Computing and Relaying : Utilizing Mobile Edge Computing for P2P Communications

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***Abstract*—Besides increasing the computing capacity of edge devices, mobile edge computing (MEC) can also be utilized to help communication. This paper proposes an MEC-assisted computing and relaying scheme to enhance the throughput of uncompressed data for mobile peer-to-peer (P2P) communications. We assume that the target data has a dynamic compression rate during the transmission from one mobile device to another through a relay node with MEC. In order to obtain the optimal transmission and compression strategy for the mobile devices and the relay node, a cost function that defines the tradeoff between energy consumption and latency time is investigated first. Then a closed-form solution is derived by minimizing the cost function with respect to practical constraints. Compared with conventional P2P communications without MEC, the proposed model breaks the bottleneck of P2P communications by decoupling the data compression rates at the two sides of MEC server. Numerical results verify the effectiveness of the proposed scheme.**

***Index Terms*—Computation offloading, computing and relaying, mobile edge computing, P2P communication.**

I. Introduction

With the fast growth of mobile devices and connections, monthly Internet traffic will reach 44 GB per capita by 2022, up from 13 GB per capita in 2017 [1]. This trend will generate a huge burden on the existing centralized network architecture, since all the resource-limited devices rely on the computation support from remote clouds. To solve this problem, decentralized mobile edge computing (MEC) has attracted great research interest [2–5]. It focuses on integrating the computing and communication resources at the edge of networks to consume the user data locally.

The MEC theory, first proposed by Cisco [6] and ETSI [7], has been applied in many scenarios, such as video stream analysis [8], intelligent video acceleration [9], computing assistance [10] and IoT gateway [11]. In these scenarios, the computing tasks of edge devices are offloaded to MEC servers or the data streams are adjusted by MEC servers to accelerate the transmission. For example, moving the video analysis away from the video camera reduces the equipment cost and saves the core network load of transporting large data video to remote clouds [8]. Also, intelligent video acceleration is realized by caching and processing multi-bit-rate video collaboratively in MEC servers [9]. Therefore, both computation offloading and communication acceleration are key research issues in MEC.

In the literature, computation offloading has been widely investigated, including the task partition strategy and the allocation of computing and communication resources. For task partition, Wang *et al.* in [12] considered the minimization of the energy consumption for the users with fixed tasks subject to offloading delay constraints. Mao *et al.* in [13] adopted both the execution delay and task failure as the performance metrics with dynamic voltage and frequency scaling (DVFS) [14] and energy harvesting techniques [15]. An offloading policy from a single user to multiple MEC servers with multi-tasks was proposed by Dinh *et al.* in [16] by minimizing the maximum execution delay. You *et al.* in [17] exploited the CPU-state information of non-causal helpers, such as powerful laptops, to design energy-efficient computing policies via peer-to-peer (P2P) links for sharing computation resources at peer mobiles. For resource allocation, You *et al.* in [18] developed an energy-efficient allocation policies for a multiuser MEC system, in which TDMA and OFDMA were considered. Computation offloading and resource allocation for indivisible tasks in wireless cellular networks with a single MEC server were investigated by Wang *et al.* in [19, 20]. Tan *et al.* in [21] proposed a virtual MEC framework that served multiple users with both edge computing and caching. In our previous work [22], we proposed a computation offloading model to maximize the processing capacity of power-constrained IoT devices with the assistance of an MEC server.

All the aforementioned research works focus on the computation offloading strategy to enhance the computing capacity of edge devices via the communication links to MEC servers or device helpers, *i.e.*, use communication to boost computation. However, there are very few research considering the use of computation to accelerate communication. In this paper, we will utilize MEC for the P2P communications among edge devices, *i.e.*, use computation to promote communication. Accelerating wireless communication by leveraging sufficient computing resource of MEC servers has many realistic ap-

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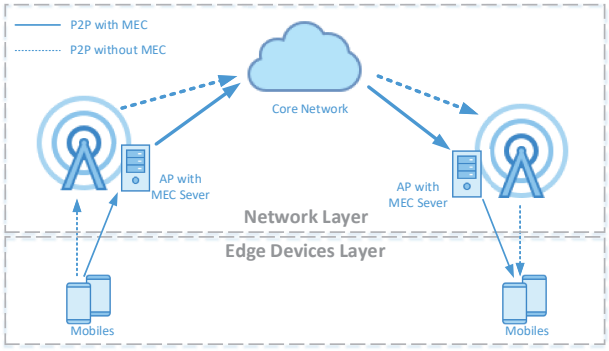
plications. On the one hand, wireless communication as an essential component of mobile computing has quite low energy efficiency since the energy required for transmission of a single bit has been measured to be over 1000 times greater than that for a single 32-bit computation [23]. Therefore, this idea can significantly reduce the energy consumption in wireless communication systems. On the other hand, some existing works, such as the adaptive multimedia streaming over wireless networks [24, 25], are effective by promoting communication via computation. In the adaptive streaming applications, the multimedia contents are encoded at multiple bit-rates and layered video chunks in remote clouds. The cross-layer optimizer selects the optimal values of the media bit-rate, the time slot allocation, and the modulation scheme to maximize the video quality perceived by users. To reduce the access delay, P2P communications instead of current content distribution network (CDN) techniques [26] will be widely adopted in the future intelligent video applications, such as real-time VR and AR applications [27, 28]. Since the P2P data streams do not go through the centralized clouds, conventional adaptive data streaming approaches will not be available.

Motivated by these observations, this paper utilizes MEC servers deployed at APs to accelerate P2P communications and proposes a novel computing and relaying model to model the accelerating process. While the wireless relaying models focus on increasing the communication capacity of wireless channels in the physical layer [29], the proposed model has a similar architecture but is devoted to improve the throughput of uncompressed data in P2P communication systems through a joint computation and transmission design in both the physical and application layers. By leveraging the joint strategy, the proposed computing and relaying model breaks the communication bottlenecks caused by the resource asymmetry of mobile devices in computation and communications.

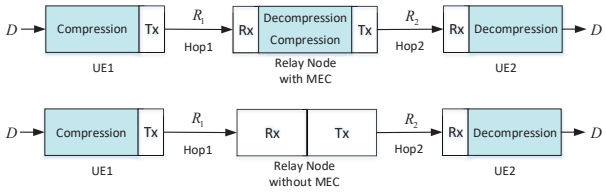
The main contributions of the paper are summarized as follows.

- A novel computing and relaying model is proposed to analyze the MEC-assisted P2P communications. By representing the APs and the core network with a virtual relay node, a computing and relaying model is established and endowed with a cost function that conveys the tradeoff between the latency during the communication processing and the energy consumption in mobile devices.
- The optimal transmission and compression strategy for the proposed model is derived by utilizing Lambert W function [30]. Compared with the conventional P2P communications, the proposed model significantly reduces the system cost (latency and energy consumption) especially while the channel state and the computing capacity of the devices are asymmetric.
- The optimal solution is further analyzed with respect to practical constraints and some insights are summarized.

The rest of the paper is organized as follows. We introduce the computing and relaying model in Section II. Section III presents the performance metric of the proposed model. In Section IV, the optimal transmission and compression strategies are derived for both MEC-assisted and conventional



(a) Application scenarios of P2P communications.



(b) Computing and relaying model with and without MEC.

Fig. 1: The MEC-assisted P2P communication system.

systems. In Section V, the optimal strategies are analyzed in practical scenarios and some insights are summarized based on the analysis. The performance of the proposed model is evaluated numerically in Section VI, followed by the conclusions in Section VII.

II. System Model

Fig. 1(a) illustrates the P2P wireless communication scenarios with and without MEC between mobile devices. In the conventional scenario, the application data, such as images or videos, are captured by the transmitting device. Then the data are compressed by the local CPU module and uploaded to the AP which serves the source device via wireless links. The AP sends the compressed data via the core network to the other AP that serves the receiving device. Finally, the receiving device decompresses it into the original application data. When the MEC servers at APs are used in the P2P communication, the compression operation in the transmitter can be offloaded to the corresponding AP, and the decompression operation in the receiver can also be performed by its AP before the downlink transmission.

The whole P2P communication architecture in Fig. 1(a) can be divided into two layers: the network layer that acts as a communication pipeline and the edge device layer that consists of mobile devices. If we assume that the transmission cost between the APs is fixed, the network layer can be modeled as a relay node. The transmitting and receiving devices are the UEs acting as the source node and the destination node, respectively. Therefore, the above P2P communication can be modeled as a computing and relaying model, as shown in Fig. 1(b). The system is described in detail as follows.

UE 1: A mobile device equipped with a computation module and a transmitting RF module. D bits of original data are collected and compressed at a compression ratio of ρ_1 using

the local computation module by UE 1. Then the compressed data are transmitted to the relay node.

Relay Node: A wireless relay with RF and computation modules. For the conventional scenario without MEC, the relay node does not have any computing capacity in the application layer. For the MEC-assisted scenario, the compressed data are re-compressed in the relay node according to the relaying strategy. The energy of the relay node is supplied by the power grid.

UE 2: A mobile device equipped with a computation module and a receiving RF module. UE 2 receives the compressed data with a compression ratio of ρ_2 from the relay node. Then the compressed data is decompressed to recover the original data D.

Note that the compression ratio is defined as the ratio of the uncompressed data to the compressed data. The computation and communication in the relaying system are assumed as follows.

Computation: The amount of computation (in CPU cycles) in the UEs is related to the amount of original data D and the compression ratio. According to [31], the CPU cycles to compress or decompress 1 bit data can be approximated as an exponential function of the compression ratio $\rho_i, i \in 1, 2$ as

$$U(\rho_i) = \xi_i(e^{\varepsilon\rho_i} - e^{\varepsilon}), \tag{1}$$

where ε and $\xi_i, i \in 1, 2$, denote constants depending on the compression method, ρ_1 is the compression ratio of UE 1 and ρ_2 is the decompression ratio of UE 2. Note that $\rho_i \in [1, \rho_{\max,i}], \forall i \in 1, 2$, and ρ_1 may restrict the feasible solution of ρ_2 for some compression algorithms.

Communication: The compressed data D/ρ_i are transmitted via the communication link in Hop i, $i \in \{1, 2\}$, assumed to be a single carrier link with bandwidth B. The wireless channels are flat fading and the channel information is perfectly known. Let $g_i = |h_i|^2/N_0$ denote the channel gain of each hop with h_i being the channel response and N_0 being the power spectral density of the noise. Then the communication rates (in bits/s) of each hop is given by

$$R_i = B\log_2(1 + p_i g_i), \tag{2}$$

where p_i is the transmitting power. Since the energy of the relay node is unconstrained, p_2 is assumed to be fixed.

The computation and communication in the proposed system are related via compression and decompression. In the conventional scenario without MEC, the data transmitted by the transmitter and the data received by the receiver have the same compression ratio, *i.e.*, $\rho_1 = \rho_2$. However, in the MEC-assisted scenario, the compression ratios ρ_1 and ρ_2 can be different, *i.e.*, $\rho_1 \neq \rho_2$.

III. Performance Metric

In P2P communications, users are sensitive to energy consumption and delay. This section presents the analytical expressions of energy consumption and delay based on the computation and communication models. Then, a cost function that describes the tradeoff between energy consumption and delay, is defined to assess the system performance.

A. Energy Consumption

The energy costs of all the mobile devices including UE 1 and UE 2 affect the system performance. According to (1), the energy consumption of UE 1 to compress D bits of data at a ratio of ρ_1 is given as

$$E_{\mathrm{c}}(\rho_1) = q_{\mathrm{c}} DU(\rho_1), \tag{3}$$

where q_c (in Joule/cycle) denotes the energy consumption for each CPU cycle. Note that $DU(\rho_1)$ (in cycles) denotes the computation required to compress D bits of data at ρ_1.

Let t_{Tx} denote the transmitting time in Hop 1. According to (2), the energy consumption in Hop 1 is

$$E_{\mathrm{Tx}}(\rho_1, t_{\mathrm{Tx}}) = p_1 t_{\mathrm{Tx}} = \frac{t_{\mathrm{Tx}}}{g} f\left(\frac{D}{\rho_1 t_{\mathrm{Tx}}}\right), \tag{4}$$

where $f(x) = \left(2^{\frac{x}{B}} - 1\right)$.

Similarly, the energy consumption for the decompression in UE 2 is given by

$$E_{\mathrm{d}}(\rho_2) = q_{\mathrm{d}} DU(\rho_2), \tag{5}$$

where q_d (in Joule/cycle) denotes the energy consumption for each CPU cycle in UE 2. According to [32], the receiving energy consumption in UE 2 is given as

$$E_{\mathrm{Rx}}(\rho_2) = q_{\mathrm{Rx}} \frac{D}{\rho_2}, \tag{6}$$

where q_{Rx} is the energy consumption for receiving each bit in UE 2.

Other energy consumption of circuits in the UEs is assumed to be constant. Since the MEC server is connected to the power grid, its energy consumption is not taken into account here.

B. Delay

According to (1), the computing delay for the compression of D bits with compression ratio ρ_1 in UE 1 is

$$t_{\mathrm{c}}(\rho_1) = DU(\rho_1)/f_{\mathrm{c}}, \tag{7}$$

where f_c (in cycles/s) is the CPU frequency of UE 1. The transmission delay in Hop 1 is t_{Tx}, which depends on the transmitting power.

Similarly, the computing delay for decompressing the received data with a ratio of ρ_2 in UE 2 can be written as

$$t_{\mathrm{d}}(\rho_2) = DU(\rho_2)/f_{\mathrm{d}}, \tag{8}$$

where f_d (in cycles/s) is the CPU frequency of UE 2. The reception delay in Hop 2 is

$$t_{\mathrm{Rx}}(\rho_2) = \frac{D}{\rho_2 R_2}. \tag{9}$$

Adaptive downlink power control is adopted in the relay node, therefore the communication rate of Hop 2 R_2 is controlled by the relay node.

Although the energy consumption of the relay node can be ignored, the computing delay T_r in the relay node needs to be considered. Note that T_r only relies on the architecture and the computing capacity of MEC servers.

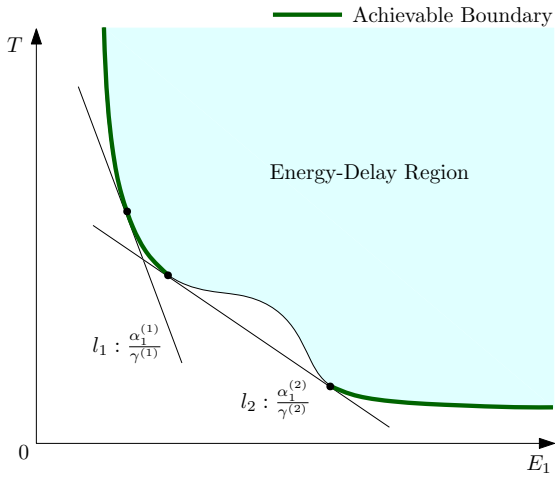


Fig. 2: The achievable boundary by minimizing the weighted sum of the energy and delay.

C. Cost Function

By considering both the computation and communications, the energy consumptions of the UEs can be written as

$$E_1 = E_{\mathrm{c}}(\rho_1) + E_{\mathrm{Tx}}(\rho_1, t_{\mathrm{Tx}}) + C_1, \tag{10}$$

$$E_2 = E_{\mathrm{d}}(\rho_2) + E_{\mathrm{Rx}}(\rho_2) + C_2, \tag{11}$$

where C_1 and C_2 are constants, denoting other energy consumption of circuits in UE 1 and UE 2, respectively. The total latency for the transmission of D bits is given by

$$T = t_{\mathrm{c}}(\rho_1) + t_{\mathrm{Tx}} + T_r + t_{\mathrm{Rx}}(\rho_2) + t_{\mathrm{d}}(\rho_2). \tag{12}$$

Note that E_1, E_2 and T all depend on the transmission and compression strategy $(t_{\mathrm{Tx}}, \rho_1, \rho_2)$. Define the whole set of the strategies as

$$\mathcal{S} = \{S = (t_{\mathrm{Tx}}, \rho_1, \rho_2) : t_{\mathrm{Tx}} > 0, \rho_i \in [1, \rho_{\max,i}], \forall i \in 1, 2\}. \tag{13}$$

Based on the expressions of E_1, E_2 and T, we have the achievable energy-delay region, *i.e.*,

$$\mathcal{R} = \{(E_1, E_2, T)_S : S \in \mathcal{S}\}. \tag{14}$$

The energy consumptions E_1, E_2 and the delay T are all determined by the strategies. Therefore, there is a tradeoff which implies that transmitting at a higher rate with low compression rates requires more energy but reduces the delay, and vice versa. However, the optimal boundary of the energy-delay region is too complicated to obtain due to the jointly mapping from $\mathcal{S}$ to $\mathcal{R}$ in the multi-objective problem. But some useful boundary points can be obtained by minimizing the weighted sum over the energy consumptions and the delay, as illuminated in Fig. 2. The weighted sum represents an intrinsic energy-delay tradeoff for the proposed system. Therefore, we have the following definition.

Definition 1 (Cost Function)**.** *The cost to transmit D bits uncompressed data from UE 1 to UE 2 in the proposed computation relay system is defined as the weighted sum over the energy consumptions and the delay, i.e.,*

$$L(t_{Tx}, \rho_1, \rho_2) = \alpha_1 E_1 + \alpha_2 E_2 + \gamma T, \tag{15}$$

where α_1, α_2, $\gamma \in [0, 1]$ are scalar weights.

According to Definition 1, the cost function can be expressed by

$$\begin{aligned} L_{\mathrm{MEC}}(t_{\mathrm{Tx}}, \rho_1, \rho_2) = & A_1(e^{\varepsilon\rho_1} - e^{\varepsilon}) + A_2 t_{\mathrm{Tx}} e^{\frac{C_0}{\rho_1 t_{\mathrm{Tx}}}} + \frac{A_3}{\rho_2} \\ & + A_4(e^{\varepsilon\rho_2} - e^{\varepsilon}) + (\gamma - A_2) t_{\mathrm{Tx}} + A_5, \end{aligned} \tag{16}$$

where $A_1 = \alpha_1 q_{\mathrm{c}} D\xi_1 + \gamma D\xi_1 / f_{\mathrm{c}}, A_2 = \alpha_1 / g, A_3 = \alpha_2 q_{\mathrm{Rx}} D + \gamma D / R_2, A_4 = \alpha_2 q_{\mathrm{d}} D\xi_2 + \gamma D\xi_2 / f_{\mathrm{d}}, A_5 = \gamma T_r + \alpha C_1 + \alpha C_2, C_0 = D \ln 2 / B$.

A_1 is related to the computing capacity of the transmitter, A_2 is related to the channel state information of Hop 1, A_3 is related to the communication condition of Hop 2, A_4 is related to the computing capacity of the receiver and C_0 is a constant related to D and bandwidth B. Note that $A_1 - A_4$ are inversely proportional to the capacities, *i.e.*, with an increasing computing capacity or a stronger communication condition, the corresponding parameter decreases. The cost function is related to the transmission and compression strategy, which consists of the transmission time t_{Tx} and the compression rates ρ_1, ρ_2.

Similar, the cost function for the scenario without MEC is given by

$$\begin{aligned} L_{\mathrm{noMEC}}(t_{\mathrm{Tx,c}}, \rho) = & (A_1 + A_4)(e^{\varepsilon\rho} - e^{\varepsilon}) + A_2 t_{\mathrm{Tx,c}} e^{\frac{C_0}{\rho t_{\mathrm{Tx,c}}}} \\ & + \frac{A_3}{\rho} + (\gamma - A_2) t_{\mathrm{Tx,c}} + A_5, \end{aligned} \tag{17}$$

where $t_{\mathrm{Tx,c}}$ is the transmitting time and ρ is the compression ratio in the scenario without MEC.

IV. Optimal Strategies

In this section, the optimal transmission and compression strategies for both the MEC-assisted and conventional scenarios are derived by minimizing the cost function.

A. MEC-assisted Scenario

Although the cost function is simplified as Equation (16), it is still complicated to analyze due to the uncertainty in T_r and the restrictive relationship between ρ_1 and ρ_2. Relaxing these constraints by setting $T_r = 0$ and $\rho_1, \rho_2 \in [1, +\infty)$, the optimization problem of minimizing the cost function is given by

$$\mathbf{P}1 : \min_{t_{\mathrm{Tx}} \in \mathbb{R}_+, \rho_1, \rho_2 \in [1, +\infty)} L_{\mathrm{MEC}}(t_{\mathrm{Tx}}, \rho_1, \rho_2). \tag{18}$$

We have following proposition.

Proposition 1. *The optimization problem $\boldsymbol{P}1$ is jointly convex in (t_{Tx}, ρ_1, ρ_2).*

Proof. The Hessian Matrix of $f(t, \rho) = te^{\frac{\alpha}{\rho t}}$ is given by

$$\mathbf{H} = \begin{bmatrix} \frac{\alpha^2}{\rho^2 t^3} & \frac{\alpha^2}{\rho^3 t^2} \\ \frac{\alpha^2}{\rho^3 t^2} & \frac{2\alpha}{\rho^3} + \frac{\alpha^2}{\rho^4 t} \end{bmatrix} e^{\frac{\alpha}{\rho t}}. \tag{19}$$

The determinant $\det(\mathbf{H}) = \frac{2\alpha^3}{\rho^5 t^3} e^{\frac{\alpha}{\rho t}}$ is positive in the support range. Therefore, $f(t, \rho) = te^{\frac{\alpha}{\rho t}}$ is jointly convex in (t, ρ). Since $A_1 e^{\varepsilon\rho_1}$, $A_4 e^{\varepsilon\rho_2}$ and $\frac{A_3}{\rho_2}$ are all convex and $(\gamma - A_2) t_{\mathrm{Tx}}$

is linear, the objective function is convex. The constraints are linear. Thus the problem is convex. □

Since the problem is convex, there is an optimal point $(t_{\text{Tx}}^*, \rho_1^*, \rho_2^*)$ to obtain the minimum cost. The necessary and sufficient Karush-Kuhn-Tucker (KKT) conditions for the optimal point is given by

$$\frac{\partial L}{\partial t_{\text{Tx}}^*} = A_2 e^{\frac{C_0}{\rho_1 t_{\text{Tx}}}} - \frac{A_2 C_0}{\rho_1 t_{\text{Tx}}} e^{\frac{C_0}{\rho_1 t_{\text{Tx}}}} + \gamma - A_2 = 0 \tag{20}$$

$$\frac{\partial L}{\partial \rho_1^*} = A_1 \varepsilon e^{\varepsilon \rho_1} - \frac{A_2 C_0}{\rho_1^2} e^{\frac{C_0}{\rho_1 t_{\text{Tx}}}} = \begin{cases} > 0, & \rho_1^* = 1 \\ = 0, & \rho_1^* > 1 \end{cases} \tag{21}$$

$$\frac{\partial L}{\partial \rho_2^*} = A_4 \varepsilon e^{\varepsilon \rho_2} - \frac{A_3}{\rho_2^2} = \begin{cases} > 0, & \rho_2^* = 1 \\ = 0, & \rho_2^* > 1 \end{cases} \tag{22}$$

which leads to the following proposition.

Proposition 2. *The optimal solution for* $\boldsymbol{P}1$ *is given by*

$$\rho_1^* = \max(1, \frac{2}{\varepsilon} W\left(\frac{\varepsilon}{2}\sqrt{\frac{A_2 C_0 C_1}{A_1 \varepsilon}}\right)) \tag{23}$$

$$\rho_2^* = \max(1, \frac{2}{\varepsilon} W\left(\frac{\varepsilon}{2}\sqrt{\frac{A_3}{A_4 \varepsilon}}\right)) \tag{24}$$

$$t_{Tx}{}^* = \frac{C_0/\rho_1^*}{W\left(\frac{\gamma e^{-1}}{A_2} - e^{-1}\right) + 1} \tag{25}$$

where $C_1 = e^{\frac{C_0}{(\rho_1 t_{Tx})^*}}$ *and* $W(\cdot)$ *is Lambert W function.*

Proof. See Appendix A. □

Proposition 2 presents the optimal transmission and compression strategy to achieve the best performance for the MEC-assisted computation relay. The succinct solution indicates that the optimal transmitting delay t_{Tx}^* and the optimal compression rate of the transmitter ρ_1^* are tightly coupled with each other.

Remark 1. *By rearranging* (25)*, we can find that* $(\rho_1 t_{Tx})^*$ *only depends on* C_0 *and* A_2*. This implies that the product of compression rate and transmitting delay is a constant which is related to the channel state and the amount of transmitted data.*

This remark indicates that the transmitting delay is inversely proportional to the compression rate, which agrees with the intuition that the larger the compression rate is, the fewer data the transmitter sends and the smaller the transmitting delay is. There is an optimal strategy, as shown in Proposition 2, to balance the energy consumption and the delay.

Remark 2. *The optimal compression rate of Hop 2* ρ_2^* *is independent of* (t_{Tx}^*, ρ_1^*)*, neither the energy status and the channel state of Hop 1. In other words, the relay node decouples the compression ratios of transmitted data in the two hops, which means that the compression ratios* ρ_1 *and* ρ_2 *can be set based on the channel and energy states of the two hops respectively.*

This remark indicates a fundamental fact in the computing and relaying model that the relay node with MEC servers breaks the communication bottleneck caused by the asymmetry of the UEs in communication and computing resources by decoupling the computation rates of the hops. However, this property may not be fully achievable due to the relationship among the compression rates, which will be further discussed in the next section.

B. Comparing with the Conventional Scenario

To further understand the computation relay, the conventional scenario without MEC is investigated in this subsection. Since the relay doesn't possess the recompression ability, the compression rates of the two hops are same. The optimization problem for the conventional system is given by

$$\mathbf{P}2: \min_{t_{\text{Tx,c}} \in \mathbb{R}_+, \rho \in [1, +\infty)} L_{\text{noMEC}}(t_{\text{Tx,c}}, \rho). \tag{26}$$

By solving the KKT conditions of this problem, the following proposition is obtained.

Proposition 3. *The problem* $\boldsymbol{P}2$ *is convex. The optimal solution of the system without MEC is given by*

$$\rho^* = \max\left(1, \frac{2}{\varepsilon} W\left(\frac{\varepsilon}{2}\sqrt{\frac{A_2 C_0 C_1 + A_3}{(A_1 + A_4)\varepsilon}}\right)\right), \tag{27}$$

$$t_{Tx,c}{}^* = \frac{C_0/\rho^*}{W\left(\frac{\gamma e^{-1}}{A_2} - e^{-1}\right) + 1}. \tag{28}$$

Proof. Refer to the proof of Proposition 2. □

In this solution, the product of the transmitting delay and compression rate is the same as that of the MEC-assisted system. However, the compression rate depends on the parameters of both two hops. Notice that the optimal compression rate without MEC relies on the resource status of both hops, while the compression rates in the MEC-assisted system rely on the parameters of their own hop. We have the following lemma.

Lemma 1. *The number* $(a + c)/(b + d)$ *always lies between* a/b *and* c/d*, where* a, b, c, d *are both rational and positive.*

Proof. Lemma 1 is obvious. □

By leveraging Lemma 1, we have the following proposition.

Proposition 4. *(a) We always have*

$$\rho_1^* \le \rho^* \le \rho_2^* \ \text{ or } \ \rho_2^* \le \rho^* \le \rho_1^*. \tag{29}$$

In other words, the conventional compression rate always lies between the two compression rates of the MEC-assisted system.

(b) With the same channel state information and energy status, the optimal cost of the MEC-assisted system is always less than the optimal cost of the conventional system, namely

$$L_{noMEC}(t_{Tx,c}^*, \rho^*) \ge L_{MEC}(t_{Tx}^*, \rho_1^*, \rho_2^*). \tag{30}$$

Proof. (a) Since the Lambert W function monotonically increases in domain $\mathbb{R}_+$, $f(x) = \frac{2}{\varepsilon} W(\frac{\varepsilon}{2}\sqrt{x})$ also monotonically increases in domain $\mathbb{R}_+$. Combining with Lemma 1, the proposition holds.

(b) This proposition easily follows by contradiction since the optimization problem **P**2 can be rewritten as

$$\begin{aligned} &\min_{t_{\text{Tx}}\in\mathbb{R}_+,\rho_1,\rho_2\in[1,+\infty)} L_{\text{MEC}}(t_{\text{Tx}},\rho_1,\rho_2) \\ &s.t. \quad \rho_1{=}\rho_2, \end{aligned} \tag{31}$$

which is the optimization problem **P**1 with an equality constraint. □

Proposition 4 (a) reveals that the MEC server decouples the compression rates of the two hops. Via recompressing in the MEC server, the computing and relaying model releases the restriction on the compression rates caused by the limited computing and communication resources in the opposite hop. The restriction brings the extra cost in the conventional system, which is significantly slacked by the computing and relaying model. Proposition 4 (b) shows the original intention of the computing and relaying model , *i.e.*, reducing the cost in P2P communications.

C. Special Cases

The above analysis gives some general solutions to the MEC-assisted and conventional P2P communication systems. Furthermore, it is valuable to investigate when the available computing and communication resources turns to extremely poor. To discuss these special cases, we have the following definition first.

Definition 2 (Cost Difference)**.** *The cost difference between the conventional and MEC-assisted systems is defined as*

$$G_{diff} = L_{noMEC}(t_{Tx,c},\rho) - L_{MEC}(t_{Tx},\rho_1,\rho_2). \tag{32}$$

Then the cost differences for various special cases are written as follows.

Case 1 (Poor Computing Capacity in UE 1)**:** When the computing capacity in UE 1 is extremely insufficient, *i.e.*, the CPU frequency is low and the energy consumption for each cycle is high, UE 1 should not compress the original data. Therefore, we have $\rho_1 = \rho = 1$ and $t_{\text{Tx}} = t_{\text{Tx,c}}$. The cost difference is given by

$$G_{\text{diff}} = A_3\left(1-\frac{1}{\rho_2}\right) + A_4(e^{\varepsilon} - e^{\varepsilon\rho_2}). \tag{33}$$

In practice, UE 1 represents the IoT devices like sensors with simple circuit configurations and powered by low-energy batteries. The sensed data are supposed to be transmitted to the MEC servers for postprocessing such as compression.

Case 2 (Poor Computing Capacity in UE 2)**:** The expected decompression rate of UE 2 reaches 1, when the computing capacity of UE 2 is very insufficient. Then we have $\rho_2 = \rho = 1$. The cost difference is given by

$$G_{\text{diff}} = (\gamma - A_2 + A_2C_1)X\left(1-\frac{1}{\rho_1}\right) + A_1(e^{\varepsilon} - e^{\varepsilon\rho_1}), \tag{34}$$

where $X = (\rho t_{\text{Tx,c}}) = (\rho_1 t_{\text{Tx}}) = \frac{C_0}{W\left(\frac{\gamma e^{-1}}{A_2} - e^{-1}\right)+1}$. This case will be common in the future since lighter terminal is the development tendency and all major computation will be offloaded to the MEC servers.

Case 3 (Poor Communication Condition in Hop 1)**:** When the wireless channel of Hop 1 experiences a deep fade, UE 1 must make its best effort to compress the original data to decrease the communication burden. Then we have $\rho_1 = \rho = \rho_{\text{max},1}$ and $t_{\text{Tx}} = t_{\text{Tx,c}}$. The cost difference is given by

$$G_{\text{diff}} = A_3\left(\frac{1}{\rho} - \frac{1}{\rho_2}\right) + A_4(e^{\rho\varepsilon} - e^{\varepsilon\rho_2}). \tag{35}$$

Due to the uncertainty of the wireless environment, Case 3 is likely to occur and so is Case 4.

Case 4 (Poor Communication Condition in Hop 2)**:** When the wireless channel of Hop 2 experiences a deep fade and the energy consumption of UE 2 for receiving each bit is large, the data stream of Hop 2 should be compressed with the best effort of the system. Thus, the compression ratios of the MEC-assisted and conventional systems are assumed to be set to the largest and same value, namely $\rho_2 = \rho = \rho_{\text{max},2}$. The cost difference is given by

$$G_{\text{diff}} = (\gamma - A_2 + A_2C_1)X\left(\frac{1}{\rho} - \frac{1}{\rho_1}\right) + A_1(e^{\varepsilon\rho} - e^{\varepsilon\rho_1}). \tag{36}$$

In these cases, only one of the compression rates affects the cost difference. Therefore, we can derive the optimal solutions by maximizing G_{diff}. According to (33) (34) (35) and (36), a universal formula is concluded as

$$g(x) = a - \frac{b}{x} - ce^{\varepsilon x}, \tag{37}$$

which has the following closed-form optimal solution.

Lemma 2. *If $x \in \mathbb{R}_+$, then $g(x)$ is concave. The maximum value is obtained when*

$$x^* = \frac{2}{\varepsilon}W\left(\frac{\varepsilon}{2}\sqrt{\frac{b}{\varepsilon c}}\right). \tag{38}$$

Proof. Since $-\frac{b}{x}$ and $-e^{\varepsilon x}$ are both concave in $x \in \mathbb{R}_+$, the linear sum $g(x)$ is concave. Then solving $g'(x) = 0$ leads to the lemma. □

Thus we have the following proposition.

Proposition 5. *The cost difference for Case 1 and 3 reaches the maximum when*

$$\rho_2^* = \max\left(1, \frac{2}{\varepsilon}W\left(\frac{\varepsilon}{2}\sqrt{\frac{A_3}{A_4\varepsilon}}\right)\right). \tag{39}$$

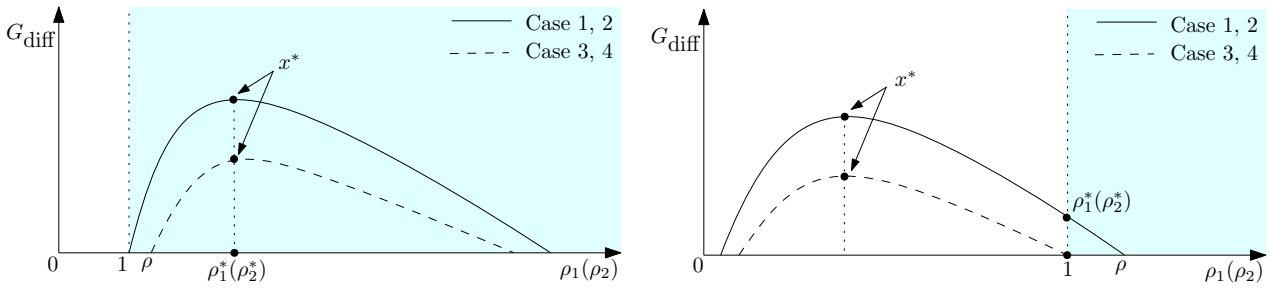
The compression rate ρ_1 equals 1 or ρ_{max}, respectively. For Case 2 and 4, the cost difference reaches the maximum when

$$\rho_1^* = \max(1, \frac{2}{\varepsilon}W\left(\frac{\varepsilon}{2}\sqrt{\frac{(\gamma - A_2 + A_2C_1)X}{A_1\varepsilon}}\right)). \tag{40}$$

The compression rate ρ_2 equals 1 or ρ_{max}, respectively.

Proof. According to Lemma 2, the solution to the problem

$$\mathbf{P}3: \max_{\rho_{1(2)}\in[1,+\infty)} G_{\text{diff}} \tag{41}$$



(a) Solution when the communication cost dominates.

(b) Solution when the computing cost dominates.

Fig. 3: Solutions to the special cases.

Case	Poor Parameter	ρ_1	ρ_2	ρ
1	f_c	1	ρ_2^*	1
2	f_d	ρ_1^*	1	1
3	g_1	$\rho_{\text{max},1}$	ρ_2^*	$\rho_{\text{max},1}$
4	g_2	ρ_1^*	$\rho_{\text{max},2}$	$\rho_{\text{max},2}$

TABLE I: Solutions to the special cases.

is easy to obtain. □

The solution is illuminated in Fig. 3. When the communication cost dominates, x^* is obtained in the feasible region. But when the computing cost dominates, x^* is located before 1 and $\rho_1^*(\rho_2^*) = 1$ is the optimal solution. The proposed solution is summarized in Table I. By rearranging (40), we find that the above result gives the same solution as Proposition 2. In the four special cases, the transmission and compression strategy for the conventional system is fixed due to the poor parameters. According to (33) and (35), the cost difference will be larger if the communication condition of Hop 2 is worse and the computing capacity of UE 2 is stronger in Case 1 and Case 3. According to (34) and (36), the cost difference will be larger if the communication condition of Hop 1 is worse and the computing capacity of UE 1 is stronger in Case 2 and Case 4. Note that $A_1 - A_4$ are inversely proportional to their corresponding capacities as mentioned in Section III. Therefore, we have the following remark.

Remark 3. *The improvement provided by the MEC-assisted relay node is determined by the strength of the computation and communication asymmetry of the UEs. For example, if $A_1 << A_2$ and $A_3 << A_4$, we will see a massive improvement.*

V. Analysis in Practical Scenarios

A general solution for the MEC-assisted P2P communication is presented in the last section. In this section, some practical scenarios are further analyzed, including the restrictive relationship among the compression ratios, the DVFS technique probably adopted in the UEs and the computing delay in the MEC server.

A. Compression Ratio Constraints

Some compression algorithms are lossless and others are lossy. For example, most video compression algorithms are lossy. A lossy compression algorithm leads to loss of information, thus only a small compression rate is available in the MEC server.

For the lossless compression, there is no restrictive relationship among compression ratios. Hence, the optimal solution for the lossless compression is given by

$$\begin{cases} \rho_1^{**} = \min(\rho_1^*, \rho_{\text{max},1}) \\ \rho_2^{**} = \min(\rho_2^*, \rho_{\text{max},2}), \\ t_{\text{Tx}}^{**} = X/\rho_1^{**} \end{cases} \tag{42}$$

where $\rho_{\text{max},i}, \forall i = 1, 2$ is the maximum compression rate of UE i depending on its computing capacity, $\rho_i^{**}, \forall i = 1, 2$ is the optimal compress rate, t_{Tx}^{**} is the optimal transmitting strategy after considering the maximum compression rates.

For lossy compression, ρ_2 is required to be not less than ρ_1. Hence $\rho_1^* *$ is the lower boundary of ρ_2^*, *i.e.*, $\rho_2^* = max(\rho_1^{**}, \rho_2^*)$. To access the quality of experience (QoE) influence of lossy compression, different metrics have been proposed for different types of media data. But to derive a more universal conclusion, the perceiving quality of users for lossy compression in the proposed model is simply bounded by the maximum compression rate ρ_{max}. If the compression rate is larger than ρ_{max}, the perceiving quality is unacceptable at the receiver. Note that the solution degrades into Case 1 if $\rho_{\text{max},1}$ equals 1 and degrades into Case 2 if $\rho_{\text{max},2}$ equals 1.

B. DVFS Technique

Assume that the DVFS technique is utilized in the proposed MEC-assisted P2P communication model. The UEs can dynamically adjust the CPU's computational frequency to adopt the power consumption and execution latency. For UE i, the computational power p_i can be modeled as

$$p_i = f_i^{\kappa} \zeta_i, \tag{43}$$

where f_i, in unit of Hz, is the CPU's computational frequency of user i and $\zeta_i > 0$ is the effective capacitance coefficient depending on chip architecture. The value κ ($\kappa \geq 2$) is a constant [33]. For simplicity, we set $\kappa = 2$ and assume that the local CPU is a single core architecture with a frequency upper bound of $f_{\text{max},i}$. Thus, the computational power satisfies $0 \leq p_i \leq f_{\text{max},i}^2 \zeta_i$.

Thus, the energy consumption of UE 1 to compress D bits of data at a ratio of ρ_1 is given by

$$\begin{aligned} E_{\mathrm{c}}(\rho_1) &= q_{\mathrm{c}} D U(\rho_1) = p_1 t_c(\rho_1) \\ &= f_c^2 \zeta_1 \frac{DU(\rho_1)}{f_c} = D\zeta_1 f_c U(\rho_1), \end{aligned} \tag{44}$$

where f_c is the dynamic frequency of UE 1, $U(\rho_1)$ is the CPU cycles to compress or decompress 1 bit data at ρ_1. Therefore, the energy consumption for each CPU cycle $q_{c(d)}$ (in Joule/cycle) can be rewritten as

$$q_{c(d)} = f_{c(d)} \zeta_{1(2)}. \tag{45}$$

Therefore, we have

$$\begin{aligned} A_1 &= \alpha_1 \zeta_1 D \xi_1 f_c + \frac{\gamma D \xi_1}{f_c}, \\ A_4 &= \alpha_2 \zeta_2 D \xi_2 f_d + \frac{\gamma D \xi_2}{f_d}. \end{aligned} \tag{46}$$

Since the function $f(x) = ax + \frac{b}{x}$ reaches the minimum $2\sqrt{ab}$ when $x = \sqrt{\frac{b}{a}}$, the minima of A_1 and A_4 are easy to derive. Note that the dynamic frequencies don't affect the optimization problem of minimizing the cost function $L_{\mathrm{MEC}}(t_{\mathrm{Tx}}, \rho_1, \rho_2)$, therefore the optimal solution in Proposition 2 still applies.

C. MEC Server Constraint

In practical scenarios, Proposition 4 (b) doesn't always hold. The optimal cost of the MEC-assisted system isn't always less than the conventional P2P communication due to the existence of computing delay in the MEC server. The computing capacity of the server is higher than that of devices but is still limited. Hence the computation in servers occupies time and causes delay to the P2P communication. The MEC server may decompress the transmitted data and re-compress it or may just compress it directly to the target ratio and the computing process may occupy one thread or multi-thread. Therefore, the computing delay in the server is quite complicated. Here, the influence of the computing delay in the server is analyzed by comparing it with the cost difference offered by the optimal relaying strategy. The desired solution with Tr is written as

$$(\rho_1^{**}, \rho_2^{**}, t_{\mathrm{Tx}}^{**}) = \begin{cases} (\rho_1^*, \rho_1^*, t_{\mathrm{Tx}}^*) & \gamma T_r < G_{\mathrm{diff}}^* \\ (\rho^*, \rho^*, t_{\mathrm{Tx,c}}^*) & \gamma T_r \geq G_{\mathrm{diff}}^*, \end{cases} \tag{47}$$

where $G_{\mathrm{diff}}^* = L_{\mathrm{noMEC}}(t_{\mathrm{Tx,c}}^*, \rho^*) - L_{\mathrm{MEC}}(t_{\mathrm{Tx}}^*, \rho_1^*, \rho_2^*)$.

D. Energy and Delay Constraints

In many practical scenarios, the energy consumption or the latency of the P2P communication system is limited. When the system delay is constrained, the optimal strategy can be obtained by minimizing the energy consumption, which is written as

$$\begin{aligned} \min_{t_{\mathrm{Tx}}, \rho_1, \rho_2} \quad & \alpha_1 E_1(\rho_1, t_{\mathrm{Tx}}) + \alpha_2 E_2(\rho_2) \\ \text{s.t.} \quad & T(t_{\mathrm{Tx}}, \rho_1, \rho_2) \leq T_C, \end{aligned} \tag{48}$$

where T_C is the delay constraint for the transmission of data D. When the energy consumption of the UEs is constrained, the optimization problem degrades into

$$\begin{aligned} \min_{t_{\mathrm{Tx}}, \rho_1, \rho_2} \quad & T(t_{\mathrm{Tx}}, \rho_1, \rho_2) \\ \text{s.t.} \quad & E_1(\rho_1, t_{\mathrm{Tx}}) \leq E_{\mathrm{S}}, \\ & E_2(\rho_2) \leq E_{\mathrm{R}}, \end{aligned} \tag{49}$$

where E_{S} and E_{R} are the energy constraints in the UEs to transmit the D bits data from UE 1 to UE 2.

As proved in Proposition 1, the Hessian Matrix of $f(t, \rho) = te^{\frac{\alpha}{\rho t}}$ is positive in the support range, thus it is jointly convex in (t, p). Therefore (4) is jointly convex in $(t_{\mathrm{Tx}}, \rho_1)$. Since (5), (6), (7), (8) and (9) are all convex in ρ_1 or ρ_1, the energy consumption $E_1(t_{\mathrm{Tx}}, \rho_1)$, $E_2(\rho_2)$ and the delay $T(t_{\mathrm{Tx}}, \rho_1, \rho_2)$ are all convex functions. Therefore, (48) and (49) are convex problems.

The two problems have a mutual Lagrange function, which is given by

$$\mathcal{L}(t_{\mathrm{Tx}}, \rho_1, \rho_2, \gamma, \alpha_1, \alpha_2) = \alpha_1 E_1 + \alpha_2 E_2 + \gamma T + C. \tag{50}$$

Note that for (48) the Lagrange multipliers α_1 and α_2 are fixed to 1 and $C = \gamma(T_r - T)$, and for (49) the Lagrange multiplier γ is fixed to 1 and $C = T_r - \alpha_1 E_{\mathrm{S}} - \alpha_2 E_{\mathrm{R}}$. It can be found that the mutual Lagrange function $\mathcal{L}$ is very similar with the cost function L, and solving $\mathcal{L}$ with the necessary and sufficient KKT conditions leads to Proposition 2. However, the unfixed Lagrange multipliers in the optimal solution need to be updated according to the dual problems. The dual problems are written as

$$\begin{aligned} \max \quad & \mathcal{D}_1(\gamma) \\ \text{s.t.} \quad & \gamma \geq 0, \end{aligned} \tag{51}$$

$$\begin{aligned} \max \quad & \mathcal{D}_2(\alpha_1, \alpha_2) \\ \text{s.t.} \quad & \alpha_1 \geq 0, \alpha_2 \geq 0, \end{aligned} \tag{52}$$

where $\mathcal{D}_{1(2)} = \min_{t_{\mathrm{Tx}}, \rho_1, \rho_2} \mathcal{L}$. Since the objective function of the dual problem is linear in the Lagrange multipliers, the dual problem is convex, and the Lagrange multipliers can be solved by subgradient projection method. The Lagrange multipliers are updated as follows:

$$\begin{aligned} &\Delta\gamma = T - T(t_{\mathrm{Tx}}^*, \rho_1^*, \rho_2^*), \\ &\Delta\alpha_1 = E_{\mathrm{S}} - E_1(\rho_1^*, t_{\mathrm{Tx}}^*), \\ &\Delta\alpha_2 = E_{\mathrm{R}} - E_2(\rho_2^*), \\ &\gamma(t+1) = [\gamma(t) - \tau_1(t)\Delta\gamma(t)]^+, \\ &\alpha_i(t+1) = [\alpha_i(t) - \tau_2(t)\Delta\alpha_i(t)]^+, \quad \forall i \in \{1, 2\}, \end{aligned} \tag{53}$$

where t is the iteration index, $\tau_1(t)$, $\tau_2(t)$ are step sizes. By updating γ and α_i using the above equations, the specific algorithm for this problem is summarized as Algorithm 1.

The algorithm gives an iterative framework to solve the energy (or delay) minimization problems with fixed delay (or energy) constraints. The general solution for the computation relay is utilized directly to deal with these practical scenarios after considering the computing delay in the server and the restriction among the compression rates. Although the optimal solution $(\rho_1^*, \rho_2^*, t_{\mathrm{Tx}}^*)$ is calculated according to Proposition

Algorithm 1 Iterative algorithm for the computing and relaying model with energy or delay constraints

1: **Initialize:**
Set $t = 0$ and $t_{\max}$ is the maximum number of iterations. Set $\gamma(t)$ (or $\alpha_1(t)$, $\alpha_2(t)$) and allowable error δ.
2: **repeat**
3: Calculate $(\rho_1^*, \rho_2^*, t_{\text{Tx}}^*)$ according to Proposition 2.
4: Update $\gamma(t+1)$ (or $\alpha_i(t+1) \forall i \in 1, 2$) from (53).
5: **if** $\|\gamma(t+1) - \gamma(t)\|_2 < \delta$ (or $\|\alpha_i(t+1) - \alpha_i(t)\|_2 < \delta$) **then**
6: Close.
7: **end if**
8: $t = t + 1$.
9: **until** $t > t_{\max}$.

2, it can be unconditionally replaced by $(\rho_1^*, \rho_2^*, t_{\text{Tx}}^*)$ if the compression ratio constraints or MEC server constraints are given.

Although the proposed computing and relaying system is analyzed under several strong assumptions, some valuable insights can be obtained for using MEC in practical applications. First, it is suitable to utilize the MEC server to promote the data throughput capacity in P2P communication systems, especially when the communication and computing resources in the two relaying hops are asymmetric. Second, when the computation operation, such as compression, is dividable, we can obtain a remarkable transmission gain by distributing the computation among the communication components that have enough computing capacity. Even if considering the possible energy and delay cost in the MEC server, the gain is available and affordable. Third, to better deal with the data computation and transmission problems, the computing and communication resources distributed among the networks should be properly integrated.

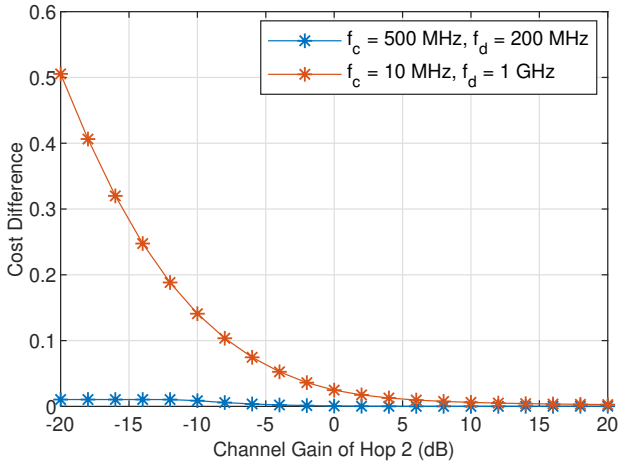


Fig. 4: Cost difference with the increasing channel gain of Hop 2.

VI. Numerical Results and Discussion

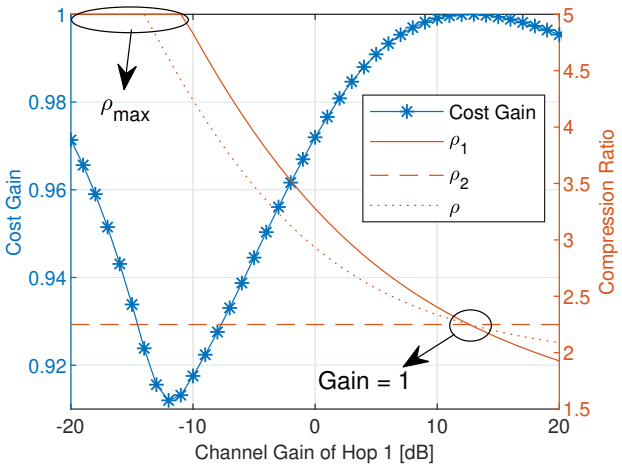
In this section, we evaluate the performance of the proposed computing and relaying model. To better show the system performance, the cost gain is defined as the ratio of the cost functions of the MEC-assisted system and the conventional system, *i.e.*,

$$\text{Cost Gain} = \frac{L_{\text{MEC}}}{L_{\text{noMEC}}}, \tag{54}$$

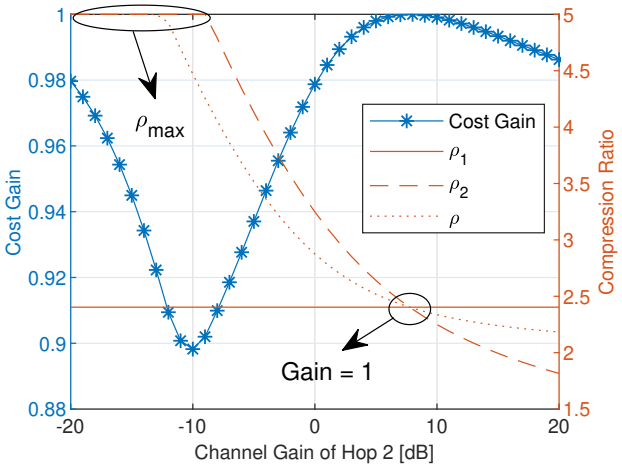
which is always less than 1 according to Proposition 4. Note that a smaller gain ratio represents better performance. The cost gain is more appropriate for the numerical evaluation than the cost difference defined by (32), since the cost difference varies dramatically with different parameters, as shown in Fig. 4. The computing and relaying model comprises one MEC relay node and two UEs, where UE 1 transmits D bits data to UE 2 through the MEC relay node. The amount of data D is set to 1024 bits and the bandwidth is 15kHz to simulate the peer-peer communication between IoT devices. The utility weights of the cost function are $\gamma = 0.5$ /Sec, $\alpha_1 = 0.25$ /Joul and $\alpha_2 = 0.25$ /Joul. The energy consumption for receiving each bit in the receiver is $q_{\text{Rx}} = 0.42 \times 10^{-6}$ J/bits according to Tale 1 of [32]. For the data compression, the required numbers of CPU cycles for compression and decompression ξ_1, ξ_2 belong to $[0, 3000]$ cycles/bit respectively, the CPU-cycle frequency is $f_{c(d)} \in [100, 1000]$ MHz, and the energy consumption per cycle is $q_{c(d)} = 1 \times 10^{-13}$ Joul/bit by default. We set the maximum compression ratio $\rho_{\max} = 5$, $\varepsilon = 0.5$, and other energy consumptions C_1 and C_2 to 0.

Fig. 5 illustrates the performance gain with different channel gains of the Hops or different CPU frequencies of the UEs. In the figure, the left y-axis represents to the gain provided by the computing and relaying model and the right y-axis represents to the optimal compression rates. Note that the compression rate is limited to $[1, 5]$ and the transmitting power of the relay node is set to 1 W. In these figures, we find that there is always a balance point where the performance gain equals 1 and $\rho = \rho_1 = \rho_2$. At this point, the MEC server doesn't work at all, and the computing and communication resources before the relay node and after the relay node are symmetric and balanced. When the channel state or the CPU frequency varies, the balance is broken and the MEC server participates in the communication. However, the cost gain line doesn't always turn down forward or backward from the balance point due to the maximum and minimum limits to the compression rate. Furthermore, it is observed that ρ is always between ρ_1 and ρ_2 in all the figures, which verifies Proposition 4. Notice that the performance gains in Fig. 5 are quite small, because the evaluation parameters are selected to show the balanced points.

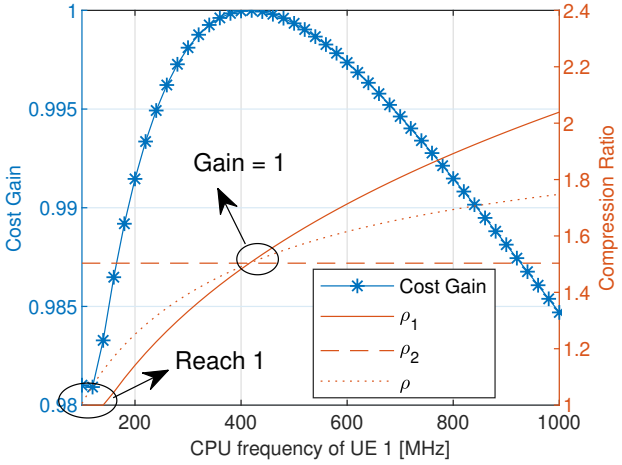
Fig. 6 shows the performance gain of the proposed system with the channel gains of Hop 1 and Hop 2. In Fig. 6 (a), the parameters of UE 1 and Hop 1 are investigated while the parameters of UE 2 and Hop 2 are fixed, *i.e.* $f_d = 1$ Ghz, $q_d = 1 \times 10^{-13}$ and $g_2 = -10$ dB. It indicates that the computing and relaying model obtains better gain when the computing capacity of UE 1 is lower, the energy efficient parameter of UE 1 q_c is worse but Hop 1 has a better channel



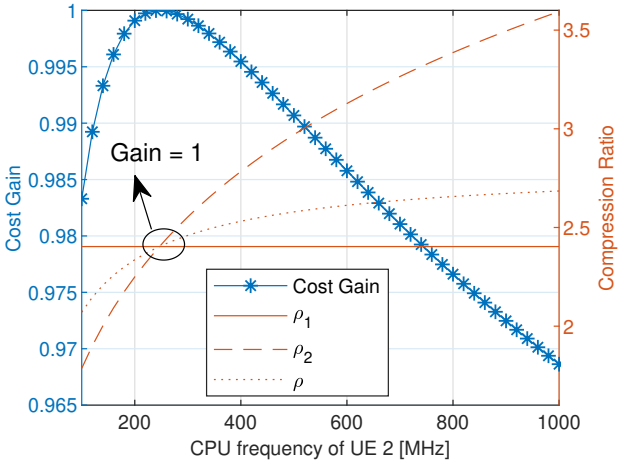
(a) Cost gain with the increasing channel gain of Hop 1. ($f_c = 500$ MHz, $f_d = 200$ MHz, $g_2 = 10$ dB)



(b) Cost gain with the increasing channel gain of Hop 2. ($f_c = 500$ MHz, $f_d = 200$ MHz, $g_1 = 10$ dB)

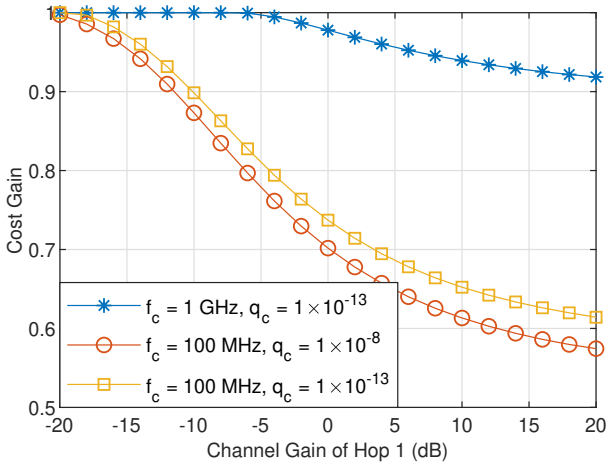


(c) Cost gain with the increasing CPU frequency of UE 1. ($f_d = 200$ MHz, $g_1 = 10$ dB, $g_2 = 10$ dB)

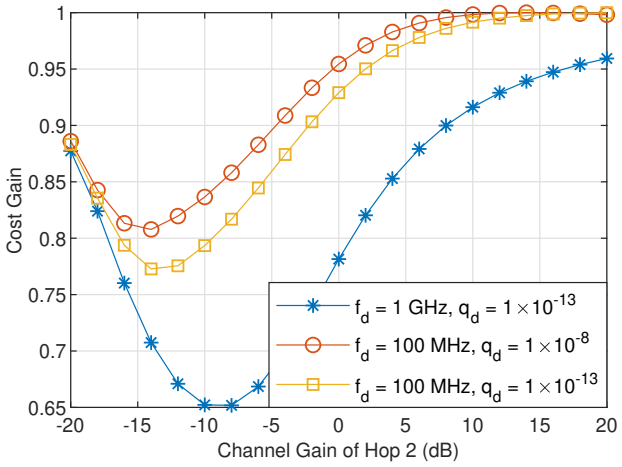


(d) Cost gain with the increasing CPU frequency of UE 2. ($f_c = 500$ MHz, $g_1 = 10$ dB, $g_2 = 10$ dB)

Fig. 5: The performance gain with the increasing channel gains and CPU frequencies.

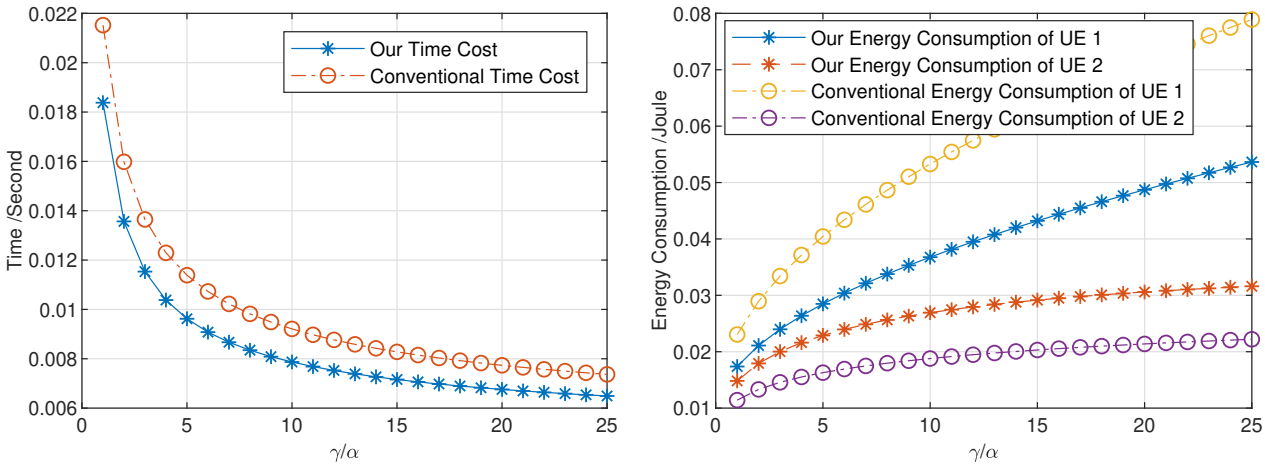


(a) Cost gain with the increasing channel gain of Hop 1.



(b) Cost gain with the increasing channel gain of Hop 2.

Fig. 6: The performance gain with the increasing channel gains for different CPU frequencies and energy efficient parameters.



(a) Latency with increasing γ/α.

(b) Energy consumption with increasing γ/α.

Fig. 7: The latency and the energy consumption of the P2P communication with increasing γ/α. Frequency of UE 1 2.3GHz, frequency of UE 2 200MHz, average channel gain of Hop 1 -10dB, average channel gain of Hop 2 10dB, size of D 1024bits.

gain. In Fig. 6 (b), the parameters of UE 1 and Hop 1 are fixed to $f_c = 100$ Mhz, $q_d = 1 \times 10^{-13}$ and $g_2 = 10$ dB. It is observed that, when the computation parameter of UE 2 turns better and the channel gain of Hop 2 turns worse, the performance gain increases before reaching the boundary of compression rate. This figure verifies that the MEC server makes a great contribution to the P2P communication system especially when the computing and communication resources are imbalanced among hops, which always exists in mobile scenes.

Fig. 7 gives the latency and the energy consumption with increasing γ/α in a practical P2P communication scenario, where a wearable sensor sends a message to a remote mobile phone. The message size D is fixed to 1024bits. The CPU frequency of the sensor CPU is set to 200MHz and that of the mobile phone is set to 2.3GHz. The other parameters are set as default. The average channel gain from the sensor to the AP node is -10dB and the average channel gain from the AP node (different from the one that serves the sensor) to the mobile phone is set to 10dB. γ and $\alpha = \alpha_1 = \alpha_2$ are weights of time cost and energy consumption respectively. A larger ratio γ/α represents less delay but more energy consumption. Monte Carlo simulation results with 10000 channel realizations are given in the figure. As we can see, the computing and relaying strategy obtains less time cost compared to the conventional strategy in Fig. 7 (a). In Fig. 7 (b), although our strategy brings less energy consumption for the sensor (UE 1), but results in more energy consumption for the mobile phone (UE 2). However, since the sensor is much more sensitive in energy than the mobile, the computing and relaying strategy can significantly extend the battery life of sensors and meanwhile reduce the latency of P2P communications.

VII. Conclusion

In this paper, we have proposed a novel computing and relaying model, in which an MEC server plays the role of the relay node to enhance the data throughput of P2P communications. By minimizing the cost function that consists of the energy consumption and latency, the optimal transmission and compression strategies for the MEC-assisted and conventional systems have been derived respectively. Then we have further considered some practical scenarios and have presented a specific algorithm for the systems with energy or delay constraints. Numerical results verify the efficiency of the proposed system. Our analysis indicates that the MEC theory can be utilized to promote P2P communications, and a lower latency and higher energy-efficiency P2P communication system can be achievable by jointly dispatching the computing and communication resources distributed in the network.

Appendix A

The relation in (20) can be rearranged as

$$\left(\frac{C_0}{\rho_1 t_{\text{Tx}}} - 1\right) e^{\frac{C_0}{\rho_1 t_{\text{Tx}}} - 1} = \left(\frac{\gamma}{A_2} - 1\right) e^{-1}, \tag{55}$$

which has the form of $x = W(x)e^{W(x)}$. Therefore, we have

$$\frac{C_0}{\rho_1 t_{\text{Tx}}} - 1 = W\left(\frac{\gamma e^{-1}}{A_2} - e^{-1}\right), \tag{56}$$

where $W(\cdot)$ is Lambert W function. Then we obtain

$$(\rho_1 t_{\text{Tx}})^* = \frac{C_0}{W\left(\frac{\gamma e^{-1}}{A_2} - e^{-1}\right) + 1}. \tag{57}$$

Set $C_1 = e^{\frac{C_0}{(\rho_1 t_{\text{Tx}})^*}}$, and (21) can be rearranged in the W function form as

$$\frac{\varepsilon\rho_1}{2} e^{\frac{\varepsilon\rho_1}{2}} = \frac{\varepsilon}{2}\sqrt{\frac{A_2 C_0 C_1}{A_1 \varepsilon}}. \tag{58}$$

By solving the combined equations of (57) (58), we can obtain t_{Tx^*} and ρ_1^*.

Similarly, the relation in (22) leads to

$$\frac{\varepsilon\rho_2}{2} e^{\frac{\varepsilon\rho_2}{2}} = \frac{\varepsilon}{2}\sqrt{\frac{A_3}{A_4 \varepsilon}}, \tag{59}$$

which finally gives ρ_2^*.

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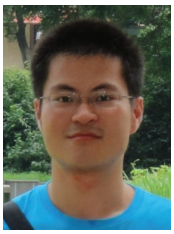

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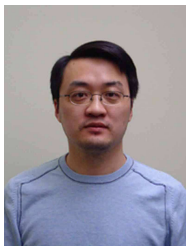

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