature. Nevertheless, the component related to their use in economics and management remains insufficiently studied. In this regard, the purpose of the study was to develop and test a comprehensive tool that uses fuzzy logic to assess the multifaceted dimensions of an organization's readiness to effectively implement a sustainable innovation strategy.

2. Materials and Methods

The process of selecting innovation development strategies is significantly complicated by the presence of uncertainty, incompleteness, and lack of data. These problems can become significant obstacles to achieving successful implementation of innovative projects, as they can lead to wrong decisions. Incorrect decisions, in turn, can have a negative impact on the overall efficiency and effectiveness of innovation projects, reducing their potential to achieve their intended goals. To overcome these problems, mathematical methods, in particular methods based on fuzzy logic, are widely used in the process of selecting innovation development strategies. It is a powerful tool that allows working effectively with inaccurate, incomplete or contradictory data. Fuzzy logic makes it possible to draw reasonable conclusions even in the face of significant uncertainty. This is especially important when traditional methods of analysis do not provide clear and unambiguous results. Fig. 1 shows the general architecture of a fuzzy expert system, which clearly demonstrates the process of data transformation within the system. The architecture is presented in such a way as to reflect the entire data processing process, from data input to final results.

To evaluate the criterion “degree of readiness to implement the innovation strategy”, the implementation of the fuzzy inference Mamdani was carried out in the FuzzyLogic Toolbox package in the Matlab environment of the R2015b version of MathWorks. The enterprises for the study were selected according to the degree of their monopoly position in the market, geographical distribution and access to official financial statements.

Figure 1. The general architecture of a fuzzy expert system



Source: built by the Authors.

Based on the use of twenty financially significant indicators, the *DCS* integral indicator – the level of crisis – was calculated. In the final version of the calculations, the vector of integral estimates includes nine variables and the free term (1):

$$DCS = 0.511 + 0.214I_1 - 0.117I_2 + 0.156I_3 + 0.081I_4 + 0.098I_5 - 0.100I_6 + 0.164I_7 + 0.084I_8 - 0.124I_9 \quad (1)$$

where I_1 – absolute liquidity indicator; I_2 – financial independence indicator; I_3 – financial stability indicator; I_4 – long-term investment coverage structure indicator; I_5 – financial risk indicator; I_6 – financial independence indicator of capitalized sources; I_7 – return on assets' indicator; I_8 – inventory turnover indicator; I_9 – own working capital indicator.

The second characteristic chosen to characterize the degree of readiness of enterprises to implement innovative activities is the indicator “use of strategic opportunities” (USO). This indicator takes into account the strengths and weaknesses of innovation-active enterprises and the growing threats of the external environment. To build the indicator use of strategic opportunities (USO), the results of the SWOT analysis, taxonomic analysis, and the improved ADL/LC model were used. Thus, the selected indicator of “use of strategic opportunities” (USO) can indirectly characterize the innovation activity of enterprises.

The next stage of building a fuzzy expert system was based on the selection of membership functions. A fuzzy logic model with numerous input variables will significantly complicate the structure of the model, as will be shown later, so the number of input variables needs to be reduced in a reasonable optimal way. In addition, when reducing the number of input variables, it is necessary to adjust the type of membership function accordingly, but at the same time to preserve the ranges of values that reflect the linguistic description of the variables for each input variable.

3. Results

Today, innovation is an undoubted imperative that allows a modern enterprise to secure its future. Assessing the degree of readiness to implement an innovation strategy is crucial for the success of enterprises in today's dynamic world. The industrial sector, being one of the main pillars of many countries' economies, faces several challenges, including climate change, sustainability requirements and growing competition. In this context, innovation is not just a way to give businesses an edge, but also a necessity for their survival and prosperity.

First and foremost, a readiness assessment allows an enterprise to understand its current capabilities and limitations. This means analysing internal resources, such as finance, technology, and human resources, as well as assessing the external environment, including market trends, regulations, and consumer needs. Understanding these aspects allows the enterprise to adapt its innovation strategy in a way that is realistic and achievable (Makedon et al., 2021). Further, an adequate assessment of the degree of readiness allows for the development of an effective innovation plan. This includes identifying key milestones, resources required, potential risks and methods to minimize them. With this approach, the innovation strategy ceases to be just a set of ideas and turns into a clear action plan, which significantly increases the chances of success.

In a rapidly evolving global marketplace, businesses need to adopt and constantly update their innovation strategies more than ever. Sustainability in this context does not simply mean environmental awareness, but encompasses economic viability and social justice, forming a model that modern businesses must look to in order to thrive in the long term (Mohammadi et al., 2021). Design represents a promising approach to navigating the complexities of innovation in the modern era. This essay examines the meaning, function and implications of such a system. The landscape of innovation is full of uncertainty and ambiguity. Traditional linear decision-making models often fail to capture the nuanced reality of business ecosystems (Akkaya et al., 2015). The integration of an expert system based on fuzzy logic makes it possible to process imprecise, ambiguous information, similar to human reasoning. The importance of this system lies in its ability to assess the readiness of an enterprise to implement sustainable innovation strategies, considering not only quantitative indicators but also qualitative data that reflect the culture, capabilities and external environment of the organization (Gupta, 2021).

Based on the analysis, the main advantages and disadvantages of the membership function are consolidated. In the case of implementing the membership function to build a fuzzy model for assessing the financial condition and bankruptcy risk of an industrial enterprise, the

variety of membership functions that can be offered is reduced to triangular, trapezoidal, S-shaped, Z-shaped and bell-shaped functions (Zumstein, 2007). Thus, the triangular and trapezoidal functions characterize uncertainty with concepts such as “mean”, “object-like” and “subject-like”. They require little information to define and are easily modified. S-shaped and Z-shaped describe uncertainty with concepts such as “small (large) quantity”, “low (high) price and income”, etc. This reflects the low or high degree of manifestation of a certain attribute. As for the U-shaped ones (those that resemble a bell), they describe the uncertainty of values with a normal distribution and require numerous parameters.

Thus, the most common are the trapezoidal and bell-shaped membership functions. The advantage of the bell-shaped function is that its values are always normal and different from zero ($\mu(x_i) \in (0;1]$), which prevents the results from being distorted by many mathematical transformations, increasing the reliability of the model (Dandoussou & Kenfack, 2023) (2):

$$\mu(x) = \frac{1}{1 + \left| \frac{x-c}{a} \right|^{2b}}, \quad (2)$$

where: a – concentration coefficient, b – steepness coefficient, c – coordinate of the maximum of the membership function.

A further part of the formation of a fuzzy logic model is the creation of fuzzy logic rules. The number of rules (r) can be determined by the formula if the number of inputs (input variables) of the model is ω , and each of them has z fuzzy sets (membership functions) (3):

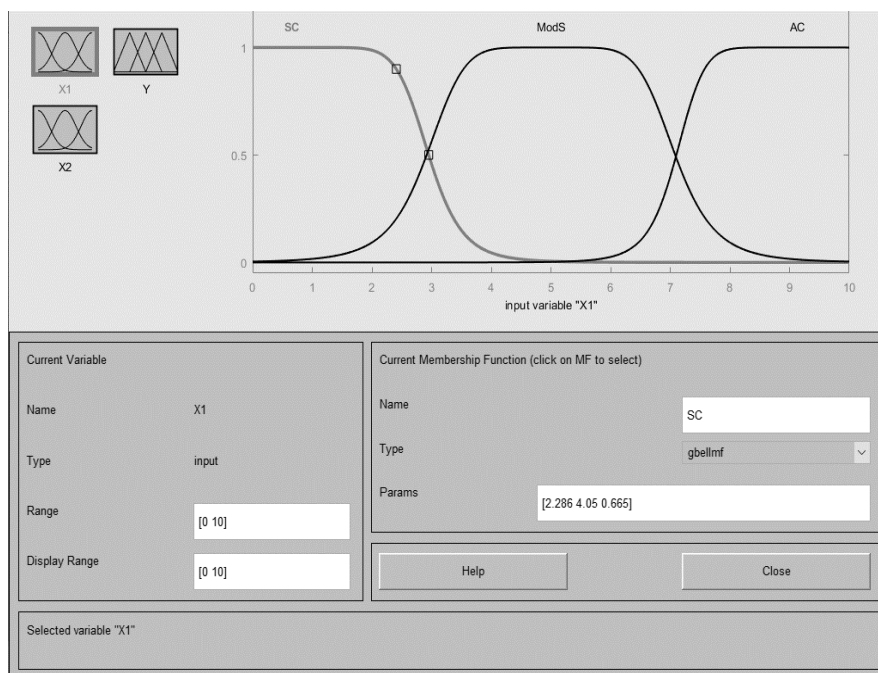
$$r = z^\omega. \quad (3)$$

Taking into account Formula 3 above, we can form a relationship between the number of logical rules and the number of model inputs (input variables) ω and the number of fuzzy sets z for each. As the number of model inputs (ω) and fuzzy sets (z) increases, the number of logical rules increases exponentially. This complicates the process of building the model. The number of fuzzy sets at each input to $z=5$ and the number of input variables to $\omega=2$ was set, so to ensure the completeness of the model, we need ($r=5^2=25$) rules. Accordingly, if the number of fuzzy sets at the input was another number, for example, 2, and the number of model inputs was 4, the number of rules would be 16. The modelling of the integral indicator was carried out using the FuzzyLogic ToolBox software within Matlab version R2015b by MathWorks. To define and visualize membership functions, the format of bell-shaped membership functions was used. Membership functions are defined in the format $\mu(x)=gbellmf(x, [a \ b \ c])$, where x is the input variable, a, b, and c are the parameters.

Figures 2, 3 and 4 show the attributes and membership functions for two input variables and one output variable. The input function X1 is shown in Figure 2.

As can be seen from Fig. 2, the variable X1 reflects the level of crisis state of the enterprise and has five attributes (membership functions): SC – severe crisis, ModC – moderate crisis, AC – absence of crisis. This function has a bell-shaped form and a coefficient of [0;10]. The membership function SC, which means a severe crisis, has parameters [2.286 4.05 0.665], ModC, which means a moderate crisis, has parameters [2.083 3.1245], and AC, which means no crisis, has parameters [2.09 4.29 9.125].

Figure 2. Graph of the membership function of the input linguistic variable X1 (level of crisis state of the enterprise)



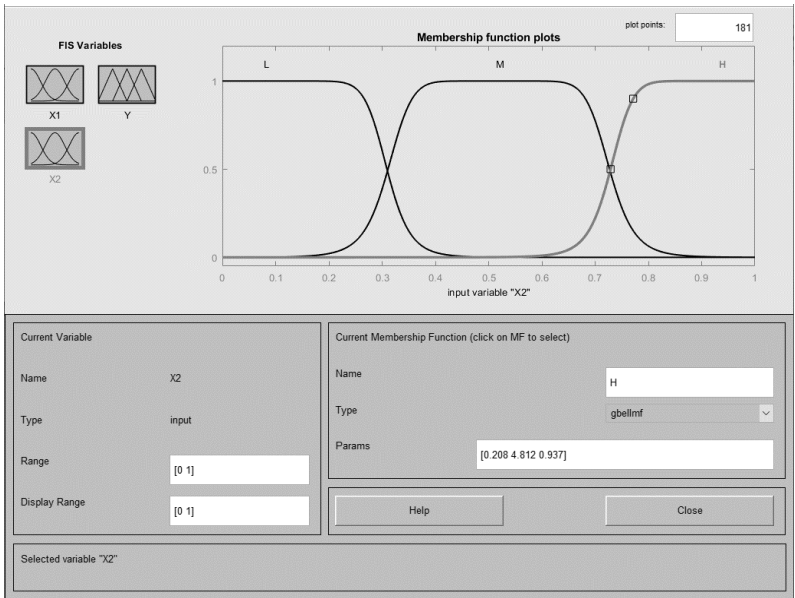
Source: built by the Authors.

Figure 3 shows the input variable X2.

Thus, Figure 3 shows that variable X2 is an indicator of the “use of strategic opportunities” (SO) by an innovative enterprise. This variable has five attributes (membership functions): *L* – low level of SO, *M* – moderate level of SO, *H* – high level of SO. The function has a bell-shaped form and a range of values [0;1]. The membership function *L*, which corresponds to a low level of SO, has the parameters [0.2285 5.29 0.0806], the function *M*, which corresponds to a moderate level of SO, has the parameters [0.208 4.462 0.519], and the function *H*, which corresponds to a high level of SO, has the parameters [0.208 4.812 0.937].

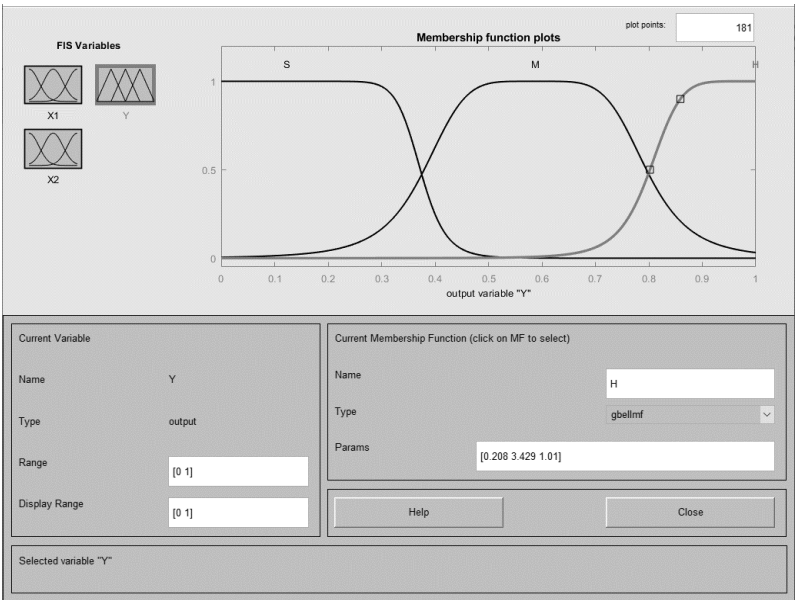
In Figure 4, the variable Y (“degree of readiness to implement the innovation strategy”) was introduced and has five attributes (membership functions): *S* – small and has parameters [0.229 6.317 0.076], *M* – moderate and has parameters [0.208 2.5 0.5876], *H* – high and has parameters [0.208 3.429 1.01].

Figure 3. Diagram of the membership function for the input linguistic variable X2 (an indicator of “use of strategic opportunities” by an innovative enterprise)



Source: built by the Authors.

Figure 4. Graph of the membership function for the output linguistic variable Y (degree of readiness to implement the innovation strategy)



Source: built by the Authors.

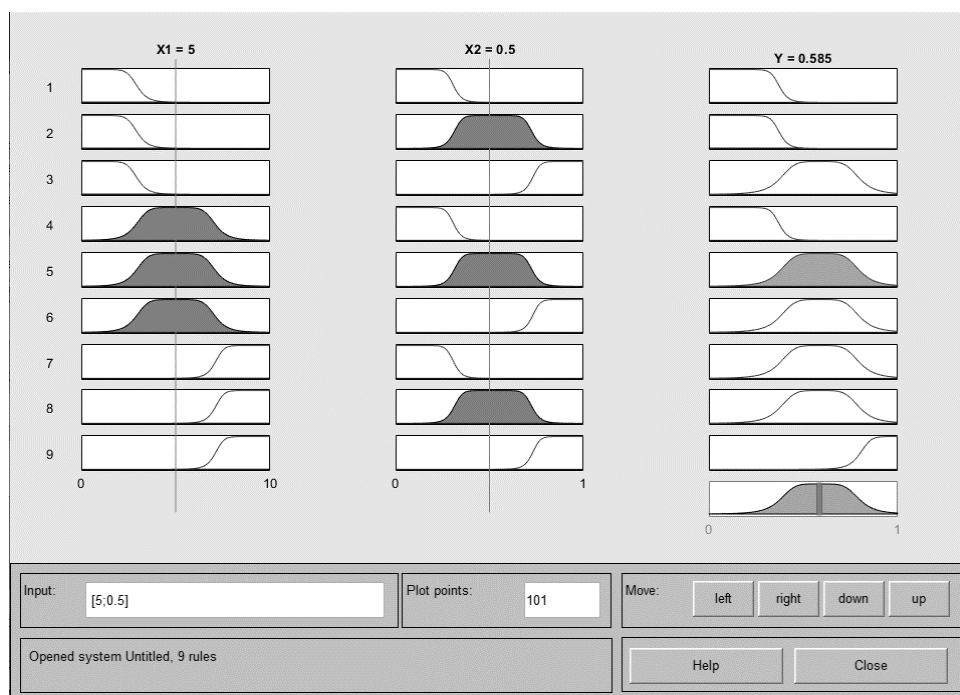
Thus, $3^2=9$ fuzzy rules were identified to infer the output variable.

The rules of fuzzy logic are outlined as follows:

1. Rule 1: If ($X1$ is SC) and ($X2$ is L), then (Y is S);
2. Rule 2: If ($X1$ is SC) and ($X2$ is M), then (Y is S);
3. Rule 3: If ($X1$ is SC) and ($X2$ is H), then (Y is M);
4. Rule 4: If ($X1$ is $ModC$) and ($X2$ is L), then (Y is S);
5. Rule 5: If ($X1$ is $ModC$) and ($X2$ is M), then (Y is M);
6. Rule 6: If ($X1$ is $ModC$) and ($X2$ is H), then (Y is M);
7. Rule 7: If ($X1$ is AC) and ($X2$ is L), then (Y is M);
8. Rule 8: If ($X1$ is AC) and ($X2$ is M), then (Y is M);
9. Rule 9: If ($X1$ is AC) and ($X2$ is H), then (Y is H).

The implementation of Mamdani's conclusion is shown in Figure 5.

Figure 5. Implementation of Mamdani's fuzzy inference in the FuzzyLogic Toolbox software of the Matlab environment by MathWorks to assess the degree of readiness for the implementation of an innovation strategy for enterprises engaged in innovation

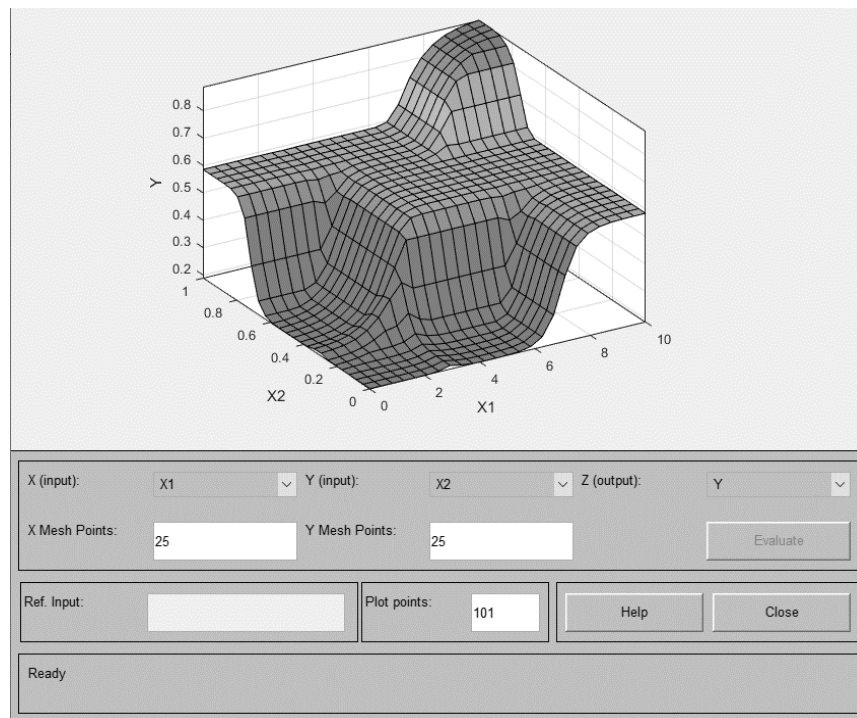


Source: built by the Authors.

The left column in Figure 5 represents the defined rules, and the next two columns show $X1=5$ and $X2=0.5$ for the input values. The value of Y is displayed in the right column for each fuzzy rule as the “degree of readiness to implement the innovation strategy” (Servin *et al.*, 2023). For example, the initial value of the degree of readiness of the enterprise to implement the innovation strategy is $Y=0.585$. The results are visualized in Matlab using the Rule Viewer visualizer. The built fuzzy inference model allows estimating the “degree of readiness to implement the innovation strategy” of innovatively active enterprises by the indicator $X1$ – level of crisis state of the enterprise and $X2$ – level of crisis state of the innovative enterprise. The indicator “use of strategic opportunities” is established.

The dependence of the output variable Y , which is the degree of readiness to implement an innovation strategy, on the input variables, is confirmed by the infinity of Y values, presented as a response surface in Fig. 6 (Sabounchi & Wei-Kocsis, 2022).

Figure 6. Modelling results



Source: built by the Authors.

The visualization of the “input-output” surface allows us to determine that at the maximum value of the indicator $X1$ “level of crisis state of the enterprise” and $X2$ high value of the indicator “use of strategic opportunities”, the output indicator Y “degree of readiness to implement the innovation strategy” reaches the maximum possible level. The visualization of the input-output surface makes it possible to determine the output indicator Y , which, in terms of the degree of readiness to implement the innovation strategy, reaches its maximum

at the maximum value of $X1$ of the indicator, which is the level of crisis state of the innovative enterprise, and at the maximum value of $X2$, which is the indicator of strategic opportunities.

Thus, innovation is crucial for business survival and growth in today's rapidly changing world, especially in the industrial sector, which faces challenges such as low wages due to climate change and increased competition. In turn, fuzzy logic models are valuable tools for assessing a company's readiness to innovate, as they handle uncertainty and complexity better than traditional methods. These models use membership functions to describe different levels of risk and readiness, providing reliable results to guide decision-making. When implemented in tools such as Matlab, they help companies visualize the relationship between levels of crisis, strategic capabilities and readiness to innovate, ensuring that they are well-prepared to operate in the global marketplace.

4. Discussion

Decision-making under uncertainty and with incomplete or insufficient data is a significant challenge when choosing innovative strategies. This problem is solved by the use of mathematical methods based on fuzzy logic, which leads to the development of intelligent systems that use multi-criteria fuzzy set theory and models for multidimensional analysis of the economic system. They are crucial for making informed economic decisions about the innovation readiness of an agricultural enterprise under conditions of uncertainty. The general structure of the fuzzy expert system demonstrates the internal process of data transformation of the system. To assess the degree of readiness to implement an innovation strategy, Mamdani fuzzy inference was applied using FuzzyLogic Toolbox software. This approach relies on several studies to comprehensively assess the readiness of an enterprise to innovate, including a study of the crisis state of thirty innovative companies based on an integrated criterion of the level of crisis state of the enterprise. Another aspect of assessing the readiness of an agricultural enterprise to innovate is the USO indicator, which reflects the company's use of strategic market opportunities. This indicator takes into account the strengths, weaknesses and growing external threats faced by innovative agricultural enterprises, including the results of SWOT and taxonomic analysis, as well as the refined ADL/LC model. The construction of a fuzzy expert system involves the selection of membership functions, which complicates the model if it is based on numerous input variables.

This research offers an innovative approach to addressing the challenges of sustainable innovation. Despite the state-of-the-art methodology and the use of fuzzy logic to accommodate uncertainties in innovation strategy planning, there are several shortcomings to this research approach: while the study effectively integrates a diverse range of input variables to assess enterprise readiness, the choice of these variables is limited by the model's ability to manage complexity. This limitation may miss critical factors influencing the innovation readiness of an enterprise that are difficult to assess or recognize within the current model; the use of generalized membership functions such as triangular, trapezoidal and bell-shaped functions offer a practical solution to simplify complex relationships. However, this approach cannot accurately capture the unique characteristics and nuances of each farm's

innovation landscape, leading to simplistic estimates that may overlook critical subtleties. Despite its cutting-edge methodology and significant contribution to the field of strategic planning under uncertainty, the study faces inherent limitations that may affect its wider application and impact. These limitations mainly focus on model specificity, data dependency, adaptability and empirical validation.

In the current study, the main goal was to build a fuzzy logic model, which was achieved: the model allows us to conclude how ready the enterprise is to implement innovative development strategies. Other scholars have also developed this type of model: as noted in the works by Badreddine et al. (2022) and Cho & Lee (2013), the process of fuzzy logical inference regarding the company's development strategy includes four key stages:

- vagueness (implementation of vagueness);
- unclear conclusion;
- warehouse;
- defuzzification (conversion to clear values).

The development of a fuzzy model requires the identification and definition of input and output variables for a fuzzy inference system. A study by Shang & Hossein (2013) presents the use of fuzzy set theory to assess the competitiveness of companies. The authors analyse the system of competitiveness indicators in the context of the proposed approach based on the balanced scorecard (BSC), which is the object of monitoring. A new approach to decision-making based on Fermatean fuzzy sets and weighted aggregated sum product assessment (WASPAS) was considered by Keshavarz-Ghorabae et al. (2020). They conducted a study based on the construction industry, paying special attention to the role of this industry in the development of society and the need for environmental management. The paper proposed a new methodology for multi-criteria decision-making to address the uncertainty inherent in valuation problems. The developed methods were tested on the problem of evaluation and selection of a green building supplier, showing stable and reliable results through sensitivity analysis and comparative analysis: it was concluded that the method proves to be effective in the face of uncertainty, and also allows for drawing conclusions based on different types of information. The possibilities of using such systems in construction were also assessed in the work of Chen & Pan (2021). The researchers summarized the current practice in this area and made recommendations for the future construction of models and the use of methods to solve problems in the direction of the complexity of modelling the development of companies under uncertainty. The models built within the framework of the work had some similarities with those in the current study; it is also worth agreeing that in the long term, the development of the use of fuzzy logic models is promising to ensure a high level of efficiency of enterprises.

In the framework of the current study, a model based on fuzzy logic was built, which made it possible to assess the degree of readiness to implement the innovation strategy for enterprises. A fairly significant number of works in modern economic science are aimed at forming new approaches to the development of companies. For example, the study by H. Doroudi et al. (2022) presents a specific approach to assessing the company's innovative progress, which consists of using a detailed algorithm. It covers the stages of creating a

database, collecting, analysing and applying information about the work of manufacturing companies. The analysis of the innovative potential of a firm is carried out by studying its key aspects, including production capabilities, financial condition, personnel, scientific achievements, marketing activities, information resources and organizational and administrative management. Protopopova et al. (2022), in turn, note that the complexity of forming a financial strategy is associated with the multidirectional goals of economic development of an enterprise and ways to achieve them. When forming a financial strategy, an innovative type of development can be used, associated with high-profit growth, but at the same time with high financial risks.

Fayomi et al. (2019) proposed approaches to the development of a comprehensive methodology for assessing the readiness of enterprises to carry out innovative activities. One of them is an approach that involves the use of quantitative indicators measured according to known standards. For example, the authors propose to evaluate innovations, profits, wages and per capita income in monetary units; the distribution of working time for the performance of production functions – in hours; and the age of the staff – in years. Mastrocinque et al. (2022) conclude that the use of neuro-fuzzy models to analyse and predict risks associated with the operation and development of enterprises is promising for several reasons:

- such models do not require assumptions about the stability of random processes or the stability of the environment;
- fuzzy logic provides an effective mechanism for formalizing expert knowledge about system development in mathematical form;
- integration of neural networks into fuzzy models allows automated adjustment of model parameters, taking into account various quantitative and qualitative aspects, which increases the accuracy of risk forecasts for enterprises;
- neuro-fuzzy methods consider the combined effect of various uncertainty and risk factors on the overall assessment.

In general, the approaches used in the current study and in the above works were similar, which indicates the adequacy of the built model. In addition, the prevalence of research on the use of fuzzy logic models indicates that the possibilities of using these approaches are relatively significant, and enterprises can benefit from the implementation of models of this kind.

5. Conclusions

To assess the readiness of an industrial enterprise to implement an innovation strategy, the methods of fuzzy set theory proved to be the most effective. In the course of the study, a fuzzy-logical model was developed to assess this degree of readiness, which takes into account various characteristics of innovation-active enterprises. The model theoretically allows taking into account numerous indicators, but in practice, the choice of these indicators must be justified, taking into account both their importance and the complexity of collecting information to assess the criterion of “degree of readiness to implement the innovation

strategy”. The study has shown that the fuzzy-logic approach allows for adaptation to complex and changing market conditions, providing a more flexible and accurate assessment of an enterprise’s readiness for innovation. Taking into account both quantitative and qualitative indicators allow for a better assessment of the enterprise’s potential, strengths and weaknesses, as well as identifying the most effective ways to implement innovations. This helps companies make more informed decisions, and increase their competitiveness and adaptability.

The created fuzzy-logical model for assessing the readiness of enterprises for innovation activity includes the following stages: involvement of two complex indicators, one of which characterizes the financial and economic activity of innovation-active enterprises, and the other – the level of use of their strategic capabilities; selection of the type and parameters of membership functions for two input and one output variable; creation of a system of 25 logical rules; calculation of the degree of readiness of enterprises for innovation activity using the fuzzy Mamdani inference; translation checking the adequacy of the built fuzzy logic model.

The built fuzzy inference model allows, by setting the values of indicator $X1$ “level of crisis state of the enterprise” and indicator $X2$ “use of strategic opportunities”, to assess indicator (Y) “degree of readiness to implement the innovation strategy” for innovation-active enterprises. It is relevant for further research to continue studying the possibility of building fuzzy logic models and drawing conclusions about their use for solving practical problems.

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