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Simulation and Machine Learning in Beyond Visual Range Air Combat: A Survey

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ABSTRACT Beyond Visual Range (BVR) air combat is an essential part of modern aerial warfare, relying on advanced radar, missile systems, and decision-support technologies. This survey provides a comprehensive overview of how simulation and Machine Learning (ML) tools have been used to analyze BVR combat, covering key methodologies, applications, and challenges. We examine how ML enables adaptive tactics to improve behavior recognition and threat assessment to enhance situational awareness. The paper also traces the historical evolution of BVR combat, outlining key engagement phases such as detection, missile launch, and post-engagement assessment. A key focus is on the role of simulation environments in modeling realistic combat scenarios, supporting pilot training, and validating AI-driven decision-making strategies. We analyze state-of-the-art simulation tools, comparing their capabilities and limitations for studying multi-agent coordination and real-time adaptability. This survey's main contributions include descriptions of ML applications in BVR air combat, evaluations of simulation tools, identifications of research gaps, and insights into future research directions. This work provides an overview of how traditional simulation approaches merge with artificial intelligence to enable advanced, effective human and autonomous decision-making systems in dynamic and contested environments.

INDEX TERMS Beyond visual range air combat, machine learning, modeling, simulation.

I. INTRODUCTION

Beyond Visual Range (BVR) air combat is a key component of modern aerial warfare, characterized by engagements occurring at distances beyond the pilot's visual sight [1]. It relies heavily on advanced radar systems, long-range missiles, and detection and tracking methods to neutralize adversaries before visual contact [2]. As the nature of air combat evolves, BVR engagements have grown in importance, demanding innovative approaches to overcome the challenges posed by long-range confrontations. The strategic significance of BVR air combat lies in its ability to allow forces to strike first while maintaining a tactical advantage [3]. However, the complexity of these engagements requires interdisciplinary technologies – including sensor fusion, target tracking, decision-making algorithms, and missile guidance systems [4], [5] – to improve engagement effectiveness, ensure mission success, and enhance pilot Situational Awareness (SA) [6].

Within Visual Range (WVR) air combat engagements occur within relatively short ranges, often involving close-range dogfighting maneuvers reliant on agility, speed, and aiming precision [7], [8]. In contrast, BVR engagements leverage advanced sensors and long-range missiles to outperform adversaries [9]. Despite this difference, BVR scenarios can transition into WVR combat as aircraft close in, requiring capabilities in both domains [10], [11].

This survey comprehensively overviews state-of-the-art methods and technologies in BVR combat, highlighting recent advancements and strategic approaches. It begins with

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a historical overview of BVR combat, tracing its evolution from early Air-to-Air Missile (AAM) systems to modern multi-sensor platforms. This perspective highlights key technological advancements and their impact on engagement strategies. Next, we examine the core phases of BVR engagements, including detection, missile launch, support, and evasive maneuvers, illustrating how methods discussed in this survey contribute to operational effectiveness. We then review key methodological approaches, such as Machine Learning (ML) algorithms for adaptive decision-making in dynamic environments and the role of Artificial Intelligence (AI) in engagements and autonomous tactics. Practical applications range from pilot decision-support systems to Unmanned Aerial Vehicles (UAV) operations. Finally, we highlight the importance of simulation tools in tactical development, pilot training, and algorithm validation. Both general-purpose and specialized platforms are discussed in the context of modeling complex combat scenarios.

To our knowledge, this is the first dedicated survey that examines simulation and ML applications in BVR combat. Existing reviews on air combat either provide a more general overview or mention BVR only as a secondary topic [12], [13], [14], [15], [16], [17], [18]. Most discussions on ML for long-range engagements are limited to related work sections of individual papers, offering only partial insights without a structured synthesis of methodologies and applications. Unlike previous works, this survey covers research across multiple studies, providing a comprehensive perspective on how ML and simulation enhance decision-making and engagement strategies. In addition, we analyze available simulation tools, highlighting their capabilities, limitations, and suitability for different applications. In this work, we also identify open challenges and research gaps that remain unexplored, offering guidance for future studies.

The key contributions of this survey are:

- A comprehensive review of ML methodologies applied to BVR, detailing their role in decision-making and autonomous tactics
- An analysis of simulation tools, comparing their capabilities and limitations for modeling realistic combat scenarios
- Identification of key challenges in integrating ML and simulation for improved tactical decision-making
- A perspective on research trends, outlining open questions and guiding future advancements in the field

A. A BRIEF HISTORY OF BVR AIR COMBAT

The origins of BVR air combat trace back to the Cold War, an era defined by rapid technological innovation and an escalating arms race. Early radar-guided missiles, such as the AIM-7 Sparrow, provided the first glimpse of long-range engagements, allowing pilots to strike adversaries from unprecedented distances [19]. However, these early systems suffered from limited accuracy and vulnerability to Electronic Countermeasures (ECM), leading to mixed performance outcomes in real-world scenarios [20].

In the 1960s and 1970s, the United States and the Soviet Union invested heavily in BVR capabilities, creating more sophisticated missile systems and advanced radar technologies. The AIM-54 Phoenix missile, used by the U.S. Navy's F-14 Tomcat, was one of the first missile systems capable of simultaneously engaging multiple targets at long ranges, contributing to a shift in air combat doctrine [21]. This missile was designed to provide air defense against Soviet bombers and their anti-ship missiles, significantly extending the engagement envelope of carrier-based aircraft [22]. The introduction of the AIM-54 Phoenix marked a key moment in BVR combat, highlighting the potential of long-range engagements [23]. However, the missile's large size and weight and reliance on inertial navigation and semi-active radar homing during the initial and midcourse phases presented operational challenges [24]. Despite these drawbacks, the Phoenix's range and speed made it an important weapon in the U.S. Navy's arsenal [25].

The 1980s and 1990s brought transformative progress with the introduction of the AIM-120 AMRAAM (Advanced Medium-Range Air-to-Air Missile). The AMRAAM's active radar homing capability enabled "fire-and-forget" tactics, allowing pilots to launch and then maneuver without maintaining radar lock, reducing their exposure to threats [24], [26]. Its compact size, compatibility with various platforms, and enhanced resistance to ECM made it a versatile and reliable weapon [27]. The adoption of the AMRAAM by NATO forces highlighted the need for compatible systems and common tactics in multinational operations [28].

In the 21st century, advancements in radar, Electronic Warfare (EW), and missile technology have significantly influenced BVR combat. Modern platforms like the F-22 Raptor and F-35 Lightning II utilize Active Electronically Scanned Array (AESA) radars, low-observable (stealth) airframes, and advanced sensor fusion systems to avoid detection and improve SA [22], [29], [30], [31]. Data links and network-centric warfare features further support coordination and target-sharing among allied forces, facilitating adaptive engagement strategies [32], [33]. EW has also played a pivotal role in shaping BVR tactics. Modern aircraft employ advanced countermeasures to disrupt enemy systems and protect themselves from incoming threats [34].

Looking ahead, the future of BVR combat will be driven by technological breakthroughs such as hypersonic missiles, which promise extended engagement ranges and drastically reduced reaction times [35]. Additionally, integrating AI and autonomous systems is expected to revolutionize BVR engagements. Unmanned platforms collaborating with human pilots can enhance decision-making, improve SA, and reduce operational risks [36], [37].

B. PHASES OF BVR AIR COMBAT

The phases of BVR air combat (Figure 1) consist of the following steps: detection, threat assessment, tactical maneuvering, missile engagement, and post-engagement

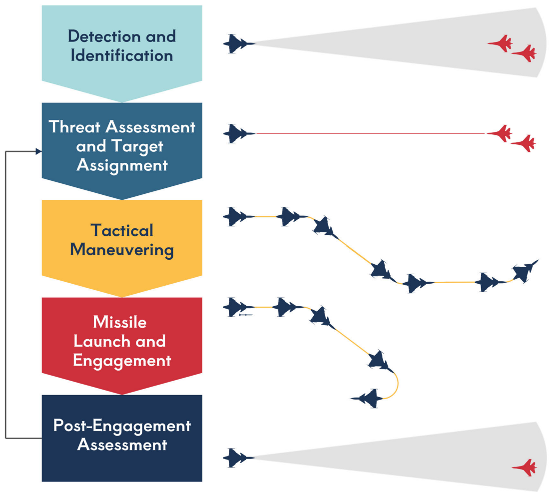

FIGURE 1. **Phases of BVR air combat.**

assessment. Advances in sensor technology, AI, and constructive simulations have significantly enhanced these phases, leading to more effective air combat strategies [38].

1) DETECTION AND IDENTIFICATION

The first phase of BVR combat is detecting and identifying enemy aircraft using advanced radar systems. These systems enable long-range target detection, allowing pilots to identify threats well before visual contact [10]. Typically, the process begins when an aircraft enters hostile airspace; radar systems are activated to search for opponents, eventually locking onto a detected target [39]. This early detection is critical to achieving a strategic advantage by enabling preemptive actions [40].

2) THREAT ASSESSMENT AND TARGET ASSIGNMENT

Once targets are detected, the next phase involves assessing their threat level and selecting the primary target for engagement. This decision-making process combines human expertise with increasingly sophisticated AI-driven systems. Methods such as Bayesian optimization and Artificial Neural Networks (ANN) have been developed to enhance decision-making [38]. Effective target selection is essential, as it dictates subsequent engagement strategies and directly influences mission outcomes [40].

3) TACTICAL MANEUVERING

Following target selection, aircraft perform tactical maneuvers to achieve optimal missile launch positions while evading enemy threats. This phase may include coordinated formations and adaptive flight maneuvers [41]. Tactical decisions involve balancing offensive positioning, evasion techniques, and maintaining favorable missile launch parameters [42]. Aircraft may perform specific maneuvers, such as cranking, to confuse enemy sensors and minimize exposure [43]. AI and ML have further refined these tactics, enabling complex, autonomous behaviors in simulations [44].

4) MISSILE LAUNCH AND ENGAGEMENT

The engagement phase is often divided into three stages:

(I) **Launch phase**: The missile is fired once the target enters the Weapon Engagement Zone (WEZ). At this stage, missiles may rely on initial guidance from the aircraft or transition directly to onboard sensors [45].

(II) **Midcourse support phase**: During this stage, the missile advances toward the target while the launching aircraft reduces its exposure to threats. Depending on the missile type, the aircraft may provide midcourse guidance, or the missile may operate autonomously using its internal systems [45].

(III) **Terminal phase**: In the final stage, the missile activates its onboard sensors to track and intercept the target autonomously. Modern "fire-and-forget" missiles excel in this phase, as they minimize the need for ongoing guidance, allowing the pilot to reposition or prepare for subsequent engagements [10], [40].

Effective missile engagement strategies weigh the probability of successfully neutralizing the target against the risk to the launching aircraft, making this phase decisive for determining BVR combat outcomes [46].

5) POST-ENGAGEMENT ASSESSMENT

The final phase involves assessing the outcome of the engagement to determine if additional actions are required. This assessment includes verifying the destruction of the target, re-evaluating the tactical situation, and planning subsequent maneuvers [42]. Although sometimes underestimated, post-engagement assessment is essential for ensuring mission success and preparing for future engagements [47].

C. OVERVIEW

This survey is based on an extensive literature review conducted using Google Scholar[1] with the keywords "Beyond Visual Range" or "BVR". The focus was on papers written in English and published within the past decade. Initially, 357 papers containing these terms were identified. After a detailed evaluation, papers that were not in English or only referenced BVR without contributing with substantive research to the field (e.g., citing another work with BVR in the title) were excluded. As of September 27, 2024, the final dataset comprised 120 papers, as summarized in Table 1.

All papers were classified according to both their primary methodology and application area, and this structure is consistently used throughout the paper. While many studies incorporate multiple methodologies or cover several application domains, each was assigned to the most prominent category in each classification. Since the terminology used for these categories may vary across the literature, we begin each corresponding section with a clarification of how the term is defined in the context of this survey.

Figure 2 illustrates the distribution of papers by year, highlighting the trend in research interest over the past

[1]https://scholar.google.com

decade. The data reveals an upward trajectory in the number of publications related to BVR air combat, particularly in recent years, highlighting the growing relevance of the topic. The lowest number of publications was recorded in 2017, with just one work, while the highest occurred in 2022 and 2023, with 23 works each. It is worth noting that the lower count for 2024 likely reflects the incomplete availability of papers for this year at the time of this study.

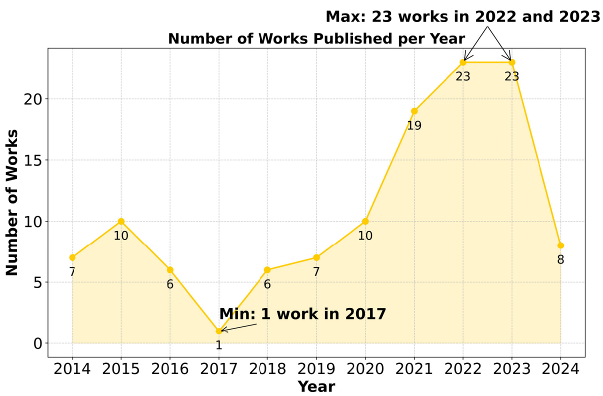

FIGURE 2. Number of articles published per year related to BVR air combat research.

The remainder of this paper is organized as follows. The application areas in the context of BVR air combat are presented in Section II. The methodologies applied to solve problems related to these application areas are described in Section III. Section IV presents simulation environments and tools that have been used to study BVR air combat problems. Section V describes open challenges regarding BVR air combat simulations. Conclusions of this work are presented in Section VI.

II. APPLICATIONS

BVR air combat research covers a diverse set of applications, ranging from autonomous decision-making to multi-agent coordination and pilot training. This section categorizes recent developments across these domains, focusing on how emerging technologies and methods improve tactical performance, adaptability, and mission outcomes.

A. AUTONOMOUS DECISION-MAKING

Autonomous decision-making involves analyzing, selecting, and executing actions that enhance situational control and combat effectiveness. Various approaches were proposed to support this capability, focusing on how agents model tactical behaviors, perform Goal Reasoning (GR), and assist or replace human pilots in complex scenarios.

A reduction method of tactic features based on granular computing was proposed in [61]. In [15] and [52], authors explored behavior modeling in the context of Computer Generated Forces (CGFs) and GR, enabling autonomous systems to make adaptable tactical decisions in rapidly changing scenarios. These capabilities supported the development of autonomous air combat agents that can complement human pilots by taking on specific tasks, such as threat engagement or support maneuvers. Along these lines, [48] developed a system designed to assist pilots by generating tactical fight strategies.

In [49], a Genetic Programming (GP) framework was presented to discover novel behaviors in air combat scenarios, contributing to more adaptable and unpredictable combat tactics. Furthermore, [50], [51] used grammatical evolution to generate adaptive CGFs and Human Behavior Models (HBMs), improving realism and adaptability in training simulations.

The work elaborated in [12] analyzed the UAV air combat decision process, dividing it into four decision-making phases: situation assessment, attack arrangement, goal assignment, and maneuvering decision. Furthermore, in [2], pilot knowledge was used to create a hierarchical framework that divided air combat into several sub-decision-making systems.

A review of Deep Reinforcement Learning (DRL) methods applied to BVR air combat situations was presented in [17]. The autonomous learning of new tactics was addressed in [57], considering a high-fidelity air combat simulation environment. In [53], an agent based on DRL was developed, being capable of simulating fighter aircraft tactics through self-play, generating novel air combat strategies. This approach enabled human pilots to interact with AI-trained agents, improving their decision-making and adaptability. In [58], a Reinforcement Learning (RL) environment was created aiming at autonomous learning of new air combat tactics and the discovery of new maneuvers.

Many studies also employed RL in one-on-one combat scenarios. For instance, [54] proposed a self-play training framework to address the action control problem in long-horizon engagements. Research in [55] introduced a DRL-based decision-making algorithm with tailored state and action spaces and an adaptive reward function, demonstrating robustness across diverse confrontation scenarios. In [59], an improved Q-network enhanced maneuvering decisions by enabling agents to approach opponents from advantageous positions. Similarly, [56] presented a DRL-based agent construction method grounded in realistic weapon simulation. Finally, [60] developed a hybrid self-play DRL agent capable of maintaining high win rates against a variety of opponents, improving both adaptability and performance.

B. BEHAVIOR RECOGNITION

Behavior recognition is important for understanding and predicting the actions of adversarial agents, informing decision-making, and strategic planning. Several studies explored methods to recognize and predict enemy behaviors under complex and uncertain combat conditions.

An integrated planning and recognition algorithm in [62] showed that proactive observation gathering accelerates behavior classification. Building on Case-Based Reasoning (CBR), [63], [64], [65] developed a Case-Based Behavior

TABLE 1. Applications and methodologies in BVR air combat.

Applications \ Methodologies	Control Theory	Evolutionary Algorithms	Game Theory	Goal Reasoning	Graphical Models	Human Performance Evaluation	Modeling and Simulation	Optimization	Reinforcement Learning	Supervised and Unsupervised Learning
Autonomous Decision-Making	[48]	[49]–[51]	–	[15]	–	–	[12], [52]	–	[2], [17], [53]–[60]	[61]
Behavior Recognition	–	–	–	[62]–[66]	[67]	–	–	–	–	[1], [68]–[71]
Guidance and Interception	[72]–[74]	[75]	–	–	[76]	–	[77], [78]	–	[79]	–
Maneuver Planning	–	–	–	–	[80]	–	[81]	[82]	[83]–[88]	–
Missile Engagement	[89]	[90]	[91], [92]	–	–	–	–	[93]	–	[38], [94]
Multi-Agent Coordination	–	–	[95], [96]	[97], [98]	–	–	[99]–[101]	[42], [102]–[104]	[3], [105]–[108]	[109]
Operational Analysis	–	–	[11], [40]	–	–	[110], [111]	[8], [46], [112]–[123]	[124]	–	[125], [126]
Pilot Training	–	–	–	–	–	[127]–[129]	[18], [130], [131]	–	[10]	–
Situation Awareness	–	–	–	–	[132]	[133]	[134], [135]	[136], [137]	[138]	[6], [47], [139]–[143]
Target Assignment	–	[144], [145]	[146]	–	–	–	–	[147]–[150]	–	[151]
Number of References	**5**	**7**	**7**	**8**	**4**	**6**	**27**	**13**	**24**	**19**

Recognition (CBBR) system that annotated agent behaviors from spatio-temporal features, improving recognition within GR-controlled UAVs. Likewise, [66] combined opponent modeling and CBR to identify adversarial team behaviors.

To handle incomplete data, [70] introduced an intention recognition method based on Multi-Granulation Rough Sets (MGRS). The study in [68] fused Dempster-Shafer theory with Deep Temporal Networks for improved classification, while [71] used a decision tree and Gated Recurrent Unit (GRU) for state prediction in one-on-one air combat. In [1], a hierarchical approach was proposed using Cascaded Support Vector Machines (CSVM) and cumulative features for multi-dimensional target classification.

To recognize tactical intent, [69] introduced an attention-enhanced swarm optimization and bidirectional GRU model (A-TSO-PBiGRU) for shift detection. Similarly, [67] applied Dynamic Bayesian Networks (DBNs) to infer causal links between flight states and tactical movements, improving formation recognition and SA.

C. GUIDANCE AND INTERCEPTION

Guidance and interception mechanisms are essential for increasing the probability of a successful missile engagement, particularly against fast and evasive targets.

Guidance strategies were compared to identify configurations that minimized interception time and maneuver load, offering improved engagement options under varying combat conditions [72]. The interception of hypersonic targets was addressed by enhancing the missile's ability to reach the target at a specific impact angle, improving the conditions for the final engagement phase [73]. In unmanned operations, aiming precision in Unmanned Combat Aerial Vehicles (UCAV) was improved through autonomous guidance techniques, enabling more effective launches against maneuvering aerial targets [74].

Maneuver decisions during missile flight were optimized to support engagement planning and increase success rates in simulated combat scenarios [75]. Real-time trajectory adjustment was achieved through probabilistic modeling of the Dynamic Attack Zone (DAZ), helping maintain accuracy despite environmental uncertainty [76]. Coordination between radars and missiles was improved by cooperative guidance models, which enhanced system-level precision in anti-aircraft defense [77].

The influence of data link quality on missile effectiveness was quantified through simulation, showing how update delays and errors impacted seeker activation and overall success [78]. Lastly, ignition control and trajectory correction for dual-pulse motor missiles were refined to support effective interception of distant targets [79].

D. MANEUVER PLANNING

Maneuver planning involves calculating a sequence of motion primitives to reach an advantageous tactical situation.

Early work in this area emphasized structured evaluation and decision models. The authors of [80] introduced a framework comprising a situation evaluation model, a maneuver decision model, and a one-on-one engagement evaluation model. In [81], a tactical decision system was developed based on environmental conditions, existing threats, target weapon performance, and air-combat rules. Incorporating broader situational factors, [82] explored Target Assignment (TA) strategies that integrated tactical positioning and weapon capabilities to improve resource allocation.

More recent research focused on learning-based approaches. [83], [84], and [85] applied DRL to maneuver planning, improving threat avoidance and target engagement in dynamic scenarios. These works considered different initial engagement conditions to train more adaptable agent models. In [86], an autonomous maneuver strategy was developed using the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm, focusing on missile evasion in one-on-one engagements. The study in [87] designed a maneuver decision-making method based on relative azimuths and distances between opponents. Finally, [88] combined DRL with Monte Carlo Tree Search (MCTS) to investigate maneuver planning without relying on prior pilot knowledge or value-based functions.

E. MISSILE ENGAGEMENT

Missile engagement and evasion require optimizing both launch timing and maneuver strategies to maximize offensive impact and survivability.

On the offensive side, [38] employed Supervised Learning (SL) to estimate optimal missile launch moments, enhancing mission effectiveness. For stealthy operations, [89] introduced a radar blind zone maneuver control method, enabling undetected approaches, while [92] analyzed missile capture areas and minimum evasive ranges. This was done to identify optimal launch distances and defensive strategies in coordinated team air combat scenarios.

On the defensive side, [90] proposed an autonomous evasive maneuver strategy for UCAV using a hierarchical multi-objective Evolutionary Algorithm (EA) to increase survivability. In [91], the missile evasion problem was modeled as a two-team zero-sum differential game, where one aircraft aimed to increase its distance from an incoming missile, while simultaneously closing in on another non-aggressive target.

In UCAV operations, [93] introduced a cooperative occupation method based on WEZ, improving coordinated positioning. Lastly, [94] addressed the challenge of information blindness after the launch of AAMs.

F. MULTI-AGENT COORDINATION

Multi-agent coordination combat enables cooperative decision-making, joint tactical execution, and improved responsiveness among autonomous platforms. Applications range from coordinated engagement strategies to dynamic team reconfiguration and human–AI teaming.

Tactical strategies for multiple UAVs were applied to decompose air-to-air confrontations into one-on-one cases, improving maneuver efficiency and engagement success [95]. Cooperative position allocation and TA were modeled as a zero-sum game, where a hybrid Double Oracle and neighborhood search algorithm improved solution quality under time constraints [96].

In [97], extensions to the Tactical Battle Manager included a distributed system for detecting discrepancies in mission data across agents, aiming to improve coordination and overall mission effectiveness. GR techniques were advanced through a character-oriented framework that improved coordination among autonomous agents operating with limited communication [98]. To support human-AI teaming, the AlphaMosaic architecture integrated human feedback into Battle Management Systems (BMS), enabling trust-based collaboration in dynamic missions [99].

Swarm intelligence was adapted to fixed-wing UCAV platforms, enabling behaviors such as formation flight, self-reorganization, and dynamic adaptation after losses [100]. A centralized AI planning system was used to coordinate multi-agent mission plans with full observability and verifiability [101]. War game simulations were employed to test coordinated fleet behavior, with tactical parameters optimized to enhance mission outcomes in matched-force engagements [102].

Tactical formations of UAVs were optimized against uncertain enemy behavior, using simulation-based evaluations [42]. A two-stage cooperative pursuit strategy was introduced, combining luring tactics and Hybrid A* path planning to increase interception success [103]. Adaptive guidance methods were designed to improve UAV occupancy using a multi-objective function and the GDT-SOS meta-heuristic [104].

Hierarchical RL architectures enabled multi-agent teams to learn both low-level and high-level tactics through self-play and scenario decomposition [3]. Multi-agent Proximal Policy Optimization (PPO) was applied to UCAV coordination, integrating domain knowledge into the reward structure to achieve improved performance [105].

A graph-based reasoning model combined expert knowledge with graph neural networks to model complex collaboration patterns and simplify decision-making in large-scale engagements [106]. An algorithm based on adversarial self-play and hierarchical policy gradients was used to learn emergent strategies that outperformed expert baselines [107]. Deep deterministic policy gradients were applied in swarm maneuvering, where inter-agent cooperation and target engagement were jointly learned [108]. Finally, neural networks and artificial potential fields were combined to support cooperative path planning against adaptive adversaries [109].

G. OPERATIONAL ANALYSIS

Operational Analysis (OA) involves using simulations, models, and metrics to evaluate combat effectiveness, support tactical planning, and inform operational decisions.

Stochastic game-based models were applied to analyze multi-aircraft engagements under uncertainty, providing insights into coordination strategies and missile allocation in BVR scenarios [11], [40]. Simulations involving human operators were used to assess pilot and team performance under realistic combat conditions, focusing on compliance with operational procedures, cognitive workload, and shared SA [46], [110], [111].

Several studies presented simulation platforms for training, tactical testing, and operational planning. These included a tactical-level air combat simulation system developed to support intelligent decision-making [8], the ASA framework designed for evaluating military scenarios in the Brazilian Air Force [112], and its cloud-based extension, ASA-SimaaS, which enabled scalable and autonomous simulation services [113]. AsaPy complemented these tools by offering post-simulation analysis capabilities using statistical and ML methods [114].

To assess fleet effectiveness, system-of-systems (SoS) simulations were used to evaluate aircraft design, platform interoperability, and mission-level success indicators such as survivability and weapon usage [115]. Parametric studies investigated how variables like radar cross-section, missile range, flight altitude, and communication delays affected outcome metrics such as probability of kill and overall combat effectiveness [116], [120], [121]. The influence of agent behavior on simulation credibility was explored through agent-based models, enhancing validation methods in both symmetric and asymmetric BVR scenarios [117].

Communication systems were addressed through the design of a dual-mode protocol that adapted to network conditions in cooperative air combat [118]. Simulation architectures emphasized scalability and flexibility, underlining the need for multi-agent systems capable of managing AI-driven entities and distributed decision-making processes [119]. Meanwhile, validation environments for high-dynamic flight conditions were developed to assess electro-optical system performance under large maneuvers [122].

Network-centric operations were modeled to analyze combat effectiveness under varying levels of synergy between sensors, command structures, and fire control systems [123]. Finally, decision-support tools were proposed based on Multi-Criteria Decision-Making (MCDM) [124], relevance vector machines [125], and improved Extreme Learning Machine (ELM) models [126], offering quantitative evaluations of fighter aircraft and tactical configurations.

H. PILOT TRAINING

Pilot training focuses on enhancing readiness and effectiveness through advanced simulation environments, performance measurement, and adaptive learning techniques. These studies aim to improve decision-making and SA in complex combat scenarios.

The approach outlined in [127] provided insights into retrospective performance evaluation to identify areas for improvement, informing targeted training adjustments. Similarly, [130] explored behavioral modeling to enhance pilot decision-making under high-stress conditions, improving the realism of training exercises.

The integration of Live, Virtual, and Constructive (LVC) environments, as discussed in [131], offers comprehensive training scenarios that combine real and simulated elements to create more realistic and immersive training. This enables pilots to experience diverse combat situations, improving adaptability under varying conditions. To further refine training outcomes, [129] proposed a performance-weighting system to optimize training outcomes, ensuring that pilots meet competency benchmarks efficiently.

The survey on adaptive training methodologies in [18] highlighted advancements in AI-driven systems that personalize training content based on pilot performance. Building on this, [10] and [128] discuss methods for rapidly adapting air combat behaviors and validating training simulations. These studies aimed to ensure that simulation systems accurately reflect real-world combat dynamics, providing practical tools to directly impact pilot training effectiveness by improving responsiveness and situational understanding.

I. SITUATIONAL AWARENESS

SA is essential for understanding the tactical environment, including the positions, actions, and intentions of both friendly and enemy aircraft. Effective SA supports informed decision-making in engagement, positioning, and evasion, ultimately enhancing combat effectiveness and survivability.

In [132], methodologies for real-time data processing were explored, enabling pilots to interpret complex information efficiently. Expanding SA to a team level, [133] demonstrated the benefits of collaborative data sharing for mission coherence and performance.

For threat assessment, [137] and [152] discuss methods to determine enemy WEZ, providing pilots with spatial awareness to avoid or confront threats strategically. Real-time threat analysis tools, such as those developed in [141], continuously updated situational data, ensuring that pilots can adapt their tactics accordingly. Furthermore, [134], [139], and [135] integrated the prediction of target intention into the assessment of threats, analyzing battlefield situations and establishing threat index systems.

AI-driven approaches to SA, like those discussed in [138] and [143], applied ML to threat detection, helping pilots anticipate and respond to potential threats more quickly. Additionally, Monte Carlo-based methods for probabilistic assessment, such as in [136], enable pilots to navigate uncertain situations with better-informed risk management. Research in [47] proposed an engagement decision support tool based on the Defensive Counter Air (DCA) operational metric. The use of Deep Neural Networks (DNN) to perform the estimation of the WEZ maximum launch range was analyzed in [140].

Additional decision support systems like [142] employed onboard sensor data and neural networks to assess shoot-down probabilities in real-time. In [6], a method to estimate maneuver flexibility under adversarial conditions was introduced, aiding formation-level decision-making.

J. TARGET ASSIGNMENT

TA involves efficiently allocating resources, such as AAMs or surface-to-air missiles and aircraft, to neutralize enemy threats. This process requires strategies to optimize engagements while minimizing resource expenditure and maximizing mission success.

Several studies focused on target allocation methodologies to improve combat effectiveness. In [146], [147], and [149], the authors discuss Multi-Target Assignment (MTA) strategies that dynamically assign missiles and aircraft to multiple targets. Likewise, [148] proposed methods for assigning multiple friendly aircraft to a set of enemy targets, focusing on coordinated attack strategies to improve the efficiency of engagement.

Studies such as [144], [150] examined algorithms that determine the optimal pairing of weapons to threats based on mission objectives and constraints, aiming to maximize kill probability while preserving resources. In [145], the authors refined this process by introducing an improved assignment model that incorporates target priority and engagement timing.

Lastly, [151] investigated a hybrid approach, combining optimization techniques with real-time tactical adjustments to adapt to evolving combat conditions.

III. METHODOLOGIES

This section outlines the methodological foundations used to address key challenges in BVR air combat, where dynamic, uncertain, and adversarial environments demand robust and adaptive decision-making. Techniques span a wide spectrum—from data-driven methods like supervised, unsupervised, and RL to structured reasoning approaches such as control theory, graphical models, and game theory. Each subsection explores the specifics of each methodology, illustrating their application and possible advantages.

A. CONTROL THEORY

Control theory employs mathematical models to guide and influence the behavior of dynamic systems, making it especially valuable in BVR air combat for precise aircraft and missile guidance, interception of maneuvering targets, and strategic positioning under uncertainty.

Guidance laws were developed to optimize interception effectiveness by balancing engagement time and maneuver load [72], while model predictive strategies improved mid-course guidance in hypersonic scenarios with terminal-angle constraints [73].

Stealthy engagement strategies integrated sliding mode control techniques with electronic support measures, enabling adaptive transitions between stealth and aggressive maneuvers to exploit enemy radar vulnerabilities [89]. Autonomous UCAV engagements similarly benefited from adaptive fuzzy control within a Model Predictive Control (MPC) framework, enhancing precision and responsiveness against agile targets [74]. Fuzzy logic was also applied to recommend combat modes using situational inputs [48].

B. EVOLUTIONARY ALGORITHMS

EAs are a class of optimization techniques inspired by biological evolution, capable of solving complex, high-dimensional, and non-convex problems.

In behavior modeling, genetic programming evolved Behavior Trees (BTs) to discover novel air combat strategies under EW effects [49]. Grammatical evolution was used to generate adaptive CGFs and HBMs by encoding subject matter expert knowledge in modular BTs, enabling dynamic responses in training simulations [50], [51].

Differential evolution algorithms introduced adaptive parameter strategies to improve convergence and robustness in tactical planning [75]. Multi-objective evolutionary approaches applied hierarchical and Pareto-based methods to balance competing goals [90].

Hybrid evolutionary methods, including genetic algorithms enhanced by simulated annealing and discrete evolutionary strategies, were applied to resource allocation and assignment tasks, where mechanisms like adaptive crossover, mutation rates, and disturbance strategies promote efficient convergence and solution diversity [144], [145].

C. GAME THEORY

Game theory offers mathematical tools for analyzing strategic interactions in adversarial and cooperative settings. In BVR air combat, it supports optimal strategies for navigation, engagement, evasion, and team coordination.

In [91], differential game theory was used to model dynamic zero-sum interactions with closed-loop control to ensure safe maneuvering under threat. On the other hand, stochastic games enabled sequential decision-making under uncertainty through subgame decomposition and equilibrium analysis [11], [40].

Pursuit-evasion games defined missile capture and evasion ranges using utilitarian formulations to guide tactical behavior [92]. For cooperation, consensus-based algorithms combined with auctions and matrix games enabled scalable and efficient resource allocation [96], [146].

Additionally, min-max approaches further simplified multi-agent engagements into pairwise confrontations, supporting fast and systematic tactical decisions [95].

D. GOAL REASONING

GR enables autonomous agents to dynamically deliberate, adapt, and reprioritize goals based on real-time context, making it well-suited for adversarial environments like BVR air combat. As discussed in the overview by [15], GR supports deliberative autonomy, dynamic goal management, and contributes to AI safety.

CBBR methods enhance GR by annotating adversarial behaviors from spatio-temporal data, improving adaptation under partial observability [63], [64]. [65] extended this with the Policy and Goal Recognizer (PaGR) system, capable of inferring and adjusting assumptions about opponent goals and strategies. Likewise, [66] combined case retrieval with learned classifications to recognize adversarial team behaviors, while [62] integrated behavior recognition with active planning in a Partially Observable Markov Decision Process (POMDP) framework to improve recognition efficiency.

Distributed GR further enabled decentralized adaptation by detecting discrepancies between expected and observed behaviors [97]. Narrative team planning supported decentralized coordination through hierarchical narrative-based goal structures, improving resilience under conditions of limited communication and uncertainty [98].

E. GRAPHICAL MODELS

Graphical models support probabilistic reasoning under uncertainty by capturing structured relationships among variables. In BVR air combat, techniques such as Bayesian Networks (BNs), DBNs, and Influence Diagrams address challenges in threat assessment, recognition, and decision-making.

DBNs were used to infer maneuver and formation tactics by modeling causal links between aircraft states and actions [67], while BNs captured missile guidance uncertainty by linking kinematic parameters to the DAZ [76].

To improve scalability, Multi-Entity Bayesian Networks (MEBNs) offered modular representations of battlefield entities and interactions [132]. Influence diagrams combined situation assessment with maneuver decisions to evaluate tactical alternatives and equipment effectiveness under operational constraints [80].

F. HUMAN PERFORMANCE EVALUATION

Human performance evaluation methodologies assess cognitive load, SA, decision-making, procedural adherence, and team effectiveness under the complex and time-critical conditions characteristic of BVR air combat. Rather than relying solely on outcome metrics (e.g., mission success), recent methodological advances emphasize internal cognitive states, team dynamics, and alignment with doctrinal procedures.

Workload was measured using modified NASA-TLX methods with enhanced weighting schemes (e.g., Swing, Analytic Hierarchy Process (AHP)) for better interpretability [129], while retrospective verbal probing provided structured, non-intrusive insights into pilots' mental models post-mission [127].

Team assessments incorporated the critical decision method to evaluate shared SA and its tactical impact [133], supported by multidimensional frameworks integrating taskwork, normative behavior, and workload within LVC simulations [110].

Normative Performance (NP) was assessed via structured observer scoring to ensure doctrinal alignment during debriefings [111], while human-agent interaction models were validated for reliability and relevance in adaptive training systems [128].

G. MODELING AND SIMULATION

Modeling and Simulation (M&S) provide a methodological foundation for representing, analyzing, and validating the complex dynamics of BVR air combat. These techniques enable the abstraction of aircraft, weapons, sensors, and command structures into executable models that support experimentation, decision-making, and system development across both tactical and strategic levels.

Several studies introduced simulation frameworks that support experimentation and decision-making. ASA [112], [113] offers a scalable, object-oriented environment with distributed execution and runtime model loading, while AsaPy [114] supports statistical and ML-based post-processing. Other contributions focused on AI-integrated systems, such as AlphaMosaic [99], a battle management architecture that supports human–AI teaming through trust-aware decision loops in dynamic BVR environments. The study in [8] introduced a tactical-level simulation system that generates data for intelligent decision-making models across human–human, human–machine, and machine–machine configurations. Similarly, [120] presented a modeling environment for analyzing tactics and maneuver effectiveness using the probability of kill (Pk) via a missile launch envelope model. Complementing these were LVC-based environments that support the iterative development of tactics, techniques, and procedures [46], including pilot co-designed training tools for asymmetric roles and after-action review visualization [130], [131]. Additional frameworks were proposed for electro-optical system testing under high-dynamic flight simulation [122] and for scaling multi-agent simulations with AI-enabled entities [119].

Agent-based M&S examined how behavioral variation influences engagement outcomes in [117]. Likewise, SoS simulations linked aircraft design variables to mission-level effectiveness by modeling interactions between manned fighters and cooperative unmanned platforms [115]. Symbolic and AI-integrated systems extend simulation's role into planning and autonomy. High-level planners decomposed multi-agent objectives into coordinated execution plans [101], while swarm-intelligent UCAV platforms simulated full-mission coordination, formation management, and mid-flight reconfiguration in response to unit loss or dynamic updates [100].

Other studies used simulation to evaluate operational variables. These included the effect of data link quality on seeker lock and Pk [78], the impact of stealth and missile range on 1-vs-1 effectiveness [116], and cooperative radar-missile guidance modeled through Monte Carlo estimation [77]. Threat assessment models incorporated both expert and data-driven weighting schemes alongside intent prediction and event impact modeling [134], [135]. The influence of communication delays on fleet-level combat effectiveness was explored through threat matrix modeling and adjudication methods [121]. Network-centric air combat was also addressed through communication protocols [118] and synergy models [123] to assess decentralized cooperation under bandwidth and latency constraints.

Beyond performance evaluation, M&S also supports behavior modeling and interface testing. BTs were used to structure decision logic for CGFs in virtual BVR simulations [52], while testbeds for electro-optical tracking under high-maneuver dynamics validated hardware behavior under simulated aerial conditions [122]. Broader overviews of UAV air combat decision modeling highlighted simulation's role in structuring multi-stage decision pipelines [12], and virtual expert systems for tactic generation model high-level reasoning across BVR and WVR conditions [81].

Additional information on the application of ML to model air combat behavior, covering both WVR and BVR engagements, was presented in [18].

H. OPTIMIZATION

Optimization aims to make the most effective use of available resources, actions, or strategies to achieve mission objectives under constraints. In BVR air combat, it provides a general framework for decision-making tasks such as engagement timing, resource allocation, and path planning. Methods span from classical optimization to bio-inspired heuristics, often tailored to dynamic, high-dimensional, and time-critical environments.

A wide range of swarm intelligence algorithms were adapted to the air combat domain. Variants of Particle Swarm Optimization (PSO) were used to handle missile-target assignment [147], cooperative UCAV occupation modeling through discrete PSO [93], and air defense target allocation under real-time constraints [150]. Additional extensions included Particle-Pair Swarm Optimization (P2SO) to co-optimize fleet parameters in symmetric war games [102], and Stochastic Dominant Learning Pigeon-Inspired Optimization (SDLPIO), which integrated payoff-based decision-making for multi-UAV target allocation [148].

Multi-objective optimization and MCDM methodologies explicitly handle trade-offs among competing objectives or decision criteria. Techniques like Gradient Descent–Truncated Symbiotic Organisms Search (GDT-SOS) systematically balanced multiple tactical parameters (e.g., distance, speed, angles) to derive optimized solutions for trajectory planning and positional guidance [104]. Similarly, MCDM approaches such as the integration of AHP and Kullback–Leibler divergence (KL-AHP), as well as TOPSIS, systematically evaluated and ranked alternative solutions according to multiple criteria, enabling strategic and tactical decision-making under uncertainty [124]. Hybrid A* path planning, guided by multi-objective considerations, enabled coordinated UAV trajectories [103]. Models based on geometric constraints and engagement zones were also used to derive best attack positions in multi-target scenarios [82], while methods like the golden section search were applied to real-time missile zone computation [137].

In distributed allocation, asynchronous consensus-based auction algorithms coordinated missile-target assignments across UAV teams, improving solution quality under limited communication [149].

In more tactical-level formation planning, metaheuristic comparisons were used to optimize UAV swarm configurations under uncertainty. In [42], six metaheuristics were evaluated in a war game setup to determine robust formation strategies against an opposing force, incorporating variability in enemy location and engagement potential.

Finally, in [136], Monte Carlo Tree Search (MCTS) was integrated with convex optimization to determine safe missile guidance trajectories in adversarial environments, supporting real-time pilot decision-making.

I. REINFORCEMENT LEARNING

RL techniques may enhance tactical creativity and efficiency by autonomously learning and adapting strategies through interactions with dynamic environments, leveraging algorithms for exploration, self-play, and expert knowledge integration. It is also one of the most common research methods in the BVR research field.

Although BVR air combat often involves multiple units per team, researchers frequently simplify the setting to one-on-one engagements to isolate tactical decision-making. The study in [10] applied RL to generate adaptive behaviors for CGFs, while [138] used PPO to model evasive behavior against incoming missiles, with a reward function based on the smallest distance between the agent and the missile. In [59], an Improved Q-network (IQN) was used to balance exploration and exploitation. The research in [86] introduced a modified TD3 algorithm for maneuver and missile engagement strategies, and [55] developed a Dueling Double Deep Q-network (D3QN) for decision-making across varied engagement conditions.

Several works explored improvements in learning efficiency and realism, such as [83], which proposed an enhanced Deep Q-network (DQN) with Long Short-Term Memory (LSTM)-based perception layers for maneuver planning. The work in [84] introduced Dynamic Quality Replay (DQR) to improve policy learning from confrontation demonstrations, with Soft Actor-Critic (SAC) outperforming other methods. In [79], DRL was integrated with singular perturbation theory to generate ignition and acceleration commands for dual-pulse AAMs, enhancing long-range guidance.

Agent construction and training methods were also explored in [56], where a SAC-based agent was trained using curriculum learning across staged tasks—flight control, guided engagement, and defeating expert systems. Similarly, [60] proposed a hybrid self-play DRL strategy, allowing agents to train against both expert systems and delayed self-play opponents to prevent local optima. In [88], authors combined RL with MCTS to learn maneuver strategies without reliance on handcrafted reward functions or expert features.

While one-on-one scenarios dominate early exploration, multi-agent reinforcement learning enables improved survivability, shared situational awareness, and tactical synergy.

Multi-Agent Proximal Policy Optimization (MAPPO) and Hierarchical Framework Embedding Expert Knowledge (H3E) frameworks incorporate hierarchical structures and expert guidance to improve coordination and efficiency across agents [2], [105]. In [85], a dual-UAV cooperative air combat strategy was proposed using prioritized sampling and a discretized action space, demonstrating effective maneuver planning and obstacle avoidance. Swarm-based strategies using Deep Deterministic Policy Gradient (DDPG) allow groups of agents to perform cooperative maneuvers in continuous control spaces [108]. Multi-agent decision networks, including hierarchical policy gradients [107] and improved Neural Fictitious Self-Play (NFSP) [3], [54], support the emergence of high-level strategies. Meanwhile, [57] introduced Key Air Combat Event Reward Shaping (KAERS) to accelerate learning via sparse but meaningful feedback, and [87] explored curriculum learning to improve convergence in dual-UAV settings. Large-scale air combat scenarios were also addressed in [106], where Graph Neural Networks (GNNs) combined with expert knowledge to reason over abstract combat relationships.

Lastly, comprehensive overviews of DRL applications in air combat simulation environments and military contexts are provided in [53] and [58], while [17] reviews broader military applications, outlining key limitations and future directions for DRL-based approaches.

J. SUPERVISED AND UNSUPERVISED LEARNING

Statistical modeling techniques, particularly those based on supervised and unsupervised learning, have been widely applied to support threat assessment, maneuver intention recognition, missile launch prediction, and combat effectiveness evaluation. These approaches rely on data from simulations or real-world exercises to model combat scenarios, extract patterns, and enhance tactical reasoning under uncertainty.

Most existing work adopts SL, where models are trained on labeled data. For example, [139] used linear discriminant analysis to preprocess threat indicators and trained an ELM for target threat assessment. For engagement decision support, [38] and [47] built tree-based models (e.g., XGBoost) to predict engagement outcomes and missile launch timing, while [140] applied a DNN to estimate the WEZ from multiple simulated launches. Reference [142], in turn, used a missile launch dataset—originated from training exercises—to train an ANN for UCAV decision support. For air combat effectiveness evaluation, [125] proposed a method based on relevance vector machine, while [126] introduced an improved ELM with M-estimation to handle gross errors in training data.

Sequence models are often used to address temporal pattern recognition. The study in [68] combined one-dimensional convolutional neural network (1DCNN) and bidirectional LSTM with evidence fusion for intent classification, while [69] introduced an attention-enhanced bidirectional GRU architecture tuned via swarm optimization. In [71], a GRU was used for enemy state prediction and a decision tree was then applied for intent recognition. In contrast, [1] employed a cascaded Support Vector Machines (SVM) framework with hierarchical feature decomposition, which, while not a sequence model per se, operates on temporal trajectory data.

SL techniques have also supported SA and post-launch assessment. For example, [6] and [143] trained deep networks to evaluate options under multiple missile threats and assess formation flexibility. In [94], random forest regression was used for dynamic post-launch missile effectiveness evaluation. In cooperative contexts, [109] employed SL to adjust parameters in path planning for multi-agent engagements, and [151] developed a back propagation (BP) neural network to support collaborative TA.

In settings with limited or incomplete data, Unsupervised Learning (UL) techniques are often used to extract structure or reduce dimensionality. For instance, [141] employed a Sparse Autoencoder (SAE) to approximate the Tactical Control Range (TCR), enabling fast inference without relying on labeled output data.

Other approaches use symbolic or hybrid reasoning frameworks that may not strictly fall under UL but operate in low-label or uncertain environments. In [70], MGRS theory was used for adversarial intent recognition, combining logic-based modeling with attribute importance ranking to support classification under uncertainty. Likewise, [61] applied granular computing to structure tactical decisions at multiple abstraction levels, proposing a feature reduction method to improve classification accuracy without relying heavily on labeled datasets.

IV. SIMULATION TOOLS

Simulation environments and tools are essential for advancing BVR air combat research, enabling the modeling of complex scenarios, evaluation of decision-making algorithms, and optimization of operational strategies. These tools range from general-purpose platforms to bespoke systems tailored to specific research needs, each offering unique capabilities to address various aspects of BVR combat.

Many platforms support interoperability through standards like HLA (High-Level Architecture) and DIS (Distributed Interactive Simulation), facilitating integration across multiple simulation systems and real-time synchronization. In this section, we describe some of the more common tools that are used in BVR air combat research. At the end of the section, we present an overview table summarizing the key tools, their features, programming languages, and interoperability capabilities.

A. AFSIM: ADVANCED FRAMEWORK FOR SIMULATION, INTEGRATION, AND MODELING

The Advanced Framework for Simulation, Integration, and Modeling (AFSIM) [153], developed by the United States Air Force Research Laboratory, is a widely used platform in BVR air combat research. AFSIM offers flexibility for modeling combat environments, integrating systems, and supporting mission planning and decision-making processes. It is commonly applied in research on cognitive control, behavior recognition, and AI [15], [62], [63], [64], [65], [66], [97], [99], [101]. AFSIM supports integration with other models, enabling real-time interactions and simulations at both strategic and tactical levels. This interoperability facilitates research in battle management and mission planning. AFSIM is not open-source and is controlled under United States government regulations.

B. ASA: AEROSPACE SIMULATION ENVIRONMENT

The Aerospace Simulation Environment (ASA, from the Portuguese *Ambiente de Simulação Aeroespacial*) [112], [113], developed by the Brazilian Air Force, is a custom-built object-oriented simulation framework in C++. ASA is designed for modeling complex aerospace operations and supports research in SA, mission planning, and operational decision-making [38], [42], [47], [53], [114], [117], [140]. ASA's flexibility allows integrating ML techniques with traditional simulations, enabling researchers to optimize tactics and predict adversarial behaviors. Its architecture also supports detailed modeling of mission parameters, aircraft systems, and weapons. ASA is not publicly available and is controlled under Brazilian government regulations.

C. BESPOKE SYSTEMS

Bespoke systems, which are developed in Python, C++, or MATLAB, are specially designed tools for study where commercially available alternatives are inadequate. Since EW models, missile guidance, and BVR techniques are frequently classified, sensitive data from commercial systems cannot be accessed for open study. Therefore, such tools are often inadequate for the complexity, security, and adaptability requirements of these scenarios. Bespoke systems are the most prevalent as these methodologies promote quick development [8], [11], [40], [55], [56], [59], [61], [67], [68], [70], [72], [73], [74], [76], [77], [79], [81], [82], [83], [84], [88], [89], [92], [93], [94], [95], [96], [98], [103], [104], [105], [108], [110], [111], [116], [118], [122], [123], [124], [125], [126], [135], [137], [139], [142], [145], [147], [148], [149], [151].

D. DCS WORLD: DIGITAL COMBAT SIMULATOR WORLD

DCS World [154] is a high-fidelity, commercially available combat flight simulator. Known for its realistic flight physics and detailed models, it is widely used in studies on decision-making and RL-based combat engagement [54], [86]. Its open architecture supports custom module development, enabling researchers to simulate dynamic, high-stakes BVR combat scenarios. This capability makes it an ideal platform for testing AI-driven agents under realistic operational conditions.

E. FLAMES: FLEXIBLE ANALYSIS AND MODELING EFFECTIVENESS SYSTEM

FLAMES [155] is a modular, commercial framework for developing and executing LVC simulations. It supports real-time visualization, scenario management, and OA, making it effective for mission planning and combat simulations [38]. Despite its adaptability, FLAMES' commercial licensing can limit accessibility, and its complexity can hinder rapid prototyping or use in resource-constrained research contexts.

F. FLSC: SWEDISH AIR FORCE COMBAT SIMULATION CENTRE

The Swedish Air Force Combat Simulation Centre (FLSC), developed by the Swedish Defense Research Agency, incorporates LVC simulations to analyze air combat scenarios. FLSC is utilized for pilot training, mission planning, and decision-support research, as well as evaluating human-AI collaboration [130], [131]. Its features contribute to enhancing SA and decision-making in joint operations. Since FLSC is operated by FOI (Swedish Defence Research Agency), access is restricted and is not publicly available, but researchers working on defense projects may gain access through FOI partnerships.

G. JSBSim

JSBSim [156] is an open-source flight dynamics model widely used in RL-based BVR studies requiring precise aircraft simulations. It supports tasks such as decision-making, maneuver optimization, and combat engagement [3], [6], [58], [60], [138], [143]. JSBSim is often integrated with platforms like Unity (IAGSim) and bespoke environments to create computationally efficient simulations for exploring autonomous decision-making in dynamic scenarios.

H. MATLAB AND SIMULINK

MATLAB [157] and Simulink [158] are widely used for simulation, control theory, and optimization research. MATLAB's mathematical capabilities support studies on decision-making and combat engagements [1], [50], [51], [69], [75], [78], [80], [90], [91], [102], [109], [120], [121], [141], [146], [150]. Simulink extends MATLAB's functionality with graphical tools for dynamic system modeling, offering a useful platform for control strategies.

I. PYTHON AND R

Python is a key tool for developing simulation environments and ML models. With libraries such as TensorFlow [159] and PyTorch [160], Python enables mission planning, RL implementation, and optimization [71], [85], [100], [136]. Its flexibility supports rapid prototyping and integration with other platforms for air combat research. R is occasionally used in air combat research for data analysis and simulation-related statistical modeling [140].

J. OTHER TOOLS

Several other tools support BVR air combat research:

- **ACE-2**: A custom simulator used for testing genetic optimization techniques in air combat maneuvering [49].
- **ACEM**: A LVC simulation environment for human performance analysis in air combat [46].
- **FTD (F/A-18C)**: Flight Training Device for the F/A-18C, used for high-fidelity simulation of pilot behavior, coordination, and training scenarios [127], [129], [133].
- **IAGSim (Unity + JSBSim)**: A custom-built simulator that combines JSBSim for flight dynamics and Unity for real-time rendering, designed for autonomous air combat research [2].
- **MACE** [161]: The Modern Air Combat Environment (MACE) is a scalable distributed simulation used for OA and testing of tactical air combat scenarios [115].
- **NLR's Fighter 4-Ship Simulator**: A simulator developed by the Netherlands Aerospace Centre (NLR) for pilot training and human-autonomy interaction in multi-aircraft engagements [128].
- **STAGE**: A framework for rapidly generating air combat scenarios used in AI and RL training [10].
- **Super Decisions**: A decision-support software implementing the AHP and Analytic Network Process (ANP), used in air combat for threat ranking and mission planning [134].
- **UnBBayes-MEBN**: A probabilistic reasoning framework based on MEBNs, applied to situation awareness and decision-making under uncertainty [132].
- **WESS**: A simulation tool for studying adaptive tactical decision-making. It has been applied in modeling dynamic combat behavior [50], [51].
- **Wukong**: A RL-based platform designed for multi-agent tactical decision-making in BVR scenarios [57], [106], [107].
- **X-Plane** [162]: A high-fidelity commercial flight simulator used in autonomous behavior validation and operational planning [48].

K. TOOLS SUMMARY

Table 2 summarizes the key tools, their primary applications, features, programming languages, and interoperability capabilities. This table includes 116 of the 120 works mapped in this work; the remaining four were survey or overview works that did not employ a specific tool. Each column provides specific information to facilitate comparison among simulation environments: **Simulation Tool** lists the name of the simulator or framework; **Key Features** highlights the main characteristics or functionalities relevant to BVR air combat research; **Programming Language** indicates the primary languages or platforms used for development or customization; **Interoperability** specifies whether the tool supports standard simulation protocols (e.g., HLA, DIS), uses custom interfaces, or lacks interoperability information; and **References Using This Simulation Tool** lists the studies that employed each tool in their experiments or analyses.

V. OPEN CHALLENGES

Despite significant advancements in air combat decision-making using RL and other advanced techniques, several open challenges remain. These challenges present exciting opportunities for future research.

Complexity of Scenarios: Current methods, such as NFSP RL and DRL with DQR, are often validated in simplified one-on-one engagements [54], [84]. Extending these approaches to multi-agent environments that reflect the complexity of real-world air combat is crucial. Promising frameworks, including swarm-based strategies leveraging DDPG and hierarchical methods like H3E, highlight potential directions for tackling this challenge [2], [108]. Additionally, TA, detection, and guidance problems predominantly assume homogeneous models of radars, aircraft, and communication nodes [118], [144], [148], [149], [163], [164], [165]. Future research can explore heterogeneous models to better capture the complexities of diverse real-world systems.

Full Observability Assumptions: Many methods, such as those based on MCTS, PPO, and CSVM, assume full observability of the environment, omitting critical aspects like radar target searching [1], [88], [166]. Techniques capable of handling partial observability, such as KAERS in BVR scenarios, offer promising solutions for enhancing model robustness and real-world applicability [57].

Computational Intensity: Approaches like MCTS, while effective, are computationally expensive and time-consuming [88]. Optimizing methods for continuous action spaces and improving computational efficiency is essential for real-time applications. Recent efforts, such as enhancing TD3 algorithms for missile engagement and evasion, demonstrate progress in this area [86].

Sensitivity to Initial Conditions: Techniques using curriculum learning and IQN often perform poorly under unfavorable initial configurations [59], [167]. Robust curriculum designs and adaptive learning rates, as seen in evolving BTs with GP, offer potential strategies for mitigating sensitivity and improving generalization [49].

Scalability and Real-Time Adaptability: Scalability remains a challenge for multi-agent approaches and hierarchical frameworks, such as MAPPO and H3E, particularly in dynamic and large-scale environments [2], [105]. Efficient methods are needed to handle cooperative scenarios, as demonstrated in TA research [96], [146].

Incorporation of Uncertainties: Many existing methods, such as those based on game theory, BNs, and SL, assume deterministic environments [1], [76]. Incorporating stochastic elements and uncertainties into these models will improve their realism and applicability to complex air combat scenarios.

Validation in Diverse Scenarios: Techniques like SAE networks for TCR and DRL-based UAV swarm models have largely been tested in static environments [108], [141]. Expanding validation to dynamic and high-dimensional scenarios, including real-time decision-making and varied combat conditions, is essential. Studies employing ANN and

TABLE 2. Overview of simulation tools in BVR air combat research.

Simulation Tool	Key Features	Programming Language	Interoperability	References Using This Simulation Tool
ACE-2	Focus on genetic-algorithm-based BVR combat scenarios	Not specified	Custom	[49]
ACEM	Focus on integrated LVC training	Not specified	Custom	[46]
AFSIM	Supports AI integration, scenario-based analysis, and cognitive models	C++	HLA, DIS	[15], [62]–[66], [97], [99], [101]
ASA	Integrates ML, modular architecture, and object-oriented design	C++	HLA, DIS	[42], [47], [53], [112]–[114], [117]
Bespoke Systems	Tailored for specific research needs with high adaptability and customizability	Python, C++, MATLAB	Custom	[8], [11], [40], [55], [56], [59], [61], [67], [68], [70], [72]–[74], [76], [77], [79], [81]–[84], [87]–[89], [92]–[96], [98], [103]–[105], [108], [110], [111], [116], [118], [122]–[126], [135], [137], [139], [142], [145], [147]–[149], [151]
DCS World	Realistic flight physics, open architecture for third-party integration	Lua, C++	Custom	[54], [86]
F/A-18C FTD	High-fidelity simulation for realistic F/A-18C training scenarios	Not specified	Not specified	[127], [129], [133]
FLAMES	Modular platform with LVC support and scalable architecture	C++	HLA, DIS	[38]
FLSC	Advanced LVC simulation, designed for real-time collaboration scenarios	Not specified	HLA, DIS	[130], [131]
IAGSim	Custom-built environment combining flight dynamics and real-time rendering	C++, Unity	Custom	[2]
JSBSim	Open-source physics-based flight dynamics model	C++	Custom	[3], [6], [58], [60], [138], [143]
MACE	LVC simulation for large-scale air combat scenarios	C++	HLA	[115]
MATLAB and Simulink	Tools for mathematical modeling, control systems, and simulation of algorithms	MATLAB	Custom	[1], [52], [69], [75], [78], [80], [90], [91], [102], [109], [120], [121], [141], [144], [146], [150]
NLR's Fighter 4-Ship simulator	Focus on collaborative training with realistic physics and AI integration	C++, Custom	Custom	[128]
Python	Script-based environment for fast experimentation	Python	Custom	[71], [85], [100], [136]
R	Statistical environment for rapid prototyping	R	Custom	[140]
STAGE	Rapid scenario generation for training and real-time experimentation	Not specified	Custom	[10]
Super Decisions	Implements AHP/ANP-based models for threat assessment	Not specified	Not specified	[134]
UnBBayes-MEBN	Implements MEBN-based reasoning for real-time updates	Java	Custom	[132]
WESS	Simulation environment structured in sequential phases to model adaptive air combat tactics	Not specified	Not specified	[50], [51]
Wukong	RL-driven platform for learning complex combat strategies	Python	Custom	[57], [106], [107]
X-Plane	High-fidelity flight simulation and real-world scenario testing	C++	Custom	[48]

granular computing approaches for cooperative air combat highlight promising steps in this direction [61], [151].

Interdisciplinary Approaches: Combining RL, Deep Learning (DL), and control theory can significantly enhance decision-making models for BVR combat. Integrating these methods allows adaptive strategies while adhering to physical constraints. For instance, hierarchical RL and BTs provide scalable frameworks for managing high-level tactics and low-level maneuvers [48], [61]. Such interdisciplinary methods will foster more robust and interpretable models.

Enhancing Training Efficiency: GP shows promise for optimizing strategies, but challenges remain in handling low-dimensional problems and reducing computational overhead. Curriculum-based RL and techniques for recognizing enemy intent can significantly improve learning efficiency and decision-making capabilities [54].

Real-World Applicability: Ensuring the real-world viability of advanced methods requires extensive validation in high-fidelity simulations. Collaboration with military and aerospace organizations can bridge the gap between research and operational deployment. Existing tools for swarm strategies and cooperative UCAV operations demonstrate the value of simulation for practical testing [105], [108].

Future Trends in Simulation Tools: Simulation tools must evolve to meet research demands as BVR combat scenarios grow in complexity. Key trends include:

- *Higher-Fidelity Multi-Agent Simulations:* Supporting larger-scale swarm coordination and high-fidelity real-time simulations on platforms like AFSIM, ASA, DCS WORLD, and FLSC.
- *Increased Interoperability:* Using standards like HLA and DIS to integrate simulations across heterogeneous systems (e.g., manned aircraft, drones, and missiles).
- *AI and ML Integration:* Embedding adaptive AI agents for real-time mission planning and decision-making [105].
- *Higher Computational Efficiency:* Optimizing simulations to handle growing complexity while enabling real-time adaptability.

By addressing these challenges, future research can develop sophisticated, scalable, and adaptable BVR decision-making models. Addressing these challenges will pave the way for robust autonomous systems capable of adapting and thriving in highly dynamic and contested air combat environments.

VI. CONCLUSION

This survey reviewed over 120 research papers on the application of simulation and ML techniques in BVR air combat. We categorized the literature based on key methodologies and application areas, emphasizing advancements in threat assessment, engagement strategies, and autonomous UAV control. Additionally, we underscored the pivotal role of simulation environments in modeling complex BVR scenarios, validating strategic approaches, and developing effective training programs, decision-making algorithms, and autonomous systems.

While significant progress has been made, our review identified several critical challenges that persist. These include ensuring scalability, achieving real-time adaptability, and managing multi-agent coordination in dynamic combat environments. Addressing computational efficiency, simulation fidelity, and the incorporation of uncertainty remains essential for the practical deployment of advanced techniques.

Future research should focus on integrating traditional simulation frameworks with AI-driven methods to overcome these challenges. Combining DL, RL, and control-theoretic approaches holds promise for creating sophisticated, scalable, and interpretable BVR combat systems.

Ultimately, this survey highlights the necessity of advanced tools and ML techniques in shaping the future of BVR air combat. By enhancing both human decision-making and autonomous capabilities, these innovations will enable air forces to operate effectively in increasingly contested and complex operational environments.

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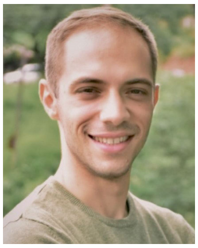

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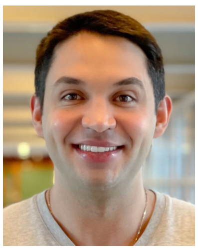

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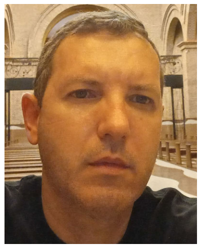

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