Secure and Energy-Efficient Offloading and Resource Allocation in a NOMA-Based MEC Network

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Abstract—Energy efficiency and security are two critical issues for mobile edge computing (MEC) networks. With stochastic task arrivals, time-varying dynamic environment, and passive existing attackers, it is very challenging to offload computation tasks securely and efficiently. In this paper, we study the task offloading and resource allocation problem in a non-orthogonal multiple access (NOMA) assisted MEC network with security and energy efficiency considerations. To tackle the problem, a dynamic secure task offloading and resource allocation algorithm is proposed based on Lyapunov optimization theory. A stochastic non-convex problem is formulated to jointly optimize the local CPU frequency and transmit power, aiming at maximizing the network energy efficiency, which is defined as the ratio of the long-term average secure rate to the long-term average power consumption of all users. The formulated problem is decomposed into the deterministic sub-problems in each time slot. The optimal local CPU-cycle and the transmit power of each user can be given in the closed-from. Simulation results evaluate the impacts of different parameters on the efficiency metrics and demonstrate that the proposed method can achieve better performance compared with other benchmark methods in terms of energy efficiency.

Index Terms—Edge computing, physical layer security, Lyapunov optimization, resource allocation, NOMA.

I. INTRODUCTION

The explosive data traffic growth, fast development, and commercialization of the 5G wireless communication networks impose great challenges on data security as well as global energy consumption [1]. In order to improve energy efficiency (EE), mobile edge computing (MEC) and non-orthogonal multiple access (NOMA) have been envisaged as two promising technologies in 5G and the forthcoming 6G wireless networks. By deploying edge servers with high computational capacities close to end users, the end users can offload partial or all computation tasks to the nearby MECs to save power as well as speed up the computing [2]. Meanwhile, by exploiting superposition coding at the transmitter and successive interference cancellation (SIC) at the receiver, NOMA brings significant changes to the multiple access. NOMA allows multiple users to share the same radio bandwidth in either power domain or code domain to improve spectral efficiency with a relatively higher receiver complexity [3].

Applying NOMA into MEC-enabled networks has recently received extensive attention due to its performance gain in both spectrum efficiency and EE [3–6]. Most of the existing works didn’t taking the security issue into account. In fact, due to the broadcast nature of the wireless link, it could be very vulnerable for the tasks to be intercepted by the eavesdroppers. The physical layer security (PLS) in the NOMA-assisted MEC networks has received many research interests [7]. The joint consideration of PLS in the NOMA assisted MEC network was studied in [8–10]. In [8], an iterative algorithm was proposed to maximize the minimum anti-eavesdropping ability in a MEC network with uplink NOMA. The authors in [9] proposed a bisection searching algorithm to minimize the maximum task completion time subject to the worst-case secrecy rate. Instead of only considering the power consumption or computing rate performance above, [10] studied the EE maximization problem for a NOMA enabled MEC network with eavesdroppers.

Most of the existing works on NOMA-assisted MEC with external eavesdroppers typically focus on the performance evaluation in the scenarios where either channel conditions or required tasks remain constant. Such an assumption makes the analysis on the computation offloading and resource allocation more tractable. However, in a dynamic environment, the dynamic behaviors of the workload arrivals and fading channels impact the overall system performance. Thus the system design that focuses on the short term performance may not work well from the long term perspective. Towards that, a stochastic task offloading model and resource allocation strategy should be adopted [11]. In this paper, we integrate PLS and study the long-term EE performance in a NOMA-enabled MEC network. By incorporating the statistical behaviors of the channel states and task arrivals, we formulate a stochastic optimization problem to maximize the long-term average EE subject to multiple constraints including task queue stability, maximum available power, and peak CPU-cycle frequency. An energy-efficient offloading and resource allocation method based on Lyapunov optimization is proposed. The simulation results validate the superior performance of the proposed method in terms of EE in a secure NOMA-assisted MEC network.

The rest of the paper is organized as follows. Section II describes the system model. In Section III, the EE maximization
problem and corresponding alternative solution are presented. Numerical results are provided in Section IV. The paper is concluded in Section V.

II. SYSTEM MODEL

In Fig. 1, an uplink NOMA communication system is considered, which consists of $N$ user equipments (UEs), one access point (AP) with the MEC server, and one external eavesdropper (Eve) near the AP. All the UEs can offload their computation tasks to the MEC while the external eavesdropper intends to intercept the confidential information. The arrival task of user $n$ at time slot $t$ is denoted as $A_n(t)$. Note that the prior statistical information of $A_n(t)$ is not required and it could be difficult to obtain in the practical systems. We focus on a data-partition-oriented computation task model. A partial offloading scheme is used, i.e., part of the task is processed locally and the remaining part of the data can be offloaded to the remote server for processing. For each UE, local computing and task offloading can be executed simultaneously.

Assuming that each UE has buffering ability, where the arrived but not yet processed data can be queued for the next time slot. Let $Q_n(t)$ be the queue backlog of UE $n$, and its evolution equation can be expressed as

$$Q_n(t+1) = \max\{Q_n(t) - R_n^{\text{off}}(t)\tau, 0\} + A_n(t),$$

where $R_n^{\text{off}}(t) = R_n^{\text{off}}(t) + R_n^{\text{loc}}(t)$ is the total computing rate of UE $n$ at time slot $t$, $R_n^{\text{off}}(t)$ and $R_n^{\text{loc}}(t)$ are secure offloading rate and local task processing rate, respectively. $\tau$ is time duration of each slot.

A. Local Computing Model

Let $f_n(t)$ denote the local CPU-cycle frequency of UE $n$, which cannot exceed its maximum value $f_{\text{max}}$. Let $C_n$ be the computation intensity (in CPU cycles per bit). Thus, the local task processing rate can be expressed as $P_n^{\text{loc}}(t) = f_n(t)/C_n$. We use the widely adopted model $P_n^{\text{loc}}(t) = \kappa_n f_n(t)$ to calculate the local computing power consumption of UE $n$, where $\kappa_n$ is the energy coefficient and its value depends on the chip architecture [12].

B. Task Offloading Model

The independent and identically distributed (i.i.d) frequency-flat block fading channel model is adopted, i.e., the channel remains static within each time slot but varies across different time slots. The small-scale fading coefficients from UE $n$ to the MEC server and to the Eve are denoted as $H_{b,n}(t)$ and $H_{e,n}(t)$, respectively. Both are assumed to be exponentially distributed with unit mean [13]. Thus, the channel power gain from UE $n$ to the MEC is given as $h_n(t) = H_{b,n}(t)g_0(d_0/d_{n,t})^\theta$, $i \in \{b,e\}$, where $g_0$ is the path-loss constant, $\theta$ is the path-loss exponent, $d_0$ is the reference distance, and $d_{n,t}$ is the distance from UE $n$ to receiver. Furthermore, to improve the spectrum efficiency, NOMA is applied on the uplink access for offloading. We assume that $h_{b,1} \leq h_{b,2} \leq \cdots \leq h_{b,N}$ and $h_{e,1} \leq h_{e,2} \leq \cdots \leq h_{e,N}$. Using SIC at the receiver side, the achievable secure offloading rate at UE $n$ can be given by

$$R_n^{\text{off}}(t) = [B \log_2(1 + \gamma_{b,n}) - B \log_2(1 + \gamma_{e,n})]^+,$$

where $B$ is the bandwidth allocated to each UE, $\gamma_{b,n} = \frac{\sum_{i=1}^N p_i(t)h_{b,i}(t) + \sigma_{b,n}^2}{\sum_{i=1}^N p_i(t)h_{b,i}(t) + \sigma_{b,n}^2}$ and $\gamma_{e,n} = \frac{\sum_{i=1}^N p_i(t)h_{e,i}(t) + \sigma_{e,n}^2}{\sum_{i=1}^N p_i(t)h_{e,i}(t) + \sigma_{e,n}^2}$ are the SINRs received by the MEC server and the Eve respectively, $p_n(t)$ is the transmit power of UE $n$, $\sigma_{b,n}^2$ and $\sigma_{e,n}^2$ are the background noise variances at the MEC and the Eve respectively. $[x]^+ = \max(x, 0)$. The power consumption for offloading can be expressed as $P_n^{\text{off}}(t) = \zeta p_n(t) + p_r$, where $\zeta$ is the amplifier coefficient and $p_r$ is the constant circuit power consumption.

III. DYNAMIC TASK OFFLOADING AND RESOURCE ALLOCATION

A. Problem Formulation

EE is defined as the ratio of the number of long term total computed bits achieved by all the UEs to the total energy consumption [14],

$$\eta(t) = \frac{\lim_{T \to \infty} \frac{1}{T} E[\sum_{t=1}^T R_{\text{tot}}(t)\tau]}{\lim_{T \to \infty} \frac{1}{T} E[\sum_{t=1}^T P_{\text{tot}}(t)\tau]} = \frac{R_{\text{tot}}}{P_{\text{tot}}\tau},$$

where $R_{\text{tot}} = \sum_{n=1}^N R_n^{\text{off}}(t)$ and $P_{\text{tot}} = \sum_{n=1}^N P_n^{\text{off}}(t) + \sum_{n=1}^N P_n^{\text{loc}}(t)$ are the total achievable rate and consumed power by all the users at $t$.

This work aims to maximize the long-term average EE for all the UEs under the constraints of resource limitations while guaranteeing the average queuing length stability. Therefore, the problem is formulated as

$$\mathbf{P}_0 : \max \quad \eta$$

$$\text{s.t.} \quad P_n^{\text{tot}}(t) \leq P_{\text{max}},$$

$$\lim_{T \to \infty} \frac{1}{T} E[|\mathbf{Q}_n(t)|] = 0,$$

$$f_n(t) \leq f_{\text{max}},$$

$$0 \leq p_n(t),$$

where $\mathbf{Q}_n(t)$ is the average queue length of UE $n$. The constraint (4b) indicates that the total power consumed by UE at time slot $t$ should not exceed the maximum allowable power $P_{\text{max}}$. (4b) requires the task buffers to be mean rate stable, which also ensures that all the arrived computation tasks can be processed within a finite delay. (4c) is the range of local computing frequency, and (4d) denotes the transmit power of each UE should not be negative.
Algorithm 1 Dynamic Resource Allocation Algorithm

1. At the beginning of the $t$th time slot, obtain $\{Q_n(t)\}, \{A_n(t)\}$.  
2. Determine $f(t)$ and $p(t)$ by solving
   \[
   \begin{aligned}
   P_2 : \max_{f_n(t), p_n(t)} & \sum_{n=1}^{N} \{Q_n(t)(R_n^\text{tot}(t) - A_n(t)) \} \\
   & + V \sum_{n=1}^{N} [R_n^\text{tot}(t) - \eta^*(t)P_n^\text{tot}(t)\]t]
   \end{aligned}
   \]
   s.t. $\{\text{(4a)}, \text{(4b)}\}$. 
3. Update $\{Q_n(t)\}$ and set $t = t + 1$. Go back to step 1.

B. Problem Transformation Using Lyapunov Optimization

The problem $P_0$ is a non-convex problem, which is difficult to be solved due to the fractional structure of the objective function and the long term queue constraint. By incorporating queue stability, the quadratic Lyapunov function is transformed into a bounded level. The problem $P_0$ can be decomposed into two sub-problems, namely the optimal CPU-cycle frequency scheduling sub-problem and the optimal transmit power allocation sub-problem, which can be solved alternately in the following.

Optimal CPU-Cycle Frequencies Scheduling: The optimal CPU-cycle frequencies $f(t)$ can be obtained by

\[
\begin{aligned}
P_{2,1} : \max_{0 \leq f_n(t) \leq f_{\max}} & \sum_{n=1}^{N} \{Q_n(t) + V(R_n^f(t) + f_n(t))/C_n \} - V\eta(t)(\kappa_n f_n^2(t) + p_r + \zeta p_n(t)) \\
\end{aligned}
\]
\begin{aligned}
\text{s.t.} & \quad \kappa_n f_n^3(t) \leq P_{\max} - P_{\off} f_n^3(t). 
\end{aligned}
\]

Since the objective function of $P_{2,1}$ and the constraints are convex with respect to $f_n(t)$, the optimal $f_n(t)$ can be given as

\[
f^*_n = \left[ \frac{(V + Q_n(t))}{3V\eta\kappa_n C_n} \right]^{\frac{1}{3}},
\]

where $f_{\max} = \min\{f_{\max}, \sqrt[3]{(P_{\max} - \zeta p_n - p_r)/\kappa_n}\}$ is the upper bound of the frequency.

Optimal Transmit Power Allocation: For the transmit power allocation optimization, the problem $P_2$ is transformed into

\[
P_{2,2} : \max_{p_n(t)} \sum_{n=1}^{N} B \ln 2(Q_n(t) + V)[\ln(\sum_{i=1}^{n} p_i(t)h_{b,i}^2 + \sigma_b^2) - \ln(\sum_{i=1}^{n} p_i(t)h_{c,i}^2 + \sigma_c^2)] + \ln(\sum_{i=1}^{n} p_i(t)h_{c,i}^2 + \sigma_c^2) + \frac{f_n}{B \ln 2C_n} \\
\]
\begin{aligned}
\text{s.t.} & \quad 0 \leq p_n(t) \leq (P_{\max} - P_{\off} f_n^3)/\zeta. 
\end{aligned}
\]

The minus logarithmic terms make the objective function not convex, which is addressed by Lemma 1 introduced in the following.

Lemma 1: By introducing the function $\phi(y) = -yx + \ln y + 1$, $\forall x > 0$, one has

\[
-\ln x = \max_{y > 0} \phi(y).
\]

The optimal solution can be achieved at $y = 1/x$. The upper bound can be given by using Lemma 1 as $\phi(y)[16]$. By setting $y_{b,n} = \sum_{i=1}^{n-1} p_i(t)h_{b,i}^2 + \sigma_b^2$ and $y_{c,n} = \sum_{i=1}^{n} p_i(t)h_{c,i}^2 + \sigma_c^2$, one has

\[
P_{2,3} : \max_{p_n(t), y_{b,n}, y_{c,n}} \sum_{n=1}^{N} B \ln 2(Q_n(t) + V)[\ln(\sum_{i=1}^{n} p_i(t)h_{b,i}^2 + \sigma_b^2) + \phi_b(y_{b,n}) + \phi_c(y_{c,n}) + \ln(\sum_{i=1}^{n} p_i(t)h_{c,i}^2 + \sigma_c^2)] + \frac{f_n}{B \ln 2C_n} - V\eta(t)(\zeta p_n(t) + p_r + \kappa_n f_n^3) - Q_n(t)A_n(t) \\
\text{s.t.} & \quad 0 \leq p_n(t) \leq (P_{\max} - P_{\off} - \kappa_n f_n^3)/\zeta.
\]
where \( \phi_{b,n}(y_{b,n}) = -y_{b,n}(\sum_{i=1}^{\frac{r-1}{2}} p_i(t)h_{b,i}^2 + \sigma_{b,n}^2) + \ln y_{b,n} + 1 \), and \( \phi_{c,n}(y_{c,n}) = -y_{c,n}(\sum_{i=1}^{\frac{r-1}{2}} p_i(t)h_{e,i}^2 + \sigma_{c,n}^2) + \ln y_{c,n} + 1 \). The problem \( P_{2,3} \) is a convex problem with respect to both \( p_n(t) \) and \( y_{b,n}, y_{c,n} \). It can be solved by using a standard convex optimization tool. After we obtain \( p^*_n(t) \), the values of \( y_{b,n}^* \) and \( y_{c,n}^* \) can be respectively given by \( y_{b,n}^* = \left( \sum_{i=1}^{\frac{r-1}{2}} p^*_i(t)(h_{b,i}^2 + \sigma_{b,n}^2) \right)^{-1} \) and \( y_{c,n}^* = \left( \sum_{i=1}^{\frac{r-1}{2}} p^*_i(t)(h_{e,i}^2 + \sigma_{c,n}^2) \right)^{-1} \). By alternately updating \( p_n(t) \) and \( y_{b,n}, y_{c,n} \), the optimal solutions of \( P_{2,3} \) can be achieved at convergence.

Remark 1: To obtain fundamental and insightful understanding of the offloading power allocation for a multi-user NOMA assisted secure MEC system, we consider a special case with two UEs [17]. The problem with respect to \( p_n \) is given as

\[
P_{2,4}: \quad \max_{p_1(t), p_2(t)} \left[ B \ln 2(V + Q_2(t)) \ln(p_2(t)h_{b,2}^2 + p_1(t)h_{b,1}^2 + \sigma_{b,2}^2) - \ln(p_1(t)h_{b,1}^2 + \sigma_{b,1}^2) - \ln(p_2(t)h_{b,2}^2 + \sigma_{b,2}^2) - \ln y_{b,1} + 1 + \ln y_{b,2} + 1 + \ln(p_1(t)h_{e,1}^2 + \sigma_{e,1}^2) + \ln(p_2(t)h_{e,2}^2 + \sigma_{e,2}^2) + \ln \sigma_{b,1}^2 + \ln \sigma_{b,2}^2 + \ln y_{e,1} + 1 + \ln y_{e,2} + 1 + \ln \sigma_{e,1}^2 + \ln \sigma_{e,2}^2 \right]
\]

where \( \sigma_{b,1} = \frac{V_0}{(V + Q_2(t)) + y_{b,2}h_{e,2}^2} \), \( b_1 = \frac{h_{b,1}^2}{h_{e,1}^2} + \frac{h_{b,2}^2}{h_{e,2}^2} - \frac{(V + Q_1(t))h_{e,1}^2}{(V + Q_2(t))h_{e,1}^2} - \frac{h_{b,1}^2}{h_{e,1}^2} - \frac{(V + Q_1(t))h_{e,2}^2}{(V + Q_2(t))h_{e,2}^2} - \frac{y_{b,2}h_{e,2}^2}{y_{b,2}h_{e,2}^2} \), and \( b_2 = \frac{h_{b,1}^2}{h_{e,1}^2} + \frac{h_{b,2}^2}{h_{e,2}^2} - \frac{(V + Q_1(t))h_{e,1}^2}{(V + Q_2(t))h_{e,1}^2} - \frac{h_{b,1}^2}{h_{e,1}^2} - \frac{(V + Q_1(t))h_{e,2}^2}{(V + Q_2(t))h_{e,2}^2} - \frac{y_{b,2}h_{e,2}^2}{y_{b,2}h_{e,2}^2} \).

IV. SIMULATION RESULTS

In this section, simulation results are provided to evaluate the proposed algorithm. The simulation settings are based on the works in [12], [17]. We consider the configuration with 2 UEs, which can be readily extended to a more general case. The system bandwidth for computing offloading is set as \( B = 1 \) MHz, the time slot duration is \( \tau = 1 \) sec, path-loss exponent is \( \theta = 4 \), the noise variance is \( \sigma_{i,j} = -60 \) dBm, where \( i \in \{b,e\}, j \in \{1, 2\} \). The size of the arrival workload \( A_i(t) \) is uniformly distributed within \( [1, 2] \times 10^6 \) bits [18]. Other parameter settings include the reference distance \( d_0 = 1 \) m, \( g_0 = -40 \) dB, \( d_{b,1} = 80 \) m, \( d_{b,2} = 40 \) m, \( d_{e,1} = 120 \) m, \( d_{e,2} = 80 \) m. \( \kappa_n = 10^{-28} \), \( P_{\text{max}} = 2 \) W, \( f_{\text{max}} = 2.15 \) GHz, \( C_n = 737.5 \) cycles/bit, the amplifier coefficient \( \zeta = 1 \), and the control parameter \( V = 10^7 \). The numerical results are obtained by averaging over 1000 random channel realizations. We consider two more cases as the benchmark schemes to compare with our proposed algorithm. In the first benchmark scheme, marked as “Full offloading”, all the tasks are offloaded to the MEC server and there is no local computation at all. The second benchmark [17] is marked as “Eve fully decode”, in which the Eve can correctly decode other users’ information. This provides a worst-case scenario for comparison.

The performance of the system EE vs time is presented in Fig. [2]. We can see that the proposed method can achieve the highest system EE compared with the other two benchmark schemes. Furthermore, owing to the flexibility of having both offloading and local computing in the proposed scheme and in the “Eve fully decode” scheme, the system can decide not to offload if the eavesdropper has a better channel on the offloading link while it can decide to offload if the link is secure enough. Therefore, these two schemes have a higher EE performance than the “Full offloading” scheme, which has to offload even when the links are insecure. The system EE stabilizes for all the three schemes after 200 time slots.

The system EE versus the average arrival task length is presented in Fig. [3]. The proposed method achieves the highest EE. For all the three schemes, EE decrease with the increase of the arrival task length because a higher workload forces the system to increase the computing rate to maintain the low queue.
level. This in turn decreases the system EE. Furthermore, we notice that the performance gap between the “Full offloading” scheme and other two schemes goes up with the increase of the task length. This demonstrates that local computing is more energy efficient and secure for processing the computation tasks when the task size goes up.

V. Conclusion

This paper aims to design a secure and energy efficient computation offloading scheme in a NOMA enabled MEC network with the presence of a malicious eavesdropper. In order to achieve a long term performance gain by considering dynamic task arrivals and fading channels, we proposed a secure task offloading and computation resource allocation scheme that aims to maximize the long-term average EE and used Lyapunov optimization framework to solve the problem. Numerical results validated the advantages of the proposed design via comparisons with two other benchmark schemes.

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