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¹Anatoly Gladun,
²Kateryna Khala,
³Oleksandr Volkov,
⁴Volodymyr Simakhin

DYNAMIC ONTOLOGY FOR SEMANTIC-PROGNOSTIC SELF-ORGANIZATION OF A UAV SWARM

Institute of Information Technologies and Systems of the NAS of Ukraine, Kyiv, Ukraine

E-mails: ¹glanat@yahoo.com ORCID 0000-0002-4133-8169,

²khala@irtc.org.ua ORCID 0000-0002-9477-970X, ³alexvolk@ukr.net ORCID 0000-0002-5418-6723,

⁴thevladsima@gmail.com ORCID 0000-0003-4497-0925

Abstract—The paper proposes a dynamic ontological model for the semantic-predictive self-organization of an unmanned aerial vehicle (UAV) swarm. A multi-layer ontological model of the UAV swarm is developed, comprising a static core, a dynamic instance layer, an agent layer with local knowledge projections, and a mechanism for semantic synchronization of agents to ensure knowledge consistency in a distributed multi-agent system. A mathematical model is formulated to formalize the processes of knowledge alignment, scenario forecasting, and optimal action selection. The organization of interactions between structural layers is examined, providing knowledge exchange, adaptive role allocation, and support for collective agent behavior. Experimental simulation conducted in the Gazebo environment for forest fire monitoring by a group of 12 UAVs confirms the effectiveness of the proposed approach: semantic consistency reached 91%, the accuracy of critical event prediction increased by 17–20%, and network load decreased by 83.4%. The developed model ensures scalability, robustness to the loss of individual agents, and efficient execution of cooperative tasks, making it suitable for the development of intelligent control systems for autonomous UAV swarms.

Keywords—Dynamic ontology, multi-agent system, UAV swarm, semantic-predictive self-organization, agent coordination.

I. INTRODUCTION

The application of unmanned aerial vehicle (UAV) swarms requires a high degree of autonomy and the ability to adapt to dynamically changing environmental conditions under resource constraints [1], [2]. The transition from single-drone deployment to complex swarm structures enables a significant expansion of area coverage and enhances the overall system resilience to the loss of individual elements [3]. The adoption of the multi-agent systems (MAS) paradigm facilitates decentralized decision-making: each UAV operates as an intelligent agent endowed with its own computational resources and local agent tasks aligned with the global mission objective [5], [7], [11]. Such MAS-based organization eliminates single points of failure and ensures flexibility in mission execution even in the presence of hardware failures or under conditions of intensive electronic warfare interference [8].

Existing UAV swarm control architectures are generally classified into three main types: centralized (sensitive to communication delays and electronic countermeasures) [2], decentralized (more robust to communication loss but typically limited to locally optimal solutions) [4], and hybrid MAS architectures [5], [6], [11] that integrate strategic planning with the capability for autonomous tactical actions at the local

level. One of the key challenges for MAS lies in organizing interaction among swarm elements at the semantic level and enabling agents to anticipate the evolution of events [2], [13]. The use of dynamic ontologies extends MAS functionality by ensuring semantic consistency of operational data obtained from swarm sensors regarding environmental changes, as well as adaptive knowledge management for effective alignment of information flows among swarm agents [7], [9], [10], [13].

A dynamic (evolving) ontology is defined as an ontological model capable of real-time adaptation under the influence of data streams from UAV swarm sensors, the emergence of new facts, or changes in the domain, thereby maintaining knowledge relevance without requiring complete model reconstruction [12]. In multi-agent systems, a dynamic ontology constitutes a distributed ontological representation of knowledge, where each agent operates on a local projection $O_i(t) \subseteq O(t)$, while the global ontology $O(t)$ evolves through mechanisms of alignment, synchronization, and consensus among agents.

Ontology-based modeling methods enable agents to correctly interpret uncertain situations observed in the external environment and to perform semantic processing of data obtained from heterogeneous

sources [4], [7], [9], [14]. This establishes the necessary foundation for the functioning of collective forecasting algorithms. The semantic representation of operational data ensures effective interaction among heterogeneous UAVs, regardless of the specifics of their sensor systems [15], [16]. The objective of this study is to develop and experimentally validate the effectiveness of semantic-predictive swarm self-organization, integrating dynamic ontologies, semantic data alignment procedures, and collective forecasting algorithms for anticipating changes in situational dynamics.

II. PROBLEM STATEMENT

Under contemporary conditions, the deployment of UAV groups increasingly involves the execution of complex cooperative tasks in dynamic environments characterized by incomplete and uncertain information. In such settings, system performance is primarily determined by each agent's ability to make autonomous decisions, flexibly redistribute functions, and promptly respond to changes occurring in the external environment.

In this context, the use of multi-agent systems and ontological knowledge models becomes particularly significant. These approaches enable the formalization of domain concepts, the specification of relationships among them, and the definition of agent communication rules. The integration of the ontological approach with self-organization mechanisms promotes knowledge consistency within the system, supports the semantic interpretation of events, and facilitates adaptive coordination of UAV group actions.

Moreover, the operation of UAVs in complex environments requires dynamic knowledge updating, adaptive reassignment of agent roles, and forecasting of event evolution. This necessitates the development of a knowledge model capable of ensuring interaction across different levels of representation and maintaining consistency in the semantic description of system states.

Thus, a relevant scientific challenge is the development of a multi-layer ontological model of a multi-agent system for UAV groups that integrates dynamic knowledge representation, semantic analysis mechanisms, and agent coordination. The implementation of such an approach is intended to enhance adaptability, knowledge consistency, and the overall efficiency of collective task execution in dynamic environments.

In addition to ensuring dynamic ontology updates based on UAV sensor data, effective mission

execution requires forecasting the occurrence of events and predicting the system's agent responses to these events, thereby supporting successful task accomplishment and overall mission fulfillment.

III. PROPOSED METHOD

The ontological model integrates a static ontology core, a dynamic instance layer, an agent-layer knowledge projection, and a semantic synchronization mechanism to ensure consistent, adaptive, and decentralized swarm operation in dynamic environments. Figure 1 illustrates the proposed four-layer ontological model that underpins the semantic-predictive self-organization of a UAV swarm. It structures the interaction between knowledge representation, agent reasoning, and coordination mechanisms.

The first layer of the model is the static ontology core, O_{Cor} , which serves as a declarative foundation: it defines a system of interrelated concepts (a class taxonomy), the relationships among them, and a set of logical axioms. Integrated inference rules (SWRL) automatically generate new knowledge; for example, a spatial localization rule associates a task with the operational zone of an agent, thereby simplifying mission monitoring:

$$\text{executes}(a,t) \wedge \text{located_in}(a,z) \rightarrow \text{located_in}(t,z).$$

The second layer is the dynamic instance layer $I(t)$, which functions as the swarm's operational memory by capturing the current state of the environment through concrete individuals ($Inst$), variable telemetry attributes (Val), and dynamic relations (Rel_{Inst}):

$$I(t) = \langle Inst, Val, Rel_{Inst} \rangle. \quad (1)$$

Continuous updating via sensor streams, mission events, and network updates ensures real-time system responsiveness.

The third layer is the agent layer, which endows each UAV with a local knowledge projection $O_i(t)$ to construct its internal world model WM_i . Using an ontological reasoner, each agent selects an optimal strategy π_i . Data exchange is performed exclusively through structured messages rather than raw data, thereby minimizing communication load and enabling decentralized decision-making.

The fourth layer is semantic synchronization, which is responsible for maintaining knowledge consistency across the system. In particular, it ensures the integrity and coherence of the dynamic instance layer among all agents operating under conditions of limited observability and asynchronous data access. The semantic synchronization

mechanism is implemented through four key components: change propagation strategy, conflict resolution, minimization of redundant network traffic, and support for ontology model evolution.

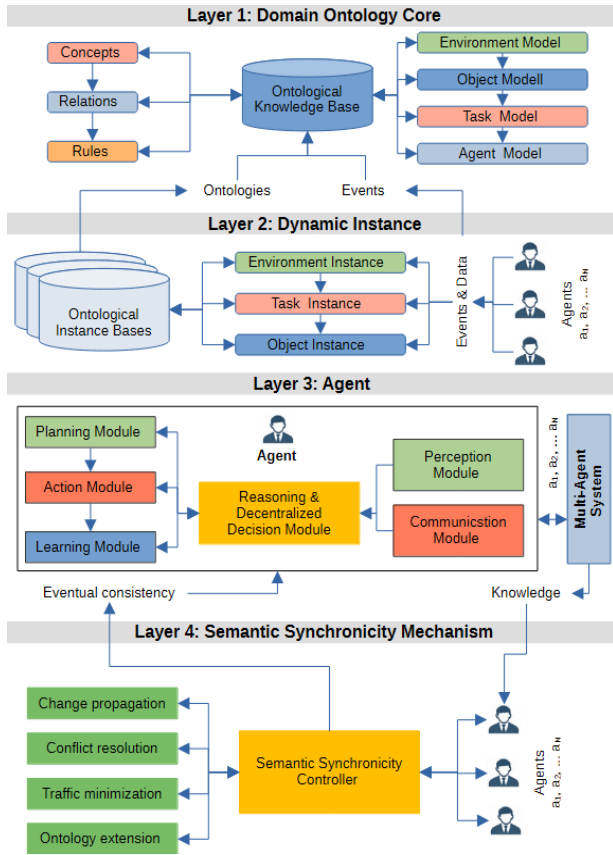


Fig. 1. Four-layer model of semantic-predictive self-organization of a UAV swarm

The change propagation strategy is based on two mechanisms: *Push*, which involves active dissemination during critical events (an agent immediately notifies all spatially or tactically related agents), and *Pull*, which enables on-demand data requests initiated by agents.

Conflict resolution addresses inconsistencies arising from concurrent updates of shared data through three approaches: prioritization of the agent with higher sensor accuracy, preference for the most recent message, or group consensus for the most critical decisions.

Minimization of redundant network traffic is achieved by combining three update mechanisms. Differentiated update frequency determines transmission priority: static data are transmitted once, dynamic data at high frequency, and critical data immediately. Delta updates involve transmitting only state changes instead of complete datasets. Update aggregation consolidates small messages into larger packets to reduce communication overhead.

Ontology model evolution occurs when an agent detects a phenomenon not represented in the existing model. In such cases, the agent initiates a proposal for a new class, which, after consistency verification, is incorporated into the ontology core.

The semantic synchronization mechanism ensures that all agents progressively achieve a consistent understanding of the environment and is based on the principle of eventual consistency:

$$\forall ag_k \in Ag(O_k(t + \Delta t) \models \text{assertion}), \quad (2)$$

where ag_k denotes an agent of the multi-agent system; $O_k(t + \Delta t)$ is the updated ontology (local knowledge base) of the agent; and *assertion* is a statement or fact that must be consistently represented within the knowledge system.

Overall, the semantic synchronization mechanism enables the swarm to attain a level of collective intelligence, supporting proactive planning in dynamic environments.

Formal description of the intelligent control model for a UAV group is represented as a tuple:

$$M = \langle O(t), Ag, \Psi, \Phi, \Pi \rangle. \quad (3)$$

Its foundation is a dynamic ontology:

$$O(t) = O_{Cor} \cup I(t), \quad (4)$$

where $O_{Cor} = \langle C, R, F, Ax \rangle$ denotes the invariant core comprising the hierarchy of concepts C , relations among them R , attribute sets F , and the axiomatics Ax , while $I(t)$ serves as the operational memory populated with up-to-date observations of individuals.

Through the axioms Ax , the system maintains knowledge consistency and is capable of autonomously inferring latent facts from the current system state, thereby establishing a logical foundation for collective interaction.

The multi-agent layer $Ag = \{ag_i \mid i = 1..n\}$ consists of autonomous agents:

$$ag_i = \langle O_i(t), WM_i, \pi_i, Com_i \rangle. \quad (4)$$

Each UAV operates on a local ontology $O_i(t)$, which is a context-dependent projection of global knowledge, significantly reducing computational costs. Based on $O_i(t)$, an internal world model WM_i is constructed, and a behavioral strategy $\pi_i: WM_i \times PS \rightarrow A$ is implemented, mapping the current state of the space PS to an action $a \in A$. The communication module Com_i enables the exchange of semantic constructs rather than raw data streams, which is essential for aligning knowledge models within the group.

The semantic alignment function Ψ is responsible for maintaining consensus within the collective by

minimizing discrepancies through the maximization of the pairwise similarity metric S_{ij} for neighboring nodes:

$$S_{ij}(t) = \frac{2 \cdot |C_i(t) \cap C_j(t)|}{|C_i(t)| + |C_j(t)|} \cdot e^{-\alpha \cdot d_{ij}(t)}. \quad (5)$$

This mechanism ensures the convergence of local representations while accounting for the geographical distance d_{ij} and the degree of overlap between conceptual spaces C . As a result, the swarm gains robustness to communication delays, and agents learn to filter informational noise from distant sources.

The cognitive function Φ implements the transition from representing the current state to predicting future events:

$$\Phi(O(t), E(t)) = \{(V_{S_m}, w_m)\}, \quad (6)$$

where V_{S_m} denotes a set of virtual scenarios and w_m represents their corresponding probabilistic weights. Using logical inference mechanisms, the system constructs probabilistic models of event evolution (e.g., “a sudden wind gust leads to a risk of trajectory deviation”). The weight w_m of each scenario is determined as the product of the statistical reliability of the involved rules and their relevance to the current environmental context $E(t)$.

The final selection of the optimal action a^* is performed by maximizing expected utility under time constraints:

$$a^* = \arg \max_{a \in A} \sum_{m=1}^M w_m \cdot U(a, V_{S_m}) \cdot \left(1 - \frac{T_a}{T_{\max}}\right). \quad (7)$$

Here, $U(a, V_{S_m})$ denotes the utility of an action within a given predicted scenario, while the factor $(1 - T_a/T_{\max})$ introduces a “delay penalty”, encouraging agents to select faster decisions. Thus, the described cycle endows the swarm with the ability to adapt to environmental dynamics while preserving the coherence of collective behavior.

IV. RESULTS

The experimental validation of the proposed architecture was conducted in the Gazebo simulation environment [17] using a forest fire monitoring scenario over an area of 1.5 km². A group of 12 unmanned aerial vehicles (UAVs) employed an ontological model comprising 53 concepts and 136 relationships. The obtained results were compared with a baseline multi-agent system lacking ontological support, in which information exchange was performed at a fixed frequency of 2 Hz. Figure 2 presents the dynamics of semantic synchronization among agents and a comparison of active UAV swarm self-organization with semantic-predictive synchronization (green) and without it (red).

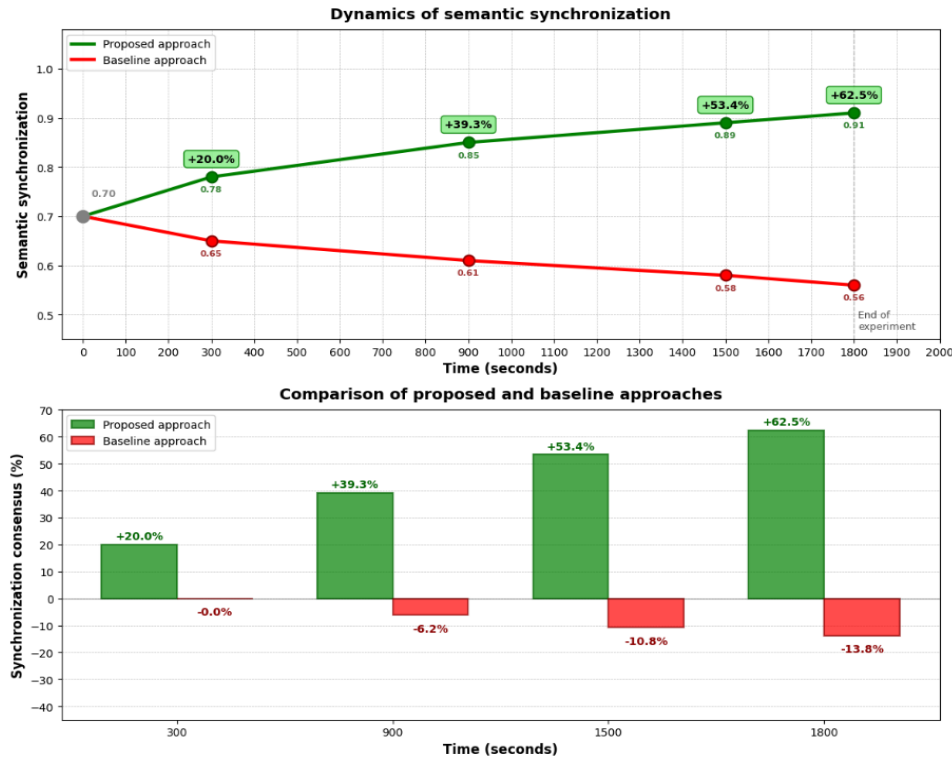


Fig. 2. Mission task execution with and without semantic synchronization of agents

The application of the proposed approach increased the level of semantic consistency within the group from 78% to 91%, whereas in the baseline scenario this indicator decreased to 56% due to the accumulation of discrepancies in environmental perception. The statistical significance of the results ($p < 0.01$ according to Student's t -test) confirms that semantic knowledge updating effectively prevents degradation of the world model under dynamic conditions.

The effectiveness of the proposed ontological model was further evaluated in terms of its ability to predict event evolution in a dynamic environment. For this purpose, a series of experiments was

conducted simulating key changes characteristic of forest fire development, including shifts in fire spread direction, the emergence of new ignition points, and variations in fire intensity within the frontal zone. The results of prediction accuracy analysis for these events are presented in Fig. 3.

Prediction generation was performed using logical inference based on rules defined in the SWRL language. The use of these rules enables integrated analysis of sensor data, incorporation of historical information, and consideration of spatial relationships among objects represented in the ontological model.

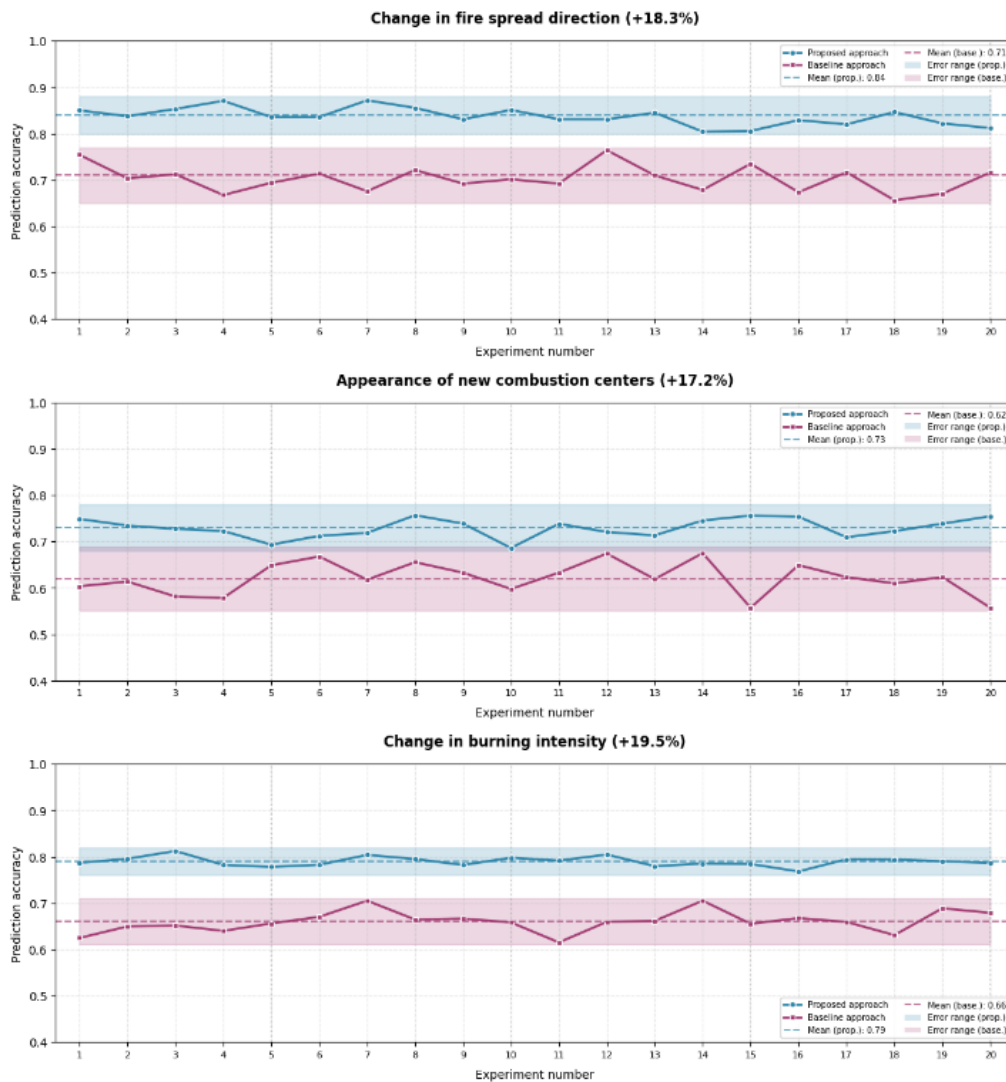


Fig. 3. Prediction accuracy for three types of events in fire dynamics

Figure 3 illustrates simulation results demonstrating the effectiveness of inter-agent synchronization and semantic-predictive UAV self-organization in fire monitoring and localization tasks. The analysis covers three key types of changes: fire spread direction, emergence of new ignition points, and fire intensity in the frontal zone.

The highest prediction accuracy (84%) was achieved for the event “change in fire spread direction”. This can be attributed to the fact that direction estimation is directly based on measurable physical parameters (wind speed and direction), which are continuously updated in the ontology via high-frequency sensor inputs. The lowest

performance was observed for the event “emergence of new ignition points” (73% versus 62%), due to the stochastic nature of ignition processes caused by non-deterministic factors (e.g., sparks, localized flare-ups). The proposed approach provides a stable improvement of 17.2% owing to the ontology’s ability to accumulate and analyze spatiotemporal patterns of prior events.

The prediction accuracy for the event “change in fire intensity” reached 79%, driven by stable correlations between vegetation type, moisture level, and combustion intensity. These dependencies are explicitly represented within the ontological taxonomy. Table I summarizes the comparative performance results of the proposed and baseline approaches.

TABLE I. SUMMARY COMPARISON OF APPROACH PERFORMANCE

Metric	Proposed Approach	Baseline Approach	Improvement / Reduction
Semantic consistency	0.91% ± 0.01	0.56% ± 0.07	+ 62.5%
Event prediction accuracy	73–84%	62–71%	+ 17–20%
Total network traffic	47.3 MB	284.6 MB	– 83.4%

Scalability analysis over a range of 6 to 24 UAVs demonstrated that the time required to reach consensus grows sublinearly, not exceeding 14.3 s for the largest group. Under these conditions, task success rates remain consistently high, indicating the absence of bottlenecks in the ontological model as the number of agents increases.

The introduction of delta compression and differentiated knowledge update mechanisms reduced network load by 83.4%. The decrease in peak traffic to 124.8 kbit/s makes the proposed architecture particularly suitable for deployment in bandwidth-constrained tactical networks, ensuring system survivability even under conditions of intensive electronic countermeasures.

V. CONCLUSIONS

The proposed semantic-predictive architecture for UAV swarm self-organization integrates multi-agent control with dynamic ontologies that serve as the cognitive layer of the system. The scientific novelty of the approach lies in shifting the focus from representing the current state to probabilistic modeling of future scenarios through ontological reasoning. This enables intelligent agent coordination and facilitates a transition to proactive planning based on adaptive scenario trees, allowing the swarm to operate effectively under conditions of high uncertainty.

The practical significance is demonstrated by a reduction in task execution time by 15–25% and a decrease in data exchange volume by 25%, which is critical for system survivability under constrained communication conditions. The proposed approach provides a foundation for the development of scalable and resilient UAV swarms. Future research will focus on improving collective forecasting algorithms under conditions of extreme dynamics and active adversarial interference.

The semantic-predictive architecture of UAV swarm self-organization further integrates

decentralized multi-agent control with dynamic ontologies functioning as the system’s cognitive layer. Its scientific contribution consists in shifting the emphasis from static state description to probabilistic modeling of future scenarios посредством ontological inference. This ensures intelligent coordination among agents and supports proactive planning based on adaptive scenario trees, enabling the swarm to function efficiently in highly uncertain environments.

The practical relevance is confirmed by a 15–25% reduction in task completion time and a 25% decrease in data exchange volume, which is critically important for maintaining system survivability under limited communication bandwidth within the UAV swarm. The proposed approach establishes a basis for constructing scalable and robust UAV groups. Further studies will aim at enhancing collective prediction algorithms in the presence of extreme dynamics and active counteraction.

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Gladun Anatoly. ORCID 0000-0002-4133-8169. Doctor of Engineering Sciences. Senior Researcher. Institute of Information Technologies and Systems of the National Academy of Sciences of Ukraine, Kyiv, Ukraine. Education: National University “Lviv Polytechnic”, Lviv, Ukraine, (1981). Research area: ontological and semantic analysis, data mining, multi-agent systems for UAV swarms. Publications: over 250 papers. E-mail: glanat@yahoo.com

Khala Kateryna. ORCID 0000-0002-9477-970X. Candidate of Science (Engineering). Institute of Information Technologies and Systems of the National Academy of Sciences of Ukraine, Kyiv, Ukraine. Education: National Technical University of Ukraine “Kyiv Polytechnic Institute”, Kyiv, Ukraine, (2011). Research area: ontological and semantic analysis, data mining, multi-agent systems for UAV swarms. Publications: over 50 papers. E-mail: khala@irtc.org.ua

Volkov Oleksandr. ORCID 0000-0002-5418-6723. Candidate of Science (Engineering). Senior Researcher. Director. Institute of Information Technologies and Systems of the National Academy of Sciences of Ukraine, Kyiv, Ukraine. Education: National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute”, Kyiv, Ukraine, (2013). Research interests: cybersecurity, complex networks, computer networks, resilience, topology. Publications: over 120 papers. E-mail: alexvolk@ukr.net

Simahin Volodymyr. ORCID 0000-0003-4497-0925. Doctor of Philosophy. Institute of Information Technologies and Systems of the National Academy of Sciences of Ukraine, Kyiv, Ukraine. Education: National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute”, Kyiv, Ukraine, (2018). Research area: unmanned aerial vehicle, automatic control system, flight dynamics modelling. Publications: over 30 papers. E-mail: thevladsima@gmail.com

А. Я. Гладун, К. О. Хала, О. Є. Волков, В. М. Сімахін. Динамічна онтологія для семантично-прогностичної самоорганізації рою БПЛА

У статті запропоновано динамічну онтологічну модель для семантично-прогностичної самоорганізації рою безпілотних літальних апаратів (БПЛА). Розроблено багаторівневу онтологічну модель рою БПЛА, що включає: статичне ядро, рівень динамічних екземплярів, агентний рівень із локальними проєкціями знань та механізм семантичної синхронізації агентів для узгодження знань у розподіленій мультиагентній системі. Сформована математична модель формалізує процеси узгодження знань, прогнозування сценаріїв та вибору оптимальних дій. Розглянуто організацію взаємодії між рівнями структури, що забезпечує обмін знаннями, адаптивний розподіл ролей та підтримку колективної поведінки агентів. Експериментальне моделювання в середовищі Gazebo для моніторингу лісової пожежі групою з 12 БПЛА підтвердило ефективність підходу: семантична узгодженість досягла 91%, точність прогнозування критичних подій зросла на 17–20%, а мережне навантаження скоротилося на 83.4%. Розроблена модель, підтримує масштабованість, стійкість до втрати окремих агентів та ефективне виконання спільних завдань, що робить її придатною для створення інтелектуальних систем керування автономними групами БПЛА.

Ключові слова: мультиагентна система, онтологічна модель, група БПЛА, координація агентів, семантичне представлення знань.

Гладун Анатолій Ясонович. ORCID 0000-0002-4133-8169. Доктор технічних наук. Старший науковий співробітник. Інститут інформаційних технологій та систем НАН України, Київ, Україна. Освіта: Національний університет «Львівська політехніка», Львів, Україна, (1981). Напрямок наукової діяльності: онтологічний та семантичний аналіз, інтелектуальний аналіз даних, мультиагентні системи для роїв БПЛА. Публікації: понад 250 публікацій. E-mail: glanat@yahoo.com

Хала Катерина Олександрівна. ORCID 0000-0002-9477-970X. Кандидат технічних наук. Інститут інформаційних технологій та систем НАН України, Київ, Україна. Освіта: Національний технічний університет України «Київський політехнічний інститут», Київ, Україна, (2011). Напрямок наукової діяльності: онтологічний та семантичний аналіз, інтелектуальний аналіз даних, мультиагентні системи для роїв БПЛА. Публікації: понад 50 публікацій. E-mail: khala@irtc.org.ua

Волков Олександр Євгенович. ORCID 0000-0002-5418-6723. Канд. техн. наук. Старш. дослідник. Директор. Інститут інформаційних технологій та систем НАН України, Київ, Україна. Освіта: Національний технічний університет України «Київський політехнічний інститут імені Ігоря Сікорського», Київ, Україна, (2013). Наукові інтереси: кібербезпека, складні мережі, комп'ютерні мережі, резильєнтність, топологія. Публікації: понад 120 публікацій. E-mail: alexvolk@ukr.net

Сімахін Володимир Михайлович. 0000-0003-4497-0925. Доктор філософії, Інститут інформаційних технологій та систем НАН України, Київ, Україна. Освіта: Національний технічний університет України «Київський політехнічний інститут імені Ігоря Сікорського», Київ, Україна, (2018). Напрямок наукової діяльності: безпілотні літальні апарати, системи автоматичного керування, моделювання динаміки польоту. Публікації: понад 30 публікацій. E-mail: thevladsima@gmail.com