A Novel Grid Resource Scheduling Model Based on Extended Second Price Sealed Auction

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Abstract

In resource-limited environment, grid users compete for limited resources, and how to guarantee tasks' victorious probabilities is one of the most primary issues that a resource scheduling model cares. In order to solve grid resources scheduling problems, a novel model, namely ESPSA (Extended Second Price Sealed Auction), is proposed. The ESPSA model introduces an analyst entity, and designs analyst's prediction algorithm based on Hidden Markov Model (HMM). In ESPSA model, grid resources are sold through second price sealed auction. Moreover, to achieve high victorious probabilities, the user brokers who are qualified to participate in the auctions will predict other players' bids and then carry out the most beneficial bids. The ESPSA model is simulated based on GridSim toolkit. Simulation results show that the ESPSA model assures a higher victorious probability and superior to other traditional algorithms. Moreover, we analyze the existence of Nash equilibrium based on simulation results.

1. Introduction

The concept of grid technology originates from electricity grid. Idle resources in grids are connected through internet and grid users can access the resources no matter where they are. Grid system is heterogeneous, multi-zone managed, large-scale and distributed. Furthermore, grid system is concerned with a dynamic collection of diverse resources and services across multiple domains, and resources apply and demand is dynamic either. As resources join and exit dynamically, the loads of grid resources change continuously. All these characteristics show that grid system needs a dynamic and high-efficiency resources scheduling algorithm, which can manage dynamic resources flexibly.

Majority grid systems fall in the category of resource-rich ones, where resources compete for limited tasks. However, sometimes, numerous tasks are submitted at the same time, leading to the undersupplying of resources, which makes tasks compete for limited resources. Whether tasks compete for resources or resources compete for tasks, the resources providers will benefit from assigning resources and the thing users need to do is paying for the resources. Thus, it is reasonable to model the resource scheduling by economic models. However, current literature on economic grid models only limits to the basic auction models where the bidders bid according to a single factor. Some algorithms integrate simple prediction methods into the bidding algorithms without assuring the victorious probability. Thus, with the increase of the complexity of grid systems, how to improve those simple bidding strategies, prediction algorithms and victorious probability is becoming urgent.

The major contributions of this paper are as follows.

- To solve the resource scheduling problem in grids, an ESPSA (Extended Second Price Sealed Auction, ESPSA) model is proposed in this paper. An analyst entity is introduced in the model to fulfill the trend that roles in grids are increasing dramatically.
- The ESPSA model extends second price sealed auction mechanism. In the extended auction, the total price is sealed while keep the resource demand quantity unsealed.
- This paper introduces a prediction algorithm based on Hidden Markov Model, improves basic bidding algorithms and increases participants' victorious probability.

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• GridSim toolkit is utilized to simulate the algorithms and the existence of Nash equilibrium is analyzed.

The rest of the paper is organized as follows: section 2 is the related work; section 3 describes the ESPSA model; section 4 elaborates the simulation and analyzes the simulation results. Section 5 draws the conclusion and discusses about the future work.

2. Related work

At present, grid resources management and dynamic scheduling based on game theory is becoming a focus of researches. A lot of work has been done by researchers and these works are usually divided into two categories. One is in resource-rich environment where resources compete for limited tasks. The other is in resource-limited environment where a large number of tasks compete for limited resources.

Authors in [1] focus on resource-rich environment. They propose a method, namely GVP, which could guarantee resources’ victorious probabilities. In their method, resources win the auction by predicting other resources’ bids based on the mean value of historical bids. However, the prediction algorithm is too simple to get accurate predictions. Paper [2] discusses a divisible auction and adopts a decentralized strategy, but users only make decisions according to resources’ historical load information without consideration of the changing trend of resources’ loads. Authors in [3] propose a hierarchical grid model, in which resources are selfish. The selfishness of resources makes them only consider their own needs when executing tasks. This kind of action delays tasks’ execution even though the tasks could accurately predict their opponents’ bids. This model couldn’t guarantee tasks’ victorious probabilities. Paper [4] proposes a resource allocation algorithm based on mobile brokers’ competing for resources. In this model, user brokers make an inaccurate prediction for resources, and they neglect the prediction of other user brokers’ behavior. Paper [5] proposes a resource allocation model that uses sequential game to predict resource load for time optimization. In this model, user brokers offer their bids in sequence, causing first-mover advantage, which make the model less popular in practical applications. Authors in [6] propose grid resource scheduling model which only considers the relationship between users and resources without considering the interactions between users. Thus, this model is too idealized to be used in practical circumstances.

All the literature listed above have made remarkable contributions to economic resources scheduling and allocation algorithm, but they can’t guarantee the accuracy of prediction of tasks’ bids let alone participants’ victorious probability. In response to these issues, a model, namely ESPSA, based on extended second price sealed auction and Hidden Markov Chain is proposed. In ESPSA model, a mass of tasks compete for limited resources, and tasks decide their best bidding price according to their resource demand quantities, their budgets and predictions of their opponents’ bids.

3. ESPSA resource allocation model and algorithm

The ESPSA model is consisted of extended second price auction algorithm, resource broker’s algorithm, user broker’s algorithm with HMM. Specifically, the extended second price auction sealed the total price of each trade and unsealed the resource demand quantity. By invoking the extended auction, the users’ and resources’ brokers represent as bidders and auctioneers respectively.

In the common second price sealed auction [7], the bidders only submit prices that they wish to pay to the auctioneer without specifying a total price or a unit price. The ESPSA model extended the common second price sealed auction by specifying that the bidders should seal their total price and unseal their resource demand quantity. Then, after each auction, the auctioneer announces the winners and amount of resource they demand. This improvement is reasonable for that the resource broker can attract more customers (resources) by announcing the amount of resources processed in each auction. It is also applicable to seal customers’ total price for privacy reason.

As Fig.1 shows, when a user wants to execute some tasks, it sends the task list to a user broker UB. After receiving the task list, in order to be qualified to take part in an auction, UB sends an application message with its expected victorious probability and amount of resource that it demands to resource broker RB. If resource broker RB agrees UB to take part in the auction, UB sends prediction request to an Analyst. On receiving the predictions, UB calculates its bid according to the prediction results. After that, it will send its bid to RB. Finally, RB sends winners to UB and resource demand quantity of UB to information service entity.

One of the differences between our model and others is the analyst entity that we proposed. An analyst gets information from the information service entity,
and provides prediction services to user brokers. The analyst entity’s prediction algorithm is based on HMM. Obviously, it satisfies the trend that roles in grids are increasing dramatically and makes the market model of grids computing much more practical.

![Figure 1. ESPSA model](image)

The detailed user broker algorithm, resource broker algorithm and ESPSA prediction algorithm is described in section 3.1, 3.2 and 3.3 respectively.

### 3.1. Algorithm of resource broker

As described above, ESPSA considers a resource-limited grid model where resource brokers need to act as auctioneers who invite auctions among user brokers. For a resource broker, if it makes a higher expected profit for resources, it will be favored by the resources. Thus, the resource broker should limit the number of the bidders in order to fulfill most of the bidders’ expected victorious probability. The number of bidders should be calculated by Eq.(1).

\[
\eta_{\text{bidder}} = \frac{1}{\min \{Pr_{i}^{\text{v}}\}} \quad (1)
\]

where \(Pr_{i}^{\text{v}}\) specifies the expected victorious probability of user broker \(UB_{i}\).

The specific algorithm of resource broker \(RB_{i}\) is described in Table 1.

<table>
<thead>
<tr>
<th>Table 1. Resource broker's algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Algorithm:</strong> Resource Broker’s algorithm</td>
</tr>
<tr>
<td><strong>Input:</strong> A set of Bidders who expect to take part in the auction (S_{\text{bidder}}), bidders’ expected victorious probability ({Pr_{i}^{\text{v}}}) and bidders’ bids.</td>
</tr>
<tr>
<td><strong>Output:</strong> Messages that invoking a auction and winning messages.</td>
</tr>
<tr>
<td>1. If (\left</td>
</tr>
<tr>
<td>2. If (\left</td>
</tr>
<tr>
<td>3. Waiting until received the bidding information ({(b_{i}, d_{i})}) from user brokers.</td>
</tr>
<tr>
<td>4. Calculate each user broker’s the unit price by (r_{i} = b_{i} / d_{i}). Set the user broker with highest (r_{i}) as the winner.</td>
</tr>
<tr>
<td>5. Send need vector (D_{i} = {d_{i}, d_{i}, ..., d_{n}, ..., d_{n}}) to Information Service Entity (shown in Figure 1).</td>
</tr>
</tbody>
</table>

### 3.2. Algorithm of user broker

User brokers need to represent users to join in the auction for resources. Apparently, user agents with higher victorious probability will get more users. The analyst entity provides predicting services. User brokers can predict other user brokers’ bids to get a high victorious probability by using the predicting services provided by an analyst.

Specifically, firstly, a user broker calculates its primitive bid by the following equation.

\[
b'_{i} = \frac{\gamma_{i}}{L} \quad (2)
\]

Where \(L\) is the load status of the resource and \(\gamma_{i}\) is a weighting factor. Then, \(UB_{i}\) sends a predicting request to the analyst and gets a set of other user brokers’ bids \(B_{\text{pre}}^{i}\). After that, \(UB_{i}\) adjusts its bid according to Eq.(3).

\[
b_{i} = \begin{cases} 
\max \{\{b_{i}\} \cup B_{\text{pre}}^{i}\} + \varepsilon, & \text{if } \alpha_{i} > \max \{\{b'_{i}\} \cup B_{\text{pre}}^{i}\} \\
\max \{\{b'_{i}\} \cup B_{\text{pre}}^{i}\} & \text{else}
\end{cases} \quad (3)
\]

The user agents’ algorithm is listed in Table 2.

<table>
<thead>
<tr>
<th>Table 2. User broker’s algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Algorithm:</strong> User Broker’s algorithm</td>
</tr>
<tr>
<td><strong>Input:</strong> A task set (T) from user.</td>
</tr>
<tr>
<td><strong>Output:</strong> Bid (b_{i}).</td>
</tr>
<tr>
<td>1. Firstly, user broker should apply to join in the auction. Send the applying request along with he expected victorious probability.</td>
</tr>
<tr>
<td>2. If the user broker is allowed to join the auction, goto step 3, else quit.</td>
</tr>
<tr>
<td>3. Calculate the primitive bid by Eq.(2).</td>
</tr>
<tr>
<td>4. Send predicting request to an analyst.</td>
</tr>
<tr>
<td>5. Waiting until received the predicting information (B_{\text{pre}}^{i}) from the analyst.</td>
</tr>
<tr>
<td>6. Adjust the bid by Eq.(3).</td>
</tr>
<tr>
<td>7. Send (b_{i}) to resource agent.</td>
</tr>
</tbody>
</table>
3.3 ESPSA model’s prediction algorithm

In ESPSA model, the entity of analyst based on HMM prediction model is introduced.

In HMM prediction model, hidden states couldn’t be got directly, but they can be deduced by observation sequences. In general, \( \lambda = (A, B, \pi) \) can be used to represent a HMM, where \( A \) represents a transition probability between state and \( B \) represents observation sequence, \( \pi \) represents initial states matrix. Given the definitions of \( A \), \( B \) and \( \pi \), the HMM can generate a observation sequence: \( Q = O_1, O_2, O_3, \ldots, O_t \).

In ESPSA model, the resource demand quantities and bids that are submitted by user brokers corresponds to observation sequence and hidden states respectively. When an auction launched, each resource broker publishes its attributes, such as process elements’ computing capacity, load status and so on. Each user broker can get the attributes. And then, User brokers use observed resource demand quantities \( D_j = \{d_{1,j}, d_{2,j}, \ldots, d_{l,j}, \ldots, d_{k,j}\} \) to predict their rivals’ bids in next round auction: \( r_j = \{r_{1,j}, r_{2,j}, \ldots, r_{l,j}, \ldots, r_{k,j}\} \). We take five bids for examples, written as \( \text{level1\_bidding}, \text{level2\_bidding}, \text{level3\_bidding}, \text{level4\_bidding} \) and \( \text{level5\_bidding} \) respectively, which correspond to the zones of \( \{0, b_1\} \), \( \{b_1, b_2\} \), \( \{b_2, b_3\} \), \( \{b_3, b_4\} \), \( \{b_4, b_5\} \), \( \{b_5, b_6\} \), \( \{b_6, b_7\} \), \( \{b_7, b_8\} \), \( \{b_8, \infty\} \).

At time \( t \), for user \( i \), its bid for resource \( j \) is \( b_{i,j}^{t} \), and its resource demand quantity for \( j \) is \( d_{i,j}^{t} \). Suppose that there exit \( m \) resources in grid system, according to HMM, the initial states at time \( t \) are:

\[
\pi = \text{states} = \{b_{1,i}^{0}, b_{2,i}^{0}, \ldots, b_{l,i}^{0}, \ldots, b_{m,i}^{0}\}
\]

And at time \( t \), the resource demand quantity matrix that user broker \( i \) observes other user brokers’ is:

\[
B = \text{observations} = \{d_{1,i}^{t}, d_{2,i}^{t}, \ldots, d_{l,i}^{t}, \ldots, d_{m,i}^{t}\}
\]

The transition matrix from hidden states at time \( t-1 \) to hidden states at time \( t \) is:

\[
A = \text{transition \_ probability} = \begin{bmatrix}
    b_{1,1} & b_{1,2} & \ldots & b_{1,m} \\
    b_{2,1} & b_{2,2} & \ldots & b_{2,m} \\
    \vdots & \vdots & \ddots & \vdots \\
    b_{l,1} & b_{l,2} & \ldots & b_{l,m}
\end{bmatrix}
\]

(6)

The emission matrix between observation sequences and hidden states is:

\[
\text{emission \_ probability}= \begin{bmatrix}
    obs_1 \quad obs_2 \quad \ldots \quad obs_m \\
    \text{sta}_1 \quad p'_{11} \quad p'_{12} \quad \ldots \quad p'_{1m} \\
    \text{sta}_2 \quad p'_{21} \quad p'_{22} \quad \ldots \quad p'_{2m} \\
    \vdots \quad \vdots \quad \ddots \quad \vdots \\
    \text{sta}_n \quad p'_{n1} \quad p'_{n2} \quad \ldots \quad p'_{nm}
\end{bmatrix}
\]

(7)

where \( p'_{ij} \) represents the probability of \( \text{obs}_j \) when in state \( \text{sta}_i \) at time \( t \), \( i = 1, 2, \ldots, n \), \( j = 1, 2, \ldots, l \).

As stated above, in ESPSA model, the hidden states are correlated with observation states by emission matrix. Specifically, given the hidden and observation states corresponding to bidding prices and resource demand quantity respectively, the ESPSA can calculate the user brokers’ bids.

4. Simulation results and analysis

The GridSim toolkit [9] is utilized in the simulation of this paper. Resource entities, user entities, broker entities and information about resource demand are considered.

4.1 Simulation parameters

It is necessary to make some initial setting reasonable by training especially the parameters used in HMM. There exist 300 resources in the resource queue, which means the user brokers may take part in at most 300 auctions. Table 3 lists the properties of the four resources.

<table>
<thead>
<tr>
<th>Name</th>
<th>Resource characteristics</th>
<th>PE number</th>
<th>A PE MIPS rating</th>
<th>Transmittin g Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>( R_0 )</td>
<td>Sun Ultra, Solaris</td>
<td>2</td>
<td>320</td>
<td>2000MB/s</td>
</tr>
<tr>
<td>( R_1 )</td>
<td>Sun Ultra, Solaris</td>
<td>4</td>
<td>350</td>
<td>2000MB/s</td>
</tr>
<tr>
<td>( R_2 )</td>
<td>Pentium/VC820, Intel</td>
<td>1</td>
<td>370</td>
<td>2500MB/s</td>
</tr>
<tr>
<td>( R_3 )</td>
<td>Pentium/VC820, Linux</td>
<td>3</td>
<td>390</td>
<td>2500MB/s</td>
</tr>
</tbody>
</table>

4.2 Simulation scenarios and results

We compare the HMM prediction model with random bidding model and average prediction model. And numerous results in predicting of bids, actual bids and victorious probability are stated in this section.
4.2.1. Comparison between prediction models. After the training of data, the maximum bid value is limited to 20. And the amount of resources is set randomly in [0,100]. After 40 rounds of auctions, from Figure 2, we can envisage the comparison between the actual bids and prediction bids. It is obvious that the trend of HMM prediction bids approximates the actual bids most of the time. However, the mean value prediction bids fluctuate without any connection with the actual bids. Thus, we can conclude from the results that the prediction model based on HMM can approximate the actual bids better than the prediction method adopted by [1].

4.2.2. Victorious probability results of a two-player game. Suppose that two user brokers (UB1 and UB2) are competing in the game. Specifically, if UB1 adopts no prediction algorithm and UB2 utilizes the HMM prediction method, the results after 300 rounds of auctions are shown in Figure 3. It can be seen from Figure 3(a) that UB2 can achieve a much higher victorious probability.

If UB1 adopts the mean value prediction method, and UB2 still uses the HMM prediction method, the results is depicted in Figure 3(b). It is apparent that UB2’s victorious probability still exceeds the UB1’s.

4.2.3. Victorious probability results of a multiplayer game. According to the results of the two-player game, it is obvious that if all the players in the n-players game adopts the HMM prediction method, the victorious probabilities will converge at around 1/n. It means the expected victorious probabilities will be a very small value if a large amount of players join the
Thus, to avoid this problem, our algorithm of resource broker sets the number of bidders. This comparison between expected victorious probability and actual victorious probability are depicted in Figure.4.

![Figure 4. Comparison between expected and actual victorious probability](image)

In ESPSA, the resource broker limits the number of user brokers in one auction by the minimum expected victorious probability. For easy of reference, we use ESPSA-NNres to represent the ESPSA algorithms without user broker number restrictions. It can be seen from Figure.4 that the difference between expected victorious probability and actual victorious probability is much smaller in the ESPSA algorithm. In the 10th round of the auction, the average expected victorious probability is 0.4 and the result by ESPSA algorithm is 0.38. However, the ESPSA-NNres algorithm only gets a victorious probability of 0.34. Moreover, in the 30th round, user brokers’ expected victorious probability is 0.58, the ESPSA’s and ESPSA-NNres’s victorious probabilities are 0.5 and 0.18 respectively.

### 4.3 Results analysis

Authors in [1] utilized a mean value prediction method. Specifically, a player calculates his rival’s bid in the current round of auction by Eq.(8),

$$\tilde{b}^i = \frac{1}{j-1} \sum_{j=1}^{j-1} b^i$$  \hspace{1cm} (8)

Then, the player only need to bid a litter higher than the prediction bid.

We adopt the Cobb-Douglas production function to calculate the actual value (As Eq.(9) shows).

$$v(T, R, \alpha) = \eta((1 - \alpha) \ln T + \alpha \ln R)$$  \hspace{1cm} (9)

$T$ represents the expected time that the user want to hold the resource. $R$ represents the amount of resources that users want to have. $\alpha$ is a weighted factor which represents the preference of $T$ and $R$. $\eta$ is the profit that brought by the unit payoff. In the experiment, we set $\eta = 20$ and $\alpha = 0.95$. Given one user broker’s historical resource demand quantities, through Eq.(9), the actual bid can be carried out.

By Eq.(8) and Eq.(9), the results are shown in Figure.2. The ESPSA algorithm performs better than the algorithm in [1] in approximating the actual value.

Figure.3 depicts the victorious probability results of random bidding, mean value prediction bidding and ESPSA prediction bidding strategies. Thus, the payoff matrixes can be given as follows.

![Figure 5. Payoff matrix 1 of a two-user game](image)

![Figure 6. Payoff matrix 2 of a two-user game](image)

From Figure.5 and Figure.6, it is obvious that the strict dominant strategy of user brokers is the ESPSA prediction strategy.

In a game, if a rational player has a strict dominant strategy, it will choose that strategy. In such way, the game reaches Nash equilibrium. For the reason that strict dominant strategy equilibrium must be a Nash equilibrium[1], the two-player game above has a Nash equilibrium:

$$S^* = (\text{ESPSA Strategy }, \text{ESPSA Strategy})$$

From the above analysis, we can conclude that the ESPSA predict strategy is superior to not only random bidding strategy but also mean value prediction strategy. Thus, all the rational players will choose the ESPSA strategy in the auction.

### 5. Conclusion and future work

The ESPSA model is proposed in this paper and the model focuses on the resource allocation problem in
grids. Firstly, we designed the interactions procedures between different entities in the ESPSA. Then, the algorithms of user and resource brokers are proposed. Specifically, in order to assure the victorious probability of each user broker, we introduce a bidder number restriction method in the resource broker’s algorithm. Moreover, the user broker gets prediction information from Analyst who adopts the HMM prediction model. Then, based on the prediction results, the user broker carries out its bid. Simulation results show that, the ESPSA algorithms bids performs better in the approximation to actual bids than random bidding and mean value predict strategy. Lastly, based on the simulation results, we analyzed the existence of Nash equilibrium.

It is worthwhile to note that the ESPSA model is much more applicable than some basic auction models. However, the network delay, fraud user, reliability of resources problems are not considered in this paper. Thus, how to make the model realistic, fulfill the QoS requirements of users and improve the resource scheduling algorithms form the next step of our work.

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7. References