AN IMPROVED PRICING APPROACH BASED ON COMBINATORIAL AUCTION METHOD IN CLOUD ENVIRONMENT

Seyyed-Mohammad Javadi-Moghaddam[1*], and Hamid Mohammadi Fard[2]

[1]Department of Computer Engineering, Bozorgmehr University of Qaenat, Iran (Islamic Republic of)
[2]The Parallel Programming Laboratory, Technical Universality of Darmstadt, Germany
*Corresponding Author

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ABSTRACT

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Cloud pricing models are essential in the context of the increasing availability of cloud service providers across the Internet and the willingness of users to use high-quality and affordable services. The double-sided combinatorial auction model has been used extensively due to its inherent characteristics. This paper presents a cost-effective pricing method that considers both the forward market and spot market. Moreover, resource requests are workflow or hybrid to support scalability and improve the number of federal cloud response requests. The evaluation results indicate more profit for both buyers and vendors simultaneously. Furthermore, the proposed algorithm reduces the waiting time and the number of pending demands, increasing users' satisfaction relative to cloud services.

Keywords: Two-way Hybrid Auction, Computational Resources, Pricing Model, Auction-based model, Cloud computing.

INTRODUCTION

Cloud computing is a widespread issue because of its advantages. Despite the variety of software and hardware provided by the cloud, clients prefer to utilize the virtual services quickly and without conflict with the complexities, such as purchase, installation, maintenance, and framework creation for use (Tabrizchi & Rafsanjani, 2020). Due to the presence of many cloud service providers on the Internet, and on the other hand, the increasing number of users willing to use such services with different Quality of Service (QoS), a competition between them arises. Buyers tend to utilize high-performance and low-cost resources. Likewise, sellers try to gain more profit by providing their services.

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Consequently, the pricing algorithm plays a significant role in maximizing profits and efficiency in resource utilization and managing the competition (Kansal et al., 2020). Pricing is a known, practical, and effective method in cloud computing. Various algorithms consider the value of resources, the quality of provided services, the amount of demand for resources, the time of resources usage, and other parameters to calculate the price. Users decide whether to use resources based on their needs, price, and quality of resources.

Although cloud computing resources are economical, various challenges remain. Pricing is particularly a problem that needs to be considered. There are two general pricing models of fixed and dynamic for resources. In fixed pricing (Abhishek et al., 2012), the cost of using resources is constant for each resource use. In contrast, the cost of using resources is determined according to different parameters in the dynamic pricing (Liu et al., 2019). Furthermore, it will change dynamically. Since dynamic pricing significantly impacts efficiency, fair competition between users, and more benefits, this paper applies it extensively.

There are several models for dynamic pricing (Yeganeh et al., 2019; Yuan et al., 2019). Each of the models focuses on a specific feature of the critical pricing elements. In a Bargaining model (Wu et al., 2019), brokers and resource providers negotiate for an arbitrary price. Registering suggested fees in the market guide is continued by the resource sellers. Then, the broker starts negotiating to reach the appropriate amount for both sides of the market. The problem with this method is much messaging. The model presented in (Zhang et al., 2019a), where the user's resource usage determines the cost of services. This method applies various parameters, such as usage time based on hours, supply, and demand. Each of these parameters can be the right candidate for new pricing models so that this article employs certain ones. The Tendering Contract-Net model (Zhang et al., 2019b) is used in distributed systems to negotiate services. In this way, the model initializes a bid. Then, the supplier offers its proposed prices. Finally, the service supplier receives the winning resource with the lowest price. Some researchers (Di Valerio et al., 2013) suggested using game theory to compute the price. Hu (Hu, 2019) introduced a method based on game theory that calculates the price using the learning curve and competition part. The algorithm proposed in (Zhang, 2020) ; first, the pricing is considered as an optimization problem. Then, a game-based model is used to adjust the price.

The auction model is one of the most widely used pricing methods in the cloud that calculate the price using a negotiation made by sellers and buyers (Dibaj et al., 2020). There are various types of auction, such as Double Dutch Auction (Jiang et al., 2018), Auction English, Auction Combination Auction (Wu et al., 2019), and Double-Sided Combinational Auction (Wang et al., 2018), that the next section discusses in more detail. At the English Auction, the model informs all auction participants about prices. They can increase their offer prices. Then, this trend continues until the participant is not willing to raise prices. At the Dutch Auction, the resource provider announces the proposed price. If there is not a buyer, the price will fall at a constant rate. The Double Auction considers the proposed price of both the seller and the buyer. Therefore, this model takes fairness into account. At Combination Auction, buyers can request a combination of resources and use their services and resources depending on their proposed price. Consequently, there is no winner in this mode, and it implements justice more effectively.

The auction pricing models, which act regarding negotiation between resource providers and service purchasers, will, in most cases, result in greater satisfaction for both sides of the markets (Wang et al., 2018). In these models, rules are laid down for the auction by the broker. Moreover, both parties are obliged to observe the principles and regulations. Some auction types include Bid-Proportional, Double Auction, Combinatorial Auction Multi-Unit, Combination Auction, and Double-Sided Combinational Auction.

The Double Auction model considers the prices of both sides in the market. Then, the final cost is estimated regarding them. Therefore, this model results in general welfare for the buyer and supplier (Angaphiwatchawal et al., 2020). In the Bid-Proportional Auction model (Tsai, 2012), resource providers advertise their resources before auctioning. Pre-auction information is available to buyers so that they can make more relevant suggestions. The disadvantage of this method is the constant demand rate per time unit. Moreover, there is no possibility to request resources in the combination method.

The flexibility and fairness of Combination Auction cause many cases to use it (Prasad et al., 2016). This model allows users to request resources in a combination way. Clients can utilize resources depending on the price of their demand. Using the idea of resource request in a combination manner and resource allocation according to the cost is a great help in increasing the flexibility of pricing models. Therefore, in this research, other factors, such as processing power and the speed in the resource choice, have been considered. The challenge of this method is that it requires precise scheduling of tasks. In (Borjigin et al., 2018; Fukuta, 2016), the researchers present an auction model with a combined auction method with copies of resources. Buyers bid their offer without knowing the price of their competitors. Different amounts are ranked for resources and randomly selected and offered to buyers. The advantage of this method is the allocation of resources in combination mode. Likewise, this method challenge is to choose prices randomly, which leads to a lack of price optimization.

Double-sided Combinational Auction (Hassanzadeh et al., 2016) is a modern and functional model with the features of the models mentioned above. Therefore, much research welcomes it. This model allows users to choose different combinations of resources. The turning point of this approach is justice and fairness. Moreover, the prices are only dependent on demand and supply. This paper aims to provide a method to improve the idea by considering new parameters for pricing and creating profits based on the model presented in (Fujiwara et al., 2012) and a double-sided combinational auction.

The combinatorial auction model is presented in (Diac, 2020), which cannot allocate different resources in different timeslots for workflows. In (Tan & Gurd, 2007), Tan suggests a double-sided auction model in which if a user needs to take multiple resources, he/she must send a request to various auctions.

All bidirectional bidding models are merely a currency unit for pricing. Other profitable features, such as less execution duration, faster response, the more significant financial benefit for the buyer and provider, are not integrated with a model when needed.

This paper proposes a double-sided combinatorial auction model. Moreover, the approach uses federal clouds to have high scalability and developmental ability. The novelty of the proposed model is the method, which calculates the profit of users and resource suppliers. For this purpose, it considers the benefit regarding the currency evaluation, the processing power, as well as the work speed in allocating the resource. When resource buyers seek high-speed critical jobs, they reserve the higher power resources. Therefore, high-speed is another benefit obtained.

The rest of the paper is organized as follows: Section 2 presents basic definitions and the proposed algorithm. Section3 presents the evaluation results and discussion. Finally, section 4 expresses the conclusion.

MATERIALS AND METHOD

Double-Sided Combinatorial Auction Model

Users may request different resources simultaneously. Moreover, sellers offer various services. The Double-sided combinatorial auction model allows ordering and delivering these types of services. The provided services' price depends on the conditions of supply and demand, which leads to fairness for both users and providers (Kumar et al., 2018).

The base model considers some assumptions:

- Service size is in an arbitrary unit. For example, service A makes 30 requests per second.
- Service includes arbitrary fractions; typically, in a 30-unit resource, ten units for user A and 20 ones for user B.
- One task is composed of smaller ones; for example, for a 40-unit, 30 units for service and ten ones for another service.
- One job can migrate from one server to another at runtime. Therefore, the task is suspended temporarily in server 1. Then, sever 2 executes it.

The hybrid auction model presented in (Kumar et al., 2018) offers two models of the market, including forwarding and spot models. The following section discusses these methods in detail.

Forward Combinatorial Auction Model

A forward auction can be applied for service allocation when there is a seller and multiple buyers (Fujiwara et al., 2012). While, in the combinatorial forward auction, buyers have requests for a combination of resources with preferences to pay if they get all resources; otherwise, they pay nothing. In this method, in the case of a resource with a more favorable price, users and suppliers attempt to replace it to gain more profit. Figures 1 and 2 show a market model including four timeslots, three service providers, and two buyers. User_1 has two services simultaneously, and user_2 requests the source at different times. In the first timeslot, user 2 takes service A. In the second timeslot, user 1 decides to have 20 units of resource A by paying more. Therefore, the model gives them to user 1. Moreover, this user needs 20 units of resource B that the model will assign to the user. At the third timeslot, provider 3 supplies the same resource at a lower price. Consequently, the user submits his/her request to provider 3 for execution. However, in the fourth timeslot, the user wants two more units of resource B. Therefore, all requested services are received from provider 3, and user_1 will resume his/her work through provider 2.

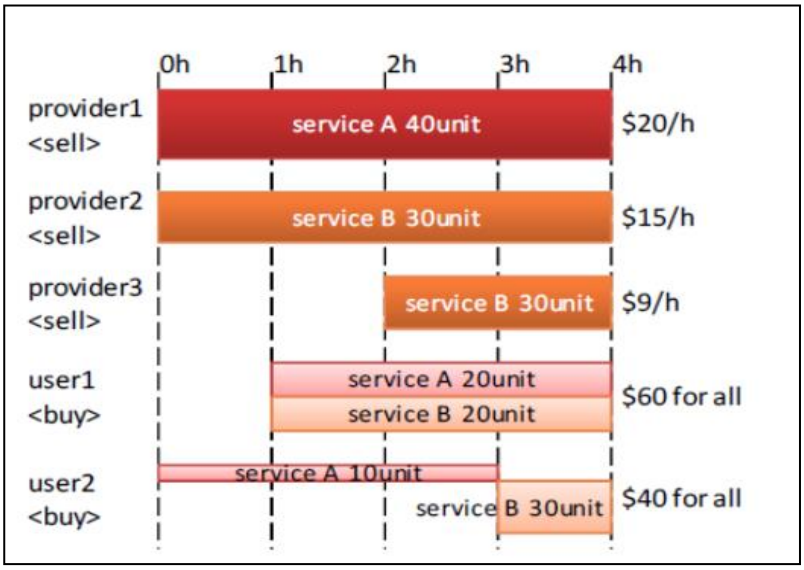


Figure. 1. The order of service request in the Forward Market (Sabzevari and Nejad, 2015).

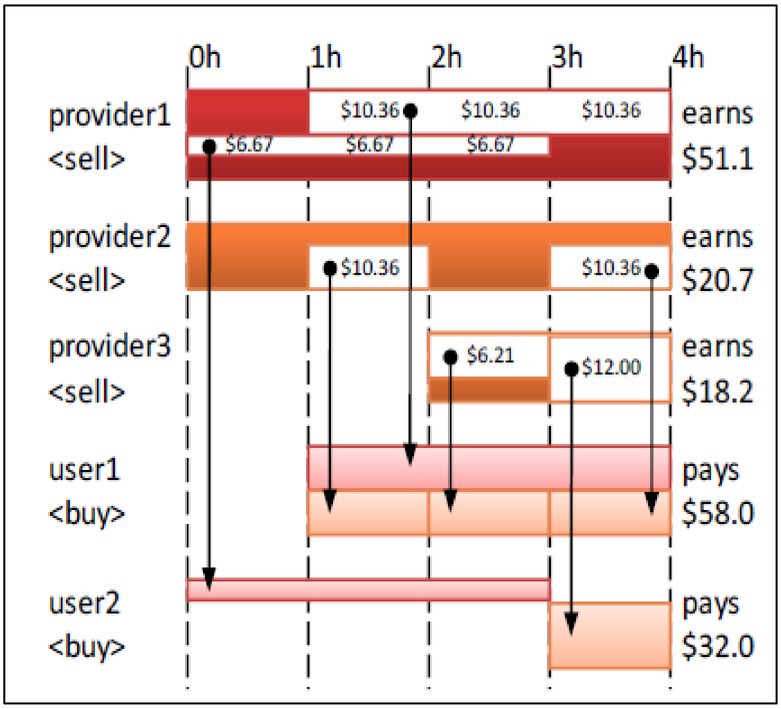


Figure. 2. The cost of the services during the timeslots in the Forward Market (Sabzevari and Nejad, 2015).

Spot Combinatorial Auction Model

In this model, there is one timeslot. The number of suppliers and resources is similar to the forward model. According to Figure 3a and 3b, both users request two services at different prices. Given that user 1 pays more money for using them, they are assigned to user_1 by the model. Thus, one client receives all or none of the resources (Kumar et al., 2018). Here, user_2 does not take any resources.

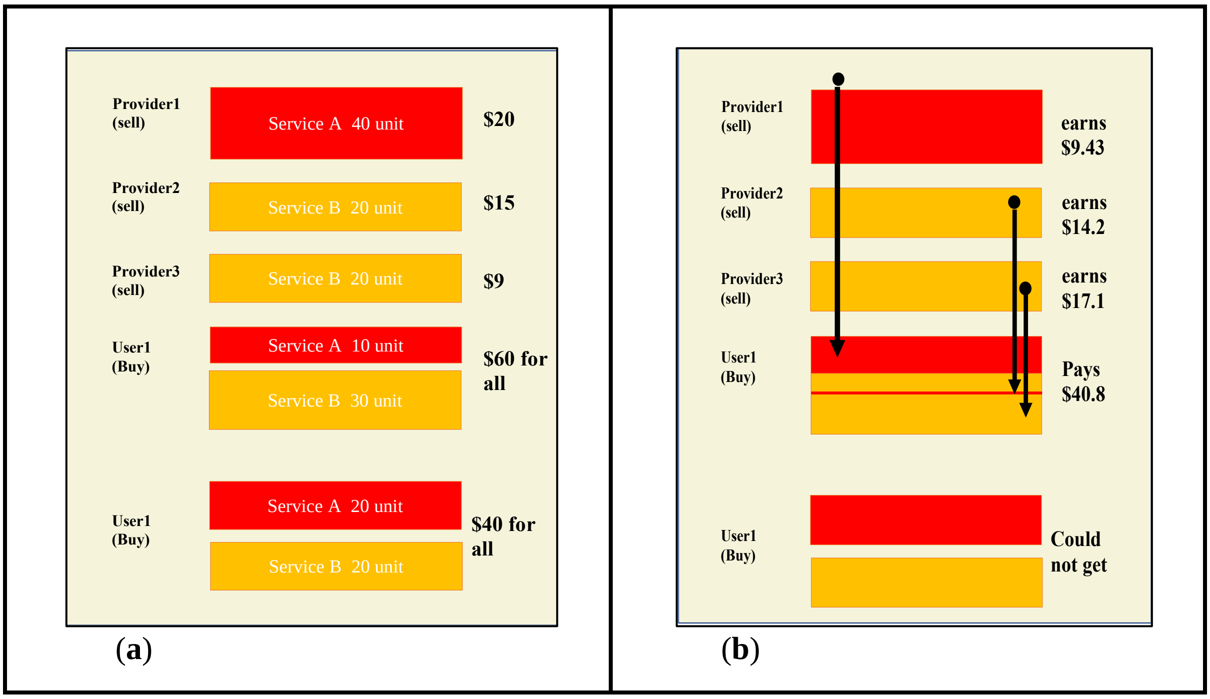


Figure 3. Combined Orders in the Spot Market a) The order of request b) The cost of the services during the timeslots (Sabzevari and Nejad, 2015).

Federal Cloud

Due to many changes in the requests, the provision of resources at the request peak is a fundamental challenge for the cloud provider (Kent, 2019). Since sellers often have a limited number of sources for the requests, the model may reject some due to a lack of resources. On the other hand, suppliers may decide to raise resources to maximize profits during busy hours.

One benefit of federal clouds is to solve this challenge by an agreement made for sharing the resources between multiple clouds. The process is as follows: Buyers submit their resource requests to the resource broker. Then, the resource broker enters into negotiations with the cloud service providers and looks for an available cloud resource. If there is no free resource in the cloud, it will send the request to another cloud. Since there are several clouds with various resources and prices, in most cases, the demand of users will be answered with a positive response.

This study uses the federal cloud regarding the scalability and expandability features.

Proposed Algorithm

This paper introduces a cost-effective algorithm that uses a double-ended combinatorial auction method. The proposed algorithm has innovations in assessing the profitability of users and providers. In this method, at the end of the auction, if a resource vendor offers a lower price or higher processing power, it is impossible to leave the resource and receive a cheaper and faster one unless the user ignores the paid cost. It is in the interest of the vendor because it can re-auction the resource at a lower price. On the other hand, the buyer may also benefit from these conditions by checking prices. The user may prefer to search in the resource queue and selects a higher-power resource that performs the task more quickly. Accordingly, the user ignores the cost of resource reservation and uses a more powerful and faster source. The high speed and processing power are the first aspects. Likewise, the cheaper factor is the second criterion in the pricing algorithm.

The proposed algorithm includes the following phases:

• ***Step 1: Initializing***

At this stage, the initial parameters, including the number of resources, suppliers, and buyers, as well as the maximum operating time and the auction duration, are determined.

• ***Step 2: Generating resources, suppliers, and buyers***

This step builds services or resources. Then, the providers are generated. Later, one or more services are assigned to them randomly. Moreover, the model produces buyers of services. This phase considers services with different power.

• ***Step 3: Getting Buyers Request List Phases***

Step 3-1: Getting Buyers Request List

In this step, the model receives a list of requests of buyers. Each buyer will send a demand depending on whether he/she needs to take the service at this timeslot and whether he/she needs to select from a spot auction or a forward auction.

Step 3-2: Holding the forward auction

If it is time to run the forward auction, it will run, and the model will reserve the services for the winners.

Step 3-3: Holding a Spot auction

If it is time to run the spot auction, it will run, and the model will reserve the resources for the winners.

Step 3-4: Allocating resources

At this stage, the model identifies the buyers who intend to use the service, which is reserved at the auction in the current timeslot, then:

• If there is a higher-level service, the current service is released, and a new one is received.

• If there is a service with a lower price with the same degree, then the current service is dropped off, and a new one is received.

• ***Step 4: Checking the termination condition***

The termination condition is the simulation time.

• ***Step 5: Compute the profit***

After processing, the price is calculated. The k-pricing method (Kumar et al., 2018) is used for the calculation of the price. Equation 1 is used to calculate the buyer's profit:

$$\boldsymbol{W = UserTotalPrice - \left(\sum_{for\ each\ service} num\ of\ TimeSlot * price\ for\ each\ timeSlot * num\ of\ Unit\right)} \quad (1)$$

where *UserTotalPrice* is the total amount offered by the buyer, *num of TimeSlot* is the number of timeslots, *price for each timeslot* is the seller's suggested price for each unit and each time slot, and *num of Unit* is the total number of service units used by the buyer. Then, the profit of buyer is computed by equation 2:

$$\boldsymbol{UserProfit = UserTotalPrice - (1 - k) * W} \quad (2)$$

where W is social welfare (Chun, 2020), and k is a constant with a value between 0 and 1. If k is high, it causes the user to pay more and consequently make less profit, and instead, the seller receives more profit and, therefore, more money from the user. K=0.5 makes the broker a fair amount to the buyer and seller to suggest.

The seller's profit is also calculated as follows. First, for each seller, the ratio of the total amount received from the buyer is determined by equation 3:

$$\boldsymbol{Ws = \frac{SellPrice}{\sum sellPrice}} \quad (3)$$

Then, the profit of seller is calculated by equation 4:

$$\boldsymbol{SellerProfit = SellPrice + (k * W * Ws)} \quad (4)$$

Figure 4 shows the proposed algorithm. Here, the higher grade for the service is a sign of more processing power for that source.

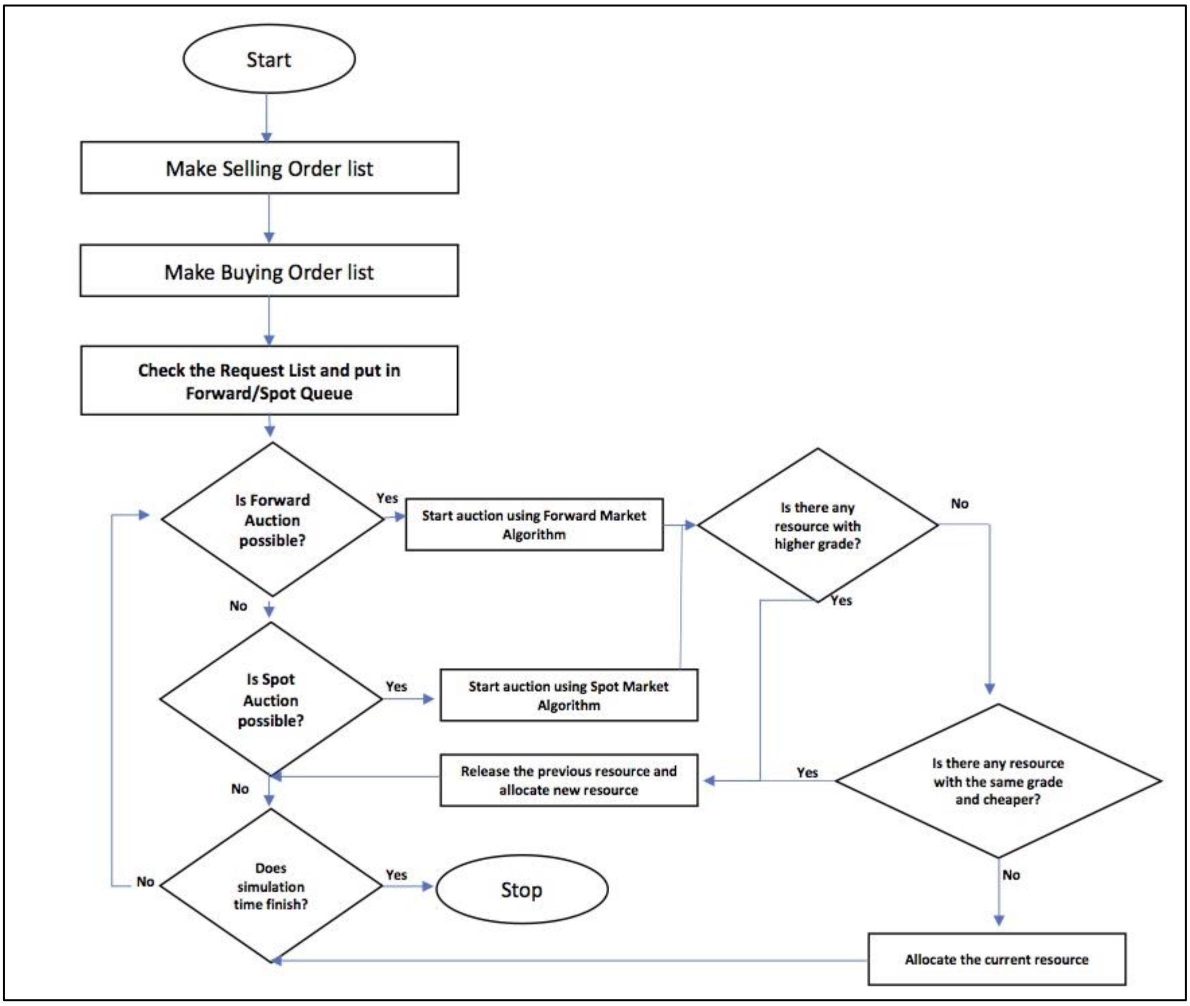


Figure 4. Flowchart of the Proposed Algorithm.

RESULTS

The proposed pricing algorithm and the **double-sided combinatorial auction model** (Kumar et al., 2018) were compared to evaluate the performance and efficiency of the proposed algorithm. The results are presented in a variety of diagrams and tables. The evaluation method has implemented two algorithms at timeslots 12, 24, 36, and 48. For comparison, the resources, requests, and vendors are accidentally initialized. Since resources, Requests and vendors are randomly assigned, the results of ten executions of the algorithms have been calculated. Finally, the average of the results and answers were received for the evaluation. The implementation language for both algorithms was Java programming. Table 1 shows the parameters used in the experiments. Moreover, Figure 5 describes the pseudocode of the proposed method. The profit of the seller is the total profit achieved by all vendors in the simulation. The buyer profit refers to the total profit earned by all buyers in the simulation. The amount exchanged expresses the total amount paid by buyers and received by vendors. The wait time also refers to the total number of slots when users wait for their service to be received. The total simulation runtime time refers to the program execution time, which is in milliseconds. The number of unanswered requests includes the total number of requests that buyers could not process their requested resource over time. The simulation method calculates the buyer and seller profits without considering these requests.

Forward/Spot Market Algorithm

Input: SellerNum, BuyerNum, ResourceNum, MaxTimeSlot, ForwardSlot, SpotSlot

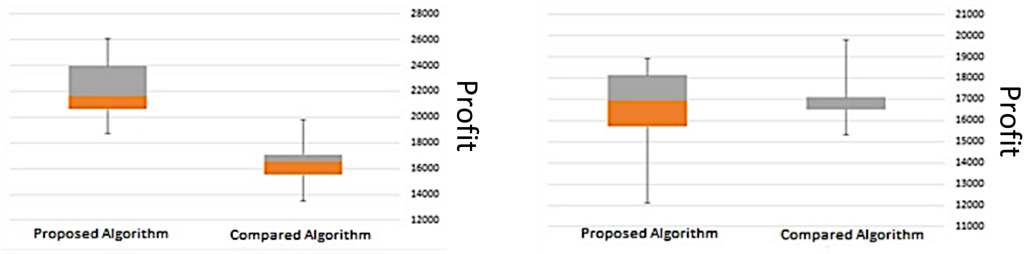
```
BookedList=Null, AssignList=Null;
Create Resource (ResourceNum);
SellAgent =Create Seller (SellerNum);
BuyerAgent = Create Buyer (BuyerNum);
SellerOrder = CreateSellerOrder (SellAgent);
BuyerOrder = CreateBuyerOrder (BuyerAgent);
for (loop=1:MaxTimeSlot)
{
      if (loop % ForwardSlot == 0)
      {//Forwar Auction
          for (i=1:BuyerOrdersize[])
                if (All resource in BuyerOrder (i) can be booked)
                     BookedList = BookedResource ();
      }
      if (loop % SpotSlot == 0)
      { // SpotAuction
                BookedList = BookedResource();
      }
AssignList = Assign Resource (BookedList);
CheckResource (AssignList);
CalculatePrice();
```

Figure 5. The pseudocode of the Proposed Algorithm.

Table 1. Parameters used in experiments

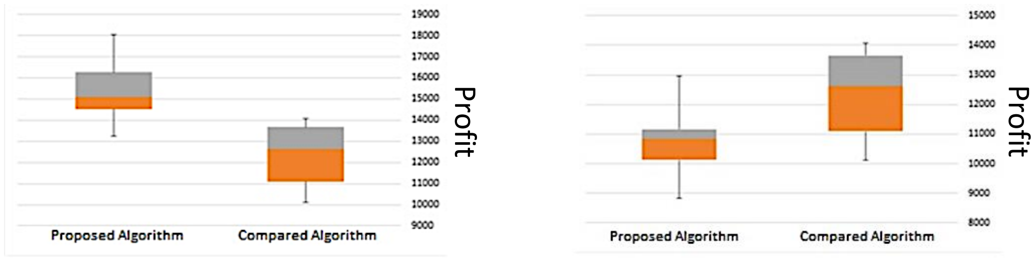
Parameter	Value
Resources	6
Buyers	20
Sellers	3
Maximum length of buying request	3
Slot of Forward Auction	4
Slot of Spot Auction	3

Figures 5-8 can help to determine and compare the distribution of the results. In these figures, the mean of profit for the buyer and the seller are depicted for the compared method and the proposed method.



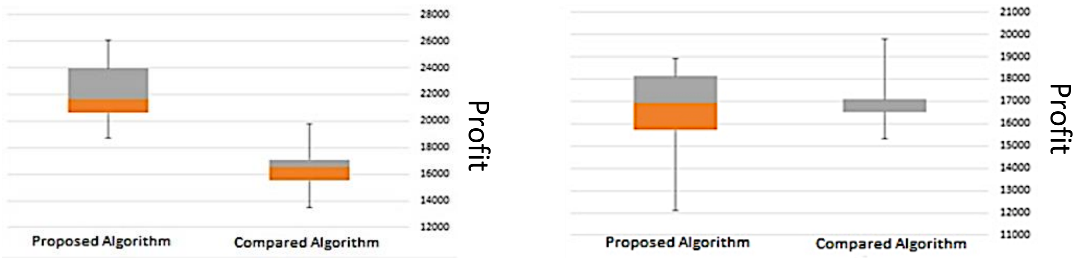
(a) **(b)**

Figure 5. a) Profit of Seller in Timeslot 12. b) Profit of Buyer in Timeslot 12.



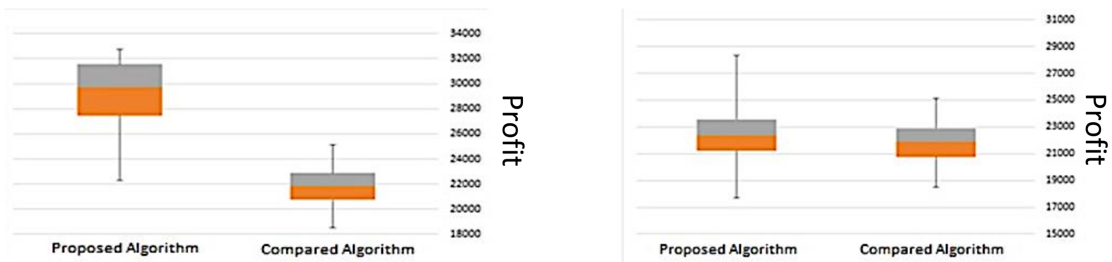
(a) **(b)**

Figure 6. a) Profit of Seller in Timeslot 24. b) Profit of Buyer in Timeslot 24.



(a) **(b)**

Figure 7. a) Profit of Seller in Timeslot 36. b) Profit of Buyer in Timeslot 36.



(a) **(b)**

Fig. 8. a) Profit of Seller in Timeslot 48. b) Profit of Buyer in Timeslot 48.

Figure 9 depicts the average timeslot when buyers are waiting for the service (booking in ten runs). In other words, vendor resources are limited. Therefore, buyers should wait until they are released and placed in the auction line. This chart specifies how many timeslots buyers expect to receive the service.

Figure 10 shows the average number of unresolved requests in the two algorithms. Due to the limited availability of services and the timeslot, the model will likely not deal with some requests (it will not give the service to them).

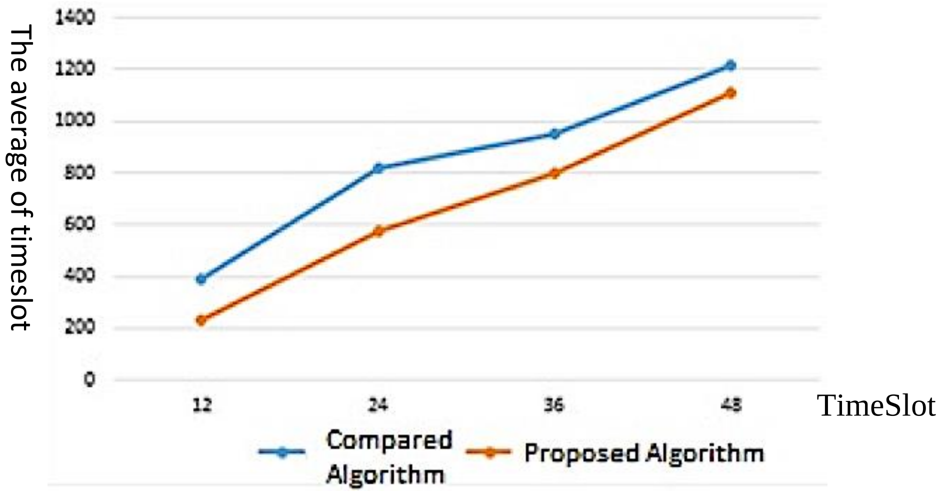


Figure 9. Chart Comparison of Expected Slots.

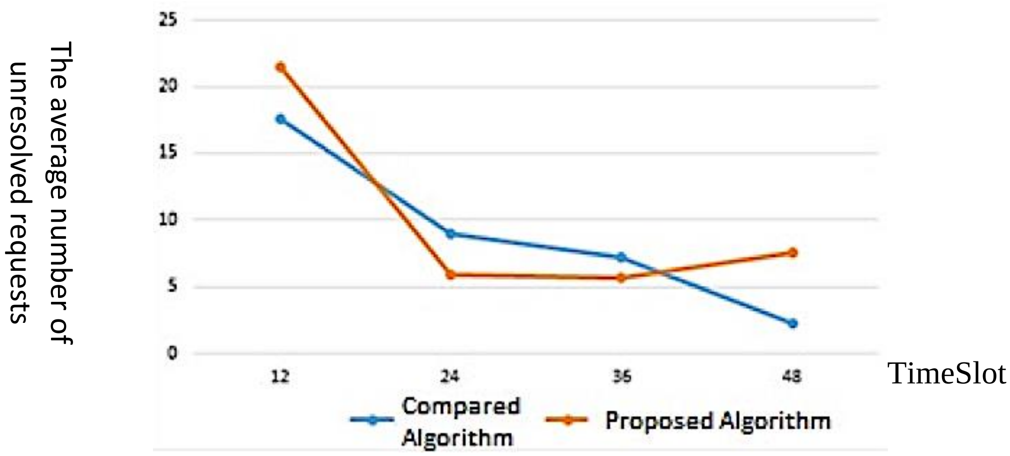
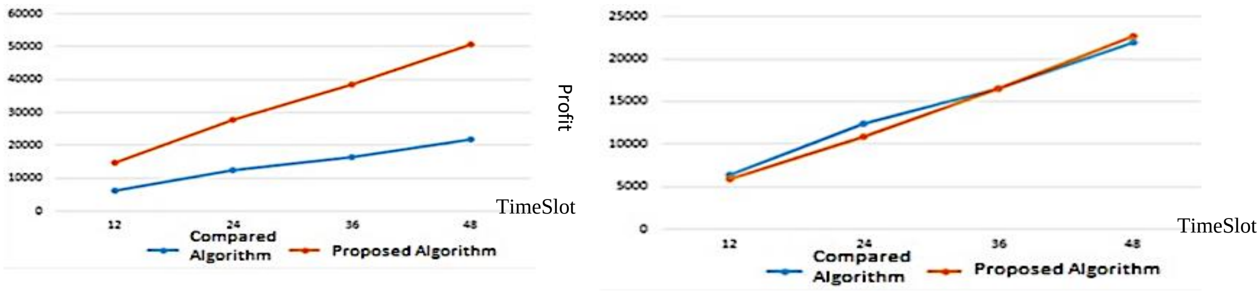


Figure 10. Compare the number of unresolved requests.

Figure 11-a compares the average value obtained for the seller profit in both algorithms over timeslots 12 through 48. In this chart, as expected, the proposed algorithm had better performance. If the system cancels service, the buyer will receive the service cost, which will provide more profit. Figure 11-b compares the average values for the buyer profit in two algorithms. Figure 11 depicts that both algorithms have almost the same result.



(a) (b)

Figure 11. Comparison Profit of Seller (a) and Buyer (b).

Table 2 shows the average results:

Table 2: Average results of evaluation

ime Slots	Methods	Average of seller profit	Average of buyer profit	Average of total exchanged	Average of waiting time to receive service (slot)	Average of not checked messages
2	**Compared Algorithm**	63140.03	6372.15	8420.61	391.7	17.6
	Proposed Algorithm	8309.01	5947.70	13776.71	228.9	21.5
4	**Compared Algorithm**	12378.36	12378.36	16221.93	821.3	9
	Proposed Algorithm	15364.14	10868.3	26678.43	572.7	5.9
6	**Compared Algorithm**	16529.36	16529.36	19986.2	951.8	7.2
	Proposed Algorithm	22055.326	16468.045	38881.34	802.7	5.7
8	**Compared Algorithm**	21920.69	21920.69	27868.81	1218.8	2.2
	Proposed Algorithm	28916.23	22621.22	49353.29	1109.5	7.6

DISCUSSION

Regarding the obtained data mean of figure 5, the proposed algorithm has achieved better values for ten different implementations, which means providing more profit for the seller (the line between the two colors shows the mean that it is orange and gray here). By comparing the minimum data (minimum), the minimum profit of the compared method is better than the proposed algorithm. Thus, it generally works better than the proposed algorithm. However, by comparing the maximum value, the proposed method provides more profit to the buyer. Of course, due to the considerable distance between the maximum value and the third quadrant, this amount cannot be considered the superiority of the proposed algorithm. If this distance was less, it could be a good reason because the data tends to the maximum value.

According to Figure 6-a, the mean value obtained for the proposed method is higher than the compared algorithm. On the other hand, the minimum and maximum values in the proposed approach are more than the compared one. As a result, the proposed algorithm has led to higher profits for the seller. Moreover, considering the minimum and maximum values, both values in the proposed method are less than the compared method. Therefore, the compared method has led to more profits for the buyer.

Figure 7-a shows a box chart of the seller in timeslot 36. Regarding the mean, the proposed algorithm has been able to provide a higher mean than the compared method; the comparison of the minimum and maximum values in both graphs confirms it. According to Figure 7-b, the compared method is more meaningful than the proposed algorithm. Although the proposed method has a higher maximum and a lower minimum than the compared method, the compared method data, given the data scattering (the distance between the second and third quarts that is half of the data), had higher values. Therefore, the compared method is more favorable and has provided more profits to vendors.

Regarding the second and middle quarters and the minimum and maximum values of Figure 8-a, the proposed method has a more favorable performance and may lead to higher profits for suppliers. Based on the mean profit of Figure 8-b, both methods are the same. However, the proposed method has a moderate and also a maximum value to the compared method. The minimum achieved in the proposed method is less than the compared method. However, about three-quarters of the data, the distance between the first quartile and the maximum value, suggested the proposed method to be efficient than the compared method.

According to Figure 9, buyers in the proposed algorithm had less time to wait. Figure 10 shows that the compared algorithm has a more uniform process. The proposed algorithm in timeslot 48 has not improved its performance (it reduced the number of unresolved requests). Moreover, the model analyzes two cases of unscheduled requests and also waiting times to satisfy buyers. The lower waiting times and the smaller number of unsolved requests indicate that the buyer's operations are speeding up. Consequently, it executes the work faster. According to Figures 9 and 10, in timeslots 24 and 36, both algorithms have provided more satisfaction for buyers. Likewise, in both timeslots 12 and 48, customer satisfaction is not possible.

CONCLUSION

The continuously increasing number of cloud service providers leads users welcomed by the services, which tend to use higher-quality and lower-priced features. On the other hand, suppliers try to achieve higher profits. Therefore, there is much competition between buyers and providers. Pricing models assist the management of these conditions. There are many pricing models; the bidding price of the bidirectional hybrid auction is significant due to its extraordinary efforts to ensure fairness and justice in resource allocation and profitability for clients and sellers. Therefore, in this research, a cost-effective algorithm based on a two-way hybrid auction is presented, which has innovation in calculating profitability. In the proposed algorithm, it is possible to have applications in both the workflow and the combination. The evaluation results show better performance of the proposed algorithm.

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