

Vadym Kozlov,  
Vadym Slyusar,  
Volodymyr Tverdokhlibov,  
Zoia Andriichuk

# INTEGRATION AND COORDINATION OF ELECTRONIC WARFARE ASSETS THROUGH LARGE-SCALE LANGUAGE MODELS

As an object of research, the work considers the process of functioning of electronic warfare (EW) means using artificial intelligence (AI) technologies based on large language models (LLM). One of the most problematic issues in increasing the efficiency of their functioning is ensuring the adaptability function in EW means, as well as timely detection of threats and formation of appropriate countermeasures. This problem is solved by implementing a multi-agent architecture, the task of which is to ensure continuous exchange of information, both between agents in the EW means themselves and in the system as a whole.

The considered method of increasing the adaptability of the system due to LLM with self-learning mechanisms provides the system with the opportunity to improve its data processing algorithms, promptly detect new types of signals and respond to changes in the parameters of the enemy's REM. Using the Retrieval-Augmented Generation (RAG) approach allows to detect and enter new types of signals into the database and quickly form appropriate recommendations for countermeasures.

An equally important component is the use of combining several EW tools into a single information network. This approach will ensure the consistency of the actions of all EW tools (agents) and the rapid exchange of information between them.

Taking into account the above, there is a possibility of significantly increasing the adaptability and efficiency of EW systems by integrating multi-agent structures using LLM, which allow optimizing resource allocation and making decisions in real time. This will ensure a high level of adaptation of EW tools, which is an important feature for working in conditions of dynamically changing electromagnetic environments.

Thanks to the proposed architecture and the use of appropriate algorithms, it is possible to obtain high indicators of classification accuracy and signal processing speed, which positively affects the adaptability of the system and the overall effectiveness of countering threats.

**Keywords:** electronic warfare, large language models, artificial intelligence, multi-agent structures, knowledge base, executive modules.

Received: 29.11.2024

Received in revised form: 25.01.2025

Accepted: 16.02.2025

Published: 27.02.2025

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## How to cite

Kozlov, V., Slyusar, V., Tverdokhlibov, V., Andriichuk, Z. (2025). Integration and coordination of electronic warfare assets through large-scale language models. *Technology Audit and Production Reserves*, 1 (2 (81)), 54–61. <https://doi.org/10.15587/2706-5448.2025.323916>

## 1. Introduction

Given the rapid dynamics of changes in the electromagnetic spectrum, the requirements for modern electronic warfare (EW) systems go beyond the capabilities of traditional approaches to solving them, therefore, the introduction of artificial intelligence (AI) technologies into EW systems is an important approach to increasing the efficiency of the functioning of these tools [1].

With the increase in digitalization and the development of AI, EW moves to a new level of efficiency, acquiring the latest tools for effective analysis and management of dynamically changing data. An important component of modern AI technologies are large language models (LLM), which are transformative neural networks capable of processing and generating large volumes of multimodal information based on training data. LLM, as a component of AI technology, play a special role in the transformation of EW tools, providing new capabilities for analyzing and processing large volumes of data during changes in the electromagnetic spectrum in the environment. These models are capable of quickly processing information from acoustic, infrared, optical and digital antenna arrays (hereinafter referred to as the DAA). This makes it possible not only to detect threats, but also to coordi-

nate (or implement) appropriate countermeasures in real time. LLM integration allows to significantly increase the speed and accuracy of decision-making, optimizing the operation of electronic warfare (EW) equipment during defensive or offensive operations of troops.

However, along with the advantages, the integration of LLM in electronic warfare (EW) equipment also requires solving a number of challenges, in particular, ensuring data security and confidentiality. It is also necessary to adapt existing EW management systems for effective interaction with the latest IT solutions, which requires significant efforts in the field of development and training of personnel.

Such integration opens up new prospects for the development of EW equipment based on robotic platforms [2], making them more adaptive and effective in response to modern threats.

In works [3, 4], the concept of LLM is formed, examples of their architectures are given, and wide possibilities in various fields of application are also demonstrated. The LLMs presented in the mentioned publications are based on the technique of deep learning on large data sets, which allows to perform a wide range of tasks.

In work [5], advanced artificial intelligence systems are considered, designed to process, understand and generate human-like text. These models are trained on large data sets. The article also discusses various

use cases of LLM in various fields of activity. In addition, the authors analyze the issues related to the implementation of LLM, including ethical issues, data biases and the need for significant computing resources. The article emphasizes the importance of high-quality training data for the successful implementation of LLM in various industries.

In the literature [6–8], OpenAI presented ChatGPT, as an LLM model designed for interaction in a conversational format. This model allows you to answer questions, admit your mistakes, challenge incorrect assumptions, and reject incorrect requests.

In [9–11], it is stated that Meta AI researchers have presented LLaMA (Large Language Model Meta AI) a collection of basic language models with the number of parameters from 7 to 65 billion. The LLMs were trained on trillions of tokens using exclusively publicly available datasets.

In [12], it is stated that another OpenAI LLM model called "o1" reached an IQ equivalent of 120, significantly exceeding the average human score. The author provides examples of questions and answers of the model, emphasizing its ability to analyze and draw conclusions based on available data. This development indicates rapid progress in the field of artificial intelligence and its capabilities approaching the human level.

In [13], the capabilities of the LLM Mistral 7B, namely a language model with 7 billion parameters. Mistral 7B outperforms Llama 2 13B in all evaluated tests, as well as Llama 1 34B in tasks related to logical thinking, mathematics and code generation. The model uses grouped-query attention (hereinafter – GQA) mechanisms to accelerate inference and sliding window attention (hereinafter – SWA) to efficiently process sequences of arbitrary length with lower inference costs.

In [14], the Gemini 1.5 LLM family is presented – a new generation of high-performance multimodal AI models. These LLMs are capable of processing and analyzing in detail information from millions of context tokens, which includes processing large-volume documents, as well as hours of video and audio, which is unprecedented among modern large language models.

In [15], the capabilities of the Claude 3.5 Sonnet LLM, which is a powerful language model from Anthropic, are considered.

Claude 3.5 Sonnet provides powerful visual processing, demonstrates improved results in text recognition, when analyzing diagrams and graphs. One of the key features of the model is the ability to agent programming, which allows it to independently write, edit and execute code, solving over 64 % of the tasks with error correction in open software.

In [16], new versions of the Grok chatbot – Grok-2 and Grok-2 Mini – are presented. These LLM models are distinguished by improved performance and the ability to generate images due to integration with the Flux 1 model from Black Forest Lab.

In [17], a series of LLM Phi-3.5 models is announced, which can be used as AI agents.

In [18–23], issues regarding the possibilities of using AI in the military sphere are considered. In particular, the main attention in [18, 19, 21] is focused on the analysis of the capabilities of AI and LLM technologies, which are designed to automate the processes of analyzing large amounts of data and supporting decision-making during military operations.

In [24], LLMs are described that are integrated into the ecosystem of war games, automating agents [25] and improving the quality of decisions in simulations, which allows players to improve their skills and military abilities, based on common logic and rules. The application of LLMs in the field of war games demonstrates the corresponding capabilities and potential in the generation and analysis of strategies, emphasizes the need for further research to improve the effectiveness of LLMs.

At present, radio-electronic means (hereinafter – REM), which emit electromagnetic signals, are characterized by high technological sophistication and perfection and, according to their qualitative characteristics, are noise-resistant, stealthy and adaptive.

The use of REM in modern weapons and military equipment (hereinafter referred to as WME) indicates the need to develop new methods and approaches to electronic countermeasures (hereinafter referred to as EC), which is a pressing task at the present time. Therefore, the purpose of the work is to determine the possibilities of using LLM and other AI technologies in EW means.

The main tasks aimed at achieving the aim in this study are:

- development of a conceptual approach to building a multi-agent architecture of EW means, covering both individual robotic platforms and their integration into a single system that ensures coordination and data exchange between heterogeneous EW agents, regardless of their location. This is implemented through the concept of a distributed system architecture of autonomous EW means (Distributed Autonomous System, DAS), which creates a single information space for effective interaction;
- implementation of a multi-agent approach with support for Retrieval-Augmented Generation (hereinafter – RAG), which provides dynamic updating of the signal knowledge base, increased classification accuracy and rapid adaptation of the system to new threats by analyzing the received data in real time.

## 2. Materials and Methods

*The object of the study* is the process of functioning of electronic warfare means with integrated AI technologies, based on LLM. Due to the implementation of multi-agent architecture, it is possible to combine heterogeneous agents, which are assigned certain functions.

During the study, a number of assumptions were made regarding the operating environment and resource limitations, which include:

- an ideal network environment for data transmission between electronic warfare agents, without taking into account delays and packet losses;
- the presence of a reliable knowledge base about the signals of various enemy REM systems, with the possibility of updating;
- operation of the system in a selected range of the electromagnetic spectrum, without taking into account crosstalk;
- limited computing resources in field conditions, which requires optimization of self-learning algorithms and signal analysis.

In order to effectively conduct modeling and achieve the set goal, the following software and hardware were used:

- Google Colab – construction and training of neural network models for signal classification and additional accuracy assessment;
- MATLAB/Simulink – simulation modeling of a complex electromagnetic environment and dynamic operation of electronic warfare equipment;
- GNU Radio – generation, reception and processing of radio signals in real time;
- SDR devices (Software Defined Radio) – modeling and analysis of radio signals.

The methodology for conducting experiments included several key stages, which include:

- creation of a simulation environment that included the formation of test sets of signals (analog, digital, interference, noise) and setting up a multi-agent system and analysis methods;
- verification of the effectiveness of the implementation of LLM and Retrieval-Augmented Generation (RAG); in particular, the accuracy of signal recognition and classification and the speed of adaptation to new types of threats were assessed;
- verification of coordination algorithms between different electronic warfare agents, which included an assessment of the reaction time to a change in the electromagnetic environment and the consistency of actions in the event of detecting several threats simultaneously;
- optimization of the distribution of computing resources between agents, taking into account hardware limitations.

The input data for the analysis consisted of real and synthetic radio signals of various types (signals of UAV control and data transmission channels, modulated signals), as well as noise and interference components. Materials containing information on the characteristics of UAV signals used in the knowledge base were used.

When studying electronic warfare means with integrated AI technologies, it is advisable to use a set of scientific methods that allows to cover both theoretical and applied aspects of the functioning of multi-agent systems based on LLM. The key methods recommended for use based on the authors' experience and used in the preparation of this work include:

- methods of analysis and synthesis, which were the basis for studying existing scientific publications and technical documentation and made it possible to identify key characteristics of electronic warfare means with the determination of the features of LLM integration into their structure;
- neural network signal classification methods used to systematize and cluster incoming radio frequency information and are the basis for building decision-making algorithms and creating a knowledge base on potential types of radiation sources;
- the method of a systems approach, which provided consideration of robotic EW platforms as a single multi-agent architecture taking into account the relationship between sensor modules, knowledge base, executive agents and coordination subsystems;
- mathematical and simulation modeling, which made it possible to create software simulations of various scenarios of the radio-electronic environment in order to evaluate the effectiveness of the proposed algorithms in a wide range of tactical conditions.

In addition, all the proposed approaches were subjected to experimental testing in simulated and real electromagnetic environments, which made it possible to identify "weak spots" in self-learning algorithms, coordinate coordination parameters between modules and optimize resource allocation in robotic EW platforms.

The complex combination of these methods of analysis, modeling, comparison and experimental testing created conditions for a comprehensive study of the possibilities of implementing multi-agent structures with LLM into robotic EW means.

**3. Results and Discussion**

Currently, electronic warfare means require high speed of processing received data, as well as high accuracy of identification and determination of positions of radio emission sources (hereinafter referred to as RES) with the possibility of adaptability to rapid changes in the electromagnetic environment in the environment. The implementation of AI technologies based on LLM allows achieving appropriate levels of technological perfection.

Robotic electronic warfare means with integrated AI technology based on multi-agent LLM models have the ability to conduct constant exchange of information between sensors and corresponding executive modules, ensuring their close interaction.

To implement such an approach, a multi-agent concept of a robotic electronic warfare means is proposed, the structural diagram of which is shown in Fig. 1.

Fig. 2 illustrates the process of functioning of the proposed robotic EW mean with integrated AI technology based on multi-agent LLM.

Let's consider in more detail the interaction of the agents presented in Fig. 2. The LLM sensory agent is responsible for the DAA operating modes, which acts as the primary source of collection and processing of electromagnetic signals of the EW mean. The main purpose of the LLM sensory agent is to DAA control during activities to detect radio signals, as well as to control the DAA operating modes during activities to find RES direction in a complex electromagnetic environment.

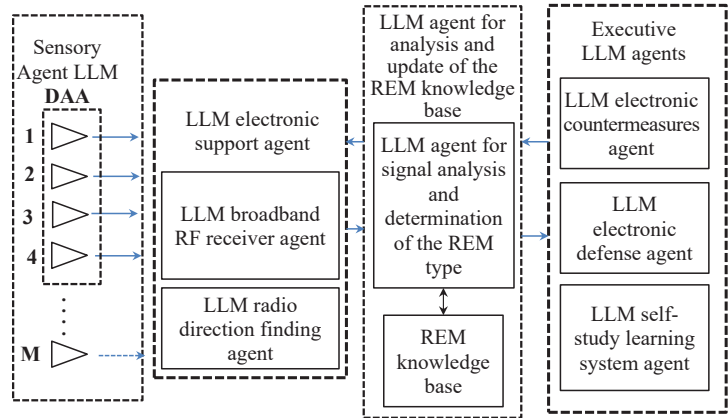


Fig. 1. Robotic EW with integrated AI technology based on LLM multi-agent models

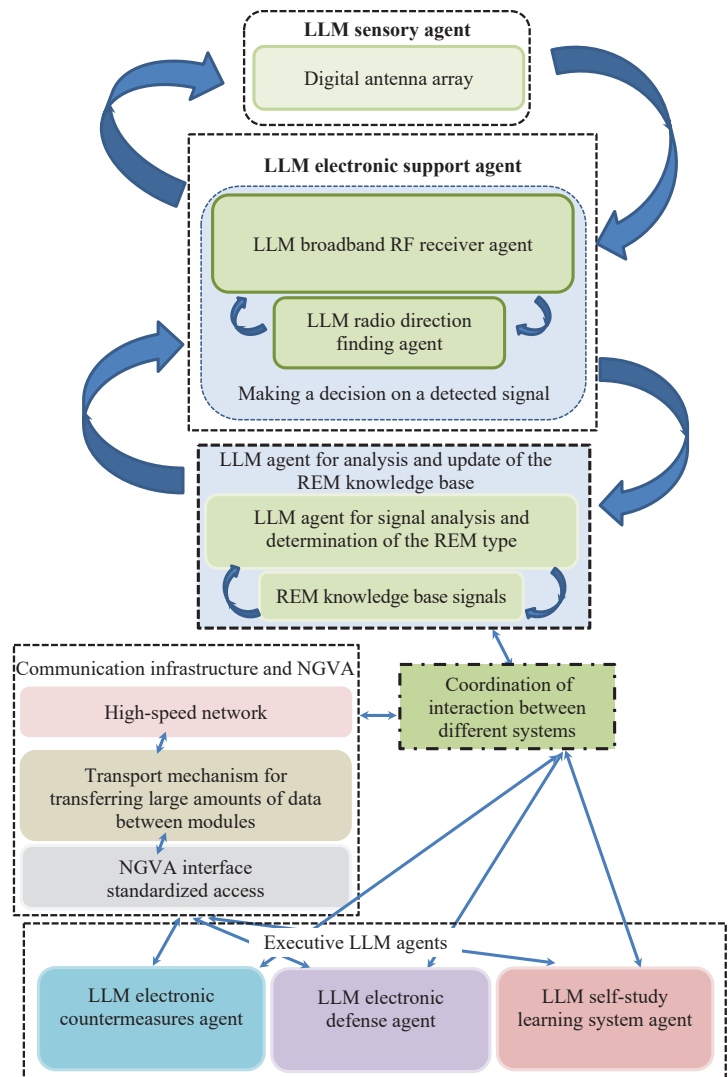


Fig. 2. The operation process of a robotic EW tool with integrated AI technology based on multi-agent LLMs

Thanks to the use of digital beamforming algorithms, the DAA LLM agent is able to control the DAA directivity pattern, which provides the ability to receive signals and find direction from different directions at once, providing a high level of spatial resolution. This allows it to work effectively in complex spectral conditions characterized by a high density of radio signals. The presence of a sensor agent ensures the system's ability to automatically adjust the parameters of the antenna array operating modes, switching from reception mode to radiation mode. In addition, the ability to change signal reception modes with the transition from broadband to narrowband allows for detailed analysis of the received signals.

Providing real-time data exchange, the agent synchronizes the operation of the antenna system with other modules of the EW tool (Fig. 1, 2).

The LLM electronic support agent is a key element of the EW tool, it is responsible for the accuracy of analyzing detected signals, their classification and making decisions regarding the detected threats. It consists of two main submodules: the LLM agent of the broadband radio frequency receiver module and the LLM agent of the direction finding module. These components provide coordinated work aimed at detecting signals in the electromagnetic environment. It is essential that the LLM agent of the broadband radio frequency receiver module is responsible for receiving signals in a wide frequency range, recording radio radiation of various types.

This agent provides primary signal processing, highlighting relevant characteristics for further analysis of the received signals. The LLM agent of the direction finding module performs the task of determining the arrival of signals from different directions (DOA, Direction of Arrival) with high accuracy. Thanks to the use of the DAA and appropriate algorithms, the spatial RES localization carried out by this agent is ensured even in difficult conditions of strong radio interference.

Taking into account the above, the main task of the LLM agent for electronic support is to ensure the correctness of decision-making regarding further actions to localize the detected threat. The solution of this task is achieved by synthesizing and analyzing data received from its submodules and using the knowledge base of the REM signals. Based on the results obtained, this agent generates recommendations for further actions, which are transmitted to other system modules, in particular to electronic countermeasure and defense agents.

Also, one of the important features of the LLM-agent for electronic support is its ability to work in real time, ensuring efficiency in decision-making even in a rapidly changing electromagnetic environment. Thanks to self-learning algorithms, the agent constantly improves its analysis models, increasing the accuracy of classification and adapting to new types of signals. This allows maintaining high efficiency even in cases where the enemy changes the characteristics of signals or uses means of masking them. In conclusion, it should be noted that the electronic support agent is an important component of the EW system, which at its stage forms the correct decision-making necessary to neutralize enemy threats and protect its own systems. The integration of the submodules of the broadband radio frequency receiver and direction finding, as well as the use of appropriate algorithms, is an effective tool for electronic warfare.

The LLM-agent of the REM knowledge base analysis and update module is responsible for in-depth analysis of signals, their classification and constant update of the REM radio signal knowledge base. This module includes two key components: the signal analysis and REM detection module agent and the knowledge base of REM signals. Their close interaction ensures accurate classification of signals and constant adaptation of the system to changes in the characteristics of the electromagnetic environment. The signal analysis and detection module agent performs the tasks of further processing and classification of signals received from sensor modules, such as the DAA, and the LLM agent of the broadband radio frequency receiver module. Using convolutional neural network algorithms, the agent performs a detailed analysis of

signal characteristics, such as frequency, amplitude, modulation and power. Based on these data, it determines the type of signal, its source of origin and the possible level of threat. In this case, it is advisable to use different forms of signal representation, both in the form of time sequences and spectrograms synthesized on their basis, similarly to what was proposed in [26] for the classification of audio signals. In addition, when processing spectrogram images, it is proposed to use the capabilities of neural networks [27] for object detection [28] and image segmentation [29].

As an example, it is possible to consider signal classification using DenseNet169 neural networks. When using the Tesla V100-SXM2-16GB GPU, the classification time was 0.1–0.2 seconds. If compared with a human operator, who has a reaction time of 0.8 seconds, the gain in classification speed for the DenseNet169 neuroagent reaches 4 times.

Using LLM in addition to convolutional neural networks allows the agent to take into account the context and relationships between signal characteristics, which ensures high classification accuracy even in difficult conditions, such as high levels of interference or multipath. At the same time, neural networks [27] for object detection [28] and image segmentation [29] should be the basis for attention mechanisms as part of LLM transformative architectures.

The knowledge base of REM signals is the central element that provides support and operation of the signal analysis and REM determination module agent. It is organized according to the RAG principle [30] and contains a data structure with detailed descriptions of the characteristics of signals belonging to different types of REM. The knowledge base is constantly updated by the LLM agent based on the analysis of new signals detected, which allows the system to adapt to the emergence of new threats or changes in the characteristics of known sources of radio radiation. The knowledge base is updated automatically using self-learning algorithms, which allows the system to maintain relevance and a high level of accuracy even in a dynamic electromagnetic environment. The main function of the signal analysis and REM detection module is to ensure the relationship and optimal balance between the current signal analysis and the constant development of the knowledge base. The corresponding agent not only classifies signals, but also transfers the received information to other modules of the system, for example, for decision-making or determination of countermeasure strategies with prediction based on the analysis of statistics of previous combat operations. The results obtained are used to update the knowledge base, which allows the EW system to respond promptly to new types of threats or changes in enemy tactics. Therefore, this module is an important tool for achieving a high level of autonomy and accuracy of EW systems. Thanks to the integration of signal analysis components and the knowledge base, the agent provides not only efficiency in classification and response, but also instant adaptation of the system when changes are detected in the electromagnetic domain.

The coordination block for interaction between different systems allows you to combine the work of modules at different levels, which ensures fast and coordinated decision-making in real time. The main role of coordination is to integrate the work of components such as sensors, analyzers, knowledge bases and executive modules. The interaction between these elements allows the system to ensure continuous exchange of information. For example, data received by the broadband radio frequency receiver module is transmitted to the signal analysis and REM tool determination module, as well as to the knowledge base for further improvement of the system. This helps to increase the accuracy of analysis and reduce the time for decision-making. Coordination also performs the function of ensuring interaction between agents of different levels, such as the electronic countermeasure agent, the electronic defense agent, and the self-learning system agent. This ensures synchronism in the execution of actions: countering enemy signals, protecting one's own systems, and constantly updating the knowledge base of signals and their sources. This is especially important in conditions

of changing electromagnetic influence, where rapid adaptation is critical for the effectiveness of the system. In addition, coordination takes into account the transmission of large volumes of data over a high-speed network. The use of transport mechanisms and standardized interfaces, such as in the architecture of NGVA vehicles, ensures stable and fast communication between system components. This allows for the efficient use of available resources, avoiding and minimizing the risks of conflicts between different systems. The key task of coordination is to ensure situational awareness and coordination of actions based on up-to-date information. It ensures that all modules work coherently as a single system, exchanging information about threats. As an example, when a new source of radio radiation is detected, the system can instantly notify all involved modules to synchronize their actions to neutralize the threat.

Thus, the coordination of interaction between different systems according to the proposed algorithm is the basis for ensuring the effective operation of the electronic warfare system. It allows integrating data, adapting to environmental changes, avoiding conflicts and achieving maximum efficiency in conditions of high dynamics of combat operations.

The communication infrastructure and NGVA architecture [31] ensure coordinated interaction between all components. This component is responsible for organizing fast and reliable information exchange, which is the basis for the effective operation of the system as a whole. Its structure includes a high-speed network, a transport mechanism and standardized NGVA interfaces, each of which performs critically important functions.

The high-speed network provides fast and uninterrupted exchange of large volumes of data between all modules of the system. This allows for the prompt transfer of signal analysis results, information about detected threats and decisions made by agents, minimizing delays and ensuring instant response. The transport mechanism performs the functions of managing data flows in the system, optimizing their distribution between different components. This allows for efficient information exchange between signal analysis agents, knowledge bases, and execution modules. In addition, the transport mechanism ensures system scalability, allowing for processing large amounts of data without loss of performance, and prioritizes data transmission, giving priority to critical tasks.

The typical NGVA interface serves as standardized access to all modules and components of the system. It allows different platforms to interact with each other using unified data transfer protocols, which significantly increases the compatibility and flexibility of the system. Thanks to NGVA, integration with other military and civilian systems becomes possible, expanding the functionality of EW. In addition, the interface provides synchronization of the operation of all components, ensuring their coordinated interaction in real time.

The communication infrastructure and NGVA provide the basis for coordinating the actions of all modules of the EW system, creating a reliable platform for information exchange, synchronization of parallel processes in time, and integration with other systems. The efficiency of their operation determines the efficiency, flexibility, and reliability of the entire system.

Executive LLM agents ensure the implementation of strategies to counter enemy signals, protect their own systems, taking into account adaptive adjustment to changes in the electromagnetic spectrum. The peculiarity of executive agents is the integration of AI technologies, in particular LLM, which provides the ability to quickly make decisions, perform actions and improve themselves thanks to self-learning mechanisms. Executive agents act as a central executive element, combining all previous stages of data processing and decision-making into a single adaptive system. Executive agents are based on the complex interaction of their key components: an electronic countermeasure agent, an electronic defense agent and a self-learning system agent. These

components provide a wide range of functions, namely, from blocking enemy signals to ensuring the stable operation of their own systems and continuous improvement of the system. Together, they form a single network of executive solutions that works in real time and provides flexibility and adaptability of the electronic warfare system.

The LLM agent of the electronic countermeasure module is responsible for disrupting the operation of enemy communications, radar systems, or navigation equipment. Based on the results obtained from the analytical modules, the agent identifies enemy signals, analyzes their characteristics, and selects the most effective countermeasure tactics. This may include both the creation of directional interference and dynamic changes in radiation characteristics to minimize the effectiveness of enemy systems. The integration of LLM algorithms allows the agent to adapt to changes in enemy tactics and provide a high level of effectiveness in various conditions. The LLM agent of the electronic countermeasure module performs the task of ensuring the stable operation of its own systems in the presence of enemy interference. Its functionality includes adaptive frequency masking, changing communication channels, using backup data transmission routes, and other methods of protection against attacks. Using LLM mechanisms, this agent is able to predict potential threats, analyze them, and develop appropriate countermeasures. Interaction with other system components allows it to receive timely data on changes in the environment and respond to them effectively, maintaining functionality even in the most difficult situations. The LLM agent of the self-learning system module ensures constant improvement and adaptation of the entire EW system. It analyzes data obtained during operations and uses it to update knowledge bases and train decision-making algorithms. This allows the system to effectively respond to new threats, change its tactics and adapt to changes in the characteristics of signals or environmental conditions. The self-learning agent is a key element that makes the EW system resistant to unknown challenges and ensures its ability to self-improve.

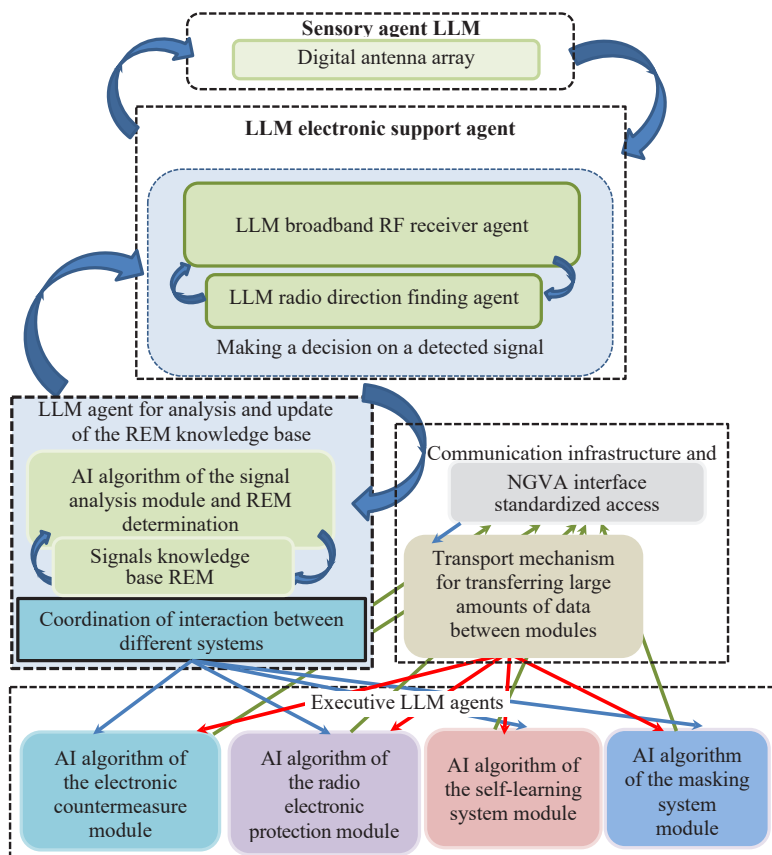
Thanks to the integration of these components, the LLM executive agents form a single adaptive mechanism that ensures the implementation of electronic warfare strategies in practice. Their ability to quickly make decisions, accurately perform tasks and continuously improve makes them an indispensable component of modern EW systems. Integration of LLM technologies allows to increase the efficiency of executive agents in dynamic conditions, to increase situational awareness in the corresponding area of responsibility of EW complexes (means).

The set of the specified robotic EW platforms should be connected into a distributed network with centralized control, which will allow to implement the mode of spatial diversity of flicker interference, spectral and energy management.

The concept of the architecture of a distributed system of autonomous EW means (Distributed Autonomous System, DAS) is also based on multi-agent LLM technologies (Multi-Agents LLM, Fig. 3).

The main feature of this architecture is the integration of intelligent agents that perform tasks of signal processing, decision-making, coordination of actions and implementation of counteraction and protection functions. The uniqueness of the approach lies in the multi-level structure, which provides high adaptability, automation and efficiency of the system. The DAS architecture is built on the interaction of various modules, each of which performs a clearly defined role in the overall system operation process. At the initial stage, data is obtained using a DAA set that are capable of receiving signals in a wide frequency range. In this case, cooperative signal processing is possible, with the specialization of individual robotic platforms in the selection of certain types of radiation sources, the distribution of electromagnetic wave ranges, signal detection sectors, etc.

DAAs provide initial information for all subsequent modules, which allows the system to function with high accuracy.



**Fig. 3.** Concept of DAS (Distributed Autonomous System) architecture based on Multi-Agents LLM

In accordance with the presented concept, further signal processing is carried out by the broadband radio frequency receiver and direction finding modules, which work in close cooperation. They are responsible for determining the parameters of signals and the angular coordinates of their sources (DOA, Direction of Arrival) with high accuracy. This data within a single platform is transmitted to the signal analysis and REM tool determination module, which identifies the radiation source and classifies it by threat level. In the absence of a source in the database of a specific EW platform, the corresponding agent has the opportunity to seek help from other robotic platforms or the cloud environment.

The use of large language models in these modules allows analyzing complex signal patterns and drawing conclusions in situations of uncertainty. An important feature of this architecture is a common knowledge base of REM signals of a set of robotic tools, which is constantly updated thanks to self-learning algorithms. This ensures the relevance of the data and allows the system to adapt to new types of signals and the tactics of their use by the enemy. The knowledge base serves as a central element for decision-making and provides support to all modules of this system. The communication infrastructure is another important element of the architecture. The use of a high-speed network and standardized NGVA interfaces of individual platforms ensures effective data exchange between all modules. This infrastructure allows the system to operate in real time, ensuring synchronization of actions and rapid response to changing situations. The final part of the architecture is the executive agents that implement cooperative strategies formed on the basis of the received data. They include electronic countermeasures, protection, masking and self-learning agents. These agents operate autonomously, but are coordinated through a common information infrastructure. They provide effective counteraction to enemy signals, protection of their own systems and constant improvement of work algorithms.

The main feature of the proposed concept is the integration of multi-level coordination and self-learning mechanisms, which al-

lows the DAS system to adapt to dynamic conditions and perform tasks with high efficiency. The multi-agent structure based on an ensemble [32] of large language models [33] and the Mixture of Experts architecture [34] provides the system with flexibility, scalability and integration with other platforms [35], which makes it an indispensable element of promising electronic warfare.

Having compared the two proposed concepts of architectures regarding the algorithms of operation of robotic EW equipment with integrated AI technology based on multi-agent LLM models (Fig. 2, 3), it is necessary to indicate that the main difference between the concepts lies in the structure of interaction between agents and the distribution of functions.

In the first concept (Fig. 2), coordination between modules is more linear, which ensures high accuracy and predictability of the system operation.

In the second concept (Fig. 3), interaction is organized through standardized interfaces, which allows creating more flexible systems that have the ability to integrate additional modules and platforms without significant changes in the basic architecture, according to the "plug and play" principle.

Despite the identified differences, both concepts have common advantages, in particular the use of LLM for signal analysis and classification, self-learning mechanisms for adaptation to changing environmental conditions, and integration with other systems.

Together, they demonstrate two different but complementary approaches to building modern EW systems based on Multi-Agents LLM.

This allows choosing the optimal architecture depending on the requirements for functionality, operability, and scalability needs.

*The practical significance of the results obtained* lies in substantiating the architectural concepts of multi-agent systems with integrated LLMs, which can be implemented not only in EW means, but also in related areas, such as surveillance systems, communication networks, and dual-purpose security platforms. This allows to increase the level of automation, reduce the reaction time to new threats and increase the accuracy of electromagnetic signal analysis. The application of the research results in the military sphere allows to optimize the load on the operator, quickly integrate the update of the knowledge base about new types of radiation sources and implement the principles of distributed control for effective coordination of actions in a complex electromagnetic environment.

*The limitations of the research* are that the presented algorithms and concepts were tested mainly on the basis of simulation modeling and test scenarios, which are not always able to fully reproduce the conditions of real combat operations. In addition, the implementation of the proposed solutions requires an appropriate hardware base (high-performance computing resources, ultra-high-speed network infrastructure, advanced antenna systems). Given the dynamic development of the enemy's REM capabilities, there is a need for regular updating of algorithms and replenishment of the knowledge base, which may also require additional time and financial resources.

*The conditions of martial law in Ukraine* during the research limit the scope of the article in the context of covering all the results obtained, as well as the level of detail of information on the technical characteristics and tactical features of the use of electronic warfare capabilities. This is due to the need to comply with security requirements and non-disclosure of information that constitutes a state secret. In addition, changes in the educational and scientific process associated with distance learning and training have affected the volume of contacts when discussing the

obtained experimental data in multidisciplinary scientific teams with expertise in the field of AI and radio engineering systems.

*Prospects for further research.* The presented results prove that the application of LLM in electronic warfare is a promising direction that contributes to the creation of autonomous, adaptive and highly effective solutions for solving electronic warfare tasks. The analysis emphasizes the importance of further research in this direction, in particular with an emphasis on improving algorithms, integration with other systems and modeling new approaches to increasing the reliability of operation in combat operations.

In addition, in the future, the capabilities of the proposed systems should be expanded by integrating with other types of weapons and military equipment, creating highly reliable information exchange channels between different branches of the armed forces and developing more universal approaches to self-learning algorithms based on new signal patterns.

Further verification in real combat conditions, as well as the development of mechanisms for protecting against enemy attempts to mislead the system (adversarial attacks), will be important directions for increasing the stability and reliability of the considered methods in the context of modern challenges of electronic warfare.

#### 4. Conclusions

The paper considers and theoretically substantiates two concepts for building multi-agent EW systems based on LLM. The first concept focuses on a single robotic vehicle (local architecture), and the second on a distributed network of autonomous vehicles (DAS) connected by standardized interfaces. Both concepts implement a specific goal of increasing the efficiency of EW systems by coordinating agents that use deep learning methods and the Retrieval-Augmented Generation (RAG) mechanism for rapid knowledge base updating.

The proposed multi-agent approaches eliminate the limitations of traditional EW systems that do not have time to adapt to the enemy's rapidly changing EW. The proposed approach using LLM allows for the recognition and classification of new types of signals in real time, which is identified in the literature as a key problem in increasing the accuracy and efficiency of EW systems.

It should be noted that the use of the RAG mechanism for the knowledge base reduces delays in entering new information and allows the system to respond to changes in the characteristics of enemy signals much faster than with known approaches. Integration through standardized interfaces allows for rapid scaling and updating of the system, which is important for networked military operations.

The improvement in efficiency is achieved through a combination of three key factors: a multi-agent architecture that allows for parallel processing and analysis of data; transformer-type LLM algorithms capable of performing in-depth analysis of radio signals in real time; a RAG mechanism that provides automatic updating of the knowledge base and makes the analysis results available to all system agents. It is thanks to such integration that it is possible to significantly increase the speed of processing identified signals and the accuracy of decision-making.

As part of the test experiment, the signal classification time using the DenseNet169 neural network on the Tesla V100-SXM2-16GB GPU was an average of 0.1–0.2 seconds. For comparison, the reaction of a human operator is approximately 0.8 seconds, so the use of DenseNet169 provides an approximately fourfold acceleration of the signal detection and identification process.

The test experiment confirms that this approach directly reduces the operator's workload, increasing the probability of timely threat detection and increasing the overall efficiency of the EW system.

The proposed solutions can be used both in military systems (to optimize the tactical and technical parameters of EW means and reduce the cognitive load on operators), and in civilian security or monitoring

systems, where fast processing of a wide range of signals and automated decision-making are required.

The research results will become the basis for the development of modern autonomous EW means. The formation of tactical and technical requirements for them, as well as for their components, should be based on the use of standardized interaction interfaces for different platforms. At the same time, the architectures presented in the article allow determining the requirements for the network infrastructure and its bandwidth, as well as for self-learning algorithms, taking into account the limited computing resources in field conditions. In general, it should be noted that the implementation of a coordinated multi-agent system based on LLM opens up prospects for creating more sustainable, adaptive and effective solutions in the field of electronic warfare.

#### Conflict of interest

The authors declare that they have no conflict of interest with respect to this study, including financial, personal, authorial or other interests that could influence the study and its results presented in this article.

#### Financing

The study was conducted without financial support.

#### Data availability

The manuscript does not contain any related data.

#### Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the presented work.

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✉ **Vadym Kozlov**, PhD, Scientific and Organizational Department, Central Research Institute of Armaments and Military Equipment of the Armed Forces of Ukraine, Kyiv, Ukraine, e-mail: [kozlovvadim545@gmail.com](mailto:kozlovvadim545@gmail.com), ORCID: <https://orcid.org/0000-0002-7708-6143>

**Vadym Slyusar**, Doctor of Technical Sciences, Professor, IEEE Member, Chief Researcher, Researcher Head Group, Central Research Institute of Armaments and Military Equipment of the Armed Forces of Ukraine, Kyiv, Ukraine, ORCID: <https://orcid.org/0000-0002-2912-3149>

**Volodymyr Tverdokhibov**, PhD, Senior Research Fellow, Head of Research Department, Central Research Institute of Armaments and Military Equipment of the Armed Forces of Ukraine, Kyiv, Ukraine, ORCID: <https://orcid.org/0000-0002-6802-9796>

**Zoia Andriichuk**, Research Fellow of Scientific and Information Department, Central Research Institute of Armaments and Military Equipment of the Armed Forces of Ukraine, Kyiv, Ukraine, ORCID: <https://orcid.org/0000-0002-3743-4035>

✉ *Corresponding author*