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Secure Computation Efficiency Maximization in NOMA-Enabled Mobile Edge Computing Networks

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ABSTRACT In this paper, a computation efficiency maximization problem is studied in a multi-user non-orthogonal multiple access (NOMA) enabled mobile edge computing (MEC) networks. Physical layer security is used to prevent multi-user computing tasks from eavesdropping. The secure computation efficiency optimization problem is formulated by optimizing the transmission power and central processing unit (CPU) frequency jointly in the NOMA-enabled MEC networks. The problem is non-concave and challenging to solve, and a low complexity sequential fractional programming is proposed to solve this problem. The numerical results are provided to verify that the proposed scheme is superior to the traditional scheme in terms of the secure computation efficiency and our designed iteration algorithm's efficiency is verified.

INDEX TERMS Mobile edge computing, non-orthogonal multiple access, partial offloading, physical layer security, computation efficiency, sequential fractional programming.

I. INTRODUCTION

Recently, new applications with advanced functions such as virtual reality (AR), mobile online games and face recognition are emerging [1]. Due to size constraints and production cost considerations of the batteries, mobile devices typically carry capacity-constrained batteries and low computation performance processors. However, the limited battery capacity and low computing capability of the mobile devices cannot support these emerging latency-sensitive and computationally intensive applications. Therefore, how to tackle these two basic performance limitation problems to enjoy services with high quality of experience is important and challenging [2].

Mobile edge computing (MEC) has become a promising technology that can significantly enhance the computing capability of wireless devices and enable a variety of computationally intensive and latency-critical emerging applications [3]. By deploying a MEC server at the edge of a network, for instance, an access point (AP), the mobile device can intensive tasks to the AP for efficient remote execution (see, e.g., [4]–[6]), which can significantly reduce the computing burden of mobile devices. There are two operation modes for MEC, namely, partial and binary computation offloading [7]. In binary computational offloading, the computing task is indivisible, and it needs to be performed by the local computing of the device itself or by offloading task into the MEC server. The computing task in partial offloading can be divided into two parts, which can be processed in parallel by offloading and local computing.

Meantime, in order to provide more users with MEC services, it is crucial important to focus on offloading techniques. Moreover, the problem of insufficient spectrum resources getting more serious. Recent research has found that NOMA can support overloaded transmission of limited resources and further improve spectral efficiency [8] and [9], which can achieve a balance between user fairness and spectral efficiency. In contrast to traditional orthogonal multiple access (OMA), such as the time division multiple access (TDMA) and frequency division multiple access (FDMA), NOMA utilizes the power domain. Because NOMA has the advantage of serve multiple users at different power levels simultaneously, the number of users who need to offload their computation tasks increases [10]. To maintain the fairness of users, NOMA finds the users with weaker channel gains and allocates more power to them. Many of the previous contributions [11]–[15] have considered OMA in the MEC network. Due to the benefits of NOMA, a NOMA-enabled MEC network was studied in [5], the base

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station (BS) receives the computational tasks offloaded by the users simultaneously, and to decoding information via successive interference cancellation (SIC).

However, due to the broadcast nature of NOMA, the security of NOMA-enabled MEC networks needs to be considered. Specifically, the computation tasks offloaded to the MEC server can be eavesdropped by the broadcast nature of wireless communications and the inherent randomness of wireless channels, computing tasks loaded by devices can also be eavesdropped by malicious users [16], which can result in threats to the security of the computation task offloading. There are currently two security methods, one is through data encryption and the other is through physical layer security. We consider physical layer security because there is no extra cost to generate the secret key, and manage the key. Physical layer security is a viable solution to guarantee the security of wireless communications where eavesdropping attacks exist, only if the channel state information (CSI) of the legitimate users is better than that of the eavesdropper (e.g., [17]–[20]). Naturally, physical layer security can be applied to NOMA-enabled MEC networks in order to achieve robust secure transmission.

Besides the security issue, energy consumption is also an important issue required to be considered. According to recent survey found that the global footprint percentage (considering carbon dioxide equivalent emissions) caused by information and communication technology (ICT) was 5% [21] and [22]. Although this ratio is small, it is rapidly increasing, and with the continuous development of communication networks, this situation will be upgraded in the near future [23]. Green communication will become more and more important in the future because energy consumption will bring a series of environmental problems. Given the importance of green communications, future research needs to focus on reducing energy consumption and reducing carbon dioxide emissions to better protect the environment. At the same time, mobile devices are often limited by energy, and it is very important to improve computing energy efficiency. The traditional energy efficiency definition in wireless communication systems concept only considers the offloading process and does not consider the computing process. In MEC networks, the energy consumption should consider both the computation and offloading process. Recently, [24] and [25] proposed the concept of computation energy efficiency, which is defined as the ratio of the total computation bits to the energy consumption. It considers both the computing process and the offloading process, which can solve the balance between computing bits and energy consumption.

A. RELATED WORK AND MOTIVATION

NOMA-enabled MEC networks have been widely studied in recent years [6], [26]–[30]. In [26], the authors studied the offloading delay minimization problem in NOMA-enabled MEC networks. In [27], the authors jointly optimize the time and power allocation to reduce the energy consumption of computation offloading in NOMA-enabled MEC networks. The MEC uses both the uplink and downlink transmissions of NOMA, and the results of the analysis are a good indication that latency and operating costs can be decreased by using NOMA into MEC networks [28]. The author in [29] studied the total energy consumption minimization problem that including local computation energy and transmission energy in an uplink NOMA-enabled MEC network. Different from [29], the authors proposed jointly optimizing the task offloading partitions, transmission time allocation, and transmit powers to minimize the total energy consumption in the NOMA-enabled MEC networks [6]. In [30], the authors exploited the full potential of both cases with binary and partial offloading via multi-antenna NOMA for minimizing the weighted sum-energy of multiuser MEC systems. However, because of the dynamic and open nature of radio propagation and the inherent randomness of wireless channel, there may exist malicious eavesdroppers that intercept the offloading information from the users.

To overcome this security problem of the MEC networks, a large number of works have been implemented [2], [31]–[34]. The authors in [31] utilized physical layer security to realize the secure computation task offloading in MEC networks by jointly optimizing the secure offloading and local computing to minimize the latency-constrained weighted sum-energy in multiuser multicarrier system. In [32], the authors have analyzed the security threats and challenges of edge paradigms from a holistic perspective, such as mobile cloud computing, mobile edge computing, and fog computing. In [2], the authors provided a comprehensive survey of the state-of-the-art MEC research with a focus on joint radio-and-computational resource management. The authors in [33] studied online security-aware edge computing under jamming attacks. A beneficial architecture has been proposed for secure unmanned aerial vehicles MEC from the perspective of the physical layer security and formulated an energy-efficient computation offloading problem in the presence of both active and passive eavesdroppers in [34].

Although NOMA-enabled MEC networks have been extensive researched [6], [27]–[30], and the secure offloading of MEC networks has been focused [2], [31]–[34]. There are few studies focused on the computation efficiency of the NOMA-enabled MEC networks. The resource allocation problem for MEC systems has been investigated in some recent works. In [35], the author studied the resource allocation problems in UAV-enabled wireless powered MEC networks under both the partial and binary computation offloading modes. The weighted sum computation rates of users were maximized by jointly optimizing the CPU frequencies, the user offloading times, the user transmit powers, and the UAV trajectory. The authors in [36] studied the average total energy minimization problem subject to the caching and deadline constraints to optimally allocate the storage resource at the base station for caching computation results as well as the uploading and downloading time durations in a multi-user cache-assisted MEC system. In [25], the authors proposed a new evaluation metric called computation efficiency in MEC systems. An optimization problem is formulated with the aim of maximizing the total computation efficiency with weight factors. The authors in [37] studied a weighted sum computation bits maximization problem in multi-user wireless powered edge computing networks with binary computation offloading policy by jointly optimizing the individual computing mode selection and system transmission time allocation.

These articles above do not consider security, but security is equally important in MEC networks, and the concept of computational efficiency is also very important. Therefore, we study a secure computation efficiency maximization in an NOMA-enabled MEC networks under the partial computation offloading mode in this paper. The CPU frequency of local computing and the transmission power of offloading are jointly optimized to maximize the secure computation efficiency while satisfying the maximum CPU frequency, the maximum transmission power and the minimum computing rate constraints.

B. CONTRIBUTIONS AND ORGANIZATION

In this paper, we investigate a secure computation efficiency maximization problem in an NOMA-enabled MEC networks with physical layer security. To the authors' best knowledge, it is the first time that the secure computation efficiency problem is studied under NOMA-enabled MEC partial offloading networks. To tackle this challenging problem, an effective scheme is designed to obtain the solution. The main contributions of this paper are summarized as follows.

- It is the first time that physical layer security is introduced to study the computation efficiency maximization problem in MEC networks with NOMA under the partial computation offloading mode. Moreover, the effect of the practical power amplifier coefficient on the computation efficiency is considered.
- The original optimization problem is a challenging non-convex and non-smooth problem due to the existing couple of optimization variables. We first propose a low complexity sequential fractional programming to approximate the problem into a convex optimization problem. When the NOMA protocol is applied, in order to tackle the challenging computation efficiency maximization problems, an iterative algorithm based on the successive convex approximation SCA) method is proposed for the partial offloading mode.
- Simulation results show that our proposed resource allocation scheme can improve the fairness among users in terms of the secure computation efficiency. It is shown that the computation efficiency obtained by our proposed SCA algorithm is superior to that of other benchmark schemes. In addition, simulation results show the tradeoff between the achievable secure computation efficiency and the computation bits.

The rest of the paper is organized as follows. Section II defines the system model. Section III formulates the secure computation efficiency maximization problem in NOMA-enabled MEC networks under the partial offloading mode and an effective scheme is proposed to achieve secure computation efficiency maximization. Section IV presents the simulation results to verify our proposed algorithm. Finally, we conclude this paper in Section V.

Notation: In this paper, italic letters denotes scalars and bold-face lower-case letters denotes vectors. For a vector a and a^T denotes its transpose, 0_N are the all-zero vectors. The gradient vector of a function $f(\mathbf{x})$ with respect to $\mathbf{x}$ are denoted by $\nabla_{\mathbf{x}} f$. $\mathbb{R}$ denotes the real number space and $\mathbb{R}^N$ denotes the space of $N \times 1$ real-valued vector. For $\mathbf{x} \in \mathbb{R}^N$ and $\mathbf{y} \in \mathbb{R}^N$, $\mathbf{x}$ is greater than or equal to $\mathbf{y}$ in a component-wise manner are denoted by $\mathbf{x} \succeq \mathbf{y}$.

II. SYSTEM MODEL

In this work, we consider a multi-user NOMA-enabled MEC network as shown in Fig. 1. The network consists of an AP that integrates with the MEC server, K users and a passive malicious eavesdropper. All nodes are assumed to be equipped with a single antenna. The physical layer security computing offloading model is considered in order to improve the security of the offloading process. Besides, we focus on partial offloading in this paper. Let h_k and g_k denote the channel power gains between the kth user to the AP and the eavesdropper, respectively. The instantaneous channel state information (CSI) of each user is known by the AP. The channel power gains are denoted by

$$h_k = d_{AP,k}^{-\delta} y_k, \tag{1a}$$
$$g_k = d_{E,k}^{-\delta} y_k, \tag{1b}$$

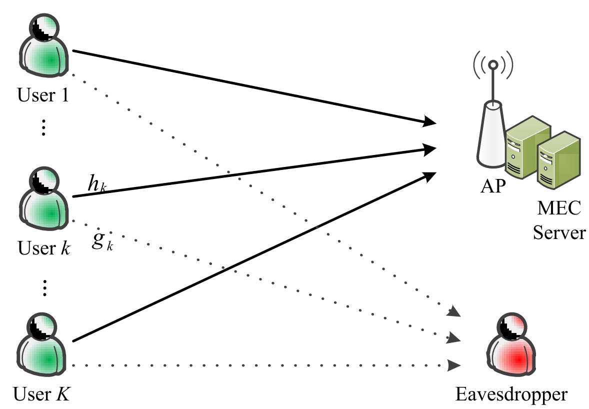

FIGURE 1. System model of NOMA-enabled MEC networks.

where $d_{AP,k}$ and $d_{E,k}$ represent the distances between the kth user to the AP and the eavesdropper, respectively. δ denotes the path loss exponent, and y_k is the Gaussian fading channel gain. Without loss of generality, the distances between the kth user and the AP is assumed to be ordered as $d_{AP,1} \geq d_{AP,2} \geq \cdots \geq d_{AP,K}$. Similarly, the distances between users and the eavesdropper are sorted as $d_{E,1} \geq d_{E,2} \geq \cdots \geq d_{E,K}$.

A. LOCAL COMPUTING MODE

As for the local computing at each user $k \in \mathcal{K}$, $\mathcal{K} = \{1, 2, \ldots, K\}$, the number of CPU cycles needed to computing one bit of raw data at the kth user are denoted by C_k. Moreover, the CPU frequency of the kth user is denoted by f_k. Thus, the computation rate of the kth user obtained by local computing

$$r_k^{loc} = f_k / C_k. \tag{2}$$

The local computing mode consumption power is expressed as a function of CPU frequency f_k, and modeled as $E_k^{loc} = \varepsilon_k f_k^3$, where ε_k represents the computational energy efficiency coefficient of CPU chips [35].

B. SECURE DATA OFFLOADING MODE

Apart from local computing, users can offload partial computation tasks to the MEC server for computing. In this paper, NOMA is applied to enable multiple users to simultaneously offload their computation tasks. According to NOMA principle, by using SIC techniques, the offloading computation rate of kth user by using physical layer security is

$$r_k^{off} = \begin{cases} B\left[R_{AP,k} - R_{E,k}\right]^+, & k \neq K, \\ B\left[\log_2(1+\frac{p_k\,|h_K|^2}{\sigma^2}) - \log_2(1+\frac{p_k\,|g_K|^2}{\sigma^2})\right]^+, & k = K, \end{cases} \tag{3}$$

where

$$R_{AP,k} = \log_2(1 + \frac{p_k\,|h_k|^2}{\sigma^2 + \sum_{j=k+1}^{K} p_j\,|h_j|^2}), \tag{4a}$$

$$R_{E,k} = \log_2(1 + \frac{p_k\,|g_k|^2}{\sigma^2 + \sum_{j=k+1}^{K} p_j\,|g_j|^2}), \tag{4b}$$

where σ^2 denotes the power of additive white Gaussian noise (AWGN) and B is the system bandwidth. $[x]^+ \triangleq \max(x, 0)$ means the bigger one between x and zero.

By defining

$$\sigma_k = \sigma^2/|h_k|^2, \tag{5a}$$

$$\eta_k = \sigma^2/|g_k|^2, \tag{5b}$$

$$\alpha_{k,j} = |h_j|^2/|h_k|^2, \tag{5c}$$

$$\gamma_{k,j} = |g_j|^2/|g_k|^2, \tag{5d}$$

the computing rate in secure offloading mode can be reformulated as

$$r_k^{off} = B\left[\log_2(1 + \frac{p_k}{\sigma_k + I_k}) - \log_2(1 + \frac{p_k}{\eta_k + H_k})\right]^+, \tag{6}$$

where

$$I_k = \begin{cases} \sum_{j=k+1}^{K} \alpha_{k,j} p_j, & k \neq K, \\ 0, & k = K, \end{cases} \tag{7a}$$

$$H_k = \begin{cases} \sum_{j=k+1}^{K} \gamma_{k,j} p_j, & k \neq K, \\ 0, & k = K, \end{cases}. \tag{7b}$$

The consumption power of secure data offloading mode can be expressed as $E_k^{off} = \zeta\,(p_k + p_r)$. Here, ζ denotes the coefficient of power amplifier, p_k represents the transmission power of the kth user, and p_r is a constant circuit power.

The secure computation efficiency of NOMA-enabled MEC networks can be defined as the secure computing rate, which is divided by the associated power consumption given as

$$\mu_{\text{CE}} = \frac{\sum_{k=1}^{K}\left[B\left[\log_2(1+\frac{p_k}{\sigma_k+I_k}) - \log_2(1+\frac{p_k}{\eta_k+H_k})\right]^+ + \frac{f_k}{C_k}\right]}{\sum_{k=1}^{K}\left[\zeta\,(p_k+p_r) + \varepsilon_k f_k^3\right]}. \tag{8}$$

III. SECURE COMPUTATION EFFICIENCY MAXIMIZATION

In this section, the secure computation efficiency maximization problem is formulated in the NOMA-enabled MEC network. In order to deal with the challenging non-smoothness and non-concave problem, a suboptimal solution is obtained by using SCA techniques.

A. PROBLEM FORMULATION

An optimized problem is formulated to maximize the secure computation efficiency among all users. Mathematically, the problem is given by

$$\text{P}_1 : \max_{\mathbf{f},\mathbf{p}} \; \mu_{\text{CE}} \tag{9a}$$

$$\text{s.t. } C1 : B\left[\log_2(1 + \frac{p_k}{\sigma_k + I_k}) - \log_2(1+\frac{p_k}{\eta_k + H_k})\right]^+ + \frac{f_k}{C_k} \geq R_k^{\min}, \quad \forall k, \tag{9b}$$

$$C2 : \zeta\,(p_k + p_r) + \varepsilon_k f_k^3 \leq P_k^{\max}, \quad \forall k, \tag{9c}$$

$$C3 : 0 \leq f_k \leq f_k^{\max}, \quad \forall k, \tag{9d}$$

$$C4 : 0 \leq p_k, \quad \forall k, \tag{9e}$$

P_1 is a secure computation efficiency maximization problem that optimizes the local computing CPU frequency f_k and the offloading transmission power p_k. To simplify the expression, $\mathbf{f} = (f_1, f_2, \ldots, f_K)^T$ and $\mathbf{p} = (p_1, p_2, \ldots, p_K)^T$ are introduced. $R_k^{\min}$ in C_1 represents the minimum computing rate of the kth user. $P_k^{\max}$ in C_2 denotes the maximum transmission power allowed by the kth user. C_3 defines the maximum CPU frequency of each user.

Through observation and analysis, it can be found that the optimal solution of P_1 is difficult to obtain for the following two reasons. First, the objective function is non-smoothness because of the operator $[\cdot]^+$. Second, despite the influence of $[\cdot]^+$, the objective function of $\mathbf{f}$ and $\mathbf{p}$ are still not associate concave. To solve the non-smoothness of the objective function of (9a), *Lemma 1* is defined as follows.

Lemma 1: The problem P_1 can be reformulated as

$$P_2 : \max_{\mathbf{f},\mathbf{p}} \ \mu \tag{10a}$$

$$\text{s.t. } C1: B\left[\log_2(1+\frac{p_k}{\sigma_k+I_k})-\log_2(1+\frac{p_k}{\eta_k+H_k})\right]^+ + \frac{f_k}{C_k} \geq R_k^{\min}, \quad \forall k, \tag{10b}$$

$$C2: \zeta\left(p_k+p_r\right)+\varepsilon_k f_k^3 \leq P_k^{\max}, \quad \forall k, \tag{10c}$$

$$C3: 0 \leq f_k \leq f_k^{\max}, \quad \forall k, \tag{10d}$$

$$C4: 0 \leq p_k, \quad \forall k, \tag{10e}$$

where

$$\mu = \frac{\sum_{k=1}^{K}\left[B\left(\log_2(1+\frac{p_k}{\sigma_k+I_k})-\log_2(1+\frac{p_k}{\eta_k+H_k})\right)+\frac{f_k}{C_k}\right]}{\sum_{k=1}^{K}\left[\zeta\left(p_k+p_r\right)+\varepsilon_k f_k^3\right]}. \tag{11}$$

Proof: The optimal solutions of problems P_1 and P_2 are denote by W_1^* and W_2^*, respectively. On the one hand, for any x, there always exists $[x]^+ \geq x$, i.e. $W_1^* \geq W_2^*$. On the other hand, the optimal solution of P_1 is denoted by $(\mathbf{f}^*, \mathbf{p}^*)$, where $\mathbf{p}^* = \left(p_1^*, p_2^*, \ldots, p_k^*\right)^T$. By defining

$$f\left(p_k\right) = \mu \tag{12}$$

and constructing the feasible solution of P_2 as $\left(\hat{\mathbf{f}}, \hat{\mathbf{p}}\right)$, we assume that $\hat{\mathbf{f}} = \mathbf{f}^*$. Then the element $\hat{\mathbf{p}}$ can be obtained from the following conditions. If $f\left(p_k^*\right) \geq 0$, then $\hat{p}_k = p_k^*$. Otherwise, $\hat{p}_k = 0$.

The target value under the feasible solution $\left(\hat{\mathbf{f}}, \hat{\mathbf{p}}\right)$ of problem P_2 is denoted by $\hat{W}$. Then, the newly constructed feasible solution $\left(\hat{\mathbf{f}}, \hat{\mathbf{p}}\right)$ ensures that $\hat{W} = W_1^*$. Because $\left(\hat{\mathbf{f}}, \hat{\mathbf{p}}\right)$ is feasible for P_2, $W_2^* \geq \hat{W}$, i.e. $W_2^* \geq W_1^*$. Thus, we can get $W_1^* = W_2^*$, which proves that P_1 and P_2 are equivalent when the secure computation efficiency is maximized. ∎

B. SUBOPTIMAL ITERATIVE ALGORITHM

Sequential fractional programming optimization can provide worthy convergence properties and lower the complexity of problems. However, it cannot be directly used to deal with P_2, because the secure computation efficiency is a fractional form. In order to tackle this problem, the original problem is simplified.

For problem P_2, the computing rate of the kth user can be expressed as

$$\begin{aligned} R_k &= B\left(\log_2(1+\frac{p_k}{\sigma_k+I_k})-\log_2(1+\frac{p_k}{\eta_k+H_k})\right)+\frac{f_k}{C_k} \\ &= B\left(\log_2\frac{\left(\eta_k+H_k\right)\left(\sigma_k+I_k+p_k\right)}{\left(\sigma_k+I_k\right)\left(\eta_k+H_k+p_k\right)}\right)+\frac{f_k}{C_k} \\ &= q_k^+(\mathbf{p}) - q_k^-(\mathbf{p}), \end{aligned} \tag{13}$$

where

$$q_k^+(\mathbf{p}) = B\log_2\left(\left(\eta_k+H_k\right)\left(\sigma_k+I_k+p_k\right)\right)+\frac{f_k}{C_k}, \tag{14a}$$

$$q_k^-(\mathbf{p}) = B\log_2\left(\left(\sigma_k+I_k\right)\left(\eta_k+H_k+p_k\right)\right). \tag{14b}$$

For the constraint (9b), it can be reformulated as

$$\begin{aligned} &B\left[\log_2(1+\frac{p_k}{\sigma_k+I_k})-\log_2(1+\frac{p_k}{\eta_k+H_k})\right]^+ + \frac{f_k}{C_k} \\ &= B\left[\log_2\frac{\left(\eta_k+H_k\right)\left(\sigma_k+I_k+p_k\right)}{\left(\sigma_k+I_k\right)\left(\eta_k+H_k+p_k\right)}\right]^+ + \frac{f_k}{C_k} \\ &= c_k^+(\mathbf{p}) - c_k^-(\mathbf{p}) + \frac{f_k}{C_k}, \end{aligned} \tag{15}$$

where

$$c_k^+(\mathbf{p}) = B\log_2\left(\left(\eta_k+H_k\right)\left(\sigma_k+I_k+p_k\right)\right), \tag{16a}$$

$$c_k^-(\mathbf{p}) = B\log_2\left(\left(\sigma_k+I_k\right)\left(\eta_k+H_k+p_k\right)\right), \tag{16b}$$

$$c_k^+(\mathbf{p}) \geq c_k^-(\mathbf{p}). \tag{16c}$$

Then, we can use the fractional programming and sequential optimization interactivity to solve P_2, the following assumption is proposed.

Assumption 1: The functions $q_k^+(\mathbf{p})$ and $q_k^-(\mathbf{p})$ in (13) and the functions $c_k^+(\mathbf{p})$ and $c_k^-(\mathbf{p})$ in (15) are concave functions for $\forall k \in \{1, \ldots, K\}$.

Under this circumstance, the objective function and the constraint expression can be written as the corresponding concave function subtraction form. It is only considered that the functions $q_k^+(\mathbf{p})$, $q_k^-(\mathbf{p})$, $c_k^+(\mathbf{p})$ and $c_k^-(\mathbf{p})$ are concavity in this section.

Because $q_k^+(\mathbf{p})$, $q_k^-(\mathbf{p})$, $c_k^+(\mathbf{p})$ and $c_k^-(\mathbf{p})$ are four non-negative functions, the original optimization problem can be expressed as

$$P_3 : \max_{\mathbf{f},\mathbf{p}} \ \frac{\sum_{k=1}^{K}\left[q_k^+(\mathbf{p})-q_k^-(\mathbf{p})\right]}{\sum_{k=1}^{K}\left[\zeta\left(p_k+p_r\right)+\varepsilon_k f_k^3\right]} \tag{17a}$$

$$\text{s.t. } C1: c_k^+(\mathbf{p}) - c_k^-(\mathbf{p}) + f_k/C_k \geq R_k^{\min}, \ \forall k, \tag{17b}$$

$$C2: c_k^+(\mathbf{p}) \geq c_k^-(\mathbf{p}), \ \forall k, \tag{17c}$$

$$C3: \zeta\left(p_k+p_r\right)+\varepsilon_k f_k^3 \leq P_k^{\max}, \ \forall k, \tag{17d}$$

$$C4: 0 \leq f_k \leq f_k^{\max}, \ \forall k, \tag{17e}$$

$$C5: 0 \leq p_k, \ \forall k, \tag{17f}$$

If *Assumption 1* holds, the objective function of (17a) and the constraint functions of (17b) and (17c) can be written as the corresponding concave function subtraction form. Thus, it is generally not concave. According to the standard fractional programming theory, non-concave results in fractional programming cannot be directly used to solve P_3.

To deal with the non-concave of P_3, it is observed that P_3 can be equivalent to a parameter problem based on the

Dinkelbach's method. The auxiliary problem is given by

$$\mathrm{P}_4 : \max_{\mathbf{f},\mathbf{p}} \sum_{k=1}^{K}\left[q_k^{+}(\mathbf{p})-q_k^{-}(\mathbf{p})\right]-\lambda\sum_{k=1}^{K}\left[\zeta\,(p_k+p_r)+\varepsilon_k f_k^3\right] \tag{18a}$$

$$\text{s.t. } C1: c_k^{+}(\mathbf{p})-c_k^{-}(\mathbf{p})+f_k/C_k \geq R_k^{\min}, \quad \forall k, \tag{18b}$$

$$C2: c_k^{+}(\mathbf{p}) \geq c_k^{-}(\mathbf{p}), \quad \forall k, \tag{18c}$$

$$C3: \zeta\,(p_k+p_r)+\varepsilon_k f_k^3 \leq P_k^{\max}, \quad \forall k, \tag{18d}$$

$$C4: 0 \leq f_k \leq f_k^{\max}, \quad \forall k, \tag{18e}$$

$$C5: 0 \leq p_k, \quad \forall k, \tag{18f}$$

where λ is a given positive value. Thus, the hidden structure in P_4 is used to obtain the conclusions as follows.

Proposition 1: For any given $\mathbf{p}_i$, we can obtained the following suboptimal problem

$$\mathrm{P}_5 : \max_{\mathbf{f},\mathbf{p}} \sum_{k=1}^{K}\left\{q_k^{+}(\mathbf{p})-\left[q_k^{-}(\mathbf{p}_i)+\left(\nabla_p q_k^{-}\mid_{\mathbf{p}=\mathbf{p}_i}\right)^T(\mathbf{p}-\mathbf{p}_i)\right]\right\} -\lambda\sum_{k=1}^{K}\left[\zeta\,(p_k+p_r)+\varepsilon_k f_k^3\right] \tag{19a}$$

$$\text{s.t. } C1: c_k^{+}(\mathbf{p})-\left[c_k^{-}(\mathbf{p}_i)+\left(\nabla_p c_k^{-}\mid_{\mathbf{p}=\mathbf{p}_i}\right)^T(\mathbf{p}-\mathbf{p}_i)\right] + \frac{f_k}{C_k} \geq R_k^{\min}, \ \forall k, \tag{19b}$$

$$C2: c_k^{+}(\mathbf{p})-\left[c_k^{-}(\mathbf{p}_i)+\left(\nabla_p c_k^{-}\mid_{\mathbf{p}=\mathbf{p}_i}\right)^T(\mathbf{p}-\mathbf{p}_i)\right] \geq 0, \ \forall k, \tag{19c}$$

$$C3: \zeta\,(p_k+p_r)+\varepsilon_k f_k^3 \leq P_k^{\max}, \ \forall k, \tag{19d}$$

$$C4: 0 \leq f_k \leq f_k^{\max}, \ \forall k, \tag{19e}$$

$$C5: 0 \leq p_k, \ \forall k, \tag{19f}$$

For any given $\mathbf{p}_i$, the left item of the objective function (19a) is a concave function, and the right item is an affine function, while the constraint functions in (19) are all affine or concave. Accordingly, we can solve P_5 by the iteration algorithm based on SCA techniques.

Proof: The upper bound of any concave function is its first-order Taylor expansion at any point. Due to $q_k^{-}(\mathbf{p})$ and $c_k^{-}(\mathbf{p})$ are concave functions, there is a formula for any power vector $\mathbf{p}_i$.

$$q_k^{+}(\mathbf{p})-q_k^{-}(\mathbf{p}) \geq q_k^{+}(\mathbf{p})-\left[q_k^{-}(\mathbf{p}_i)+\left(\nabla_p q_k^{-}\mid_{\mathbf{p}=\mathbf{p}_i}\right)^T(\mathbf{p}-\mathbf{p}_i)\right], \tag{20a}$$

$$c_k^{+}(\mathbf{p})-c_k^{-}(\mathbf{p}) \geq c_k^{+}(\mathbf{p})-\left[c_k^{-}(\mathbf{p}_i)+\left(\nabla_p c_k^{-}\mid_{\mathbf{p}=\mathbf{p}_i}\right)^T(\mathbf{p}-\mathbf{p}_i)\right]. \tag{20b}$$

It can be seen that the gradients in (20) can be represented as a closed form. Hence, (19a), (19b) and (19c) show the lower bounds of (17a), (17b) and (17c), respectively. By evaluating the $\mathbf{p}_i$, the lower bounds in (20) are tight. Thus, for $\mathbf{p} = \mathbf{p}_i$, it immediately follows that (19a), (19b) and (19c) are equal to (17a), (17b) and (17c), respectively. In the same way, for $\mathbf{p} = \mathbf{p}_i$, it can be shown that the gradients of (19a), (19b) and (19c) are equal to those of (17a), (17b) and (17c). Hence, the propositional proof is completed. ■

It is observed that P_5 is concave and can be readily solved by using CVX. For any $\mathbf{p}_i$, P_5 can be solved by Algorithm 1 which is based on using the SCA method. In Algorithm 1, R^i denotes the value of the objective function of P_5 at the ith iteration. When $R^i - R^{i-1} = 0$, the optimal resource allocation scheme and the maximum computation efficiency are obtained. The optimal solution for the transmission power in offloading and the CPU frequency in local computing are denoted as $p_k^{opt,i}$ and $f_k^{opt,i}$, respectively. ξ is the error tolerance for the computation efficiency iteration and N is the maximum iteration number. The details for Algorithm 1 can be found in Table 1.

TABLE 1. The iteration algorithm based on using SCA.

Algorithm 1: The iteration algorithm for P_5.

1: **Setting:**
  $P_k^{\max}$, $R_k^{\min}$, $f_k^{\max}$, and the tolerance errors ξ;
  the maximum iteration number N.
2: **Initialization:**
  $\lambda_i = \lambda_0$ and the iterative index $i = 0$;
3: **Repeat:**
  solve P_5 by using *proposition 1* for given $\mathbf{p}_i$;
  obtain the solution $p_k^{opt,i}$ and $f_k^{opt,i}$;
  update λ_i using the SCA algorithm;
  if $\left|R^i - R^{i-1}\right| \leq \xi$
    the maximum secure computation efficiency R^i is obtained;
    break;
  else
    update the iterative number $i = i + 1$;
  end
 end Repeat
4: **Obtain solution:**
  f_k^{opt} and p_k^{opt}.

IV. SIMULATION RESULTS

In this section, simulation results are given to evaluate the performance of our proposed the computation efficiency (CE) maximization scheme, as compared to other benchmark schemes, namely, partial offloading with OMA, only local computing and only global offloading. Moreover, the CE obtained by the proposed scheme is also compared with that of the traditional computation bits (CB) maximization scheme. Finally, we evaluated the converge performance of the proposed algorithm by simulation results.

We randomly generate 50,000 channel realizations with parameters $y_k \sim \mathcal{CN}(0, 1)$, the path loss exponent $\delta = 3$. The distance set from the users to the AP and the eavesdropper, can be generated by an arithmetic sequence. Specifically, distances are denoted by $D_{AP} = \{d_{AP,1}, d_{AP,2}, \cdots, d_{AP,K}\}$ and $D_E = \{d_{E,1}, d_{E,2}, \cdots, d_{E,K}\}$, respectively. Here, it is assumed that $D_{AP} = \{d_{AP,k} | d_{AP,k} = K - k + 1, \forall k\}$ and $D_E = \{d_{E,k} | d_{E,k} = K - k + 1, \forall k\}$ for simplicity. Part of simulation parameter settings in Table 2 refer to the works in [25], [38], if without specific explanation.

TABLE 2. Simulation parameters.

Parameters	Notation	Typical Values
Numbers of Users	K	2
The noise power	σ^2	10^{-8}
The communication bandwidth	B	$2 * 10^4$ Hz
The constant circuit power	p_r	0.05 W
The number of cycles for one bit	C	10^3 cycles/bit
The capacitance coefficient	ϵ	10^{-28}
The Maximum transmission power	$P_{\max}$	2 W
The Minimum computing rate	$R_{\min}$	10^4 bits
The amplifier coefficient	ζ	3
The tolerance error	ξ	10^{-4}

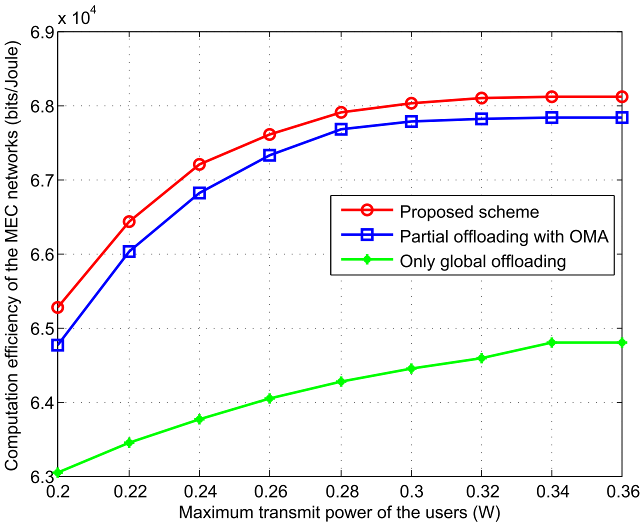

FIGURE 2. The computation efficiency versus the maximum transmission power of the users.

Fig. 2 shows the CE versus maximum transmission power of the users under three schemes, namely, the proposed scheme in this paper, partial offloading with OMA scheme, and only global offloading scheme, respectively. It is observed that our proposed scheme can achieve a better CE than that of the other two schemes. The reason is that the offloading efficiency is higher when NOMA is applied compared to that of OMA. In addition, under the CE of all the schemes, the CE increases with the maximum transmission power of the users firstly. Besides, when the maximum transmission power of the users is large enough, the CE reaches to a constant. Moreover, it can be seen that the partial offloading with OMA scheme achieved a better CE than that of the only global offloading scheme. The reason is that in partial offloading with OMA scheme, the resources can be allocated flexibly to computation offloading and local computing.

Fig. 3 shows the CE versus the minimum computing rate of the users comparison results among four schemes, namely, the proposed scheme in this paper, partial offloading with OMA scheme, only local computing scheme and only global offloading scheme. It can be observed that the CE obtained by our proposed algorithm are superior to those of other

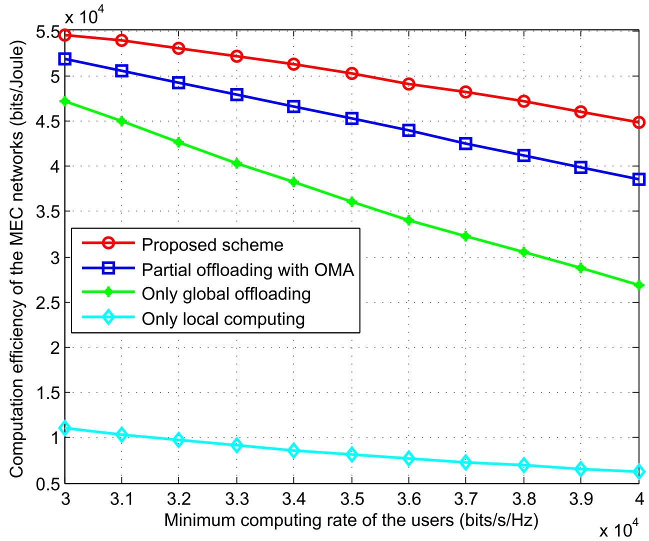

FIGURE 3. The computation efficiency versus the minimum computing rate of the users.

schemes. Moreover, it can be seen that the CE obtained by the proposed scheme in this paper or the other two schemes decreases with the increase of the required minimum computing rate of the users.

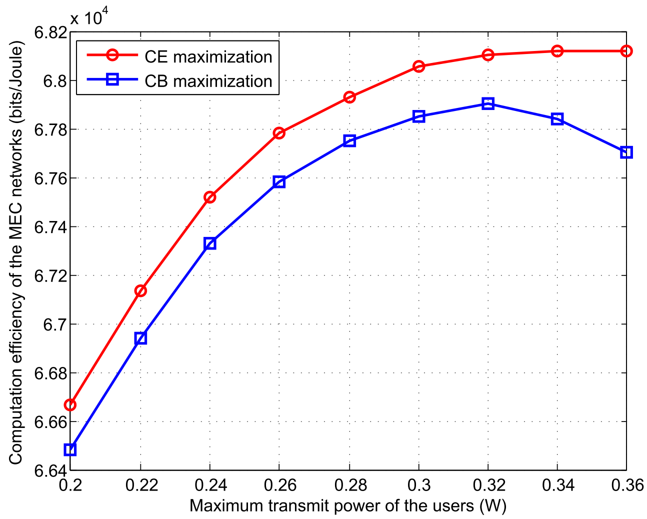

FIGURE 4. The computation efficiency obtained by SCA algorithm versus the maximum transmission power of the users under our proposed the computation efficiency maximization scheme and the computation bits maximization scheme.

Fig. 4 shows the computation efficiency obtained by using the algorithm versus the maximum transmission power of the users under our proposed computation efficiency maximization scheme and computation bits maximization scheme. As shown in Fig. 4, with the maximum transmit power of the users increases, the CE obtained by our proposed scheme increases and reaches to a stable value. As a comparison, the traditional CE calculated by CB is lower than that of the value in our proposed scheme with the same maximum transmit power of the users. This proves the superiority of our proposed framework. Besides, it is seen that when the maximum transmission power reaches to a certain value, the traditional CE calculated by CB is decreased. This result demonstrates the fact that the increasing rate of the total computation power is greater than the increasing rate of CB, and there is a tradeoff between the CE and the CB.

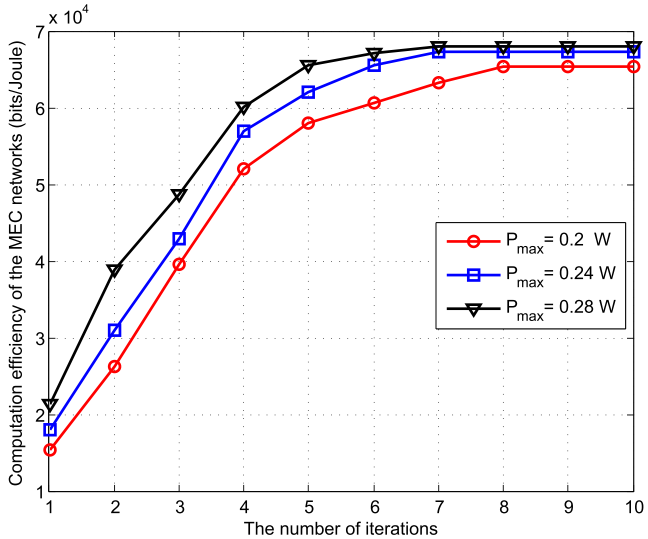

FIGURE 5. The computation efficiency versus the number of iterations under different maximum transmission powers.

Fig. 5 illustrates the convergence behaviors of our proposed SCA algorithm. The maximum transmission power of the users is set as $P_k^{\max} = 0.2,\ 0.24,\ 0.28\ W$. It is observed that the proposed algorithm converges rapidly, which shows that our proposed algorithm is effective in terms of the convergence rate. As shown in Fig. 5, the secure computation efficiency obtained by our proposed SCA algorithm increases with the number of iterations firstly and then with a few iterations is achieved to converges. Moreover, the value of computation efficiencies achieved by three different maximum transmit power matches the trend of that value in Fig. 2.

V. CONCLUSION

The computation efficiency maximization problem was studied in a NOMA-enabled MEC network with physical layer security. To address this challenging problem, we first formulated the secure computation efficiency problem by jointly optimizing the transmission power of offloading and the CPU frequency of local computing. An iterative algorithm based on using SCA techniques is designed to obtain the solution of the optimization problem. Simulation results shown that NOMA is superior to OMA in terms of computation efficiency maximization. It was also shown that the computation efficiency achieved by using our proposed scheme is better than that of other benchmark schemes. Moreover, the tradeoff between the computation efficiency and computation bits was found.

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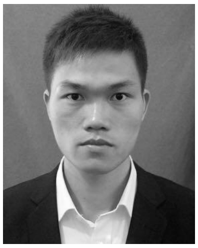

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