Auction-based Data Transaction in Mobile Networks: Data Allocation Design and Performance Analysis

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Abstract—Currently, the volume of mobile data traffic is experiencing an unprecedented increase due to the proliferation of highly capable smartphones, laptops and tablets. To meet this explosive demands of mobile traffic, the mobile data offloading technology was proposed to move traffic load of cellular networks to other wireless networks provided by infrastructures such as small-cell base stations. In this work, an infrastructure-free offloading method, based on the hotspot function of smartphones, is proposed to realize the data transaction among mobile users. In this transaction, mobile users with redundant data perform as accessible Wi-Fi hotspots, and sell their mobile data to users with data requirements. Considering the scenarios with single and multiple data sellers, the basic auction and networked auction frameworks are introduced to model the process of data transaction, respectively. Additionally, high efficiency data allocation mechanisms are designed in this work, which decides how to allocate the amount of data to be sold over days in a month and how to schedule the data transaction in different time slots in a single day, based on the auction models established. In order to optimize the performance of data transaction systems, the behaviors of mobile users, such as changing demands of data selling and buying, are considered when designing the data allocation mechanisms. Simulation results indicate that introducing the prediction information of user behaviors can effectively improve the performance of data allocation, and achieve a high-efficiency data transaction.

Index Terms—Data transaction, allocation mechanism design, auction, mobile networks, CPSO.

1 Introduction

In recent decades, the mobile data traffic is experiencing an enormous growth due to the significant penetration of smartphones, as well as Web 2.0 and a large number of applications with high bandwidth requirements. Researchers have predicted that each person will consume on average as much as 5 GB of data each month by 2020 [1], [2]. To meet this increasing and high speed data requirements, many new communication techniques and standards are provided, such as LTE Release 8, which can achieve a high peak data rates of 300 Mbps on the downlink and 75 Mbps on the uplink for a 20 MHz bandwidth [3]. Additionally, ultra-dense heterogeneous networks, which consists of a large number of small-cell base stations (SBSs) to provide data offloading, was proposed as an another solution to relief the heavy traffic load brought to the macro base stations [4], [5]. Through data offloading, the data traffic from mobile users can be sent over SBSs, such as femto base stations and Wi-Fi hotspots, when these SBSs are available, otherwise traffic is delivered over the cellular networks.

However, almost all data offloading studied recently can only be implemented with assistance of external infrastructures, i.e., SBSs. Sometimes these SBSs are operated by the mobile network operators (MNOs), while usually the SBSs are owned by some third parties, which means that MNOs need to rent these SBSs if they want to utilize them for data offloading. Meanwhile, due to the introduction of these external and heterogeneous infrastructures, resource management problems, such as power control and mobile user equipment scheduling, become more complicated and challenging, especially for networks with densely deployed SBSs and a large number of mobile users. Moreover, system stability, protocol compatibility and switching, traffic fairness, network congestion control, etc., will pose great challenge for data offloading. In order to avoid these problems above, we propose a novel infrastructure-free approach to implement data offloading, i.e., operating the data transaction among the mobile users by turning on the Wi-Fi hotspot function of smartphones, in this work.

1.1 Motivation

Currently, to face the increasing data demands of mobile users, all MNOs, such as AT&T in the US, Giffgaff in the UK and China Mobil, have offered many optional monthly data plans with different amount of data. While the arbitrary of the data plan regulations made by different MNOs are the same, i.e., if the data in the current data plan is not running

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out by the end of a month, the remaining data will not be cumulative to the next month data plan. On the other hand, when the monthly data has been used out before the end of a month, mobile users have to purchase some extra data with a higher price than monthly plans, otherwise they will suffer a lower speed of data service. Therefore, the opposite results leading by these regulations come down to the following situations. On the one hand, users buying data plans with large amount of data might still hold a lot of unconsumed data at the end of a months. On the other hand, users with little amount of data might use out their data before the end of a month. As a consequence, this contradiction between the redundancy and demands of data resource make it possible for the two types of mobile users to make an internal data transaction between them, which is operated without any third party infrastructures. According to a certain rule or contract of data transaction, "data owners" can sell their unused data to those "data requesters" at a lower price compared with the market price.

1.1.1 Feasibility of data transaction

The direct data dealing is never not allowed among the mobile users, no matter whether they are belonging to the same MNO. However, the *hotpot* function of current smartphones makes this data transaction between data owners and requesters mentioned above to become a reality. By unlocking hotspot mode, hotspot phones will allow other mobile phones or wireless devices to access them and a phone-to-phone communication via WiFi interface can be realized [6], [7].

1.1.2 Effective and efficient data transaction

Working as a Wi-Fi hotspot means more energy consumption and possible threat of personal information. So it is reasonable for data owners to sell their data with a price as high as possible. On the other hand, for data requesters, buying data through this data transaction can obtain high-speed data service by a relatively lower price. So these requesters have the motivation to fuel the transaction and compete for the data resource when there are many data requesters. This competitive relationship can be modeled by auction mechanisms effectively. So in this work, we will introduce the auction models to describe the operation of data transaction.

1.1.3 Changing demands of selling and buying data

The demands of selling and buying data always change over time for data owners and requesters, respectively. To be specific, the closer to the end of a month, the more urgent the data owners are to sell their data. Similarly, number of data requesters will increase when the end of a month is coming, and the willing to buy data through data transaction tends to be much stronger. Then tendency of data selling and buying will further influence the price of data. So how to allocate the amount of data to be sold in every day over a month, especially the days in the last part of a month, and how to schedule data auction in a single day are very important to maximize utilities of data owners satisfy data demands of requesters at the same time. In this work, we will design different data allocation mechanisms to realize high-efficiency data transaction, based on auction models.

1.2 Contribution

Main contributions of this paper are summarized as follows.

- We establish a basis auction framework for the data transaction system with only one data seller. Based on this model, the data allocation mechanisms are designed to decide how to sell the extra data in different days to optimize the expected income for the data owner. In this work, we consider that the urgency of data selling and buying are changing over time, when maximizing the income of the data owner. In addition, the transaction efficiency is also considered to achieve a further optimization of the income. Simulation results validate that the designed allocation mechanism can increase the total income of the system, and meanwhile the data transaction efficiency can be also guaranteed.
- We propose a networked data transaction system, in which there are multiple data owners operating their own basic data auction, based on a networked auction model. To describe the movement of data bidders among different auctions, a data-demands-driven mobility model is proposed, which can make sure that both the data supply and the demand can be satisfied at the same time. In addition, the designed mobility model can also improve the efficiency of data transaction.
- Based on the networked data transaction system established, we design three different data allocation mechanisms to decide how to sell data in a single day for every data auctioneer in the system, to maximize the income obtained in each time slot, each auctioneer's income or the entire income of the system. To optimize the system performance, the prediction of the data bidders' movement is considered when designing the allocation mechanisms. Simulation results demonstrate that the prediction based data allocation can bring more income for data auctioneers than non-prediction approach.

The reminder of this paper is organized as follows. We first review the relevant literature in Section 2. In Section 3, the data allocation mechanisms are designed for the basic auction model based data transaction. Data allocation mechanisms based on the networked auction model are proposed in Section 4. The approximate solving of optimization problems based on cooperative particle swarm for data allocation is introduced in Section 5. Simulations are shown in Section 6, and conclusions are drawn in Section 7.

2 Related Work

Mobile data offloading by applying SBSs in heterogeneous networks, as a feasible solution to deal with the increasing of mobile data requirement and services, has attracted more and more attention. With assistance of heterogeneous SBSs, the throughput of cellular networks can be greatly improved. To model and analyze the relationship between data requirements and providing, many economics based theory have been introduced to the mobile data offloading problems . In [8], a user-centered opportunistic offloading approach was proposed based on a network formation game, in which the users autonomously formed a cooperative network, and promised device-to-device sharing with their adjacent users. A coalitional game framework was proposed in [9] to improve the performance of mobile data offloading in wireless mesh networks, by savings the base stations' power consumption and reimbursements for mesh users. A competitive game was established for mobile computing offloading problem in [10], in which each user pursued to minimize its own energy consumption, and the game formulated was subject to the real-time constraints imposed by the job execution deadlines, user specific channel bit rates, and the competition over the shared communication channel. In [11], Nash bargaining game combining with the group bargaining theory was analyzed for the mobile traffic offloading in HetNets, in which the social welfare maximization and the fairness of resource sharing were both considered.

Auction has become an important and effective theory in network economics. In recent yearsy, auction mechanisms have been introduced to deal with dynamic spectrum optimization, spectrum sharing, device-to-device communications and many other issues in wireless networks [12], [13], [14]. To deal with the increasing of mobile data traffic, a novel spectrum sharing framework for the cooperation and competition between LTE and Wi-Fi in the unlicensed band were designed based on the an effective auction model in [15], in which the LTE provider performed as the auctioneer (buyer), and the APOs were the bidders who compete to sell the rights of onloading the APOs' traffic to the LTE provider. In [16], a multi-objective auction-based switching-off scheme was designed for heterogeneous networks to foster the opportunistic utilization of the unexploited small-cells capacity, and an energy and cost efficiency was achieved by the designed bidding strategy and pricing rule. In order to increase the network capacity dynamically and adaptively, a reverse auction model was established to formulate the mobile data offloading problem in [17], in which three alternative greedy algorithms were introduced to solve the offloading problem. In [18], a hierarchical combinatorial auction was designed for the virtualization issues in 5G cellular networks, based on a truthful and sub-efficient resource allocation framework.

However, as mentioned above, all these current studies focus on the mobile data offloading depending on applying third party infrastructures. The internal transaction among mobile users to realize data offloading has been hardly investigated. In this user-initiative data offloading, it is necessary to study the influence of human behaviors on data transaction performance. So in this work, the statistics feature of data requests, rest amount of mobile data owned by data sellers are consider to optimize the efficiency and balancing of data allocation. In addition, for the data transaction system with multiple data sellers, the prediction information of data requester' movement among different data auctions is introduced into the data allocation design to optimize the system performance.

3 Data Allocation of Single Data Provider

In this section, a classic basic data action, first established in [19], [20], will be introduced to model a series of successive transaction among a single data owner and multiple potential data buyers as bidders. In each of the successive transaction, the data owner operate an auction to sell a fixed size of his/her unconsumed and unnecessary data from his/her data plan. In a later section, this basic auction will be extended into a networked auction for the data transaction system with multiple data owners. Before proceeding further, we summarize the main notations used throughout the following sections in Table 1.

TABLE 1
List of Main Notations in the Basic Auction (B) and Networked Auction (N) Formulation for Data Transaction.

Parameter	Definition
λ	bid arrival rate for data owner (B)
λ_i	bid arrival rate for the ith data owner (N)
δ	increment of data bids
h	highest price that data requesters intend to pay
r_c / $r_{c,i}$	rate parameter of exponential distributed considering time for the data owner (B) / the ith data owner (N)
r_s / $r_{s,i}$	rate parameter of exponential distributed service time for the data owner (B) / the ith data owner (N)
v_0	beginning state of data auction / starting price of data auction
v_j	state of that j data bids have arrived / price of the jth bid made by data requesters
v_h	state that that highest bid has been made / highest bid made by data requesters
A_j	state of the jth bid is accepted
n_i	number of data requesters in auction i (N)
x_i	price has been reached in auction i (N)
$f_{i,j}$	probability of each bidder in auction i gives a bid (N)
C	total amount of data left (B)
D	total days left to sell data (B)
c_d / c_{id}	amount of data to be sold on day d (B) for data seller i (N)
M	total time slots for a day (N)
N	number of data sellers (N)
z_{im}	data to be sold in time slot m for seller i (N)

3.1 Basic auction mechanism

The process of the auction-based data transaction with a single data seller is shown in Fig. 1. In this work, we assume that the automatical operation of data auction can be realized through a special application installed in both of the data owners' and bidders' smartphones. This assumption is feasible since there are already many mature mobile applications which make the auction-based transaction become true, especially on some e-commerce platforms. Then we will introduce the elements and operations in the automatic data auction as follows.

(1) Data auctioneer: The mobile user with unconsumed and needless mobile data. To meet data requirements requested by more mobile users, we assume that, instead of selling all data as a whole, data is cut into "data blocks" with a certain size, and in each round of auction, only one block of data can be sold. Then the data owner will perform as a auctioneer to operate a series of successive data auction.

(2) Data requesters: The mobile users who have run out their mobile data and have the data requirements. In each

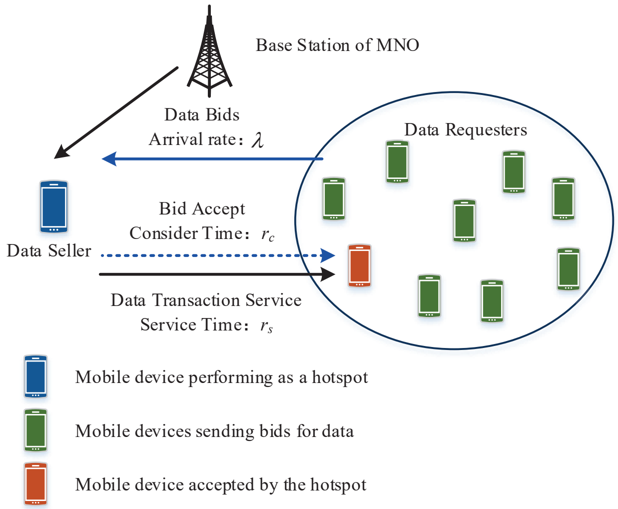


Fig. 1. Basic data auction with single auctioneer.

round of data auction, all data requesters are potential data buyers and give bids for the data.

(3) Beginning of a basic auction: The data owner starts an auction by unlocking the hotspot mode of his/her phone, sets the starting price v_0 of one block of data planned to sell, and then waits for bids.

(4) Bid arrivals: The personal mobile business for a single user arrives according to a Poisson process with a certain rate, and therefore the average time between successive arrivals is the reciprocal of the arrival rate [21], [22], [23]. During the data auction, every time when the business arrivals to the phone of a data requester, a data bid will be triggered. We assume that the data bid providing is a public information which can be observed by both the data owner and other data requesters. The business arrivals for different mobile users are independent and identically distributed (i.i.d.), so that the bid arrivals for the data owner can be still regarded as a statistic process obeying Poisson distribution 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. In addition, potential buyers will stop increasing the price of bid as long as the highest price h, at which data requesters intend to pay, is reached. The value of h can be set as a constant lower than the market price of data.

(5) Auctioneer decisions: After each bid arrives, the data owner waits for a random "considering time" to determine whether to accept the current bid or not. Assume that the consider time has an exponential distribution with average r_c^{-1} and the memoryless property. If the next bid arrives before the end of the considering time, then this considering process is repeated for this new bid. On the contrary, if the considering time expires and still no new bid arrives, the data owner will accept the latest data requester's offer, allow him/her to access into the hotspot and complete the data transaction with this successful data bidder. Due to the memoryless property of the considering time, potential data buyers cannot use the ongoing observations of considering time to give bids. Furthermore, the remaining considering time at any time point after an arrived bid has the same distribution as the initial considering time.

(6) Data transaction procedure: The data transaction will last a "service time" before starting a new round of data auction by the data owner. The service time is modeled as an exponentially distributes time with rate r_s, and is i.i.d. and memoryless in different rounds of auctions.

Remarks: According the "auctioneer decisions" step, we notice that if the data owner decides to wait a long time for the next bid , he/she might have a chance to get a higher-price offer, but the cost is a long time consumption. Conversely, short "considering time" will lead to a frequently repeated auctions, in each of which the data owner tends to get a low-price offer due to his/her weak patience. So for the data seller, how to select appropriative "considering time" to optimize the income, specifically, the income per unit time that the auctions bring to the data owner? Furthermore, the willing of selling and buying data of the data owner and requesters is always changing over days, as explained in Section 1.1.3. So how to allocate the amount of rest redundant data to be sold in different days before the end of a month, plays an important role when maximizing the income of the data owner and satisfying demands of data requesters. Next, we will pay attention to the problems above and design the data allocation mechanisms to optimize the performance of the basic auction-base data transaction system.

3.2 Data allocation for single-auctioneer transaction

The mathematic model and system performance of the basic auction model have been well established and analyzed in [24], in which many important economical characteristics of basic auction model are derived and provided with closed-form expressions. First, we introduce this auction model into the data transaction system, and summarize some of important results obtained in [24] as Lemma 1.

Lemma 1. *In a data auction system with only one data auctioneer, the starting price of the data is v_0. The data bids arrive as a sequence of Poisson arrivals with arrival rate λ, and every bid increases the value of offer by δ. The data requesters stop providing bids when the offer price reaches h. The data seller accepts the bid after a considering time, which follows an exponential distribution with average r_c^{-1}, and starts a new round of data auction after the service time, which also follows an exponential distribution with average r_s^{-1}. Then the average income of the data owner from a single round data auction is*

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

where $\rho = \frac{\lambda}{\lambda + r_c}$. The total average time that every round of data auction lasts is

$$T = \lambda^{-1} + r_c^{-1} + r_s^{-1}. \tag{2}$$

The average income per unit time for the data owner is

$$E_I^0 = \frac{E_I}{T} = \left(\lambda^{-1} + r_c^{-1} + r_s^{-1}\right)^{-1} \cdot \left(v_0 + \delta \cdot \frac{1-\rho^h}{1-\rho}\right). \tag{3}$$

To be general, let $v_0 = 0$ and $\delta = 1$, the average income per unit time can be gotten as

$$E_I^G = \frac{E_I}{T} = \left(\lambda^{-1} + r_c^{-1} + r_s^{-1}\right)^{-1} \cdot \frac{1-\rho^h}{1-\rho}. \tag{4}$$

Proof: See [24].

Consider that the total amount of data left is C, and the data seller plans to sell all of his/her data in the last D days of the month. Let c_d $(d = 1, 2, ..., D)$ denote the amount of data planned to be sold on the dth day. As assumed previously, in each round of data auction, only one-unit amount of data can be sold. Then on the dth day, c_d rounds of data auction are needed for the data auctioneer to sell the amount of c_d data. We use $\lambda(d)$ to denote the arrival rate of data bid on the dth day, and $r_c^{-1}(d)$ to denote the average considering time of the data seller on the dth day. As mentioned previously, the urgency of selling and buying data from the data provider and requesters, respectively, change over time. Therefore, we assume that $\lambda(d)$ and $r_c(d)$ satisfy the following settings:

$$\lambda(d_1) \leq \lambda(d_2), \ \forall d_1 < d_2; \tag{5a}$$

$$r_c(d_1) \leq r_c(d_2), \ \forall d_1 < d_2, \tag{5b}$$

which imply than the closer to the end of a month, the more frequently the data requesters make bids, as well as the data seller accepts the offers.

According to Lemma 1, the average income of the data auctioneer from a single round of data auction on the dth day is

$$E_I(d) = \frac{1 - \rho^h(d)}{1 - \rho(d)}, \ d = 1, 2, \cdots, D, \tag{6}$$

where $\rho(d) = \lambda(d)/[\lambda(d) + r_c(d)]$. Then if all allocated data is sold, the total expected income can be achieved is

$$E(d) = c_d \cdot \frac{1 - \rho^h(d)}{1 - \rho(d)}, \ d = 1, 2, \cdots, D. \tag{7}$$

To maximize the total income of D days, we establish the following income maximization problem for the data allocation.

$$\max \ \sum_{d=1}^{D} c_d \cdot \frac{1 - \rho^h(d, c_d)}{1 - \rho(d, c_d)}, \tag{8a}$$

$$\text{s.}t. \ \sum_{d=1}^{D} c_d \leq C, \tag{8b}$$

$$c_d \leq C - \gamma(D - d), \ \forall d = 1, 2, \cdots, D. \tag{8c}$$

In (8a),

$$\rho(d, c_d) = \frac{\lambda(d)}{\lambda(d) + r_c(d, c_d)}. \tag{9}$$

Constraint (8c) indicates that the total amount of data allocated to be sold in D days from $d = 1$ to $d = D$ should not exceed the amount of total data C left on the first day ($d = 1$). In constraint (8b), $\gamma > 0$ is set as a constant to denote the amount of data consumed by the data owner every day. We can also consider γ as the amount of data to be reserved for the seller's own data demands. To guarantee that the data owner will have plenty data to consume in the following D days after allocating his/her data, the amount of $\gamma(D - d)$ data needs to be reserved on the dth day. Therefore, constraint (8b) provides the upper limit of the amount of data allocated on the dth day.

3.2.1 Efficiency Aware Data Allocation

According to (8), we can notice that if $E_I(d)$, the average income of the data auctioneer from a single round auction, is high, the data allocation mechanism formulated by this income maximization problem will allocate more data to that day to maximize the total expected income the data auctioneer. With a fixed considering time, selling more data means that the data auction will last longer according to (2), which reduces the efficiency of the data transaction. When the data auctioneer anticipates a higher efficiency as well as a optimized income, it is necessary to design a data allocation method which can achieve a tradeoff between the total income and time cost. To realize this tradeoff, we design an efficiency-aware data allocation (EADA), in which the considering time, r_c in (9), is modified by the following rule:

$$r_c^{EADA}(d, c_d) = r(d)\left[1 + \varphi_1(d, c_d)\right], \tag{10}$$

where

$$\varphi_1(d, c_d) = 1 - e^{-\left[\frac{c_d}{C - \gamma(D-d)}\right]^2}. \tag{11}$$

According to the definition in (11), r_c^{ECDA} in (10) is an increasing function of the allocated amount of data to sell on the dth day, c_d. In other words, when the amount of allocated data is large, the EADA mechanism will adjust the seller's considering time to improve the data transaction efficiency and increase the average income per unit time of the data seller. On the contrary, when the allocated data is little on a day, the considering time tends to be longer to increase the expected income of a single round of auction. The upper limit of the allocated data, $C - \gamma(D - d)$, performs as a control factor to modify the increasing speed of the bid acceptation rate with increasing c_d. In addition, $r(d)$ in (11) is the original rate of bid acceptation, which has the property given by (5b).

3.2.2 Efficiency and Request Aware Data Allocation

Through (6) and (9), we can obtain the first order partial derivative of E_I, the average income of a round of data auction, with respect to variable λ: $\partial E_I/\partial\lambda > 0$. This result holds for both mechanisms of original data allocation and EADA. Therefore, low rate of data bid will reduce the income of the data auctioneer. By the both of the data allocation methods above, little or even no data will be allocated to days with small λ, especially when the data bid arrival rate is smaller than the rate of bid acceptation. In other words, the requests from data bidders on these days are hardly met if the bid arrival rate is small, which may also result from that there are not too many data requesters. To meet the data requests in days with small λ, we design an efficiency and request aware data allocation (ERADA) mechanism, in which the considering time is adjusted to fit the data bid arrival rate according to

$$r_c^{ERADA}(d, c_d) = r(d)\left[1 + \varphi_1(d, c_d)\right]\varphi_2(\lambda(d), r(d)), \tag{12}$$

where $r(d)$ is defined similar to EADA, $\varphi_1(d, c_d)$ is defined as (11), and $\varphi_2(\lambda(d), r(d))$ is obtained by

$$\varphi_2(\lambda(d), r(d)) = e^{\min\left\{\frac{\lambda(d) - r(d)}{r(d)}, 0\right\}}. \tag{13}$$

According to (13), when $\lambda(d) < r(d)$, then we can get

$$\varphi_2(\lambda(d), r(d)) = \exp\left\{\frac{\lambda(d) - r(d)}{r(d)}\right\} < 1. \tag{14}$$

Consequently, the considering time to accept the data bid can be expended. Then the expected incomes of the data seller increase potentially, and more data will be allocated to the corresponding days. On the other hand, when $\lambda(d) \geq r(d)$, some data can be allocated to the corresponding days through applying EADA. Therefore, r_c remains the same as EADA, i.e., $\varphi_2(\lambda(d), r(d)) = 1$.

4 Networked Action Model for Data Transaction with Multiple Auctioneers

In the precious section, we establish and analyze the data allocation problem for a single data auctioneer. According the proposed mechanisms of EADA and ERADA, the expected incomes of the data seller can be optimized with a high efficiency, and the data requests from data buyers can be satisfied as much as possible. By applying EADA and ERADA, the data seller can make decisions that how to allocate his/her rest data to remaining days before the end of a month. The next problem is that after the amount of data to be sold in a single day has been decided, then how to operate data auctions to achieve a further optimization of the daily income?

As analyzed previously, the proposed income maximization problems in (8) is based on the fact that the needs of data selling and buying vary over time within a month. However, in a certain day d, specifically, during the period of data transaction on this day, the rate of arrival data bids remains relatively stable, i.e., with $\lambda(d)$. In addition, by the designed EADA and ERADA, the average considering time can be optimized according to (10) and (12), respectively, when c_d has been determined. In a data transaction system with only one data auctioneer, this auctioneer can operate the basis data auction introduced in Section 3.1, and the expected maximum income can be achieved when applying EADA and ERADA. However, when there are multiple data auctioneers, who share the same community of potential data requesters, then some system status, such as the number of data requesters in a single auction, the data bid arrival rates, etc., may change if the mobility of data requesters among different auctions is allowed. Therefore, it is necessary to analyze the data auction and allocation mechanisms for a networked data transaction system, in which more than one data owners are planning to sell their fixed amounts of data. Fortunately, with assistance of current mobile social networks, some system status in auctions operated by different data owners can be shared among users, i.e., referring to both the data sellers and requesters, through the social platforms. This status information can be very helpful for the further performance improvement. Consequently, how to model the networked data transaction system and how to make advantage of the system status information to design an efficient data auction and allocation mechanism become essential problems to be studied.

In this section, we extend the basis data transaction model into the networked system to discuss the data transaction processes operated by multiple data auctioneers. The networked data transaction system model and the mobility model are shown in Fig. 2. A system-status-aware mobility model is designed for data requesters. Then we analyze the stationary probabilities of the networked auction system for the performance estimation. Furthermore, to maximize the income of every data auctioneer, three data allocation mechanisms are proposed in this part.

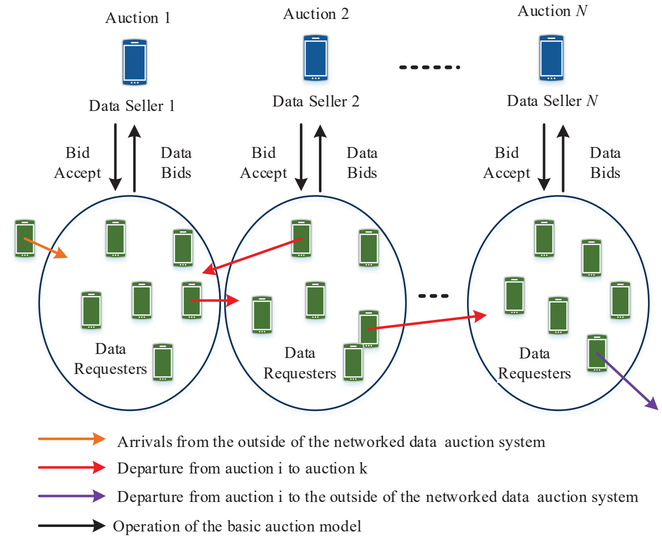


Fig. 2. Networked data auction system and the mobility model.

4.1 Networked auction model

The classic networked auction model has been formulated in [24]. In this part, we first introduce the established mathematical model in [24] as follows.

Consider that there are N data suctions operated by N data sellers in the system at the same time. These sellers 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. Then the state of the networked data auction system can be described as the pair of vector $(\mathbf{n}(t), \mathbf{X}(t))$. In each of these 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 $n_i(t)$ in 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 the $n_i(t)$ potential buyers are allowed to give the next bid. As a consequence, we can define the bid arrival rate in auction i as

$$\lambda_i(n_i, v_j) = (n_i - 1)\lambda_i f_{i,j}, \tag{15a}$$

$$\lambda_i(n_i, 0) = n_i \lambda_i, \tag{15b}$$

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 i.i.d. random variable having an exponential distribution.

4.2 Mobility model

In this this part, we will design a mobility model for the data requesters based on the mobile bidder model (MBM) established in [24].

In a networked data transaction system operated by N data auctioneers, we consider that the data requesters can enter and leave the whole system, as well as moving from one auction to another in the system. Then how to design a mobility model to describe the moving of these potential data buyers, is an important issue to keep balance of the number of participants in each auction, optimize the efficiency of the system and maximize the expected income of each data sellers. In order to achieve these objectives above, we introduce some prediction-based factors that may affect the user behaiours, and then propose a system-status-aware mobility model for the networked data transaction, which can reflect the mobile users' rationality and further improve the performance of the networked data transaction.

Next, we will formulate the mobility of data requesters. 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 ($v_0 \leq v_i \leq v_{h_i}$). Then the dynamic parameters of the mobile model are defined as follows.

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

(2) Departure from the ith auction: Consider 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. Moreover, consider the situation that when a new round of the auction is operated by auctioneer i, all the data bidders are allowed to departure from this auction. The the rate of departure from auction i can be given as follows

$$\mu_i(n_i, v_j) = (n_i - 1)\mu_i, \tag{16a}$$

$$\mu_i(n_i, 0) = n_i \mu_i, \tag{16b}$$

where $\mu_i > 0$ is the departure rate of each data bidder in auction i. The definitions above are similar to the rate of bid arrivals formulated in (15).

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

Denote P_{iD} as the probability that the data bidders in auction i leave the entire networked transaction system.

- *Departure from auction i to auction k:*

In the auction-based networked data transaction system, mobile users with data requests are allowed to shift from one auction to another. We assume that the amount of rest data to be sold in the day can be updated and observed by other auction participants in the networked system. This assumption is reasonable and feasible because this kind of information can be provided by data owners, and broadcasted to data requested through the relevant mobile applications. Then the data requesters transfer among different auctions according to the amount of remaining data to be sold in these auctions. We represent the transition probability from auction k to auction i with P_{ki}, which is given by

$$P_{ki} = (1 - P_{kD}) \cdot \frac{c_{i,rest}}{\sum_{j=1}^{N} c_{i,rest}}, \quad i, k = 1, 2, \cdots, N. \tag{17}$$

According to (17), data requesters more likely tend to participate the data auction operated by the data owners with more remaining data, which can give them more chances and higher probability to get the data quickly and successfully. In addition, the definition of transition probability in (17) essentially guarantees

$$\sum_{k=1}^{N} P_{ik} + P_{iD} = 1. \tag{18}$$

4.3 Expected income of the networked system

To optimize the data auction performance and maximize the incomes of data auctioneers through effective data allocation mechanism, it is important to analyze the stationary distribution and the expected income of the networked data transaction system. The stationary probabilities of the number of data requesters in each auction have been analyzed in [24], the main results of which are summarized as Lemma 2.

Lemma 2. *In a networked data auction system, data bidders arrive and departure from auction i with rate λ_i and μ_i, respectively. According to the mobility model of data requesters established in Section 4.2, the approximate stationary probabilities of data auctioneer i ($i = 1, 2, \cdots, N$) and the stationary probability of the networked data transaction system are given by*

$$\pi(n_i) = \frac{\psi_i^{n_i} e^{-\psi_i}}{\psi_i (n_i - 1)!}, \tag{19a}$$

$$\pi(\mathbf{n}) \approx \prod_{i=1}^{N} \frac{\psi_i^{n_i} e^{-\psi_i}}{\psi_i (n_i - 1)!}, \tag{19b}$$

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

$$\varphi_i = \lambda_i^0 + \sum_{k=1}^{N} \varphi_k P_{ki}. \tag{20}$$

When the bid arrivals and the data transactions are very frequent, which means that for all $i = 1, 2, \cdots, N$, $\mu_i << r_{c,i}$, then $\forall n_i > 0$, $k_i > 0$, the stationary solution $\pi(\mathbf{X} | \mathbf{n})$ is given by

$$\pi(\mathbf{X} | \mathbf{n}) \approx \prod_{i=1}^{N} \pi_i(x_i | n_i), \tag{21}$$

where

$$\pi_{j|n_i}^i = \pi_{0|n_i}^i \prod_{l=1}^{j} \frac{\lambda_i (n_i - 1) f_{i,l-1}}{r_{c,i} + \lambda_i (n_i - 1) f_{i,l}}, \tag{22a}$$

$$\pi_{0|n_i}^i = \left[1 + \sum_{j=1}^{h_i} \prod_{l=1}^{j} \frac{\lambda_i (n_i - 1) f_{i,l-1}}{r_{c,i} + \lambda_i (n_i - 1) f_{i,l}} \right]^{-1}. \tag{22b}$$

Proof: See [24].

Based on these results in Lemma 2, we further derive the average of the income per unit time for every data owner in the system, and we the results in Theorem 1.

Theorem 1. *In a networked data auction system with N data auctioneers, data bidders arrive and departure from auction i with rate λ_i and μ_i, respectively. Consider the situation that the bid arrivals and the data transactions are very frequent. According to the mobility model of data requesters established in Section 4.2, expected income E_{i,n_i} for auction i when there are n_i data requesters in this auction is given by*

$$E_{i,n_i} = \sum_{j=1}^{h_i} j P_a^i \left(j \left| n_i \right.\right), \tag{23}$$

where

$$P_a^i \left(j \left| n_i \right.\right) = \frac{r_{c,i}}{\lambda_i n_i} \prod_{l=1}^{j} \frac{\lambda_i \left(n_i - 1\right) f_{i,l-1}}{r_{c,i} + \lambda_i \left(n_i - 1\right) f_{i,l}}. \tag{24}$$

The average of the income per unit time for the data owner i is given by

$$E_i^0 = \sum_{n_i=1}^{\infty} \frac{\psi_i^{n_i} e^{-\psi_i}}{\psi_i \left(n_i - 1\right)!} \frac{r_{c,i} \sum_{j=1}^{h_i} j \prod_{l=1}^{j} \frac{\lambda_i (n_i-1) f_{i,l-1}}{r_{c,i}+\lambda_i (n_i-1) f_{i,l}}}{1 + \sum_{j=1}^{h_i} \prod_{l=1}^{j} \frac{\lambda_i (n_i-1) f_{i,l-1}}{r_{c,i}+\lambda_i (n_i-1) f_{i,l}}}. \tag{25}$$

Proof: See Appendix.

4.4 Data allocation for networked data transaction

Based on the obtained analytical results given in the last section, we will design some efficient data allocation mechanisms for the networked data transaction system in the following part.

Consider a networked data transaction system with N data sellers, each of them needs to sell all allocated data in a certain duration $[0, T]$. Data requesters are allowed to enter, departure from any of N data auctions according to the mobility model introduced in Section 4.2.

For a certain day $d = 1, 2, \cdots, D$, vector $\mathbf{c} = \{c_{1d}, c_{2d}, \cdots, c_{id}, \cdots, c_{Nd}\}$, determined by the EADA or ERADA proposed previously, denotes the amounts of data allocated to be sold for each of the N data sellers. In following work, we apply the ERADA mechanism and the rate of considering time of data auctioneer $i = 1, 2, \cdots, N$ modified by (12) - (14). Then for data seller i, we have

$$r_{c,i}\left(d, c_{id}\right) = r_i\left(d\right)\left[1 + \varphi_1\left(d, c_{id}\right)\right] \varphi_2\left(\lambda\left(d\right), r_i\left(d\right)\right), \tag{26}$$

$\forall i = 1, 2, \cdots, N$. When the requests of data is far more than the data can be provided, then $\varphi_2\left(\lambda\left(d\right), r\left(d\right)\right) = 1$, and the rate of considering time for each data auctioneer i is

$$r_{ci}\left(d, c_{id}\right) = r_i\left(d\right)\left[1 + \varphi_1\left(d, c_{id}\right)\right]. \tag{27}$$

Consider that the duration $[0, T]$ is slotted into M time slots, each of them is indexed by $m = 1, 2, \cdots, M$. We assume that in every time slot, the number of data bidders in every auction is stable. Then let $\mathbf{n}\left(m\right) = \{n_1\left(m\right), n_2\left(m\right), \cdots, n_N\left(m\right)\}$ denote the number of data bidders in auction i at time slot m, $\forall i,\ m$. For each time slot m, we express the allocated amount of data to be sold for every data seller i in the system by $\mathbf{z_m} = \{z_{1m}, z_{2m}, \cdots, z_{Nm}\}$.

4.4.1 Non-cooperative Distributed Data Allocation (NDDA)

According to Theorem 1, when there are $n_i\left(m\right)$ data requesters in auction i at time slot m, and the amount of data to sold is z_{im}, then the expected income of data auctioneer i can be given by

$$\begin{aligned} z_{im} E_{i,n_i}\left(m\right) &= z_{im} \sum_{j=1}^{h_i} j P_a^i \left(j \left| n_i\left(m\right) \right.\right) \\ &= z_{im} \sum_{j=1}^{h_i} j \frac{r_{c,i}}{\lambda_i n_i\left(m\right)} \prod_{l=1}^{j} \frac{\lambda_i \left(n_i\left(m\right) - 1\right) f_{i,l-1}}{r_{c,i} + \lambda_i \left(n_i\left(m\right) - 1\right) f_{i,l}}. \end{aligned} \tag{28}$$

Then at every time slot $m = 1, 2, \cdots, M$, each data requester solves the following optimization problem to maximize his/her expected income of current time slot:

$$\max\ f_{z_{im}|\mathbf{z_m}} = z_{im} E_{i,n_i}\left(m\right), \tag{29a}$$

$$\text{s.t.}\ \ z_{im} \geq \min\left\{c_{id} - \sum_{t=1}^{m-1} z_{it}, z_{\min}\right\}, \forall i = 1, 2, \cdots, N, \tag{29b}$$

$$z_{im} \leq \min\left\{c_{id} - \sum_{t=1}^{m-1} z_{it}, z_{\max}\right\}, \forall i = 1, 2, \cdots, N, \tag{29c}$$

$$\sum_{i=1}^{N} z_{im} \leq z_{ch}. \tag{29d}$$

In (29b) and (29c), are obtained by

$$z_{\min} = \frac{1}{M} \cdot \max\left\{c_{1d}, c_{2d}, \cdots, c_{id}, \cdots, c_{Nd}\right\}, \tag{30a}$$

$$z_{\max} = \kappa z_{\min},\ \ \kappa > 1, \tag{30b}$$

respectively.

Remarks: In constraint (29b), lower bound $z_{\min}$ shown in (30a) ensures that the data owner with the most amount of data to sold on the current day can sold out all of his/her data before time slot $m = M$ ends. $\left(c_{id} - \sum_{t=1}^{m-1} z_{it}\right)$ in (29b) is provided for the case that the remaining data of a auctioneer at time slot m is less than $z_{\min}$, then all his/her remaining data needs to be sold during time slot m. The low bound of allocated amount of data in each time slot can keep the data allocation mechanism efficient. On the other hand, due to the duration of every time slot is limited, the amount of data can be transacted in one time slot is constrained by an upper bound, which is denoted by $z_{\max}$ in constraints (29c) and (30b). In addition, $\left(c_{id} - \sum_{t=1}^{m-1} z_{it}\right)$ in (29c) plays a constraining role when the rest data is less than $z_{\max}$. Constraint (29d) is determined by the channel capacity.

4.4.2 Prediction-based Cooperative Distributed Data Allocation (PCDDA)

As mentioned above, the amount of rest data of different data auctioneers to be sold is accessible information for all data requesters having arrived and planning to enter into the system. According to the mobility model introduced in Section 4.2, data requesters in auction i will move to auction k with probability P_{ik}, which is determined by the amount of remaining data to be sold in auction k, i.e., $c_{k,rest}$. In other words, the number of data requester in every auction during the following time slots can be predicted in sense of probability, according to the public information of rest amount of data. Then by applying the results in Lemma 2 and Theorem 1, the expected income of current time slot can be predicted by (23) for a fixed number of data requesters. In addition, the potential average income of the next time slot can also be predicted through (25) by predicting mobility trend of data requesters. Considering this prediction information, data owners can make better decisions on how much data to sell in the current time slot for maximizing the total income of M time slots.

Consider the previous assumption that the number of data requesters in each auction does not change. Then we assume that the bidders transition probability from auction k to i after time slot m, $P_{ki}\left(m^{+}\right)$, is determined by the rest amount of data after finishing the allocation of m time slots:

$$P_{ki}\left(m^{+}\right) = \left(1 - P_{kD}\right) \cdot \frac{c_{id} - \sum_{t=1}^{m} z_{it}}{\sum_{j=1}^{N} \left(c_{jd} - \sum_{t=1}^{m} z_{jt}\right)}. \tag{31}$$

If P_{kD}=P_D, $\forall k = 1, 2, \cdots, N$, then

$$\begin{aligned} P_i\left(m^{+}\right) &\triangleq P_{ki}\left(m^{+}\right) \\ &= \left(1 - P_D\right) \cdot \frac{c_{id} - \sum_{t=1}^{m} z_{it}}{\sum_{j=1}^{N} \left(c_{jd} - \sum_{t=1}^{m} z_{jt}\right)}. \end{aligned} \tag{32}$$

According to (20), we can get

$$\boldsymbol{\varphi}\left(m\right) = \boldsymbol{\lambda}^0 + \mathbf{P}\left(m^{+}\right) \boldsymbol{\varphi}\left(m\right), \tag{33}$$

where

$$\boldsymbol{\varphi}\left(m\right) = \left[\varphi_1\left(m\right) \;\; \varphi_2\left(m\right) \;\; \cdots \;\; \varphi_N\left(m\right)\right]^{\mathrm{T}}, \tag{34a}$$

$$\boldsymbol{\lambda}^0 = \left[\lambda_1 \;\; \lambda_2 \;\; \cdots \;\; \lambda_N\right]^{\mathrm{T}}, \tag{34b}$$

and

$$\begin{aligned} \mathbf{P}\left(m^{+}\right) &= \begin{bmatrix} P_{11}\left(m^{+}\right) & P_{21}\left(m^{+}\right) & \cdots & P_{N1}\left(m^{+}\right) \\ P_{12}\left(m^{+}\right) & P_{22}\left(m^{+}\right) & \cdots & P_{N2}\left(m^{+}\right) \\ \vdots & \vdots & \ddots & \vdots \\ P_{1N}\left(m^{+}\right) & P_{2N}\left(m^{+}\right) & \cdots & P_{NN}\left(m^{+}\right) \end{bmatrix} \\ &\triangleq \begin{bmatrix} P_1\left(m^{+}\right) \\ P_2\left(m^{+}\right) \\ \vdots \\ P_N\left(m^{+}\right) \end{bmatrix} \cdot \underbrace{\begin{bmatrix} 1 & 1 & \cdots & 1 \end{bmatrix}}_{N}. \end{aligned} \tag{35}$$

Then solve the equation (33) and we can get the solutions as

$$\varphi_i\left(m\right) = \lambda_i + \frac{\sum_{j=1}^{N} \lambda_j}{P_D} P_i\left(m^{+}\right), \quad i = 1, 2, \cdots, N. \tag{36}$$

Therefore, applying results in Lemma 2 and Theorem 1, the future expected income of the rest amount of data for data owner i at time slot m can be calculated by

$$E_i\left(m^{+}\right) \triangleq \left(c_{id} - \sum_{t=1}^{m} z_{it}\right) \cdot \sum_{n_i=1}^{\infty} E_{i,n_i}\left(m\right) \pi\left(n_i\right), \tag{37}$$

where $E_{i,n_i}\left(m\right)$ and $\pi\left(n_i\right)$ are obtained by (23) and (19a), respectively, and ψ_i in (19a) is determined by φ_i in (36).

Consider that every data auctioneers is selfish and intends to maximize his/her own total expected income of the M time slots. Then we establish the following income maximization problem for each data auctioneer i $(i = 1, 2, \cdots, N)$ at time slot m $(m = 1, 2, \cdots, M)$.

$$\max \;\; f_{z_{im}} = z_{im} E_{i,n_i}(m) + \omega^{M-m} E_i\left(m^{+}\right) \tag{38a}$$

$$\text{s.t.} \;\; z_{im} \geq \min\left\{c_{id} - \sum_{t=1}^{m-1} z_{it}, z_{\min}\right\}, \forall i = 1, 2, \cdots, N, \tag{38b}$$

$$z_{im} \leq \min\left\{c_{id} - \sum_{t=1}^{m-1} z_{it}, z_{\max}\right\}, \forall i = 1, 2, \cdots, N, \tag{38c}$$

$$\sum_{i=1}^{N} z_{im} \leq z_{ch}. \tag{38d}$$

In (38a), $\omega \in (0, 1]$ denotes the discount rate of the future income considered at the current time slot.

At the beginning of every time slot, each data owner publishes the rest amount of his/her data, observes the number of data requesters in his/her auction, and then solve the optimization problem in (38) to determine how much data to be sold in the current time slot.

4.4.3 Prediction-based Centralized Data Allocation (PCDA)

According to PCDDA designed in the previous section, if every data auctioneer solves the optimization problem locally to maximize his/her own expected income instead of a central process, the optimal solution for each data auctioneer cannot ensure that constraint (38d) is always satisfied. In other words, the distributed mechanism may cause data auctioneers to fail to get the maximum income they anticipate. Concerning this issue, we design a prediction-based centralized data allocation (PCDA) mechanism to maximize the income of all data auctioneers. To achieve this centralized optimization, we assume that there is a data fusion center which operates the PCDA and determine how much data to be sold for every data seller in each time slot. Wish assistance of current mobile network platform, this assumption is rational and enforceable. The objective function of PCDA is shown as (39), and the constraints are the same as those of NDDA and PCDDA, i.e., (29b) - (29d) and (38b) - (38d), respectively.

$$\max \;\; \sum_{i=1}^{N} \left[z_{im} E_{i,n_i}(m) + \omega^{M-m} E_i\left(m^{+}\right)\right]. \tag{39}$$

5 Operation of Data Allocation for Data Transaction Systems

5.1 Approximate solving of optimization problems

In the previous two sections, we establish the income maximization problems for the data allocation. For a large time scale, the data owner can decide how much data to be sold in the following days before the end of a month, by applying EADA and ERADA. Then for a smaller time scale, data owners can determine how to schedule the data auctions in a single day by considering the peer data auctioneers behaviours, through NDDA, PCDDA or PCDA. However, we can also notice that it is difficult to achieve the closed-form solutions for optimization problems formulated as (8), (29), (38) and (39). To find the optimal solution approximately, an efficient and effective stochastic and cooperation-based optimization technique, called cooperative particle swarm optimization (CPSO) algorithm [25], will be introduced to

Protocol 1 CPSO Algorithm [25].

Initialization:

Create and initialize n one-dimensional PSOs: P_j, $j = 1, 2, \cdots, n$;
Define:
$g(j, z) \equiv (P_1 \cdot \hat{\mathbf{y}}, P_2 \cdot \hat{\mathbf{y}}, \cdots, P_{j-1} \cdot \hat{\mathbf{y}}, z, P_{j+1} \cdot \hat{\mathbf{y}}, \cdots, P_n \cdot \hat{\mathbf{y}})$;
Iterations T.

for $t \leq T$ **do**
  for $j = 1, 2, \cdots, n$ **do**
    for $i = 1, 2, \cdots, s$ **do**
      if $f(g(j, P_j \cdot \mathbf{x}_i)) < f(g(j, P_j \cdot \mathbf{y}_i))$ **then**
        $P_j \cdot \mathbf{y}_i = P_j \cdot \mathbf{x}_i$
      end if
      if $f(g(j, P_j \cdot \mathbf{y}_i)) < f(g(j, P_j \cdot \hat{\mathbf{y}}))$ **then**
        $P_j \cdot \hat{\mathbf{y}} = P_j \cdot \mathbf{y}_i$
      end if
    end for
    Update P_j by PSO with (40) and (41).
  end for
end for

our work to solve the income maximization problems. CPSO was proposed based on the traditional particle swarm optimization (PSO), and the term of *swarm* indicates multiple particles. In PSO, each particle refers to a possible solution of the optimization problem. In every iteration, each particle finds its own best solution and then accelerates in the direction of this position, as well as in the direction of the global best position having been found at present. The update process is operated as follows:

$$\begin{aligned} v_{ij}(t+1) = & w v_{ij}(t) + c_1 \zeta_{1i}(t) \left[y_{ij}(t) - x_{ij}(t) \right] \\ & + c_2 \zeta_{2i}(t) \left[\hat{y}_j(t) - x_{ij}(t) \right], \end{aligned} \tag{40}$$

$$\mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1), \tag{41}$$

where $j = 1, 2, \cdots, s$, and s is the swarm size. $\mathbf{x}_i = [x_{i1} \;\; x_{i2} \;\; \cdots \;\; x_{in}]$ is the current position in the search space, $\mathbf{v}_i = [v_{i1} \;\; v_{i2} \;\; \cdots \;\; v_{in}]$ is the current velocity, $\mathbf{y}_i = [y_{i1} \;\; y_{i2} \;\; \cdots \;\; y_{in}]$ is the local best position, n is the number of particles, c_1 and c_2 are acceleration coefficients, and random sequences $\zeta_1, \; \zeta_{2i} \sim U(0, 1)$ [26].

In PSO, there is only one swarm with s particles, which tries to find the optimal n-dimensional vector. While in CPSO, this n-dimensional vector is decomposed into n swarms, each of which has s particles. These n swarms cooperatively optimize the one-dimensional vector. The main processes of CPSO are shown in Protocol 1.

5.2 Data allocation for data transaction

In this part, we will introduce how to operate data allocation in different days and different time slots in one day for the auction-based data transaction system.

As mentioned previously, the elements of the networked data transaction, including data auctioneers, the number of data auctioneers, data requester arrival rates, etc., change over time. Therefore, for a certain data owner, he/she cannot determine how to allocate his/her extra data into rest days through a networked auction mechanism, according to the current data transaction network. In this work, we design a data allocation mechanism based on the basic data auction and networked data auction, for a large time scale (referring to days) and a small time scale (referring to time slots), respectively. Specifically, for every data owner who has extra data and plans to sell the data during the rest days before the month ends, he/she makes decision on how to allocate the data into different days according to the ERADA mechanism based on the basic data auction model. To achieve a maximum expected total income of D days, the data owner optimizes the bid acceptation rate r_c and obtains c_d, the amount of data to be sold on a certain day d. Then the data owner recognizes and establishes a networked data transaction system with other data owners planning to sell data on this day. Then by applying the networked data allocation mechanism, i.e., DNNA, PCDDA or PCDA designed in Section 4.4, every data owner can decide how to allocate the amount of c_{id} data into different time slots on day d to maximum the expected income of his/her own (by DNNA or PCDDA) or the entire networked data transaction system (by PCDA). The operation of the proposed data allocation mechanism is shown in Protocol 2.

Protocol 2 Data allocation for data transaction.

Initialization:

Bid arrival rate: $\lambda(d)$;
Original bid acceptation rate: $r(d)$;
Number of days left before the end of the month: D.
Number of time slots in a single day to operate data transaction: M.

Each data seller i operates the following processes:
for $d = 1, 2, \cdots, D$ **do**
  if $\lambda(d) - r_c(d)$ **then**
    $\varphi_2(\lambda(d), r(d)) = \exp\left\{ \frac{\lambda(d) - r_c(d)}{r_c(d)} \right\}$;
  else
    $\varphi_2(\lambda(d), r(d)) = 1$.
  end if
  Apply ERADA, solve it by CPSO and obtain optimal c_{id} and $r_{c,i}$.
  for $m = 1, 2, \cdots, M$ **do**
    Recognize and establish the structure of the networked data transaction system;
    Submit the amount of his/her rest data $c_{id} - \sum_{t=1}^{m} z_{it}$;
    Predict the stationary probability of the number of data requesters $\mathbf{n}(m)$;
    Apply PCDDA/PCDA, solve it by CPSO and obtain optimal z_{im} ($\mathbf{z_m} = \{z_{1m}, z_{2m}, \cdots, z_{Nm}\}$).
  end for
end for

Output:

Amount of allocated data to sell on the day d: c_{id};
Amounts of allocated data to sell in time slot m: $\mathbf{z_m}$;
Optimized did acceptation rate: $r_{c,i}$.

6 Simulation Results

In this section, we will evaluate the performance improvement of the designed allocation mechanisms for the data transaction systems with single data auctioneer and multiple data auctioneers.

TABLE 2
Simulation parameters.

Case	β_1^λ	β_2^λ	$\beta_1^{r_c}$	$\beta_2^{r_c}$	σ_λ	σ_r
Case 1	0.35	9	0.35	9	6	5
Case 2	0.35	9	0.35	9	5	6
Case 3	0.35	10	1	9	5	5
Case 4	0.15	10	1.25	9	5	5

6.1 Data allocation for transaction systems with single auctioneer

First of all, we introduce the scenario setup for simulations. We consider a data transaction system with only one data seller, who plans to sell his/her rest data with amount of $C = 100$ in following $D = 10$ days. The amount of data to be reserved for the data owner's own consumption every day is set as $\gamma = 5$. The highest price data requesters can accept is set as $h = 10$, and the service time is $r_s = 1$. To reflect the changing demands of buying and selling data from the data requesters and data owner, denoted by (5a) and (5b), respectively, arrival rates of data bids and original considering time are given by

$$\lambda(d) = \beta_2^\lambda - \left(\beta_2^\lambda - \beta_1^\lambda\right) e^{-(d/\sigma_\lambda)^2}, \tag{42a}$$

$$r_c(d) = \beta_2^{r_c} - \left(\beta_2^{r_c} - \beta_2^{r_c}\right) e^{-(d/\sigma_r)^2}. \tag{42b}$$

where β_1^λ, β_2^λ, $\beta_1^{r_c}$, $\beta_2^{r_c}$, σ_λ and $\sigma_r > 0$ are constants, $d = 1, 2, \cdots, 10$. For comparison purposes, we consider four cases with different original bid acceptance rates and bid arrival rates, the parameter settings of which are shown in Table 2. These settings for the four cases can reflect different relationships between $\lambda(d)$ and original $r_c(d)$, which will further influence the data allocation policies.

First, we test the convergence of the proposed allocation algorithms and the expected maximum total income for the data owner by applying EADA and ERADA for data transaction system with single data seller. For CPSO algorithm, the number of particles is set as 6, and the number of iterations is set as 120. The simulation results of the first 25 iterations for the four cases are shown in Fig. 3. As shown in Fig. 3, the maximum expected total income for the data seller can be achieved by applying three data allocation mechanisms, after about 15 iterations by applying CPSO algorithm. In addition, for all of the four cases, the data seller can obtain the maximum income when utilizing ERADA (denoted by dotted lines), which is followed by the data allocation method based on the original considering time (denoted by solid lines), and EADA (denoted by dashed lines) performs the worst among the three mechanisms. The weak performance of EADA on data seller's income results from the its efficiency-aware property, which mean that there is a tradeoff between the total income and time cost. On the other hand, when we consider the influence of the data bids arrival rates, and then modify the considering time according to the bid arrivals in ERADA, the total income for the data seller can be also improved, meanwhile the efficiency can be still guaranteed. In addition, we notice that for Case 1, the bid arrival rates are always larger than the bid acceptation rates, then the incomes obtained by the data seller by applying EADA and ERADA are the same, which results from the definition in (13).

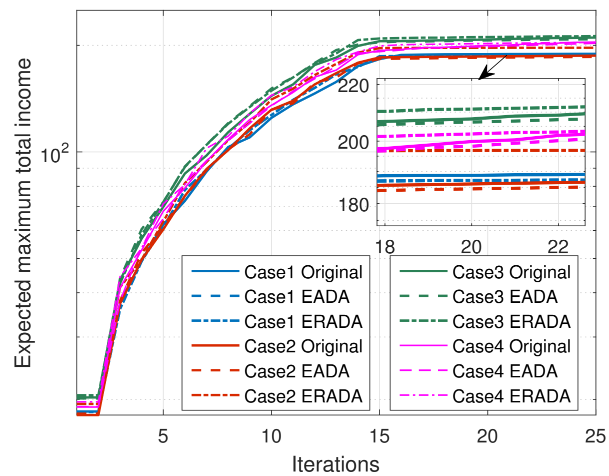
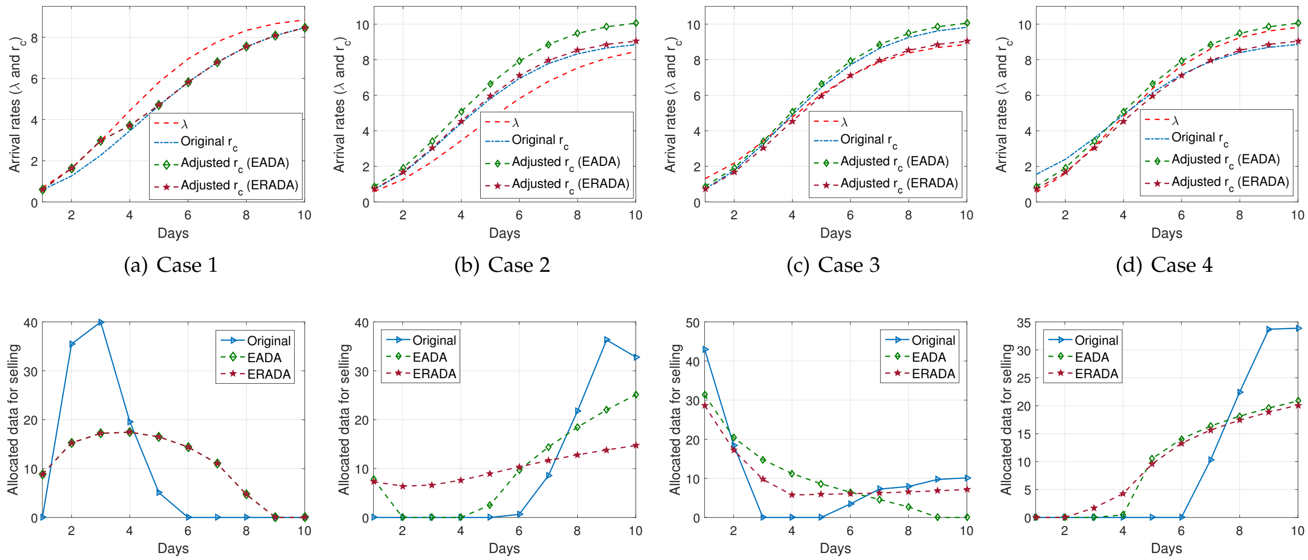


Fig. 3. Achieved maximum total income for the data auctioneer obtained by CPSO, for the four cases when applying three allocation methods.

For a further revelation to see how the proposed data allocation mechanisms optimize the performance of the data transaction system, we analyze the modified considering time and the amount of data allocated for each day. For the four cases illustrated by Table 2, we apply the three data allocation methods based on original r_c, EADA and ERCDA. Then for the $D = 10$ days, the modified r_c and the amount of data allocated in each day are shown in Fig. 4(a) - Fig. 4(d) and Fig. 4(e) - Fig. 4(h), respectively.

- For Case 1, the rates of bid acceptance are always lower than bid arrival rates in the ten days. Similar to results in Fig. 3, the two proposed data allocation mechanisms, i.e., EADA and ERADA, get the same adjusted r_c and amount of data allocated for every day. Results in Fig. 4(e) also indicate that without modification of r_c, the data tends to be allocated to the beginning days when $\lambda(d) > r_c(d)$, $\forall d$, which means that the data requests during the later days cannot be satisfied at all. Through the modification of considering time at the beginning days according to (10) and (12), the average time of considering time is shortened from $d = 1$ to $d = 5$, as shown in Fig. 4(a). Then the data are allocated to the ten day with more balance.
- Results of Case 2, the opposite situation to Case 1, are shown in Fig. 4(b) and Fig. 4(f), which indicate that EADA and ERADA will lead to different considering time modification and data allocation when $\lambda(d) < r_c(d)$. Moreover, results in Fig. 4(b) reflect the tradeoff effect of EADA for the income and time cost, i.e., larger r_c means higher frequency of bid acceptation and less time consumption. In addition, ERADA can achieve a further tradeoff between the original r_c and adjusted r_c^{EADA}, which can obtain the best data allocation balancing among the three allocation methods and the optimized income for the data seller at the same time.



(a) Case 1 (b) Case 2 (c) Case 3 (d) Case 4

(e) Case 1 (f) Case 2 (g) Case 3 (h) Case 4

Fig. 4. Adjusted considering time and data allocation for the data auctioneer in every day.

- As shown in Fig. 4(c), for Case 3, $\lambda > r_c$ in the beginning days, and then $\lambda < r_c$ during the rest days, which is opposite to Case 4, as shown in Fig. 4(d). The optimized balancing effect of ERADA can be also verified by results in Fig. 4(g) and Fig. 4(h).

Based on the obtained maximum total income shown in Fig. 3, and the adjusted considering time and the amount of data allocated shown in Fig. 4, we calculate the total data transaction operation time of the 10 days and the average income per unit time for the data seller by applying the three allocation algorithms. The results are shown in Table 3, which indicates that although EADA will bring less total income for the data seller, the average income per unit time is higher than that obtained without considering time modification. Meanwhile, the least time consumption can be achieved by EADA, comparing with another two allocation methods. In addition, ERADA receives the highest total income, which is also shown in Fig 3. This best performance of ERADA results from its adaption to the bid arrival rate, which also leads to larger time cost to operate the transaction than EADA. However, the efficiency can also be improved by ERADA than the original considering time, for most cases. For case 4, as an exception, ERADA does not perform better than the original considering time method, which results from the allocation-balance improvement of ERADA. Specifically, we can notice that for Case 4, without any considering time modification, all data is allocated to the last four days, which means that the data requests of earlier six days cannot be served at all, and in addition, the total time cost tends to be very small comparing to EADA and ERADA, which increases the average income.

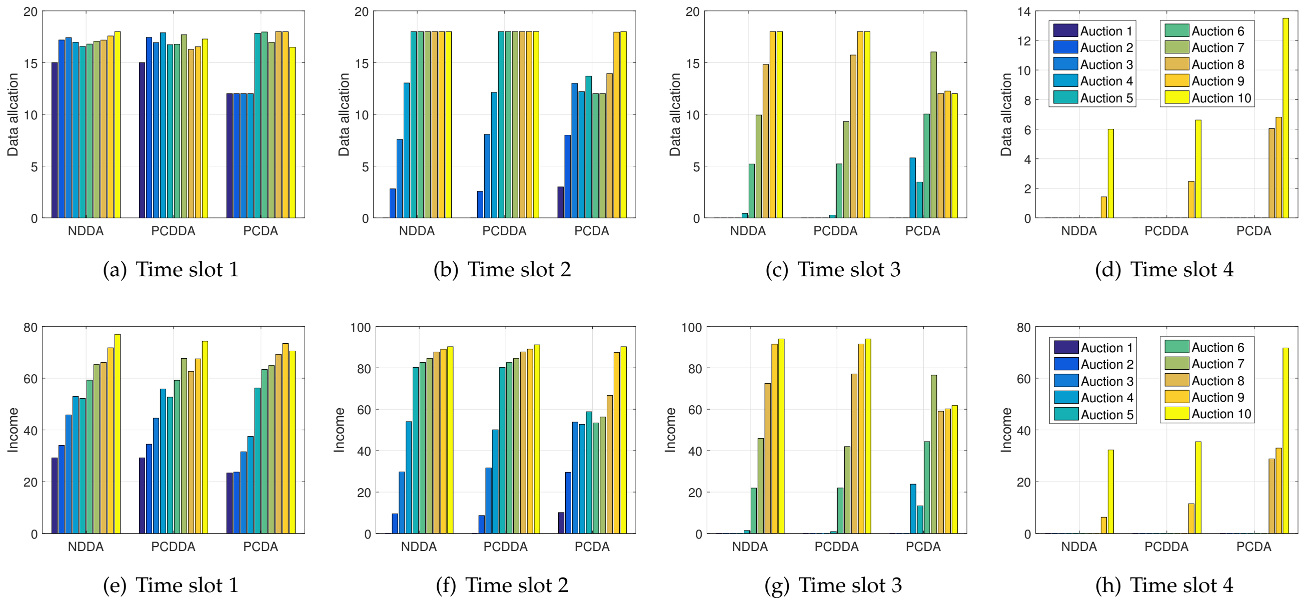
6.2 Data allocation for transaction systems with multi-auctioneer

In this section, we will test the performance of the networked data allocation for the data transaction system with multiple auctioneers. In the simulations, we consider that there are $N = 10$ data sellers with different amount of data to be sold in a single day, i.e., with values from set $\{15, 20, 25, 30, 35, 40, 45, 50, 55, 60\}$. and these sellers are numbered by an ascending sort order according to the amount of data they plan to sell in $M \leq 5$ time slots in a single day. In addition, bids arrival rates λ_i $(i = 1, 2, \cdots, 10)$ for different data auctioneers and the bid acceptation rates $r_{c,i}$ are obtained by the single-auctioneer data transaction system in the previous simulations, by applying ERADA. Moreover, the numbers of particle and iterations are set as 20 and 80, respectively when applying the CPSO algorithm.

By applying the three networked data allocation mechanisms, i.e., NDDA, PCDDA and PCDA designed in Section 4.4, the allocated amount of data and corresponding income for each of the 10 auctioneer in every time slot are shown in Fig. 5. The three mechanisms finish the data transaction in four time slots. Results in Fig. 5(a) - Fig. 5(d) indicate that NDDA and PCDDA can finish the data transaction faster than PCDA. To be specific, Auction 1 with the least amount of data sells out all of auctioneer's data in

TABLE 3
Simulation results of income and efficiency obtained by applying three allocation methods for data transaction system with single auctioneer.

	Algorithm	Case 1	Case 2	Case 3	Case 4
Total income	Original	189.2919	187.0193	210.4264	203.9975
	EADA	187.4022	185.5160	208.0609	202.7293
	ERADA	197.4599	196.8851	212.3980	204.2962
Total time	Original	8.5566	8.5566	6.6608	7.3510
	EADA	8.2486	7.9895	6.3544	7.0858
	ERADA	8.2486	8.4573	6.7222	7.5536
Average income	Original	22.1223	21.8567	31.5918	27.7509
	EADA	22.7192	23.2199	32.7428	28.6106
	ERADA	23.9386	23.2799	31.5965	27.0462



(a) Time slot 1 (b) Time slot 2 (c) Time slot 3 (d) Time slot 4

(e) Time slot 1 (f) Time slot 2 (g) Time slot 3 (h) Time slot 4

Fig. 5. Data allocation and income for each data auctioneer by applying NDDA, PCDDA and PCDA in networked data auction system.

the first time slot through NDDA and PCDDA, while two time slots are needed when applying PCDA. In addition, eight auctioneers finish the data transaction in three time slots by NDDA and PCDDA, while three auctioneers with the most data amount still have data to be sold in the fourth time slot by PCDA. Moreover, allocation results also indicate that with some prediction information obtained by the information sharing and cooperation of auctioneers, i.e., the number of data bidders in each auction and their probable movement among different auctions, PCDDA does not operate allocation radically, which means that data owners tend to preserve some amount of data and sell it in later time slot. This behavior can be reflected more obviously in Fig. 5(d), in which PCDDA has more data allocated to this time slot than NDDA does. With the prediction information and global income optimization for the entire system, this conservative performance is presented much more prominently when applying PCDA.

Then we analyze the economics performance of the three networked data allocation methods. We further process the obtained results in Fig. 5(e) - Fig. 5(h), and get the total income of the $N = 10$ data auctioneers and their total income in every time slot. Results are shown in Fig. 6. Results in Fig. 6(a) indicate that the higher total income can be obtained for every data seller by PCDDA than by NDDA, which benefits from the prediction information utilization and the income maximization for the entire auction period. Moreover, when applying PCDA, which pursues a global income maximization, the total income of some data auctioneers is sacrificed, meanwhile, the other auctioneers will get more total income.

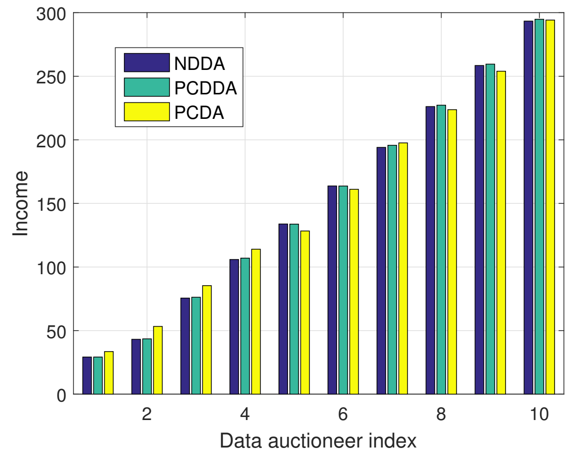
Without any prediction information, NDDA is operated to maximize the income of the current time slot. As a result, in the beginning time slots, the total income by NDDA is higher than the other two methods, which is achieved by scarifying the income in later time slots. This phenomenon is presents in Fig. 6(b). Fig. 6(b) also indicates the total incomes of the ten data auctioneers in the entire four time slots, which can be considered as the system income. As shown in Fig. 6(b), higher system income can be achieved by PCDDA than NDDA resulting from the prediction information. In addition, PCDA performs the best on the system income due to its global optimization objective, although the income obtained in some single time slot might be lower than NDDA and PCDDA.

7 Conclusion

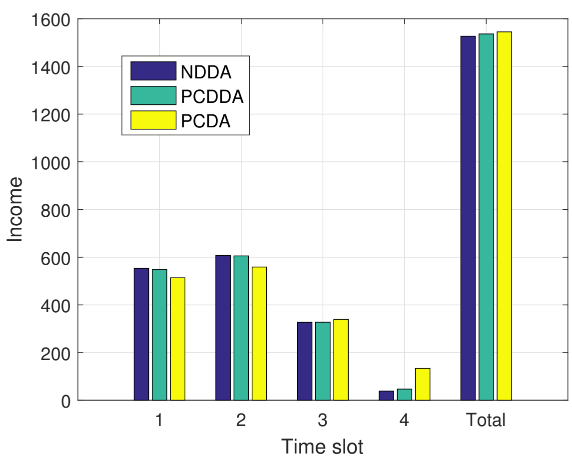
In this paper, we have proposed a novel data transaction system for mobile networks based on the basic and networked auction models. In addition, the data allocation mechanisms have been designed to make decisions that how to sell the rest data in different days, and then for each day, how to sell the allocated data in a system with multiple data sellers, to improve the performance of the system, maximize the income of the data sellers and satisfy the demands of data requesters. Simulation results for the system with single data auctioneer indicate that, the modification of considering time according to the rest amount of data can improve the efficiency of the data transaction, although the total income for the data seller might decrease due to the tradeoff between the income and time cost. In addition, when the data bid arrival rates are considered, the system efficiency and total income of the data seller can be both guaranteed, and meanwhile, the best data allocation balancing effect can be also achieved. Simulation results for the networked data transaction system demonstrate that the prediction information of data bidders' movement can improve the income for every data auctioneer effectively.

Appendix A
Proof of Lemma 1

Proof:



(a) Income obtained by auctioneers



(b) Income obtained in time slots

Fig. 6. Income obtained by different auctioneers and in time slots by applying NDDA, PCDDA and PCDA in networked data auction system.

The local stationary equations of the networked auction system can be given by

$$\lambda_i(n_i,0)\,\pi^i_{0|n_i} = \lambda_i(n_i,0)\sum_{j=1}^{h_i}\pi^i_{A_j|n_i} = (r_{c,i}+\lambda_i(n_i,v_1))\,\pi^i_{1|n_i}\,, \tag{43a}$$

$$\lambda_i(n_i,v_{j-1})\pi^i_{j-1|n_i} = (r_{c,i}+\lambda_i(n_i,v_j))\pi^i_{j|n_i}\,, j=1,2,\cdots,h_i-1, \tag{43b}$$

$$\lambda_i\left(n_i,v_{h-1}\right)\pi^i_{h-1|n_i} = r_{c,i}\pi^i_{h|n_i}\,, \tag{43c}$$

$$r_{c,i}\pi^i_{j|n_i} = \lambda_i\left(n_i,0\right)\pi^i_{A_j|n_i}\,,\quad j=1,2,\cdots,h_i. \tag{43d}$$

According to (43d) and (22b), we get

$$\pi^i_{A_j|n_i} = \frac{r_{c,i}\pi^i_{j|n_i}}{\lambda_i(n_i,0)} = \frac{r_{c,i}}{\lambda_i n_i}\pi^i_{0|n_i}\prod_{l=1}^{j}\frac{\lambda_i(n_i-1)f_{i,l-1}}{r_{c,i}+\lambda_i(n_i-1)f_{i,l}}, \tag{44}$$

and then

$$P^i_a(j\,|n_i) = \frac{\pi^i_{A_j|n_i}}{\sum_{k=1}^{h_i}\pi^i_{A_k|n_i}} = \frac{r_{c,i}}{\lambda_i n_i}\prod_{l=1}^{j}\frac{\lambda_i(n_i-1)\,f_{i,l-1}}{r_{c,i}+\lambda_i(n_i-1)\,f_{i,l}}. \tag{45}$$

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

$$E_{i,n_i} = \sum_{j=1}^{h_i} jP^i_a\left(j\,|n_i\right), \tag{46}$$

$$T_{i,n_i} = \frac{1}{n_i\lambda_i}\left(1+\sum_{j=1}^{h_i}\prod_{l=1}^{j}\frac{\lambda_i\left(n_i-1\right)f_{i,l-1}}{r_{c,i}+\lambda_i\left(n_i-1\right)f_{i,l}}\right), \tag{47}$$

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

$$E^0_{i,n_i} = \frac{E_{i,n_i}}{T_{i,n_i}} = \frac{r_{c,i}\sum_{j=1}^{h_i} j\prod_{l=1}^{j}\frac{\lambda_i(n_i-1)f_{i,l-1}}{r_{c,i}+\lambda_i(n_i-1)f_{i,l}}}{1+\sum_{j=1}^{h_i}\prod_{l=1}^{j}\frac{\lambda_i(n_i-1)f_{i,l-1}}{r_{c,i}+\lambda_i(n_i-1)f_{i,l}}}. \tag{48}$$

Then according to (19a), the average of the income per unit time for the data owner i is given by

$$\begin{aligned} E^0_i &= \sum_{n_i=1}^{\infty} E^0_{i,n_i}\pi\left(n_i\right) \\ &= \sum_{n_i=1}^{\infty}\frac{\psi_i^{n_i}e^{-\psi_i}}{\psi_i\left(n_i-1\right)!}\frac{r_{c,i}\sum_{j=1}^{h_i} j\prod_{l=1}^{j}\frac{\lambda_i(n_i-1)f_{i,l-1}}{r_{c,i}+\lambda_i(n_i-1)f_{i,l}}}{1+\sum_{j=1}^{h_i}\prod_{l=1}^{j}\frac{\lambda_i(n_i-1)f_{i,l-1}}{r_{c,i}+\lambda_i(n_i-1)f_{i,l}}}. \end{aligned} \tag{49}$$

This completes the proof of Theorem 1.

References

[1] R. W. Heath Jr, M. Honig, S. Nagata, S. Parkvall, and A. C. Soong, "LTE-advanced pro: Part 3 [guest editorial]," *IEEE Communications Magazine*, vol. 54, no. 7, pp. 52–53, Jul. 2016.

[2] J. Zhang, G. Fang, C. Peng, M. Guo, S. Wei, and V. Swaminathan, "Profiling energy consumption of DASH video streaming over 4G LTE networks," in *Proceedings of the 8th International Workshop on Mobile Video*. Klagenfurt, Austria, ACM, 3 May 2016, pp. 1–6.

[3] A. Ghosh, R. Ratasuk, B. Mondal, N. Mangalvedhe, and T. Thomas, "LTE-advanced: next-generation wireless broadband technology," *IEEE Wireless Communications*, vol. 17, no. 3, pp. 10–22, Jun. 2010.

[4] F. Mehmeti and T. Spyropoulos, "Performance analysis of mobile data offloading in heterogeneous networks," *IEEE Transactions on Mobile Computing*, vol. 16, no. 2, pp. 482–497, Feb. 2017.

[5] K. Poularakis, G. Iosifidis, I. Pefkianakis, L. Tassiulas, and M. May, "Mobile data offloading through caching in residential 802.11 wireless networks," *IEEE Transactions on Network and Service Management*, vol. 13, no. 1, pp. 71–84, Jan. 2016.

[6] X. Sun, S. Hu, L. Su, T. Abdelzaher, P. Hui, W. Zheng, H. Liu, and J. Stankovic, "Participatory sensing meets opportunistic sharing: Automatic phone-to-phone communication in vehicles," *IEEE Transactions on Mobile Computing*, vol. 15, no. 10, pp. 2550–2563, Oct. 2016.

[7] R. Sims and C. Bauer, "Handling a device changing from 3G to Wi-Fi without breaking established connections," in *New Trends in Networking, Computing, E-learning, Systems Sciences, and Engineering*. Springer, 2015, pp. 193–197.

[8] T. Wang, Y. Sun, L. Song, and Z. Han, "Social data offloading in d2d-enhanced cellular networks by network formation games," *IEEE Transactions on Wireless Communications*, vol. 14, no. 12, pp. 7004–7015, Dec. 2015.

[9] A. Apostolaras, G. Iosifidis, K. Chounos, T. Korakis, and L. Tassiulas, "A mechanism for mobile data offloading to wireless mesh networks," *IEEE Transactions on Wireless Communications*, vol. 15, no. 9, pp. 5984–5997, Sept. 2016.

[10] E. Meskar, T. D. Todd, D. Zhao, and G. Karakostas, "Energy aware offloading for competing users on a shared communication channel," *IEEE Transactions on Mobile Computing*, vol. 16, no. 1, pp. 87–96, Jan. 2017.

[11] L. Gao, G. Iosifidis, J. Huang, L. Tassiulas, and D. Li, "Bargaining-based mobile data offloading," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 6, pp. 1114–1125, Jun. 2014.

[12] V. S. S. Nadendla, S. K. Brahma, and P. K. Varshney, "Optimal spectrum auction design with 2-d truthful revelations under uncertain spectrum availability," *IEEE/ACM Transactions on Networking*, vol. 25, no. 1, pp. 420–433, Feb. 2017.

[13] C.-Y. Wang, H.-Y. Wei, and W.-T. Chen, "Resource block allocation with carrier-aggregation: A strategy-proof auction design," *IEEE Transactions on Mobile Computing*, vol. 15, no. 12, pp. 3142–3155, Feb. 2016.

[14] H. Kebriaei, B. Maham, and D. Niyato, "Double-sided bandwidth-auction game for cognitive device-to-device communication in cellular networks," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 9, pp. 7476–7487, Sept. 2016.

[15] H. Yu, G. Iosifidis, J. Huang, and L. Tassiulas, "Auction-based coopetition between lte unlicensed and wi-fi," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 1, pp. 79–90, Jan. 2017.

[16] A. Bousia, E. Kartsakli, A. Antonopoulos, L. Alonso, and C. Verikoukis, "Multiobjective auction-based switching-off scheme in heterogeneous networks: To bid or not to bid?" *IEEE Transactions on Vehicular Technology*, vol. 65, no. 11, pp. 9168–9180, Nov. 2016.

[17] S. Paris, F. Martignon, I. Filippini, and L. Chen, "An efficient auction-based mechanism for mobile data offloading," *IEEE Transactions on Mobile Computing*, vol. 14, no. 8, pp. 1573–1586, Aug. 2015.

[18] K. Zhu and E. Hossain, "Virtualization of 5g cellular networks as a hierarchical combinatorial auction," *IEEE Transactions on Mobile Computing*, vol. 15, no. 10, pp. 2640–2654, Oct. 2016.

[19] E. Gelenbe and K. Velan, "An approximate model for bidders in sequential automated auctions," in *Agent and Multi-Agent Systems: Technologies and Applications. Third KES International Symposium, KES-AMSTA 2009*. Uppsala, Sweden, 3-5 Jun. 2009.

[20] ——, "Analysing bidder performance in randomised and fixed-deadline automated auctions," in *Agent and Multi-Agent Systems: Technologies and Applications, 4th KES International Symposium, KES-AMSTA 2010*. Gdynia, Poland, 23-25 Jun. 2010.

[21] K. Lee, J. Lee, Y. Yi, I. Rhee, and S. Chong, "Mobile data offloading: How much can WiFi deliver?" *IEEE/ACM Transactions on Networking (TON)*, vol. 21, no. 2, pp. 536–550, Apr. 2013.

[22] C. W. Leong, W. Zhuang, Y. Cheng, and L. Wang, "Call admission control for integrated on/off voice and best-effort data services in mobile cellular communications," *IEEE Transactions on Communications*, vol. 52, no. 5, pp. 778–790, May 2004.

[23] S. G. Sitharaman, "Modeling queues using Poisson approximation in IEEE 802.11 ad-hoc networks," in *2005 14th IEEE Workshop on Local & Metropolitan Area Networks*. Crete, Greece, IEEE, 18-21 Sept. 2005.

[24] E. Gelenbe, "Analysis of single and networked auctions," *ACM Transactions on Internet Technology (TOIT)*, vol. 9, no. 2, p. 8, May 2009.

[25] F. Van den Bergh and A. P. Engelbrecht, "A cooperative approach to particle swarm optimization," *IEEE transactions on evolutionary computation*, vol. 8, no. 3, pp. 225–239, Jun. 2004.

[26] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in *Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on*. Nagoya, Japan, IEEE, 4-6 Oct. 1995.