Maximizing User Service Satisfaction for Delay-Sensitive IoT Applications in Edge Computing

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Abstract—The Internet of Things (IoT) technology provisions unprecedented opportunities to evolve the interconnection among human beings. However, the latency brought by unstable wireless networks and computation failures caused by limited resources on IoT devices prevents users from experiencing high efficiency and seamless user experience. To address these shortcomings, the integrated Mobile Edge Computing (MEC) with remote clouds is a promising platform to enable delay-sensitive service provisioning for IoT applications, where edge-clouds (cloudlets) are co-located with wireless access points in the proximity of IoT devices. Thus, computation-intensive and sensing data from IoT devices can be offloaded to the MEC network immediately for processing, and the service response latency can be significantly reduced. In this paper, we first formulate two novel optimization problems for delay-sensitive IoT applications, i.e., the total utility maximization problems under both static and dynamic offloading task request settings, with the aim to maximize the accumulative user satisfaction on the use of the services provided by the MEC, and show the NP-hardness of the defined problems. We then devise efficient approximation and online algorithms with provable performance guarantees for the problems in a special case where the bandwidth capacity constraint is negligible. We also develop efficient heuristic algorithms for the problems with the bandwidth capacity constraint. We finally evaluate the performance of the proposed algorithms through experimental simulations. Experimental results demonstrate that the proposed algorithms are promising in reducing service delays and enhancing user satisfaction, and the proposed algorithms outperform their counterparts by at least 10.8 percent.

Index Terms—Cost modeling, resource optimization and allocation, service provisioning, delay-sensitive IoT applications, maximum profit generalized assignment problems, approximation algorithms, online algorithms, task offloading and scheduling, service delay, user satisfaction of using services, mobile edge computing (MEC)

1 Introduction

INTERNET of Things (IoT) is emerging as part of the infrastructures for advancing a large variety of applications involving the connection of intelligent devices, thereby leading to smart communities [18]. It urgently needs infrastructures and algorithms to provide effective services for delay-sensitive IoT applications, such as online gaming, augmented reality (AR), virtual reality (VR), smart cities, and autonomous vehicles. Due to the limited computing and storage resources of most IoT devices, it is common to offload computing-intensive or large storage tasks of various applications to remote clouds for processing [13]. This task offloading however suffers from a seriously high latency and network congestion in IoT infrastructures [11]. It thus is inappropriate to offload delay-sensitive IoT applications to remote clouds for processing [17]. Mobile edge computing (MEC) has emerged as a key technology to reduce network traffic, improve user experience, and enable various IoT applications [3]. The cloudlets (edge servers) are placed at the edges of core networks to provide cloud-capability services in the proximity of IoT devices and their mobile users to reduce the service response time, thereby meeting the stringent latency requirements of IoT applications.

With the fast development of 5G, MEC promises to greatly reduce the data processing delay for IoT services, by deploying computing resource (e.g., cloudlets) within the proximity of IoT devices [3]. Fuelled by the 5G technology, it is expected that the 5G-supported MEC will be the promising platform for delay-sensitive IoT services for various IoT applications. To explore the potential of MEC to support IoT applications, in this paper we deal with offloading task services in MEC for delay-sensitive IoT applications, where IoT devices are resource-constrained, by offloading their tasks to cloudlets or a remote cloud for processing. We here consider an integrated platform that consists of the remote cloud and a set of local cloudlets forming an MEC network for IoT service provisioning, where IoT devices or mobile

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users can offload their tasks to the platform for processing, and different offloading task service requests have different service delay requirements. We aim to devise efficient scheduling algorithms for assigning requests to different cloudlets or the remote cloud while meeting their service delay requirements. This poses the following challenges.

For a set of offloading task requests, which requests should be assigned to a local cloudlet and which ones should be assigned to the remote cloud for processing, considering the heterogeneity of both computing resource and processing capability of cloudlets and the remote cloud. How to assign different requests to different cloudlets or the remote cloud such that the average user experience of using the services provided by the platform is maximized while keeping the workload among all cloudlets as balanced as possible, where a user satisfaction is inversely proportional to the extra service delay beyond the user's delay threshold; and how to develop a cost model to quantify a user satisfaction of using a service provided by the platform. In this paper, we will address the challenges and develop efficient approximation and online algorithms for delay-sensitive service provisioning for IoT applications in an integrated MEC platform.

The novelty of the work in this paper lies in that we consider the user satisfaction of using services provided by an MEC network and a remote cloud for delay-sensitive IoT applications, through maximizing the accumulative user satisfaction when different users offload their tasks with different service delay requirements. A novel metric to measure user satisfaction of using a service is proposed, and efficient approximation and online algorithms for the defined problems under both static and dynamic user service demands are then devised.

The main contributions of this paper are presented as follows.

- We consider user service satisfaction of using services provided by an MEC network and a remote cloud for delay-sensitive IoT applications, by formulating two novel user service satisfaction problems. We also show that the defined problems are NP-hard.
- We devise approximation and online algorithms with provable performance guarantees for special cases of the defined problems when the bandwidth capacity constraint is negligible. We also develop efficient heuristic algorithms for the problems with the bandwidth capacity constraint too.
- We evaluate the performance of the proposed algorithms through experimental simulations. Experimental results demonstrate that the proposed algorithms are promising.

The rest of the paper is organized as follows. Section 2 summarizes the related work on service provisioning in MEC. Section 3 introduces the system model, notions, notations, problem definitions, and NP-hardness proofs of the defined problems. Section 4 devises an approximation algorithm and an efficient heuristic algorithm for the total utility maximization problem without and with the bandwidth capacity constraint, respectively. Section 5 deals with dynamic user service request admissions without the knowledge of future arrivals for a given time horizon, and efficient online algorithms for the problem are developed. Section 6 evaluates the proposed algorithms empirically, and Section 7 concludes the paper.

2 Related Work

With the emergence of complicated and resource-hungry mobile applications in the Internet of Things (IoT) and smart cities, implementing user tasks on cloudlets of an MEC network becomes an important approach to shorten service response delays, reduce the energy consumption of mobile devices, and improve the user experience of using services. Task offloading in MEC networks has been extensively studied in recent years. Most existing work focused on minimizing the energy consumption of mobile devices, or the end-to-end delay of a task execution through partitioning a task into two parts: one part is offloaded to the cloudlets in the MEC for execution and another part is processed by the mobile device itself. Most task offloading concentrated on such a single task offloading.

There are extensive investigations on admitting a set of requests with the aim to minimize the average service delay of offloaded tasks. For example, Gouareb *et al.* [5] considered the problem of minimizing the total service delay of implementation of a service function chain in MECs, by proposing a heuristic. Huang *et al.* [7] considered the delay-sensitive service placement and migration in an MEC network by proposing heuristic algorithms for the problem. Jia *et al.* [8] studied task offloading in an MEC with the aim to minimize the average delay of all admitted requests, by incorporating queuing delays at both Access Points (APs) and cloudlets. Lyu *et al.* [12] investigated the joint optimization of both task admission decisions and efficient resource allocation to minimize the total energy consumption in an MEC network while the delay requirements are met. They proposed a task admission approach to achieve the asymptotic optimality by pre-admitting resource-restrained mobile devices. Xu *et al.* [25] considered the delay-aware service offloading problem in MEC with each request having a specific service requirement. They aimed to minimize the service cost through Virtual Network Function (VNF) instance placement, sharing, and migration, by developing online algorithms for request admissions. They however did not include the remote cloud as an alternative processing source. Xu *et al.* [26] also studied delay-aware service placement in MEC to minimize the operational cost, by assuming that the specified delay of each request cannot be violated, and they developed an approximation algorithm for the problem. Xia *et al.* [22] considered a set of delay-aware tasks to be offloaded to an MEC network with the aim to minimize the service cost. They provided a cost model, and proposed a heuristic for the problem based on the built cost model. Xia *et al.* [23] recently considered service caching in MEC to meet service delay requirements by proposing efficient approximation and heuristic algorithms.

Although the aforementioned investigations on delay-aware task offloading have been extensively studied in the past several years, there are only a handful of studies that take into account service provisioning in MEC platforms for delay-sensitive IoT applications. For example, Alameddine

et al. [1] studied a joint task offloading for application assignment and resource allocation in an MEC network, by formulating a dynamic task offloading and scheduling problem. They developed a mixed integer linear programming solution and a heuristic solution for the problem. Arisdakessian *et al.* [2] adopted game theory and designed preference functions for IoT devices and edge nodes based on several metrics. By adopting the preference functions, they developed centralized and distributed algorithms for the assignment of IoT services to edge nodes to minimize the IoT service delay and execution makespan. Ma *et al.* [14], [15] studied NFV-enabled unicasting and multicasting problems with service function chain requirements, they developed heuristic and online algorithms for the problems. Samanta *et al.* [16] developed a dynamic microservice provisioning scheme for IoT devices in MEC environments, by formulating a novel model that incorporates both the service delay and service price into consideration. Song *et al.* [18] investigated the task assignment for IoT applications in an MEC network while meeting the Quality of Service (QoS) requirement of each task. They proposed a heuristic algorithm to achieve efficient network resource utilization for each microservice admission. Xu *et al.* [24] considered the operational cost minimization problem for implementing IoT applications with Service Function Chain (SFC) requirements, by focusing on IoT application placement in an MEC network by developing both randomized and heuristic placement algorithms. Yu *et al.* [27] studied the problem of IoT service provisioning with the objective to meet computing, network bandwidth and QoS requirements of each IoT application. They devised approximation algorithms to deal with the IoT service provisioning under various scenarios, respectively.

Unlike the aforementioned works focusing on either the cost minimization problem or the delay-aware service placement problem in MEC networks, in this paper we consider a set of offloading task requests from IoT devices with different service delay requirements, in which all requests must be served by either cloudlets in an MEC network or a remote cloud. We aim to maximize the accumulative user satisfaction of using the services provided by the integrated platform of the MEC network and the remote cloud. It also must be mentioned that this paper is an extension of a conference paper [10].

3 Preliminaries

In this section, we first introduce the system model, we then give notions, notations, and the modeling of user service satisfaction of using services. We finally quantify the user satisfaction on a provided service in an MEC network, and define the problems precisely.

3.1 System Model

Consider a heterogeneous MEC network that is represented by an undirected graph $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$, where $\mathcal{AP}$ is the set of Access Points (APs), V is the set of cloudlets, v_0 is the remote cloud, and E is the set of links between APs. Each cloudlet (edge cloud) $v \in V$ is co-located with an AP, and connected through a high-speed optical cable, thus the communication delay between them is negligible. However, not each AP is co-located with a cloudlet, and the number of cloudlets usually is far smaller than that of APs. Each cloudlet $v \in V$ is associated with a computing capacity $C_v > 0$ and a packet processing rate μ_v. Node v_0 is a remote cloud with unlimited computing and storage resources. Therefore, the remote cloud v_0 has the maximum packet processing rate, compared with cloudlets. Each link $e \in E$ has a bandwidth capacity $B(e)$. We further assume that each AP in the MEC network is connected to the remote cloud v_0 through a gateway in the MEC network, and the communication delay is far larger than the communication delay between any pair of APs in the MEC network.

We assume that different cloudlets have different computing resource capacities and different processing capabilities. For a given offloading task, the assignment of the task to different cloudlets will result in different computing delays as the workloads and computing capabilities at different cloudlets are different.

We consider a given time horizon that is further divided into T equal time slots. Within each time slot t, let $\mu^t_{v_j}$ represent the processing rate of cloudlet $v_j \in V$, and $C^{'t}_{v_j}$ the residual computing capacity of v_j at time slot t, where $C^{'1}_{v_j} = C_{v_j}$ for all $v_j \in V$, and $\mu^t_{v_0}$ is the processing capability of node v_0, which is the maximum one, i.e., $\mu^t_{v_0} = \max\{\mu^t_{v_j} \mid 0 \leq j \leq |V|\}$. We further assume that the data rate $\gamma^t_{l_i}$ for task offloading of a request r_i from its nearby AP l_i at time slot t is fixed.

Although data uploading from an IoT device to its nearby AP is the bottleneck of some delay-sensitive applications, it becomes insignificant with the adoption of the 5G technology. Also, given a communication metric (e.g., the link congestion or the euclidean distance between the two endpoints of each physical link), let $d^t(e)$ be the transmission delay on a link e in the MEC, which is fixed at each time slot t. However, the values of the mentioned parameters may change at different time slots. For the sake of convenience, we will drop index t from these parameters if no confusion arises from the context.

3.2 The Service Delay of an Offloading Task for Service

Consider a set R of requests, each user service request $r_i \in R$ can be expressed by a tuple $r_i = \langle s_i, b_i, l_i, D_i, \beta_i \rangle$, where s_i is the task size (volume), b_i is the demanded bandwidth resource, the user of r_i is under the coverage of AP l_i, D_i is the service delay requirement threshold, and $\beta_i \cdot D_i$ is the maximum service delay the user could tolerate with a constant $\beta_i \geq 1$. Denote by $c(s_i)$ the demanded computing resource to process the offloaded task of request r_i. *The service delay of a request* consists of the uploading delay, the communication delay of routing the data from the data source to the cloudlet (or the remote cloud) for the data processing, and the processing delay of the task at the cloudlet (or the remote cloud), which are as follows.

The uploading delay $d_{upload}(r_i)$ of an offloading task r_i through its located AP l_i is

$$d_{upload}(r_i) = \frac{s_i}{\gamma_{l_i}}, \tag{1}$$

where γ_{l_i} is the uplink data rate of AP l_i, which can be calculated by the following Shannon-Hartley formula [20].

$$\gamma_{l_i} = W_{l_i} \log_2(1 + \frac{\kappa_i}{\sigma^2}), \tag{2}$$

where W_{l_i} is the total bandwidth of AP l_i divided by the number of users under its coverage, κ_i is the transmission power of IoT device of request r_i, and σ^2 is the noise power.

An offloading task will be served by either a cloudlet or the remote cloud $v_j \in V \cup \{v_0\}$, *the communication delay* $d_{comm}(r_i, v_j)$ of offloading task r_i to node v_j is

$$d_{comm}(r_i, v_j) = \begin{cases} \sum_{e \in P_i(v_j)} d(e), & \text{if } v_j \in V \\ d_{comm}(r_i, v_0), & \text{otherwise } (v_j = v_0), \end{cases} \tag{3}$$

where $P_i(v_j)$ is a routing path of request r_i between its AP location l_i and the AP location of cloudlet v_j, $d(e)$ is the communication delay on a link e, and $d_{comm}(r_i, v_0)$ is the communication delay of routing the task of r_i from AP l_i to the remote cloud through the gateway.

The processing delay $d_{comp}(r_i, v_j)$ of an offloading task r_i at cloudlet or the remote cloud v_j is

$$d_{comp}(r_i, v_j) = \frac{s_i}{\mu_{v_j}}, \tag{4}$$

where s_i is the task size of request r_i, and μ_{v_j} is the processing rate of cloudlet (or the remote cloud).

The service delay $d(r_i, v_j)$ of offloading task r_i to node v_j for service thus is defined as follows.

$$d(r_i, v_j) = d_{upload}(r_i) + d_{comm}(r_i, v_j) + d_{comp}(r_i, v_j). \tag{5}$$

Note that we do not include the delay of returning the result to the user as the result usually is no larger than the uploading volume of data, and the delay of returning the result thus is omitted.

3.3 User Service Satisfaction of Using a Service

In most IoT applications, each service request does have its expected delay threshold and maximum tolerable delay requirement. A task offloading request usually can be represented by a tuple $r_i = \langle s_i, b_i, l_i, D_i, \beta_i \rangle$, where D_i is its delay threshold, if the actual service delay is beyond its threshold D_i, the service may still be acceptable by the user. However, in terms of the service experience, the user of request r_i may not be happy about the service. In other words, the service satisfaction of a user for his requested service can be expressed by a non-increasing function of the service delay he experienced. If a service delay is within the specified threshold, the user satisfies the service with 100 percent; otherwise, his satisfaction with the service is inversely proportional to the extra service delay beyond the user's delay threshold. Specifically, assume that a user request $r_i \in R$ is assigned to cloudlet or the remote cloud v_j for service, then its service delay is $d(r_i, v_j)$ by Eq. (5). If $d(r_i, v_j)$ is no greater than D_i, the user satisfies the service with 100 percent; otherwise, his satisfaction on the service will dramatically decrease with the increase on the value of $d(r_i, v_j)$, and the maximum tolerant service delay of the user is $\beta_i \cdot D_i$, where $\beta_i \geq 1$ is a constant, representing a certain degree of the delay tolerance of the user. If a service delay is beyond the maximum tolerant service delay of the user, the user satisfaction on the service will become zero. We thus model a user service satisfaction of using a service provided by an MEC network and a remote cloud through *a non-increasing utility function* as follows.

$$u(r_i, v_j) = \begin{cases} (\lambda - \lambda^{\frac{[d(r_i, v_j) - D_i]^+}{\beta_i \cdot D_i}}), & \text{if } d(r_i, v_j) \leq \beta_i \cdot D_i \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

where $[x]^+ = \max\{x, 0\}$, and $\lambda > 1$ is a constant that indicates the delay sensitivity.

It can be seen from Eq. (6) that if the service delay is no greater than D_i, $[d(r_i, v_j) - D_i]^+ = 0$, then $\lambda^0 = 1$, and the utility gain of the user is $u(r_i, v_j) = \lambda - 1 > 0$, implying the user is 100 percent satisified. Otherwise, if the service delay is within the delay range of $(D_i, \beta_i \cdot D_i]$, i.e., $0 < d(r_i, v_j) - D_i \leq (\beta_i - 1) \cdot D_i$, then $\frac{[d(r_i, v_j) - D_i]^+}{\beta_i \cdot D_i} = \frac{d(r_i, v_j) - D_i}{\beta_i \cdot D_i} \leq \frac{(\beta_i - 1) \cdot D_i}{\beta_i \cdot D_i} = \frac{\beta_i - 1}{\beta_i} < 1$, and the utility value $u(r_i, v_j) = \lambda - \lambda^{\frac{d(r_i, v_j) - D_i}{\beta_i \cdot D_i}} \leq \lambda - \lambda^{\frac{\beta_i - 1}{\beta_i}} < \lambda - 1$, i.e., the user satisfaction decreases with the growth of the delay duration and is impacted by both λ and β_i. A larger value of λ means that the utility obtained is more sensitive than that of a smaller λ, and a larger β_i implies that the user of request r_i is more tolerable to his service delay. When the actual service delay $d(r_i, v_j) > \beta_i \cdot D_i$ that is beyond the maximum tolerant service delay of the user of r_i, then $u(r_i, v_j) = 0$ by the utility function definition, and the user satisfaction is 0 percent. Thus, the value of β_i reflects the service delay tolerance of the user of request r_i at a certain extent.

3.4 Problem Definitions

In this paper, we consider the service provisioning in an integrated platform that consists of an MEC network and a remote cloud for delay-sensitive IoT applications, by formulating two novel optimization problems.

Problem 1: Given an MEC network $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ with a given set R of requests, each request $r_i = \langle s_i, b_i, l_i, D_i, \beta_i \rangle$ in R is expressed by a tuple, where s_i is the size of the offloading task, b_i is the demanded bandwidth resource, l_i is the physical location of the offloading task, D_i is the ideal tolerable delay threshold, and $\beta_i \cdot D_i$ is the maximum tolerable service delay of the request. *The total utility maximization problem* is to maximize the utility sum of all requests in R, i.e., the total user experience of using the services provided by the MEC network, subject to computing capacities on cloudlets and bandwidth capacities on links in G.

As network service providers provide continuing services for their consumers, in the defined problem so far, we have only considered user requests at a given time slot t, where the data rate γ_l^t assigned for each user under the coverage of an AP $l \in \mathcal{AP}$ is fixed at time slot t. However, the value of $\gamma_l^{t'}$ will change at a different time slot $t' \neq t$ which will be determined by the number of users under the coverage of AP l at that time slot. Meanwhile, the transmission delay $d^{t'}(e)$ on a link e in G at time slot t' can also be changed, which is impacted not only by the link length but also the congestion on the link. The processing rate μ_v^t of a

node $v \in V \cup \{v_0\}$ may vary at different time slots too. In the following we consider the dynamic user service request admissions within a finite time horizon that consists of T equal time slots.

Problem 2: Given an MEC network $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ and a finite time horizon that consists of T equal time slots, assume that user service requests arrive one by one without the knowledge of future arrivals, *the online average total utility maximization problem* is to maximize the average sum of accumulative utilities of all admitted requests per time slot within the given time horizon, subject to both computing capacities on cloudlets and bandwidth capacities on links in G.

Theorem 1. *The total utility maximization problem in an MEC network $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ is NP-hard.*

Proof. We show the claim by a reduction from a well-known NP-hard problem – the maximum profit Generalized Assignment Problem (GAP) that is defined as follows [4]. Given n items and m bins, if item i is packed to bin j, it results in a profit $p_{i,j}$ and a size $s_{i,j}$. Usually the size of each item i at different bins is fixed, i.e., $s_{i,j} = s_{i,j'}$ even if $j \neq j'$, and each bin has a capacity. The problem is to pack as many items as possible to the m bins such that the total profit of the packed items is maximized, subject to bin capacities.

We consider a special case of the total utility maximization problem where the bandwidth resource consumption of each request is negligible, by assuming that there is abundant bandwidth resource on each link in the MEC network. Thus, the routing path of routing the offloaded task of request r_i to cloudlet v is the routing path from AP l_i to cloudlet v with the least communication delay. There are $(|V| + 1)$ bin, where bin $\mathcal{B}_0$ corresponds to the remote cloud with unlimited computing capacity, and each of the other bins corresponds to a cloudlet v with the capacity of C_v. Each item i corresponds to a request r_i. For each bin $\mathcal{B}_j$, each item has the size $s_{i,j} = c(s_i)$ and profit $p_{i,j} = u(r_i, v_j)$. The total utility maximization problem for this special case is to maximize the total utility gain by admitting as many requests as possible, subject to the computing capacities on cloudlets. It can be seen that this special problem is equivalent to the maximum profit GAP. Hence, the total utility maximization problem is NP-hard. □

4 Algorithms for the Total Utility Maximization Problem

In this section, we deal with the total utility maximization problem. We first consider a special case of the problem where there are abundant bandwidth resources on links, for which we formulate an integer linear programming (ILP) solution for the problem when the problem size is small. Otherwise, we devise an approximation algorithm with a provable approximation ratio for the problem, by reducing the problem to the maximum profit GAP problem. An approximate solution to the latter in turn returns an approximate solution to the former. We also devise an efficient heuristic algorithm for the problem under the bandwidth capacity constraint too.

4.1 ILP and Approximation Algorithms for the Problem Without the Bandwidth Capacity Constraint

We deal with the total utility maximization problem without the bandwidth capacity constraint on links, by assuming that each link has abundant bandwidth resource. We start with the ILP formulation as follows.

$$\text{Maximize} \quad \sum_{i=1}^{|R|} \sum_{j=0}^{|V|} u(r_i, v_j) \cdot x_{i,j}, \tag{7}$$

subject to the following constraints.

$$\begin{aligned} &\text{Eq. (1), (2), (3), (4), (5), (6),} \\ &\quad \forall i, j, \quad 1 \leq i \leq |R|,\ 0 \leq j \leq |V| \\ &\sum_{j=0}^{|V|} x_{i,j} \leq 1, \quad \forall i, \quad 1 \leq i \leq |R| \end{aligned} \tag{8}$$

$$\sum_{i=1}^{|R|} x_{i,j} \cdot c(s_i) \leq C_{v_j}, \quad \forall j, \quad 0 \leq j \leq |V| \tag{9}$$

$$x_{i,j} \in \{0, 1\}, \quad \forall i, j, \quad 1 \leq i \leq |R|, \quad 0 \leq j \leq |V|. \tag{10}$$

where variable $x_{i,j}$ is a binary variable, and $x_{i,j} = 1$ implies that offloading task r_i will be served by cloudlet/the remote cloud v_j with $0 \leq j \leq |V|$. Constraint (8) ensures that each request is assigned to at most one node for service. Constraint (9) ensures that the accumulative resource demand by all requests assigned to a node is no more than the capacity of the node. Recall that we assume that the remote cloud is node v_0 with unlimited computing resource. Note that for each request r_i in Eq. (3), its routing path $P_i(v_j)$ to cloudlet $v_j \in V$ is a shortest path in G between AP l_i and cloudlet v_j, and the weight of each link e in $P_i(v_j)$ is the transmission delay, i.e., d_e, because each link is assumed to have abundant bandwidth resource.

We then devise an approximation algorithm for the problem by reducing it to the maximum profit GAP, which is a well-known NP-hard problem and there is an efficient approximation algorithm for it [4].

The reduction is as follows. There are $(|V| + 1)$ bins, where bin $\mathcal{B}_0$ corresponds to the remote cloud with unlimited computing resource, the rest $|V|$ bins correspond to the $|V|$ heterogeneous cloudlets, where $\mathcal{B}_j$ with $1 \leq j \leq |V|$ represents cloudlet $v_j \in V$ with capacity C_{v_j}. There are $|R|$ requests. Recall that request $r_i \in R$ is located at AP l_i if it is assigned to cloudlet v_j for service with the computing resource consumption $c(s_i)$, then the utility gain is $u(r_i, v_j)$ by Eq. (6), which is determined by the experienced service delay $d(r_i, v_j)$. In other words, if we pack request r_i to bin $\mathcal{B}_j$, it generates a profit $u(r_i, v_j)$ with size $c(s_i)$, where $1 \leq j \leq |V|$; otherwise (if r_i is sent to the remote cloud v_0 for service), its service delay is $d(r_i, v_0)$, and the utility gain is $u(r_i, v_0)$. Note that when the utility obtained by packing a request to a bin is zero, the request will not be admitted. The detailed algorithm is given in `Algorithm 1`.

4.2 Heuristic Algorithm for the Problem With the Bandwidth Capacity Constraint

We now consider the problem under the bandwidth capacity constraint by developing a greedy algorithm that proceeds iteratively.

Algorithm 1. An Approximation Algorithm for the Total Utility Maximization Problem Without the Bandwidth Capacity Constraint

Input: $|V|$ cloudlets with each $v_j \in V$ having computing capacity C_{v_j}, a remote cloud v_0 with unlimited computing capacity, i.e., $C_{v_0} = \infty$, a set of requests R with each request $r_i = \langle s_i, b_i, l_i, D_i, \beta_i \rangle$.

Output: Admit as many requests as possible from R that maximizes the utility sum of admitted requests.

1: Calculate the shortest path between each cloudlet and each AP, and the weight of each link is the communication delay on the link.
2: Construct an instance of the GAP, where each request $r_i \in R$ has a corresponding item i with size $c(s_i)$ and the profit $u(r_i, v_j)$. Each cloudlet v_j or the remote cloud corresponds to a bin $\mathcal{B}_j$ with bin capacity $cap(\mathcal{B}_j) = C_{v_j}$, where $0 \leq j \leq |V|$;
3: Find an approximate solution A to the GAP problem with maximizing the utility sum, by invoking the approximation algorithm due to Cohen *et al.* [4];
4: **for** any request $r \in A$ with utility zero **do**
5: $A \leftarrow A \setminus \{r\}$; /* remove request r from the solution */;
6: **end for** ;
7: **return** the solution A as the solution of the total utility maximization problem without the bandwidth capacity constraint.

At each iteration, for a request $r_i \in R$ to be offloaded, we first identify the set of cloudlets $V' \subseteq V$ and the set of links $E' \subseteq E$ with sufficient residual computing resource and bandwidth resource to accommodate request r_i, respectively. We then find a routing path $P_i(v_j)$ in the induced subgraph $G' = (\mathcal{AP} \cup V' \cup \{v_0\}, E')$ of graph $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ with the least communication delay from location l_i of request r_i to cloudlet $v_j \in V'$, through links in E'. Then, the utility gain of assigning request r_i to cloudlet v_j through the routing path $P_i(v_j)$ can be obtained. Because the remote cloud v_0 has the unlimited computing resource, the remote cloud can be identified as the offloading node of the request too. Among all nodes in $V' \cup \{v_0\}$, we then identify a node $\hat{v_i}$ with the maximum utility gain for request r_i. However, if the maximum utility gain of assigning request r_i to the node $\hat{v_i}$ is zero, the request r_i will be rejected. Among all requests to be offloaded, we identify a request $r_{i'}$ with the maximum utility gain for its admission. If request $r_{i'}$ is assigned to a cloudlet, the residual computing resource on the cloudlet and residual bandwidth resource on the links in the routing path are then updated accordingly. This procedure continues until all requests are either admitted or rejected. The detailed algorithm is given in `Algorithm` 2.

4.3 Algorithm Analysis

In the following we first analyze the approximation ratio and time complexity of the approximation algorithm, `Algorithm` 1. We then analyze the time complexity of the heuristic algorithm, `Algorithm` 2.

Algorithm 2. A Heuristic Algorithm for the Total Utility Maximization Problem With the Bandwidth Capacity Constraint

Input: $|V|$ cloudlets with each $v_j \in V$ having computing capacity C_{v_j}, a remote cloud v_0 with unlimited computing capacity, i.e., $C_{v_0} = \infty$, each link $e \in E$ connecting cloudlets has a bandwidth capacity, and a set of requests R with each request $r_i = \langle s_i, b_i, l_i, D_i, \beta_i \rangle$.

Output: Admit as many requests as possible from R that maximizes the utility sum of admitted requests.

1: $\mathbb{R} \leftarrow R$; /* the requests to be offloaded */
2: $A \leftarrow \emptyset$; /* the solution */
3: **while** $\mathbb{R} \neq \emptyset$ **do**
4: **for** each request $r_i \in \mathbb{R}$ **do**
5: Identify the set of cloudlets $V' \subseteq V$ and the set of links $E' \subseteq E$ with sufficient residual resource for r_i;
6: Find the routing path $P_i(v_j)$ from AP l_i to each cloudlet $v_j \in V'$ with the least communication delay, through links in E';
7: Calculate the utility gain $u(r_i, v_j)$ if r_i is assigned to each cloudlet $v_j \in V'$ through the routing path $P_i(v_j)$;
8: Calculate the utility gain $u(r_i, v_0)$ if r_i is assigned to the remote cloud v_0.
9: Find node $\hat{v_i} \in V' \cup \{v_0\}$ with the maximum utility gain $u(r_i, \hat{v_i})$ for request r_i;
10: **if** $u(r_i, \hat{v_i}) = 0$ **then**
11: r_i is rejected;
12: $\mathbb{R} \leftarrow \mathbb{R} \setminus \{r_i\}$;
13: **end if** ;
14: **end for** ;
15: Find request $r_{i'} \in \mathbb{R}$ with the maximum utility gain, and admit request $r_{i'}$ by assigning request $r_{i'}$ to node $\hat{v_{i'}}$;
16: $A \leftarrow A \cup \{r_{i'}\}$; $\mathbb{R} \leftarrow \mathbb{R} \setminus \{r_{i'}\}$;
17: **if** $\hat{v_{i'}}$ is a cloudlet **then**
18: Update the residual resource on cloudlet $\hat{v_{i'}}$ and the links on the routing path $P_{i'}(\hat{v_{i'}})$;
19: **end if** ;
20: **end while** ;
21: **return** the solution A as the solution of the total utility maximization problem with the bandwidth capacity constraint;

Lemma 1. *Given an MEC network $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ and a set R of user requests, the upper bound on the optimal solution of the total utility maximization problem in G is $(\lambda - 1) \cdot |R|$.*

Proof. The claim of that the optimal solution is upper bounded by $(\lambda - 1) \cdot |R|$ is shown as follows. If a request $r_i \in R$ can be served within its specified delay threshold, i.e., $d(r_i, v_j) \leq D_i$, the utility obtained by this service is $(\lambda - 1)$; if $D_i < d(r_i, v_j) \leq \beta_i \cdot D_i$, its utility is $\lambda - \lambda^{\frac{d(r_i, v_j) - D_i}{\beta_i \cdot D_i}} < \lambda - 1$; otherwise, its utility is 0. □

Theorem 2. *Given an MEC network $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ and a set R of offloading task requests, there is an approximation algorithm, `Algorithm` 1, for the total utility maximization problem without the bandwidth capacity constraint, which delivers an approximate solution with a $\frac{1}{2+\epsilon}$ approximation*

ratio. The time complexity of the approximation algorithm is $O(|V| \cdot |\mathcal{AP}|^2 + (|V|+1) \cdot |R| \cdot \log \frac{1}{\epsilon} + \frac{|V|+1}{\epsilon^4})$, *where* ϵ *is a constant with* $0 < \epsilon \leq 1$.

Proof. The approximation ratio of the proposed algorithm, `Algorithm 1` can be obtained by adopting the analysis of the approximation algorithm due to Cohen *et al.* [4]. The solution delivered by the algorithm is no less than $\frac{1}{2+\epsilon}$ times the optimal one, where ϵ is a constant with $0 < \epsilon \leq 1$.

The running time of `Algorithm 1` is analyzed as follows. Finding the shortest paths between each cloudlet and each AP takes $O(|V| \cdot |\mathcal{AP}|^2)$ time, while the approximation algorithm due to Cohen *et al.* [4] takes $O((|V|+1) \cdot |R| \cdot \log \frac{1}{\epsilon} + \frac{|V|+1}{\epsilon^4})$ time. Thus, the time complexity of `Algorithm 1` is $O(|V| \cdot |\mathcal{AP}|^2 + (|V|+1) \cdot |R| \cdot \log \frac{1}{\epsilon} + \frac{|V|+1}{\epsilon^4})$. □

Theorem 3. *Given an MEC network* $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ *and a set* R *of offloading task requests, there is an algorithm,* `Algorithm 2`, *for the total utility maximization problem with the bandwidth capacity constraint, which delivers a feasible solution, and its time complexity is* $O(|R|^2 \cdot |\mathcal{AP}|^2)$.

Proof. It can be seen that the solution delivered by `Algorithm 2` is feasible because no specified constraint is violated. The time complexity of `Algorithm 2` is analyzed as follows.

There are at most $|R|$ iterations. Within each iteration, a request with the maximum utility gain from the remaining requests is admitted. The time of calculating the utility gain of admitting a request r_i is dominated by the time of finding the shortest path from the location of request r_i to each cloudlet with sufficient computing resource through links with sufficient bandwidth resource for r_i, which takes $O(|\mathcal{AP}|^2)$ time. Thus, the time complexity of the proposed algorithm is $O(|R|^2 \cdot |\mathcal{AP}|^2)$. □

5 Online Algorithms for the Online Average Total Utility Maximization Problem

In this section, we study dynamic user service request admissions, where user service requests arrive one by one without the knowledge of future arrivals, and all arrived requests will be considered in the beginning of the next time slot. We start with a special case of the problem where the bandwidth capacity constraint is not considered, for which we devise an online algorithm with a provable competitive ratio. We then develop an efficient online algorithm for the problem with the bandwidth capacity constraint.

Notice that once an admitted request finishes its service, its occupied resources will be released back to the system in the end of the time slot it leaves. Thus, the available capacity of each cloudlet or link at each time slot is its residual capacity at that time slot, and those occupied resources are not available for new request admissions at the next time slot.

5.1 Online Algorithm for the Problem Without the Bandwidth Capacity Constraint

Denote by $C_v(i)$ the residual computing resource at cloudlet $v \in V$ before considering request r_i, and $C_v(1) = C_v$ initially. If request r_i is assigned to cloudlet v for service, $C_v(i+1) = C_v(i) - c(s_i)$, where $c(s_i)$ is the demanded computing resource of request r_i. Otherwise, request r_i is assigned to the remote cloud for service, and nothing has to be done because the remote cloud has unlimited resource. To capture the computing resource usage on cloudlets, a computing resource usage cost model is introduced as follows.

$$w_v(i) = C_v(\alpha^{1-\frac{C_v(i)}{C_v}} - 1), \tag{11}$$

where $\alpha > 1$ is a turning parameter reflecting the sensitivity of the workload at each cloudlet v, and $1 - \frac{C_v(i)}{C_v}$ is the utilization ratio of cloudlet v.

The normalized computing resource cost of assigning offloading request r_i to cloudlet v thus is

$$\psi_v(i) = \frac{w_v(i)}{C_v} = \alpha^{1-\frac{C_v(i)}{C_v}} - 1 \tag{12}$$

Upon the arrival of request r_i, we first identify the set $V' \subseteq V$ of cloudlets with sufficient residual computing resource to accommodate request r_i. Then we find the shortest routing path from the located AP l_i of request r_i to each cloudlet $v \in V'$ and calculate the utility gain if request r_i is assigned to cloudlet v through the shortest routing path. Among all cloudlets in V', we identify the set of cloudlets $\mathcal{Q}_i \subseteq V'$ with the positive utility gains for request r_i, and request r_i is assigned to the cloudlet in $\mathcal{Q}_i$ with the minimum normalized computing resource cost by Eq. (12). If no such cloudlet exists, request r_i can then be assigned to the remote cloud with unlimited computing resource. However, if the utility gain brought by assigning request r_i to the assigned node is 0 (i.e., $d(r_i, v_j) > \beta_i \cdot D_i$), the request can be rejected.

We now assume that request r_i is assigned to node $v' \in V \cup \{v_0\}$ with the utility gain u_i. If request r_i is assigned to the remote cloud (i.e., $v' = v_0$) with a positive utility gain, it indicates that the request will be admissible. Although r_i is admissible, its admission needs further examination to avoid consuming too much resource, by adopting an admission control policy. That is, request r_i will be rejected if both the following conditions are met. (i) The normalized computing resource cost of cloudlet $v' \in V$ that will accommodate request r_i is greater than $|V| \cdot u_i$, i.e., $\psi_{v'}(i) > |V| \cdot u_i$; and (ii) assigning request r_i to the remote cloud will result in the zero utility gain (i.e., exceeding the maximum tolerable service delay). Note that if condition (i) is met while condition (ii) is violated (i.e., assigning request r_i to the remote cloud will result in a positive utility gain), request r_i is admitted and assigned to the remote cloud.

The detailed online algorithm with a provable competitive ratio is given in `Algorithm 3`.

5.2 Online Algorithm for the Problem With the Bandwidth Capacity Constraint

We then deal with the online average total utility maximization problem with the bandwidth capacity constraint by devising an efficient online algorithm as follows.

Recall that for the problem without the bandwidth capacity constraint, we introduce a computing resource cost

model to capture the dynamic consumptions of computing resources on cloudlets. Similarly, we here introduce the bandwidth resource cost model to capture the dynamic bandwidth resource consumptions of links as follows.

$$w_e(i) = B_e(\delta^{1-\frac{B_e(i)}{B_e}} - 1), \tag{13}$$

where $\delta > 1$ is a turning parameter reflecting the sensitivity of the workload at each link e, B_e is the bandwidth capacity of link $e \in E$, $B_e(i)$ is the residual bandwidth resource on link $e \in E$ before considering request r_i, and $1 - \frac{B_e(i)}{B_e}$ is the utilization ratio of link e.

The normalized bandwidth cost of link $e \in E$ for request r_i thus is

$$\psi_e(i) = \frac{w_e(i)}{B_e} = \delta^{1-\frac{B_e(i)}{B_e}} - 1. \tag{14}$$

The normalized bandwidth cost on a routing path $P_i(v)$ of request r_i then is $\sum_{e \in P_i(v)} \psi_e(i)$.

The *total normalized cost* of assigning request r_i to cloudlet v through the routing path $P_i(v)$ consists of the normalized computing resource cost $\psi_v(i)$ on v and the normalized bandwidth cost on $P_i(v)$, i.e.,

$$\phi(P_i(v)) = \psi_v(i) + \sum_{e \in P_i(v)} \psi_e(i). \tag{15}$$

Similar to `Algorithm` 3, the proposed online algorithm proceeds as follows. Upon the arrival of request r_i, we first identify the set of cloudlets $V' \subseteq V$ and the set of links $E' \subseteq E$ with sufficient computing and bandwidth resources to accommodate request r_i. We then assign each cloudlet $v \in V'$ and each link $e \in E'$ with a normalized computing resource cost $\psi_v(i)$ by Eq. (12) and a normalized bandwidth resource cost $\psi_e(i)$ by Eq. (14), respectively. We third find a routing path $P_i(v_j)$ in the induced subgraph $G' = (\mathcal{AP} \cup V' \cup \{v_0\}, E')$ of graph $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ with the least communication delay on the path from location l_i of request r_i to each cloudlet $v_j \in V'$. Hereafter, among all cloudlets in V', we finally identify the set of cloudlets $\mathcal{Q}_i \subseteq V'$ with the positive utility gains for request r_i through the associated routing paths. Then, among all cloudlets in $\mathcal{Q}_i$, we assign request r_i to cloudlet $v' \in \mathcal{Q}_i$ through its routing path with the minimum total normalized cost by Eq. (15). If no such a cloudlet exists, the request can be assigned to the remote cloud v_0. However, if the utility gain brought by such an assignment is 0, the request will be rejected.

Assuming that request r_i is assigned to node $v' \in V \cup \{v_0\}$ with the utility gain u_i. If request r_i is assigned to the remote cloud (i.e., $v' = v_0$) with a positive utility gain, it will be admitted. Although r_i is admissible with the utility gain u_i when it is assigned to cloudlet $v' \in V$, its admission needs further to be examined to avoid consuming too much resource through an admission control policy. That is, request r_i will still be rejected if both the following conditions are met: (i) The normalized computing resource cost of cloudlet v' or the normalized bandwidth resource cost of the routing path $P_i(v')$ is greater than $|V| \cdot u_i$, i.e., $\psi_{v'}(i) > |V| \cdot u_i$ or $\sum_{e \in P_i(v')} \psi_e(i) > |V| \cdot u_i$; and (ii) the utility gain is zero if the request is assigned to the remote cloud. Note that if condition (i) is met while condition (ii) is violated (i.e., assigning request r_i to the remote cloud will result in a positive utility gain), request r_i is admitted and assigned to the remote cloud.

Algorithm 3. Online Algorithm for the Online Average Total Utility Maximization Problem Without the Bandwidth Capacity Constraint

Input: $|V|$ cloudlets with each $v_j \in V$ having computing capacity C_{v_j}, a remote cloud v_0 with unlimited computing capacity, i.e., $C_{v_0} = \infty$, a set of requests R with each request $r_i = \langle s_i, b_i, l_i, D_i, \beta_i \rangle$ arrived one by one, there is no knowledge of future request arrivals.

Output: Maximize the average total utility gain of admitted requests per time slot within the time horizon.

$A \leftarrow \emptyset$; /* the solution */
while request r_i arrives **do**
  Identify the set of cloudlets $V' \subseteq V$ with sufficient residual computing resource for r_i;
  Find the routing path $P_i(v_j)$ from AP l_i to each cloudlet $v_j \in V'$ with the smallest communication delay;
  $\mathcal{Q}_i \leftarrow \emptyset$; /* the set of candidate cloudlets for r_i */
  for each cloudlet $v_j \in V'$ **do**
    Calculate the utility gain of assigning request r_i to cloudlet v_j;
  if its utility gain is positive **then**
    $\mathcal{Q}_i \leftarrow \mathcal{Q}_i \cup \{v_j\}$;
  end if ;
  end for ;
  if $\mathcal{Q}_i = \emptyset$ **then**
    if assigning r_i to remote cloud makes positive utility **then**
      Admit r_i by assigning r_i to remote cloud;
    else
      Reject r_i;
    end if ;
  else
    Identify the cloudlet $v' \in \mathcal{Q}_i$ with the minimum normalized cost by Eq. (12). And calculate the utility gain u_i if request r_i is assigned to cloudlet v';
    if $\psi_{v'}(i) > |V| \cdot u_i$ **then**
      if assigning r_i to remote cloud makes positive utility **then**
        Admit r_i by assigning r_i to remote cloud;
      else
        Reject r_i;
      end if ;
    else
      Admit r_i by assigning r_i to cloudlet v';
      Update the residual computing resource of cloudlet v';
    end if ;
  end if ;
  if r_i is admitted **then**
    $A \leftarrow A \cup \{r_i\}$;
  end if
end while ;
return a feasible solution A to the online average total utility maximization problem without the bandwidth capacity constraint;

The detailed algorithm is given in `Algorithm` 4.

Algorithm 4. A Heuristic Algorithm for the Online Average Total Utility Maximization Problem With the Bandwidth Capacity Constraint

Input: $|V|$ cloudlets with each $v_j \in V$ having computing capacity C_{v_j}, a remote cloud v_0 with unlimited computing capacity, i.e., $C_{v_0} = \infty$, each link $e \in E$ connecting cloudlets has a bandwidth capacity, and a set of requests R with each request $r_i = \langle s_i, b_i, l_i, D_i, \beta_i \rangle$ arrived one by one, there is no knowledge of future request arrivals.

Output: Maximize the average total utility gain of admitted requests per time slot within the time horizon.

$A \leftarrow \emptyset$; /* the solution */
while request r_i arrives **do**
  Identify the set of cloudlets $V' \subseteq V$ and the set of links $E' \subseteq E$ with sufficient residual resource for r_i;
  Find the routing path $P_i(v_j)$ from AP l_i to each cloudlet $v_j \in V'$ with the least communication delay, through links in E';
  $\mathcal{Q}_i \leftarrow \emptyset$; /* the set of candidate cloudlets for r_i */
  for each cloudlet $v_j \in V'$ **do**
    if the utility gain $u(r_i, v_j)$ of assigning r_i to node v_j through $P_i(v_j)$ is positive **then**
      $\mathcal{Q}_i \leftarrow \mathcal{Q}_i \cup \{v_j\}$;
    end if ;
  end for ;
  if $\mathcal{Q}_i = \emptyset$ **then**
    if assigning r_i to remote cloud makes positive utility **then**
      Admit r_i by assigning r_i to remote cloud;
    else
      Reject r_i;
    end if ;
  else
    Identify the cloudlet $v' \in \mathcal{Q}_i$ and its routing path $P_i(v')$ with the minimum total normalized cost by Eq. (15). And calculate the utility gain u_i by assigning r_i to v' through $P_i(v')$;
    if $\psi_{v'}(i) > |V| \cdot u_i$ **OR** $\sum_{e \in P_i(v')} \psi_e(i) > |V| \cdot u_i$ **then**
      if assigning r_i to remote cloud makes positive utility gain **then**
        Admit r_i by assigning r_i to remote cloud;
      else
        Reject r_i;
      end if ;
    else
      Admit r_i by assigning r_i to cloudlet v' through $P_i(v')$;
      Update the residual resource of v' and links on $P_i(v')$;
    end if ;
  end if ;
  if r_i is admitted **then**
    $A \leftarrow A \cup \{r_i\}$;
  end if
end while ;
return a feasible solution A to the online average total utility maximization problem with the bandwidth capacity constraint;

5.3 Algorithm Analysis

The rest is to analyze the competitive ratio and time complexity of `Algorithm` 3. The time complexity of `Algorithm` 4 is also analyzed.

Let R be the set of requests arrived for the given time horizon. Denote by $\mathcal{Z}(i) \subseteq R$ the set of requests admitted by `Algorithm` 3 prior to the arrival of request r_i, and u_{max} and u_{min} the maximum and minimum utility gains of admitting any request, respectively. Following Eq. (6), for a request r_i, $u_{max} = \lambda - 1$ when $d(r_i, v_j) \le D_i$, while $u_{min} = \min_{r_i \in R}\{\lambda - \lambda^{\frac{\beta_i - 1}{\beta_i}}\}$ when $d(r_i, v_j) = \beta_i \cdot D_i$, and both u_{max} and u_{min} are constants.

Lemma 2. *Given an MEC network $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ and a finite time horizon that consists of T time slots, let R be the set of requests arriving one by one within the given time horizon, denote by $\mathcal{Z}(i)$ the set of requests admitted by `Algorithm` 3 prior to the arrival of request r_i. Then, the sum of usage cost of all cloudlets is*

$$\sum_{v \in V} w_v(i) \le 2 \cdot |V| \cdot \log_2 \alpha \cdot \sum_{r_{i'} \in \mathcal{Z}(i)} (c(s_{i'}) \cdot u_{i'}), \tag{16}$$

where α is a constant with $2|V| \cdot u_{max} + 2 \le \alpha \le 2^{\frac{C_{min}}{c_{max}}}$, $u_{max} = \lambda - 1$, $C_{min} = min\{C_v \mid v \in V\}$, and $c_{max} = \max\{c(s_i) \mid r_i \in R\}$.

The proof of Lemma 2 is contained in Section 1 of the supplementary materials file, which can be found on the Computer Society Digital Library at http://doi.ieeecomputersociety.org/10.1109/TPDS.2021.3107137..

Denote by $\mathcal{D}(i)$ the set of requests admitted by the optimal solution but rejected by `Algorithm` 3 prior to the arrival of request r_i, and denote by $\mathcal{H}(i)$ the set of requests admitted by both the optimal solution and `Algorithm` 3 prior to the arrival of request r_i. It can be seen that set $\mathcal{D}(i) \cup \mathcal{H}(i)$ is the set of admitted requests by the optimal solution. Then, for each request $r_i \in \mathcal{H}(i)$, we have

$$u_i^* \le \frac{u_{max}}{u_{min}} \cdot u_i, \tag{17}$$

where u_i^* and u_i are the utility gains of admitting request r_i by the optimal solution and `Algorithm` 3, respectively, while u_{max} and u_{min} are the maximum and minimum utilities by admitting any request, which are constants.

Lemma 3. *Given an MEC network $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ and a finite time horizon that consists of T time slots, let R be the set of requests arriving one by one over the time horizon, denote by $\mathcal{D}(i)$ the set of requests admitted by the optimal solution but rejected by `Algorithm` 3 prior to the arrival of request r_i. Denote by $v_{i'}^*$ the node in the optimal solution to which request $r_{i'} \in \mathcal{D}(i)$ is assigned. We have $v_{i'}^* \in V$, $\forall r_{i'} \in \mathcal{D}(i)$, i.e., the requests in the set $\mathcal{D}(i)$ are assigned to cloudlets instead of the remote cloud in the optimal solution.*

Proof. We prove the lemma by contradiction. We assume that there is a request $r_{i'} \in \mathcal{D}(i)$ that is assigned to the remote cloud in the optimal solution. It can be seen that if a positive utility gain can be obtained when $r_{i'}$ is assigned to the remote cloud, then $r_{i'}$ can be assigned to the remote cloud by `Algorithm` 3. However, request $r_{i'}$ is rejected by `Algorithm` 3. This results in a contradiction. □

Lemma 4. *Given an MEC network $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ and a finite time horizon that consists of T time slots, let R be*

the set of requests arriving one by one over the time horizon, denote by $\mathcal{D}(i)$ the set of requests admitted by the optimal solution but rejected by `Algorithm 3` *prior to the arrival of request r_i. Denote by $v_{i'}^*$ the node in the optimal solution to which request $r_{i'} \in \mathcal{D}(i)$ is assigned, and denote by $u_{i'}^*$ the utility for request $r_{i'} \in \mathcal{D}(i)$ in the optimal solution. Then, for each request $r_{i'} \in \mathcal{D}(i)$, we have*

$$\psi_{v_{i'}^*}(i') > |V| \cdot \frac{u_{min}}{u_{max}} \cdot u_{i'}^*, \tag{18}$$

when $2|V| \cdot u_{max} + 2 \leq \alpha \leq 2^{\frac{C_{min}}{c_{max}}}$.

The proof of Lemma 4 is contained in Section 2 of the supplementary materials file, available online.

Lemma 5. *Given an MEC network $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ and a finite time horizon that consists of T time slots, let R be the set of requests arriving one by one over the time horizon, denote by $\mathcal{D}(i)$ the set of requests admitted by the optimal solution but rejected by* `Algorithm 3` *prior to the arrival of request r_i. Denote by $\mathbb{P}_{opt}(i)$ and $\mathbb{P}(i)$ the total utilities of admitted requests by an optimal solution and the solution delivered by* `Algorithm 3` *prior to the arrival of request r_i, respectively. We have*

$$\mathbb{P}_{opt}(i) \leq \frac{u_{max}}{u_{min}} \cdot \mathbb{P}(i) + \sum_{r_{i'} \in \mathcal{D}(i)} u_{i'}^*. \tag{19}$$

Proof. Recall that $\mathcal{D}(i) \cup \mathcal{H}(i)$ is the set of admitted requests by the optimal solution. We have

$$\begin{aligned}\mathbb{P}_{opt}(i) &= \sum_{r_{i'} \in \mathcal{H}(i)} u_{i'}^* + \sum_{r_{i'} \in \mathcal{D}(i)} u_{i'}^* \\ &\leq \frac{u_{max}}{u_{min}} \cdot \sum_{r_{i'} \in \mathcal{H}(i)} u_{i'} + \sum_{r_{i'} \in \mathcal{D}(i)} u_{i'}^*, \qquad \text{by Eq. (17)} \\ &\leq \frac{u_{max}}{u_{min}} \cdot \mathbb{P}(i) + \sum_{r_{i'} \in \mathcal{D}(i)} u_{i'}^*.\end{aligned} \tag{20}$$

Ineq. (20) holds because $\mathcal{H}(i)$ is the subset of admitted requests by `Algorithm 3`. □

Theorem 4. *Given an MEC network $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ and a finite time horizon that consists of T time slots, let R be the set of requests arriving one by one over the time horizon, there is an online algorithm with a competitive ratio of $O(\log |V|)$,* `Algorithm 3`*, for the online average total utility maximization problem without the bandwidth capacity constraint, which takes $O(|\mathcal{AP}|^2)$ time to admit each request when $\alpha = 2|V| \cdot u_{max} + 2$, where u_{max} is the maximum utility gain of a request.*

The proof of Theorem 4 is contained in Section 3 of the supplementary materials file, available online.

Theorem 5. *Given an MEC network $G = (\mathcal{AP} \cup V \cup \{v_0\}, E)$ and a finite time horizon that consists of T time slots, let R be the set of requests arriving one by one over the time horizon, there is an online algorithm,* `Algorithm 4`*, for the online average total utility maximization problem with the bandwidth capacity constraint.*

Proof. It can be seen that the solution delivered by `Algorithm 4` is feasible because all constraints imposed on the problem are met.

The time complexity of `Algorithm 4` for a request admission is dominated by the time of finding the routing paths with the least communication delay from AP l_i to cloudlets with sufficient resource for request r_i, which takes $O(|\mathcal{AP}|^2)$ time. □

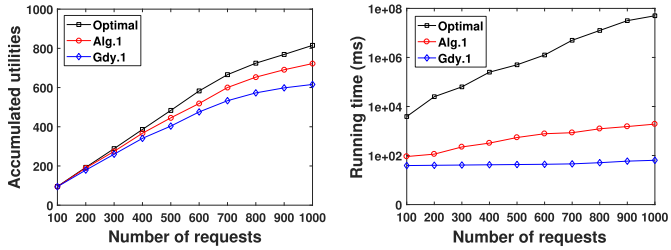
6 Performance Evaluation

In this section we conduct the performance evaluation on the proposed algorithms. We also investigate the impact of important parameters on the performance of the proposed algorithms.

6.1 Environment Setting

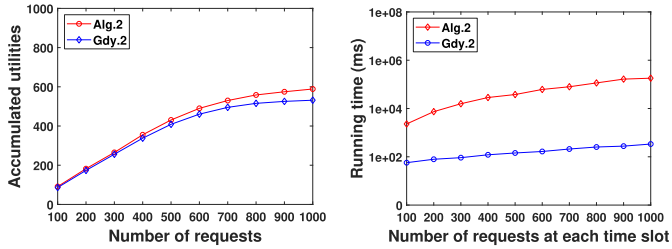
We consider a heterogeneous MEC network consisting of 200 APs, 10 percent of which are co-located with cloudlets [9], [26]. The topologies of MEC networks are generated by GT-ITM [6]. For each AP, the bandwidth at each time slot is drawn from 20 MHz to 40 MHz randomly [19], the signal-to-noise ratio (i.e., $\frac{\kappa_i}{\sigma^2}$) of an AP is set as 30 dB [21]. For each cloudlet, the capacity varies from 3,000 MHz to 7,000 MHz [25] and its processing rate varies from 0.5 MB to 2 MB per ms [15]. For each request, its task size is randomly drawn from 1 MB to 5 MB [18], the demanded computing resource is randomly drawn from 20 MHz to 300 MHz [26] and the demanded bandwidth resource ranges from 5 Mbps to 50 Mbps [27]. The delay requirement threshold of a request is randomly drawn from 10 ms to 50 ms [15], and β_i ranges from 1 to 3. The bandwidth capacity of each link varies from 200 Mbps to 2,000 Mbps [15], and the transmission delay of a link at each time slot is chosen from 2 ms to 5 ms randomly [25], while the transmission delay from an AP to the remote cloud through the gateway varies from 80 ms to 100 ms. We further assume the processing rate of the remote cloud is 20 MB per ms. Parameter λ is set as 2 and parameter ϵ is set as 0.5. The turning parameters α and δ are set as $2|V| \cdot u_{max} + 2$, where $|V|$ is the number of cloudlets and $u_{max} = \lambda - 1$. We assume that there are 100 time slots and 1000 requests arrive at each time slot one by one. The duration of each request is randomly drawn from 1 to 3 time slots [15]. The result in each figure is the mean of the results by applying an algorithm on 20 MEC network instances of the same size, where the running time of an algorithm is the actual amount of time to find a solution, based on a desktop with a 3.60 GHz Intel 8-Core i7-7700 CPU and 16 GB RAM. Unless specified, the above parameters will be adopted in the default setting.

To evaluate `Algorithm 1` (referred to as `Alg.1`) for the total utility maximization problem without the bandwidth capacity constraint, we propose two comparison benchmarks. One is the ILP solution (7) (referred to as `Optimal`) which is the optimal solution to the problem; another is a greedy algorithm (referred to as `Gdy.1`), which picks requests in R randomly, and assigns the picked request to the cloudlet (or the remote cloud) with the maximum utility gain, this procedure continues until all requests are assigned. To study `Algorithm 2` (referred to as `Alg.2`) for the total utility maximization problem with the bandwidth



(a) The accumulated utilities (b) The running time

Fig. 1. Performance of different algorithms for the total utility maximization problem without the bandwidth capacity constraint.



(a) The accumulated utilities (b) The running time

Fig. 2. Performance of different algorithms for the total utility maximization problem with the bandwidth capacity constraint.

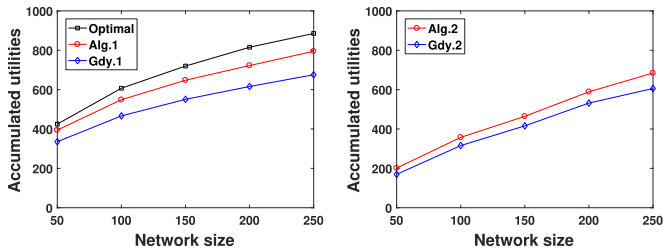
capacity constraint, we also give a comparison algorithm for it, which is a greedy algorithm (referred to as Gdy.2) that requests are picked randomly. For each picked request, it first finds a routing path with the least communication delay from the location of the request to each cloudlet with sufficient computing resource, through the links with sufficient bandwidth resource for the request. It then assigns the request to the cloudlet (or the remote cloud) with the maximum utility gain. This procedure continues until all requests are assigned.

To investigate the performance of Algorithm 3 (referred to as Alg.3) for the online average total utility maximization problem without the bandwidth capacity constraint, a comparison online algorithm (referred to as Gdy.3) is proposed, which is the online version of Gdy.1. To evaluate Algorithm 4 (referred to as Alg.4) for the online average total utility maximization problem with the bandwidth capacity constraint, a greedy algorithm (referred to as Gdy.4), which is the online version of Gdy.2, is also proposed for the performance evaluation purpose.

6.2 Performance Evaluation of the Proposed Algorithms for the Total Utility Maximization Problem

We first studied the performance of Alg.1 against algorithms Optimal and Gdy.1, by varying the number of requests from 100 to 1,000. We then evaluated the performance of Alg.2 against algorithm Gdy.2, by varying the number of requests from 100 to 1,000. Figs. 1 and 2 depict the accumulated utilities and running times of different algorithms for the total utility maximization problem without and with the bandwidth capacity constraint. It can be seen from Fig. 1a that when the number of requests reaches 1,000, the performance achieved by algorithm Gdy.1 is 88.5 percent of that by Alg.1 while the performance achieved by Alg.1 is 85.2 percent of that by algorithm Optimal. Meanwhile, it can be seen from Fig. 2a that Alg.2 outperforms algorithm Gdy.2 on the performance improvement by at least 10.8 percent with 1,000 requests. The rationale behind is that both Alg.1 and Alg.2 better utilize the network resource by provisioning satisfying services to more users, compared with the greedy algorithms, and they take much less running time in comparison with the ILP solution that takes a much longer running time.

We then studied the impact of network size on the proposed algorithms with 1,000 requests, by varying the number of APs from 50 to 250. Recall that 10 percent of APs are co-located with cloudlets. Figs. 3a and 3b demonstrate the



(a) Performance of different algorithms for the total utility maximization problem without the bandwidth capacity constraint (b) Performance of different algorithms for the total utility maximization problem with the bandwidth capacity constraint

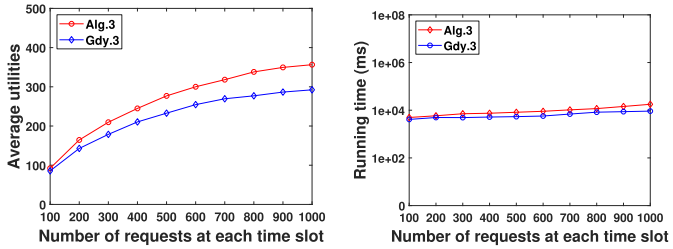
Fig. 3. The impact of network size on the performance of the proposed algorithms

accumulated utilities by different algorithms for the total utility maximization problem without and with the bandwidth capacity constraint. We can see from Fig. 3a that when the network size is 250, the performance achieved by algorithm Gdy.1 is 76.3 percent of that by Alg.1 while the performance achieved by Alg.1 is 84.8 percent of that by Optimal. The similar performance behaviors can be observed in Fig. 3b too. This is because both Alg.1 and Alg.2 facilitate the efficient cooperation between the remote cloud and local cloudlets to maximize the accumulated user satisfaction when the network size is large.

6.3 Performance Evaluation of the Proposed Algorithms for the Online Average Total Utility Maximization Problem

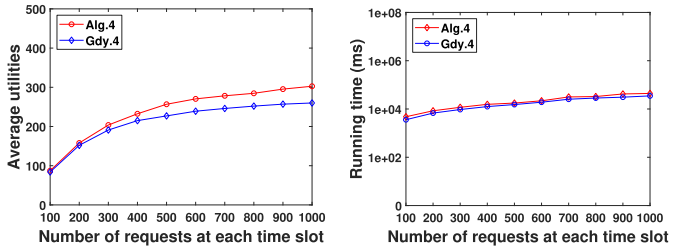
We first studied the performance of Alg.3 and Alg.4 against algorithms Gdy.3 and Gdy.4, respectively, by varying the number of requests arriving at each time slot from 100 to 1,000, over the time horizon (100 time slots). Figs. 4 and 5 plot the average utilities and running times of different algorithms for the online average total utility maximization problem without and with the bandwidth capacity constraint. With 1,000 requests arriving at each time slot, in Fig. 4a algorithm Alg.3 outperforms Gdy.3 by 22.1 percent, while in Fig. 2a algorithm Alg.4 outperforms Gdy.4 by 16.4 percent. This can be justified by that either Alg.3 or Alg.4 establishes an efficient admission control policy to admit requests with larger utility gain but less resource consumption, without any knowledge of future request arrivals.

The rest is to investigate the impact of important parameters on the performance of the proposed algorithms including parameters β_i, α, and δ, where parameter β_i reflects the service delay tolerance of user u_i, parameters α and δ reflect



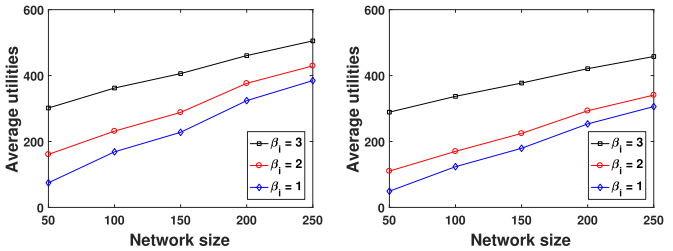
(a) The average utilities (b) The running time

Fig. 4. Performance of different algorithms for the online average total utility maximization problem without the bandwidth capacity constraint.



(a) The average utilities (b) The running time

Fig. 5. Performance of different algorithms for the online average total utility maximization problem with the bandwidth capacity constraint.

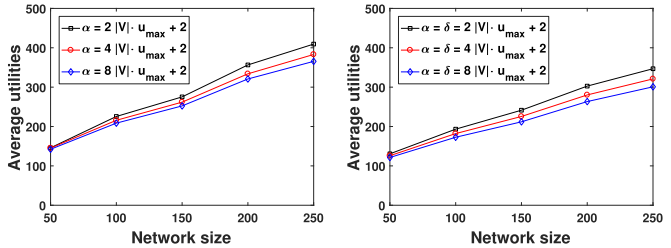


(a) Performance of Alg.3 for the online average total utility maximization problem without the bandwidth capacity constraint (b) Performance of Alg.4 for the online average total utility maximization problem with the bandwidth capacity constraint

Fig. 6. The impact of β_i on the performance of the proposed algorithms.

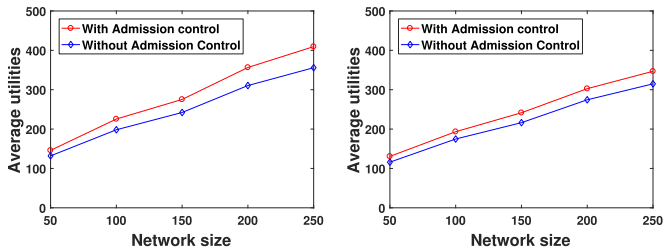
the sensitivity of the workload at each cloudlet and link, respectively. We also study the performance of the online algorithms with and without adopting the admission control policy. For the sake of convenience, in the rest experimental simulations, it is assumed that the time horizon consists of 100 time slots and 1,000 requests arrive at each time one by one.

We first evaluated the impact of parameter β_i on the performance of the proposed algorithms, by varying the network size from 50 to 250. Fig. 6 illustrates the impact of parameter β_i on the proposed algorithms Alg.3 and Alg.4 when $\beta_i = 1$, 2, and 3 respectively. It can be seen from Fig. 6a that when the network size is 50, the performance of Alg.3 with $\beta_i = 1$ is 24.8percent of itself with $\beta_i = 3$. When the network size is 250, the performance of Alg.3 with $\beta_i = 1$ is 76.2 percent of itself with $\beta_i = 3$. The similar performance behavior can be found in Fig. 6b. The rationale behind is that a larger β_i leads to a larger tolerable service delay and more requests can be admitted. In addition, when the network size is small (i.e., the available computing resource is very limited), the mobile users have to better utilize the remote cloud to process their requests that result in



(a) Performance of Alg.3 for the online average total utility maximization problem without the bandwidth capacity constraint (b) Performance of Alg.4 for the online average total utility maximization problem with the bandwidth capacity constraint

Fig. 7. The impacts of the parameter α and δ on the performance of the proposed algorithms.



(a) Performance of Alg.3 for the online average total utility maximization problem without the bandwidth capacity constraint (b) Performance of Alg.4 for the online average total utility maximization problem with the bandwidth capacity constraint

Fig. 8. The impacts of the admission control policy on the performance of the proposed algorithms.

longer service delays. Thus, a larger β_i is important in admitting requests when the network size is small.

We then studied the impact of parameter α on the performance of the algorithm Alg.3, and the impacts of parameter α and δ on the performance of the algorithm Alg.4, by varying the network size from 50 to 250. Fig. 7a demonstrates the performance of Alg.3 with parameter $\alpha = 2|V| \cdot u_{max} + 2$, $4|V| \cdot u_{max} + 2$, and $8|V| \cdot u_{max} + 2$, respectively, where $|V|$ is the number of cloudlets, and $u_{max} = \lambda - 1$ is the maximum possible utility gain for a request. While Fig. 7b shows the performance of Alg.4 with parameter $\alpha = \delta = 2|V| \cdot u_{max} + 2$, $4|V| \cdot u_{max} + 2$, and $8|V| \cdot u_{max} + 2$, respectively. As depicted by Fig. 7a, when the network size is 250, the performance of Alg.3 with $\alpha = 8|V| \cdot u_{max} + 2$ is 89.3 percent of itself with $\alpha = 2|V| \cdot u_{max} + 2$. The similar performance behavior can be found in Fig. 7b. The justification is that with a larger α or δ, the normalized cost of computing resource or bandwidth resource becomes higher by Eqs. (12) and (14), and it intends to be conservative and reject requests.

We finally investigated the impact of the admission control policy, by varying the network size from 50 to 250. Figs. 8a and 8b plot the performance of algorithms Alg.3 and Alg.4 with and without the admission control policy. It can be seen from Fig. 8a that when the network size is 250, the performance of Alg.3 without the admission control policy is 86.9percent of itself with the admission control policy. The similar performance behavior can be found in Fig. 8b. This can be justified by that with a reasonable admission control policy, the requests with larger utility gains but less computing resource consumption will be admitted. Thus,

the admission control policy is important to deal with the dynamic request admissions.

7 Conclusion

In this paper, we studied the user satisfaction on the use of services for delay-sensitive IoT applications in an edge computing environment, by offloading user service requests to either the remote cloud or local cloudlets in an MEC network. We first formulated two novel optimization problems and showed their NP-hardness. We then proposed efficient approximation and heuristic algorithms for the admissions of a set of requests. We also developed online algorithms for the admissions of dynamic requests without the knowledge of future arrivals. We finally evaluated the performance of the proposed algorithms through experimental simulations. Experimental results demonstrate that the proposed algorithms are promising.

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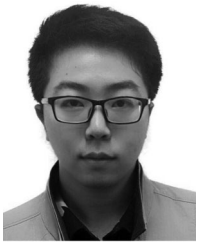

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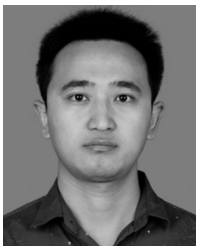

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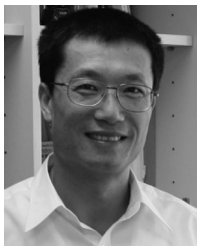

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