State-Aware Application Placement in Mobile Edge Clouds

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Abstract: Placing applications within Mobile Edge Clouds (MEC) poses challenges due to dynamic user mobility. Maintaining optimal Quality of Service may require frequent application migration in response to changing user locations, potentially leading to bandwidth wastage. This paper addresses application placement challenges in MEC environments by developing a comprehensive model covering workloads, applications, and MEC infrastructures. Following this, various costs associated with application operation, including resource utilization, migration overhead, and potential service quality degradation, are systematically formulated. An online application placement algorithm, App_EDC_Match, inspired by the Gale-Shapley matching algorithm, is introduced to optimize application placement considering these cost factors. Through experiments that employ real mobility traces to simulate workload dynamics, the results demonstrate that the proposed algorithm efficiently determines near-optimal application placements within Edge Data Centers. It achieves total operating costs within a narrow margin of 8% higher than the approximate global optimum attained by the offline precognition algorithm, which assumes access to future user locations. Additionally, the proposed placement algorithm effectively mitigates resource scarcity in MEC.

1 INTRODUCTION

The growth of mobile technology, coupled with the rollout of 5G networks, paves the way for a new era of applications characterized by stringent demands for minimal jitter, low latency, and extensive bandwidth. As an example, real-time gaming applications necessitate response times of mere milliseconds to forestall substantial Quality of Service (QoS) degradation (Pantel and Wolf, 2002). Likewise, virtual reality applications employing head-tracked systems mandate latencies below 16 ms to maintain perceptual stability, preserving the illusion of reality (Ellis et al., 2004).

In recent years, there has been a significant shift away from conventional centralized cloud computing data centers towards the adoption of a distributed computing infrastructure known as Mobile Edge Clouds (MECs). MECs are designed to decentralize computing and storage resources to the network edge, specifically within Edge Data Centers (EDCs) located in close proximity to end-users. These EDCs are often strategically placed, such as being colocated with central office locations (Kavak et al., 2015). Recent research efforts (Mehta et al., 2016; Tong et al., 2016) have introduced the concept of hierarchical MECs, incorporating heterogeneous costs and capacities. In this hierarchical structure, data centers (DCs) are organized into different layers. DCs in higher layers offer greater computational capacities at lower cost but are situated farther from end-users, resulting in increased latency and bandwidth expenses. MECs offer exceptional flexibility, allowing for the placement of applications that align with their specific requirements. This versatility strikes a balance between cost-effective computation and proximity to end-users. In fact, many algorithms have been proposed for *placing stateless applications on MECs*, including dynamic placement algorithms for efficiently dealing with user mobility (Li et al., 2022; Shang et al., 2022; Apat et al., 2023; Nguyen et al., 2019). Nonetheless, a *significant number of envisioned MEC applications exhibit stateful characteristics*. Take, for instance, augmented reality applications, which entail the storage of generated meshes, world data, textures, and more. Utilizing stateless placement algorithms for such stateful applications entails the risk of incurring unnecessary costs, primarily attributed to the bandwidth needed to migrate user

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state from one EDC to another.

In this paper, we tackle the challenge of placing stateful applications in an MEC environment. Our approach begins with a comprehensive modeling of the various costs associated with hosting stateful applications on MECs. These costs encompass the r*esource cost*, which includes both computing and application bandwidth expenses, as well as *the QoS degradation cost* and *migration costs*. Subsequently, we introduce an online state-aware application placement strategy, denoted as *App_EDC_Match*, inspired by the well-known Gale-Shapley matching algorithm (Gale and Shapley, 1962). The primary objective of the proposed strategy is to discover placement solutions that match applications with EDCs, resulting in the lowest resource cost and bandwidth consumption across the physical network links.

We conducted a comprehensive evaluation of the proposed algorithms within an MEC topology encompassing EDCs distributed throughout the San Francisco area. To simulate user mobility patterns, we employed real mobility traces derived from taxi movement data in San Francisco. Additionally, we modeled user transitions between applications using a Markov model. The evaluation compared the total operating costs generated by the App_EDC_Match algorithm against those produced by a precognition placement algorithm, which possesses knowledge of future user locations. Furthermore, we conducted extensive experimental comparisons of the proposed placement algorithm's performance and behavior across different application types, including compute-intensive and bandwidth-intensive applications.

The contributions of this paper are three-fold:

- A comprehensive cost model is provided for hosting stateful applications on MECs (see Section 2).
- An efficient online state-aware placement strategy for distributing applications among EDCs with the goal of minimizing the overall operating costs (see Section 3).
- Extensive experiments to evaluate the performance of the proposed placement strategy (see Section 5).

The experimental results show the efficiency of the proposed online placement algorithm for optimizing application placements among EDCs. It achieves a total operational cost only 8% higher than the approximate global optimum determined by the precognition offline algorithm. Furthermore, the proposed algorithm effectively addresses workload balancing within MECs, mitigating resource scarcity challenges.

2 PROBLEM DEFINITION

In this section, we first describe models for each component considered in the application placement problem, namely the MEC infrastructure, applications, user mobility, workload and cost model. Based on these models, we then formulate a formal statement of the problem to be solved.

2.1 Mobile Edge Clouds

MECs with a hierarchy of geo-distributed EDCs have proven to be efficient infrastructures for meeting envisioned MEC workloads (Tong et al., 2016; Bartolomeo et al., 2023; Yang et al., 2018; Wang et al., 2017). We therefore focus on a MEC with EDCs organized into a hierarchical topology in this work (see Figure 1).

We model a MEC as a set of N EDCs geographically distributed within an area, denoted $\mathcal{E} = \{i|i = 1,2,...,N\}$. Each EDC is identified by a geographic location loc_i and a layer that e_i belongs to. In layer 1, every EDC e_i is collocated with a cellular base station or a WiFi access point, from which the end-users send requests to an application hosted by the MEC. Each EDC is equipped with a certain number of servers that provide a pool of virtualized computing resources. EDCs in higher layers feature greater computing capacities. We use C_i to denote the computing capacity of e_i.

The interconnection between the EDCs is represented by the following network model. We denote the set of all physical network links in the MEC as $\mathcal{L} = \{j|j = 1,2,...,M\}$. Each link l_j connects e_i with its closest ancestor and is characterized by its network delay d_j and a maximum bandwidth – also known as the bandwidth capacity – denoted B_j. Thus, it is worth noting that $M = N - 1$. Any pair of EDCs can communicate by following the shortest network path. Let $\mathcal{P}_{i,i'} \subseteq \mathcal{L}$ be the set of all physical network links on the shortest path between two EDCs e_i, $e_{i'}$. Here, it is worth noting that total bandwidth consumed on a particular physical network link l_j is equal to the sum of the bandwidth consumed on all paths $\mathcal{P}_{i,i'}$ containing l_j.

2.2 Application

Let $\mathcal{A} = \{p|p = 1,2,..,P\}$ be the set of applications hosted in the MEC. An application p is characterized by the following parameters:

- **Compute** ξ_p^c describes the amount of computational resource units required by p to serve an end-user. The unit is CPU $\times$ seconds/user.

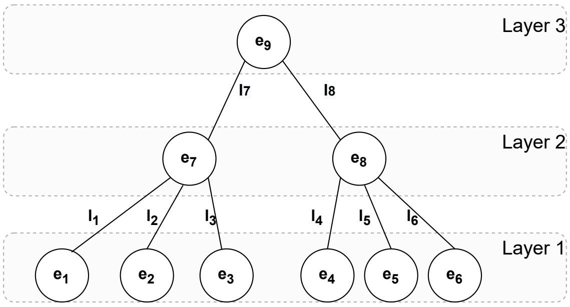


Figure 1: Our model of an MEC, showing the organization of EDCs into various layers and physical network linking the EDCs.

- **Bandwidth** ξ_p^b describes the amount of network bandwidth required by p to serve an end-user. The unit is KB/user.
- **State** ξ_p^s describes the amount of state stored by p for each served end-user. This is the amount of network bandwidth required to transfer the application from one EDC to another. The unit is KB/user.

We use compute-bandwidth-usage-ratio per application request (CPU-h/GB), denoted as A_{cl} (Mehta et al., 2016), to determine whether a specific application is compute-intensive or bandwidth-intensive. A_{cl} takes values in the range $[0.01, 10]$. To guarantee the target QoS, the system must allocate resources (both compute and bandwidth) that can handle the total workload generated by users.

2.3 User and Workload

We consider a set of users $\mathcal{U} = \{k | k = 1, 2, ..., K\}$ that dynamically move around in the area covered by the MEC. In time slot t, user k connects wirelessly to the physically closest EDC, called the *connecting* EDC. The access delay, i.e., the delay due to the wireless network between k and the connecting EDC i is denoted as $d_{k,t}$.

In each time slot t, user k connect to application $p \in \mathcal{A}$ that is specified in $\lambda_{k,t}$. After each time slot, user k may continue using the same application or change to a different application.

To serve the user, the placement algorithm must allocate capacity to the application in a *serving EDC*. Depending on the placement algorithm's decision, the serving EDC may or may not coincide with the connecting EDC. Let $s_{k,t,i}$ denote the decision about whether or not the requested application p of user k is hosted on i at time slot t. Formally:

$$s_{k,t,i} = \begin{cases} 1, & \text{if } p \text{ is hosted in EDC } i \text{ for user } k \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

and

$$\sum_i s_{k,t,i} = 1 \quad (2)$$

Let $\mathrm{tb}_{j,t}$ be the total bandwidth (i.e. the bandwidth allocated for serving applications plus the bandwidth needed to migrate applications) allocated from link j in time slot t. This gives us the expression:

$$\mathrm{tb}_{j,t} = \xi_{j,t}^b + \xi_{j,t}^s \quad (3)$$

whereas, $\xi_{j,t}^b$ is total bandwidth allocated on network link j for serving applications in time slot t, and $\xi_{j,t}^s$ is total bandwidth allocated on network link j for migrating applications in time slot t.

2.4 Operating Cost

To serve the end-users, the system responsible for placing applications hosted in MECs must take various costs into consideration:

- **The Resource Cost:**
  This cost refers to the compute and bandwidth cost, which abstract all the regular costs due to hardware, service maintenance, energy consumption, and so on. While real cloud computing systems employ intricate unit pricing functions, considering factors like supply and demand, resource utilization, instance types, and pricing tiers, our modeling approach simplifies this by assuming an inverse proportionality between the current capacities of compute resource at EDC i and network link j with their respective unit prices. This simplification adheres to micro-economic principles, particularly the law of supply and demand (Moore, 1925), and acknowledges the influence of economy-of-scale effects on energy and maintenance costs. It is worth noting that the resource unit price function (as defined in equation 4 below) can be customized to align with stakeholder definitions and specific scenarios.
  Let $g_*(.)$ be the function that determines the resource unit price:
  $$g_*(x_t) = (u_{\max} - u_{\min}) \times x_t + u_{\min} \quad (4)$$
  Here,
  $$x_t = \begin{cases} \sum_k \frac{s_{k,t-1,i} \times \xi^c_{\lambda_{k,t-1}}}{C_i}, & \text{for the compute resource} \\ \frac{\mathrm{tb}_{j,t-1}}{B_j}, & \text{for the bandwidth resource} \end{cases} \quad (5)$$
  and $u_{\min}, u_{\max}$ are the minimum and maximum resource unit price, which are predefined differently for each EDC i and network link j.
  The resource cost Cost_{res} is then calculated as below:

$$\mathrm{Cost}_{res} = \sum_t \sum_i \sum_k s_{k,t,i} \times \left(g_i \times \xi^c_{\lambda_{k,t}} + \sum_{j \in \mathcal{P}_{i,\mathrm{loc}_{u_k,t}}} g_j \times \xi^b_{\lambda_{k,t}} \right) \quad (6)$$

Here, $\mathcal{P}_{\mathrm{loc}_{k,t},i}$ is the network path as defined in Section 2.1.

The total bandwidth allocated on a particular physical network link j for serving applications is equal to the sum of the bandwidth consumed on paths $\mathcal{P}_{\mathrm{loc}_{k,t},i}$ go through j, which is decided by $s_{k,t,i}$:

$$\xi^b_{j,t} = \sum_k \sum_{j \in \mathcal{P}_{\mathrm{loc}_{k,t},i}} s_{k,t,i} \times \xi^b_{\lambda_{k,t}} \quad (7)$$

- **The Migration Cost:** This cost is associated with migrations, i.e. the transfer of a user's application p hosted on EDC i at time $t-1$ to another EDC i' in time slot t. It is related to the size of the application's state data (or service profile) for each user. Transferring such data across EDCs requires bandwidth from the inter-EDC-network connecting i and i'.

  We define the migration flag as $\mathrm{MF}_{k,t,i,i'}$, which takes a value of 1 if and only if user k requests the same application in successive time slots (i.e., $\lambda_{k,t} = \lambda_{k,t-1}$), and that application is placed on different EDCs in those time slots (i.e., $\langle s_{k,t} \cdot s_{k,t-1} \rangle = 0$):

$$\mathrm{MF}_{k,t,i,i'} = \begin{cases} 1, & \lambda_{k,t} = \lambda_{k,t-1}, \\ & \text{and } s_{k,i',t} = 1 \\ & \text{and } s_{k,i,t-1} = 1 \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

  Here, i is the source EDC and i' is the destination EDC of the migration.

  Then, the total migration cost is calculated as:

$$\mathrm{Cost}_{mig} = \sum_t \sum_k \sum_i \sum_{i'} (\mathrm{MF}_{k,t,i,i'} \times \sum_{j \in \mathcal{P}_{i,i'}} g_j \times \xi^s_{\lambda_{k,t}}) \quad (9)$$

  Here, the total bandwidth allocated on a network link l_j for application migrations is equal to the sum of the bandwidth allocated to migrate applications on paths $\mathcal{P}_{i,i'}$ going through l_j:

$$\xi^s_{j,t} = \sum_k \sum_i \sum_{i'} \mathrm{MF}_{k,t,i,i'} \times \sum_{j \in \mathcal{P}_{i,i'}} \xi^s_{\lambda_{k,t}} \quad (10)$$

- **The Service Quality Degradation Cost:** This cost stems from delays due to three factors: i) the start-up time of new virtual resources to host new applications requested by users; ii) the wireless network delay between user k and the connected EDC e_i; and iii) the delay due to data transmission between network link l_j (including data transmission due to an application's state migration, if any).

  Given $\xi^c_{\lambda_{k,t-1}}$ and $\xi^c_{\lambda_{k,t}}$, we calculate the increment of the resource allocation for EDC e_i between two time slots t and $t-1$ as below:

$$\delta_{t,i} = \max\left\{ \sum_k \left(s_{k,t,i} \times \xi^c_{\lambda_{k,t}} - s_{k,t-1,i} \times \xi^c_{\lambda_{k,t-1}} \right), 0 \right\} \quad (11)$$

  Denoting the average start-up time for a new virtual resource as st, we assume the new virtual resources are invoked in parallel at each EDC e_i in each time slot t. The start-up time of the new added virtual resources, $d_{st,t}$, is thus given by the following expression:

$$d_{st,t} = \begin{cases} st, & \text{for } \delta_{t,i} > 0 \\ 0, & \text{for } \delta_{t,i} = 0 \end{cases} \quad (12)$$

  To model the relationship between the network latency and the injection bandwidth for each physical link l_j, we treat the relative latency as a function of the offered traffic for a simple network. As shown previously (Moudi and Othman, 2020; Dally and Towles, 2004), the network latency in an interconnection network rises to infinity as throughput approaches saturation. In such cases, the relationship is well described by an exponential distribution. It is worth noting that in our model, we constrain the total bandwidth allocation on each link l_j at time t to the link's maximum bandwidth. Consequently, we do not account for potential waiting times, such as queuing latency, that may be present in an actual network. We model the network delay at link l_j using an exponential distribution:

$$\mathrm{delay}_{j,t} = \frac{e^{\left(\frac{\mathrm{tb}_{j,t}}{B_j}\right)}}{1 - \frac{\mathrm{tb}_{j,t}}{B_j}} + d_j \quad (13)$$

  Let cc_{qos} be the unit price of the service quality downgrade due to delay. The service quality degradation cost, Cost_{qos}, can then be calculated as follows:

$$\text{Cost}_{qos} = \text{cc}_{qos} \times \sum_t \left(d_{st,t} \quad + \left(\sum_k d_{k,t} + \sum_{l_j} \text{delay}_{l_j,t} \right) \right) \tag{14}$$

2.5 Cost Optimization Formulation

Having describing different costs of placing applications on MECs to serve end-users respecting to QoS. The total cost is the sum of all the aforementioned costs, i.e., $\text{Cost}_{res} + \text{Cost}_{mig} + \text{Cost}_{qos}$. The application placement optimization problem can be formalized as:

$$\text{minimize:} \qquad \mathbb{P} = \text{Cost}_{res} + \text{Cost}_{mig} + \text{Cost}_{qos} \tag{15}$$

$$\text{subject to:} \qquad \sum_k \xi^c_{\lambda_{k,t}} \times s_{k,i,t} \leq C_i, \forall i, t, \tag{16}$$

$$\text{tb}_{j,t} \leq B_j, \forall j, t \tag{17}$$

Here, constraints 16 and 17 ensure that the system's capacity limit is not exceeded (i.e. the load on each EDC does not exceed its compute capacity; and the traffic through each network link does not exceed its maximum bandwidth).

In summary, in each time slot $t \in \mathcal{T}$, the system must decide $s_{k,t,i}$, i.e., on which EDCs to place the requested application p of user k. These decisions determine the total compute resource allocation at each EDC e_i, and total bandwidth usage at each link l_j. The decision should be made so as to guarantee that the aggregated operating cost over time window $\mathcal{T}$ is minimized.

3 ONLINE APPLICATION PLACEMENT ALGORITHM

In this section, we first present the mathematical transformation to simplify the original placement problem presented in Section 2. Subsequently, we establish the NP-hardness of the placement problem, highlighting the impracticality of obtaining an exact solution within polynomial time. In light of these challenges, we introduce the *App_EDC_Match* placement strategy, an online placement algorithm designed to address the placement problem efficiently within polynomial time.

3.1 Mathematical Transformation and NP-Hardness Proof

It is undoubtedly true that in time slot t the placement decisions made in previous time slots cannot be changed. However, the placement of applications in the preceding time slot $t-1$ will impact the placement decision at time t. Therefore, the original total operation cost $\mathbb{P}$ from Equation (15) can be re-written as follows (with $\mathcal{T} = [1, T]$):

$$\mathbb{P}_{t \in [1,T]} = \mathbb{P}_{t \in [1,T-1]} + \mathbb{P}_{t=T} \tag{18}$$

Finding an optimal operating cost $\mathbb{P}_{t \in [1,T]}$ thus becomes a recursive process of finding an optimal operating cost $\mathbb{P}_{t=T}$ based on the current system's state, and the assumption that the application placements decided in the previous time slots $t \leq T-1$ are optimal. In each time slot $t \in \mathcal{T}$, the total compute resource allocated at each EDC e_i, $\sum_k \xi^c_{k,t-1} \times s_{k,t-1,i}$ and the total bandwidth resource allocated at each network link l_j, $\text{tb}_{j,t-1}$ are known. These values together with the users' application requests and their location during t are the inputs for the placement problem, $\mathbb{P}_{t=T}$. Therefore, the original placement problem transforms into an assignment problem: to which EDC should each user's requested applications be assigned so as to minimize the total operating cost at every time slot t. This problem has been proven to be NP-hard (Fisher et al., 1986).

Obtaining an optimal solution for the application placement problem in polynomial time is considered impossible unless $P = NP$. Consequently, our focus shifts to the development of efficient algorithms capable of delivering near-optimal solutions for minimizing $\mathbb{P}_{t=T}$ within a polynomial time frame. In pursuit of this goal, we present the *App_EDC_Match* placement strategy, an efficient heuristic algorithm inspired by the widely recognized *Gale-Shapley* matching problem.

3.2 App_EDC_Match Placement Strategy

In general, our problem of assigning requested applications to EDCs in each time slot t to minimize $\mathbb{P}_{t=T}$ is analogous to the *college admissions* discussed by Gale and Shapley (Gale and Shapley, 1962). In the college admissions problem, each student proposes to their most preferred available college, while colleges can only hold a limited number of proposals at a time. Subsequently, a solution is derived to match students with colleges based on their preferences and constraints, with the goal of optimizing criteria such as overall satisfaction or fairness. The set of n EDCs

$\mathcal{E}$ can be compared to the set of n colleges, in which each $e_i \in \mathcal{E}$ has a designated "quota" C_i. Similarly, the set of m requested applications, to be assigned to the n EDCs, can be compared to the m applicants to be assigned to the n colleges. Inspired by this parallel, we introduce the *App_EDC_Macth* placement strategy leveraging the *Gale-Shapley* algorithm as presented in Algorithm 1.

The algorithm receives inputs that encompass the application placement solution from time $t-1$, compute resource availability at each EDC, and bandwidth availability at each network link up to time t (line 1). Subsequently, the algorithm updates the compute unit price and bandwidth unit price at each EDC e_i and network link l_j respectively (line 2). Moving forward, the algorithm proceeds to construct the application preference matrix $\mathbb{M}_{\text{app}}(n \times m)$, where each column p ranks EDCs in decreasing order of the operating cost incurred when placing application p on them (line 3). Similarly, the algorithm formulates an EDC preference matrix $\mathbb{M}_{\text{edc}}(m \times n)$, where each column i ranks the requested applications in decreasing order of the bandwidth consumption when placed on EDC e_i (line 4). This preference ensures that each application is hosted on an EDC that minimizes network congestion. Finally, it invokes the matching method to perform the assignment, using the two matrices above as inputs (line 5).

For n EDCs and m applications, the time complexity of the *App_EDC_Match* placement strategy is $O(n \times m)$.

1: **Input**: The application placement from $t-1$,
Datacenters resource capacity up to t,
Network links bandwidth capacity up to t,
User locations u_k and workload $W = \lambda_{k,t}$ at t

2: **Update**: compute unit price of each EDC i,
bandwidth unit price of each network link j
  3: **Calculate** $\mathbb{M}_{\textbf{app}}$ $(n \times m)$ – the application preference matrix, in which each column p ranks EDCs in the order of resulting lowest operating cost if application p is placed on it
  4: **Calculate** $\mathbb{M}_{\textbf{edc}}$ $(m \times n)$ – the EDC preference matrix, in which each column i rank applications in the order of consuming least bandwidth
5: **Matching** ($\mathbb{M}_{\textbf{app}}$, $\mathbb{M}_{\textbf{edc}}$)
6: **return** $s_{k,i}$, cost

Algorithm 1: App_EDC_Match placement strategy.

4 EXPERIMENTAL SETTING

This section presents our simulation-based evaluation. First, we describe an MEC infrastructure with EDCs distributed in a metropolitan area connected in tree topology. Then, we describe the parameters of simulated applications and end-users workload. Finally, we describe the implementation and setup of our proposed placement algorithm, as well as the baseline placement algorithm.

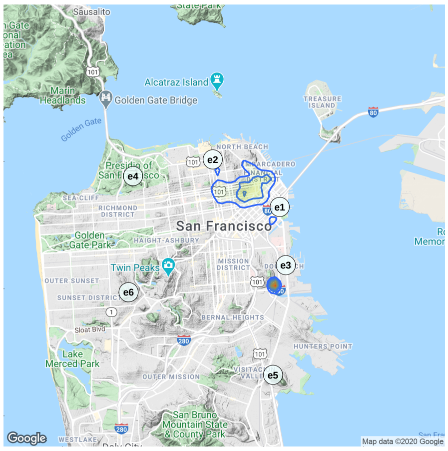


Figure 2: Distribution of 6 EDCs collocated with cellular base stations in layer 1.

4.1 Infrastructure: an MEC Platform

We simulate a hierarchical MEC platform with EDCs distributed over a metropolitan area, drawing on a previously reported MEC model (Mehta et al., 2016). The capacities of EDCs in different layers and their compute unit price (min, max) are presented in Table 1 together with the capacities and prices of the network links between subsequent layers. The physical network links between layer 1 and layer 2 are modeled as OC-3 (i.e., optical carrier level 3), while the links between layer 2 and layer 3 are modeled as OC-12.

EDCs in layer 1 are distributed across the area and collocated with base stations, allowing end-users to connect directly. The geo-coordinates of theses EDCs are taken from a dataset of the real-world locations of cellular towers in San Francisco, US[1]. From this dataset we selected 6 different tower locations as layer 1 EDC deployment sites, as shown in Figure 2. While datacenter deployment is not the main focus of the current work, the locations were selected to maximize the coverage of areas with high densities of end-users in the experimental mobility trace dataset, as discussed in Section 4.3.

[1]http://www.city-data.com/towers/cell-San-Francisco-California.html

Table 1: Experiment Configuration.

MEC topology		
Layer	Capacity (#VMs)	Cost ($/CPU-h)
1	150	(0.115, 0.206)
2	1500	(0.091, 0.127)
3	15000	(0.075, 0.086)
Netwok Link		
Link	Capacity (Mbps)	Cost ($/GB)
OC3	155	(0.3078, 0.46)
OC12	622	(0.98, 1.47)
Application		
A_{cl} (CPU-h/GB)	(0.01, 10)	

4.2 Application

We simulate different applications specified by their resource usage. We use the *compute-bandwidth-usage-ratio* per user (CPU-h/GB), denoted as A_{cl} (Mehta et al., 2016), which is in range of $[0.01, 10]$ to generate 10 different applications with different CPU usage and bandwidth usage. Additionally, each application has an average state size that determines the bandwidth required to transfer the application's state during a migration action. In stateful application migration, there is a general tendency that links the size of the migrating operator with the incoming data rate: the higher the load, the larger the saved state (Cardellini et al., 2016). Therefore, for the sake of simplicity, we model the state size as a linear function of the average bandwidth usage of the application:

$$\text{state\_size} = \nu \times \text{bandwidth\_usage} \tag{19}$$

Here, ν is a uniform random deviate in the range $(0.5, 1)$.

4.3 User Mobility and Workload

We use real mobility traces of San Francisco-based Yellow cab vehicles (Piorkowski et al., 2009) to simulate user mobility because the data reflect the movements of end-users (i.e., taxi) in the same geographic area as our simulated MEC. Specifically, the dataset traces the mobility behavior of 536 taxi cabs in the San Francisco Bay area over 25 days starting on May 17th, 2008. The original dataset contains 4 attributes: longitude, latitude, datetime, and number of people in the car. We preprocess the trace to remove all invalid records by setting a maximum velocity of $V_{\max} = 115km/h$ based on the relevant urban traffic regulations.

We assume that the locations of users do not change within any given time slot t, but may change from one time slot to another. We set the length of a time slot to 1 minute. In each time slot t, a user connects to an application hosted on the MEC. The session length is the smallest integer greater than or equal to an exponential random variable with a rate parameter of:

$$\text{rate} = \frac{1}{\text{average\_session\_length}} \tag{20}$$

where *average_session_length* is the average session duration for users using a specific application. This parameter was set to values corresponding to the average session duration of virtual reality users in the United States during the 2nd and 3rd quarters of 2019, as reported in (Observer Analytics, 2022). For every time slot t, we check if the current session is over. If the session is over, the user uniformly selects another application. The simulation records the following data for each user in every time slot: the layer 1 EDC to which the user connects, the application to which the user is linked, and the allocated amounts of CPU, bandwidth, and state size.

4.4 Off-line Placement Strategy - Precognition Strategy

To evaluate the performance of our algorithm, we compare it to the following approximately optimal off-line placement strategy. The strategy is *precognition* because it has access to complete future information for the whole time window of $\mathcal{T}$. Specifically, it is aware of end-users' locations, their requested applications, and the available capacity of each EDC and network link at every time slot in $\mathcal{T}$. While such future information is not available in a real-world setting, this approach allows us to determine how close our proposed placement algorithm is to an approach based on perfect information. To this end, we apply *Simulated annealing* (SA) (Van Laarhoven and Aarts, 1987), a meta-heuristic technique, to find the approximate global optimum. In essence, given all the above-mentioned information over time window $\mathcal{T}$, we transform the placement problem into a problem of finding the shortest path. We use a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ to represent all the possible placement decisions within $\mathcal{T}$, in which the weight put on each edge between two vertices (in successive time slots) is the operating cost returned for each time slot $t \in \mathcal{T}$. Hence, the shortest path from the starting vertex (i.e., when $t = -1$) to the end vertex (i.e., when $t = T + 1$) corresponds to the minimum total operating cost for the whole time window $\mathcal{T}$. The pseudo-code of the precognition strategy is presented in Line 2.

The input of the algorithm are data on the MEC system including the compute resource capacity of the EDCs, the bandwidth capacity of the network links, and complete workload information for a time window $\mathcal{T}$. The Simulated Annealing algorithm also requires the specification of two parameters: the *Temperature T*, which must be sufficiently high; and the *CoolingFactor* $c \in (0,1)$, which determines the expected time budget for the algorithm to seek solutions. Initially, the algorithm takes the best solution returned by the proposed algorithm as the starting point (line 2). This is done to initialize it with the best solution found so far, avoiding the algorithm starting with a worse solution. For each iteration of the loop (line 3 - 9), the algorithm generates a neighboring solution by randomly shaking the current solution (i.e., changing the placement at a specific time slot t). The algorithm then determines whether the new solution will be accepted or not using a probability method (line 6). The new solution is selected as the best solution if its cost less than the best cost (line 7).

With N EDCs, K users, and a time window of length T, there are in total $(N^K)^T$ possible solutions in the search space. Therefore, if these parameters are set to large numbers, it is impossible for the precognition algorithm to find the optimum solution in a fixed amount of time. Hence, we run the algorithm using small values of these parameters in the experiments. The approximate minimum operating cost returned by the precognition strategy is taken as a benchmark for evaluating how close the App_EDC_Match placement strategy get to the global optimum.

4.5 Evaluation Metrics

We evaluate the performance of our approach based on the following metrics:

- **Total Cost:** As previously defined in Section 2, this metric serves as a benchmark for the algorithm's effectiveness, with the goal of minimizing overall costs $\mathbb{P}$.
- **Resource Usage:** We measure the utilization of EDCs and network links. This gives us an indication of the behavior of each placement strategy and their ability to avoid capacity shortage.
- **Mean Execution Time:** This metric measures the time required by the placement algorithm to make placement decisions.

Our experiments were conducted on a single-threaded PC equipped with an Intel i7-4790 CPU and 32 GB of RAM.

1: **Input**: Temperature T,
Cooling factor c,
Initial placement s_0 and its operating cost cost_0,
Datacenters resource capacity,
Network links bandwidth capacity,
User locations and workload in the whole time window W

2: **Initialize**: $s_{\text{best}} \leftarrow s_0$
$\text{cost}_{best} \leftarrow \text{cost}_0$
$s_{\text{current}} \leftarrow s_0$
$\text{cost}_{\text{current}} \leftarrow \text{cost}_0$
$\text{temp}_{\text{current}} \leftarrow T$

3: **do**
4: Create new solution s_{new} by randomly
5: taking a neighbor of s_{current}
6: Calculate cost_{new} for s_{new}
7: **if** *Math.random()* $< e^{\frac{cost_{current} - cost_{new}}{temp_{current}}}$ **then**
$s_{\text{current}} \leftarrow s_{\text{new}}$
$\text{cost}_{\text{current}} \leftarrow \text{cost}_{\text{new}}$
end
8: **if** $cost_{current} < cost_{best}$ **then**
$s_{\text{best}} \leftarrow s_{\text{current}}$
$\text{cost}_{\text{best}} \leftarrow \text{cost}_{\text{current}}$
end
9: $\text{temp}_{\text{current}} \leftarrow \text{temp}_{\text{current}} \times c$
10: **while** $\text{temp}_{\text{current}} > 1$
11: **return** s_{best} and $\text{cost}_{\text{best}}$

Algorithm 2: Precognition placement strategy.

5 RESULT AND DISCUSSION

In this section, we present the experimental results obtained and provide a comprehensive discussion on the efficacy of the proposed placement strategy by addressing various questions below.

5.1 How Does the Achieved Total Operating Cost Using the Proposed Placement Algorithm Compare to that of the Baseline Algorithm?

The goal of addressing this question is to quantitatively assess how well the proposed online placement strategy performs in terms of cost savings compared to the offline placement strategy. As mentioned earlier, when dealing with a large search space, the precognition placement strategy cannot find an approximate optimal solution within a reasonable time frame. Therefore, we conduct experiments with a reduced number of users and a shortened time window. To achieve this, we randomly select an appropriate number of users and their corresponding workloads within the reduced time window, all derived from the original trace. For the precognition strategy, we set the *Temperature* parameter to 10e+11, and the *CoolingFac-*

Table 2: The total operating cost difference between the proposed strategy and the precognition strategy in different experiment settings. CompInApp: Compute-intensive application; BandInApp: Bandwidth-intensive application.

#User	T	CompInApp	BandInApp
3	1	0	0
	3	0.05	0.05
	5	0.07	0.07
	10	0.05	0.08
	20	0.05	0.02
	30	0.05	0.01
5	1	0	0
	3	0.03	0.02
	5	0.02	0.03
	10	0.05	0.07
	20	0.02	1.5e−3
	30	0.01	0.01
10	1	0	0
	3	0.04	0.03
	5	0.05	0.06
	10	4.8e−3	4.4e−3
	20	0.03	0.03
	30	0.03	0.02

tor parameter to 0.995, to ensure it obtains a solution within a reasonable amount of time. We collect the results obtained from both algorithms and calculate the deviation in total operating costs using the following formula:

$$\text{cost\_difference} = \frac{\text{cost}_{(\text{proposed})} - \text{cost}_{(\text{precognition})}}{\text{cost}_{(\text{precognition})}}$$

In Table 2, we show the differences in total operating costs achieved with the App_EDC_Match strategy and the precognition strategy across different settings of numbers of users (i.e., 3, 5, and 10 users) and time window lengths (i.e., 1, 3, 5, 10, 20, and 30 time slots). As observed, the total operating costs achieved with the App_EDC_Match placement strategy are pretty close to the approximate optimal values returned by the precognition strategy, with a maximum deviation of approximately 8%.

5.2 What Are The Execution Times of the Proposed Placement Algorithm?

We now evaluate the scalability of the App_EDC_Match placement strategy and its suitability for real MECs, where real-time decision-making is crucial. As presented in Section 3, the App_EDC_Match strategy's execution time depends on the number of EDCs n and the number of users m, i.e., its time complexity is $O(n \times m)$. To verify that the execution time of App_EDC_Match scales linearly with the number of users in a fixed MEC infrastructure, we measure the mean execution time per time slot for the proposed strategy with varying number of users. In essence, we use the same emulated MECs as in previous experiments and increase the number of users per experiment.

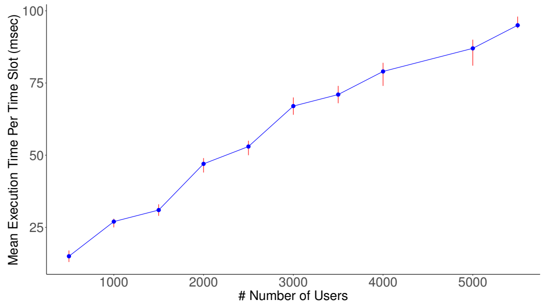


Figure 3: Mean execution time per time slot for the proposed online placement strategy with the number of users ranging from 500 to 5500. The red vertical line connects the maximum and minimum observed execution times.

Figure 3 shows the mean execution time per time slot of App_EDC_Match as the number of users is raised from 500 to 5500 users. As observed, the execution time per time slot increases linearly with the number of users. Moreover, the execution time of App_EDC_Match starts off considerably lower but experiences a rapid increase. Nonetheless, the execution times per time slot remain reasonably small, staying below 100 ms for the experiment with 5500 users, which is well below the length of the time slots (1 minute). As a result, the App_EDC_Match algorithm is well-suited for deployment in real MEC systems to rapidly determine placement solutions that approach the near-global optimum.

5.3 Where Are Applications Placed by the Proposed Algorithm?

We analyse the results produced by the App_EDC_Match placement strategy to better understand its behavior. Figure 4 shows the distribution of applications throughout the entire experiment. For the bandwidth-intensive applications, to minimize network bandwidth utilization and thereby reduce overall operational costs, the App_EDC_Match strategy prioritizes the placement of applications on the EDC to which the application's users directly connected. Consequently, 91% of bandwidth-intensive applications are placed on the

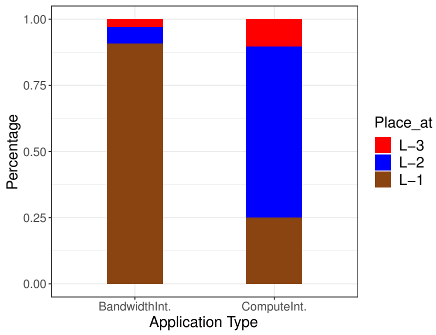


Figure 4: Behavior of the proposed placement strategy with bandwidth-intensive (BandwidthInt.) and compute-intensive (ComputeInt.) applications. L-1, L-2, L-3 denote layers 1, 2, and 3 in the emulated MEC, respectively.

connecting EDCs of the users, while approximately 5.8% are placed on layer 2 EDCs, and the remaining 3.2% being placed on layer 3 EDCs.

In case of compute-intensive applications, the App_EDC_Match strategy leverages higher-capacity resources from EDCs in upper layers, which typically offer lower compute resources unit prices. More specifically, approximately 25.1% of the compute-intensive applications are placed on the EDCs directly connected to users, while a larger portion, roughly 64.5% are placed on layer 2 EDCs, and the remaining 10.4% of these applications are placed on layer 3 EDCs. These observed results show the effectiveness of App_EDC_Match in achieving a balanced and efficient utilization of resources within MEC infrastructure.

Taking the analysis a step further, we investigate the utilization of compute resources within EDCs at each layer and the utilization of network bandwidth (expressed as a percentage of the total capacity) in network links during a peak workload scenario characterized by a high volume of concurrent users. Figure 5 shows the experimental results with compute intensive applications. In the previous experiment, we observed that the App_EDC_Match strategy effectively distributes compute intensive applications leveraging the greater computing capabilities of EDCs in higher layers (layer 2 and 3). As a result, the workload is not significantly concentrated in EDCs in layer 1, leading to average resource utilization rates of 54.2% for EDCs in layer 1, 17.5% for EDCs in layer 2, and 11.4% for EDCs in layer 3 (Figure 5a). Regarding bandwidth usage, we observe an average bandwidth usage of 11.9% on the links connecting layer 2 and layer 3, while the links connecting layers 1 and 2 exhibited an average bandwidth utilization of 18.3% (Figure 5b).

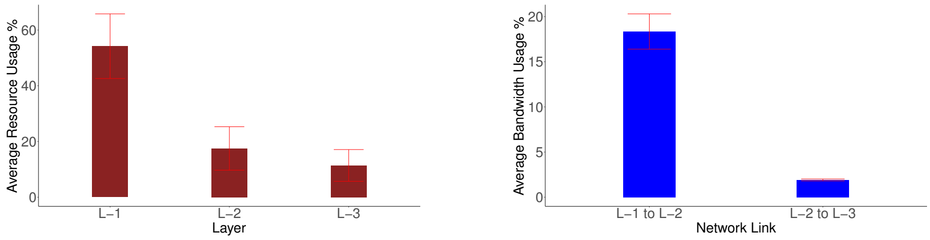
Figure 6 presents the experimental results related to bandwidth-intensive applications. Since these applications demand fewer compute resources, we observe that the App_EDC_Match strategy primarily utilizes compute resources from EDCs in layer 1. This results in an average resource usage of 24.8% for EDCs in this layer, while the corresponding values for EDCs in layers 2 and 3 are 1.3% and 0.8%, respectively (Figure 6a). Consequently, this application placement pattern impacts bandwidth usage in the network links. There is a higher concentration of bandwidth utilization on the links connecting layer 1 and layer 2, with an average of 3.9%. In contrast, the links between layer 2 and layer 3 demonstrate less concentrated bandwidth usage, averaging 1.1% (Figure 6b). These results not only show the effectiveness of the App_EDC_Match placement strategy, but also provide further confirmation of the findings in (Mehta et al., 2016), which underscore the advantages of introducing intermediate layers of EDCs, including cost savings, prevention of compute capacity shortages, and the mitigation of network congestion within MECs environment.

6 RELATED WORK

In this section, we explore research efforts addressing the MEC application placement problem.

Ouyang et al. (Ouyang et al., 2019) introduced an online service placement method for MECs, prioritizing user latency and service migration cost. Their approach utilizes a Thompson-sampling based online learning algorithm to adaptively select service locations based on user preferences, resulting in improved performance compared to alternative methods, as demonstrated through theoretical analysis and performance evaluation. Farhadi et al. (Farhadi et al., 2021) introduced a two-time-scale framework for optimizing service placement and request scheduling, considering various constraints. Their algorithms demonstrated efficient polynomial-time performance and consistently achieved high optimization levels. Similarly, Gao et al. (Gao et al., 2021) addressed online service placement in MECs, dividing it into selecting the access network and determining service deployment locations. They aimed to enhance QoS by balancing factors like access and communication delays, using an iterative-based algorithm to approach optimality. Smolka et al. (Smolka et al., 2023) proposed a decentralized method for dynamic edge application placement. Each edge node autonomously decides through auctions to minimize application latency individually.

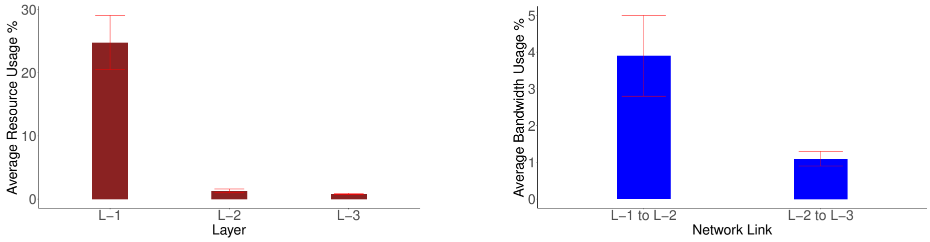
These previous works primarily focus on high-



a Compute resource usage.

b Bandwidth usage.

Figure 5: Experiment with compute-intensive applications.



a Compute resource usage.

b Bandwidth usage.

Figure 6: Experiment with bandwidth-intensive applications.

level abstractions of applications and are most efficient when dealing with general, stateless applications. Our work builds upon these existing efforts, particularly in understanding the cost components associated with application placement operations. Nevertheless, we incorporate additional aspects to our approach to the problem. Firstly, we consider dynamic workloads that vary from one time slot to another. Secondly, we explicitly incorporate data exchange costs, especially the bandwidth cost, along the network path connecting the EDC co-located with the nearest tower to the end-user and the EDC responsible for managing the end-user's workload.

7 CONCLUSION AND FUTURE WORK

In this paper, we tackle the challenge of deploying stateful applications in MEC environments. Our approach begins with a comprehensive modeling of the anticipated workloads, applications, and MEC infrastructures. Subsequently, we define and analyze the various costs associated with application operation, encompassing resource utilization costs, migration cost, and the costs incurred due to service quality degradation. Lastly, we introduce an efficient online placement algorithm driven by the *Gale-Shapley* matching algorithm. The experiments reveal that the proposed algorithm enables MECs to make swift decisions on allocating capacity for applications, resulting in total operating costs that are no more than 8% higher than the approximate global optimum obtained from an offline precognition algorithm. Moreover, it effectively facilitates workload balancing, mitigating resource scarcity challenges for MECs.

We envision several promising directions for future research. While the proposed placement algorithm treats all applications equally, it is essential to acknowledge that real-world scenarios often involve mission-critical applications with strict locality requirements. These applications necessitate being hosted on resources from EDCs in close proximity to end-users. As a result, we intend to enhance the application model presented in this study to incorporate application priorities. Subsequently, we will adapt our proposed placement algorithms to account for these priority considerations. Secondly, we plan to explore distributed placement algorithms designed for deployment across all EDCs. Ideally, these distributed algorithms should exhibit execution times independent of the number of EDCs. This investigation aims to further optimize and scale our placement strategies in large-scale MEC environments.

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