E3S Web of Conferences **549**, 08009 (2024) https://doi.org/10.1051/e3sconf/202454908009
TransSiberia 2024

Comparison of ChatGPT and Bard for using in hybrid intelligent information systems

Radmir Kim[1], *Anton* Kotsenko[1], *Aleksandr* Andreev[1], *Dmitry* Aladin[1], and *Oleg* Varlamov[1*]

[1]Bauman Moscow State Technical University, 2-ya Baumanskaya Street, 5/1, Moscow, 105005, Russian Federation

Abstract. The purpose of this paper is to conduct research and comparative analysis of modern large language models, in particular, such as ChatGPT and Google Bard. As part of the research, the analysis of the advantages and disadvantages of advanced artificial intelligence technologies in various fields of application was carried out. Optimal conditions for using these models were identified, and methods for overcoming the identified shortcomings of large language models based on the mivar approach were proposed. Special attention is paid to the areas of application of large language models, such as providing a quick and effective response to user requests, as well as their use in training and staff adaptation tasks. This paper analyzes large language models, taking into account their integration methods, as well as the possibilities of creating personalized systems for automating communications. The research results include an analysis and comparison of the capabilities of LLM and identifying their advantages and disadvantages with a focus on the problem of “hallucinations”. The paper also proposes hypotheses about the potential overcoming of LLM limitations using the mivar approach. The results of experiments with ChatGPT confirm the relevance of creating structured knowledge and automating the process of building mivar data models, as well as indicate the prospects for combining LLM and the mivar approach. This can reduce the likelihood of generating erroneous information, increase the interpretability of results, and ensure more effective use of language models in various scenarios of artificial intelligence use.

1 Introduction

Creating new intelligent natural language processing technologies for machine learning artificial intelligence (AI) is essential. Intelligent dialogue systems are already solving many business problems. It should be investigated which methods will better solve natural language understanding (NLU) problems when building complex AI systems.

The development of mivar technologies of logical artificial intelligence has been going on for quite some time. They have proven themselves well in solving tasks in the format of production networks because they allow finding a solution with linear computational

* Corresponding author: ovarlamov@gmail.com

complexity [1]. Mivar technologies are actively used to create expert systems in the following areas: management of educational programs at the university [2], detailed description of knowledge in a scientific discipline [3], detection of bank check fraud [4], intelligent plant care systems [5], decision-making on the safety of thermolabile blood components [6], optimization of the process of preparing fresh frozen plasma for transfusion [7], diagnosis of diabetes [8], artificial intelligence in medicine [9], mechanical engineering [10] and many other areas. When creating hybrid artificial intelligence (AI) systems, mivar technologies have also found their place. They can be implemented in a wide variety of activities: creating a brief overview of judicial practice [11], detecting energy theft in smart grids using explainable attention maps [12], using metagraphs to represent data sets [13] to overcome limitations [14] and improve existing knowledge bases [15], for tasks of analysis and classification [16] of equivalent logical operations [17], solving first-order logical equations with exhaustive search for solutions [18].

The approach of hybrid AI with the application of mivar technologies includes neural network methods. Neural networks can be used for sentiment analysis based on text and audio data [19], for processing media information [20] and its optimal encoding [21], for working with satellite images [22] and with text queries [23]. In addition, hybrid AI can be used in the development of polymer microstructures [24] and composites [25], in modeling heat exchangers [26], as well as in the formation of intelligent technological units [27]. The use of mivar technologies in conjunction with a neural network approach can simplify the process of data analysis from LiDAR for the task of finding trees and estimating their diameter [28] and for measuring active gases affecting the climate for carbon landfills [29]. Mivar technologies can cope not only with decision-making but also with intelligent analysis of pulsed EPR for recognizing 3D objects by an optical location system [30]. The most promising area of application of the mivar approach and hybrid AI is the development of robotics [31] and navigation systems of robotic complexes [32], as well as the creation of intelligent vehicle control systems [33]. One of the complex tasks in this area is pathfinding [34] with planning the shortest route for a robotic complex [35]. Especially many conditions need to be taken into account when moving autonomous transport on public roads [36].

Moreover, other types of artificial intelligence are developing, primarily based on neural network technologies. When using a banking application, we will encounter AI in the same intelligent assistant or bot when communicating. There are other examples: we are already routinely surrounded by recommendation systems using AI. They suggest the most appropriate products or services to users based on their behavior on a website or their purchase history. There are voice assistants like Apple's Siri or Google Assistant, which use AI to recognize your voice and execute various commands. And automatic translators like Google Translate and Yandex Translator translate texts into different languages on the fly, etc. The final user of all these AI-based products and systems is a human being, so an integral part of the development of the entire cluster of conversational, dialogue-based AI is high-quality processing of user requests. This task includes both solving various text understanding tasks, such as defining user intentions based on context, and generating organic and human-understandable answers. Thus, one of the main achievements of recent years is that generative artificial intelligence has extended the capabilities of Natural Language Processing (NLP) tools in terms of comprehension accuracy and ability to generate high-quality answers.

In the context of machine learning, ChatGPT and BERT models can be applied to a variety of natural language processing tasks. One of the potential applications of these models can be the analysis of technical documentation: ChatGPT and BERT models can be used to analyse technical documentation and extract relevant information. This will help engineers to find relevant information quickly and improve their productivity. ChatGPT and BERT can also be useful in the field of error diagnosis – models can be trained to diagnose faults in mechanical systems based on natural language descriptions of symptoms and key performance indicators. This can help engineers to quickly identify and troubleshoot problems in mechanical systems. In summary, the topic of this paper is relevant and important for the creation of new intelligent natural language processing technologies in mechanical engineering.

2 Large Language Models

The breakthrough was the Large Language Model (LLM), a powerful large linguistic (language) model (LLM) that is huge in size and trained on large amounts of textual data. An LLM has the ability to generate texts, answer questions, translate languages and perform other tasks using its large trained base. An example of an LLM is the GPT-3 (Generative Pre-trained Transformer 3) model developed by OpenAI. GPT-3 is one of the largest and most powerful language models, consisting of 175 billion parameters. It is trained on a wide range of textual data and can generate coherent and informative query responses, as well as perform a variety of language tasks.

Another example of LLM is the BERT (Bidirectional Encoder Representations from Transformers) model developed by Google. BERT is a large language model trained on large amounts of text data. It demonstrates outstanding results in natural language processing tasks, including question-answering systems, text classification, and many other tasks. The most perspective models are Bard from Google, as another representative of LLM, and GPT family models from OpenAI, the most popular of which is ChatGPT. Research is needed to explore the application of these AI technologies in a variety of domains, as well as to determine the best conditions for using certain models.

3 Stages of evolution of dialogue systems

Dialogue systems have already undergone a long evolutionary path. While at the very beginning of the way such systems could only answer pre-defined questions, now they have become more complex and capable of understanding the context, analyzing it and giving a rather realistic answer. Today, conversational digital systems can be created on the synthesis of various AI technologies: they are neural networks, expert systems of logical AI, etc. Due to their ability to remember the history of interaction with users and take into account their preferences and needs, such systems can create a more personalized conversational experience and increase the level of empathy simulation. The main benchmarks in the development of such systems are:

1. 1960s – MTI professor Joseph Weizenbaum developed a computer program called Eliza. The chatbot functioned on the basis of keywords. The creation of Eliza gave an advancement in natural language processing.
2. 1970s – the creation of the Parry program by Kenneth Colby. The program simulated a person with schizophrenia. It was thought that "Parry" could help train medical students before they practiced treating patients. Parry was believed to be the first chatbot to pass the Turing test.
3. 1980s – Rollo Carpenter created Jabberwacky, a program designed to imitate human conversation in an entertaining way. The program was able to learn from past experiences and evolve eventually.
4. 1990s – in 1992 Creative Labs developed Dr. Sbaitso, a software capable of simulating the speech synthesis of a psychologist. And in 1995, Richard Wallace presented a project simulating chat with a woman, A.L.I.C.E.

 https://doi.org/10.1051/e3sconf/202454908009

5. 2000s – SmarterChild was created by ActiveBuddy. The program was designed to communicate naturally with users. SmarterChild is the antecedent of Apple's Siri.
6. The 2010s – the beginning of the era of Virtual Advisors and Assistants. Apple released Siri in 2010, Google released Google Now in 2012, Microsoft released Cortana and Amazon released its Alexa program in 2014, and Yandex released Alice in 2017.
7. 2020s – the era of large language models. In 2022, OpenAI launches ChatGPT based on GPT-3.5, and in 2023, ChatGPT based on GPT-4. Also, in 2023, Google releases an experimental Bard model in opposition to OpenAI.

In summary, the development of conversational digital systems from Eliza to today's systems has been a long and complex process that has involved the use of various methods and technologies to create effective and personalized systems.

4 Peculiarities of development of modern language models

The global generative artificial intelligence market was valued at USD 10.63 billion in 2022 and is expected to grow at a CAGR of 34.2% during the forecast period. The market is majorly segmented on the basis of component, technology, end-use, and region. The leading market players in the technology segment are:

- Transformers;
- Generative Adversarial Networks;
- Variational Auto-encoders;
- Diffusion Networks.

Transformers segment accounted for the largest market revenue share in 2022 and is expected to maintain its position throughout the forecast period. This is mainly attributed to the rapid adoption of various applications such as text-to-image conversion and growing demand for natural language processing. Users are realizing the benefits offered by transformer solutions and this is contributing to its popularity. Over the last few years, the most popular solutions for building dialogue systems have been transformer-based models, specifically various derivatives of the BERT model architecture, which have become rather quickly popular. It is not surprising, as numerous BERT-based models have become SOTA for various natural language processing tasks. Today, however, there is quite a bit of discussion around GPT-based models such as ChatGPT and Bard. Based on the number of different releases of GPT and BERT models in recent years, we can assume that the paradigm of dialogue systems is changing, and GPT-based models have a great perspective for dialogue systems. [5]

In summary, the situation with the application of AI solutions may change in the coming years. The point is that if we review history, AI has had several "winters". They were caused by overestimated and unjustified expectations of AI technology, which was accompanied by a further decline in interest and, as a consequence, a reduction in funding in this area of research. More recently, it seemed that a new prolonged period of loss of interest in AI was beginning, or in other words, the end of the "autumn" and the beginning of the third "winter", but the outbreak was the development of generative AI, especially OpenAI with its ChatGPT solution. The fact is that over the past 10 years, technology corporations, including microchip manufacturers, have spent tens of billions of dollars on research and development of AI technologies. But the companies' profits have not increased along with the huge increase in their costs.

In addition, more and more energy, resources, and money were spent on training, for example, large neural networks, but the output became more and more modest. And then ChatGPT-3 appears, then ChatGPT-3,5 is released at the same time, followed by ChatGPT-4, and we are already on the subject of releasing ChatGPT-5, which again stimulates the interest of large corporations in the perspective technology. Microsoft has already released an updated Bing search engine with intelligent chat capabilities, and Google its AI solution Bard. The "race" of generative AI has begun, and perhaps this will make a difference, or perhaps it is just a temporary boost in the face of an error on the time line. In any case, this "race" benefits the final user, including specialists in the mechanical engineering industry, because AI is first and foremost a helper for humans, a tool that expands their capabilities in both mastering and acquiring new knowledge.

5 GPT and Bard models

Bard and GPT are two different artificial intelligence models used for text generation and response to queries. The main differences are in the architecture of the neural network. Bard uses transformer technology for text generation – LaMDA, for dialogue application. And GPT is more of a general language model based on Transformer architecture and trained in self-supervised mode on a large corpus of text data.

The main difference between Bard and GPT is that Bard uses a bidirectional model, which allows it to better understand context and generate higher quality text. GPT, on the other hand, uses a unidirectional model and is trained on a wider range of data, allowing it to generate text in a variety of styles and genres. As of June 2023, Bard is still officially under development, but it has learnt to perform many types of tasks such as: "thoughtfully" follow instructions and fulfil user requests; use its knowledge to respond to questions in a comprehensive and informative way; and generate a variety of textual content such as poems, code, scripts, emails, etc. Bard has direct access to the Internet and its data is constantly updated, so it is always learning something new.

ChatGPT, as the most popular model of the GPT family, can in turn understand and generate human-like text, making it a powerful tool for various applications such as dialogue agents, content generation, and question answering systems. It is worth noting that while ChatGPT is impressive in its ability to generate coherent responses, it can sometimes produce incorrect or meaningless answers. It is essentially a statistical model that relies on patterns in the data and it does not have true insight or knowledge like a human. The training process for ChatGPT involves training on a huge amount of textual data, but the model does not have access to the Internet or current real-time events. The knowledge and information available to ChatGPT-3.5 is based on the data on which it has been trained, with an expiration date of September 2021. As a result, the model may not be up to date or able to provide real-time information. Overall, Bard and GPT are 2 powerful artificial intelligence models that are used for text generation and query answering. Both models have their advantages and disadvantages, and the choice between them depends on the specific task and the quality and speed requirements.

6 Advantages and disadvantages of modern language models

Every year, the technologies and algorithms used to create chatbots are becoming more advanced. Businesses have a clear growing need to automate communications with customers and users, which stimulates further development of dialogue technologies. Modern language models have already carved out a distinct category and have become an important tool for many companies, organizations and everyday users. They are used to automate communication with customers, relieving the burden on call centers and support services, providing quick and efficient answers to frequently asked questions, and are used in onboarding and employee adaption tasks. The advantages of GPT and Bard models include ease of use, great functionality and the ability to generate realistic quality answers. Language models have never been so close to the final user - due to the flexible system of few-shot learning, users can accompany the system with training examples and give it their own unique tasks, correcting the output of the system with hints. This user-friendly nature is what makes the GPT and Bard models so popular. The quality of responses is one of the main advantages, as it was GPT-based models that revolutionized the generation of meaningful realistic text. Due to this, users became more loyal to dialogue systems and started to adopt them in their daily lives, which is enhanced by their extensive use today. Another contribution of modern models is the simplification of information search on the Internet by generating a specific answer to a user's question.

Despite the advances in text processing, the GPT and Bard models have a number of disadvantages. The main one is the problem of "hallucination" of language models. This problem is related to one of the main limitations of such models, which is that these models can only generate text based on what they have seen in their training data previously. That is, if the data on which they were trained was limited or contained some errors or was not reliable, then the models will also make errors in their responses. Although modern models have complex architectures, they are still language models that generate words step by step, so they can generate absolutely any text, which can be either true or false. Various solutions to this problem are now being developed, as it is a cornerstone in the development of GPT (Generative Pre-trained Transformer) models, but there is no specific solution yet, so it is a significant drawback of current language models. The relevance of the answers provided is problematic.

One of the main differences between ChatGPT and Bard is the data source. Bard, in addition to being trained on a large corpus of texts, has access to the internet, so it has the most up-to-date information. ChatGPT-3.5 sources, as mentioned, end with data for 2021, so the model is limited in the relevance of some data. So, Bard has more data to gather real-time information. However, at this point, it is hard to judge which chatbot is better as both are in the early stages of development. ChatGPT is effective at generating and summarizing text queries because it stores dialogue histories, unlike Bard. Bard, on the other hand, does a better job of answering questions by providing more relevant information.

7 Possibilities for integration and creation of your own systems

Both language models are similar in that they have the ability to generate text, however, they have serious differences in terms of integration and building their own personalized systems. Initially, OpenAI launched ChatGPT as a classic chatbot, but updates have made it a much more powerful tool for various areas of application. A system of plugins and integrations for connecting to ChatGPT was added to the model, which significantly expands the capabilities of the model. Plugins, for example, allow interaction with PDF files, compile and run code, create diagrams, and much more. In addition, ChatGPT integrates with Microsoft Bing for web search and with DALLE-3 for creating images. In addition, ChatGPT can be integrated with any application that provides access to the API. There are two methods to create an integration with ChatGPT:

1. Using the OpenAI API - creating an integration using the OpenAI API involves sending requests to the API and specifying the GPT model that should process the request
2. Using various integration platforms - creating an integration using services, as a rule, the platform provides a visual constructor for creating various interactions between applications on the network.

In addition to this, ChatGPT has tools for creating its own personalized versions of ChatGPT, which can use additional knowledge and skills for specific user tasks. Google Bard, at the moment, does not have such functionality and can only interact with the Google search system without any plugins, which makes ChatGPT a more functional and universal tool in terms of application.

8 The idea of the mivar approach for LLM and checking the results of the generative model

The combination of the mivar approach with large language models can be one of the solutions to combat the shortcomings of LLM. The unification of these two approaches can lead to an increase in interpretability and a reduction in the "hallucination" effect of generative language models. Let's highlight the main advantages of combining these two approaches. The integration of the "IF-THEN" rule-building algorithm with the generative model will partially solve one of the main problems of all neural network models - the problem of non-interpretability of the output. The combination of the power of generative models, such as ChatGPT, with mivar technologies allows automating the process of building rules and knowledge bases, creating potentially more efficient and widely applicable artificial intelligence models.

With the verification of the output of the generative model, it is possible to combat the problem of "hallucinations" of generative models. A simplified architecture is presented in Figure 1.

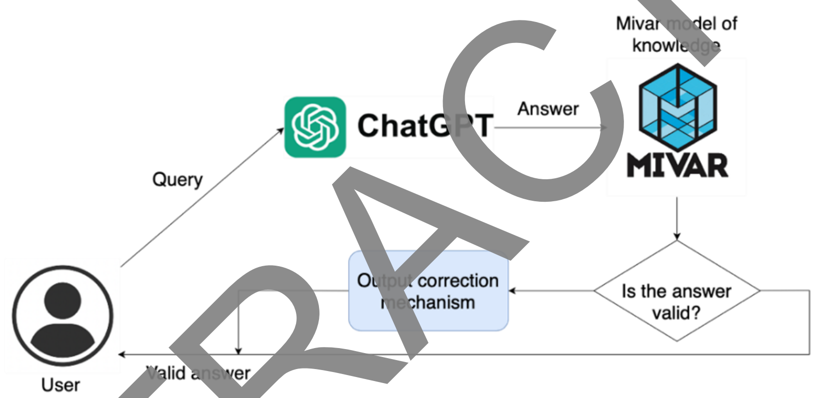

Fig. 1. Validation of the generative model output.

The combination of generative and mivar models can provide the necessary balance between flexibility and structured knowledge. However, to implement this hypothesis, knowledge bases are needed, which are implemented by experts, and there is a significant problem - the need for a large number of experts, which complicates their deployment and effective functioning. The lack of access to a sufficient number of experts leads to a limitation of the potential for building knowledge bases. The mivar approach provides a structured way of formalizing knowledge, but it turns out to be not efficient enough, as a huge number of experts are needed to build large mivar data models. In this context, the generation of mivar data models using GPT is an important step in the development of expert systems and the implementation of models capable of getting rid of the shortcomings of large language models today.

9 Creation of mivar knowledge bases using generative models

Large language models provide a unique opportunity to bypass the limitations of expert systems related to the lack of experts. Models are capable of processing a huge amount of data, which allows creating mivar models without involving a large number of experts, as the task of building rules is replaced by tasks of checking and correcting the generated ones. The generation of mivar data models using LLM provides the opportunity to automate the process of forming knowledge bases, thereby reducing dependence on the number of experts. If LLM can create extensive knowledge bases with comparable quality with experts or at least can reduce the necessary number of cognitive analysts due to the automation of processes, this will open new horizons for the development of AI in various areas. The scheme of interaction between LLM and mivar technologies is shown in Figure 2.

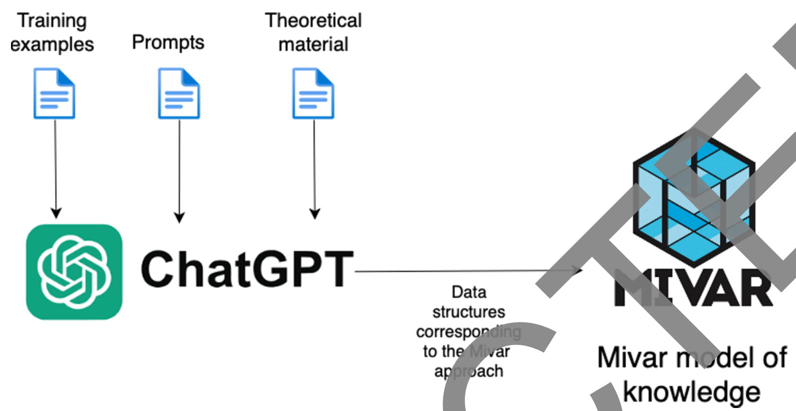

Fig. 2. Formation of a mivar knowledge model using LLM.

As part of this research, we worked on creating a specialized version of ChatGPT by introducing new instructions and information. We used ChatGPT4, providing the model with a brief summary of articles on mivar technologies and requested the development of a mivar rule matrix for the IPS/IDS system, including 30 rules. This experiment allowed us to assess the depth and flexibility of the model in understanding and processing specialized requests. Then we added new instructions and uploaded specialized information to create a model that more accurately meets the needs of developing mivar expert systems. As a result of an expert evaluation of the generated rules, it was found that with the help of LLM it is possible to optimize the creation of structured knowledge in the form of rules, which can later be used to automate the process of building mivar knowledge bases and implementing mechanisms for verifying the output of generative models.

10 Conclusion

Current language models are analyzed, their characteristics are analyzed, and their advantages and disadvantages are identified. Bard uses a bidirectional model and has a greater understanding of context, which makes it a better choice for tasks related to language analysis and text comprehension. It is capable of generating longer and more coherent answers, which may be useful for some tasks. On the other hand, GPT uses a unidirectional model and is trained on a wider range of data, making it a better choice for tasks involving text generation in a variety of genres and styles. Bard has a larger model size than GPT, which may mean it will run slower but generate more accurate answers. GPT conversely can generate faster but with less accuracy. Whether choosing Bard or GPT depends on the specific task to be solved. If you need to understand the context and meaning of the text, Bard will do a better job. If it is necessary to generate text in different styles and genres, then GPT will be a more suitable tool. But this is still not enough to create new intelligent natural language processing technologies for machine learning artificial intelligence and machine learning. The research results confirm the importance of automating the process of working with mivar models. They also point to the possibility of combining large linguistic models and the mivar approach, which can reduce the likelihood of obtaining incorrect data, increase the clarity of the results, and make the use of language models in various artificial intelligence scenarios more efficient.

References

1. O. Varlamov, Big Data Research **25**, 100241 (2021) https://doi.org/10.1016/j.bdr.2021.100241
2. T. Guzeva, A. Parsheva, V. Babin, at al., Lecture Notes in Networks and Systems **509**, 651–659 (2023) https://doi.org/10.1007/978-3-031-11058-0_65
3. T. Guzeva, S. Egorov, K. Smetankin, at al., Lecture Notes in Networks and Systems **509**, 643–650 (2023) https://doi.org/10.1007/978-3-031-11058-0_64
4. U. Grigorev, Y. Shashkin, A. Ploutenko, et al., *Bank checks fraud detection based on the analysis of event trends in data-flow systems*, in Proceedings of the International Conference on Internet of Things, Big Data and Security, IoTBDS - Proceedings, vol. 2023-April, pp. 97-104 (2023) https://doi.org/10.5220/0011727300003482
5. D. V. Aladin, E. V. Aladina, D. A. Chuvikov, at al., IOP Conference Series: Earth and Environmental Science **954(1)**, 012004 (2022) https://doi.org/10.1088/1755-1315/954/1/012004
6. O. O. Varlamov, D. A. Chuvikov, V. N. Lemondzhava, at al., Biomedical Engineering **55(5)**, 355–359 (2022) https://doi.org/10.1007/s10527-022-10135-0
7. V. N. Lemondzhava, T. Yu. Lemondzhava, A. G. Gudkov, et al., AIP Conference Proceedings **2605** (2023) https://doi.org/10.1063/5.0110400
8. H. Kim, D. A. Chuvikov, D. V. Aladin, at al., Biomedical Engineering **54(6)**, 421–424 (2021) https://doi.org/10.1007/s10527-021-10053-7
9. D. Shamaev, Lecture Notes in Networks and Systems **597**, 519-528 (2023) https://doi.org/10.1007/978-3-031-21438-7_41
10. A. Volkov, O. Varlamov, Journal of Physics: Conference Series **2131(3)**, 032003 (2021) https://doi.org/10.1088/1742-6596/2131/3/032003
11. M. O. Taran, G. I. Revunkov, Y. E. Gapanyuk, Studies in Computational Intelligence **1064**, 466-475 (2023) https://doi.org/10.1007/978-3-031-19032-2_48
12. D. O. Ishkov, V. I. Terekhov, K. S. Myshenkov, *Energy theft detection in smart grids via explainable attention maps*, in Proceedings of the 2023 5th International Youth Conference on Radio Electronics, Electrical and Power Engineering, REEPE 2023 (2023) https://doi.org/10.1109/REEPE57272.2023.10086919
13. Y. E. Gapanyuk, Pattern Recognition and Image Analysis **33(3)**, 300-305 (2023) https://doi.org/10.1134/S1054661823030124
14. D. Fedyukin, D. Gromozdov, Y. Gapanyuk, Studies in Systems, Decision and Control **457**, 207-218 (2023) https://doi.org/10.1007/978-3-031-22938-1_14
15. R. Tsarev, S. H. Azizam, A. Sablinskii, et al., Lecture Notes in Networks and Systems **723**, 209-216 (2023) https://doi.org/10.1007/978-3-031-35317-8_18
16. D. A. Gurianov, K. S. Myshenkov, V. I. Terekhov, *Software development methodologies: analysis and classification*, in Proceedings of the 2023 5th International Youth Conference on Radio Electronics, Electrical and Power Engineering, REEPE 2023 (2023) https://doi.org/10.1109/REEPE57272.2023.10086852

17. V. S. Popov, *Equivalence of logical operations and other operations in Python programming language*, in Proceedings of the 2023 5th International Youth Conference on Radio Electronics, Electrical and Power Engineering, REEPE 2023 (2023) https://doi.org/10.1109/REEPE57272.2023.10086928
18. V. S. Popov, *First-order logical equations with parameter and their exhaustive search solutions*, in Proceedings of the 2023 5th International Youth Conference on Radio Electronics, Electrical and Power Engineering, REEPE 2023 (2023) https://doi.org/10.1109/REEPE57272.2023.10086751
19. Y. Verina, D. Tolstoukhov, D. Egorov, et al., AIP Conference Proceedings **2819** (2023) https://doi.org/10.1063/5.0137948
20. A. Kanev, M. Nazarov, D. Uskov, V. Terentyev, *Research of different neural network architectures for audio and video denoising*, in Proceedings of the 2023 5th International Youth Conference on Radio Electronics, Electrical and Power Engineering, REEPE 2023 (2023) https://doi.org/10.1109/REEPE57272.2023.10086862
21. M. V. Belodedov, R. V. Fonkants, R. R. Safin, *Development of an algorithm for optimal encoding of WAV files using genetic algorithms*, in Proceedings of the 2023 5th International Youth Conference on Radio Electronics, Electrical and Power Engineering, REEPE 2023 (2023) https://doi.org/10.1109/REEPE57272.2023.10086837
22. A. I. Kanev, A. V. Tarasov, A. N. Shikhov, et al., Sovremennye Problemy Distantsionnogo Zondirovaniya Zemli iz Kosmosa **20(3)**, 136-151 (2023) https://doi.org/10.21046/2070-7401-2023-20-3-136-151
23. R. Kim, A. Kotsenko, A. Andreev, at al., E3S Web of Conferences **515**, 03016 (2024) https://doi.org/10.1051/e3sconf/202451503016
24. D. S. Tikhonova, A. Y. Abramochkin, A. S. Borodulin, et al., Polymer Science - Series D **16(2)**, 307-312 (2023) https://doi.org/10.1134/S1995421223020442
25. A. Valishin, N. Beriachvili, E3S Web of Conferences **376** (2023) https://doi.org/10.1051/e3sconf/202337601041
26. N. A. Lavrov, S. I. Khutsieva, V. A. Shananin, Chemical and Petroleum Engineering **58(11-12)**, 917-924 (2023) https://doi.org/10.1007/s10556-023-01183-8
27. V. V. Bukhtoyarov, V. S. Tynchenko, V. A. Nelyub, et al., Electronics (Switzerland) **12(1)** (2023) https://doi.org/10.3390/electronics12010215
28. I. A. Grishin, V. I. Terekhov, *Procedure for locating trees and estimating diameters using LiDAR data*, in Proceedings of the 2023 5th International Youth Conference on Radio Electronics, Electrical and Power Engineering, REEPE 2023 (2023) https://doi.org/10.1109/REEPE57272.2023.10086843
29. V. V. Dyachenko, V. A. Devisilov, V. G. Shemanin, Ecology and Industry of Russia **27(6)**, 30-35 (2023) https://doi.org/10.18412/1816-0395-2023-6-30-35
30. L. Labunets, *Intellectual analysis of pulsed RCS for 3D objects recognition by an optical location system*, in Proceedings of SPIE - The International Society for Optical Engineering, vol. 12564 (2023) https://doi.org/10.1117/12.2669242
31. O. Varlamov, D. Aladin, Machine Intelligence Research (2024) https://doi.org/10.1007/s11633-023-1473-1
32. A. D. Volgina, D. S. Kirillov, A. N. Kravtsov, et al., *The Robot-Guide for Indoor Navigation*, in Proceedings of the 2023 5th International Youth Conference on Radio

Electronics, Electrical and Power Engineering, REEPE 2023 (2023) https://doi.org/10.1109/REEPE57272.2023.10086707

33. D. A. Chuvikov, D. V. Aladin, L. E. Adamova, at al., Journal of Physics: Conference Series **2061(1)**, 012123 (2021) https://doi.org/10.1088/1742-6596/2061/1/012123
34. A. Kotsenko, A. Andreev, R. Kim, at al., E3S Web of Conferences **515**, 04018 (2024) https://doi.org/10.1051/e3sconf/202451504018
35. A. Kotsenko, A. Bazanova, R. Kim, at al., E3S Web of Conferences **515**, 03017 (2024) https://doi.org/10.1051/e3sconf/202451503017
36. M. Potashnikov, V. Shishkina, A. Muravev, A. Kartashov, E3S Web of Conferences **402** (2023) https://doi.org/10.1051/e3sconf/202340204001