MUHAMMAD AL-XORAZMIY
NOMIDAGI TATU FARG'ONA FILIALI

FERGANA BRANCH OF TUIT
NAMED AFTER MUHAMMAD AL-KHORAZMI

"AL-FARG'ONIY AVLODLARI"

ELEKTRON ILMIY JURNALI | ELECTRONIC SCIENTIFIC JOURNAL

TA'LIMDAGI ILMIY, OMMABOP VA ILMIY TADQIQOT ISHLARI

4-SON 1(8)
2024-YIL

TATU, FARG'ONA
O'ZBEKISTON

ISSN 2181-4252

O‘ZBEKISTON RESPUBLIKASI RAQAMLI TEXNOLOGIYALAR VAZIRLIGI

MUHAMMAD AL-XORAZMIY NOMIDAGI TOSHKENT AXBOROT TEXNOLOGIYALARI UNIVERSITETI FARG‘ONA FILIALI

Muassis: Muhammad al-Xorazmiy nomidagi Toshkent axborot texnologiyalari universiteti Farg‘ona filiali.
Chop etish tili: O‘zbek, ingliz, rus.
Jurnal texnika fanlariga ixtisoslashgan bo‘lib, barcha shu sohadagi matematika, fizika, axborot texnologiyalari yo‘nalishida maqolalar chop etib boradi.

Учредитель: Ферганский филиал Ташкентского университета информационных технологий имени Мухаммада ал-Хоразми.
Язык издания: узбекский, английский, русский.
Журнал специализируется на технических науках и публикует статьи в области математики, физики и информационных технологий.

Founder: Fergana branch of the Tashkent University of Information Technologies named after Muhammad al-Khorazmi.
Language of publication: Uzbek, English, Russian.
The magazine specializes in technical sciences and publishes articles in the field of mathematics, physics, and information technology.

2024 yil, Tom 1, №4
Vol.1, Iss.4, 2024 y

ELEKTRON ILMIY JURNALI

ELECTRONIC SCIENTIFIC JOURNAL

«Al-Farg‘oniy avlodlari» («The descendants of al-Fargani», «Potomki al-Fergani») O‘zbekiston Respublikasi Prezidenti administratsiyasi huzuridagi Axborot va ommaviy kommunikatsiyalar agentligida 2022-yil 21 dekabrda 054493-son bilan ro‘yxatdan o‘tgan.

Jurnal OAK Rayosatining 2023-yil 30 sentabrdagi 343-sonli qarori bilan Texnika fanlari yo‘nalishida milliy nashrlar ro‘yxatiga kiritilgan.

Tahririyat manzili:
151100, Farg‘ona sh.,
Aeroport ko‘chasi 17-uy,
202A-xona
Tel: (+99899) 998-01-42
e-mail: info@al-fargoniy.uz

FARG’ONA - 2024 YIL

Jurnal quyidagi bazalarda indekslanadi:

Eslatma! Jurnal materiallari to'plamiga kiritilgan ilmiy maqolalardagi raqamlar, ma'lumotlar haqqoniyligiga va keltirilgan iqtiboslar to'g'riligiga mualliflar shaxsan javobgardirlar.

MUNDARIJA | ОГЛАВЛЕНИЕ | TABLE OF CONTENTS

MUNDARIJA | ОГЛАВЛЕНИЕ | TABLE OF CONTENTS

MUNDARIJA | ОГЛАВЛЕНИЕ | TABLE OF CONTENTS

FUZZY RULE BASE DESIGN FOR NUMERICAL DATA ANALYSIS

Ergashev Otabek Mirzapulatovich
Associate Professor of the Department of Information Technologies, Fergana branch of the Tashkent University of Information Technologies,
Address: Fergana, 150118, st. Mustakillik, building 185,
E-mail: ergashev1984otabek@gmail.com

Abstract: Fuzzy logic has become increasingly prominent in addressing uncertainties inherent in decision-making processes across various domains. A pivotal component of fuzzy systems is the rule base, which establishes the relationships between inputs and outputs. While traditionally constructed based on expert knowledge or iterative learning from numerical data, there is a growing need to design rule bases solely from numerical data in scenarios lacking expert input. This paper explores methodologies for constructing rule bases from numerical data, considering challenges such as selecting appropriate membership functions and determining rule structures. We discuss the advantages, limitations, and novel techniques to enhance the efficiency and effectiveness of rule base design in fuzzy systems. By tackling the problem of rule base design from numerical data, this research advances fuzzy systems’ capabilities, paving the way for more robust and adaptable solutions in various application domains.

Keywords: Fuzzy logic, Rule base design, Numerical data, Membership functions, Fuzzy systems, Decision-making, Uncertainty, Expert systems, Control systems, Data-driven modeling

Introduction. Fuzzy logic has emerged as a powerful tool for dealing with uncertainty and imprecision in decision-making processes. In many real-world applications, particularly in control systems and decision support systems, the ability to handle vague and uncertain information is crucial for achieving robust and effective solutions. Fuzzy systems, based on fuzzy set theory and fuzzy logic, provide a framework for modeling and reasoning with such uncertain information. One key aspect of fuzzy systems is the rule base, which defines the relationships between inputs and outputs in the system. Traditionally, rule bases are constructed based on expert knowledge or through iterative learning from numerical data. However, in scenarios where expert knowledge is limited or unavailable, constructing a rule base solely from numerical data becomes imperative. [1]

In this context, the problem of designing a rule base from numerical data becomes paramount. This problem entails transforming numerical data into a set of rules that can effectively capture the underlying patterns and relationships in the data. The resulting rule base should enable the fuzzy system to make accurate and reliable decisions or control actions based on the given inputs. This paper aims to explore various methodologies and techniques for constructing rule bases from numerical data. We delve into the challenges and considerations involved in this process, including the selection of appropriate membership functions, the determination of rule structures, and the evaluation of rule quality. Additionally, we discuss the advantages and limitations of different approaches and propose novel methods to enhance the effectiveness and efficiency of rule base design in fuzzy systems.

Literature Analysis and Methodology. The methods section of this study involves several key steps designed to ensure accuracy, reliability, and meaningful outcomes from the analysis. First, relevant numerical datasets were gathered from various sources, including experiments, simulations, and real-world observations. The collected data underwent a thorough cleaning and preprocessing phase to eliminate noise, outliers, and inconsistencies, thereby ensuring high-quality and reliable data for subsequent analysis.

Next, the identification of key variables was performed to pinpoint the most influential factors affecting the decision-making process or control system under investigation. This step relied on a combination of domain expertise and advanced data analysis techniques to determine the most relevant input and output variables. [3]

Finally, a robust rule base was constructed by exploring methodologies to derive rules from numerical data. Clustering algorithms, such as k-means and fuzzy c-means, were employed to identify patterns and relationships within the data, which were then converted into fuzzy rules. Additionally, rule extraction techniques, such as decision tree induction and genetic algorithms, were investigated to automatically derive meaningful rules that align with the study's objectives.

The methodology adopted in this study is comprehensive and systematic, ensuring that every step contributes effectively to achieving the research objectives. The first phase involved collecting numerical datasets from diverse sources such as experimental setups, computer simulations, and real-world observations. These datasets were meticulously cleaned and preprocessed to enhance their quality. This step involved handling missing values, removing outliers, normalizing data, and resolving inconsistencies to create a reliable foundation for subsequent analysis. The focus on high-quality data was critical to ensuring accurate insights and robust conclusions.

The second phase involved the identification of key variables that significantly impact the decision-making process or the system being analyzed. This step was pivotal in narrowing down the focus to the most influential factors. A combination of domain-specific knowledge and advanced data analysis techniques was employed to identify relevant input and output variables. Statistical methods and exploratory data analysis techniques, including correlation analysis and feature importance evaluations, were applied to verify the significance of the selected variables. This ensured that the study's focus remained on variables that directly influenced outcomes. [2]

The construction of the rule base formed the core of the study, as it encapsulated the relationships between variables and defined the system's decision-making logic. The process involved exploring various methodologies for rule generation from numerical data. Clustering algorithms, such as k-means and fuzzy c-means, were employed to detect patterns and group data points based on similarity. These clusters were then translated into fuzzy rules, providing a systematic way to capture complex relationships. Additionally, rule extraction techniques, such as decision tree induction and genetic algorithms, were used to automatically derive rules from data. These techniques offered complementary approaches, with decision trees providing a structured, interpretable framework and genetic algorithms optimizing rule sets for higher performance.

The integration of these methodologies ensured a comprehensive approach to analyzing data and deriving meaningful insights. Each step was iteratively refined to ensure that the developed fuzzy logic system or control model was both accurate and adaptable to real-world applications.

Results. The construction of the rule base was a pivotal step in developing the fuzzy system, where numerical data were processed and systematically utilized to establish a comprehensive set of rules. Clustering algorithms played a central role in this process by identifying inherent patterns and relationships within the data. These patterns were then translated into fuzzy rules, capturing the essential structure of the data. Complementing this approach, rule extraction techniques such as decision tree induction and genetic algorithms were employed to derive interpretable rules automatically. These methods facilitated the generation of a robust and reliable rule base, ensuring that the system could effectively model the underlying dynamics of the data.

Refinement and optimization of the rule base were undertaken to enhance its overall performance. Techniques aimed at pruning redundant or irrelevant rules were applied, resulting in a streamlined and efficient rule base. This pruning process reduced computational complexity while maintaining the system's accuracy and effectiveness. Additionally, optimization strategies were implemented to further improve the rule base. Adjustments were made to membership function parameters and rule weights, ensuring optimal alignment between the rules and the data. This iterative refinement process enhanced the system’s performance, making it more robust and adaptable to diverse scenarios. [4]

Fuzzy systems, rooted in fuzzy set theory and fuzzy logic, constitute a vital class of intelligent information systems. These systems rely on fuzzy modeling to structure and parameterize their components, enabling the formalization and analysis of semi-structured, incomplete, and uncertain information inherent in complex domains. Fuzzy systems often employ fuzzy production systems (FPS), characterized by "if-then" rules, akin to conventional production systems. FPS utilize linguistic approximations, drawn from expert knowledge or data analysis, to describe system behaviors.

At the computational level, FPS serve as flexible mathematical structures capable of accurately approximating complex systems, including nonlinear ones, through fuzzy inference mechanisms. As universal approximators, FPS find applications in diverse expert systems such as control, forecasting, and decision making.

In many regulatory problems, information required for control system development comprises numerical data from sensors and qualitative insights from experts. While fuzzy regulatory systems primarily leverage qualitative knowledge, challenges arise when only numerical data are available for fuzzy system design.

Addressing this challenge, iterative learning processes facilitate the construction of rule bases for fuzzy systems. Despite their advantages, iterative learning can be time-consuming. However, a method exists to combine numerical data with linguistic rules efficiently. This approach involves supplementing existing rule bases with rules derived from numerical data, ensuring the integration of both types of information into the fuzzy system design.

This integration process offers several advantages. Firstly, it enhances the comprehensiveness of the rule base by incorporating both quantitative and qualitative insights, thereby improving the system’s ability to handle complex real-world scenarios. Secondly, it reduces the time and effort required for rule base development, as it leverages existing numerical data to generate rules, circumventing the need for extensive manual rule creation.

Furthermore, by combining numerical information with linguistic rules, the resulting fuzzy system becomes more adaptable and responsive to changes in the environment or input data. This adaptability is crucial for applications such as real-time control systems or dynamic decision-making processes, where quick adjustments based on changing conditions are necessary.

Overall, the approach of integrating numerical data with linguistic rules not only addresses the challenge of rule base creation in fuzzy systems but also enhances the system’s effectiveness, efficiency, and adaptability in diverse application domains. As such, it represents a valuable strategy for designing robust and intelligent information systems capable of effectively navigating the complexities of uncertain and dynamic environments.[6]

Building fuzzy rules

Let’s imagine a scenario where we’re simplifying the creation of a rule base for a fuzzy system with two inputs and one output. This setup involves defining rules that govern how the inputs relate to the output within the fuzzy logic framework. Obviously, this requires training data in the form of a set of pairs

$(x_1(i), x_2(i), d(i)), i = 1,2..., (1)$

where $x_1(i), x_2(i)$ are the signals applied to the input of the fuzzy control module, and $d(i)$ is the expected (reference) value of the output signal. The task is to form such fuzzy rules so that the control module constructed on their basis, upon receiving input signals, generates correct (having the smallest error) output signals.

Step 1. Dividing the spaces of input and output signals into regions.

Imagine that we know the minimum and maximum values of each signal. From them, you can determine the intervals in which the valid values are found. For example, for an input signal x_1, we denote such an interval $[x_1^-, x_1^+]$. If the values of x_1^- and x_1^+ are unknown, then you can use the training data and choose from them, respectively, the minimum and maximum values

$x_1^- = min(x_1), x_1^+ = max(x_1)$ (2)

Similarly, for the signal x_2 we define the interval $[x_2^-, x_2^+]$, and for the reference signal d- the interval $[d^-, d^+]$. [5]

Each interval defined in this way is divided into (2*N*+1) regions (segments), and the value of *N* for each signal is selected individually, and the segments can have the same or different lengths. Separate areas are denoted as follows: M_N (Small N, ..., (Small 1), *S* (Medium), D_1(Large 1), ..., D_N (Large N) and for each of them we define one membership function. Fig. 1 shows an example of such a division, where the definition area of the signal x_1 is divided into five subareas *N*=2, the signal x_2 - into seven subareas *N*=3, while the definition area of the output signal *y* is divided into five subareas *N*=2.

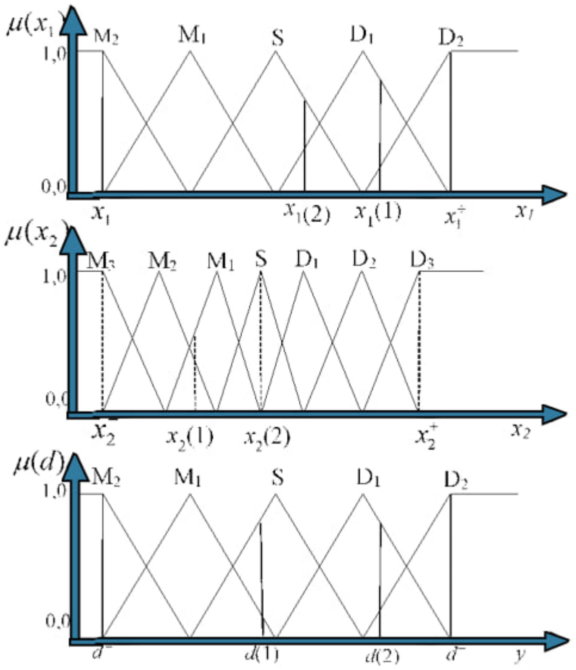

Fig. 1. Separation of spaces of input and output signals into regions and corresponding membership functions.

Each membership function adopts a triangular shape, where one vertex aligns with the center of the region, representing a function value of 1. The other two vertices align with the centers of neighboring regions, corresponding to function values of 0. While this division serves as an example, alternative approaches for partitioning input and output spaces into distinct regions and employing different membership function shapes are also viable. [7]

Step 2. Building fuzzy rules based on training data.

First, we determine the degrees of membership of the training data $(x_1(i), x_2(i) \text{and} d(i))$ in each area identified in step 1. These degrees will be expressed by the values of the membership functions of the corresponding fuzzy sets for each data group. For example, for the case shown in fig.1, the degree of belonging of a given $x_1(1)$ to the area D_1 is 0.8, to the area D_2 - 0.2, and to the remaining areas - 0. Similarly, for a given $x_1(2)$, the degree of membership in the area *S* is 1, and to the remaining areas - 0. Now let’s compare training data $(x_1(i), x_2(i) \text{and} d(i))$ to the areas in which they have the maximum degree of membership. Note that $x_1(1)$ has the highest degree of belonging to the area D_1, and $x_2(2)$ - to the area *S*. Finally, for each pair of training data, one rule can be written, i.e.

$(x_1(1), x_2(1); d(1)) \Rightarrow$
$\{x_1(1)[max: 0,8_v\ D_1], x_2(1)[max: 0,6_v$
$M_1]; d(1)[max: 0,9_v S]\} \Rightarrow$
$R^{(1)}.\text{IF}(x_1 \text{this} D_1 \text{AND} x_2 \text{this} M_1)\text{THEN}(y \text{this} S); \Rightarrow$
$(x_1(2), x_2(2); d(2)) \Rightarrow$
$\{x_1(2)[max: 0,7_b\ S], x_2(2)[max: 1,0_b\ S]; d(2)[max: 0,7_v D_1]\}$
$\Rightarrow$
$R^{(2)}.\text{IF}(x_1 \text{this} S \text{AND} x_2 \text{this} S)\text{THEN}(y \text{this} D_1);$

Step 3. Assigning a degree of truth to each rule. [8]

As a rule, there are a large number of pairs of training data, for each of them one rule can be formulated, so there is a high probability that some of these rules will be inconsistent. This applies to rules with the same premise (condition), but with different consequences (conclusions). One way to solve this problem is to assign a so-called degree of truth to each rule, and then choose from among the rules that contradict each other the one with the highest degree. Thus, not only is the problem of conflicting rules resolved, but their total number is significantly reduced. For a rule of the form

$R.\text{IF}(x_1 \text{this} A_1 \text{AND} x_2 \text{this} A_1) \text{THEN} (y \text{this} B),$ (3)

the degree of truth, denoted as SP(R), is defined as

$\text{SP}(R) = \mu_{A_1}(x_1) \cdot \mu_{A_2}(x_2) \cdot \mu_B(y)$ (4)

Thus, the first ($R^{(1)}$) rule from our example has a degree of truth

$\text{SP}(R^{(1)}) = \mu_{D_1}(x_1) \cdot \mu_{M_1}(x_2) \cdot \mu_S(y) = 0{,}8 \times 0{,}6 \times 0{,}9 = 0{,}432$ (5)

and the second rule is

$\text{SP}(R^{(2)}) = \mu_{S_1}(x_1) \cdot \mu_S(x_2) \cdot \mu_{D_1}(y) = 0{,}7 \times 1{,}0 \times 0{,}7 = 0{,}49$ (6)

Step 4. Creating a base of fuzzy rules.

The method of constructing the base of fuzzy rules is shown in fig. 2. This base is represented by a table that is filled with fuzzy rules as follows: if the rule has the form

$R^{(1)}.\text{IF}(x_1 \text{this} D_1 \text{AND} x_2 \text{this} M_1) \text{THEN} y \text{this} S,$ (7)

then at the intersection of the row D_1 (corresponding to the signal x_1) and the column M_1 (signal x_2) we enter the name of the fuzzy set present in the consequence, i.e. S (corresponding to the output signal y). If there are several fuzzy rules with the same premise, then the one that has the highest degree of truth is selected from them.

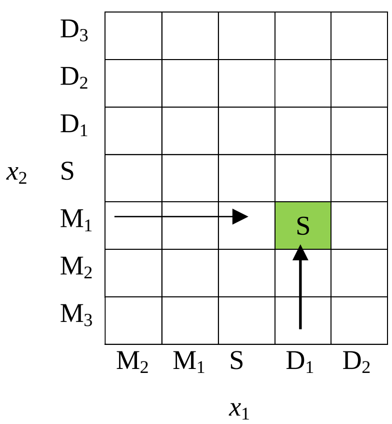

Fig. 2. Form of fuzzy rule base

Step 5. Defuzzification. [9]

Our task is to determine, using the base of rules, the mapping $f: (x_1, x_2) \to \bar{y}$, where $\bar{y}$ is the output value of the fuzzy system. When determining the quantitative value of the control action $\bar{y}$ for data, input signals (x_1, x_2), it is necessary to perform a defuzzification operation. First, for the input signals (x_1, x_2), using the product operation, we combine the premises (conditions) of the k-th fuzzy rule. Thus, the so-called degree of activity of the k-th rule is determined. Its value is calculated by the formula

$\tau^{(k)} = \mu_{A_1(k)}(x_1)\mu_{A_2(k)}(x_2)$ (8)

For example, for the first $R^{(1)}$ rule, the degree of activity is determined by the expression

$\tau^{(1)} = \mu_{D_1}(x_1)\mu_{M_2}(x_2)$ (9)

To calculate the output value $\bar{y}$, we use the defuzzification method by the average center

$\bar{y} = \frac{\sum_{k=1}^{N} \tau^{(k)} \bar{y}^{(k)}}{\sum_{k=1}^{N} \tau^{(k)}}$ (10)

The approach discussed can be readily extended to fuzzy systems with any number of inputs and outputs. Figure 3 illustrates an algorithm for constructing a rule base, depicted in the form of a block diagram. This diagram provides a foundation for developing a suitable software implementation. [10]

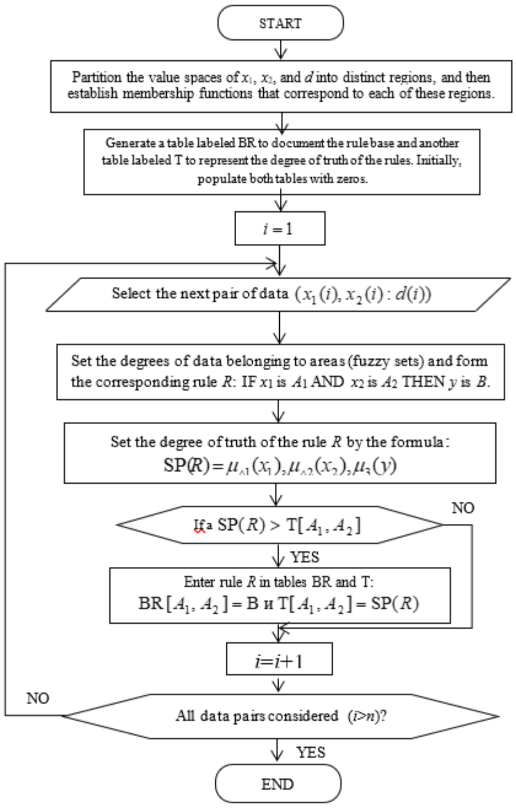

Fig. 3. Block diagram of building a rule base based on numerical data.

The process of generating rules according to the outlined algorithm heavily relies on the arrangement of membership functions of fuzzy sets. During simulation experiments, diverse variants of these functions were explored, resulting in varying qualities of control for each rule base. However, determining the optimal placement of membership functions remains an independent challenge beyond the scope of this paper. [11]

In this presented training scheme, pairs of training data serve as initial information, ultimately resulting in a mapping from the input data space to the output space. This method possesses both the capability to train the mapping from available examples and the property of generalization, enabling satisfactory output signals even for new input signals not present in the training sample. Consequently, this method embodies a highly versatile, model-free trainable fuzzy system applicable to a broad spectrum of control problems.

The term "model-free" indicates that a mathematical model of the control process isn't necessary for problem-solving, while "trainable" denotes the system's ability to accumulate knowledge from examples. The advantages of this method are underscored by the following points:

1) It serves as a universal approach for constructing a rule base from numerical data, often serving as the initial phase in constructing a fuzzy control module when only numerical data are available.

2) It offers a straightforward procedure for rule base construction, significantly reducing the time required compared to more iterative training methods like neuro-fuzzy systems.

3) There exists considerable freedom in selecting membership functions, granting ample flexibility in designing systems for diverse applications. [12]

Conclusion. In conclusion, the integration of numerical data with linguistic rules presents a promising approach for enhancing the design and performance of fuzzy systems. By combining quantitative and qualitative insights, this method not only enriches the rule base but also streamlines the development process, mitigating the challenges associated with rule creation in complex domains. Moreover, this integration fosters adaptability and responsiveness, crucial traits for systems operating in dynamic environments where quick adjustments are essential. Overall, this approach stands as a valuable strategy for crafting robust and intelligent information systems capable of effectively addressing the intricacies of uncertain and ever-changing real-world scenarios. As research and applications in fuzzy systems continue to evolve, the integration of numerical data with linguistic rules promises to remain a cornerstone for advancing the effectiveness, efficiency, and adaptability of these intelligent systems across various domains.

References

1. N. R. Yusupbekov, A. R. Marakhimov, H. Z. Igamberdiev, and Sh. X. Umarov. An adaptive fuzzy-logic traffic control system

in conditions of saturated transport stream. 2016. The Scientific World Journal Volume 2016 |Article ID 6719459 | https://doi.org/10.1155/2016/6719459.

2. Y. Ge, “A two-stage fuzzy logic control method of traffic signal based on traffic urgency degree,” *Modelling and Simulation in Engineering*, vol. 2014, Article ID 694185, 6 pages, 2014.
3. F. Sattar, F. Karray, M. Kamel, L. Nassar, and K. Golestan, “Recent advances on context-awareness and data/information fusion in ITS,” *International Journal of Intelligent Transportation Systems Research*, vol. 14, no. 1, pp. 1–19, 2016.
4. Sidikov I.X., Umurzakova D.M. (2019) Adaptive neuro-fuzzy regulating system of the temperature mode of the drum boiler // International Journal of Advanced Research in Science, Engineering and Technology, 6(1): 7869-7872.
5. Эргашев О. М., Эргашева Ш. М. Алгоритмы динамической фильтрации с учетом инерции измерительного устройства //Universum: технические науки. – 2020. – №. 2-1 (71).
6. Mirzapolatovich E. O., Eralievich T. A., Mavlonzhonovich M. M. Analysis of Static Characteristics Optoelectronic Level Converters Liquids and Gases Based on Hollow Light Guides //EUROPEAN JOURNAL OF INNOVATION IN NONFORMAL EDUCATION. – 2022. – Т. 2. – №. 6. – С. 29-31.
7. Ahmad Kermani, Seyed Mohamad Kargar, Fuzzy modelling of combustion efficiency and control of excess air flow case study: 320-MW steam unit/Isfahan Power Plant/Iran. *Clean Energy*, Volume 5, Issue 2, June 2021, Pages 229–242, https://doi.org/10.1093/ce/zkab005
8. Эргашев, О. М. (2018). Обеспечение информационной безопасности радиотехнических систем. *Теория и практика современной науки*, (6 (36)), 689-691.
9. Ergashev, O. (2023). АХБОРОТ-КОММУНИКАЦИЯ ТЕХНОЛОГИЯЛАРИНИНГ МАМЛАКАТЛАР РИВОЖЛАНИШИДАГИ АҲАМИЯТИ. *Engineering problems and innovations*.
10. Эргашев, О. М. Анализ Процесса Разработка Информационной Системы Предприятия. *Innovative developments and research in education*, *1*(7), 30-35.
11. Эргашев, О. М. (2023). Интеллектуальный оптоэлектронный прибор для учета и контроля расходом воды в открытых каналах. *Al-Farg’oniy avlodlari*, *1*(4), 60-65.
12. Mirzapulatovich, E. O. (2023). UNDERWATER REMOTELY CONTROLLED ROBOT FOR CLEANING BOTTOM SPLIT FROM RESERVOIRS AND MAIN CHANNELS. *Best Journal of Innovation in Science, Research and Development*, *2*(11), 717-721.