Economy Aware Token-Based Incentive Strategy to Promote Device-to-Device (D2D) Relay Use in Mobile Networks

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Abstract—*Device-to-device (D2D)* relay enhances the capacity of a mobile network. If the channel quality of a *user equipment (UE)* is bad, the UE asks a neighbor to get its data from the base station and forward the data to it by using D2D communication. Since cellular and D2D communication can share spectrum resources, the spectral efficiency will rise. As UEs are owned by self-interested users, they may not provide relay services gratis. Thus, some incentive methods let UEs exchange tokens to buy and sell relay services. However, they assume that each relay service is worth one token and offers a fixed data rate, which lacks flexibility. Through the *law of supply and demand*, this paper proposes an *economy aware token-based incentive (EAT-BI)* strategy. A *supplier* (i.e., the service provider) charges different prices for its relay service with different rates. A *consumer* (i.e., the service requestor) takes different policies to choose a supplier based on its tokens and may bargain with suppliers to avoid starvation. Simulation results show that EAT-BI can efficiently promote D2D relay use and increase throughput with different mobility models of UEs.

Index Terms—D2D, incentive, relay, supply and demand, token.

1 INTRODUCTION

In a mobile network, two nearby *user equipments (UEs)* can communicate with each other without connecting to a *base station (BS)*. This technique is called *device-to-device (D2D) communication* and widely used in 5G systems [1]. Cooperative relay can be carried out by D2D communication to improve performance. Fig. 1 gives an example, where UE u_i wants to receive downlink data, but its channel quality from the BS is not good (e.g., u_i is farther from the BS). Thus, u_i can ask neighbor u_j whose channel quality is better to get data from the BS on behalf of u_i. Then, u_j forwards data to u_i via D2D communication. Such cooperative relay is known as *D2D relay*. Since channel quality from the BS to u_j and that from u_j to u_i is good, D2D relay offers higher data rates, as compared with the case that u_i gets data directly from the BS. Moreover, D2D and cellular communication can share the spectrum resource, so network capacity increases [2].

Since UEs are usually owned by self-interested users, they may not unconditionally provide relay services. Thus, incentive is essential to prompt UEs to serve as relay nodes to exert the effectiveness of D2D relay, where token-based methods are especially fit for mobile networks [3], [4], [5]. They employ tokens as virtual currencies for UEs to perform transactions of relay services. UE u_i can ask another UE u_j to act as its relay node by paying tokens to u_j, as Fig. 1 shows. We call u_j and u_i *supplier* and *consumer*, respectively, as u_j sells the relay service and u_i buys that service. In this way, most UEs could be willing to provide relay services, because they can earn tokens for later use.

The existing token-based methods assume that the consumer gives the supplier one token to buy its relay service. However, this assumption constrains each supplier to provide only one choice of the relay service, where the supplier uses the fixed transmitted power to relay data to the consumer. In fact, just like real trading, a supplier could offer multiple choices of the relay service with different channel qualities (which can be easily done by adjusting its power) and charged for different prices. Thus, those poor UEs (i.e., with just few tokens) can have an opportunity to buy "cheaper" relay services to avoid starvation. Doing so gives far more flexibility to D2D relay and improves the overall performance.

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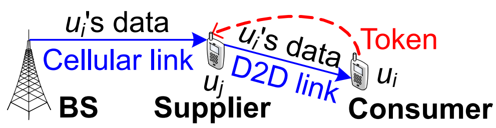


Fig. 1: Using D2D communication to realize cooperative relay.

This paper proposes an *economy aware token-based incentive (EAT-BI)* strategy, which considers the *law of supply and demand* in economics. Depending on its own tokens, consumer u_i has different *price elasticity of demand (PED)*. When u_i has enough tokens, its PED is relatively inelastic. Thus, u_i adopts a rate-preferred policy, which chooses the supplier offering the best data rate. Otherwise, u_i's PED is relatively elastic, so it takes a price-preferred policy, which looks for a cheaper service. However, if u_i cannot find suitable suppliers (e.g., due to high prices), it bargains with suppliers. With the *price elasticity of supply (PES)*, a supplier can provide a discount by adjusting the price and quality of its service. Through simulations, we show that EAT-BI not only improves D2D throughput but also reduces the number of non-served consumers, compared with other methods.

2 PRELIMINARY

This section discusses the mode selection for UEs and briefly introduces the law of supply and demand.

2.1 Cellular and D2D Modes

Each UE can directly talk with the BS, which we call the *cellular mode*. However, some UEs may have bad channel quality from the BS due to interference and fading [6]. To improve the transmission efficiency, they can ask neighbors to forward data from the BS, which is called the *relay mode*. Specifically, we adopt the two-hop relay, where each UE u_i can select at most one UE u_j to be its relay node. In this case, the transmission from the BS to u_i is replaced by the two-hop transmission "BS $\to u_j \to u_i$".

Given bandwidth $W_{b,i}$ of the link between the BS (denoted by b) and u_i, u_i's data rate in the cellular mode is

$$R_{b,i} = W_{b,i} \times \log_2(1 + S_{b,i}). \tag{1}$$

Here, $S_{b,i}$ denotes the *signal-to-interference-plus-noise ratio (SINR)* from the BS to u_i, which is estimated by [7] [8]

$$S_{b,i} = \frac{G_{b,i} \times T_{b,i}}{N_0^2 + I_i}, \tag{2}$$

where $G_{b,i}$ and $T_{b,i}$ are the BS's channel gain and transmitted power to send data to u_i, respectively, N_0^2 is the noise power, and I_i is the interference that u_i encounters in the cell. On the other hand, suppose that u_i gets its data via the relay of UE u_j. Then, u_i's data rate in the relay mode is

$$R^{(j)}_{b,i} = W^{(j)}_{b,i} \times \log_2(1 + S^{(j)}_{b,i}). \tag{3}$$

To improve resource utilization, D2D link (u_j, u_i) reuses the spectrum resource allocated to cellular link (b, u_j), so we have $W^{(j)}_{b,i} = W_{b,i}$. Besides, SINR $S^{(j)}_{b,i}$ is calculated by [9]

$$S^{(j)}_{b,i} = \frac{S_{b,j} \times S_{j,i}}{1 + S_{b,j} + S_{j,i}}, \tag{4}$$

where $S_{j,i}$ is derived from Eq. (2) by replacing b with j. In practice, each UE measures its SINR from the BS to let the BS choose the modulation and coding scheme to send data [10]. Thus, u_j tells u_i SINR $S_{b,j}$ in the response to u_i's query. On getting u_j's response, u_i measures SINR $S_{j,i}$ from u_j. In this way, u_i can calculate $S^{(j)}_{b,i}$ by Eq. (4).

Let D_i be u_i's traffic demand. If $R_{b,i} \geq D_i$, u_i chooses the cellular mode to get data directly from the BS. Otherwise, u_i prefers using the relay mode to improve performance. In particular, a neighbor u_j is considered as a *candidate* of u_i's suppliers (for relay services) if u_j meets three conditions:

- **C1.** u_j is neither sending nor receiving data. In other words, u_j's transceiver is idle, so it is able to relay u_i's data.
- **C2.** $S^{(j)}_{b,i} \geq S_{b,i} + \varphi$. Based on Eqs. (1) and (3), u_i's data rate can rise by using the relay mode via u_j.
- **C3.** $T^{\min}_j \leq T_{j,i} \leq T^{\max}_j$. This condition puts the lower and upper bounds on u_j's power for relaying data to u_i.

Among all candidates, u_i picks the most suitable supplier to be the relay node, which depends on its tokens and the prices asked by suppliers, as discussed in Section 4.

2.2 Law of Supply and Demand

In economics [11], *demand* is the willingness of a consumer to buy a product. When nothing else changes, the quantity of demand for the product is usually greater at lower prices than higher prices. On the other hand, *supply* is the quantity of a product that a supplier is willing to provide. Normally, the supplier prefers offering a greater quantity of the product at higher prices than lower prices, if nothing else changes.

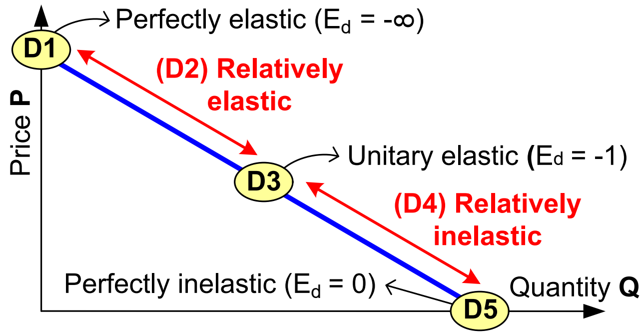
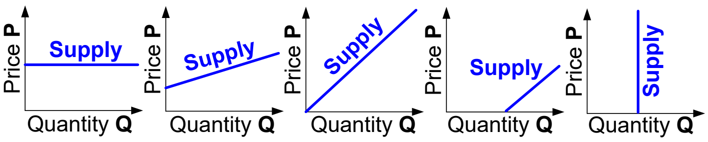


Fig. 2: The demand curve.

Let P and Q be the price and quantity of a product, respectively. Then, PED E_d is a measurement of the change ΔQ in consumption of that product in regard to the change ΔP in its price, where $E_d = -\left(\frac{\Delta Q}{Q}\right) / \left(\frac{\Delta P}{P}\right) = -\lim_{\Delta P \to 0} \frac{\Delta Q}{\Delta P} \times \frac{P}{Q} = -\frac{dQ}{dP} \times \frac{P}{Q}$. Fig. 2 gives the demand curve with five types of PED. Type D1 ($E_d = -\infty$) is the *perfectly elastic demand*, where any increase in the price makes the demand fall to zero. This type models products that have their value defined by law (e.g., currency). For example, if an ordinary 100-dollar bill is sold for anything more than \$100, no one will purchase that bill. Type D2 ($-\infty < E_d < -1$) is the *relatively elastic demand*. Let $\tilde{M}_{\mathrm{D}}$ and $\tilde{M}_{\mathrm{P}}$ be the magnitude of change in the quantity of demand and price, respectively. Since $\tilde{M}_{\mathrm{D}} > \tilde{M}_{\mathrm{P}}$, the supplier's revenue raises when the price reduces. Type D2 is also known as "small profits and good sales". Type D3 ($E_d = -1$) is the *unitary elastic demand*, where $\tilde{M}_{\mathrm{D}} = \tilde{M}_{\mathrm{P}}$. Thus, changing the price has no impact on the revenue. Type D4 ($-1 < E_d < 0$) is the *relatively inelastic demand*, where $\tilde{M}_{\mathrm{D}} < \tilde{M}_{\mathrm{P}}$. The revenue increases as the price rises. Type D5 ($E_d = 0$) is the *perfectly inelastic demand*, where changes in the price will not affect the demand's quantity. It models products vital to survival. For example, a man is going to die of thirst in a desert. To survive, he could give all his money for buying water. This paper adopts types D2 and D4, as they have a noticeable impact on the behavior of consumers but will not cause extreme conditions (i.e., types D1 and D5).

PES E_s estimates responsiveness to a product's supply by changing its price. $E_s = \left(\frac{\Delta Q}{Q}\right) / \left(\frac{\Delta P}{P}\right) = \lim_{\Delta P \to 0} \frac{\Delta Q}{\Delta P} \times \frac{P}{Q} = \frac{dQ}{dP} \times \frac{P}{Q}$. PES contains five types, as shown in Fig. 3. Type S1 ($E_s = \infty$) is the *perfectly elastic supply*. The supply's quantity is unlimited at a given price, but changing the price leads to no quantity of supply. This type is theoretical. Type S2 ($1 < E_s < \infty$) is the *relatively elastic supply*, where $\tilde{M}_{\mathrm{S}} > \tilde{M}_{\mathrm{P}}$ and $\tilde{M}_{\mathrm{S}}$ is the magnitude of change in the quantity of supply. It models products that can be massively manufactured and easily distributed (e.g., plastic toys). Type S3 ($E_s = 1$) is the *unitary elastic supply*, where $\tilde{M}_{\mathrm{S}} = \tilde{M}_{\mathrm{P}}$. Type S4 ($0 < E_s < 1$) is the *relatively inelastic supply*, where $\tilde{M}_{\mathrm{S}} < \tilde{M}_{\mathrm{P}}$. An example is nuclear power plants, which take much effort to construct. Type S5 ($E_s = 0$) is the *perfectly inelastic supply*, where the supply's quantity will not be affected by the price. Type S5 is fit for products with limited quantities (e.g., paintings of deceased artists). As the costs of relay services for UEs are not large, type S2 is the most suitable to model the behavior of suppliers in our work.



(a) Type S1 (b) Type S2 (c) Type S3 (d) Type S4 (e) Type S5

Fig. 3: Five types of supply curves.

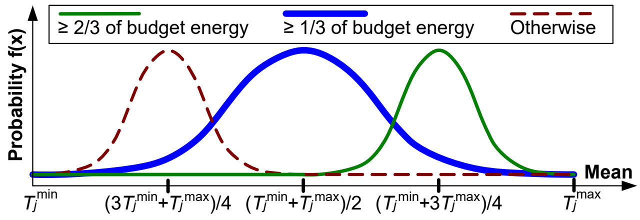


Fig. 4: Gaussian distributions for the selection of power $T_{j,i}$.

3 Related Work

3.1 Issues of D2D Communication

How to let D2D and cellular communication share the BS's spectrum resource is widely discussed. Duong et al. [12] allot resources to UEs based on their relative distances, so as to reduce interference among UEs and support more D2D links. The study [13] finds out the maximum pairs between cellular UEs and D2D links by the Gale-Shapley scheme, whose result achieves the Pareto optimality [14]. A graph-coloring method is proposed in [15] for D2D links to reuse the resources allocated to cellular UEs with negligible interference. Given the traffic demand of each D2D sender, the work [7] decides its transmission period and power to save energy and satisfy the demand. By using a game-theoretic approach, the study [16] finds the correlation among D2D and cellular UEs for resource sharing to improve the energy efficiency. The work [17] combines the maximal independent set and a knapsack solution to handle resource sharing between cellular and D2D communication. Liu et al. [18] develop a two-stage mechanism to allocate channels for D2D links and decide their transmitted power. Lai et al. [19] propose a pure D2D model to allow D2D links sharing resources without involving cellular UEs. In [8], the deep reinforcement learning is applied to select channels and decide power for D2D UEs. The study [20] handles the D2D resource and power management problem in the scenario where multiple operators collocate in a BS and share resources. Evidently, the above studies have different objectives with ours.

Some studies discuss cooperative relay by D2D communication. The study [21] proposes a relay discovery method to reduce periodic discovery transmissions of D2D UEs and save their energy. The work [22] transfers services of UEs among different cells via D2D relay, so as to balance loads of BSs and turn off idle BSs. Wu et al. [23] model the relay selection problem by multi-objective linear programming and solve it by the fuzzy and entropy theories. The study [24] picks relay nodes based on the communication range and social relationship of each UE. With deep learning, the work [25] builds the community relationship between D2D UEs to find the best relay node. In [26], the Q-learning technique is used to solve the relay selection problem. As can be seen, these studies assume that UEs are compliant to offer relay services. When most UEs are owned by self-interested users, this assumption may not be valid.

3.2 Incentive Methods for D2D Relay

To inspire UEs to act as relay nodes, three types of incentive methods are developed. In *resource-exchanging methods*, when UE u_i asks a neighbor u_j to relay its data, u_i has to compensate u_j by giving a portion of its resource, where the resource can be the transmission time [27], relay service [28], or bandwidth [29]. However, these methods request u_i to compensate u_j right after getting u_j's relay service, no matter whether u_j needs u_i's assistance or not, which may degrade the performance of D2D relay.

In *indirect-reciprocity-based methods* [30], [31], each UE observes the relaying behavior of neighbors to evaluate their reputation. If a UE refuses relaying data many times, it will have bad reputation. As a penalty, other UEs decline to provide relay services to that UE. In these methods, UEs keep exchanging their evaluations to track reputation, which is carried out by the omnidirectional broadcast. However, this is difficult to implement in mobile networks due to using the MIMO and beam-forming techniques [32].

Token-based methods [3], [4] adopt tokens as virtual currencies to let UEs trade in relay services. Each UE earns tokens by relaying data for its neighbors. If it needs help from others, the UE can purchase their relay services by paying tokens. The work [33] analyzes the relationship between the number of tokens and the profit in D2D relay. A supervised learning method is proposed in [5] to help each UE decide whether to sell its relay service. The study [34] applies a *Markov decision process (MDP)* to model the trade of relay services, which aims at maximizing the long-term utility of each UE. The utility is defined by the difference between the benefit that a UE obtains when getting data via D2D relay and the cost that the UE pays for relay services. To avoid some UEs hoarding tokens maliciously, three token circulation methods are developed in [35]. Since tokens can preserve value, token-based methods are more flexible than resource-exchanging and indirect-reciprocity-based methods. However, the above token-based methods assume that each relay service has an identical price (i.e., one token). It motivates us to propose the EAT-BI strategy that relaxes this assumption and applies the law of supply and demand to token transactions, so as to promote D2D relay use.

4 System Model

Let us consider one cell that covers a set $\hat{\mathcal{U}}$ of UEs, where they can move and have the ability of D2D relay. We slice time into periods to facilitate management. In each period, the BS arranges a subset $\hat{\mathcal{U}}_{\text{DL}}$ of UEs from $\hat{\mathcal{U}}$ for downlink communication. The period length should be long enough for a UE $u_i \in \hat{\mathcal{U}}_{\text{DL}}$ to obtain its downlink data in the relay mode, which includes the time for u_i to choose its mode (as discussed in Section 2.1), the time for u_i to negotiate with its candidates to pick out a relay node u_j, and the time to perform the two-hop transmission "BS $\rightarrow u_j \rightarrow u_i$". Moreover, the channel quality and locations of u_i and u_j cannot change significantly. One good choice of the period length is a frame defined in 5G, which is 10 ms.

Each UE in $\hat{\mathcal{U}}$ is given some initial tokens. If u_i asks u_j to relay its data, u_i has to pay tokens to u_j. Unlike the existing token-based methods, we propose using *micro-tokens*

TABLE 1: Summary of notations used in the EAT-BI strategy.

notation	definition
$\hat{\mathcal{U}}$, $\hat{\mathcal{U}}_{\text{DL}}$	sets of all UEs and the UEs that will get downlink data
$\hat{\mathcal{N}}_i$, $\hat{\mathcal{C}}_i$	sets of neighbors and supplier candidates of a UE u_i
$S_{b,i}$, $R_{b,i}$	u_i's SINR and data rate (from the BS)
$T_{j,i}$	u_j's power to relay data to u_i ($T_j^{\min} \leq T_{j,i} \leq T_j^{\max}$)
Γ	the number of m-tokens equivalent to a token
M_i	the number of m-tokens owned by u_i
P_j	service's price asked by u_j ($P_{\min} \leq P_j \leq P_{\max}$)
δ_C	a threshold for u_i to choose between Algos. 2 and 3
δ_S^{H}, δ_S^{L}	two thresholds for a supplier to decide its discount
γ_1, γ_2, γ_3	reduction ratio of the price
λ_1, λ_2, λ_3	reduction ratio of the transmitted power

(m-tokens), where Γ m-tokens are equivalent to a token ($\Gamma > 1$). It brings two benefits by using one m-token to be the unit of transaction prices. First, the value of (original) tokens is not diluted, so there is no inflation of tokens. Second, UEs can provide more fine-grained prices of their relay services, which adds flexibility to token-based methods.

Let $P_{\max}$ and $P_{\min}$ denote the maximum and minimum legal prices, respectively. Suppose that the transmitted power of supplier u_j used to relay data is $T_{j,i}$. Then, u_j charges a number P_j of m-tokens for its relay service:

$$P_j = \max\left\{ \left\lfloor \frac{T_{j,i} - T_j^{\min}}{T_j^{\max} - T_j^{\min}} \times P_{\max} \right\rfloor, P_{\min} \right\}. \tag{5}$$

Here, price P_j is proportional to power $T_{j,i}$, which is u_j's cost on the D2D relay. According to Eq. (5), when u_j is willing to use the maximum power $T_j^{\max}$, which provides the best channel quality for the D2D relay, the price is set to $P_{\max}$. On the contrary, if u_j offers the worst channel quality by using the minimum power $T_j^{\min}$, the price is set to $P_{\min}$. Furthermore, we can set $T_{j,i}$ based on a Gaussian distribution, whose probability density function is $f(x) = e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}/(\sigma\sqrt{2\pi})$, where μ is the mean and σ is the standard deviation. Specifically, the mean depends on the ratio of u_j's residual energy E_j to its budget energy E_{BE} used for D2D relay, as shown in Fig. 4. When $E_j \geq \frac{2}{3}E_{\text{BE}}$, we set $\mu = \frac{1}{4}(T_j^{\min} + 3T_j^{\max})$. If $\frac{1}{3}E_{\text{BE}} \leq E_j < \frac{2}{3}E_{\text{BE}}$, we set $\mu = \frac{1}{2}(T_j^{\min} + T_j^{\max})$. Otherwise, we set $\mu = \frac{1}{4}(3T_j^{\min} + T_j^{\max})$. In this way, when u_j has more energy, there is a higher possibility that u_j chooses a larger value of $T_{j,i}$, and vice versa.

We modify the protocol in [35] for UEs to exchange messages for the trade of relay services. When UE u_i wants to buy the relay service from another UE u_j, u_i sends a *relay request* to u_j. If u_j is willing to act as a relay node, it sends u_i a *relay reply* that contains the price of its relay service. Once u_i also accepts the price, it sends u_j a *relay confirmation*, which involves the transfer of m-tokens from u_i to u_j. Let M_i be the number of u_i's m-tokens. A number P_j of m-tokens will be transferred from u_i to u_j. Therefore, we have $M_i = M_i - P_j$ and $M_j = M_j + P_j$. With the relay confirmation, u_j notifies the BS that it will help relay u_i's data. In this case, the BS sends u_i's data to u_j by using u_i's *resource blocks (RBs)*, and u_j reuses these RBs to forward the data to u_i. Notice that if u_i cannot afford the price, u_i may ask u_j for a discount by sending a *bargaining message*. Then, u_j sends a relay reply that includes the new price to u_i. To save the message cost, the above bargaining procedure can be performed at most once. Like [5], we assume that these messages are protected by some security mechanisms (e.g., authentication by the public-key cryptography). Thus, no UE can defraud others of their tokens by tampering messages.

Our problem asks how to select the supplier for each consumer, such that network throughput can be maximized. Table 1 summarizes the notations used in EAT-BI.

Algorithm 1: The EAT-BI Strategy

1 **foreach** $u_i \in \hat{\mathcal{U}}_{\text{DL}}$ **do**
2   **if** *$R_{b,i} \geq D_i$ or $M_i < P_{\min}$* **then**
3   let u_i use the cellular mode and then continue;
4   $\hat{\mathcal{C}}_i \leftarrow \emptyset$;
5   **foreach** $u_j \in \hat{\mathcal{N}}_i$ **do**
6   **if** *u_j is idle, $S_{b,i}^{(j)} \geq S_{b,i} + \varphi$, and $P_{\min} \leq P_j \leq P_{\max}$* **then**
7       $\hat{\mathcal{C}}_i \leftarrow \hat{\mathcal{C}}_i \cup \{u_j\}$;
8   **if** $\hat{\mathcal{C}}_i = \emptyset$ **then**
9   let u_i use the cellular mode and then continue;
10   **if** $M_i > \delta_C$ **then**
11   pick a supplier u_j from $\hat{\mathcal{C}}_i$ by Algo. 2;
12   **else**
13   pick a supplier u_j from $\hat{\mathcal{C}}_i$ by Algo. 3;
14   **if** *u_j = null* **then**
15   find a supplier u_j by Algo. 4;
16   **if** *no supplier is found* **then**
17   u_i gets data in the cellular mode;
18   **else**
19     $M_i \leftarrow M_i - P_j$ and $M_j \leftarrow M_j + P_j$;
20   u_i gets data in the relay mode via u_j;

5 THE PROPOSED EAT-BI STRATEGY

Algo. 1 gives EAT-BI's pseudocode. In lines 2–3, we judge whether UE u_i gets data directly from the BS by two conditions: 1) u_i itself can meet demand D_i (i.e., $R_{b,i} \geq D_i$), or 2) u_i is too poor to afford any relay service (i.e., $M_i < P_{\min}$). If so, u_i chooses the cellular mode, and we check the next UE in $\hat{\mathcal{U}}_{\text{DL}}$. Otherwise, we find a set $\hat{\mathcal{C}}_i$ of supplier candidates for u_i, whose code is shown in lines 4–7. Let $\hat{\mathcal{N}}_i$ be the set of u_i's neighbors. The if-statement in lines 6–7 picks candidates from $\hat{\mathcal{N}}_i$ by the three conditions in Section 2.1. From Eq. (5), condition C3 (i.e., $T_j^{\min} \leq T_{j,i} \leq T_j^{\max}$) implies that $P_{\min} \leq P_j \leq P_{\max}$. In line 6, we replace condition C3 by the condition $P_{\min} \leq P_j \leq P_{\max}$, so u_i need not query u_j about its power $T_{j,i}$. However, if $\hat{\mathcal{C}}_i = \emptyset$ (i.e., no candidate), u_i has to use the cellular mode, as shown in lines 8–9.

In lines 10–15, u_i adopts different methods to select a suitable supplier from $\hat{\mathcal{C}}_i$ to be its relay node, which depends on the number M_i of its m-tokens. If u_i has more than δ_C m-tokens (which means that u_i is relatively rich), it uses the *rate-maximizing selection (RMS) method* in Algo. 2 to choose a supplier that offers the best data rate. Otherwise, u_i uses the *budget-oriented selection (BOS) method* in Algo. 3 to look for a cheaper relay service. However, if no supplier is found by Algo. 3, u_i uses the *bargaining method* in Algo. 4 to ask for a discount from some UEs in $\hat{\mathcal{C}}_i$ and find a supplier accordingly, as shown in lines 14 and 15.

Algorithm 2: The RMS Method

1 $\texttt{SORT}(\hat{\mathcal{C}}_i,\, S_{b,i}^{(j)})$;
2 **foreach** $u_j \in \hat{\mathcal{C}}_i$ **do**
3   **if** $M_i \geq P_j$ **then**
4   **return** u_j;
5 **return** null;

If no supplier is found by Algo. 4, u_i has to get data directly from the BS. Otherwise, u_i pays P_j m-tokens to u_j, and asks u_j to relay data. The code is given in lines 16–20. Theorem 1 analyzes the time complexity of Algo. 1.

Theorem 1. Suppose that $\hat{\mathcal{U}}_{\text{DL}}$ contains ζ_{U} UEs and every UE in $\hat{\mathcal{U}}$ has no more than ζ_{N} neighbors. Algo. 1 takes time of $\zeta_{\text{U}}(O(\zeta_{\text{N}}) + \max\{\tau_2, \tau_3 + \tau_4\})$, where τ_2, τ_3, and τ_4 are the computational time of Algos. 2, 3, and 4, respectively.

Proof: In Algo. 1, the outer for-loop repeats ζ_{U} times. The if-statement in lines 2–3 spends a constant time to check if u_i should use the cellular mode. As $|\hat{\mathcal{N}}_i| \leq \zeta_{\text{N}}$, the inner for-loop in lines 5–7 has at most ζ_{N} iterations. In the inner for-loop, the if-statement in lines 6–7 checks three conditions C1, C2, and C3. As discussed in Section 2.1, it is easy to estimate SINR $S_{b,i}^{(j)}$ in condition C2. Thus, the if-statement takes $O(1)$ time, and the inner for-loop requires $O(\zeta_{\text{N}})$ time. Moreover, the if-statement in lines 8–9 consumes $O(1)$ time. Then, u_i chooses between Algo. 2 and Algo. 3 (including Algo. 4) to find a supplier from $\hat{\mathcal{C}}_i$. Since the code in lines 10–11 and the code in line 12–15 are mutually exclusive, the code in lines 10–15 spends time of $\max\{\tau_2, \tau_3 + \tau_4\}$. Finally, each statement in lines 16–20 takes $O(1)$ time. To sum up, the time complexity of Algo. 1 is $\zeta_{\text{U}}(O(\zeta_{\text{N}}) + \max\{\tau_2, \tau_3 + \tau_4\})$. □

Below, we detail the RMS, BOS, and bargaining methods in Sections 5.1, 5.2, and 5.3, respectively. After that, we make a discussion on the EAT-BI strategy in Section 5.4.

5.1 The RMS Method

The RMS method takes a rate-preferred policy, which makes UE $u_i \in \hat{\mathcal{U}}_{\text{DL}}$ adopt type D4 of PED (i.e., relatively inelastic demand, where $-1 < E_d < 0$). Thus, u_i seeks to choose the relay service with the best quality (i.e., offering the maximum data rate), as it has ample m-tokens.

Algo. 2 presents RMS's pseudocode. Line 1 sorts u_i's supplier candidates in $\hat{\mathcal{C}}_i$ decreasingly based on SINR $S_{b,i}^{(j)}$, as denoted by $\texttt{SORT}(\hat{\mathcal{C}}_i,\, S_{b,i}^{(j)})$. From Eq. (3), since the chosen candidate will reuse u_i's RBs to relay data (i.e., bandwidth $W_{b,i}^{(j)}$ is the same for each candidate in $\hat{\mathcal{C}}_i$), higher SINR $S_{b,i}^{(j)}$ implies higher data rate $R_{b,i}^{(j)}$. That is why we replace data rate $R_{b,i}^{(j)}$ with SINR $S_{b,i}^{(j)}$ in line 1. Doing so helps reduce computation. The for-loop in lines 2–4 picks a candidate u_j from $\hat{\mathcal{C}}_i$, and check if u_i can afford to pay the price asked by u_j (i.e., $M_i \geq P_j$). If so, u_i selects u_j to be its relay node. Theorem 2 analyzes the time complexity of RMS.

Theorem 2. Suppose that each UE has at most ζ_{N} neighbors. Algo. 2 requires $O(\zeta_{\text{N}} \log_2 \zeta_{\text{N}})$ time in the worst case.

Proof: In Algo. 2, line 1 sorts the candidates in $\hat{\mathcal{C}}_i$. Since $|\hat{\mathcal{C}}_i| \leq |\hat{\mathcal{N}}_i| = \zeta_{\text{N}}$, line 1 consumes $O(\zeta_{\text{N}} \log_2 \zeta_{\text{N}})$ time. Then, the for-loop in line 2–4 repeats at most ζ_{N} times, where each statement takes $O(1)$ time. Thus, the total time complexity is $O(\zeta_{\text{N}} \log_2 \zeta_{\text{N}}) + \zeta_{\text{N}} \times O(1) = O(\zeta_{\text{N}} \log_2 \zeta_{\text{N}})$. □

Algorithm 3: The BOS Method

1 $\hat{\mathcal{C}}_i^{\mathbf{A}} \leftarrow \emptyset$;
2 **if** $M_i - \lceil \beta \times M_i \rceil \geq P_{\min}$ **then**
3     $M_i^{\mathbf{B}} \leftarrow \lceil \beta \times M_i \rceil$;
4 **else**
5     $M_i^{\mathbf{B}} \leftarrow M_i$;
6 **foreach** $u_j \in \hat{\mathcal{C}}_i$ **do**
7   **if** $P_j \leq M_i^{\mathbf{B}}$ **then**
8         $\hat{\mathcal{C}}_i^{\mathbf{A}} \leftarrow \hat{\mathcal{C}}_i^{\mathbf{A}} \cup \{u_j\}$;
9 **if** $\hat{\mathcal{C}}_i^{\mathbf{A}} = \emptyset$ **then**
10   **return** null;
11 **return** $\arg\max_{\forall u_j \in \hat{\mathcal{C}}_i^{\mathbf{A}}} S_{b,i}^{(j)}$;

5.2 The BOS Method

When a UE $u_i \in \hat{\mathcal{U}}_{\text{DL}}$ is not rich (i.e., $M_i \leq \delta_C$), it inclines to leave some m-tokens for later use. In this case, u_i's PED will be relatively elastic (i.e., type D2, where $-\infty < E_d < -1$). In view of this, the BOS method takes a price-preferred policy for u_i to select its supplier.

Algo. 3 gives BOS's pseudocode, where $\hat{\mathcal{C}}_i^{\mathbf{A}}$ is the subset of candidates in $\hat{\mathcal{C}}_i$ whose prices are *acceptable* by u_i. Specifically, u_i tries to keep the budget for buying the current relay service below $M_i^{\mathbf{B}}$, which is set to $\lceil \beta \times M_i \rceil$, where $0 < \beta < 1$, as shown in lines 2–3. However, if the number of residual m-tokens is fewer than $P_{\min}$ after buying the relay service (i.e., $M_i - \lceil \beta \times M_i \rceil < P_{\min}$), u_i should bring all the m-tokens into the budget (i.e., $M_i^{\mathbf{B}} = M_i$). That is because too few m-tokens remain, and u_i cannot afford any relay service in the next time if it does not earn m-tokens from others. The code is given in lines 4–5.

In lines 6–8, we put those candidates that offer prices no larger than $M_i^{\mathbf{B}}$ into set $\hat{\mathcal{C}}_i^{\mathbf{A}}$. If $\hat{\mathcal{C}}_i^{\mathbf{A}}$ is empty, which means that u_i has very few m-tokens, or all candidates in $\hat{\mathcal{C}}_i$ charge too much, the BOS method returns a null value, as shown in lines 9–10. Otherwise, among all candidates in $\hat{\mathcal{C}}_i^{\mathbf{A}}$, u_i chooses the one whose SINR $S_{b,i}^{(j)}$ is the best, as line 11 shows. Theorem 3 analyzes the time complexity of BOS.

Theorem 3. Algo. 3 requires $O(\zeta_{\text{N}})$ time, where ζ_{N} is the maximum number of neighbors of each UE in $\hat{\mathcal{U}}$.

Proof: As $\hat{\mathcal{C}}_i^{\mathbf{A}} \subseteq \hat{\mathcal{C}}_i \subseteq \hat{\mathcal{N}}_i$, we have $|\hat{\mathcal{C}}_i^{\mathbf{A}}| \leq |\hat{\mathcal{C}}_i| \leq |\hat{\mathcal{N}}_i| = \zeta_{\text{N}}$. Each statement in lines 1–5 consumes $O(1)$ time. The for-loop in lines 6–8 takes $O(\zeta_{\text{N}})$ time, and the if-statement in lines 9–10 spends $O(1)$ time. It spends $O(\zeta_{\text{N}})$ time to find the candidate in $\hat{\mathcal{C}}_i^{\mathbf{A}}$ with the maximum SINR by line 11. To sum up, the total time complexity is $O(\zeta_{\text{N}})$. □

5.3 The Bargaining Method

According to lines 13–15 in Algo. 1, the bargaining method is executed only if the BOS method cannot find any supplier for a UE $u_i \in \hat{\mathcal{U}}_{\text{DL}}$ due to the insufficient budget or high fees charged by neighbors. In this case, u_i will ask them for a discount. Algo. 4 gives the pseudocode of the bargaining method. In line 1, we sort all candidates in $\hat{\mathcal{C}}_i$ by their SINRs $S_{b,i}^{(j)}$ decreasingly.

Algorithm 4: The Bargaining Method

1 SORT($\hat{\mathcal{C}}_i$, $S_{b,i}^{(j)}$);
2 **foreach** $u_j \in \hat{\mathcal{C}}_i$ **do**
3 $\quad$ $(P'_j, S'^{(j)}_{b,i}) \leftarrow \text{Discount}(u_j)$;
4 $\quad$ **if** $M_i \geq P'_j$ *and* $S'^{(j)}_{b,i} \geq S_{b,i} + \varphi$ **then**
5 $\quad\quad$ **return** u_j;
6 **return** null;

Algorithm 5: The Discount Procedure

1 **if** $M_j > \delta_S^{\mathrm{H}}$ **then**
2 $\quad$ $P'_j \leftarrow \max\{\lceil \gamma_1 \times P_j \rceil, P_{\min}\}$ and $T'_{j,i} \leftarrow \lambda_1 \times T_{j,i}$;
3 **else if** $\delta_S^{\mathrm{L}} < M_j \leq \delta_S^{\mathrm{H}}$ **then**
4 $\quad$ $P'_j \leftarrow \max\{\lceil \gamma_2 \times P_j \rceil, P_{\min}\}$ and $T'_{j,i} \leftarrow \lambda_2 \times T_{j,i}$;
5 **else**
6 $\quad$ $P'_j \leftarrow \max\{\lceil \gamma_3 \times P_j \rceil, P_{\min}\}$ and $T'_{j,i} \leftarrow \lambda_3 \times T_{j,i}$;
7 **if** $T'_{j,i} < T_j^{\min}$ **then**
8 $\quad$ $T'_{j,i} \leftarrow T_j^{\min}$ and $P'_j \leftarrow P_{\min}$;
9 Compute $S'^{(j)}_{b,i}$ based on $T'_{j,i}$ by Eq. (4);
10 **return** $(P'_j, S'^{(j)}_{b,i})$;

The for-loop in lines 2–5 iteratively picks a candidate u_j from $\hat{\mathcal{C}}_i$ and asks u_j to lower its price. This is done by the *Discount procedure*, which returns a new price P'_j and the corresponding SINR $S'^{(j)}_{b,i}$ (i.e., updated quality of u_j's relay service), where $P'_j < P_j$ and $S'^{(j)}_{b,i} < S^{(j)}_{b,i}$. Then, u_i judges whether to choose u_j to be its relay node by two conditions: 1) u_i can afford the new price (i.e., $M_i \geq P'_j$), and 2) even if u_j's SINR reduces, u_i can still improve the data rate by using the relay mode via u_j (i.e., $S'^{(j)}_{b,i} \geq S_{b,i} + \varphi$). The second condition removes those candidates whose services cannot meet u_i's demand. The code is given in lines 4–5. However, if no supplier can be found, the bargaining method returns a null value, as shown in line 6. The time complexity of this method is presented in Theorem 4.

Theorem 4. Let ζ_{N} be the maximum number of neighbors of all UEs. Algo. 4 takes time of $O(\zeta_{\mathrm{N}} \log_2 \zeta_{\mathrm{N}}) + \zeta_{\mathrm{N}}\tau_5$, where τ_5 is the computational time of the Discount procedure.

Proof: In Algo. 4, line 1 consumes $O(\zeta_{\mathrm{N}} \log_2 \zeta_{\mathrm{N}})$ time to sort $\hat{\mathcal{C}}_i$. The for-loop repeats at most ζ_{N} times, where line 3 requires τ_5 time to execute the Discount procedure, and lines 4–5 take a constant time. Then, line 6 returns a null value and spends $O(1)$ time. Thus, the time complexity of Algo. 4 is $O(\zeta_{\mathrm{N}} \log_2 \zeta_{\mathrm{N}}) + \zeta_{\mathrm{N}}(\tau_5 + O(1)) + O(1) = O(\zeta_{\mathrm{N}} \log_2 \zeta_{\mathrm{N}}) + \zeta_{\mathrm{N}}\tau_5$. □

Supplier u_j uses the Discount procedure to decide the amount of reduction in its price P_j and power $T_{j,i}$ for the relay (which decides SINR $S^{(j)}_{b,i}$), whose pseudocode is given in Algo. 5. If a supplier has more m-tokens, its willingness to reduce the price decreases, and vice versa. In view of this, we divide u_j's financial situation (i.e., the number M_j of its m-tokens) into three levels by using two thresholds δ_S^{H} and δ_S^{L}: *rich* (i.e., $M_j > \delta_S^{\mathrm{H}}$), *ordinary* (i.e., $\delta_S^{\mathrm{L}} < M_j \leq \delta_S^{\mathrm{H}}$), and *poor* (i.e., $M_j \leq \delta_S^{\mathrm{L}}$). If u_j is rich, ordinary, and poor, the new price P'_j will be $\max\{\lceil \gamma_1 \times P_j \rceil, P_{\min}\}$, $\max\{\lceil \gamma_2 \times P_j \rceil, P_{\min}\}$, and $\max\{\lceil \gamma_3 \times P_j \rceil, P_{\min}\}$, respectively, where $0 < \gamma_3 < \gamma_2 < \gamma_1 < 1$. Specifically, the new price cannot be smaller than $P_{\min}$ (i.e., the lowest legal price), so P'_j is set to $\max\{\lceil \gamma_k \times P_j \rceil, P_{\min}\}$ instead of simply $\lceil \gamma_k \times P_j \rceil$, for $k = 1, 2, 3$. On the other hand, the new power $T'_{j,i}$ is set to $\lambda_1 \times T_{j,i}$, $\lambda_2 \times T_{j,i}$, and $\lambda_3 \times T_{j,i}$ when u_j is rich, ordinary, and poor, respectively, where $0 < \lambda_3 < \lambda_2 < \lambda_1 < 1$. We suggest setting $\gamma_k \leq \lambda_k$ $(k = 1, 2, 3)$. In this way, though u_j reduces its price, the service quality (in terms of data rate) will not deteriorate sharply. The code is given in lines 1–6.

In lines 7–8, we handle a special case where u_j reduces its power too much, such that $T'_{j,i}$ is below the minimum power $T_j^{\min}$. In this case, the new power should be adjusted to $T_j^{\min}$ and the price is set to $P_{\min}$ accordingly. With Eq. (4), we can find the new SINR $S'^{(j)}_{b,i}$ based on power $T'_{j,i}$. Then, line 10 returns the result $(P'_j, S'^{(j)}_{b,i})$. Theorem 5 analyzes the time complexity of the Discount procedure.

Theorem 5. The time complexity of Algo. 5 is $O(1)$.

Proof: Each statement in lines 1–8 takes $O(1)$ time. Line 9 uses Eq. (4) to compute $S'^{(j)}_{b,i}$ by the new power $T'_{j,i}$, which requires a constant time (as discussed in Theorem 1). Since line 10 only returns the result, the time complexity is $O(1)$. □

In our design, suppliers take type S2 of PES. In Fig. 3(b), the slope of the supply curve is between 0 and 1. Thus, the supply is elastic, where products (i.e., relay services) can be easily produced. In this case, most suppliers are willing to lower their prices to earn m-tokens. Besides, when a supplier has fewer m-tokens, the amount of reduction in its price is larger, which implies that the supplier has more willingness on the discount to attract consumers. On the other hand, the possibility that consumers with only few m-tokens can buy (cheap) relay services also rises. In this way, we can promote D2D relay use and increase network throughput.

5.4 Discussion

We discuss the rationale of the EAT-BI strategy. In the past token-based methods, the charge for every relay service is a token, which has two drawbacks. First, most consumers prefer the suppliers that provide better-quality services. Thus, those suppliers whose channel qualities are not good cannot attract customers to buy their services. This evidently wastes relay services and reduces system performance. Second, if each UE is given a few initial tokens as starting, some UEs may use up tokens soon (as relay services are relatively expensive). If they cannot earn tokens from others in a short time, these UEs cannot buy relay services and thus have to use the cellular mode to receive data at low speeds. Although the problem may be solved by giving more initial tokens to UEs, this solution could reduce the willingness of UEs to provide relay services (because they have many tokens).

EAT-BI adopts m-tokens in the trade of relay services, where Γ m-tokens are equivalent to a token, to support more fine-grained and flexible pricing. Accordingly, suppliers can provide different qualities of relay services by adjusting their transmitted power. Based on the financial status, each consumer $u_i \in \hat{\mathcal{U}}_{\mathrm{DL}}$ uses different methods to select its supplier. If u_i is rich (i.e., $M_i > \delta_C$), its PED is relatively inelastic (i.e., type D4). Thus, u_i adopts the RMS method in Algo. 2 to choose a supplier that offers the best quality of service. Otherwise, u_i is more conservative on spending m-tokens and its PED becomes relatively elastic (i.e., type D2). In this case, u_i uses the BOS method in Algo. 3 to look for cheaper services and

TABLE 2: Simulation parameters.

parameter	value
General parameters:	
BS	bandwidth: 10 MHz; power: 46 dBm
UE	number: 100∼1500; power: 13∼23 dBm
traffic	full-buffer traffic model
mobility	models: LIM, RWM, MAM; speed: 1.6∼2 m/s
Parameters relevant to the communication model:	
path loss	BS to UE: $128.1 + 37.6 \log_{10}$ distance(BS, u_i)
	UE to UE: $148 + 40 \log_{10}$ distance(u_i, u_j)
propagation loss	urban macrocell model
shadow fading	zero-mean log-normal distribution
noise (N_0^2)	spectrum density: -174 dBm/Hz
Token-related parameters:	
initial m-tokens	100 (= 10 tokens)
legal prices	$P_{\min} = 1$, $P_{\max} = 10$
thresholds	$\delta_C = 50$, $\delta_S^{\mathrm{H}} = 75$, $\delta_S^{\mathrm{L}} = 25$
discounts	price: $\gamma_1 = 0.9$, $\gamma_2 = 0.7$, $\gamma_3 = 0.5$
	power: $\lambda_1 = 0.95$, $\lambda_2 = 0.8$, $\lambda_3 = 0.65$

save m-tokens. However, if u_i still cannot afford the prices, it uses Algo. 4 to bargain with suppliers, so as to increase the possibility to purchase the relay service. Besides, the Discount procedure in Algo. 5 takes PES into consideration, where a supplier is more willing to provide a higher discount when it is not rich. The above designs distinguish our EAT-BI strategy from the existing token-based methods and promote D2D relay use. Theorem 6 gives the time complexity of the EAT-BI strategy.

Theorem 6. Given ζ_{U} UEs in $\hat{\mathcal{U}}_{\mathrm{DL}}$, the time complexity of EAT-BI is $O(\zeta_{\mathrm{U}}\zeta_{\mathrm{N}} \log_2 \zeta_{\mathrm{N}})$, where $|\hat{\mathcal{N}}_i| \leq \zeta_{\mathrm{N}}$, $\forall u_i \in \hat{\mathcal{U}}$.

Proof: Based on Theorems 1–5, EAT-BI's time complexity is $\zeta_{\mathrm{U}}(O(\zeta_{\mathrm{N}}) + \max\{O(\zeta_{\mathrm{N}} \log_2 \zeta_{\mathrm{N}}), O(\zeta_{\mathrm{N}}) + O(\zeta_{\mathrm{N}} \log_2 \zeta_{\mathrm{N}}) + O(\zeta_{\mathrm{N}})\}) = O(\zeta_{\mathrm{U}}\zeta_{\mathrm{N}} \log_2 \zeta_{\mathrm{N}})$. □

6 PERFORMANCE EVALUATION

We evaluate performance by OMNet++, where one macrocell covers 100 to 1500 UEs (i.e., $\hat{\mathcal{U}}$) whose range is 1 km. Table 2 presents simulation parameters. For the connection model, we pick 1/3 UEs in $\hat{\mathcal{U}}$ to get downlink data (i.e., $\hat{\mathcal{U}}_{\mathrm{DL}}$) in each period. As discussed in Section 4, the period length is 10 ms. Those UEs not selected may sell relay services to others to earn tokens/m-tokens in that period. Moreover, we adopt the full-buffer traffic model [36], so every UE in $\hat{\mathcal{U}}_{\mathrm{DL}}$ always has data to receive. In this way, no UE will squander RBs when it is selected for downlink communication.

Since multiple UEs are picked to receive data in every period, there will be multiple flows (or connections) generated in the simulation. On the other hand, as the number of UEs in $\hat{\mathcal{U}}$ increases, more UEs will be added to $\hat{\mathcal{U}}_{\mathrm{DL}}$ to get downlink data and compete for the fixed spectrum resource. In particular, when $|\hat{\mathcal{U}}| \geq 1100$, the BS may not have enough resource to serve all UEs in $\hat{\mathcal{U}}_{\mathrm{DL}}$. In this case, we can view it as a congested scenario.

UEs can move in the cell, where we adopt three mobility models. In the *linear mobility (LIM) model*, a UE has the linear motion with a fixed speed. In the *random-waypoint mobility (RWM) model*, each UE arbitrarily picks a location to move toward with a random speed. After arriving at the location, it pauses for a while and selects the next location. In the *mass mobility (MAM) model*, each UE moves along a straight line for a random period of time. If the UE wants to make a turn, it uses a normally distributed random number, whose average is equal to the previous direction and standard deviation is 30 degrees, to choose the new moving direction. The MAM model describes the movement of a node with momentum (i.e., the node does not abruptly stop or turn).

For the communication model, we consider the fading effects caused by path loss, propagation loss, and shadow. The path loss is decided by the distance between a UE and its sender (i.e., the BS or another UE), which is measured in km. For the propagation loss, we consider the environment in a dense urban area. We model shadow fading by a log-normal distribution whose standard deviation is 10 dB and 3 dB for cellular and D2D communication, respectively.

Then, let us discuss token-related parameters. Similar to currencies, we use a decimal system and set Γ to 10. Each UE is given 100 initial m-tokens (i.e., 10 tokens) for a start. Since the transmitted power of a UE ranges between 13 dBm and 23 dBm (which can be divided into 10 intervals), we set $P_{\min} = 1$ and $P_{\max} = 10$. Thus, each interval of power can map to a price. Besides, the maximum legal price (i.e., $P_{\max}$) is equivalent to a token, so we can provide a fair comparison between the methods using m-tokens and the methods using tokens. As for thresholds, δ_C is used to judge whether a UE is rich or poor, which makes the UE take different policies to select a supplier. Here, we set $\delta_C = 50$ (i.e., 1/2 of initial m-tokens). Moreover, δ_S^{H} and δ_S^{L} help a supplier decide its discount. We set $\delta_S^{\mathrm{H}} = 75$ and $\delta_S^{\mathrm{L}} = 25$ (i.e., 3/4 and 1/4 of initial m-tokens, respectively). In Algo. 5, we set $\gamma_1 = 0.9$, $\gamma_2 = 0.7$, and $\gamma_3 = 0.5$, which means that a supplier gives a discount of 10%, 30%, and 50%, respectively. To avoid over-degrading the service quality, we add 0.05, 0.1, and 0.15 to power coefficients λ_1, λ_2, and λ_3, respectively. That is why $\lambda_1 = 0.95$, $\lambda_2 = 0.8$, and $\lambda_3 = 0.65$ in Table 2.

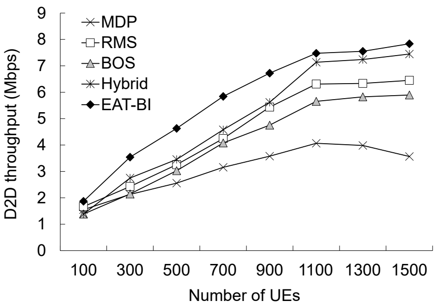
We compare the EAT-BI strategy with four methods. As discussed in Section 3.2, the *MDP method* [34] aims to maximize the long-term utility of UEs. In the *RMS method*, each UE adopts Algo. 2 to select a supplier that provides the best data rate. The *BOS method* in Algo. 3 asks UEs to select suppliers based on their budgets to save m-tokens. The *hybrid method* combines RMS and BOS. In other words, it is the EAT-BI strategy without the bargaining method (i.e., removing lines 14 and 15 from Algo. 1). In MDP, each relay service is charged for one token. Except for MDP, the unit of transaction prices is one m-token in all other methods. The simulation time is 3600 seconds.

Next, we measure system performance in terms of D2D throughput, network throughput, and non-served consumers in Sections 6.1, 6.2, and 6.3, respectively. Then, Section 6.4 discusses the effect of token-related parameters.

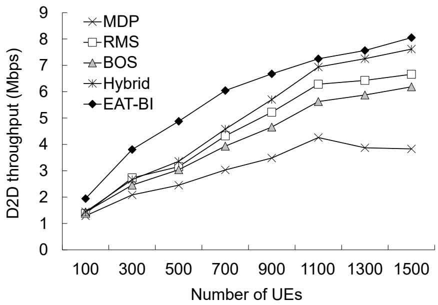
6.1 D2D throughput

In a period, let $\phi_{\mathrm{R}}(u_i)$ be the number of data bits that a UE $u_i \in \hat{\mathcal{U}}_{\mathrm{DL}}$ gets from the BS via relay node(s), and $t_{\mathrm{R}}(u_i)$ be the amount of time (in seconds) that u_i spends to receive data by using the relay mode. The amount of D2D throughput in the period is defined by $\sum_{u_i \in \hat{\mathcal{U}}_{\mathrm{DL}}} \phi_{\mathrm{R}}(u_i)/t_{\mathrm{R}}(u_i)$. Then, we take the average of D2D throughput in all periods.

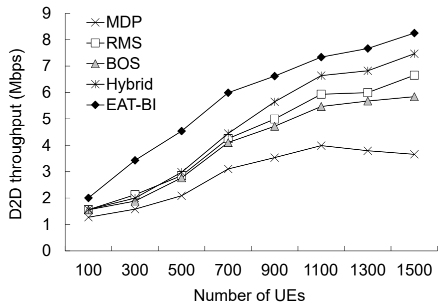
Fig. 5(a)–(c) show D2D throughput of each method, which rises as $|\hat{\mathcal{U}}|$ grows. That is because each UE in $\hat{\mathcal{U}}_{\mathrm{DL}}$ has more choices of suppliers to offer relay services. However, when the network becomes congested (i.e., $|\hat{\mathcal{U}}| \geq 1100$), the magnitude of rise in D2D throughput diminishes. In the MDP method, D2D throughput even starts degrading. That explains why there exist turning points in D2D throughput of most methods



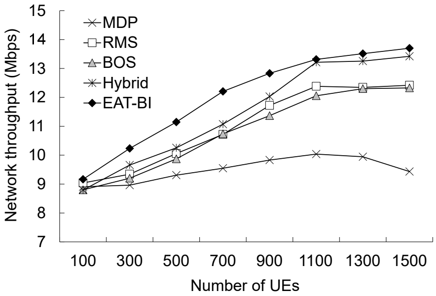
(a) D2D throughput (LIM model)



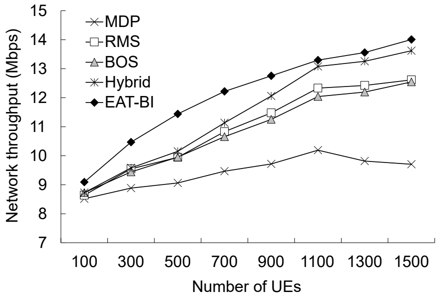
(b) D2D throughput (RWM model)



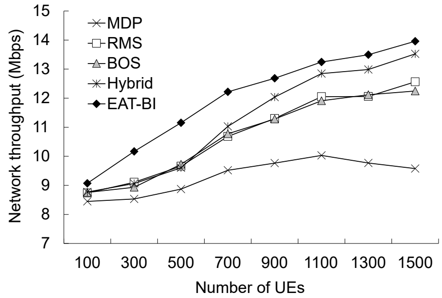
(c) D2D throughput (MAM model)



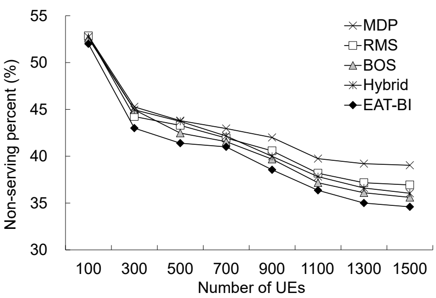
(d) Network throughput (LIM model)



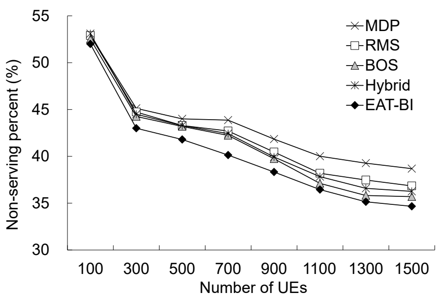
(e) Network throughput (RWM model)



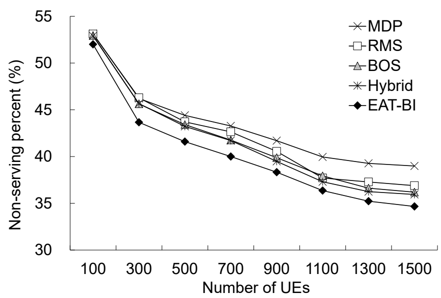
(f) Network throughput (MAM model)



(g) Non-served consumers (LIM model)



(h) Non-served consumers (RWM model)



(i) Non-served consumers (MAM model)

Fig. 5: Comparison of system performance with different mobility models.

TABLE 3: Improvement percent by EAT-BI.

(a) D2D throughput				
model	MDP	RMS	BOS	hybrid
LIM	84.93%	25.87%	38.77%	14.78%
RWM	90.13%	27.73%	39.13%	16.82%
MAM	99.23%	33.43%	43.18%	22.04%
(b) Network throughput				
model	MDP	RMS	BOS	hybrid
LIM	26.52%	9.19%	10.91%	4.82%
RWM	28.49%	10.28%	11.53%	5.70%
MAM	28.83%	11.40%	11.94%	6.82%
(c) Non-served consumers				
model	MDP	RMS	BOS	hybrid
LIM	8.51%	4.85%	2.62%	3.24%
RWM	8.73%	5.15%	2.85%	3.93%
MAM	8.88%	5.25%	4.02%	4.06%

when there are 1100 UEs. This phenomenon also shows the effect of congestion on D2D throughput.

MDP charges a token (= 10 m-tokens) every relay service. Some UEs in $\hat{\mathcal{U}}_{\mathtt{DL}}$ may use up tokens quickly and cannot afford any relay service after that (unless their signal qualities improve and they can sell others relay services to earn tokens). Other methods use m-tokens to offer fine-grained and flexible prices. In this way, some relay services become cheaper, so more UEs in $\hat{\mathcal{U}}_{\mathtt{DL}}$ can buy relay services. That explains why other methods have higher D2D throughput than MDP, without depending on the mobility model. Among all affordable relay services, the RMS method chooses the service with the best data rate. The BOS method asks UEs to leave some m-tokens for later use. Thus, RMS has higher D2D throughput than BOS. The hybrid method combines RMS and BOS, which encourages rich UEs to buy better services and asks poor UEs to save m-tokens. Thus, the hybrid method outperforms RMS and BOS. By allowing poor UEs to bargain with suppliers, our EAT-BI strategy could help them obtain relay services. Thus, EAT-BI always has the highest D2D throughput.

In Table 3(a), we give the improvement percent of D2D throughput by EAT-BI, as compared with the MDP, RMS, BOS, and hybrid methods. Let $X_{\mathtt{EAT-BI}}$ and $X_{\mathtt{other}}$ be the amount of average D2D throughput (with different numbers of UEs) of EAT-BI and a method for comparison, respectively. Then, it is defined by $\frac{X_{\mathtt{EAT-BI}} - X_{\mathtt{other}}}{X_{\mathtt{other}}} \times 100\%$. EAT-BI performs the best with the MAM model, followed by RWM and LIM models. The reason is that the MAM model will not make UEs abruptly stop/turn (as compared with the RWM model), and they can move more freely (as compared with the LIM model). In this case, each UE in $\hat{\mathcal{U}}_{\mathtt{DL}}$ could have more choices of suppliers, which raises the probability for the UE to find a good supplier in EAT-BI.

6.2 Network throughput

Let $\phi_{\text{C}}(u_i)$ be the number of data bits that a UE $u_i \in \hat{\mathcal{U}}_{\text{DL}}$ gets directly from the BS and $t_{\text{C}}(u_i)$ be the amount of time that u_i spends to receive data by using the cellular mode in a period. The amount of cellular throughput in the period is defined by $\sum_{u_i \in \hat{\mathcal{U}}_{\text{DL}}} \phi_{\text{C}}(u_i)/t_{\text{C}}(u_i)$. Then, network throughput will be the sum of D2D throughput and cellular throughput, where we take the average of network throughput in all periods.

Fig. 5(d)–(f) compare network throughput. When u_i's channel quality from the BS is good enough to satisfy its demand (i.e., $R_{b,i} \geq D_i$), u_i gets data from the BS directly. Besides, if u_i prefers the relay mode but no supplier is found, u_i has to adopt the cellular mode. In this case, u_i's cellular throughput will be pretty low (as its channel quality from the BS is bad). Therefore, there is little difference in cellular throughput of each method. That is why the trend of network throughput in Fig. 5(d)–(f) is similar to the trend of D2D throughput in Fig. 5(a)–(c). Specifically, network throughput rises as there are more UEs in $\hat{\mathcal{U}}$. The ranking of methods in Fig. 5(d)–(f) is also the same with that in Fig. 5(a)–(c), that is, EAT-BI > hybrid > RMS > BOS > MDP.

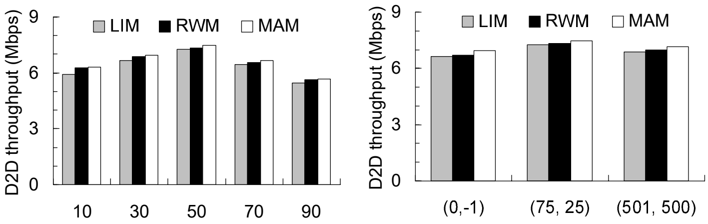
Table 3(b) gives the improvement percent of network throughput by EAT-BI, whose definition is similar to that discussed in Section 6.1. The result shows the superiority of our EAT-BI strategy on improving network throughput, and it performs the best with the MAM model.

6.3 Non-served Consumers

The *non-serving percent* of consumers is defined as the percentage of non-served UEs in $\hat{\mathcal{U}}_{\text{DL}}$, where a UE is *non-served* if it needs relay services but cannot find any supplier. A lower non-serving percent implies that the method helps consumers better utilize their tokens/m-tokens on buying relay services. From Fig. 5(g)–(i), when the number of UEs in $\hat{\mathcal{U}}$ grows, the non-serving percent reduces. That is because each consumer has more choices of suppliers. As each relay service is worth a token in the MDP method, some consumers may fast run out of their tokens. In this case, they cannot afford relay services (until these UEs earn enough tokens). That is why MDP has the highest non-serving percent.

Other methods can reduce non-served consumers by using a smaller unit of transaction prices (i.e., m-tokens). The RMS method lets consumers splash out their m-tokens on high-quality services, whereas the BOS method asks consumers to look for cheaper services to save m-tokens. Thus, BOS has a lower non-serving percent than RMS. Since the hybrid method is a combination of RMS and BOS, its non-serving percent is between them. Thanks to the bargaining method in Algo. 4, our EAT-BI strategy allows poor consumers to request suppliers for discounts, so it can further decrease the non-serving percent.

Table 3(c) presents the improvement percent of non-served consumers by EAT-BI. Let $Y_{\texttt{EAT-BI}}$ and $Y_{\texttt{other}}$ be the average number of non-served consumers (with different numbers of UEs) of EAT-BI and one chosen method for comparison, respectively. Then, this improvement percent is defined by $\frac{Y_{\texttt{other}}-Y_{\texttt{EAT-BI}}}{Y_{\texttt{other}}} \times 100\%$. Since UEs stably move in the MAM model, EAT-BI will have the best performance accordingly. Even with other mobility models, EAT-BI can efficiently reduce non-served consumers than other methods.



(a) Effect of δ_C (b) Effect of $(\delta_S^{\text{H}}, \delta_S^{\text{L}})$

Fig. 6: Effect of token-related parameters.

6.4 Effect of Token-related Parameters

Lastly, we study the effect of token-related parameters on the performance of the EAT-BI strategy. Based on the results in Sections 6.1, 6.2, and 6.3, higher D2D throughput implies higher network throughput and lower non-serving percent, so we use D2D throughput as the performance metric. The number of UEs in $\hat{\mathcal{U}}$ is set to 1100 (i.e., congested scenario).

Fig. 6(a) shows the effect of δ_C, which affects how a UE u_i chooses its supplier. Based on lines 10–15 in Algo. 1, if δ_C is too small (i.e., δ_C = 10), u_i usually selects suppliers by using the RMS method. If δ_C is too large (i.e., δ_C = 90), u_i prefers using the BOS method. Since RMS lets u_i choose a supplier that offers the best data rate while BOS forces u_i to save m-tokens, EAT-BI has higher D2D throughput when δ_C = 10, as compared with that when δ_C = 90. By setting δ_C = 50, we can strike a good balance between RMS and BOS. In this case, EAT-BI can achieve the highest D2D throughput.

In Algo. 5, a supplier decides the amount of discount via two thresholds δ_S^{H} and δ_S^{L}. Fig. 6(b) shows D2D throughput by setting $(\delta_S^{\text{H}}, \delta_S^{\text{L}})$ to $(0, -1)$, $(75, 25)$, and $(501, 500)$. When $(\delta_S^{\text{H}}, \delta_S^{\text{L}}) = (0, -1)$, each supplier offers 10% discount and set $P'_j = 0.95P_j$, where P'_j and P_j are new and original power, respectively. In this case, some poor UEs still cannot afford to pay new prices, thereby degrading D2D throughput. On the other hand, when $(\delta_S^{\text{H}}, \delta_S^{\text{L}}) = (501, 500)$, all suppliers offer 50% discount but set $P'_j = 0.65P_j$. Though poor UEs may afford to pay new prices, the service quality become worse. By setting $(\delta_S^{\text{H}}, \delta_S^{\text{L}})$ to $(75, 25)$, we can make suppliers provide different discounts and service qualities. In this way, the UEs with relatively more m-tokens can choose services with better qualities to improve performance, while the UEs with very few m-tokens can still buy (bad-quality) services to avoid starvation. That is why EAT-BI has the highest D2D throughput when $(\delta_S^{\text{H}}, \delta_S^{\text{L}}) = (75, 25)$.

7 Conclusion

D2D relay provides an alternative way for UEs to get data efficiently when their signal quality from the BS is not good. As the owners of most UEs are self-interested, token-based methods let UEs carry out transactions of relay services by using tokens. In these methods, each relay service has the identical price (i.e., one token), which lacks flexibility. Thus, we use m-tokens to provide fine-grained service prices, and propose the EAT-BI strategy to help UEs select relay nodes based on the law of supply and demand. When a consumer is rich, it finds a supplier whose service achieves the maximum data rate. Otherwise, it preferentially chooses cheaper services to save m-tokens. If the consumer cannot find any suitable relay node due to high prices requested by suppliers, it can bargain with suppliers to seek for discounts. Through simulations, we verify that EAT-BI not only improves throughput but also reduces non-served consumers, as compared with the MDP, RMS, BOS, and hybrid methods.

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