Journal of Computer Science and Electrical Engineering
ISSN: 2663-1946
DOI: https://doi.org/10.61784/jcsee3062

COGNITIVE COLLABORATION-BASED DECISION-MAKING FRAMEWORK FOR MANNED/UNMANNED AERIAL VEHICLE SYSTEMS

YiDuo Wang*, HeLin Wang, EnNing Liu, WenXuan Liu, QiLian Ge
School of Computer Science and Technology, Dalian University of Technology, Dalian 116024, Liaoning, China.
Corresponding Author: YiDuo Wang, Email: yw542@student.le.ac.uk

Abstract: This paper investigates a cognitive collaboration-based decision-making framework for manned/unmanned systems, aiming to address the limitations of traditional methods in situation assessment, task allocation, and path planning. Firstly, a dual layer coupled situation and threat assessment model is constructed using Dynamic Intuitionistic Fuzzy Cognitive Maps (DIFCM) and Genetic Algorithms (GA), achieving collaborative optimization of global situation inference and local threat quantification. Secondly, an adaptive task allocation mechanism is designed by integrating an improved Contract Net Protocol with UAV intelligent emotional modes, effectively balancing task execution efficiency and resource utilization. Finally, an emotion-driven improved A* algorithm is introduced, enhancing the adaptability and safety of path planning in dynamic threat environments through dynamic threat avoidance radii and cognitive load feedback mechanisms. Simulation experiments demonstrate that the proposed algorithm improves replanning response time by 23% compared to traditional path planning algorithms under sudden threats, while reducing path threat costs by 58%. The research outcomes provide new theoretical exploration and practical references for manned/unmanned collaborative tasking and decision-making in intelligent mission scenario, aiming to advance the theoretical and practical development of deep human-machine intelligence integration.
Keywords: Manned/Unmanned collaborative combat; DIFCM; Manned aircraft cognitive load; Improved A* algorithm; UAV intelligent emotional mode; Genetic algorithm

1 INTRODUCTION

Future strategic scenarios are becoming increasingly intricate, making independent operations by either humans or machines insufficient. Effective collaboration between humans and unmanned systems, combining human judgment with robotic accuracy, is key to advanced intelligent strategies. Programs like "Loyal Wingman" and Su-57–"Okhotnik" validate its effectiveness [1]. This highlights the need for a full-process framework covering "situational awareness → threat assessment → mission decision → path planning." Key challenges include task allocation, interaction mechanisms, and performance evaluation, while current research overlooks UAV attributes, environmental factors, and cross-level cognitive interaction. Seamlessly integrating human cognition with machine autonomy remains crucial for enhancing collaborative work effectiveness.

Research on core technical systems for collaborative decision-making includes several key studies. Fu reviews U.S. programs like the Software-Enabled Control Plan and the Common Architecture for Manned-Unmanned Systems [2], which facilitate mission planning, decision-making, and standardized communication between manned aircraft and UAVs. In contrast, domestic research remains largely theoretical. Wu models collaborative air strategic scenarios as a partially observable Markov decision process (POMDP), employing distributed training to address environmental non-stationarity and centralized training to mitigate computational challenges [3], suitable for heterogeneous multi-aircraft formations. Xie introduces a direction-finding cross-target localization model, proposing variable-curvature Dubins curves for low-speed maneuvering targets and an optimal control model with penalty function-based trajectory planning for high-speed targets [4], achieving localization accuracy improvements of 36.9% and 23.5% in two scenarios. In collaborative task decision-making, Zhong presents a hybrid fuzzy cognitive map (HFCM) decision method [5], establishing an interactive decision framework with intervention strategies derived from RBFCM and IFCM. Xue builds a decision requirement reasoning model using fuzzy grey cognitive maps (FGCM) and particle swarm optimization (PSO) to refine weight learning [6], enabling rapid task selection. Liu proposes an ACO-A* hybrid path planning algorithm with a dynamic grid environment and k-means clustering for improved UAV collaborate maneuver decision-making [7]. Lastly, Gu outlines international advancements in manned/unmanned teaming [1], proposing integration architectures and future research directions in collaborative control.

Existing research often focuses on isolated decision-making aspects, lacking a comprehensive framework integrating "situational awareness → threat assessment → task allocation." This study optimizes decision-making through cognitive collaboration, advancing human-machine integration [8]. By combining dynamic intuitionistic fuzzy cognitive maps, genetic algorithms, and emotional adaptive mechanisms, it constructs a full-process model while incorporating a cognitive load quantification module. A data-knowledge dual-driven approach refines weight learning, and an emotional state transition matrix enables UAVs to adapt autonomously. Unlike prior work, this framework couples human cognition with machine autonomy, validated through simulation. It enhances adaptability via bidirectional human-machine interaction and improves coherence across decision-making stages, addressing challenges like fragmented decision logic and response delays.

2 COLLABORATIVE DECISIONING MODEL

2.1 Collaborative Decision-Making Mechanism

The core of the manned/unmanned collaborative system is a "human cognition-led, machine intelligence-enhanced" decision-making framework. By integrating manned aircraft control with UAV autonomy, complementary collaborative effectiveness is achieved. The heterogeneous nature of these systems provides significant advantages but also introduces challenges: manned aircraft, with greater payload and tactical flexibility, can perform critical tasks, but their survival requirements and performance differences complicate decision-making. The dynamic authority allocation mechanism optimizes decision-making and task execution by assessing operator workload and task attributes in real time. Figure 1 illustrates a typical scenario: the manned aircraft, as mission commander, sets objectives and strategies, while the UAV performs reconnaissance and tasking based on real-time data, feeding task status back. Dynamic authority allocation and closed-loop control enable efficient task handling in complex environments [9].

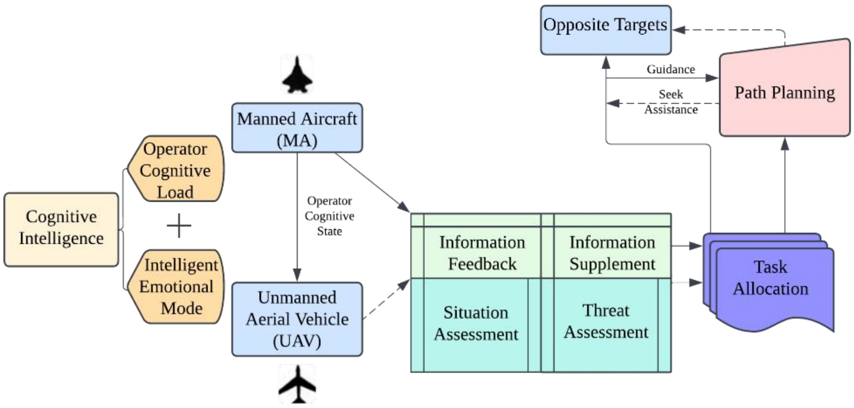

Figure 1 Task Scenario of Manned/Unmanned Collaborative Decision-Making

2.2 Situation and Threat Assessment Model

The modeling of task situation and threat assessment is the core cognitive layer of the human-machine collaborative decision-making system. Its essence lies in constructing a hybrid reasoning framework that integrates human experiential knowledge with machine computational capabilities. Based on intuitionistic fuzzy cognitive map theory, this paper proposes a dual-layer coupled assessment architecture: the first layer employs Dynamic Intuitionistic Fuzzy Cognitive Maps (DIFCM) to achieve global situation evolution inference, while the second layer utilizes a Genetic Algorithm-enhanced Threat Assessment Network (GATAN) to precisely quantify local threats. The two layers form a synergistic enhancement effect through shared key state variables and weight adjustment mechanisms, reducing model complexity while improving adaptability to dynamic mission scenarios.

2.2.1 DIFCM

As a key tool for complex system modeling, cognitive map theory has been widely applied in social network analysis and economic system simulation since Axelrod's foundational work [10]. However, traditional cognitive maps face two major limitations when addressing high-dimensional uncertainties in modern systems like highly dynamic mission perception networks: (1) reliance on binary causal reasoning based on Boolean logic [11], which restricts the representation of fuzzy relationships, and (2) the absence of dynamic topology optimization, leading to rigid knowledge structures. To overcome these challenges, Iván S introduced Fuzzy Cognitive Maps (FCMs) [12], achieving three breakthroughs: (I) integrating fuzzy membership functions for continuous-value causal reasoning, (II) developing concept node activation models using nonlinear transfer functions, and (III) optimizing weight matrices to enable dynamic topology evolution. Mathematically, FCMs can be modeled as weighted directed graphs $FCM=(G,E,W)$, where the concept node set $C=\{C_i\}_{i=1}^{n}$ represents key system elements (e.g., threat levels), and the directed edge set $E\subseteq C\times C$ describes causal influence paths between nodes. In the weight matrix:

$$W=\begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n_c} \\ w_{21} & w_{22} & \cdots & w_{2n_c} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n_c1} & w_{n_c2} & \cdots & w_{n_cn_c} \end{bmatrix}, \tag{1}$$

$w_{ij}(j=1,2,...,n)$ indicates the degree and direction of the influence of concept node C_i on C_j with $w_{ij} \in [-1,1]$. When there is no causal relationship between C_i and C_j, or when $i=j$, $w_{ij}=0$ holds. By introducing intuitionistic fuzziness to node information and adjacency weight matrices and replacing the weighted summation and threshold functions in traditional FCM models with intuitionistic fuzzy ordered weighted averaging (IFOWA) operators, the Intuitionistic Fuzzy Cognitive Map (IFCM) model $IFOWA=(C,w_i,OWA_e)$ is obtained. The values of node state information and inter-node association information lie within $[0,1]$. Defining the relevant weight vector of the IFOWA operator as $e=(e_1,e_2,...,e_n)^T$, where $e_j \in [0,1], j=1,2,...,n$, the IFCM reasoning process is as follows. Let the influence of node $C_i(i=1,2,...,n)$ on node C_j through directed arcs at time t be:

When $i=j$,

$$\begin{aligned} r_{ij}(t) &= <\mu_{r_{ij}(t)}, \nu_{r_{ij}(t)}> = C_i(t) \otimes w_{ij}(t) = <\mu_{C_i(t)}, \nu_{C_i(t)}> \otimes <\mu_{w_{ij}(t)}, \nu_{w_{ij}(t)}> \\ &= <\mu_{C_i(t)}\mu_{w_{ij}(t)}, \nu_{C_i(t)} + \nu_{w_{ij}(t)} - \nu_{C_i(t)}\nu_{w_{ij}(t)}> \end{aligned} \tag{2}$$

When $i \neq j$, $r_{ij}(t)=C_j(t)$, and the value of node $C_j(t)$ at time $t+1$ is

$$\begin{aligned} c_j(t+1) &= IFOWA[r_{1j}(t), r_{2j}(t), ..., r_{nj}(t)] = e_1 r_{\sigma(1)j}(t) \oplus e_2 r_{\sigma(2)j}(t) \oplus ... \oplus e_n r_{\sigma(n)j}(t) \\ &= \left\langle 1-\prod_{k=1}^{n}(1-\mu_{r_{\sigma(k)j}(t)})^{e_{kj}}, \prod_{k=1}^{n}\nu_{r_{\sigma(k)j}(t)}^{e_{kj}} \right\rangle = \left[1-\prod_{k=1}^{n}(1-\mu_{r_{\sigma(k)j}(t)})^{e_{kj}}, 1-\prod_{k=1}^{n}\nu_{r_{\sigma(k)j}(t)}^{e_{kj}} \right] \end{aligned} \tag{3}$$

In engineering implementation, IFCM functions as a state propagation system based on fuzzy logic, following the steps of initializing concept node states, iteratively updating via weighted causal networks, and stabilizing outputs. Initially, environmental states (e.g., threat levels, resource distribution) are loaded, and states are propagated using intuitionistic fuzzy operators until fluctuations fall within a predefined threshold, leading to stable decision outputs. Unlike traditional cognitive maps, which offer static conclusions, the DIFCM model incorporates time-series variables and inter-node associations, enhancing real-time adaptability and memory.

2.2.2 Genetic Algorithm

Evolutionary algorithms, inspired by biological evolution, are population-based optimization methods that efficiently address complex scenario decision-making by simulating natural selection and genetic variation. Their core mechanism involves dynamically evolving populations within the solution space, iteratively refining solutions through selection, recombination, and mutation as shown in Figure 2.

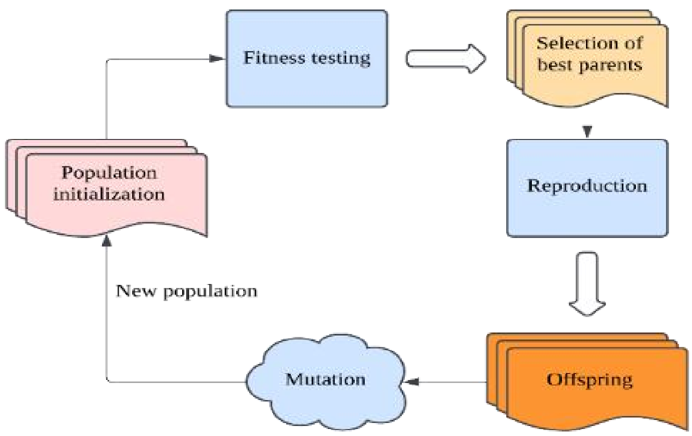

Figure 2 Evolutionary Learning Algorithm

Current mainstream branches of evolutionary algorithms include Genetic Algorithms (GA), Ant Colony Optimization (ACO), Asexual Reproduction Optimization (ARO), and the Jaya algorithm. Each variant exhibits differentiated characteristics in the task of Fuzzy Cognitive Map (FCM) weight learning as shown in Table 1:

Table 1 Property of Evolution Algorithms

Algorithm	Core Operation	FCM Features	Limitations
GA	Selection/Crossover/Mutation	Strong global search capability	Convergence speed sensitive to parameters
Ant Colony Optimization	Pheromone deposition/Path selection	Distributed collaborative optimization	High memory usage
Asexual Reproduction Optimization	Cloning/Gene fragment recombination	High local search efficiency	Prone to premature convergence
Jaya Algorithm	Favorable-avoidance strategy	No need to adjust control parameters	Significant performance degradation in high -dimensional problems

Genetic algorithms, with their robust operator system and global convergence, are ideal for FCM weight matrix learning. Their evaluation includes: 1) encoding scenario element correlations through chromosomes; 2) customizing fitness functions for tasking effectiveness; and 3) utilizing parallel computing for timely joint decision-making. This study uses an adaptive genetic algorithm, with pseudocode in Algorithm 1.

Algorithm 1 Genetic Algorithm

Algorithm 1 Genetic Algorithm

Initialize population $P_0 = \{w_i^{(0)}, w_j^{(0)}\}_{i=1}^{N}$
repeat
  repeat
    $w_i \leftarrow$ Arithmetic Crossover: $w_i^{'} = \alpha w_i + (1-\alpha) w_i$, where $\alpha \sim U(0,1)$
    $w_j \leftarrow$ Multi-Point Crossover: $w_j^{'} = \Phi(w_j, w_i, k)$, k is random cut point
    $w_i^{'} \leftarrow$ Gaussian Mutation: $w_i^{''} = w_i^{'} + \mathrm{N}(0, \sigma^2)$
    $w_j^{'} \leftarrow$ Polynomial Mutation: $w_j^{''} = w_j^{'} + \Delta(q)$, q is mutation intensity
    Compute Fitness $f(w_i^{''}) = 1/(1+\sum d_{ij})$
  until generate offspring population Q_t satisfy $|Q_t| = N$
  Select parents $P_{t+1} = \arg\max_{w \in P_t \cup Q_t} \{f(w)\}$
until $\max f(w) > \theta$ **or** $t > T_{\max}$

As shown in Figure 3, the construction of DIFCM is based on six core situational elements ($(C_i, i = 1, 2, ..., 6)$) and three environmental control variables. The causal relationships between nodes are characterized by an interval intuitionistic fuzzy weight matrix $W = [w_{ij}]_{6\times6}$, where each weight $w_{ij} = <[\mu_{ij}^L, \mu_{ij}^U], [\nu_{ij}^L, \nu_{ij}^U]>$ is determined by expert groups using an improved Delphi method [13].

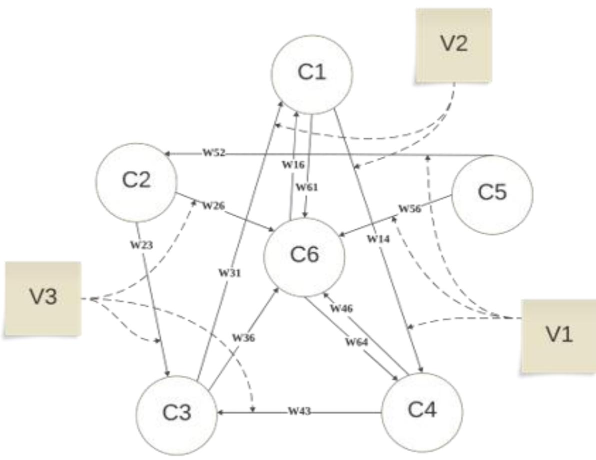

Figure 3 Conceptual Nodes of the Situation and Threat Assessment Model

The threat assessment network focuses on eight-dimensional elements, and its weight matrix construction abandons traditional expert weighting methods in favor of data-driven optimization using an improved genetic algorithm. The chromosome encoding scheme is designed as follows: for 11 sets of weight parameters, the membership degree μ_{ij} and non-membership degree ν_{ij} are concatenated to form a 22-dimensional real-valued vector:

$$chromosome = [\mu_{18}, \nu_{18}, \mu_{21}, \nu_{21}, \mu_{28}, \nu_{28}, ...\mu_{78}, \nu_{78}, \mu_{87}, \nu_{87}] \ . \tag{4}$$

The population size is set as $P=55$ to ensure search space coverage. The fitness function is defined as:

$$Fitness = \frac{1}{1+\frac{1}{T}\sum_{t=1}^{T}\left|N_8^{sim}(t)-N_8^{ref}(t)\right|}, \tag{5}$$

where N_8 represents the threat level synthesis node, and its reference value N_8^{ref} is calibrated based on expert evaluation results from historical missions. The genetic operations adopt a hierarchical strategy:

(1) Selection Phase: Roulette wheel selection is used, where the probability of each chromosome being selected is proportional to its fitness:

$$P_i = \frac{Fitness_i}{\sum_{j=1}^{P} Fitness_i}. \tag{6}$$

(2) Crossover Phase: Directed arithmetic crossover is performed on selected parent individuals, with new weights calculated as:

$$\mu_{ij}^{'} = \alpha\mu_{ij}^{(p)} + (1-\alpha)\mu_{ij}^{(q)}, \alpha \sim U(0.2, 0.8). \tag{7}$$

(3) Mutation Phase: Cauchy-Gaussian hybrid mutation is applied to 10% of the individuals:

$$\mu_{ij}^{''} = \mu_{ij}^{'} + \delta(\lambda C(0,1)) + (1-\lambda)\mathrm{N}(0,1)). \tag{8}$$

Here, λ controls the mutation intensity distribution and δ is the step size coefficient. The algorithm termination conditions are set as either a fitness improvement of less than 0.1% for 100 consecutive generations or reaching the upper limit of 300 iterations.

Table 2 Part of conceptual nodes of the model

Conceptual Nodes	Implication
C_1	Destructive Capability of Opposing Equipment Systems
C_2	Cognitive Load of Manned Aircraft Operators
C_3	UAV Equipment Systems
C_4	Manned and Unmanned Rear Support Systems
C_5	Manned and Unmanned Information Systems
C_6	Advantage/Disadvantage Level of Our Situation Status
$^*V_1$	Atmospheric Density
$^*V_2$	Opposing Support
$^*V_3$	Manned Aircraft Operator Intervention

Note: * is environmental control variable.

As shown in Table 2, manned aircraft operators influence the assessment process through two interfaces: Environmental Control Variable Adjustment, where weather changes affect value ranges and atmospheric density compensation, and DIFCM, which generates situational index vectors that integrate cognitive load in threat assessment. The cognitive foundation module uses interval intuitionistic fuzzy numbers to represent expert knowledge and scenario uncertainty. The hybrid learning framework combines genetic optimization and rule-based reasoning, reducing subjective reliance while ensuring interpretability. A bidirectional mapping mechanism guides human cognition to correct UAV assessment deviations.

2.3 Task Allocation and Path Planning Model

In manned/unmanned collaborative tasking systems, task allocation and path planning are key decision-making elements that ensure operational effectiveness. Balancing task efficiency, resource use, and adaptability, this paper presents a cognitive intelligence-based framework using an improved Contract Net Protocol (CNP) and adaptive A* algorithm for efficient resource scheduling and safe path generation in dynamic mission environments.

2.3.1 Contract Net Protocol

The task allocation problem is a multi-constraint, multi-objective optimization challenge, complicated by scenario uncertainties and the collaboration of heterogeneous platforms as shown in Figure 4:

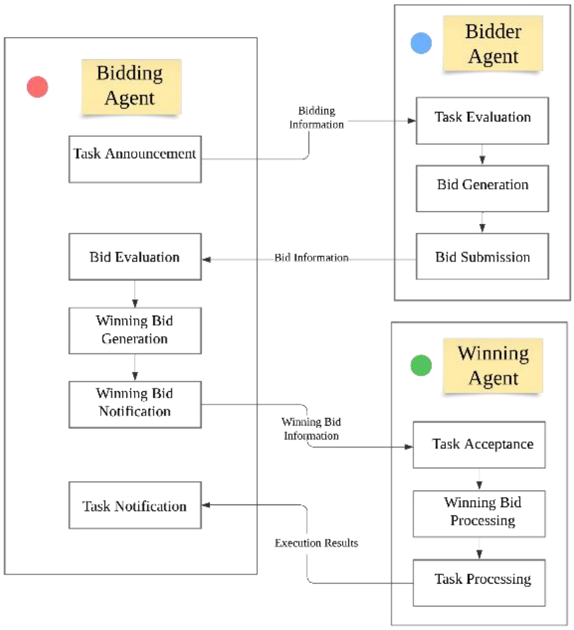

Figure 4 Flowchart of the Enhanced Contract Net Protocol Algorithm

Traditional CNP simulates market bidding but neglects human cognitive load and UAV autonomy. To overcome this, the cognitive intelligence-based collaborative decision-making model includes the cognitive state of manned aircraft operators in task allocation. The task allocation matrix is defined as $X_{N\times M}$, where the element $x_{ij}=1$ represents the assignment of target to UAV i. The task effectiveness function $U(X)$ is composed of a profit function $E(X)$, a cost function $C(X)$, and a profit adjustment function $D(X)$:

$$U(X)=E(X)-C(X)+D(X). \tag{9}$$

The profit function $E(X)$ integrates target value, damage probability, and operator reliability factors, with its mathematical model expressed as:

$$E_u=\frac{V_{TARGET_j}\cdot P_k\cdot e^{-\delta t}}{1+e^{-h\lambda}}, \tag{10}$$

where V_{TARGET_j} represents the strategic value of the target, δ is the operator error rate, P is the UAV's probability of target destruction, and t is the current time. The cost function V_{TARGET_j} quantifies UAV loss risk and target threat intensity:

$$C_u=k_1\cdot UAV_{V_i}\left(1-\prod_{j=1}^{m}(1-P_j)\right)+k_2\cdot threat_{ij}, \tag{11}$$

where UAV_{V_i} is the asset value of UAV i, P_j is the damage probability when executing a task on target j, and the weight coefficients k_1 and k_2 satisfy $k_1+k_2=1$. To enhance the adaptability of task allocation, UAV intelligent emotions are introduced into the profit adjustment function, with values dependent on three emotional modes (fear, relaxation, aggression) and task profit intervals as shown in Table 3. The preference coefficient α is calibrated through regression analysis of historical mission data, ensuring decision logic aligns with actual mission requirements.

Table 3 Impact of Different Emotional Modes on UAV Task Selection

Emotional Mode	Task Preference	Profit Adjustment Value
Fear	Low risk, low reward	Low
Relaxation	Medium-low risk, medium reward	Average
Aggression	High risk, high reward	High

2.3.2 Self-adaptive A star algorithm

A star algorithm, as a typical representative of heuristic search algorithms, holds significant theoretical value and engineering significance in the field of grid-based environment path planning [14]. By constructing a cost evaluation function that balances actual path costs and heuristic estimates, the algorithm achieves efficient search while ensuring global optimality. Its core mathematical model can be expressed as:

$$f(n) = g(n) + h(n), \tag{12}$$

where n represents the current expanded node, $g(n)$ is defined as the cumulative actual path cost from the start point to node n, and $h(n)$ is the heuristic function used to estimate the minimum expected cost from node n to the target point. This study adopts the Euclidean distance:

$$h(n) = \sqrt{(x_n - x_{goal})^2 + (y_n - y_{goal})^2} \tag{13}$$

as the heuristic function. This function satisfies the admissibility condition (i.e., it does not exceed the true path cost), thereby ensuring the algorithm's optimality. Core algorithm as shown in Algorithm 2:

Algorithm 2 Classic A* Path Planning Algorithm

Algorithm 2 Classic A* Path Planning Algorithm

Algorithm A_star(Start point s_{start}, Target point s_{goal}, Cost function $c : S \times S \to \mathbb{R}^+$)
Initialize OpenList $O = \varnothing$, CloseList $C = \varnothing$
Set $g(s_{start}) = 0$
O.insert$(s_{start}, f(s_{start}))$
while $O \neq \varnothing$ **do**
  $s_{current} = O$.extract_min()
  if $s_{current} == s_{goal}$ **then**
    return $reconstruct\_path(s_{current})$
  C.add($s_{current}$)
  for $s_{neigh} \in Neighbors(s_{current})$ **do**
    if $s_{neigh} \in C$ **then continue**
    $g_{tent} = g(s_{current}) + c(s_{current}, s_{neigh})$
    if $g_{tent} < s_{neigh}$ **then**
      $g(s_{neigh}) = g_{tent}$
      $f(s_{neigh}) = g(s_{neigh}) + h(s_{neigh})$
      $Parent(s_{neigh}) = s_{current}$
      if $s_{neigh} \notin O$ **then**
        O.insert$(s_{neigh}, f(s_{neigh}))$
return $Failure$

Theoretically, the A* algorithm is guaranteed to be both complete and optimal: it will return a feasible path if a solution exists, and it ensures global optimality when the heuristic function satisfies admissibility [15]. To enhance the algorithm's adaptability in dynamic scenario environments, this study introduces UAV intelligent emotion mode settings as part of the collaborative decision-making model.

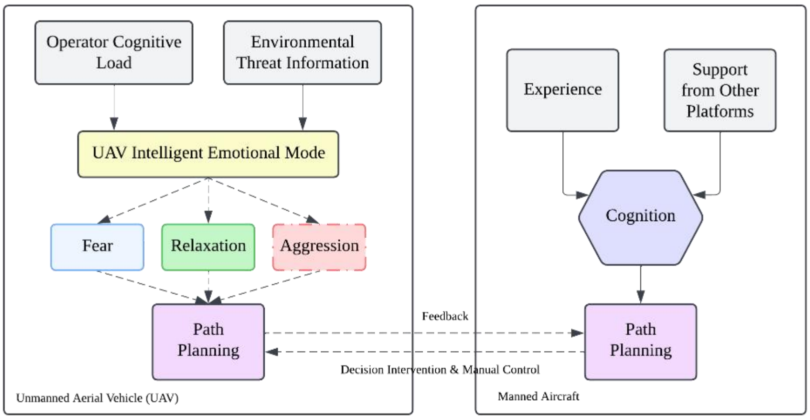

Figure 5 Path Planning Model

Of which basic structure is shown in Figure 5 the path planning problem can be formalized as a network graph search problem, where the node set $S=\{s_1,s_2,...,s_m\}$ represents the discretized scenario space, and the set of all feasible paths from the start point to the target point is $E=\{e_k \mid e_k=(s_{i_1},s_{i_2},...,s_{im})\}$. Defining the path $e_k \in E$ with adjacent node pairs (s_i,s_j), their connecting edges are denoted as $V(s_i,s_j)$, and the flight cost as d_{ij}. The UAV trajectory planning problem can then be modeled as:

$$\min f(e_k)=\sum_{(s_i,s_j\in E)} d_{ij} \text{, s.t. } s_i \in E, s_j \in E, e_k \in E. \tag{14}$$

The heuristic function $h(s_i)$ uses Euclidean distance to estimate the remaining flight distance, ensuring algorithm convergence and optimality. To address dynamic threat environments, an emotion-dependent threat avoidance radius is designed as:

$$D=\mathrm{R}\cdot \mathrm{e}^{(1-1/R)\cdot(1-C_w)}, \tag{15}$$

where R is the threat influence radius, and the UAV intelligent emotional mode C_w is determined by parameters α and β as shown in Table 4.

Table 4 Determination Range of UAV Intelligent Emotional Modes

Value of C_w	Emotional mode
$C_w<\alpha$	Fear
$\alpha\le C_w\le\beta$	Relaxation
$C_w>\beta$	Aggression

Human-machine collaboration mechanisms are integrated throughout the task allocation and path planning process. Operators can intervene through two types of interfaces: at the task allocation level, dynamically adjusting emotional mode thresholds or manually specifying high-value targets; at the path planning level, setting temporary no-fly zones or modifying threat avoidance parameters. When path risk exceeds the operator's preset threshold, an alarm signal is triggered, suggesting task termination or replanning as shown in Figure 6. This bidirectional information flow design ensures the stability and real-time performance of the human-machine decision-making loop.

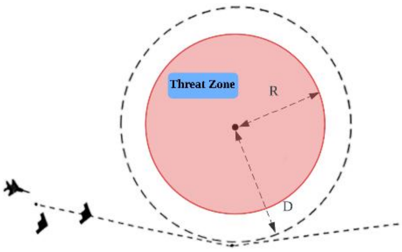

Figure 6 Schematic Diagram of Threat Avoidance Radius

The model improves traditional methods with three innovations: 1) modeling cognitive load and emotions as endogenous decision variables, removing the need for human experience; 2) designing an emotion-threat-coupled path cost function to balance safety and economy; and 3) creating a task-path joint optimization framework to reduce risks from local optimization. Its value lies in advancing collaborative decision-making from static rule-driven to dynamic cognition-guided evolution, enabling deeper human-machine intelligence integration.

3 RESULTS AND ANALYSIS

To validate the effectiveness of the proposed manned/unmanned collaborative decision-making framework, a simulation experimental system was constructed based on the MATLAB platform. The experimental design follows a progressive logic of "modular verification-scenario simulation-comprehensive evaluation," with a focus on analyzing the performance of three core modules: threat assessment, task allocation, and path planning, in comparison with traditional methods. In the verification of the situation and threat assessment module, a genetic algorithm was used to optimize the 11 sets of weights in the Intuitionistic Fuzzy Cognitive Map (IFCM). The population size was set to 200, with a crossover probability of 0.8 and a mutation probability of 0.15. After 300 iterations, the convergence curve is shown in Figure 7. Experimental data indicate that the optimal fitness value stabilized at 0.812 (Best curve), and the population mean converged to 0.813, demonstrating the algorithm's strong global search capability and stability. The optimized membership and non-membership heat matrix reveals that the membership values of key threat nodes (e.g., target radar detection accuracy N_8) are concentrated in the [0.6, 0.85] range. In sudden threat response tests, the model's re-evaluation time was 0.87 seconds, meeting the real-time requirements of dynamic battlefields as shown in Figure 8.

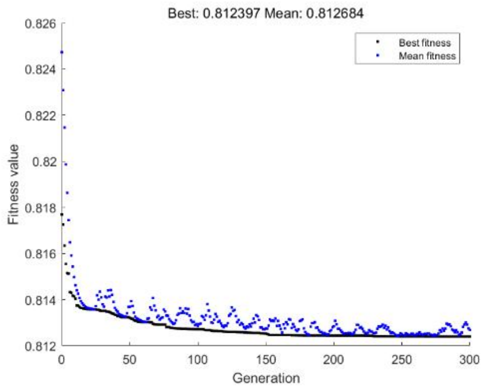

Figure 7 IFCM Genetic Algorithm Optimization

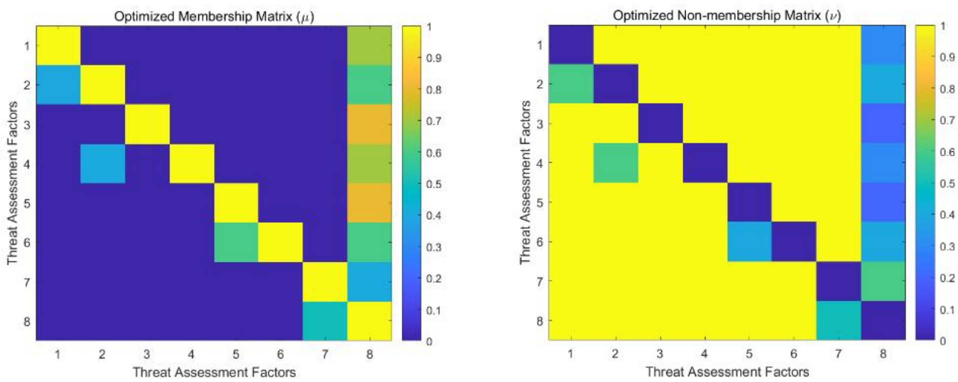

Figure 8 Optimized Threat Assessment Membership and Non-Membership Matrix

Based on the improved Contract Net Protocol (CNP) task allocation model, a tasking scenario was constructed with four heterogeneous UAVs targeting six opposite objectives. The heatmap of bid values optimized by Particle Swarm Optimization (PSO) shows that UAV4, equipped with electronic countermeasure devices, achieved bid values of 0.51 and 0.47 for high-value targets T1 and T4, respectively. UAV1, in aggressive mode, increased its bid intensity for high-risk target T1 by 26.8%. Compared to UAV2 with the same emotional mode, UAV3, when assigned to accept signals with higher operator cognitive load, saw its intelligent emotional mode's influence on bidding relatively suppressed, enhancing the safety and effectiveness of human-machine collaboration strategies as shown in Figure 9.

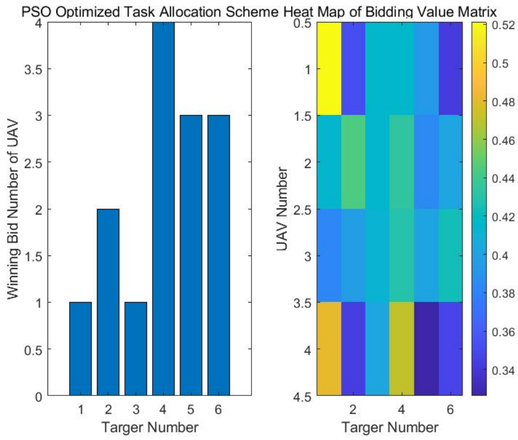

Figure 9 Heatmap of Task Allocation Scheme and Bid Value Matrix Optimized by PSO

In an 800×600 grid tasking environment with six fixed threat sources, the improved A* algorithm was used for path planning. A comparison of routes under three emotional modes shows that the fear mode (C=0.15) had an average threat cost of 0.17, a 58% reduction compared to the aggressive mode, but with a 22.3% increase in path length. The aggressive mode (C=0.85) resulted in a total threat cost of 165, while the relaxed mode (C=0.5) achieved the best balance, with standard deviations of path length and threat cost being only 43% and 52% of the other modes, respectively. The algorithm's average planning time was 0.64 seconds, and the sudden threat replanning response time was 1.43 seconds, a 63% improvement over the traditional RRT algorithm. Path planning situation map as shown in Figure 10.

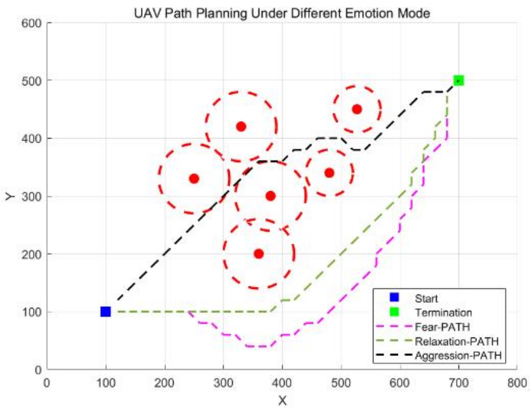

Figure 10 UAV Path Planning Situation Map Under Different Emotion Modes

Overall the collaborative decision-making framework proposed in this paper has been validated at the algorithmic level. Its core value lies in revealing the intrinsic relationships of threat elements through weight optimization heatmaps, quantifying UAV capability differences using bid value distribution characteristics, and demonstrating the effectiveness of the emotional adaptive mechanism through path comparison experiments. Future work should further develop hardware-in-the-loop simulations and incorporate reinforcement learning strategies to optimize algorithm convergence, advancing theoretical research toward practical applications.

4 CONCLUSIONS AND OUTLOOKS

This paper addresses decision-making optimization in manned/unmanned collaborative tasking by proposing a cognitive collaboration-based decision-making framework. Through the deep integration of Dynamic Intuitionistic Fuzzy Cognitive Maps (DIFCM), Genetic Algorithms (GA), and an improved A* algorithm, a full-process model covering "situation assessment, threat analysis, task allocation, and path planning" is constructed. Experimental results show that the framework surpasses traditional methods in threat assessment accuracy, task allocation efficiency, and path planning safety. Specifically, DIFCM, optimized by genetic algorithms, enhances the real-time performance and accuracy of threat assessment. The improved Contract Net Protocol, incorporating UAV intelligent emotional modes, enables adaptive task allocation. Meanwhile, the emotion-driven A* algorithm demonstrates superior path planning in dynamic threat environments. The key innovation lies in coupling human cognitive characteristics with machine autonomous decision-making, reducing dependence on human experience and offering a novel methodological perspective for manned/unmanned collaborative mission.

Future research should integrate advanced reinforcement learning strategies to improve algorithm convergence and adaptability. Additionally, hardware-in-the-loop simulations are necessary to validate the framework's practical applicability, ensuring its robustness in real-world tasking scenarios.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Gu H, Xu C. Human-Machine Collaborative Teamwork Technology. Command Information Systems and Technology, 2017, 8(06): 33-41.
[2] Fu J, Zhang D, Wang M, et al. UAV Trajectory Planning for Target Localization Accuracy Enhancement. Acta Armamentarii, 2023, 44(11): 3394-3406.
[3] Wu Y. Research on Active Perception Methods for UAV Swarm Target Search. Shanghai Institute of Technology, 2020.
[4] Xie Y, Lu Y, Guan C, et al. Key Issues in Cooperative Aerial Tasking and Multi-Agent Reinforcement Learning. Aircraft Design, 2023, 43(01): 6-10.
[5] Zhong Y, Yao P, Zhang J, et al. Interactive Cooperative Decision-Making in Human-Machine Systems Based on HFCM. Systems Engineering—Theory & Practice, 2021, 41(10): 2748-2760.
[6] Xue Z, Zhang Y, Chen J. Research on Hybrid Active Interactive Decision-Making for Unmanned-Manned Aircraft. Aeronautical Science and Technology, 2022, 33(05): 44-52.
[7] Liu B, Wei X, Qu H, et al. Collaborative Decision-Making in Human-Machine Aerial Systems. Advances in Aeronautical Engineering, 2023, 14(06): 63-72.
[8] Chen J, Liang J, Cheng L, et al. Multi-UAV Cooperative Decision-Making Modeling Based on FCM. Acta Aeronautica et Astronautica Sinica, 2022, 43(07): 377-394.
[9] Luo Y, Ding D, Tan M, et al. A Review of Autonomous Decision-Making Methods for Unmanned Aerial Vehicles. Acta Aeronautica et Astronautica Sinica, 2025: 1-30.
[10] Robert Axelrod. Structure of Decision. Princeton University Press, 2015.
[11] Thong N T, Smarandache F, Hoa N D, et al. A novel dynamic multi-criteria decision making method based on generalized dynamic interval-valued neuromorphic set. Symmetry, 2020, 12.
[12] Iván S, Anne C, Anna D, et al. Fuzzy cognitive mapping in participatory research and decision making: a practice review. Archives of Public Health, 2024, 82(1): 76-76.
[13] Zhida S. Use of Delphi in health sciences research: A narrative review. Medicine, 2023, 102(7): e32829-e32829.
[14] Guo Z. Efficient path planning method based on A-STAR//Department of Civil & Environmental Engineering, Brunel University London, Department of Computer and Information Sciences, University of Strathclyde. Proceedings of the 2023 International Conference on Mechatronics and Smart Systems. Ulster College Shaanxi University of Science and Technology, 2023: 196-205.
[15] Erke S, Bin D, Yiming N, et al. An improved A-Star based path planning algorithm for autonomous land vehicles. International Journal of Advanced Robotic Systems, 2020, 17(5).