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SURVEY

A Systematic Mapping Study of UAV-Enabled Mobile Edge Computing for Task Offloading

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ABSTRACT Utilizing Unmanned Aerial Vehicles (UAVs) as flying edge nodes to support task offloading from terminal devices has recently attracted significant research attention. However, the literature lacks a systematic perspective on this emerging topic. The goals are to understand the volume and trends of research, identify use case scenarios and proposed architectures, classify the core topics addressed, explore group techniques explored, recognize task types considered, and summarize open issues needing further work. Publications are mapped by type and source from 2019 to 2023 to assess the maturity and activity level in this field over time. Various use case scenarios for UAV-enabled Mobile Edge Computing (MEC) task offloading are identified and categorized, and different proposed architectures for offloading between UAV-MEC platforms are summarized. Techniques for offloading decision-making and performance enhancement are grouped to identify popular and less explored methods. The literature is also mapped based on the types of tasks considered for offloading to UAV-enabled MEC platforms to recognize the focus areas. Open issues that are briefly discussed across papers but require additional research are summarized on basis of the gaps identified. This systematic perspective consolidates existing research in an organized manner to guide future works and establish a coherent taxonomy to organize future studies and reviews. Overall, mapping trends helps characterize research maturity, guiding its continued development.

INDEX TERMS Unmanned aerial vehicle (UAV), mobile edge computing (MEC), task offloading, systematic mapping study (SMS).

I. INTRODUCTION

An Unmanned Aerial Vehicle (UAV) is a self-navigating aircraft that operates without a human pilot. UAVs can fly autonomously, following predetermined flight plans or adjusting their routes in real-time based on their surroundings [1]. These sophisticated devices are equipped with a range of sensors, computer units, cameras, GPS devices, and receivers. These devices have applications in military and civilian sectors [2], [3]. In certain scenarios, UAVs can be mobile base stations integrated with Mobile Edge Computing (MEC) capabilities. They collect data from a specific area, process it, obtain the result, and then transmit it back to users and other nearby drones [4]. UAV network deployment can be faster than establishing traditional network infrastructure systems. Hence, utilizing UAVs as the foundation of mobile infrastructure networks in remote areas proves advantageous [5].

MEC servers can be positioned at different locations near the source of data, such as base stations, aggregation points, customer premises, wireless access points, or even drones. MECs play an important role in processing, analyzing,

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and storing data that require low latency or are location-specific [6]. Having servers placed close to where the data are generated provides several advantages. This results in a lower latency for applications since the data do not have to travel long distances. Users can still access services even if the cloud or internet goes down. It also enhances the overall user experience for latency-sensitive applications [7]. This proximity is especially helpful for technologies that involve Augmented Reality (AR), Virtual Reality (VR), the Internet of Things (IoTs), video analysis, and similar areas. Since MEC servers are near network edges, they can handle the real-time processing and analytics needs of these emerging technologies more effectively compared to remote cloud servers [8].

Despite considerable research efforts, comprehensive assessments of optimization approaches for UAV offloading, considering the interplay between aspects such as communication cost, energy consumption, end-to-end delay, and security protection are lacking [9]. Again, the dynamism introduced owing to rapidly changing UAV locations and heterogeneous edge infrastructures demands efficient solutions. UAVs reduce network congestion, speed up data analysis, and improve response times. However, limited resources on edge devices can lead to performance issues during peak traffic. MEC has extensions for next-generation networks such as 5G and 6G [10], including Vehicular Edge Computing (VEC) where roadside units act as edge servers for vehicles [11]. Task offloading to edge servers helps reduce delays and energy consumption. Additionally, UAVs can serve as MEC units, bringing computing power closer to users, vehicles, and IoT devices [12].

With advancements in battery, processor, and wireless technologies, UAVs are being increasingly deployed for various applications across several domains. However, resource constraints on UAV platforms pose significant challenges for the onboard execution of computationally intensive and latency-critical tasks. Offloading partial or complete workloads from resource-constrained IoTs or drones to powerful edge/cloud servers has emerged as a promising solution [13]. However, optimizing the offloading process in UAV environments involves addressing unique challenges arising from intermittent connectivity, high mobility, and security vulnerabilities [14]. Several techniques have been proposed that focus on minimizing the execution latency and cost of developing UAV as MEC [15] while maximizing energy efficiency and accounting for factors such as varying wireless channels, dynamic trajectories [16], and location privacy [17]. Meanwhile, offloading sensitive tasks and data to third-party platforms introduces new security and privacy concerns [18].

Research on UAV-enabled MEC has focused on various aspects, including offloading optimization, trajectory planning, energy efficiency, latency reduction, and resource allocation. Mathematical techniques such as sequential convex approximation (SCA), game theory, and deep Monte Carlo tree algorithms have been proposed to optimize offloading decisions and enhance security and computing capacity [19]. Additionally, machine learning and Artificial Intelligence (AI) techniques as Deep Reinforcement Learning (DRL) have been employed to predict the positions of ground-based users and UAVs, optimize task offloading, and improve energy efficiency. The use of UAVs in 5G mobile networks has also been explored to reduce end-to-end latency and improve communication reliability [20].

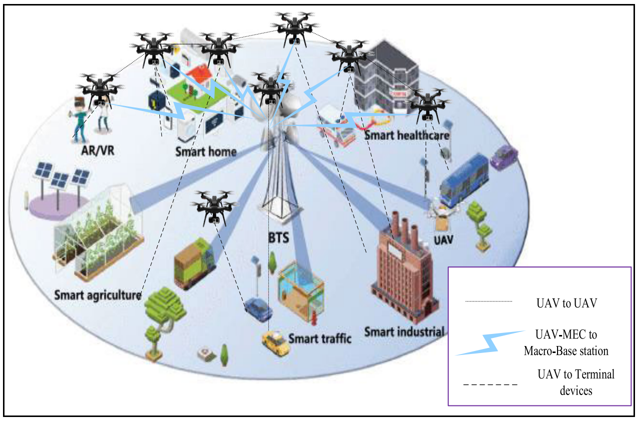

FIGURE 1. **Task offloading in UAV-assisted MEC environment with multiple UAVs (this figure is partially adapted from [24]).**

UAV-MECs have significant applications in various domains such as smart cities, smart agriculture, AR/VR, smart homes, smart healthcare, smart industries, and smart traffic [21], as illustrated in Figure 1. In smart cities, MEC enables real-time interaction, local processing, delay reduction, improved spectral efficiency, improved QoS and QoE, network demand prediction, improved security and privacy, virtualization and service orchestration, energy efficiency, efficient data management, high data rates, high availability, and customized services [22], [23]. UAVs, on the other hand, assist in Ultra-Reliable Low-Latency Communications (URLLC), particularly in AR/VR systems. UAV-MECs are used for real-time monitoring, firefighting, disaster management, military applications, and agricultural operations, providing solutions through their ease of movement in three-dimensional environments. The combination of UAVs and MECs offers immense potential for enhancing efficiency, safety, and effectiveness in these domains [23].

A. MOTIVATION AND CONTRIBUTION OF THE STUDY

There is a lack of systematic analysis of the current state of using UAV-MEC task offloading in 5G networks. Due to the importance of this topic and the absence of a systematic review, we conducted a Systematic Mapping Study (SMS) to explore and analyze the utilization of UAVs as MECs for executing offloaded data. The objective is to analyze the usage of task offloading in UAV-enabled MEC networks, focusing on architecture, UAV-MEC-related scenarios, techniques, task types, and open issues. Our intention is not to propose new methods or tools, but to conduct an SMS using the updated guidelines to analyze literature published between January 2019 and December 2023 related to data offloading in UAV-enabled MEC networks.

In contrast to comprehensive surveys and Systematic Literature Reviews (SLRs), SMSs do not aim to synthesize evidence. Researchers may choose to conduct SMSs instead of literature surveys or SLRs for several reasons, including mapping the research field, identifying research gaps, providing a foundation for future research, handling diverse literature, and conducting exploratory research. The SMS provides an overview of the existing literature and identifies the extent, nature, and distribution of research on a specific topic. This mapping helps researchers understand the landscape of the field and identify areas that have been extensively studied or gaps that require further investigation. These gaps represent areas where limited research has been conducted or where further exploration is needed. Identifying research gaps can guide future research efforts and help researchers focus on areas that have not been extensively studied [24], [25]. For example, instead of addressing every specific challenge, its reasons, and possible solutions regarding task offloading in UAV-MEC networks, we used a methodology based on updated SMS guidelines [25] to generate incidents, concepts, and categories. The outcome is a classification of challenges with illustrative examples.

The process of conducting an SMS involves searching for relevant studies on specific topics from sources such as the ACM Digital Library, IEEE Explore, and Science Direct, selecting studies based on predetermined criteria through titles, abstracts, and keywords, extracting original content from the selected studies, and analyzing the extracted data to answer research questions. This SMS serves as an initial reflection on the research and practice conducted in the past five years regarding task offloading in UAV-enabled MEC. This SMS presents task offloading architectures in UAV-MEC that provide a framework for categorizing and organizing different aspects of UAV-MEC offloading. The scenarios, task types, and core network topics for task offloading in UAV networks are presented. This study highlighted the open issues in the UAV-enabled MEC offloading ecosystems. We believe that this approach will help researchers by providing a clearer and smoother path to navigate through the emerging trend of using UAV-MECs for task offloading.

This systematic mapping review provides novel insights by analyzing the research trends published over five years to understand research trends in UAV-MEC offloading, identify use case scenarios and architectures, classifying addressed topics and explore techniques, recognize research focus areas based on task types, and summarizing challenges and open issues requiring future work to guide the field and uncover gaps. By addressing these seven questions, this review provides insights into the key aspects, scenarios, technical areas, and remaining deficiencies in this emerging domain.

The main contributions of our SMS paper are to answer seven research questions (in Section III) as follows:

- The SMS can provide a high-level understanding of the volume and trends of research on computation offloading in UAV-MEC networks over the past 5 years by mapping publications by type and source. This approach helps assess the maturity and activity levels.
- It can identify and categorize the different use case scenarios explored in the literature for using UAV task offloading in MEC networks and summarize the various architectures proposed in existing works for task offloading between UAV-MEC platforms and terminal devices.
- The core topics addressed in this research area can be classified and quantified based on concepts in selected papers. Additionally, techniques for offloading decisions and enhancement explored in primary studies can be grouped to identify popular and less investigated methods.
- The literature can be mapped based on the types of tasks considered for offloading to UAV-enabled MEC platforms to recognize the focus.
- Challenges and open issues that are briefly discussed but need further research can be summarized based on the gaps identified in the reviewed literature.

This study provides a valuable overview of the current state of research in UAV-MEC for task offloading, highlighting the key open issues in this area. It also identifies areas where further research is needed to fully realize the potential of UAV-MEC for improving wireless communication networks. The taxonomy facilitates the organization and mapping of the literature in a coherent framework to achieve the objectives of the SMS study, as illustrated in Figure 2.

In this survey, an SMS review of UAV-enabled MEC computation offloading is conducted, and it is organized as follows:

- Section II: Related Work.
- Section III: Methodology.
- Section IV: Distribution of Selected Studies on Task Offloading in UAV-Enabled MEC.
- Section V: Scenarios for Using Task Offloading in UAV-Enabled MEC.
- Section VI: The Architecture of Task Offloading in UAV-Enabled MEC.
- Section VII: Core Objectives of Task Offloading in UAV-Enabled MEC.
- Section VIII: Techniques Used to Enhance Task Offloading in UAV-MEC.
- Section IX: Types of Tasks Offloaded to UAV-MEC.
- Section X: Open Issues on Task Offloading in UAV-MEC.
- Section XI: presents the conclusions.

II. RELATED WORK

In this section, we discuss the relevant systematic survey related to MEC data offloading.

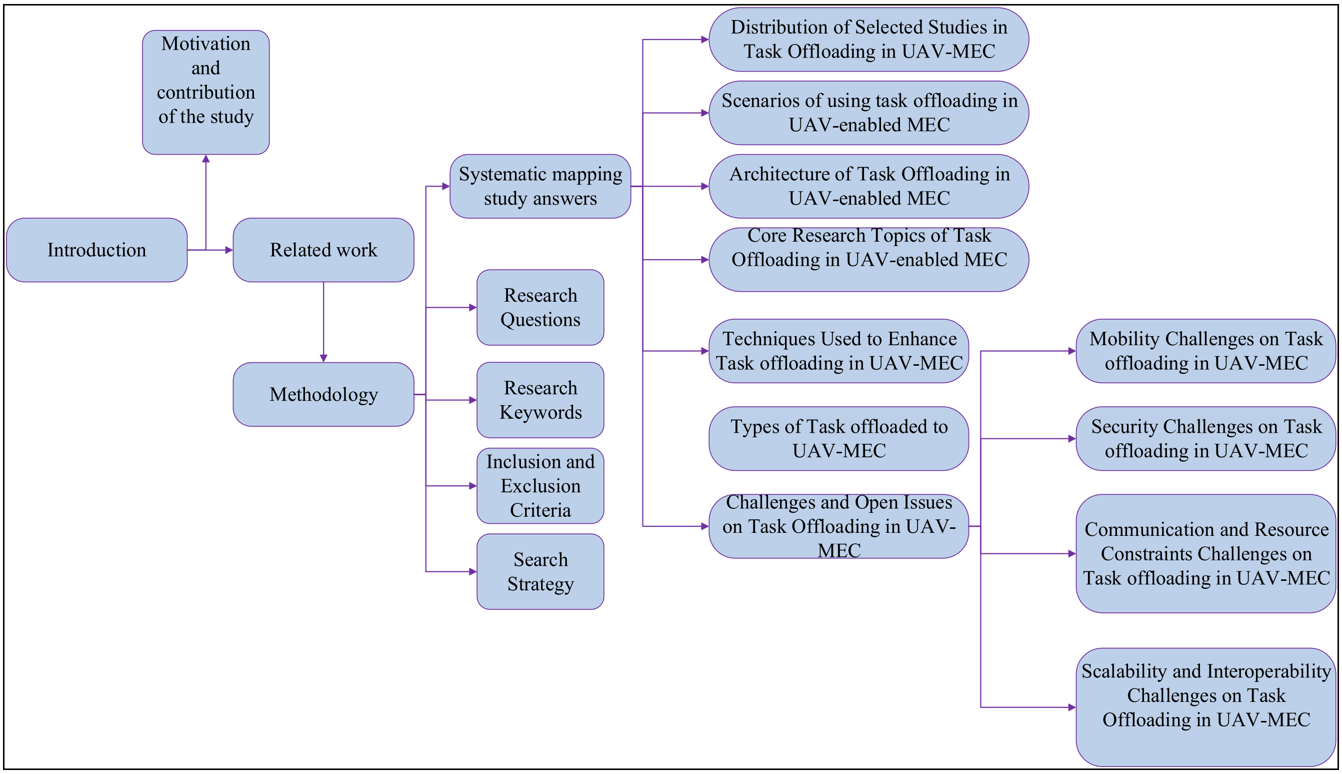

FIGURE 2. Systematic mapping study taxonomy.

The authors of [25] have conducted a survey on computation offloading approaches in MEC from the viewpoint of machine learning. The surveys have categorized the existing research into three groups: reinforcement learning-based, supervised learning-based, and unsupervised learning-based mechanisms. The authors evaluated and compared these categories based on several performance metrics, case studies, techniques, and evaluation tools used in each approach. Additionally, a survey [26] presented a systematic literature review on UAV-based Internet of Vehicles (IoV). A taxonomy was developed to organize different perspectives on the UAV-based IoV. Five research questions about the UAV-based IoV were answered by explaining the metrics used and presenting the objectives, techniques, and scenarios considered in relevant papers. In [27] on the other hand, the authors have conducted a systematic survey on secure communication in IoT-based UAV networks. Papers on existing attacks, limitations, and recommendations are analyzed. Physical/logical attacks and prevention schemes such as trajectory planning and lightweight authentication are discussed. Research challenges and areas for further study are identified. Furthermore, a survey [28] presented a systematic survey that specifically focused on reinforcement learning and deep reinforcement learning approaches for task offloading in MEC systems. The authors have evaluated and classified the relevant research papers based on various criteria, including use cases, network architectures, objectives, algorithms, decision approaches, and time-varying characteristics. To assist readers in identifying relevant papers based on specific features, the survey includes tables summarizing the key information.

On the other hand, [29] has conducted a systematic review of machine learning use case scenarios in IoDs, discussing current technologies and challenges. Papers on different machine-learning techniques used for tasks such as path planning, target tracking, and anomaly detection in drone networks were surveyed. In addition, the authors of [30] presented a systematic review of machine learning-from task offloading point of view in edge and fog computing. This topic discussed in papers using techniques such as deep learning, reinforcement learning, and swarm intelligence for task allocation, and resource management. It covered objectives, architectures, algorithms, and open challenges. The survey [31] also performed a systematic mapping study on edge computing. It's classified contributions according to the computing model, application domain, edge resources, and technical focus to identify active research areas and gaps. Another SLR survey [32] surveyed reinforcement learning methods for computation offloading and classifying papers based on network models, objectives, algorithms, and solution approaches. It's aimed to provide a comprehensive overview of RL applications and existing literature in this area to help identify open challenges. For instance, the work [33] presented an SLR on UAV- MEC that investigated and studied data on the

TABLE 1. A comparison of systematic review related to edge computing.

Refs.	Type of network	Publication Year	security	Review type	Open issue	offloading	UAV	Covered Year
[25]	Machine learning-offloading in MEC	2020	Not presented	Systematic literature review	presented	presented	Not presented	2013-2020
[26]	UAV-based Internet of Vehicles	2023	presented	Systematic literature review	presented	Not presented	Not presented	2018-2022
[27]	IoT-based UAV	2023	presented	Systematic literature review	presented	Not presented	presented	2018-2023
[28]	Reinforcement learning in MEC	2023	Not presented	comprehensive survey+ systematic	presented	presented	presented	2020-2021
[29]	Internet of drones-machine learning	2023	Not presented	Systematic literature review	presented	Not presented	Not presented	2020-2021
[30]	Machine learning-Offloading in Edge and Fog computing	2023	Not presented	Systematic literature review	Not presented	presented	Not presented	2015-2022
[31]	Edge computing	2023	Not presented	Systematic mapping study	presented	presented	Not presented	2001-2019
[32]	Reinforcement learning for offloading MEC	2023	presented	Systematic literature review	presented	presented	Not presented	2017-2021
[33]	UAV-enabled MEC	2022	presented	Systematic literature review	presented	Not presented	presented	2016-2021
[34]	Placement in MEC	2022	Presented	Systematic literature review	presented	presented	Not presented	2017-2021
[35]	Edge Computing	2022	Presented	A Systematic Lecture Study	Not presented	presented	Not presented	2010-2020
[36]	UAV Security	2022	Presented	Systematic review	presented	Not presented	presented	2015-2021
[37]	UAV-aided MEC network security	2022	Presented	systematic literature review	Presented	Presented	Presented	2019-2022
This survey	Task offloading in UAV-enabled MEC		presented	Systematic mapping study	presented	presented	presented	2019-2023

current state of the art or preferred reporting items. The study has categorized research in the UAV-MEC domain into various categories, such as energy efficiency, resource allocation, security, architecture, and latency. Moreover, the review [34] identified the challenges faced in dynamic service placement in MEC, such as resource allocation, service migration, and load balancing. The review highlighted the importance of considering factors such as latency, energy efficiency, and network conditions in dynamic service placement decisions. Different application scenarios for dynamic service placement in MEC explored, including smart cities, IoT, and vehicular networks. The tudy [35] proposed a systematic study for hybrid intelligent Non-orthogonal Multiple Access (NOMA) system for next-generation millimeter-wave (mmWave) end-edge cloud vehicle systems that incorporated high-throughput satellite, edge-founded station, and end-vehicle nodes. The researchers also explored the application of NOMA in various domains, such as Radio Access Networks (RANs), video coding, vehicular networks, and MIMO-MEC systems.

To address security aspects, the review [36] mapping over 100 relevant studies published between 2015 and 2021, provided a systematic perspective on the state of research addressing vulnerabilities in drone technologies. It was identified major trends and highlighted ongoing challenges guiding further research toward developing robust countermeasures against drone related threats. The review [37] analyzed main databases to map contributions based on security mechanisms such as authentication, access control and encryption. Findings were discussed according to categories such as authorization techniques and intrusion detection methods. Additionally, the paper identified challenges requiring ongoing efforts and potential future directions.

The lack of a systematic mapping study makes it difficult for researchers to identify the key findings and gaps in the research on UAV-MEC computation offloading. It also makes it difficult for researchers to stay up-to-date on the latest developments in this field. There have been several surveys and studies on the topic of using UAVs as MECs for computation offloading. However, it appears that there are no recent systematic mapping studies specifically focused on this emerging trend. To the best of our knowledge, our systematic mapping study is the first in this field. It aims to provide a comprehensive overview of the major trends and research directions in UAVs for task offloading. The study covers seven research questions to address various aspects of this topic and identify any gaps or areas where further investigation is needed. Table 1 provides a comparison between existing systematic literature reviews.

TABLE 2. Defined research questions (RQs).

Research question	Rationale
RQ1: What is the level of activity in the area of task offloading computing for UAV-MEC, and how are the selected studies distributed by reference type across the publication year and journal?	To assess the current level of research and overall trends in order to better understand the appeal of task offloading in UAV-MEC network, it would be helpful to compare the volume of research across different publication years and journals. This can provide insights into the level of maturity of task offloading in UAV-MEC.
RQ2: What are the scenarios for using UAV task offloading in a UAV-enabled MEC network?	There are many working areas related to the topic of task offloading in the UAV-MEC network. The answer to this RQ helps researchers and practitioners understand the current focus.
RQ3: What is the architecture of task offloading in UAV-enabled MEC?	Through analyzing the relationships between task offloading and UAV-MEC, and the mapping of task offloading technologies to those components, this RQ intends to understand the architecture of using task offloading in the UAV-MEC network from a systematic viewpoint.
RQ4: What are the main research areas or topics within the field of task offloading in the UAV-enabled MEC network?	To gain insight into the current state of research involving offloading in UAV-MEC systems, it would be useful to identify and categorize the different topics that have been studied. An evaluation of the distribution and frequency of publications across these various research areas could provide insight into which topics have received the most focus to date.
RQ5: Which techniques are more commonly used in offloading decision-making and enhanced task offloading in the UAV-MEC network?	To better understand the decision-making processes involved in offloading tasks to UAV-MEC, it would be useful to identify the primary techniques that have been employed. These techniques could include approaches such as reinforcement learning, game theory, heuristics, and others.
RQ6: What are the different types of tasks that can be offloaded to UAV-enabled MEC?	to explore the potential benefits and possibilities of leveraging UAV-enabled MEC for task offloading. By identifying the types of tasks that can be offloaded, we can optimize resource allocation, reduce latency, and expand the overall performance of MEC networks.
RQ7: What are the open issues of using task offloading in UAV-enabled MEC?	Through identifying the open issues of using task offloading in the UAV-MEC network, this RQ helps researchers form new research directions in this area and practitioners become aware of the weak points of using task offloading in UAV-enabled MEC.

III. METHODOLOGY

Drones have recently received much attention in the literature, primarily in the engineering, military, and computer science fields. For this paper, we have expressed our interest in investigating UAV-MEC offloading and related issues. Importantly, we ignore any issue not related to task offloading.

A. RESEARCH QUESTIONS

The objective of the SMS is to explore and analyze the state of the art of task offloading in UAV-enabled MEC. We further decomposed the objective into seven RQs. The answers to the research questions are presented in the sequence that are listed in Table 2.

B. RESEARCH KEYWORDS

When choosing research keywords for a systematic mapping study on task offloading in UAV-MEC, it is important to consider the specific focus and scope of the study. The main concepts include "task offloading" "UAV (Unmanned Aerial Vehicle)," and "MEC (Mobile Edge Computing)." Generate a list of related terms and synonyms for each main concept. For "task offloading," we include terms such as "computational offloading," or "offloading decision-making. The terms from each main concept to create potential research keywords were combined. We combine "task offloading" with "UAV" and "MEC" to create keywords "UAV task offloading," "task offloading in UAV networks," or "MEC-enabled task offloading." drone, unmanned aerial vehicle, mobile edge computing, MEC, edge computing, fog computing. In conclusion, we use the terms: UAV task offloading

- Task offloading in drone networks
- Computational offloading in UAV-MEC
- Task offloading decision-making in UAV-MEC networks
- MEC, or fog computing, enables task offloading in UAV networks.

C. INCLUSION AND EXCLUSION CRITERIA

We used the following inclusion criteria to choose studies from the database search results based on [38] and [39]:

1. The paper is about task offloading in MEC-enabled in UAVs.
2. The paper was published between January 2019 and December 2023.
3. Selecting papers with high technical quality for the task of offloading in UAV-MEC.

The following exclusion criteria were used:

E1: The paper addresses either task offloading or the UAV separately.

E2: The paper focuses on the topic of task offloading in drones and MEC. Specifically, it explores the concept of using UAVs as Internet of Drones (IoDs) framework to offload data to ground MEC.

E3: The paper mentions offloading in UAV-MEC without going into detail, implying that no data can be extracted to answer the RQs.

E4: The paper is gray literature (non-peer-reviewed material such as newsletters, magazine articles, and preprints).

E5: The paper is written in a language other than English.

E6: The paper is a secondary study (e.g., literature review, survey, and systematic review).

D. SEARCH STRATEGY

One of the major factors for such a surge in the published literature is the growing contributions and collaboration of UAVs in data offloading to UAV-MEC. The study execution process is shown in Figure 3, which follows PRISMA 2020 [40]. In Science Direct, we created a search string consisting of a keyword search for "UAV," which yielded

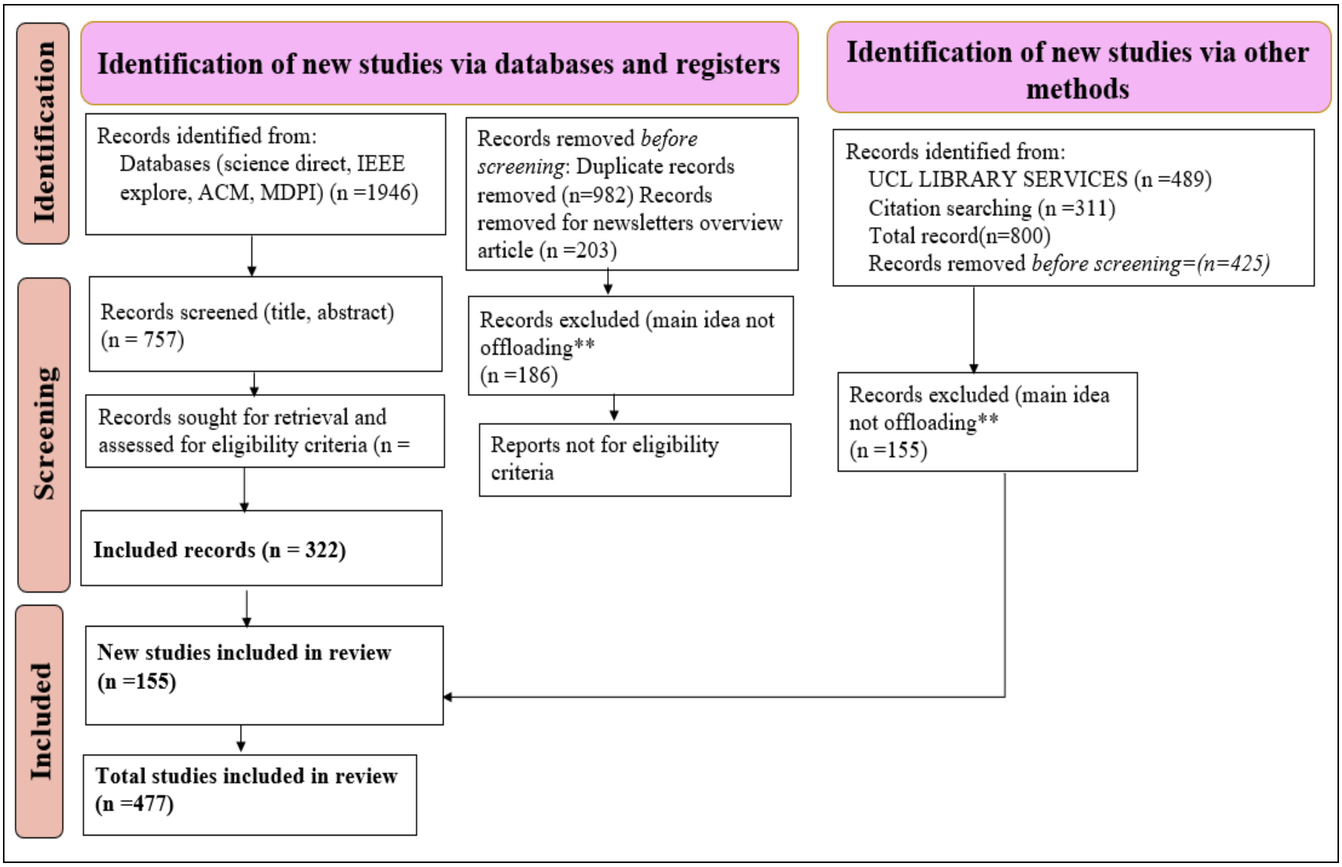

FIGURE 3. PRISMA research study databases and inclusion/exclusion factors of article selection.

24,422 documents. We then limited the results to the assigned subject offloading, which yielded 13,590 documents, and we limited the results to subject task offloading, which yielded 6,736 articles. We narrowed the search to UAV task offloading journal articles, conference papers, or book chapters (666 documents), and then to articles published in the last five years, beginning in January 2019 (663 documents). Finally, we eliminated review articles and editorial reports, resulting in a total of 153 documents. We ran the search again in IEEE Xplore, ACM, Wiley, and Springer to obtain 322 articles. Then we preformed snowball searching from libraries of other organizations, such as UCL LIBRARY SERVICES, as well as citation search to obtain 155 articles. After the search and selection phases, as shown in Figure 3, we identified and collected 477 relevant studies on the topic of task offloading in UAV-enabled MEC.

Other organizations, such as the UCL library service and citation searching, provided access to a wider range of academic publications beyond the scope of Scopus and the Web of Science. This helped uncover additional relevant articles that may have been omitted from the mainstream databases. These databases also involve examining the reference lists of key papers retrieved from the initial searches. Any publications cited in these reference lists that met the eligibility criteria were also included in the mapping study. This backward snowballing technique helped identify important works related to task offloading in UAV-MEC networks that were found through library catalogs alone [41].

IV. DISTRIBUTION OF SELECTED STUDIES IN TASK OFFLOADING IN UAV-MEC NETWORKS

This section reports the answer to RQ1. The statistical analysis of the number of publications in different years is presented, along with the percentage of studies on different reference types. Also, most journal names that are published on task offloading in UAV-MEC. Furthermore, the authors named connected to key words and countries. The number has increased steadily since 2019 and reaches a peak in 2023, as shown in Figure 4. The number of studies grew substantially annually during this period. In Figure 4, the distribution of 477 publications from 2019 to 2023 is shown. Overall, there seems to be a dramatic increase in the number of publications on task offloading in UAV-MEC in 2022 and 2023. The exaggerated increase in the number of publications in task offloading suggests a growing interest, research activity, and contributions to the field. As the field continues to evolve and mature, it is expected that the number of publications will continue to increase, reflecting ongoing

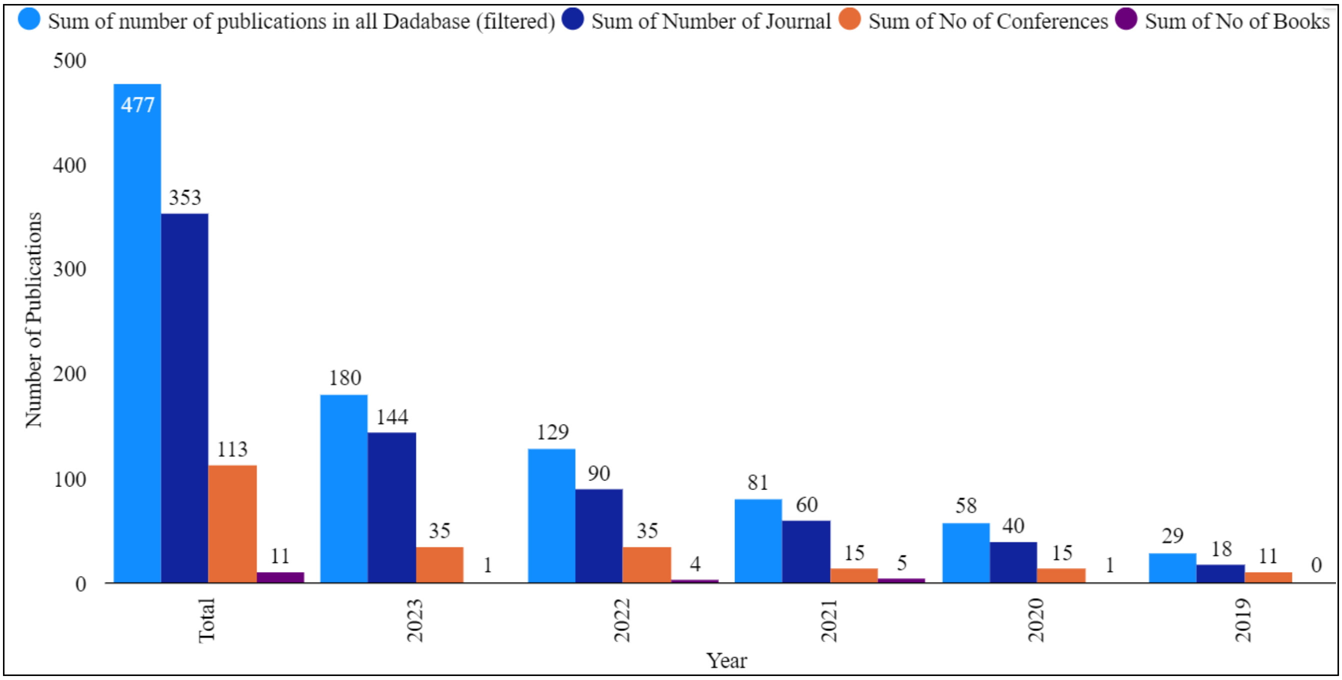

FIGURE 4. Number of publications in UAV task offloading in last the 5 years.

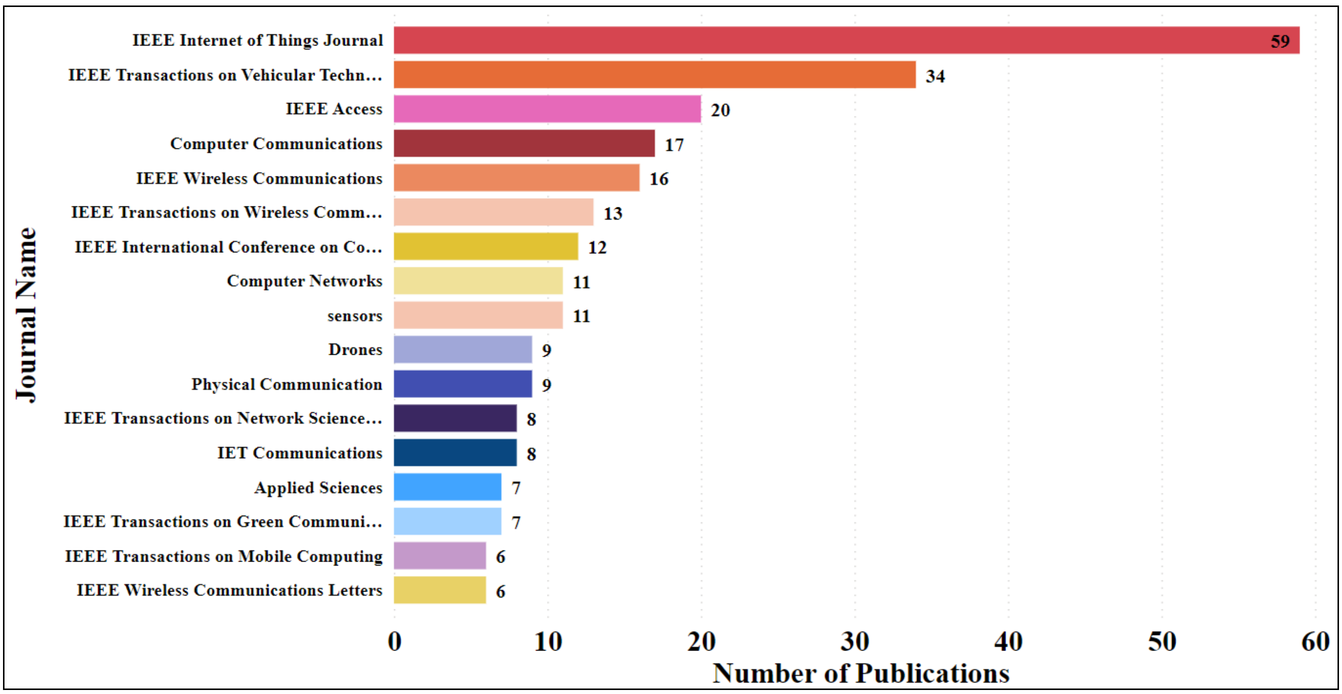

FIGURE 5. Number of publication articles in specific journals.

advancements, discoveries, and applications in UAV-MEC task offloading.

Figure 5 shows the number of articles published in a specific journal, providing a visual representation of its publication trends over time. Figure 5 provides a visual representation of the journal's productivity and growth over the five-year period. According to Figure 5, the journal with the highest number of published articles on task offloading in UAV-MEC is the IEEE Internet of Things, with a total of 59 articles.

This indicates that the journal has a strong focus on this research area and has been actively publishing related

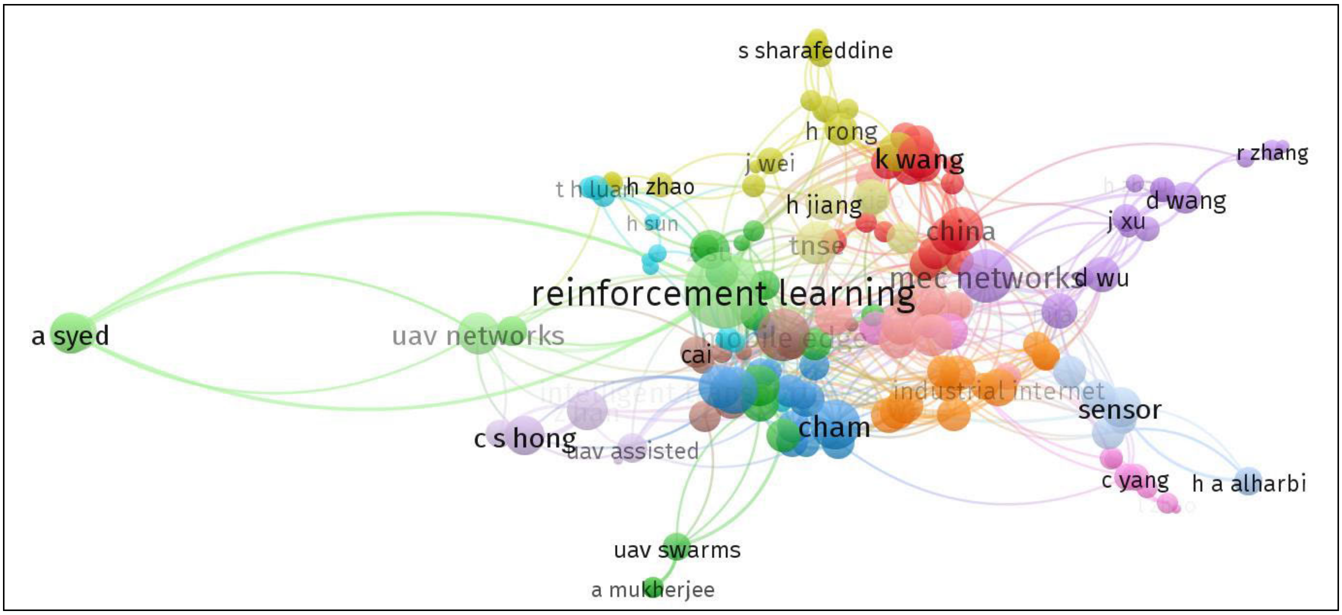

FIGURE 6. Mapping for authors with keywords and countries using VOSviewer.

studies. The second journal mentioned is IEEE Transactions on Vehicular Technology, with 34 articles. This journal also demonstrates a significant interest in task offloading in UAV-MEC. The third journal, IEEE Access, has published 20 articles on the topic. While the number of articles is lower than that of the first two journals, it still signifies a notable contribution to the field. It's important to note that Figure 5 only provides information for journals with six or more articles published on task offloading in UAV-MEC. If other journals have published fewer than six articles, they may not be included. This could explain why there might be journals missing from the visualization. The VOSviewer map [42] Figure 6 represents the connections between authors, keywords, and countries that have published more than 3 articles in a UAV working as an MEC for computation offloading. The size of the nodes (circles) represents the number of publications; it's clear that reinforcement learning has the greatest one, and the thickness of the lines (edges) represents the strength of the connection between two nodes. According to our map, China clearly has the highest publication rate among the other countries. This means that Chinese authors have published more articles in UAVs as MEC for task offloading research than authors from other countries.

V. SCENARIOS FOR USING TASK OFFLOADING IN UAV-ENABLED MEC

This section reports the answer to RQ2. With the integration of MEC technology, UAVs can also serve as MEC servers, providing data processing services for nearby terminal devices. When ground-based stations are busy or unable to process user data, users can offload their data processing tasks to the MEC server carried by the UAV. This offloading reduces the bandwidth pressure on ground-based stations and enables efficient data processing.

The scenarios of task offloading to UAV-MEC included the following:

A. EMERGENCY/DISASTER RESPONSE SITUATIONS

UAVs carrying computing resources can act as floating MEC platforms to provide on-demand computation and networking to disaster relief teams. This helps deliver services when ground infrastructure is damaged [43]. The author in [44] proposed a solution for the Deep Deterministic Policy Gradient (DDPG) and Long Short-Term Memory (LSTM)-based task offloading and resource allocation algorithms for UAV-assisted LEO satellite edge computing, which show promise for emergencies. The algorithm utilized RL and LSTM to optimize task allocation and resource allocation in real time. By considering the state of the system and previous observations, the algorithm can make informed decisions on task offloading and resource allocation, considering factors such as computational task size and satellite resource availability.

B. LIVE STREAMING/VIDEO ANALYTICS

UAVs fitted with edge servers can process and analyze live video/audio streams from wearables and cameras on the ground to detect events and relay insights in real-time. This helps with tasks such as search and rescue, surveillance, crowd monitoring, etc. [45]. UAVs with edge servers help locate missing people by continuously analyzing thermal camera feeds and automatically detecting human signatures using AI models during search operations. For example, the work [46] explored the use of edge-to-fog computing architecture to enable efficient data processing and communication among drones in a swarm. The video task involved demonstrating the implementation and performance of the proposed edge-to-fog collaborative computing framework using a swarm of drones. This task may include showcasing the communication protocols, data processing algorithms, and coordination mechanisms employed in the system. The video task aims to provide a visual representation of the collaborative computing capabilities of the swarm of drones and highlight the benefits of using edge-to-fog computing in this context.

C. TEMPORARY NETWORK EXTENSION

UAVs with MEC hardware can provide temporary MEC capabilities in areas with network outages or during mass gatherings where ground infrastructure gets overloaded. Their mobility helps extend coverage. UAV-MECs placed in rural areas during events can function as aerial Wi-Fi or cellular hot-spots connected to edge servers onboard to deliver internet access and low-latency services to end users [47]. The workflow in [48] involved task offloading from the terminal device to the UAV-MEC, task processing in the UAV-MEC system, and potential further offloading to Base Stations (BS) with the help of a Software-Defined Network (SDN). The proposed framework utilized DRL-based control methods to optimize resource allocation, including computational resources, bandwidth, and storage, based on task requirements and network conditions. The goal is to enhance the efficiency of task processing and improve the overall coverage extension.

D. MOBILE VR/AR APPLICATIONS

UAV-MEC servers deployed near users can support mobile VR/AR applications by hosting edge services and processing graphical/sensor data with low latency. This enhances interactive experiences [49]. The research [50] focused on addressing the limitations of IoT devices in terms of processing power and battery life for VR/AR applications by leveraging UAV-MEC with Intelligent Reflection Surfaces (IRS) infrastructure. The proposed optimization framework considers factors such as time, power, phase shift design, and local computational resources to optimize the placement of UAV-MEC-IRS and allocate resources efficiently.

E. INDUSTRIAL IoT

UAV-MECs enable deployment of edge services closer to terminal devices in changing environments such as factory floors, etc., allowing real-time offloading and processing of IoT data with low latency. In addition, UAV-MEC platforms above factory floors run AI/Meaning Learning (ML) models on sensor data from machinery in real-time to predict failures and maintenance needs [51], [52]. The proposed approach in [52] for computation-intensive Industrial Internet of Things (IIoT) applications began by partitioning the application into a directed acyclic graph (DAG) comprising multiple collaborative tasks. Subsequently, a joint optimization problem is formulated based on the models of processor resources and energy consumption for the task offloading scheme. To optimize this problem, a cooperative resource allocation approach is proposed to address the constraints of resource availability and communication latency.

F. VEHICULAR EDGE COMPUTING (VEC)

UAVs equipped with edge capabilities can collaborate with connected vehicles to dynamically form aerial-ground vehicular clouds for sharing computation, data, and wireless access [53]. The approach in [54] proposed a DRL-based approach to optimize channel sharing and task offloading decisions in impermanent UAV-assisted VEC networks. The proposed learning algorithm considers channel conditions, computing resources, and task requirements to make decisions that minimize task completion time while ensuring fair resource allocation. The performance of the planned approach is estimated through simulations, which demonstrate its effectiveness in improving network performance and reducing task completion time compared to traditional approaches.

G. SMART AGRICULTURE

UAV-MECs equipped with edge servers analyze fields for moisture and nutritional deficiencies and detect diseases in crops/livestock in real time. Insights help optimize yields [55]. The proposed approach [56] used graph neural network reinforcement learning (GNN-RL) to model the heterogeneous network as a graph, which includes UAV-MECs and terminal devices. The RL algorithm is then used to learn the optimal task offloading decisions based on the graph representation. The GNN-RL approach took into account the heterogeneity of the network, including the different computing capabilities and communication resources of the nodes, as well as the dynamic nature of the network due to the mobility of UAVs. The performance of the proposed approach is evaluated through simulations, which demonstrate its effectiveness in improving the network performance and reducing task completion time compared to traditional task offloading approaches.

H. SMART CITIES

UAV-MEC platforms monitor traffic, infrastructure, and stream analytics to authorities, enabling efficient resource allocation and rapid emergency responses throughout changing urban environments. Road authorities employ UAV-MEC to trace vehicle movements and detect jams/accidents via real-time streaming analytics from overhead cameras at the edge and routing traffic accordingly [57]. The proposed life-cycle in [58] included the registration, authentication, and offloading of vehicles to UAV-MECs. The authors used blockchain technology to warrant the security and privacy of the data exchanged between the vehicles and UAV-MECs in smart cities. The proposed framework also includes a smart contract-based offloading mechanism that enables vehicles and UAVs to offload their tasks to the edge servers in a secure and efficient manner. The simulations demonstrate its effectiveness in improving the security and efficiency of UAV-assisted vehicle networks.

I. EMERGENCY RESPONDER TRACKING

UAVs equipped with edge servers can track the locations of first responders such as police, and firefighters, etc. in real-time during disasters/emergencies. This helps coordinate relief efforts. Furthermore, UAVs deployed with edge capabilities can monitor endangered animal populations using sensors, cameras, and computer vision models run at the edge. This enables conservation authorities to study patterns and protect wildlife. Additionally, law enforcement agencies can use UAV-MEC systems to trace suspected criminals on the run. Onboard edge servers process surveillance footage and guide the drone's trajectory in pursuit [59], [60]. For instance, the framework in [61] consisted of a task allocation algorithm that assigns search tasks to different UAVs based on their remaining energy and distance to the search area, and a communication scheduling algorithm that minimizes the communication overhead between the UAV-MECs and the ground edge server. The edge server performs computationally intensive tasks such as image processing and target detection, while the UAV-MECs perform low-level tasks such as data collection and preprocessing. The proposed framework also included an energy management mechanism that monitors the energy consumption of the UAVs and adjusts their speeds and search patterns to minimize energy consumption. Table 3 shows the comparison between different scenarios of task offloading in the UAV-MEC network.

VI. THE ARCHITECTURE OF TASK OFFLOADING IN UAV-ENABLED MEC

This section reports the answer to RQ3. The classification system for UAV-MEC is based on their mobility, or hierarchy. The UAV-MEC can be classified by mobility into two main categories: static and mobile.

A. STATIONARY UAV-MEC

This category refers to UAV-MEC systems where the UAV remains stationary at a fixed location. Stationary UAV-MEC can be further classified into different subcategories:

1) **Fog-based UAV-MEC**: In fog-based UAV-MEC, the edge infrastructure consists of fog nodes that are deployed close to the terminal devices, or IoTs. These fog nodes provide computing and storage capabilities, enabling efficient task offloading and processing in real-time. Communication between the terminal devices, or IoTs, and UAV fog nodes is typically wireless and low-latency [95]. The paper [96] proposed a framework for multi-access computation offloading in marine networks using UAV-MECs and hybrid NOMA and Frequency Division Multiple Access (FDMA) techniques. The framework enabled multiple ships to offload their computation tasks to a UAV-mounted fog server via NOMA and FDMA for multiple access and resource allocation. The authors formulated the computation offloading problem as a Mixed Integer Nonlinear Programming (MINLP) problem and proposed an algorithm based on alternating optimization and successive convex approximation to solve it. The proposed algorithm iteratively optimized the task offloading decisions, NOMA power allocation, and FDMA sub-channel allocation to minimize the total energy consumption of the network while meeting the latency requirements of the applications.
2) **Collaborative UAV-MEC**: In collaborative UAV-MEC, multiple stationary UAVs work together in a coordinated manner to process offloaded tasks. The UAVs within the collaborative groups may distribute tasks among themselves based on factors such as workload, proximity, or resource availability. This collaboration enhances task execution efficiency and enables load balancing [97]. The objective of [94] was to minimize the overall delay of terminal device tasks by optimizing the task offloading ratio, the hovering position of the UAV-MEC, and the computing resource allocation of the Electric Vehicle (EV) and UAV-MEC. Authors formulated the problem as a Nonlinear Programming (NLP) problem and then decomposed it into EV-related and UAV-MEC related subproblems using the Block-Coordinate-Descent (BCD) method. For the EV-related subproblem, authors determined the optimal offloading ratio by equating the computing time on the UAV to its offloading time and proved the feasibility of this method. For the UAV-related subproblem, it used NOMA and Successive Interference Cancellation (SIC) techniques to enhance communication efficiency. They then obtained the optimal hovering position by using the Successive Convex Approximation (SCA) technique twice to convert this subproblem into a convex problem.
3) **Tethered UAV-MEC**: Tethered UAV-MEC involves UAVs that are physically connected to the ground through a tether, which provides power and data connectivity. The tethered UAV can process offloaded tasks for the nearby terminal devices while remaining in a fixed position. This configuration allows for longer flight times and continuous offloading without concerns about battery life. Figure 7 shows the architecture of task offloading in UAV-MEC. The paper [64] was providing MEC services in zones with no infrastructure using a tied UAV-MEC system. The framework aims to minimize the energy consumption of the UAV and terminal devices while ensuring task completion

TABLE 3. The key requirements and benefits of using UAV-MEC in different scenarios.

No	Scenario	Typical Application	Key Requirements	Benefits of UAV-MEC	Number of related studies	Limitations	Examples of related studies
1	Emergency Response	Disaster relief coordination	Temporary connectivity, computing, and localization of responders	Rapid deployment, and location tracking with low latency	30	Reliability and availability of UAVs/network during crisis	[62] [63] [43] [64] [65]
2	Live video analytics	Surveillance and event monitoring	Processing of real-time video/sensor feeds	Real-time analysis and insights over large areas	14	Latency constraints, bandwidth limitations, quality degradation	[66] [67] [68] [69] [70]
3	Network Extension	Rural connectivity and event coverage	Aerial base stations, WiFi hotspots	Extends cellular coverage and internet access	103	Finite battery/fuel, regulatory restrictions on airspace use	[71] [2] [72] [73] [74]
4	Mobile VR/AR	Immersive applications	Fast rendering, sensor data	Enhances interactive experiences	9	Requires high bandwidth, low latency graphics/video	[49] [75] [76] [50]
5	Smart Agriculture	Crop monitoring analytics	Hyperspectral camera feeds, modeling	Optimizes farm operations yields	5	Dependence on weather, geographic scale of deployment challenges	[77] [3] [78]
6	Industrial IoT	Plant maintenance and quality control	Edge data processing and predictive maintenance	Mission-critical support for manufacturing	12	Large scale deployment and management costs. Complex integration	[79] [80] [81]
7	Vehicular Edge Computing	Content sharing connectivity	Inter-vehicle resource sharing	Augments ground networks in sparse areas	39	Reliability and security of wireless backhaul from fast moving UAVs	[62] [82] [83] [53] [84]
8	Smart Cities	Traffic control, infrastructure monitoring	Stream analytics, computer vision models	Supports efficient urban resource allocation	82	Density of UAVs, public acceptance, privacy/security at large scale	[85] [86] [87] [88] [74]
9	Target Tracking	Search and rescue and wildlife monitoring	Real-time object detection classification	Guides time-critical operations with low	23	Accuracy and reliability of location services in all conditions	[89] [90] [91] [92] [93]

deadlines. The authors propose an energy-efficient task scheduling algorithm that dynamically allocates tasks to the UAV and terminal devices based on their computing capabilities, energy consumption, and communication latency. The algorithm considers the tethered UAV's limited mobility and energy constraints. The authors also propose a novel energy harvesting mechanism that uses solar panels to recharge the battery of UAV-MECs.

B. MOBILE UAV-MEC

This category refers to UAV-MEC systems where the UAV is mobile and capable of moving within a given area or following a predefined trajectory. Mobile UAV-MEC can be further classified into different subcategories:

1) **Fog-based UAV-MEC**: In fog-based mobile UAV-MEC, the terminal device and IoTs offload tasks to nearby UAV-MEC fog nodes as they moves within the network coverage area. The fog nodes provide computing resources and support seamless task offloading and processing during the UAV's mobility [98]. For example, the work [99] aimed to minimize the energy consumption and delay of IoT devices while ensuring task completion deadlines. The authors proposed a joint optimization algorithm that dynamically allocates tasks to UAVs and fog servers based on their computing capabilities, energy consumption, and communication latency. The algorithm considered the limited energy and computing resources of IoT devices and the mobility of UAV-MECs.

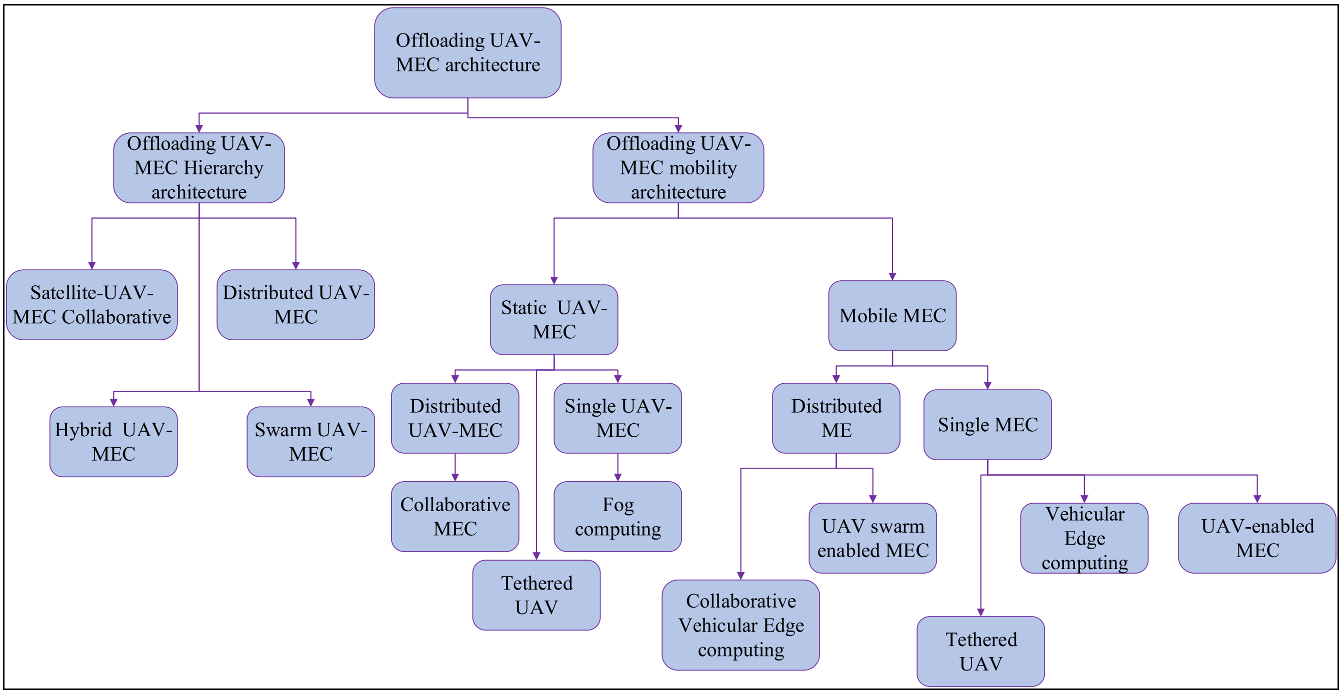

FIGURE 7. Classification of UAV-MEC architecture.

2) **UAV Swarm-enabled MEC**: UAV swarm-enabled MEC involves a group of mobile UAVs working together as a swarm to collectively process offloaded tasks. The swarm operates in a coordinated manner, distributing tasks among the individual UAVs based on swarm algorithms, communication protocols, and task requirements. This approach enables parallel processing, fault tolerance, and scalability [79]. For instance, the work [100] aimed to minimize the latency and energy consumption of the UAV-MEC swarm while ensuring task completion deadlines. The authors propose a DRL-based algorithm that dynamically allocates computing tasks to UAV-MECs based on their computing capabilities, energy consumption, and communication latency. The algorithm considered the mobility and collaboration of the UAV-MEC swarm, as well as the uncertainty and dynamic nature of the surveillance environment. Table 4 compares the mobility architectures below:

Task sizes vary depending on the use case and application. The latency and energy consumption values are estimates and may vary depending on a variety of factors, including the specific implementation, network conditions, and environmental factors. Because stationary UAV-MEC systems (fog-based, collaborative, and tethered) do not require the UAV to move, they have lower latency and energy consumption than mobile UAV-MEC systems (fog-based and UAV Swarm-enabled). Mobile UAV-MEC systems, on the other hand, can provide greater flexibility and adaptability, as well as the ability to offload tasks in real time while the UAV-MEC is in flight. Table 4 shows that the total number of papers summed across these three categories for the UAV-MEC (stationary), tethered UAV-MEC (stationary), and fog-based UAV-MEC (mobile) is 477. It's worth noting that the task size can have an impact on latency and energy consumption. Larger tasks, for example, may necessitate more processing power and time, resulting in increased latency and energy consumption. Smaller tasks may also necessitate less processing power and time, resulting in lower latency and energy consumption. The task offloading hierarchical architecture in UAV-MEC can be classified by layer hierarchy as follow:

1) **Satellite-UAV-MEC Collaborative Architecture**: When necessary, UAVs with MEC capability can collaborate with satellites or the larger MEC infrastructure. When satellite connectivity is available, UAVs can communicate with satellites to exchange data, receive updates, or transmit processed data to a larger network. UAV-MECs can offload specific tasks or heavy data to nearby MEC servers for more intensive processing or to leverage additional computational resources in scenarios where the large MEC infrastructure is accessible [44]. Paper [116] proposed a collaborative inference algorithm for UAV-MECs using a Low-Earth-Orbit (LEO) satellite network. The algorithm aimed to improve the accuracy and latency of image recognition tasks for UAV-MECs by leveraging the computing resources of the LEO satellite network. The authors proposed a novel communication protocol that enables efficient data transmission between UAV-MECs and

TABLE 4. Comparison of different subcategories of UAV-MEC systems.

Subcategory	Typical size of task	Latency	Energy Consumption	Number of publications	Limitations	Examples of related studies
Fog-based UAV-MEC (stationary)	Medium to large (50 M to > 50 M)	Low (<10 ms)	Moderate (depending on the number of fog nodes and their distance from the UAV)	56	Limited coverage area due to stationary position, single point of failure if fog node goes down	[100] [101] [102] [80] [103]
Collaborative UAV-MEC (stationary)	Medium to large (50 M to > 50 M)	Low (<10 ms)	Moderate (depending on the number of UAVs in the collaborative group and their distance from the edge infrastructure)	7	Coordination overhead between multiple nodes	[104] [105] [106]
Tethered UAV-MEC (stationary)	Large (> 50 M)	Very low (<5 ms)	Low (since the UAV is physically connected to the ground and does not require battery power)	1	Restricted mobility due to tether, additional complexity from tether management	[64]
Fog-based UAV-MEC (mobile)	Small to medium (5 M to < 50 M)	Medium (10-100 ms)	Moderate to high (depending on the UAV's speed and the number of fog nodes it needs to communicate with)	417	Handling offloads as UAV moves between coverage zones, maintaining backhaul connectivity during mobility	[77] [107] [108] [109] [110]
UAV Swarm-enabled MEC (mobile)	Small to medium (5 M to < 50 M)	Medium (10-100 ms)	High (since the swarm requires coordination and communication among multiple UAVs, which can increase energy consumption)	52	Coordination of large numbers of autonomous UAVs, contention as UAVs compete for wireless resources	[111] [112] [113] [114] [81]

satellites, as well as a collaborative inference algorithm that distributes the image recognition tasks among multiple satellites.

2) **Centralized UAV-MEC Architecture**: A centralized entity, such as a ground-base station or a cloud server, manages the task offloading process in this architecture. Although UAVs serve as relays or MEC servers, decision-making and coordination are centralized [48]. The paper [117] examined the issue of offloading computational tasks for Software-Defined Vehicular Network (SDVN)-supported services in a UAV-enabled Mobile Edge Computing MEC system. In this scenario, a single UAV and a single edge server (ES) are provided to handle the workload from vehicles moving within a specific region. Each vehicle in the region periodically submits requests to the UAV-enabled MEC system until it exits the region, with each request being treated as a computational task that can be processed locally on the vehicle, on the UAV-MEC, or on the ES. The problem model is formulated using multiple communication and energy consumption models. The main objectives are to minimize total time delays and energy consumption. A dynamic scheduling framework based on a greedy heuristic is proposed to solve the problem under investigation.

3) **Distributed UAV-MEC Architecture**: In a distributed architecture, task offloading decision-making and coordination are distributed among the UAV-MECs themselves. Each UAV-MEC can make independent decisions based on local information and, if necessary, collaborate with other UAV-MECs [79]. The paper [118] proposed a distributed and collective intelligence framework for computation offloading in aerial edge networks, where multiple AVs are employed as flying edge servers to provide computing services to terminal devices. The framework aims to minimize the latency and energy consumption of terminal devices while maximizing the utilization of the UAV-MECs computing resources. The authors proposed a distributed offloading algorithm that enables the terminal devices to make offloading decisions collaboratively and dynamically based on the current network conditions. The algorithm considered the computing capabilities, communication latency, and energy consumption of the UAV-MECs and terminal devices, as well as the mobility of the UAVs.

4) **Hybrid UAV-MEC Architecture**: A hybrid of centralized and distributed architectures that employs a hierarchical structure in which some UAV-MECs serve as coordinators or cluster heads, making decisions on

TABLE 5. Comparison between hierarchy architecture of task offloading in UAV-MEC.

Architecture	Coordination	Scalability	Reliance on Infrastructure	Autonomy vs Management	Number of publications	Limitations	Examples of Related studies
Satellite-UAV-MEC	Leverages satellites for wider connectivity and MEC/satellite resources for intensive tasks	Limited by satellite coverage	Requires available satellite/MEC infrastructure	Centralized coordination	21	High latency due to added hop via satellite, dependence on space-based infrastructure Cost and complexity of satellite integration	[122] [123] [124] [125] [126]
Centralized UAV-MEC	Single controller handles coordination	Bottleneck as scale increases	No additional infrastructure needed	Low autonomy, easy management	120	Single point of failure if central node fails, bottleneck and latency with long haul backhaul, limited by coverage of central controller	[127] [128] [129] [130] [131]
Distributed UAV-MEC	Distributed coordination protocols	More scalable	Self-reliant	High autonomy, overhead in coordination	312	Increased coordination overhead, challenges in resource haring/task allocation	[71] [132] [87] [109] [133]
Hybrid UAV-MEC Architecture	Cluster heads provide a layer of coordination	Scalable with hierarchy	Self-reliant	Balanced autonomy and management	71	Complexity of managing different frameworks, selection of optimal offloading strategy, failure domains across centralized and distributed components	[134] [67] [68] [135] [136]
UAV Swarm enabled MEC	Collective intelligence through cooperation	Adapts to scale dynamically	Self-reliant	High autonomy and coordination through protocols	52	Coordination and reliability across large numbers of UAVs, interference and contention as swarm size increases	[137] [138] [139] [114] [57]

behalf of a group of UAVs within their cluster. These coordinators can communicate with one another to share information and make higher-level decisions [119]. For example, the framework in [120] consisted of a group of UAVs that serve as flying edge servers to collect and process data from IoT devices in a given area. The authors proposed a clustering algorithm that groups the IoT devices based on their spatial and communication proximity and dynamically assigns a UAV to each cluster to serve as the cluster head. The cluster heads are responsible for collecting data from their member devices, processing the data locally using the UAV-MEC's computing resources, and transmitting the processed data to the central server. The proposed framework also includes an energy-efficient data transmission scheme that minimizes the energy consumption of IoT devices by dynamically adjusting the transmission power and data rate based on the channel conditions and data requirements.

5) **Swarm UAV-MEC Architecture:** In a swarm architecture, a swarm of UAV-MECs performs task offloading and resource allocation. The swarm's behavior can be dynamically adjusted based on the environment and the tasks. This architecture leverages the collective intelligence and cooperation of the UAV swarm to enhance task offloading and resource distribution [100], [121]. For example, in the framework [122], several UAVs are organized as edge servers to deliver computing services to terminal devices. The authors proposed a cooperative task offloading algorithm that enables terminal devices to offload their computation-intensive tasks to nearby UAV-MECs in a cooperative manner, thereby reducing their computational burden and energy consumption. The algorithm considered the computing capabilities, communication latency, and energy consumption of both terminal devices and UAVs. The authors also proposed a UAV-MEC swarm formation strategy that optimizes the positions and trajectories of the UAV-

MECs to minimize communication latency and improve computing performance. Table 5 compares hierarchy architectures.

As shown in Table 5, the satellite-UAV-MEC leverages existing infrastructure but relies on its availability. Centralization has the simplest management but limits scalability. Distributed is most autonomous and scalable, but has an overhead. Hierarchical methods balance autonomy and scalability through layers. The UAV swarm architecture dynamically adapts through cooperation [141].

VII. CORE OBJECTIVES OF TASK OFFLOADING IN UAV-ENABLED MEC

This section reports the answer to RQ4. This research focuses on developing efficient algorithms and strategies for determining which tasks from terminal devices should be offloaded to UAV-based MEC servers. The following are the primary or trending research topics in the field of task offloading in UAV-enabled MEC networks:

A. COST

considering task offloading to UAV-MEC systems includes evaluating the economic implications of offloading tasks to the edge infrastructure [142]. Computational resource usage, communication costs (e.g., bandwidth consumption, data transfer fees), and infrastructure maintenance expenses can all be included in the cost. The goal is to minimize costs while meeting application requirements by optimizing task allocation and offloading strategies [102], [143]. The paper [144] investigated a UAV-enabled MEC system in which terminal devices offload their computing tasks to UAV-MECs for processing. In scenarios with multiple computing tasks, in order to minimize computing costs, it is crucial to effectively allocate tasks to devices. To tackle this challenge, the authors proposed a Non-cooperative Game model-based Power Allocation (NGPA) scheme, which aims to minimize transmission energy consumption by determining the optimal power allocation strategy for devices. Additionally, the problem of task allocation was approached as a bilateral match between devices and UAV-MECs to minimize overall computing costs.

B. ENERGY MANAGEMENT

Energy efficiency is an important aspect of UAV-MEC systems. UAVs are typically powered by small onboard batteries, so effective energy management is critical for maximizing flight time and operational capabilities [145]. Task offloading decisions can consider the energy consumption of both the terminal device and the UAV-MEC infrastructure to reduce energy consumption and extend the operational lifespan of the UAV [146]. For instance, the work [147] proposed an online distributed optimization algorithm for energy-efficient computation offloading in air-ground integrated networks. Terminal devices can offload their computational tasks to nearby UAV-MECs or ground BSs for processing. The algorithm aimed to minimize the total energy consumption of the network while meeting the computation delay requirements of the devices. The authors proposed a distributed optimization algorithm that enables each device to make computation offloading decisions in an online manner based on the current network conditions. The algorithm considered the computing capabilities, energy consumption, and communication latency of both the devices and the UAV-MECs, or BSs. The authors also proposed a pricing mechanism that incentivizes the devices to offload their tasks to the most energy-efficient UAV-MECs, or BSs.

C. LATENCY MANAGEMENT

The delay or response time experienced during task offloading and processing is referred to as latency. Low-latency communication between terminal devices and the mobile edge infrastructure is critical in UAV-MEC systems, especially for real-time or delay-sensitive applications [148]. Latency reduction ensures timely task offloading, quick data processing, and efficient feedback transmission, allowing for responsive and interactive UAV applications [149]. For instance, the work [150] focused on improving the performance and efficiency of IoV systems by leveraging the capabilities of UAVs and edge computing. This approach utilizes DRL techniques to optimize the task offloading process, where computational tasks are offloaded from IoV devices to nearby UAV-MECs. By using DRL, the system can learn and make intelligent decisions on when and where to offload tasks, considering factors such as network conditions, computational resources, and energy consumption. This optimization aims to enhance the overall system performance, reduce latency, and improve the quality of service for IoV applications.

D. QoS (QUALITY OF SERVICE) ENHANCEMENT

Meeting specific performance requirements and service-level agreements (SLAs) are important QoS considerations in task offloading to UAV-MEC. Latency, reliability, throughput, availability, bandwidth, task partitioning and scheduling, and other relevant indicators are examples of QoS metrics. To ensure the desired level of service and user satisfaction, task offloading decisions should consider the applications or users QoS requirements [151], [152].The authors [153] proposed an approach that combines Improved Particle Swarm Optimization (IPSO) with Deep Neural Networks (DNN) to optimize the operation of UAV-MEC networks. The objective is to provide efficient task offloading for terminal devices while offering short-term network services during emergencies. The scheme addresses the challenge of making fast decisions in a changing environment. The problem was formulated as a MINLP problem, considering factors such as reducing terminal device energy consumption, shortening terminal device latency, and ensuring fairness in offloading. The IPSO algorithm is employed to solve the problem, and a trained neural network is utilized for making quick decisions based on high-quality labeled data.

E. TASK COLLABORATION CONTROL

When several UAVs work together to process offloaded tasks, this process is referred to as task collaboration. By facilitating fault tolerance, resource sharing, load balancing, and more effective task execution, collaboration can improve system performance. In a cooperative group, UAV-MECs can assign tasks to each other according to workload, proximity, resource availability, or predefined collaboration algorithms [154]. For example, the work [155] proposed a collaborative scheme among UAV-MECs to share the workload and provide computational services to devices outside of traditional networks. The paper specifically focused on the task topology of offloading in UAV-MEC networks, considering dependencies between subtasks. The authors presented an optimization problem to minimize user latency by jointly managing the offloading decision for dependent tasks and allocating communication resources of UAV-MECs. In order to solve this NP-hard problem, research divided it into two subproblems: the offloading decision problem and the communication resource allocation problem. A metaheuristic approach was proposed to find a suboptimal solution for the offloading decision problem, while convex optimization was used for the communication resource allocation problem.

F. TRAJECTORY CONTROL

Because UAVs are highly mobile, this field of study attempts to solve the problems associated with controlling UAV-MEC mobility in task offloading situations. The aforementioned involves enhancing UAV trajectory planning, handover protocols, and task migration tactics to guarantee smooth task offloading and reduce disturbances resulting from UAV maneuvers [156]. Reference [157] formulated trajectory control as a Markov decision process that can be solved via DRL. The interaction between the agent and environment through trial-and-error allowed for derivation the optimal trajectory policies via DRL without a priori information about the environmental dynamics. The author of [158] studied improving the distribution of devices and planning the trajectory of UAVs to enhance the performance of MEC systems. This approach utilized matching theory, which is a mathematical framework for solving optimization problems involving the allocation of resources. By transforming the multi-objective optimization problem into a single-objective problem using a weighted-sum approach, the goal is to minimize the weighted sum of the delay and energy consumption. The solution involved decomposing the problem into subproblems and solving them sequentially, considering factors such as the UAV-MEC trajectory, computing resource allocation, and time allocation.

G. SECURITY MANAGEMENT

To ensure the confidentiality, integrity, and availability of data and communications in UAV-MEC systems, security management is critical. Secure communication connections, authentication techniques, data encryption, access control policies, and intrusion detection systems are all required for task offloading to UAV-MEC. The implementation of comprehensive security measures aids in mitigating potential hazards and threats to the operation and sensitive data of UAV-MEC networks [159], [160]. This reduces exposure during transit. Edge resources such as UAV-MEC servers also have fewer access points and smaller attack surfaces than large clouds. Therefore, processing sensitive data locally at the edge provides stronger protection against network attacks and unauthorized access [161].

The use of UAV-MECs in networks allows for improved data processing and communication capabilities, but it also introduces challenges in task scheduling and resource allocation. By leveraging blockchain technology, as in [162], the proposed mechanism aimed to provide a decentralized and secure solution for task matching, ensuring fairness and transparency in the allocation process. This paper explored the potential benefits and challenges of integrating blockchain into UAV-assisted MEC networks and proposed a multi-task matching mechanism to enhance the overall performance and efficiency of the network. In Table 6, the comparison of objectives for task offloading to UAV-MEC is based on the search results. A multi-agent reinforcement learning technique was implemented in [163] where UAVs and edge servers are agents. The agents learn optimal policies through interactions to minimize energy consumption while meeting latency constraints. Contextual information such as channel state, task types and edge workload is incorporated through a context network.

As shown in figure 8, energy consumption minimization is a crucial research objective in UAV-MEC task offloading. The efficient utilization of energy resources is essential for the successful operation of UAV-MEC networks. By minimizing energy consumption, various benefits can be achieved, such as prolonged flight time for UAV-MECs, increased battery life, reduced operational costs, and improved overall system performance [188]. According to Figure 8, energy, and latency, which are major cost components, have the most papers that aim to reduce both or one of them (energy and latency). Improving QoS helps to reduce latency and optimize resource/energy usage. Task collaboration and trajectory control affect how tasks are assigned and UAVs are maneuvered for offloading. Typically, the goal is efficient resource management to minimize latency and energy consumption. Even security management requires authentication and encryption, which adds to the overhead [189]. Therefore, while papers investigate various aspects, the underlying goals are usually latency/energy optimization or cost reduction.

In terms of cost, optimizing utility and dynamic pricing models have been less explored than have technical

TABLE 6. Comparison of the core research topics in task offloading to UAV-MEC.

Concept	Description	Optimization Objective	Key Factors Considered	Number of publications	Limitations	Example of Related Study
Cost	Economic implications of task offloading to edge infrastructure	Minimizing costs	Computational resource usage and communication costs	79	Significant infrastructure investment required for setting up UAV-MEC networks at scale	[163] [101] [164] [165] [166]
Energy	Efficient management of power consumption for UAVs and edge infrastructure	Minimizing energy usage	UAV energy consumption, infrastructure energy consumption	122	Limited battery capacity of UAVs constrains operational time and computing resource availability	[167] [168] [169] [170] [171]
Latency	Delay or response time experienced during task offloading and processing	Minimizing latency	Communication latency, data processing time	79	Latency increases with multiple hops of communication between UAVs, edge nodes and cloud	[172] [173] [43] [174] [175]
QoS (Quality of Service)	Performance requirements and service-level agreements	Meeting QoS requirements	Latency, reliability, throughput, availability	87	Maintaining SLAs for applications with stringent quality requirements	[62] [176] [177] [178] [179]
Task Collaboration	Cooperative efforts among multiple UAVs for offloading and processing tasks	Enhancing system performance	Workload distribution, proximity, and resource availability	48	Coordination overhead in distributing collaborative workloads across multiple mobile edge nodes	[71] [180] [181] [115]
Trajectory Control	Management and optimization of UAV flight paths during task offloading	Optimizing UAV movements	Energy consumption, communication optimization	84	Offloading decisions can impact pre-planned UAV flight routes and trajectories	[182] [183] [79] [184] [185]
Security Management	Measures to protect data, communications, and system integrity	Ensuring system security	Authentication, encryption, access control and intrusion detection	56	Securing device identities, data transmission and edge service access points across wireless network	[86] [167] [186] [184]

performance optimization. More economic models that address complete overall cost-benefit tradeoffs using non-technical metrics such as revenue generation are needed. Current research focuses on technical layer enhancements to reduce costs indirectly rather than through direct valuation and monetization strategies. Costs in UAV-MEC offloading networks can be better understood with more holistic frameworks that incorporate both technical and economic dimensions. Notably, the total number of papers reflected in Table 6 exceeds 477 since these papers could address several research topics.

VIII. TECHNIQUES USED TO ENHANCE TASK OFFLOADING IN UAV-MEC

This section reports the answer to RQ5. Some major strategies that have improved task offloading decision-making in UAV-MEC networks include the following:

A. MACHINE LEARNING AND REINFORCEMENT LEARNING

Machine learning and reinforcement learning are strategies that include training models to optimize offloading decisions based on previous experiences and feedback. Algorithms as Q-learning and deep Q-networks can learn from previous data to make intelligent task offloading decisions [190]. DRL is a machine learning subfield that combines deep learning and reinforcement learning techniques. It can be used to optimize the decision-making process for task allocation and offloading in the context of task offloading in the UAV-MEC network [191]. The UAV-MEC can learn to make intelligent decisions based on its current state, environmental factors, and desired objectives by training an agent using DRL algorithms [192]. To make efficient task offloading decisions, DRL can consider factors, such as cost, energy consumption, latency, and QoS requirements [193].

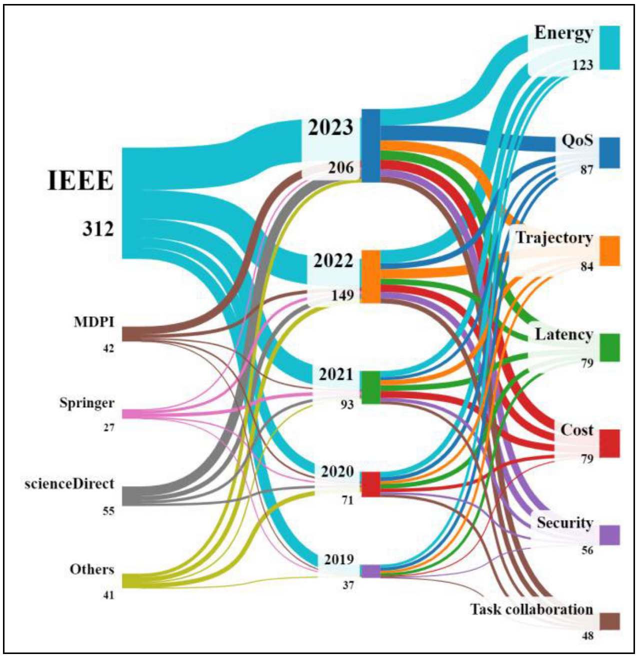

FIGURE 8. Sankey diagram for Core research topic publications with publishers.

The authors of [194] optimized the computation offloading process in a wireless sensor network for marine renewable energy smart grids. This system aimed to minimize energy consumption and improve the efficiency of the smart grid by offloading computational tasks from the sensors to the UAV-MECs. The offloading decisions are based on factors, such as CPU utilization, transmission time slots, transmission power, and computing resource utilization. Various optimization algorithms and techniques, such as duality-based optimization, game theory, and reinforcement learning, are employed to achieve energy optimization and cost reduction.

B. CONTEXT AWARENESS

Dynamic context elements in the communication layer such as available bandwidth, delays, channel quality, computing loads, movement patterns, and energy limits while offloading are considered. UAV-MEC networks can adjust their offloading tactics based on the current environment [195]. The research paper [128] focused on addressing the challenges of deploying a multi-UAV system for data collection in infrastructure-deficient environments. The paper proposed a solution that optimizes the trajectory planning of the Access UAV-MEC (A-UAV) to ensure fair access to dynamically moving Inspection UAV-MECs (I-UAVs) in different time slots. The optimization model aims to minimize the distance traveled by the A-UAV and generate a fair access schedule for the I-UAVs. Additionally, the paper introduces a Lyapunov-based online optimization approach to minimize energy consumption and queue backlogs in the system.

C. GAME THEORY

By modeling the task offloading problem as a non-cooperative game, effective strategies can be derived utilizing ideas such as Nash equilibria. Game theory can aid in the analysis of interactions between UAV- MEC nodes and terminal devices, as well as the identification of the appropriate offloading strategies that maximize overall network performance [134]. The goal in [196] was to optimize a cost function based on energy and latency by cooperatively optimizing task offloading, MEC server choice, transmission power, UAV path, and CPU frequency allocation. In order to address this issue, the authors proposed an alternating iterative approach using the block descent method. The approach consists of three layers: the first layer utilizes a game theoretic approach to solve the subproblems of task offloading and server selection. The second layer handles the transmission power allocation through a geometric waterfalling technique and optimizes the UAV-MEC trajectory via successive convex approximation. The third layer address the computational resource subproblem by allocating CPU frequencies through a gradient descent method. To reduce the computation time, the proposed method divides the UAV-MEC flight trajectory into shorter timeframe segments.

D. AUCTION-BASED APPROACHES

Using auctions between devices and UAV-MEC nodes can allow for distributed and efficient work allocation. Devices can bid to have their tasks offloaded to UAV-MEC nodes, and the allocation is dependent on the bids. This method enhances justice and efficiency in decision-making while offloading tasks [162]. For instance, the author in [197] proposed an online auction mechanism for task offloading with privacy preservation in a UAV-assisted mobile edge computing network. The network consisted of a group of UAVs that serve as flying edge servers to provide computing services to terminal devices. The authors proposed a privacy-preserving task offloading mechanism that enables terminal devices to securely offload their computational tasks to nearby UAV-MECs without revealing their private data. The mechanism uses homomorphic encryption and secret sharing techniques to ensure data privacy and security.

E. CLUSTERING AND GROUP COORDINATION

By organizing nodes into clusters led by UAV-MEC cluster heads, coordinated offloading within groups can be facilitated. UAV-MEC networks can maximize resource consumption and overall system performance by grouping devices and coordinating their offloading decisions [198]. The authors of [120] proposed a multi-UAV computing framework that enables UAV-MECs to offload computing tasks from IoT devices and perform computing tasks collaboratively, thereby reducing energy consumption and improving the data transmission efficiency of the IoT network. They used a clustering algorithm to group the IoT devices based on their geographical locations and communication requirements. The UAV-MECs are then assigned to clusters based on their computing capabilities and energy levels. The authors also proposed a task scheduling algorithm that enables the UAVs to efficiently offload the computing tasks from the IoT devices to the UAVs and perform the computing tasks collaboratively.

F. DEADLINE-AWARE SCHEDULING

It is critical to consider work completion deadlines when meeting real-time requirements. UAV-MEC networks can schedule activities in a way that ensures timely processing while minimizing latency by including deadline limitations in the offloading decision-making process [152]. For example, the work in [199] focused on optimizing task offloading and UAV-MEC scheduling to maximize service satisfaction. The research aimed to enhance the user experience and system performance by considering factors such as task offloading decision, UAV selection, transmission power allocation, and UAV-MEC trajectory optimization. The goal was to minimize energy consumption, reduce latency, and improve overall system efficiency.

G. PRIORITY-BASED QUEUEING

By prioritizing key jobs in queues, latency-sensitive processes can be optimized. UAV-MEC networks can ensure that time-critical jobs are performed with minimal delay by assigning higher priorities to them, boosting overall system performance [200], [201]. The model in [202] considered the dynamic changes in computing tasks produced by the inner-city transportation network, in which the task delay was calculated by queueing theory. When the number of tasks exceeds the capacity of edge servers, some tasks are offloaded to UAV-MECs. The goal is to minimize task delay and computing costs.

H. OFFLOADING AND CACHING COORDINATION

Using caching results from prior offload decisions can reduce redundant processing. UAV-MEC networks can reduce computational and communication overhead by storing and reusing previously offloaded results, resulting in increased efficiency [203]. The two time scales in [204] joined service caching and task offloading for UAV-assisted MEC are used to optimize the caching and offloading decisions in a coordinated manner, taking into account the dynamic nature of the network and the varying demands of the users. This was done by considering two-time scales: a short time scale for caching decisions and a longer time scale for offloading decisions. At the short time scale, the system dynamically determined which services or data should be cached at the edge servers or UAVs based on the current user demands and network conditions. The approach helped to improve the response time for frequently requested services and reduced the need for frequent data transfers. At a longer time, scale, the system decided when and which tasks should be offloaded from user devices to edge servers or cloud resources. The decision was based on factors such as the computational capabilities of the user devices, the availability of edge servers or cloud resources, and the network conditions. By intelligently offloading tasks, the system can optimize its overall system performance and energy efficiency. A comparison of techniques used to enhance task offloading in UAV-MEC is illustrated in Table 7.

According to Table 7, DRL is often used for solving task offloading problems in UAV-MEC. In the context of task offloading in UAV-MEC, DRL algorithms can be employed to make intelligent decisions on when and where to offload tasks to UAV-MEC servers, considering factors such as network circumstances, resource availability, and task requirements. DRL algorithms can adapt to dynamic and uncertain environments, allowing UAV-MECs to make real-time decisions based on changing conditions [227]. This is particularly important in UAV-MEC systems, where network conditions and resource availability can vary rapidly. DRL enables UAVs to learn optimal offloading policies through trial and error, improving the overall performance and efficiency of the system [228]. By continuously interacting with the environment and receiving feedback, UAV-MECs can learn to help improve offloading decisions over time.

Furthermore, Table 7 shows that context awareness allows dynamic adaptation to varying network conditions, but collecting and disseminating real-time context information adds overhead. In the context of game theory, it provides a mathematical framework to model complex interactions but deriving optimal strategies can be computationally intensive. Auction-based approaches distribute resource allocation in a self-organizing manner, but auction design and coordination introduce complexity. Furthermore, clustering facilitates group cooperation; however, given network dynamics, determining optimal cluster structures and leadership is difficult. Although deadline-aware scheduling ensures latency sensitivity, incorporating deadlines strictly limits optimization. Although computational profiling enables selective offloading, task resource estimations are not always accurate. Priority queueing ensures time-critical processing, but unfairness can occur with higher priority tasks. Caching past results leverage temporal task correlations for efficiency gains, but cache management introduces storage overhead. Therefore, in the future, hybrid models can be evaluated to balance trade-offs based on application needs. For optimal offloading governance in real-world UAV-MEC networks, system designs must be optimized across techniques.

IX. TYPES OF TASKS OFFLOADED TO UAV-MEC

This section reports the answer to RQ6. In UAV-enabled MEC, various types of tasks can be offloaded to optimize resource utilization and improve overall system performance.

TABLE 7. Techniques used to enhance task offloading in UAV-MEC.

Technique	Description	Advantages	Disadvantages	Number of publications	Limitations	Examples of Related studies
Machine learning and reinforcement learning	These techniques involve training models to optimize offloading decisions based on past experiences and feedback.	- Can learn from historical data to make informed decisions. - Can adapt to changing network conditions.	- Requires a large amount of training data. - May have high computational overhead.	167	Reliance on large datasets, computationally expensive training process	[204] [108] [164] [70] [205]
Context awareness	Considers dynamic context factors such as available bandwidth, delays, computation loads, mobility patterns, and energy constraints.	- Allows for more informed offloading decisions. - Can adapt offloading strategies based on the current context.	- Requires accurate and up-to-date context information. - May have high overhead for context sensing.	74	Overhead of continuously monitoring dynamic context parameters	[137] [206] [129] [207] [208]
Game theory	Models the task offloading problem as a non-cooperative game to derive optimal strategies using concepts such as Nash equilibria.	- Analyzes interactions between UAVs and MEC nodes. - Maximizes overall network performance.	- Requires knowledge of game theory concepts and techniques. - May have high computational complexity.	42	Assumptions of rational behavior may not always hold in real deployments	[163] [209] [87] [210] [211]
Auction-based approaches	Uses auctions among devices and UAV-MEC nodes for distributed and efficient task allocation.	- Promotes fairness and efficiency in task offloading. - Enables optimal allocation based on bids.	- Requires a well-designed auction mechanism. - May have high communication overhead.	6	Delay and signaling overhead in coordinating auctions	[212] [213] [161]
Clustering and group coordination	Organizes nodes into clusters led by UAV cluster heads to facilitate coordinated offloading within groups.	- Optimizes resource utilization within clusters. - Improves overall system performance.	- Requires efficient clustering algorithms. - May have high overhead for cluster coordination.	30	Managing coordination across large numbers of clusters/groups	[167] [214] [174] [81] [215]
Deadline-aware scheduling	Considers task completion deadlines to meet real-time requirements.	- Ensures timely processing and minimizes latency. - Meets real-time requirements.	- Requires accurate estimation of task completion times. - May have high computational overhead for scheduling.	20	Challenges in optimizing schedules with variable application deadlines	[182] [216] [217] [218] [219]
Priority-based queueing	Prioritizes critical tasks in queues to optimize latency-sensitive processing.	- Improves overall system performance. - Ensures timely processing of critical tasks.	- Requires accurate task prioritization mechanisms. - May have high overhead for queue management.	9	Inability to guarantee strict priority-based execution under load	[220] [221]
Caching and offloading coordination	Leverages results caching from previous offload decisions to minimize redundant processing.	- Reduces computation and communication overhead. - Improves efficiency.	- Requires efficient caching and coordination mechanisms. - May have high storage overhead	15	Caching decisions based on predictions may not always hold true	[137] [222] [223] [224] [225]

These tasks can be categorized into different types based on their characteristics and requirements. The following are some of the different types of tasks that can be offloaded to UAV-enabled MEC:

A. COMPUTATION-INTENSIVE TASKS

These tasks require significant computational resources and can benefit from offloading to the UAV or the edge cloud. Examples include, complex data processing, machine learning algorithms, and image/video analytics [229]. Running pre-trained deep learning models for on-device predictions and classifications. Offloading of machine learning inference refers to the process of transferring the computational tasks from a terminal device to the UAV-MEC infrastructure. This offloading is performed to increase computational capabilities and resources available in the UAV-MEC, thereby improving the efficiency and performance of the inference process [230]. For example, the paper [48] explored the use of DRL and SDN techniques in UAV-assisted networks to improve computational resource efficiency. The task offloading process starts with the identification of computationally intensive tasks by the terminal devices. The task offloading request was then sent to the DRL-SDN, which analyzed the request and determine the appropriate network resources and UAV-MEC allocation for task processing. The DRL-SDN configured rule installation based on state observations and evaluation indicators such as network congestion, computational capabilities, and energy efficiency. The terminal device transmitted the task data to the designated UAV-MEC for processing, and once completed, the SDN notified the terminal device about the status.

B. DATA-INTENSIVE TASKS

These tasks involve the transmission and processing of large amounts of data. Offloading these tasks to the UAV-MEC can reduce the latency and bandwidth requirements on the terminal device. Examples include, big data analytics, data mining, and data aggregation [231]. Offloading data-intensive tasks to UAV-MEC offers advantages such as, reduced latency, optimized bandwidth usage, efficient data processing, and improved energy efficiency. These benefits make UAV-MEC a promising approach for handling data-intensive tasks in various domains [192]. For instance, the Flying-RIS in [232] is a UAV-MEC equipped with a programmable meta-surface that can reflect and refract the wireless signals to improve the signal quality and coverage of the UAV-MEC network. The authors proposed a joint optimization framework for trajectory planning, phase shift design, and IoT device big data association to maximize network performance. The framework considered the channel conditions, computing capabilities, and energy levels of the IoT devices and the MEC server. The authors also proposed a DDPG-based approach to predict channel conditions and optimize the Flying-RIS phase shift design.

C. LATENCY-SENSITIVE TASKS

These tasks have strict latency requirements and need to be processed quickly. Offloading these tasks to the UAV-MEC can reduce the processing time and improve real-time responsiveness. Examples include, AR/VR applications, real-time video streaming, and online gaming [233]. Certain tasks, such as AR, real-time video streaming, and online gaming, have very strict latency requirements due to their interactive and real-time nature. Processing these latency-sensitive tasks on terminal devices alone may not meet the low latency needs as mobile CPUs/GPUs have limited capacity. Offloading such latency-critical tasks to UAV-MEC resources can help reduce the overall task processing latency [234].

The algorithm in [235] combined the advantages of two other algorithms: the DDPG algorithm for continuous action spaces and the Generalized Stochastic Approximation (GSA) algorithm for off-policy learning. In a disaster scenario, UAV-MECs analyzed and processed the collected data. However, the time it took to complete this process can be critical, especially in situations where resources are limited or where there is an urgent need for information. The WMDDPG-GSA algorithm could help optimize task completion time by learning an optimal policy for controlling UAVs and MECs in a disaster scenario.

D. ENERGY-INTENSIVE TASKS

Energy intensive tasks consume significant energy on the terminal device. Offloading these tasks to the UAV-MEC can reduce energy consumption and extend the battery life of the terminal device. Examples include, complex simulations, cryptographic operations, and intensive signal processing [236]. Due to their resource-intensive computations, tasks such as complex simulations, intensive cryptographic operations, and signal processing impose high energy demands on terminal devices. Performing such energy-intensive tasks on resource-constrained terminal devices can quickly drain the battery. This results in poor battery life and a poor user experience. Offloading these computationally heavy duties to resources with an adequate power supply such as UAV-MEC can help reduce the energy consumption on terminal devices.

The authors of [237] proposed a joint optimization framework for task routing, UAV-MEC placement, and IRS phase shift design to minimize task completion time and energy consumption. The framework considered channel conditions, computing capabilities, and energy levels of the UAV-MECs-IRSs, and IoT devices. The authors also proposed a DRL-based approach to enable the UAV-MECs to learn the optimal task routing decisions based on the current network conditions.

E. AR/VR RENDERING AND GAMING

Offloading of AR/VR rendering refers to the process of transferring the computational tasks involved in rendering AR or VR content from a terminal device to a remote UAV-MEC infrastructure [238]. This offloading is typically performed to leverage the higher computational capabilities and resources available on UAV-MEC servers, resulting in improved performance and user experience. The offloading process involves sending the raw sensor data (such as camera feed or motion tracking data) from the AR/VR device to the UAV-MEC. The server then performs resource-intensive rendering tasks, such as 3D modeling, image processing, and graphics rendering, and sends the processed data to the AR/VR device for display [239]. On the other hand, portions of intensive mobile games, such as environment rendering, physics simulations, and AI are also offloaded to UAV-MEC.

This offloading mechanism is commonly used in cloud gaming, where the heavy computational tasks required for gaming are performed on powerful servers and the processed data are streamed back to the user's device for display and interaction, but in the case of immersive gaming or immersive VR/AR where the latency is critical the UAV-MEC can be used for offloading [240]. The paper [241] demonstrated the potential of a UAV-aided hybrid cloud/mobile-edge computing architecture to meet the complex demands of future Extended Reality (XR) applications by leveraging the capabilities of the central cloud, edge computers, and UAV-MECs. The paper categorized XR devices into two types: strong and weak devices. It introduces a cooperative NOMA scheme that pairs strong and weak devices to enhance QoE of users for XR devices. The scheme intelligently selected either direct or relay links for weak XR devices. To strike a balance between system throughput and fairness, the paper formulated a sum logarithmic-rate maximization problem.

F. LOCATION-BASED TASKS

Certain tasks require up-to-date location-based information or location-aware services to function properly. Examples include, GPS navigation, location-targeted advertising, and analysis of geospatial sensor data. Offloading these kinds of tasks to UAV-MECs can take advantage of their mobility. UAV-MECs are not stationary such as traditional edge devices but can move through the airspace and dynamically collect real-time data about the environment [242]. By performing location-dependent computations on the UAV itself, tasks such as GPS navigation can benefit from the UAV's immediate knowledge of its current coordinates [243]. The authors of [244] considered a scenario where UAV-MECs are used to collect data and perform computations in areas affected by a disaster, and where there are limited computational resources available on the ground. The authors proposed an algorithm that used the concept of "parking resources" to schedule computation tasks among the available UAV-MECs depending on location. Parking resources refer to the computational resources that are available on the UAVs while these resources are not in flight, such as when resources are landing or recharging. The algorithm aims to minimize the total completion time of all computation tasks while ensuring fairness among the UAV-MECs.

G. SECURITY-SENSITIVE TASKS

Some computational tasks involve sensitive data that needs to be securely processed and protected for privacy reasons. Examples include, encrypting confidential information, authenticating users, and analyzing surveillance video footage. Offloading these types of security-critical tasks to UAV-MEC servers can help enhance security and privacy compared to performing them in the cloud [245]. By pushing sensitive workloads to the UAV-MEC edge, sensitive data do not need to travel long distances through the internet backbone to reach remote cloud data centers. It is important to note that the suitability of task offloading depends on various factors, such as network conditions, task characteristics, and resource availability. The decision to offload a specific task in UAV-MEC is typically based on optimizing performance metrics such as latency, energy consumption, and resource employment. This classification helps identify suitable use cases [246], [247]. The approach in [132] involved learning a risk function that quantifies the risks associated with different task offloading strategies and then selecting the strategy with the lowest risk. The risk function considered factors such as network conditions, UAV-MEC resources, and mission requirements and was used to evaluate different task offloading strategies. The strategy with the lowest risk was selected for execution in real-time, allowing for adaptive decision-making based on current network conditions and mission requirements. The approach used RL techniques to learn the risk function over time based on feedback from real-world task offloading scenarios. By continuously learning from feedback and adapting to changing network conditions, the approach can help ensure that IoT tasks are executed efficiently and effectively while minimizing the risks associated with task offloading in UAV-MECs. Table 8 compares types of tasks offloaded to UAV-MEC server.

Table 8 categorizes different types of tasks that can benefit from UAV-MEC offloading based on their characteristics and requirements. This classification helps identify suitable use cases. Performance improvement in computation-intensive, energy-intensive, and graphics-heavy AR/VR tasks can be achieved by leveraging more UAV-MEC resources for processing. Moreover, latency-sensitive tasks benefit as proximity to UAV-MEC lowers overall processing latency, improving real-time responsiveness for applications. Location-dependent tasks are well-suited for UAV-MEC offloading given UAV mobility and the ability to dynamically process environmental sensor data. Furthermore, security-sensitive tasks enjoy enhanced security by avoiding long-distance transit through untrusted networks and local processing at the protected UAV/edge layer. A wide range of applications from diverse domains such as analytics, gaming, mapping, and surveillance can take advantage of UAV-MEC infrastructure based on their workload characteristics.

X. OPEN ISSUES ON TASK OFFLOADING IN UAV-MEC

This section reports the answer to RQ7. Task offloading in UAV-MEC faces several open issues, which are actively being investigated. The following are some key challenges and open issues in this field:

A. MOBILITY CHALLENGES ON TASK OFFLOADING IN UAV-MEC

The high mobility of UAV-MECs can have a significant impact on the task offloading process in UAV-MEC networks.

TABLE 8. The comparison of different types of tasks offloaded to UAV-MEC server.

Task Type	Description	Example Tasks	Resource Intensive	Latency Sensitive	Security Sensitive	Energy Intensive	Benefits of UAV-MEC Offloading	Number of publications	Limitations	Examples of publications
Computation -Intensive Tasks	Tasks requiring intensive CPU processing	Image analysis, modeling, and simulation	High CPU Usage (>75%)	Medium-Low (50 ms-20 ms)	Low (Not directly dealing with sensitive data)	Medium (Moderate energy usage)	Leverage higher computing power of UAV/edge to improve efficiency and performance.	48	Limited resources on individual UAVs may not support large/complex models and algorithms	[102, 122, 128, 248]
Energy-Intensive Tasks	Tasks requiring significant energy	GPU-heavy tasks, sensor streaming	Variable	Variable	Low (Not directly dealing with sensitive data)	Very High (Heavily constrained by available energy/battery levels)	Reduce latency and optimize bandwidth usage on terminal devices.	126	UAV battery and processing constraints impact onboard execution	[67, 167, 223, 249, 250]
Latency-Sensitive Tasks	Tasks requiring low latency	AR/VR, controls, real-time analytics	Variable	Very High (<5 ms)	Variable	Variable	Lower processing time to improve real-time responsiveness.	82	Unreliable wireless links affect real-time responsiveness for tasks with tight deadlines	[127, 251-253]
Data intensive Tasks	Tasks related to file/data storage	Storing large maps/datasets, and backups	High Storage Usage (>75%)	Low (> 50 ms)	Medium (Some protection needed based on sensitivity of data)	Low (Minimal impact on energy resources)	Reduce energy consumption to extend mobile battery life.	3	Limited onboard storage capacities pose challenges for large datasets	[107, 109, 163, 177, 225]
AR/VR Rendering and gaming	Graphics-intensive rendering	3D modeling, environment views	High CPU, GPU, and Storage (>75%)	High (5 ms-20 ms)	Low (Not directly dealing with sensitive data)	High (Significant portion of energy budget consumed)	Leverage higher computing power of UAV/edge to improve performance and user experience.	9	Resources required for high-fidelity graphics may exceed UAV/edge server capabilities	[75, 99, 205, 254]
Localization and Mapping tasks	Location/environment mapping	Drone navigation, autonomous vehicles	Medium CPU, Storage (< 75%)	High (5 ms-20 ms)	Medium (Some protection needed based on sensitivity of data)	Medium (Moderate energy usage)	Take advantage of UAV mobility and onboard sensing for real-time location-dependent processing.	19	Sensors and computing limits onboard UAVs for real-time positional needs	[113, 137, 254-256]
Security-Sensitive Tasks	Tasks involving sensitive data	Authentication, encryption, access control	Medium CPU (< 75%)	Medium (20-50ms)	Very High (Requires strict security controls and hardware isolation)	Medium (Moderate energy usage)	Enhance security and privacy by processing locally at UAV/edge with fewer access points.	58	Onboard CPUs have restricted capability to handle encrypting/authenticating sensitive payloads	[58, 159, 212, 257, 258]

There are several ways in which high mobility can affect task offloading:

1) **Communication Disruptions**: Because UAV-MECs are mobile, their location and connectivity with the ground network can change frequently. This can cause communication breakdowns and task offloading delays. As UAV-MECs travel through different areas, they may encounter varying network conditions, such as signal strength and interference. These unstable network connections can have an impact on task offloading reliability and performance [259].
2) **Dynamic Resource Availability**: As UAV-MECs move, the availability of computing and communication resources can change rapidly. Decisions about task offloading must consider dynamic resource availability and select the best UAV-MEC server for offloading based on factors, such as proximity, resource utilization, and network conditions [260].
3) **Task Migration and Handover**: Tasks can be offloaded from terminal devices to UAVs in UAV-MEC networks and vice versa. Due to high mobility of UAV-MECs, task migrations between UAVs and terminal devices may occur frequently as they move into and out of each other's coverage areas. To minimize disruptions and ensure efficient task execution, this task migration process must be carefully managed. Due to the high

mobility of UAV-MECs, frequent handovers for user terminals or IoTs between different UAV-MECs may occur [261]. These handovers add extra communication overhead, such as signaling and control messages, which can reduce task offloading efficiency. This can to rapid change of network topology in UAV-MEC systems due to the mobility of UAV-MECs, making it challenging to maintain stable and reliable communication links [262].

B. SECURITY CHALLENGES ON TASK OFFLOADING IN UAV-MEC

Task offloading in UAV-MEC systems brings several security challenges that need to be addressed to ensure the integrity, confidentiality, and availability of data and services. These challenges include the following:

1) **Data Privacy and Confidentiality**: When offloading tasks to MEC servers on UAVs, sensitive data may be transmitted through wireless channels, increasing the susceptibility to eavesdropping and unauthorized access. Ensuring data privacy and confidentiality is crucial for protecting sensitive information [84].
2) **Authentication and Authorization**: UAV-MEC systems require robust authentication mechanisms to verify the identity of both the UAV-MEC server and terminal devices. Unauthorized access to the system can lead to malicious activities, data breaches, and service disruptions. Proper authorization mechanisms should also be in place to control access to resources and prevent unauthorized task offloading [259].
3) **Integrity and Trustworthiness**: Task offloading involves transmitting data and code between the UAV-MEC server and terminal devices. Ensuring the integrity of the transmitted data and code is essential for preventing tampering, unauthorized modifications, and the injection of malicious code. The trustworthiness of the UAV-MEC server is also crucial for ensuing that it executes the offloaded tasks correctly and does not compromise the system [263].
4) **Malware and Intrusion Detection**: UAV-MEC systems are vulnerable to malware and intrusion attacks. Malicious code can be injected into the offloaded tasks, compromising the integrity and security of the system. Robust malware and intrusion detection mechanisms should be implemented to detect and mitigate such threats [259].
5) **Resource Sharing and Isolation:** Multiple UAV-MECs are raising concerns about resource sharing and isolation. Proper mechanisms should be in place to ensure that each UAV-MEC's tasks and data are isolated from others, preventing unauthorized access and interference [58].
6) **Access control**: Task offloading involves granting access to different users or systems. It is important to implement strong access control mechanisms, such as multi-factor authentication and least privilege principles, to ensure that only authorized individuals or systems can access the offloaded tasks [264].
7) **Vendor-specific Vulnerabilities**: When using UAV-MECs from different vendors in UAV-MEC swarm cooperation, it is important to consider that each vendor may have different security vulnerabilities. Conducting thorough security assessments and audits of UAV-MECs and their associated software and hardware components can help identify and address these vulnerabilities [265].
8) **Blockchain Cryptocurrency Fees**: The cryptocurrency fees on the blockchain platform are used to reward miners who successfully manage their mined blocks into the blockchain for all transactions [266]. To encourage UAV-MEC providers to contribute their computational resources to blockchain mining, a new incentive mechanism is required. At the same time, the required incentive mechanism can prevent some UAV-MEC providers from cooperating on the private blockchain [267].
9) **Blockchain Time for Agreement:** The consensus procedure in the blockchain is well known to take the most time during transaction generation. However, the number of UAV-MEC servers in a private blockchain is limited, which significantly reduces the consensus time [268], [269].

C. COMMUNICATION AND RESOURCE CONSTRAINTS CHALLENGES ON TASK OFFLOADING IN UAV-MEC

Task offloading in UAV-MEC systems presents several communication and resource constraint challenges that need to be addressed to ensure accurate decision making. These challenges include the following:

1) **Limited bandwidth and high latency**: UAV-MECs operate in wireless communication networks, which may have limited bandwidth and high latency, making it challenging to offload tasks efficiently. UAV-MECs may experience intermittent or unreliable communication links due to factors, such as signal interference or obstacles, which can affect the reliability of task offloading [126].
2) **Limited computing resources**: UAVs have limited computing resources compared to traditional terrestrial MEC servers, which can limit the types and sizes of tasks that can be offloaded [270].
3) **Offloading decision algorithms**: Developing efficient and intelligent algorithms to make optimal task offloading decisions based on factors, such as task characteristics, network conditions, and resource availability is a complex challenge [271].
4) **Dynamic task offloading**: Task offloading decisions need to be made dynamically in real-time, considering the changing network conditions, task requirements, and resource availability, which requires efficient decision-making mechanisms.

5) **Trade-off between local and remote processing**: Determining whether to offload a task to a remote MEC server or process it locally on the UAV involves considering factors, such as latency, energy consumption, and resource availability, which requires careful trade-off analysis [250].

D. SCALABILITY AND INTEROPERABILITY CHALLENGES ON TASK OFFLOADING IN UAV-MEC

Task offloading in UAV-MEC systems brings several scalability and interoperability challenges that need to be addressed to ensure the large-scale UAV-MEC networks. These challenges include the following:

1) Managing a large-scale UAV-MEC system with numerous UAVs and servers while ensuring efficient task offloading and resource management is a non-trivial task.
2) Designing scalable architectures, protocols, and algorithms to handle the increasing system complexity is an open issue [272].
3) Ensuring interoperability and standardization across different components and interfaces is crucial for seamless integration and widespread adoption of UAV-MEC technologies.
4) The development of common frameworks, protocols, and standards is an ongoing effort [273].

E. CHALLENGING OF DYNAMIC PRICING ON TASK OFFLOADING IN UAV-ENABLED MEC

The challenges of dynamic pricing on task offloading in UAV-enabled MEC can be attributed to several factors. The following are some key challenges:

1) **Resource Allocation**: Dynamic pricing requires efficient resource allocation to ensure optimal task offloading. This involves determining the appropriate allocation of computing resources, network bandwidth, and energy consumption for each task offloaded to the UAV-enabled MEC network [274].
2) **Real-time Pricing**: Dynamic pricing relies on real-time information and market conditions to determine the pricing for task offloading. This requires accurate and up-to-date data on resource availability, network conditions, and user demands. Ensuring the availability and accuracy of this information can be a challenge in UAV-enabled MEC systems [233].
3) **Task Scheduling:** Dynamic pricing necessitates efficient task scheduling to maximize resource utilization and minimize costs. Task scheduling involves determining the order and timing of task offloading to optimize resource allocation and meet user requirements. However, in UAV-enabled MEC systems, the mobility of UAVs and the dynamic nature of the network environment can complicate task scheduling [275].
4) **Quality of Service (QoS):** Dynamic pricing should consider the QoS requirements of different tasks and users. QoS parameters such as latency, reliability, and throughput need to be considered when determining the pricing for task offloading. Ensuring that the QoS requirements are met while optimizing resource allocation and pricing can be a challenge in UAV-enabled MEC systems [276], [277].
5) **User Fairness**: Dynamic pricing should also consider fairness among users. It is important to ensure that the pricing strategy does not favor certain users or tasks over others. Achieving fairness in task offloading and pricing can be challenging, especially when there are varying user demands and resource constraints in UAV-enabled MEC systems [189].
6) **Security and Privacy**: Dynamic pricing involves the exchange of sensitive information between users, UAVs, and MEC servers. Ensuring the security and privacy of this information is crucial for maintaining user trust and protecting against unauthorized access or data breaches. Implementing robust security measures and privacy-preserving mechanisms can be challenging in UAV-enabled MEC systems [37].
7) **Pricing Uncertainty**: As prices change dynamically based on network load and demand, there is uncertainty for UAV-MECs in determining optimal offloading strategies to minimize costs [278].
8) **Delayed Pricing Information**: UAV-MECs may not have timely access to the latest price updates from global originalities in large networks, making offloading decisions suboptimal [279], [280].
9) **Non-cooperative Servers**: Different UAV-MEC servers' operators may adopt non-cooperative pricing policies making it difficult for UAV-MECs to coordinate offloading across multiple servers [240].
10) **Limited UAV-MEC Resources**: UAVs have constraints such as energy, bandwidth, and processing, and dynamic pricing can further strain them if offloading decisions are not optimized carefully [281].
11) **Mobility Factor**: The fast movement of UAV-MECs means that pricing and network conditions change rapidly, requiring dynamic real time offloading adaptation [256], [282].

XI. CONCLUSION

We established a path for categorizing and organizing the various aspects of UAV-based MEC task offloading architectures by conducting a systematic mapping study. This is intended to help researchers and practitioners navigate the emerging trend of using UAVs for task offloading. In addition, we addressed critical topics such as scenarios, core network considerations, and task types for task offloading in UAV-MEC networks. We have contributed to improving task offloading and overall system performance by investigating the techniques used in offloading decision-making in UAV-MEC networks. In addition, we identified the open issues within the UAV-enabled MEC offloading ecosystem. We hope to inspire further research and advancements in this field by shedding light on these areas.

Future studies can focus on the real-world deployment and evaluation of UAV-MEC systems for task offloading. This can involve conducting field experiments, security studies, and case studies to assess the performance, scalability, and practicality of task offloading in UAV-MEC systems in different application scenarios.

Systematic review studies, such as our SMS, can offer a thorough examination of each aspect of task offloading in UAV-MEC through a Systematic Literature Review (SLR). Each of the main topics identified in this paper can be further explored in future research to address more specific research questions.

Based on the contributions of this SMS paper, several promising directions for future research have emerged. One potential area for investigation is to further explore the use of advanced machine learning techniques, such as deep reinforcement learning, to optimize task offloading and resource management in highly dynamic UAV-assisted MEC networks. Another promising area is to investigate the potential of integrating blockchain technology for secure and decentralized task offloading and resource management with untrusted entities involved in task offloading. Additionally, the role of multi-modal sensing and fusion in enhancing task offloading and resource management in UAV-assisted MEC networks should be investigated. By addressing these open challenges and exploring these future research directions, the research community can further advance the state-of-the-art in UAV-assisted MEC networks and unlock new applications and services for the IoTs and beyond.

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