

Wireless Networks for Mobile Edge Computing: Spatial Modeling and Latency Analysis

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Abstract

It is envisioned that next-generation wireless networks will provide users ubiquitous low-latency computing services using devices at the network edge, called *mobile edge computing* (MEC). The key operation of MEC, *mobile computation offloading* (MCO), is to offload computation intensive tasks from users. Since each edge device comprises an *access point* (AP) and a *computer server* (CS), a MEC network can be decomposed as a *radio access network* (RAN) cascaded with a *CS network* (CSN). Based on the architecture, we investigate *network constrained* latency performance, namely *communication latency* (comm-latency) and *computation latency* (comp-latency) under the constraints of RAN coverage and CSN stability. To this end, a spatial random network is constructed featuring random node distribution, parallel computing, non-orthogonal multiple access, and random computation-task generation. Based on the model and under the said network constraints, we derive the scaling laws of comm-latency and comp-latency with respect to network-load parameters (including density of mobiles and their task-generation rates) and network-resource parameters (including bandwidth, density of APs and co-located CSs, CS computation rate). For instance, the comm-latency grows inversely with the bandwidth and sub-linearly with the expected number of mobiles per AP/CS, but decreases with the allowed fraction of mobiles following a power function with a negative exponent. Essentially, the analysis involves the interplay of theories of stochastic geometry, queueing, and parallel computing. Combining the derived scaling laws quantifies the tradeoffs between the latency, network coverage and network stability. The results provide useful guidelines for MEC-network provisioning and planning to minimize the latency by avoiding either cascaded RAN or CSN being a performance bottleneck.

I. INTRODUCTION

Besides the pursuit of gigabit access, another key mission of 5G systems is to provide users ubiquitous computing services (e.g., multimedia processing, gaming and augmented reality) using servers at the network edge, called *mobile edge computing* (MEC) [1]. Compared with cloud computing, MEC can dramatically reduce latency by avoiding transmissions over the backhaul network, among many other advantages such as security and context awareness [2], [3]. Most existing work focuses on designing MEC techniques by merging two disciplines: wireless communications and mobile computing. In this work, we explore a different direction,

namely the design of large-scale MEC networks with infinite nodes. To this end, a model of MEC network is constructed featuring spatial random distribution of network nodes, wireless transmissions, parallel computing at servers. Based on the model and under network performance constraints, the latencies for communication and computation are analyzed by applying theories of stochastic geometry, queueing, and parallel computing. The results yield useful guidelines for MEC network provisioning and planning.

A. Mobile Edge Computing

In the area of MEC, one research thrust focuses on designing techniques for enabling low-latency and energy-efficient *mobile computation offloading* (MCO), which offloads computation intensive tasks from mobiles to the edge servers [4]–[11]. In [4], considering a CPU with a controllable clock, the optimal policy is derived using stochastic-optimization theory for jointly controlling the MCO decision (offload or not) and clock frequency with the objective of minimum mobile energy consumption. A similar design problem is tackled in [5] using a different approach based on Lyapunov optimization theory. Besides MCO, the battery lives of mobile devices can be further lengthened by energy harvesting [6] or wireless power transfer [7]. The optimal policies for MEC control are more complex as they need to account for energy randomness [6] or adapt the operation modes (power transfer or offloading) [7]. Designing energy-efficient MEC techniques under computation-deadline constraints implicitly attempts to optimize the latency-and-energy tradeoff. The problem of optimizing this tradeoff via computation-task scheduling is formulated explicitly in [8] and [9] and solved using optimization theory. In addition, other design issues for MEC are also investigated in the literature such as optimal program partitioning for partial offloading [10] and data prefetching based on computation prediction [11].

Recent research in MEC focuses on designing more complex MEC systems for multiuser MCO [12]–[18]. One important issue is the joint radio-and-computation resource allocation for minimizing sum mobile energy consumption under their deadline constraints. The problem is challenging due to the multiplicity of parameters and constraints involved in the problem including multi-user channel states, computation capacities of servers and mobiles, and individual deadline and power constraints. A tractable approach for solving the problem is developed in [12] for a single-cell system comprising one edge server for multiple users. Specifically, a so-called *offloading priority function* is derived that includes all the parameters and used to show a simple threshold based structure of the optimal policy. The problem of joint resource allocation

in multi-cell systems is further complicated by the existence of inter-cell interference. An attempt is made in [13] to tackle this problem using optimization theory. In distributed systems without coordination, mobiles make individual offloading decisions. For such systems, it is proposed in [14] that game theory is applied to improve the performance of distributed joint resource allocation in terms of latency and mobile energy consumption.

Cooperation between edge servers (or edge clouds) allows their resource pooling and sharing, which helps overcome their limitations in computation capacity. Algorithms for edge-cloud cooperation are designed in [15] based on game theory that enables or disables cooperation so as to maximize the revenues of edge clouds under the constraint of meeting mobiles' computation demands. Compared with the edge cloud, the central cloud has unlimited computation capacity but its long distance from users can incur long latency for offloading. Nevertheless, cooperation between edge and central clouds is desirable when the formers are overloaded. Given such cooperation, queueing theory is applied in [16] to analyze the latency for computation offloading. On the other hand, cooperation between edge clouds can support mobility by migrating computation tasks between servers. Building on the migration technology, a MEC framework for supporting mobility is proposed in [17] to adapt the placements of offloaded tasks in the cloud infrastructure depending on the mobility of the task owners. Besides offloaded tasks, computing services can be also migrated to adapt to mobility but service migration can place a heavy burden on the backhaul network or result in excessive latency. To address this issue, the framework of service duplication by virtualization is proposed in [18].

Prior work considers small-scale MEC systems with several users and servers/clouds, allowing the research to focus on designing complex MCO techniques and protocols. On the other hand, it is also important to study a large-scale MEC network with infinite nodes as illustrated in Fig. 1, which is an area not yet explored. From the practical perspective, such studies can yield guidelines and insights useful for operators' provisioning and planning of MEC networks.

B. Modeling Wireless Networks for Mobile Edge Computing

In the past decade, stochastic geometry has been established as a standard tool for modeling and designing wireless networks, creating an active research area [19]. A rich set of spatial point processes such as *Poisson point process* (PPP) and cluster processes have been used to model node locations in a wide range of wireless networks such as cellular networks [20], heterogeneous networks [21], and cognitive radio networks [22]. Based on these network models and applying

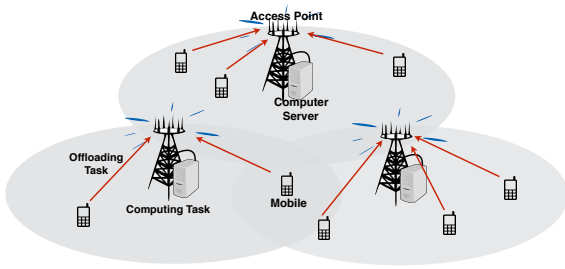


Figure 1: A MEC network where mobiles offload computation tasks to *computer servers* (CSs) by wireless transmission to *access points* (APs).

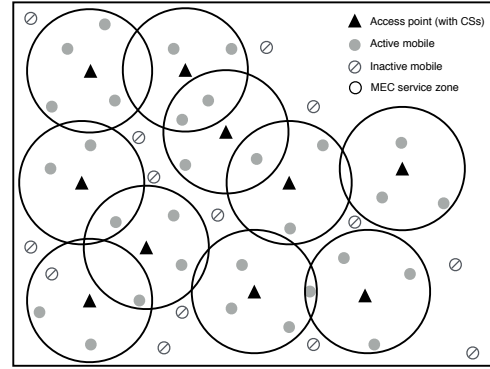


Figure 2: The spatial model of a MEC network.

mathematical tools from stochastic geometry, the effects of most key physical-layer techniques on network performance have been investigated ranging from multi-antenna transmissions [23] to multi-cell cooperation [24]. Recent advancements in the area can be found in numerous surveys such as [25]. Most existing work in this area shares the same theme of how to cope with interference and hostility of wireless channels (e.g., path loss and fading) so as to ensure high coverage and link reliability for *radio access networks* (RAN) or distributed device-to-device networks. In contrast, the design of large-scale MEC networks in Fig. 1 has different objectives, all of which should jointly address two aspects of network performance, namely *wireless communication and edge computing*.

Modeling a MEC network poses new challenges as its architecture is more complex than a traditional RAN and can be decomposed as a RAN cascaded with a *computer-server network* (CSN) as illustrated in Fig. 3. The power of modeling MEC networks using stochastic geometry lies in allowing network performance to be described by a function of a relatively small set of network parameters. To be specific, as shown in Fig. 3, the process of mobiles is parametrized by mobile density, the RAN by channel bandwidth and *access-point* (AP) density, and the CSN by CS density and CS computation capacity. Besides the parameters, the performance of a MEC network is measured by numerous metrics. Like small-scale systems (see e.g., [8] and [9]), the *link-level* performance of the MEC network is measured by latency, which can be divided into latency for offloading in the RAN, called *communication latency* (comm-latency) and latency for computing at CSs, called *computation latency* (comp-latency). At the network level, the coverage of the RAN of a MEC network is typically measured by *connectivity probability* (also called coverage probability [25]), quantifying the fraction of users having reliable links to APs. A similar metric, called *stability probability*, can be defined for measuring the stability of the

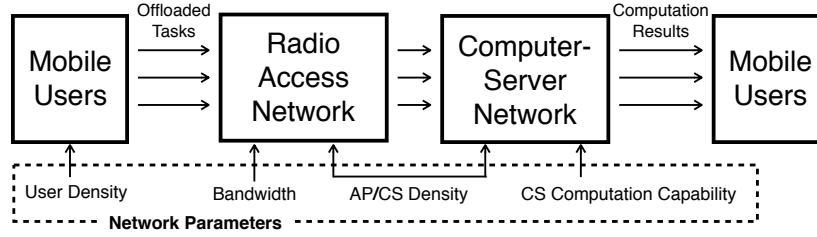


Figure 3: The decomposition view of the MEC network.

CSN, quantifying the fraction of CSs having finite comp-latency. There exist potentially complex relations between these four metrics that are regulated by the said network parameters. Existing results focusing solely on RAN (see e.g., [25]) are insufficient for quantifying these relations. Instead, it calls for developing a more sophisticated analytical approach integrating theories of stochastic geometry, queueing, and parallel computing.

Last, it is worth mentioning that comm-latency and comp-latency have been extensively studied in the literature mostly for point-to-point systems using queueing theory (see e.g., [26], [27]). However, studying such latency in large-scale networks is much more challenging due to the existence of interference between randomly distributed nodes. As a result, there exist only limited results on comm-latency in such networks [28]–[30]. In [28], the comm-latency given retransmission is derived using stochastic geometry for the extreme cases with either static nodes or nodes having high mobility. The analysis is generalized in [29] for finite mobility. Then the approach for comm-latency as proposed in [28] and [29] is further developed in [30] to integrate stochastic geometry and queueing theory. Compared with these studies, the current work considers a different type of network, namely the MEC network, and explores a different research direction, namely the tradeoff between comm-latency and comp-latency under constraints on the mentioned network-level performance metrics.

C. Contributions

In this work, we make the first attempt to investigate *network-constrained latency performance* of large-scale MEC networks, referring to comm-latency and comp-latency experienced by offloading mobiles under constraints on network coverage and stability. Most existing work on MEC focuses on link-level performance for point-to-point links (see e.g., [11]) or single-cell systems (see e.g., [12]) where the said network constraints are not considered. However, such constraints directly affect link performance in large-scale MEC networks and quantifying such effects is crucial especially for network provisioning and planning. For example, to serve dense mobiles, more bandwidth should be allocated for interference mitigation to satisfy the network-coverage constraint. Consequently, the bandwidth for data transmissions of individual

links reduces, resulting in longer comm-latency. The analysis of network-constrained latency performance is challenging due to the complex network architecture as shown in Fig. 3 and the multiplicity of performance metrics and parameters. In this work, we propose an approach building on a spatial network model described shortly and the joint applications of tools from diversified areas including stochastic geometry, queueing, and parallel computing.

The model of the MEC network proposed in this work features spatial random distributions of nodes, parallel computing at CSs, random task generation at mobiles, and spread-spectrum for radio access. The locations of co-located pairs of CS and AP and the mobiles are distributed as two independent homogeneous PPPs, with densities λ_b and λ_m , respectively. Each AP provides offloading service to mobiles within a given distance, creating a circular *service zone* for each AP as illustrated in Fig. 2. A mobile within more than one service zone randomly selects a single AP to connect. Then, a mobile is *connected* to the network if the mobile is within the service zone of at least one AP and the receive *signal-to-interference ratio* (SIR) at the AP is above a given threshold. Consider transmissions in the RAN (see Fig. 3). Multiple access is enabled by spread spectrum [31], which underpins the technology of code-domain *Non-Orthogonal Multiple Access* (NOMA) to be deployed in 5G systems for enabling massive access [32]. Using the technology, interference is suppressed by a parameter called spreading factor, denoted as G . However, the data bandwidth for each link is also reduced by the factor G , which thereby regulates the tradeoff between comm-latency and connectivity probability. Time is divided into slots and a certain number of slots comprises a frame which is used for offloading a single task. We consider two typical multiuser transmission modes, *synchronous* and *asynchronous* offloading, corresponding aligned frame boundaries across mobiles and independent transmissions, respectively. Next, consider the generation of computation tasks at mobiles and their computation at CSs. Each mobile generates a single task with a fixed size in each slot with a fixed probability and the generation processes for different mobiles are *independent and identically distributed* (i.i.d.). Each CS computes multiple tasks simultaneously by parallel computing realized via creating a number of *virtual machines* (VMs). The stochastic model of parallel computing proposed in [33] is adopted, where the expected comp-latency for a task exponentially increases with the number of VMs and both computation capacity and so call input/output (I/O) interference are represented by corresponding parameters.

Based on the above model, the comm-latency and comp-latency are analyzed under constraints on network connectivity and stability probabilities. The findings are summarized as follows.

Communication latency: The expected comm-latency for an offloaded task, denoted as T_{comm} , is minimized under a constraint on the network connectivity probability. This is transformed into a constrained optimization problem of the spreading factor G . Solving the problem yields the minimum T_{comm} . The result shows that when mobiles are sparse, the full bandwidth should be allocated for data transmission so as to minimize T_{comm} . However, when mobiles are dense, spread spectrum with large G is needed to mitigate interference for satisfying the network-coverage constraint, which increases T_{comm} . As a result, the minimum T_{comm} diminishes inversely proportional to the channel bandwidth B and as a power function of the allowed fraction of disconnected users with a negative exponent, but grows sub-linearly with the expected number of mobiles per AP (or CS), λ_m/λ_b . In addition, T_{comm} is a monotone increasing function of the task-generation probability per slot that saturates as the probability approaches one.

RAN offloading throughput: The RAN throughput, which determines the load of the CSN (see Fig. 3), can be measured by the expected task-arrival rate at a typical AP (or CS). The rate is shown to be a *quasi-concave* function of λ_m/λ_b defined earlier, which first increases and then decreases as the ratio grows. In other words, the expected task-arrival rate is low in both sparse and dense networks. The maximum rate, denoted as $\bar{\Lambda}^*$, is proportional to the bandwidth.

Computation latency for asynchronous offloading: First, to maximize CS computing rates, it is shown that the dynamic number of VMs at each CS should be no more than a derived number to avoid suffering rate loss due to their I/O interference. Then to ensure stable CSN, it is shown that the resultant maximum computing rate should be larger than the task-arrival rate $\bar{\Lambda}^*$ scaled by a factor larger than one, which is determined by the allowed fraction of unstable CSs. Based on the result for parallel computing, tools from stochastic geometry and M/M/m queues are applied to derive bounds on the expected comp-latency for an offloaded task, denoted as T_{comp} . The bounds show that the latency is *inversely proportional* to the maximum computing rate and *linearly proportional* to the total task-arrival rate at the typical CS (or AP). Consequently, T_{comp} is a quasi-concave function of λ_m/λ_b while T_{comm} is a monotone increasing function.

Computation latency for synchronous offloading: Bounds on T_{comp} are also derived for the case of synchronous offloading. The results have similar properties as the asynchronous-offloading counterparts. However, simulation results show that synchronization increases T_{comp} by causing burstiness in task arrivals at CSs.

Network provisioning and planning Combining the above results suggest the following guidelines for network provisioning and planning. Given a mobile density, the AP density should

be chosen for maximizing the RAN offloading throughput under the network-coverage constraint. Then sufficient bandwidth should be provisioned to simultaneously achieve the targeted comm-latency for offloading a task. Last, given the mobile and RAN parameters, the CS computation capacities are planned to achieve the targeted comp-latency for a offloaded task as well as enforcing the network-stability constraint. The derived analytical results simplify the calculation in the specific planning process.

II. MODELING MEC NETWORKS

In this section, a mathematical model of the MEC network as illustrated in Fig. 1 is presented.

A. Network Spatial Model

APs (and thus their co-located CSs) are randomly distributed in the horizontal plane and are modelled as a homogeneous PPP $\Omega = \{Y\}$ with density λ_b , where $Y \in \mathbb{R}^2$ is the coordinate of the corresponding AP. Similarly, mobiles are modelled as another homogeneous PPP $\Phi = \{X\}$ independent of Ω and having the density λ_m .

Define a *MEC-service zone* for each AP, as a disk region centred at Y and having a fixed radius r_0 , denoted by $\mathcal{O}(Y, r_0)$ (see Fig. 2). A mobile can access a AP for computing if it is covered by the MEC-service zone of the AP. It is possible that a mobile is within the service ranges of more than one AP. In this case, the mobile randomly selects a single AP to receive the MEC service. As illustrated in Fig. 2, combining the randomly located MEC-service zones, $\cup_{Y \in \Omega} \mathcal{O}(Y, r_0)$, forms a *coverage process*. Covered mobiles are referred to as *active* ones and others *inactive* since they remain silent. To achieve close-to-full network coverage, let the fraction of inactive mobiles be no more than a small positive number δ . Then the radius of MEC-service zones, r_0 , should be set as $r_0 = \sqrt{\frac{\ln \frac{1}{\delta}}{\pi \lambda_b}}$ [25]. Given r_0 , the number of mobiles covered by an arbitrary MEC service zone follows a Poisson distribution with mean $\lambda_m \pi r_0^2$. Consider a typical AP located at the origin. Let X_0 denote a typical mobile located in the typical MEC service zone $\mathcal{O}(o, r_0)$. Without loss of generality, the network performance analysis focuses on the typical mobile.

B. Model of Mobile Task Generation

Time is divided into slots having a unit duration. Consider an arbitrary mobile. A computation task is randomly generated in each slot with probability p , referred to as the *task-generation rate*. Task generations over two different slots are assumed to be independent. The mobile has a unit buffer to store at most a single task for offloading. A newly generated task is sent for offloading when the buffer is empty or otherwise computed locally. This avoids significant queueing

delay that is unacceptable in the considered case of latency-sensitive mobile computation. For simplicity, offloading each task is assumed to require transmission of a fixed amount data. The transmission of a single task occupies a single *frame* lasting L slots. The mobile checks whether the buffer is empty at the end of every L slots and transmits a stored task to a serving AP. Define the *task-offloading probability* as the probability that the mobile's buffer is occupied, denoted as p_L . Equivalently, p_L gives the probability that at least one task is generated within one frame:

$$p_L = 1 - (1 - p)^L. \quad (1)$$

Thereby, the task-departure process at a mobile follows a Bernoulli process with parameter p_L provided the radio link is reliable (see discussion in the sequel).

C. Radio Access Model

Consider an uplink channel with the fixed bandwidth of B Hz. The channel is shared by all mobiles for transmitting data containing offloaded tasks to their serving APs. The CDMA (or code-domain NOMA) is applied to enable multiple access. For CDMA based on the *spread-spectrum technology*, each mobile *spreads* every transmitted symbol by multiplying it with a *pseudo-random* (PN) sequence of *chips* (1s and -1 s), which is generated at a much higher rate than the symbols and thereby spreads the signal spectrum [31]. The multiple access of mobiles is enabled by assigning unique PN sequences to individual users. A receiver then retrieves the signal sent by the desired transmitter by multiplying the multiuser signal with the corresponding PN sequence. The operation suppresses interference and *de-spreads* the signal spectrum to yield symbols. Let G denote the *spreading factor* defined as the ratio between the chip rate and symbol rate, which is equivalent to the number of available PN sequences. The cross-correlation of PN sequences is proportional to $\frac{1}{G}$ and approaches to zero as G increases. As a result, the interference power is reduced by the factor of G [31].¹ On the other hand, the price for spread spectrum is that the bandwidth available to individual mobiles is reduced by G , namely $\frac{B}{G}$.

Uplink channels are characterized by path-loss and small-scale Rayleigh fading. Assuming transmission by a mobile with the fixed power η , the received signal power at the AP is given by $\eta g_X |Y - X|^{-\alpha}$, where α is the path-loss exponent, the $\exp(1)$ *random variable* (RV) g_X represents Rayleigh fading and $|X - Y|$ denotes the Euclidian distance between X and Y .

¹For the special case of synchronous multiuser transmissions, orthogonal sequences (e.g., Hadamard sequences) can be used instead of PN sequences to achieve orthogonal access [31]. However, the maximum number of simultaneous users is G , making the design unsuitable for massive access.

Based on the channel model, the power of interference at the typical AP Y_0 , denoted by I , can be derived as follows. Among potential interferers for the typical AP, the fraction of δ is outside MEC-service zones. Given random task generation discussed earlier, each interferer transmits with probability p_L . Consequently, the active interferers form a PPP given by $\tilde{\Phi}$ with density $(1 - \delta)p_L\lambda_m$ resulting from thinning Φ . It follows that the interference power I can be written as $I = \frac{1}{G} \sum_{X \in \tilde{\Phi}} \eta g_X |X|^{-\alpha}$, where the factor $\frac{1}{G}$ is due to the spread spectrum. Consider an interference-limited radio-access network where channel noise is negligible. The received SIR of the typical mobile is thus given as

$$\text{SIR}_0 = \frac{g_{X_0} |X_0|^{-\alpha}}{\frac{1}{G} \sum_{X \in \tilde{\Phi}} \eta g_X |X|^{-\alpha}}. \quad (2)$$

The condition for successful offloading is that SIR exceeds a fixed threshold θ depending on the coding rate. Specifically, given θ , the spectrum efficiency is $\log_2(1 + \theta)$ (bits/sec/Hz) [25]. It follows that to transmit a task having a size of ℓ bits within a frame, the frame length L should satisfy $L = \frac{G\ell}{B \cdot t_0 \cdot \log_2(1 + \theta)}$ (in slots) where t_0 is the length of a slot (in sec). Define the minimum time for transmitting a task using the full bandwidth B as $T_{\min} = \frac{\ell}{B \cdot t_0 \cdot \log_2(1 + \theta)}$ for ease of notation, giving $L = GT_{\min}$.

Assumption 1 (Slow Fading). We assume that channels vary at a much slower time scale than that for mobile computation. To be specific, the mobile locations and channel coefficients $\{g_X\}$ remain fixed in the considered time window of computation offloading.

This assumption is made from simplifying analysis and can be justified by the fact that typical applications of MEC are latency critical and require computation speeds faster than channel variations. The current results can be straightforwardly extended to the case of fast fading by adding retransmission delay derived using the same method as in [28]. By Assumption 1, mobiles' SIRs remain constant and thereby mobiles can be separated into *connected* and *disconnected* mobiles. To be specific, a mobile is connected to an AP if the corresponding SIR is above the threshold θ or otherwise disconnected.

We consider both *synchronous* and *asynchronous* multiuser transmissions defined in existing wireless standards such as 3GPP LTE. For synchronous transmissions, the frame boundaries of different users are aligned so as to facilitate protocols such as control signaling and channel feedback. Synchronization incurs network overhead for implementing a common clock as well as increases latency. For asynchronous transmissions, the said constraint on frame boundaries is not applied and thus the transmission of each mobile is independent of those of others. The

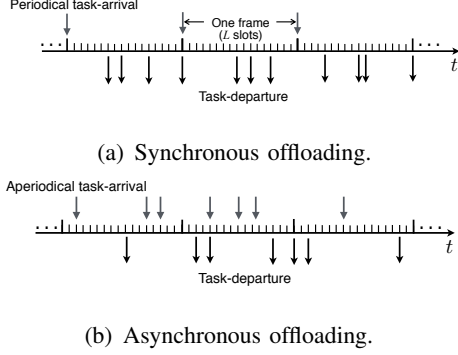


Figure 4: Task arrival & departure of two offloading modes.

transmissions modes lead to different task-arrival models for CSs. Specifically, given synchronous transmissions, the offloaded tasks arrive at a CS in batches and periodically as illustrated in Fig. 4(a). The number of arrival tasks in each batch is random depending on the number of connected mobiles in the same MEC-service zone. On the other hand, given asynchronous transmissions, the offloaded tasks arrive at an AP at different time instants as illustrated in Fig. 4(b).

D. Edge-Computing Model

1) *Parallel-Computing Model*: Upon their arrivals at APs, tasks are assumed to be delivered to CSs without any delay and queue at the CS buffer for computation on the first-come-first-served basis. Moreover, each CS is assumed to be provisioned with large storage modelled as a buffer with infinite capacity. At each CS, parallel computing of multiple tasks is implemented by creating *virtual machines* (VM) on the same *physical machine* (PM) [33]. VMs are created asynchronously such that a VM can be added or removed at any time instant. It is well known in the literature that simultaneous VMs interfere with each other due to their sharing common computation resources in the PM e.g., CPU, memory, buses for I/O. The effect is called *I/O interference* that reduces the computation speeds of VMs. The model of I/O interference as proposed in [33] is adopted where the expected computation time for a single task, denoted by T_c , is a function of the number of VMs, m :

$$T_c(m) = T_0(1 + d)^{m-1}, \quad (3)$$

where T_0 is the expected computation time of a task in the case of a single VM ($m = 1$) and d is the degradation factor due to I/O interference between VMs. One can observe that T_c is a monotone increasing function of d . For tractability, we assume that the computation time for a task is an $\exp(T_c)$ RV following the common assumption in queueing theory [33].

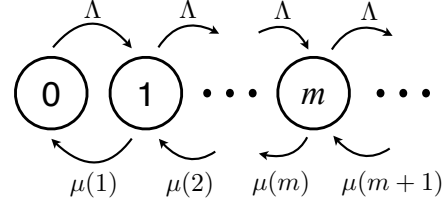


Figure 5: Markov chain modeling the tasks queueing for computation at the typical CS where Λ is the arrival rate and $\mu(m)$ is the computation rate given m waiting tasks.

2) *CS Queuing Model*: The general approach of analyzing comp-latency relies on the interplay between parallel-computing and queueing theories. In particular, for the case of asynchronous offloading, the task arrival at the typical AP is approximated as a Poisson process for the following reasons. Due to the lack of synchronization between mobiles, the time instants of tasks arrivals are approximately uniform in time. Furthermore, at different time instants, tasks are generated following i.i.d. Bernoulli distributions based on the model in Section II-B. It is well known that a stochastic process with these properties can be suitably approximated as a Poisson process [34].

Assumption 2. For the case of asynchronous offloading, given N connected mobiles and the spreading factor G , the task arrivals at the typical AP are approximated as a Poisson process with the arrival rate of $\Lambda(N, G) = \frac{Np_L}{L} = \frac{Np_L}{GT_{\min}}$.

The Poisson approximation is shown by simulation to be accurate in Appendix III. Given the Poisson arrival process and exponentially distributed computation time, the random number of tasks queueing at the typical CS can be modelled as a continuous-time Markov chain as illustrated in Fig. 5 [26]. In the Markov chain, Λ denotes the task-arrival rate in Assumption 2 and $\mu(k)$ denotes the CS-computation rate (task/slot) given k tasks in the CS. The CS-computation rate is maximized in the sequel by optimizing the number of VMs based on the queue length.

Last, the result-downloading phase is not considered for brevity. First, the corresponding latency analysis is similar to that for the offloading phase. Second, the latency for downloading is negligible compared with those for offloading. The reasons are that computation results typically have small sizes compared with offloaded tasks and furthermore downlink transmission rates are typically much higher than uplink rates.

E. Performance Metrics

The network performance is measured by two metrics: *comm-latency* and *comp-latency*. The definitions of metrics build on the design constraints for ensuring network connectivity and stability defined as follows.

Definition 1 (Network Coverage Constraint). The RAN in Fig. 3 is designed to be ϵ -connected, namely that the portion of mobiles is no less than $(1 - \epsilon)$, where $0 < \epsilon \ll 1$.

The fraction of connected mobiles is equivalent to the *success probability*, a metric widely used for studying the performance of random wireless networks [25]. For the MEC network, the

success probability is renamed as *connectivity probability* and defined for the typical mobile as the following function of the spreading factor G :

$$p_c(G) = \Pr(\text{SIR}_0 \geq \theta), \quad (4)$$

where SIR_0 is given in (2). Then the network coverage constraint can be written as $p_c(G) \geq (1 - \epsilon)$. Under the connectivity constraint, most mobiles are connected to APs. Then the comm-latency, denoted as T_{comm} , is defined as the *expected* duration required for a connected mobile to offload a task to the connected AP successfully. The latency includes both waiting time at the mobile's buffer and the transmission time.

Next, consider the computation load of the typical AP. Since the number of mobiles connected to the AP is a RV, there exists non-zero probability that the AP is overloaded, resulting in infinite queueing delay. In this case, the connected mobiles are referred to as being *unstable*. To ensure most mobiles are stable, the following constraint is applied on the network design.

Definition 2 (Network Stability Constraint). The CSN in Fig. 3 is designed to be ρ -stable, namely that the fraction of stable CSs is no less than $(1 - \rho)$, where $0 < \rho \ll 1$.

The fraction ρ is equivalent to the probability that the typical CS is stable, denoted as p_s . Under the stability constraint, most connected mobiles are stable. Then the comp-latency, denoted by T_{comp} , is defined for the typical connected mobile as the *expected* duration from the instant when an offloaded task arrives at the serving CS until the instant when the computation of the task is completed, which includes both queueing delay and actual computation time.

Last, given the above definitions, the network is referred to as being *communication-limited* (comm-limited) if $T_{\text{comm}} \gg T_{\text{comp}}$ and *computation-limited* (comp-limited) if $T_{\text{comm}} \ll T_{\text{comp}}$.

III. COMMUNICATION LATENCY ANALYSIS

In this section, the comm-latency defined in the preceding section is analyzed building on results from the literature of network modeling using stochastic geometry. Then the latency is minimized by optimizing the spreading factor for CDMA, which regulates the tradeoff between the transmission rates of connected mobiles and network-connectivity performance.

A. Feasible Range of Spreading Factor

As mentioned, the spreading factor G is a key network parameter regulating the tradeoff between network coverage and comm-latency. To facilitate subsequent analysis, under the network constraint in Definition 1, the feasible range of G is derived as follows. The result is useful

for minimizing the comm-latency in the next sub-section. To this end, consider the connectivity probability defined in (4). Using a similar approach as the well-known one for deriving network success probability using stochastic geometry (see e.g., [20]), we obtain the following result with the proof omitted for brevity.

Lemma 1 (Connectivity Probability). Given the spreading factor G , the connectivity probability of a typical mobile is given as

$$p_c(G) = \frac{1 - \exp(-\xi(G))}{\xi(G)}, \quad (5)$$

where $\xi(G)$ is defined as

$$\xi(G) = \frac{2(1-\delta)(1-(1-p)^{G^{\text{T}_{\min}}}) \ln \delta^{-1}}{\alpha} \mathcal{B}(\alpha) \left(\frac{\lambda_m}{\lambda_b} \right) \left(\frac{\theta}{G} \right)^{\frac{2}{\alpha}}, \quad (6)$$

and $\mathcal{B}(\alpha) \triangleq \int_0^1 \kappa^{\frac{2}{\alpha}-1} (1-\kappa)^{-\frac{2}{\alpha}} d\kappa$ denotes the Beta function.

Recall that the network coverage constraint in Definition 1 requires that $p_c(G) \geq (1-\epsilon)$. Note that G is an important system parameter affecting both the transmission rates and the connectivity probability as elaborated in the following remark.

Remark 1 (Transmission Rates vs. Connectivity). The spreading factor G of CDMA controls the tradeoff between mobile transmission rates and network connectivity probability. On one hand, increasing G reduces the bandwidth, $\frac{B}{G}$, available to each mobile, thereby reducing the transmission rate and increasing comm-latency. As the result, given longer frames with the task-generation rate being fixed, more mobiles are likely to have tasks for offloading at the beginning of each frame, increasing the density of interferers. On the other hand, growing G suppresses interference power by the factor G via spread spectrum. As a result, the connectivity probability grows. Given the two opposite effects, one should expect that in the case of a stringent connectivity constraint, either small or large value for G is preferred but not the moderate ones.

Next, the effects of the spreading factor as discussed in Remark 1 are quantified by deriving the feasible range of G under the connectivity constraint. Define the Lambert function, $W(x)$, as the solution for the equation $W(x)e^{W(x)} = x$. Then using the result in Lemma 1, the coverage constraint $p_c(G) \geq (1-\epsilon)$ is equivalent to $\xi(G) \leq \mathcal{F}(\epsilon)$ with the function $\mathcal{F}(\epsilon)$ defined as

$$\mathcal{F}(\epsilon) = W \left(-\frac{e^{-\frac{1}{1-\epsilon}}}{1-\epsilon} \right) + \frac{1}{1-\epsilon}. \quad (7)$$

Notice that $\lim_{\epsilon \rightarrow 0} \frac{d}{d\epsilon} W\left(-\frac{e^{-\frac{1}{1-\epsilon}}}{1-\epsilon}\right) = 1$. Moreover, $W\left(-\frac{e^{-\frac{1}{1-\epsilon}}}{1-\epsilon}\right) = -1$ at $\epsilon = 0$. It follows that from these two results that $\mathcal{F}(\epsilon)$ can be approximated as

$$\mathcal{F}(\epsilon) \approx 2\epsilon, \quad \epsilon \ll 1. \quad (8)$$

In addition, $\xi(G)$ is maximized at the point of $G = g_0$ of which the existence and uniqueness are proved in Lemma 2. If $\xi(g_0) \leq \mathcal{F}(\epsilon)$, it is straightforward that any G satisfies the condition of (7). Otherwise, the feasible range of G satisfying the connectivity is provided in Proposition 1.

Lemma 2 (Properties of $\xi(G)$). The function $\xi(G)$ in (6) attains its maximum at $G = g_0$ with

$$g_0 = \frac{\alpha W\left(-\frac{2}{\alpha}e^{-\frac{2}{\alpha}}\right) + 2}{\alpha T_{\min} \ln(1-p)}. \quad (9)$$

Moreover, $\xi(G)$ is monotone increasing in the range $[-\infty, g_0]$ and monotone decreasing in the range $[g_0, \infty]$.

Proof: See Appendix VI-A. □

Proposition 1 (Feasible Range of Spreading Factor). Under the network connectivity constraint, the feasible range of G is $G \geq 1$ if $\xi(g_0) \leq \mathcal{F}(\epsilon)$, where g_0 is given in (9). If $\xi(g_0) > \mathcal{F}(\epsilon)$, the feasible range of G is $\mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2$ where

$$\mathcal{S}_1 = \{G \in \mathbb{Z}^+ | 1 \leq G \leq g_a\}, \quad \mathcal{S}_2 = \{G \in \mathbb{Z}^+ | G \geq g_b\}, \quad (10)$$

where g_a and g_b are the two roots of the equation $\xi(G) = \mathcal{F}(\epsilon)$.

Based on Lemma 2, the function $\xi(G)$ is monotone increasing over \mathcal{S}_1 but monotone decreasing over \mathcal{S}_2 . In addition, if $g_a < 1$, \mathcal{S}_1 is empty and the feasibility range of G reduces to \mathcal{S}_2 .

B. Communication Latency

Recall that the comm-latency of connected mobiles T_{comm} comprises the expected waiting time for offloaded tasks at mobiles, denoted as $T_{\text{comm}}^{(a)}$, and transmission delay, denoted as $T_{\text{comm}}^{(b)}$. Consider the expected waiting time. Recalling that the offloading protocol in Section II-B, the first task arrival during L slots is delivered to the offloading buffer and the subsequent tasks are forwarded to the local computation unit. Let K denote the slot index when an offloaded task arrives at the offloading buffer. It follows that the probability distribution of K follows a conditional geometric distribution, i.e., $\Pr(K = k) = \frac{p(1-p)^{k-1}}{1-(1-p)^L}$, where $k = 1, 2, \dots, L$ and the normalization term $1 - (1-p)^L$ gives the probability that at least one task arrives during a single frame. Thereby, the expected waiting time is given as

$$T_{\text{comm}}^{(a)} = \sum_{k=1}^L (L-k) \frac{p(1-p)^{k-1}}{1-(1-p)^L} = \frac{L}{1-(1-p)^L} - \frac{1}{p}. \quad (11)$$

Next, consider the transmission time for a single task in a frame that spans L slots. Recall that $L = GT_{\min}$ where T_{\min} is the minimum time for transmitting a task as defined earlier. Combining $T_{\text{comm}}^{(b)} = GT_{\min}$ and $T_{\text{comm}}^{(a)}$ in (11) gives the following result.

Lemma 3 (Comm-Latency). Given the spreading factor G , the comm-latency of the typical mobile T_{comm} (in slot) is given as

$$T_{\text{comm}}(G) = GT_{\min} + \frac{GT_{\min}}{1 - (1-p)^{GT_{\min}}} - \frac{1}{p}, \quad (12)$$

where T_{\min} is the minimum time for transmitting a task using full bandwidth.

Next, consider the minimization of the comm-latency over the spreading factor G . Using (12), it is straightforward to show that the comm-latency $T_{\text{comm}}(G)$ is a monotone increasing function of G . Therefore, minimizing comm-latency is equivalent to minimizing G . It follows from Proposition 1 that the minimum of G , $G^* = \min_{G \in \mathcal{S}} G$, is given as

$$G^* = \begin{cases} g_b, & \mathcal{S}_1 = \emptyset, \\ 1, & \text{otherwise.} \end{cases} \quad (13)$$

Substituting G^* into (12) gives the minimum comm-latency as shown in the following theorem.

Theorem 1 (Minimum Comm-Latency). By optimizing the spreading factor G , the minimum com-latency (in slot), denoted as T_{comm}^* , is given as follows.

- 1) If \mathcal{S}_1 in (10) is non-empty,

$$T_{\text{comm}}^* = T_{\min} + \frac{T_{\min}}{1 - (1-p)^{T_{\min}}} - \frac{1}{p}, \quad (14)$$

where $T_{\min} = \frac{\ell}{B \cdot t_0 \cdot \log_2(1+\theta)}$.

- 2) If \mathcal{S}_1 is empty,

$$T_{\text{comm}}^* = g_b T_{\min} + \frac{g_b T_{\min}}{1 - (1-p)^{g_b T_{\min}}} - \frac{1}{p}, \quad (15)$$

where g_b is specified in Proposition 1.

Consider the second case in Theorem 1. The comm-latency T_{comm}^* can be approximated in closed-form if $g_b T_{\min}$ is sufficiently large. For this case, $[1 - (1-p)^{g_b T_{\min}}] \approx 1$ and thus the function $\xi(G)$ in (6) can be approximated as

$$\xi(G) \approx \frac{2(1-\delta) \ln \delta^{-1}}{\alpha} \mathcal{B}(\alpha) \left(\frac{\lambda_m}{\lambda_b} \right) \left(\frac{\theta}{G} \right)^{\frac{2}{\alpha}}. \quad (16)$$

It follows from Theorem 1 and (8) that if \mathcal{S}_1 is empty and $g_b T_{\min}$ is large,

$$T_{\text{comm}}^* \approx 2g_b T_{\min} - \frac{1}{p}, \quad (17)$$

where

$$g_b \approx \left[\frac{(1 - \delta) \ln \delta^{-1} \mathcal{B}(\alpha)}{\alpha \epsilon} \left(\frac{\lambda_m}{\lambda_b} \right) \right]^{\frac{\alpha}{2}} \theta. \quad (18)$$

Remark 2 (Sparse Network vs. Dense Network). The first and second cases in Theorem 1 correspond to sparse and dense networks, respectively, as measured by the mobile-to-AP density ratio λ_m/λ_b . In the first case ($\mathcal{S}_1 \neq \emptyset$), the network is sufficiently sparse, namely the ratio λ_m/λ_b is sufficiently small, such that the optimal spreading factor $G^* = 1$ and the resultant comm-latency is independent of the ratio as shown in the theorem. In other words, for this case, it is optimal to allocate all bandwidth for increasing the transmission rate instead of reducing it for the purpose of suppressing interference to satisfy the network connectivity constraint. In contrast, in the second case ($\mathcal{S}_1 = \emptyset$), the network is relatively dense and it is necessary to apply spread spectrum to reduce interference so as to meet the connectivity requirement, corresponding to $G^* > 1$. As the result, the minimum comm-latency scales with the density ratio as $T_{\text{comm}}^* \propto \left(\frac{\lambda_m}{\lambda_b} \right)^{\frac{\alpha}{2}}$ as one can observe from (18).

Remark 3 (Effects of Network Parameters). Substituting $T_{\min} = \frac{\ell}{B \cdot t_0 \cdot \log_2(1+\theta)}$ into (17) gives that for a relatively dense network, the comm-latency scales as

$$T_{\text{comm}}^* \propto \frac{\ell}{B} \left(\frac{\lambda_m}{\epsilon \lambda_b} \right)^{\frac{\alpha}{2}} - \frac{1}{p}. \quad (19)$$

The scaling laws shows the effects of network parameters including the task size ℓ , bandwidth B , mobile density λ_m and AP density λ_b , and the task-generation probability per slot p .

C. Task-Arrival Rates at APs/CSs

The offloading throughput of the RAN represents the load of the CSN (see Fig. 3). The throughput can be measured by the expected task-arrival rate (in number of tasks per slot) at the typical AP (equivalently the typical CS). Its scaling law with the expected number of mobiles per AP, λ_m/λ_b , is not straightforward due to several factors. To be specific, the total bandwidth is fixed, the spread factor grows nonlinearly with λ_m/λ_b , and the likelihood of task-generation probability per frame varies with the frame length. To address this issue, the task arrivals at the typical AP are characterized as follows.

Consider the case of asynchronous offloading. Based on the model in Section II-B, the probability that a mobile generates a task for offloading in each frame is

$$p_L^* = 1 - (1 - p)^{L^*}, \quad (20)$$

where L^* is the frame length given the optimal spreading factor G^* in (13). The expected task-offloading rate (in number of tasks per slot) for the typical mobile, denoted as β^* , is given as $\beta^* = \frac{p_L^*}{L^*}$. Since $L^* = G^* T_{\min}$,

$$\beta^* = \frac{1 - (1 - p)^{G^* T_{\min}}}{G^* T_{\min}}. \quad (21)$$

where $\beta^* = p_L^* \cdot G^* T_{\min}$. Let $\bar{\Lambda}^*$ denote the expected task-arrival rate at the typical AP (or CS). Then $\bar{\Lambda}^* = \bar{N} \beta^*$ where \bar{N} is the expected number of mobiles connected to the AP. Since $\bar{N} = (1 - \delta)(1 - \epsilon) \frac{\lambda_m}{\lambda_b}$,

$$\bar{\Lambda}^* = (1 - \delta)(1 - \epsilon) \frac{\lambda_m}{\lambda_b} \beta^*. \quad (22)$$

Remark 4 (Effects of Network Parameters). Using (13), (18) and (21), one can infer that

$$\bar{\Lambda}^* \propto \begin{cases} p \frac{\lambda_m}{\lambda_b}, & \frac{\lambda_m}{\lambda_b} \rightarrow 0, \\ B \left(\frac{\lambda_m}{\lambda_b} \right)^{-\frac{\alpha}{2} + 1}, & \frac{\lambda_m}{\lambda_b} \rightarrow \infty. \end{cases} \quad (23)$$

The first case corresponds to a sparse network whose performance is not limited by bandwidth and interference. Then the expected task arrival-rate grows linearly with the task-generation probability per slot, p , and the expected number of mobiles per AP, λ_m/λ_b . For the second case, in a dense network that is bandwidth-and-interference limited, the rate grows linearly the bandwidth B , but decreases with λ_m/λ_b . The reason for the decrease is the bandwidth for offloading is reduced so that a larger spreading factor is available for suppressing interference to meet the network-coverage requirement. Consequently, the load for the CSs is lighter for a dense (thus comm-limited) network, reducing comp-latency as shown in the sequel.

Consider tasks arrivals for the case of synchronous offloading. Unlike the asynchronous counterpart with arrivals spread over each frame, the tasks from mobiles arrive the typical AP at the beginning of each frame. Thus, it is useful to characterize the expected number of task arrivals per frame, denoted as \bar{A}^* , which can be written as $\bar{A}^* = \bar{N} p_L^*$. It follows that

$$\bar{A}^* = (1 - \delta)(1 - \epsilon) \frac{\lambda_m}{\lambda_b} p_L^*. \quad (24)$$

Remark 5 (Effects of Network Parameters). In a dense network ($\lambda_m/\lambda_b \rightarrow \infty$), it can be obtained from (13), (18), and (20) that $p_L^* \approx 1$. Then it follows from (24) that the expected number of tasks per frame increases linearly with the expected number of mobiles per AP, λ_m/λ_b .

IV. COMPUTATION LATENCY ANALYSIS: ASYNCHRONOUS OFFLOADING

This section aims at analyzing the comp-latency of the asynchronous offloading where task arrival and departure are randomly distributed over time. Given the Markov model of Fig. 5, we derive the network stability condition in Definition 2 and bounds of the average comp-latency.

A. Optimal Control of VMs

On one hand, creating a large number of VMs at the typical CS can slow down its computation rate due to the mentioned I/O interference between VMs. On the other hand, too few VMs can lead to marginal gain from parallel computing. Therefore, the number of VMs should be optimally controlled based on the number of waiting tasks. To this end, let $\mu(m)$ denote the computation rate given m VMs. Given the computation model in (3), it follows from $\mu(m) = m/T_c(m)$ that:

$$\mu(m) = \frac{m}{T_0}(1+d)^{1-m}. \quad (25)$$

By analyzing the derivative of $\mu(m)$, one can find that the function is monotone increasing before reaching a global maximum and after that it is monotone decreasing. Thereby, the value of m that maximizes $\mu(m)$, denoted as m_{\max} , can be found with the integer constraint

$$m_{\max} = \text{round}\left(\frac{1}{\ln(1+d)}\right), \quad (26)$$

where $\text{round}(x)$ rounds x to the nearest integer. The said properties of the function $\mu(m)$ and the derived m_{\max} in (26) suggest the following optimal VM-control policy.

Proposition 2 (Optimal VM Control). To maximize the computation rate at the typical CS, the optimal VM-control policy is to create m_{\max} VMs if there are a sufficient number of tasks for computation or otherwise create as many VMs as possible until the buffer is empty. Consequently, the maximum computation rate, denoted as $\mu^*(m)$, given m tasks at the CS (being computed or in the buffer) is

$$\mu^*(m) = \begin{cases} \frac{m}{T_0}(1+d)^{1-m}, & 1 \leq m \leq m_{\max}, \\ \frac{m_{\max}}{T_0}(1+d)^{1-m_{\max}}, & m > m_{\max}, \end{cases} \quad (27)$$

where m_{\max} is given in (26).

For ease notation, the maximum computation rate, $\mu(m_{\max})$, is re-denoted as μ_{\max} hereafter.

B. Computation Rates under Network Stability Constraint

This subsection focuses on analyzing the condition for the maximum computation rate of the typical CS to meet the network stability constraint in Definition 2. The analysis combines the

results from queueing theory, stochastic geometry and parallel computing. The said constraint requires ρ -fraction of mobiles, or equivalently ρ -fraction of CSs, to be stable, namely that comp-latency is finite. According to queueing theory, stabilizing a typical CS requires that the task-arrival rate Λ should be strictly smaller than the maximum departure rate $\mu^*(m_{\max})$: $\Lambda < \mu_{\max}$ [26]. Note that the former is a RV proportional to the random number of mobiles, N , connected to the typical CS while the latter is a constant. Then the stability probability p_s is given as

$$p_s = \Pr[\Lambda < \mu_{\max}] = \Pr\left[N < \frac{\mu_{\max}}{\beta^*}\right], \quad (28)$$

where β^* is the task-offloading rate given in (21). It follows from the network spatial model that N is a Poisson distributed RV with the mean $\bar{N} = (1 - \delta)(1 - \epsilon)\frac{\lambda_m}{\lambda_b}$. Using the distribution and (28) and applying Chernoff bound, we can obtain an upper bound on the maximum computation rate required to meet the stability constraint as shown below.

Proposition 3 (Computation Rates for ρ -Stability). For the CSN to be ρ -stable, a sufficient condition for the maximum computation rate of the typical CS is given as

$$\mu_{\max} \geq \bar{\Lambda}^* \cdot \exp\left(W\left(\frac{-\ln(\rho)}{\bar{N}e} - \frac{1}{e}\right) + 1\right), \quad (29)$$

where $W(\cdot)$ is the Lambert function, the expected mobiles connected to the typical CS $\bar{N} = (1 - \delta)(1 - \epsilon)\frac{\lambda_m}{\lambda_b}$, and $\bar{\Lambda}^*$ represents the expected arrival rate given in (22).

Proof: See Appendix VI-B. □

The above result shows that to satisfy the network-stability constraint, the maximum computation rate of each CS, μ_{\max} , should be larger than the expected task-arrival rate, $\bar{\Lambda}^*$, scaled by a factor larger than one, namely the exponential term in (29). Moreover, the factor grows as the stability probability $(1 - \rho)$ increases.

Last, it is useful for subsequent analysis to derive the expected arrival rate conditioned on that the typical CS is stable as shown below.

Lemma 4 (Expected Task-Arrival Rates for Stable CSs). Given that the typical CS is stable, the expected task-arrival rate is given as

$$\mathbb{E}[\Lambda | \Lambda < \mu_{\max}] = \bar{\Lambda}^* \left(1 - \frac{\Pr(N = \lfloor R \rfloor)}{1 - \rho}\right), \quad (30)$$

where $R = \frac{\mu_{\max}}{\beta^*}$ measures the maximum number of mobiles the CS can serve, β^* is the task-offloading rate per mobile in (21), \bar{N} and $\bar{\Lambda}^*$ follow those in Proposition 3, and the Poisson distribution function $\Pr(N = n) = \frac{\bar{N}^n e^{-\bar{N}}}{n!}$.

Proof: See Appendix VI-C. □

C. Expected Computation Latency

In this subsection, the expected comp-latency, T_{comp} , is analyzed using the Markov chain in Fig. 5 and applying queueing theory. Exact analysis is intractable due to the fact that the departure rate $\mu(m)$ in the Markov chain is a non-linear function of state m . This difficulty is overcome by modifying the Markov chain to give two versions corresponding to a M/M/ m and a M/M/1 queues, yielding an upper and a lower bounds on T_{comp} , respectively.

First, consider upper bounding T_{comp} . To this end, the departure rate $\mu(m)$ in the Markov chain in Fig. 5 with the following lower bound obtained by fixing all exponents as $(1 - m_{\text{max}})$:

$$\mu^-(m) = \begin{cases} \frac{m}{T_0}(1+d)^{1-m_{\text{max}}}, & 1 \leq m \leq m_{\text{max}}, \\ \frac{m_{\text{max}}}{T_0}(1+d)^{1-m_{\text{max}}}, & m > m_{\text{max}}. \end{cases} \quad (31)$$

As a result, the modified Markov chain is a M/M/ m_{max} queue. The corresponding waiting time, denoted as T_{comp}^+ , upper bounds T_{comp} since it reduces the computation rate. Applying classic results on M/M/ m queues (see e.g., [26]), the waiting time, T_{comp}^+ , for task arrival rate Λ is

$$T_{\text{comp}}^+(\Lambda) = \frac{m_{\text{max}}}{\mu^-(m_{\text{max}})} + \frac{\tau \left(\frac{\Lambda}{\mu^-(m_{\text{max}})} \right)^{m_{\text{max}}}}{m_{\text{max}}! \mu^-(m_{\text{max}}) \left(1 - \frac{\Lambda}{m_{\text{max}} \mu^-(m_{\text{max}})} \right)^2}, \quad (32)$$

where the coefficient τ is given as

$$\tau = \left[\sum_{m=0}^{m_{\text{max}}-1} \frac{1}{m!} \left(\frac{\Lambda}{\mu^-(m_{\text{max}})} \right)^m + \sum_{m=m_{\text{max}}}^{\infty} \frac{m_{\text{max}}^{m_{\text{max}}-m}}{m_{\text{max}}!} \left(\frac{\Lambda}{\mu^-(m_{\text{max}})} \right)^m \right]^{-1}. \quad (33)$$

Using (30), (31) and (32), the upper bound is given in the following theorem.

Theorem 2.A (Comp-Latency for Asynchronous Offloading). Consider asynchronous offloading. The average comp-latency is upper bounded as

$$T_{\text{comp}} \leq \frac{m_{\text{max}}}{\mu_{\text{max}}} + \left(\frac{m_{\text{max}}}{\mu_{\text{max}}} \right)^2 \cdot \frac{\bar{\Lambda}^*}{(m_{\text{max}} - 1)! (m_{\text{max}} - 1)^2} \cdot \left(1 - \frac{\Pr(N = \lfloor R \rfloor)}{1 - \rho} \right), \quad (34)$$

where R follows that in Lemma 4, and $\bar{\Lambda}^*$ and μ_{max} are specified in (22) and (27), respectively.

Proof: See Appendix VI-D. \square

Note that the positive factor $\left(1 - \frac{\Pr(N=\lfloor R \rfloor)}{1-\rho} \right)$ accounts for Poisson distribution of mobiles.

Next, a lower bound on T_{comp} is obtained as follows. One can observe from the Markov chain in Fig. 5 that for states $m \leq m_{\text{max}}$, the departure rates are smaller than the maximum, μ_{max} . The reason is that for these states, there are not enough tasks for attaining the maximum rate by parallel computing. Then replacing all departure rates in the said Markov chain with the

maximum μ_{\max} leads to a lower bound on T_{comp} . The resultant Markov chain corresponds to a M/M/1 queue. Then using the modified Markov chain and the well-known results from M/M/1 queue (see e.g., [26]), the comp-latency for given arrival rate Λ can be lower bounded as

$$T_{\text{comp}}(\Lambda) \geq \frac{1}{\mu_{\max} - \Lambda}. \quad (35)$$

By taking expectation over Λ and applying Jensen's inequality,

$$T_{\text{comp}} = E[T_{\text{comp}}(\Lambda)] \geq E\left[\frac{1}{\mu_{\max} - \Lambda} \mid \Lambda < \mu_{\max}\right] \geq \frac{1}{\mu_{\max} - E[\Lambda \mid \Lambda < \mu_{\max}]}. \quad (36)$$

Using (36) and Lemma 4, we obtain the following result.

Theorem 2.B (Comp-Latency for Asynchronous Offloading). Consider asynchronous offloading. The average comp-latency is lower bounded as

$$T_{\text{comp}} \geq \frac{1}{\mu_{\max} - \bar{\Lambda}^* \cdot \left(1 - \frac{\Pr(N=\lfloor R \rfloor)}{1-\rho}\right)}, \quad (37)$$

where R follows that in Lemma 4, and $\bar{\Lambda}^*$ and μ_{\max} are specified in (22) and (27), respectively.

Remark 6 (Computation-Resource Provisioning). Consider a MEC network provisioned with sufficient computation resources, $\mu_{\max}/\bar{\Lambda}^* \gg 1$. It follows from Theorem 2.B

$$T_{\text{comp}} \geq \frac{1}{\mu_{\max}} \left(1 + \frac{c_1 \bar{\Lambda}^*}{\mu_{\max}}\right),$$

where c_1 is a constant. This lower bound has a similar form as the upper bound in Theorem 2.A. From these results, one can infer that the comp-latency for asynchronous offloading can be approximated written in the following form:

$$T_{\text{comp}} \approx \frac{c_2}{\mu_{\max}} \left(1 + \frac{c_3 \bar{\Lambda}^*}{\mu_{\max}}\right), \quad \frac{\mu_{\max}}{\bar{\Lambda}^*} \gg 1, \quad (38)$$

where $\{c_2, c_3\}$ are constants. The result suggests that to contain comp-latency, the provisioning of computation resources for the MEC network must consider two factors. First of all, the maximum computation rate, μ_{\max} , for each CS must be sufficient large. At the same time, the computation rate must scale linearly with the total arrival rate such that the computation resource allocated for a single offloaded task, measured by the ratio $\mu_{\max}/\bar{\Lambda}^*$, is sufficiently large.

D. MEC Network Provisioning and Planning

Combining the results from the preceding analysis on comm-latency and comp-latency yields some guidelines for the provisioning and planning of a MEC network as discussed below. Assume that the network is required to support computing for mobiles with density λ_m with targeted

expected comm-latency T_{comm} and comp-latency T_{comp} . The network resources are quantified by the bandwidth B , the density of AP (or CS) λ_b , the maximum computing rate of each CS μ_{max} .

First, consider the planning of the RAN. Combining the above results suggest the following guidelines for network provisioning and planning. As shown in Section III-C, under the network-coverage constraint $(1-\epsilon)$, the expected task-arrival rate at a AP, representing the RAN offloading throughput, is a quasi-concave function of the expected number of mobiles per AP, λ_m/λ_b , with a global maximum. Therefore, given a mobile density λ_m , the AP density should be chosen for maximizing the RAN offloading throughput. Next, based on results in Theorem 1 and (21), sufficient large channel bandwidth B should be provisioned to achieve the targeted T_{comm} for given mobile and AP densities, mobile task-generation rates, and task sizes.

Next, consider the planning of the CSN. Under the network-stability constraint, the maximum CS computing rate for parallel computing should be planned to be larger than the expected task-arrival rate scaled by a factor larger than one, which is determined by the allowed fraction of unstable CSs (see Proposition 3). Then, the maximum computing rate should be further planned to achieve the targeted T_{comp} for computing an offloaded task using Theorems 2.A and 2.B.

V. COMPUTATION LATENCY ANALYSIS: SYNCHRONOUS OFFLOADING

In the preceding section, the process of asynchronous task arrival at a CS can be approximated using a Markov chain, allowing tractable analysis of comp-latency using theories of M/M/ m and M/M/1 queues. This approach is inapplicable for synchronous offloading and the resultant periodic task arrivals at the CS. Though tractable analysis in general is difficult, it is possible for two special cases defined as follows.

Definition 3 (Special Cases: Light-Traffic and Heavy-Traffic). A *light-traffic* case refers to one that the task-arrival rate is much smaller than the computation rate such that the queue at the CS is always empty as observed by a new arriving task. In contrast, a *heavy-traffic* case refers to one that the task-arrival rate is close to the computation rate such that there are always at least m_{max} tasks in the queue.

The comp-latency for these two special cases are analyzed to give insights into the performance of CSN with underloaded CSs and those with overloaded CSs.

A. Expected Computation Latency with Light-Traffic

First, the dynamics of the task queue at the typical CS is modelled as follows. Recall that task arrivals are periodical, occurring at the beginning of every frame. Consider the typical CS.

Let Q_t and A_t denote be the numbers of existing and arriving tasks at the beginning of frame t , respectively, and C_t the number of departing tasks during frame t . Then the evolution of Q_t can be described mathematically as

$$Q_{t+1} = \max [Q_t + A_{t+1} - C_t, 0]. \quad (39)$$

The general analysis of comp-latency using (39) is difficult. The main difficulty lies in deriving the distribution of C_t that depends on the number of VMs that varies continuously in time since the computation time for simultaneous tasks are random and inter-dependent. To overcome the difficulty, consider the case of light-traffic where a number of offloaded tasks arrives at the typical CS to see an empty queue and an idling sever. Correspondingly, the evolution equation in (39) is modified such that given $A_{t+1} \neq 0$, $Q_t = C_t = 0$, yielding $Q_{t+1} = A_{t+1}$.

Next, given this simple equality, deriving the expected comp-latency reduces to analyzing the latency for computing a random number of A tasks at the CS, which arrives at the beginning of an arbitrary frame. Without loss of generality, the tasks are arranged in an ascending order in terms of computation time and referred to as Task $1, 2, \dots, A$. Moreover, let \mathcal{L}_n denote the expected computing time for Task n and hence $\mathcal{L}_1 \leq \mathcal{L}_2 \leq \dots \leq \mathcal{L}_A$. Then the expected comp-latency T_{comp} can be written in terms of $\{\mathcal{L}_n\}$ as

$$T_{\text{comp}} = E_A \left[\frac{\sum_{n=1}^A \mathcal{L}_n}{A} \middle| A > 0 \right]. \quad (40)$$

To obtain bounds on T_{comp} in closed form, a useful result is derived as follows. Given m VMs, recall that the computation time of a task follows the exponential distribution with the mean being the inverse of the computation rate $\mu(m)$ in (27). Using the memoryless property of exponential distribution, a useful relation between $\{\mathcal{L}_n\}$ is obtained as

$$\mathcal{L}_n = \mathcal{L}_{n-1} + \frac{1}{\mu(m)} = \begin{cases} \mathcal{L}_{n-1} + \frac{1}{\mu_{\max}}, & 1 \leq n \leq A - m_{\max} + 1, \\ \mathcal{L}_{n-1} + \frac{1}{\mu(A - n + 1)}, & \text{otherwise,} \end{cases} \quad (41)$$

with $\mathcal{L}_0 = 0$. Note that $\mu(1) \leq \mu(m) \leq \mu_{\max}$ for all m . Thus, it follows from (41) that

$$\frac{n}{\mu_{\max}} \leq \mathcal{L}_n \leq \frac{n}{\mu(1)}. \quad (42)$$

Substituting (42) into (40) gives

$$\frac{1}{\mu_{\max}} \cdot E_A \left[\frac{\sum_{n=1}^A n}{A} \middle| A > 0 \right] \leq T_{\text{comp}} \leq \frac{1}{\mu(1)} \cdot E_A \left[\frac{\sum_{n=1}^A n}{A} \middle| A > 0 \right]. \quad (43)$$

Recalling the number of arriving tasks \mathcal{A} follows a Poisson RV with mean \bar{A}^* of (24), bounds on the comp-latency is obtained shown in the following theorem.

Theorem 3 (Comp-Latency for Synchronous Offloading). Consider the case of synchronous offloading with *light-traffic*. The expected comp-latency can be bounded as

$$\frac{1}{2\mu_{\max}} \left(1 + \frac{\bar{A}^*}{1 - e^{-\bar{A}^*}} \right) \leq T_{\text{comp}} \leq \frac{1}{2\mu(1)} \left(1 + \frac{\bar{A}^*}{1 - e^{-\bar{A}^*}} \right).$$

where \bar{A}^* is the expected number of arriving tasks to the typical CS per frame given in (24).

Remark 7 (Comparison with Asynchronous Offloading). From the results in the above theorem, one can infer that for the current case, the comm-latency can be approximated as

$$T_{\text{comp}} \approx \begin{cases} \frac{1}{\mu(1)}, & \bar{A}^* \rightarrow 0, \\ \frac{\bar{A}^*}{2\mu(m_{\max})}, & \bar{A}^* \gg 1. \end{cases} \quad (44)$$

Comparing the expression with the counterpart for asynchronous offloading in (38), it is unclear which case leads to longer comp-latency. However, simulation shows that in general, synchronizing offloading tends to incur longer latency by overloading CSs and thereby suffering more from I/O interference in parallel-computing.

B. Expected Computation Latency with Heavy-Traffic

This subsection focuses on analyzing the expected comp-latency, T_{comp} , for the case of heavy-traffic as defined in Definition 3. For this case, with the queue being always non-empty, the equation in (39) describing the queue evolution reduces to $Q_{t+1} = Q_t + \mathcal{A}_t - \mathcal{C}_t$. The key step in deriving T_{comp} is to apply the said equation to the analysis of the expected queue length. The technique involves taking expectation of the squares of the two sides of the equation as follows:

$$E[Q_{t+1}^2] = E[(Q_t + \mathcal{A}_t - \mathcal{C}_t)^2] = E[Q_t^2] + E[(\mathcal{A}_t - \mathcal{C}_t)^2] + 2E[Q_t(\mathcal{A}_t - \mathcal{C}_t)]. \quad (45)$$

Since Q_t , \mathcal{A}_t and \mathcal{C}_t are independent of each other and $E[Q_{t+1}^2] = E[Q_t^2]$ given the stable CS,

$$E[Q] = \frac{E[\mathcal{A}^2] + E[\mathcal{C}^2] - 2E[\mathcal{A}]E[\mathcal{C}]}{2(E[\mathcal{C}] - E[\mathcal{A}])}, \quad (46)$$

where the subscripts t of Q_t , \mathcal{A}_t and \mathcal{C}_t are omitted to simplify notation. Given the number of connected mobiles, N , the number of arrival tasks \mathcal{A} follows a Poisson distribution with the first and second moments being $E(\mathcal{A} | N) = Np_L^*$ and $E(\mathcal{A}^2 | N) = Np_L^* + (Np_L^*)^2$ respectively, where the task-offloading probability p_L^* is given in (20). Next, under the heavy-traffic assumption, the total computation rate of the CS is μ_{\max} . It follows that the departure process at the

typical CS is Poisson distributed where the first and second moments are $E[C] = \mu_{\max} L^*$ and $E[C^2] = \mu_{\max} L^* + [\mu_{\max} L^*]^2$, respectively. Substituting the results into (46) gives

$$E[\mathcal{Q} | N] = \frac{N p_L^*}{\mu_{\max} L^* - N p_L^*} + \frac{1}{2} \cdot (\mu_{\max} L^* - N p_L^*) + \frac{1}{2}. \quad (47)$$

In addition, to satisfy the condition for stabilizing the CS, the arrival rate $E[\mathcal{A}]$ should be strictly smaller than the departure rate $E[C]$. This places a constraint on the maximum of N , namely that $N \leq \lfloor R \rfloor$ with R defined in Lemma 4. Under this constraint, applying Little's theorem obtains the expected comp-latency T_{comp} as

$$T_{\text{comp}} = \left\{ E \left[\frac{E[\mathcal{Q} | N]}{E[\mathcal{A} | N]} \middle| N \leq \lfloor R \rfloor \right] - \frac{1}{2} \right\} \cdot L^*. \quad (48)$$

Combining (47) and (48) yields the main result of this sub-section as shown below.

Theorem 4 (Comp-Latency for Synchronous Offloading). Consider the case of synchronous offloading with heavy-traffic. The expected comp-latency is given as

$$T_{\text{comp}} = \left\{ \frac{1}{p_L^*} E \left[\frac{1}{R - N} \right] + \frac{1}{2} \left(R + \frac{1}{p_L^*} \right) E \left[\frac{1}{N} \right] - 1 \right\} L^*, \quad (49)$$

where the constant R and the distribution of N follow those in Lemma 4.

Remark 8 (Comparison with Asynchronous Offloading). By applying Jensen's inequality, the comp-latency of (49) can be lower bounded as

$$T_{\text{comp}} \geq \frac{1}{\mu_{\max} - c_4 \bar{\Lambda}^*} + \frac{L^*}{2} \cdot \frac{\mu(m_{\max})}{c_4 \bar{\Lambda}^*} + \frac{1}{c_4 \bar{\Lambda}^*} - L^*, \quad (50)$$

where c_4 is a constant. Since for the case of heavy-traffic, the task-arrival rate $c_4 \bar{\Lambda}^*$ approaches the maximum computation rate μ_{\max} ,

$$\boxed{T_{\text{comp}} \geq \frac{1}{\mu_{\max} - c_4 \bar{\Lambda}^*}, \quad c_4 \bar{\Lambda}^* \rightarrow \mu_{\max}.} \quad (51)$$

The above lower bound has the same form as the synchronous-offloading counterpart in (37). Both diverge as the task-arrival rate approaches the maximum computation rate.

VI. SIMULATION RESULTS

In this section, analytical results on comm-latency and comp-latency are evaluated by simulation. The simulation parameters have the following default settings unless specified otherwise. The densities of APs and mobiles are $\lambda_b = 2 \times 10^{-2} \text{ m}^{-2}$ and $\lambda_m = 5 \times 10^{-2} \text{ m}^{-2}$, respectively. The SIR threshold is set as $\theta = 1 \text{ dB}$ and the path-loss exponent is $\alpha = 3$. For the network coverage parameter δ is $\delta = 10^{-2}$, corresponding to the radius of MEC service zone being

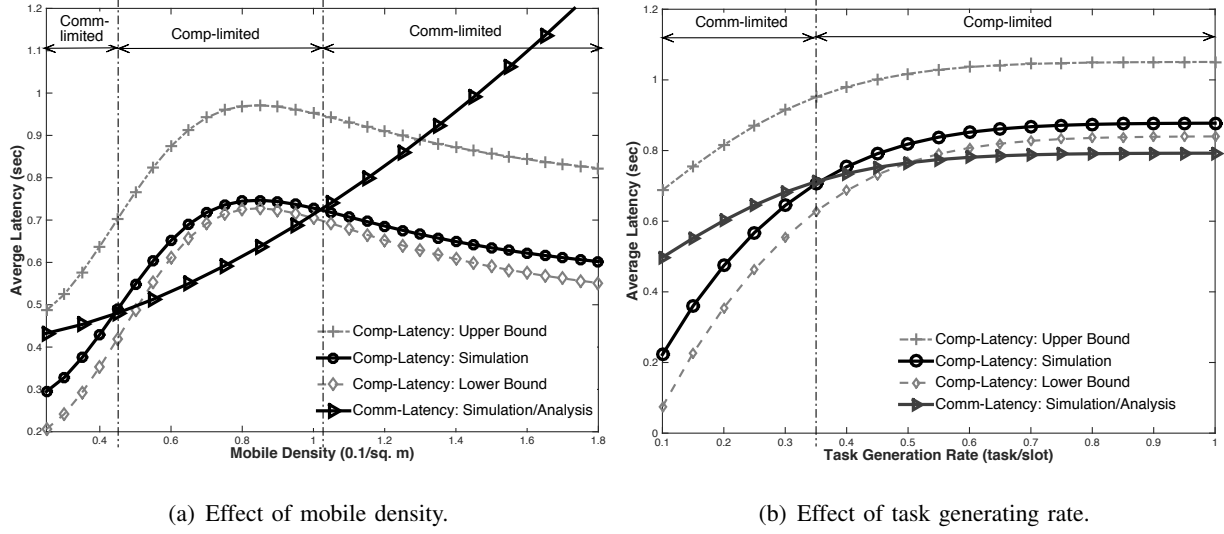
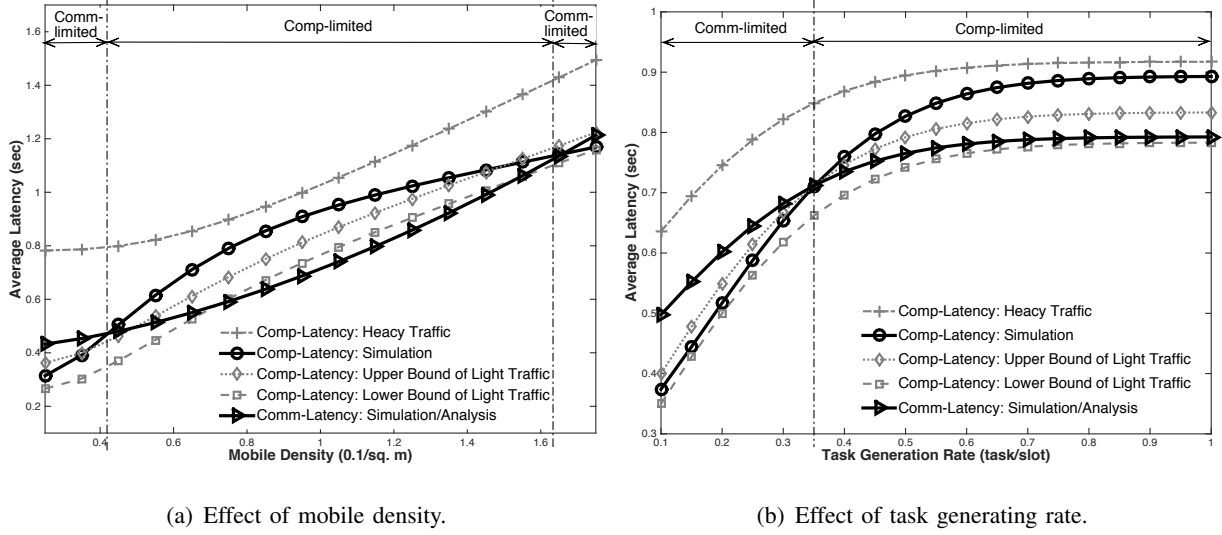


Figure 6: Comparisons between comm-latency and comp-latency for the case of asynchronous offloading.

$r_0 = 12\text{m}$. The total bandwidth is $B = 6\text{ MHz}$. The data size per task is fixed as $\ell = 0.5 \times 10^6$ bits. The single-task computation time T_0 in the parallel-computation model is set as $T_0 = 0.1$ (sec) and the factor arising from I/O interference is $d = 0.2$. The task generation probability per slot is $p = 0.2$. The parameters ϵ and ρ are both set as 0.05.

Fig. 6 compares expected comm-latency and comp-latency for the case of asynchronous offloading. The effects of mobile density λ_m and task generating rate p are investigated and several observations can be made. As shown in Fig. 6(a), the expected comp-latency as a function of the mobile density is observed to exhibit the *quasi-concavity* described in Remark 2. In contrast, the expected comm-latency is a monotone increasing function following the scaling law in Remark 3. These properties lead to the partitioning of the range of mobile density into three network-operation regimes as indicated in Fig. 6(a). In particular, the middle range corresponds to comp-limited regime while others are comm-limited. Next, consider the effect of task-generation rate at mobiles, specified by the task-generation probability p . Both types of latency are observed to converge to corresponding limits as the rate grows. Their different scaling laws result in the partitioning of the range of task-generation rate into comm-limited and comp-limited regimes. Last, one can observe from both figures that the lower bound on comp-latency as derived in (37) is tighter than the upper bound therein.

Fig. 7 compares expected comm-latency and comp-latency for the case of synchronous offloading. The same observations in the case of synchronous offloading also apply in the current case except that the quasi-concavity of the expected comp-latency with respect to mobile density is not shown in the considered range. Some new observations can be made as follows. Comparing



(a) Effect of mobile density.

(b) Effect of task generating rate.

Figure 7: Comparisons between comm-latency and comp-latency for the case of synchronous offloading. Fig. 6 and 7 shows that synchronizing offloading results in longer comp-latency. Next, the center of the comp-limited range in Fig. 7(a) corresponds to the case of heavy-traffic studied in Section V-B. Consequently, the derived upper bound on expected comp-latency for this case is tight. For other ranges of mobile density, the bounds derived for the case of light traffic are tighter. Last, Fig. 7(b) shows that the expected comp-latency is tightly approximated by bounds derived for the light-traffic case when the task-arrival rate is small (≤ 0.3) and by that for the heavy-traffic case when the rate is large (> 0.7), validating the results.

APPENDIX I

A. Proof of Lemma 2

The first derivative of $\xi(G)$ for G given in (6) can be derived as:

$$\frac{\partial \xi(G)}{\partial G} = -\frac{\Delta}{\alpha} \left(G^{-\frac{2+\alpha}{\alpha}} (\alpha G T_{\min} \ln(1-p)(1-p)^{G T_{\min}} - 2(1-p)^{G T_{\min}} + 2) \right), \quad (52)$$

where $\Delta = \frac{2(1-\delta) \ln \delta^{-1}}{\alpha} \mathcal{B}(\alpha) \left(\frac{\lambda_m}{\lambda_b} \right) \theta_{\alpha}^{\frac{2}{\alpha}}$. The existence of g_0 is easily proved because (52) is strictly positive and negative when $G \rightarrow 0$ and $G \rightarrow \infty$ respectively. Next, the solution of g_0 to solve $\frac{\partial \xi(G)}{\partial G} = 0$ is $g_0 = \frac{\alpha W\left(-\frac{2}{\alpha} e^{-\frac{2}{\alpha}}\right) + 2}{\alpha T_{\min} \ln(1-p)}$, where $W(x)$ is the Lambert function. Since the value inside the Lambert function is negative, there are two candidates for g_0 : one is from the principle branch of Lambert function $W\left(-\frac{2}{\alpha} e^{-\frac{2}{\alpha}}\right)$, and the other is the lower branch $W_{-1}\left(-\frac{2}{\alpha} e^{-\frac{2}{\alpha}}\right)$. The principle branch makes $g_0 = 0$, but the lower branch satisfies $g_0 > 0$, completing the proof.

B. Proof of Proposition 3

Applying Chernoff bound on p_s in (28) makes

$$p_s \geq 1 - \exp\left(-\frac{\mu_{\max}}{\beta^*} \ln\left(\frac{\mu_{\max}}{\bar{N}\beta^*}\right) + \frac{\mu_{\max}}{\beta^*} - \bar{N}\right) \geq 1 - \rho, \quad (53)$$

which is equivalent to $\mu_{\max} \geq \bar{\Lambda}^* \cdot \exp\left(W\left(\frac{-\ln(\rho)}{\bar{N}e} - \frac{1}{e}\right) + 1\right)$ as Proposition 3 shows.

C. Proof of Lemma 4

Noting the expect task arrival of stable CSs is proportional to the average number of connected mobiles. Therefore, we have $E[\Lambda | \Lambda < \mu_{\max}] = \beta^* \cdot \frac{\sum_{n=1}^R n \cdot \frac{\bar{N}^n e^{-\bar{N}}}{n!}}{1-\rho} = \bar{N}\beta^* \left(1 - \frac{\Pr(N=\lfloor R \rfloor)}{1-\rho}\right)$, where $\Pr(N = \lfloor R \rfloor) = \frac{\bar{N}^{\lfloor R \rfloor} e^{-\bar{N}}}{\lfloor R \rfloor!}$, ending the proof.

D. Proof of Theorem 2.A

Substituting $\tau = 1$ into (32) and then applying $\left(\frac{\Lambda}{\mu^-(m_{\max})}\right)^{m_{\max}} \leq \frac{\Lambda}{\mu^-(m_{\max})}$ as well as $\left(1 - \frac{\Lambda}{m_{\max}\mu^-(m_{\max})}\right)^2 \leq \left(1 - \frac{1}{m_{\max}}\right)^2$ give an upper bound of $T_{\text{comp}}^+(\Lambda)$ as

$$T_{\text{comp}}^+(\Lambda) \leq \frac{m_{\max}}{\mu^-(m_{\max})} + \frac{\frac{\Lambda}{\mu^-(m_{\max})}}{m_{\max}! \mu^-(m_{\max}) \left(1 - \frac{1}{m_{\max}}\right)^2}. \quad (54)$$

The spatial average on (54) based on Lemma 4 gives the final result in Theorem 2.A.

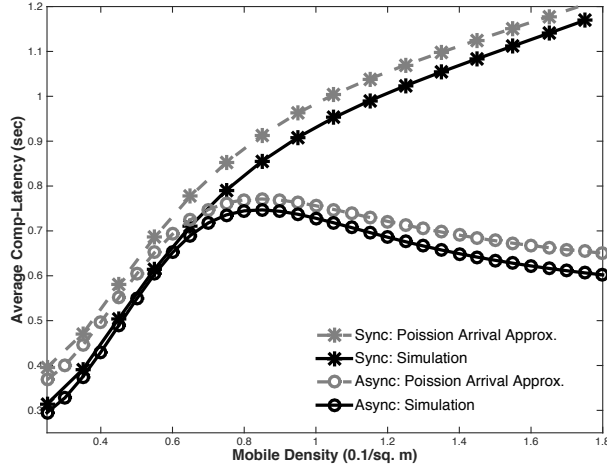
APPENDIX II: SUMMARY OF NOTATION

Notation	Meaning
$\Omega, \lambda_b, \Phi, \lambda_m$	PPP of APs, density of Ω , PPP of mobiles, density of Φ
$r_0, \mathcal{O}(Y, r_0)$	Offloading range, MEC service zone
L, p, p_L	Number of slots per frame, task-generating rate at mobile, task-offloading probability
$\eta, g, \alpha, \theta, G$	Transmit power of AP, fading factor, path-loss exponent, SIR threshold, spreading factor
t_0, B, ℓ, d	Slot length (in sec), bandwidth per channel, number of bits per task, degradation factor of I/O interference
$T_0, T_{\text{comm}}, T_{\text{comp}}$	Expected computation time per task, average comm-latency, average comp-latency
$\Lambda, \mu, m_{\max}, \mu_{\max}$	Task arrival rate to CS, computation rate, maximal number of VMs, maximum computation rate
$\mathcal{A}_t, \mathcal{C}_t, \mathcal{Q}_t$	Number of task arrival at frame t , number of task departure during frame t , the remaining tasks at frame t
ϵ, ρ, \bar{N}	Network coverage parameter, network stability parameter, expected number of mobiles connected to a AP
$\beta^*, \bar{\Lambda}^*, \bar{A}^*$	Expected task offloading rate, expected task arrival rate, expected number of arrival tasks per frame

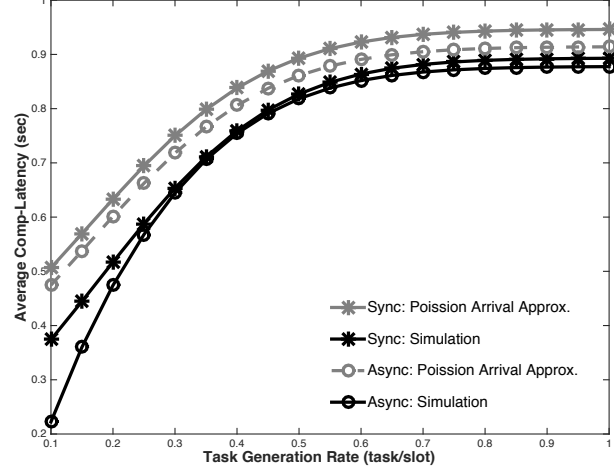
APPENDIX III: SUPPLEMENTARY SIMULATION RESULTS

In Fig. 8, the the comp-latency of the Poisson arrival assumption of task-arrival process is compared with that under the Poisson arrival assumption of Assumption 2, showing that the tasks arrival process at AP can be well approximated to the Poisson task arrival assumption.

Figs. 9 and 10 show the effects of the computation capability of CS, the computation time T_0 and the degradation factor d , on the comp-latency for asynchronous and synchronous offloading cases, respectively. Both of the comp-latencies increase exponentially when the CS's capability becomes worse, namely T_0 or d become larger, which agrees with the intuition.

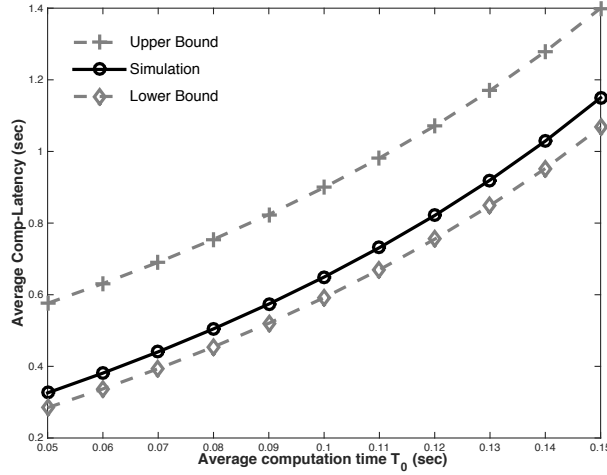


(a) Effect of mobile density.

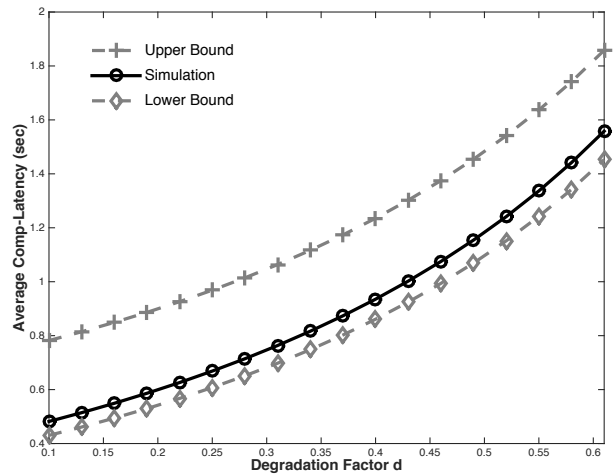


(b) Effect of task generating rate.

Figure 8: Comparison to the Poisson Approximation in Assumption 2.



(a) Effect of edge-computing time per task.



(b) Effect of degradation factor due to I/O interference.

Figure 9: The performance of average latencies for the asynchronous offloading case.

Finally, we plot the average comp-latency ratio of asynchronous and synchronous offloading cases in Fig. 11. The ratios in both figures are smaller than 1 because the comp-latency of the asynchronous offloading is always smaller than the synchronous counterpart. Specifically, in Fig. 11(a), the ratio first stays constant when mobile density is small and then decreases with mobile density grows. As mobiles becomes denser, the number of offloading tasks at the beginning of each frame increases, resulting in severe I/O interference than the asynchronous counterpart of which the task arrivals are distributed over frame. On the other hand, in Fig. 11(b), it is observed that the ratio grows and then converges to a constant when p increases. In other words, the gap of comp-latency between two offloading cases is becoming smaller when the

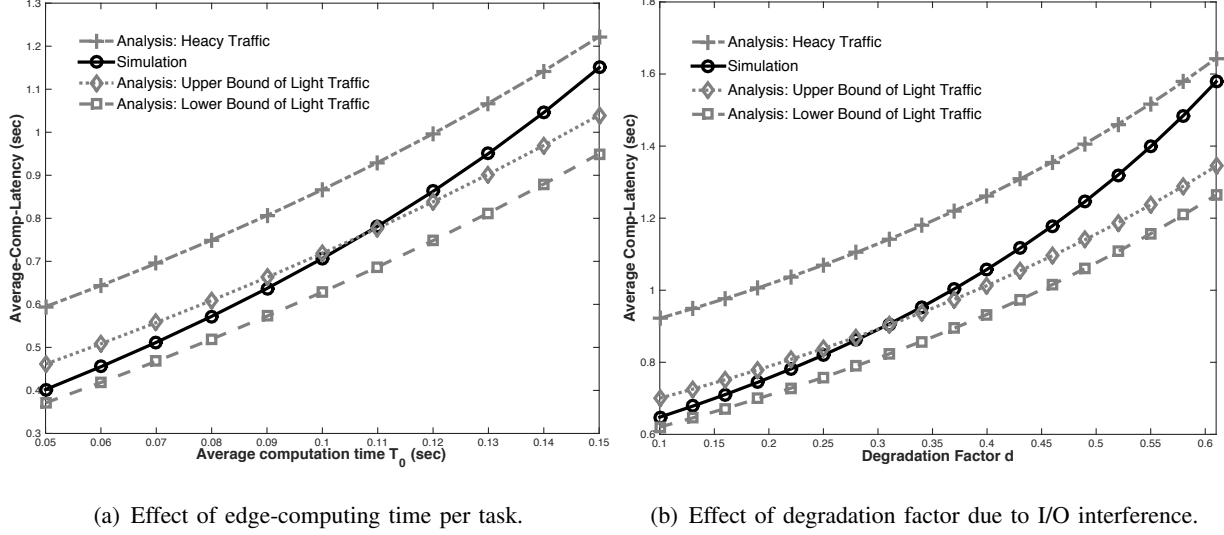


Figure 10: The performance of average latencies for the synchronous offloading case. Both the light- and heavy-traffic cases are plotted.

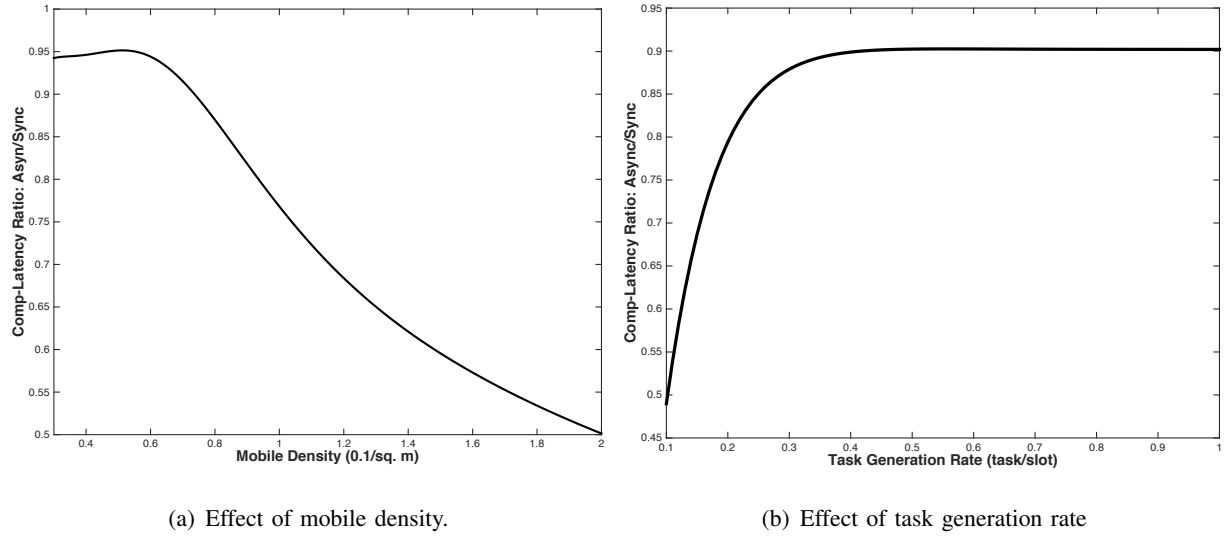


Figure 11: The average comp-latency ratio: asynchronous offloading over synchronous offloading. task arrival becomes heavier, aligning with the discussion in Remark 8.

REFERENCES

- [1] F. ETSI, Sophia Antipolis, “Mobile-edge computing introductory technical white paper,” *Mobile-Edge Comput. Ind. Initiative, White Paper*, Sep. 2014.
- [2] T. Taleb, K. Samdanis, B. Mada, H. Flinck, S. Dutta, and D. Sabella, “On multi-access edge computing: A survey of the emerging 5G network edge architecture & orchestration,” *IEEE Commun. Surveys Tuts.*, vol. 19, pp. 1657–1681, May 2017.
- [3] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, “A survey on mobile edge computing: The communication perspective,” *to appear in IEEE Commun. Surveys Tuts.*

- [4] W. Zhang, Y. Wen, K. Guan, D. Kilper, H. Luo, and D. O. Wu, "Energy-optimal mobile cloud computing under stochastic wireless channel," *IEEE Trans. Wireless Commun.*, vol. 12, pp. 4569–4581, Sep. 2013.
- [5] J. Kwak, Y. Kim, J. Lee, and S. Chong, "DREAM: Dynamic resource and task allocation for energy minimization in mobile cloud systems," *IEEE J. Sel. Areas Commun.*, vol. 33, pp. 2510–2523, Dec. 2015.
- [6] Y. Mao, J. Zhang, and K. Letaief, "Dynamic computation offloading for mobile-edge computing with energy harvesting devices," *IEEE J. Sel. Areas Commun.*, vol. 34, pp. 3590–3605, Dec. 2016.
- [7] C. You, K. Huang, and H. Chae, "Energy efficient mobile cloud computing powered by wireless energy transfer," *IEEE J. Sel. Areas Commun.*, vol. 34, pp. 1757–1771, Mar. 2016.
- [8] Y. Kao, B. Krishnamachari, M. Ra, and F. Bai, "Hermes: Latency optimal task assignment for resource-constrained mobile computing," *to appear in IEEE Trans. Mobile Comput.*
- [9] J. Liu, Y. Mao, J. Zhang, and K. Letaief, "Delay-optimal computation task scheduling for mobile-edge computing systems," in *Proc. of IEEE Int. Symp. Inf. Theory*, pp. 1451–1455, Jul. 2016.
- [10] S. Mahmoodi, R. Uma, and K. Subbalakshmi, "Optimal joint scheduling and cloud offloading for mobile applications," *to appear in IEEE Trans. Cloud Comput.*
- [11] S.-W. Ko, K. Huang, S.-L. Kim, and H. Chae, "Live prefetching for mobile computation offloading," *IEEE Trans. Wireless Commun.*, vol. 16, pp. 3057–3071, May 2017.
- [12] C. You, K. Huang, H. Chae, and B. Kim, "Energy-efficient resource allocation for mobile-edge computation offloading," *IEEE Trans. Wireless Commun.*, vol. 16, pp. 1397–1411, Mar. 2016.
- [13] S. Sardellitti, G. Scutari, and S. Barbarossa, "Joint optimization of radio and computational resources for multicell mobile-edge computing," *IEEE Trans. Signal Inf. Process. Netw.*, vol. 1, pp. 89–103, Jun. 2015.
- [14] X. Chen, L. Jiao, W. Li, and X. Fu, "Efficient multi-user computation offloading for mobile-edge cloud computing," *IEEE/ACM Trans. Networking*, vol. 24, pp. 2795–2808, Oct. 2016.
- [15] R. Kaewpuang, D. Niyato, P. Wang, and E. Hossain, "A framework for cooperative resource management in mobile cloud computing," *IEEE J. Sel. Areas Commun.*, vol. 31, pp. 2685–2700, Dec. 2013.
- [16] B. Rimal, D. Van, and M. Maier, "Mobile-edge computing vs. centralized cloud computing in fiber-wireless access networks," in *Proc. of IEEE INFOCOM Workshop*, pp. 991–996, 2016.
- [17] T. Taleb, A. Ksentini, and P. Frangoudis, "Follow-me cloud: When cloud services follow mobile users," *to appear in IEEE Trans. Cloud Comput.*
- [18] I. Farris, T. Taleb, H. Flinck, and A. Iera, "Providing ultra-short latency to user-centric 5G applications at the mobile network edge," *Trans. Emerging Telecomm. Techn.*, Mar. 2017.
- [19] H. ElSawy, E. Hossain, and M. Haenggi, "Stochastic geometry for modeling, analysis, and design of multi-tier and cognitive cellular wireless networks: A survey," *IEEE Commun. Surveys Tuts.*, vol. 15, pp. 996–1019, Jan. 2013.
- [20] J. G. Andrews, F. Baccelli, and R. K. Ganti, "A tractable approach to coverage and rate in cellular networks," *IEEE Trans. Commun.*, vol. 59, pp. 3122–3134, Nov. 2011.
- [21] H. Dhillon, R. Ganti, F. Baccelli, and J. Andrews, "Modeling and analysis of k-tier downlink heterogeneous cellular networks," *IEEE J. Sel. Areas Commun.*, vol. 30, pp. 550–560, Mar. 2012.
- [22] A. Sakr and E. Hossain, "Cognitive and energy harvesting-based D2D communication in cellular networks: Stochastic geometry modeling and analysis," *IEEE Trans. Commun.*, vol. 63, pp. 1867–1880, Mar. 2015.
- [23] R. Vaze and R. W. Heath, "Transmission capacity of ad-hoc networks with multiple antennas using transmit stream adaptation and interference cancellation," *IEEE Trans. Inf. Theory*, vol. 58, pp. 780–792, Feb. 2012.
- [24] Y. Lin and W. Yu, "Downlink spectral efficiency of distributed antenna systems under a stochastic model," *IEEE Trans. Wireless Commun.*, vol. 13, pp. 6891–6902, Dec. 2014.

- [25] M. Haenggi, J. Andrews, F. Baccelli, O. Dousse, and M. Franceschetti, "Stochastic geometry and random graphs for the analysis and design of wireless networks," *IEEE J. Sel. Areas Commun.*, vol. 27, pp. 1029–1046, Jul. 2009.
- [26] D. Bertsekas and R. Gallager, *Data networks*. Prentice Hall, 1992.
- [27] S. Barbarossa, S. Sardellitti, and P. Di Lorenzo, "Communicating while computing: Distributed mobile cloud computing over 5g heterogeneous networks," *IEEE Signal Proc. Mag.*, vol. 31, pp. 45–55, Nov. 2014.
- [28] M. Haenggi, "The local delay in poisson networks," *IEEE Trans. Inf. Theory*, vol. 59, pp. 1788–1802, Mar. 2013.
- [29] Z. Gong and M. Haenggi, "The local delay in mobile poisson networks," *IEEE Trans. Wireless Commun.*, vol. 12, pp. 4766–4777, Sep. 2013.
- [30] Y. Zhong, M. Haenggi, T. Quek, and W. Zhang, "On the stability of static poisson networks under random access," *IEEE Trans. Wireless Commun.*, vol. 64, pp. 2985–2998, Jul. 2016.
- [31] S. Verdú and S. Shamai, "Spectral efficiency of cdma with random spreading," *IEEE Trans. Inf. Theory*, vol. 45, pp. 622–640, Mar. 1999.
- [32] L. Dai, B. Wang, Y. Yuan, S. Han, C.-L. I, and Z. Wang, "Non-orthogonal multiple access for 5g: solutions, challenges, opportunities, and future research trends," *IEEE Commun. Mag.*, vol. 53, pp. 74–81, Sep. 2015.
- [33] D. Bruneo, "A stochastic model to investigate data center performance and qos in iaas cloud computing systems," *IEEE Trans. Parallel Distrib. Syst.*, vol. 25, pp. 560–569, Mar. 2014.
- [34] K. Sriram and W. Whitt, "Characterizing superposition arrival processes in packet multiplexers for voice and data," *IEEE J. Sel. Areas Commun.*, vol. 4, pp. 833–846, Sep. 1986.