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Current development and future prospects of multi-target assignment problem: A bibliometric analysis review

Shuangxi Liu[a,b], Zehuai Lin[c], Wei Huang[a,b,*], Binbin Yan[c]

[a]College of Aeospace Science and Engineering National University of Defene Technology, Changsha 410073, China

[b]Hypersonic Technology Laboratory, National University of Defense of Technology, Changsha 410073, China

[c]School of Astronautics, Northwestern Polytechnical University, Xi′an 710072, China

*Corresponding author Email-address: gladrain@163.com.

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Abstract

The multi-target assignment (MTA) problem, a crucial challenge in command control, mission planning, and a fundamental research focus in military operations, has garnered significant attention over the years. Extensively studied across various domains such as land, sea, air, space, and electronics, the MTA problem has led to the emergence of numerous models and algorithms. To delve deeper into this field, this paper starts by conducting a bibliometric analysis on 463 Scopus database papers using CiteSpace software. The analysis includes examining keyword clustering, co-occurrence, and bursts, with visual representations of the results. Following this, the paper provides an overview of current classification and modeling techniques for addressing the MTA problem, distinguishing between static multi-target assignment (SMTA) and dynamic multitarget assignment (DMTA). Subsequently, existing solution algorithms for the MTA problem are reviewed, generally falling into three categories: exact algorithms, heuristic algorithms, and machine learning algorithms. Finally, a development framework is proposed based on the "HIGH" model (high-speed, integrated, great, harmonious) to guide future research and intelligent weapon system development concerning the MTA problem. This framework emphasizes application scenarios, modeling mechanisms, solution algorithms, and system efficiency to offer a roadmap for future exploration in this area.

Keywords: Multi-target assignment; Offensive and defensive confrontation; Cooperative operation; Modeling mechanism; Solution algorithm; CiteSpace analysis

1. Introduction

Nowadays, scientific and technological advancements have brought about significant changes in the traditional forms of warfare. Information technology, in particular, has transformed mechanized warfare into informational warfare [1-6]. The combat forces in informational warfare comprise primarily of informational warfare units for both parties involved. For example, in modern air combat, opposing parties primarily perform aerial attacks and engage in multi-dimensional combat across land, sea, air, space, and electronic dimensions to achieve efficient strikes from multiple levels and directions. This leads to a collaborative adversarial situation that presents a multidimensional confrontation, multiple sources of information, and the participation of various roles [7-12].

As a result, based on information systems that interact with various resources, future warfare will be predominantly characterized by system-to-system confrontation [13-18]. Taking Fig. 1 as an example, it implies that the outcome of warfare will no longer depend solely on the advancement of single systems or platforms, but also on the degree of cooperation among various combat elements within the system. Generally, combat cooperation involves planning, scheduling, and other fields. Precise and efficient combat cooperation facilitates the resolution of conflicts and contradictions in multiple dimensions such as time, space, frequency, tasks, and effects among different cooperative parties. Furthermore, it contributes to the development of high-quality combat action schemes, laying the foundation for achieving ideal combat effect-to-cost ratios.

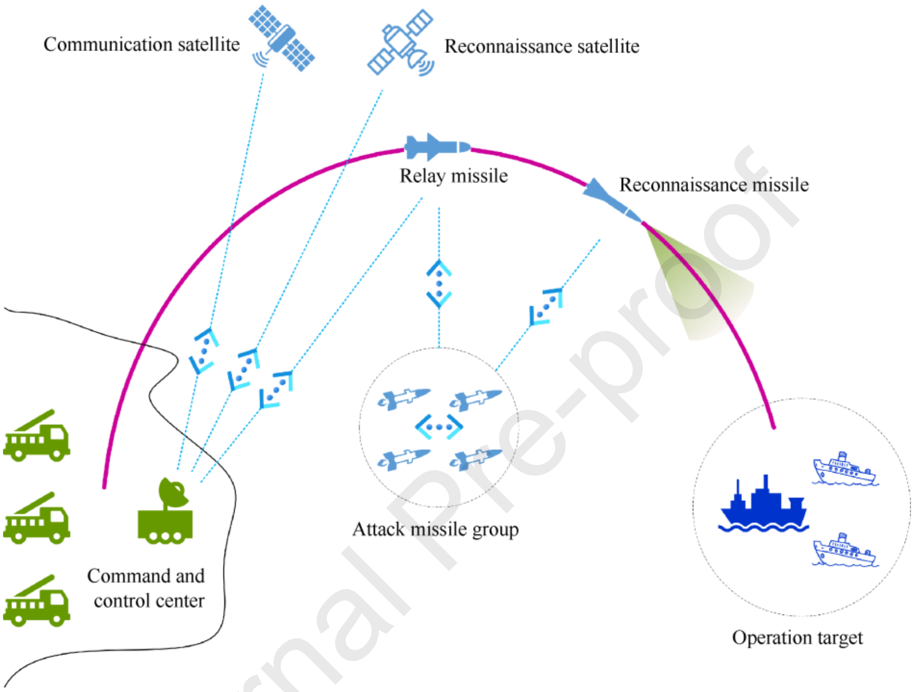

Fig. 1. Decription of cooperative operations.

Therefore, with the ongoing advancement of future systematic warfare, it is important to study how the defending party can effectively assign weapons to attacking targets [19-23] (It also applies to the offensive part). This is known as the multi-target assignment (MTA) problem, which is one of the fundamental issues in the field of military operational research [24-28]. MTA aims to solve how to optimally assign various combat weapons to multiple targets in order to achieve the commander's combat intentions [29-31]. It is also a key issue that needs to be addressed in the fields of command and control automation and intelligence. The MTA problem was first proposed by Manne when researching ballistic missile defense operational optimization, and was initially referred to as the missile allocation problem (MAP) [32]. It aimed to assign interceptors to intercept ballistic missiles that were attacking and achieve the most optimal protection for the defending party. Since then, the MAP has received wide attention from military and academic researchers in fields such as combat operational research, command and control, aerospace engineering and automation [33-35], and the basic MAP model has been gradually extended to different combat fields, becoming the well-known MTA problem today.

Indeed, the MTA problem is essentially a class of combinatorial optimization problems with characteristics such as multi-constraints, nonlinearity, and multiple objectives [36, 37]. As the types and numbers of weapons and targets increase, the number of solutions will increase exponentially. As one of the key links in control decision-making, the real-time, accuracy, and effectiveness of collaborative target assignment schemes will directly determine whether better combat effectiveness can be achieved in military confrontations and whether operational resources can be minimized. In the 1980s, Lloyd et al. [38] proved that the MTA is a non-deterministic polynomial complete (NP-C) problem with multiple parameters and constraints.

Currently, the MTA problem is also facing new challenges and development opportunities with the wide application of new technologies and equipment, such as artificial intelligence and unmanned systems in the military field. The application of unmanned systems has spawned many new combat styles, such as swarm warfare and cross-domain unmanned swarm collaborative warfare. Therefore, studying MTA technology under new combat styles based on existing MTA research will be a critical research topic in the future intelligent and unmanned combat field. This paper systematically summarizes the current development trends in the field of the MTA problem, and prospects for future development directions. The main contributions are as follows.

(I) This paper conducts a bibliometric analysis of studies related to the MTA problem in Scopus from 1985-2023, using the CiteSpace software to derive insights. The analysis encompasses the annual publication amount, keyword clustering, keyword co-occurrence, and keyword bursting. These analytical results form the basis for summarizing the current achievements in this field and outlining future development trends.

(2) This paper presents a comprehensive review of the fundamental principles of the MTA problem, including classification, analysis and solving algorithms. It examines different aspects like static multi-target assignment (SMTA) and dynamic multi-target assignment (DMTA). Additionally, a detailed analysis of the current solving algorithms in this field is provided, highlighting their respective advantages and disadvantages.

(3) In light of the existing advancements in the MTA problem, a development framework is proposed based on "HIGH" model (high-speed, integrated, great, harmonious), with a focus on high-speed confrontation demand, integrated modeling ability, great solution for performance, and harmonious command and control principles. This framework aims to provide insights for the future research in this field.

The remaining content of this paper is organized as follows. Section 2 provides an overview and summary of the MTA problem from three perspectives: development, classification, and algorithm. Section 3 proposes a development framework for the future direction of the MTA problem based on the "HIGH" model (high-speed, integrated, great, harmonious), and main conclusions are presented in Section 4.

2. Overview of MTA

2.1. Development

In this section, it aims to conduct a comprehensive study on recent trends, primary research directions, and accomplishments in the field of MTA problem using the visual analysis approach of the CiteSpace software[1]. It employs a general methodology that is suitable for analyzing and understanding the progression within different fields [42-46]. In this paper, the literature was collected from the Scopus database, and the search strategy utilized the keywords "multi-target assignment", "multi-target allocation", "weapon target assignment" or "weapon target allocation". The search period ranged from the inception of the database to 2023[2]. After screening and excluding irrelevant literature, a total of 463 papers were selected for bibliometric analysis.

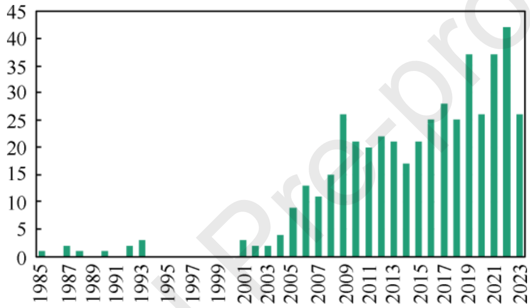

Fig. 2. Annual distribution of publications related to the MTA problem.

Based on the perspective of publication time, statistical analysis was conducted on 463 papers. According to the theory of bibliometrics, the distribution of publication years can reflect to some extent the research level and development of a field. The annual publication amount is shown in Fig. 2. In general, the evolution of the MTA problem can be roughly categorized into three phases.

(1) Between 1985 and 2004, the number of papers published each year was relatively low, with no more than 5 papers per year. This indicates that the research on MTA problems was still in its infancy, suggesting a lower level of attention and limited resources and support from the academic community or research institutions.

(2) From 2005 to 2015, there was a certain increase in the publication amount, but it did not exceed 25 papers per year. This reveals that the research on MTA problems was still in the exploration stage.

(3) After 2015, the publication amount continued to rise, indicating that the MTA problem has become a current hot topic and frontier.

Then, the data was imported into CiteSpace V.6.1.R6for transformation and analysis: The pruning operation was performed using Pathfinder and pruning sliced network methods, with the rest of the

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[1] CiteSpace is a freely available Java-based tool for visualizing and analyzing trends and patterns in scientific literature, particularly in the domain of academic citations [39-41]. It can be downloaded from https://citespace.podia.com/

[2] The data deadline for bibliometric analysis in this paper is May 2023. Although not the most recent date, trend analysis suggests that our conclusions are dependable and robust. Therefore, these data sources remain valid and useful.

parameters set to default. Based on the standard parameter settings of CiteSpace software, keyword clustering, keyword co-occurrence, and keyword burst analysis were conducted on the 463 papers mentioned above. Combining manual reading of the literature and visualization of the data, a detailed analysis of the information obtained from the results was conducted.

Fig.3 presents the result of keyword clustering based on 463 selected papers using CiteSpace software. This result consists of 430 nodes and 1013 edges, with a network density of 0.011. The clustering module value (Q value) and average silhouette value (S value) are indicators used to evaluate the effectiveness of the clustering. It is generally considered that $Q \geq 0.3$ indicates a significant clustering structure; $S \geq 0.5$ suggests a reasonable clustering, and $S \geq 0.7$ implies convincing clustering results [47-52]. It can be observed that $Q = 0.7861$ and $S = 0.9009$, indicating highly significant clustering structure and credible results.

The clustering results of the keywords can effectively reflect various research focuses within the field. As shown in Fig. 3, there are 21 labels representing 21 clusters. Each cluster label signifies a group of co-occurring keywords within the network. The cluster numbers range from #0 to #20, with higher numbers indicating fewer keywords in the cluster and conversely, lower numbers suggesting a larger number of keywords within the cluster. It can be observed that clustering numbers #O to #6 mainly focus on "optimization". This indicates that for the MTA problem, there are lots of studies centered around optimization, with multiple research achievements in this field. Clustering numbers #7 to #9 primarily focus on "allocation", highlighting that current WTA issues predominantly involve scenarios like air-to-air and air-to-ground. Additionally, these issues have progressively evolved from traditional WTA problems to encompass multi-stage WTA challenges. On the other hand, clustering numbers #10 to #20 predominantly concentrate on "constraints", encompassing aspects such as real-time processing, group targets, motion tracking, probability functions, and more. This suggests that scholars in the present stage are gradually shifting their research on the MTA problem from traditional optimization problems to addressing multi-objective optimization problems that consider the coupled influence of multiple constraint conditions. The research scenarios become more complex and closer to real combat situations.

The co-occurrence results of keywords provide a visual representation of the temporal evolution of their distribution and highlights the dynamic nature of the research frontier, which showcases the dynamic trends and provides insights for predicting future developments. As shown in Fig. 4, the horizontal axis represents the years, while the keywords are arranged in different time zones based on their first appearance. Notably, "multi-target assignment" has been a prominent research area since 1985. Over time, an increasing number of keywords emerge, indicating the continuous expansion of research fields and the incorporation of multiple disciplines. From a temporal perspective, the focus of WTA problems evolved significantly between 2000 and 2010. During this period, research primarily addressed simple single-objective scenarios, with solving algorithms predominantly relying on traditional heuristic methods. However, after 2015, the emphasis shifted towards multi-objective and multi-stage scenarios. Consequently, the algorithms developed during this later period began to incorporate learning-based approaches. These findings suggest promising research prospects in the MTA domain.

The keyword burst indicates that a potential topic has attracted special attention from scholars during a certain period. It can be used to identify emerging trends in research fields and reflect the time variation of research focus in a particular field [53, 54]. Extracting the top 20 keywords in terms of burst intensity, the *burst words" in this field from 1985 to 2023 are shown in Fig.5. In this result, "Begin" represents the year when the core topic surged, "End" represents the year when it sharply declined, and "Strength" represents the burst intensity. It can be observed that scholars have conducted extensive research on MTA problems, and there is a high overlap in the clustering keywords, indicating close collaborative connections within the field and comprehensive and in-depth research. Furthermore, the keyword "optimization" appears consistently throughout the period from 1985 to 2023, indicating that most existing research treats MTA as an optimization problem, which aligns with the understanding of this problem from a military perspective.

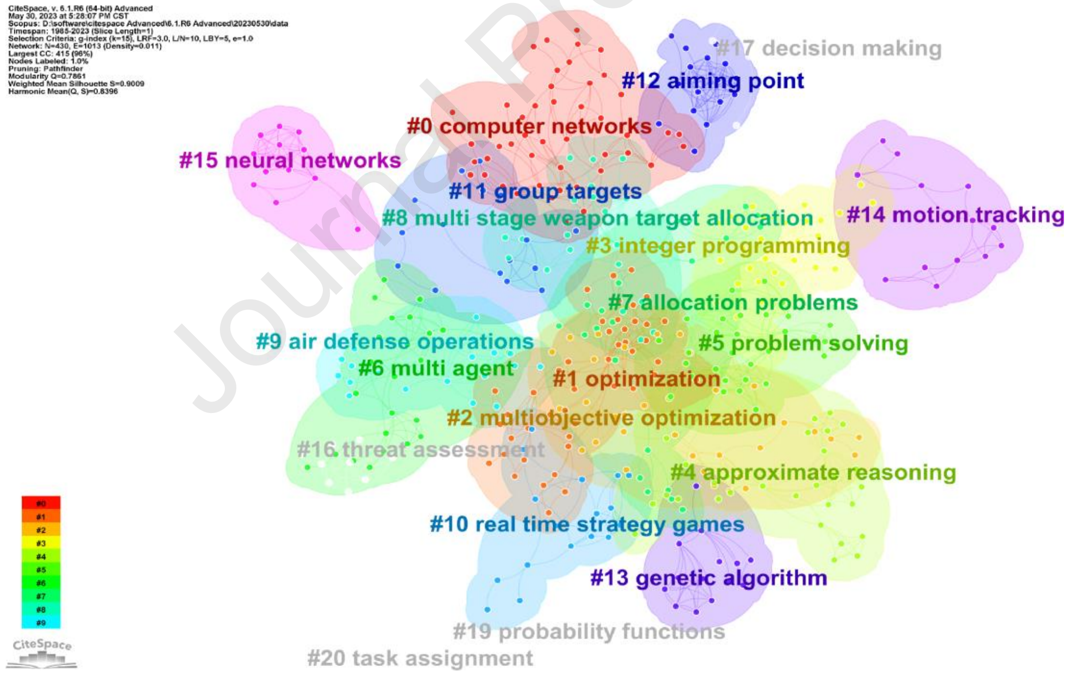


Fig. 3. Result of keyword clustering.

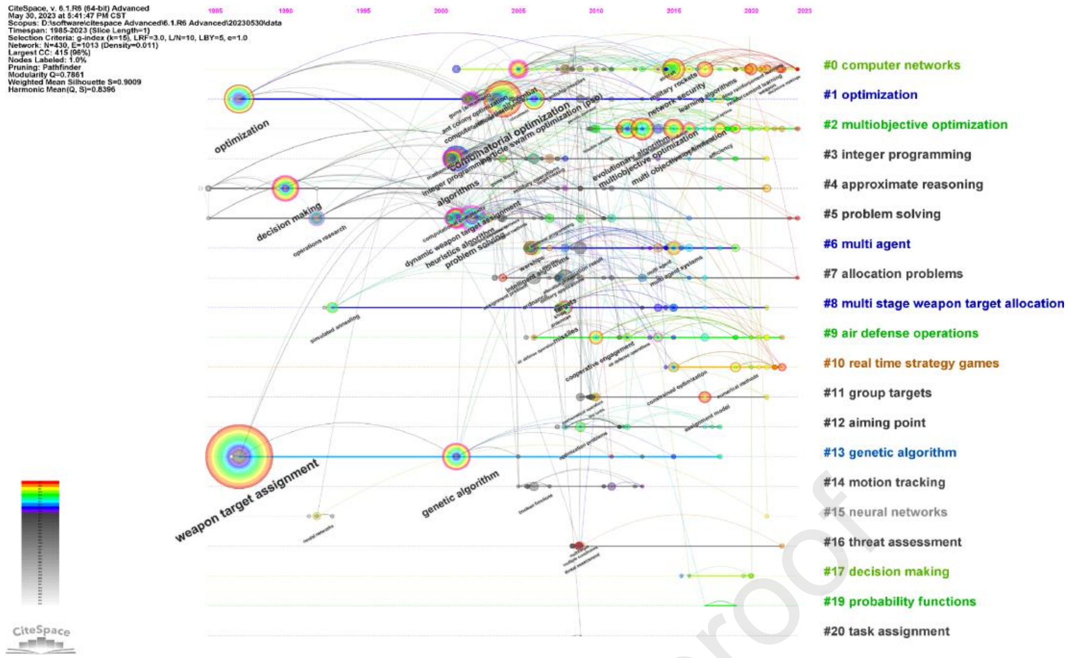
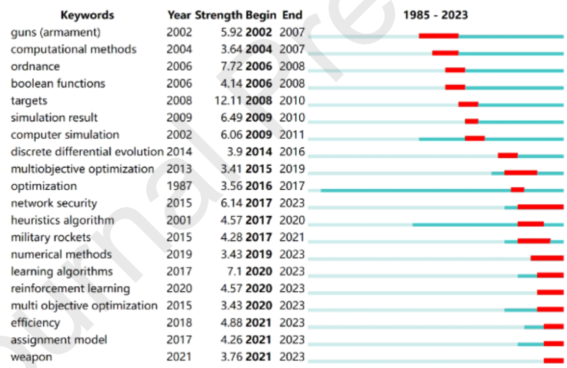


Fig. 4. Result of keyword co-occurrence.



Top 20 Keywords with the strongest citation bursts

Keywords	Year	Strength	Begin	End	1985 - 2023
guns (armament)	2002	5.92	**2002**	2007	
computational methods	2004	3.64	**2004**	2007	
ordnance	2006	7.72	**2006**	2008	
boolean functions	2006	4.14	**2006**	2008	
targets	2008	12.11	**2008**	2010	
simulation result	2009	6.49	**2009**	2010	
computer simulation	2002	6.06	**2009**	2011	
discrete differential evolution	2014	3.9	**2014**	2016	
multiobjective optimization	2013	3.41	**2015**	2019	
optimization	1987	3.56	**2016**	2017	
network security	2015	6.14	**2017**	2023	
heuristics algorithm	2001	4.57	**2017**	2020	
military rockets	2015	4.28	**2017**	2021	
numerical methods	2019	3.43	**2019**	2023	
learning algorithms	2017	7.1	**2020**	2023	
reinforcement learning	2020	4.57	**2020**	2023	
multi objective optimization	2015	3.43	**2020**	2023	
efficiency	2018	4.88	**2021**	2023	
assignment model	2017	4.26	**2021**	2023	
weapon	2021	3.76	**2021**	2023	

Fig. 5. Result of keyword burst.

2.2. Classification

Based on the introduction of time variables, existing MTA problems can be divided into two categories: SMTA and DMTA problems. SMTA aims to solve the target assignment plan for the moment based on the current offensive and defensive situation. Specifically, since it does not take time factors into account, the allocation results are instantaneous. However, DMTA introduces time variables and thus can be regarded as the multi-stage assignment of targets. The first stage is similar to SMTA, while the subsequent target allocation plan is influenced by the effectiveness of the attack in the previous stage, and the remaining weapons are used to continue allocating to targets that have not yet been effectively attacked.

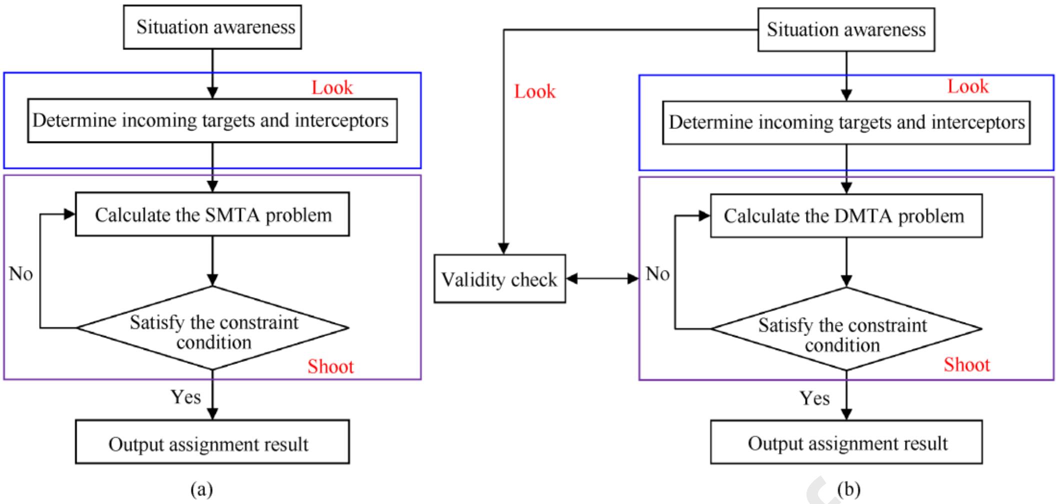


Fig. 6. The target allocation process of MTA problems.

2.2.1. SMTA

The premise of the SMTA problem is generally based on the assumption that all detection information of incoming targets has been obtained, including the number of targets, payload, reachable attack range, and other attributes. Moreover, the number and attributes of the targets are assumed to remain constant, as well as the allocated interceptor group. On this basis, SMTA problems complete target interceptions immediately after the allocation schemes are generated, without considering changes in the battlefield situation. Therefore, it can be simplified as a nonlinear integer programming problem under predefined constraints. Assuming that there are m interceptors and n incoming targets, with $m \geq n$ to ensure sufficient interceptor coverage for each target. The following constraints are generally considered as well.

Assumption1. [55] Each interceptor must be assigned to at least one target.

Assumption 2. [56] Each interceptor can be assigned to at most one target.

In SMTA problems, only one allocation calculation is considered. Thus, based on the look-shoot strategy, the target allocation process of the SMTA problem is illustrated in Fig. 6(a). Here, a typical SMTA modeling framework is presented. In the SMTA process, the defense party can use detection information to estimate the threat level of all incoming targets, thereby determining the interception priority for each target. The threat level of each target in the group is defined as $\boldsymbol{T} = [T_1, T_2, ..., -T_n]$. Therefore, the interceptor-target allocation scheme can be described as

$$\boldsymbol{Z} = \begin{pmatrix} z_{11} & \cdots & z_{1n} \\ \vdots & z_{ij} & \vdots \\ z_{m1} & & z_{mm} \end{pmatrix} \tag{1}$$

where $1 \leq i \leq m$ and $1 \leq j \leq n$ denote the i-th interceptor and the j-th target, respectively. z_{ij} denotes the weight of allocating target j to interceptor i, with a value of either O or l. Specifically, if $z_{ij} = 0$, it indicates that target j is not allocated to interceptor i.

Given the information on target and interceptor attributes, it is possible to compute or estimate the corresponding probability of successful interception. The probability matrix P for successful interception can be defined as follows.

$$\boldsymbol{P} = \begin{pmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & z_{ij} & \vdots \\ p_{m1} & & p_{mm} \end{pmatrix} \tag{2}$$

where P_{ij}, denotes the probability that interceptor *i* successfully intercepts target *j*.

Thus, based on Eq. (1) and Eq. (2), the probability ***P***, that target *j* is successfully intercepted can be described as

$$P_j = 1 - \prod_{i=1}^{n} \left(1 - p_{ij}\right)^{z_{ij}} \tag{3}$$

Therefore, the SMTA problem can be transformed into the optimization problem of performance indicators under constraints. Based on Eqs. (1)- (3), the sum of the product of each target's threat level and interception success rate can be calculated and denoted as the multi-objective indicator *E*.

$$E = \sum_{j=1}^{n} z_{ij} = 1 \tag{4}$$

where *E* evaluates the quality of the generated allocation scheme, and the constraint condition is expressed as

$$\sum_{j=1}^{n} z_{ij} = 1 \tag{5}$$

Table 1

Typical modeling methods for the SMTA problem.

Studies	Year	Main characteristics
Manne [32]	1958	The original formulation of the SMTA problems
Soland [33]	1973	Introducing the game theory into the problem
Kwon et al. [57]	1999	Converting the problem into an integer programming problem by establishing a linear objective function and non-linear constraints.
Ahujo [58]	2007	Applying a logarithmic transformation to the objective
Li et al. [59]	2009	Transforming the allocation problem into a binary program by limiting the number of interceptors of each type to one.
Rosenberger et al. [60]	2005	Transforming the allocation problem into a knapsack one by assuming that each target can only be assigned one interceptor.
Karasakal [61]	2008	Considering all defended objectives to be equally important and aims to maximize the anticipated damage to incoming targets.
Shalumov et al. [62]	2017	Applying the multi-agent theory into the problem

Currently, based on the study conducted by Manne in 1958, various modeling methods have been discussed for SMTA problems considering different constraints or simplifications. These methods can be summarized as shown in Table 1.

2.2.2. DMTA

The DMTA problem usually considers that the combat situation changes in real time during the engagement process, such as the number of incoming targets, movement status and other relevant parameters, and the interceptors can make real-time dynamic supplementary changes, etc. Therefore, the interception success probability of the interceptor against any target will also change in real time.

In order to consider the interception suitability of DMTA problems, based on the study in Ref. [63], several fundamental concepts are introduced as follows.

Definition l. Visual time window t_v, this refers to the period in which the target is visually exposed (detected)to a potential interception from the defensive part, indicating the possibility of the target being intercepted within this time window.

Definition 2. Engagement time window t_e. This refers to the minimum time required for the interceptor to lock and attack its target, which is determined by the combined response time of the defense system and the flying or guiding time of the interceptor.

Definition 3. Interception time window t_a. It refers to the period where the interceptor has the ability to achieve a successful interception against its target.

Then, based on the above definitions, it can be derived that $t_a = t_v - t_e$. Furthermore, it is evident that in order to effectively intercept the target, it is necessary to ensure that $t_v > t_e$, in the DMTA problem.

Generally, according to the look-shoot-look strategy [29, 61], the target allocation process of the DMTA problem is presented in Fig. 6(b). This problem can be approached as a series of SMTA processes, with a frequency of ta time units, during which the interceptor updates the combat situation and computes an optimal allocation strategy until the interception task is completed. Because the DMTA model is more complex, the research on this problem is just in the initial stage. Specifically, based on the performance of the battlefield observation orientation-decision-action (OODA) chain, it is generally anticipated that $t_d \geq t_a$.

Remark 1. Research on the multi-stage MTA problem concentrates on the division of one's own weapons into multiple stages or waves in order to effectively engage incoming targets. The objective is to optimize the allocation of weapon resources during the multi-stage combat process, given specific conditions. This problem falls under a relatively unique category of MTA problems and is occasionally considered as part of the DMTA problems.

Remark 2. As shown in Fig.7, the difficulty of the DMTA problems is influenced not only by dynamic changes in the time dimension but also by the impact of uncertainties on the allocation process. These uncertainties primarily come from the spatial, time, and information dimensions, which are coupled with time, resulting in a highly complex allocation calculation process.

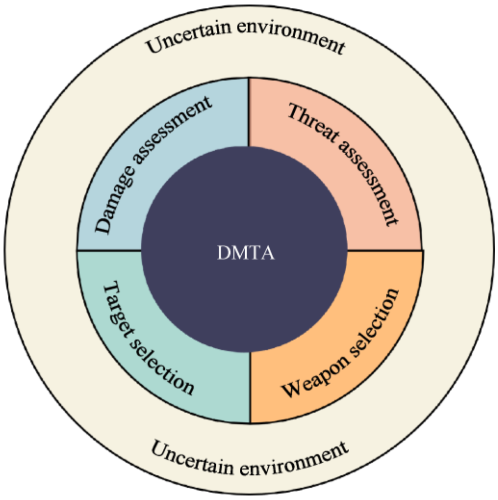


Fig. 7. Coupled analysis of DMTA problems.

2.3. Analysis

Using Fig. 8 as a reference, assume that there are three "attackers" attacking the "operational target", with four "interceptors" defending against the "attackers" to protect the "operational target". This scenario illustrates the key features of the MTA problem. The current research on the MTA problem mainly focuses on problem modeling and algorithm design. Generally, the analysis process of his type of problem mainly includes the following four steps.

(1) Model assumptions. There are various uncertainties or factors that cannot be accurately determined in actual battlefields. Therefore, it is necessary to make reasonable assumptions when constructing the model to highlight the main research content.

(2) Establishing the objective function. There are two main types of objective functions for the MTA problem, based on offensive and defense parties, respectively [64]. In the first strategy, the task is to minimize the threat value of the attacker in the process of surprise defense; in the later one, the task is to maximize the operational effectiveness of the defender in the interception process.

(3) Selection of constraints. In the process of solving the MTA problem, it is necessary to fully consider the weapon performance, interception strategy equipment and ammunition quantity, operational feasibility, and other constraints so that the final assignment result meets the actual operational requirements [65].

(4) Solution algorithm design. Given the constraints, the objective function is solved to obtain the optimal allocation scheme. The solution algorithm is required to have high speed, accuracy, and real-time capability.

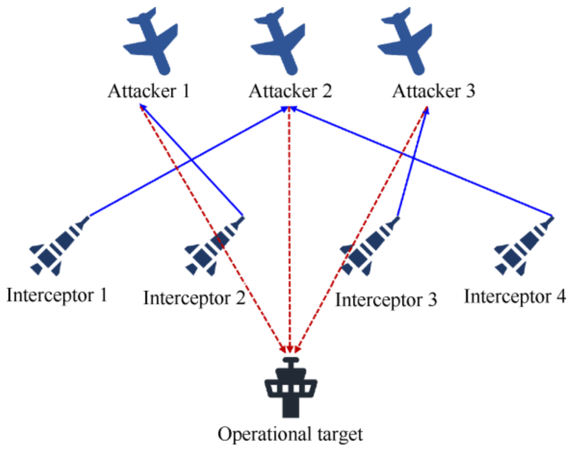


Fig. 8. Schematic diagram of the MTA problem (The blue arrow in the figure indicates the defensive interception by the "interceptors" against the "attackers", while the red arrow indicates the attack by the "attackers" on the "operational target".)

Among the four aforementioned steps, step 2 is of paramount importance. The core of this step lies in the modeling of target threat attributes (which holds true from both the offensive and defensive perspectives). Target threat attribute modeling primarily involves two components: threat element extraction and threat index modeling. Only through meticulous modeling and analysis of the target's threat attributes can the optimal allocation of targets be achieved. Using an air defense and anti-missile combat scenario as an example, a concise analysis of target threat attribute modeling is presented as follows.

In actual combat scenarios, a wide range of information is typically gathered about the target, including its nature, type, speed, acceleration, path angle, fight height, fight time, and interference capability. This attribute information encom-passes both quantitative and qualitative descriptions. Consequently, due to the threat capabilities and attack intentions of aerial targets, threat element extraction primarily focuses on two attributes: capability and intention. Additionally, to integrate both subjective and objective factors in assessing threat attributes, the subjective judgment of decision-makers in air and missile defense is also considered as a threat element. And a detailed calculation example of objective function for the MTA problem is presented in Appendix A Section.

As depicted in Fig. 9, among various threat attributes, target type, speed, and interference intensity are directly related to the target's threat capability; Route shortcut, flight height and flight time reveal the target's attack intentions; Subjective judgment reflects the preferences of decision-makers in air and missile defense. Building on the aforementioned threat attributes of aerial targets, a model can be developed to quantify the threat level associated with these attributes in the subsequent target allocation process.

Remark 3. The SMTA problem can be regarded as a one-time allocation process with relatively low coupling between uncertainties and the allocation process. Thus, compared to the SMTA problem, DMTA requires dynamic identification of targets and determination of available weapons. Consequently, the solving algorithms must have excellent real-time performance to make timely decisions on target allocation.

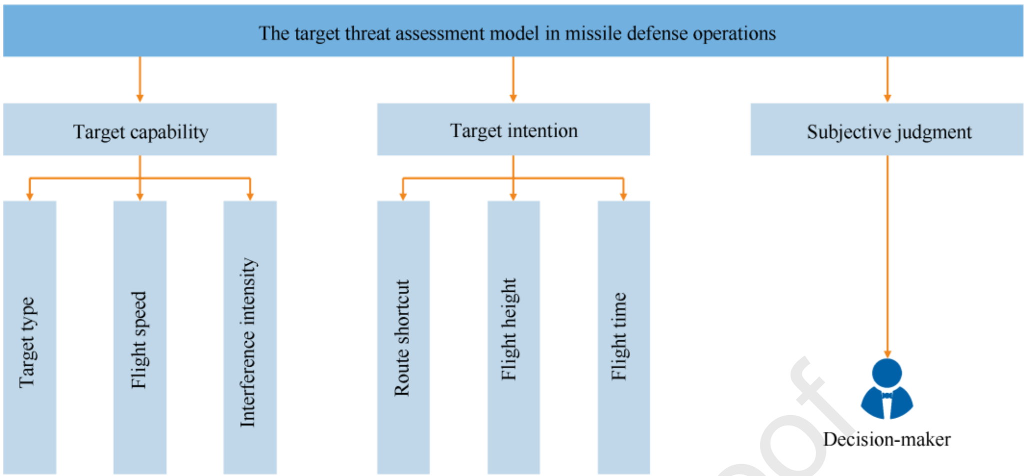


Fig. 9. Target threat assessment model in missile defense operations.

2.4. Algorithm

Given the NP-complete nature of MTA problems, developing efficient solving algorithms has long been a research focus and challenge in this domain. Currently, these algorithms are broadly categorized as exact algorithms and approximate algorithms. Among approximate algorithms, the main categories include rule-based heuristic algorithms and machine learning algorithms. The main algorithm classification is illustrated in Fig. 10.

2.4.1. Exact algorithm

The exact algorithms commonly employed to solve MTA problems involve the enumeration method, branch-and-bound method, dynamic programming method and Hungarian method.

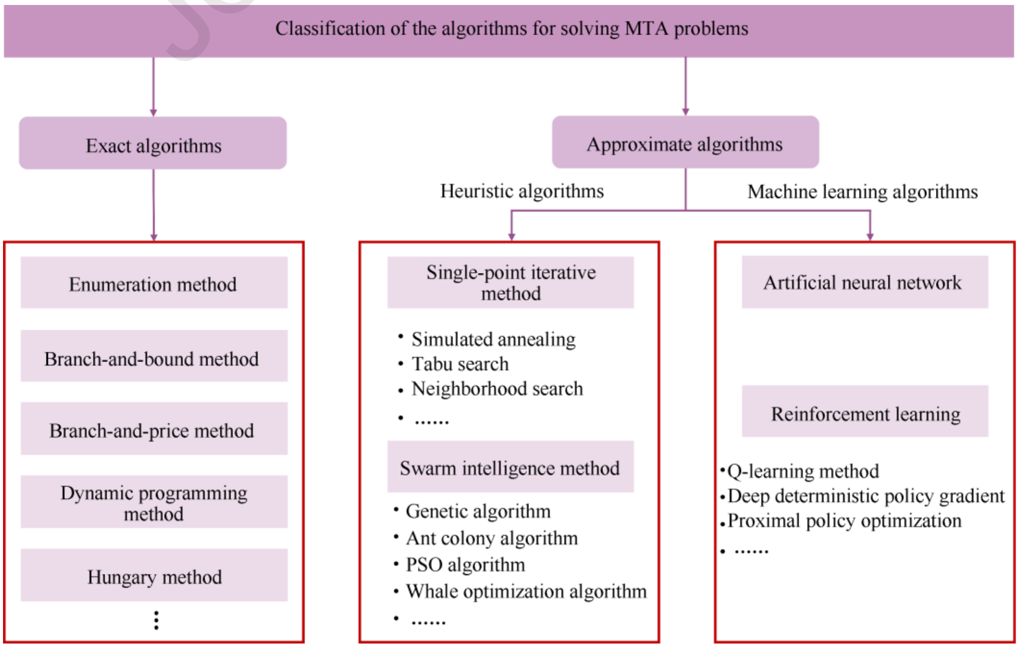


Fig. 10. Classification of the algorithms for solving MTA problems.

(1) Enumeration method

This method is based on the assumption that the number of possible allocation results is finite [66-69]. It involves identifying all feasible solutions that meet the constraint function, calculating the corresponding performance indexes for each solution, and then selecting the allocation scheme that yields the best performance index. This approach is particularly suitable for solving MTA problems with a limited number of potential allocation results. In response to the challenge of selecting discrete levels of reliable subtractive area and point defenses to safeguard a group of targets against ballistic missiles, Soland [33] developed a scheme that integrates enumeration and branch-and-bound techniques. The objective is to minimize the overall damage inflicted on the targets by an optimal attack conducted by a specified quantity of reliable offensive missiles of a single kind.

(2) Branch-and-bound method

This method is commonly used for solving integer programming problems [70-73]. It involves repeatedly partitioning the entire feasible solution space into smaller and smaller subsets, known as branches. For each subset, an objective lower bound is calculated (for minimization problems), which is referred to as bounding. After each branching, subsets that have bounds exceeding the known objective value of feasible solutions are no longer further branched, eliminating many subsets from consideration. This is known as pruning. The remaining subsets are added to the feasible set, and a branching node is selected from the feasible set for expansion. This process continues until a feasible solution is found or the feasible set becomes empty. Rosenberger et al. [60] expanded upon the basic MTA problem by introducing the possibility of multiple target assignments per platform, and the problem was formulated as a linear integer programming problem. Based on this formulation, an algorithm was developed using the branch-and-bound framework. This algorithm enumerates feasible tours of assets/resources, which can be computationally intensive when dealing with a large number of sources and targets. Meanwhile, it ensures that an optimal solution is found. Simulation results demonstrated the practical applicability of these methods and their usefulness in tasks such as sensor tasking and resource allocation problems. Kline et al. [74] proposed a nonlinear branch-and-bound approach for solving the MTA problem using an untransformed non-linear model. Additionally, two heuristics were developed based on a branch and bound algorithm and the optimal solution to the quiz problem. Simulation results substantiated that the proposed algorithm exhibits excellent convergence performance, capable of solving large-scale problems in a fraction of the time, typically within ten thousandths. Additionally, by combining the branch-and-bound and column generation methods, some improved solutions referred to as branch-and-price schemes were investigated in Refs. [75-78].

(3) Dynamic programming method

The dynamic programming method is commonly employed to solve problems that exhibit certain optimal characteristics [24, 79-82]. These types of problems often have numerous feasible solutions, each associated with a specific value. The objective is to identify the solution that offers the optimal value. The fundamental principle involves breaking down the problem at hand into smaller, solvable subproblems. By initially solving these subproblems and subsequently integrating their solutions, we can obtain the answer to the original problem. This approach also entails storing the solutions to previously addressed subproblems in a table for easy retrieval. In this way, unnecessary repetitive computations are avoided, leading to significant time savings. A tabular structure is frequently used to record the answers to all subproblems, regardless of their future utility. Based on the study conducted by Ahuja et al. [58], Lu et al. [83] developed an integer linear programming (ILP) model to linearly represent the exact solution for the MTA problem. Additionally, to reduce the number of possible columns in the ILP, they employed branch-and-price method. The average execution time of our exact algorithm for solving the instances mentioned in Ref. [58] was 4.68 seconds. Especially, the algorithm took less than 108 seconds for the most challenging case, and only 0.40 seconds for the case involving 80 weapons and 80 targets.

Bertsekas [24] transformed the MTA problem into a dynamic programming (or Markovian) decision problem. To address the computational intractability caused by the large number of states and complex modeling issues, a neuro-dynamic programming framework was utilized. In this framework, neural network architectures were trained on simulated data to approximate the cost function. This approach effectively avoids the computational challenges associated with exact methods. Ahner et al. [84] investigated a two-stage MTA problem, where the first stage tasks are known and the arrivals of second stage tasks follow a random distribution. To determine optimal allocation strategies, a combination of simulation and mathematical programming was employed within a dynamic programming framework. The unique structure of the allocation problem was utilized to recursively update functional approximations that represent future rewards using subgradient information.

(4) Hungary method

The Hungarian method is a combinatorial optimization algorithm that solves the assignment problem in polynomial time [85-88]. It is widely used in the field of operations research. Zhang et al. [89] conducted a comparative analysis of the time consumption and stability between the traditional Hungarian algorithm and intelligent optimization algorithms. Their findings demonstrate that the establishment of an adaptable Hungarian algorithm for all types of MTA problems, achieved through the proposal of a unified efficiency matrix. To address the issues of low efficiency in network air defense operations and the difficulty in evaluating target assignment schemes, Zhang et al. [90] proposed a model for the efficiency function of network cooperative fire control using an improved Hungarian algorithm. This improved algorithm enables the one-time allocation of weapon targets without the need for repeated transformation of the cost matrix. Inspired by the Hungarian algorithm, Du et al. [91] proposed a novel approach that incorporates special weighting factors to determine the optimal allocation process based on the applicant's cost and benefit. This scheme is applicable for both square and non-square cost matrices, and exhibits a similar time consumption as the traditional Hungarian algorithm.

Overall, the exact algorithm is highly effective in resolving small-scale MTA problems. However, as the problem scale increases, the number of variables and constraints also increase, leading to a considerable increase in the time complexity of this approach. This will result in the occurrence of "combinatorial explosion" phenomenon. Considering the large number of parameters involved in practical battlefield scenarios, the exact algorithm requires a significant amount of time for calculations, making it unsuitable for solving large-scale MTA problems.

2.4.2. Heuristic algorithm

The heuristic algorithms are commonly adopted to solve MTA problems includes single-point and multi-point iterative methods.

(l) Single-point iterative method

The single-point iterative method generates another solution based on a single solution in each iteration, which can be seen as searching and jumping point by point in the solution space to gradually improve the current solution. Luo et al. [92] introduced an improved simulated annealing algorithm for the optimization of command, control, communication, and information in air defense systems. Their approach utilized iterative length to determine the annealing temperatures and employed an optimal solution reserve. The simulation results demonstrated that this algorithm exhibited robust capabilities in locating optimal solutions and achieved rapid convergence. Since the simulated annealing algorithm is easy to fall into the local optimal solution, Fu and Wang [93] introduced the greedy algorithm into it to propose a greedy simulated annealing algorithm. This facilitates a local greedy search after each iteration to explore additional solutions and enhance the overall quality of the solution. As a result, this modification enhances the effectiveness of the allocation process. Xin et al. [65] proposed a comprehensive asset-based model for solving the DMTA problem, which incorporates capability constraints, strategy constraints, and resource constraints. The model utilizes virtual permutation and tabu search methods to achieve optimal decision-making in real-time DMTA scenarios. This approach demonstrates competence in delivering high-quality decision makings.

Chang et al. [94] studied the multi-stage MTA problem with an emphasis on the attacking flexibility for targets in different stages. They developed a binary nonlinear integer programming model and introduced an improved adaptive large-scale neighborhood search (ALNS) algorithm. The simulation results showed that, in most cases, the ALNS algorithm outperformed both exact methods and metaheuristics in terms of achieving higher-quality solutions in a shorter time period. Ahuja et al. [58] proposed an exact algorithm to solve the general MTA problem. Their approach employs a set of lower bounding schemes that provide a lower bound for the problem, as well as a very large-scale neighborhood searching algorithm that yields an approximate solution. This method is capable of obtaining the exact solution for medium-sized instances (e.g., 80 weapons and 80 targets); however, it requires a long execution time (16.2 hours) [95].

(2) Swarm intelligence method

Since the early 1960s, numerous researchers from various fields have shown great interest in many swarm optimization algorithms, which have gained widespread attention and possess unique advantages in optimization problems. Li et al. [59] proposed a genetic algorithm (GA) to address the MTA problem with spatial constraints. In their approach, a chromosome was encoded as a binary matrix with "forbidden bits" representing the constraints. Additionally, they introduced a novel operator called "circle-swap" to serve as a functional mutation operator for the matrix-type chromosome with forbidden bits. This can ensure the validity of the chromosome as a solution throughout the allocation process. Regarding the problem of DMTA, Kong et al. [96] devised an improved multi objective particle swarm optimization (MPSO) algorithm. They incorporated various learning strategies for the dominated and non-dominated solutions of the algorithm to facilitate targeted learning and evolution. Additionally, to overcome the issue that the algorithm easily falls into local optimum, they included a search strategy based on simulated binary crossover (SBX) and polynomial mutation (PM). This strategy allowed for the exchange of elitist information between the external archive and enhanced exploratory efficiency. On this basis, an adaptive simulated annealing-particle swarm optimization strategy was proposed by Liu et al. [37] for the air-ground MTA problem. They incorporated adaptive improvements into the traditional PSO algorithm and combined it with the simulated annealing algorithm. This integration aims to enhance the convergence speed and overcome the drawback of the PSO algorithm easily getting trapped in local extreme points. The strategy exhibited excellent performance in terms of convergence speed and global optimization capabilities.

In recent years, with the development of various bio-inspired optimization algorithms [97-103], they have also been applied to the MTA problem. Zhang et al. [27] introduced the whale optimization algorithm (WOA)as a solution to the MTA problem. The objective was to optimize combat effectiveness by fairly allocating weapon unit resources from weapon systems to threat targets, while determining the optimal decision matrix. Rezende et al. [104] combined the ant colony optimization with the greedy strategy to solve the MTA problem considering large scale air combat scenarios. Simulations results demonstrated that the proposed algorithm can obtain high-quality results and have a fast convergence performance. To address the slow convergence rate and low search efficiency in solving the DMTA problem, Chang et al. [29] proposed an improved artificial bee colony (ABC) algorithm. This algorithm incorporated a novel initialization method that utilizes rule-based heuristic factors. In addition, they introduced a ranking selection and elite guidance mechanism to improve the search efficiency of the ABC algorithm. Especially, the heuristic factor initialization method was combined with the improved ABC algorithm for the DMTA problem, which utilizes integer encoding based on the characteristics of DMTA.

In general, heuristic algorithms have are relatively simple algorithm framework and are capable of solving large-scale MTA problems. They also require shorter computation time. However, most of these algorithms are based on specific rules, resulting in lower adaptability, robustness, and stability 2.4.3. Machine learning algorithm

In 2000, Bertsekas et al. [24] firstly adopted Neural Dynamic Programming (NDP) strategy to solve the missile defense problem. NDP is a type of reinforcement learning method that handles the curse of dimensionality by using approximate cost-reward functions based on neural networks. It does not require an explicit system model but uses a simulator as a substitute model to train neural network structures and obtain suboptimal strategies. In recent years, with the rapid development of artificial intelligence technology, machine learning algorithms have gained widespread attention in the field of MTA research [25, 105, 106, 107, 108, 109]. Li et al. [25] proposed an intelligent model for the SMTA problem using deep reinforcement learning method. This approach addressed the challenges faced by traditional algorithms in terms of modeling difficulties and low search efficiency. Additionally, they constructed a Markov Decision Process (MDP) for MTA tasks based on this planning and solving model. The experimental results demonstrated that this proposed model effectively generated satisfactory solutions in both small-scale and large-scale scenarios. In order to address the issues commonly encountered when applying existing task assignment methods to ground-to-air confrontation, such as low efficiency in handling complex tasks and interactive conflicts in multiagent systems, Liu et al. [105] proposed a multiagent architecture known as the one-general agent with multiple narrow agents (OGMN). Additionally, considering the sluggish performance of traditional dynamic task assignment algorithms, they developed the proximal policy optimization for assignment process of general and narrow agents (PPO-TAGNA) algorithm. This algorithm can enhance the assignment process for both general and narrow agents.

For the MTA problems considering dynamic environment and multiple constraints, machine learning algorithms still demonstrate enormous potential for applications [107, 28, 34, 110]. Unbalanced scheduling of unmanned ground combat vehicles and inadequate target strikes are prevalent in complex urban battlefields. Wang et al. [28] introduced a novel architecture for multi-weapon target assignment and developed a multi-objective artificial bee colony (MOABC) algorithm with an elite strategy. Additionally, to address the impact of the mutation operator on multi-objective assignment, they proposed an improved deep Q- learning network with a self-adaptive variation operator and integrated the state representation of the nectar source with the overall allocation scheme. Shokoohi et al. [107] proposed a reinforcement learning-based solver for the problem of dynamic distributed constraints in the DMTA problem. Their approach demonstrated that reinforcement learning techniques can provide an alternative solution method over time, with computational efficiency surpassing that of sequential distributed constraint optimization problem solvers. Karasakal et al. [34] introduced a new solution for the DMTA problem in a naval task group. They focused on rescheduling surface-to-air missiles (SAMs) that were already scheduled to intercept anti-ship missiles (ASMs). They utilized a bi-objective model to maintain high efficiency while handling dynamic disruptions, considering both the efficiency of SAM systems and the schedule stability. In addition, they proposed a novel approach to assist decision-makers in selecting a Pareto optimal solution that addresses the time-sensitivity of rescheduling decisions and the enormous amount of information to be processed. Liu et al. [110] introduced a "time sampling DWTA model" This model segmented the decision-making process by establishing specific time intervals for data collection. By doing so, it effectively captures real-time fluctuations in the target threat level, enabling prompt decision-making. To enhance the efficiency of calculations, the Proximal Policy Optimization (PPO) method was employed to address this model. Li et al. [111] developed an improved Deep Deterministic Policy Gradient (DDPG) algorithm to address the traditional DWTA problem. This algorithm incorporates a double noise mechanism to broaden the action search range and introduces a prioritized experience replay mechanism. Compared to other reinforcement learning algorithms, the agent trained with the improved DDPG demonstrates a higher win rate and greater rewards during confrontations. Consequently, it exhibits superior allocation results.

In general, machine learning algorithms have the ability to continuously learn and evolve, and well-trained models have good allocation performance. However, these algorithms require significant computational resources, which can easily lead to the "curse of dimensionality", Additionally, they have poor interpretability and still have ample room for further research.

Overall, the representative studies on different solving algorithms for MTA problems are summarized in Table 2, along with their advantages and disadvantages. From an algorithmic perspective, enhancing the effectiveness of solving the MTA problem continues to be an area of notable research significance and promise in both the present and future periods.

Table 2

Summary of the algorithms for solving MTA problems

Attribute	Classification	Studies	Advantages	Disadvantages
Exact	Enumeration	[33]	The given problem can be solved to obtain an exact optimal solution, which is easy to	Difficulty in solving large-scale problems; Accurate mathematical models are.
	Branch-and-bound	[60]		
	Branch-and-price	[75-78]		
	Dynamic programming	[83,24,84]		

	Hungary	[83,24,84]	comprehend and implement	Generally required
Hounristic: single point	Simulated annealing	[92,93]	The algorithm framework can be easily implemented and allow for extensive exploration of the solution space.	The algorithm exhibits long computational time and lacks robustness.
	Tabu search	[65]		
	Neighborhood search	[58,94]		
Heuristic: swarm intelligence	Genetic algorithm	[59]		The allocation results highly depend on the rules, and it is generally prone to getting trapped in local optima.
	Ant colony algorithm	[104]		
	PSO algorithm	[37]	The algorithm effectively leverages domain-specific knowledge to achieve fast solving time and high efficiency.	
	Whale optimization	[27]		
Machine learning	Artificial neural network	[34]	The algorithm can continuously learn and evolve, showing a high execution efficiency.	The algorithm requires high-quality training data and powerful computing capabilities and has poor interpretability.
	Reinforcement learning	[28, 105, 106, 110, 111]		

3. Future prospects

Indeed, the MTA problem belongs to the fundamental and challenging issues in the fields of command control and mission planning. Over the past 80 years of development, the MTA problem has gone through several stages and the related research has gradually become diverse and deepened. As shown in Fig. 11, this paper proposes a development framework based on the "HIGH" model[3] (high-speed, integrated,

3 The name "High" is derived from the initial letters of the four short sentences: high-speed, integrated, great, harmonious.

great, harmonious), focusing on the application scenarios, modeling mechanisms, solution algorithms, and system efficiency of the MTA problem, and provides prospects for its future development direction.

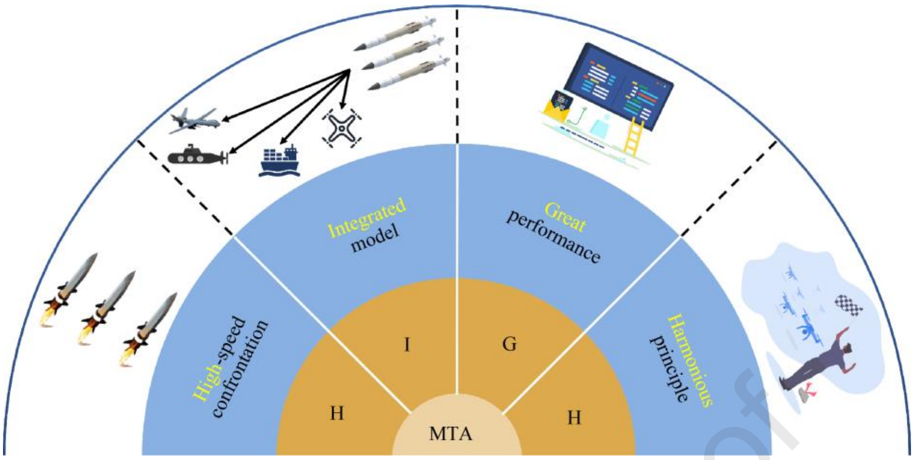


Fig. 11. Description of the development framework for the MTA problem based on the "HIGH" model (high-speed, integrated, great, harmonious).

3.1. High-speed confrontation demand

The MTA problem has expanded from typical defense operations such as ground defense, naval defense, and aerial interception to various operational domains including air, space, land, sea, and electromagnetic warfare. In recent years, with the continuous development of high-speed-related technologies, military powers worldwide are actively developing new conventional strategic strike capabilities represented by high-speed vehicles [112-116]. These efforts aim to advance the process of high-speed vehicles from technological breakthroughs, demonstration, and validation to weaponization across various platforms such as sea, land, air, and space. The emergence of high-speed vehicles completely breaks down the traditional boundaries between air and space defense, pushing warfare into a high-speed and high-confrontation era [117, 118, 119]. As shown in Fig. 12, high-speed vehicles have been used many times in actual combat in the "Russia-Ukraine conflict".

Fig. 12. Hypersonic vehicles have been used in the "Russia-Ukraine conflict" (On March 18. 2022, the Russian military employed the "Dagger" high-speed missile to attack a significant underground missile and aviation ammunition depot of the Ukrainian armed forces in Ivano Frankivsk Oblast, located in the western region of Ukraine. This marked the inaugural deployment of high-speed weapons in actual

combat, historically unprecedented [120, 121]).

The MTA problem related to such targets involves elements in the domains of air, space, land, sea, and electromagnetic warfare. As relevant technologies mature, high-speed vehicles will undoubtedly trigger the evolution and innovation of operational styles, tactics, and strategies, profoundly impacting the battlefield environment. Currently, countries around the world lack effective defense capabilities against high-speed vehicles, and basic research in this field is still in its early stages. Therefore, expediting cross-domain target allocation problem research focused on scenarios involving high-speed vehicles in offensive and defensive confrontations is crucial in promoting the intelligent development of future weapon systems.

3.2. Integrate modeling ability

The integration of information systems has become a fundamental form of warfare in future warfare, leading to conflicts and contradictions in various dimensions such as time, space, frequency, tasks, and effects between both offensive and defensive parties. Furthermore, with the development and evolution of concepts such as mosaic warfare, cross-domain operations, and collaborative operations, combat units in future warfare will be interwoven and interconnected across air, land, sea, and electromagnetic domains. These combat units exhibit diverse physical attributes, and it is of paramount importance to fully leverage and take into account their unique features in MTA problems. This highlights the importance of efficiently utilizing these combat units. In recent years, modeling methods in the field of MTA have expanded from mathematical programming techniques such as integer and mixed integer programming to include game theory, dynamic programming, multi-agent systems, network flow, and other methods. Notably, it is essential to establish integrated MTA models that consider the coupling and coordination between different units, taking into account external uncertainties, while expanding the application capabilities of the DMTA problems. This forms the foundation for addressing MTA challenges in future warfare.

3.3. Great solution for performance

Due to the NP-hard nature of MTA, solving algorithms has always been a focus of research in this field. Scholars have attempted various exact algorithms and intelligent optimization algorithms to solve the MTA problem. With the iterative updates of warfare modes, future MTA problem-solving algorithms face demands such as large-scale systems, systematic applications, high real-time computing, and limited computing resources. Traditional exact algorithms cannot meet these requirements. With the development and updates of artificial intelligence, machine learning, and other related theories, it is feasible to enhance the ability to solve MTA problems by researching offline deep training learning and online rapid application solution algorithms. At the same time, improving the rules of attack and defense between different combat units and accelerating the improvement of computer hardware resources can effectively promote the efficient application of future solution algorithms and assist in generating more suitable MTA solutions.

It is worth noted that the recent rise and rapid development of Large Language Models (LLMs) have significantly invigorated the approach to MTA problems. LLMs offer several advantages over traditional learning methods, including reduced cost, enhanced learning efficiency, and greater convenience and flexibility [122-125]. Their extensive knowledge base, strong generalization capabilities, and proficient logical reasoning and information integration skills position them as valuable assets for advancing the field of MTA in the future.

3.4. Harmonious command and control principles

In fact, the MTA problem permeates every aspect of warfare and is highly B: intertwined with the OODA combat chain. However, existing research has paid little attention to the integration of the MTA problem with fields such as command and control, reconnaissance-strike fusion, and effectiveness evaluation, 2 thus lacking potential practical applications in future warfare. It is crucial to achieve efficient strike/defense of targets through reasonable target allocation. Therefore, establishing a harmonious and integrated command and control principle, bridging the MTA problem with the OODA combat chain, can not only enhance combat effectiveness but also provide more favorable decision-action instructions for commanding officers, ensuring that the offense-defense confrontation leans towards the advantageous side.

4. Conclusions

This paper provides a systematic review and synthesis of the MTA problem, focusing on four aspects: basic development, problem classification, modeling methods, and solution algorithms. Additionally, bibliometric analysis of this research field is conducted using the CiteSpace software. Based on these findings and considering the new challenges brought by intelligent and collaborative warfare, we analyze the development trends of the MTA problem and propose a development framework based on the "HIGH" model, providing reference for future research.

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Data Availability Statement

To obtain the literature data utilized for CiteSpace analysis in this paper, please reach out to the corresponding author.

Appendix A. An example calculation of the objective function for the MTA problem

This section provides a detailed calculation example of objective function for the MTA problem based on Fig. 9, specifically focusing on target capability and target intention [37, 126, 127].

Appendix A.1.Target capability

Target capability encompasses three primary components: target type, speed, and interference intensity.

(1) Target type

Based on expert assessments and specialized knowledge, aerial threats can be categorized according to their level of threat. Researchers generally classify aerial targets into four main categories: the first category includes tactical ballistic missiles, air-to-ground missiles, and anti-radiation missiles, denoted as s_1; the second category consists of large bombers, denoted as s_2; the third category comprises fighter-bombers, denoted as s_3; and the fourth category includes helicopters, denoted as S_4- Additionally, decoys and false targets are classified as the fifth category, denoted as s_5. Consequently, the model for target type is structured as follows.

$$T_{\text{type}} = \begin{cases} \text{type}_{s_2};\ x = s_1 \\ \text{type}_{s_2};\ x = s_2 \\ \text{type}_{s_3};\ x = s_3 \\ \text{type}_{s_4};\ x = s_4 \\ \text{type}_{s_5};\ x = s_5 \end{cases} \tag{A1}$$

where x denotes the target type, and a corresponding threat level is determined based on the incoming target's type.

(2) Flight speed

Flight speed serves as an indicator of how easily the defending party can capture a target. A higher speed target can evade missile strikes more readily and reach the attacked location more quickly, thus decreasing the missile's attack possibility. Conversely, slower targets find it more challenging to escape missile action, requiring less firepower to achieve successful defense and thus representing a lower threat level. Assuming the target's flight speed V_T ranges from 0 to 500 m/s, the model for flight speed is formulated as follows.

$$T_v = \begin{cases} v_{\mathrm{T}} / 64 - 0.3, & 0 \le v_{\mathrm{T}} \le 300 \\ (v_{\mathrm{T}} - 315)/56 - 0.3, & 300 < v_{\mathrm{T}} \le 351 \\ (v_{\mathrm{T}} - 336)/216 - 0.05, & 351 < v_{\mathrm{T}} \le 445 \\ (v_{\mathrm{T}} - 365)/226 + 0.12, & 445 < v_{\mathrm{T}} \le 480 \\ (v_{\mathrm{T}} - 480)/456 + 0.68, & 480 < v_{\mathrm{T}} \le 500 \end{cases} \tag{A2}$$

(3) Interference intensity

Due to electronic interference by the target during the confrontation, the missile will be subject to interference during interception. A common way to model interference intensity is as follows.

$$T_{\mathrm{r}} = \begin{cases} 1, & \text{Very strong} \\ 0.8, & \text{Strong} \\ 0.5, & \text{Moderate} \\ 0.2, & \text{Weak} \\ 0, & \text{No} \end{cases} \tag{A3}$$

Appendix A.2.Target intention

Target's attack intentions usually consist of three primary components: route shortcut, fight height and flight time.

(1) Route shortcut

Shortcut route parameter is essential for evaluating the threat level posed by an incoming target to the defender. It quantifies the proximity of the incoming target to the attacked target. This parameter typically measures the distance from the attacked target to the Closest Point of Approach (CPA). The CPA represents the point along the target's trajectory that is nearest to the attacked target. The distance r_{cpa} between the attacked target and the CPA directly reflects the threat level. A greater distance indicates a lower threat, while a smaller distance signifies a higher threat. A common method for modeling route shortcut is outlined as follows.

$$T_{\mathrm{CPA}} = \begin{cases} 1 - r_{\mathrm{CPA}} / 400, & 0 \le r_{\mathrm{CPA}} \le 5 \\ (12 - r_{\mathrm{CPA}})/460 + 0,98, & 0 < r_{\mathrm{CPA}} \le 10 \\ (22 - r_{\mathrm{CPA}})/1000 + 0,78, & 10 < r_{\mathrm{CPA}} \le 15 \\ (27 - r_{\mathrm{CPA}})/1000 + 0,58, & 15 < r_{\mathrm{CPA}} \le 22 \\ (30 - r_{\mathrm{CPA}})/1000 + 0,58, & 22 < r_{\mathrm{CPA}} \le 30 \\ (40 - r_{\mathrm{CPA}})/8000 + 0,02, & 30 < r_{\mathrm{CPA}} \le 40 \end{cases} \tag{A4}$$

(2) Flight height

Flight height parameter measures the altitude at which a defense system must engage an incoming target. A higher altitude indicates that the missile must fly higher, reducing the threat posed by the target and increasing the likelihood of successful interception. Conversely, a lower altitude suggests that the target is closer to the defense system, thereby increasing the threat level. Consequently, the model for flight height h is structured as follows.

$$T_h = \begin{cases} 1, & 0 \le h \le 800 \\ e^{-10^{-8}(h-800)^2}, & h>800 \end{cases} \tag{A5}$$

(3) Flight time

Flight time serves as a key parameter for assessing the threat level of a target. A shorter flight time indicates that the incoming target can reach the attacked target quickly, thereby posing a greater threat. Conversely, a longer fight time suggests that the target is unlikely to pose an immediate threat to the attacked target. The following outlines a common method for modeling fight time t_{arrive}.

$$T_{\text{arrive}} = \begin{cases} 3\left(170 - t_{\text{arrive}}\right)/150, & 0 \le t_{\text{arrive}} \le 115 \\ 2\left(237 - t_{\text{arrive}}\right)/250 + 0.4, & 15 < t_{\text{arrive}} \le 230 \\ 2\left(362 - t_{\text{arrive}}\right)/550 + 0.5, & 30 < t_{\text{arrive}} \le 355 \\ 3\left(487 - t_{\text{arrive}}\right)/550 + 0.57, & 55 < t_{\text{arrive}} \le 480 \\ \left(525 - t_{\text{arrive}}\right)/100 + 0.5, & 80 < t_{\text{arrive}} \le 510 \\ 1.5\left(740 - t_{\text{arrive}}\right)/600 + 0,38, & 110 < t_{\text{arrive}} \le 460 \\ 1.5\left(1370 - t_{\text{arrive}}\right)/1390, & 140 < t_{\text{arrive}} \le 1350 \end{cases} \tag{A6}$$

Remark 4. Subjective judgment assesses a decision maker's ability and intention to evaluate the current threat. Specific threat values should be determined based on the actual situation, thus omitting the need for a specific mathematical model.

Remark 5. Utilizing the established target threat assessment mode land the specific guidance laws of the missile, along with Eq. (4), we can formulate a general objective function F designed to minimize the survival probability of enemy targets.

$$F = \min \sum_{j=1}^{n} T_j \left[1 - \prod_{i=1}^{n} \left(1 - p_{ij}\right)^{z_{ij}} \right] \tag{A7}$$

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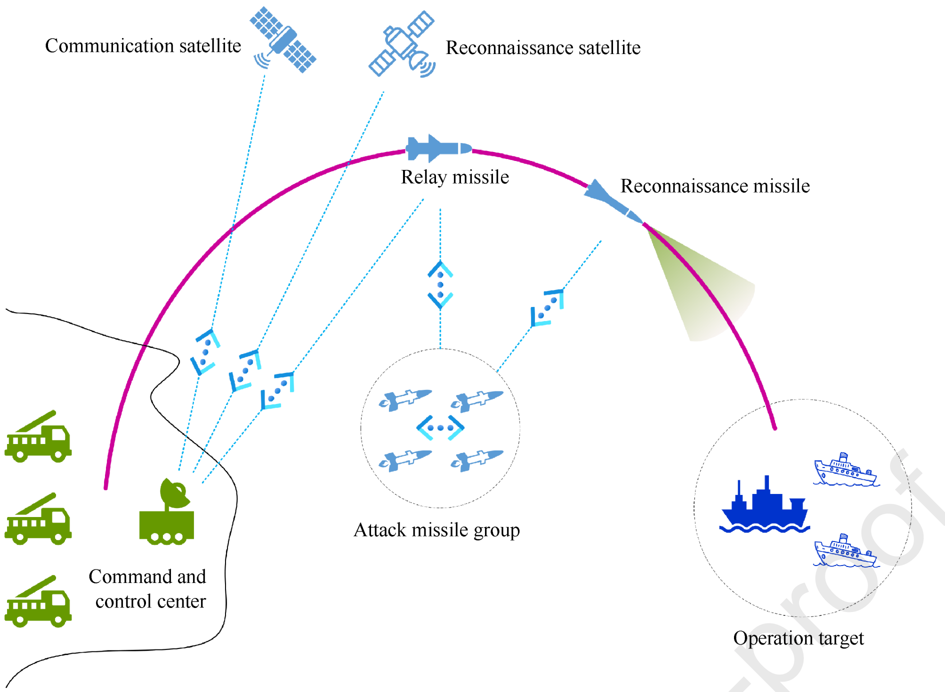
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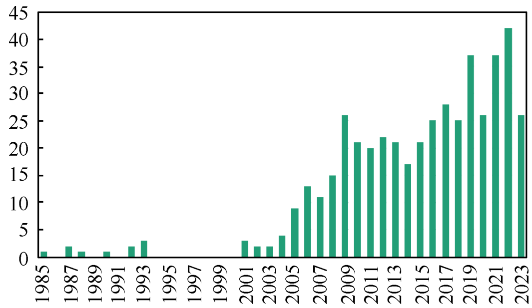
Reconnaissance satellite
Relay missile
Reconnaissance missile
Attack missile group
Command and control center
Operation target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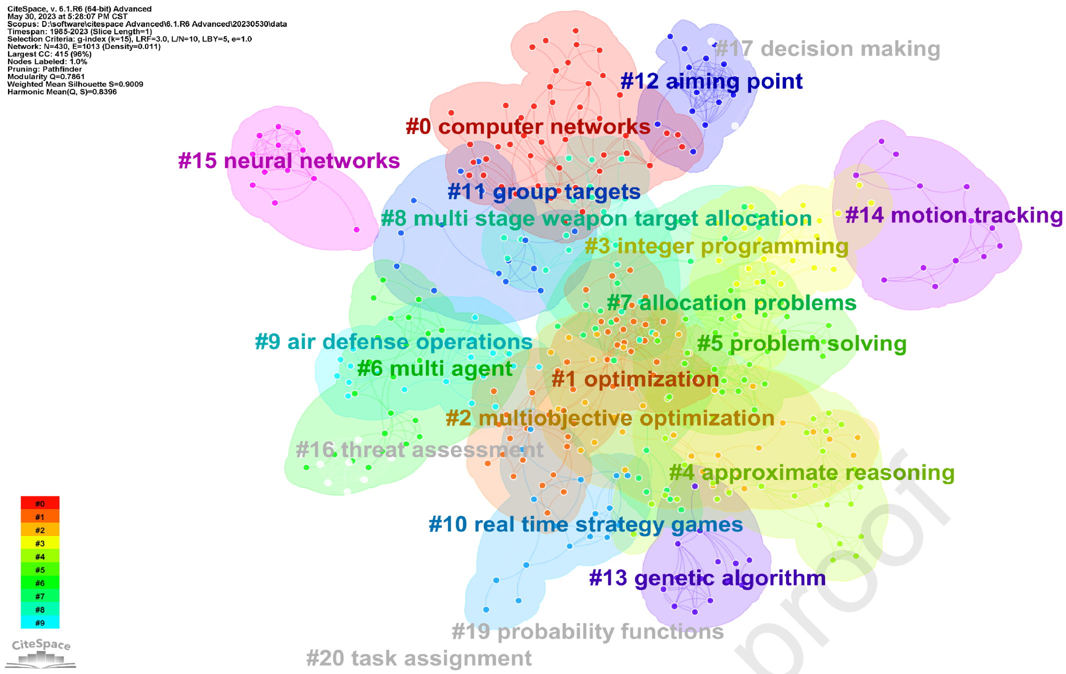
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Network: N=430, E=1013 (Density=0.011)
Largest CC: 415 (96%)
Nodes Labeled: 1.0%
Pruning: Pathfinder
Modularity Q=0.7861
Weighted Mean Silhouette S=0.9009
Harmonic Mean(Q, S)=0.8396
#17 decision making
#12 aiming point
#0 computer networks
#15 neural networks
#11 group targets
#8 multi stage weapon target allocation
#14 motion tracking
#3 integer programming
#7 allocation problems
#9 air defense operations
#5 problem solving
#6 multi agent
#1 optimization
#2 multiobjective optimization
#16 threat assessment
#4 approximate reasoning
#10 real time strategy games
#13 genetic algorithm
#19 probability functions
#20 task assignment
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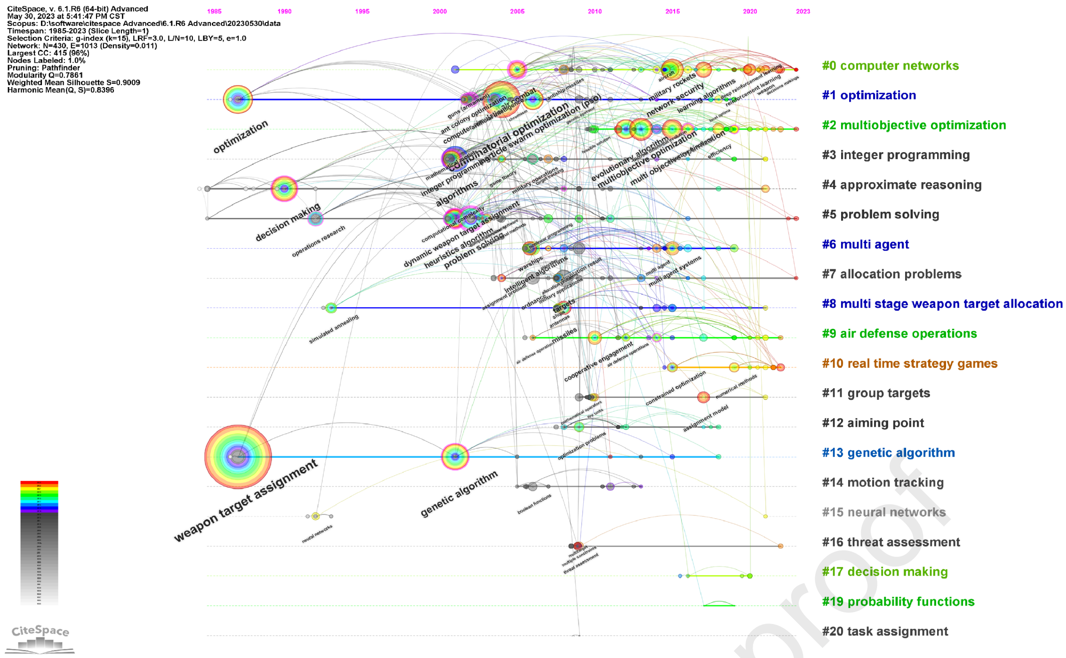
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optimization
decision making
weapon target assignment
genetic algorithm
combinatorial optimization
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#5 problem solving
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#7 allocation problems
#8 multi stage weapon target allocation
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#11 group targets
#12 aiming point
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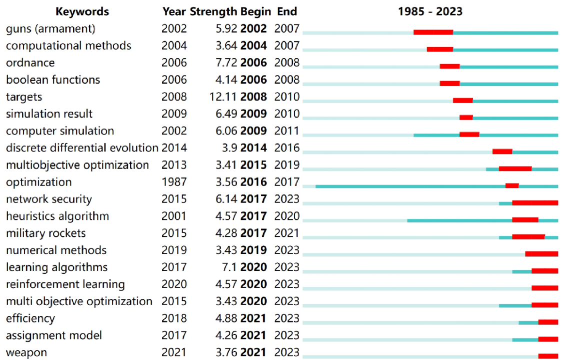
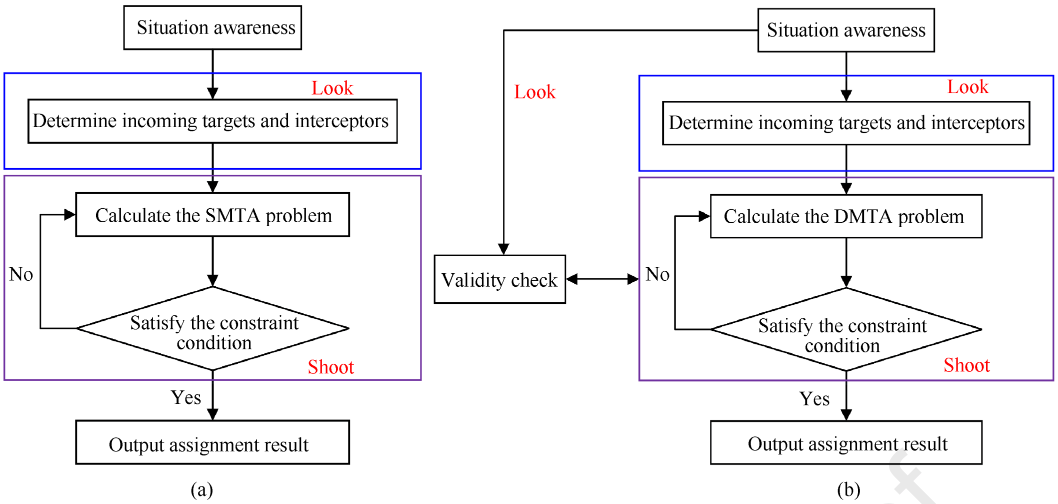
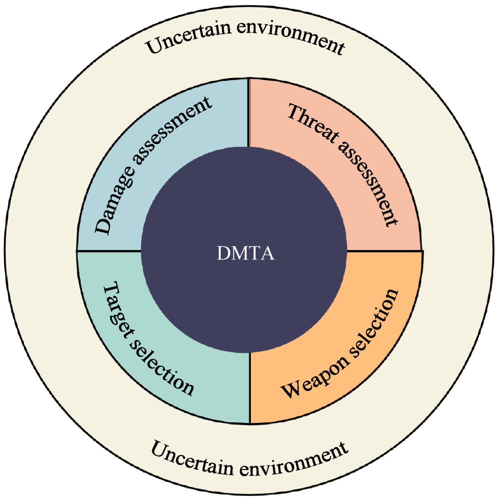
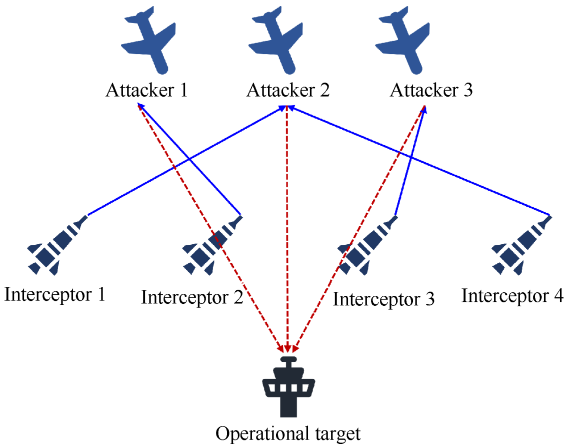
Top 20 Keywords with the strongest citation bursts

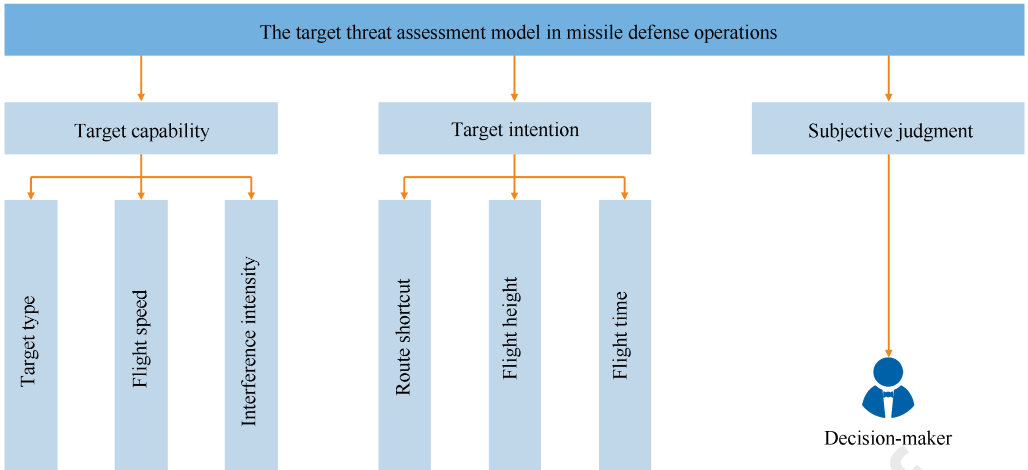


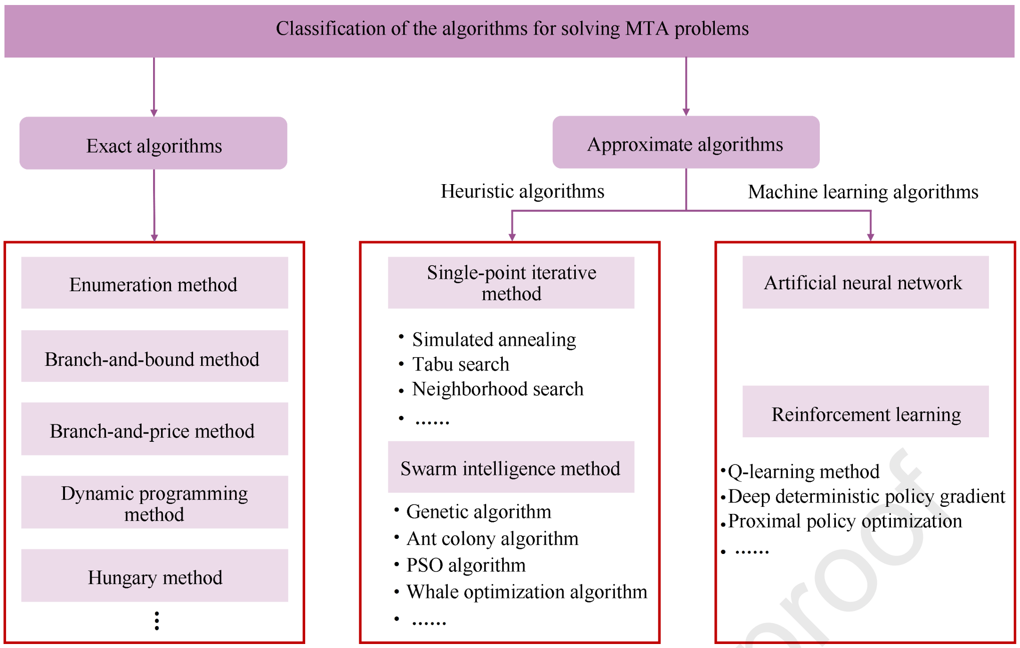

Situation awareness
Look
Determine incoming targets and interceptors
Calculate the SMTA problem
No
Satisfy the constraint condition
Shoot
Yes
Output assignment result
(a)
Look
Validity check
Situation awareness
Look
Determine incoming targets and interceptors
Calculate the DMTA problem
No
Satisfy the constraint condition
Shoot
Yes
Output assignment result
(b)

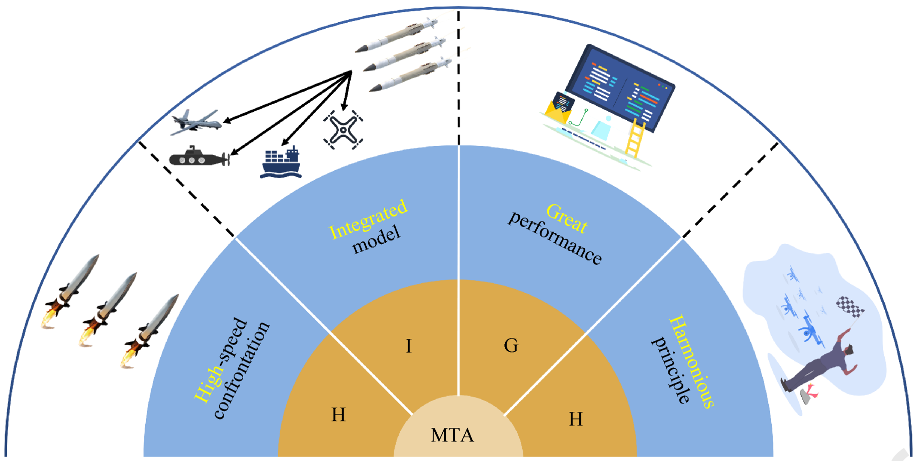

Uncertain environment
Damage assessment
Threat assessment
DMTA
Target selection
Weapon selection
Uncertain environment



Attacker 1
Attacker 2
Attacker 3
Interceptor 1
Interceptor 2
Interceptor 3
Interceptor 4
Operational target


The target threat assessment model in missile defense operations
Target capability
Target intention
Subjective judgment
Target type
Flight speed
Interference intensity
Route shortcut
Flight height
Flight time
Decision-maker


Classification of the algorithms for solving MTA problems
Exact algorithms
Approximate algorithms
Heuristic algorithms
Machine learning algorithms
Enumeration method
Branch-and-bound method
Branch-and-price method
Dynamic programming method
Hungary method
Single-point iterative method
Simulated annealing
Tabu search
Neighborhood search
......
Swarm intelligence method
Genetic algorithm
Ant colony algorithm
PSO algorithm
Whale optimization algorithm
......
Artificial neural network
Reinforcement learning
Q-learning method
Deep deterministic policy gradient
Proximal policy optimization
......


High-speed confrontation
Integrated model
Great performance
Harmonious principle
H
I
G
H
MTA


...for the first time
to destroy an
underground arms depot...

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The author is an Editorial Board Member/Editor-in-Chief/Associate Editor/Guest Editor for *[Journal name]* and was not involved in the editorial review or the decision to publish this article.

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