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Outage Probability Analysis for UAV-Aided Mobile Edge Computing Networks

Jun Liu[1], Yuwei Zhang[1], Jing Wang[1], Tao Cui[1], Lin Zhang[1], Chao Li[2], Kai Chen[3,*], Sun Li[4], Sunli Feng[5], Dongqing Xie[6], Dahua Fan[7,8], Jianghong Ou[7,8], Yun Li[9], Haige Xiang[10], Kaimeno Dube[11], Abbarbas Muazu[12], Nakilavai Rono[13], Fusheng Zhu[14], Liming Chen[15], Wen Zhou[16], and Zhusong Liu[17]

[1]Information Research Center, Tsinghua University, Beijing, China
(e-mail: {junliu.thu, yzhang.thu, jingwang.thu, taocui, lzhang.ee}@ieee.org).
[2]Advanced Research Center, Hamdard University, Pakistan (e-mail: chaoli.eecs@ieee.org).
[3]Huawei Technologies, Stockholm, Sweden (e-mail: kchen.huawei@ieee.org).
[4]Advanced Information Research Center of Xi'an Jiaotong University, China (e-mail: lisun@ieee.org).
[5]King Abdullah University of Science and Technology (KAUST), Kingdom of Saudi Arabia (e-mail: slfeng@ieee.org).
[6]Information Research Center, Anhui University of Technology, China (e-mail: dqxie@ieee.org).
[7]Henan University of Technology, Zhengzhou, China (e-mail: {dahuafan,jianghongou}@ieee.org).
[8]Starway Communication, Guangzhou, China (e-mail: {dahuafan,jianghongou}@ieee.org).
[9]University of Illinois Urbana-Champaign, Urbana, USA (e-mail: yunli.ericsson@ieee.org).
[10]Information Research Center of Peking University, China (e-mail: haigexiang@ieee.org).
[11]Vaal University of Technology, Andries Potgieter Blvd, South Africa (e-mail: Kaimeno.Dube@ieee.org).
[12]Baze University, Airport Road, Abuja, Nigeria (e-mail: Abbarbas.Muazu@ieee.org).
[13]Rongo University, Rongo, Kenya (e-mail: Nakilavai.Rono@ieee.org).
[14]Guangdong New Generation Communication and Network Innovative Institute (GDCNi), Guangzhou, China (e-mail: fushengzhu.gdcni@hotmail.com).
[15]Electric Power Research Institute of CSG, Guangzhou, China (e-mail: lmchen_CSPG@hotmail.com).
[16]Nanjing Forestry University, Nanjing, China (e-mail: wenzhou.nfu@gmail.com).
[17]Anhui University of Technology, Anhui, China (e-mail: zhusongliu@ieee.org).

Abstract

This paper studies one typical mobile edge computing (MEC) system, where a single user has some intensively calculating tasks to be computed by M edge nodes (ENs) with much more powerful calculating capability. In particular, unmanned aerial vehicle (UAV) can act as the ENs due to its flexibility and high mobility in the deployment. For this system, we propose several EN selection criteria to improve the system whole performance of computation and communication. Specifically, *criterion I* selects the best EN based on maximizing the received signal-to-noise ratio (SNR) at the EN, *criterion II* performs the selection according to the most powerful calculating capability, while *criterion III* chooses one EN randomly. For each EN selection criterion, we perform the system performance evaluation by analyzing outage probability (OP) through deriving some analytical expressions. From these expressions, we can obtain some meaningful insights regarding how to design the MEC system. We finally perform some simulation results to demonstrate the effectiveness of the proposed MEC network. In particular, criterion I can exploit the full diversity order equal to M.

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1. Introduction

Nowadays, there has been a tremendous trend to the development and application of internet of things (IoT) and industrial IoT (IIoT), thanks to the rapid development of communication and computation technologies [1–4]. In the IoT and IIoT networks, an ever-increasing number of nodes are accessing the system, which causes a huge amount number of communication and computation [5–7]. This imposes a severe overload on the system operation [8–10]. To reduce the overload, some calculating techniques have been proposed, among which cloud computing is a promising one. Specifically, cloud computing can help compute the intensively calculating tasks to the cloud server to accomplish the computation through wireless transmission. In some practical environments, especially when the channel state is poor, the transmission latency and energy consumption (EC) becomes unacceptably high, which severely limits the development and application of both IoT and IIoT networks [11–13].

To support the application of IoT and IIoT networks, some communication techniques have been proposed to reduce the latency and EC during the communication and computation [14]. For example, massive multiple-input multiple-output (MIMO) can be deployed at transceivers to provide a huge amount of spatial diversity order, which can help reduce the transmission latency and EC rapidly. Similar to the massive MIMO, intelligent reflecting surface (IRS) has been recently proposed, which can help achieve the advantages of MIMO in the spatial diversity, and meanwhile reduce the implementation energy. The authors in [15–18] have extensively studied the IRS technique from the various aspects of system design, performance evaluation, and optimization. Due to the huge amount of antennas in the communication systems and the associated ever-increasing implementation complexity, some intelligent algorithms should be used in the communication systems. In this area, the authors in [19] applied the dilated convolution techniques to help reduce the implementation complexity in acquiring the channel state information (CSI), and [20] utilized some deep learning based reception schemes to help reduce the implementation complexity in the receiver design.

Besides the above advanced communication techniques, some advanced computing techniques have been proposed to support the development and application of IoT and IIoT networks. Among these techniques, mobile edge computing (MEC) is a typical one which deploys the powerful calculating resources from the edge nodes (ENs) nearby the users. This deployment can help reduce the transmission latency and EC significantly. Various researches have been made to improve the system whole performance of MEC networks by optimizing the offloading ratio, which decides the part of tasks to be calculated by the ENs. For example, the authors in [21–24] derived analytical expressions of offloading strategy for some typical MEC networks such as one-to-one and one-to-two MEC networks. For some more complicated MEC networks, some intelligent algorithms such as deep-Q networks (DQN) based deep reinforcement learning (DRL) algorithms can be applied to find a feasible solution to the offloading strategy, in order to help enhance the system performance by reducing the latency and EC during the communication and computation.

This paper studies one typical MEC system, where a single user has some intensively calculating tasks to be computed by M UAV-aided ENs with much more powerful calculating capability. For this system, we propose several EN selection criteria to improve the system whole performance of computation and communication. Specifically, *criterion I* selects the best EN based on maximizing the received signal-to-noise ratio (SNR) at the EN, *criterion II* performs the selection according to the most powerful calculating capability, while *criterion III* chooses one EN randomly. For each EN selection criterion, we perform the system performance evaluation by analyzing outage probability (OP) through deriving some analytical expressions. From these expressions, we can obtain some meaningful insights regarding how to design the MEC system. We finally perform some simulation results to demonstrate the effectiveness of the proposed MEC network. In particular, criterion I can exploit achieve the full diversity order equal to M.

2. System Model

Fig. 1 illustrates the structure of the considered MEC network, consisting of M ENs $\{EN_m|1 \le m \le M\}$ which are helpful to the intensively calculating tasks coming from the user S. In practice, UAV can act as the ENs due to its high mobility and flexibility. Due to the limitation in the size, each node in the network has only one antenna. The channels in the MEC network are subject to Rayleigh fading, and we choose one best EN among M ones at each time slot.

Without loss of generality, the m-th EN is assumed to be chosen to assist the computation from the user S. As we assume that the user does not have the calculating capability by itself, all the tasks should be completely offloaded to the EN_m for computation. In other words, we consider the full offloading strategy. In this case, the transmission data rate from user S to the EN_m is

$$R_m = W \log_2 \left(1 + \frac{P}{\sigma^2}|h_m|^2\right), \tag{1}$$

*Corresponding author. Email: kchen.huawei@ieee.org

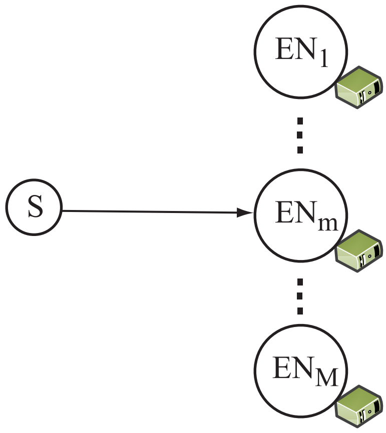

Figure 1. System model of a MEC network with multiple ENs.

where W is the wireless bandwidth, P is the transmit power at the ENs, and σ^2 is the variance of the additive white Gaussian noise (AWGN) at the ENs, i.e., P/σ^2 is the transmit signal-to-noise ratio (SNR). Notation $h_m \sim \mathcal{CN}(0, \alpha)$ denotes the channel parameter from user S to the EN_m. From R_m, we can write the transmission latency as

$$t_{1m} = \frac{L}{R_m}, \tag{2}$$

$$= \frac{L}{W \log_2\left(1 + \frac{P}{\sigma^2}|h_m|^2\right)}, \tag{3}$$

where L is the task length. After successfully offloading the whole task to the EN_m, the EN_m starts to calculate the task, and the corresponding calculating latency is,

$$t_{2m} = \frac{L\eta}{f_m}, \tag{4}$$

where η denotes the number of CPU cycles to compute one bit, and f_m denotes the calculating capability at the ENs. In particular, f_m may vary because of many factors including dynamic processes in the ENs. In this work, the uniform distribution is used to model the distribution of f_m, given by

$$f_{f_m}(x) = \begin{cases} \frac{1}{f_{\max} - f_{\min}}, & \text{If } x \in [f_{\min}, f_{\max}] \\ 0, & \text{Else} \end{cases}, \tag{5}$$

where $f_{\min}$ and $f_{\max}$ denote the minimal and maximal calculating capabilities at the ENs, respectively. From t_{1m} and t_{2m}, we can write the system whole latency during the communication and computation as

$$t_m = t_{1m} + t_{2m}, \tag{6}$$

$$= \frac{L}{W \log_2\left(1 + \frac{P}{\sigma^2}|h_m|^2\right)} + \frac{L\eta}{f_m}. \tag{7}$$

3. Edge node selection criteria

In this part, we present several EN selection criteria for the considered system. Note that selecting the EN may affect the system latency performance significantly. As the latency is affected by both the wireless channel and calculating capability, the EN selection can be performed either based on the channel quality or the calculating capability. Specifically, we present criterion I to select the best EN as

$$m^* = \arg \max_{1 \le m \le M} |h_m|^2, \tag{8}$$

which maximizes the received SNR at the ENs. Besides this criterion, we also provide criterion II to select the best EN as

$$m^* = \arg \max_{1 \le m \le M} f_m, \tag{9}$$

which is equivalent to maximizing the calculating capability at the ENs. In addition to these two criteria, we also consider criterion III which selects the best EN randomly. For each criterion, we will give the performance evaluation through giving the analytical expression of outage probability from the perspective of latency

4. Outage probability analysis

This section give the performance evaluation of the three EN selection criteria, by deriving the system outage probability in terms of latency. For each criterion, the network OP with the selected EN_{m^*} is written as

$$P_{out} = \Pr(t_{m^*} > \gamma_{th}), \tag{10}$$

where γ_{th} is a given latency threshold related the practical application scenarios. For the three EN selection criterion, we will give the closed-form expression of P_{out} one by one, in the following.

4.1. Outage probability analysis of criterion I

For criterion I, its outage probability in terms of latency is given by

$$P_{I,out} = \Pr(t_{m^*} \geq \gamma_{th}), \tag{11}$$

$$= \underbrace{\Pr\left(|h_{m^*}|^2 \leq \frac{2^{\frac{L/W}{\gamma_{th}-L\eta/f_{m^*}}}-1}{P/\sigma^2}, f_{m^*} \geq \frac{L\eta}{\gamma_{th}}\right)}_{G_1} + \underbrace{\Pr\left(f_n \leq \frac{L\eta}{\gamma_{th}}\right)}_{G_2} \tag{12}$$

where G_1 and G_2 can be computed. Considering the PDFs of $|h_{m^*}|^2$ and f_{m^*}, i.e., $p_{|h_{m^*}|^2}(v)$ and $p_{f_{m^*}}(x)$, we can write the expression of G_1 and G_2 as,

$$G_1 = \int_{\frac{L\eta}{\gamma_{th}}}^{\infty} \int_0^{\frac{2^{\frac{L/W}{\gamma_{th}-L\eta/x}}-1}{P/\sigma^2}} p_{f_{m^*}}(x), p_{|h_{m^*}|^2}(v) dv dx, \tag{13}$$

$$G_2 = \int_0^{\frac{L\eta}{\gamma_{th}}} p_{f_m}(x) dx. \tag{14}$$

Specifically, if $\frac{L\eta}{\gamma_{th}} > f_{max}$ holds, we can readily obtain $G_1 = 0$, $G_2 = 1$. When $f_{min} < \frac{L\eta}{\gamma_{th}} < f_{max}$ holds, we can have,

$$p_{f_{m^*}}(x) = \begin{cases} \frac{1}{f_{max}-f_{min}}, & \text{if } x \in [f_{min}, f_{max}], \\ 0, & \text{else.} \end{cases}, \tag{15}$$

$$p_{|h_{m^*}|^2}(v) = \frac{M}{\alpha} e^{-v/\alpha}(1-e^{-v/\alpha})^{M-1}. \tag{16}$$

From the above equations, we can compute G_1 as

$$G_1 = \int_{\frac{L\eta}{\gamma_{th}}}^{f_{max}} \int_0^{\frac{2^{\frac{L/W}{\gamma_{th}-L\eta/x}}-1}{P/\sigma^2}} \frac{M}{\alpha} e^{-v/\alpha}(1-e^{-v/\alpha})^{M-1} \frac{1}{f_{max}-f_{min}} dv dx \tag{17}$$

$$= \frac{1}{f_{max}-f_{min}} \int_{\frac{L\eta}{\gamma_{th}}}^{f_{max}} \left(1 - e^{-\frac{2^{\frac{L/W}{\gamma_{th}-L\eta/x}}-1}{\alpha P/\sigma^2}}\right)^M dx \tag{18}$$

$$= \frac{1}{f_{max}-f_{min}} \sum_{m=0}^{M} \binom{M}{m} (-1)^m \int_{\frac{L\eta}{\gamma_{th}}}^{f_{max}} e^{-m\frac{2^{\frac{L/W}{\gamma_{th}-L\eta/x}}-1}{\alpha P/\sigma^2}} dx \tag{19}$$

$$\approx \frac{1}{f_{max}-f_{min}} \sum_{m=0}^{M} \binom{M}{m} (-1)^m \sum_{j=1}^{J} e^{-m\frac{2^{\frac{L/W}{\gamma_{th}-L\eta/v_j}}-1}{\alpha P/\sigma^2}} \sqrt{1-\theta_j} \tag{20}$$

where J is a large number and

$$\theta_j = \cos\left(\frac{(2j-1)\pi}{2J}\right), \tag{21}$$

$$v_j = \frac{f_{max}(1+\theta_j) + L\eta/\gamma_{th}(1-\theta_j)}{2}. \tag{22}$$

Similarly, we can compute the analytical expression of G_2 as,

$$G_2 = \int_{f_{min}}^{\frac{L\eta}{\gamma_{th}}} \frac{1}{f_{max}-f_{min}} dx, \tag{23}$$

$$= \frac{\frac{L\eta}{\gamma_{th}} - f_{min}}{f_{max}-f_{min}}. \tag{24}$$

By applying the analytical results of G_1 and G_2 into (12), a closed-form expression of $P_{out,I}$ is obtained, which is readily to be calculated.

4.2. OP analysis of criterion II

For the OP analysis of criterion II, we can analyze as follows. Specifically, if $\frac{L\eta}{\gamma_{th}} > f_{max}$ holds, we can have $G_1 = 0$ and $G_2 = 1$. On the other hand, if $f_{min} < \frac{L\eta}{\gamma_{th}} < f_{max}$ hold, we have the PDF of f_{m^*} as,

$$p_{f_{m^*}}(x) = \begin{cases} \frac{M(x-f_{min})^{M-1}}{(f_{max}-f_{min})^M}, & \text{if } x \in [f_{min}, f_{max}], \\ 0, & \text{else.} \end{cases}. \tag{25}$$

From the expression of $p_{f_{m^*}}(x)$, we can compute the analytical expression of G_1 as

$$G_1 = \int_{\frac{L\eta}{\gamma_{th}}}^{f_{max}} \int_0^{\frac{2^{\frac{L/W}{\gamma_{th}-L\eta/x}}-1}{P/\sigma^2}} \frac{1}{\alpha} e^{-v/\alpha} \frac{M(x-f_{min})^{M-1}}{(f_{max}-f_{min})^M} dv dx, \tag{26}$$

$$= \frac{1}{f_{max}-f_{min}} \int_{\frac{L\eta}{\gamma_{th}}}^{f_{max}} \left(1 - e^{-\frac{2^{\frac{L/W}{\gamma_{th}-L\eta/x}}-1}{\alpha P/\sigma^2}}\right) \frac{M(x-f_{min})^{M-1}}{(f_{max}-f_{min})^M} dx, \tag{27}$$

$$\approx \frac{1}{f_{max}-f_{min}} \sum_{j=1}^{J} \left(1 - e^{-\frac{2^{\frac{L/W}{\gamma_{th}-L\eta/v_j}}-1}{\alpha P/\sigma^2}}\right) \frac{M(v_j-f_{min})^{M-1}}{(f_{max}-f_{min})^M} \sqrt{1-\theta_j}. \tag{28}$$

Similarly, we compute the analytical expression of G_2 as

$$G_2 = \int_{f_{min}}^{\frac{L\eta}{\gamma_{th}}} \frac{N(x-f_{min})^{N-1}}{(f_{max}-f_{min})^N} dx \tag{29}$$

$$= \left(\frac{\frac{L\eta}{\gamma_{th}} - f_{min}}{f_{max}-f_{min}}\right)^M. \tag{30}$$

By applying the analytical results of G_1 and G_2 into (12), a closed-form expression of $P_{out,II}$ is obtained, which is readily to be calculated.

4.3. OP analysis of criterion III

For the OP analysis of criterion III, we can analyze as follows. Specifically, if $\frac{L\eta}{\gamma_{th}} > f_{max}$ holds, we can have $G_1 = 0$ and $G_2 = 1$. On the other hand, if $f_{min} < \frac{L\eta}{\gamma_{th}} < f_{max}$ holds, the closed-form expressions of G_1 and G_2 are

$$G_1 = \int_{\frac{L\eta}{\gamma_{th}}}^{f_{max}} \int_0^{\frac{2^{\frac{L/W}{\gamma_{th}-L\eta/x}}-1}{P/\sigma^2}} \frac{1}{\alpha} e^{-v/\alpha} \frac{1}{f_{max}-f_{min}} dv dx, \quad (31)$$

$$= \frac{1}{f_{max}-f_{min}} \int_{\frac{L\eta}{\gamma_{th}}}^{f_{max}} \left(1 - e^{-\frac{2^{\frac{L/W}{\gamma_{th}-L\eta/x}}-1}{\alpha P/\sigma^2}}\right) dx, \quad (32)$$

$$\approx \frac{1}{f_{max}-f_{min}} \sum_{j=1}^{J} \left(1 - e^{-\frac{2^{\frac{L/W}{\gamma_{th}-L\eta/v_j}}-1}{\alpha P/\sigma^2}}\right) \sqrt{1-\theta_j}, \quad (33)$$

and

$$G_2 = \int_{f_{min}}^{\frac{L\eta}{\gamma_{th}}} \frac{N(x-f_{min})^{N-1}}{(f_{max}-f_{min})^N} dx, \quad (34)$$

$$= \frac{\frac{L\eta}{\gamma_{th}} - f_{min}}{f_{max}-f_{min}}. \quad (35)$$

By applying the analytical results of G_1 and G_2 into (12), a closed-form expression of $P_{out,III}$ is obtained, which is readily to be calculated.

5. Simulation results

This section provides some simulations to show the effectiveness of the proposed EN selection criteria. In particular, we normalize the distance from UAV to ENs to unity, and hence the average channel gain α is equal to 1. The transmit SNR is $P/\sigma^2 = 20$dB. For each EN, the CPU frequency varies in the range of $[0.5, 5]$GHz. As to the requirements of calculating task, each bit of task requires 10 CPU cycle, i.e., $\eta = 10$. Moreover, the maximum latency for the task γ_{th} is set to 0.5s. If not specified, the bandwidth for transmission W is 100MHz and the length of task L is 10 Mbits.

Figs. 2-4 demonstrate the closed-form and simulated OPs of the several EN selection criteria with respect to the task length L, where the wireless bandwidth is 100MHz, the number of ENs varies in $\{1, 2, 3\}$, and L varies in [10,100]Mbits. Specifically, Fig. 2, Fig. 3 and Fig. 4 are associated with criterion I, II and III, respectively. By observing these three figures, one can find that for each criterion, the closed-form OP fits well with the simulation value, which shows the effectiveness and correctness of the derived closed-form expressions. Moreover, the system OP result becomes larger with an increased value of L, as a larger task will impose a heavier overload on the system communication and computation. In this case, the system overall latency will increase, which will make the system OP become worse. In further, for criterion I and II, the system OP becomes better when M increases, as more ENs are helpful to reduce the system communication and calculating latency. In this case, a better EN with a better wireless channel or calculating capability can be selected to improve the system performance. In contrast, the system performance remains unchanged with M for criterion III, as criterion III performs the random selection and its performance is irrespective of the number of ENs.

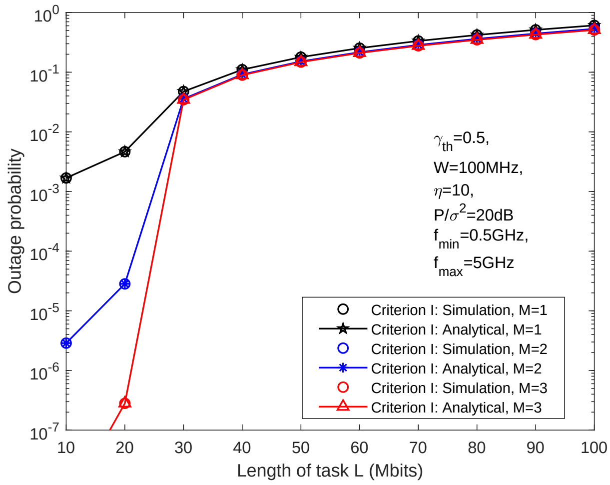

Figure 2. Outage probability versus the task length L for criterion I.

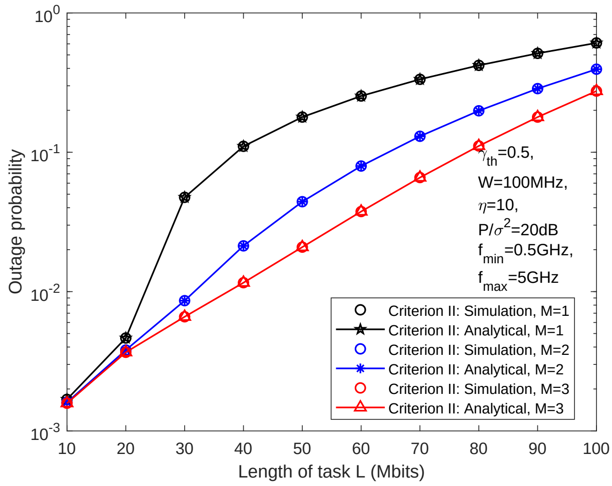

Figure 3. Outage probability versus the task length L for criterion II.

Figs. 5-7 illustrate the closed-form and simulated OPs of the several EN selection criteria versus the wireless bandwidth W, where the task length is 10Mbits, the

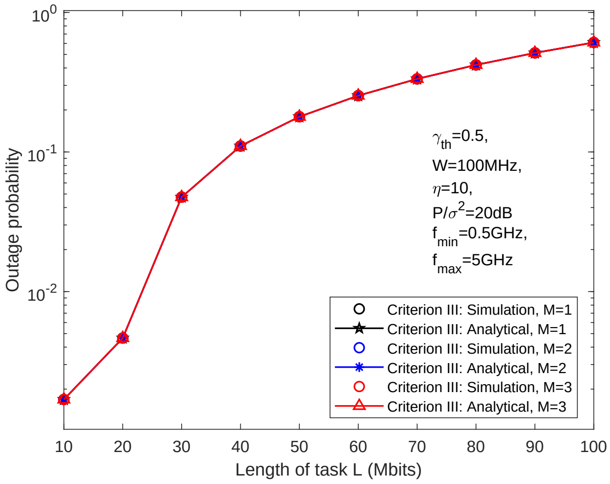

Figure 4. Outage probability versus the task length L for criterion III.

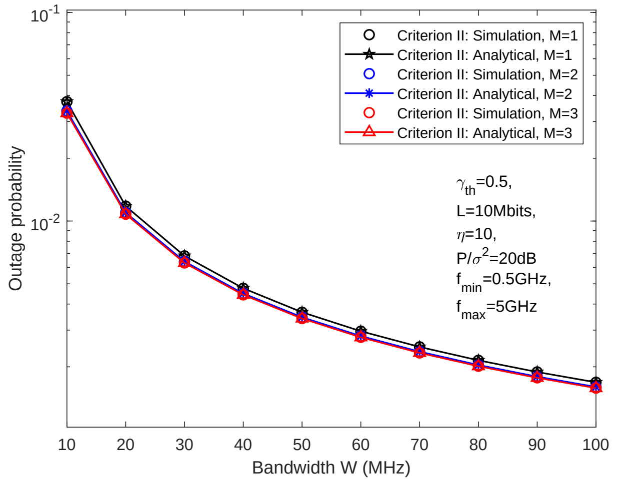

Figure 6. Outage probability versus bandwidth W for criterion II.

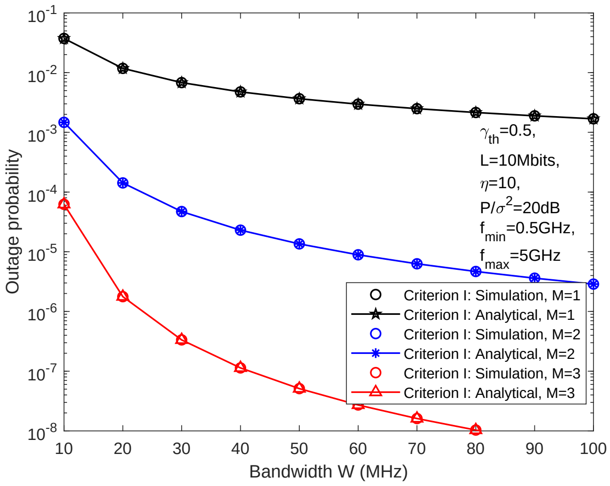

Figure 5. Outage probability versus bandwidth W for criterion I.

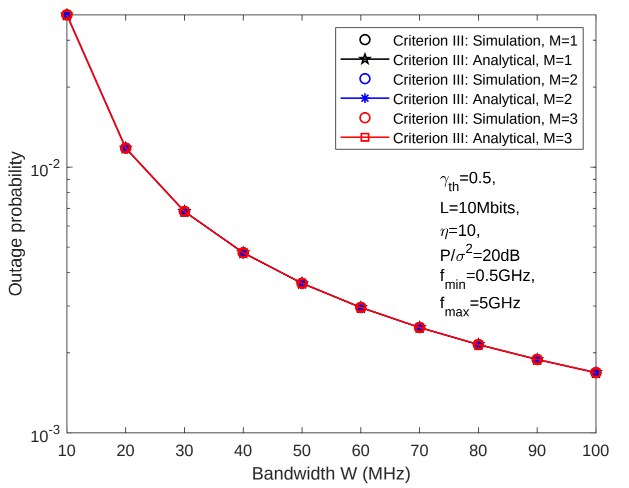

Figure 7. Outage probability versus bandwidth W for criterion III.

number of ENs varies in $\{1, 2, 3\}$, and W varies in the range of [10,100]MHz. Specifically, Fig. 5, Fig. 6 and Fig. 7 are associated with criterion I, II and III, respectively. By observing these three figures, one can find that for each criterion, the closed-form OP fits well with the simulated value, which verifies the usefulness and correctness of the provided closed-form OP expressions. Moreover, the system OP becomes smaller with an increased W, as a larger W can help improve the quality of wireless transmission, which is helpful in reducing the communication latency. In this case, the system overall latency will decrease, which will improve the system outage probability eventually. In further, for criterion I and II, the system OP is improved with a larger M, as more ENs are helpful to reduce the system communication and calculating latency. In this case, a better EN with a better wireless channel or calculating capability can be selected to improve the system performance. In contrast, the system performance remains unchanged with M for criterion III, as criterion III performs the random selection and its performance is irrespective of the number of ENs.

6. Conclusions

This article studied one typical MEC network, where a single user had some calculating tasks to be calculated by M UAV-aided ENs with much more powerful calculating capability. For this system, we proposed several EN selection criteria to help improve the system whole performance of computation and communication. Specifically, *criterion I* selected the best EN based on maximizing the received signal-to-noise ratio (SNR) at the EN, *criterion II* performed the selection according to the most powerful calculating capability, while *criterion III* choosed one EN randomly. For each criterion, we performed the system performance evaluation by analyzing the OP through deriving some analytical expressions. From these expressions, we could obtain some useful and meaningful insights regarding how to design the network.We finally presented some simulation results to depict the effectiveness of the proposed criteria. In particular, criterion I could exploit the full diversity order equal to M.

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