Academic Journal of Emerging Technologies
ISSN Print: 3104-4417
ISSN Online: 3104-4425
CD ISSN: 3104-4433
https://doi.org/10.63313/AJET.2004

A Survey on Multi-Agent Based Combat Task and Resource Matching Technology

Qian Liu. Xin Xing and Chengzhi Wang
North Automatic Control Technology Institute, Taiyuan, 030006, China

How to cite this paper: Liu, Q., Xing, X., & Wang, C. (2026). A survey on multi-agent based combat task and resource matching technology. Academic Journal of Emerging Technologies, 4(1), 11–24. ISSN Print: 3104-4417, ISSN Online: 3104-4425.
https://doi.org/10.63313/AJET.2004
Published: 2026-10-30

Copyright © 2026 by author(s) and Erytis Publishing Limited.
This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).
http://creativecommons.org/licenses/by/4.0/



Abstract

Under the backdrop of modern intelligent warfare, rapidly matching heterogeneous combat resources to combat tasks under multiple constraints has become the key to seizing battlefield initiative. Traditional centralized command and decision-making suffer from long cycles and poor robustness, making them ill-suited to adapt to the rapidly changing battlefield situation. This paper summarizes multi-agent based combat task and resource matching technology, defines the core concepts of agents and multi-agent systems, and formally describes the NP-hard nature of the problem along with its three major solution paradigms. It analyzes the current state of domestic and international research from four dimensions: task modeling, task decomposition, resource matching algorithms, and military agent technology. By comparing various methods, the paper outlines the technological evolution from qualitative hierarchical decomposition toward large language model-based intelligent planning. Research indicates that current studies are gradually shifting towards a path combining large models with reinforcement learning. Future research could further focus on directions such as hybrid intelligence, trustworthy AI, and cross-domain human-machine collaboration.

Keywords

Multi-Agent; Combat Resource Matching; Task Decomposition; Intelligent Negotiation; Resource Allocation

1. Introduction

With the full transition of modern warfare into the era of intelligence, the battlespace has expanded from the traditional land, sea, and air domains to the space, cyberspace, electromagnetic, and cognitive domains. Concepts successively proposed by the U.S. military, including Distributed Lethality, Multi-Domain Operations, and Decision-Centric Warfare, have profoundly revealed the win mechanism of future warfare: constructing highly resilient and adaptive kill webs through massive, heterogeneous, and distributed combat nodes, and thereby suppressing adversaries through decision superiority. In this context, the matching

between combat missions and resources, as the core link connecting operational intent with physical strike effects, is of critical importance.

However, the extreme complexity of the modern battlefield environment poses unprecedented challenges to resource matching. First, the number of operational mission requirements often far exceeds the number of resources that can be deployed, and these resources are highly heterogeneous. Thus, the primary challenge is to achieve optimal combinations across the capability gap. Second, the highly contested nature of the battlefield means that combat resources are continuously exposed to enemy reconnaissance, jamming, and even physical destruction, so resource matching systems must possess strong dynamic replanning and fault-tolerance capabilities. Third, due to adjustments in operational plans, sudden changes in the battlefield situation, and enemy target maneuvering, mission requirements exhibit highly dynamic and time-varying characteristics, making static pre-allocation schemes difficult to meet real-world operational needs. Finally, modern combat missions are often highly composite; a single platform is rarely able to complete them independently, and multi-platform, cross-domain coordination is required, which substantially increases the dimensionality and computational difficulty of the matching problem.

In the face of these challenges, traditional command and control models are increasingly inadequate. Centralized command architectures rely on one or a few high-level command nodes to collect global information and make decisions, which not only imposes heavy communication burdens but also creates the risk that the entire combat system may collapse if the central node is degraded or destroyed. Moreover, as the problem scale grows, the computational complexity of centralized optimization increases exponentially, making it difficult to satisfy the second-level or even millisecond-level decision timeliness required by modern warfare. Therefore, the key to winning modern warfare lies in the ability to rapidly, accurately, and adaptively organize dispersed and heterogeneous combat resources into an integrated force tailored to specific operational missions.

In recent years, the rapid development of artificial intelligence has offered a new pathway for addressing this challenge. In particular, large language models (LLMs), represented by GPT, Qwen, and DeepSeek, have demonstrated powerful capabilities in natural language understanding, logical reasoning, and knowledge generalization. Built upon agent application frameworks such as AutoGen, CrewAI, and Dify, LLMs can serve as the “brain” of intelligent agents, endowing them with the ability to comprehend complex instructions, invoke external tools, and conduct multi-step reasoning, thereby significantly enhancing their professionalism and flexibility in complex scenarios. When multiple agents are organized into a multi-agent system through collaboration, competition, or negotiation mechanisms, the advantages of distributed computing and swarm intelligence can be further leveraged to achieve decentralized resource matching and task execution.

This paper presents a comprehensive literature review on multi-agent-based combat resource matching. It first clarifies the key technical concepts of agents and multi-agent systems, and formulates the mathematical nature and solution paradigms of the combat resource matching problem. It then systematically surveys recent domestic and international research progress along four dimensions: task modeling, task decomposition, resource matching algorithms, and military agent applications, with particular emphasis on the emerging trend of integrating intelligent planning with market-based negotiation mechanisms in the era of large language models. Finally, the paper summarizes the limitations of existing studies and provides an outlook on future technological directions.

2. Key Technical Concepts

2.1. Agent Technology

An agent is a core concept in artificial intelligence, referring to a software entity or physical system that can perceive its environment, make autonomous decisions, and take actions to achieve specified goals. In the context of combat resource matching, an agent is not merely a computational unit, but also a proxy for a combat node with both cognitive and execution capabilities. Modern agent technology, especially the new generation of agents augmented by large language models, exhibits five key characteristics.

First, autonomy. An agent can operate independently without human intervention and make decisions based on its internal state and the external environment. In extreme battlefield conditions where communication is limited or command links are disrupted, such autonomy becomes a cornerstone for sustaining the operation of the combat system.

Second, perception. An agent can acquire external inputs in real time through sensors, data interfaces, or natural language interaction. This includes not only physical sensor data such as radar and electro-optical observations, but also semantic information such as higher-level commands, friendly situational updates, and enemy threats. The introduction of large language models enables agents to process large volumes of unstructured data and extract key elements from massive battlefield intelligence.

Third, extensibility. An agent is not a closed system; it can integrate various external tools through standardized interfaces, such as API services, database queries, fire-effect computation modules, and path-planning algorithms. This "brain-plus-limbs" architectural design allows agents to flexibly extend their capability boundaries and adapt to evolving operational requirements.

Fourth, adaptability. The battlefield environment is highly dynamic, and agents must be able to adjust their behavioral strategies in real time in response to changes in mission requirements, resource status, and enemy actions. Through reinforcement learning or online reasoning, agents can optimize their execution paths and

transition from pre-designed behavior to adaptive decision-making.

Fifth, interactivity. Agents can exchange information, negotiate intentions, and coordinate tasks through standardized communication protocols. Such interaction involves not only data transmission, but also semantic-level understanding and consensus building, which is a prerequisite for multi-agent collaborative operations.

2.2. Multi-Agent Systems

A multi-agent system (MAS) is a complex distributed system composed of multiple agents integrated through collaboration, competition, or negotiation mechanisms. In combat resource matching, an MAS can decompose a global optimization problem into multiple local interaction problems, thereby effectively reducing computational complexity and improving system robustness and scalability. According to agent homogeneity, MASs can be mainly divided into two categories.

Homogeneous multi-agent systems consist of agents with identical or similar capabilities, structures, and objectives. Such systems are commonly employed in scenarios such as unmanned aerial vehicle (UAV) swarm reconnaissance and sensor network construction. Their advantages lie in relatively simple communication protocols, mature coordination algorithms, and ease of large-scale deployment. However, when confronted with complex cross-domain combat missions, homogeneous systems exhibit notable functional limitations due to their limited capability diversity.

Heterogeneous multi-agent systems, by contrast, comprise agents with different capabilities, roles, platforms, or objectives. A representative example is a joint strike formation consisting of airborne early warning aircraft, fighter aircraft, electronic warfare aircraft, unmanned aerial vehicles, and ground fire units. Heterogeneous MASs more closely reflect the complex operational requirements of real-world combat environments and can achieve multiplicative improvements in system effectiveness through complementary capabilities. At the same time, heterogeneous MASs face greater coordination challenges, including semantic interoperability, adaptation of heterogeneous communication protocols, design of complex negotiation mechanisms, and conflict resolution.

2.3. The Combat Mission–Resource Matching Problem

The combat mission–resource matching problem is, in essence, a constrained combinatorial optimization problem. Formally, let the set of combat missions be $T = \{t, t, \ldots, t_n\}$, and the set of available combat resources be $R = \{r, r, \ldots, r_m\}$. Each task t_i has an attribute vector $A_i = \{c_i, w_i, l_i, d_i, \ldots\}$, where c_i is the required capability vector, w_i is the priority weight, l_i is the spatial location, and is the time window, etc. Each resource r_j has an attribute vector $B_j = \{cap_j, s_j, \cos t_j, \ldots\}$, where cap_j is the capability vector, s_j is the current state (such as ammunition, fuel, health), and $\cos t_j$ is the movement or

consumption cost function.

The objective of matching is to find an assignment matrix $X=\{x_{ij}\}$, $(x_{ij}\in\{0,1\})$,such that the overall combat effectiveness function $F(X)$ is maximized subject to the following constraints:

(1)Capability Coverage Constraint: The sum of capabilities of the resource combination assigned to task t_i must be greater than or equal to the task requirement c_i ;

(2)Temporal Feasibility Constraint: The arrival time and execution time of resources must fall within the task time window d_i ;

(3)Mutual Exclusion and Synergy Constraint: Certain resources cannot be assigned to multiple tasks simultaneously, or certain tasks must be completed collaboratively by a specific combination of resources;

(4)Resource State Constraint: The assignment scheme must not result in the resource state falling below a safety threshold.

Due to the involvement of multi-dimensional nonlinear constraints and the large scale of tasks and resources, this problem exhibits extremely high computational complexity and is a typical NP-hard problem. To address such problems, existing research has primarily formed three major solution paradigms:

Centralized optimization methods rely on high-level command nodes to collect global information, construct a complete mathematical model, and solve it. The advantages of this approach lie in the high quality of the solution and strict satisfaction of constraints. However, its disadvantages are also evident: there is a significant computational bottleneck, a high risk of single-point failure, and it is difficult to adapt to the frontline battlefield environment where conditions change dynamically on a second-by-second basis.

Distributed negotiation-based optimization methods model tasks and resources as autonomous agents, achieving decentralized matching consensus through interaction mechanisms such as bidding, tendering, and negotiation. The advantages of this approach include strong robustness, support for heterogeneous access, and distributed computational load. However, the negotiation process is prone to becoming trapped in local optima or deadlocks; the solution quality is typically suboptimal; and communication overhead increases with the number of agents.

Learning-driven methods utilize techniques such as machine learning and reinforcement learning to learn matching policies end-to-end from historical data or simulation environments. Their advantages lie in fast inference speeds, the ability to handle high-dimensional nonlinear relationships, and online generalization capabilities. Nevertheless, these methods suffer from a heavy reliance on large volumes of high-quality training data, poor interpretability of policies, and the potential for sharp performance degradation in unseen extreme scenarios.

3. Research Status at Home and Abroad

3.1. Research Status on Task Modeling

Combat mission modeling is the logical starting point for resource matching. Its core lies in transforming ambiguous operational intent into formalized descriptions that are interpretable and computable by computers. Foreign research in this field started earlier, and mature theoretical frameworks and standard systems have been established. Represented by the U.S. military, the Department of Defense Architecture Framework (DoDAF) is widely adopted as the theoretical basis. Through standardized views, DoDAF clearly describes the mapping relationships among operational scenarios, business processes, and system functions, effectively addressing the transformation from operational requirements to equipment capabilities[1]. In terms of practical application, the Laboratory for System of Systems Architectures at the C3I Center of George Mason University in the United States has proposed structured description methods and object-oriented description methods for C4ISR architectures. Wagenhals et al. [2] utilized the IDEF0 language to refine complex operational missions into functional flows, following the top-down, stepwise refinement principle of the structured approach. Meanwhile, Bienvenu et al.[3] employed the Unified Modeling Language (UML), iteratively refining the system functional model in an object-oriented manner by designing class diagrams, sequence diagrams, and state diagrams. These two approaches complement each other and constitute the cornerstone of U.S. military operational architecture design.

Although domestic research on combat mission modeling started relatively late, it has developed extremely rapidly in recent years, showing a trend of multi-method integration and data-driven enhancement. Ji Junliang et al. [4] established UML use case diagrams, class diagrams, sequence diagrams, and activity diagrams for multi-layer missile defense collaborative combat missions, and innovatively adopted Petri net methods to conduct formal analysis and verification of the model, effectively addressing the limitations of UML models in describing dynamic behaviors and detecting deadlocks. Zhang Ze et al.[5] combined IDEF0 and IDEF3 modeling methods to conduct uncertainty-aware combat mission modeling for unmanned combat units seizing key control points, with a particular focus on the impact of battlefield information gaps and enemy countermeasures on mission processes. With the evolution of DoDAF, Wang Xinyao et al. [6] constructed a collaborative combat architecture model for manned/unmanned aerial vehicles under the DoDAF 2.02 framework, based on data-centric design principles and the DoDAF Meta-model (DM2) development methodology, achieving standardized descriptions of data interactions among heterogeneous platforms. Furthermore, Zhao Yufei[7] proposed an attribute-extraction-based combat mission modeling method, which enhances the model's ability to understand natural language instructions by extracting key semantic attributes of missions, thereby laying the foundation for mission modeling in the era of large language models.

3.2. Research Status on Task Decomposition

Task decomposition is the process of refining high-level operational directives issued by superiors into several specific, explicit, and interrelated subtasks, serving as a bridge connecting strategic decision-making with tactical execution. Currently, combat task decomposition methods are mainly categorized into three types: qualitative, quantitative, and intelligent planning.

Qualitative hierarchical decomposition methods primarily rely on expert experience and military doctrines, decomposing overall combat missions into a hierarchical and mutually independent subtask tree based on specific decomposition criteria. Cao Yuhua et al. [8] systematically studied conceptual representation methods for combat task decomposition and proposed a hierarchical decomposition framework based on "objective-task-action." Chang Qing et al. [9] further explored combat task decomposition strategies and standardized description methods, emphasizing semantic consistency and logical completeness during the decomposition process. While these methods are intuitive and easy to understand, they struggle to handle complex coupling constraints and dynamic adjustments.

Quantitative modular decomposition methods focus on data and functional coupling, clustering discrete multi-task sets into a smaller number of task modules according to the principle of strong intra-module cohesion and weak inter-module coupling. Pang et al. [10] proposed a multi-granularity task decomposition mechanism based on density peaks, which can automatically identify task clusters based on the similarity of task attributes, providing theoretical support for the parallel processing of large-scale tasks.

Intelligent planning methods, particularly Hierarchical Task Networks (HTN), represent a current research hotspot. HTN is a problem-solving approach based on hierarchical abstraction and domain knowledge, which recursively decomposes complex tasks into atomic actions through predefined decomposition rules. Höller et al. [11] proposed an HTN planning algorithm based on heuristic forward search, significantly improving planning efficiency. In China, Jiang Yihong et al. [12] analyzed HTN-based combat task decomposition techniques and explored their applicability in joint operations scenarios. Bao Shanghua et al. [13] proposed a multi-level formation task decomposition method based on an extended HTN decomposition framework, addressing the limitations of traditional HTN in handling cross-level collaborative tasks. More recently, Zeng Yan et al. [14] explored an agent modeling method based on hybrid HTN/Behavior Tree (BT) planning, combining the logical reasoning capabilities of HTN with the real-time responsiveness of BT, thereby providing a new paradigm for task decomposition in complex dynamic environments. With the introduction of large language models, automatic task decomposition based on semantic understanding is gradually replacing manual rules, emerging as a new direction in intelligent planning [15].

3.3. Research Status on Resource Matching

Combat resource matching is the execution phase following task decomposition, with its core objective being to find an optimal allocation scheme under given constraints. Existing research mainly focuses on four categories: optimization methods, heuristic algorithms, market mechanism-based algorithms, and intelligent learning-based algorithms.

Optimization methods, including integer programming, constraint programming, and exhaustive search, aim to obtain globally optimal solutions. Chen Honghui et al. [16] established a matching model between combat tasks and resources and explored exact solution algorithms. Kleeman and Lamont [17] investigated the multi-objective constrained assignment problem and proposed a solution framework based on evolutionary computation. Jungmok [18] , targeting the network-centric warfare environment, comprehensively considered multiple constraints such as protected areas, kill radii, and damage rates. By employing clustering algorithms to mathematically formulate the complex weapon-target engagement decision problem, the study verified its effectiveness in assisting commanders with rapid fire allocation decisions. However, due to the NP-hard nature of these problems, exact algorithms are often infeasible when dealing with large-scale instances.

Heuristic algorithms focus on finding satisfactory solutions within an acceptable time frame. Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Simulated Annealing (SA) are the mainstream choices. Liu Jian et al. [19] investigated combat task allocation and resource scheduling based on a genetic algorithm, designing encoding schemes and operators tailored to battlefield constraints, which improved the algorithm's operational efficiency by 76.4%. Yuan et al.[20] proposed an optimization method for combat resource allocation based on the Restricted Tournament Selection Social Genetic Algorithm (RTS2GA), introducing a restricted tournament selection strategy to enhance population diversity and incorporating the sociological concept of "group effect" with social operators to accelerate convergence. Peng Yunfei et al. [21] combined game theory with an improved ant colony algorithm to construct a Bayesian hybrid game analysis model, addressing the fire allocation optimization problem under multi-wave air raids. They established a game confrontation model between attackers and defenders and successfully obtained the Nash equilibrium solution.

Market mechanism-based methods achieve distributed resource allocation by simulating transaction behaviors in economic markets, naturally aligning with multi-agent negotiation paradigms. Classic algorithms include the Contract Net Protocol (CNP) and auction algorithms. The Contract Net algorithm simulates the tendering-bidding-awarding-contracting mechanism in commercial activities, resolving distributed task-resource allocation problems through negotiation among

multiple agents capable of communication and information processing. Zhang Chuanhao et al.[22] designed a loitering munition allocation algorithm based on an optimized Contract Net, determining strike task allocation priority by target threat levels and introducing standard strike effectiveness and node self-assessment to exclude low-benefit nodes. Simulation results showed that the total number of information transmissions required for allocation was reduced by an average of 47.89%. Zhao and Li [23] addressed dynamic collaborative task-resource allocation for heterogeneous multi-unmanned platforms by improving the Contract Net algorithm through mental coefficients, a blackboard model, and a buffer pool mechanism, constructing a hybrid improved Contract Net algorithm that significantly enhanced allocation efficiency and solution rationality. Sun Jiawei et al.[24] , to improve resource allocation efficiency for composite unit combat tasks, combined multi-agent models with auction and genetic algorithms to complete an iterative process of capability optimization, individual optimization, and collaborative optimization. Eşer and Yilmaz [25] proposed an auction algorithm specifically designed for heterogeneous UAV swarms, employing a second-lowest-price auction mechanism as an incentive to encourage honest bidding from UAV nodes, thereby improving system stability and efficiency. Additionally, Pang et al. [26] designed a hybrid strategy combining reinforcement learning with Stackelberg game theory to dynamically allocate computational tasks and idle mobile vehicle resources, verifying that the proposed scheme effectively reduces task offloading costs.

With the development of big data and computing power, matching methods based on machine learning and deep learning have become a new trend. Lei Moohan [27] proposed a hybrid algorithm combining CE-Q reinforcement learning with K-means clustering for multi-robot foraging tasks, addressing the dimensionality explosion problem in reinforcement learning algorithms. This hybrid strategy reduced repetitive exploration time by 40% in simulated military task experiments. Guo Hongyu et al. [28] investigated submarine attack-defense confrontation training and command decision-making based on deep reinforcement learning, designing a two-dimensional action space capable of simultaneous action allocation and platform matching. Through mutual game confrontation and distributed training on a wargaming platform, they achieved intelligent decision-making for submarines during confrontation. He Zhaoyi[29] focused on joint multi-domain operations, studied intelligent task planning techniques, and explored the integration of deep learning with planning algorithms. The DeepGreen method proposed by Gin et al. [30] demonstrated the potential of deep learning in solving nonlinear boundary value problems, providing new ideas for resource matching under complex constraints. Chen Jun et al.[31] focused on heterogeneous edge clusters, investigating online task scheduling based on resource matching and emphasizing the value of edge intelligence in low-latency scenarios.

3.4. Research Status on Military Agent Technology

Military agent technology has moved beyond the stage of single automated execution and is evolving in depth toward multi-agent collaboration, autonomous decision-making, and cross-domain integration. Currently, major military powers around the world have positioned military agent technology as a core direction for defense modernization, engaging in intense technological competition centered on autonomy, intelligence, and collaboration.

Western countries represented by the United States have long held an advantage in the field of military agents and are accelerating the strategic transition of agent technology from decision-support tools to autonomous combat systems. A series of key U.S. programs, including the Offensive Swarm-Enabled Tactics (OFFSET), Skyborg, and Gremlins projects, have completed multiple multi-agent collaborative combat experiments in field environments. During these experiments, individual agent units relied on advanced formation control algorithms and collaborative attack-defense mechanisms to achieve highly autonomous swarm behavior, demonstrating strong system-of-systems combat potential. In 2026, the U.S. Department of Defense plans to integrate large language models such as Grok and GPT into tactical edge systems to enable real-time battlefield intelligence summarization, intelligent wargaming of operational plans, and natural language command parsing and execution, thereby significantly compressing the closed-loop time of the "Observe–Orient–Decide–Act" (OODA) kill chain and improving tactical response speed and decision quality. At the same time, other Western countries are also actively promoting the practical application of agent technology. The UK's "Autonomous Warrior" exercise program has achieved efficient intelligent interaction between individual combat units and UAV swarms. Sweden has integrated an AI-assisted air combat system into its JAS 39E Gripen-E fighter, enabling autonomous multi-target threat assessment, tactical maneuver planning, and engagement control capabilities.

Domestic research in the field of military agents has also conducted extensive cutting-edge work. In 2019, the China Academy of Electronics and Information Technology released the Multi-agent Combat Arena (MaCA), the first lightweight multi-agent confrontation and training platform in China capable of simulating military operations. Heterogeneous multi-agent confrontation competitions held on this platform have promoted research on human-machine confrontation intelligence in military applications. Cui Xiaolong et al. [32] designed the "AiWu+" system architecture based on "digital human + large model + large system + big data," enabling the construction, orchestration, and deployment of agents, and extending end-to-end coordination and command control for manned/unmanned platforms, thereby providing reference for major national defense projects and the research and practical application of intelligent command. Zhang Yidan et al. [15] systematically analyzed the integrated evolution of reinforcement learning and

large models, prospecting their application prospects in military decision-making and pointing out that the hybrid paradigm of "LLM as the cognitive hub + RL as the policy optimizer" will be the mainstream direction in the future.

4. Summary and Outlook

4.1. Summary of Research Progress

In summary, significant progress has been achieved in combat resource matching technology based on multi-agent negotiation. At the theoretical level, the conceptual framework of agents and multi-agent systems has become increasingly mature, and the formal description and solution paradigms for combat resource matching problems have been largely established. At the methodological level, task modeling is transitioning from single-view to multi-view, data-driven approaches; task decomposition is evolving from qualitative rules toward hybrid HTN/large model planning; and resource matching is shifting from centralized optimization toward the integration of distributed negotiation and learning-driven methods. At the application level, practical combat experiments in countries such as the United States and the United Kingdom, along with the development of domestic platforms such as MaCA and "AiWu+," have provided solid support for technology implementation. In particular, the introduction of large language models has offered breakthrough tools for addressing long-standing bottlenecks such as semantic interoperability among heterogeneous agents, automatic decomposition of complex tasks, and processing of unstructured intelligence. These efforts indicate that hybrid architectures, which can balance global optimality, local adaptability, and interpretability, are poised to become the core direction for future intelligent combat resource matching.

4.2. Existing Limitations and Challenges

Despite the substantial achievements, existing research still faces numerous challenges. First, insufficient dynamic adaptability. Current distributed negotiation algorithms struggle to balance convergence speed and solution quality in highly dynamic, high-confrontation environments, and lack explicit modeling of adversarial countermeasures. Second, lack of interpretability and trustworthiness. Deep learning-driven resource matching strategies operate as "black boxes," making it difficult for commanders to understand their decision logic and establish trust in high-risk combat scenarios. Third, immature human–machine collaboration mechanisms. Current research predominantly focuses on fully autonomous systems, with insufficient investigation into interaction protocols, dynamic authority allocation, and cognitive load management for human–machine hybrid intelligence. Finally, the gap between simulation and real-world deployment. Existing algorithms are mostly validated in idealized simulation environments, with inadequate consideration of practical constraints such as communication latency, packet loss,

and sensor noise, leading to significant performance degradation during actual deployment.

4.3. Future Development Directions

Looking ahead, combat resource matching technology based on multi-agent negotiation will exhibit the following development trends:

First, hybrid intelligence paradigms will become mainstream. Sole reliance on either large language models or reinforcement learning has inherent limitations. Future systems will adopt a hybrid architecture of "LLM cognitive reasoning + RL policy optimization + traditional algorithm fallback." LLMs will handle high-level task understanding and anomaly handling, RL will manage mid-to-low-level rapid decision-making, and traditional algorithms will provide deterministic guarantees under extreme conditions, achieving complementary advantages.

Second, trustworthy AI and explainable decision-making. Research will focus on enhancing the transparency and traceability of agent decisions. Through techniques such as causal reasoning, attention visualization, and counterfactual explanation, the resource matching process will become "visible, understandable, and controllable" for commanders. Meanwhile, safety alignment and value constraints will be strengthened to ensure agent behavior complies with rules of engagement and ethical norms.

Third, human–machine collaboration and cognitive augmentation. The paradigm will evolve from "human-in-the-loop" to "human-in-the-swarm," investigating dynamic role allocation, intent alignment, and trust calibration mechanisms for human–machine hybrid agents. Technologies such as brain–computer interfaces and augmented reality will be leveraged to deeply integrate the computational advantages of agents with human intuition and creativity, achieving synergistic gains at the cognitive level.

Fourth, cross-domain interoperability and standardization. Efforts will be made to establish agent communication protocols and ontology standards across military branches and allied nations, enabling seamless integration and semantic interoperability among heterogeneous platforms. Blockchain-based decentralized trust mechanisms will be developed to ensure data consistency and behavioral auditability in distributed environments.

Fifth, combat-realistic simulation and digital twins. High-fidelity, multi-physics-coupled battlefield digital twin environments will be constructed, incorporating practical constraints such as communications, electromagnetics, and weather into simulations. Large-scale, high-intensity adversarial testing and algorithmic iteration will be conducted to accelerate the transition of technology from the laboratory to the battlefield.

Combat resource matching technology based on multi-agent systems is a core enabling technology for intelligent warfare. With the in-depth development of large

models, multi-agent collaboration, and complex systems theory, this technology will demonstrate greater adaptability and robustness in actual combat scenarios. Future research should further break down the barriers between theoretical models and engineering applications, promoting the leap of multi-agent collaboration technology from "decision support" to "autonomous combat," thereby providing critical support for the construction of intelligent, distributed new operational systems.

References

[1] Hao, L. (2017). Study on the DoDAF-based UUV formation system collaborative anti-submarine architecture modeling. Revista de la Facultad de Ingenieria, 32(16), 947–951.

[2] Wagenhals, L. W., Shin, I., Kim, D., et al. (2000). C4ISR architectures: II. A structured analysis approach for architecture design. Systems Engineering, 3(4), 248–287.

[3] Bienvenu, M. P., Shin, I., & Levis, A. H. (2000). C4ISR architectures: III. An object-oriented approach for architecture design. Systems Engineering, 3(4), 288–312.

[4] Ji, J., Wang, M., Wen, Y., et al. (2020). Conceptual modeling of multi-layer missile defense collaborative mission planning based on UML and Petri nets. Military Operations Research and Systems Engineering, 34(4), 68–74.

[5] Zhang, Z., Wu, F., Wang, M., et al. (2019). Uncertain combat mission modeling for unmanned combat units. Fire Control and Command Control, 44(4), 97–100.

[6] Wang, X., Cao, Y., Sun, H., et al. (2020). DoDAF-based system-of-systems architecture modeling for manned/unmanned aircraft collaborative combat. Systems Engineering and Electronics, 42(10), 2265–2274.

[7] Zhao, Y. (2021). Combat mission modeling method based on attribute extraction. Ship Electronic Engineering, 41(4), 74–78.

[8] Cao, Y., Feng, S., & Xu, X. (2007). Research on conceptual representation methods for combat mission decomposition. Computer Simulation, 24(8), 1–4

[9] Chang, Q., Liu, D., & Yang, Y. (2023). Research on combat mission decomposition strategies and standardized description methods. Command Control and Simulation, 45(5), 84–91.

[10] Pang, Z. L., Wang, G. Y., & Yang, J. (2018). A multi-granularity decomposition mechanism of complex tasks based on density peaks. Big Data Mining and Analytics, 1(3), 245–256.

[11] Höller, D., Bercher, P., Behnke, G., et al. (2020). HTN planning as heuristic progression search. Journal of Artificial Intelligence Research, 67, 835–880.

[12] Jiang, Y., Yu, R., Xu, C., et al. (2024). Analysis of combat mission decomposition technology based on HTN. Integrated Circuit Applications, 41(9), 41–43.

[13] Bao, S., Wang, J., Zhang, X., et al. (2025). Multi-level mission decomposition method for formations based on an extended HTN decomposition framework. Command Control and Simulation, 47(5), 24–35.

[14] Zeng, Y., Yang, M., Wang, B., et al. (2024). Agent modeling method based on HTN/BT hybrid planning. In Proceedings of the 36th China Simulation Conference (pp. 35–41). China Simulation Federation.

[15] Zhang, Y., Chen, Z., Zhao, X., et al. (2024). A new paradigm for multi-agent decision-making: Technical analysis of the integrated evolution of reinforcement learning and large models and prospects for military applications. In Proceedings of the 1st National Conference on Large Models and Decision Intelligence (pp. 74–81).

[16] Chen, H., Zhao, L., Rui, H., et al. (2008). Research on matching models and solution algorithms between combat missions and resources. Systems Engineering and Electronics, 30(9), 5.

[17] Kleeman, M. P., & Lamont, G. B. (2007). The multi-objective constrained assignment problem. In Evolutionary and bio-inspired computation: Theory and applications (Vol. 6563, p. 13).

[18] Jungmo, M. (2017). Constrained target clustering for military targeting process. Defence Science Journal, 67(5), 523..

[19] Liu, J., Chen, G., & Li, X. (2023). Research on combat mission allocation and resource scheduling based on genetic algorithms. Ordnance Industry Automation, 42(7), 59–63.

[20] Yuan, S., Ren, Y., Zhou, H., et al. (2025). Optimization of combat resource allocation based on restricted tournament selection social genetic algorithm. International Journal of Computational Intelligence Systems, 18(1), 220.

[21] Peng, Y., Yang, Q., Yang, G., et al. (2025). Air defense fire allocation model based on game theory and improved ant colony algorithm. Ordnance Industry Automation, 44(7), 79–82.

[22] Zhang, C., Li, H., Yu, H., et al. (2023). Mission allocation algorithm and model for loitering munitions based on contract net. Journal of Detection and Control, 45(1), 84–90.

[23] Zhao, M., & Li, D. C. (2021). Collaborative task allocation of heterogeneous multi-unmanned platform based on a hybrid improved contract net algorithm. IEEE Access, 9, 78936–78946.

[24] Sun, J., Du, W., Li, Z., et al. (2025). Combat mission allocation method based on improved auction-genetic algorithm. Fire Control and Command Control, 50(6), 62–70.

[25] Eşer, M., & Yilmaz, A. E. (2024). Auction-based distributed task allocation algorithm for drone swarms. Niğde Ömer Halisdemir Üniversitesi Mühendislik Bilimleri Dergisi, 13(4).

[26] Pang, S. C., Chen, B. Y., He, X., et al. (2025). Incentive-driven computation offloading and resource pricing strategy in vehicular edge computing assisted with idle mobile vehicles. Simulation Modelling Practice and Theory, 138.

[27] Lei, M. (2014). Research on multi-robot foraging tasks based on a hybrid CE-Q reinforcement learning and K-means clustering algorithm [Master's thesis, Lanzhou University of Technology].

[28] Guo, H., Chu, Y., Liu, Z., et al. (2022). Research on command decision-making for submarine attack and defense training based on deep reinforcement learning. Command Control and Simulation, 44(1), 103–111.

[29] He, Z. (2023). Research on intelligent mission planning technology for joint multi-domain operations [Doctoral dissertation, Nanjing University of Aeronautics and Astronautics].

[30] Gin, C. R., Shea, D. E., Brunton, S. L., et al. (2021). DeepGreen: Deep learning of Green's functions for nonlinear boundary value problems. Scientific Reports, 11(1), 1–14.

[31] Chen, J., Wang, X., Zeng, H., et al. (2025). Online task scheduling for edge heterogeneous clusters based on resource matching. Modern Electronics Technique, 48(6), 31–38.

[32] Cui, X., Gao, Z., Ji, W., et al. (2024). "AIWU-LLM+": Development and empirical study of a military large-model system. Data Acquisition and Processing, 39(3), 588–597.