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REGULAR PAPER

A Cutting-Edge Approach to Multi-UAV Mission Planning Using Enhanced Constraint Satisfaction

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Abstract
Multi-task planning for diverse UAVs and missions can be approached as a Constraint Satisfaction Problem (CSP) where the Temporal CSP (TCSP) method adds time-based sequential task modeling. The Enhanced Temporal Constraint Satisfaction Problem (ETCSP) method innovatively merges dynamic domain features with a MIQP (Mixed Integer Quadratic Programming) based scoring system to optimally assign UAVs to tasks, moving beyond traditional greedy algorithms. This approach includes an enhanced forward checking method that evaluates task suitability and UAV compatibility in real-time using dynamic programming, thus refining search precision. The ETCSP model was tested in two phases, initially assigning various tasks and then employing CSP methods to monitor task changes over time. Results show that the generic TCSP method requires 61 UAVs to complete 70 tasks, while the Enhanced TCSP achieves the same with only 48 UAVs—which is roughly a 21% reduction in UAV usage. Similarly, the Enhanced method completes the task package in about 3800 min and with 1142 L of fuel, compared to 4855 min and 1615 L for the TCSP method, translating to approximately a 22% reduction in time and a 29% reduction in fuel consumption.

Keywords Constraint Satisfaction · Dynamic Domain · Dynamic Programming · Mission Planning · Multi-Objective · Multi-task Planning · NP-hard · UAVs

1 Introduction

In recent years, Unmanned Aerial Vehicles (UAVs) have taken on roles comparable to those involving human participation in aviation. UAVs have become highly preferred, particularly for tasks that are dull, dirty, and dangerous (3D) tasks, due to their reduced costs and risks. As autonomy and optimization advance in the aviation sector, and risks and costs decrease accordingly, UAVs have become accessible to many industries without requiring significant financial investments. In this context, there is a need for the rapid planning of various types of tasks and their specific optimization for systems. Consequently, the demand for easily adaptable frameworks to quickly provide reasonable solutions has increased. Constraint satisfaction problems (CSP) can help solve complex problems effectively and offer both an understandable and easily adaptable infrastructure and method for various problems.

The systems developed to enhance the autonomy capabilities and provide decision support for Unmanned Aerial Vehicle Systems (UAS) are generally examined under three main components: Guidance, Navigation, and Control. The subset of the Guidance component, which includes mission planning and decision-making processes, can be performed either concurrently, distributed, or centrally, both before and during the mission. This area has recently witnessed a wide range of methods being explored to enable autonomous processes. Currently, UAVs operate either fully autonomously or with partial intervention in places requiring human support, generally executing predefined tasks. However, effective planning becomes challenging as the constraints and complexity of tasks increase. One of the earliest examples of academic studies related to UAVs,"The Pilotless Aircraft,"was published

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in 1916 due to the need for mission planning capabilities in the operational field during World War I Low [1]. However, the first academic studies focusing on the practical use of technology emerged half a century later. Although the study titled"Ryan Firebee,"published in 1963, stands as one of the first examples of UAVs being used in the real world[2], until the 2000 s, studies in the field of UAV mission planning fell below expectations, primarily due to high costs and limited experience[3]. Nevertheless, it is observed that research in this field has significantly increased since the 2000s[4]. Figure 1 was generated using data from scopus by querying with the keywords UAV, Drone and UAS until 2025 [5].

Especially since the early 2010 s, UAVs are used in various fields such as telecommunications, health[7], logistics[8], traffic control[8], public safety[9], forest monitoring[10], military missions [11] and many others [4]. As the areas of UAV applications have expanded, problem domains have similarly increased and become more complex. It is observed that more effective assignment methods are needed for task allocation based on the usage areas and problem types of UAVs. This study focuses on the task planning problem required for all complex UAV missions, emphasizing how task assignments can be optimized.

This study advances multi-UAV mission planning through five key contributions. (i) We propose ETCSP formulation that injects a dynamic domain into each task-pair time window, allowing the search to adapt online rather than relying on static, greedy assignments. (ii) The model integrates node/arc consistency, backtracking and forward checking with a mixed-integer quadratic-programming (MIQP) multi-objective score, balancing fuel, time and airborne-risk factors in real-time. (iii) A novel airborne-reassignment mechanism enables mid-mission task swaps without intermediate landing, cutting redundant take-off/landing cycles while preserving worst-case complexity at $\mathcal{O}(n^m)$. (iv) Extensive simulations across seven perturbed scenarios and 1.000-run Monte-Carlo tests show consistent performance gains ~ 22% shorter makespan, 29% lower fuel and 21% fewer UAVs than a baseline TCSP solver. (v) Comprehensive sensitivity and error analyses identify fuel-burn rate, task/base location and tank capacity as dominant factors, providing actionable guidelines for future large-scale deployments.

This paper is organized into six sections as literature review, definition of the relevant problem, test result & their interpretations, discussion and conclusion & future directions.

2 Literature Review

Research on mission planning problems for UAVs has been classified into mathematical programming, heuristic approaches, reinforcement learning algorithms, and constraint satisfaction problem (CSP) based methods. Mission planning consists of two main functions: mission assignment and route planning, with mission assignment being critical especially in heterogeneous UAV formations [12] [13].

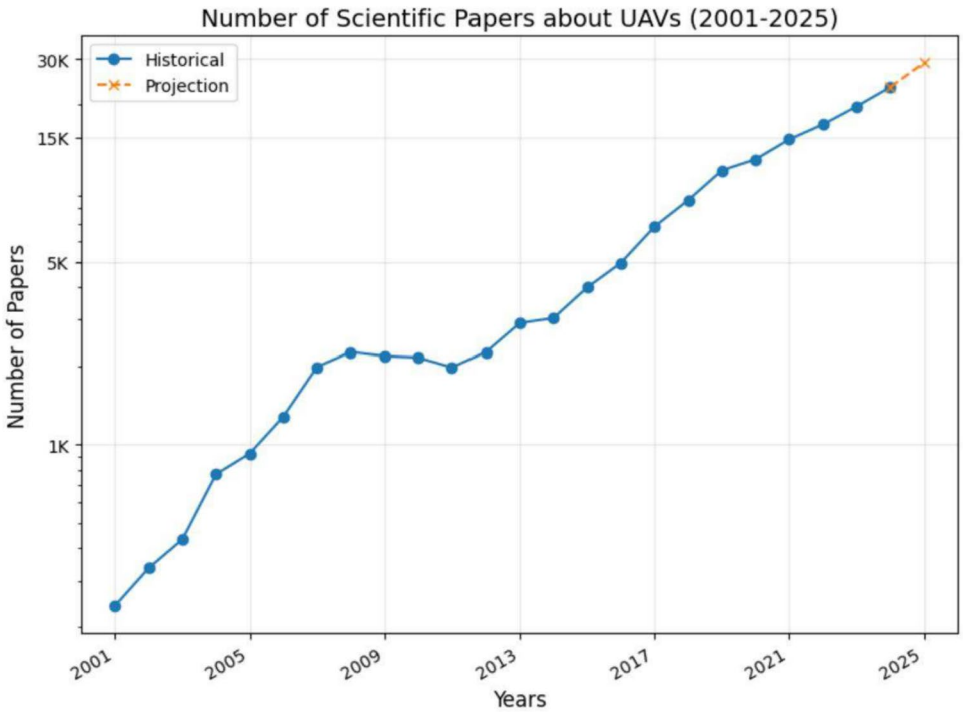


Fig. 1 Number of scientific studies carried out using UAVs between 2001 and 2025 [4, 6]

2.1 Task Assignment-Based on Mathematical Programming

Task assignment is rooted in Combinatorial Optimization Problems (COP) [14]. Until the 2010 s, common approaches included Exhaustive Algorithm, Branch-and-Bound (B&B), and Hungarian Algorithm [15]. Exhaustive Method uses brute force, making it impractical for large solution spaces [16], while Ramirez et al. demonstrated a successful B&B algorithm application [17]. Mixed Integer Linear Programming (MILP) models have been widely studied [18]. Kingston et al. applied MILP to air-to-ground attack assignments, calculating time constraints for optimal results [19]. Doherty introduced a Temporal Action Logic (TAL) infrastructure for task planning, testing it on unmanned helicopters [20]. Recent studies have demonstrated the effectiveness of decentralized Markov Decision Process (Dec-MDP) frameworks in UAV mission planning, particularly for swarm coordination and multi-target tracking applications [21]. The ReSSAC project at ONERA employed dynamic programming and Markov Decision Process (MDP) for search and rescue operations [22].

2.2 Heuristic-Based Task Assignment

Various AI methods have addressed UAV task planning, including CSP, Evolutionary Algorithms, Swarm Intelligence, and Machine Learning. Common approaches reduce problems to Multiple Traveling Salesman Problem (MTSP) [23] and Vehicle Routing Problem (VRP) [24], with hybrid approaches combining MTSP–GSP and Multiple Depot Vehicle Routing Problem (MDVRP) models [25]. Shima et al. showed genetic algorithms outperform classical optimization methods in computational complexity [26]. Genetic algorithms also proved effective for heterogeneous UAV task assignment [27]. Edison and Shima researched route planning using the Dubins Car Model [28] and Shima et al. developed a modified genetic algorithm with target–bundle-based coding [26]. Huang et al. compared Improved Particle Swarm Optimization (IPSO), Ant Colony Optimization (ACO), and Genetic Algorithm (GA), finding that GA produced accurate results but had inferior time complexity [29]. Geng et al. designed a modified PSO algorithm focusing on adaptable assignment solutions [30]. Other notable methods include the Wolf Pack Search algorithm [31], Tabu Search [32], enhanced genetic algorithms [33], and Grouping Ant Colony Optimization (GACO) [34]. For decentralized task assignment, research has focused on the Consensus-Based Bundle Algorithm (CBBA) [35] and its extension with distributed reassignment [36]. Bethke et al. proposed an algorithm extending the Receding-Horizon Task Assignment (RHTA) [37], later compared with greedy methods [38]. Zhang et al. proposed a clone selection algorithm for simultaneous multi-objective optimization [39], while another study developed a two-phase approach addressing flight time and payload capacity constraints [40].

2.3 Reinforcement Learning-Based Task Assignment

Complex wartime situations require optimal real-time decision-making, revealing limitations in traditional algorithms. Reinforcement Learning (RL), inspired by behavioral psychology, learns optimal strategies through environmental rewards [41] and has been applied to target assignment and intelligent control [42]. Q-learning has been proposed to address multi-objective optimization limitations [43]. Gao et al. employed deep reinforcement learning for task scheduling and route planning [44], while Luo used it for enemy missile-target assignment [45]. Zhao et al. developed a rapid Q-learning-based task allocation algorithm [46], and Liu et al. proposed a multi-agent reinforcement learning network for dynamic task allocation [47]. Multi-Objective Deep Reinforcement Learning (MODRL) algorithms train multiple policies using different reward functions. Sullivan et al. designed a MODRL algorithm based on Proximal Policy Optimization (PPO) [43], though the simulation–reality gap remains an open question [48].

2.4 Constraint Satisfaction Problem-Based Task Assignment

Multi-UAV task assignment requires clearly defined constraints and relationships when using CSP approaches [4] [49] [50] [51]. Task assignment represents a "constraint-containing combinatorial optimization problem" classified as NP-hard due to its time complexity [51]. CSP-based research began in 1968 with minimum path cost studies [52], gaining momentum approximately 20 years later [29, 53]. Ramirez et al. demonstrated successful UAV task assignment using a simple CSP model [54] and later combined Multi-Objective Genetic Algorithm (MOGA) with CSP. They developed an optimization function using B&B to minimize costs and flight time, then conducted studies using MOGA for multi-objective fitness functions [55]. In recent years, CSP and TCSP-based approaches have been directly applied to multi-UAV mission planning and route-optimization problems. Matlekovic and Schneider-Kamp formulated coverage-path planning for multi-UAV infrastructure inspection as a CSP and showed that their solver minimizes total inspection time [56]. Montemanni and Dell'Amico tackled a parallel-drone scheduling VRP with several CP formulations, demonstrating that constraint-programming models can optimally solve complex truck-and-drone logistics problems [57]. Jeong et al. addressed temporally constrained task allocation for heterogeneous UAV fleets, proposing a

re-balancing algorithm with a novel loiter-time variable that significantly reduces makespan [58]. Wang et al. designed a resilient multi-objective mission-planning framework that integrates task pre-assignment and in-flight re-assignment, using TCSP-like rescheduling to maintain mission reliability [59]. Additionally, Gao et al. modeled real-time airspace deconfliction for UAV swarms as a CSP and computed optimal separation times [60], while Li et al. planned HALE-UAV surveillance paths via a temporal CSP, improving fuel–coverage trade-offs on long-endurance missions [61]. In another study focusing on adapting the constraint satisfaction problem to the task-planning domain, the successful completion of all tasks is compulsory and constitutes the primary priority. Although the approach effectively reduces total fuel consumption and mission duration, risk is not explicitly considered. Moreover, a UAV assigned to a task while airborne can only be reassigned to the immediately subsequent task; if it is unsuitable for that particular task—even though it may be suitable for later tasks—it is directed to land. [62] Collectively, these studies confirm that the CSP/TCSP paradigm can yield scalable, optimal or near-optimal solutions in contemporary UAV applications, thus underpinning the relevance of our proposed ETCSP model. Several significant challenges remain across all approaches, including the simulation-to-reality gap, scalability limitations as the number of UAVs increases, adaptation to rapidly changing environments, and managing heterogeneous UAV capabilities. Hybrid methods like MOGA-CSP [20] and emerging RL-guided mathematical programming approaches show promise in balancing these competing concerns by leveraging the strengths of multiple methodologies. Table 1 shows the pros and cons of methodologies in detail.

3 Problem Definition and Construction of the Proposed ETCSP Model

The task planning problem is classified as a challenging optimization problem known as NP-hard (Non-deterministic Polynomial-time Hard). Traditional graph search and logic-based algorithms are inadequate for this problem due to their excessive computational requirements.

Unmanned Aerial Systems (UAS) developed to enhance autonomy capabilities and provide effective decision support are generally examined under three main components: Guidance, Navigation, and Control. Within the guidance component, task planning can be classified into subcomponents of task assignment and route planning, as illustrated in Fig. 2. Similarly, route planning consists of components such as path and trajectory planning. The path planning process aims to efficiently determine a path by solving optimization problems related to obstacle avoidance, fluidity, etc. In trajectory planning, aspects such as timing, maneuvers, speed and altitude are addressed in coordination with path planning.

This study aims to address the task planning and decision-making problems under the guidance section, specifically focusing on selecting Unmanned Aerial Vehicles (UAVs) with high-level autonomy for various types of tasks under different flight constraints, aiming to minimize cost or risk. In the task planning processes employed in this study, it is assumed that Ground Control Stations are in continuous communication with UAVs, and the UAVs follow the most accurate route for the planned task. Within the scope of route planning, it is assumed that the UAV (Unmanned Aerial Vehicle) follows a straight two-dimensional path to the mission area and autonomously performs all necessary maneuvers during the mission assuming

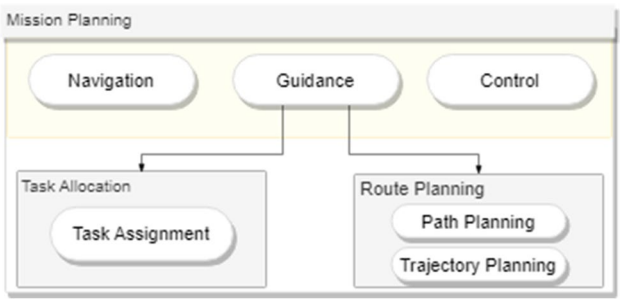


Fig. 2 Guidance and its subcomponents in mission planning

Table 1 Comparative analysis and research gaps

Method	Advantages	Disadvantages	Applicability
Mathematical Programming (MILP)	Produces optimal solutions; Well-defined mathematical foundation	High computational complexity; Limited scalability	Small-scale problems with strict optimality requirements
Heuristic Approaches	Faster computation; Handles large-scale problems	No guarantee of optimality; Parameter tuning challenges	Medium to large-scale problems with reasonable optimality requirements
Reinforcement Learning	Adapts to dynamic environments; Improves with experience	Sim-to-real gap; Data hungry; Black-box nature	Dynamic environments with available training data
CSP-Based Methods	Effective constraint handling; Flexible problem formulation	NP-hard complexity for large problems	Problems with complex constraints and moderate size

average fuel consumption and no signal loss or adverse weather conditions. These assumptions were adopted to simplify the analytical examination of the model. In UAV mission planning, the role of human factors (e.g., human decision-making processes, cognitive load) is excluded. All decisions are assumed to be made fully autonomously based on data.

The construction of the CSP model necessitates the segmentation into variable, constraint, and domain sections. The foundation of CSP relies on the accurate determination of constraints and their relationships. Constraints can be classified in various ways and should be examined from different perspectives. Based on their characteristics, constraints can be classified as unary, binary, and high-order; global–local; hard-soft nature of constraints; precedence; temporal; static-dynamic; dependent-independent; simple-complex; direct–indirect. These classifications are crucial for understanding the nature of constraints and achieving accurate modeling.

This study is primarily structured around dynamic temporal CSP modeling. Constraints independent of time are clustered as static constraints before TCSP modeling to reduce computational complexity. Here, time is designated as the foundational constraint, and the associated dynamic dependent constraints are identified as fuel and location. All other constraints are considered as static and independent constraints. Proper classification of constraints is essential to reduce the time complexity of the application. The subtopics of mission planning are task assignment and route planning. Route planning, in this study, is approached within the scope of determining the task prioritization, timing, and trajectory speeds of UAVs. For this purpose, dynamic domain capabilities are added to the TCSP (Temporal Constraint Satisfaction Problem), where the UAV that receives the highest score across the entire task domain is assigned instead of a greedy approach. The impact of this assignment on subsequent tasks is examined through Forward Checking. At this point, the power of dynamic programming allows the Forward Checking method to inspect not only the next task but also all other tasks with pending constraints. This improvement enables the evaluation of the suitability of UAVs for tasks in windows of consecutive time-dependent task pairs, facilitating easier access to optimal solutions in the solution space. The quality of the generated solution allows optimization methods to converge to better results by focusing on a smaller and more reasonable search space.

Thus, the ETCSP model has been adapted for the improvement of the solution. The ability to create a dynamic domain in the time window of task pairs and to calculate the effects of forward checking on subsequent variables (tasks) according to time constraints has been added.

3.1 CSP Based Task Planning

CSP provides a flexible and meaningful framework for modeling and solving problems with complex constraints and relationships between variables. Particularly, it organizes extensive problems into manageable parts by breaking down real-world problems. It is frequently used in artificial intelligence, operations research, optimization, (time-based) planning, configuration, and other fields.

This section describes the structure of the Enhanced Temporal Constraint Satisfaction Model (ETCSP) and explains how backtracking, forward checking, and arc/node consistency methods are hybridized and adapted for UAV task planning. The model aims to optimize both static and dynamic constraints (location, fuel, duration) to enable effective UAV assignment. In the first stage, all constraints are reduced to two variables to narrow the solution space and UAV domains are then created for each task in a mission. Subsequently, dynamic variables are calculated, and appropriate assignments are determined through control methods. These processes are detailed according to the operational sequence shown in Fig. 3.

3.1.1 Node Consistency (NC)

Node Consistency is not applied for the initial task but is used in subsequent tasks by re-evaluating assignment constraints with updates from forward checking and arc consistency. The domain is updated by analyzing the status of airborne UAVs and landed UAVs from the previous tasks for the next flight.

3.1.2 Backtracking (BT)

Unlike classical methods, backtracking is employed to explore alternative solutions for optimization. When the most suitable candidate cannot be found, it searches for alternative solutions and enables fuel/time savings during transitions between tasks.

3.1.3 Arc Consistency (AC)

Arc Consistency is employed to eliminate incompatible UAVs between tasks. It operates in a hybrid manner by considering forward checking records from previous tasks. UAVs are removed from the domain when task completion is impossible due to conflicts, insufficient fuel, or similar constraints.

Successful candidates are then scored by MIQP based Multi Objective method. questioning how well tasks are assigned within the scope of the entire mission and optimizing them to avoid local optima with the help of hybridization NC, BT and AC. Then, the best candidate is allocated.

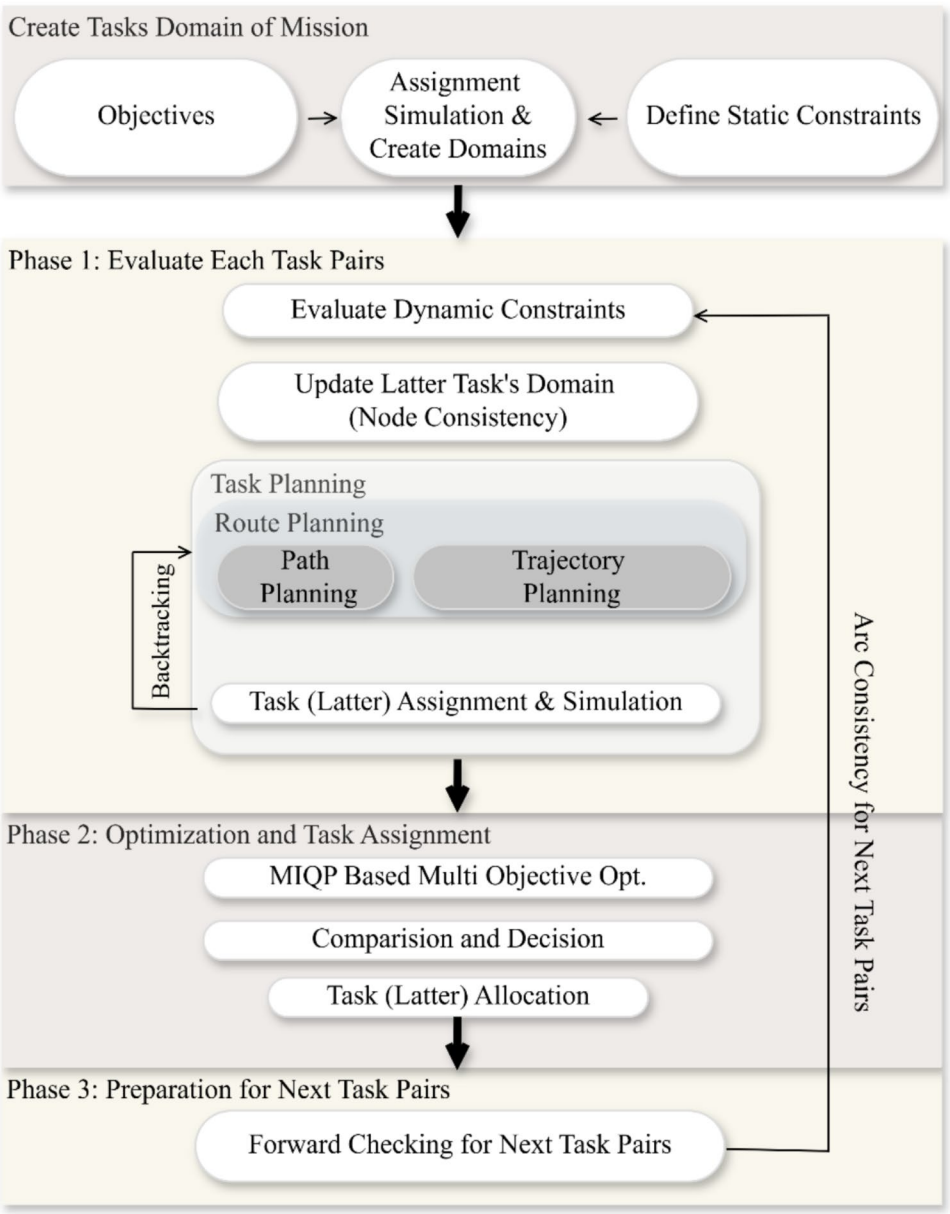


Fig. 3 General steps of the proposed method in mission planning

3.1.4 Forward Checking (FC)

When a UAV is assigned to a task, its impact on subsequent tasks is evaluated. If deemed unsuitable, it is removed from the relevant domain. All airborne UAVs that have not landed are individually examined for their domain in subsequent tasks.

These methods enhance the model's effectiveness by enabling seamless transitions between tasks (without landing) and optimizing resource utilization.

3.2 Proposed Model of Mission Planning with ETCSP

CSP can be conceptualized as a framework or a tree structure that enables the functioning of search or optimization methods. While having its own search methodologies, it can also serve to generate appropriate solutions for metaheuristic methods. The main research topics in this study are presented in Fig. 4.

To model UAV mission planning as a real-world problem, each task must have a definite start time. In the

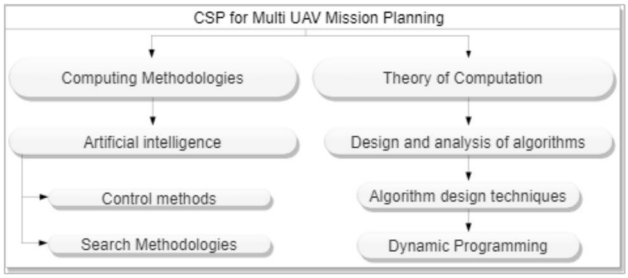


Fig. 4 Different methodologies for UAV mission planning

context of UAV mission planning, tasks are modeled as variables, and the domain represents UAVs that satisfy the constraints. In the initial stage, unary constraints, i.e., constraints affecting only one variable, are identified. These include parameters such as the flight altitude, speed, entry permission to the region, internal payload, and fuel requirements for a single task.

Static and dynamic constraints are distinguished, with static constraints requiring no further examination in the later stages of the problem. However, dynamic constraints, such as fuel and location, which may change over time, are recalculated after each task.

The sets of tasks, aircraft, and airbases used are defined below. Additionally, the parameters employed in the model are presented in Table 2.

$\tau \doteq \{T_1, T_2, \ldots, T_t\}$ Taskset,
$U \doteq \{U_1, U_2, \ldots, U_u\}$ UAV set,
$\mathcal{A} \doteq \{Ab_1, Ab_2, \ldots, Ab_a\}$ Airbase set.

Table 2 Parameters used in mathematical modeling

Symbol	Definition	Type	Unit
$\boldsymbol{\tau}$	Task set	Parameter (Set)	-
U	UAV set	Parameter (Set)	-
$\mathscr{A}$	Airbase set	Parameter (Set)	-
$\boldsymbol{\Omega}$	Coefficient to minimize the completion time	Parameter	0–20
$\boldsymbol{\theta}$	Coefficient to minimize risk	Parameter	0–20
$\boldsymbol{\alpha}$	Coefficient to minimize the total fuel consumption	Parameter	0–20
$\boldsymbol{d_{t,u}}$	Distance between task t and UAV u	Parameter	km
$\boldsymbol{v_u}$	UAV u speed	Parameter	km/hour
$\boldsymbol{\beta_u}$	UAV u fuel consumption rate	Parameter	L/km
$\boldsymbol{F_u^{max}}$	UAV u max fuel capacity	Parameter	L
$\boldsymbol{F_u^{remained}}$	UAV u remaining fuel	Parameter	L
$\boldsymbol{T_t^{task}}$	Task t duration	Parameter	hour
$\mathbf{x}_{i,u}$	Task t—UAV u assignment variable	Decision Variable (Binary)	0/1
$\boldsymbol{F_{t,u}^{ingress}}$	Task t—UAV u ingress fuel	Decision Variable	L
$\boldsymbol{F_{t,u}^{loiter}}$	Task t—UAV u loiter fuel	Decision Variable	L
$\boldsymbol{F_{t,u}^{task}}$	Task t—UAV u task fuel	Decision Variable	L
$\boldsymbol{F_{t,u}^{egress}}$	Task t—UAV u egress fuel	Decision Variable	L
$\boldsymbol{T_{t,u}^{takeoff}}$	Task t—UAV u takeoff time	Decision Variable	time
$\boldsymbol{T_{t,u}^{start}}$	Task t—UAV u task start time	Decision Variable	time
$\boldsymbol{T_{t,u}^{end}}$	Task t—UAV u task end time	Decision Variable	time
$\boldsymbol{T_{t,u}^{landing}}$	Task t—UAV u landing time	Decision Variable	time
$\boldsymbol{D_{t,u}^{ingress}}$	Task t—UAV u ingress duration	Decision Variable	hour
$\boldsymbol{D_{t,u}^{loiter}}$	Task t—UAV u loiter duration	Decision Variable	hour
$\boldsymbol{D_{t,u}^{task}}$	Task t—UAV u task duration	Decision Variable	hour
$\boldsymbol{D_{t,u}^{egress}}$	Task t—UAV u egress duration	Decision Variable	hour
$\boldsymbol{Z_{t,y,u}}$	UAV u assignment to task t and task y	Decision Variable (Binary)	0/1
$\boldsymbol{x_{t,u}}$	UAV u assignment to task t	Decision Variable	0/1/2
$\boldsymbol{H_{t,u}}$	The Airborne status of UAV u during task t	Decision Variable (Binary)	0/1
$\boldsymbol{TScore_{t,u}}$	Task score of UAV u	Decision Variable	0–100

3.2.1 Decision Variables

Decision variables represent the primary decision mechanisms that shape the solution to the problem, while constraints refine these variables. Four such decision variables "Assignment", "Time", "Fuel" and "Risk" have been defined and then formulated in accordance with the constraints.

Assignment Variable In this formulation, when two different tasks (t, y) are to be carried out by the same UAV u, the order of these tasks must be determined. This requirement can be expressed as $Z_{t,y,u} + Z_{y,t,u} = 1$ if both tasks are assigned to the same UAV. Here, "Z" indicates that the same UAV is assigned to both tasks in a specific sequence, and when this holds true, "Z" takes a value of 1. Specifically, $Z_{t,y,u}$ and $Z_{y,t,u}$ are set so that one equals "1" while the other equals 0. Consequently, the "Z" variable records which task is performed first (reflecting an Allen "Before/Meets" relationship) and stores that ordering information.

The parameter x in Eqs. (4–5) denotes the situation where the same UAV is assigned to two distinct tasks. Its value is 2 if the same UAV is indeed assigned to both tasks; if not, x takes a value of 1 or less. In that case, "Z" is expected to be zero, thus enforcing a strict "XOR" condition.

Time Variables For a single task assignment, time-related variables include takeoff time for task $T_{t,u}^{takeoff} \geq 0$,

task end time $T_{t,u}^{end} \geq 0$, loiter duration $D_{t,u}^{loiter}$, ingress duration $D_{t,u}^{ingress}$, task duration $D_{t,u}^{task}$ and egress duration $D_{t,u}^{egress}$.

Fuel Related Variables For a single task assignment, fuel-related variables include ingress fuel $F_{t,u}^{ingress}$, loiter fuel $F_{t,u}^{loiter}$, egress fuel $F_{t,u}^{egress}$, return fuel $F_{u}^{remained}$ and max fuel F_{u}^{max}.

Risk Variables Risk assessment applies to UAVs that remain airborne from a prior task and are reassigned to a new one. Let Air$\in\{0,1\}$ be an indicator variable: a "0″ value implies no risk assessment is needed. In this context, the ratio of remaining fuel to maximum fuel $\frac{F_{u}^{remained}}{F_{u}^{max}}$ is computed. The higher this ratio is—along with a greater number of "reachable" upcoming tasks (represented by a parameter p which represents availableTasks")—the lower the risk becomes.

3.2.2 Constraints

In this model, the constraints define the rules that decision variables must satisfy. Below, we detail both static constraints—such as UAV fuel capacity, mission time frames and payload requirements—and dynamic, time-dependent constraints involving factors like position and fuel levels. A UAV is expected to meet its own resources (e.g., speed, fuel capacity, access permissions, payload) and the task-specific requirements (e.g., time, location, payload needs) within the designated timeframe.

Temporal Constraints

Temporal constraints are examined in two ways: single-task temporal constraints and inter-task temporal constraints. Single-task constraints focus solely on the timing requirements of individual task. Inter-task constraints consider the sequencing and timing between pairs of consecutive tasks.

For single-task assignments, a UAV must be able to take off from its base, arrive at the mission location on time, complete the mission, and return to its base. Inter-task temporal constraints arise when a UAV already airborne is assigned to a new task. In this scenario, the UAV must arrive at the new task location within the required timeframe, complete the task, and have sufficient fuel to land at the nearest base afterward.

Equation (1) states that the mission start time $T_{t,u}^{start}$ equals the sum of the takeoff time $T_{t,u}^{takeoff}$ and the ingress duration $D_{t,u}^{ingress}$. Similarly, Eq. (2) defines the mission end time $T_{t,u}^{end}$ as the sum of the mission start time $T_{t,u}^{start}$ and the mission duration $D_{t,u}^{task}$.

$$\forall t \in \tau \wedge \forall u \in U \; x_{t,u} \in \{0,1\}$$

$$x_{t,u} = \begin{cases} 1, & \textit{if Task t assigned to UAV u,} \\ 0, & \textit{otherwise.} \end{cases}$$

$$T_{t,u}^{start} = T_{t,u}^{takeoff} + D_{t,u}^{ingress} \tag{1}$$

$$T_{t,u}^{end} = T_{t,u}^{start} + D_{t,u}^{task} \tag{2}$$

When all static and dynamic constraints between task pairs are satisfied and there is no temporal conflict, the same UAV can be assigned to both tasks, as expressed in Eq. (4), meaning UAV u can be assigned to tasks x_t and x_y. If a conflicting situation arises, as described in Eq. (5), a different UAV must be assigned to the subsequent task. A conflict occurs if the temporal relations between the task pair do not satisfy either"T_1 is before T_2"or"T_1 meets T_2"as defined in Allen's interval algebra in Table 3.

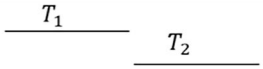
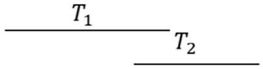
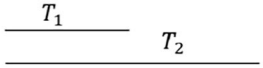
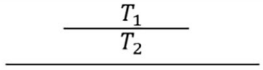
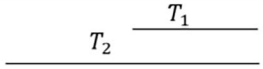
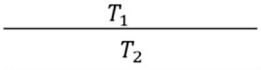
$$x_{t,y,u} \in \{0,2\} \; Z_{t,y,u} \in \{0,1\} \tag{3}$$

$$x_{t,u} + x_{y,u} = 2 \Rightarrow Z_{t,y,u} + Z_{y,t,u} = 1 \tag{4}$$

$$x_{t,u} + x_{y,u} \leq 1 \Rightarrow Z_{t,y,u} + Z_{y,t,u} = 0 \tag{5}$$

When planning a UAV's task from the base, the takeoff time $T_{t,u}^{takeoff}$ is calculated by subtracting the ingress

Table 3 Allen's ınterval algebra

Relation	Illustration	Interpretation
$T_1 < T_2$		T_1 takes place before T_2
$T_1 m\ T_2$		T_1 meets T_2
$T_1 o\ T_2$		T_1 overlaps T_2
$T_1 s\ T_2$		T_1 starts T_2
$T_1 d\ T_2$		T_1 during T_2
$T_1 f\ T_2$		T_1 finishes T_2
$T_1 = T_2$		T_1 is equal to T_2

duration $D_{t,u}^{ingress}$ from the task start time $T_{t,u}^{start}$ as indicated in Eq. (6).

$$x_{t,u} \in \{0,1\}$$

$$\forall t \in \tau \wedge \forall u \in U \rightarrow T_{t,u}^{takeoff} = T_{t,u}^{start} - D_{t,u}^{ingress} \tag{6}$$

The ingress duration $D_{t,u}^{ingress}$ for a UAV departing from a base to a task location is determined by dividing the distance $d_{i,u}$ by the UAV's maximum speed v_u^{max} as expressed in Eq. (7).

$$\forall t \in \tau \wedge \forall u \in U\ D_{t,u}^{ingress} = \frac{d_{i,u}}{v_u^{max}} \tag{7}$$

In scenarios where a UAV is already airborne due to a prior task, the start time of a subsequent task, denoted as $T_{y,u}^{start}$ must not be earlier than the sum of the end time of the preceding task $T_{t,u}^{end}$ and the ingress duration to the new task location $D_{y,u}^{ingress}$. This constraint ensures that a UAV is not assigned to overlapping tasks, thereby preventing temporal conflicts. The same methodology applies whether the UAV is transitioning between tasks while airborne or initiating a task from a ground base.

$$\forall t, y \in \tau \wedge \forall u \in \mathrm{U}\ T_{y,u}^{start} \geq T_{t,u}^{end} + D_{y,u}^{ingress} \tag{8}$$

If the constraint in Eq. (8) is satisfied, allowing the UAV to reach the subsequent task without landing, the loiter time, denoted as $D_{y,u}^{loiter}$. $D_{y,u}^{loiter} \geq 0$ must be non-negative and start time of next task $T_{y,u}^{start}$ must be bigger than sum of the current task's end time $T_{t,u}^{end}$ and duration of flight to next task's location $D_{y,u}^{ingress}$. This duration is calculated as presented in Eq. (9).

$$\forall t, y \in \tau \wedge \forall u \in \mathrm{U}\ D_{y,u}^{loiter} = T_{y,u}^{start} - \left(T_{t,u}^{end} + D_{y,u}^{ingress}\right) \tag{9}$$

For a UAV u departing from a base to execute a task y, the loiter time $D_{y,u}^{loiter}$ is zero, as expressed in Eq. (10).

$$\forall y \in \tau \wedge \forall u \in \mathrm{U}\ D_{y,u}^{loiter} = 0 \tag{10}$$

After completing a task, the egress duration $D_{y,u}^{egress}$ for UAV u to return to the nearest base $\mathcal{A}_{y,u}^{nearest} = a$ is calculated by dividing the distance $d_{y,a}$ by the UAV's maximum speed v_u^{max} as shown in Eq. (11):

$$\forall y \in \tau \wedge \forall u \in \mathrm{U}\ D_{y,u}^{egress} = \frac{d_{y,a}}{v_u^{max}} \tag{11}$$

Altitude Constraint: For a UAV to be assigned to a task, its operational altitude range $AltInt_u$ must encompass the task's required altitude interval $AltInt_t$ as expressed in Eq. (12):

$$\forall t \in \tau \wedge \forall u \in \mathrm{U}\ AltInt_{t,u} \rightarrow AltInt_t \sqsupseteq AltInt_u \tag{12}$$

Sensor Constraint: Eq. (13) ensures that a UAV possesses the necessary sensors to perform a mission. Specifically, the set of sensors available on UAV u denoted as S_u must include all sensors required by task t represented by S_t:

$$\forall t \in \tau \wedge \forall u \in \mathrm{U}\ S_t \sqsubseteq S_u \tag{13}$$

Permission Constraint: As indicated in Eq. (14), a UAV can be assigned to a task only if its "clearance level" $Perm_u$ matches the task's required authorization $Perm_t$:

$$\forall t \in \tau \wedge \forall u \in \mathrm{U}\ Perm_t = Perm_u \tag{14}$$

Fuel Constraint: For each task, the total fuel $\sum F_{t,u}$ required by the assigned UAV u, encompassing the fuel to fly the task location $F_{t,u}^{ingress}$, loiter fuel until the new task

start $F_{t,u}^{loiter}$, fuel for task execution $F_{t,u}^{task}$, and fuel to leave for next task or landing $F_{t,u}^{egress}$ must not exceed the UAV's fuel capacity. This condition is articulated in Eq. (15):

$$\forall t \in \tau \wedge \forall u \in \mathrm{U} \ \sum F_{t,u} = F_{t,u}^{ingress} + F_{t,u}^{loiter} + F_{t,u}^{task} + F_{t,u}^{egress} \tag{15}$$

Here, it's important to note that UAVs may commence tasks either from a base or while airborne from a previous task $F_{t,u}^{ingress}$. For UAVs launching from a base, the loiter time is zero.

Fuel consumption during ingress to the task area is calculated using Eq. (16). Here, the fuel $F_{t,u}^{ingress}$ required for UAV u to reach task is calculated multiplying the distance between the UAV and the task location $d_{t,u}$ and UAV's fuel consumption rate β_u.

$$\forall t \in \tau \wedge \forall u \in \mathrm{U} \ F_{t,u}^{ingress} = d_{t,u} \times \beta_u \tag{16}$$

The fuel consumption during the task execution, denoted as $F_{t,u}^{task}$ is calculated by multiplying the task duration $D_{t,u}^{task}$ by the average speed $v_{t,u}^{avr}$ and the UAV's fuel consumption rate β_u as shown in Eq. (17):

$$\forall t \in \tau \wedge \forall u \in \mathrm{U} \ F_{t,u}^{task} = D_{t,u}^{task} \times v_{t,u}^{avr} \times \beta_u \tag{17}$$

Similarly, the fuel required for the egress phase $F_{t,u}^{egress}$ is determined by multiplying the distance between the task location and the nearest base $d_{t,u}$ by the UAV's fuel consumption rate β_u as expressed in Eq. (18):

$$\forall t \in \tau \wedge \forall u \in \mathrm{U} \ F_{t,u}^{egress} = d_{t,u} \times \beta_u \tag{18}$$

For UAVs already airborne and assigned to a subsequent task, it is essential to verify that the remaining fuel is sufficient to complete the next task and return to base. This verification ensures that the total fuel required, including fuel to reach task destination $F_{t,u}^{ingress}$, fuel to loitering until task time $F_{t,u}^{loiter}$, fuel to fly on task $F_{t,u}^{task}$ and fuel to go for next task $F_{t,u}^{egress}$ does not exceed the UAV's maximum fuel capacity F_u^{max} as stipulated in Eq. (19):

$$\forall t \in \tau \wedge \forall u \in \mathrm{U} \ F_{t,u}^{ingress} + F_{t,u}^{loiter} + F_{t,u}^{task} + F_{t,u}^{egress} < F_u^{max} \tag{19}$$

3.2.3 Objective Function

The objective is to optimally assign the given tasks to the UAVs, considering constraints related to fuel, risk, and time. Constraints are categorized into static and dynamic types, like the Constraint Satisfaction Problem (CSP) framework. Static constraints include the operational altitude range of the task, required payloads, and airspace access permissions. Dynamic constraints encompass variables such as fuel consumption and time, which are influenced by the distance between the UAV and the task location. The goal is to evaluate the suitability of each UAV for a given task by assessing compliance with these constraints.

Risk assessment is particularly crucial for UAVs that are already airborne and may be assigned additional tasks. The remaining fuel of an airborne UAV, $F_{t,u}^{remained}$ is evaluated relative to its maximum fuel capacity, F_u^{max} Additionally, the number of subsequent tasks within the UAV's operational scope, denoted as"k,"is considered; a higher number of accessible tasks corresponds to a lower risk. Equation (20) formalizes this risk assessment. A higher computed value indicates a lower risk level. The parameter"Air"is set to zero for UAVs that are grounded, as they do not benefit from the advantages considered in this risk assessment. The parameters"p"and"r"are calibration factors that should be adjusted based on problem scale and risk perception, and they require validation through various test scenarios.

$$\forall t \in \tau \wedge \forall u \in \mathrm{U} \ max\left[\theta \sum_{t \in T} \sum_{u \in U} Air * p * \frac{F_{t,u}^{remained}}{F_u^{max}} + k * r\right] \tag{20}$$

To ensure that the same UAV is assigned to both tasks in a pair, the temporal relationships between these tasks must align with specific conditions. According to Allen's Interval Algebra, the permissible relations are"T_1 precedes T_2"or"T_1 meets T_2". If the tasks do not satisfy these temporal constraints, different UAVs must be assigned to each task. In the mathematical model, the tasks T_i and T_j are represented as x_t and x_y, respectively.

The objective function is defined as a quadratic (nonlinear) function (MIQP) aiming to minimize fuel consumption, time and risk, as shown in Eq. (21). This function considers the sum of fuel consumed during ingress $F_{y,u}^{ingress} + F_{y,u}^{loiter} + F_{y,u}^{task} + F_{y,u}^{egress}$. Each of these components is multiplied by the binary variable $x_{t,u}$ indicating whether UAV u is assigned to task T. Similarly, the total flight time, comprising ingress, loitering, task execution and egress durations $\left(D_{y,u}^{ingress} + D_{y,u}^{loiter} + D_{y,u}^{task} + D_{y,u}^{egress}\right)$ are multiplied by $x_{t,u}$. The resulting value is then adjusted by a risk reduction factor.

To mitigate risk, the model prioritizes assigning UAVs to multiple consecutive tasks without requiring intermediate landings. The risk assessment considers the ratio of the UAV's remaining fuel to its maximum fuel capacity $\frac{F_{t,u}^{remained}}{F_u^{max}}$, along with the number of subsequent tasks within its operational scope (available tasks), denoted as"r". The parameter"p"is calibration factor that can be adjusted based on the problem's scale and specific risk considerations. The"Air"coefficient equals"1"if the UAV is assigned to a new task while airborne; otherwise, it is"0". Therefore, risk is evaluated only when an airborne UAV is assigned a new

task, indicating that risk decreases under these circumstances. Additionally coefficient α minimizes the total fuel consumption used in flights, Ω reduces the completion time for all tasks, and θ identifies the UAV with the greatest endurance capability from those currently airborne in order to minimize the overall risk in mission assignments.

$$\forall t, y \in \tau \wedge \forall u \in \mathrm{U}$$

$$\min\left[\alpha \sum_{t,y\in T}\sum_{u\in U}\left(F_{y,u}^{ingress}+F_{y,u}^{loiter}+F_{y,u}^{task}+F_{y,u}^{egress}\right)x_{t,u}+\Omega\sum_{t,y\in T}\sum_{u\in U}(D_{y,u}^{ingress}+D_{y,u}^{loiter}+D_{y,u}^{task}+(D_{y,u}^{egress})x_{t,u}*\left(\frac{1}{\max\left[\theta\sum_{i\in T}\sum_{u\in U}Air*p*\frac{F_{t,u}^{remained}}{F_{u}^{max}}+k*r\right]}\right)\right] \quad (21)$$

UAVs that fail to meet the requirements of the next task are guided to land at the nearest base after the last task and are removed from the list. A notable aspect here is that, beyond the forward checking method in TCSP, the advantage of dynamic programming is utilized to address the assignment of airborne aircraft to subsequent tasks, a crucial aspect in real-world problems. Forward checking is not limited to verifying the feasibility of only the next task but ensures alignment of airborne UAV constraints with subsequent tasks for which they qualify.

3.3 Implementation of the Enhanced TCSP Model

In this section, the proposed ETCSP model has been tested on synthetic data generated within the scope of the designed scenarios. For this purpose, a dynamically-based approach specific to the program has been implemented. This approach has allowed for a thorough understanding of the problem's background and the appropriate adjustment of all parameters affecting problem performance. Although using modeling tools and solvers such as Gecode, Opturion-CPX and Choco can provide advantages in terms of ease and speed in modeling and solving general problems, adapting them to the dynamics of the problem poses some challenges. For these reasons, a solver for the TCSP model has been written in Python to improve the CSP model (integration of metaheuristic algorithms, dynamic domain capability, examining relationships between task pairs on a different plane, etc.). Coding the entire process instead of using a modeling tool enables a better understanding

Table 4 Synthetic data for the task description

Task ID	Actions	Duration/ Minutes	Time	Zone altitude Window/km	Restricted Zone	Order	Location
1	Pictures of an area	25	13:30	[3 – 5]	No	5	6
2	Reconnaissance of an area	65	13:50	[1 – 4]	No	7	4
3	Real-time monitoring of an area	10	15:00	[2 – 4.75]	Yes	8	8
4	Pictures of an area	20	17:00	[0.9 – 9.25]	No	4	9
5	Reconnaissance of an area	35	17:35	[0.4 – 5.75]	No	3	7
6	Real-time monitoring of an area	20	21:00	[3.85 – 5]	No	6	6
7	Pictures of an area	40	21:05	[3.85 – 5]	No	1	5
8	Pictures of an area	15	21:30	[1 – 6]	No	2	3
9	Pictures of an area	25	21:40	[1 – 5]	No	9	2
10	Reconnaissance of an area	5	23:55	[2 – 6.75]	Yes	10	5

Table 5 Synthetic data for the UAVs description

UAV ID	Speed Interval km/h	Altitude Interval km	Fuel consumption L/km	Type	WingType
1	[90 – 110]	[0.3 – 6.5]	0.159	2	1
2	[90 – 200]	[0.3 – 6]	0.159	2	1
3	[110 – 190]	[0.8 – 10]	0.2	3	1
4	[90 – 250]	[0.3 – 10]	0.272	3	1
5	[90 – 800]	[0.3 – 10]	0.00159	2	1
6	[0 – 110]	[0.3 – 2]	0.459	1	2
7	[0 – 110]	[0.3 – 2]	0.459	1	2



Fig. 5 Initial UAV-to-task assignment based on unary constraints

of the intricacies of TCSP and allows for improvements based on the problem's purpose. The tasks defined within the created scenario are as shown in Table 4.

Similarly, the existing UAVs and their characteristics are indicated in Table 5.

3.4 Simulation of the Model

The planning of UAV missions is fundamentally the execution of m UAVs performing n tasks. Each task occurs in a specific area within a defined timeframe and requires various sensors depending on the nature of the task. task categories and the necessary payload, Available Payloads, Task Location Coordinates, UAVs Equipments and UAVs dynamic data are presented in Supplementary Material 1.

Initially, to allocate aircraft to tasks, the operational domain for each variable is determined based on static and unary constraints (UAV's available altitude, region access permission, embedded payload). Figure 5 illustrates the operational domain for each variable according to unary constraints.

Subsequently, the evolution of operational domains for tasks over time is investigated based on dynamic constraints such as fuel, payload, location status, duration, etc., which vary over time for task accomplishment which is illustrated in Fig. 6. After examining dynamic constraints on a task-by-task basis, the final operational domains for all tasks are determined. In this scenario, the most suitable UAV is assigned to each task based on a predefined formula, taking into account constraints like fuel and time from UAVs within the specified operational domain. The problem is

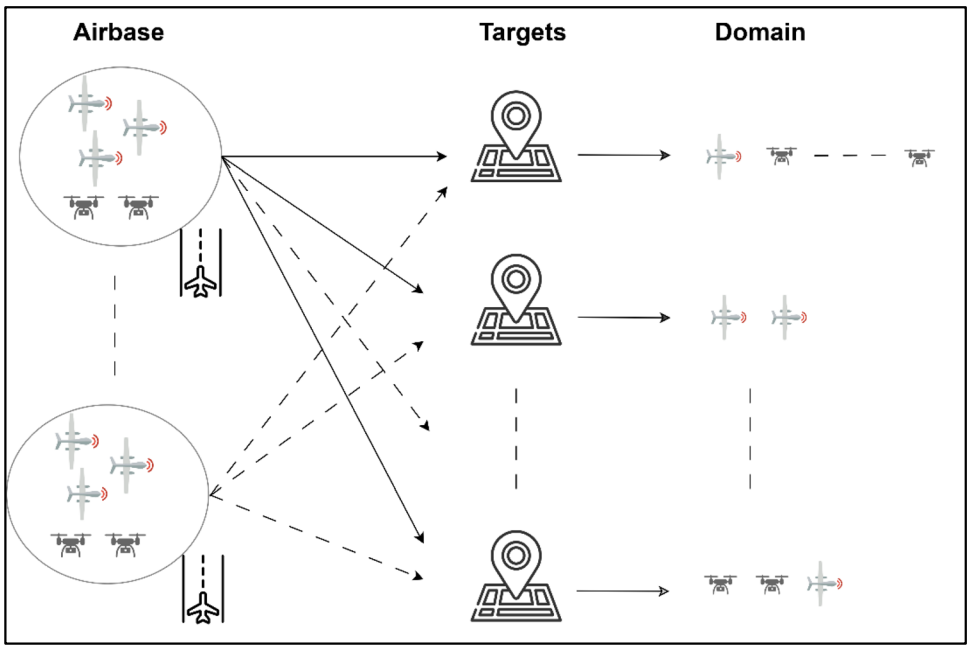


Fig. 6 Multi-UAVs Assignment to Multi-tasks

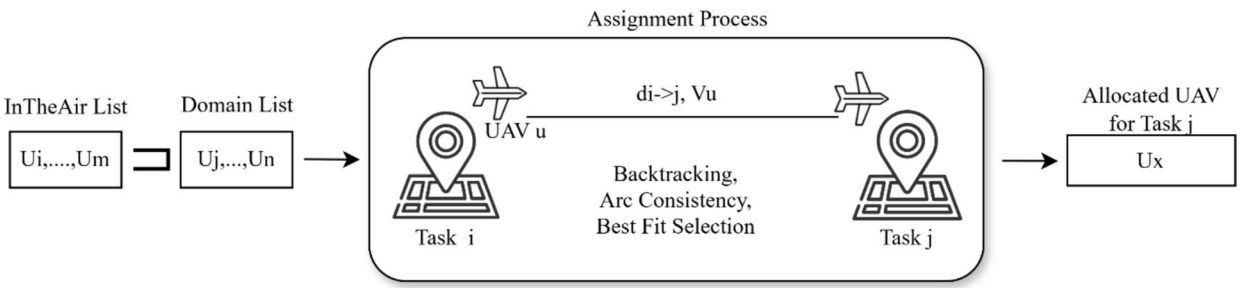


Fig. 7 Temporal Task Pairs Window

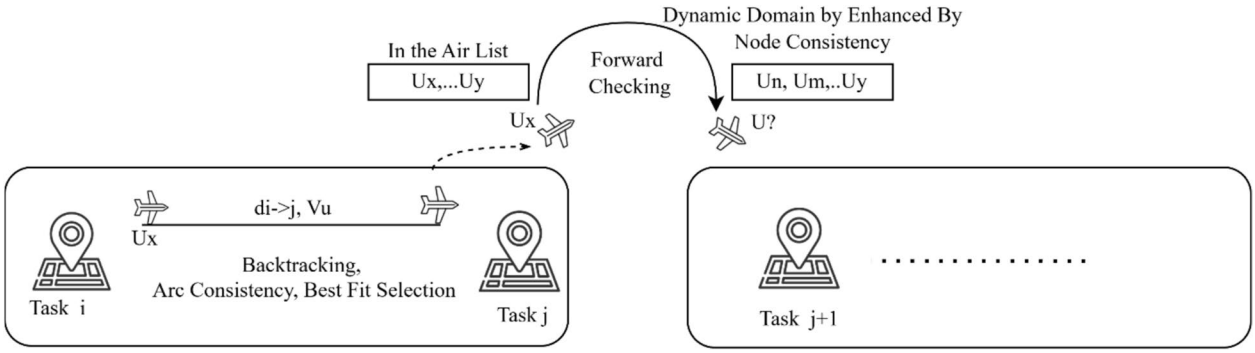


Fig. 8 Temporal Task Pairs Windows' Transition

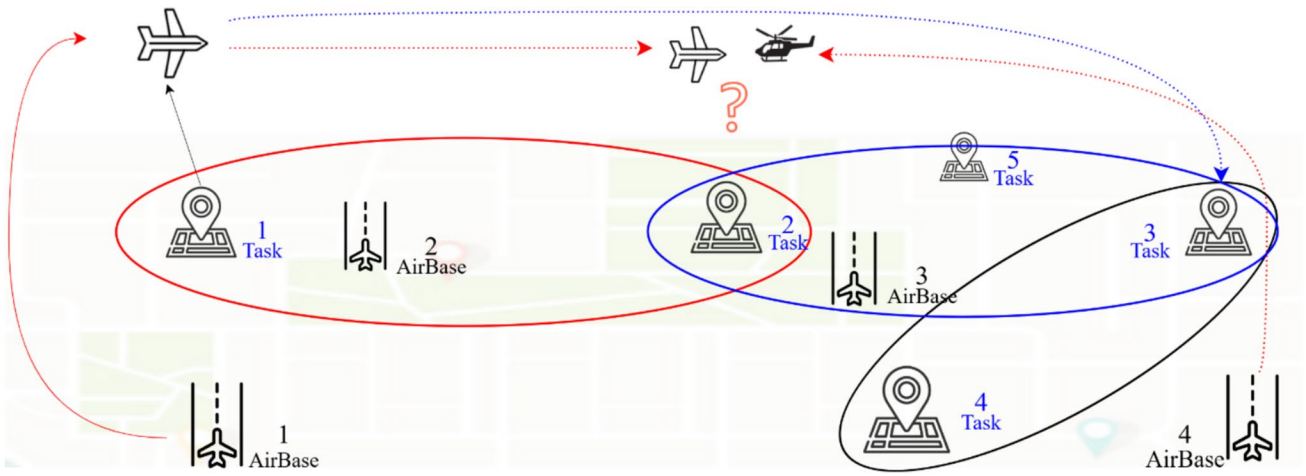


Fig. 9 Summary of temporal task pairs windows

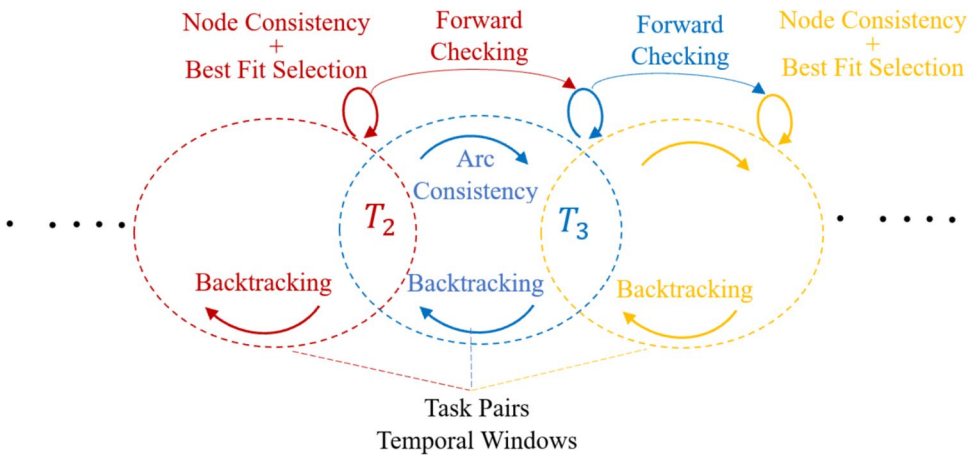


Fig. 10 Mission breakdown structure

Table 6 Modified task times

T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}
"13:30"	"14:10"	"15:50"	"16:00"	"16:35"	"18:00"	"20:05"	"21:00"	"21:40"	"22:25"

Table 7 UAV-1 capabilities

UAV Dynamics_ID	Rmnd Fuel	Initial Fuel	Fuel Tank	Loc	Restricted zone	Py1	Py2	Opt Py3	Opt Py4
UAV 1	'207.52 L'	'97.52 L'	'100 L'	'1'	'YES'	'1'	'2'	'3'	

Table 8 Modified task scenarios

T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}
Real-time monitoring	Reconnais-sance	Real-time monitoring	Reconnais-sance	Pictures of an area	Real-time monitoring	Pictures of an area	Pictures of an area	Real-time monitoring	Recon-nais-sance

Table 9 Modified fuel consumptions

U_1	U_2	U_3	U_4	U_5	U_6	U_7
'0.159 L/km'	'0.000159 L/km'	'0.2 L/km'	'0.272 L/km'	'0.9 L/km'	'0.455 L/km'	'0.455 L/km'

Table 10 UAV-2 capabilities

UAV Dynamics_ID	Rmnd Fuel	Initial Fuel	Fuel Tank	Loc	Restricted zone	Py1	Py2	Opt Py3	Opt Py4
UAV 2	'158.48 L'	'158.48 L'	'160 L'	'1'	'NO'	'1'	'2'	'3'	'7'

Table 11 UAV-7 modified fuel consumptions

UAV Dynamics_ID	Rmnd Fuel	Initial Fuel	Fuel Tank	Loc	Restricted zone	Py1	Py2	Opt Py3	Opt Py4
UAV 7	'580.15 L'	'580.15 L'	'60 L'	'1'	'NO'	'1'	'2'	'3'	'7'

Table 12 Modified fuel consumptions

U_1	U_2	U_3	U_4	U_5	U_6	U_7
'0.159 L/km'	'0.159 L/km'	'0.2 L/km'	'0.272 L/km'	'0.59 L/km'	'0.455 L/km'	'0.155 L/km'

now suitable for repeating similar processes, examining the temporal constraints of consecutive pairs of tasks after each assignment.

The pairs of tasks are sequentially examined in an iterative fashion until all tasks are successfully completed, considering time and associated dynamic constraints. The collapsing of tasks over time are checked according to Allen's Interval Algebra [17] in Table 3.

At the beginning of the pairwise checks, the effects of the previous task assignment and the update of the status of UAVs in the air are examined. For this purpose, dynamic domain updates are first performed within each task as Node consistency. Based on the current situation, the most suitable UAV is then sought for the updated operational domain between task pairs. In this process, if an appropriate UAV is found through Backtracking (BT), Arc Consistency (AC) and the search for the best score, it is assigned as illustrated in Fig. 7.

Table 13 Modified task & airport coordinates

LocationID	X	Y
1	'−2.247'	'39.877469'
2	'−0.242'	'38.87571'
3	'−1.167'	'39.962202'
4	'−3.235'	'38.869057'
5	'−1.259'	'39.880317'
6	'1.786'	'38.747955'
7	'−0.437'	'40.0828'
8	'−0.378'	'42.50884'
9	'−2.001'	'40.131169'
10	'−3.239'	'39.875361'
11	'−1.214'	'33.747955'

Table 14 Modified task scenarios

T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}
Real-time monitoring	Reconnaissance	Pictures of an area	Pictures of an area	Reconnaissance	Real-time monitoring	Pictures of an area	Pictures of an area	Pictures of an area	Reconnaissance

Table 15 Modified UAVs placed at different airbases

U_1	U_2	U_3	U_4	U_5	U_6	U_7
'7'	'1'	'9'	'9'	'10'	'7'	'1'

In subsequent assignments, the scoring of UAVs between task pairs is calculated according to the Eq. (21) in Sect. 3.2. In the next step, the Forward Checking (FC) method is applied between the next task pairs, thus establishing a chain that ensures the temporal continuity between task pairs as illustrated in Fig. 8. Initially, the first task is assigned the first UAV in the domain T_1.

The factors considered in UAV selection include prioritizing airborne UAV, minimizing total fuel and time spent on the task, and ensuring the potential to perform subsequent tasks. The process of assigning to different tasks is shown in Fig. 9 with a different color for each task. Determining the most effective UAV assignment is intricate even with only five tasks and three vehicles. Mirroring many time-series problems, the calculus becomes challenging because it must account for multiple interdependent possibilities—where each UAV took off, where it will land, and which subsequent tasks it should undertake.

Each color represents an iteration for each task pair. The methods used throughout the entire process are summarized in Fig. 10. The loop continues until the last pair is analyzed and an allocation is completed.

4 Test Results and Discussion

4.1 Performance Comparison of ETCSP vs. Generic TCSP

Within the scope of the research, the assignments generated by both the TCSP and ETCSP methods were analyzed and compared by sequentially implementing the modifications presented in the data. The initial test scenario corresponds to the default configuration presented in the tables above.

In the second test scenario, task start times have been modified as shown in Table 6. Additionally, the impact of setting the fuel tank of UAV-1 to'207.52 L'as shown in Table 7 to increase its sequential usage has been investigated in terms of selections and scores.

In the third iteration, only the task contents have been modified as presented in Table 8.

In the fourth iteration, the fuel consumptions of the UAVs have been modified as shown in Table 9. The fuel tank and payload of UAV-2 have been changed as presented in Table 10.

In the fifth iteration, the fuel tank and payload of UAV-7 have been modified as shown in Table 11, and the fuel consumption values for the preferred UAVs in previous tests have been altered as seen in Table 12, and their effects have been observed.

In the sixth iteration, the coordinates of tasks and airbases have been modified to assess their effects on the selections, as seen in Table 13 and the task contents have been modified as presented in Table 14.

In the seventh iteration, the deployment of UAVs to different bases has been carried out as seen in Table 15 to observe its effects.

When examining the outputs of the 3rd iteration in Table 16 and Table 17, it is observed that UAVs with significantly higher scores are selected with the Enhanced TCSP. The selection of UAVs has resulted in a reduction of up to one-third in both time and fuel savings per mission. Additionally, achieving all tasks with only two takeoffs and landings instead of 5 is a notable improvement.

While Tables 18 and 19 show UAVs with the highest scores being selected, there are UAVs with significantly

Table 16 3rd simulation results with enhanced TCSP

Task	UAV	IngPath	RtnPath	EndT	IngrDur(hrs)	Loiter	StartT	TaskDur	EgrsDur	TotalDur
2	5	'Avr'	'Max'	'14:55'	0.21	0	'13:50'	'65'	0.20	**65.41**
3	3	'Avr'	'Max'	'15:10'	21.92	0	'15:00'	'10'	16.21	48.12
4	5	'Avr'	'Max'	'17:20'	2.7	**2.04**	'17:00'	'20'	4.87	**29.60**
5	5	'Avr'	'Max'	'18:10'	2.7	**0.21**	'17:35'	'35'	3.86	**41.32**
6	5	'Avr'	'Max'	'21:20'	17.1	**2.55**	'21:00'	'20'	27.15	**66.74**

Table 17 3rd simulation results with the generic TCSP

Task	UAV	IngPath	RtnPath	EndT	IngrDur(hrs)	Loiter	StartT	TaskDur	EgrsDur	TotalDur
2	2	'Avr'	'Max'	'14:55'	0.63	0.00	'13:50'	'65'	0.63	66.26
3	3	'Avr'	'Max'	'15:10'	21.91	0.00	'15:00'	'10'	16.21	48.12
4	4	'Avr'	'Max'	'17:20'	12.76	0.00	'17:00'	'20'	12.76	45.52
5	2	'Avr'	'Max'	'18:10'	11.83	0.00	'17:35'	'35'	11.83	58.67
6	3	'Avr'	'Max'	'21:20'	80.55	0.00	'21:00'	'20'	80.55	181.10

Table 18 5th Simulation results with Enhanced TCSP

Task	UAV	IngPath	RtnPath	EndT	IngrDur(hrs)	Loiter	StartT	TaskDur	EgrsDur	TotalDur
2	**7**	**'Avr'**	**'Max'**	**'14:55'**	**1.66**	**0.00**	**'13:50'**	**'65'**	**1.66**	**68.32**
3	1	'Avr'	'Max'	'15:10'	32.86	0.00	'15:00'	'10'	24.32	67.18
4	3	'Avr'	'Max'	'17:20'	14.46	0.00	'17:00'	'20'	14.46	48.92
5	**7**	**'Avr'**	**'Max'**	**'18:10'**	**15.86**	**2.40**	**'17:35'**	**'35'**	**31.20**	**84.46**
6	**7**	**'Avr'**	**'Max'**	**'21:20'**	**123.95**	**0.77**	**'21:00'**	**'20'**	**219.69**	**364.40**
7	4	'Avr'	'Max'	'21:45'	0.51	0.00	'21:05'	'40'	0.51	41.01
8	5	'Avr'	'Max'	'21:45'	1.60	0.00	'21:30'	'15'	1.60	18.21
9	4	'Avr'	'Max'	'22:05'	0.19	0.00	'21:40'	'25'	0.19	25.37

Table 19 5th Simulation Results with Generic TCSP

Task	UAV	IngPath	RtnPath	EndT	IngrDur(hrs)	Loiter	StartT	TaskDur	EgrsDur	TotalDur
2	**2**	**'Avr'**	**'Max'**	**'14:55'**	**0.63**	**0.00**	**'13:50'**	**'65'**	**0.63**	**66.26**
3	1	'Avr'	'Max'	'15:10'	32.86	0.00	'15:00'	'10'	24.32	67.18
4	3	'Avr'	'Max'	'17:20'	14.46	0.00	'17:00'	'20'	14.46	48.92
5	**2**	**'Avr'**	**'Max'**	**'18:10'**	**11.83**	**0.00**	**'17:35'**	**'35'**	**11.83**	**58.67**
6	**1**	**'Avr'**	**'Max'**	**'21:20'**	**149.15**	**0.00**	**'21:00'**	**'20'**	**120.83**	**289.97**
7	1	'Avr'	'Max'	'21:45'	22.23	0.00	'21:05'	'40'	0.86	63.09
8	3	'Avr'	'Max'	'21:45'	9.70	0.00	'21:30'	'15'	4.76	29.46
9	4	'Avr'	'Max'	'22:05'	0.19	0.00	'21:40'	'25'	0.19	25.37

Table 20 Syntetic Data Produced as Assigned UAVs to the Tasks in Simulation Tests

Task Test	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}
1	**1**	**3**	**1**	**5**	**5**	**5**	**3**	**4**	**5**	**3**
	1	2	1	3	1	1	1	3	4	3
2	**1**	**1**	**1**	**5**	**5**	**5**	**3**	**3**	**4**	**3**
	1	1	1	3	1	5	1	3	1	3
3	**3**	**5**	**3**	**5**	**5**	**5**	**2**	**3**	**4**	**4**
	3	2	3	3	2	3	2	4	5	3
4	**1**	**2**	**1**	**3**	**2**	**2**	**4**	**3**	**4**	**3**
	1	2	1	3	1	1	1	2	3	3
5	**1**	**7**	**1**	**3**	**7**	**7**	**4**	**5**	**4**	**3**
	1	2	1	3	1	1	1	3	4	3
6	**5**	**3**	**3**	**5**	**1**	**5**	**3**	**1**	**5**	**3**
	5	1	3	3	1	5	1	3	5	3
7	**1**	**5**	**1**	**5**	**5**	**5**	**3**	**4**	**4**	**3**
	1	2	1	3	1	1	1	3	4	3

Table 21 Syntetic data produced as total scores for each tasks in simulation tests

Iterations		U_1	U_2	U_3	U_4	U_5	U_6	U_7
TCSP	Time (min.)	648.9	459.7	500.1	656.5	**648.9**	1290.6	646.9
	Fuel (lt)	218.1	141.2	235.9	155.7	**218.1**	421.7	220.5
ENHANCED TCSP	Time (min.)	**377.7**	**367.03**	**356.3**	**509.4**	717.8	**1084.9**	**378.6**
	Fuel (lt)	**93.9**	**101.8**	**86.3**	**108.3**	293.01	**366.9**	**92.3**

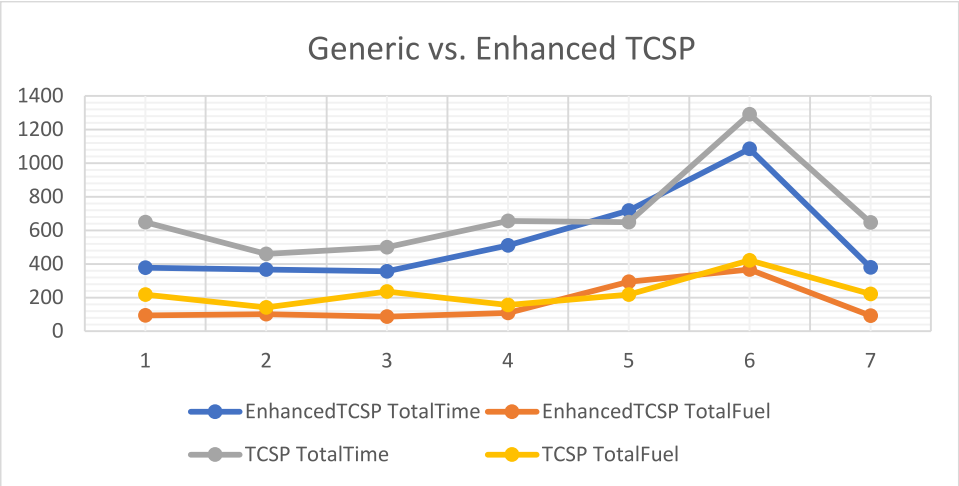


Fig. 11 Generic TCSP vs. Enhanced TCSP Total Time and Total Fuel Scores

different fuel consumption in a heterogeneous fleet (such as helicopters and MALE, HALE-class fixed-wing UAVs, etc.). The coefficients k, p, and r in formula (20–21) for fuel calculation are optimized based on general cases, and they might not effectively suppress the impact of other variables. In the 5th iteration, when tasks five (5) and six (6) are examined, UAV-7 with the highest local score is selected despite poor performance in terms of time and fuel. This is because it is assigned to a new task while in the air, and it has a large fuel capacity. However, it is evident that this is not the correct decision within the task package. As seen, although the Enhanced TCSP demonstrates great success in finding the local best and preventing local optima, it cannot be expected to perform optimally throughout the entire process with the formulated approach.

After all test iterations, Table 20 displays the selected UAVs for each test iteration, with the first row representing the ETCSP and the second row representing the generic TCSP. The total scores for the selected UAVs for each task, calculated according to the formula (21) in Sect. 3.2, are presented in Table 21. The similarity in terms of time and fuel costs between the Enhanced TCSP approach and the generic TCSP is illustrated in Fig. 11. Due to consistent results obtained in numerous tests, noteworthy test results have been compiled and presented.

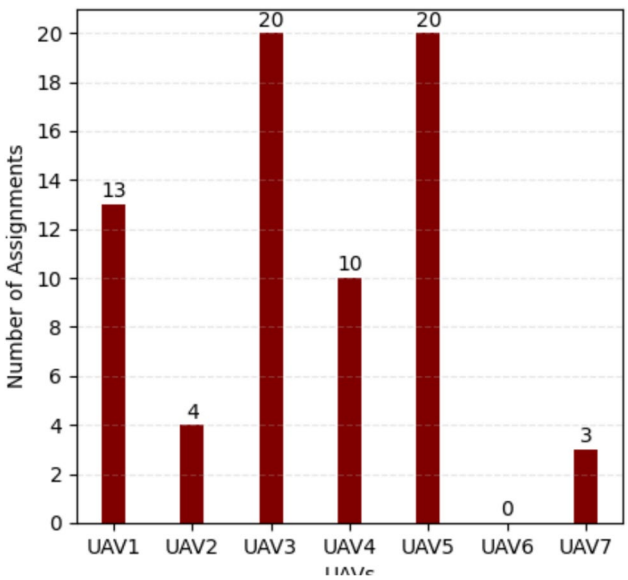


Fig. 12 Total Usage Frequency of UAVs (TCSP Approach)

Total Usage Frequency of UAVs are shown in Fig. 12 and Fig. 13 respectively.

In Fig. 14 and Fig. 15, the heatmaps show which UAVs were assigned to which tasks across all 7 test iterations.

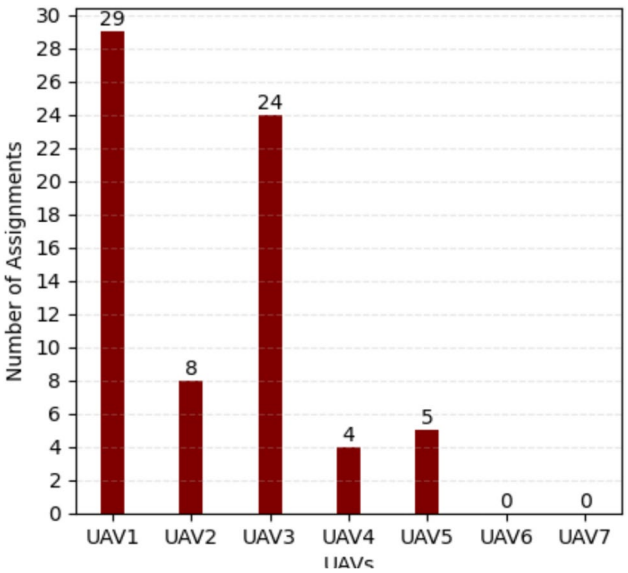


Fig. 13 Total Usage Frequency of UAVs (ETCSP Approach)

When the total test results are examined, it is observed that 70 tasks are completed with 61 UAVs using the TCSP method, while with the Enhanced TCSP, 48 UAVs are used. Similarly, the task package, which is completed with approximately 3800 min and 1142 L of fuel using the Enhanced TCSP, is accomplished in approximately 4855 min and 1615 L of fuel with the TCSP method.

4.2 Error Analysis

This section is examined in Supplementary Material 2.

5 Discussion

The test findings demonstrate that the proposed Enhanced TCSP approach provides distinct advantages over the conventional generic TCSP method. By optimizing resource utilization, the Enhanced algorithm completes the mission package with fewer UAVs, in less time, and with lower fuel consumption, which translates to a significant increase in efficiency for multi-UAV mission planning. In particular, the ~ 21% reduction in the number of UAVs required and the ~ 20–30% decreases in total mission duration and fuel consumption suggest that operational costs and time can be substantially improved in practical applications. Improvements of this magnitude underscore that the Enhanced TCSP model effectively integrates dynamic constraints and multi-objective optimization, elevating planning efficiency to a statistically and practically significant level by international standards.

The performance comparison at the individual UAV level provides a more detailed insight into the nature of these gains. Most UAVs showed significant improvements in mission duration and fuel usage under the Enhanced TCSP. For instance, UAV-3's fuel consumption was reduced by up to 63% with the Enhanced TCSP compared to the generic TCSP (dropping from 235.9 L to 86.3 L), while its mission completion time decreased by about 29% (from 500.1 min to 356.3 min). Similarly, UAV-1 and UAV-7 each experienced nearly identical improvements, completing missions roughly 41% faster and using 57–58% less fuel. These consistent gains demonstrate that the Enhanced TCSP algorithm can deliver comparable

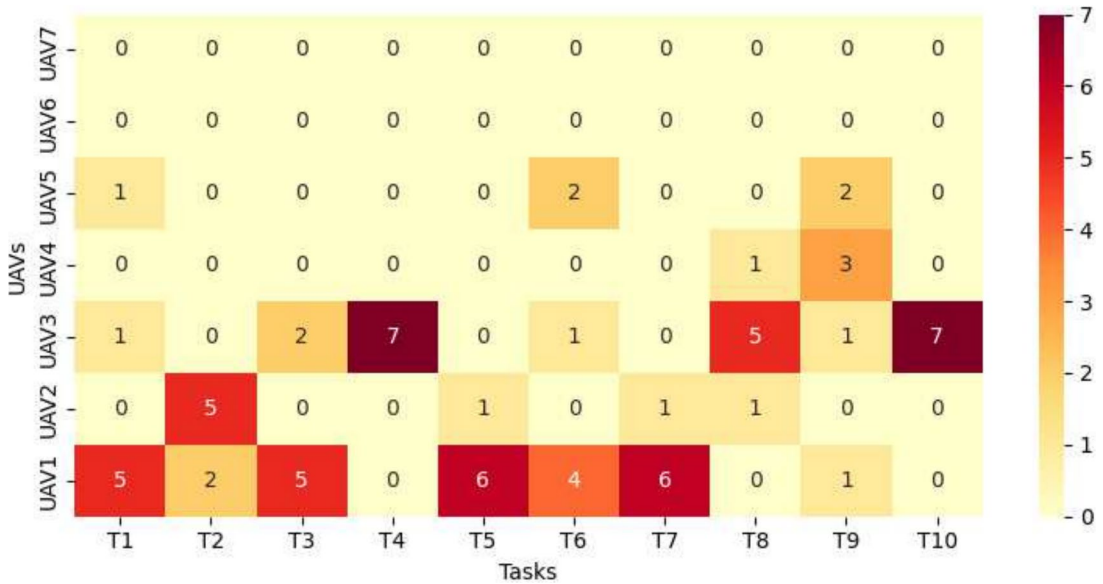


Fig. 14 Task Assignment Frequency of UAVs (TCSP Approach)

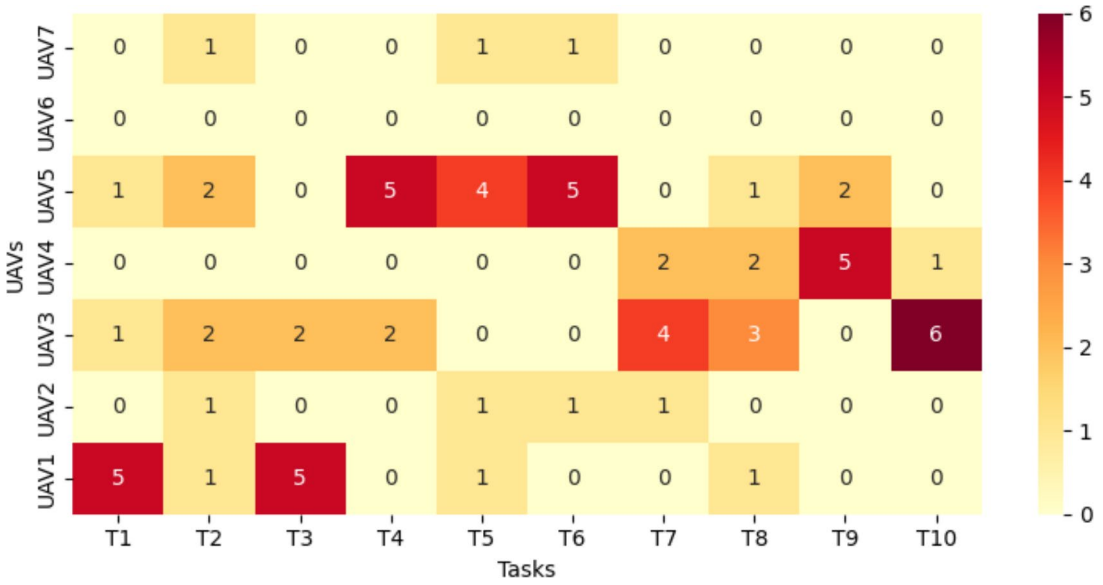


Fig. 15 Task Assignment Frequency of UAVs (ETCSP Approach)

performance benefits across different UAVs, effectively optimizing based on each platform's capabilities and operational profile. The improvements are also highly statistically significant (with $p < 0.005$ for each case), confirming that the observed differences are not due to chance.

However, the performance gains were not uniform for every UAV. For example, UAV-5 unexpectedly exhibited a slightly longer mission time (~10% increase) and higher fuel consumption (~34% increase) under the Enhanced TCSP scenario (for UAV-5, Enhanced: 717.8 min and 293.0 L vs. Generic: 648.9 min and 218.1 L). While the increase in time was not statistically significant ($p \approx 0.058$), the additional fuel usage was notable ($p \approx 0.011$). This outlier suggests that the improved algorithm, in the course of optimizing overall performance, can assign a heavier workload to certain UAVs and consequently reduce that vehicle's individual efficiency. In other words, the Enhanced TCSP may accept burdening some platforms more in order to minimize total mission cost, which in specific cases can lead to poorer performance for an individual UAV compared to the generic method. Nevertheless, such exceptions are rare in the overall trend and have a limited scope of impact relative to the broader system-wide gains.

For real-world applications, it is crucial that the performance advantages persist under uncertainty. In this regard, Monte Carlo simulations (e.g., 1000 iterations with random ± 10–15% fluctuations in fuel consumption rates and task durations) demonstrated that the superiority of the Enhanced TCSP is maintained even in uncertain conditions. The obtained averages show that even with added variability, the Enhanced TCSP still completes missions faster and with less fuel than the generic method. For example, over 1000 trials the Enhanced TCSP achieved an average total completion time of ~3801 min (±285 min standard deviation) compared to ~4854 min (±364 min) for the Generic TCSP; similarly, average fuel consumption was ~1142 L (±57 L) for Enhanced vs ~1615 L (±81 L) for Generic. The performance distributions of the two algorithms remained distinctly apart at the 95% confidence level: the 95% confidence interval for total time with Enhanced TCSP (~3790–3812 min) did not overlap with that of Generic TCSP (~4840–4868 min), and a similar separation was observed in fuel usage. These results indicate that the Enhanced TCSP approach exhibits a consistent superiority even under uncertainty, i.e. its performance is robust against variability in real-world conditions. Such robust performance in mission planning suggests that the Enhanced algorithm is likely to continue delivering reliably better results than the generic approach even in the face of unexpected changes or noise in operational parameters.

A thorough analysis of the results also included a sensitivity study to determine how responsive the model is to changes in various parameters. Firstly, the algorithms' responses to changes in fuel consumption parameters were examined: the Enhanced TCSP was found to be considerably more responsive to fluctuations in fuel usage than the Generic TCSP. In one scenario, for instance, reducing the fuel burn rate of a particular UAV (UAV-7) led to about a ~46% improvement in overall performance with the Enhanced TCSP, whereas the improvement was only ~4% under the Generic method (similarly, for another UAV, a fuel parameter improvement yielded ~35% gain in Enhanced vs ~13% in Generic). This disparity indicates that the Enhanced TCSP's algorithm places greater emphasis on fuel efficiency, quickly translating changes in fuel-related

parameters into performance gains. Indeed, a regression-based sensitivity index analysis quantitatively confirms that the fuel consumption rate is a highly influential factor on mission outcomes (standardized coefficient ~ 0.81; sensitivity index 1.73; $p < 0.001$).

As part of the sensitivity analysis, the effects of other system parameters on performance were also examined. The resulting sensitivity indices indicate that the factors with the greatest impact on mission planning performance are task location and UAV base location (each with standardized coefficients above 0.8, corresponding to sensitivity indices in the ~ 1.7–1.9 range, $p < 0.001$). This finding reveals that spatial factors (i.e., where missions take place and where UAVs are based) play a critical role in determining total mission duration and efficiency. Variables such as fuel tank capacity and the aforementioned fuel consumption rate were also found to have very high influence (sensitivity indices on the order of ~ 1.4–1.5, $p < 0.001$), underscoring that fuel-related constraints significantly shape the planning outcomes. Other parameters like task duration and task type showed relatively lower yet still significant effects (e.g., sensitivity index ~ 1.19 for task duration and ~ 0.89 for task type, $p < 0.001$). Collectively, these analyses highlight that the success of the Enhanced TCSP approach depends on certain critical factors and that careful calibration of these parameters is necessary to maximize the model's performance.

Moreover, the examination of specific test cases provided important insight into the algorithm's decision-making strategy regarding the local vs. global optimum balance. In one scenario (from Test 5), the Enhanced TCSP algorithm assigned UAV-7 to a task because it had a high local score in the algorithm's evaluation; however, this choice led to a deviation from the global optimum in terms of overall time and fuel. In fact, the solution with UAV-7 turned out to be 28.8% slower in total mission time and consumed more fuel compared to the theoretically best possible assignment (global optimum). In contrast, the assignment made by the Generic TCSP for the same tasks (a UAV-2/UAV-1 combination) yielded a result closer to the global optimum (about 12.3% slower than the best possible), and an alternative assignment using UAV-3 achieved the actual optimal outcome (minimal time and fuel). This analysis shows that while the Enhanced TCSP excels at maximizing a composite score, it can occasionally sacrifice the absolute optimal solution. In other words, the algorithm's focus on a high local score can cause it to miss the globally best outcome. This finding indicates the need to balance local and global objectives within the Enhanced approach's decision mechanism; aligning the algorithm's evaluation criteria more closely with global mission efficiency will be important to avoid such deviations in the future.

In a multi-UAV mission planning context, the assumptions adopted here are intended to simplify scenario comprehension and monitoring, while simultaneously outlining a progression toward full autonomy under a **human-on-the-loop** paradigm. This perspective implies a future scenario in which human intervention in the operation of autonomous systems is minimized to avoid introducing delays or inefficiencies. Consequently, human operators are expected to be limited to a **supervisory control** role; they would intervene only to abort operations in emergencies or to make minor adjustments in response to unforeseen circumstances. Within such a framework, providing only high-level mission objectives is deemed sufficient, as the autonomous system can independently handle all lower-level decision-making and execution details."Recent studies have highlighted advancements in autonomous UAV mission planning frameworks emphasizing minimal human intervention, such as dynamic reassignments [59], real-time conflict resolution within UAV swarms [60] and optimized task allocations in heterogeneous UAV formations [58].

The study acknowledges several limitations, which are critical to contextualize the findings without undermining the methodological rigor:

5.1 Simulation Dependency

The model was validated on simulation data that does not fully encapsulate real-world dynamics (e.g., abrupt weather shifts, communication disruptions).

5.2 Scalability Constraints

While effective for high-dimensional problems (e.g., 7^{10}), computational latency escalates in scenarios exceeding 100 tasks, hindering practical deployment.

5.3 Static Constraint Assumptions

The framework lacks full support for dynamic constraints, such as real-time task cancellations or emergent mission additions during operation.

5.4 Idealized Environmental Conditions

Real-world factors, including terrain roughness, swarm communication delays, and weather variability, remain unintegrated.

Table 22 shows the performance comparison between the methods.

6 Conclusion and Future Directions

In this study, complex UAV mission planning was modeled within the Constraint Satisfaction Problem (CSP) framework and addressed through the Enhanced Temporal Constraint

Table 22 State of the Art Method's Performance Comparison

Method	Task Requirement	Optimization Objectives (Priority)	Performance (Fuel, Time, Success, Risk)
Hybrid MOGA-CSP (Ramirez et al., 2015) [17]	All tasks are mandatory (no optional tasks)	Multi-objective optimization using a Pareto approach – simultaneously optimizes multiple criteria such as fuel consumption, mission time (makespan), distance, etc., without a fixed priority weighting. Mission success is assumed (all tasks must be done by design); risk is not included as an objective	Generate balanced mission plans that complete all tasks with low fuel usage and short completion times, offering trade-offs on a Pareto frontier. Achieves better cost-effectiveness (fuel/time) than non-multi-objective methods, but it does not incorporate risk or adapt to UAV failures (no resilience)
Resilient Mission Planning (Wang et al., 2025) [59]	All tasks are treated as mandatory (tasks are reassigned if a UAV cannot complete them)	Multi-objective optimization with a focus on mission reliability and safety – prioritizes completing all tasks successfully under potential failures and minimizing risk, while secondarily optimizing fuel and mission time. In practice, mission success (task completion rate) and risk reduction are top priorities, with fuel and time considered after mission safety requirements	Delivers high mission success rates even in uncertain or failure-prone scenarios by reassigning tasks dynamically (strong resilience). It actively minimizes operational risk, ensuring tasks are completed safely, though this can incur somewhat higher fuel usage or longer routes to guarantee robustness. Overall fuel/time efficiency is sacrificed if needed to preserve mission completion and UAV safety
ETCSP (Enhanced TCSP)	All tasks are mandatory (no optional tasks)	Multi-objective optimization emphasizing efficiency – jointly minimizes mission duration, fuel consumption and risk for the entire task set. Objectives are treated together (time, fuel costs and risks are both optimized) to plan continuous multi-task sorties (reducing unnecessary take-offs/landings). Mission success is a given (all tasks assigned); risk is only addressed indirectly by reducing takeoff/landing cycles (which lowers failure risk)	Achieves all tasks with significantly lower total fuel usage and shorter completion time clearly compared to earlier methods. By enabling UAVs to perform multiple tasks per flight, it cuts down idle time and refueling cycles, enhancing efficiency. This method yields the best fuel and time performance of the two, though it does not actively handle real-time failures (less resilient than Wang et al.'s approach) and only implicitly reduces risk by minimizing total sorties

Satisfaction Problem (ETCSP) methodology. Results from comprehensive error, sensitivity, and uncertainty analyses confirmed that ETCSP significantly outperforms the classical Generic TCSP approach. Specifically, ETCSP reduced mission duration by approximately 22%, fuel consumption by 29%, and UAV usage by around 21%. Monte Carlo simulations reinforced the algorithm's robustness under uncertainty.

A key innovation contributing to ETCSP's superior performance is its unique airborne reassignment capability, enabling dynamic mid-mission adjustments without requiring UAVs to return to base. This feature effectively reduces risks, saves fuel, and minimizes unnecessary takeoff/landing cycles, significantly enhancing mission flexibility and efficiency while incurring no major additional computational complexity. For example, key constraint-checking functions operate in constant or linear time (O(1) or O(T), ensuring that ETCSP's overall worst-case time complexity remains approximately O(D^T), with best-case performance around O($T.A$) where D is task domain, T is Tasks and A is an UAV in task. However, sensitivity analyses revealed the algorithm's vulnerability to local optimum traps and high responsiveness to parameter variations, particularly in fuel consumption rates, task locations, and UAV base positioning. Therefore, careful parameter calibration remains essential for maximizing ETCSP's effectiveness.

As future work, the integration of reinforcement learning (RL) or adaptive artificial intelligence (AI) approaches could further enhance the ETCSP framework by enabling autonomous adaptation to dynamic mission conditions and real-time optimization of UAV assignments.

For real-world deployment, ETCSP can be embedded into existing UAV mission control systems by leveraging modular software architectures such as microservice architecture. To address scalability, parallel computing techniques or distributed decision-making schemes could be employed, while integration challenges might be mitigated by standardized communication protocols and thorough field validations.

Future research directions include:

6.1 Adaptive Parameter Optimization

Developing adaptive, automated tuning mechanisms for critical parameters to improve robustness and performance.

6.2 Hybrid Algorithm Approaches

Combining ETCSP with metaheuristic methods (e.g., NSGA-II, Deep-Q Learning) or alternative CSP strategies to mitigate local optimum traps and explore global solutions effectively.

6.3 Stochastic Mission Models

Transitioning from deterministic to stochastic modeling to more accurately represent real-world uncertainties and dynamic operational environments.

6.4 Scalability and Computational Efficiency

Evaluating and enhancing ETCSP's scalability for large-scale UAV fleets through hybridization with parallel computing and quantum-inspired optimization algorithms.

6.5 Expanded Constraint Integration

Integrating additional mission constraints, such as swarm coordination, air-to-air refueling (AAR), and mission priority classifications, to broaden operational flexibility.

6.6 Real-World Validation and Post-Mission Optimization

Conducting real-world UAV field tests and developing frameworks for post-mission strategies and real-time re-planning.

These advancements are expected to significantly enhance the theoretical flexibility and practical applicability of UAV mission planning, driving the development of resilient, efficient autonomous systems capable of operating effectively in complex, dynamic environments.

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Declarations

Conflict of interest Emre AYVAZ reports that administrative support was provided by Konya Technical University. He declares that he has no conflict of interest.

Ethical Approval This article does not contain any studies with human participants or animals performed by any of the authors.

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