

Article

Intelligent UAV Trajectory Design and Task Offloading for UAV-Assisted Edge Computing in Urban Road Scenarios

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Abstract

With the rapid proliferation of internet of vehicles applications, vehicle users in urban road scenarios face ever-increasing demands for low-latency and energy-efficient processing of computation-intensive tasks. The traditional fixed terrestrial infrastructure offers limited coverage in complex urban environments, making it difficult to satisfy the differentiated quality of service requirements of large-scale vehicle populations. To fully exploit the advantages of unmanned aerial vehicles (UAVs) in terms of flexible deployment and on-demand service provisioning, we propose a UAV-assisted mobile edge computing architecture tailored for urban road scenarios. By modeling realistic urban road terrain with varying elevations, we construct a two-tier cooperative network consisting of multiple rotary wing UAVs and ground vehicles. Aiming at maximizing the total system energy consumption, we formulate a mixed integer nonlinear programming problem that minimizes total system energy consumption through joint optimization of UAV flight trajectories and vehicle task offloading decisions while comprehensively accounting for task latency constraints, UAV flight velocity constraints, and the impact of three-dimensional terrain on air-to-ground channels. Considering the high-dimensional, non-convex, mixed integer, and strongly coupled nature of the problem, we design a genetic algorithm (GA)-based UAV trajectory design and offload allocation algorithm. The proposed approach encodes UAV trajectories as real-valued vectors and offloading decisions as binary vectors, employs a penalty function method to handle constraints, and achieves efficient global search through tournament selection, single-point crossover, and Gaussian mutation operators. Simulation results verify that the proposed algorithm converges reliably to feasible solutions under varying task data sizes and vehicle densities and achieves up to 20.6% energy savings compared to the benchmark schemes. The experimental results validate the necessity and effectiveness of jointly optimizing UAV trajectory and task offloading in urban road scenarios.

Keywords: UAV networks; edge computing; resource optimization; UAV trajectory design; task offloading



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1. Introduction

With the rapid advancement of internet of vehicles (IoV) communication technologies, modern vehicles are increasingly equipped with a wide array of advanced onboard sensors

and applications. Computation-intensive tasks such as multimedia processing for vehicle-to-road collaboration, object recognition, and latency-sensitive online decision-making have been growing rapidly, imposing stringent demands for powerful computing capability and ultra-low processing latency [1]. Although traditional cloud computing offers abundant computational resources, the complex urban road environment often causes link fluctuations and extended transmission distances, making it difficult to simultaneously meet the low-latency and high-reliability requirements of these services. However, in complex urban road environments, the fixed terrestrial infrastructure inherently suffers from limited coverage. On one hand, constrained wireless backhaul capacity and limited available spectrum make it challenging to simultaneously serve high-density vehicle populations. On the other hand, building obstructions, street canyon effects, and three-dimensional (3D) terrain undulations lead to temporally varying and spatially heterogeneous air-to-ground (A2G) channel conditions, further restricting the stable performance of edge computing.

To tackle these challenges, mobile edge computing (MEC) has surfaced as a promising paradigm that places computational resources at the network periphery, enabling task execution in close proximity to the terminals, substantially lowering latency and improving the overall service efficiency of the system [2]. To improve coverage and provide on-demand services, MEC systems augmented by unmanned aerial vehicles (UAVs) have progressively arisen as a compelling solution. UAVs can maneuver flexibly in 3D space and, by adjusting their spatial positions and flight trajectories, provide vehicles with superior communication links and more favorable computation offloading opportunities, thereby improving overall system performance [3].

In UAV-assisted MEC, the system performance depends not only on the offloading decisions (i.e., whether a vehicle transfers its computational task to an edge server, how the offloading duration is determined, and how target computing resources are allocated), but also heavily on UAV trajectory planning. On one hand, the position of a UAV determines the instantaneous link quality of the A2G channel, which in turn influences the transmission rate and communication energy consumption. On the other hand, UAV maneuvering also affects the available service time window, thereby influencing the tradeoff between task latency and energy consumption. Therefore, jointly optimizing vehicle task offloading and UAV flight trajectories becomes the key to achieving optimal system energy efficiency in urban scenarios. However, this joint optimization problem typically presents multiple challenges. First, offloading variables often exhibit binary characteristics, causing the problem to be a mixed integer nonlinear programming (MINLP). Second, the channel model, rate expressions, and UAV kinematic constraints are mutually coupled, making both the objective function and the constraints non-convex. Third, physical limitations—including task latency bounds, UAV velocity, and onboard energy—further compound the complexity of the feasible region. Consequently, understanding how to obtain high-quality solutions while ensuring feasibility remains a significant research challenge.

Existing studies often fix the UAV trajectory or adopt simple pre-defined paths, simplifying the problem to offloading and resource allocation optimization [4], or optimize only the UAV trajectory [5]. Although such approaches can reduce modeling complexity, they often fail to fully exploit the synergistic gains between the two aspects. When offloading decisions and trajectory variations are not synchronized, tasks may be offloaded during periods with poor link conditions, leading to increased transmission energy consumption or unmet latency constraints. Meanwhile, some studies have considered joint optimization of UAV deployment, user-UAV association, task offloading, scheduling, and bandwidth allocation [6]. However, most existing works assume two-dimensional planar or flat terrain environments, and few have explicitly incorporated realistic urban road terrain with elevation variations into the joint optimization of UAV trajectory and task offloading.

Beyond the challenges of computation and communication latency, urban road transportation is also a major contributor to air pollution and greenhouse gas emissions. Intelligent transportation systems have been increasingly recognized as effective solutions for energy conservation and emission reduction in transport networks [7]. Recent studies have demonstrated that trajectory optimization and intelligent control can significantly reduce both energy consumption and pollutant emissions such as CO_2 and particulate matter in mixed-traffic environments [8].

To address the above issues, this paper proposes a UAV-assisted edge computing architecture tailored for urban road scenarios. By considering the 3D obstruction effects and A2G channel disparities caused by realistic urban road terrain, we establish a two-tier cooperative network composed of multiple UAVs and ground vehicles. Building upon this framework, we jointly optimize decision-making for offloading vehicle tasks and UAV flight trajectories to minimize the total energy consumption of the system. The principal contributions of this work are summarized below.

- We construct a two-tier cooperative MEC network architecture comprising multiple UAVs and ground vehicles distributed along urban roads with varying elevations. In contrast to existing studies that commonly assume flat ground or simplified terrain models, this work explicitly integrates 3D road terrain into the system modeling process, characterizing the channel disparities of vehicle-to-UAV A2G links under varying spatial positions and elevation undulations. This provides a more realistic representation of A2G propagation characteristics in urban road scenarios and establishes an accurate physical foundation for the subsequent joint optimization.
- Targeting the total system energy consumption optimization requirements of terminal aerial cooperative computing in urban road scenarios, we formulate a MINLP model, the core objective of which is to minimize the energy consumption of the entire system. This model collectively optimizes both the UAV flight trajectory and the vehicle task offloading decisions within a unified framework, simultaneously incorporating task latency constraints, UAV flight velocity and kinematic constraints, as well as terrain-aware A2G channel characteristics. It systematically characterizes the coupling relationship between computation offloading and wireless transmission processes, captures the energy and latency tradeoff mechanism inherent in urban vehicular edge computing, and fully reveals the interplay between trajectory variations, link quality, and offloading effectiveness.
- Considering the high-dimensional, non-convex, strongly coupled, and mixed-integer nature of the formulated problem, we design a genetic algorithm (GA)-based joint optimization method. A unified chromosome structure is adopted to realize real-valued encoding of trajectory variables and binary encoding of offloading variables, while the penalty function method is employed to embed constraints such as latency and kinematic limits into the fitness evaluation process. At the search level, tournament selection, single-point crossover, and Gaussian mutation operators are combined to enhance population diversity and global exploration capability, thereby improving the efficiency of exploring the complex feasible region. Simulation results show that, compared to the baseline approach, the proposed method can optimize UAV trajectories and reduce total system energy consumption by up to 20.6%, validating the necessity and effectiveness of jointly optimizing UAV trajectory and task offloading in urban road scenarios.

The rest of this paper is structured as follows. Section 2 surveys the relevant literature. Section 3 details the system model. Section 4 formulates the optimization problem. Section 5 introduces the GA-based optimization approach. Section 6 presents the simulation results

and a comparative analysis. Finally, Section 7 concludes the paper and outlines directions for future research.

2. Related Work

In recent years, UAV-assisted MEC has attracted widespread attention from academia and industry because of its deployment flexibility, 3D mobility, and on-demand service provisioning capabilities. A considerable body of literature has been devoted to key issues including UAV communication modeling, path optimization, allocation of resources, and task offloading. This section reviews and summarizes existing works from UAV A2G channel modeling and trajectory optimization, task offloading and resource allocation, and metaheuristic solutions.

A2G channel characteristics between UAVs and terrestrial users fundamentally determine communication performance. He et al. [9] evaluated the channel characteristics of large- and small-scale UAVs operating at flight altitudes of 300 m and 400 m in rural environments. Their results demonstrated that increasing the UAV altitude within a certain range can significantly improve the line of sight (LoS) probability and thereby reduce path loss. Chen et al. [10] further indicated that the LoS probability in A2G channels exhibits regular variations with the elevation angle. Li et al. [11] analyzed power consumption across different flight phases, providing a reference for UAV energy consumption modeling. Dai et al. [12] proposed a general thrust power consumption model for rotary wing UAVs that incorporates UAV velocity, acceleration, and direction changes and incorporates the actual thrust-to-weight ratio, thereby capturing propulsion energy more realistically. On this basis, they maximized UAVs' efficiency by optimizing both user scheduling and flight path characteristics. In terms of trajectory optimization, Luo et al. [13] devised a convergent approach for independent collision-free route planning of UAVs with static obstacles and dynamic threats. Weng et al. [14] addressed the collaborative truck and UAV delivery problem by proposing a hybrid metaheuristic optimization algorithm designed to minimize the total completion time for all delivery tasks. Li et al. [15] examined the problem of obstruction-free route planning in urban areas and used Dubin's geometric paths and the Floyd algorithm to generate the shortest, complete, obstruction-free routes that minimize energy consumption. For multi-UAV cooperative scenarios, Kong et al. [16] proposed a multi-agent deep deterministic policy gradient approach for UAV path planning to achieve energy consumption reduction and policy coordination. Recent relevant contributions include González-Baldizón et al. [17], who proposed a hybrid LQC-conditional LSTM autoencoder for fault diagnosis in quadrotor UAVs, achieving high accuracy and demonstrating the effective synergy between classical control and deep learning for trajectory-related tasks—an integration that mirrors our GA-based joint optimization approach. Additionally, Khaneghaei et al. [18] provided a comprehensive review of hybrid optimization algorithms for multi-agent UAV path planning, categorizing methods from classical to AI-based and identifying open challenges such as real-time adaptability and realistic agent dynamics, which directly align with the future research directions we outline in our conclusion.

In UAV-assisted MEC systems, ground users typically face a binary choice between local computing and computation offloading, making appropriate offloading decisions critical for balancing task latency and system energy consumption. Pervez et al. [19] considered a network supported by multiple UAVs and optimized a cost function that accounts for both energy consumption and latency by optimizing decisions regarding task allocation, MEC server selection, transmission capability, UAV trajectories, and CPU resource allocation. Wang et al. [20] developed a 3D MEC system with multiple UAVs for cooperative A2G communication and created models for communication, computation, and the energy consumption of UAV flights; they minimized total energy consumption of the system

through joint optimization of task distribution, UAV flight paths, and resource allocation in edge computing. Zhang et al. [21] partitioned the service area into several sub-regions, enabling end users to offload tasks to the corresponding UAVs providing computing services, and subsequently formulated a joint optimization problem covering offloading decisions, allocation of resources, and path planning. Furthermore, Liu et al. [22] suggested a deep reinforcement learning algorithm to jointly optimize the selection of the overflight point for UAVs, the time allocation for task collection, transmission performance, channel selection, and task allocation ratios, with the aim of improving the overall performance of UAV-based MEC. Qi et al. [23] investigated UAV-assisted MEC with mobile user devices; the goal was to optimize the average completion times for all tasks by optimizing communication bandwidth, CPU capacity, task allocation ratios, and the 3D positioning of UAVs in a coordinated manner. In addition, Zhong et al. [24] integrated non-orthogonal multiple access with UAV assisted MEC to provide more efficient computing services, constructed a systemic model for task allocation and UAV deployment in order to minimize the overall cost of the service, formulated the problem as a game involving task allocation and UAV deployment, theoretically proved the existence of at least one Nash equilibrium strategy, and proposed a game-theory-driven decentralized algorithm to achieve this strategy while providing theoretical performance analysis. Within the broader framework of space-air-ground integrated networks, Mao et al. [25] investigated the simultaneous optimization for UAV position and resource planning within a hybrid cloud edge computing architecture, integrating cloud, aerial edge, and vehicular resources into a unified optimization model for overall coordination.

Since the jointly optimized allocation of UAV trajectories and tasks typically exhibits high-dimensional, non-convex, and mixed-integer characteristics, traditional convex optimization methods often require substantial relaxation and approximation, which limits solution accuracy and computational efficiency. Consequently, metaheuristic algorithms have been widely adopted in related problems due to their general independence from gradient information, strong adaptability to mixtures of discrete and continuous variables, and robust global search capabilities. Zhang et al. [26] investigated UAV positioning based on an improved particle swarm optimization (PSO) method, aiming to reduce complexity and positioning errors. Zhu et al. [27] investigated the problem of task scheduling in UAV-based MEC systems with the objective of optimizing both cost and execution time, and proposed the NSGA-II algorithm. The algorithm represents solutions as two-dimensional position sequences and solves the problem through a feasible solution generation method along with carefully designed crossover, mutation, and selection operators; the crossover operation incorporates simulated annealing-based local search, two novel mutation strategies are introduced, and algorithm performance is evaluated based on Pareto metrics. Regarding path planning and obstacle avoidance, Ma et al. [28] proposed a mixed algorithm. This method combines an enhanced simulated annealing (SA) process with an extended APF model to help UAVs continuously rotate and avoid local minima created by nearly closed obstacles. Regarding wireless resource and queue modeling, Liu et al. [29] targeted 5G MEC heterogeneous networks with multiple mobile devices capable of energy harvesting and proposed dynamic optimization schemes for both static and dynamic subchannel scenarios. These schemes jointly coordinate offloading decisions and wireless resource allocation, enabling dynamic adjustment as wireless communication resources and computation demands vary, thereby minimizing the average execution delay of the system. Dong et al. [30] formulated the task offloading problem as an optimization problem and proposed task offloading strategies based on PSO and Quantum PSO. Song et al. [31] studied the general design of calculating servers and user load distribution in edge telecommunications networks that support wireless backhaul, employing a GA to model the evolutionary mechanism, which

minimizes the average service latency while satisfying user delay requirements. Zheng et al. [32] addressed the issue of low search efficiency caused by insufficient coordination among UAVs by proposing a decentralized real-time search trajectory planning method using a model predictive controller. The search aim was decomposed into a distributed constraint optimization problem, where overall optimization is achieved through interaction among neighboring UAVs. To alleviate local optimum issues, an enhanced GA was proposed, featuring a crossover operation and a local search framework that can be activated at any time; solution quality is further improved by storing global optimal solutions. Additionally, Attalah et al. [33] proposed combining heuristic GA with cloud computing techniques for task offloading optimization in UAV networks, where GA is used to transfer tasks from UAVs to cloud base stations and from cloud UAVs to other cloud UAVs to minimize transmission latency while maintaining high storage and processing capacity.

In summary, the existing research has laid a solid foundation in areas such as UAV A2G channel modeling, trajectory optimization, task offloading, and metaheuristic solutions. Nevertheless, the majority of prior works have not explicitly incorporated realistic urban road terrain elevation variations into the modeling of UAV-assisted edge computing systems. Moreover, trajectory optimization and offloading decisions are often treated in a decoupled or hierarchical manner, weakening the deep coupling relationship between the two. To address these shortcomings, this paper develops a terrain-aware UAV-assisted vehicular edge computing framework, formulates a joint trajectory and offloading decision optimization model, and designs an efficient GA for solving the problem.

3. System Model

This section presents the network model, channel model, task and computation model, UAV propulsion energy model, and the formulation of the problem.

3.1. Network Model

As shown in Figure 1, we consider a MEC network supported by a UAV deployed in an urban road scenario. The road exhibits elevation variations along its longitudinal direction. The system comprises I vehicle users, denoted by set $\mathcal{I} = \{1, 2, \dots, I\}$. The two-dimensional horizontal positions of vehicles are fixed, and the location of vehicle i is represented as $\mathbf{L}_i = (x_i, y_i, h_i)$, where h_i denotes the road elevation at that position. The road elevation for each vehicle is obtained from a synthetic urban terrain profile generated by a superposition of Gaussian functions; the obstruction effects of buildings and street canyons are statistically characterized by the elevation-angle-dependent LoS probability in the A2G channel model.

Each vehicle possesses local computing capability and can also offload computation-intensive tasks to the aerial UAVs for processing. The system deploys J UAVs, represented by the set $\mathcal{J} = \{1, 2, \dots, J\}$. The UAVs operate at a constant altitude H for providing edge computation services. The entire mission period is discretized into T equal slots, with each slot having a duration of τ seconds. In the t -th time slot, the horizontal position of UAV j is represented as $\mathbf{L}_j[t] = (x_j[t], y_j[t])$, and the trajectories of all UAVs are defined as $\mathbf{V} = \{\mathbf{L}_j[t] \mid \forall j \in \mathcal{J}, \forall t \in \mathcal{T}\}$, where $\mathcal{T} = \{1, 2, \dots, T\}$. The planned trajectories are assumed to be executable by the UAVs using standard onboard navigation and control systems. In urban environments where GPS signals may be unreliable, the waypoints can still be tracked using alternative localization techniques such as inertial navigation, visual odometry, or cellular network-based positioning without affecting the fundamental optimization framework. For simplicity, the UAV altitude H is assumed to be constant during the mission. The wireless connections between vehicles and UAVs are mainly characterized by the LoS probability and path loss. The main symbols are shown in Table 1.

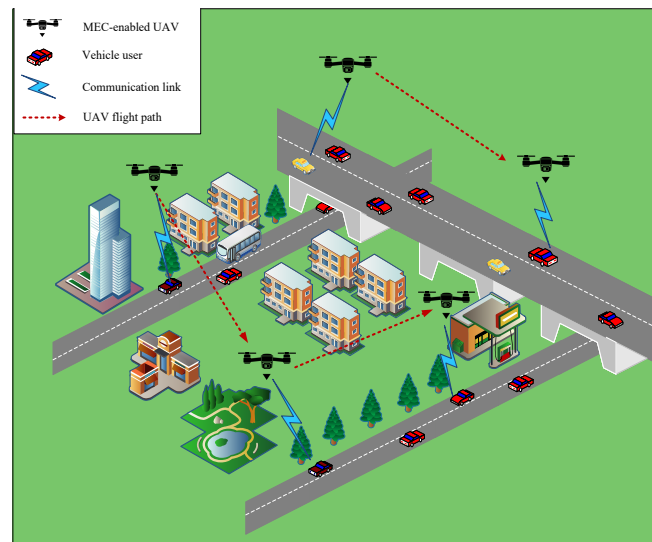


Figure 1. Network model.

Table 1. Main Symbols.

Symbol	Description
$\mathcal{I}, \mathcal{J}$ and $\mathcal{T}$	Set of vehicles, UAVs and time slots
$\mathbf{V}$	Trajectories of all UAVs
α	Offloading decision vector of all vehicles
$\mathcal{S}_j[t]$	Set of vehicles associated with UAV j at time slot t
$j_i^*[t]$	Index of the UAV associated with vehicle i at time slot t
p_{tx}	Transmit power of each vehicle
D_i	Task input data size of vehicle i
C_i	Required CPU cycles per bit of the task of vehicle i
T_i^{max}	Maximum tolerable latency of the task of vehicle i
f_i	Local CPU frequency of vehicle i
f_u	CPU frequency of UAV edge server
$T_i^{\text{loc}}, T_i^{\text{off}}$	Local and offloading latency of vehicle i
$E_i^{\text{loc}}, E_i^{\text{off}}$	Local and offloading energy consumption of vehicle i
$P_{\text{fly}}(v)$	UAV propulsion power
v_{max}	Maximum allowable flight velocity of UAV
E_j^{fly}	Total flight energy consumption of UAV j
E	Total system energy consumption

3.2. Channel Model

Consider the A2G channel between the UAVs and ground vehicles. The 3D Euclidean distance between vehicle i and UAV j at the t -th time slot is given by

$$d_{ij}[t] = \sqrt{(x_i - x_j[t])^2 + (y_i - y_j[t])^2 + (h_i - H)^2}. \quad (1)$$

The elevation angle $\theta_{ij}[t]$ (in radians) is expressed as

$$\theta_{ij}[t] = \arctan2\left(H - h_i, d_{ij}^{\text{hor}}[t]\right), \quad (2)$$

where $\arctan2(\cdot, \cdot)$ is the four quadrant inverse tangent function, and

$$d_{ij}^{\text{hor}}[t] = \sqrt{(x_i - x_j[t])^2 + (y_i - y_j[t])^2}, \quad (3)$$

which represents the horizontal distance from vehicle i to UAV j . The A2G channel LoS probability $P_{ij}^{\text{LoS}}[t]$ is modeled as an S-shaped function in terms of the elevation angle $\theta_{ij}[t]$, expressed as

$$P_{ij}^{\text{LoS}}[t] = \frac{1}{1 + \alpha_1 e^{-\alpha_2(\theta_{ij}[t] - \alpha_1)}}, \quad (4)$$

where $\alpha_1, \alpha_2 > 0$ are environment-dependent constants. Accordingly, the non-line-of-sight (NLoS) probability is

$$P_{ij}^{\text{NLoS}}[t] = 1 - P_{ij}^{\text{LoS}}[t]. \quad (5)$$

The path loss (in dB) consists of the free-space path loss and an additional attenuation component is given by

$$PL_{ij}[t] = 20 \log_{10} \left(\frac{4\pi f_c d_{ij}[t]}{c} \right) + P_{ij}^{\text{LoS}}[t] \eta_{\text{LoS}} + (1 - P_{ij}^{\text{LoS}}[t]) \eta_{\text{NLoS}}, \quad (6)$$

where f_c refers to the carrier frequency, c denotes the velocity of light, η_{LoS} and η_{NLoS} represent the additional losses (in dB) under LoS and NLoS conditions, correspondingly. Furthermore, the channel power gain is expressed as $g_{ij}[t] = 10^{-PL_{ij}[t]/10}$.

Each UAV employs a shared-bandwidth non-orthogonal multiple access scheme to provide communication services for its associated vehicles. Let $\mathcal{S}_j[t] \subseteq \mathcal{I}$ denote the group of vehicles connected to UAV j at time t . All vehicles within the same group share the total bandwidth B_u . The signal-to-interference-plus-noise ratio (SINR) for vehicle i associated with UAV $j_i^*[t]$ is expressed as

$$\gamma_i[t] = \frac{p_{\text{tx}} g_{i,j_i^*}[t]}{\sum_{k \in \mathcal{S}_{j_i^*}[t] \setminus \{i\}} p_{\text{tx}} g_{k,j_i^*}[t] + N_0 B_u}, \quad (7)$$

where p_{tx} is the transmit power of the vehicle (assumed identical for all vehicles) and N_0 is the noise power spectral density. Following Shannon's formula, for a given vehicle i at time t , the achievable uplink data rate is

$$R_i[t] = B_u \log_2(1 + \gamma_i[t]). \quad (8)$$

3.3. Task and Computation Model

Each vehicle is required to complete a computation-intensive task, characterized by a triplet $\langle D_i, C_i, T_i^{\text{max}} \rangle$. Here, D_i represents the size of input data (in Mbits), C_i represents the number of processor cycles required to process one bit of data (in cycles/bit), T_i^{max} represents the maximum allowable task delay (in seconds). The task can either be executed locally at the vehicle or offloaded to the associated UAV edge server through a wireless link for processing. To formulate this decision, a binary offloading decision variable $\alpha_i \in \{0, 1\}$ is introduced. Specifically, $\alpha_i = 1$ means that vehicle i transmits its task to an UAV, while $\alpha_i = 0$ means that the task is executed locally. We assume that the UAVs are equipped with sufficient onboard energy to sustain the entire mission, allowing us to focus on the joint optimization of trajectory and offloading decisions without considering energy depletion constraints.

When vehicle i opts for local computing (i.e., $\alpha_i = 0$), the task processing latency and the corresponding energy consumption for local computation are given by

$$T_i^{\text{loc}} = \frac{D_i \cdot C_i}{f_i}, \quad (9)$$

and

$$E_i^{\text{loc}} = \kappa f_i^2 \cdot (D_i \cdot C_i), \quad (10)$$

where f_i denotes localized CPU computing ability for vehicle i and κ denotes the effective capacity coefficient associated with the chip architecture.

When vehicle i chooses to offload its computation task (i.e., $\alpha_i = 1$), the task data must be transmitted to the associated UAV through the uplink. The achievable transmission rate during offloading $R_i[t]$ depends on the channel conditions in that time slot. Assume that each vehicle's offloading transmission, if selected, occurs entirely within the final time slot $t = T$, when the UAVs have reached their optimized service positions. The achievable rate for vehicle i in this slot is denoted as $R_i[T]$. The total offloading latency includes two parts: the uplink transmission latency and the computation latency on the UAV, expressed as

$$T_i^{\text{off}} = \frac{D_i}{R_i[T]} + \frac{D_i \cdot C_i}{f_u}. \quad (11)$$

The offloading energy consumption comprises the energy consumed by vehicle i for transmitting the task data and the energy consumed by the UAV edge server for executing the computation task, given by

$$E_i^{\text{off}} = p_{\text{tx}} \cdot \frac{D_i}{R_i[T]} + \kappa f_u^2 \cdot (D_i \cdot C_i), \quad (12)$$

where f_u (in cycles/s) represents the computing capacity of the UAV's edge server and p_{tx} represents the uplink transmission power for the vehicle. As shown in [34], the delay and power consumption associated with feedback of results are neglected here, since the size of the output data is typically much smaller than the size of the input data.

3.4. UAV Propulsion Energy Model

The propulsion power consumed by the motor of a UAV during flight is closely related to its flight velocity v . This paper adopts the classic power consumption model for rotary-wing UAVs, which comprises three parts: blade profile power, induced power, and fuselage drag power [35], is given by

$$P_{\text{fly}}(v) = P_0 \left(1 + \frac{3v^2}{v_{\text{tip}}^2} \right) + P_{\text{ind}} \left(\sqrt{1 + \frac{v^4}{4v_0^4}} - \frac{v^2}{2v_0^2} \right)^{\frac{1}{2}} + \frac{1}{2} d_0 \rho s A_r v^3, \quad (13)$$

where P_0 and P_{ind} correspond to the blade profile power and the induced power during hover, respectively; v_{tip} indicates the rotor blade tip velocity; v_0 is the mean induced velocity of the rotor in hover; d_0 stands for the fuselage drag ratio; ρ represents the air density; s denotes the rotor solidity; and A_r refers to the rotor disc area.

Then, the instantaneous velocity of UAV j in the t -th time slot can be calculated from the position difference between adjacent time slots as

$$v_j[t] = \frac{\|\mathbf{L}_j[t] - \mathbf{L}_j[t-1]\|}{\tau}. \quad (14)$$

It is important to emphasize that, in our optimization framework, the UAV trajectory is directly parameterized by position coordinates, and the velocity is subsequently derived from position differences using Equation (14). Therefore, the trajectory planning process does not involve numerical integration of velocity signals, and the accumulation of velocity

integration errors, which is a common concern in dead-reckoning and inertial navigation systems, does not arise during the optimization stage.

For $t = 1$, the UAV is considered to be in a hovering state, i.e., $v_j[1] = 0$. The overall flight energy expenditure of UAV j throughout the complete mission duration is

$$E_j^{\text{fly}} = \sum_{t=1}^T P_{\text{fly}}(v_j[t]) \cdot \tau. \quad (15)$$

4. Problem Formulation

This paper aims to minimize the total energy consumption by jointly optimizing the UAV trajectories $\mathbf{V}$ and the vehicular offloading decisions α , under the constraints of task latency requirements and UAV flight limitations. Irrespective of the chosen computation mode, the task generated by each vehicle i must be finished within its maximum allowable latency. Specifically, if $\alpha_i = 0$, the constraint $T_i^{\text{loc}} \leq T_i^{\text{max}}$ must be satisfied; if $\alpha_i = 1$, the constraint $T_i^{\text{off}} \leq T_i^{\text{max}}$ must be satisfied. If a vehicle cannot satisfy the above constraints under a given offloading decision and UAV trajectory, the current solution is considered infeasible.

The total energy consumption of the system comprises three parts: the energy consumed by local computing, the energy for task offloading, and the propulsion energy of the UAVs. It is formulated as

$$E = \sum_{i=1}^I \left[(1 - \alpha_i) E_i^{\text{loc}} + \alpha_i E_i^{\text{off}} \right] + \sum_{j=1}^J E_j^{\text{fly}}. \quad (16)$$

Accordingly, the optimization problem is formally stated as

$$\begin{aligned} & \min_{\mathbf{V}, \alpha} E \\ & \text{s.t.} \\ & \text{C1: } \alpha_i \in \{0, 1\}, \quad \forall i \in \mathcal{I}, \\ & \text{C2: } (1 - \alpha_i) T_i^{\text{loc}} + \alpha_i T_i^{\text{off}} \leq T_i^{\text{max}}, \quad \forall i \in \mathcal{I}, \\ & \text{C3: } v_j[t] \leq v_{\text{max}}, \quad \forall j \in \mathcal{J}, \forall t \in \mathcal{T}, \\ & \text{C4: } 0 \leq x_j[t] \leq x_{\text{max}}, \\ & \quad 0 \leq y_j[t] \leq y_{\text{max}}, \quad \forall j \in \mathcal{J}, \forall t \in \mathcal{T}, \end{aligned} \quad (17)$$

where x_{max} and y_{max} denote the side lengths of the mission area. Constraint C1 indicates that the offloading decision is a binary variable. Constraint C2 ensures that the offloading latency satisfies the constraint. Constraint C3 restricts the UAV velocity to not exceed the maximum allowable velocity v_{max} to guarantee flight safety and satisfy kinematic constraints. Constraint C4 confines the UAV flight within the designated area.

The formulated problem belongs to the class of MINLP problems. As the objective function and constraints are both non-convex and nonlinear and incorporate both continuous and discrete variables, it cannot be readily tackled by conventional convex optimization techniques. To handle this challenge, we will design a metaheuristic solution framework based on a GA, which encodes trajectory points as real-valued vectors and offloading decisions as binary vectors, and integrates constraint penalty terms into the fitness function, thereby enabling an effective solution to the above joint optimization problem.

5. GA Based UAV Trajectory Design and Offload Allocation Algorithm

This section introduces a GA-based algorithm for UAV trajectory planning and offloading allocation to address problem (17).

5.1. Proposed Algorithm

As a global search metaheuristic that simulates the process of natural evolution, the GA does not rely on gradient information and exhibits favorable adaptability to mixed discrete continuous variables. It has been widely applied in the fields of UAV path planning and resource allocation [36,37]. This section elaborates on the design of the GA tailored for the formulated problem. The core of the GA lies in mapping the optimization variables into chromosome structures that can undergo genetic operations. In this paper, both the UAV trajectories $\mathbf{V}$ and the vehicle offloading decisions α need to be optimized simultaneously.

Since the trajectory points are continuous variables, a real-valued encoding scheme is adopted. The two dimensional positions of UAV j across all T time slots are flattened in chronological order, forming a real valued vector of length $2T$: $\mathbf{x}_j^{\text{traj}} = [x_j[1], y_j[1], x_j[2], y_j[2], \dots, x_j[T], y_j[T]]$. The trajectory vectors of all J UAVs are concatenated to obtain the trajectory chromosome segment, which are given by

$$\mathbf{X}^{\text{traj}} = [\mathbf{x}_1^{\text{traj}}, \mathbf{x}_2^{\text{traj}}, \dots, \mathbf{x}_J^{\text{traj}}]. \quad (18)$$

The offloading decisions are binary variables and are encoded using a binary scheme. The decision variables of all I vehicles are arranged sequentially to form a binary vector of length I , which are given by

$$\mathbf{X}^{\text{off}} = [\alpha_1, \alpha_2, \dots, \alpha_I]. \quad (19)$$

Thus, the complete chromosome is given by $\mathbf{X} = [\mathbf{X}^{\text{traj}}, \mathbf{X}^{\text{off}}]$.

The fitness function serves as the core criterion for evaluating the quality of individuals. GAs are typically designed for unconstrained optimization, whereas the problem in this paper involves task latency constraints and UAV velocity constraints. Accordingly, a penalty function approach is adopted to convert the constrained problem into an unconstrained formulation. The fitness function is constructed as the summation of the total system energy consumption and the penalty terms associated with constraint violations:

$$\mathcal{F}(\mathbf{X}) = E(\mathbf{X}) + \lambda_1 \Phi_{\text{delay}}(\mathbf{X}) + \lambda_2 \Phi_{\text{velocity}}(\mathbf{X}), \quad (20)$$

where $E(\mathbf{X})$ is the total system energy consumption corresponding to individual $\mathbf{X}$; $\Phi_{\text{delay}}(\mathbf{X})$ and $\Phi_{\text{velocity}}(\mathbf{X})$ denote the penalty terms for latency constraint violation and velocity constraint violation, respectively; and $\lambda_1, \lambda_2 > 0$ are the penalty coefficients.

The pseudo-code of the GA for solving the problem is presented in Algorithm 1. In Algorithm 1, a tournament selection strategy is adopted. In each selection round, k individuals ($k = 2$) from the current population are randomly selected, and their fitness values are compared. The individual that is lower in fitness wins and is included in the next generation's population. This procedure is repeated N_{pop} times until the new population is complete. Since the chromosome contains both a real-coded part and a binary-coded part, the crossover operators need to be designed separately.

Gaussian mutation is utilized in trajectory part mutation. For each trajectory coordinate gene, a Gaussian perturbation is applied with probability p_m : $x \leftarrow x + \mathcal{N}(0, \sigma_m^2)$. After mutation, the coordinates are clipped to remain within the region boundaries. And Bit-flip mutation is employed in the offloading decision part mutation. For each binary gene, its value is flipped (0 to 1, or 1 to 0) with probability p_m .

Algorithm 1 GA-Based UAV Trajectory Design and Offload Allocation Algorithm

Input: Population size N_{pop} , maximum number of iterations K , crossover probability p_c , mutation probability p_m , penalty coefficients M_{delay} and P_{velocity} .

Output: Optimal trajectory $\mathbf{V}$, optimal offloading decision α , minimum system energy consumption E^* .

```

1: Initialize the population  $\mathcal{P}_0 = \{\mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_N\}$ ;
2: Compute the fitness  $\mathcal{F}(\mathbf{X}_i)$  of each individual in the initial population, and record the globally optimal individual  $\mathbf{X}_{\text{best}}$  and its fitness  $\mathcal{F}_{\text{best}}$ ;
3: for  $k = 1 : K$  do
4:    $\mathcal{P}_{\text{new}} \leftarrow \emptyset$ ;
5:   while  $|\mathcal{P}_{\text{new}}| < N_{\text{pop}}$  do
6:     Tournament selection: Randomly select two individuals from  $\mathcal{P}_{k-1}$ ; the one with the lower fitness is added to  $\mathcal{P}_{\text{new}}$ ;
7:   end while
8:   for  $i = 1 : N_{\text{pop}}/2$  do
9:     if  $\text{rand}() < p_c$  then
10:      Perform a single point crossover on the  $(2i - 1)$ -th and  $2i$ -th individuals in  $\mathcal{P}_{\text{new}}$ ;
11:    end if
12:  end for
13:  for  $i = 1 : N_{\text{pop}}$  do
14:    for each gene do
15:      if  $\text{rand}() < p_m$  then
16:        Apply Gaussian mutating and bit-flipping mutating to the trajectory and offloading decisions, respectively;
17:      end if
18:    end for
19:  end for
20:  Compute the fitness of the new population  $\mathcal{P}_{\text{new}}$ ;
21:  Update the global best individuals  $\mathbf{X}_{\text{best}}$  and  $\mathcal{F}_{\text{best}}$ ;
22:   $\mathcal{P}_k \leftarrow \mathcal{P}_{\text{new}}$ ;
23: end for
24: Decode  $\mathbf{V}$  and  $\alpha$  from  $\mathbf{X}_{\text{best}}$  and output  $E^* = \mathcal{F}_{\text{best}}$ .

```

5.2. Complexity Analysis of Proposed Algorithm

The primary computational overhead of the proposed algorithm lies in fitness evaluation. A single fitness evaluation requires traversing T time slots to compute the distances, elevation angles, path losses, and transmission rates for $I \times J$ vehicle–UAV pairs, with a complexity of $\mathcal{O}(T \cdot I \cdot J)$, computing the flight energy consumption of J UAVs, with a complexity of $\mathcal{O}(T \cdot J)$, and calculating the task latency and energy consumption for I vehicles, with a complexity of $\mathcal{O}(I)$. Hence, the time complexity of a single fitness evaluation is $\mathcal{O}(T \cdot I \cdot J)$. Since N_{pop} individuals must be evaluated for each generation and the algorithm operates over K generations, the total time complexity of the algorithm equals $\mathcal{O}(K \cdot N_{\text{pop}} \cdot T \cdot I \cdot J)$. The space complexity depends mainly on the memory required for the population, which is $\mathcal{O}(N_{\text{pop}} \cdot (2JT + I))$.

Remark 1. It is important to note that the proposed GA is designed for offline trajectory planning and offloading decision optimization, which is performed prior to mission execution. The optimized waypoints and offloading decisions are then loaded onto the UAVs and vehicles for execution. Therefore, the GA does not need to be executed in real time during the mission, and the computational time required for the optimization is acceptable for pre-mission planning.

6. Simulation Results

To validate the effectiveness of the proposed algorithm, numerical simulations are performed, and performance comparisons are carried out with several baseline algorithms.

6.1. Simulation Setup

The simulation environment is configured as a $500 \text{ m} \times 500 \text{ m}$ rectangular region, where three roads are laid out, and $I = 30$ vehicular users are randomly placed. Specifically, the road network is configured as a grid-like layout consisting of one horizontal arterial road and two vertical arterial roads, with each road having a width of 30 m. Ten vehicles are uniformly and randomly distributed along each road segment, resulting in a total of 30 vehicles. For each vehicle, the horizontal coordinates (x_i, y_i) are generated accordingly, and the elevation h_i is obtained by interpolating the corresponding road terrain profile. The terrain profiles are synthesized using a superposition of Gaussian functions to model realistic urban elevation undulations. The system deploys $J = 3$ UAVs serving as mobile edge servers, flying at a fixed altitude of $H = 180 \text{ m}$ to ensure clearance above the highest terrain point. The mission duration is partitioned into $T = 5$ time slots, with each slot lasting $\tau = 1 \text{ s}$. The random seed is fixed for deterministic replication. The remaining key simulation parameters are listed in Table 2.

In this paper, urban road scenarios are characterized by the presence of roads with three-dimensional elevation variations, surrounding buildings that affect A2G channel conditions, and spatially distributed vehicle users requiring computation services. We focus on the static vehicle distribution case, where vehicles remain at fixed positions during the optimization horizon, and do not consider dynamic traffic flow elements such as acceleration, deceleration, or traffic light control, which are left for future investigation.

Table 2. The Values of the Main Simulation Parameters.

Simulation Parameter	Value
K	2000
p_c	0.8
p_m	0.1
$v_{\max}$	20 m/s
D_i	1 Mbits
C_i	500 cycles/bit
$T_i^{\max}$	5 s
f_i	5 GHz
f_u	10 GHz
τ	1 s
B_u	100 MHz
p_{tx}	1 W
N_0	−174 dBm/Hz
c	$3 \times 10^8 \text{ m/s}$
f_c	2.4 GHz
$\eta_{\text{LoS}}, \eta_{\text{NLoS}}$	1 dB, 20 dB
κ, κ_u	$10^{-27} \text{ J/cycle}^2$
N_{pop}	30
p_c, p_m	0.8, 0.1

Table 2. Cont.

Simulation Parameter	Value
κ, κ_u	$10^{-27} \text{ J/cycle}^2$
κ, κ_u	$10^{-27} \text{ J/cycle}^2$
κ, κ_u	$10^{-27} \text{ J/cycle}^2$
κ, κ_u	$10^{-27} \text{ J/cycle}^2$

6.2. Performance of Proposed Algorithm Under Various Parameters

Figure 2 presents the optimized three-dimensional flight trajectories of the three UAVs, together with the terrain and vehicle distribution. Figure 3 further depicts the horizontal-plane projections of the UAV trajectories. It can be observed from the figures that the trajectories of all three UAVs exhibit favorable smoothness. The displacement between adjacent time slots is significantly smaller than the maximum allowable displacement per time slot imposed by the velocity constraint, i.e., $v_{\max} = 20 \text{ m/s}$. Consequently, the velocity penalty term is not triggered, which verifies the satisfaction of the velocity constraint. Meanwhile, the three UAVs exhibit complementary spatial distributions, effectively avoiding service overlap and reducing unnecessary mutual interference.

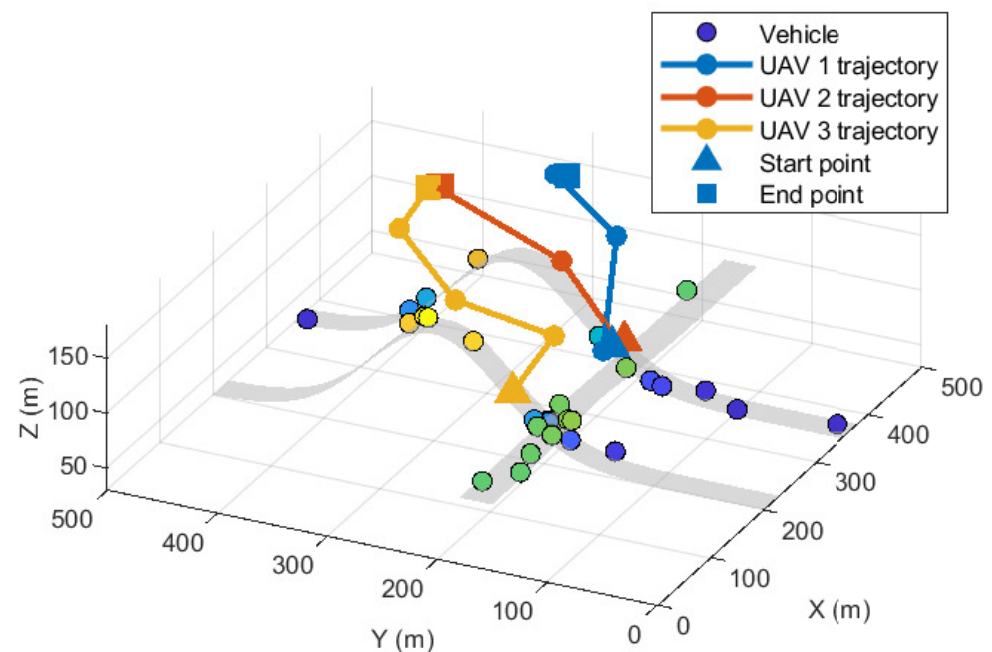


Figure 2. 3D trajectories and system scenarios.

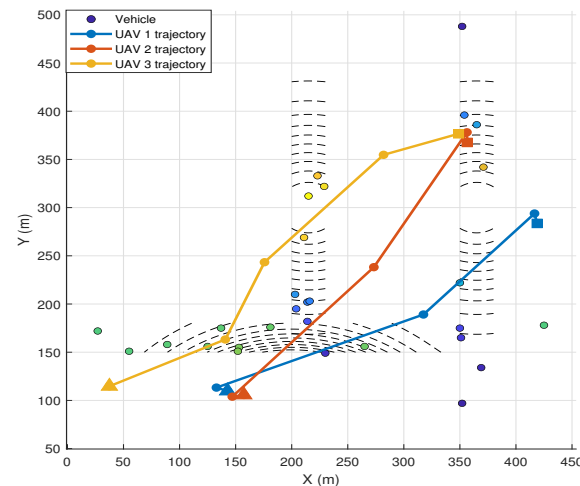


Figure 3. 2D UAV trajectories.

Figure 4 illustrates the spatial distribution of the optimized task offloading decisions. Different colors and marker shapes represent vehicles that perform local computing and those that offload computation to different UAVs, respectively, along with the final positions of the UAVs. Statistical results show that among the 30 vehicles, 25 choose to offload their tasks to UAVs for processing, while only five vehicles opt for local computing, yielding an offloading ratio of 83.3%. Further observation of the spatial distribution reveals that the five vehicles performing local computing are mainly located at the coverage edge areas of the UAVs, where the channel conditions are relatively poor, resulting in offloading rates that are insufficient to provide an energy-efficiency advantage. Therefore, while ensuring the latency requirements, the algorithm tends to select local processing for these edge vehicles, thereby achieving optimization of the total energy consumption. The final optimized total system energy consumption is 5301.63 J.

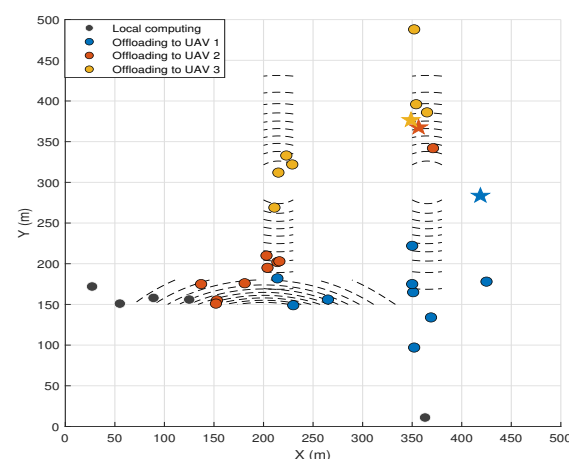


Figure 4. Task offloading decision.

On this basis, the number of UAVs J is set to two, three, and four while keeping other parameters unchanged. Figure 5 shows the two-dimensional trajectories when the number of UAVs is 2. It can be observed that in this setting, the coverage span of each UAV within a time slot is relatively larger, aiming to cover as many vehicles as possible under limited UAV resources. When the number of UAVs increases to 4, as shown in Figure 6, the coverage capability of the UAVs is further enhanced, enabling finer matching

with the vehicle distribution and improved link accessibility. Table 3 summarizes the final total system energy consumption and offloading ratios under different numbers of UAVs. Overall, as the number of UAVs increases, the total coverage capability of the system is enhanced, and the average distance between vehicles and UAVs is shortened, thereby improving the offloading rates and making more vehicles inclined to offload their tasks.

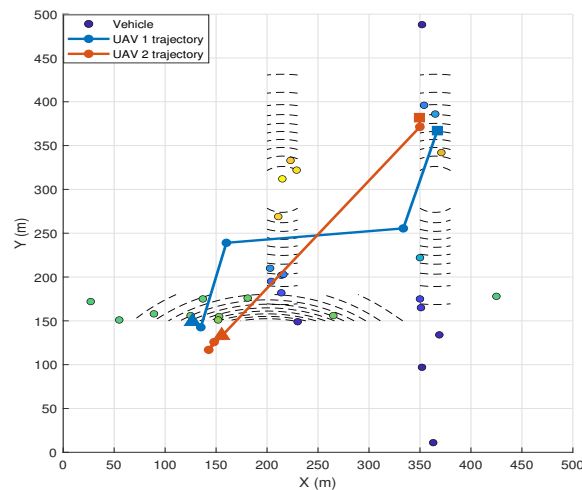


Figure 5. 2D UAV trajectories in $J = 2$.

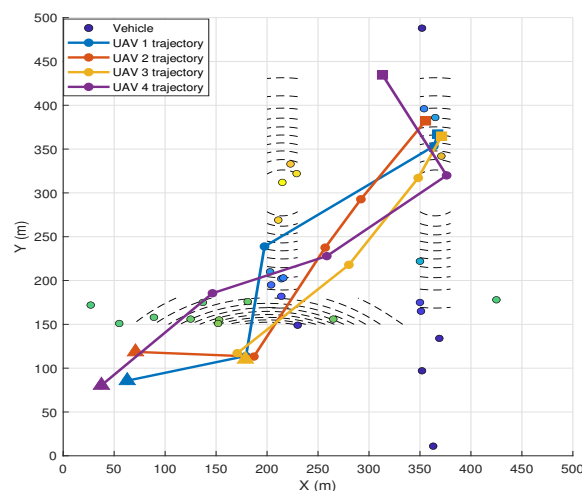


Figure 6. 2D UAV trajectories in $J = 4$.

As shown in Table 3, when the number of UAVs increases from 2 to 3, the offloading ratio improves from 60.0% to 83.3%, while the total system energy consumption rises from 3185.28 J to 5301.63 J. With a further increase to four UAVs, the offloading ratio increases to 93.3%, but the total system energy consumption also notably rises to 8167.78 J. The preceding results demonstrate that, while deploying more UAVs markedly improves task offloading coverage and the offloading success rate, it simultaneously leads to increased system energy expenditure. Consequently, in real-world deployment, a balance between the offloading ratio and total energy consumption must be struck to attain superior overall system performance.

Table 3. Results of the UAV Quantity Comparison Experiment.

Number of UAVs	Offloading Ratio	Total Energy Consumption (J)
2	60.0%	3185.28
3	83.3%	5301.63
4	93.3%	8167.78

6.3. Algorithm Performance Comparison

To validate the efficacy and superiority of the proposed method across multiple dimensions, the proposed scheme (denoted as “Proposed” hereafter) is benchmarked against the following baseline algorithms:

- **Local-only (LO)** : All tasks are processed locally at the terminal side without offloading or related decision-making. This method can be regarded as a performance lower bound in the absence of cooperative computing mechanisms, serving to quantify the benefits brought by the multi-end coordination of the proposed scheme.
- **No UAV trajectory optimization (NTO)**: The joint UAV trajectory optimization is removed, i.e., the UAV motion process does not participate in the optimization. This setting isolates the impact of trajectory optimization on overall performance, thereby further verifying the necessity of the proposed scheme within the joint optimization framework.
- **PSO (Particle Swarm Optimization)**: The PSO algorithm is adopted as a representative swarm intelligence metaheuristic. PSO approximates the optimal solution in the search space through swarm cooperation and velocity update mechanisms.
- **SA (Simulated Annealing)**: The SA algorithm is employed as a local–global compromise method based on random perturbation. Through the temperature annealing strategy, SA allows the acceptance of inferior solutions with higher probability in the early stages to mitigate the risk of falling into local optima. By comparing with SA, the effectiveness of the proposed scheme and the rationality of its search strategy can be validated from the perspectives of capability to escape local optima and solution robustness.

Figures 7 and 8 present the two-dimensional UAV trajectories and the corresponding offloading decision diagrams generated by PSO and SA under the benchmark settings, respectively. The results show that PSO achieves a total system energy consumption of 4541.49 J with an offloading ratio of 96.7%, while SA achieves 5225.85 J with an offloading ratio of 100%. However, a closer examination of the trajectory quality reveals that both PSO and SA produce rather disordered trajectories with noticeable overlaps between trajectory segments. More importantly, we observed that these trajectories violate the UAV velocity constraint $v_j[t] \leq v_{\max}$ in multiple time slots, rendering them infeasible solutions to the constrained optimization problem. The lower nominal energy values reported by PSO and SA are therefore achieved at the cost of constraint violation, as the penalty mechanism in these algorithms does not sufficiently enforce feasibility. In contrast, the proposed GA consistently converges to fully feasible solutions with smooth, spatially continuous trajectories that satisfy all latency and velocity constraints. Across all simulation scenarios, the proposed GA consistently produced feasible solutions satisfying both the latency constraint and the velocity constraint. Therefore, when comparing algorithms based on their best feasible solutions, the proposed GA demonstrates superior overall performance. This result highlights the importance of constraint handling in joint trajectory and offloading optimization and validates the effectiveness of the penalty function and evolutionary search strategy adopted in our GA design.

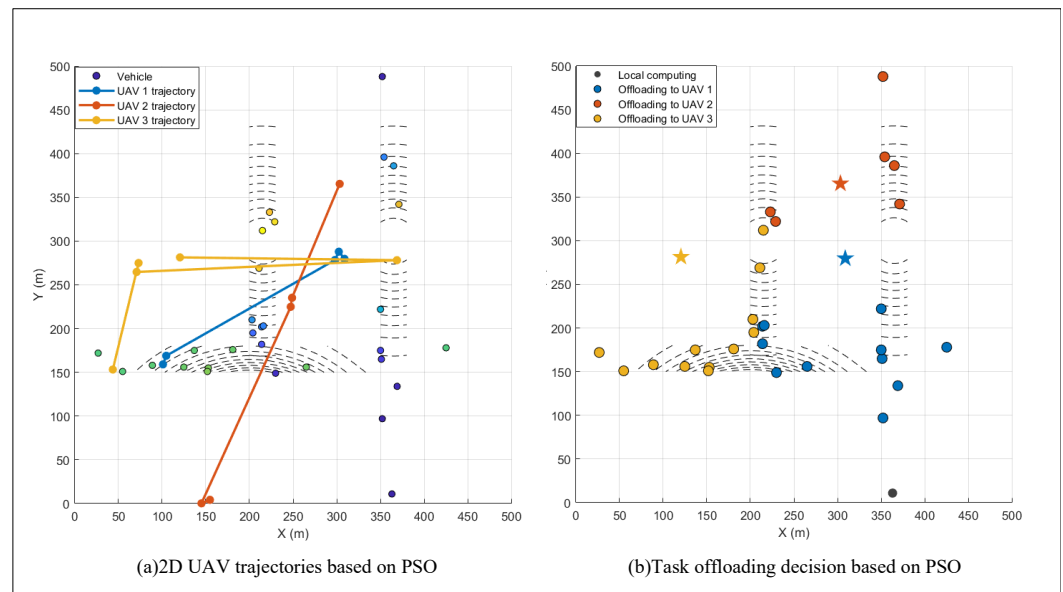


Figure 7. UAV 2D Trajectories and Task Offloading Decisions under PSO.

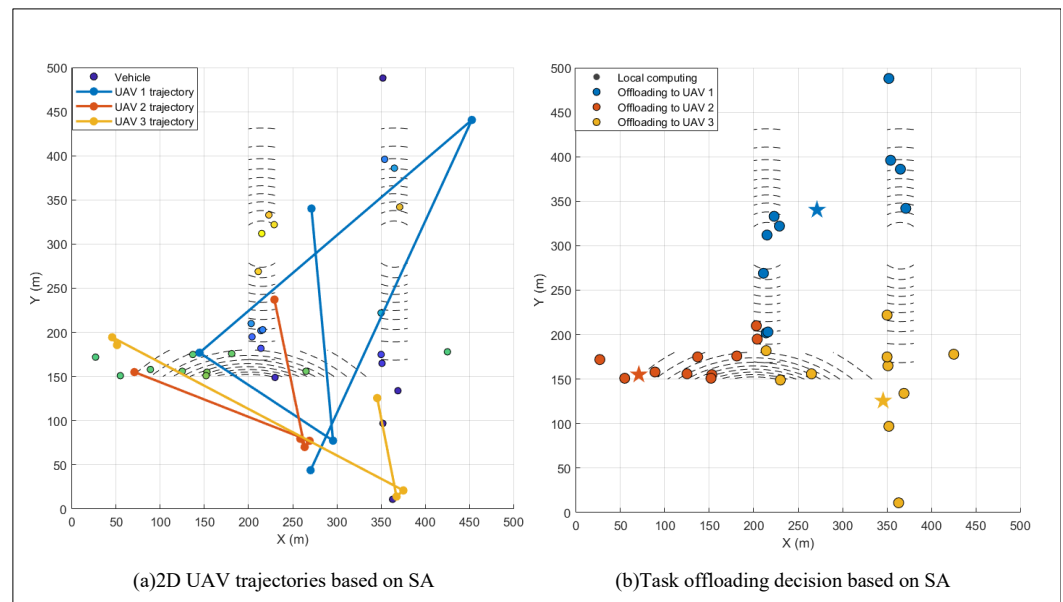


Figure 8. UAV 2D Trajectories and Task-Offloading Decisions under SA.

Figure 9 shows the comparison of the total system energy consumption among the proposed scheme, LO, and NTO under different task input data sizes D_i . From the overall trend, as D_i increases from 1 Mbit to 17 Mbits, the total energy consumption of all schemes exhibits an upward trend. This is because both the computational overhead and the communication overhead increase linearly with the data size. Furthermore, at all levels of D_i , the proposed joint optimization scheme consistently achieves the lowest total energy consumption, indicating that the jointly optimized trajectory and offloading decisions can effectively reduce energy consumption. Taking $D_i = 1$ Mbits as an example, the total energy consumption of GA is 5301.63 J, while those of LO and NTO are 5926.92 J and 6682.72 J, respectively. The GA scheme saves approximately 10.5% and 20.6% energy compared with LO and NTO, respectively. Moreover, as the data size increases, the advantage of GA becomes more pronounced, demonstrating that under high load conditions, the joint trajectory and offloading optimization can more effectively improve the A2G link quality.

and offloading allocation, thereby further amplifying the total system energy consumption gain and exhibiting its stability and adaptability under different task loads.

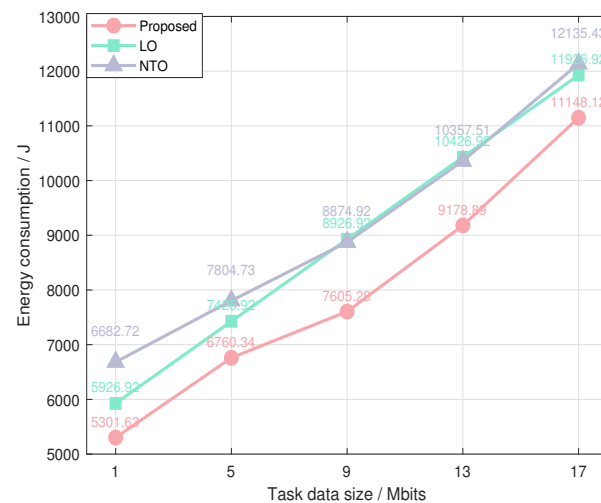


Figure 9. System total energy consumption vs. task input data size.

Figure 10 depicts the comparison curves of the total system energy consumption as the number of vehicles varies. From the overall trend, as the number of vehicles increases from 10 to 70, the total energy consumption of the proposed scheme consistently remains at the lowest level and shows a trend of a slight decrease followed by stabilization, indicating that the scheme possesses good robustness to the vehicle scale. In contrast, the total energy consumption of the LO scheme fluctuates narrowly between 6026 J and 6177 J without exhibiting an obvious monotonic trend, whereas the total energy consumption of the NTO scheme increases monotonically from 6602.62 J to 7124.38 J, indicating that the scheme without trajectory optimization faces higher communication and flight energy consumption costs when serving more vehicles. The reason why the proposed scheme can maintain a stable or even slightly decreasing energy consumption performance as the number of vehicles changes is mainly attributed to the flexibility of its joint optimization framework. As the number of vehicles increases, the spatial distribution of vehicles becomes denser, making it easier for the UAVs to find optimal hovering positions that cover multiple vehicles during trajectory optimization, thereby reducing flight energy consumption. Meanwhile, the offloading decision can dynamically select the offloading ratio, offloading part of the computing tasks to the UAVs for execution and using the UAVs' computing resources to share the local computing pressure, thereby avoiding the linear increase in local computing energy consumption with the number of vehicles. Although the UAV computing energy consumption increases with the number of offloaded vehicles, the trajectory optimization effectively improves the offloading link quality and reduces the communication energy consumption per vehicle so that the total energy consumption can be controlled. The proposed joint optimization scheme exhibits optimal total system energy consumption performance under different vehicle densities and is insensitive to the increase in the number of vehicles, making it particularly suitable for practical edge computing scenarios with dense vehicles and high task concurrency.

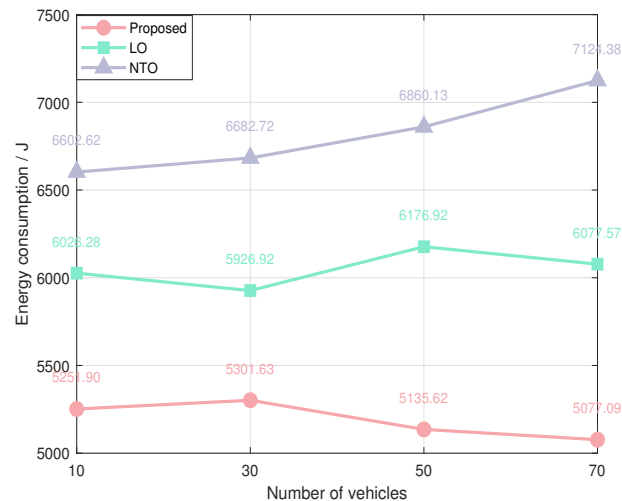


Figure 10. System total energy consumption vs. number of vehicles.

7. Conclusions and Future Work

This paper has examined the joint optimization of UAV flight trajectories and task offloading decisions within a UAV-enabled MEC network specifically designed for urban roadway environments. To this end, a two-tier cooperative network architecture comprising multiple UAVs and ground vehicles has been constructed. On this basis, we have formulated a MINLP model to minimize the total energy consumption through the joint optimization of UAV trajectories and vehicle task offloading decisions while jointly accounting for task latency constraints, UAV flight velocity constraints, and terrain-aware channel characteristics. To tackle the non-convex, strongly coupled, and mixed-integer nature of the formulated problem, a GA-based joint optimization algorithm has been designed. Simulation findings confirm that the proposed algorithm achieves an offloading ratio of 83.3% under the benchmark settings, with the total system energy consumption reduced to 5301.63 J. Comparative experiments reveal that the proposed method saves up to 20.6% in overall energy consumption relative to the LO and NTO benchmark schemes and consistently attains the minimum energy usage across varying task data sizes and vehicle densities. Future work may explore the extension to scenarios with mobile vehicles and dynamic task arrivals, incorporate more sophisticated multi-UAV cooperative strategies, and investigate the integration of machine learning techniques to further enhance the adaptability and real-time performance of the optimization framework. Additionally, incorporating realistic navigation constraints, including the effects of GPS signal availability and positioning errors in urban canyons, into the trajectory optimization framework represents an important direction for future research to enhance the practical applicability of the proposed approach.

Author Contributions: X.W. and W.C. have written the manuscript. P.D. has put forward the idea of this manuscript. J.G. has provided the folders and revised the manuscript. X.L. and K.C. have collected the data and conducted the simulations. All authors have read and agreed to the published version of the manuscript.

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References

1. Xue, J.; Wang, L.; Yu, Q.; Mao, P. Multi-Agent Deep Reinforcement Learning-Based Partial Offloading and Resource Allocation in Vehicular Edge Computing Networks. *Comput. Commun.* **2025**, *234*, 108081.
2. Ning, Z.; Hu, H.; Wang, X.; Guo, L.; Guo, S.; Wang, G.; Gao, X. Mobile Edge Computing and Machine Learning in the Internet of Unmanned Aerial Vehicles: A Survey. *ACM Comput. Surv.* **2023**, *56*, 13. <https://doi.org/10.1145/3604933>
3. Du, P.; Xiao, T.; Cao, H.; Qing, C.; Mumtaz, S. MADDPG-Based Resource Allocation for Integrated Communication, Sensing and Computing in Drone-Assisted IoV Networks. *IEEE Trans. Veh. Technol.* **2026**, *75*, 11159–11172. <https://doi.org/10.1109/TVT.2025.3633518>
4. Liu, B.; Liu, C.; Peng, M. Computation Offloading and Resource Allocation in Unmanned Aerial Vehicle Networks. *IEEE Trans. Veh. Technol.* **2023**, *72*, 4981–4995.
5. Kim, S.J.; Lim, G.J. A Real-Time Rerouting Method for Drone Flights Under Uncertain Flight Time. *J. Intell. Robot. Syst.* **2020**, *100*, 1355–1368. <https://doi.org/10.1007/s10846-020-01214-z>
6. Zhao, M.; Zhang, R.; He, Z.; Li, K. Joint Optimization of Trajectory, Offloading, Caching, and Migration for UAV-Assisted MEC. *IEEE Trans. Mob. Comput.* **2025**, *24*, 1981–1998. <https://doi.org/10.1109/TMC.2024.3486995>
7. Lv, Z.; Shang, W. Impacts of intelligent transportation systems on energy conservation and emission reduction of transport systems: A comprehensive review. *Green Technol. Sustain.* **2023**, *1*, 100002. <https://doi.org/10.1016/j.grets.2022.100002>
8. Dong, C.; Hu, P.; Li, N.; Chen, W.; Li, Y.; Ni, D.; Xie, N.; Wang, H. An iterative optimization method for sustainable environmental improvement under mixed CAV-HDV traffic. *Energy* **2025**, *322*, 135552. <https://doi.org/10.1016/j.energy.2025.135552>
9. He, Y.; Wang, Y.; Yue, H.; Chen, J. Analysis of Low-Altitude UAV-to-Ground Channel Characteristics in Rural Environment. In Proceedings of the 2024 IEEE 7th International Conference on Electronic Information and Communication Technology (ICEICT), Xi'an, China, 31 July–2 August 2024; pp. 1081–1085. <https://doi.org/10.1109/ICEICT61637.2024.10671069>
10. Chen, L.; Zhang, W.; Alouini, M.S. Correlation of Line-of-Sight Probabilities in Aerial-Terrestrial Communications: Modeling, Analysis, and Application. *IEEE Trans. Veh. Technol.* **2024**, *73*, 7049–7065. <https://doi.org/10.1109/TVT.2023.3337423>
11. Li, H.; Zhan, Z.; Wang, Z. Energy-Consumption Model for Rotary-Wing Drones. *J. Field Robot.* **2024**, *41*, 1940–1959.
12. Dai, X.; Duo, B.; Yuan, X.; Tang, W. Energy-Efficient UAV Communications: A Generalized Propulsion Energy Consumption Model. *IEEE Wirel. Commun. Lett.* **2022**, *11*, 2150–2154.
13. Luo, Y.; Lu, J. 3D JPS Path Optimization Algorithm and Dynamic-Obstacle Avoidance Design Based on Near-Ground Search Drone. *Appl. Sci.* **2022**, *12*, 7333. <https://doi.org/10.3390/app12147333>
14. Weng, Y.-Y.; Wu, R.-Y.; Zheng, Y.-J. Cooperative Truck-Drone Delivery Path Optimization under Urban Traffic Restriction. *Drones* **2023**, *7*, 59. <https://doi.org/10.3390/drones7010059>
15. Li, Y.; Liu, M.; Wang, S.; Zhang, L. Path Planning of Electric VTOL UAV Considering Minimum Energy Consumption in Urban Areas. *Sustainability* **2022**, *14*, 13421. <https://doi.org/10.3390/su142013421>
16. Kong, X.; Ni, C.; Li, Y.; Yu, J.; Wang, X.; Zhang, H. Energy Consumption Optimization of UAV-Assisted Traffic Monitoring Scheme with Tiny Reinforcement Learning. *IEEE Internet Things J.* **2024**, *11*, 21135–21145. <https://doi.org/10.1109/JIOT.2024.3365293>
17. González-Baldizón, Y.; Fragosó-Mandujano, J.-A.; Urbina-Brito, N.; Chandomí-Castellanos, E.; Bermúdez-Rodríguez, J.-I.; Pérez-Pérez, E.-J.; Guzmán-Rabasa, J.-A. A Hybrid Algorithm for Fault Diagnosis in Nonlinear UAV Systems Using Conditional LSTM Autoencoders. *Algorithms* **2026**, *19*, 463. <https://doi.org/10.3390/a19060463>
18. Khaneghaei, M.; Asadi, D.; Ebrahimi, B.; Tutsoy, Ö.; Chashmi, Y.N. Intelligent Hybrid Optimization Algorithms for Multi-Agent Aerial Robots Path Planning: Review of the Recent Emerging Trends and Open Research Directions. *Artif. Intell. Rev.* **2026**, *59*, 94.
19. Pervez, F.; Sultana, A.; Yang, C.; Zhao, L. Energy and Latency Efficient Joint Communication and Computation Optimization in a Multi-UAV-Assisted MEC Network. *IEEE Trans. Wirel. Commun.* **2024**, *23*, 1728–1741.
20. Wang, M.; Li, R.; Liu, Y.; Zhang, S. Multi-UAV Assisted Air-Ground Collaborative MEC System: DRL-Based Joint Task Offloading and Resource Allocation and 3D UAV Trajectory Optimization. *Drones* **2024**, *8*, 510. <https://doi.org/10.3390/drones8090510>
21. Zhang, Y.; Kuang, Z.; Feng, Y.; Hou, F. Task Offloading and Trajectory Optimization for Secure Communications in Dynamic User Multi-UAV MEC Systems. *IEEE Trans. Mob. Comput.* **2024**, *23*, 14427–14440.
22. Liu, S.; Yang, H.; Xiao, L.; Zheng, M.; Lu, H.; Xiong, Z. Learning-Based Resource Management Optimization for UAV-Assisted MEC Against Jamming. *IEEE Trans. Commun.* **2024**, *72*, 4873–4886.
23. Qi, Q.; Shi, T.; Qin, K.; Luo, G. Completion Time Optimization in UAV-Relaying-Assisted MEC Networks With Moving Users. *IEEE Trans. Consum. Electron.* **2024**, *70*, 1246–1258. <https://doi.org/10.1109/TCE.2023.3278470>

24. Zhong, Y.; Chen, Y.; Shu, J.; Zhao, J.; Cui, Z.; Huang, J. Edge Service-Oriented Game-Theoretic Joint Optimization of UAV Deployment and Hybrid-NOMA Task Offloading in MEC Networks. *IEEE Trans. Serv. Comput.* **2026**, *19*, 1190–1203. <https://doi.org/10.1109/TSC.2026.3668786>
25. Mao, S.; Liu, L.; Hou, X.; Atiquzzaman, M.; Yang, K. Multi-Domain Resource Management for Space–Air–Ground Integrated Sensing, Communication, and Computation Networks. *IEEE J. Sel. Areas Commun.* **2024**, *42*, 3380–3394. <https://doi.org/10.1109/JSAC.2024.3459026>
26. Zhang, W.; Zhang, W. An Efficient UAV Localization Technique Based on Particle Swarm Optimization. *IEEE Trans. Veh. Technol.* **2022**, *71*, 9544–9557. <https://doi.org/10.1109/TVT.2022.3178228>
27. Zhu, J.; Wang, X.; Huang, H.; He, P.; Malekian, R. A NSGA-II Algorithm for Task Scheduling in UAV-Enabled MEC System. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 9414–9429. <https://doi.org/10.1109/TITS.2021.3120019>
28. Ma, B.; Ji, Y.; Liu, H.; Chen, L. A Multi-UAV Formation Obstacle Avoidance Method Combined with Improved Simulated Annealing and an Adaptive Artificial Potential Field. *Drones* **2025**, *9*, 390. <https://doi.org/10.3390/drones9060390>
29. Liu, L.; Yuan, X.; Chen, D.; Zhang, N.; Sun, H.; Taherkordi, A. Multi-User Dynamic Computation Offloading and Resource Allocation in 5G MEC Heterogeneous Networks With Static and Dynamic Subchannels. *IEEE Trans. Veh. Technol.* **2023**, *72*, 14924–14938.
30. Dong, S.; Xia, Y.; Kamruzzaman, J. Quantum Particle Swarm Optimization for Task Offloading in Mobile Edge Computing. *IEEE Trans. Ind. Inform.* **2023**, *19*, 9113–9122.
31. Song, H.; Gu, B.; Son, K.; Choi, W. Joint Optimization of Edge Computing Server Deployment and User Offloading Associations in Wireless Edge Network via a Genetic Algorithm. *IEEE Trans. Netw. Sci. Eng.* **2022**, *9*, 2535–2548.
32. Zheng, J.; Ding, M.; Sun, L.; Liu, H. Distributed Stochastic Algorithm Based on Enhanced Genetic Algorithm for Path Planning of Multi-UAV Cooperative Area Search. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 8290–8303. <https://doi.org/10.1109/TITS.2023.3258482>
33. Attalah, M.A.; Zaidi, S.; Alghamdi, T.; Alshahrani, S. Task-Offloading Optimization Using a Genetic Algorithm in Hybrid Fog Computing for the Internet of Drones. *Sensors* **2025**, *25*, 1383. <https://doi.org/10.3390/s25051383>
34. Dai, M.; Wu, Y.; Qian, L.; Su, Z.; Lin, B.; Chen, N. UAV-Assisted Multi-Access Computation Offloading via Hybrid NOMA and FDMA in Marine Networks. *IEEE Trans. Netw. Sci. Eng.* **2023**, *10*, 113–127.
35. Cabuk, U.C.; Tosun, M.; Dagdeviren, O.; Ozturk, Y. Modeling Energy Consumption of Small Drones for Swarm Missions. *IEEE Trans. Intell. Transp. Syst.* **2024**, *25*, 10176–10189.
36. Yuan, J.; Liu, Z.; Li, Y.; Wang, Q. Global Optimization of UAV Area Coverage Path Planning Based on Good Point Set and Genetic Algorithm. *Aerospace* **2022**, *9*, 86. <https://doi.org/10.3390/aerospace9020086>
37. Bai, X.; Jiang, H.; Li, C.; Ullah, I.; Maryam, M.; Bashir, A.K. Efficient Hybrid Multi-Population Genetic Algorithm for Multi-UAV Task Assignment in Consumer Electronics Applications. *IEEE Trans. Consum. Electron.* **2025**, *71*, 2395–2406.

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