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A GMM-Based Spatio-Temporal Distribution Knowledge Transfer MOEA/D for Dynamic Multi-UAV Cooperative Path Planning

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Abstract

Multi-UAV cooperative path planning in time-varying environments requires balancing flight efficiency, threat avoidance, and coordination consistency while responding rapidly to environmental changes. To address slow population recovery, insufficient inter-task cooperation, and unreliable reuse of historical search information, this paper proposes a Gaussian mixture model (GMM)-based spatio-temporal knowledge transfer multi-objective evolutionary algorithm within the MOEA/D framework, termed STKTM-MOEA/D. The proposed method represents mission requirements and flight constraints using objective functions and feasibility constraints. Elite decision vectors selected through non-dominated sorting and crowding-distance ranking are used to construct GMMs that probabilistically describe promising search regions. Each GMM captures the locations, dispersions, and relative importance of multiple high-quality regions, providing a unified distribution-level knowledge representation for spatial and temporal transfer. Spatial knowledge transfer jointly considers task similarity and distribution complementarity between the main and auxiliary tasks to improve collaborative search. Temporal knowledge transfer retrieves reliable historical GMMs from a knowledge pool according to environmental similarity. After an environmental change, an adaptive reconstruction strategy combines current elites, temporally transferred individuals, spatially transferred individuals, and randomly generated exploratory individuals. The reconstructed population then continues MOEA/D evolution, environmental selection, GMM updating, and knowledge-pool updating under the new environment, improving convergence, diversity, and adaptability. Experiments on 14 DF and 5 FDA problems show that STKTM-MOEA/D achieves the best mean MIGD on 10 problems. In multi-UAV path planning, it attains a 100% success rate and outperforms KTM-DMOEA in HV, PD, and runtime, demonstrating strong effectiveness and efficiency in dynamic environments.

Keywords: dynamic multi-objective optimization; evolutionary multi-task optimization; multi-UAV path planning; Gaussian mixture model; spatio-temporal knowledge transfer

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1. Introduction

In recent years, unmanned aerial vehicles (UAVs) have been widely employed in various applications, including target reconnaissance, regional surveillance, disaster response, and cooperative strike missions, owing to their high maneuverability, rapid

deployment capability, and strong environmental adaptability [1–3]. As mission complexity and operational scale continue to increase, multi-UAV systems demonstrate superior mission efficiency and coverage capability compared with single-UAV systems, particularly in large-scale and complex environments. Consequently, generating safe, efficient, and coordination-compliant flight paths for multiple UAVs has become an important research topic in intelligent unmanned systems [4].

The objective of path planning is to generate a safe trajectory from the starting point to the destination while satisfying various operational constraints [5]. In this study, path planning and trajectory generation are regarded as two closely related but distinct layers of autonomous UAV operation. Path planning aims to determine a collision-free waypoint sequence or geometric route from an initial state to a destination, whereas trajectory generation further specifies a time-parameterized motion profile, including velocity, acceleration, heading angle, climb angle, and control inputs. The proposed method focuses on the online planning layer. Specifically, it generates dynamically feasible waypoint-based cooperative paths and arrival-time-consistent schedules, while a lower-level flight controller is assumed to track the generated references. To improve planning reliability, the proposed model explicitly incorporates flight distance, threat exposure, arrival-time consistency, maneuverability limits, terrain clearance, and inter-UAV separation constraints. Therefore, although the proposed method does not directly generate actuator-level trajectories, the disadvantages of waypoint-based path planning are alleviated by embedding maneuverability bounds, safety margins, terrain clearance, and inter-UAV separation constraints into the optimization model. This ensures that the generated paths are not only geometrically feasible but also suitable for subsequent trajectory tracking and online replanning.

For multi-UAV cooperative missions, the planning layer must simultaneously account for flight efficiency, threat avoidance, collision prevention, and coordination requirements among UAVs. These objectives and constraints are often conflicting; therefore, multi-UAV cooperative path planning is commonly formulated as a multi-objective optimization problem [6]. As the number of UAVs increases, the decision dimension, constraint coupling, and search space expand significantly, making the planning problem substantially more challenging. In practical missions, threat locations, threat radii, threat states, and coordination requirements may vary over time, which can invalidate previously feasible or Pareto-optimal paths. Therefore, the dynamic multi-UAV cooperative path-planning problem considered in this study specifically refers to online adaptive replanning in time-varying operational environments, where environmental and mission-related changes may require the population to rapidly recover and update the planned cooperative paths.

Existing multi-UAV path planning approaches mainly include graph-search methods [7], sampling-based methods [8], artificial potential field methods [9], and evolutionary optimization algorithms [10–13]. Although these methods achieve satisfactory performance in low-dimensional or static environments, most of them employ single-objective formulations or weighted aggregation strategies, which require predefined objective weights. In complex dynamic scenarios, however, environmental conditions and mission requirements continuously change, making fixed weights incapable of accurately capturing the real-time trade-offs among flight distance, threat exposure, and coordination constraints. In contrast, multi-objective optimization methods can simultaneously obtain a set of Pareto-optimal solutions, providing a more effective representation of conflicting objectives and offering multiple candidate trajectories for decision-makers. Despite their practical significance, most existing studies still assume static environments. In real-world missions, obstacle distributions, radar threat regions, and mission constraints may vary over time, causing previously optimal trajectories and

Pareto-optimal solution sets to become obsolete. Consequently, multi-UAV cooperative path planning is more appropriately formulated as a dynamic multi-objective optimization problem (DMOP).

To address DMOPs, various environmental response strategies have been developed, including random reinitialization [14], memory-based approaches [15], prediction-based models [16], and multi-population cooperative mechanisms. Although these methods can alleviate performance degradation caused by environmental changes, most of them are still built upon single-task optimization frameworks and primarily rely on information from the current population for recovery. When environmental changes occur frequently or exhibit large magnitudes, relying solely on current population information often fails to locate newly emerging high-quality regions in a timely manner, resulting in delayed responses, reduced population diversity, and premature convergence.

Recently, evolutionary multitasking optimization (EMT) has attracted considerable attention due to its ability to improve search efficiency through information sharing across tasks. By constructing auxiliary tasks and transferring useful knowledge, EMT can accelerate the convergence of the main task while enhancing global exploration capability [17]. Nevertheless, existing EMT methods still suffer from two major limitations. First, most approaches rely on individual-level knowledge representations, which are sensitive to random perturbations and incapable of consistently characterizing the overall population distribution. Second, the utilization of historical environmental knowledge remains insufficient, and effective mechanisms for temporal knowledge reuse are still lacking, thereby restricting adaptability in complex dynamic environments.

In this work, knowledge is considered at two complementary levels. First, domain knowledge provided by mission planners and UAV operational rules is encoded into the objective functions and constraints, including flight distance, threat exposure, cooperative arrival-time consistency, maneuverability limits, terrain clearance, and inter-UAV safety separation. These formulations specify the conditions under which a cooperative path can be regarded as feasible and high-quality. Second, evolutionary knowledge is extracted from historically successful populations during the optimization process. Instead of directly storing a limited number of elite solutions, the proposed method employs GMMs to represent promising decision regions and transfers their distributional characteristics across related tasks and environmental states.

The proposed temporal transfer mechanism is conceptually related to experience replay in reinforcement learning, as both mechanisms reuse historical information to improve adaptation to changing environments. However, they differ fundamentally in their objectives, stored information, and update mechanisms. Experience replay stores and resamples state-action-reward transitions to update a policy or value function. In contrast, STKTM-MOEA/D stores GMM-based distributions fitted from elite decision vectors, together with environmental features, knowledge-quality indicators, and reliability indicators. These distribution models are retrieved according to environmental similarity and are used to reconstruct populations after environmental changes. Therefore, the proposed mechanism does not involve a policy network, a value function, Bellman updates, or reward-driven action learning.

Motivated by the above observations, this paper proposes a Gaussian mixture model-based spatio-temporal knowledge transfer multi-task dynamic multi-objective optimization algorithm, termed STKTM-MOEA/D.

The main contributions of this work are summarized as follows.

- (1) A dynamic multi-UAV cooperative path-planning model is established. In this model, domain knowledge from mission requirements and UAV operational rules is encoded through path-length, threat-exposure, and arrival-time-consistency

objectives, together with maneuverability, terrain-clearance, and inter-UAV safety constraints.

- (2) A GMM-based distribution-level knowledge representation mechanism is developed. The proposed mechanism characterizes multiple promising decision regions in terms of their locations, spreads, and mixture weights, thereby providing a stable knowledge carrier for subsequent transfer. Its effectiveness is further verified through an ablation variant in which distribution-level transfer is replaced by individual-level transfer.
- (3) A spatio-temporal knowledge transfer mechanism is designed to exploit both inter-task and historical environmental information. Specifically, spatial transfer selects and samples related auxiliary-task distributions according to a unified similarity-complementarity criterion, whereas temporal transfer retrieves reliable historical GMMs from the knowledge pool based on environmental similarity.
- (4) An environment-driven adaptive population reconstruction strategy is proposed. Once an environmental change is detected, the population is reconstructed using retained elite individuals, temporally transferred individuals, spatially transferred individuals, and randomly generated exploratory individuals. The reconstructed population is then further optimized through MOEA/D evolution, environmental selection, GMM updating, and knowledge-pool updating under the current environment.

The remainder of this paper is organized as follows. Section 2 reviews the related work. Section 3 presents the proposed STKTM-MOEA/D algorithm in detail. Section 4 describes the experimental setup and analyzes the results. Section 5 demonstrates the application of the proposed method to multi-UAV path planning. Finally, Section 6 concludes the paper and discusses future research directions.

2. Background and Motivation

This section first introduces the definitions of dynamic multi-objective optimization and evolutionary multitasking optimization. It then reviews the literature on multi-UAV cooperative path planning and related studies. Finally, the research motivations behind the proposed work are presented.

2.1. DMOP

Without loss of generality, DMOP can be formulated as follows:

$$\begin{aligned}
 \min \quad & F(x, t) = [f_1(x, t), f_2(x, t), \dots, f_m(x, t)]^T \\
 \text{s.t.} \quad & g_q(x, t) \leq 0, \quad q = 1, 2, \dots, Q, \\
 & h_r(x, t) = 0, \quad r = 1, 2, \dots, R, \\
 & x \in \Omega(t) \subseteq \mathbb{R}^n.
 \end{aligned} \tag{1}$$

where t denotes the current environmental state, $\Omega(t) \subseteq \mathbb{R}^n$ is the time-dependent feasible decision space, and $x = (x_1, x_2, \dots, x_n)^T \in \Omega(t)$ denotes the decision vector. The objective vector $F(x, t) \in \mathbb{R}^m$ consists of m scalar objective functions, where $f_i(x, t)$ denotes the value of the i -th objective evaluated for $\mathbf{x}$ under environmental state t , $i = 1, 2, \dots, m$. The functions $g_q(x, t)$ and $h_r(x, t)$ denote the time-dependent inequality and equality constraints, respectively.

In dynamic environments, both the Pareto-optimal set (PS) and the Pareto-optimal front (PF) evolve over time and can be expressed as follows:

$$PS(t) = \{x^* \in \Omega(t) \mid \nexists x \in \Omega(t), F(x, t) \prec F(x^*, t)\} \tag{2}$$

$$PF(t) = \{F(x, t) \mid x \in PS(t)\} \quad (3)$$

where the symbol $<$ denotes the Pareto dominance relation.

For the multi-UAV application considered in this work, x represents the waypoint coordinates and motion-related variables of all UAVs. The objective vector quantifies total flight distance, accumulated threat exposure, and cooperative arrival-time inconsistency. The time-dependent constraints represent UAV maneuverability, terrain clearance, inter-UAV separation, and dynamic threat-region avoidance. Accordingly, environmental changes may modify the objective functions, the constraint functions, or both, thereby changing the feasible region and invalidating previously optimal solutions. This formulation provides the basis for applying STKTM-MOEA/D, because the algorithm can respond to changes in $F(x, t)$ and $\Omega(t)$ by reconstructing the population using temporally retrieved and spatially transferred distribution knowledge. In complex dynamic scenarios, such changes may further induce significant shifts in the PS and PF, increasing the difficulty of dynamic optimization [18].

In this paper, the dynamic multi-UAV cooperative path-planning problem specifically refers to online adaptive replanning in time-varying operational environments. The dynamic factors considered in this study include changes in threat locations, threat radii, threat states, and task coordination requirements. Once an environmental change is detected, the previous population is partially reconstructed using historical and inter-task distribution knowledge, and the algorithm then continues optimization under the updated environment.

2.2. EMT

In the proposed framework, the multitask optimization problem consists of a main task and an auxiliary task [19]. The main task represents the original dynamic multi-UAV cooperative path-planning problem, whereas the auxiliary task preserves the same decision representation and hard feasibility constraints but relaxes selected objective penalties. The two tasks are formulated as follows:

$$\begin{aligned} \min F^m(W, t) &= [f_1(W, t), f_2(W, t), f_3(W, t)]^T \\ \text{s.t. } g_q(W, t) &\leq 0, \quad q = 1, 2, \dots, Q. \\ \min F^a(W, t) &= [f_1(W, t), \eta f_2(W, t), \kappa f_3(W, t)]^T \\ \text{s.t. } g_q(W, t) &\leq 0, \quad q = 1, 2, \dots, Q \\ &0 < \eta \leq 1, \quad 0 < \kappa \leq 1. \end{aligned} \quad (4)$$

where W denotes the waypoint-based decision vector of all UAVs and is the application-specific form of the general decision vector x in Equation (1). Accordingly, $f_1(W, t)$, $f_2(W, t)$, and $f_3(W, t)$ denote the total flight distance, accumulated threat exposure, and cooperative arrival-time inconsistency under environmental state t , respectively. The constraint set $g_q(W, t)$ includes UAV maneuverability, terrain-clearance, inter-UAV separation, dynamic threat-region avoidance, and decision-boundary constraints. The coefficients η and κ are the relaxation factors for the threat-exposure and arrival-time-consistency objectives, respectively.

The auxiliary task is not an independent UAV mission. It shares the same initial and terminal positions, waypoint encoding, dynamic environment, and hard safety constraints with the main task. By relaxing selected objective penalties, the auxiliary task explores feasible trade-off regions that may not be sufficiently covered by the main-task population. Before entering the main-task candidate population, all transferred individuals are re-evaluated using the original objectives and constraints of the main task.

The explicit formulations of $f_1(W, t)$, $f_2(W, t)$, $f_3(W, t)$, and the corresponding feasibility constraints are given in Section 5.1.

Knowledge transfer between different tasks requires their decision variables to be represented in a common coordinate system. Therefore, the task-specific decision vectors are mapped into a unified normalized search space, denoted by Ω^D . For a general multitask optimization problem, the dimension of the unified space is defined as follows:

$$D = \max(d_i), i = 1, 2, \dots, K \quad (5)$$

In the present framework, the main and auxiliary tasks employ the same waypoint encoding and therefore have identical decision dimensions, i.e., $d_m = d_a = D$. Hence, Equation (5) gives the general definition of the unified space, while no dimensional padding is required in the current implementation. Equations (6) and (7) are subsequently used to normalize the waypoint variables and map the transferred individuals back to the original decision space.

The unified normalized space provides the common representation used for GMM fitting, task-similarity evaluation, distribution-complementarity calculation, and cross-task sampling. Therefore, the task distributions compared in Section 3.2 are defined in the same coordinate system and are not affected by differences in variable scale.

For an original decision variable x_j , the normalization mapping into the unified search space is defined as follows:

$$y_j = \frac{x_j - L_j}{U_j - L_j} \quad (6)$$

where L_j and U_j are the lower and upper bounds of the decision variable x_j , respectively, and y_j denotes the normalized representation of x_j in the unified search space.

During the fitness evaluation stage, the normalized decision variables are transformed back to the original search space using the following mapping:

$$x_j = L_j + (U_j - L_j) \cdot y_j \quad (7)$$

Utilizing a unified search space allows for knowledge sharing among tasks and facilitates collaborative search, which enhances the efficiency of solving complex optimization problems.

2.3. Related Work

Multi-UAV cooperative path planning typically involves multiple objectives, including flight distance, energy consumption, threat avoidance, and inter-UAV collision avoidance. These objectives often conflict with one another, so the problem is generally formulated as a multi-objective optimization problem. Existing approaches can be broadly categorized into weighted multi-objective (WMO) methods and Pareto-based multi-objective (PMO) methods.

WMO methods typically employ weighted-sum strategies to convert multiple objectives into a single-objective optimization problem, with predefined weights reflecting the relative importance of each objective. Early studies often integrated WMO with classical path-planning algorithms for multi-UAV trajectory optimization. For example, some studies constructed weighted objective functions based on A* and Dijkstra algorithms to balance flight distance and threat exposure [20]. Additionally, intelligent optimization methods such as particle swarm optimization (PSO) [21], ant colony optimization (ACO) [22], and artificial potential field (APF) [23] have been applied to UAV path planning. These methods offer high computational efficiency and perform well in low-dimensional static scenarios. However, WMO approaches rely on fixed weights, which limits their adaptability to dynamic changes in objective relationships and typically

yields only a single trade-off solution, inadequately capturing the conflicts among multiple objectives.

In contrast, PMO methods can simultaneously generate a set of Pareto-optimal solutions, providing decision-makers with multiple trajectory options. With the development of multi-objective evolutionary algorithms (MOEAs), algorithms such as NSGA-II [24], MOEA/D [25], MOPSO [26], and SPEA2 have been widely applied to multi-UAV cooperative path planning. For instance, Zhang et al. employed a MOEA/D-based framework to solve multi-UAV path planning, achieving a favorable balance between flight distance and threat avoidance [27]. Some studies have further incorporated constrained multi-objective optimization to integrate UAV maneuverability, collision avoidance, and threat-region constraints within a unified framework. Overall, PMO methods are better suited than WMO methods for handling multi-objective conflicts, but most studies still assume static environments, limiting their applicability to dynamic threats and time-varying mission constraints.

To address multi-objective optimization in dynamic environments, various environmental response strategies have been proposed, including memory-based approaches, prediction models, multi-population cooperation, and diversity maintenance. Memory-based methods store elite solutions or PS from previous environments to enhance population recovery after environmental changes. Branke [28] was among the first to introduce memory mechanisms into dynamic optimization, preserving historically effective solutions to improve adaptation to periodic environmental changes. Subsequently, Deb et al. [29] utilized external archives to retain historical PS and guide population search after environmental shifts. While these methods leverage historical knowledge to accelerate recovery, substantial environmental changes can render past solutions incompatible, potentially causing knowledge obsolescence.

Prediction-based methods estimate PS or trajectory trends to accelerate algorithmic response to new environments. For example, Muruganantham et al. [30] proposed a Kalman filter-based dynamic multi-objective optimization method that predicts changes in the PF to enhance environmental responsiveness. Zhou et al. [31] used historical population trends to forecast the location of future PS. More recently, machine learning techniques have been applied in dynamic optimization; for instance, Jiang et al. [32] combined transfer learning with regression models to improve population initialization quality under dynamic conditions. While predictive methods can speed up environmental responses, accumulated prediction errors in complex dynamic scenarios may compromise solution quality and trajectory stability.

Additionally, multi-population cooperation and diversity maintenance methods are commonly employed in dynamic optimization. Goh and Tan [33] proposed a competitive-cooperative evolutionary framework, enhancing search capabilities in dynamic environments through information exchange among multiple subpopulations. Ruan et al. [34] investigated the effect of diversity maintenance on prediction performance in dynamic multi-objective optimization, demonstrating that appropriate diversity preservation enhances search stability. Other studies have introduced strategies such as random perturbation, reinitialization, and dynamic mutation to improve exploration in unknown environments. However, most of these approaches still rely on single-task optimization frameworks, depending primarily on information from the current population, with limited integration of inter-task cooperation and historical environmental knowledge.

In summary, existing dynamic multi-objective optimization methods still exhibit several limitations in multi-UAV dynamic path planning. First, single-task optimization frameworks cannot effectively exploit potential inter-task cooperation, resulting in reduced search efficiency and insufficient population recovery in complex dynamic

environments. Second, current evolutionary multitask methods primarily rely on task similarity for knowledge transfer, underutilizing complementary information among tasks, which limits solution diversity and global exploration capability. Finally, many knowledge transfer approaches still employ individual-level representations that are sensitive to random perturbations, making it difficult to stably characterize the overall population distribution; moreover, the reuse of historical environmental knowledge remains inadequate, limiting sustained adaptability to dynamic conditions.

To address these challenges, this paper proposes a GMM-based spatio-temporal knowledge transfer multi-task dynamic multi-objective optimization algorithm, STKTM-MOEA/D. This approach employs GMM to model the distribution of potential high-quality regions, replacing traditional individual-level knowledge representations with distribution-level knowledge. It integrates spatial knowledge transfer based on task similarity and complementarity with temporal knowledge transfer through a time-varying knowledge pool, enabling coordinated utilization of inter-task knowledge and historical environmental information. This combined mechanism enhances optimization performance and adaptability in complex dynamic environments.

3. The Proposed Algorithm

This section presents the proposed STKTM-MOEA/D framework, whose information flow and evolutionary procedure are illustrated in Figure 1. The algorithm maintains separate populations for the main task and the auxiliary task and constructs GMMs from the elite decision vectors of both populations. When no environmental change is detected, the similarity and complementarity between the two task distributions are evaluated, and spatially transferred individuals are generated from the auxiliary-task GMM and inserted into the main-task candidate population. When an environmental change is detected, relevant historical GMMs are retrieved from the temporal knowledge pool according to the current environmental feature. The retrieved distributions are combined to construct a temporal transfer GMM, from which temporally transferred individuals are generated. Meanwhile, spatially transferred individuals are produced according to the current task relationship. The retained elites, temporally transferred individuals, spatially transferred individuals, and randomly generated individuals are then used to reconstruct the main-task population. After either response process, the main and auxiliary populations continue MOEA/D evolution, environmental selection, GMM updating, and temporal knowledge-pool updating under the current environment. Algorithm 1 presents the pseudocode of STKTM-MOEA/D.

Algorithm 1: STKTM-MOEA/D

Input: dynamic multi-objective problem F , population size N , neighborhood size T , maximum number of generations $MaxGen$, weight-vector set Λ , and knowledge-pool capacity H .

Output: approximate non-dominated solution set of the main task;

- 1 Initialize the main-task population P_m and auxiliary-task population P_a ;
- 2 Evaluate P_m and P_a under the initial environment;
- 3 Construct initial GMMs G^m and G^a from elite individuals;
- 4 Initialize the temporal knowledge pool $\mathcal{K}$ with capacity H ;
- 5 **while** the termination condition is not satisfied **do**
- 6 Detect environment changed;
- 7 **if** an environmental change is detected **then**
- 8 Extract the current environmental feature vector E_i ;
- 9 Retrieve Top- K similar historical knowledge units from $\mathcal{K}$;
- 10 Construct the temporal transfer GMM G_i ;

```

11      Generate temporally transferred individuals  $P_t$ ;
12      Generate spatially transferred individuals  $P_s$  according to the current task
      relationship;
13      Adaptively reconstruct the main-task population  $P_m$  using the retained elite
      individuals  $P_e$ , the temporally transferred individuals  $P_t$ , the spatially transferred
      individuals  $P_s$ , and the randomly generated exploratory individuals  $P_r$ ;
14  else
15      Generate spatially transferred individuals  $P_s$  according to the current task
      relationship;
16      Insert  $P_s$  into the main-task candidate population;
17  end if
18  Perform MOEA/D evolution for the main and auxiliary tasks;
19  Conduct environmental selection under the current environment;
20  Update  $G^m$  and  $G^a$  using the current elite individuals of the main and auxiliary
      tasks, respectively;
21  Update the temporal knowledge pool  $\mathcal{K}$  using the current GMMs and their
      associated environmental, quality, and reliability information;
22  end while
23  Output the approximate non-dominated solution set of the main task.

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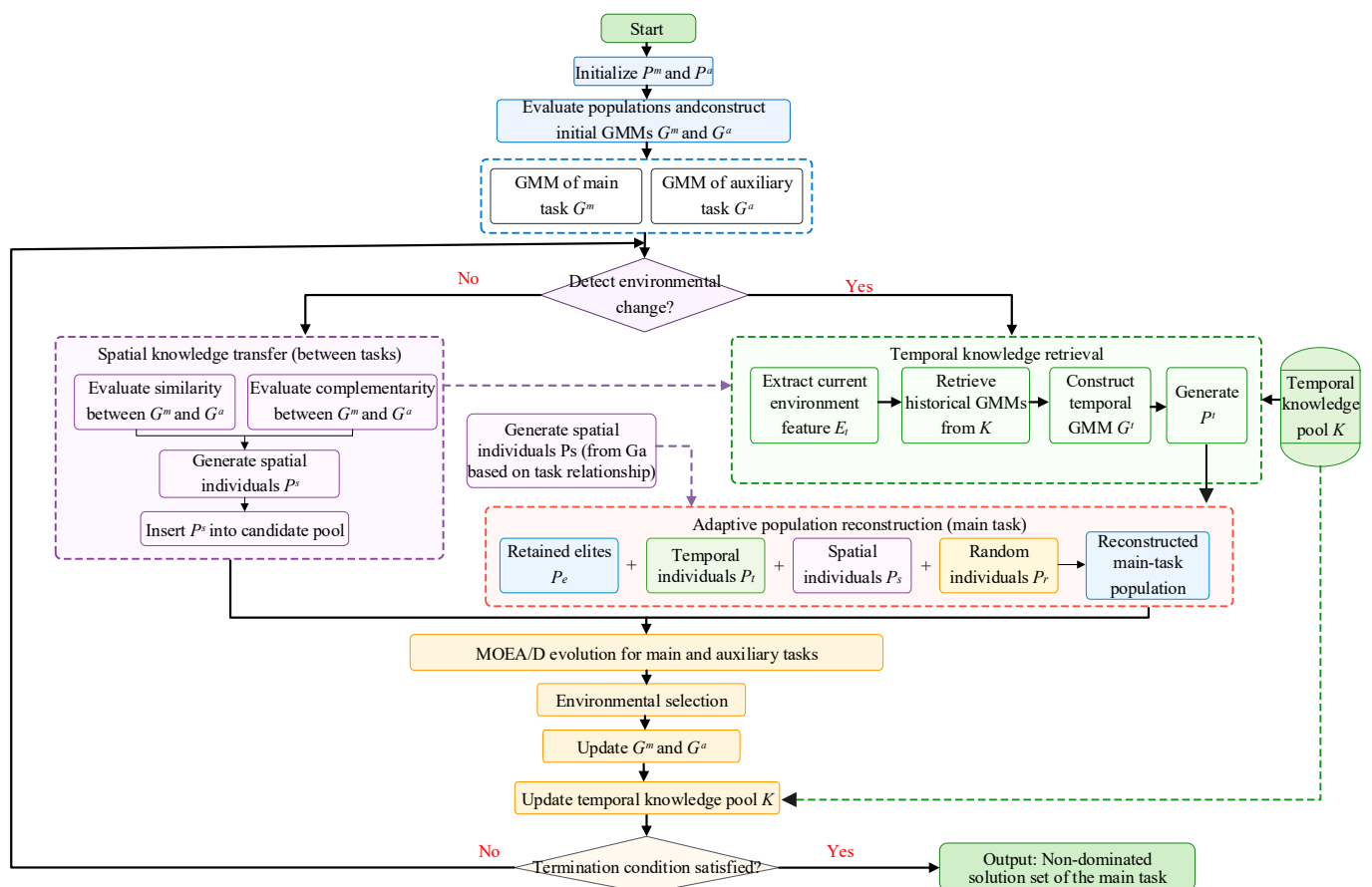


Figure 1. Information flow and evolutionary procedure of STKTM-MOEA/D.

Subsequently, Section 3.1 introduces the GMM-based distribution modeling mechanism; Section 3.2 describes spatial knowledge transfer; Section 3.3 details the temporal knowledge transfer and adaptive population reconstruction mechanisms; finally, Section 3.4 analyzes the computational complexity of the algorithm.

3.1. Distribution Modeling Based on GMM

In dynamic environments, Pareto-optimal regions evolve continuously with environmental changes, rendering traditional individual-level knowledge representations inadequate for reliably characterizing the overall population distribution. To address this issue, Li et al. [35] incorporated Gaussian distribution modeling into multi-objective multitask optimization and demonstrated that distribution-level knowledge representations can facilitate more stable knowledge transfer. Motivated by this idea, the proposed method employs a Gaussian mixture model (GMM) to probabilistically model potential high-quality regions of the population. The constructed GMM serves as a unified distribution-level knowledge carrier for both spatial and temporal knowledge transfer, thereby enabling more robust knowledge representation and transfer.

The current task population is defined as follows:

$$P = \{x_1, x_2, \dots, x_N\}, x_i \in \mathbb{R}^D \quad (8)$$

For spatial knowledge transfer between the main and auxiliary tasks, a multi-component Gaussian mixture model is utilized to characterize the population distribution. The corresponding probability density function is formulated as a weighted sum of multiple Gaussian components, given by:

$$\begin{aligned} p(x) &= \sum_{k=1}^C \pi_k \mathcal{N}(x | \mu_k, \Sigma_k) \\ \sum_{k=1}^C \pi_k &= 1, \\ \pi_k &\geq 0, k = 1, 2, \dots, C \end{aligned} \quad (9)$$

where C denotes the number of Gaussian components. The mean vector μ_k and covariance matrix Σ_k represent the location and dispersion of the k -th Gaussian component, respectively. The coefficient π_k denotes the corresponding mixture weight, satisfying $\sum_{k=1}^C \pi_k = 1$ and $\pi_k \geq 0$. These conditions ensure that the GMM defines a valid probability density. A larger π_k indicates that the corresponding component accounts for a larger proportion of the selected elite samples.

Unlike individual-level transfer, which directly copies or perturbs a limited number of elite solutions, the GMM retains the center, spread, and relative weight of each promising region. The mean vectors provide location information, the covariance matrices describe variable correlations and search ranges, and the mixture weights reflect the relative importance of different regions. Consequently, transferred individuals are generated from the estimated population structure rather than from isolated samples. The contribution of this distribution-level representation is further examined through the STKTM-NoG ablation variant in Section 4.3.

During GMM construction, potential elite individuals are first selected based on non-dominated sorting and crowding distance, and the GMM parameters are then estimated. Subsequently, probabilistic sampling from the constructed GMM is performed to generate transferred individuals. By modeling multiple elite clusters rather than transferring only isolated elite solutions, the GMM preserves both the central locations and dispersion patterns of promising regions, thereby providing structured distributional information for subsequent spatial and temporal transfer.

The GMM is trained using the expectation-maximization algorithm. The non-dominated elite solutions are used as training samples, and the number of Gaussian components is fixed to $C = 3$. The EM algorithm is initialized using k -means clustering and iteratively estimates the mixture parameters until convergence. New offspring solutions are generated by sampling from the learned Gaussian mixture distribution.

3.2. Spatial Knowledge Transfer

Existing EMT studies have shown that effective task selection strategies can significantly enhance knowledge transfer performance. Lin et al. [36] proposed a bi-objective knowledge transfer framework that jointly considers transfer gain and the risk of negative transfer. Subsequently, Lin et al. [35] further demonstrated that, besides task similarity, complementary information among tasks can also provide valuable guidance for optimization. Inspired by these observations, a distribution relationship-based spatial knowledge transfer mechanism is proposed in this work. Specifically, GMMs are utilized to model the potential high-quality regions of different task populations. The auxiliary task shares the same dynamic environment and mission endpoints as the main task, but adopts relaxed threat-exposure and coordination penalties, thereby providing complementary search information. Task similarity is employed to evaluate the proximity of search centers, whereas task complementarity is introduced to quantify differences in distribution structures. Source tasks are then selected according to the joint assessment of similarity and complementarity, enabling effective knowledge transfer that improves convergence while maintaining adequate exploration capability. Similarity and complementarity provide different forms of transfer information. A high similarity indicates that the promising regions of the two tasks are located close to each other and is therefore useful for accelerating convergence. Complementarity reflects differences in the distribution structures of the task populations and may provide search directions that are insufficiently represented in the main-task population. Considering both criteria prevents the transfer mechanism from selecting either unrelated distributions with a high risk of negative transfer or nearly identical distributions that contribute little additional information. The overall framework of the proposed spatial knowledge transfer mechanism is illustrated in Figure 2.

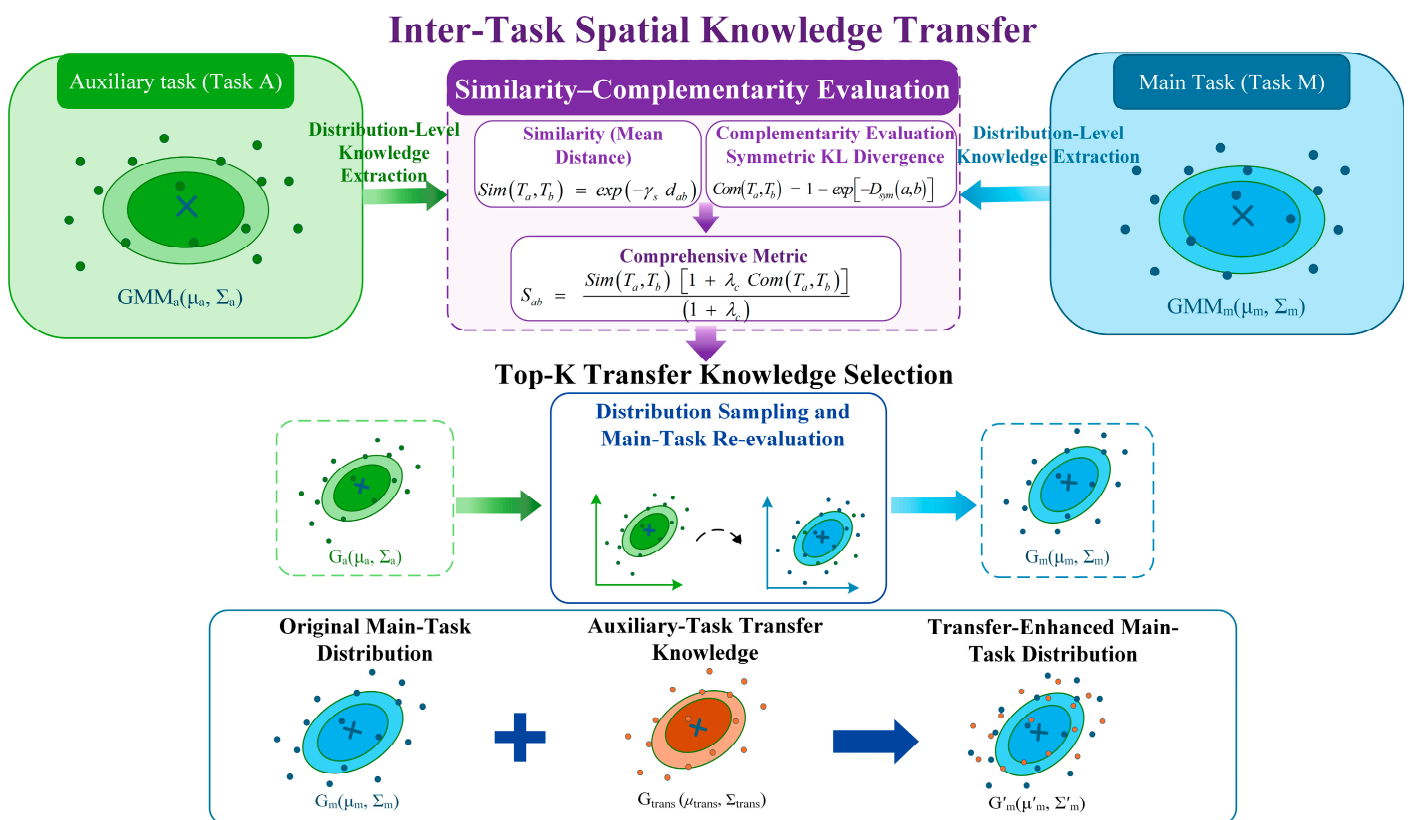


Figure 2. Schematic Illustration of Spatial Knowledge Transfer.

Let $\bar{\mu}_a$ and $\bar{\mu}_b$ denote the moment-matched mean vectors of the GMMs associated with tasks T_a and T_b , respectively, and let $\bar{\Sigma}_a$ and $\bar{\Sigma}_b$ denote the corresponding moment-matched covariance matrices. The normalized distance between the promising centers of the two tasks is defined as follows:

$$d_{ab} = \frac{\|\bar{\mu}_a - \bar{\mu}_b\|_2}{\|\bar{\mu}_a\|_2 + \|\bar{\mu}_b\|_2 + \varepsilon} \quad (10)$$

The task similarity is then calculated as:

$$\text{Sim}(T_a, T_b) = \exp(-\gamma_s d_{ab}) \quad (11)$$

where ε is a small constant introduced to avoid division by zero, and $\gamma_s > 0$ is the similarity-decay coefficient. A larger value of $\text{Sim}(T_a, T_b)$ indicates that the promising regions of the two tasks are located closer to each other in the search space, implying a higher level of task relatedness. Consequently, transferring knowledge from similar tasks can effectively accelerate the convergence of the target task.

However, knowledge sharing based solely on task similarity may lead to a loss of population diversity. Therefore, a task complementarity metric is introduced to quantify the distributional discrepancy between task distributions. Each GMM is approximated by its moment-matched Gaussian distribution, denoted as $N_a = N(\bar{\mu}_a, \bar{\Sigma}_a)$ and $N_b = N(\bar{\mu}_b, \bar{\Sigma}_b)$. The symmetric Kullback–Leibler divergence is defined as:

$$D_{\text{sym}}(a, b) = \frac{1}{2} [D_{\text{KL}}(N_a \parallel N_b) + D_{\text{KL}}(N_b \parallel N_a)] \quad (12)$$

The task complementarity metric is then normalized as:

$$\text{Com}(T_a, T_b) = 1 - \exp[-D_{\text{sym}}(a, b)] \quad (13)$$

A larger value of $\text{Com}(T_a, T_b)$ indicates a greater distributional discrepancy between the two tasks, including differences in promising-region locations, spreads, or orientations. Such complementary information can enhance exploration and improve population diversity.

To quantify the intensity of spatial knowledge transfer, a joint transfer score is defined by jointly considering task similarity and complementarity:

$$S_{ab} = \frac{\text{Sim}(T_a, T_b) [1 + \lambda_c \text{Com}(T_a, T_b)]}{(1 + \lambda_c)} \quad (14)$$

The spatial transfer sampling ratio ρ_s is then determined as follows:

$$\rho_s = \min\{\rho_{\max}, \max[\rho_{\min}, \rho_{\min} + (\rho_{\max} - \rho_{\min}) S_{ab}]\} \quad (15)$$

where $\lambda_c \geq 0$ controls the contribution of complementarity, and $\rho_{\min}$ and $\rho_{\max}$ denote the lower and upper bounds of the spatial transfer ratio, respectively. Therefore, spatial transfer is strengthened only when the auxiliary task is sufficiently related to the main task while still providing complementary distributional information. This strategy helps reduce the risk of negative transfer from unrelated auxiliary tasks.

A larger Com value implies a greater discrepancy between the distribution structures of two tasks in the search space, indicating stronger task complementarity. Knowledge transfer from complementary tasks can enhance the exploration of unexplored regions, improve population diversity, and reduce the risk of premature convergence to local optima.

Based on the above observations, both task similarity and task complementarity are jointly considered for source task selection. Specifically, probabilistic sampling is

performed from the selected GMM distributions to generate transferred individuals, which are subsequently injected into the target population to promote collaborative search among tasks. Compared with conventional individual-level knowledge transfer, the proposed distribution-level transfer mechanism provides a more stable representation of potential high-quality regions, thereby improving the effectiveness and reliability of knowledge transfer. The pseudocode of the proposed spatial knowledge transfer mechanism is presented in Algorithm 2.

Algorithm 2: Spatial Knowledge Transfer Mechanism

Input: Main task population P_m , auxiliary task population P_a , spatial transfer size N_s ;

Output: Spatially transferred individuals P_s ;

- 1 Construct GMM distribution models G^m and G^a based on the elite individuals in P_m and P_a , respectively;
 - 2 Compute the task similarity Sim between the main and auxiliary tasks;
 - 3 Compute the task complementarity Com ;
 - 4 Determine the spatial transfer sampling ratio based on Sim and Com ;
 - 5 Perform probabilistic sampling from the auxiliary task GMM G^{aux} ;
 - 6 Generate the set of spatially transferred individuals P_s ;
 - 7 Apply boundary repair to any individuals in P_s that exceed search space limits;
 - 8 Return P_s .
-

3.3. Temporal Knowledge Transfer and Adaptive Population Reconstruction

Environmental changes may cause shifts in Pareto-optimal regions, rendering the search information contained in the current population gradually obsolete. Considering that dynamic environments often exhibit temporal correlations, the high-quality distribution information accumulated in historical environments can still provide valuable guidance for search in new environments. To exploit such information, a temporal knowledge transfer mechanism is developed and integrated with an adaptive population reconstruction strategy. A schematic illustration of the proposed temporal knowledge transfer mechanism is shown in Figure 3. After an environmental change is detected, the current environmental feature vector E_t is extracted and compared with the historical environmental features stored in the knowledge pool.

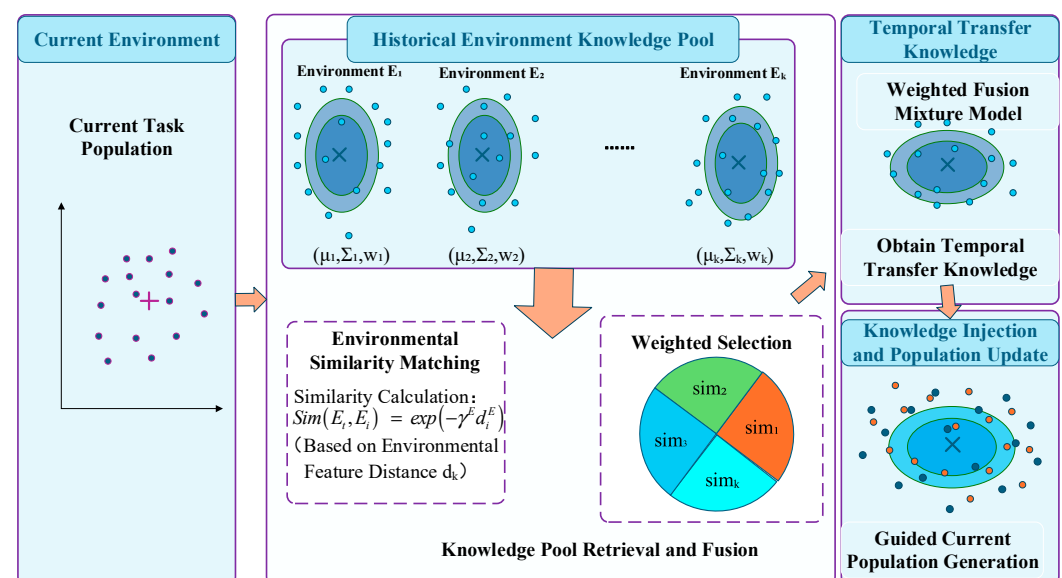


Figure 3. Schematic Illustration of Temporal Knowledge Transfer.

To detect environmental changes, an environment detection strategy based on the variation in population objective values is adopted. Let f_t and f_{t-1} denote the population objective values at the current and previous environmental states, respectively. The environmental change intensity is defined as follows:

$$\Delta_t = \frac{1}{N} \sum_{i=1}^N \frac{\|f_t - f_{t-1}\|}{\|f_{t-1}\| + \varepsilon} \quad (16)$$

where N denotes the number of individuals used for detection, and ε is a small constant to prevent division by zero. Considering that objective values may exhibit local random fluctuations in dynamic environments, a change-smoothing mechanism is further introduced to enhance the stability of environment detection:

$$\bar{\Delta}_t = \lambda \bar{\Delta}_{t-1} + (1 - \lambda) \Delta_t \quad (17)$$

where λ is the smoothing factor, which is set to 0.7 in this study.

Subsequently, the severity of the detected environmental change is classified according to the smoothed and normalized change intensity as follows:

$$Stage = \begin{cases} mild, \bar{\Delta}_t < \theta_1, \\ medium, \theta_1 \leq \bar{\Delta}_t < \theta_2, \\ severe, \bar{\Delta}_t \geq \theta_2. \end{cases} \quad (18)$$

where θ_1 and θ_2 are the lower and upper thresholds used to distinguish mild, moderate, and severe environmental changes, respectively. Because the change intensity in Equation (16) is normalized by the magnitude of the previous objective values and subsequently smoothed by Equation (17), the resulting indicator is dimensionless and comparable across successive environmental states. The thresholds were selected through preliminary sensitivity experiments using representative dynamic benchmark instances. Candidate threshold combinations were examined with respect to post-change convergence recovery and population diversity. Values that were too small caused minor objective fluctuations to be classified as moderate or severe changes, whereas excessively large values delayed population reconstruction after substantial environmental changes. Based on this analysis, $\theta_1 = 0.05$ and $\theta_2 = 0.20$ were adopted. These values were fixed before the comparative experiments and were applied consistently to all benchmark problems; they were not returned for individual test instances.

To preserve useful knowledge from historical environments, a time-varying knowledge pool is constructed following the historical knowledge storage mechanism in [37]. The capacity of the knowledge pool is set to $H = 10$, allowing up to ten historical knowledge units to be retained. Each historical knowledge unit contains the environmental feature vector, the corresponding GMM parameters, a knowledge-quality indicator, and a reliability indicator. When the knowledge pool reaches its maximum capacity, the historical knowledge unit with the lowest comprehensive retention value is removed to maintain the effectiveness and timeliness of the stored knowledge.

$$K_i = \{G_i, E_i, Q_i, R_i\} \quad (19)$$

where G_i denotes the Gaussian knowledge model corresponding to the current environment, E_i represents the environmental features, Q_i indicates the quality of the knowledge, and R_i denotes the reliability of the knowledge. The environmental features are composed of the mean and variance of the objectives of elite individuals, which characterize the current environmental state. The knowledge quality is used to evaluate the optimization performance of the historical population associated with this knowledge.

For the i -th historical knowledge unit, the normalized environmental distance is defined as:

$$d_i^E = \frac{\|E_t - E_i\|_2}{\|E_t\|_2 + \|E_i\|_2 + \varepsilon} \quad (20)$$

where d_i^E denotes the normalized environmental distance between the current environment and the i -th historical environment.

The environmental similarity is then calculated using a bounded exponential function:

$$\text{Sim}(E_t, E_i) = \exp(-\gamma^E d_i^E) \quad (21)$$

where $\gamma^E > 0$ is the environmental similarity-decay coefficient. A larger value of $\text{Sim}(E_t, E_i)$ indicates that the corresponding historical environment is more similar to the current environment.

The algorithm retrieves the Top- K historical knowledge units with the largest environmental similarity values. To construct the temporal transfer distribution, the selected historical GMMs are fused as:

$$G_t(x) = \sum_{i \in \text{Top-}K} \alpha_i G_i(x) \quad (22)$$

where the transfer weight of the i -th historical knowledge unit is defined as:

$$\alpha_i = \frac{\text{Sim}(E_t, E_i) Q_i R_i}{\sum_{j \in \text{Top-}K} \text{Sim}(E_t, E_j) Q_j R_j} \quad (23)$$

where Q_i denotes the normalized quality indicator of the historical knowledge unit, and R_i denotes its reliability indicator. In this work, Q_i is estimated from the normalized mean decomposition fitness of the elite population associated with the knowledge unit, while R_i is defined according to the stability of the knowledge unit across recent optimization stages. Therefore, historical knowledge units with higher environmental relevance, better optimization quality, and more stable performance are assigned larger transfer weights.

Environmental similarity measures whether a historical distribution remains relevant to the current environment, whereas the quality and reliability indicators describe whether the stored knowledge previously provided effective and stable search guidance. Their joint use prevents historical GMMs from being selected solely according to environmental proximity. Consequently, knowledge that is environmentally similar but unreliable, or reliable but weakly related to the current environment, receives a limited transfer weight, thereby improving the stability of historical knowledge reuse. After constructing the temporal transfer mixture model, probabilistic sampling is performed from G_t to generate temporally transferred individuals P_t .

Nevertheless, relying exclusively on historical distribution knowledge may lead to a loss of population diversity. Since different levels of environmental change require different trade-offs between knowledge exploitation and exploration, an adaptive population reconstruction strategy is developed based on the detected environmental change intensity.

The reconstructed population is composed of four types of individuals:

$$P_{new} = P_c \cup P_t \cup P_s \cup P_r \quad (24)$$

where P_c denotes the current elite individuals used to preserve existing convergence information; P_t represents temporally transferred individuals used to recover historical promising regions; P_s denotes spatially transferred individuals that introduce collaborative knowledge from other tasks; and P_r represents randomly generated exploratory individuals used to enhance the exploration capability of the population.

The reconstruction ratios of these four types of individuals under different environmental change stages are defined as follows:

$$(\rho_c, \rho_t, \rho_s, \rho_r) = \begin{cases} (0.70, 0.10, 0.15, 0.05), & \text{Stage} = \text{mild}, \\ (0.45, 0.20, 0.25, 0.10), & \text{Stage} = \text{medium}, \\ (0.20, 0.20, 0.40, 0.20), & \text{Stage} = \text{severe}. \end{cases} \quad (25)$$

Under varying environmental change intensities, the adaptive population reconstruction dynamically adjusts the proportions of current elite individuals, temporally transferred individuals, spatially transferred individuals, and randomly generated exploratory individuals to balance convergence and exploration capabilities. After reconstruction, population quality is ensured through duplicate individual detection and boundary repair. In combination with the temporal knowledge transfer mechanism, the algorithm can effectively leverage historical knowledge and rapidly adapt to new environments. Algorithm 3 presents the pseudocode for temporal knowledge transfer and adaptive population reconstruction.

Algorithm 3: Temporal Knowledge Transfer and Adaptive Population Reconstruction

Input: Current main task population P_m , auxiliary task population P_a , knowledge pool K , population size N , environmental change thresholds θ_1, θ_2 ;

Output: Reconstructed main task population P_m ;

- 1 Compute the environmental change intensity Δ_i ;
 - 2 Determine the environmental change *Stage* based on Δ_i ;
 - 3 **if** *Stage* $\neq$ none **then**
 - 4 Extract the current environmental feature vector E_i ;
 - 5 Select the *Top-K* most similar historical knowledge units from the knowledge pool K ;
 - 6 Compute the weights α_i based on $\text{Sim}(E_i, E_i)$ and reliability;
 - 7 Construct the temporal transfer mixture model G_i ;
 - 8 Perform probabilistic sampling from G_i to generate temporally transferred individuals P_t ;
 - 9 Generate spatially transferred individuals P_s based on the distribution relationship between main and auxiliary tasks;
 - 10 Determine the reconstruction ratios of P_e, P_t, P_s, P_r according to the current *Stage*;
 - 11 Select the current elite individuals P_e and generate random exploratory individuals P_r ;
 - 12 Form the new population $P_m^{\text{new}} = P_e \cup P_t \cup P_s \cup P_r$;
 - 13 Apply boundary repair and duplicate replacement on P_m^{new} ;
 - 14 $P_m \leftarrow P_m^{\text{new}}$;
 - 15 **else**
 - 16 Maintain the standard environmental selection procedure;
 - 17 **end if**
 - 18 return P_m .
-

3.4. Complexity Analysis

This section analyzes the computational complexity of STKTM-MOEA/D. The algorithm mainly involves the following key steps: MOEA/D evolution, GMM distribution modeling, environmental change detection, spatio-temporal knowledge transfer, and environmental selection. For clarity, the relevant symbols are defined as follows: population size N , decision dimension D , number of objectives M , number of GMM components K , knowledge pool size H , Neighborhood size T , and maximum number of iterations G . The computational complexity of MOEA/D environmental selection is approximately $O(MNT)$ [37]; GMM distribution modeling, which primarily involves estimating the mean vectors, covariance matrices, and mixture component

parameters, has a complexity of roughly $O(CND^2)$; environmental change detection typically reevaluates objective values for a subset of representative individuals, with complexity $O(NM)$; temporal knowledge transfer requires retrieving the historical knowledge units most similar to the current environment from the knowledge pool, with complexity $O(HD)$; and spatial knowledge transfer has complexity $O(ND)$. Therefore, the overall complexity per iteration can be expressed as $O(MNT + CND^2 + HD + ND)$. Since spatio-temporal knowledge transfer is only triggered upon environmental change, the additional computational overhead is relatively manageable. Ignoring lower-order terms, the overall time complexity of STKTM-MOEA/D over G iterations is $O(G(MNT + CND^2))$.

4. Experimental Evaluation

In this section, comprehensive experiments are conducted on the FDA and DF benchmark suites, as well as multi-UAV dynamic cooperative path planning scenarios, to evaluate the performance of the proposed STKTM-MOEA/D. First, comparative experiments against several representative dynamic multi-objective optimization algorithms are performed. Then, ablation studies are carried out to investigate the contributions of the key components. Finally, the effectiveness and practical applicability of the proposed algorithm are further validated in multi-UAV dynamic cooperative path planning scenarios.

4.1. Performance Metrics and Experimental Setup

To comprehensively evaluate the performance of the proposed STKTM-MOEA/D on DMOPs, the mean inverted generational distance (MIGD) is employed as the primary performance metric. MIGD measures the proximity between the obtained solution set and the true PF.

The Inverted Generational Distance (IGD) is defined as follows:

$$IGD(P, P^*) = \frac{1}{|P^*|} \sum_{u \in P^*} \min_{v \in P} \|u - v\|^2 \quad (26)$$

where $\|\cdot\|$ denotes the Euclidean distance.

Since the PS evolves over time in DMOPs, the Mean Inverted Generational Distance (MIGD) is employed to assess the overall performance of an algorithm across the entire optimization process [38]. The MIGD metric is defined as follows:

$$MIGD = \frac{1}{T} \sum_{t=1}^T IGD(P_t, P_t^*) \quad (27)$$

where T denotes the number of environmental changes, and P_t and P_t^* represent the solution set obtained and the true PF at the t -th environment, respectively.

To assess the performance of STKTM-MOEA/D, DNSGA-II, SGEA, MMTL-DMOEA, and KT-MDMOEA are employed as benchmark algorithms. Experiments are performed on the FDA and DF series of dynamic multi-objective benchmark problems. Each algorithm is independently executed 30 times, unless otherwise stated, the key parameters of STKTM-MOEA/D are set as follows: $C = 3$ for the number of Gaussian components, $H = 10$ for the knowledge pool capacity, $Top-K = 3$ for historical environment retrieval, $\varepsilon = 10^{-6}$ for environmental change detection, and $\lambda = 0.7$ for the smoothing factor. These parameter settings remain fixed across all benchmark problems and multi-UAV dynamic cooperative path planning experiments.

All experiments were conducted on a workstation equipped with an Intel Core i9-13900HX processor (Intel Corporation, Santa Clara, CA, USA), 64 GB of RAM, and an NVIDIA GeForce RTX 4090 GPU (NVIDIA Corporation, Santa Clara, CA, USA). The proposed algorithm and all comparison algorithms were implemented in MATLAB

R2024b (The MathWorks, Inc., Natick, MA, USA). The benchmark experiments were conducted using PlatEMO 4.12, an evolutionary multi-objective optimization platform developed by Tianjin University, Tianjin, China. All experiments were executed under the Windows 11 operating system (Microsoft Corporation, Redmond, WA, USA).

For the DF and FDA benchmark suites, n_t denotes the severity parameter controlling the magnitude of environmental change, whereas τ_t denotes the environmental change interval, namely, the number of generations between two consecutive environmental updates. Unless otherwise stated, the benchmark experiments use $n_t = 5$ and $\tau_t = 10$. These settings are applied consistently to all compared algorithms. The characteristics of the benchmark problems are summarized in Table 1.

Table 1. Characteristics of the Benchmark Problems.

Problem	Characteristics	Dynamic Behavior
DF1	Continuous, convex	PF translates in the objective space
DF2	Continuous, convex	PF translates with slight deformation
DF3	Continuous, linear	PF moves linearly
DF4	Convex→concave oscillation	PF convexity changes periodically
DF5	Multi-modal, discontinuous	PF splits/merges
DF6	Degenerate front	PF degenerates with changing dimensions
DF7	Convex, biased	PF translates and stretches
DF8	Concave, multi-modal	PF rotates with local oscillations
DF9	Mixed type	PF moves piecewise dynamically
DF10	2→3 objective switching	New objective added
DF11	Time-varying constraints	Constraints tighten/relax periodically with t
DF12	High-dimensional objective dynamics	Objective space dimension gradually increases to 3
DF13	High-dimensional objective dynamics	Objective space dimension gradually increases to 4
DF14	High-dimensional objective dynamics	Objective space dimension gradually increases to 5
FDA1	Continuous, convex	PF translates in the objective space
FDA2	Continuous, concave	PF translates with slight deformation
FDA3	Continuous, linear	PF moves linearly
FDA4	Convex→concave oscillation	PF convexity changes periodically
FDA5	Multi-modal, discontinuous	PF splits/merges

4.2. Benchmark Performance Analysis

The MIGD results of all algorithms on the DF and FDA series benchmark problems are presented in Tables 2 and 3, respectively. In these tables, the symbols “+”, “=”, and “−” indicate that STKTM-MOEA/D performs significantly worse than, statistically equivalent to, or significantly better than the corresponding comparison algorithm according to the Wilcoxon rank-sum test at a significance level of 0.05. Bold-face values denote the best-performing algorithm on each problem. The “+/=−” row summarizes the total numbers of wins, ties, and losses for each comparison algorithm. To further assess overall performance, the Friedman test is employed to obtain comprehensive rankings of the algorithms. The results are shown in Figures 4 and 5, where a smaller average rank indicates better performance.

Table 2. Mean MIGD Values and Standard Deviations Obtained by Each Algorithm on the DF Series Test Problems.

Problem	DNSGA-II	SGEA	MMTL-DMOEA	KTM-DMOEA	STKTM-MOEA/D
DF1	1.1683×10^{-1} (1.26×10^{-2}) –	3.6224×10^{-2} (1.80×10^{-2}) –	5.9291×10^{-2} (2.40×10^{-1}) –	8.9281×10^{-5} (1.07×10^{-5}) +	2.0793×10^{-2} (2.27×10^{-3})
DF2	1.0552×10^{-1} (8.03×10^{-3}) –	7.8480×10^{-2} (8.84×10^{-3}) –	8.6744×10^{-2} (3.50×10^{-1}) –	7.3874×10^{-3} (8.57×10^{-4}) +	4.3143×10^{-2} (4.31×10^{-3})
DF3	2.1879×10^{-1} (9.66×10^{-3}) –	1.8670×10^{-1} (9.68×10^{-3}) –	4.1379×10^{-1} (2.06×10^{-1}) –	2.0215×10^{-1} (4.79×10^{-2}) –	1.7710×10^{-1} (2.03×10^{-2})
DF4	1.0642×10^{-1} (1.04×10^{-2}) –	7.0607×10^{-2} (5.45×10^{-3}) –	3.1904×10^{-1} (6.87×10^{-2}) –	1.4304×10^{-2} (9.51×10^{-3}) –	1.1122×10^{-2} (1.04×10^{-2})
DF5	7.2407×10^{-2} (5.31×10^{-3}) –	2.5630×10^{-2} (1.59×10^{-3}) –	9.6472×10^{-2} (4.48×10^{-2}) –	1.1405×10^{-2} (3.96×10^{-4}) +	2.0095×10^{-2} (3.18×10^{-3})
DF6	1.8436×10^0 (1.01×10^{-1}) –	1.6879×10^0 (2.24×10^{-1}) –	1.0222×10^0 (8.74×10^{-1}) –	5.0666×10^{-1} (7.47×10^{-3}) –	4.7901×10^{-1} (5.66×10^{-2})
DF7	2.7301×10^{-1} (2.47×10^{-2}) –	2.3168×10^{-1} (4.44×10^{-2}) –	6.7788×10^{-1} (4.64×10^{-2}) –	3.5994×10^{-1} (7.70×10^{-2}) –	1.3656×10^{-1} (1.32×10^{-2})
DF8	1.3317×10^{-1} (1.59×10^{-2}) –	1.2211×10^{-1} (2.00×10^{-3}) –	7.1966×10^{-2} (3.63×10^{-3}) +	6.1312×10^{-2} (3.93×10^{-4}) +	8.9476×10^{-2} (8.73×10^{-3})
DF9	1.9721×10^{-1} (2.93×10^{-2}) –	5.6234×10^{-1} (9.69×10^{-2}) –	1.4824×10^0 (7.77×10^{-1}) –	6.2947×10^{-1} (7.85×10^{-1}) –	1.3178×10^{-1} (1.88×10^{-2})
DF10	2.6019×10^{-1} (6.54×10^{-3}) –	2.0852×10^{-1} (2.31×10^{-3}) –	2.6358×10^{-1} (7.72×10^{-2}) –	1.9811×10^{-1} (2.12×10^{-3}) –	1.8180×10^{-1} (2.90×10^{-2})
DF11	2.8523×10^{-1} (3.95×10^{-3}) +	3.0136×10^{-1} (3.98×10^{-3}) +	5.7567×10^{-1} (8.83×10^{-3}) –	5.6087×10^{-1} (2.55×10^{-3}) –	5.2113×10^{-1} (5.42×10^{-2})
DF12	1.0595×10^{-1} (7.01×10^{-3}) +	8.8486×10^{-2} (3.93×10^{-3}) +	1.7654×10^{-1} (4.05×10^{-2}) –	7.1991×10^{-2} (7.00×10^{-3}) +	1.5825×10^{-1} (2.32×10^{-2})
DF13	2.5035×10^{-1} (2.25×10^{-2}) –	1.4382×10^{-1} (7.64×10^{-3}) –	4.5704×10^{-1} (7.29×10^{-2}) –	5.1298×10^{-2} (6.75×10^{-3}) –	4.3086×10^{-2} (6.40×10^{-3})
DF14	4.3182×10^{-1} (7.99×10^{-2}) –	1.2494×10^{-1} (2.37×10^{-1}) –	6.3454×10^{-1} (1.15×10^0) –	8.0902×10^{-2} (2.16×10^{-2}) –	6.5381×10^{-2} (9.00×10^{-3})
+/-/=	2/12/0	2/12/0	1/13/0	5/9/0	

Note: “+”, “–”, and “=” indicate that the proposed algorithm performs significantly better, significantly worse, or statistically similar compared with the corresponding comparison algorithm, respectively.

Table 3. Mean MIGD Values and Standard Deviations Obtained by Different Algorithms on the FDA Series Benchmark Problems.

Problem	DNSGA-II	SGEA	MMTL-DMOEA	KTM-DMOEA	STKTM-MOEA/D
FDA1	4.4393×10^{-2} (2.01×10^{-3}) +	1.6557×10^{-2} (1.06×10^{-3}) +	1.6083×10^{-1} (1.92×10^{-2}) –	4.1785×10^{-2} (4.18×10^{-2}) +	6.3081×10^{-2} (8.94×10^{-3})
FDA2	2.0113×10^{-2} (4.65×10^{-3}) +	1.7455×10^{-2} (6.09×10^{-3}) +	8.6766×10^{-2} (9.05×10^{-3}) –	9.1652×10^{-3} (5.27×10^{-3}) +	2.6789×10^{-2} (6.80×10^{-3})
FDA3	6.0811×10^{-2} (3.19×10^{-3}) –	4.3982×10^{-2} (3.66×10^{-3}) +	2.0110×10^{-1} (2.89×10^{-2}) –	2.8396×10^{-2} (1.68×10^{-2}) +	5.8769×10^{-2} (5.66×10^{-3})
FDA4	3.0872×10^{-1} (2.30×10^{-2}) –	1.3521×10^{-1} (1.49×10^{-2}) –	1.3671×10^{-1} (7.53×10^{-3}) –	8.1076×10^{-2} (2.80×10^{-3}) –	7.3526×10^{-2} (1.48×10^{-2})
FDA5	3.8706×10^{-1} (2.66×10^{-2}) –	2.0861×10^{-1} (2.44×10^{-2}) –	2.9716×10^{-1} (5.40×10^{-2}) –	1.1181×10^{-1} (2.70×10^{-2}) –	9.8535×10^{-2} (3.63×10^{-2})
+/-/=	2/3/0	3/2/0	0/5/0	3/2/0	

Note: “+”, “−”, and “=” indicate that the proposed algorithm performs significantly better, significantly worse, or statistically similar compared with the corresponding comparison algorithm, respectively.

IGD vs No. of Changes for Five Algorithms on DF1 – DF14



Figure 4. Average IGD Values of the DF Series with $n_t = 5$ and $\tau_t = 10$.

IGD vs No. of Changes for Five Algorithms on FDA1 – FDA5

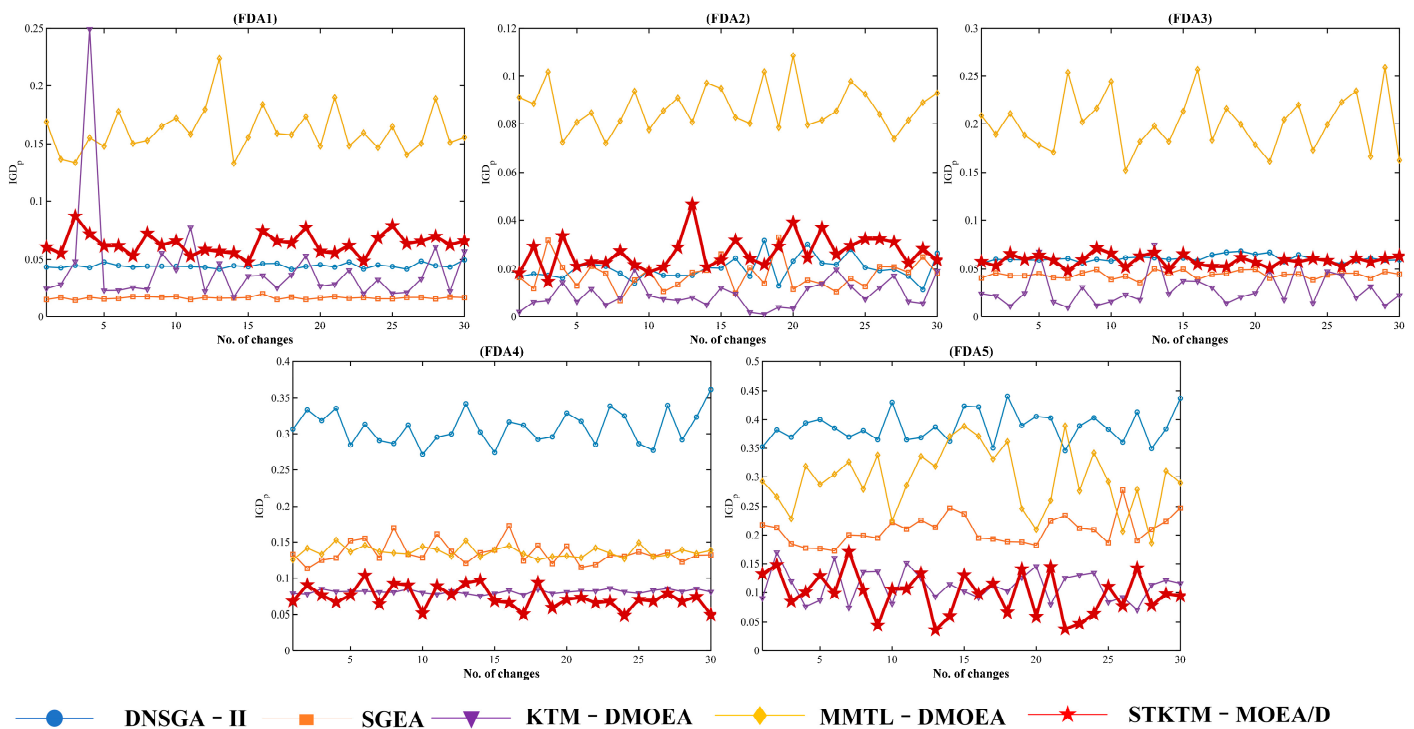


Figure 5. Average IGD Values of the FDA Series with $n_t = 5$ and $\tau_t = 10$.

4.2.1. DF Series

As can be observed from Table 2, STKTM-MOEa/D achieves the best MIGD values on DF3, DF4, DF6, DF7, DF9, DF10, DF13, and DF14, while maintaining performance comparable to KT-MDMOEa on DF1, DF2, DF5, and DF8. Overall, STKTM-MOEa/D consistently outperforms DNSGA-II, SGEA, and MMTL-DMOEa, with its advantages becoming more evident on challenging dynamic benchmark problems, such as DF9, DF10, DF13, and DF14. These observations indicate that the proposed algorithm is capable of maintaining superior solution quality and environmental adaptability as the dynamicity and complexity of the optimization problem increase.

Examining the dynamic change curves in Figure 4 further reveals that DNSGA-II and MMTL-DMOEa exhibit significant performance fluctuations across most test problems, particularly on DF6, DF9, and DF14, where IGD values increase markedly during certain environmental change phases. In contrast, STKTM-MOEa/D maintains consistently low and stable IGD levels across most environmental change stages, indicating its ability to rapidly recover population search capability after environmental changes and sustain a stable optimization process.

The superior performance of STKTM-MOEa/D can be primarily attributed to the spatio-temporal knowledge transfer mechanism and the GMM-based distribution-level knowledge representation. Temporal knowledge transfer leverages effective search experiences from historical environments to accelerate population recovery after environmental changes; spatial knowledge transfer exploits task similarity and complementarity to provide diversified search information for the target task; and GMM-based distribution modeling stably characterizes potential high-quality regions, thereby enhancing the reliability of knowledge transfer.

Therefore, Figure 4 directly supports the claimed environmental responsiveness and population recovery capability of STKTM-MOEa/D. The lower and more stable IGD curves indicate that the proposed spatio-temporal distribution knowledge transfer

mechanism can reduce performance fluctuations and accelerate recovery after environmental changes.

4.2.2. FDA Series

As can be observed from Table 3, STKTM-MOEA/D achieves the best MIGD values on FDA4 and FDA5, while maintaining performance comparable to KT-MDMOEA on FDA1–FDA3. Overall, STKTM-MOEA/D outperforms DNSGA-II, SGEA, and MMTL-DMOEA on 2, 3, and 5 benchmark problems, respectively, and exhibits a large number of statistically comparable results with KT-MDMOEA. More importantly, its superiority becomes increasingly evident on FDA4 and FDA5 as the environmental dynamicity intensifies. These results demonstrate the effectiveness of the proposed algorithm in PF and maintaining high solution quality in complex dynamic environments. The observed performance gains can be mainly attributed to the proposed spatio-temporal knowledge transfer mechanism and GMM-based distribution-level knowledge representation. By jointly exploiting historical environmental knowledge and inter-task collaborative information, STKTM-MOEA/D can rapidly recover search capability after environmental changes. Furthermore, the GMM-based distribution modeling strategy provides a stable characterization of potential high-quality regions, thereby enhancing both knowledge transfer effectiveness and environmental adaptability.

As illustrated in Figure 5, DNSGA-II and MMTL-DMOEA exhibit significant performance fluctuations on FDA4 and FDA5, whereas STKTM-MOEA/D consistently maintains lower and more stable IGD values across most environmental change stages. This observation demonstrates that the proposed algorithm is capable of rapidly recovering search capability following environmental changes while sustaining robust optimization performance in complex dynamic environments.

4.2.3. Discussion and Limitations

While STKTM-MOEA/D demonstrates superior performance on most DF benchmark problems and FDA4–FDA5, its advantage becomes less pronounced on FDA1–FDA3. A possible explanation is that these benchmark problems mainly involve relatively simple and continuous PF translations, where the search space structure remains stable over time. Under such mild environmental dynamics, lightweight knowledge transfer strategies can already provide sufficient guidance for population evolution.

In contrast, the proposed STKTM-MOEA/D incorporates GMM-based distribution modeling, spatial knowledge transfer, temporal knowledge reuse, and adaptive population reconstruction. Although these mechanisms significantly improve environmental adaptability under complex and rapidly changing conditions, their benefits may not be fully exploited in simple dynamic scenarios.

In addition, the effectiveness of GMM-based distribution modeling may gradually decrease as the decision space dimensionality increases, since covariance estimation becomes more computationally demanding. Future work will investigate adaptive probabilistic models and dynamic component selection mechanisms to further improve scalability and robustness in large-scale dynamic optimization problems.

Therefore, Figure 5 further verifies the generality of the proposed mechanism on dynamic benchmark problems with different PF movement patterns. The results show that GMM-based temporal reuse and spatial complementary transfer jointly contribute to stable convergence and improved adaptability under time-varying environments.

4.3. Ablation Study

To investigate the contribution of each key component in STKTM-MOEA/D, four ablation variants are constructed for comparative evaluation. Specifically, STKTM-NoS

removes the spatial knowledge transfer mechanism, STKTM-NoT removes the temporal knowledge transfer mechanism, STKTM-NoG replaces the proposed GMM-based distribution-level knowledge representation with conventional individual-level knowledge representation, and STKTM-NoR removes the adaptive population reconstruction mechanism and employs a fixed reconstruction ratio instead. Four representative benchmark problems, namely DF4, DF7, DF9, and DF14, are selected for the ablation study, covering dynamic optimization scenarios with low, moderate, and high levels of complexity. All algorithms are evaluated under identical parameter settings and independently executed 30 times. The corresponding MIGD results are summarized in Table 4, while the logarithmic-scale IGD convergence curves are illustrated in Figure 6.

Table 4. MIGD Results of STKTM-MOEA/D and Its Four Variants on DF4, DF7, DF9, and DF14.

Problem	STKTM-MOEA/D	STKTM_NoS	STKTM_NoT	STKTM_NoG	STKTM_NoR
DF4	1.1122×10^{-2} (1.04×10^{-2})	1.8643×10^{-2} (1.73×10^{-2})	1.5237×10^{-2} (1.28×10^{-2})	2.0463×10^{-2} (1.92×10^{-2})	1.7425×10^{-2} (1.66×10^{-2})
DF7	1.3656×10^{-1} (1.32×10^{-2})	2.1845×10^{-1} (2.67×10^{-2})	1.9732×10^{-1} (2.31×10^{-2})	2.5631×10^{-1} (3.84×10^{-2})	2.1467×10^{-1} (2.95×10^{-2})
DF9	1.3178×10^{-1} (1.88×10^{-2})	2.4268×10^{-1} (4.13×10^{-2})	3.5874×10^{-1} (6.52×10^{-2})	2.9183×10^{-1} (5.74×10^{-2})	3.1042×10^{-1} (5.93×10^{-2})
DF14	6.5381×10^{-2} (9.00×10^{-3})	1.7314×10^{-1} (3.11×10^{-2})	2.7315×10^{-1} (5.18×10^{-2})	2.1046×10^{-1} (4.36×10^{-2})	2.4863×10^{-1} (4.95×10^{-2})

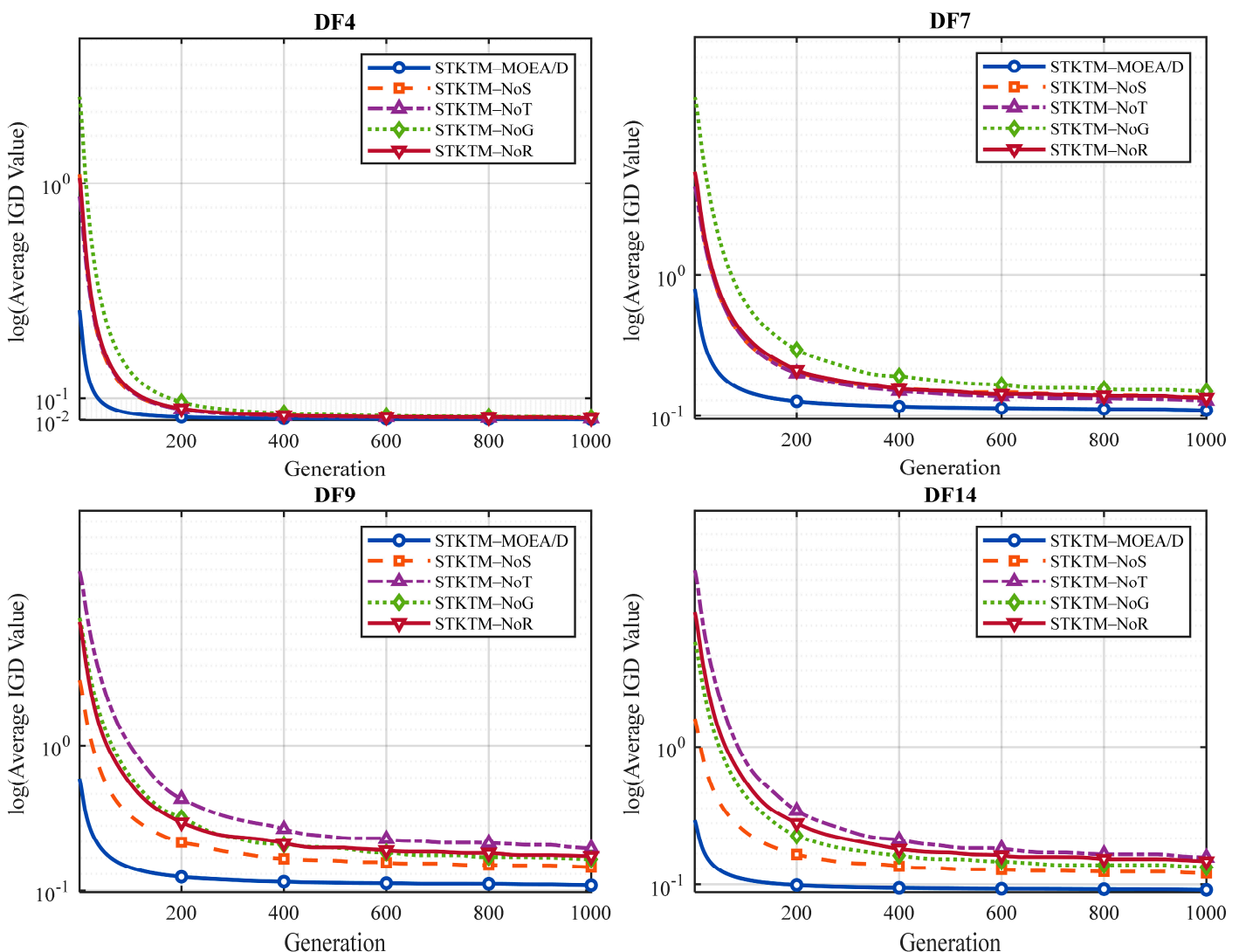


Figure 6. Average IGD Results of All Tasks Obtained by STKTM-MOEA/D and Its Four Variants on DF4, DF7, DF9, and DF14.

As can be observed from Table 4, the complete STKTM-MOEA/D achieves the best or near-best performance on all benchmark problems, whereas all ablation variants suffer from varying degrees of performance degradation. These results demonstrate that temporal knowledge transfer, spatial knowledge transfer, GMM-based distribution modeling, and adaptive population reconstruction each make significant contributions to the overall performance improvement of the proposed algorithm. More importantly, the synergy among these components enables STKTM-MOEA/D to effectively balance convergence, diversity, and adaptability, thereby achieving superior optimization performance in dynamic environments.

As illustrated in Figure 6, STKTM-NoT exhibits the most pronounced performance degradation on DF9 and DF14, with its convergence curves recovering slowly after environmental changes, indicating that temporal knowledge transfer plays a critical role in population recovery. By reusing effective distribution information from historical environments, this mechanism provides more reliable search guidance for new environments. STKTM-NoS shows noticeable performance drops on DF7 and DF9, demonstrating that spatial knowledge transfer can leverage inter-task collaborative information to supplement the target task with effective search experiences, thereby improving search efficiency and solution set quality. The convergence curves of STKTM-NoG fluctuate more and show poorer stability in later stages, suggesting that GMM-based distribution-level knowledge representation can more stably characterize potential high-quality regions than individual-level transfer. This result further supports that distribution-level transfer reduces sensitivity to random perturbations in individual elites, since knowledge is sampled from a fitted distribution rather than copied from a few isolated solutions. STKTM-NoR shows particularly severe degradation on DF14 and experiences larger fluctuations after environmental changes, indicating that a fixed-ratio reconstruction strategy struggles to adapt to varying environmental change intensities, whereas adaptive population reconstruction adjusts search strategies according to the degree of change, better balancing convergence and diversity.

In summary, temporal knowledge transfer, spatial knowledge transfer, GMM-based distribution modeling, and adaptive population reconstruction all play essential roles in the performance enhancement of STKTM-MOEA/D. Specifically, these components improve environmental responsiveness, inter-task collaboration, the robustness of knowledge representation, and the adaptability of population reconstruction, respectively. Through their integration, the proposed algorithm achieves superior overall performance in DMOPs.

5. Multi-UAV Dynamic Cooperative Path Planning Experiments

To demonstrate the practical applicability of STKTM-MOEA/D, the algorithm is applied to a multi-UAV dynamic cooperative path planning scenario. The experiments incorporate flight distance, threat costs, and multiple real-world constraints, and the performance is compared against DNSGA-II, SGEA, MMTL-DMOEA, and KT-MDMOEA. Analysis of the path planning results and cooperative optimization effectiveness under dynamic environments confirms the capability of the proposed algorithm in complex engineering settings.

From the optimization perspective, domain adaptation-based transfer has been shown to reduce distribution discrepancies among related tasks and improve the effectiveness of evolutionary multitasking [39]. This observation is consistent with the use of a common normalized space and distribution-level transfer between the main and

auxiliary tasks in the proposed framework. In addition, many-objective evolutionary optimization has been successfully applied to multi-UAV cooperative trajectory planning, indicating its suitability for coordinating multiple conflicting planning objectives [40].

5.1. Multi-UAV Dynamic Cooperative Path Planning Model

The proposed method operates at the online planning layer and outputs waypoint-based reference paths. The low-level attitude stabilization and actuator-level tracking are assumed to be handled by the onboard flight controller. To ensure planning-layer dynamic feasibility, a discrete-time kinematic model is used for each UAV:

$$\begin{aligned}x_{i,j+1} &= x_{i,j} + v_{i,j} \cos(\gamma_{i,j}) \cos(\psi_{i,j}) \Delta t \\y_{i,j+1} &= y_{i,j} + v_{i,j} \cos(\gamma_{i,j}) \sin(\psi_{i,j}) \Delta t \\z_{i,j+1} &= z_{i,j} + v_{i,j} \sin(\gamma_{i,j}) \Delta t\end{aligned}\quad (28)$$

where $v_{i,j}$, $\psi_{i,j}$, and $\gamma_{i,j}$ denote the speed, heading angle, and climbing angle of UAV i at waypoint j , respectively. This formulation captures the time-varying coupling between position, speed, heading, and climbing motion at the planning layer. It does not claim to replace a full six-degree-of-freedom flight dynamics model. Instead, nonlinear flight behavior and actuator limitations are conservatively represented through maneuverability bounds and safety margins.

Assume that the system contains M UAVs. The trajectory of the i -th UAV consists of a sequence of path waypoints and is defined as follows:

$$W_i = \{P_{i,0}, P_{i,1}, \dots, P_{i,D}\} \quad (29)$$

where $P_{i,j} = (x_{i,j}, y_{i,j}, z_{i,j})$ denotes the coordinates of the j -th waypoint of the i -th UAV. The trajectories of all UAVs collectively form the overall cooperative trajectory:

$$W = \{W_1, W_2, \dots, W_M\} \quad (30)$$

Under the dynamic environment at time t , the multi-UAV cooperative path planning problem is formulated as the following dynamic multi-objective optimization problem:

$$\min F(W, t) = [f_1(W, t), f_2(W, t), f_3(W, t)]^T \quad (31)$$

where $f_1(W, t)$, $f_2(W, t)$, and $f_3(W, t)$ denote the total flight distance, accumulated threat exposure, and cooperative arrival-time inconsistency under environmental state t , respectively. The total flight distance is defined as follows:

$$f_1(W, t) = \sum_{i=1}^M \sum_{j=1}^{L-1} \|P_{i,j+1}(t) - P_{i,j}(t)\|_2 \quad (32)$$

where M denotes the number of UAVs, L denotes the number of waypoints of each UAV, and $P_{i,j}(t)$ denotes the j -th waypoint of UAV i under environmental state t .

The accumulated threat exposure quantifies the influence of enemy radar, obstacles, and hazardous regions on the UAVs during flight and is defined as follows:

$$f_2(W, t) = \sum_{i=1}^M \sum_{j=0}^L \sum_{k=1}^K q_k(t) \exp[-\|P_{i,j} - O_k(t)\|_2^2 / (2R_k^2(t))] \quad (33)$$

The cooperative cost is used to measure the coordination consistency among multiple UAVs, primarily reflecting the differences in arrival times of the UAVs at the mission area:

$$\begin{aligned}f_3(W, t) &= (1/M) \sum_{i=1}^M (T_i - \bar{T})^2 \\ \bar{T} &= (1/M) \sum_{i=1}^M T_i\end{aligned}\quad (34)$$

The cooperative cost measures the arrival-time inconsistency among UAVs. Here, T_i denotes the total flight time of UAV i , and $\bar{T}$ denotes the average arrival time of all UAVs.

A smaller f_3 indicates better temporal coordination among the UAVs. The cooperative objective is optimized jointly with flight distance and threat exposure, whereas collision avoidance remains a hard safety constraint.

In addition, the multi-UAV path planning process must satisfy the following constraints: During flight, the UAV's speed, turning angle, and climbing angle must satisfy the maneuverability limits, i.e.,

$$\begin{aligned} v_{\min} &\leq v_{i,j} \leq v_{\max} \\ |\psi_{i,j+1} - \psi_{i,j}| &\leq \Delta\psi_{\max} \\ |\gamma_{i,j+1} - \gamma_{i,j}| &\leq \Delta\gamma_{\max} \\ R_{\text{turn},i,j} &\geq R_{\min} \\ R_{\text{turn},i,j} &= v_{i,j}\Delta t / \left[2\sin(|\psi_{i,j+1} - \psi_{i,j}| / 2) \right] \end{aligned} \quad (35)$$

where $v_{\min}$ and $v_{\max}$ denote the allowable speed range, $\Delta\psi_{\max}$ and $\Delta\gamma_{\max}$ denote the maximum heading-angle and climbing-angle variations between adjacent waypoints, and $R_{\min}$ denotes the minimum turning radius. These constraints provide a planning-layer approximation of UAV maneuverability and prevent the optimizer from generating geometrically feasible but dynamically unrealistic paths.

To prevent collisions among UAVs, a minimum safety distance must be maintained between any pair of UAVs at all times:

$$d_{i,t}(t) \geq d_{\min} + 2\varepsilon_p, \quad i \neq m \quad (36)$$

where $d_{i,m}$ denotes the Euclidean distance between UAVs i and m , $d_{\min}$ represents the minimum safety distance, and ε_p denotes the upper bound of position estimation and tracking errors. By introducing ε_p into the separation constraint, the model explicitly reserves a safety margin for localization and tracking uncertainties, thereby improving the reliability of the planned paths under uncertain execution conditions.

The UAV flight altitude must remain above the terrain safety height while avoiding dynamic threat areas:

$$\begin{aligned} z_{i,j} &\geq H(x_{i,j}, y_{i,j}) + H_{\min} + \varepsilon_p, \\ \|P_{i,j} - O_k(t)\|_2 &\geq R_k(t) + d_{\text{safe}} + \varepsilon_p \end{aligned} \quad (37)$$

where $P_{i,j} = (x_{i,j}, y_{i,j}, z_{i,j})$ denotes the position of UAV i at waypoint j , $H(x_{i,j}, y_{i,j})$ denotes the terrain elevation at the corresponding horizontal location, $H_{\min}$ is the minimum terrain-clearance altitude, and ε_p denotes the upper bound of position estimation and tracking errors. In addition, $O_k(t)$ and $R_k(t)$ denote the center position and effective radius of the k -th dynamic threat region at time t , respectively, and d_{safe} represents the additional safety buffer around the threat region. The second constraint is applied only to hard no-fly threat regions, whereas radar regions that can be traversed with risk are handled through the threat cost f_2 rather than as hard constraints.

To characterize the dynamic environment, a dynamic threat region model is further introduced. Let $O_k(t) = [x_k(t), y_k(t), z_k(t)]$ denote the center position of the k -th threat region and $R_k(t)$ denote its effective radius in environment t . When an environmental change occurs, the position and influence range of the threat region are updated according to:

$$\begin{aligned} O_k(t+1) &= O_k(t) + \Delta O_k(t), \\ R_k(t+1) &= \text{clip}[R_k(t) + \Delta R_k(t), R_{\min,k}, R_{\max,k}] \end{aligned} \quad (38)$$

The variations satisfy $\|\Delta O_k(t)\|_2 \leq \delta_{O,k}$ and $|\Delta R_k(t)| \leq \delta_{R,k}$, where $\delta_{O,k}$ and $\delta_{R,k}$ denote bounded environmental uncertainty levels. The additional safety margins in the constraints provide conservative protection against bounded position-estimation, tracking, and threat-region prediction errors.

Accordingly, the multi-UAV dynamic cooperative path planning problem can be formulated as the following dynamic multi-objective optimization model:

$$\begin{aligned} \min F(W, t) &= [f_1(W, t), f_2(W, t), f_3(W, t)]^T, \\ \text{s.t. } C_q(W, t) &\leq 0, \quad q = 1, 2, \dots, Q. \end{aligned} \quad (39)$$

where $g_q(W, t)$ denotes the q -th application-specific inequality constraint under environmental state t , and Q is the total number of constraints.

By jointly considering path length, threat avoidance, and cooperative flight objectives, together with maneuverability, terrain, and safety constraints, the proposed model provides a realistic and comprehensive representation of the multi-UAV cooperative path planning problem in dynamic environments.

5.2. Multi-UAV Path Planning Performance Analysis

Figure 7 illustrates the optimization results of the five algorithms on the multi-UAV path planning problem. It can be observed that all algorithms are capable of generating feasible trajectories that satisfy the prescribed constraints; however, substantial differences in solution quality remain. Specifically, trajectories generated by DNSGA-II and SGEA exhibit noticeable detours, resulting in increased flight distances. Although MMTL-DMOEA and KT-MDMOEA achieve improved path quality, some of their trajectories still pass relatively close to threat regions. In contrast, STKTM-MOEA/D produces smoother and more efficient trajectories, maintaining shorter flight distances while effectively avoiding both threat regions and complex terrain. These results demonstrate its superior capability in multi-UAV cooperative path planning. Moreover, the PF distributions further highlight the effectiveness of the proposed method. The non-dominated solutions obtained by STKTM-MOEA/D are generally distributed in the lower-left region of the objective space compared with those of the competing algorithms, indicating lower flight distance and threat costs simultaneously. In addition, the resulting PF is more continuous and well distributed, suggesting that STKTM-MOEA/D achieves a more favorable trade-off between the two conflicting objectives while maintaining superior convergence and diversity characteristics.

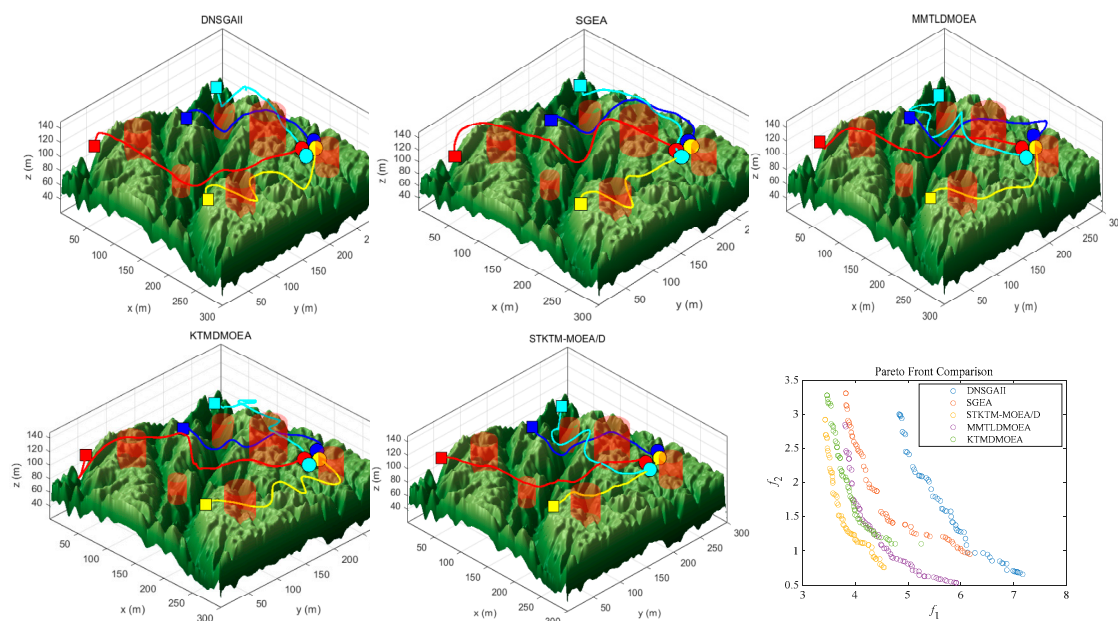


Figure 7. Optimization Results of Five Algorithms on Multi-UAV Path Planning.

As shown in Table 5, STKTM-MOEA/D achieves the highest HV and PD values, indicating better convergence and coverage of the obtained Pareto solution set and providing more diverse trade-off solutions. In terms of feasibility, STKTM-MOEA/D consistently generates constraint-satisfying trajectories across multiple independent runs, with a success rate of 1.00. Regarding computational cost, STKTM-MOEA/D obtains the lowest total runtime among the compared algorithms under the same experimental configuration, with an average runtime of 232.30 s. This result suggests that the proposed spatio-temporal knowledge transfer mechanisms do not introduce excessive optimization overhead and can improve overall search efficiency. These results demonstrate that STKTM-MOEA/D effectively balances convergence, diversity, and adaptability in complex dynamic environments, further confirming its effectiveness and practical potential for multi-UAV dynamic cooperative path planning.

However, total runtime alone is insufficient to fully demonstrate hard real-time feasibility. For online UAV replanning, the average and worst-case replanning times after each environmental change, denoted by t_r and $t_{r,max}$, respectively, should be further evaluated. Nevertheless, the proposed framework has online replanning potential at the planning layer because environmental changes trigger population reconstruction rather than complete re-optimization from scratch. Historical GMMs and spatially transferred distributions provide informative initial populations for the updated environment, thereby reducing the recovery burden of subsequent MOEA/D evolution. The framework can be considered suitable for online replanning when $t_{r,max}$ is shorter than the available planning interval of the UAV mission. Since the present study mainly reports total runtime under simulation settings, real-time replanning performance will be further investigated in future onboard implementation studies.

Table 5. Performance Metrics of Five Algorithms on Multi-UAV Path Planning.

Algorithm	HV	PD	Success Rate	Runtime (s)
DNSEGAI	0.7632 ± 0.0124	$3.16 \times 10^7 \pm 2.30 \times 10^6$	0.93	260.83
SSEA	0.7958 ± 0.0108	$3.54 \times 10^7 \pm 2.00 \times 10^6$	0.95	263.04
MMTLDMOEA	0.8279 ± 0.0081	$4.36 \times 10^7 \pm 1.60 \times 10^6$	0.98	255.85
KTMDMOEA	0.8316 ± 0.0084	$4.18 \times 10^7 \pm 1.70 \times 10^6$	0.98	245.85
STKTM-MOEA/D	0.8463 ± 0.0065	$4.82 \times 10^7 \pm 1.40 \times 10^6$	1.00	232.30

6. Conclusions

To address the challenges of delayed environmental response, unstable knowledge transfer, and limited population recovery in multi-UAV cooperative path planning under complex dynamic environments, a GMM-based Spatio-Temporal Knowledge Transfer Multi-Task Dynamic Multi-Objective Evolutionary Algorithm, termed STKTM-MOEA/D, is proposed. The proposed method employs GMMs to characterize potential high-quality regions of the population, enabling a transition from conventional individual-level knowledge representation to distribution-level knowledge representation. Moreover, a collaborative spatio-temporal knowledge transfer framework is developed, in which spatial knowledge transfer exploits task similarity and complementarity to facilitate inter-task collaboration, while temporal knowledge transfer reuses historical environmental knowledge through a time-varying knowledge pool to enhance population recovery after environmental changes. Furthermore, an environment-driven adaptive population reconstruction strategy is introduced to achieve a better balance between convergence and diversity.

Comprehensive experimental studies on benchmark problems and multi-UAV cooperative path planning applications demonstrate that STKTM-MOEA/D consistently

achieves superior performance in convergence, diversity, and adaptability compared with several state-of-the-art dynamic multi-objective optimization algorithms. The results further verify that the integration of spatio-temporal knowledge transfer and GMM-based distribution-level knowledge representation can effectively improve environmental response capability and search efficiency in complex dynamic environments.

The proposed method is designed as a planning-layer optimization framework. It explicitly considers time-varying threats, bounded environmental uncertainty, inter-UAV safety separation, terrain clearance, and maneuverability limits. Nevertheless, the current study does not incorporate a complete six-degree-of-freedom nonlinear flight dynamics model or actuator-fault dynamics into the optimization loop. The generated paths are assumed to be tracked by a lower-level flight controller. Future work will integrate higher-fidelity UAV dynamics, state-estimation uncertainty, and hardware-in-the-loop or field-flight validation to further assess the reliability of the proposed method in realistic autonomous flight missions.

Future research will focus on developing dynamic auxiliary task generation and adaptive task association modeling to further enhance the adaptability of the algorithm in complex dynamic environments. Moreover, strategies for lightweight distribution modeling and parallel computing acceleration will be investigated to mitigate computational overhead in high-dimensional dynamic optimization problems, thereby improving the algorithm's engineering applicability in large-scale, complex scenarios.

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