A Survey on Digital Twin-Assisted Task Offloading in Remote IoT Networks

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***Abstract*—The integration of Digital Twin (DT) technology with unmanned aerial vehicle (UAV)-enabled mobile edge computing (MEC) introduces a transformative paradigm for intelligent task offloading in remote Internet of Things (IoT) environments. This survey investigates the pivotal role of DT in enhancing task offloading efficiency within UAV-MEC networks by enabling real-time virtualization, predictive analytics, and intelligent decision-making. We review recent advances in algorithmic frameworks that leverage DTs for optimized task distribution, resource allocation, and UAV coordination. Furthermore, the paper identifies key challenges and outlines promising future directions for developing robust, low-latency, and energy-efficient offloading solutions. This work provides valuable insights into the design of intelligent, adaptive, and resilient DT-assisted task offloading architectures for next-generation UAV-MEC-enabled IoT systems.**

***Index Terms*—Digital twin, Unmanned aerial vehicle, Mobile edge computing, Task offloading, Remote IoT.**

I. Introduction and Motivation

A. Introduction

The exponential growth of IoT devices has transformed various sectors by enabling real-time data collection, processing, and communication. Applications such as wearable health monitors, smart control systems, traffic sensors, and environmental monitoring devices are driving the demand for computation-intensive services, including online gaming, facial recognition, virtual reality, augmented reality, and mixed reality [1]. However, deploying such devices in remote or harsh environments presents critical challenges due to their limited computing capacity, constrained bandwidth, and restricted energy availability.

To address these limitations, the integration of IoT devices with UAV-assisted MEC systems has emerged as a promising solution [2]–[6]. UAV-MEC systems provide low-latency, on-demand computational services near the data source, making them particularly suitable for dynamic and mission-critical scenarios such as disaster relief, environmental surveillance, and remote monitoring. By enabling resource-constrained IoT devices to offload computationally heavy tasks, these systems can significantly reduce latency, conserve energy, and improve overall responsiveness [7].

Nevertheless, optimizing task offloading in UAV-MEC networks remains a complex problem. The high mobility of UAVs, their limited onboard energy, and finite computational resources create dynamic and constrained environments that require intelligent and adaptive decision-making. In time-sensitive applications like emergency response, rapid and accurate offloading strategies are essential to meet strict latency and energy requirements [8].

In this context, DT technology has emerged as a transformative enabler. By leveraging real-time sensing, historical data, and intelligent modeling, DTs create high-fidelity virtual replicas of physical entities—such as UAVs and IoT devices—enabling continuous monitoring, simulation, and optimization of system performance [2], [9]. Within UAV-MEC frameworks, DTs facilitate the development of proactive, context-aware task offloading strategies that adapt to environmental changes and resource fluctuations in real time.

This paper presents a comprehensive survey of recent advances in DT-assisted task offloading within UAV-MEC networks, focusing on their application to remote IoT deployments. It aims to offer a systematic understanding of the enabling technologies, design methodologies, key challenges, and open research issues in this emerging area.

B. Motivation

The increasing adoption of IoT devices in remote and infrastructure-deficient environments highlights the urgent need for intelligent, energy-efficient, and low-latency task execution frameworks. Traditional cloud-based architectures are often inadequate in such settings due to their dependency on stable backhaul connections, leading to excessive latency and poor reliability [1]. MEC addresses this gap by bringing computational resources closer to the data source, thereby reducing transmission delays and improving responsiveness. Meanwhile, UAVs introduce additional flexibility by serving as mobile MEC platforms capable of adapting to changing network topologies and user distributions.

Despite their potential, UAV-MEC networks face significant challenges. These include UAV mobility, limited onboard resources, and dynamic user demands, all of which complicate the design of efficient task offloading strategies. In response, Digital Twin technology offers a powerful paradigm for dynamic optimization. By creating virtual models of UAVs, IoT devices, and the operating environment, DTs support real-time decision-making through continuous simulation, predictive analytics, and adaptive control.

While research interest in DT-assisted UAV-MEC networks is growing, the field remains fragmented, and a unified understanding of design frameworks, algorithmic solutions, and system-level trade-offs is still lacking. This survey seeks to bridge that gap by exploring how DTs can enhance coordination, efficiency, and intelligence in task offloading for remote IoT networks.

This survey aims to fill this gap and makes the following key contributions:

- We provide a concise technical overview of UAV-MEC systems and the role of Digital Twin technology in enabling intelligent task offloading.
- We summarize algorithmic techniques—such as reinforcement learning, heuristic optimization, and clustering—that support DT-driven offloading decisions.
- We identify critical challenges in DT-assisted task offloading, including UAV trajectory planning, real-time resource allocation, and synchronization under uncertainty.
- We highlight future research directions such as lightweight DT modeling, multi-objective optimization, and integration with next-generation 6G networks.

II. Background and Enabling Technologies

A. UAV-MEC Architecture

One of the defining objectives of 6G networks is to provide ubiquitous communication and computing coverage across diverse and dynamic environments. However, such pervasive access cannot be achieved through terrestrial infrastructure alone. In many scenarios—such as disaster-stricken zones affected by earthquakes or floods, and remote areas like maritime regions, deserts, or dense forests—traditional terrestrial MEC infrastructure becomes impractical or unavailable due to factors such as infrastructure damage, high deployment costs, and limited base station coverage.

To address these limitations, UAV-assisted MEC has emerged as a critical enabler for communication and task offloading in such environments. UAVs offer high mobility, rapid deployment, and cost-effective, flexible operation, making them well-suited for delivering on-demand computing services to edge devices in infrastructure-deficient areas [10], [11]. By functioning as airborne MEC nodes, UAVs can bring computational resources closer to end-users, thus reducing latency and supporting timely decision-making—especially in *time-sensitive applications* such as survivor detection or real-time video preprocessing during disaster response missions.

Moreover, UAV-based computing networks are not limited to static disaster scenarios. Their deployment is equally valuable in vehicular edge computing, where UAVs can dynamically supplement or replace roadside units, adjusting to real-time traffic patterns and environmental conditions to ensure seamless task offloading [12], [13]. Other aerial platforms, such as *airships and balloons*, further enhance the scalability and coverage of airborne edge networks.

The integration of UAVs with MEC offers several key benefits:

- Latency and energy reduction through optimized task offloading.
- Edge caching support for faster content delivery.
- Ultra-reliable low-latency communications (URLLC) for mission-critical IoT services.
- Extended coverage and computing power for B5G/6G use cases, including smart farming, remote monitoring, and military operations.

Additionally, the line-of-sight characteristic of ground-to-air links enhances the efficiency and reliability of UAV-assisted data transmissions [14], making UAV-MEC particularly suitable for delay-sensitive and energy-constrained applications.

Despite these advantages, UAV-MEC systems face significant challenges. The mobility of UAVs and the dynamic behavior of ground users result in fluctuating computational demands, variable user densities, and frequently changing UAV trajectories. These complexities hinder global optimization and can compromise system efficiency, stability, and even security [3].

To overcome these challenges, UAV-integrated MEC platforms enable resource-constrained IoT devices to offload tasks, thereby reducing end-to-end latency, easing local processing loads, and enhancing responsiveness—particularly in remote or bandwidth-limited environments. However, managing such UAV-MEC networks necessitates adaptive resource allocation, energy-aware operation, and resilient control mechanisms. Achieving robust performance under these dynamic conditions requires the deployment of intelligent optimization and coordination strategies that can support real-time decision-making and reliable service delivery.

B. Digital Twin

Digital twin technology has emerged as a transformative paradigm that bridges the physical and digital worlds. By enabling the real-time virtualization of physical entities and environments, DT facilitates intelligent communication, coordination, and decision-making across these two domains [4], [15], [16]. Through continuous bi-directional interaction, DTs support real-time monitoring, simulation, and predictive analytics, allowing systems to respond proactively to changing conditions. This capability makes DT a powerful tool for adaptive and intelligent network resource management, particularly in dynamic and resource-constrained environments.

In the context of UAV-assisted UAV-MEC networks, DT architecture is typically composed of four core modules [17]:

- Physical Layer: Includes real-world UAVs, IoT devices, and the surrounding environment where computation tasks originate and are executed.
- Digital Twin Network: A centralized server constructs and maintains a high-fidelity virtual replica of the physical system, continuously updated with real-time data.
- Machine Learning Module: Processes state information from the DT model to make intelligent decisions, such as adaptive UAV deployment and task offloading.
- Communication Interface: Enables seamless data exchange between physical and digital layers using 4G/5G, satellite, or wireless communication technologies.

DT technology has demonstrated significant potential in various aspects of networking and communications, including system modeling, physical data processing, cloud computing,

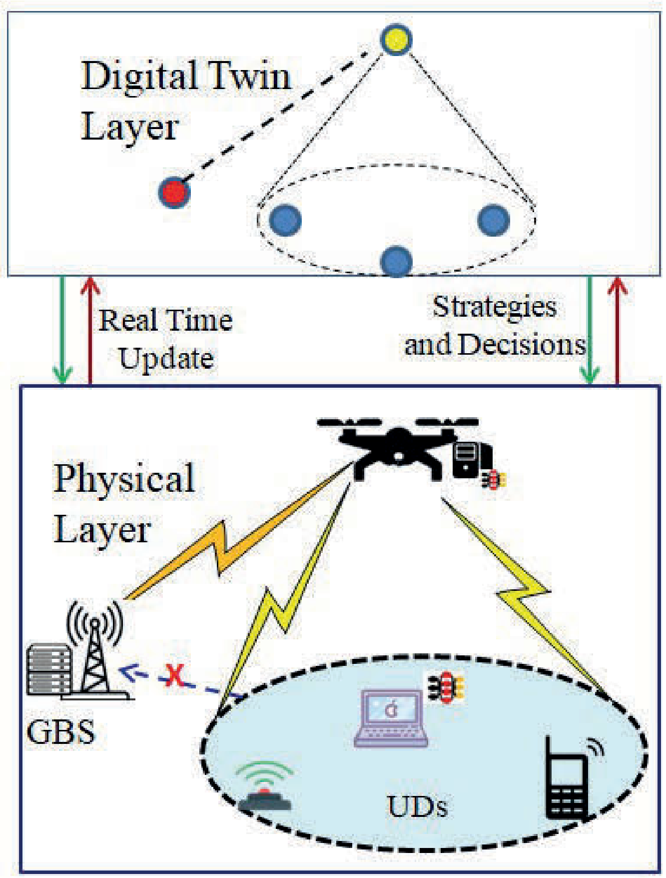

Fig. 1. DT-assisted Offloading Model.

and edge computing [18]. As a result, DT has garnered growing interest among researchers [19]–[22]. For instance, the work in [19] investigates DT-assisted task offloading in MEC to minimize power consumption and processing delay. Similarly, [20] proposes a DT-enabled framework to reduce offloading latency in edge networks. In the context of beyond 5G smart grid systems, [21] employs DT for intelligent access control and authorization. Moreover, studies such as [22] leverage DT to enhance edge network performance in Industrial Internet of Things (IIoT) scenarios. These representative works highlight the wide-ranging applicability and transformative potential of DT in next-generation networked systems.

Overall, Digital Twin technology is poised to become a foundational element in 6G and beyond, enabling context-aware, real-time, and adaptive systems that operate efficiently across dynamic and complex environments. Fig. 1 illustrates a DT-assisted offloading model where the Digital Twin Layer continuously receives real-time updates from the Physical Layer (including UAVs and UDs) and provides optimized strategies and decisions. In the absence of a functional ground base station, the UAV acts as a mobile MEC server, enabling efficient task offloading from remote user devices. This feedback loop enhances adaptability and decision-making in dynamic or infrastructure-limited environments.

III. Role of DT in UAV-MEC Task Offloading

DT technology plays a pivotal role in enhancing task offloading within UAV-assisted MEC systems. In such networks, UAVs function as mobile edge servers that deliver computational services to UDs, especially in remote, disaster-prone, or dynamic environments. However, efficient task offloading remains challenging due to UAV mobility, resource limitations, fluctuating channel conditions, and the need for timely decision-making.

To address these issues, DTs serve as intelligent enablers that virtualize physical entities and network dynamics in real time, providing a basis for predictive analytics and adaptive optimization. The key roles of DT in UAV-MEC task offloading are as follows [2], [5], [6], [15], [23]–[25]:

- Real-time Virtual Representation: DTs maintain high-fidelity digital replicas of UAVs, UDs, and the surrounding environment to enable continuous monitoring, control, and synchronization.
- Predictive Analytics: DTs forecast UAV trajectories, system dynamics, channel conditions, and task workloads, enabling proactive and intelligent decision-making.
- Offloading Strategy Optimization: By simulating alternative strategies in the digital space, DTs assist in selecting optimal offloading policies under constraints such as latency, energy, and computation capacity.
- Adaptive Resource Allocation: DTs facilitate dynamic reallocation of computational, communication, and energy resources by analyzing real-time context and user demands.
- Mobility and Coverage Management: Through accurate mobility modeling, DTs ensure service continuity and optimize UAV positioning in highly dynamic environments.
- Latency Reduction: DTs support pre-coordination of offloading tasks, reducing synchronization delays and improving system responsiveness.
- Resilience Under Uncertainty: DTs improve system robustness in volatile, infrastructure-limited scenarios by enabling virtual testing, rapid reconfiguration, and fault prediction.
- Intelligent Control Integration: When combined with AI/ML models, DTs support autonomous UAV trajectory planning, scheduling, and offloading decisions.
- Scenario Simulation and Testing: DTs offer a cost-effective and safe platform for evaluating "what-if" scenarios and refining strategies without disrupting physical operations.

IV. Problem Solving Approaches in DT-Assisted Task Offloading

Recent research on DT-assisted task offloading has introduced a diverse range of intelligent algorithms and computational methodologies to address the complex challenges posed by UAV-MEC environments. These challenges include constrained UAV resources, dynamic network conditions, mobility-induced uncertainties, and stringent latency and energy requirements. The adopted problem-solving approaches can be broadly classified into four categories: optimization-based methods, clustering and scheduling algorithms, predictive modeling, and reinforcement learning-based algorithms.

A. Optimization-Based Algorithms

Traditional optimization techniques are widely employed to solve joint decision-making problems in DT-enabled UAV-MEC systems. These methods aim to determine optimal or near-optimal solutions under constraints such as delay, power, and computation capacity. Mixed integer nonlinear programming is frequently used to model both discrete and continuous variables, while difference of convex programming enables tractable handling of non-convex problems. Branch-and-Bound algorithms deliver exact solutions for smaller problem instances, and heuristic methods such as genetic algorithms and particle swarm optimization offer scalable alternatives for large-scale systems. For example, in [2], a difference-of-convex penalty-based algorithm (DCPA) is proposed alongside benchmark methods like branch-and-bound (B&B) and relaxed heuristic algorithm (RHA). The study highlights how DT integration enhances optimization, especially when coupled with K-means-based UAV positioning. The framework aims to reduce latency and increase the number of connected IoT devices by jointly optimizing UAV placement and IoT association in energy-harvesting UAV-MEC systems.

B. Clustering and Scheduling Algorithms

Clustering and scheduling techniques are integrated into DT frameworks to optimize task distribution, UAV deployment, and resource management. Clustering algorithms such as K-Means and DBSCAN classify devices or tasks based on proximity, resource demand, or similarity, aiding in efficient service coverage and UAV positioning. Scheduling algorithms like priority-based scheduling and earliest deadline first (EDF) prioritize task execution based on deadlines or quality of service needs, which is critical in latency-sensitive applications. In [25], K-means clustering is employed for UAV deployment, while an alternative optimization (AO) strategy refines power allocation, offloading ratios, and processing rates. The study focuses on minimizing end-to-end latency and achieving URLLC by jointly optimizing communication and computation variables.

C. Predictive Modeling and Estimation

DT-based systems leverage predictive modeling for proactive resource management and task offloading. Estimation methods like Kalman Filters and Bayesian Inference are used to predict UAV positions, channel quality, and device states in real time. Time-series forecasting approaches—such as ARIMA and long short-term memory networks—are used to anticipate traffic load, mobility patterns, and future task demands. In [5], a multi-armed bandit framework is employed, where stability-aware UCB-based online matching algorithm (SUOMA) is applied for dynamic task offloading. This model effectively addresses uncertainty in disaster response scenarios where there is a mismatch between UAV computational capabilities and urgent ground user needs. The DT-enabled framework ensures robust matching through online estimation and feedback.

D. Reinforcement Learning (RL)-Based Algorithms

Reinforcement learning has become a powerful tool in DT-assisted task offloading due to its ability to handle high-dimensional, time-varying, and partially observable environments. These algorithms utilize real-time feedback from the DT to continuously refine policies for task offloading, UAV trajectory control, and resource allocation. Common RL techniques include deep Q-network (DQN), double DQN (DDQN), proximal policy optimization (PPO), deep deterministic policy gradient (DDPG), and soft actor-critic (SAC). For instance, in [17], a DQN-based algorithm is proposed alongside a greedy heuristic to optimize UAV deployment and offloading decisions using DT-generated data. The results demonstrate that DT-enhanced approaches significantly outperform traditional methods in QoS and system performance.

Similarly, [26] proposes a DT-driven offloading strategy for UAV-MEC systems under uncertain conditions, using a DDQN algorithm to jointly optimize UAV trajectory, terminal association, and power allocation with the goal of minimizing energy consumption.

In [23], a markov decision process (MDP) is used to model UAV trajectory and resource allocation in a vehicular edge computing scenario. A PPO-based deep reinforcement learning algorithm is applied to minimize energy consumption while ensuring low-latency execution.

The dynamic digital twin edge air-ground architecture introduced in [6] uses a DDPG algorithm to address a complex joint optimization problem involving IIoT device association, UAV trajectory, and offloading decisions. This approach yields significant gains in both energy efficiency and delay minimization.

In [27], the authors propose a DT synchronization framework incorporating semantic communication. A DRL-based algorithm with actor-critic architecture is used to minimize synchronization latency and energy consumption. The framework achieves notable performance gains, including up to 57.14% reduction in synchronization energy.

Lastly, [24] presents a soft actor-critic (SAC)-based approach to jointly optimize synchronization strategy, transmission power, and computational resource allocation. The study addresses mobility-induced uncertainties and focuses on minimizing the average DT synchronization latency across time-varying UAV-MEC systems.

E. Critical Trade-off Analysis

The above categories offer complementary strengths but also exhibit trade-offs that must be considered when selecting suitable approaches.

- **Computational complexity:** Optimization-based algorithms (e.g., DCPA, B&B) provide near-optimal solutions but are computationally intensive, limiting their applicability in real-time UAV-MEC scenarios. RL-based

TABLE I
SUMMARY OF DT-ASSISTED TASK OFFLOADING APPROACHES IN UAV-MEC NETWORKS

Algorithm Used	DT Role	Objective	Key Features	Ref.
Optimization-Based Algorithms (e.g. DCPA compare with B&B and RHA)	Real-time simulated environment	Minimize latency and maximize the associated IoT devices	Optimizing UAV placement and IoT device association, with energy harvesting.	[2]
Clustering and Scheduling (K-means clustering and AO)	Simulation	Minimize end-to-end latency	Jointly optimizes power, offloading factor, and processing rates of IoT and MEC-UAV servers.	[25]
Predictive Modeling (SUOMA)	Real-time prediction	Minimize uncertainty-induced delay	Online matching with prediction under uncertain network states.	[5]
Greedy heuristic and DQN Algorithm	Virtual modeling	Minimize distance and delay	DT-guided UAV deployment and task prioritization for POI areas.	[17]
DRL- DDQN algorithm	Predict the network state accurately	Minimize energy consumption	Jointly optimize MTU association, UAV trajectory, transmission power, and computation capacity.	[26]
DRL-based PPO Algorithm	Not specified	Minimize energy consumption	Joint UAV trajectory and resource management for vehicular networks.	[23]
DRL-based DDPG Algorithm	Real-time control and state prediction	Minimize energy consumption	Joint optimization of UAV trajectory, IIoT device association, offloading, and resource allocation.	[6]
Lyapunov optimization and DRL-based Algorithm	Synchronization	Minimize synchronization latency	Semantic communication-based DT synchronization for UAV-MEC.	[27]
DRL-based SAC Algorithm	Synchronization	Minimize average DT synchronization latency	Jointly optimizing the synchronization strategy, transmission power, and resource allocation for both UDs and BS.	[24]

methods (e.g., PPO, SAC), on the other hand, enable online adaptability but incur high training overhead and convergence challenges.

- **Data requirements:** Predictive modeling approaches (e.g., SUOMA) rely heavily on historical and real-time data for accurate forecasting, while RL-based methods leverage DT-generated simulated data, reducing dependence on costly real-world datasets.
- **Scalability and adaptability:** Heuristic optimization techniques scale well but often sacrifice optimality, whereas RL approaches achieve strong adaptability in dynamic and uncertain environments such as UAV trajectory planning and IoT task scheduling.

In summary, the integration of DT enhances all these approaches by enabling real-time simulation, proactive control, and semantic communication, thereby significantly improving energy efficiency, latency, and reliability in UAV-MEC task offloading. Table 1 provides a consolidated comparison of representative DT-assisted task offloading approaches, highlighting algorithms, DT roles, objectives, and key features.

V. CHALLENGES, TRENDS, AND FUTURE DIRECTIONS

DT-assisted task offloading in UAV-MEC networks holds great promise for improving computational efficiency, responsiveness, and adaptability in dynamic environments. However, several key challenges must be addressed to unlock its full potential. A primary difficulty lies in the high computational and communication overhead of constructing and maintaining high-fidelity DT models. Continuous real-time synchronization consumes significant energy and bandwidth, often exceeding the resource budgets of UAVs and IoT devices. Synchronization delays can lead to outdated digital replicas, resulting in suboptimal or erroneous offloading decisions.

The inherent mobility of UAVs and dynamic network topologies further complicate task scheduling and resource allocation. Fluctuating channel quality, shifting coverage zones, and unpredictable user demands introduce uncertainty that requires robust, real-time adaptation. Scaling DT systems to accommodate large numbers of UAVs, IoT devices, and concurrent tasks without overwhelming computational or bandwidth resources also necessitates lightweight modeling and distributed coordination. Moreover, security and privacy remain critical concerns, as continuous data collection and modeling expose vulnerabilities in mission-critical or adversarial environments. The integration of AI/ML intensifies these issues, as reliable training data, fast convergence, and explainability must be achieved under constrained resources.

To address these challenges, future research must advance lightweight, scalable DT architectures tailored to UAV-MEC networks. Promising directions include uncertainty-aware optimization frameworks for managing physical–virtual interactions, collaborative task offloading across heterogeneous UAVs, and the use of generative models (e.g., GANs and diffusion models) to enhance DT fidelity through contextual data generation such as spectrum maps or oblique imagery. Priority-aware scheduling mechanisms, particularly for delay-sensitive scenarios like disaster relief, are also essential. Furthermore, semantic communication offers significant potential to reduce synchronization overhead by transmitting only task-relevant features instead of raw data, thereby improving efficiency.

Looking ahead, several research trends are poised to shape the evolution of DT-assisted UAV-MEC systems. Integration with 6G and beyond will be pivotal, as technologies such as reconfigurable intelligent surfaces (RIS), terahertz (THz) communication, and integrated sensing and communication will enable high-capacity, low-latency DT services. Multi-UAV collaborative frameworks will become increasingly important for coordinating large-scale and heterogeneous UAV swarms in complex IoT environments. In parallel, AI-augmented lightweight DTs leveraging foundation models and generative AI will provide context-aware modeling and predictive optimization while maintaining compact structures suitable for resource-limited platforms. Finally, hybrid algorithmic frameworks that combine optimization, reinforcement learning, and predictive modeling are expected to balance computational complexity, adaptability, and real-time performance, driving the practical deployment of intelligent, scalable DT-assisted UAV-MEC networks.

VI. Conclusion

This paper presents a comprehensive survey of the state-of-the-art in DT-assisted task offloading within UAV-MEC networks, with a particular focus on supporting computation in remote, infrastructure-limited, or disaster-prone environments. By enabling real-time virtualization, predictive analytics, and intelligent control, DTs significantly enhance the adaptability, responsiveness, and efficiency of offloading decisions and resource management. The survey explores key enabling technologies, algorithmic frameworks, major challenges, and promising research directions. Although notable advancements have been achieved through optimization, clustering, predictive modeling, and reinforcement learning approaches, unresolved issues such as uncertainty quantification, coordination among heterogeneous UAVs, semantic-aware synchronization, and cross-layer co-design persist. Future research in these areas is critical to unlocking the full potential of DTs for achieving low-latency, energy-efficient, and reliable task execution in dynamic UAV-MEC scenarios.

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