A fuzzy multiple-criteria approach to planning the energy needs of enterprises

Anatoliy Sachenko[1,†], Oksana Chereshnyuk[1,*,†], Svitlana Sachenko[1,†], Ruslan Brukhanskyi[1,†] and Aleksandra Czupryna-Nowak[2,†]

[1] *West Ukrainian National University, Lvivska Street 11, 46008 Ternopil, Ukraine*
[2] *Politechnika Śląska, ul. Akademicka 2A, 44-100 Gliwice, Poland*

Abstract
The article presents a fuzzy-multiple approach to planning the energy needs of enterprises, which takes into account the influence of uncertain, variable and interrelated factors of the production process. Four groups of factors are considered – technical, energy, environmental-climatic and organizationalproduction, which comprehensively affect the level of electricity consumption. The use of fuzzy logic allows you to build adaptive forecasting models that can work with incomplete or contradictory data and reflect the real conditions of the functioning of enterprises. The developed model in the MATLAB environment provides increased accuracy of calculations, optimization of energy consumption and increased stability of energy supply. The proposed approach creates the basis for the formation of intelligent energy management systems that contribute to increasing the efficiency of electricity use and energy sustainability of enterprises.

Keywords
Consumption, energy demand planning, fuzzy system, fuzzy logic, energy management, adaptive modeling, energy efficiency.

1. Introduction

Electricity consumption at enterprises depends on a large number of interrelated factors – from technological processes and the type of equipment to the level of production workload and climatic conditions. Energy consumption increases longer operating time, the intensity of equipment operation, and the increase in the time of its operation. At the same time, consumption is also influenced by organizational aspects – the efficiency of energy resource management, the rate of downtime and the energy-saving culture of the staff. In conditions of energy instability, frequent outages and voltage fluctuations, enterprises are forced to carefully plan their electricity use. Rational energy planning allows not only to minimize the risks of production stoppages, but also to ensure the continuity of customer orders. Optimization of work schedules, implementation of backup power systems and energy-efficient technologies are becoming key tools of modern management. Businesses that can predict energy consumption and quickly adapt to changes gain a significant competitive advantage [1]. Thus, energy sustainability becomes an important element of competitiveness and long-term business development.

2. Related work

With the increasing demand for energy and growing concerns about climate change and resource depletion, efficient energy management has become a top priority for individuals, organizations,

AIT&AIS'2025: International Scientific Workshop on Applied Information Technologies and Artificial Intelligence Systems, December 18–19 2025, Chernivtsi, Ukraine
1* Corresponding author.
† These authors contributed equally.
as@wunu.edu.ua (A. Sachenko); o.chereshnyuk@wunu.edu.ua (O. Chereshnyuk); s.sachenko@wunu.edu.ua (S. Sachenko); r.brukhanskyi@wunu.edu.ua (R. Brukhanskyi); aleksandra.nowak@polsl.pl (A. Czupryna-Nowak)
0000-0002-0907-3682 (A. Sachenko); 0000-0001-5067-3463 (O. Chereshnyuk); 0000-0001-8225-1820 (S. Sachenko); 0000-0002-9360-1109 (R. Brukhanskyi); 0000-0001-8565-1029 (A. Czupryna-Nowak)

and governments alike. The efficient use of energy resources and the reduction of energy consumption have attracted significant attention in recent years [2].

The rise in energy consumption in both the industrial and private sectors is one of the key trends in modern economic development, directly affecting the environmental situation and the energy security of countries. Industrialization, production automation, the expansion of technological processes, and the transition to digital management models require increasing amounts of energy. The growing demand for electricity in industry is driven by the intensification of production processes, the introduction of energy-intensive equipment, and the expansion of production capacities in sectors such as metallurgy, the chemical industry, mechanical engineering, and IT [3, 4]. In 2022, final energy consumption in the EU industrial sector reached 9,489 PJ and 8,990 PJ in 2022. The industrial sector remains the largest consumer of electricity [5].

In parallel with industry, energy consumption in the private sector is also growing. The main drivers of this process include urbanization, the rising level of population well being, the widespread use of household appliances and electronics, as well as the development of electric heating and air-conditioning systems. The increase in the size of residential buildings, the introduction of electric vehicles, and the transition to renewable energy sources (which require their own energy storage and conversion systems) also contribute to the growing load on the power grid. In 2023, per capita electricity consumption in the EU residential sector amounted to 1.5 MWh (1545 kWh) per person. This figure varied significantly across EU countries – from less than 1 MWh per capita in Romania, Poland, and Latvia to 3.8 MWh in Sweden and 4 MWh in Finland [6].

At the same time, this trend poses challenges for the energy system, highlighting the need to improve energy efficiency, modernize infrastructure, and encourage the adoption of resource-saving technologies. Without systematic energy management and a transition to rational energy consumption models, further growth in energy demand may result in excessive load on the energy system, increased electricity costs, and adverse environmental consequences [7].

Numerous studies have examined how energy data analysis can contribute to reducing energy consumption in production [8–10]. Research on methods for calculating planned electricity consumption indicators is a key element in shaping an enterprise's energy strategy, as it ensures the validity of management decisions in the field of resource efficiency. Rational forecasting and planning of electricity consumption enable the optimization of production processes, reduction of energy costs, and improvement of the enterprise's resilience to fluctuations in the energy market [11].

Therefore, in the process of planning the activities of an enterprise, it is necessary to ensure energy-efficient use and management of facilities, which is an important prerequisite for maintaining competitiveness in the market [12]. Therefore, the increase in energy consumption by industry and the private sector is not only a manifestation of economic development but also an important signal of the need to implement effective energy-saving strategies, innovative technologies, and governmental programs that support a sustainable energy balance.

3. Methods and materials

3.1. Proposed approach

To increase the accuracy of forecasting and adaptability of the resource management system, it is proposed to use a fuzzy-set approach to energy consumption planning, which takes into account the influence of uncertain, variable and interrelated factors of the production process. The fuzzy-set approach allows for more accurate planning of electricity consumption, since it takes into account the uncertainty and multifactorial nature of real production processes [13]. In traditional planning methods, all parameters are presented in the form of clear values, but in practice, most of them, for example, the level of equipment utilization, the influence of temperature, demand fluctuations or the duration of outages, are of a variable, unpredictable nature. The use of fuzzy sets allows these factors to be described not only as "high" or "low", but in intermediate gradations of "partially high", "moderate", etc., which better corresponds to real conditions. This approach allows for the construction of forecasting models that can work with fuzzy, incomplete or contradictory data [14]. Thanks to this, it is possible to obtain more realistic scenarios of electricity consumption, taking into account risks and possible fluctuations in production load. As a result, the enterprise can more effectively distribute energy resources, minimize losses and increase the stability of energy supply. Thus, the fuzzy-multiple approach contributes to the formation of a flexible energy planning system capable of adapting to conditions of uncertainty.

For energy consumption planning, it is proposed to take into account a number of factors, namely:

1. Technical.
2. Energy.
3. Ecological and climatic.
4. Organizational and production.

Technical factors in the proposed model include electricity consumption, equipment efficiency, and production volume for the forecast period. In fact, these indicators can be measured in digital terms, which is a standard approach to energy consumption planning. The combined analysis of these factors allows for a more accurate forecast of energy needs and the identification of efficiency reserves.

Energy factors include power losses in the power grid, power factor, and supply voltage, since they determine the efficiency of electricity use at the enterprise. Power losses in the network, power factor, and supply voltage are affected by the condition and configuration of the power grid (cable wear, line length, quality of connections and transformers), the nature and magnitude of the load, and the type of consumers with high inductance. The external quality of electricity, the presence and configuration of reactive power compensation systems, and the level of energy management with continuous monitoring and load planning are also decisive. This is an external factor, since it depends on the quality of electricity supply, the condition of external power grids, and the stability of voltage parameters that the enterprise cannot directly control. A comprehensive assessment of these factors allows you to increase energy efficiency, reduce technical losses, and ensure reliable operation of production equipment.

It is advisable to include the predicted temperature regime, the level of natural lighting and the area of production facilities as ecological and climatic factors, since they directly affect the need for heating, ventilation, air conditioning and artificial lighting. Within the framework of energy consumption planning, these factors can be assessed using monthly meteorological forecasts, which allow taking into account expected temperature fluctuations, daylight hours and seasonal changes in illumination. This approach provides the opportunity to pre-calculate the load on climate control and lighting systems, optimizing electricity consumption in accordance with real environmental conditions.

Organizational and production factors include the intensity of shift work, equipment load factor, the level of automation of production processes and the energy consumption culture of personnel, since they determine the efficiency of electricity use in the daily activities of the enterprise. The intensity of shift work affects the duration of equipment operation and the total daily amount of energy consumption, and the load factor characterizes the degree of use of installed capacities. A high level of automation, in turn, reduces the human factor, but can increase energy consumption due to the constant operation of automated systems. Energy culture reflects behavioral aspects of staff, such as turning off equipment during non-working hours or following energy-saving practices.

The study of these factors using a fuzzy set approach is appropriate, since most of them are qualitative, not just quantitative in nature. For example, the level of energy consumption culture or automation efficiency is difficult to assess with clear numerical indicators. The use of fuzzy sets allows us to take into account concepts such as “high”, “medium” or “low” levels of influence, describe them in a gradational manner and take into account uncertainty in the data. This provides for the construction of a more flexible analysis model that can reflect real production conditions and the interdependence between technical, organizational and behavioral factors of energy consumption.

3.2. Structure of a fuzzy system

The study of these factors using a fuzzy-multiple approach is appropriate, since most of them are qualitative rather than purely quantitative in nature. For example, in the context of electricity consumption planning, the use of fuzzy logic opens up the possibility of creating intelligent forecasting systems that are able to work with incomplete, variable, or fuzzy data. Such systems enable enterprises to analyze a wide range of factors – from technological parameters to climatic conditions – and, based on them, to develop adaptive energy strategies. The use of fuzzy logic algorithms in combination with analytical modeling methods helps to increase the accuracy of energy consumption forecasts, reduce the risks of overspending, and ensure the stability of enterprise operations under conditions of fluctuating energy supply [15].

In addition, specialized software based on fuzzy-multiple algorithms can operate in real time, responding to changes in production load, electricity prices, or external weather conditions. This allows enterprises to promptly adjust equipment schedules, optimize capacity utilization, and minimize peak loads [16]. This approach eliminates subjectivity in the decision-making process, provides an objective assessment of energy risks, and creates prerequisites for the implementation of automated energy resource planning – a key factor in improving the energy efficiency and competitiveness of modern enterprises.

The effectiveness of automation is difficult to assess using clear numerical indicators. The application of fuzzy sets makes it possible to account for concepts such as “high,” “medium,” or “low” levels of impact, describe them in a gradational manner, and incorporate uncertainty in the data. This enables the construction of a more flexible analytical model that can reflect real production conditions and the interdependence between technical, organizational, and behavioral factors influencing energy consumption. The indicator of energy consumption adjustment based on quality factors is used to increase the accuracy of planned calculations of electricity required for production. Its essence lies in multiplying the basic energy needs by a correction factor, which takes into account the set of technical parameters of the equipment, climatic and ecological-production conditions, as well as organizational and technological features of the process. This approach allows you to obtain more realistic estimates of energy consumption, reflecting the impact of external and internal factors on production efficiency.

For system analysis, four factors influencing compliance indicators have been identified: legislative regulation of activities, the existing range of goods, products, or services, human resources, and technological aspects of operations. The MATLAB R 2018a software is used to develop the fuzzy system.

The overall structure of the proposed fuzzy system is presented in Figure 1.

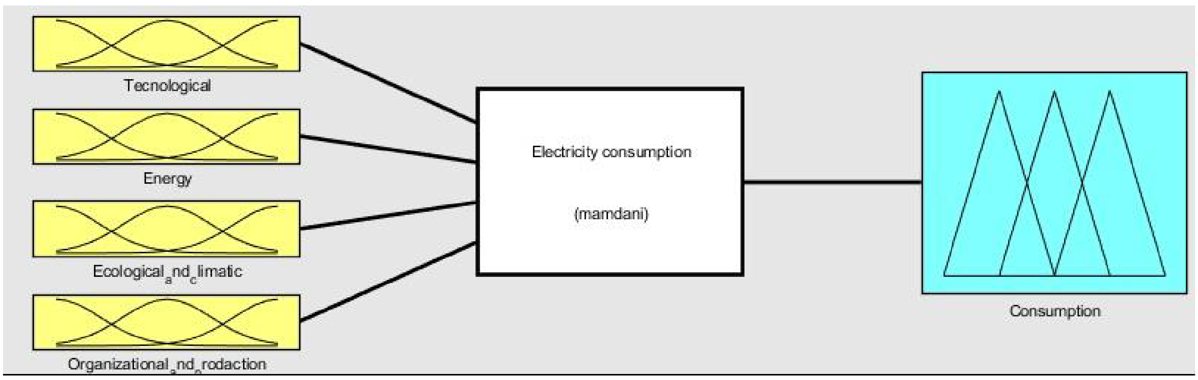

Figure 1: General view of the additional consumption systems for energy resource planning.

3.3. Model of planning electricity consumption

When building an electricity consumption planning model in MATLAB, it is advisable to use a fuzzy-multiple approach, since it allows you to take into account not only quantitative, but also qualitative indicators that significantly affect energy consumption [17]. Such indicators include the level of personnel energy consumption culture, equipment stability, organizational discipline or change management efficiency - factors that are difficult to express in exact numerical values, but which significantly affect total electricity consumption.

Unlike classical mathematical models, where all variables must have clear numerical values, in MATLAB can create fuzzy models in which concepts such as "high load", "moderate automation" or "low energy efficiency" are described in the form of membership functions [18]. This allows you to model real production conditions where the influence of factors changes gradually, rather than discretely. This approach provides a more flexible and realistic forecast of energy consumption, making the model adaptive to uncertainty, the human factor and dynamic changes in the production environment. The higher the level of equipment wear, the higher the technical variable indicator, which leads to a decrease in its energy efficiency and an increase in electricity consumption.

To assess the accuracy of the proposed fuzzy system for determining the coefficient of electricity consumption for energy resource planning, the results of its operation are shown in Figure 8. The obtained data demonstrate how the model reacts to changes in input parameters, such as the level of equipment loading, production intensity, temperature regime and other factors and forms a forecast of energy consumption taking into account the degree of uncertainty. This allows us to assess the efficiency and stability of the system, as well as to check the correspondence of the predicted values to the actual results of electricity consumption.

For the variable, the following classification is proposed:

1. Small value $s \in [0; 0.25)$.
2. Medium value $m \in (0.25; 0.7)$.
3. High value $h \in (0.7; 1)$.

Figure 2 presents the general form of the membership functions for the Technical variable.

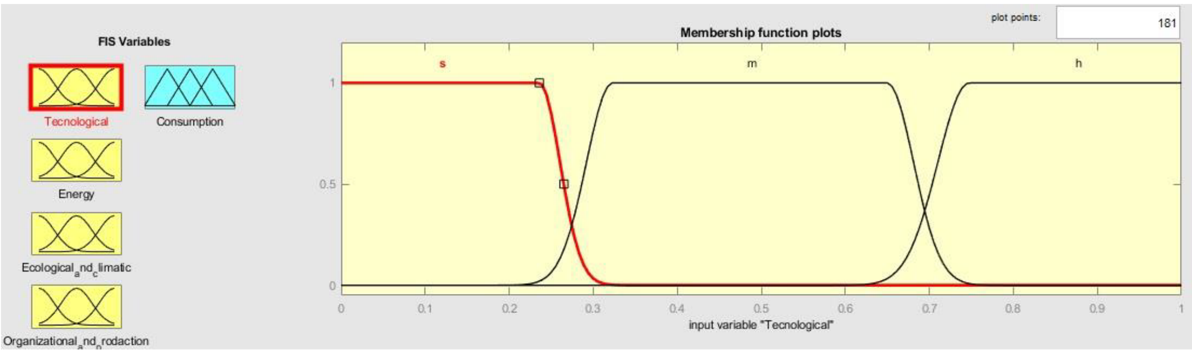

Figure 2: Membership functions of the Technical variable.

Power systems directly affect the conductivity of electricity through the parameters of voltage, frequency and quality of electric current. The condition and configuration of the power grid, in particular the level of losses in the lines and the efficiency of transformation, determine the degree of electrical conductivity under different load conditions. Optimization of power systems through modern control and automation technologies helps to increase the stability of conductivity and minimize energy losses.

For the Energy variable, the boundaries are defined as follows:

1. Small value $s \in [0; 0.05)$.

2. Medium value $m \in (0.05; 0.25)$.
3. High value $h \in (0.25; 1)$.

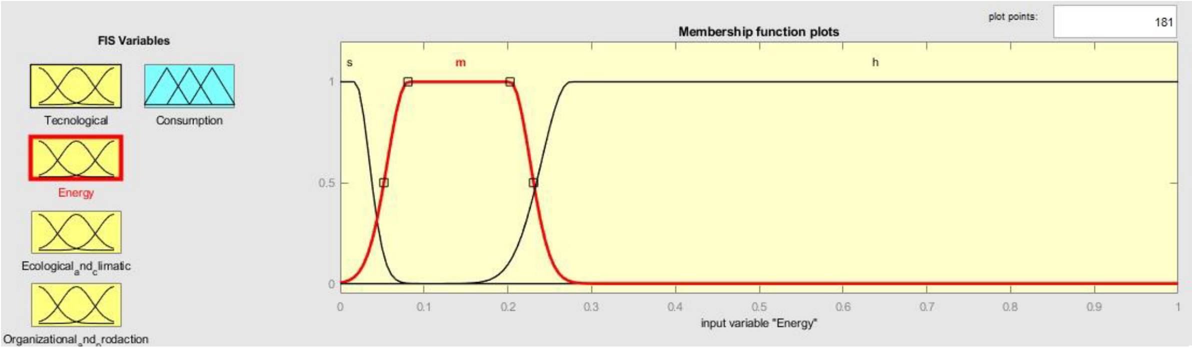

Figure 3: Membership functions of the Energy variable.

Climatic conditions are one of the key factors determining the level of electricity consumption in enterprises and in the household sector. A decrease in temperature in the cold season leads to an increase in the need for electric heating and cooling, while in the hot season the load increases due to the use of air conditioning systems. Fluctuations in temperature, humidity and daylight hours form the seasonal dynamics of electricity consumption, which must be taken into account when planning energy balances. If the deviation of actual weather conditions from the reference indicators increases, the impact of environmental and climatic factors on the energy consumption of the enterprise increases. Changes in temperature, humidity or atmospheric pressure cause additional load on the energy supply systems and adjust the planned consumption indicators.

For the Ecological and Climatic variable, the boundaries are defined as follows:

1. Small value $s \in [0; 0.27)$.
2. Medium value $m \in (0.27; 0.58)$.
3. High value $h \in (0.58; 1)$.

Figure 4 shows a general view of the membership functions of the Ecological and Climatic variable.

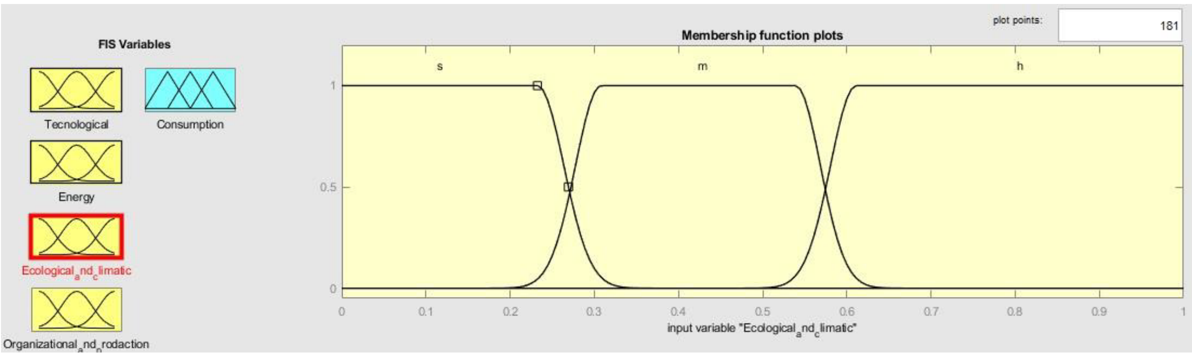

Figure 4: Membership functions of the Ecological and Climatic variable.

The organizational and production variable reflects the level of efficiency of production process management, in particular planning, maintenance and equipment operation control. Its increase indicates failures in the organization of production or irrational use of resources, which may cause additional energy losses and an increase in electricity consumption.

For the Organizational and Production variable, the boundaries are defined as follows:

1. Small value $s \in [0; 0.15)$.
2. Medium value $m \in (0.15; 0.5)$.
3. High value $h \in (0.5; 1)$.

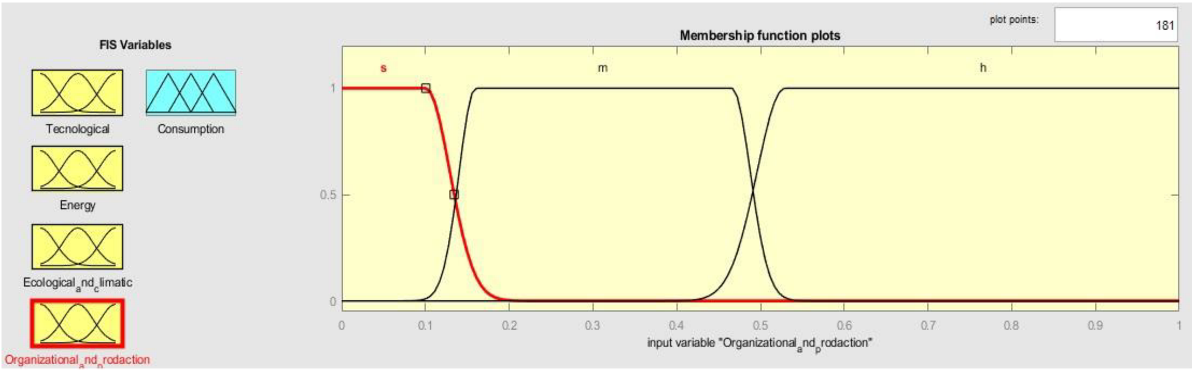

Figure 5: Membership functions of the Organizational and Production variable.

Although the basic system for calculating electricity consumption involves multiplying the volume of manufactured products by the specific energy consumption of equipment per unit of output, in practice this approach does not take into account the influence of additional factors. Such factors include the technical condition of equipment, organizational and production conditions, as well as environmental and climatic deviations, which together form additional energy costs for the enterprise [19].

To assess the fuzziness of the system of the additional consumption coefficient of the enterprise, the Mamdani mechanism should be used, since the relationship between the input and output variables corresponds to the logical conclusion "if-then". To determine the additional consumption coefficient, a Gaussian-type function is used.

For the, the characteristics are defined as follows:

1. Small level $s \in [0; 0.35)$.
2. Medium level $m \in (0.35; 0.7)$.
3. High level $h \in (0.7; 1)$.

Figure 6 shows a general view of the membership functions of the output of the fuzzy additional consumption systems for energy resource planning.

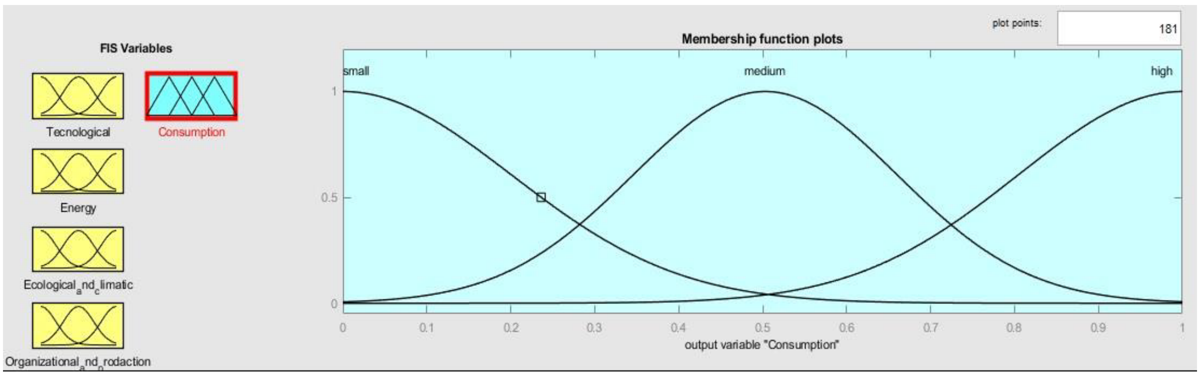

Figure 6: The membership functions of the output of the fuzzy additional consumption systems for energy resource planning.

In the power consumption planning model, each input variable has three states, namely low, medium and high, as well as an additional state that indicates the absence of information. If data is missing for two variables, the system interprets this as an increased level of uncertainty, which may indicate the risk of overspending or shortage of energy resources. In the case when information is missing for three variables, it becomes impossible to form an accurate forecast of power consumption, since the model loses the basic guidelines for assessing the current state.

To create a fuzzy planning system, $4 \times 4 \times 4 \times 4 - 13 = 242$ rules were defined, which form the basis of logical dependencies between input parameters and the level of expected power consumption. This structure allows the model to adapt to different production scenarios and provide flexible forecasting of the energy needs of the enterprise. Figure 7 shows an example of building a rule base for a fuzzy power consumption planning system.

31. If (Tecnological is m) and (Energy is s) and (Ecological_and_climatic is m) and (Organizational_and_prodaction is s) then (Consumption is small) (1)
32. If (Tecnological is m) and (Energy is s) and (Ecological_and_climatic is m) and (Organizational_and_prodaction is m) then (Consumption is medium) (1)
33. If (Tecnological is m) and (Energy is s) and (Ecological_and_climatic is m) and (Organizational_and_prodaction is h) then (Consumption is medium) (1)
34. If (Tecnological is m) and (Energy is s) and (Ecological_and_climatic is h) and (Organizational_and_prodaction is s) then (Consumption is medium) (1)
35. If (Tecnological is m) and (Energy is s) and (Ecological_and_climatic is h) and (Organizational_and_prodaction is m) then (Consumption is high) (1)
36. If (Tecnological is m) and (Energy is s) and (Ecological_and_climatic is h) and (Organizational_and_prodaction is h) then (Consumption is high) (1)
37. If (Tecnological is m) and (Energy is m) and (Ecological_and_climatic is s) and (Organizational_and_prodaction is s) then (Consumption is small) (1)
38. If (Tecnological is m) and (Energy is m) and (Ecological_and_climatic is s) and (Organizational_and_prodaction is m) then (Consumption is small) (1)
39. If (Tecnological is m) and (Energy is m) and (Ecological_and_climatic is s) and (Organizational_and_prodaction is h) then (Consumption is medium) (1)
40. If (Tecnological is m) and (Energy is m) and (Ecological_and_climatic is m) and (Organizational_and_prodaction is s) then (Consumption is medium) (1)
41. If (Tecnological is m) and (Energy is m) and (Ecological_and_climatic is m) and (Organizational_and_prodaction is m) then (Consumption is medium) (1)
42. If (Tecnological is m) and (Energy is m) and (Ecological_and_climatic is m) and (Organizational_and_prodaction is h) then (Consumption is medium) (1)
43. If (Tecnological is m) and (Energy is m) and (Ecological_and_climatic is h) and (Organizational_and_prodaction is s) then (Consumption is medium) (1)
44. If (Tecnological is m) and (Energy is m) and (Ecological_and_climatic is h) and (Organizational_and_prodaction is m) then (Consumption is high) (1)
45. If (Tecnological is m) and (Energy is m) and (Ecological_and_climatic is h) and (Organizational_and_prodaction is h) then (Consumption is high) (1)
46. If (Tecnological is m) and (Energy is h) and (Ecological_and_climatic is s) and (Organizational_and_prodaction is s) then (Consumption is small) (1)
47. If (Tecnological is m) and (Energy is h) and (Ecological_and_climatic is s) and (Organizational_and_prodaction is m) then (Consumption is medium) (1)
48. If (Tecnological is m) and (Energy is h) and (Ecological_and_climatic is s) and (Organizational_and_prodaction is h) then (Consumption is medium) (1)
49. If (Tecnological is m) and (Energy is h) and (Ecological_and_climatic is m) and (Organizational_and_prodaction is s) then (Consumption is medium) (1)
50. If (Tecnological is m) and (Energy is h) and (Ecological_and_climatic is m) and (Organizational_and_prodaction is m) then (Consumption is medium) (1)
51. If (Tecnological is m) and (Energy is h) and (Ecological_and_climatic is m) and (Organizational_and_prodaction is h) then (Consumption is high) (1)
52. If (Tecnological is m) and (Energy is h) and (Ecological_and_climatic is h) and (Organizational_and_prodaction is s) then (Consumption is high) (1)

Figure 7: An example of building a rule base.

4. Case study

To assess the accuracy of the proposed fuzzy system for determining the coefficient of electricity consumption for energy resource planning, the results of its operation are shown in Figure 8. The obtained data demonstrate how the model reacts to changes in input parameters, such as the level of equipment loading, production intensity, temperature regime and other factors and forms a forecast of energy consumption taking into account the degree of uncertainty. This allows us to assess the efficiency and stability of the system, as well as to check the correspondence of the predicted values to the actual results of electricity consumption.

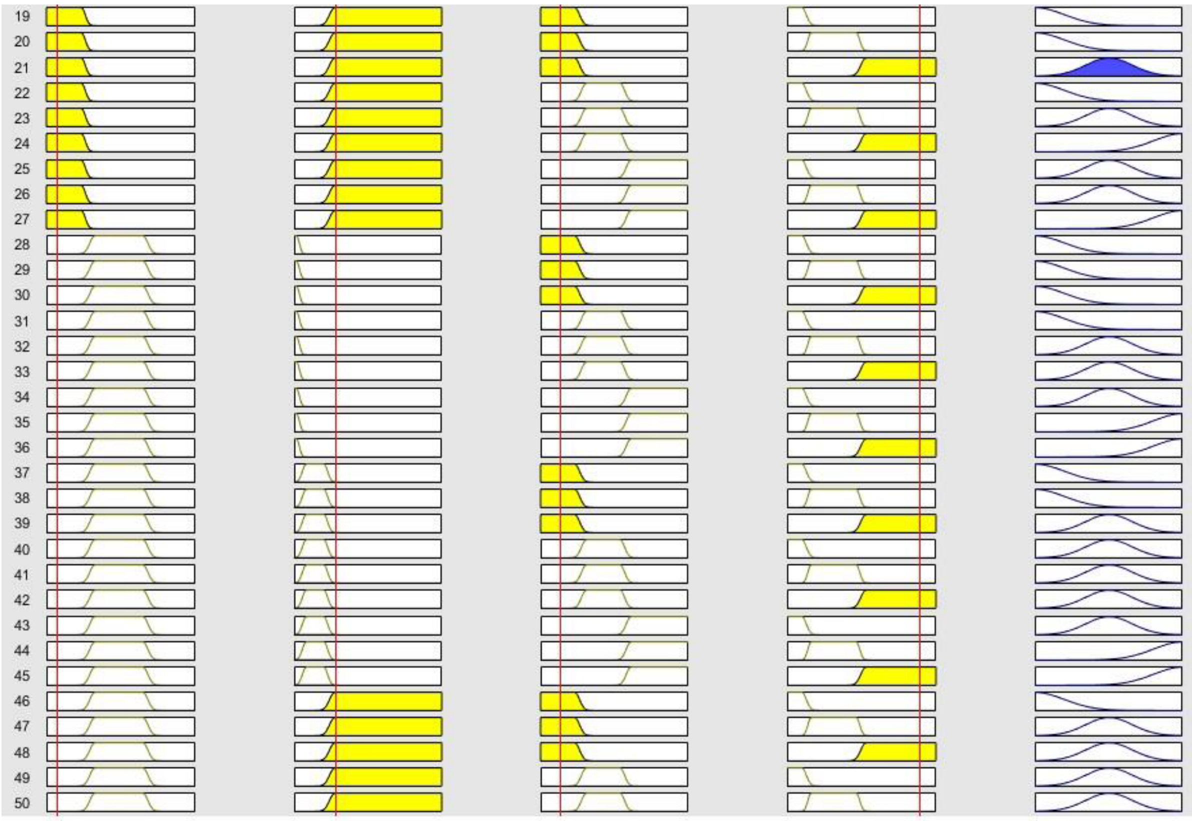

Figure 8: Results of the fuzzy system of the fuzzy additional consumption systems for energy resource planning.

The dependence of the value of the output variable on certain input data is represented by the value surfaces shown in Figure 9.

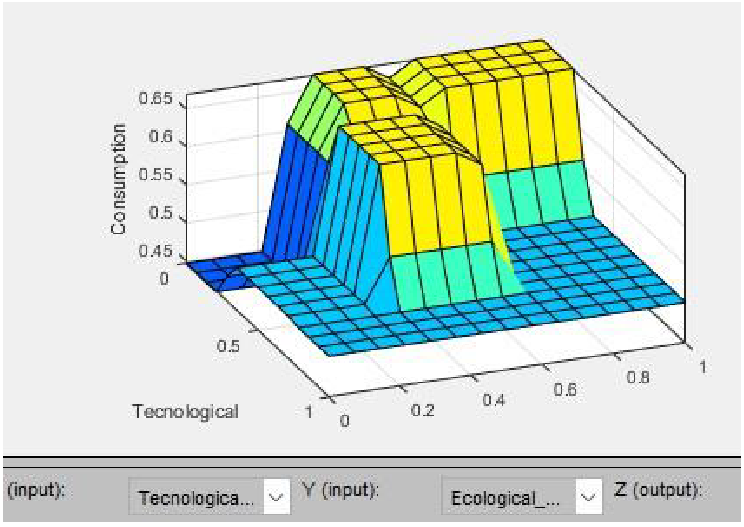

Figure 9: Dependence of technical and ecological-climatic variable.

5. Conclusion

The developed fuzzy-set approach to planning energy needs of enterprises allows to increase the accuracy of forecasting and adaptability of the energy management system in conditions of uncertainty. Unlike traditional methods, the proposed model takes into account not only quantitative, but also qualitative variables – technical, energy, environmental-climatic and organizational-production factors, which comprehensively affect the level of electricity consumption. The use of fuzzy logic provides the possibility of modeling real production conditions in which the values of parameters change gradually, rather than discretely, which allows to obtain more realistic forecasts of energy consumption.

The use of a fuzzy set system in the MATLAB environment creates the prerequisites for the formation of an intelligent energy planning system capable of working with incomplete or contradictory data, automatically responding to changes in production load, power supply quality or climatic conditions. The practical implementation of such an approach will contribute to reducing energy losses, increasing the efficiency of electricity use and ensuring the stability of the functioning of enterprises. In the future, the fuzzy-multiple model can be integrated into energy management systems, forming the basis for creating digital "smart" solutions for energy-efficient production management.

Declaration on Generative AI

During the preparation of this work, the authors used GPT to check grammar and spelling. After using this tool, the authors reviewed and edited the content as necessary and bear full responsibility for the content of the publication.

References

[1] A. Schwung, S. X. Ding, Actor-critic reinforcement learning for energy optimization in hybrid production environments, Int. J. Comput 18 (4) (2019) 360–371. doi:10.47839/ijc.18.4.1607.

[2] M. Heydari, A. Heydari, M. Amini, Energy management and energy consumption: A comprehensive study, World Information Technology and Engineering Journal 10 (4) (2023) 22–28.

[3] Y. Fathy, M. Jaber, Z. Nadeem, Digital twin-driven decision making and planning for energy consumption, J. Sens. Actuat. Netw. 10 (2021). doi:10.3390/jsan10020037.

[4] T. E. Lee, S. A. Haben, P. Grindrod, Modelling the electricity consumption of small to medium enterprises, in: G. Russo, V. Capasso, G. Nicosia, V. Romano (Eds.), Progress in industrial

mathematics at ECMI 2014, Springer International Publishing, Cham, Switzerland, 2016, pp. 341–349 doi:10.1007/978-3-319-23413-7_45.

[5] Eurostat, Supply, transformation and consumption of electricity, 2025. URL: https://ec.europa.eu/eurostat/databrowser/view/nrg_cb_e/default/table?lang=en.

[6] Eurostat, Electricity and heat statistics, 2025. URL: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Electricity_and_heat_statistics.

[7] I. U. Rakhmonov, N. N. Niyozov, N. N. Kurbonov, B. S. Umarov, Forecasting of electricity consumption by industrial enterprises with a continuous nature of production, in: Proceedings of Rudenko International Conference "Methodological Problems in Reliability Study of Large Energy Systems", RSES '2022, EDP Sciences, Les Ulis, France, 2023. doi:10.1051/e3sconf/202338401030.

[8] S. Henning, W. Hasselbring, H. Burmester, et al., Goals and measures for analyzing power consumption data in manufacturing enterprises, J. Data Inf. Manag. 3 (2021) 65–82. doi:10.1007/s42488-021-00043-5.

[9] P. A. Stanchev, G. I. Vacheva, N. L. Hinov, Analysis of electrical energy consumption of industrial enterprises based on IoT, in: Proceedings of the 59th Int. Sci. Conf. Information, Communication and Energy Systems and Technologies, ICEST '2024, IEEE, New York, NY, 2024, pp. 174–176. doi:10.1109/ICEST62335.2024.10639794.

[10] J. Oh, D. Min, Prediction of energy consumption for manufacturing small and medium-sized enterprises (SMEs) considering industry characteristics, Energy 300 (2024). doi:10.1016/j.energy.2024.131621.

[11] O. Sinchuk, R. Strzelecki, T. Beridze, I. Peresunko, V. Baranovskyi, D. Kobeliatskyi, V. Zapalskyi, Model studies to identify input parameters of an algorithm controlling electric supply/consumption process by underground iron ore enterprises, Mining of Mineral Deposits 17 (2023) 93–101. doi:10.33271/mining17.03.093.

[12] S. Vats, S. K. Sharma, S. Kumar, A switch based resource management method for energy optimization in cloud data center, Int. J. Comput. 20 (1) (2021) 85–91. doi:10.47839/ijc.20.1.2103.

[13] G. Grigoraș, B.-C. Neagu, O. Ivanov, Aggregate Method based on Expert System for Electricity Consumption Forecasting of Small and Medium Enterprises," in: Proceedings of the 11th Int. Symp. Advanced Topics in Electrical Engineering, ATEE ‘2019, IEEE, New York, NY, 2019, pp. 1–6. doi:10.1109/ATEE.2019.8724966.

[14] A. Sachenko, B. Derysh, L. Dubchak, S. Sachenko, O. Chereshnyuk, Real-time military vehicle classification via convolutional neural networks, in: Proceedings of the Modern Data Science Technologies Doctoral Consortium 2025, MoDaST '2025, CEUR Workshop Proceedings, Aachen, Germany, 2025, pp. 239–251.

[15] O. Kozlov, Information Technology for Designing Rule Bases of Fuzzy Systems Using Ant Colony Optimization, Int. J. Comput. 20 (4) (2021) 471–486. doi:10.47839/ijc.20.4.2434.

[16] H. Ahmed, M. Nassereddine, Empowering energy efficiency: Fuzzy logic weather prediction in smart energy management, in: Proceedings of the 2024 International Conference on Electrical, Computer and Energy Technologies, ICECET '2024, IEEE, New York, NY, 2024, pp. 1–6, doi:10.1109/ICECET61485.2024.10698513.

[17] N. Vasylkiv, L. Dubchak, A. Sachenko, Estimation method of information system functioning quality based on the fuzzy logic, in: Proceedings of the Modern Machine Learning Technologies and Data Science Workshop 2020, MoMLeT+DS '2020, CEUR Workshop Proceedings, Aachen, Germany, 2020, pp. 40–56.

[18] B. Tarle, M. Akkalaksmi, Improving classification performance of neuro-fuzzy classifier by imputing missing data, Int. J. Comput. 18 (4) (2019) 495–501. doi:10.47839/ijc.18.4.1619.

[19] V. Dzhedzhula, I. Yepifanova, Y. Kravchyk, Use of the theory of fuzzy sets in determining the level of enterprise security, in: Proceedings of the 12th International Conference on Advanced Computer Information Technologies, ACIT '2022, IEEE, New York, NY, 2022, pp. 311–315, doi:10.1109/ACIT54803.2022.9913150.