Data Transaction Modeling in Mobile Networks: Contract Mechanism and Performance Analaysis

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Data Transaction Modeling in Mobile Networks: Contract Mechanism and Performance Analaysis

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***Abstract*—We consider auction mechanism design and performance analysis for data transactions in mobile social networks. Existing mobile network plans can result in some users ending a monthly plan with excess data, while others may have to pay a costly fee to buy more data. Thus we suggest data auctions with a single seller, or a multiple-seller networked data auction, that operate in mobile social networks, to deal with the asymmetry between extra unused data resources and urgent data demands. Based on earlier work on the analysis of auctions, we design the data transaction mechanism, and summarise the analysis on state transmission, stationary probabilities of the system, and the expected income for data sellers. To improve the efficiency and performance of the system, a socially-aware mobility model is also proposed. The proposed data auction mechanisms and friendship-based mobility model are then simulated as operating on Flickr, a real-world online social network database. Results show that the number of data bidders in different auctions can be balanced through the proposed mobility model, and also increase the income per unit time of sellers in the networked data auction.**

I. Introduction

Currently, with new spectrum licenses and upgrading technologies from WCDMA to LTE and LTE-A, wireless communication has entered a new era of high-speed 4G, which can reach to high peak data rates of 300 Mbps on the downlink and 75 Mbps on the uplink for a 20 MHz bandwidth, according to LTE Release 8 [1]. With this high speed of data support of 4G LTE networks and their commercial deployment, as well as the rapid penetration of smart phones, wireless data traffic is experiencing an exponential increase.

To face the increase data demands of mobile users, almost all mobile network operators (MNOs) have introduced different kinds of monthly 4G data plans in which, if the data plan does not run out by the end of a month, the remaining data will not be cumulated to the next month's plan. On the other hand, when usage thresholds are reached before the end of a month, users need to buy extra data at a relatively high price. These two opposite cases could lead to deals among users whereby users hitting their data limitation would trade with those that still have not reached the limit in a given plan period.Though currently such data limit dealing is not allowed among mobile users, we imagine that such transactions could be implemented through phone-to-phone communications among users through WiFi hotspots that would allow mobile phones or other wireless devices to access phone-to-phone communications via the WiFi interface [2]. When accessed phones have data requirements, the requested data can be received first by the hotspot phones through 4G networks. Then hotspot phones switch the data into a WiFi signal, and transmit it to the corresponding accessed phones, making the previously suggested data transaction a reality.

However, a market mechanism is needed to achieve economic efficiency and optimization for buyers and sellers of the data limits, which is the subject of this paper. Obviously data limit owners and buyers would require deals to be made quickly before the end of the month, to avoid wasting resources and paying high costs. Thus automated auctions [3] are a suitable scheme to deal with the asymmetry between the available data limit resource and the data limit demands. They have have been studied as an important and effective tool in network economics applied to wireless networks for dynamic spectrum allocation, femtocell access, mobile data offloading other issues [4]. A double-auction mechanism was designed for a market where MNOs lease third-party owned WiFi or femtocell APs to offload mobile data traffic [5]. An auction-based incentive framework for a cellular service provider to leverage resources from third-party owners on demand by buying capacity through reverse auctions, was proposed in [6]. An auction scheme that enables the efficient usage of base station resources under low traffic [7] was proposed to maximize third-party income and minimize energy consumption. However, the relationship among mobile users is not considered in recent work, which focuses mainly on channel quality, and on requirements from the two sides of an auction. Since mobile social networks (MSNs) are experiencing an unprecedented growth, they can also provide platforms to operate data limit auctions. Moreover, and their topology can also important information and support to the auction mechanism with high efficiency and performance. So in this work, we introduce an auction based data transaction mechanism and then operate it on the real-world online social network Flickr. A mobility model based on the friendship of the MSNs are proposed to improve the efficiency of the networked data transaction and optimize the economic properties of the system.

The paper is organized as follows. In Section II, the basic auction model for data transactions is described. The networked auction introduced in [8] and the friendship based mobility model are discussed in Section III. Simulations are shown in Section IV, and conclusions are drawn in Section V.

II. Basic Data Auction with a Single Auctioneer

First, we introduce the process of the auction for the data transaction with a single data seller. Such systems have been analysed previously in [9], [10]. We assume that the auction process is operated automatically on both of the data owners' and bidders' smart phones. This assumption is feasible and can be implemented by a special AP residing on the platform of social networks. The elements and operations in the automatic data auction are described as follows:

- *Data owner (auctioneer, data seller):*

The MSN user with unconsumed and needless mobile data. We assume that the data owner will operate a series of successive data auction, and each time he/she only sells a certain size of the data traffic. This assumption can avoid a long time connection and data transmitting with a single data requester. In addition, a large data size in a single will due to a high starting price and is not necessary for the requester.

- *Data requesters (data bidders, potential data buyers):*

The MSN users having ran out their mobile data.

- *Beginning of a basic auction:*

The data owner starts an auction by unlocking his/her hotspot mode of phone, setting the starting price v_0 of a certain size of his/her data planned to sell, and then waits for bids.

- *Bid arrivals:*

The personal mobile business for a single user, such as emails, text messages and other information pushing services, arrives according to a Poisson process with a certain rate λ_0, and the average time between successive arrivals is the reciprocal of the arrival rate [11]–[13]. We assume that each business arrival triggers a bid, which is a public information can be observed by the data owner and other data requesters. The business arrivals for different mobile users are independent and identically distributed (i.i.d.), so the bid arrivals for the data owner are still a sequence of Poisson arrivals with arrival rate λ. If a bid is not accepted by the data owner, then the next bid will increase the value of the offer by fixed δ, as long as the highest price V that data requesters intend to pay. In the data auction, potential buyers' individual rationality is considered, which means that when the value V is reached, data requesters will stop bidding and increasing the offer.

- *Auctioneer decisions:*

After each bid, the data owner waits for a random "considering time", which has an exponential distribution with average r_c^{-1} and the memoryless property, to determine whether to accept the current bid. If the next bid arrives before the end of the considering time, then this considering process is repeated. Conversely, the data owner will accept the data requester's offer, allow him/her to access into the hotspot and complete the data transaction with this successful data bidder.

- *Data transaction procedure:*

The data transaction will last a "service time", which is modeled as an exponentially distributes time with rate r_s, before starting a new round of data auction by the data owner. Moreover, service time in different rounds of auctions are i.i.d.

According the "auctioneer decisions" step, we notice that if the data owner decides to wait for the next bid a long time, he/she might get a higher offer for the data provided, but the cost is time waste. Conversely, short "considering time" results in a frequently repeated auctions, in each of which the data owner tends to get a low offer due to his/her weak patience.

A. Mathematical model

In this part, we use the mathematical model in [3] for the data auction process. It is a continuous time Markov chain $\{X_t : t \geq 0\}$ with state space

$$\mathbb{X} = \{v_0, v_1, v_2, \cdots, v_h, A_1, A_2, \cdots, A_h\} \tag{1}$$

that models any auction in the sequence. Let t_n be the start time of the nth data auction, then $\{t_n, n \geq 1\}$ implies a series of repeat auctions for data owned by a social network user. The states in (1) are defined as follows.

- Beginning state or starting price: $X_{t_n} = v_0$ is the beginning state of the nth round of the data auction. To simplify the mathematical expression, states v_0 also corresponds to the value of starting price, given by the data owner.
- Bid arrival states: $X_{t_n+t} = v_j$ $(j = 1, 2, \cdots, h)$ denotes the state that j bids have arrived in the nth round of the data auction at time $t_n + t$ and the current value reached is $v_j = v_0 + j\delta$, where δ is the increment vale size between two adjacent bids. We can notice that $t_n + t < t_{n+1}$ holds intrinsically. State v_j $(j = 1, 2, \cdots, h)$ is also the value of current price made by a social network user who wants to buy the data form the owner. In addition, v_h denotes the highest bid that data buyers will make, and satisfy $v_h = v_0 + h\delta \leq V$ and $v_0 + (h+1)\,\delta > V$. This constraint indicates that when the highest price V that buyers intend to pay is fetched, buyers among the social network will not bid for the data. The value of price V is determined by the buyers individually, and it can be both a random variable and constant associate with the data pricing by mobile operators.
- Bid acceptation states: $X_{t_n+t} = A_j$ $(j = 1, 2, \cdots, h)$ denotes the state the jth bid is accepted by the data seller at time $t_n + t$ in the nth auction. The corresponding bidder will get the permission to access the phone hotspot of the data provider and use the mobile data traffic, at price $v_j = v_0 + \delta h$.

According to these definitions, the transition rate from bid arrival state v_j to v_{j+1} $(j = 1, 2, \cdots, h-1)$ is λ, the transition rate from state v_j to acceptation state A_j is r_c, and the transition rate from A_j to beginning state v_0 is r_s.

B. Average income per unit time for the data owner

We use $P\,(X = x)$ to denote the stationary probability distribution of state x $(x \in \mathbb{X})$ in the Markov chain. Then we get the vector of stationary probability distribution $\pi = \{\pi_0, \pi_1, \cdots \pi_j, \pi_{A_1}, \pi_{A_2}, \cdots, \pi_{A_j}\}$, where

$$\pi_0 = P(X = v_0), \tag{2a}$$
$$\pi_j = P(X = v_j), \ j = 1, 2, \cdots, h, \tag{2b}$$
$$\pi_{A_j} = P(X = A_j), \ j = 1, 2, \cdots, h. \tag{2c}$$

Assume the value of the value sold data V is a constant, and then the max round of h is a constant therefore. Then we obtain the local stationary equations as follows:

$$\lambda\pi_0 = r_s \sum\nolimits_{j=1}^{h} \pi_{A_j}, \tag{3a}$$
$$(\lambda + r_c)\,\pi_j = \lambda\pi_{j-1}, \ j = 1, 2, \cdots, h-1, \tag{3b}$$
$$r_c\pi_h = \lambda\pi_{h-1}, \tag{3c}$$
$$r_c\pi_j = r_s\pi_{A_j}, \tag{3d}$$

With constraints

$$\pi_0 + \sum\nolimits_{j=1}^{h} \left[\pi_j + \pi_{A_j}\right] = 1, \tag{4}$$

we can get the stationary transition probabilities of each state of the successive data auction.

To get the average expected income of the data owner, we only need to consider the *bid acceptation states* A_j $(1 \le j \le h)$. So we define the conditional probability of state A_j given the situation that the bids are accepted by the data owner:

$$P_a(j) = \frac{\pi_{A_j}}{\sum_{k=1}^{h} \pi_{A_k}}, \quad j = 1, 2, \cdots, h. \tag{5}$$

According to (3) and (4), we get

$$P_a(j) = \frac{r_c}{\lambda}\rho^j, \ j = 1, 2, \cdots, h-1, \tag{6a}$$
$$P_a(h) = \rho^{h-1}, \tag{6b}$$

where $\rho = \frac{\lambda}{\lambda + r_c}$. Then the average income of the data owner from a single round data auctions is

$$E_I = \sum_{j=1}^{h} (v_0 + j\delta)\, P_a(j) = v_0 + \delta \cdot \frac{1-\rho^h}{1-\rho}. \tag{7}$$

The total average time T that every round of data auction lasts is the total average time between successive entries into beginning state v_0 [8]. In addition, the average time spend in state v_0 in every round of data auction is λ^{-1}, then $T = \lambda^{-1}/\pi_0$. According to (3) and (4), we get

$$\pi_0 = \frac{r_s r_c}{r_s r_c + \lambda(r_s + r_c)}. \tag{8}$$

The total average time every round of data auction lasts is

$$T = \lambda^{-1} + r_c^{-1} + r_s^{-1}. \tag{9}$$

Then the average income per unit time for the data owner is

$$E_I^0 = \frac{E_I}{T} = \left(\lambda^{-1} + r_c^{-1} + r_s^{-1}\right)^{-1} \cdot \left(v_0 + \delta \cdot \frac{1-\rho^h}{1-\rho}\right). \tag{10}$$

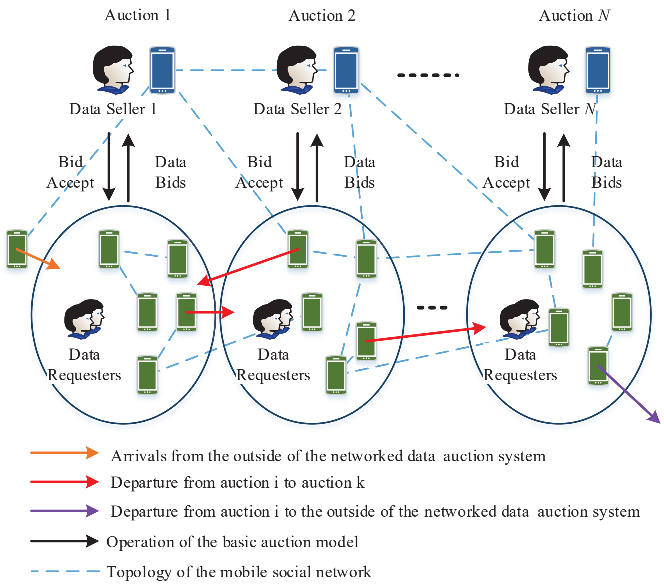


Fig. 1. Networked data auction system and the mobility model.

III. Networked Action Model for Data Transaction with Multiple Auctioneers

In this section, we expND the basic auction model from [3] into the networked system developed in [8] with multiple data sellers planning to sell their extra mobile data. A social relationship based mobility model is then designed to describe the potential data buyers' mobility among different auctions operated by data auctioneers. Then we analyze the stationary probabilities of the networked auction system for the performance estimation. The networked data auction system model and the mobility model are shown in Fig. 1.

In [8] there are N data suctions operated by N data sellers in the system at the same time, which are numbered by $i = 1, 2, \cdots, N$. Let $\mathbf{n}(t) = \{n_1(t), n_2(t), \cdots, n_N(t)\}$ denote the numbers of potential data buyers in auction i at time t, and $\mathbf{X}(t) = \{x_1(t), x_2(t), \cdots, x_N(t)\}$ denote the price has been reached in auction i at time t. Similar to the basic auction, $x_i(t) \in \{v_0, v_1, \cdots, v_{h_i}\}$, and v_{h_i} is the highest price that data requesters intend to pay in auction i. In each of N auctions, the auction rule and strategy are similar to the basic auction. We consider that the bid arrival rate in each auction is dependent on the price $x_i(t)$ and number of bidders $n_i(t)$ of this auction. In addition, for current achieved prices v_j $(j = 1, 2, \cdots, h)$, there are at least one potential data buyer has given a bid and he/she will not give the next bid. Contrarily, if current price is v_0, which means the beginning of a new round of auction, then each of $n_i(t)$ potential buyers can give the next bid. Consequently, we define the bid arrival rate in auction i as

$$\lambda_i(n_i, v_j) = (n_i - 1)\,\lambda_i f_{i,j}, \ \lambda_i(n_i, 0) = n_i\lambda_i, \tag{11}$$

where $f_{i,j} = P(v_j < v_{h_i})$, and $\lambda_i > 0$ is the rate of that each data bidder in auction i gives a bid. Moreover, similar to the basic auction model, we set $r_{c,i}^{-1}$ to be the average considering time of auctioneer i, which is an independent and identically random variable having an exponential distribution.

A. Mobility model

As defined previously, the state of the networked data auction system can be described as the pair of vector $(\mathbf{n}(t), \mathbf{X}(t))$. Considering that data requesters can arrive and leave the whole system, as well as moving from one auction to another in the system, how to design a mobility model to describe the moving of these potential data buyers is an important issue to keep balance of the participants' number in each auction, optimize the efficiency of the system and maximize the expected income of each data sellers. In this this part, we will design a mobile model based on the Mobile Bidder Model established in [8], and then introduce the relationship or friendship of the auction participants, including data sellers and bidders, which can reflect the mobile users' rationality and ensure that information security on some level.

Consider that in auction i at time t, the number of potential data buyers is n_i and the current achieved bid is v_i ($v_0 \le v_i \le v_{h_i}$), then

1) Arrivals from the outside of the system: Data requesters arrive into auction i from the outside of the networked auction system according to a Poisson process with rate λ_i^0.

2) Departure from the ith auction: We define the rate of departure from auction i as follows, which are similar to the definition of the rate of bid arrivals formulated as Euq. (11).

$$\mu_i(n_i, v_j) = (n_i - 1)\mu_i, \tag{12a}$$

$$\mu_i(n_i, 0) = n_i \mu_i, \tag{12b}$$

where $\mu_i > 0$ is the departure rate of each data bidder in auction i. (12a) indicates that the bidder providing the current highest price for the data cannot leave auction i until that the next bid arrives or the data seller decides to accept his/her bid. (12b) represents the situation that a new round of the auction is operated by auctioneer i, then all the data bidders are allowed to departure from this auction.

- *Departure from auction i to the outside of the system:*

Let P_{iD} denote the probability that the data bidders in auction i leave the whole networked auction system.

- *Departure from auction i to auction k:*

In the networked data auction system, mobile users with data request are allowed to shift from one auction to another. A rational transition can help improve the efficiency, expected income of the data sellers and even the information security of the social mobile network. To realize these objects, we define a social strength based transition weight in this part. First, we provide some indexes reflecting the influence between the two users in a social network as follows.

Value strength: Value strength I_{ki}^v is defined as the social influence of user k on user i:

$$I_{ki}^v = \frac{f(C_i \backslash C_k)}{f(C_i)}, \tag{13}$$

where C_i and C_k represent the sets of node i's and k's neighbors, respectively, and $C_i \backslash C_k$ represents the difference set of C_i against C_k. Similarly, we can define $I_{ik}^v = f(C_k \backslash C_i)/f(C_k)$. In (13), $f(\cdot)$ is a function of set, which is defined as the modular arithmetic for simplicity in this work, i.e., $f(C) = |C|$.

Define the transition weight from auction i to auction k as a linear combination of the reciprocal of value strength $1/I_{ki}^v$ and $1/B_k$, the reciprocal of betweenness centrality of node k:

$$w_{ik} = \omega_i \left[\alpha (I_{ki}^v)^{-1} + (1-\alpha) B_k^{-1} \right], \tag{14}$$

where $\alpha > 0$, and $\omega_i > 0$ is a normalization parameter to present the channel quality or other status of the mobile device held by data seller i. We represent the transition probability from auction i to auction k with P_{ik}, which is defined as

$$P_{ik} = \frac{w_{ik}(1 - P_{iD})}{\sum_{m=1}^{N} w_{im}}, \quad i, k = 1, 2, \cdots, N. \tag{15}$$

Remarks: Notice that $\sum_{k=1}^{N} P_{ik} + P_{iD} = 1$. In addition, w_{ik} in (14) reflects both the influence of auctioneer k on auctioneer i and the importance of auctioneer k in the social mobile network. On the one hand, the more common friends sharing with auctions i and k, the more likely potential data buyers in auction i will shift to auction k. On the other hand, the betweenness centrality is an index to evaluate the importance of a node in the network. w_{ik} changes inversely with the betweenness centrality of auctioneer k, which can help to keep the balance of the data bidders' number in every auction.

B. Stationary distribution and expected income of the system

Denote the stationary probability distributions as

$$\pi_{j|n_i}^i = P(x_i = v_j | n_i), \quad j = 0, 1, \cdots, h_i, \tag{16a}$$

$$\pi_{A_j|n_i}^i = P(x_i = A_j | n_i), \quad j = 1, \cdots, h_i. \tag{16b}$$

The stationary distribution of the system can be derived by the Chapman-Kolmogorov equations [8]. Due to the limited space, we do not provide analysis in detail in this paper. Furthermore, assume that data bidders are very active, which means that when there is at least one potential data buyer in an auction, the probability that no bid arrives is rather small. In addition, consider that when a bid is accepted at auction i, auctioneer i starts a new round of auction immediately. Then the approximate stationary solution of data auctioneer i and the mobility model introduced in Section III-A are

$$\pi(n_i) = \frac{\psi_i^{n_i} e^{-\psi_i}}{\psi_i (n_i - 1)!}, \quad i = 1, 2, \cdots, N, \tag{17a}$$

$$\pi(\mathbf{n}) \approx \prod_{i=1}^{N} \frac{\psi_i^{n_i} e^{-\psi_i}}{\psi_i (n_i - 1)!}, \tag{17b}$$

respectively, where $\psi_i = \varphi_i / \mu_i$, and $\{\varphi_i | i = 1, 2, \cdots, N\}$ are the solutions of the following linear equations:

$$\varphi_i = \lambda_i^0 + \sum_{k=1}^{N} \varphi_k P_{ki}, \quad i = 1, 2, \cdots, N. \tag{18}$$

Then we obtain the average number of data requesters in auction i in the steady state as

$$E(n_i) \approx \frac{e^{-\psi_i}}{\psi_i} \sum_{n=1}^{\infty} \frac{n \psi_i^n}{(n-1)!} = 1 + \psi_i. \tag{19}$$

In addition, when the bid arrivals and the data transactions are very frequent, which means that for all $i = 1, 2, \cdots, N$,

$\varphi_i, \mu_i << r_{c,i}$, then $\forall n_i > 0,\ k_i > 0\ (i = 1, 2, \cdots, N)$, the stationary solution $\pi(\mathbf{X}\,|\mathbf{n})$ is given by

$$\pi(\mathbf{X}\,|\mathbf{n}) \approx \prod_{i=1}^{N} \pi_i(x_i\,|n_i), \tag{20}$$

where

$$\pi^i_{j|n_i} = \pi^i_{0|n_i} \prod_{l=1}^{j} \frac{\lambda_i(n_i - 1) f_{i,l-1}}{r_{c,i} + \lambda_i(n_i - 1) f_{i,l}}, \tag{21a}$$

$$\pi^i_{0|n_i} = \left[1 + \sum_{j=1}^{h_i} \prod_{l=1}^{j} \frac{\lambda_i(n_i - 1) f_{i,l-1}}{r_{c,i} + \lambda_i(n_i - 1) f_{i,l}}\right]^{-1}. \tag{21b}$$

The detailed analysis for (17) - (21) are provided in [8].

Next, we analyze the expected income for each data auctioneer in the system. With assumptions above, the local stationary equations of the networked auction system are obtained as:

$$\lambda_i(n_i,0)\,\pi^i_{0|n_i} = \lambda_i(n_i,0)\sum_{j=1}^{h_i}\pi^i_{A_j|n_i} = (r_{c,i}+\lambda_i(n_i,v_1))\,\pi^i_{1|n_i}, \tag{22a}$$

$$\lambda_i(n_i,v_{j-1})\pi^i_{j-1|n_i} = (r_{c,i}+\lambda_i(n_i,v_j))\pi^i_{j|n_i},\ j=1,2,\cdots,h_i-1, \tag{22b}$$

$$\lambda_i(n_i,v_{h-1})\,\pi^i_{h-1|n_i} = r_{c,i}\pi^i_{h|n_i}, \tag{22c}$$

$$r_{c,i}\pi^i_{j|n_i} = \lambda_i(n_i,0)\,\pi^i_{A_j|n_i},\quad j=1,2,\cdots,h_i. \tag{22d}$$

According to (22d) and (21b), we get

$$\pi^i_{A_j|n_i} = \frac{r_{c,i}\pi^i_{j|n_i}}{\lambda_i(n_i,0)} = \frac{r_{c,i}}{\lambda_i n_i}\pi^i_{0|n_i}\prod_{l=1}^{j}\frac{\lambda_i(n_i-1)f_{i,l-1}}{r_{c,i}+\lambda_i(n_i-1)f_{i,l}}, \tag{23}$$

and then

$$P^i_a(j\,|n_i) = \frac{\pi^i_{A_j|n_i}}{\sum_{k=1}^{h_i}\pi^i_{A_k|n_i}} = \frac{r_{c,i}}{\lambda_i n_i}\prod_{l=1}^{j}\frac{\lambda_i(n_i-1)\,f_{i,l-1}}{r_{c,i}+\lambda_i(n_i-1)\,f_{i,l}}. \tag{24}$$

Expected income E_{i,n_i} and the total average time T_{i,n_i} that every round of data auction lasts for auction i when there are n_i potential data buyers in this auction are

$$E_{i,n_i} = \sum_{j=1}^{h_i} jP^i_a(j\,|n_i), \tag{25}$$

$$T_{i,n_i} = \frac{1}{n_i\lambda_i}\left(1+\sum_{j=1}^{h_i}\prod_{l=1}^{j}\frac{\lambda_i(n_i-1)\,f_{i,l-1}}{r_{c,i}+\lambda_i(n_i-1)\,f_{i,l}}\right), \tag{26}$$

respectively. Consequently, we obtain the average of the income per unit time for the data owner i as:

$$E^0_{i,n_i} = \frac{E_{i,n_i}}{T_{i,n_i}} = \frac{r_{c,i}\sum_{j=1}^{h_i} j\prod_{l=1}^{j}\frac{\lambda_i(n_i-1)f_{i,l-1}}{r_{c,i}+\lambda_i(n_i-1)f_{i,l}}}{1+\sum_{j=1}^{h_i}\prod_{l=1}^{j}\frac{\lambda_i(n_i-1)f_{i,l-1}}{r_{c,i}+\lambda_i(n_i-1)f_{i,l}}}. \tag{27}$$

Then according to (17a), the average of the income per unit time for the data owner i is given by

$$\begin{aligned} E^0_i &= \sum_{n_i=1}^{\infty} E^0_{i,n_i}\pi(n_i) \\ &= \sum_{n_i=1}^{\infty}\frac{\psi_i^{n_i}e^{-\psi_i}}{\psi_i(n_i-1)!}\frac{r_{c,i}\sum_{j=1}^{h_i} j\prod_{l=1}^{j}\frac{\lambda_i(n_i-1)f_{i,l-1}}{r_{c,i}+\lambda_i(n_i-1)f_{i,l}}}{1+\sum_{j=1}^{h_i}\prod_{l=1}^{j}\frac{\lambda_i(n_i-1)f_{i,l-1}}{r_{c,i}+\lambda_i(n_i-1)f_{i,l}}}. \end{aligned} \tag{28}$$

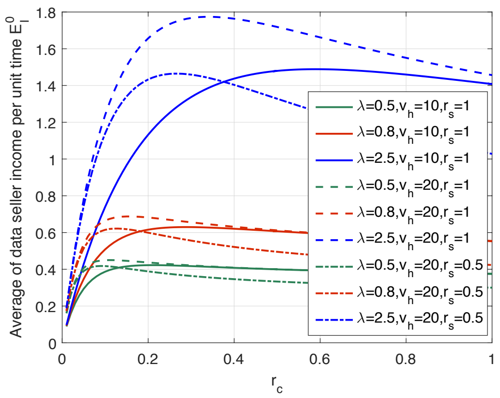


Fig. 2. Average income per unit time for data seller versus considering time, rate of bid arrivals, highest data price and service time in basic auction.

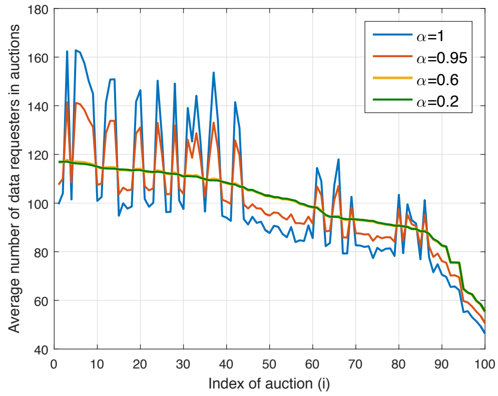


Fig. 3. Average number of data requesters versus α in different auctions.

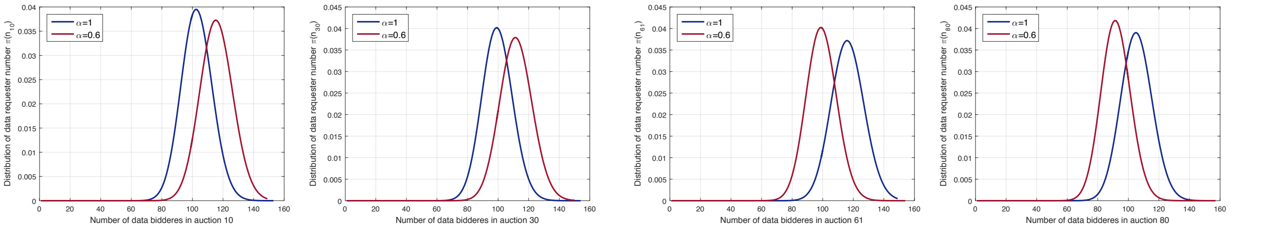
IV. Simulation Results

A. Basic data auction system

First, we analyze the effect of considering time r_c, rate of bid arrivals λ, highest data price v_h and service time r_s on E^0_I, the average income per unit time for the data owner in the basic auction. Simulation results are shown in Fig. 2. Results indicate that average income of data seller increases with increasing λ and decreasing r_s^{-1}, the latter means higher service rate. For the same other parameters setting, increasing v_h brings higher income for the data seller. However, with r_c increasing, E^0_I for different v_h tend to the same value due to the seller's quick acceptance of the data bids. Results in Fig. 2 also indicate that E^0_I is convex function of r_c. Increasing r_c brings larger E^0_I when its value is small, which results from that the longer considering time is, the more data bids will arrive. On the other hand, as r_c keeping growing, the low deal rate will pull down the income of unit time for the data seller.

B. Networked data auction system

The simulation for the networked data auction is operated based on the topology of Flickr, a real-world online social network database. The Flickr graph dataset contains 5899882 edges connecting 80513 users, and the edge represents the connection between two users. For data transaction application, we select randomly $N = 100$ users as the data sellers in the networked auction in the simulation, and these auctioneers



(a) Action 10 (b) Auction 30 (c) Action 61 (d) Auction 80

Fig. 4. Distributions of data requester number versus α in selected auctions.

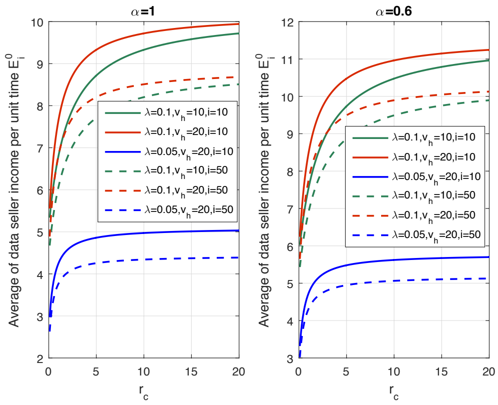


Fig. 5. Average of the income per unit time for selected data sellers versus considering time, rate of bid arrivals, highest data price in networked auction.

are numbered by 1 to 100 according to their increasing betweenness centrality. The rest users in Flickr are considered as potential data buyers, who can arrive into and departure from the entire auction system, and are allowed to move toward 100 auctions according to the mobility model established in Section III-A. Set $P_{iD} = 0.01$, $\lambda_i = \mu_i = 0.01$, $\omega_i = 1$ and define $f_{i,l} = 1 - \frac{l}{h_i}$ $(i = 1, 2, \cdots, 100)$. In general, we set $v_0 = 0$ and $\delta = 1$, then $x_i(t) \in \{0, 1, 2, \cdots, h_i\}$.

First, we analyze the performance of the designed mobility model. In the stationary state, the average number of data requesters in the $N = 100$ auctions are shown in Fig. 3 for different $\alpha \in \{1, 0.95, 0.6, 0.2\}$, the weighted factor representing the importance of value strength I^v in the transition probability defined in (14) and (15). In addition, we selected 4 auctions $(i = 10, 30, 61, 80)$, and the distribution of the number of data requesters in each of these auctions are shown in Fig. 4. Results in Fig. 3 and Fig. 4 demonstrate that the number of data bidders in different auctions can be balanced through introducing betweenness centrality, which improves the efficiency of the entire system and avoid the situation that a large amount of data requesters gather in the same auction.

The data seller's average income per unit time E_i^0 when auctioneers $i = 10$ and $i = 50$ in the networked data auction system are shown in Fig. 5. The effect of different factors is similar to the basic auction model. The results also indicates that considering betweenness centrality in the mobility can increase the expected income per unit time of data sellers.

V. Conclusion

In this paper, we propose a novel data transaction mechanism for MSNs. Using previous mathematical analysis on basic and networked auctions [3], [8], we propose a socially-aware mobility model that improves the efficiency of the networked auctions. Simulation results illustrate the performance of the proposed data transaction system and mobility model.

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