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Distributed Edge Computing Aided Environmental Severity Monitoring for Power Grid Equipment in Nakagami-m Fading Channels

Guangmao Li, Gang Du, Hongbin Wang, Hongling Zhou, Jie Yang, and Zhikai Pang

Abstract—**This study explores the concept of multiuser mobile edge computing (MEC) networks aided environmental severity monitoring for power grid equipment, where an MEC server facilitates the computation of tasks from N users via wireless transmission in the presence of Nakagami-m fading channels. To analyze the system performance, we first define the system outage probability based on energy consumption, where the outage event is triggered when the energy required to complete the users' tasks exceeds a specified threshold. We then develop an analytical expression for the system outage probability in Nakagami-m fading channels and provide a high signal-to-noise ratio (SNR) asymptotic analysis. Additionally, we optimize the system performance by adjusting the task offloading ratios. Finally, simulation and numerical results in Nakagami-m fading channels validate the proposed methods. The results show that the performance of multiuser MEC networks can be improved by increasing the bandwidth or energy consumption threshold for environmental severity monitoring in power grid equipments.**

Index Terms—**Edge computing, offloading optimization, outage probability, Nakagami-m fading.**

I. Introduction

Information technology has rapidly evolved, leading to the speedy upgrading of mobile communication networks. The fifth-generation (5G) mobile communication network has now been extensively implemented and it is readily accessible to the public, providing an efficient support for Internet of Things (IoT) networks. The key applications of 5G include enhanced mobile broadband, low-latency and high-reliability transmission, and massive machine-type communication. These applications not only serve industries like the industrial Internet of Things, augmented reality (AR) and virtual reality (VR), but also drive the advancement of other information technologies such as big data, cloud computing, blockchain, and the metauniverse.

Under the tide of thriving digital economy, the future beyond 5G (B5G) and sixth-generation (6G) networks face new challenges from the demand on the massive communication and massive computing [1]–[4]. According to the National Data Resource Survey Report, the global data volume was 67ZB in 2021, 80% among which was wireless data, with an average growth rate exceeding 26% in the past three years, which poses high requirements on the design of the future B5G/6G network [5]–[8]. In particular, with the rapid development of artificial intelligence, how to train AI models from massive data to intelligently complete computing tasks is the application demand of industries such as the industrial Internet of Things and an important landing point for B5G/6G industrial applications. However, as the computing power and data continue to grow, the number of parameters in the AI models is also showing explosive growth. Taking the ChatGPT model as an example, which has swept the world recently, , the number of parameters and pre-training data volume of each generation of GPT model are exploding, which can be called "the bigger, the better." The GPT-2 published in February 2019 had 150 million parameters and a pre-training data volume of approximately 5GB, while the GPT-3 in May 2020 had 175 billion parameters and a pre-training data volume of 40G. The ChatGPT model launched in November 2022 has a parameter volume of 100 billion.

The European Telecommunications Standardization Association introduced the mobile edge computing (MEC) architecture in 2014 to address the difficulties posed by the massive amount of communication data and computing tasks in communication networks. MEC integrates edge computing into the mobile network architecture, moving storage and computing services from cloud data centers to the edge of the mobile network, such as base stations and wireless access points. This provides local access to computing, storage, network, and communication resources, reducing latency and enhancing user experience. MEC has become a critical technology for 5G and B5G/6G networks, offering ultra-low latency, high energy efficiency, and reliable wireless transmission services. According to Cisco's global cloud index data, in 2021, the world generated 106 ZB of data traffic, with only 21 ZB data at the center. Over 70% of global traffic requires communication and computation from the edge devices. With the support of edge computing architecture, the future B5G/6G network will be able to integrate with artificial intelligence, enabling ultra-strong communication, computation, and intelligence capabilities. This integration will enable human-machine-object interconnectivity, upgrading information transmission to integrated information perception-communication-computation-control, and supporting intelligent edge network applications such as smart cities, industrial automation, autonomous driving, and smart homes.

This article delves into the topic of multiuser MEC net-

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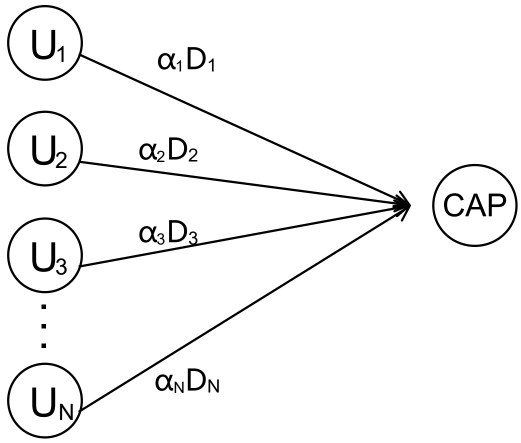

Fig. 1. System model of multiuser MEC networks in Nakagami-m fading channels.

works, where N users' computational tasks are processed by a MEC server through wireless transmission in Nakagami-m fading environments. The system outage probability, taking into account both communication and computing energy consumption, is firstly defined, with an outage occurring if the energy consumption exceeds a given threshold. The system performance is then analyzed through an analytical expression for the system outage probability and an asymptotic expression with high signal-to-noise ratio (SNR). The system is further optimized by adjusting task offloading ratios. Numerical and simulation results are presented to validate the system analysis and optimization in the multiuser MEC network, providing valuable insights for edge computing system design.

II. System Model

The system model of multiuser MEC networks in Nakagami-m fading channels is displayed in Fig. 1. In this model, there are N mobile users who require offloading of their computational tasks to a nearby computing access point (CAP). In the considered system, the user U_n $(1 \leq n \leq N)$ has the computational task, whose size is D_n and can be computed at local or the CAP. We use $\{\alpha_n \mid n = 1, 2, \ldots, N\}$ to represent the offloading ratio of user U_n. The offloading is through the wireless channels in the networks, where we consider a general fading model of Nakagami-m channel to model the wireless links in this system [9]–[12]. In the following, we will discuss the computing and communication process for calculating the tasks.

Firstly, as the local computation part is $(1-\alpha_n)$, its latency can be given by [13]–[16]

$$T_l = \frac{(1-\alpha_n)\mu D_n}{C_n}, \tag{1}$$

where μ is required CPU cycle for each bit of the task, C_n is the local computational capability of U_n. The energy consumption of the local computation part can be given by [17]–[19]

$$E_l = (1-\alpha_n)\mu D_n C_n^2. \tag{2}$$

As for the α_n part of the task, it first needs to be transmitted to the CAP through the wireless channel g_n. The achievable data rate of user U_n can be written as [20], [21]

$$R_n = B \log_2 \left(1 + \frac{P_n |g_n|^2}{\sigma^2}\right) \tag{3}$$

where B is the wireless bandwidth of the transmission link, P_n is the transmit power of U_n, and $g_n \sim \mathrm{Naka}(m, \lambda_n)$ is the Nakagami-m fading channel. Moreover, σ^2 is used to denote the AWGN variance. With R_n, we can then have the transmission latency of U_n as

$$T_t = \frac{\alpha_n D_n}{R_n}. \tag{4}$$

The corresponding energy consumption of the task transmission can be written as [22]

$$E_t = P_n T_t. \tag{5}$$

The CAP with the computational capability of C_{CAP} will then calculate the offloaded task. Specifically, the CAP allocate its computational capability to all N users, where β_n is the allocation ratio. Therefore, we can have the CAP computation latency and energy consumption as

$$T_{CAP} = \frac{\alpha_n \mu D_n}{\beta_n C_{CAP}}. \tag{6}$$

$$E_{CAP} = \alpha_n \mu D_n (\beta_n C_{CAP})^2. \tag{7}$$

According to (1), (4), and (6), we have the total latency for executing the computational task of U_n task as

$$T_{total}^n = \max\{T_l, T_t + T_{CAP}\}. \tag{8}$$

According to (2), (5), and (7), we have the total energy consumption for executing the computational U_n's task as

$$E_{total}^n = E_l + E_t + E_{CAP}. \tag{9}$$

III. System Outage Probability Analysis

We proceed to analyze the outage performance on the multiuser MEC networks via Nakagami-m fading channels. Firstly, we give the definition of the outage for user U_n, where the outage occurs when the computing energy consumption is higher than a given threshold E_{th}, given by

$$P_{out}^n = \Pr\left[E_{total}^n \geq E_{th}^n\right], \tag{10}$$

where E_{th} is the given energy consumption threshold.

A. Analytical expression

With the given offloading ratio and computation capability allocation ratio, the local computation energy consumption and the CAP computation consumption is known. We can write the outage probability for user U_n as

$$P_{out}^n = \Pr\left[E_l^n + E_t^n + E_{CAP}^n \geq E_{th}\right] \tag{11}$$

$$= \Pr\left[\frac{P_n \alpha_n D_n}{B \log_2\left(1 + \frac{P_n |g_n|^2}{\sigma^2}\right)} \geq E_{th} - E_l^n - E_{CAP}^n\right]. \tag{12}$$

By using some transformation, we can further write the expression of P_{out}^n as,

$$P_{out}^n = \Pr\left[\log_2\left(1+\frac{P_n|g_n|^2}{\sigma^2}\right) \le \frac{P_n\alpha_n D_n}{B(E_{th}-E_l^n-E_{CAP}^n)}\right] \quad (13)$$

$$= \Pr\left[|g_n|^2 \le \frac{2^{\frac{P_n\alpha_n D_n}{B(E_{th}-E_l^n-E_{CAP}^n)}}-1}{P_n/\sigma^2}\right]. \quad (14)$$

As the wireless channels between the users and CAP experience Nakagami-m fading, we can write the distribution of $|g_n|^2$ as,

$$f_{|g_n|^2}(x) = \frac{m^m x^{m-1}}{\lambda_n^m \Gamma(m)} e^{-\frac{mx}{\lambda_n}}, \quad (15)$$

where $\Gamma(\cdot)$ is the Gamma function. From the distribution of $|g_n|^2$ in (15), we can write the cumulative density function (CDF) of $|g_n|^2$ as,

$$F_{|g_n|^2}(x) = \int_0^x f_{|g_n|^2}(x)dx, \quad (16)$$

$$= \frac{m^m}{\lambda_n^m\Gamma(m)}\int_0^x x^{m-1}e^{-\frac{mx}{\lambda_n}}dx, \quad (17)$$

$$= 1-e^{-\frac{mx}{\lambda_n}}\sum_{k=0}^{m-1}\frac{1}{k!}\left(\frac{mx}{\lambda_n}\right)^k. \quad (18)$$

By applying the above result into (14), we can obtain the analytical expression of P_{out}^n as

$$P_{out}^n = 1-e^{-\frac{m\frac{2^{\frac{P_n\alpha_n D_n}{B(E_{th}-E_l^n-E_{CAP}^n)}}-1}{P_n/\sigma^2}}{\lambda_n}} \times \sum_{k=0}^{m-1}\frac{1}{k!}\left(m\frac{2^{\frac{P_n\alpha_n D_n}{B(E_{th}-E_l^n-E_{CAP}^n)}}-1}{P_n\lambda_n/\sigma^2}\right)^k. \quad (19)$$

From the above equation, we can write the system average outage probability as,

$$P_{out} = \frac{1}{N}\sum_{n=1}^N \Pr\left[E_{total}^n \ge E_{th}\right] \quad (20)$$

$$= \frac{1}{N}\sum_{n=1}^N P_{out}^n \quad (21)$$

$$= \frac{1}{N}\sum_{n=1}^N \left(1-e^{-\frac{m\frac{2^{\frac{P_n\alpha_n D_n}{B(E_{th}-E_l^n-E_{CAP}^n)}}-1}{P_n/\sigma^2}}{\lambda_n}} \times \sum_{k=0}^{m-1}\frac{1}{k!}\left(m\frac{2^{\frac{P_n\alpha_n D_n}{B(E_{th}-E_l^n-E_{CAP}^n)}}-1}{P_n\lambda_n/\sigma^2}\right)^k \right. \quad (22)$$

B. Asymptotic expression

To get some more insights on the system design of multiuser MEC networks with Nakagami-m fading channels, we further derive the asymptotic expression of P_{out} with high SNR. Specifically, the asymptotic $F_{|g_n|^2}(x)$ is,

$$F_{|g_n|^2}(x) \simeq \frac{m^m}{\Gamma(m)}\left(\frac{x}{\lambda_n}\right)^m. \quad (23)$$

From the asymptotic $F_{|g_n|^2}(x)$, we can write the asymptotic expression of outage probability as,

$$P_{\text{out}} \simeq \frac{1}{N}\sum_{n=1}^N\frac{m^m}{\Gamma(m)}\left(\frac{2^{\frac{P_n\alpha_n D_n}{B(E_{th}-E_l^n-E_{CAP}^n)}}-1}{\lambda_n P_n/\sigma^2}\right)^m, \quad (24)$$

$$= P_{\text{out}}^{\text{asym}}, \quad (25)$$

where the approximation $\lim_{v\to 0} e^{-v} \simeq 1-v$ is employed. We can get some insights from $P_{\text{out}}^{\text{asym}}$, in the following,

- The system performance improves with a larger value of B, as a larger bandwidth can help offload the computational tasks to the CAP and reduce the energy consumption.
- The system outage probability becomes smaller with a larger value of P_n, as a larger transmit power can help reduce the offloading latency effectively.
- The value of P_{out} becomes smaller with the value of λ_n, as the channel quality is enhanced by the increase of λ_n.
- The system performance is improved with the value of m, due to the improved channel quality of wireless channels.

IV. System optimization

To enhance the system performance of the multiuser MEC networks with Nakagami-m fading channels, we proceed to optimize the system performance by allocating the computational tasks between the users and CAP. From the expression of $P_{\text{out}}^{\text{asym}}$, we optimize the offloading ratios $\{\alpha_n|1\le n\le N\}$ as,

$$\textbf{P1:} \min_{\{\alpha_n|1\le n\le N\}} \quad 1\text{N}\sum_{n=1}^N\frac{m^m}{\Gamma(m)}\left(\frac{2^{\frac{P_n\alpha_n D_n}{B(E_{th}-E_l^n-E_{CAP}^n)}}-1}{\lambda_n P_n/\sigma^2}\right)^m, \quad (26a)$$

$$\text{s.t.} \quad \alpha_n\in[0,1]. \quad (26b)$$

Considering that the users can offload their computational tasks independently, i.e., the task offloading of users does not interact with each other, we can equivalently write the optimization problem **P1** as,

$$\textbf{P2:} \min_{\{\alpha_n|1\le n\le N\}} \quad \frac{2^{\frac{P_n\alpha_n D_n}{B(E_{th}-E_l^n-E_{CAP}^n)}}-1}{\lambda_n P_n/\sigma^2}, \quad (27a)$$

$$\text{s.t.} \quad \alpha_n\in[0,1]. \quad (27b)$$

By further analyzing the above optimization problem **P2**, we can find that such optimization is also equivalent to minimizing

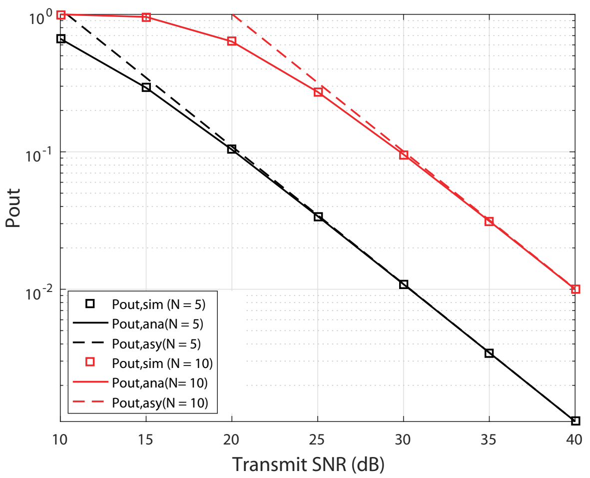

Fig. 2. System outage probability versus the transmit SNR.

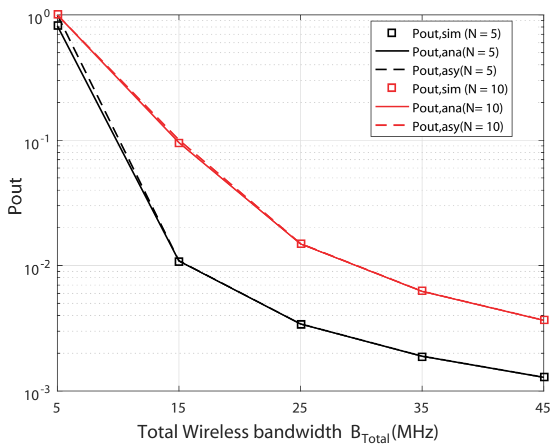

Fig. 3. System outage probability versus the bandwidth B.

the value of $\frac{P_n \alpha_n D_n}{B(E_{th}-E_l^n-E_{CAP}^n)}$, which is equal to

$$\begin{aligned}
&\min\left(\frac{P_n \alpha_n D_n}{B(E_{th}-E_l^n-E_{CAP}^n)}\right) \\
&= \min\left(\frac{\alpha_n}{E_{th}-(1-\alpha_n)\mu D_n C_n^2-\alpha_n \mu D_n(\beta_n C_{CAP})^2}\right), \quad (28) \\
&= \min\left(\frac{\alpha_n}{E_{th}-\mu D_n C_n^2+\alpha_n \mu D_n C_n^2-\alpha_n \mu D_n(\beta_n C_{CAP})^2}\right), \quad (29) \\
&= \min\left(\frac{1}{\frac{E_{th}-\mu D_n C_n^2}{\alpha_n}+\mu D_n C_n^2-\mu D_n(\beta_n C_{CAP})^2}\right). \quad (30)
\end{aligned}$$

From the above equation, we can find that the optimal value of α_n is equal to 0 if $E_{th}-\mu D_n C_n^2>0$ holds, or equal to 1 otherwise, i.e.,

$$\alpha_n^* = \begin{cases} 0, & \text{If } E_{th}-\mu D_n C_n^2>0 \\ 1, & \text{Else} \end{cases} \quad (31)$$

In this way, we can solve the optimization problem of finding the optimal offloading ratios for the considered system.

V. Numerical and Simulation results

In this section, results from numerical and simulation studies are presented for multiuser MEC networks operating in Nakagami-m fading channels. Unless stated otherwise, the value of α_n is assumed to be 0.5. The number of users, N, is set to 5 and 10, respectively. Each user is assigned a task size of 30 Mb, and user U_n has a computational capability of 0.01 GHz while the CAP has a computational capability of 0.5 GHz. The transmit power at each user is set to 1 W, the variance of AWGN is 0.001, and μ is set to 10. The average channel gain in the Nakagami-m fading channels is set to unity with $m=1$, although the results can be easily extended to other values of m. We set the energy consumption threshold to 3.

Fig.2 and Table 1 depict the value of outage probability on the multiuser MEC networks with $N=5$, where the transmit SNR changes in [10, 40]dB. As seen from Fig.2 and Table 1, the value of system outage probability drops swiftly when the transmit SNR becomes large. The phenomenon of that is due to the fact that increasing SNR can effectively enhance the channel capacity and improve the network transmission performance, which can essentially reduce the system outage probability, enhancing the users' quality of experience in further. Moreover, the analytical results and the asymptotic results can both fit the simulation results very well, which shows the availability of the derived closed-form formula for the system outage probability.

The system outage probability on multiuser MEC networks is illustrated in Fig. 3 and Table 2 in relation to the system total bandwidth B_{total}. The total wireless bandwidth ranges from 5 MHz to 45 MHz, with each user's wireless bandwidth being equal to B_{total}/N. The results of the figure and table show that the outage probability decreases with increasing wireless bandwidth, due to the higher transmission rate. The consistency between the simulation, analytical, and asymptotic results confirms the accuracy of (22) and (24). Additionally, it can be seen that the outage probability with $M=5$ is lower than that with $M=10$ because fewer users receive more bandwidth resources, thus improving the system performance.

In Fig. 4 and Table 3, the system outage probability for different users in multiuser MEC networks is plotted as the task size varies from 20 Mb to 40 Mb, with N set to 5 and 10, respectively. As shown in Fig. 4, when $N=5$, the simulation, analytical, and asymptotic results all have similar outage probabilities. However, as N increases to 10, the asymptotic result has a lower outage probability compared to the others, particularly for larger task sizes. Additionally, the outage probability for $N=10$ is greater than that of $N=5$, indicating that an increase in the number of users exacerbates the outage. Furthermore, the outage probability increases as the task size increases due to the increased communication resources required to complete the transmissions, resulting in a higher probability of failure.

The system outage probability on multiuser MEC networks is shown in Fig.5 and Table 4 with respect to the varying energy threshold E_{th}, which ranges from 1.8 to 3.4 for N

TABLE I
NUMERICAL OUTAGE PROBABILITY VERSUS THE TRANSMIT SNR.

SNR	10	15	20	25	30	35	40
$P_{out,sim}$ (N=5)	0.6650	0.2924	0.1036	0.0339	0.0108	0.0034	0.0010
$P_{out,ana}$ (N=5)	0.6651	0.2924	0.1036	0.0340	0.01088	0.0034	0.0010
$P_{out,asy}$ (N=5)	/	0.3459	0.1094	0.0345	0.0109	0.0034	0.0010
$P_{out,sim}$ (N=10)	0.9999	0.9585	0.6343	0.2727	0.0956	0.0312	0.0100
$P_{out,ana}$ (N=10)	0.9999	0.9585	0.6344	0.2725	0.0957	0.0313	0.0100
$P_{out,asy}$ (N=10)	/	/	/	0.3182	0.1006	0.0318	0.0100

TABLE II
NUMERICAL OUTAGE PROBABILITY VERSUS THE BANDWIDTH B.

Bandwidth	5	15	20	25	30
$P_{out,sim}$ (N=5)	0.8175	0.0108	0.0033	0.0018	0.0012
$P_{out,ana}$ (N=5)	0.8175	0.0108	0.0034	0.0018	0.0012
$P_{out,asy}$ (N=5)	1	0.0109	0.0034	0.0018	0.0012
$P_{out,sim}$ (N=10)	1	0.0956	0.01494	0.0062	0.0036
$P_{out,ana}$ (N=10)	1	0.0957	0.01489	0.0062	0.0036
$P_{out,asy}$ (N=10)	1	0.1006	0.01500	0.0062	0.0036

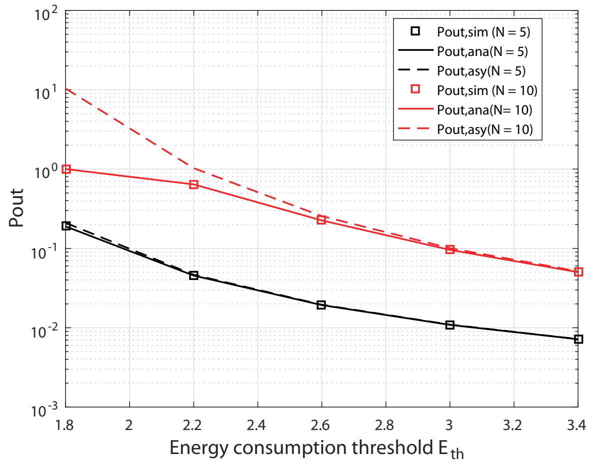

Fig. 5. System outage probability versus the energy consumption threshold E_{th}.

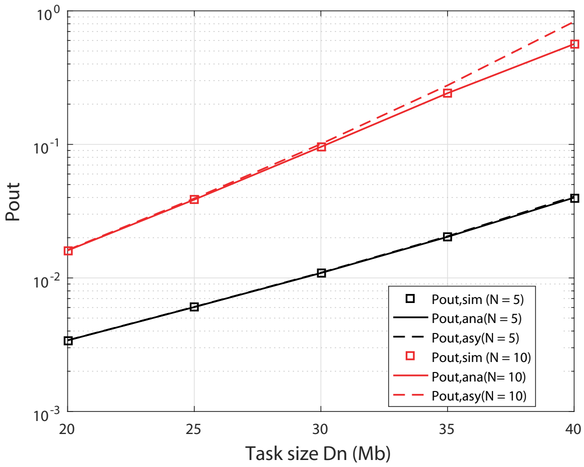

Fig. 4. System outage probability versus the task size D_n.

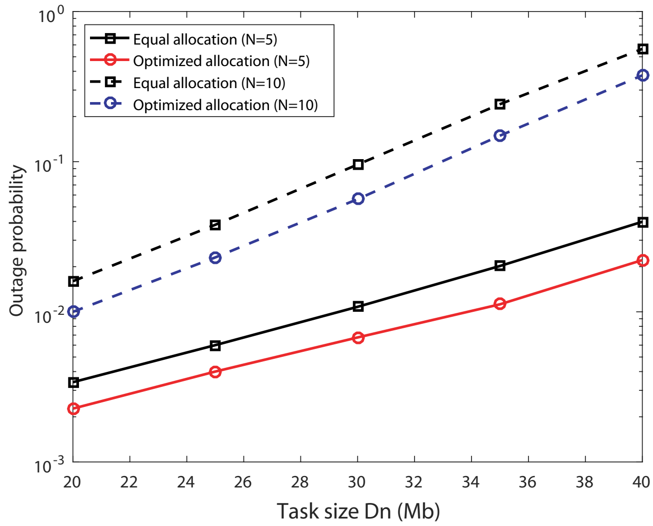

Fig. 6. Performance comparison of two offloading schemes versus the task size D_n.

values between 5 and 10. The figure and table demonstrate that the analytical results closely match the simulation results for all values of N. This confirms the accuracy of the derived analytical outage probability. Furthermore, when E_{th} becomes larger, the asymptotic results approach the analytical results, verifying the validity of the proposed asymptotic results. Additionally, it can be seen that the system performance improves as E_{th} increases, as a larger threshold allows for more energy to be consumed in computing and offloading. These results further support the proposed analytical process.

The performance comparison of the system outage probability on multiuser MEC networks, obtained by different users, is presented in Fig. 6 as the task size varies from 20 Mb to 40 Mb, with N set to 5 and 10 respectively. The figure depicts two offloading schemes, the equal allocation and the optimized allocation (as shown in (31)). The results in Fig. 6 indicate that the optimized offloading proposed in

TABLE III
NUMERICAL OUTAGE PROBABILITY VERSUS THE TASK SIZE D_n.

D_n	20	25	30	35	40
$P_{out,sim}$ (N=5)	0.0034	0.0060	0.0108	0.0202	0.0398
$P_{out,ana}$ (N=5)	0.0034	0.0060	0.0108	0.0202	0.0399
$P_{out,asy}$ (N=5)	0.0034	0.0060	0.0109	0.0204	0.0407
$P_{out,sim}$ (N=10)	0.01601	0.0386	0.0956	0.2415	0.5637
$P_{out,ana}$ (N=10)	0.01605	0.0385	0.0957	0.2416	0.5639
$P_{out,asy}$ (N=10)	0.01618	0.0393	0.1006	0.2766	0.8299

TABLE IV
NUMERICAL OUTAGE PROBABILITY VERSUS THE ENERGY CONPSUMPTION THRESHOLD E_{th}.

E_{th}	1.8	2.2	2.6	3	3.4
$P_{out,sim}$ (N=5)	0.1895	0.0453	0.0191	0.0108	0.0071
$P_{out,ana}$ (N=5)	0.1895	0.0454	0.0193	0.0108	0.0071
$P_{out,ast}$ (N=5)	0.2101	0.0465	0.0194	0.0109	0.0071
$P_{out,sim}$ (N=10)	0.9999	0.6410	0.2252	0.0956	0.0502
$P_{out,ana}$ (N=10)	0.9999	0.6409	0.2252	0.0957	0.0502
$P_{out,asy}$ (N=10)	/	/	0.2551	0.1006	0.0515

the paper outperforms the equal offloading scheme for both $N = 5$ and $N = 10$, as it effectively utilizes the computing resources between the users and CAP, resulting in reduced energy consumption. Additionally, the system performance deteriorates with an increase in D_n or N due to the increased burden from intensive tasks, leading to a higher P_{out} value.

VI. CONCLUSIONS

In this article, we improved the performance of multiuser MEC networks by analyzing the system. The computational tasks were transmitted to the MEC server over Nakagami-m fading channels. To define the system computing outage probability, we considered both the energy consumption from communication and computing, and defined the outage as occurring if the energy consumption is larger than the predetermined threshold. We analyzed the system performance by determining the analytical expression for the system outage probability and presenting an asymptotic expression for high SNR. Additionally, we optimized the system performance by adjusting the task offloading ratios. Numerical and simulation results were presented to validate our analysis and optimization, providing insights into designing edge computing systems in multiuser MEC networks.

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