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Joint wireless and cloud resource allocation based on parallel auction for mobile edge computing

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Abstract: A joint resource allocation algorithm based on parallel auction (JRAPA) is proposed for mobile edge computing (MEC). In JRAPA, the joint allocation of wireless and cloud resources is modeled as an auction process, aiming at maximizing the utilities of service providers (SPs) and satisfying the delay requirements of mobile terminals (MTs). The auction process consists of the bidding submission, winner determination and pricing stages. At the bidding submission stage, the MTs take available resources from SPs and distance factors into account to decide the bidding priority, thereby reducing the processing delay and improving the successful trades rate. A resource constrained utility ranking (RCUR) algorithm is put forward at the winner determination stage to determine the winners and losers so as to maximize the utilities of SPs. At the pricing stage, the sealed second-price rule is adopted to ensure the independence between the price paid by the buyer and its own bid. The simulation results show that the proposed JRAPA algorithm outperforms other existing algorithms in terms of the convergence rate and the number of successful trades rate. Moreover, it can not only achieve a larger average utility of SPs but also significantly reduce the average delay of MTs.

Key words: parallel auction; mobile edge computing; joint resource allocation; fast matching

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Mobile edge computing (MEC) is regarded as a promising technology, which can bridge the gap between the demands of applications and the restricted capabilities of mobile terminals (MTs)[1-2]. MEC servers are deployed at the base stations (BSs) in close proximity to mobile subscribers to execute latency-sensitive services, thereby extending the computing, storage and data processing capabilities of MTs.

Little existing literature focuses on resource allocation in MEC systems. The non-cooperative matrix game was formulated in Ref. [3] to solve the resource sharing problem among the cloudlets. Meneguette et al.[4] proposed an effective protocol based on vehicle-to-vehicle (V2V) communication. Nevertheless, due to the search for super nodes in the algorithm, additional time overhead was needed. In Ref. [5], the authors modeled the uplink data transmission of the vehicular network into an equilibrium program with the equilibrium constraints problem. The Bayesian alliance game and automatic learning machine[6] were applied to deal with a large amount of spatio-temporal information. Based on the Markov decision process (MDP), a motion prediction algorithm for dynamic resource allocation was investigated in Ref.[7], which greatly reduced the offloading time and energy consumption. In Ref. [8], a resource allocation algorithm based on the semi-Markov decision process (SMDP) was proposed, which considered the heterogeneous vehicular network and the impact of road side units to maximize long-term utility.

A joint cloud and wireless resource allocation based on evolutionary game (JRAEG)[9] was proposed to solve the service selection problem in heterogeneous networks. A power-delay tradeoff algorithm was proposed in Ref. [10], which applied a joint task offloading and proactive caching method to minimize computing latency. In Ref. [11], users with different computation capabilities shared a single edge server. A convex optimization problem was formulated to minimize the energy consumption. An iterative algorithm[12] was proposed to solve a non-convex optimization problem in the multicell MEC scenario. In Ref. [13], an energy-efficient cooperative computation method was proposed, in which the computational applications can be partitioned into several tasks to be executed in peer nodes.

Although the literature above provided effective approaches to solve the resource allocation problem for the MEC system, there are still some disadvantages in these approaches. The game theory requires multiple iterations between the MTs and BSs, which brings the problem of low convergence speed and large latency. The Markov decision process increases the information interaction between the terminals and the MEC servers, which brings great delay. The auction theory is a well-researched field in economics that has been applied in resource management with the advantages of high efficiency and low computation complexity[14-17]. Therefore, we propose a wireless and cloud resource allocation algorithm based on the

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combinational parallel auction for MEC systems.

We propose a joint resource allocation algorithm based on parallel auction (JRAPA), including bidding submission, winner determination and pricing stages to maximize the utilities of the service providers (SPs) and satisfy the delay requirements of MTs at the same time. The MTs take available resources from SPs and distance factors into account to decide the bidding priority. A resource constrained utility ranking (RCUR) algorithm is put forward to match the SPs and MTs at the winner determination stage. Moreover, the wireless resource auction and cloud resource auction are processed in parallel, which accelerates the convergence speed of the auction process.

1 System Model

The system model studied in this paper is shown in Fig. 1, which includes MTs, BSs, MEC servers, the core network (CN) and central cloud (CC).

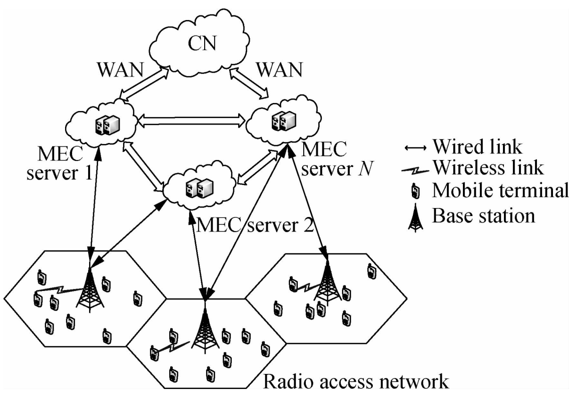

Fig. 1 An example of MEC system

1.1 Network model

The CC is composed of massive servers, which is the central computational service provider of the whole system. MEC servers are applied to supplement the CC, so that applications can be processed close to the MTs. The MEC servers and BSs are connected through reliable optical fibers, and they are connected to the CN through a wide area network (WAN). In addition, MTs are connected to the BSs through the LTE/5G wireless network. The wired connection between MEC servers and BSs allows the MEC server to provide auxiliary functions for offloading decision making and resources allocation, which guarantees the low delay and high reliability requirements of the applications. Without loss of generality, we assume that each BS only connects with one MEC server.

1.2 Communication model

It is assumed that there are J MTs, denoted as $J = \{1, 2, \ldots, J\}$. The number of BSs/MEC servers is N, which is expressed as $N = \{1, 2, \ldots, N\}$. Orthogonal sub-channels are allocated to MTs connected to each BS, which indicates that there are no interfaces among MTs. The channel between each BS is composed of a fixed path-loss, a slowly varying lognormal shadowing and rayleigh fast fading. The transmission power of MT j is denoted by p_j. The uplink transmission rate of MT j connected to BS i is expressed as

$$R_{ij} = B_{ij}\log_2\left(1 + \frac{p_j g_{ij}}{\sigma_{ij}^2}\right) \tag{1}$$

where B_{ij} is the bandwidth allocated to MT j, and g_{ij} refers to the channel gain between MT j and BS i. σ_{ij}^2 is defined as the power of additive Gauss white noise (AWGN).

1.3 Computation model and problem formulation

1.3.1 Computation model of MTs

When a MT needs to offload a task, it should pay the corresponding remuneration to encourage SPs to provide wireless and cloud resources. The utility function of MT j is

$$U_{\mathrm{MT}}(j) = \sum_{i=1}^{N} m_{ij}(t_{0,j} - t_{i,j}) - V_j^{\mathrm{B}} B_{ij} - V_j^{\mathrm{M}} f_{ij} \tag{2}$$

where m_{ij} is a two-value variable to show the matching relationship between SP i and MT j, and $m_{ij} \in \{0, 1\}$. $t_{0,j}$ is the time for MT j to execute a task locally. V_j^{B} is the bidding price of MT j for a unit wireless resource, and V_j^{M} is the bidding price for a unit computation resource. s_j refers to the number of CPU instructions that MT j requests, and b_j is the bandwidth required to upload the task. $t_j^{\max}$ is the delay constrain of MT j. The total delay between MT j and SP i is denoted as

$$t_{ij} = \frac{b_j}{R_{ij}} + \frac{s_j}{f_{ij}} + t_{ij}^{\mathrm{match}} \tag{3}$$

where B_{ij} and f_{ij} are the wireless and cloud resources that MT j required. The matching time between MT j and SP i is denoted as t_{ij}^{match}.

1.3.2 Utility function of BSs

We need to consider how to maximize the revenue of BSs. The optimization problem is

$$\max \sum_{j=1}^{J} U_B(i,j) = \sum_{j=1}^{J} m_{ij}(V_j^{\mathrm{B}} - \lambda_i^{\mathrm{B}}) B_{ij}$$
$$\text{s.t.} \quad \sum_{j=1}^{J} B_{ij} \leqslant B_i^{\mathrm{ava}} \tag{4}$$

where λ_i^{B} represents the cost of BS i for the allocating unit wireless resource, and B_i^{ava} is the available wireless resource of BS i.

1.3.3 Utility function of MEC servers

It is necessary to consider how to maximize the revenue of MEC servers. Similarly, the optimization problem is

$$\max \sum_{j=1}^{J} U_{\mathrm{M}}(i,j) = \sum_{j=1}^{J} m_{ij}(V_j^{\mathrm{M}} - \lambda_i^{\mathrm{M}}) f_{ij}$$

$$\text{s. t.} \qquad \sum_{j=1}^{J} f_{ij} \leqslant f_i^{\text{ava}} \tag{5}$$

where λ_i^{M} represents the cost of MEC server i for allocating unit cloud resource, and f_i^{ava} is the available cloud resource of MEC server i.

2 Joint Resource Allocation Algorithm based on Parallel Auction

The resource allocation in the MEC system needs to meet the real-time requirements of tasks. In this section, we propose a parallel auction algorithm to realize the joint allocation of the wireless and cloud resources, aiming at maximizing the utilities of SPs and meeting the delay requirements of MTs at the same time.

2.1 Auction model

The basic auction model of JRAPA is illustrated in Fig. 2. MTs are resource buyers, while BSs and MEC servers are resource sellers. We regard BSs and MEC servers as the auctioneers of wireless and cloud resource auction, respectively. Hence, no additional charge is required. The bidding and pricing information of both buyers and sellers is private.

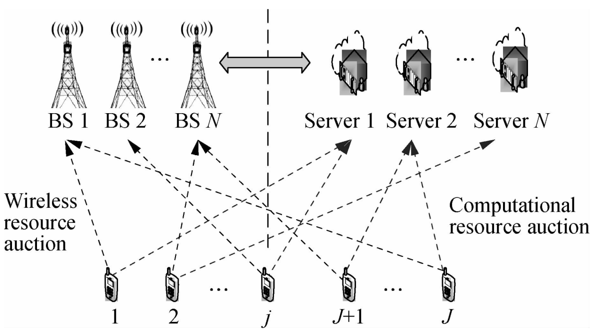

Fig. 2 The auction model

As shown in Fig. 3, due to the independence of wireless and cloud request channels, the auction of wireless and cloud resources can be processed in parallel. One MT transmits the wireless and cloud resource request while signaling to the BS at the same time. After receiving the

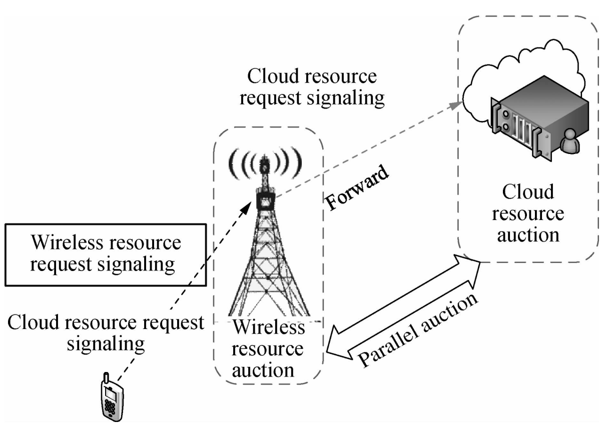

Fig. 3 The description of parallel auction

two signals, the BS will conduct the wireless resource auction, and the cloud resource request signaling is forwarded to the MEC server to conduct the cloud resource request auction. Parallel auction of wireless and computation resources can achieve fast matching of sellers and buyers, which can meet the low latency requirement of the system.

2.2 Parallel auction algorithm description

An auction mechanism with clear rules will be adopted to prevent dishonest transactions between buyers and sellers. One trade in the parallel auction is successful when both the wireless and cloud resources required by one MT are satisfied. The auction process can be divided into three stages: the bidding submission stage, winner determination stage and pricing stage.

2.2.1 Bidding submission

Each MEC server and each BS broadcast its available cloud resource f_i^{ava} and wireless resource B_i^{ava}, respectively. When receiving the resource information, MT j prioritizes the SPs according to priority factor $o_{i,j}$, which takes the available resources of the BS and MEC server , the distance d_{ij} between SP i and MT j into account.

$$o_{i,j} = \alpha \frac{B_i^{\text{ava}}}{B_{ij}} + \beta \frac{f_i^{\text{ava}}}{f_{ij}} + \gamma \frac{1}{d_{ij}} \tag{6}$$

where α, β, γ are the available wireless resource factor, available cloud resource factor and distance factor, respectively, and $\alpha + \beta + \gamma = 1$.

The priority vector is $\boldsymbol{O}_j^{\text{sorted}} = \{o_{1,j}^{\text{sorted}}, o_{2,j}^{\text{sorted}}, \ldots, o_{N,j}^{\text{sorted}}\}$.

In each round, MT j submits its bidding vector (B_{ij}, f_{ij}, V_j^{B}, V_j^{M}), where V_j^{B} and V_j^{M} are the unit bidding price for wireless and cloud resources of MT j, respectively. When the MT and SP match successfully, the MT stops bidding for wireless and cloud resources.

2.2.2 Winner determination

We define a match matrix $\boldsymbol{M} = \{m_{ij}\}_{N \times J}$ to describe the relationship between MTs and SPs, where $m_{ij} \in \{0, 1\}$. $m_{ij} = 1$ means that SP i and MT j matches, while $m_{ij} = 0$ refers to that MT j fails to match SP i. Also, we assume that $\sum_{i=1}^{N} m_{ij} \leqslant 1$, which indicates an MT can only choose service from at most one SP.

We propose a resource constrained utility ranking (RCUR) algorithm to match the MTs and SPs. After receiving the bidding vectors, BS i and MEC server i first calculate the utility vector, respectively. The descending utility vector is obtained as $\boldsymbol{U}_{\text{B}}(i) = \{U_{\text{B}}(i, 1), \ldots, U_{\text{B}}(i, K_i)\}$ and $\boldsymbol{U}_{\text{M}}(i) = \{U_{\text{M}}(i, 1), \ldots, U_{\text{M}}(i, K_i)\}$, where K_i represents the number of MTs bidding for BS and MEC server i. BS and MEC server i choose the MT whose utility ranks top in $\boldsymbol{U}_i^{\text{B}}$ and $\boldsymbol{U}_i^{\text{M}}$, respectively, as the winner, and update $(f_i^{\text{ava}}, B_i^{\text{ava}})$ as

$$B_i^{\text{ava}} = B_i^{\text{ava}} - B_{ij} \tag{7}$$

$$f_i^{\text{ava}} = f_i^{\text{ava}} - f_{ij} \tag{8}$$

A winner will not take part in the auction in the next round, and its utility is removed from the utility vectors. The above process will be repeated until $B_i^{\text{ava}} < \varphi^{\text{B}}$ or $f_i^{\text{ava}} < \varphi^{\text{M}}$ holds, where φ^{B} and φ^{M} are the predetermined wireless and cloud resource threshold, respectively. It is noted that if one auction (for example, the auction at the MEC servers) is successful and another auction failed for the same MT, the MT fails to obtain the required resources.

The losers should improve their bidding strategies in the next round. The bidding price update by the functions $V_j^{\text{B}} = V_j^{\text{B}} + \Delta_j^{B} V_j^{\text{B}}$ and $V_j^{\text{M}} = V_j^{\text{M}} + \Delta_j^{\text{M}} V_j^{\text{M}}$, where $\Delta_j^{\text{B}}, \Delta_j^{\text{M}}$ are steps of the price adjustment for unit wireless and cloud resources, respectively.

2.2.3 Pricing stage

An auction should be constructed while the price paid by the buyer is independent of its own bids[16]. At the pricing stage, we adopt the sealed second-price rule, where each winning MT pays the second-high bidding price in the winner set.

Assume that the winners of SP i are expressed as $J_i^W = \{j_1, j_2, \ldots, j_{w_i}\}$, where w_i is the number of winners. Taking the unit wireless resource pricing of the BS as an example, we assume that the bidding price of winners is ranked as $\boldsymbol{V}_i^{\text{B}} = \{V_{i,j_1}^{\text{B}}, V_{i,j_2}^{\text{B}}, \ldots, V_{i,j_{w_i}}^{\text{B}}\}$, where $V_{i,j_1}^{\text{B}} \geqslant V_{i,j_2}^{\text{B}} \geqslant \ldots \geqslant V_{i,j_{w_i}}^{\text{B}}$. According to the second-price rule, the payment for each winner is

$$P_{i,j_n}^{\text{B}} = \begin{cases} V_{i,j_{n+1}}^{\text{B}} & n = 1, 2, \ldots, w_i - 1 \\ \tilde{V}_{i,j_{w_i}}^{\text{B}} & n = w_i \end{cases} \tag{9}$$

where $\tilde{V}_{i,j_{w_i}}^{\text{B}}$ is the payment of the winner whose bidding price is $V_{i,j_{w_i}}^{\text{B}}$, and it is assumed that $\lambda_i^{\text{B}} \leqslant \tilde{V}_{i,j_{w_i}}^{\text{B}} \leqslant V_{i,j_{w_i}}^{\text{B}}$. By calculating the pricing of the winner of each BS, the wireless resource pricing matrix $\boldsymbol{P}^{\text{B}} = \{P_{ij}^{\text{B}}\}_{N \times J}$ is determined.

Similarly, the MEC servers will also obtain the pricing matrix $\boldsymbol{P}^{\text{M}} = \{P_{ij}^{\text{M}}\}_{N \times J}$ according to the sealed second-price rule.

$$P_{i,j_n}^{\text{M}} = \begin{cases} V_{i,j_{n+1}}^{\text{M}} & n = 1, 2, \ldots, w_i - 1 \\ \tilde{V}_{i,j_{w_i}}^{\text{M}} & n = w_i \end{cases} \tag{10}$$

where $\tilde{V}_{i,j_{w_i}}^{\text{M}}$ is the payment of the winner whose bidding price is $V_{i,j_{w_i}}^{\text{M}}$, and it is assumed that $\lambda_i^{\text{M}} \leqslant \tilde{V}_{i,j_{w_i}}^{\text{M}} \leqslant V_{i,j_{w_i}}^{\text{M}}$.

2.3 Proposed algorithm description

The proposed JRAPA algorithm is described in Algorithm 1, which describes the bidding submission, winner determination and pricing stages of multiple auction rounds to decide the match matrix and pricing matrix. $r^{\max}$ is the maximum auction rounds in the algorithm.

The RCUR algorithm in the winner determination stage is illustrated in Algorithm 2, in which the utilities of SPs are ranked in a descending order to determine the winners, and available wireless and cloud resources are updated with the iterations.

In Algorithm 2, $\boldsymbol{U}(i,j)$ is the utility of the BS or MEC server, which depends on the requested resource. J_i^{C} refers to the set of candidate MTs, and K_i is the number of MTs in J_i^{C}. $\varphi^{\text{B}}, \varphi^{\text{M}}$ are the resource thresholds of BSs and MEC servers, respectively.

Algorithm 1 JRAPA algorithm

Input: J, N, $(B_{ij}, f_{ij}, t_j^{\max}, V_j^{\text{B}}, V_j^{\text{M}})$, $r^{\max}$;
Output: M, P.
Initialization: $\alpha, \beta, \gamma, J, J_i^W, (f_i^{\text{ava}}, B_i^{\text{ava}})$.
for each particle $r = 1$: $r^{\max}$ do
Bidding submission
Each MT in J calculates $o_{i,j}$ according to Eq. (6).
Sort $o_{i,j}$ in a descending order, and O_j^{sotred} is obtained.
MT bids to the BS and MEC server according to the first element in O_j^{sotred}.
Winner determination
for each particle $i = 1$: N do
BS and MEC server i utilize Algorithm 2 to decide winners. 6:
end for
for $j \in J$ do
$V_j^{\text{B}} = V_j^{\text{B}} + \Delta_j^{\text{B}} V_j^{\text{B}}$
$V_j^{\text{M}} = V_j^{\text{M}} + \Delta_j^{\text{M}} V_j^{\text{M}}$
$O_j^{\text{sorted}} = O_j^{\text{sorted}} - \{o_{ij}\}$
end for
end for
Pricing stage
Each MT pays according to (9) and (10).

Algorithm 2 RCUR algorithm

Input: K_i, $(B_{i,j}, f_{i,j}, V_j^{\text{B}}, V_j^{\text{M}})$, $U(i,j)$, J, $J_i^{\text{C}}, f_i^{\text{ava}}$, B_i^{ava}.
Output: M, J_i^{W}.
for each particle $i = 1$: K_i do
Calculate the utility for each MT in J_i^{C}.
end for
Sort the utility $U(i,j)$ in a descending order. $\boldsymbol{U}_i = [U_i(i,1), U_i(i,2), \ldots, U_i(i,K_i)]$.
for each particle $i = 1$: K_i do
if $B_i^{\text{ava}} \geqslant \varphi^{\text{B}}$ or $f_i^{\text{ava}} \geqslant \varphi^{\text{M}}$ do
$B_i^{\text{ava}} = B_i^{\text{ava}} - B_{ij}$ or $f_i^{\text{ava}} = f_i^{\text{ava}} - f_{ij}$
$J_i^{\text{C}} = J_i^{\text{C}} - \{k\}$, update U_i.
$J_i^{\text{W}} = J_i^{\text{W}} + \{k\}$
end for

2.4 Properties of JRAPA algorithm

Definition 1 A feasible auction mechanism should satisfy the following properties:

- Computational efficiency. The auction outcome should be completed with a polynomial time complexity.
- Individual rationality. The utility of the buyers and sellers should not be less than zero, which means that no winning buyer is charged more than its bidding, and no winning seller is paid less than its cost.
- Budget balance. The gain of the auctioneer is defined as U_i^A, which is equal to the price paid by the buyers subtracting the payment to the sellers. The gain of the auctioneer should be no less than zero.

Lemma 1 The JRAPA is computationally efficient.

Proof In Algorithm 1, in each single-round auction, sorting the priority factors takes $O(NJ\log(NJ))$ time at the bidding submission stage. According to Algorithm 2, at the winner determination stage, there are at most J MTs for each SP. As a consequence, the time complexity of sorting the utility vector is $O(NJ\log(J))$, and the while-loop takes at most $O(NJ)$ time. For bidding strategy adjustment, there are at most J MTs in set J. Hence, it has the time complexity of $O(J)$. Since the auction process will be conducted $r^{\max}$ times, the overall time complexity of Algorithm 1 is $O(r^{\max}NJ\log(NJ))$.

In other words, JRAPA will converge to a final resource allocation and pricing results in a polynomial time with respect to N, J and $r^{\max}$, and JRAPA is computationally efficient.

Lemma 2 The JRAPA is individually rational.

Proof On the one hand, for winning buyers, we adopt the sealed second-price rule at the pricing stage, so the payment to sellers is less than the bidding of the winning MT. For winning sellers, as described in previous section, $P_i^B \geqslant \lambda_i^B$ and $P_i^M \geqslant \lambda_i^M$. Therefore, the utilities of SPs are more than zero.

On the other hand, the utilities of MTs in the loser set J_L are zero. Since the utilities of both sellers and buyers are not less than zero, the proposed JRAPA is individually rational.

Lemma 3 The JRAPA is budget balanced.

Proof The MEC servers and BSs are auctioneers, which take charge of the whole auction process in JRAPA. No extra charge is required. The total profit of MEC servers and BSs gained as auctioneers are $\sum_{i=1}^{N} U_i^A = 0$.

To conclude, the proposed JRAPA is budget balanced.

3 Performance Evaluation

In this section, we use a computer simulation to evaluate the performance of the proposed JRAPA algorithm, and compare the performance of the JRAPA mechanism with other algorithms.

3.1 Simulation setup

We consider a simulation scenario where 3 BSs and 3 MEC servers randomly locate on a 1000-meter road. The initial available resources of BSs and MEC servers are {55, 50, 60} MHz, {7 000, 8 000, 7 500} Mega/s, respectively. We set the channel gain of the MTs following the Gaussian distribution $CN(\mu_0, \sigma_0^2)$, where $\mu_0 = 10$, $\sigma_0^2 = 1$. The transmission power MT j is set to be $\sigma_{ij} = 1$. The wireless and cloud resource requests as well as the delay constraint are randomly distributed on the intervals (0, 2) MHz, (20, 100) Mega/s, and (5, 10) ms, respectively. The fixed transmission power is $p_j = 20$ dBm, and $\forall j \in J$. The factors in Eq. (6) are $\alpha = 0.3$, $\beta = 0.3$, and $\gamma = 0.4$. Moreover, the wireless and cloud bidding price are distributed within (5, 10) \$/MHz and (0, 1) \$/Mega, respectively. We set the cost of the wireless unit and cloud resource to be $\lambda_i^M = 0.1$, and $\lambda_i^B = 0.1$. The maximum auction round $r^{\max}$ are set to be 20, and the bidding price adjustment steps of MT j are $\Delta_j^M = 0.1$ and $\Delta_j^B = 0.1$.

3.2 Simulation results

Fig. 4 describes the resource utilization rates of three SPs. In the JRAPA, the resource utilization rates of all three SPs increase when the number of MTs varies from 50 to 200. Since the auction is processed in parallel to achieve faster matching between buyers and sellers, successful trade increases with the increasing number of MTs, and as a result, the resource utilization shows a rising trend. However, when the number of MTs is larger than 200, utilization is no longer increasing. It is due to the limited resource capabilities of SPs, which fail to completely meet the requirements of the MTs.

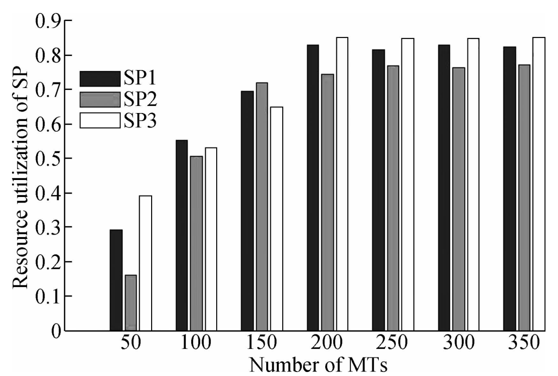

Fig. 4 Average resource utilization of SPs with respect to the number of MTs

We then investigate the convergence speed of the proposed JRAPA algorithm. The successful trade rate (STR) is defined as the proportion of winning MTs. We compare the performance of JRAPA with three algorithms: motion-prediction-based resource allocation (MPRA) [7], one-shot sealed combinational auction (OSCA) and multi-round sealed sequential algorithm (MSSA) [15]. In

MPRA, each MT chooses a SP based on motion-prediction, and the SP determines the winners according to the first come first service (FCFS) rule. SSCA is a one-round auction. According to the MSSA, the MT sequentially bids to a SP by means of polling in each iteration.

In Fig. 5, the STR of four algorithms is compared when the number of MTs is 100. It is clear that the number of successful trades in MPRA, MSSA and JRAPA shows an upward trend with the iteration times, while in OSCA, the value remains constant. After 3 iterations, the successful trade rate in JRAPA achieves the maximum. The RCUR algorithm and the bidding priority determination in JRAPA increase the successful trade in the auction. In conclusion, the convergence speed of the JRAPA is faster than other algorithms and the maximum STR in the JPARA is 81.82%, 100% and 156.41% larger than that of MPRA, OSCA and MSSA, respectively.

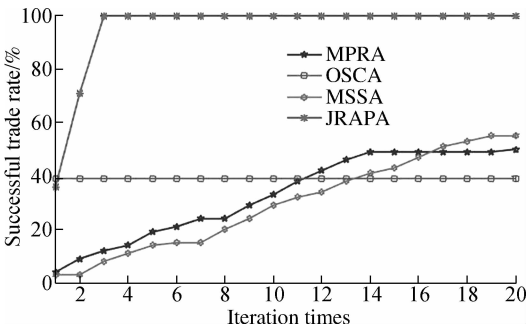

Fig. 5 Successful trade rate comparison

Fig. 6 shows the average utilities of SPs in different algorithms. Since the MPRA determines the winners according to the FCFS rule, the average utility of SPs in MPRA is revealed randomly. The average utility in the JPARA is 107.91%, 66.02% and 29.44% larger than that of MPRA, OSCA and MSSA, respectively. At the winner determination stage, SPs always choose the MT with the highest utility as the winner in each round of the auction, as a result of which the successful trade rate and average utility of SPs are higher than those of other algorithms.

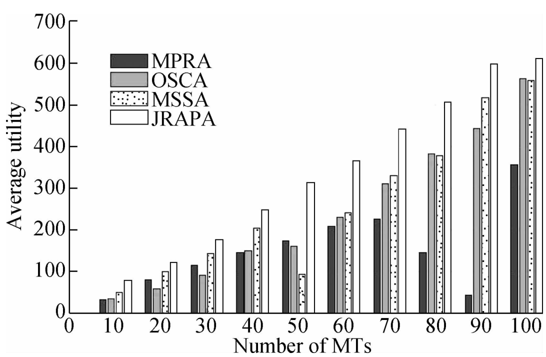

Fig. 6 Average utility of SPs with respect to the number of MTs

The delay of MTi is calculated by Eq. (3), and the average delay is $\sum_{i=1}^{J} t_i/J$. As shown in Fig. 7, compared with MPRA, OSCA and MSSA, the delay in JRAPA is reduced by 46.67%, 41.46% and 33.33% on average, respectively. On the one hand, since the wireless resource auction and cloud resource auction are processed in parallel, the matching delay between buyers and sellers is significantly reduced. On the other hand, the MTs take available resources of SPs and distance factors into account to determine the bidding priority, which decreases the processing time. As a result, the proposed JRAPA can well meet the latency requirement of MTs, and the delay is significantly reduced compared with other algorithms.

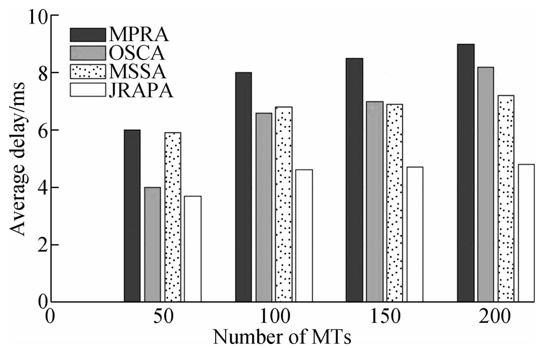

Fig. 7 Average delay comparison

4 Conclusion

In this paper, we propose a JRAPA algorithm for MEC system, which includes the bidding submission, winner determination and pricing stages, aiming at maximizing the utilities of SPs and satisfying the delay requirements of the MTs. At the bidding submission stage, the MTs take available resources from SPs and distance into account to determine the bidding priority. At the winner determination stage, a RCUR algorithm is put forward to match the SPs and MTs, and the wireless resource auction and cloud resource auction are processed in parallel to achieve the fast matching of the buyers and the sellers, thus reducing the complexity of the algorithm and system delay. A sealed second-price rule is adopted at the pricing stage to ensure the independence between the price paid by the buyer and its own bid. The JRAPA algorithm is proved to be computationally efficient, individually rational and budget-balanced. Simulation results illustrate that the proposed JRAPA algorithm achieves a better performance in terms of the number of successful trades and utilities of the SPs. Moreover, compared with MPRA, OSCA and MSSA, the delay in JRAPA is significantly reduced.

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移动边缘计算系统中基于并行拍卖的无线资源与云资源联合分配

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摘要：提出了一种移动边缘计算场景下基于并行拍卖的无线资源与云资源联合优化分配算法. 该算法将无线资源与云资源的联合分配建模为拍卖过程，旨在最大化资源供应者的效用，同时满足用户时延需求. 该拍卖包括投标、胜者决定以及定价阶段. 在投标阶段，用户综合考虑可用资源以及距离等因素来决定投标向量和投标优先级，从而减少处理时延，提高成功交易率. 在胜者决定阶段，提出基于资源约束的效益排序算法来决定拍卖的胜者与失败者，从而最大化资源供应者的效益. 在定价阶段，采用密封次高价定价法来保证资源定价与投标价格的独立性. 仿真结果表明，与现有算法相比，所提算法收敛速度更快，成功交易率更高，资源提供者的平均效益和用户任务处理时延更优.

关键词：并行拍卖；移动边缘计算；联合资源分配；快速匹配

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