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COGNITIVE AI PLATFORM FOR AUTONOMOUS NAVIGATION OF DISTRIBUTED MULTI-AGENT SYSTEMS

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Abstract. This paper presents a concept for a cognitive AI platform that enables autonomous navigation of distributed multi-agent systems, exemplified by UAV swarms. The proposed architecture integrates a ground control center with cognitive services and a multi-layered onboard subsystem, supporting a continuous loop of learning, adaptation, execution, and behavioral model updates. Several core mission scenarios are introduced, such as reconnaissance, search and rescue, target neutralization, and deception, showcasing the swarm's ability to operate autonomously and in a decentralized manner, even under adversarial conditions. An example of a search and rescue mission implementation plan using a cognitive platform that includes adaptive planning, SLAM navigation, swarm coordination, and deep object recognition is presented. The results were partially supported by the National Research Foundation of Ukraine, grant No. 2025.06/0022 "AI platform with cognitive services for coordinated autonomous navigation of distributed systems consisting of a large number of objects".

Keywords: artificial intelligence, UAV swarm, autonomous navigation, cognitive platform, multi-agent systems, behavior trees, digital twin, SLAM.

INTRODUCTION

In modern conditions of increasingly complex combat environment, active electronic warfare, and loss of reliable satellite connection network, a critical need arises for creating autonomous, decentralized control framework for distributed systems, particularly swarms of unmanned aerial vehicles (UAV). In this context the development of a cognitive AI platform, capable of guaranteeing the coordinated navigation of a multitude of agents prohibited from interaction with a centralized control point or external infrastructure, becomes especially important [1–3]. This kind of environment requires not only sufficient autonomy level of individual agents (drones), but also a wholesome approach to the organization of their collective behavior implemented through cognitive self-learning, self-organization, adaptation algorithms, and resilient inter-agent information exchange. The theoretical and methodological basis for constructing this kind of platform was described in [4–10], in particular the impossibility of full consistency of agents: swarm agents cannot have a fully coordinated movement direction on spherical surfaces (as well as on large single-connected compact manifold surfaces without edges, including geoids), which compromises at least ant colony algorithms, requiring the selection of special points as regrouping zones [5, Theorem 1].

The AI platform for autonomous navigation of distributed multi-agent systems is viewed as an integral architecture that combines two closely interconnected components: the on-board component functioning directly at each of the autonomous agents, particularly the UAV, and the ground control center that provides learning, simulation, validation and strategic system control. Both components are functionally and logically interconnected, and together they form a cognitive AI platform in a broad sense – as an intellectual, self-learning architecture, capable of adaptation to the changes in environment, and self-improvement on the basis of accumulated experience.

The on-board component of the AI platform provides the completely autonomous functioning of its agents. It implements the capability for independent navigation without the GPS (Global Positioning System) satellite signals, making decisions in real time, decentralized swarm coordination, and adaptation in case of losing individual agents, or changes in the environment. Its functioning is based on the on-board AI modules, sensor systems, stygmergy algorithms, decentralized planning, reinforcement learning methods, self-learning and self-organization, SLAM (Simultaneous Localization and Mapping) methods, and other modern approaches [11–13]. This component in particular implements the cognitive behavior during missions: each drone is able to orient itself, perform the assigned tasks, and interact with other swarm agents without centralized control.

The ground control center performs the role of the strategic brain center of the system. It provides both primary, and cyclical training of the neural networks, modeling mission scenarios in the simulation environment using digital twins [14–17], testing and validation of the models, as well as the generation of the behavioral politics for on-board implementation. The ground center aggregates information from OSINT/ESINT sources, adapts the models to the operational context using analytics, supports visualization, monitoring and strategic correction. Through secure human-machine interface the operator obtains access to parametrization of missions, system state management, and updates to the AI modules software.

The interaction between the on-board and ground systems is organized as a closed cognitive loop. In the pre-missionary phase, the ground control center implements the training of models, mission modeling; creates the digital twins for drones, and uploads the updated algorithms to the on-board systems. This process involves analytical modules that aggregate OSINT (Open-Source Intelligence) for adaptation to the current context. During missions, the drones operate autonomously, performing swarm coordination, and in case the secure connection is available, transmit telemetry to the center which conducts monitoring and provides corrections if necessary. After the mission, the collected data is analyzed, log files are checked for anomalies, the models are tweaked, and the new cycle of training is started. Thus, the system is capable of continuous cognitive evolution – it learns on its own experience, gradually increasing the efficiency and resilience to new challenges of modern combat environment.

The cognitive AI platform is the only intellectual architecture system that includes ground and on-board components that jointly form the adaptive and viable complex for coordinated autonomous navigation of a UAV swarm. This complex functions within a continuous loop of adaptation and improvement, encompassing pre-mission preparation, autonomous task completion, post-mission analysis, and further additional training. This loop implements the concept of a cognitive core as a system capable of forming, updating and generalizing knowledge based on its own experience, react to the variable conditions, support collective behavior of agents, and retain efficiency in a complex, dynamic, and hostile environment.

The purpose of this research is to create architecture and principles of the system operation where each UAV behaves as an autonomous cognitive agent, capable of navigating without GPS, make decisions based on the local information, exchange signals with its neighbors using stygmergy or a mesh network, while acting within a single coordinated environment (the swarm). The construction of a new generation cognitive AI platform that combines adaptivity, resilience and scalability, is envisioned, enabling the UAV swarm to operate independently of external control, and efficiently complete the assigned tasks (missions) even under critical circumstances. This research is aimed at implementing the swarm intelligence in defense and rescue technologies, and forms the theoretical and engineering base for the next generation of double purpose autonomous systems.

THE GROUND CONTROL CENTER FOR THE AI PLATFORM WITH COGNITIVE SERVICES

The ground control center for neural network training is a critical architecture element of the general AI platform for cognitive control of the autonomous drone swarm. It performs the functions of development, testing, adaptation, security check, and preparation of the behavior strategies and cognitive models that will be uploaded to each of the drones before the actual mission assignment. The structure of this center is modular, logically decentralized, but centralized by computational power. It includes the following main functional blocks (Fig. 1):

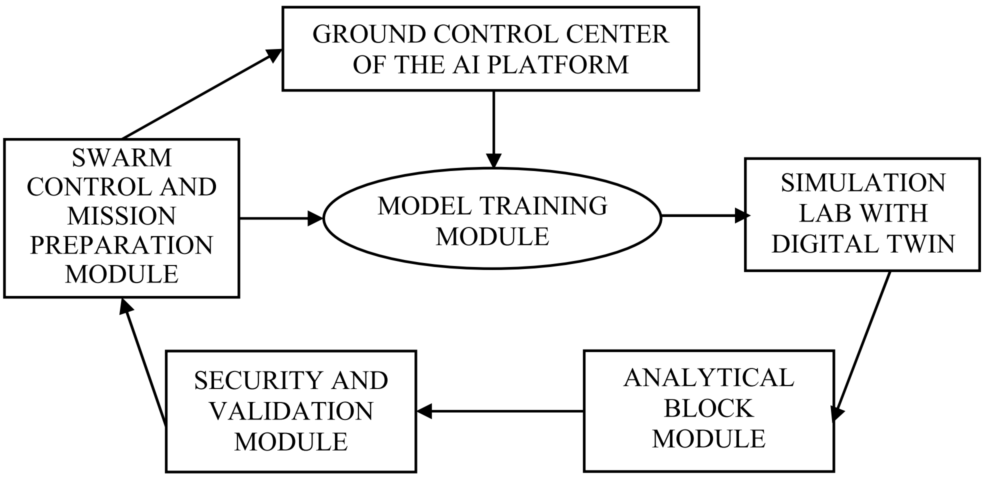

Fig. 1. The architecture of the ground center of the AI platform

Model training module. This block is responsible for the primary and recurrent training of the neural networks that will be applied in drone systems. The technologies involved include Reinforcement Learning models, self-learning models, perception models for detection and tracking of objects, as well as graph neural networks (GNN) for optimization of behavior in swarm configurations. The training is performed both on the historical data, and the data obtained during previous missions.

Simulation lab with digital twin. The digital twin of the ground center is a critical element of the general AI platform architecture that allows to test the neural network behavior in complex and variable scenarios. Here both the standard situations are simulated, and the stress scenarios, including the loss of the swarm elements, navigation under interference, electronic warfare conditions. This stage provides adaptivity and resilience of the trained behavior even before the real operation.

Analytical block. This module conducts the analysis of open-source data (OSINT). Analytical insight regarding the potential risks, typical tactics of the enemy, or features of the mission territory can be promptly integrated in the process of preparation for the real mission, increasing the relevance of the drone behavior. This may include, in particular, the location of the notable objects, relevant mission details, maps etc.

Security and validation module. Following the primary training, all models are tested to ensure they meet resilience, security, and durability requirements. In particular, this check includes a model's capability of detecting anomalies, restoration after errors, resilience to attacks at the data level, connection channels, and model integrity. Validation is the obligatory stage before the mission implementation.

Swarm control and mission preparation module. This block represents the control interface that aggregates the results from all other blocks and prepares the behavior model for uploading to the drones; forms the detailed missions; distributes the tasks among agents; plans the route networks; defines the zonal priorities. This module is used to upload the prepared cognitive software to the drones before their assignment to the real or test mission. The center also performs the functions of the swarm state monitoring, interactive control, and strategy adaptation in real time.

As the Fig. 1 shows, the interaction between the sub-systems of the ground control center is organized as a closed cognitive loop that guarantees the wholesome functioning of the drone swarm control system. In this loop the models formed in the training module are automatically transferred to the simulation lab, where they are subject to testing under the circumstances as close as possible to the real environment. The simulation results are analyzed by the validation module that makes the decision regarding the fitness of the models for combat use. The OSINT module works in parallel, generating the contextual scenarios using open-source intelligence data; these scenarios are integrated into the training processes, increasing adaptivity and relevance of the trained models.

When the neural networks complete all verification stages, the swarm control center uploads them on-board of the drones, initiating missions, and performing their accompaniment, monitoring and correction in real time. Thus, the ground center acts as a "cognitive foundry" of the system – the environment where the artificial intelligence is not only created but also evolves under the influence of the new data, combat experience, and strategical analysis. Here the intellectual potential of the swarm is formed, allowing the drones to act as intelligent autonomous agents with high adaptation abilities, mutual understanding, and collective behavior in the complex and hostile environment.

BASIC SCENARIOS (MISSIONS) FOR THE AUTONOMOUS NAVIGATION OF THE DISTRIBUTED MULTI-AGENT SYSTEMS

In modern combat and rescue conditions the scenarios for the drone swarm constitute the basis for the cognitive behavior of the autonomous agents that function within the integral AI platform. These scenarios are not just simple instructions – they represent the structured, multi-component algorithmic descriptions, preliminarily modeled in the ground control center. Due to the involvement of digital simulation environments (such as Gazebo or AirSim), analytical modeling, mission planning tools (such as QGroundControl), and machine learning methods, the scenarios achieve high adaptivity to the complex and dynamic environment. After modeling they are saved in JSON, XML, TensorRT, ONNX [18] etc. formats, and are uploaded to the computational blocks of each drone through a secure channel before the mission starts.

The content of these scenarios includes several critically important functional blocks: mission planning, autonomous navigation, recognition, decision making, and swarm coordination. The planner contains the vectorized task description, temporal parameters, action sequences, and defined objectives. The autonomous navigation modules provide route planning in real time using SLAM, localization and obstacle avoidance algorithms. The recognition components are responsible for the processing of sensor data from cameras, thermal imagers and radars, allowing them to detect objectives, obstacles and threats. The decision making is implemented through cognitive models capable of situational analysis, and producing reactions based on environment assessment. Finally, the swarm coordination provides the dynamic distribution of roles between agents, syncing of the trajectories, and coordinated behavior within the swarm [19].

The unique nature of these scenarios lies in their ability to activate the onboard drone cognitive modules that provide adaptive behavior even in case of the absent connection to the control center, external interference, or the shifting environment. In other words, the drones not only implement the previously assigned actions, but also learn from the current situation, predict risks, and react collectively. This is made possible by the integration of reinforcement learning methods, graph neural networks, and large language models that enable flexible, situational cognition at the swarm level [20].

Let us provide a list of basic scenarios:

Scenario 1: *Enemy territory reconnaissance.* The drone swarm distributes the reconnaissance area (e.g., 10×10 km), with each sub-area assigned to an individual drone. The results are obtained as a shared locality map. The scenario is performed by 6–12 drones that cover up to 100 km^2 in 15–40 minutes.

Scenario 2: *Targeted strike with autonomous guidance.* Several drones attack the target from different directions, overcoming air defenses by dispersed planning. Up to 7 drones attack the target's coordinates in 3–10 minutes after its detection.

Scenario 3: *Communication relay.* The drone swarm creates a temporary mesh network, providing connection under electronic warfare. For example, 5–15 drones create a 5–10 km long linear network, providing communication for 20–60 minutes.

Scenario 4: *Search and rescue*. The swarm autonomously scouts the destruction zone, detecting people and animals by performing scanning with distribution of routes. Up to 20 drones are used, with coverage area 10–40 km^2 for one hour.

Scenario 5: *"Death ring" swarm attack.* The drones fly round the target from all directions, forming a ring, and strike it simultaneously. In this scenario 5–10 drones are used, with 100–500 m attack radius during 5–15 minutes.

Scenario 6: *Scattering false targets/misinformation.* The swarm scatters imitation objects to mislead the enemy or mask the actual swarm's goals, by performing a coordinated placement of false targets (vehicle imitations), or modeling the behavior of a real vehicle column. During 10–30 minutes 5–10 drones place signal imitators along the 20 km route, using GPS and waypoint navigation (a drone moves from one waypoint to another in a predetermined sequence).

The compiled scenario (mission) parameters are given in Table 1.

Table 1. The compiled scenario (mission) parameters for UAV swarms

Scenario	Drone quantity	Surface/length of coverage	Duration	Communication/ protocol
Scenario 1. *Enemy territory reconnaissance*	6–12	Up to 100 km²	15–40 minutes	DDS or ROS topics + sensors (LIDAR/camera)
Scenario 2. *Targeted strike with autonomous guidance*	Up to 7	Depends on target (up to 10 km)	3–10 minutes	MAVLink/mesh connection
Scenario 3. *Communication relay*	5–15	5–10 km	20–60 minutes	DDS+RTPS with real-time QoS profile
Scenario 4. *Search and rescue*	Up to 20	10–40 km²	Up to 1 hour	ROS topics + thermal imager
Scenario 5. *Death ring*	5–10	Attack radius up to 500 m	5–15 minutes	ROS2 + DDS
Scenario 6. *Scattering false targets*	5–10 depending on the route	Up to 20 km route	10–30 minutes	MAVLink with waypoint navigation

So, the scenarios for the drone swarm become the key element for the cognitive AI platform, combining high precision planning, realistic simulation, analytical adaptation, and self-learning. Their exploitation not only increases mission efficiency, but also provides resilience to the uncertainty factors, which is critical in the environment where each second and each decision is significant.

ON-BOARD COMPONENT OF THE AI PLATFORM WITH COGNITIVE SERVICES

The on-board component is a key functional environment where the autonomous intelligence of each drone in the swarm is implemented. This is the place where the integration of cognitive models, sensory perception, swarm interaction, flight control, and adaptive decision making in real time is performed. The architecture of this component (Fig. 2) is multi-layered and includes a number of modules that jointly ensure the independence of the drone from external control, its self-learning capacity, and flexible reaction to a dynamic environment.

Let us consider each module of the architecture presented in Fig. 2, reviewing its functions, and their mutual interaction.

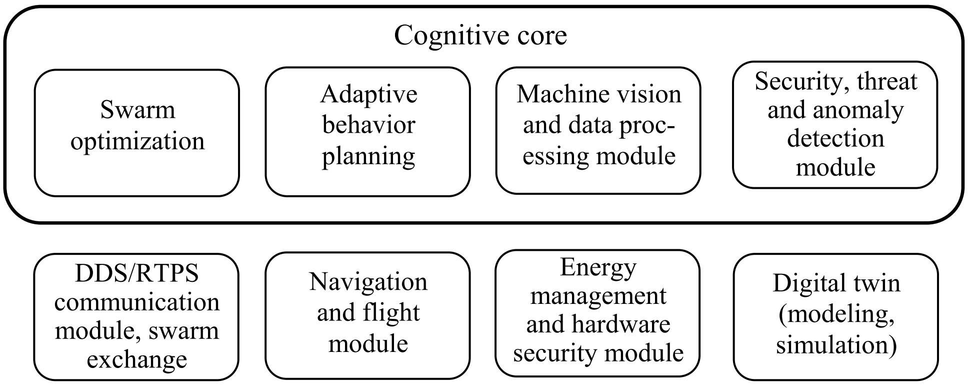

Fig. 2. The structural scheme of the on-board component of the AI platform with cognitive services

The center of the architecture is comprised of the cognitive core that acts as a drone's "brain", and is responsible for situational analysis, adaptation and decision making. Its fundament is the *Swarm coordination* module, implemented using the hybrid approach where the swarm AI methods are applied using a hybrid scheme: the Behavioral trees (BTs), and Global swarm optimization (Global Best PSO) that can reconfigure in real time depending on the changes in the environment [21–22]. This allows each agent to form the sequence of actions, independently react to the loss of communication, emergence of new threats, or changes in objectives.

Combined with the *Adaptive behavior planning* module that analyzes risks, priorities and current context, the system acquires the ability for conscious decision making even having incomplete information. It performs the incremental onboard learning (given the appropriate resources), bufferization of the field data, and the backhaul retraining loop implementation – the transmission of the collected data to the ground control center, with the subsequent updates in the models. This mechanism forms the basis of the system evolution, as it allows to take previous experience into account in the future missions. This approach allows to coordinate local trajectories, synchronize agent sub-groups, and sustain the overall mission goals at the lower autonomy level.

To enable these cognitive processes, the drone requires a constant flow of information about the environment. This task is achieved by the *Machine vision and data processing* module that aggregates the data from cameras, ultra-sonic sensors etc., forming the local space maps using SLAM algorithms [23–24]. An important feature of this layer is its capability for semantic classification of the objects (e.g., enemy units, civilians, allied units), and detection of the situational patterns that allow to construct not only a spatial, but also a behavioral model of the environment.

For coordinated interaction among the swarm elements, the platform contains the *communication* module, based on low latency DDS/RTPS protocols. It provides the interchange of statuses between agents by behavioral subtree broadcast, and allows to maintain the swarm coordination without the centralized control [25–27]. Even in case of losses or disruption in network channels the module remains operational due to the QoS control network that allows to duplicate critical data, and adapt priorities.

The physical implementation of the cognitive core is done by the *Navigation and flight* module that is the interface to the autopilots like PX4 or ArduPilot. It performs maneuvers, passing route points and avoiding obstacles, while relying on the visual odometry and SLAM data to ensure collision safety.

At the same time, the *Security, threat and anomaly detection* module is responsible for self-observation: temperature monitoring, CPU/GPU load, system degradation detection, and activates fail-safe scenarios, or dynamically reschedules the swarm tasks in case of losses of individual agents. Detecting anomalies in time series of sensory indicators allows the system to automatically react to potential threats, detect compromised swarm participants, analyzing the irregular patterns in input data. This approach is more flexible than the traditional heuristic rules in robotized systems [4].

A strategically important link is the *Digital twin* module – a limited representation of a fully functional digital twin deployed in the ground control center. On-board this module is responsible for maintaining the relevant strategies, simulation of the partial actions, and asynchronous renewal of the behavioral models [14–17]. It guarantees the autonomous behavior even in case of a complete connection loss, synchronizing data later.

Finally, the stability and security of the system is sustained by the *Energy management and hardware security* module that includes communication encryption, agent authentication, multi-layered service backup, and power management. This module allows the system to adapt to power supply limitations, lowering the sensor operation intensity, or switching to the energy-saving mode in critical moments. The whole multi-layered system provides the autonomous, adaptive and resilient UAV swarm operation even in hostile or unpredictable environment, implementing the modern approaches to the on-board cognitive management.

SCENARIO 4 (SEARCH AND RESCUE) IMPLEMENTATION PLAN EXAMPLE

The operational situation: after a large-scale earthquake in some region several settlements were ruined. There is a risk of further collapses, and the access for the ground rescue groups is limited. An autonomous scanning of territory with a total area of nearly 30 km^2 is required to find the victims, designate safe evacuation zones, and transmit the coordinates to the ground forces.

The employment of the AI platform. To implement the scenario, a swarm system of 16 autonomous quadcopters will be deployed. The drones will be equipped with thermal imagers, RGB cameras, and laser rangefinders (LiDARs). The computational platform of each drone allows local image processing, map charting, and decision making. SLAM navigation, along with visual odometry and obstacle avoidance module, will be used to form local maps, and dynamically plan routes in real time. The behavioral coordination in the swarm will be implemented on the base of combined Behavior Trees and Graph Neural Networks that will allow adaptively distribute the tasks between agents, avoid duplication of the search zones, and optimize the area coverage.

The platform will ensure:

- distribution of the swarm into sub-groups of 4 drones with partial (~10%) overlap of the areas for increased probability of object detection;
- detection of heat anomalies using a pre-trained neural network;
- suppressing background noise (e.g., heat from transport or infrastructure);
- exchanging scanned area tags, and analysis results between participants.

For synchronization of the swarm behavior the implementation of the sub-tree broadcast protocol is planned that will transmit the minimal context every few seconds. Communication between agents is planned to be achieved through the ROS Topics + DDS with QoS parameters stack, providing reliable data exchange.

The expected data to be utilized includes:

- previous mission simulation models, formed on the base of satellite image data, topographical data and OSINT;
- fallback behavior scenarios for cases of connection loss or situation change.

The transmission to the ground center is conducted through relay drones that hover at up to 120 m height and form the mesh network. They transmit:

- local maps;
- visual confirmations;
- coordinates of detected objects and safe areas;
- GPS/SLAM log files.

The expected results include:

- detection of the potentially alive targets using thermal signatures;
- coverage map charting, and marking the risk areas;
- designation of safe routes for evacuation;
- transmission of the structured coordinates and statuses to the operational headquarters.

CONCLUSIONS

1. The developed AI platform for the autonomous navigation of UAV swarms presents a fundamentally new approach to handling the distributed multi-agent systems under conditions of a complex, dynamic, and hostile environment. Its architecture combines the ground control center, and the autonomous on-board subsystem, providing a continuous loop of adaptation, learning and evolution for artificial intelligence during each of the mission stages, from pre-mission modeling, to post-mission analysis. The ground control center performs the functions of simulation, training, validation and strategic coordination, while each drone, due to its cognitive core, sensory stack and communication modules, implements autonomous navigation, recognition, and decision making without centralized control.

2. A number of basic scenarios (missions) is formed that cover a broad spectrum of combat and humanitarian tasks. These scenarios include both classic objectives (reconnaissance, targeted strikes, communication relay), and specialized missions (search and rescue, misinformation, “death ring” strike), proving the platform’s scalable and universal nature in dynamic environments. Formalization and typification of such scenarios allow to not just quickly adapt the swarm to new conditions but also form a repository for behavioral patterns that will be improved using the principles of cognitive learning over time.

3. An on-board component of the AI platform with cognitive services was developed by combining a cognitive core, a sensor and analytical layer, navigation, communication, and security modules. Each drone in the system can act independently, adapt to the changes in environment, make critical decisions in real time, and interact with other agents without centralized control. The hybrid application of the AI swarm intelligence methods "Behavior Trees" and "Global swarm optimization", and SLAM methods provides situational prediction and flexible reaction. The availability of power management, self-observation, and local knowledge updates additionally fortifies the system's survivability, and the digital twin module provides the asynchronous swarm evolution even after connection loss. All these functional capabilities prove that the on-board component is not just a computational node, but an accomplished cognitive agent, able to conduct missions within the decentralized new generation architecture.

4. A model search and rescue scenario of people after a catastrophe is proposed, where a drone swarm autonomously scans the investigated area, detects heat anomalies, identifies casualties, and transmits the coordinates for evacuation.

In preparing this manuscript, we used ChatGPT 4.0 to improve the style.

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КОГНІТИВНА AI-ПЛАТФОРМА ДЛЯ АВТОНОМНОЇ НАВІГАЦІЇ РОЗПОДІЛЕНИХ БАГАТОАГЕНТНИХ СИСТЕМ / М.З. Згуровський, П.О. Касьянов, Н.Д. Панкратова, Ю.П. Зайченко, І.О. Савченко, Т.В. Шовкопляс, Л.С. Палійчук, А.М. Титаренко

Анотація. Подано концепцію когнітивної AI-платформи для автономної навігації розподілених багатоагентних систем на прикладі рою безпілотних літальних апаратів. Запропоновано архітектуру, яка поєднує наземний центр із когнітивними сервісами та багаторівневу бортову підсистему, що забезпечують безперервний цикл навчання, адаптації, виконання та оновлення поведінкових моделей. Сформульовано базові сценарії місій, зокрема розвідка, пошук і рятування, ураження цілей, дезінформація, які демонструють можливості рою до автономної, децентралізованої взаємодії навіть у ворожому середовищі. Представлено приклад плану реалізації місії пошуку і рятування із використанням когнітивної платформи, що включає адаптивне планування, SLAM-навігацію, ройову координацію та глибоке розпізнавання об'єктів. Результати частково підтримано Національним фондом досліджень України, грант № 2025.06/0022 «AI-платформа з когнітивними сервісами для координованої автономної навігації розподілених систем, що складаються з великої кількості об'єктів».

Ключові слова: штучний інтелект, рій дронів, автономна навігація, когнітивна платформа, мультиагентні системи, поведінкові дерева, цифровий двійник, SLAM.