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# Cloud Broker: Customizing Services for Cloud Market Requirements

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**Abstract:** Cloud providers offer various purchasing options to enable users to tailor their costs according to their specific requirements, including on-demand, reserved instances, and spot instances. On-demand and spot instances satisfy short-term workloads, whereas reserved instances fulfill long-term instances. However, there are workloads that fall outside of either long-term or short-term categories. Consequently, there is a notable absence of services specifically tailored for medium-term workloads. On-demand services, while offering flexibility, often come with high costs. Spot instances, though cost-effective, carry the risk of termination. Reserved instances, while stable and less expensive, may have a remaining period that extends beyond the duration of users' tasks. This gap underscores the need for solutions that address the unique requirements and challenges associated with medium-term workloads in the cloud computing landscape. This paper introduces a new cloud broker that introduces IaaS services for medium-term workloads. On one hand, this broker strategically reserves resources from providers, and on the other hand, it interacts with users. Its interaction with users is twofold. It collects users' preferences regarding commitment term for medium-term workloads and then transforms the leased resources based on commitment term, aligning with the requirements of most users. To ensure profitability, the broker sells these services utilizing an auction algorithm. Hence, in this paper, an auction algorithm is introduced and developed, which treats cloud services as virtual assets and integrates the depreciation over time. The findings affirm the lack of services that fulfill medium workloads while ensuring the financial viabilty and profitability of the broker, given that the estimated return on investment (ROI) is acceptable.

**Keywords:** cloud broker; dynamic pricing; auction strategy; pricing options; commitment term; customized services



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## 1. Introduction

Infrastructure as a service (IaaS) is experiencing rapid growth as organizations are rapidly embracing IaaS solutions to decrease the complexity associated with handling physical infrastructure [1]. Cloud providers offer various purchasing options to empower users to tailor their costs according to their specific requirements, such as on-demand, reserved instances, and spot instances. Reserved instances favor stable long-term workloads, since they provide users with a significant discount compared to on-demand instances. On-demand instances cost more than reserved instances; however, users can purchase them according to the actual running time of their applications, so they are suitable for sporadic short-term workloads. Spot instances are also ideal for short-term use cases that could use cheaper instances but can handle sudden disruptions, such as batch processing and data analysis [2].

While these options offer users the flexibility to tailor costs according to their requirements and workload, they lack the prospect to customize the commitment term for instances where computing resources are required for workloads that fall outside of either long-term or short-term categories. Hence, there exists a lack of services suitable for medium-term workloads where on-demand services prove excessively costly; spot instances carry the risk of termination, and the reserved instances, while stable and less expensive, may have a prolonged remaining period once users' tasks are completed. Users that need stable compute resources for durations longer than several hours but shorter than one or three years may end up paying more than necessary. This is because on-demand pricing is expensive, reserved instances entail long commitment terms, and spot instances lack stability [3,4].

To address this challenge, the current paper introduces a cloud broker that acts as a intermediary between users and cloud providers and negotiates the relationships between cloud providers and cloud users [5]. This intermediary establishes a marketplace specializing in offering infrastructure as a service (IaaS) instances tailored for medium-term workloads. This is essential because on-demand and spot instances are suitable for short-term workloads, while reserved instances are typically utilized for longer-term commitments.

Initially, the broker strategically reserve resources from various providers. Acknowledging the lack of IaaS services suited for medium-term workloads, the broker introduces a dedicated medium-term marketplace. The broker collects and analyzes users' requirements and transforms the leased services into stable medium-term services aligned with the prevailing demands.

Cloud brokers, like any business model, aim to be profitable and increase revenues but at the same time assist users in cutting costs. This dual objective is reflected by the adoption of an auction strategy for the sale of brokers' services. Auction mechanisms involve bidders competing simultaneously, and this benefits sellers [6]. Additionally, brokers offer services like flexible purchasing options tailored to specific duration requirements, and sell them by using an auction algorithm. The proposed algorithm integrates the depreciation of an IaaS service over time, offering advantageous services to users. The algorithm is named Dynamically Defined Algorithm (DDA). The algorithm is evaluated based on Amazon instances, since Amazon is the leader in the IaaS market.

This broker provides significant advantages to users. Users benefit from substantial cost savings by opting for favorable commitment terms. Additionally, they sidestep vendor lock-in problems due to the broker's marketplace. By offering services from multiple providers, the broker enables users to switch vendors seamlessly, without facing excessive fees, legal hurdles, or technical challenges.

The rest of the paper is organized as follows: Section 2 presents related works, whereas Section 3 describes the broker's marketplace. Section 4 introduces the proposed auction strategy and Section 5 presents the experimental results of the algorithm. Finally, Section 6 concludes the paper.

## 2. Related Work

The cloud broker serves as a crucial intermediary between cloud service providers and users, facilitating resource management, negotiating service-level agreements, and promoting cloud interoperability. This role is pivotal within the cloud environment, akin to its importance in conventional business models. The primary objective of a cloud broker is profitability, achieved while offering substantial benefits to users. Numerous papers in the relevant literature delve into the concept of the cloud broker, exploring its multifaceted roles and the factors associated with it. These studies contribute to a deeper understanding of the functionalities, challenges, and potential advancements within the realm of cloud brokerage.

### *2.1. Cloud Broker Roles*

The primary function of a broker is to empower the customer organization to select the most suitable vendor based on their business requirements. To this end, in [7], the authors described a novel brokerage-based architecture in the cloud, where the cloud brokers were responsible for the service selection. They designed an efficient indexing structure, called

B cloud-tree, for managing the information of a large number of cloud service providers. Finally, they developed the service selection algorithm that recommended the most suitable cloud services to the cloud consumers.

In [8], the authors introduced Schlouder, a broker of IaaS cloud resources able to provision and schedule independent jobs or static workflows according to strategies chosen by the client. This broker was an open-source project, in which new provisioning strategies could be plugged in by third parties. The effectiveness of the tool was demonstrated through experiments involving actual applications and platforms

A simulation-based approach for cloud brokerage ecosystems was explored in [9]. The tool was based on JAVA and JavaScript Object Notation (JSON) technologies. Its architecture, functionalities, and technological choices were described and were evaluated in a case study [9]. In addition, the broker effectively manages and optimizes cloud resources. In [10], the authors developed a dynamic resource provision model to predict the customer requests. This tool minimized the cloud customers' cost and increased the brokers' profitability.

In [11], the authors presented a resource management approach for deploying three-tier applications over a broker-based multicloud environment. Experiments were conducted on an extended cloudsim simulator using realistic session workloads that were synthesized based on different statistical distributions. Results indicated that the proposed environments led to improved resource utilization.

In [12], the authors addressed the cloud resource management problem in multicloud environments, focusing on reducing the monetary cost and the execution time of consumer applications using infrastructure as a service of multiple cloud providers. They proposed an efficient biased random-key genetic algorithm. The computational experiments over a large benchmark suite generated based on real cloud market resources indicated that the performance of the proposed approach outperformed the approaches proposed in the literature.

Moreover, a cloud broker facilitates and manages negotiations between providers and cloud users. In [13], a smart broker was described, implementing a multicriteria decision-making (MCDM) method to maximize utility function so that the customer could choose services with required QoS performances. In addition, a negotiation model for the SLA and a context-based SLA contract ontology in IP Multimedia Subsystem (IMS) network was also proposed to provide users with a clear model to express their requirements and preferences. In [14], brokers settled negotiation models for the service-level agreement focusing on security issues. The proposed techniques and architectures were the result of jointly applying the security metrology-related techniques being developed by the EU FP7 project ABC4Trust and, the framework for SLA-based negotiation and cloud resource brokering proposed by the EU FP7 mOSAIC project.

Finally, a cloud broker is often correlated with cloud interoperability. In [15] authors proposed a new approach of cloud brokers' functional architecture to the cloud in order to deal with interoperability semantic and technical issues. They presented the cloud broker of an authentication system based on federated identity that secures and optimizes reliable access; this would increase technical interoperability. In addition, they set up a mechanism for dynamic management of services required by the user, which would increase the semantic aspect of interoperability.

Additionally, in [16], the researchers introduced a cloud broker designed to bridge the interoperability divide among various software-as-a-service (SaaS) providers. They implemented and assessed the proposed cloud broker using a real enterprise application dataset. The migration process was successfully executed, functioning in accordance with a predetermined mapping model.

Lastly, in [17], a meta-broker model was outlined. This model orchestrated various cloud brokers to establish a responsive cross-exchange and service automation system while providing transparency to users. The authors simulated an intercloud environment to measure the average execution time for numerous users, simultaneously submitting a significant number of services. The outcomes demonstrated efficient performance levels when employing the meta-brokering solution.

### 2.2. Profitability of a Cloud Broker

In [18], a novel type of broker was introduced, which relied on outsourcing virtual machines (VMs) to customers. This paper introduced the virtual machine planning problem, aimed at maximizing the broker's profit. The paper proposed several efficient smart heuristics to allocate a set of VM requests from customers to available prebooked ones, thus maximizing the broker's earnings.

Furthermore, in [19], a pricing scheme known as priority pricing was designed to address idle resource waste, while also ensuring fairness and prioritizing certain users. In addition, in [20], they concentrated on sporadic workload, wherein the computing requirements of users were maybe less than an hour. Two algorithms were introduced to maximize the profit of cloud brokers. These algorithms utilized dynamic pricing to adjust user demand within quantized billing cycles and were inspired by the ski-rental problem.

In [21], a profit maximization problem was formulated, incorporating optimal multiserver configuration and VM pricing. The paper also introduced a heuristic method to tackle this optimization challenge. Moreover, in [22], the concept of the cloud broker was presented as a new intermediary between cloud providers and users. This intermediary role was characterized by a multiserver setup, alongside revenue and cost models. Additionally, the paper emphasized the significant influence of users' demand on the broker's profit maximization dilemma.

The authors of the current paper examined broker's profitability in [23]. They introduced a profit maximization economic model, which introduced time-based stable cloud bundles into the retail market. Specifically, the proposed broker reserved a quantity of infrastructure from an IaaS provider for an extended period. Within this timeframe, corresponding to the evaluation period of the investment, the broker created bundles and offered them in the marketplace for a shorter duration, at a price higher than the reserved price but less than the current on-demand price of the provider for each time period. Various pricing policies were considered, aiming to estimate the profit and consumer surplus generated by each policy.

### 2.3. Auction Strategy in Cloud

In an open, competitive market, like the cloud computing market, providers set an auction strategy to maximize their profits. Auctions are a well-established strategy in the cloud market for resource allocation [24] and are one of the most popular economic approaches for pricing [25]. Different types of auctions are utilized to suit various situations. Among the auction formats employed in cloud pricing are single-sided, double-sided, first price, and second price auctions [26].

In [27], the authors proposed a set of bidding strategies to minimize the cost and volatility of resource provisioning. They evaluated their model and indicated how users should bid optimally on spot instances to reach different objectives with desired levels of confidence. Moreover, in [28], the authors proposed a static bidding strategy for minimizing the monetary cost of a batch job with hard deadline constraints. The problem was formulated as a Markov chain process and dynamic programming was used in order to highlight the optimal bid in polynomial time. Amazon spot instance prices were used for the evaluation of the model and the proposed algorithm successfully outperformed two state-of-the-art dynamic bidding strategies (Amazing, DBA), and several deadline agnostic static bidding strategies with minimum cost.

In [29], two different scenarios, based on cloud brokers, were discussed. Initially, brokers adopted bidding to reserve computing resources from remote public clouds, whereas as in the second scenario, brokers cooperated in the bidding, aiming at a minimum average cost of resources. Finally, in [26] a dynamic online double auction mechanism (DODAM) for users and cloud brokers was developed, based on the pricing for cloud computing services. As derived by the results, the proposed algorithm outperformed similar double auction models in terms of social welfare.

*2.4. Aim and Contribution of This Work*

The proposed broker offers an IaaS service for medium-term workloads, addressing the issue of idle resource waste. The broker collects users requirements based on commitment term and provides IaaS services with customized terms in alignment with market trends. Through the transformation of reserved instances into stable instances with medium-term commitment terms and selling them at a discounted rate, the broker optimizes resource utilization, effectively minimizing wastage. Moreover, this work explores specific market requirements that may not have been fully met in the literature. This targeted approach can lead to more tailored services, catering to a wider range of user requirements.

Within the cloud market, Amazon EC2 established a reserved instance marketplace. This platform enabled cloud users to trade their AWS unused reserved instances, which came with varying contract lengths and pricing options. This initiative aimed to prevent the wastage of unused reservations and offered users a means to optimize their resources effectively. The underlying concept of the marketplace is to empower teams with enhanced flexibility and cost savings, recognizing the inherent challenge of accurately predicting workload demands in advance. However, the AWS marketplace is no longer allowing its customers to resell reserved instances, starting 15 January 2024 [30]. Despite this, the concept of a medium-term marketplace remains trustworthy, particularly given its introduction by Amazon, a leader in the cloud market. This broker, leveraging the Amazon marketplace, provides a platform where users can procure medium-term instances sourced from various providers.

In the literature, the authors in [18,19,22] addressed idle resource waste by introducing a broker that leased reserved instances but transformed them into on-demand instances and sold them at a lower price than providers. Moreover, the authors of the current work in [31] introduced a broker that sells time-based instances to cover a specific gap in the market and literature. In our prior study, we substantiated the profitability of a broker specializing in the sale of medium-term instances. In this present paper, we unveil the medium-term cloud marketplace associated with the broker and present an auction algorithm. To the best of our knowledge, no existing research introduces a marketplace offering medium-term solutions akin to ours.

Adopting auction strategy has been adopted in the cloud market. It has been already utilized in the cloud market by Amazon AWS, which offers to users the option to purchase spot instances via bidding [32]. In the literature, authors have proposed auction algorithms in spot instances [27,28] and mobile computing [29]. In the current paper, we introduce and develop an auction mechanism that integrates cloud services' depreciation in stable instances and considers IaaS services as virtual assets. This algorithm empowers the broker to provide users with advantageous cloud services, thereby establishing a competitive edge over other providers or brokers. Finally, it provides practical insights that can benefit industry stakeholders and cloud service providers.

## 3. Cloud Broker: Medium-Term Workload Marketplace

Currently, users that need medium-term instances are faced with two suboptimal choices: either paying more for on-demand services or committing to reserved instances without fully utilizing them. To address this gap, the cloud broker introduces a novel purchasing option that offers a medium commitment term. This approach allows users to align their resource allocation with their actual requirements, avoiding unnecessary costs associated with overpaying for on-demand services or underutilizing reserved instances. Figure 1 illustrates an overview of the purchasing options in the cloud market, including brokers' services.

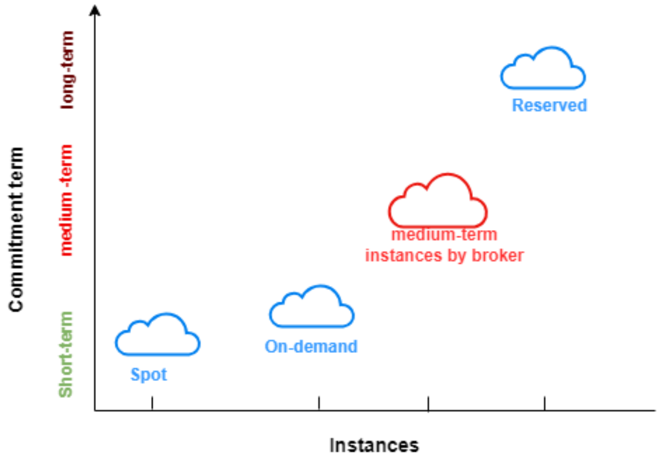


**Figure 1.** Brokers' services in the cloud market.

The cloud broker marketplace includes the following entities, as presented in Figure 2:

- Providers: Cloud providers act as sellers and supply brokers with IaaS services.
- Users: Cloud users acquire cloud services for their medium-term workloads.
- Broker: Initially, the cloud broker interacts with providers and leases reserved instances, gaining a significant discount. Then, the broker interacts with users using a twofold approach.
  - The broker collects users' requirements concerning commitment term for medium-term workloads. Based on these demands, the broker introduces VMs with commitment terms that meet the requirements of the majority of users.
  - Lastly, the broker sells the VMs using an auction algorithm.

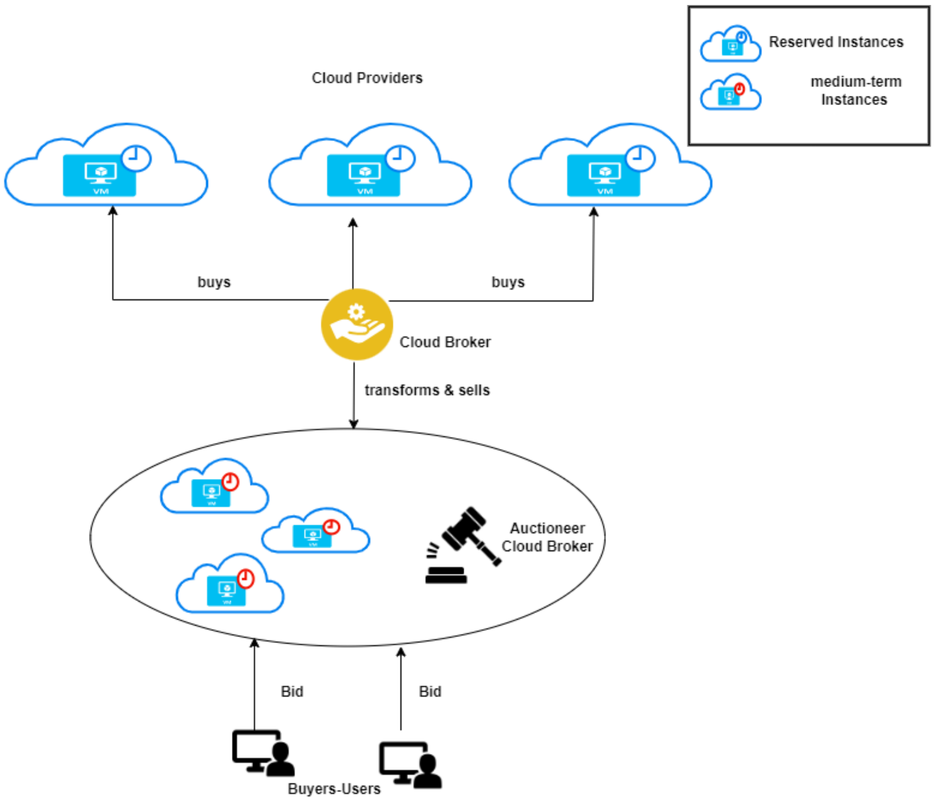


**Figure 2.** Overview of cloud broker marketplace.

*Engaging Users: The Dual Interaction of the Broker*

The broker has a dual interaction with the users.

- It generates VMs for the medium term, tailored to meet the demands of medium-term workloads.
- It acts as auctioneer and performs an auction algorithm for the sale of the VMs.

Firstly, users register on broker's marketplace, requiring VMs for medium-term workloads. Subsequently, they submit their commitment term requirements as $K = [k_1, k_2, \ldots k_n]$, where $k_i$ denotes the commitment term for user $i$. The collected requirements provide insights into the market trend for the duration of the medium-term workloads, enabling the broker to identify a commitment term $k$ that satisfies the requirements of the majority of users. The communication flow between users and brokers for the VMs creation is represented in Figure 3.

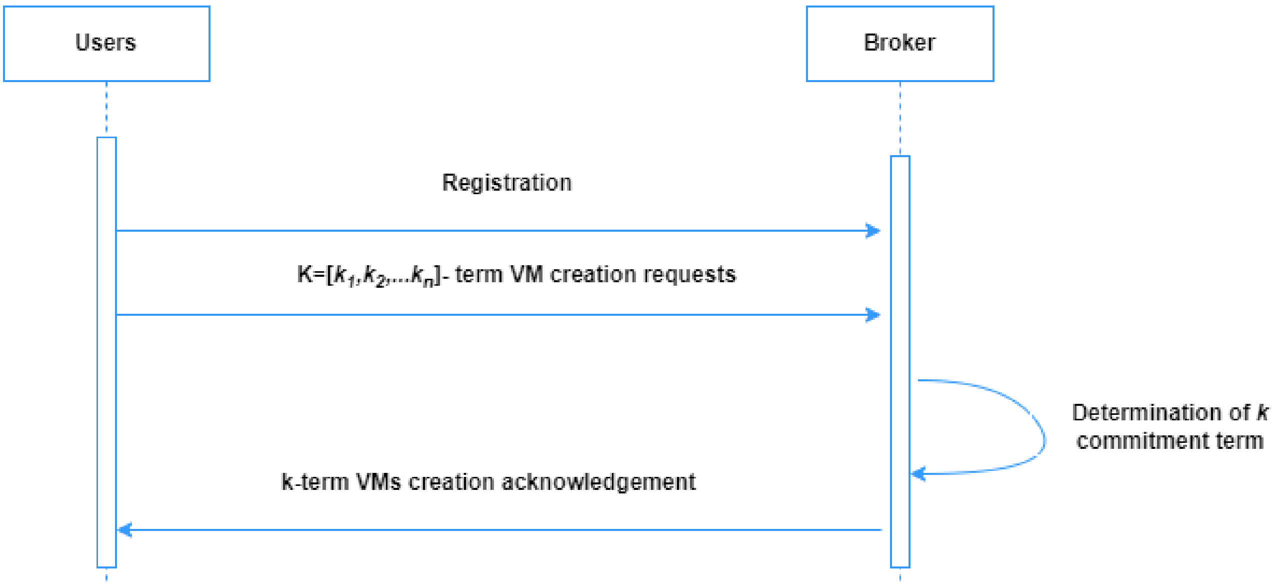


**Figure 3.** Communication flow between users and brokers for the VMs creation.

After the VM creation, the broker sells the VMs by using an auction algorithm. The developed algorithm, named Dynamically Defined Algorithm (DDA), integrates the depreciation of cloud services throughout the reserved duration of the service. Specifically, depreciation represents the decrease in the value of an asset due to its continuous deterioration through its useful life [33]. The term depreciation is employed similarly to its application with physical assets, based on the assumption that the cloud service is a virtual asset. In this context, broker sets maximum and minimum limits in each bidding cycle, denoting the depreciation over time.

Figure 4 illustrates the sequence diagram of the auction. The cloud broker and users are the required entities in the proposed auction model. These entities are explained as follows:

- The broker announces VMs with a specified commitment term ($k$) and incorporates the cost reduction resulting from the depreciation of the cloud service by establishing maximum and minimum limits on the bids of the users. Finally, the bids of the winning bidders are accepted, and the resources are allocated accordingly.
- Cloud users bid and acquire cloud services.

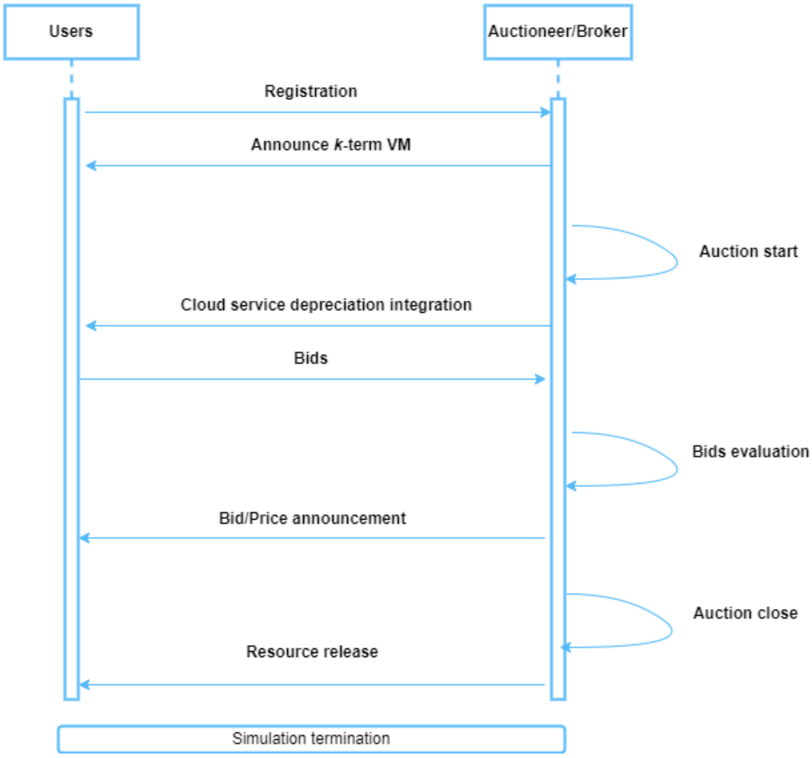


**Figure 4.** Dynamically Defined Algorithm sequence diagram.

## 4. Proposed Auction Strategy

In this section, we present the design and the mathematical formulation of the auction mechanism.

### *4.1. Auction Mechanism Design*

The primary objective of the broker is to achieve profitability and maintain competitiveness. Therefore, the Dynamically Defined Algorithm incorporates two auctioning methods: English auction and Vickrey auction. The fundamental concept of the proposed algorithm is to initially cover the cost of the investment. Once this objective is met, the broker transitions to a competitive strategy aimed at achieving minimum prices. To achieve this, the algorithm combines elements of both English and Vickrey auctions. In an English auction, the auctioneer starts with a low price and gradually increases it until no bidder is willing to bid higher than the current highest price. On the other hand, in a Vickrey auction, the highest bidder wins the item at the price of the second-highest bid [23,34].

In this spirit, the English auction is initially employed to cover the investment cost, ensuring profitability. Subsequently, the Vickrey auction is utilized to regulate the actual value of the VM, enabling end-users to reduce spending costs. This sequential use of both auction types allows for effective cost management and competitive pricing strategies within the cloud broker framework. Figure 5 illustrates the switching between the selected auction algorithms.

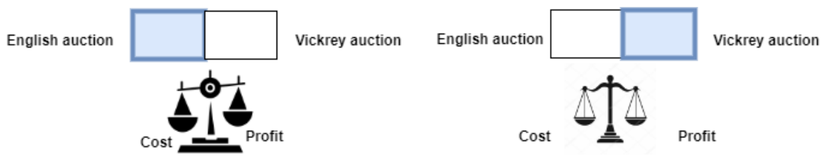


**Figure 5.** English and Vickrey switching.

### 4.2. Mathematical Formulation of the DDA Algorithm

The cloud broker leases reserved instances for $t_{res}$ years (either 1-year or 3-year terms) at price $C_0$, gaining a significant discount ($dis$) compared to on-demand price $P_{ond}$. Since the broker introduces medium-term services, the proposed services are outsourced for a shorter billing cycle ($k$), such as a 3-month billing cycle.

DDA has the following input values:

- On-demand price $P_{ond}$;
- Leasing time from the provider (commitment term), $t_{res}$;
- The discount offered by the provider, ($dis$);
- Selected billing cycle based on users requirements, $k$.

The proposed algorithm returns the following:

- It establishes bidding values by defining minimum and maximum limits during the auction, taking into account the depreciation of cloud service prices over time.
- It estimates return of investment (ROI) and the utilization of the VMs, evaluating the broker's profitability [35].

In our algorithm, the time period is denoted as bidding cycles, in which users, who are interested in purchasing VMs, can freely join and leave the auction during the $N$ cycles. The numbers of $N$ bidding cycles are indicated in Equation (1).

$$N = \frac{t_{res}}{k} \tag{1}$$

where $t_{res}$ is the leasing period from the cloud providers and $k$ is the customized lease term that the broker offers to users.

The depreciation of cloud service is integrated in the algorithm; thus, a new variable is introduced, Dynamically Defined Variable (DDV), based on Equation (2). $DDV$ is a variable that assesses the amount of time that has passed since the beginning of the lease ($t$), and corresponds to the cost reduction of the cloud service due to a service's depreciation [36].

$$DDV = \frac{(t_{res} - t)}{t_{res}} \tag{2}$$

where $t_{res}$ is the commitment term of the reversed instance, leased from the provider, and $t$ is the amount of time that has passed since the beginning of the lease. The variable $t$ fluctuates between [0, $t_{res}$]. The variables $t_{res}$ and $t$ represent months.

Due to depreciation, in each bidding cycle, the broker indicates to bidders a maximum and minimum limit, between which buyers are able to place their bids. The maximum limit represents the provider's on-demand price since consumers have the option to lease directly from the provider, bypassing the broker. It is denoted as $D_{ond} = (D_{ond_1}, D_{ond_2}, \ldots D_{ond_i}, \ldots, D_{ond_N})$,where $i = 1, 2, 3, 4 \ldots N$, and it changes in each bidding cycle due to depreciation, as presented in Equation (3). In the first bidding cycle, $D_{ond}$ is obviously at the level of the on-demand price ($P_{ond}$) offered by cloud providers. For subsequent cycles, it is reduced by $DDV$.

$$D_{ond} = \frac{P_{ond}}{N} \times DDV \tag{3}$$

where $P_{ond}$ is the cloud provider on-demand price, $N$ is the number of bidding cycles, and $DDV$ corresponds to the cost reduction of the cloud service due to a service's depreciation in the corresponding bidding cycle.

The minimum limits of each bidding cycle are represented by $MinBid$. In each bidding cycle, the broker sells the resources and gains revenues ($R$). $R = [R_1, R_2, \ldots, R_i, \ldots, R_N]$ represents the revenue per cycle $i$, $i = 1, 2, 3, 4 \ldots N$. The remaining cost is reduced after each cycle if the bidding is successful. In the first bidding cycle ($i$ = 0), the cost is $C_0$, and in the subsequent cycles, the remaining cost is diminished by deducting the profit of each cycle. Equation (4) represents the calculation of $MinBid$ in each bidding cycle $i$, whereas Figure 6 graphically shows the limits of the DDA.

$$Minbid = \frac{C_0 - \sum_{m=1}^{i-1} R_m}{N} \times \text{DDV} \tag{4}$$

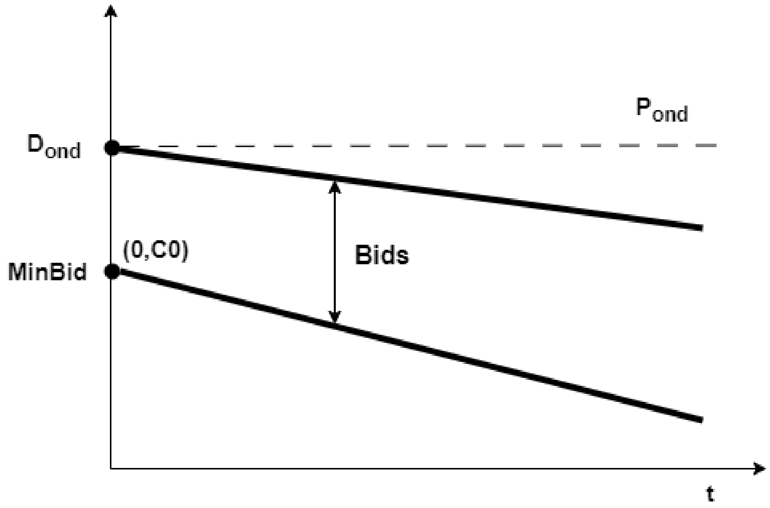


**Figure 6.** Limits of the DDA.

To assess the profitability of the broker, the return of investment (ROI) [35] is calculated. The $ROI$ value depends on both the total profit ($P$) and the original cost of the investment ($C_0$), as presented in Equations (5) and (6).

$$P = C_0 - \sum_{i=1}^{N} R_i, \tag{5}$$

where $R_i$ is the revenue of each bidding cycle.

$$ROI(\%) = \frac{P - C_0}{C_0} \times 100 \tag{6}$$

In addition to the $ROI$, the algorithm also calculates the cloud resource utilization. Utilization is defined as the ratio between the valid bidding cycles ($G$) during which the cloud resource was utilized by a bidder and the total bidding cycles $N$. Utilization aids the broker in predicting the future need for cloud resources and achieving better resource utilization overall.

$$Utilization\ (\%) = \frac{G}{N} \times 100 \tag{7}$$

The DDA algorithm of the broker was tested with various combinations of variables. The proposed algorithm was implemented in a Python environment. The conceptual view of the algorithm is outlined in Algorithms 1 and 2.

**Algorithm 1** Broker algorithm.

**Require:** $VMs[]$ ▷ Array of Available VMS
**Require:** $Duration$ ▷ Duration of Lease in Months
**Require:** $NumBids$ ▷ Number of Bids per Auction
**Require:** $Sims$ ▷ Number of Simulations to run
**Require:** $Pond$ ▷ On-Demand Price
**Require:** $Discount$ ▷ % Discount of Pond
**Require:** $N$ ▷ When bidding occurs (e.g., 1 month)
  $VMROI[] \leftarrow null$
  $VMusage[] \leftarrow null$
  **for** $i \leftarrow 0$ to $Sims$ **do**
    **for** $j \leftarrow 0$ to VMs.length **do**
      $VMROI[] \leftarrow null$
      $VMusage[] \leftarrow null$
      **for** $z \leftarrow 0$ to VMs[j] **do**
        $Bids[] \leftarrow null$
        $Payment \leftarrow 0$
        $Profit \leftarrow 0$
        $Cost \leftarrow \frac{(Pond \times (100 - Discount))}{100}$
        $OriginalCost \leftarrow Cost$
        $Utilization \leftarrow 0$
        **for** $Timer \leftarrow 0$ to Cycles **do**
          $ddv \leftarrow \frac{Duration - (Timer \times Cycles)}{Duration}$
          $Dond \leftarrow \frac{Pond}{Cycles} \times ddv$
          $Minbid \leftarrow \frac{Cost}{Cycles} \times ddv$
          **if** $Minbid < 0$ **then**
            $Minbid \leftarrow 0$
          **end if**
          $Mean \leftarrow \frac{(Dond + Minbid)}{2}$
          $Stdev \leftarrow \frac{(Dond - Minbid)}{2}$
          $BiddingFunction$
        **end for**
      **end for**
    **end for**
  **end for**
    **Returns** ROI and Utilization Charts

**Algorithm 2** Function: bidding.

  $Outliers \leftarrow 0$
  **for** $x \leftarrow 0$ to NumBids **do**
    $bid \leftarrow RandomNormal(Mean, Stdev)$
    **if** $Bid \leq MindBid$ OR $Bid > Dond$ **then**
      $Outliers \leftarrow Outliers$ +1
    **else if** $Bid \geq Dond$ **then**
      $Normbids[] \leftarrow 0$
    **else if then**
      $Normbids[] \leftarrow Bid$
    **end if**
  **end for**

**Algorithm 2** *Cont.*

**if** $Outliers < \frac{NumBids}{2}$ **then**
  **if** $Cost \geq P$ **then** ▷ British Auction
    $Payment \leftarrow max(Normbids[])$
  **else if then** ▷ Second Best Bid
    $Normbids[].remove(max(Normbids[]))$
    $Payment \leftarrow max(Normbids[])$
  **end if**
  **if** $Payment > 0$ **then**
    $Cost \leftarrow Cost - Payment$
    $P \leftarrow P + Payment$
    $Utilization \leftarrow Utilization + 1$
  **end if**
  $VMROI[] \leftarrow \frac{P-C_0}{C_0}$
  $VMusage[] \leftarrow \frac{Utilization \times 100}{cycles}$
**end if**

## 5. Experimental Results

In this section, we explain the experiment setup, which involves simulating the bidding procedure and evaluating the algorithm using two investment scenarios on Amazon's cloud services. While there are numerous cloud providers offering a variety of solutions, Amazon has consistently maintained its leadership in the IaaS market [37], holding the largest share for several years, as indicated by data on cloud market share. Therefore, Amazon was selected for evaluation of the algorithm. Amazon provides reserved instances with substantial discounts (up to 75%) compared to on-demand pricing.

### 5.1. Experiment Setup

The bidding procedure was simulated using a normal distribution (ND), which was employed to generate the bids. The mean and standard deviation of the ND were set as the *Minbid* and the *Dond* price, respectively, as presented in Equations (8) and (9).

$$Mean = \frac{Dond + Minbid}{2} \tag{8}$$

$$Standard\ Deviation = \frac{Dond - Minbid}{2} \tag{9}$$

Due to constraints on the selling price, bids generated at *Dond* or below *Minbid* were deemed outliers, indicating disinterest from bidders in the auction. If more than half of the bidders fall into this category, the corresponding bidding cycle is considered invalid, and the VM is assumed not to be sold for that period, resulting in decreased total usage of the cloud service. The broker then continues bidding with updated maximum and minimum limits. Additionally, the total number of valid bidding cycles is denoted by $G$.

### 5.2. Results

The evaluation of the DDA algorithm is based on the following assumptions:

- The broker leases IaaS reserved services from Amazon AWS, gaining a significant discount [38].
- The algorithm undergoes testing in two distinct investment scenarios, serving as diverse use cases to assess results in terms of both profitability and utilization. The broker leases VMs from Amazon for 1 year and 3 years, respectively, and the discount that it gains from the provider varies in each scenario.
- The broker transforms the commitment terms for both 1-year and 3-year instances into a 6-month commitment term ($k$ = 6).

The input parameters of the algorithm are as follows:

- 1 Year investment scenario:
  - $Pond$ = EUR 1679.28;
  - $Discount$ = 41.22%;
  - Provider commitment term, $t_{res}$ = 12 (months);
  - $k$ commitment term, $k$ = 6 (6-month commitment term).
- 3 Year investment scenario:
  - $Pond$ = EUR 5037.00;
  - $Discount$ = 67.72%;
  - Provider commitment term, $t_{res}$ = 36 (months);
  - $k$ commitment term, $k$ = 6 (6-month commitment term).

The broker offers IaaS services with a 6-month commitment term ($k = 6$). Based on Equation (1), in the 1-year scenario, the broker performs two bidding cycles, ($N = 2$), whereas in the 3-year scenario, the broker performs six bidding cycles, ($N = 6$). The maximum and minimum limits for each scenario are estimated according to Equations (3) and (4). (3) and (4) are clearly decreased during each bidding cycle, owing to the depreciation of the service, giving the broker a competitive edge over providers.

In the 1-year scenario, the broker integrates depreciation and starts the auction with $D_{ond}$ set at EUR 839.64, whereas (4). is UER 493.54. It is obvious that (4).is approximately 41% lower than (3). In the second bidding cycle, the broker offers a further reduction, with (4) approximately 81% lower than (3).

In the 3-year scenario, the broker starts the auction with (3). set at EUR 839.5, while $Min_bid$ is EUR 274.35. At the outset of the auction, (4) is approximately 67% lower than (3). By the final bidding cycle, (4) averages a very low price ( EUR 14.1), indicating that the auctioning algorithm provides value not only to the broker but also to the users.

Overall, in both scenarios, the broker offers advantageous bidding ranges, leading to significant cost reductions for users. This demonstrates the effectiveness of the auctioning algorithm in optimizing resource utilization and delivering value to all parties involved. Figure 7 presents the price reduction of (4) and (3).

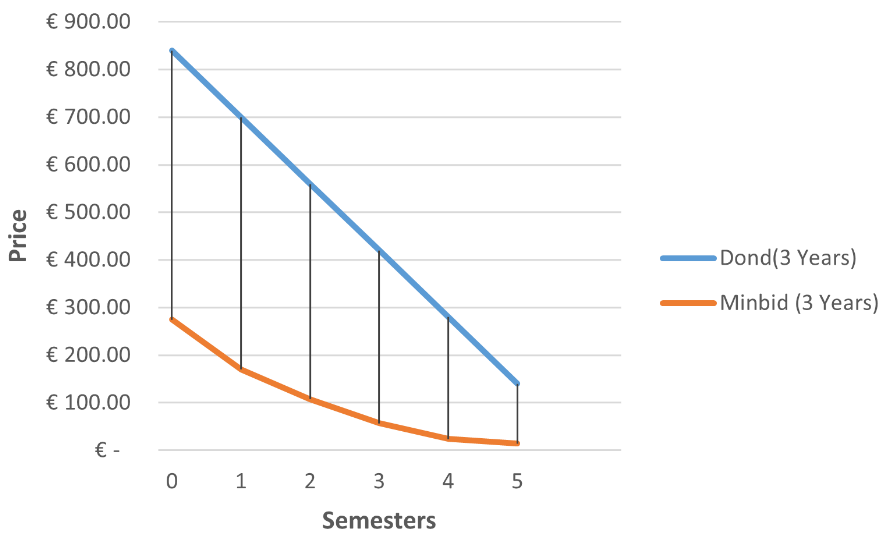


**Figure 7.** $D_{ond}$ and $Minbid$ limits for 3-year scenario.

Each scenario is tested for various purchased VMs (1, 10, 100, 250, 500, 1000). The variations of VMs provide2 a better understanding of the algorithm's function and how to enable the broker's decision making about the investment and offer the best pricing for the bidder.

We estimated the ROI and the utilization values based on Equations (6) and (7), and the results are presented in Table 1.

**Table 1.** ROI utilization.

| | 1-Year | 3-Year |
|---|---|---|
| ROI | 5.06% to 12.78% | 17.89% to 23.88% |
| Utilization | 78.33% to 82.83% | 77.11% to 82.02% |

Regarding ROI, we observe a consistent trend across both scenarios, with the results indicating promising potential for profit generation. Importantly, based on these findings, selling VMs using the proposed algorithm proves to be a secure method for yielding profit, even with a modest investment (e.g., 10 VMs). The 3-year investment appears to be more advantageous in terms of ROI value. This conclusion is entirely rational, considering that the broker secures leases from Amazon at a minimum price and benefits from a significantly greater discount compared to the one-year scenario. Additionally, when the broker acquires more than 250 VMs for auctioning, the total ROI becomes stable, with no significant improvement beyond 23% (3-year scenario) and 12.78% (1-year scenario), as presented in Figure 8.

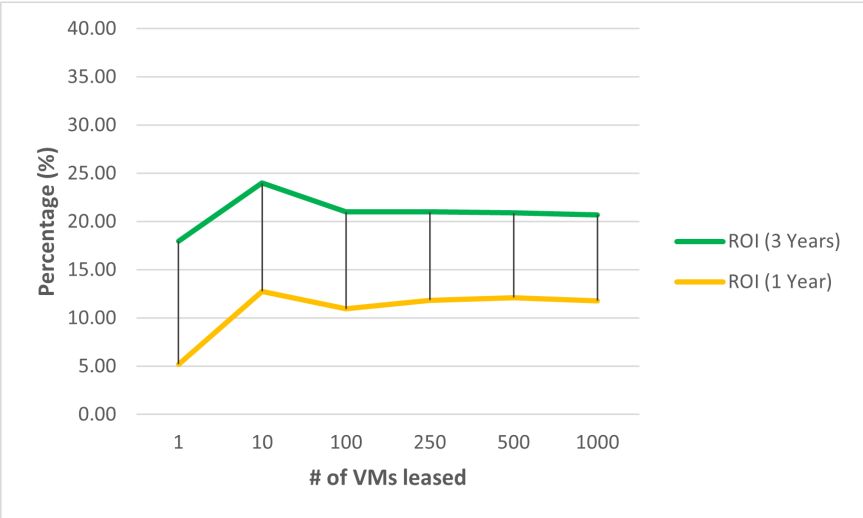


**Figure 8.** ROI (%) of broker algorithm.

Additionally, the utilization of VMs is notably high in both scenarios, as illustrated in Figure 9. However, in the 1-year scenario, utilization exceeds that of the 3-year scenario, particularly when the broker leases between 200 and 1000 VMs. Despite the 3-year scenario being more profitable than the 1-year scenario, the latter can provide the broker with fewer idle resources. In the 1-year investment scenario, the resources are more aligned with current computing demands, whereas in the 3-year investment scenario, resources may be less up-to-date. This highlights a trade-off between profitability and resource utilization, with shorter-term investments potentially offering better alignment with current demand dynamics.

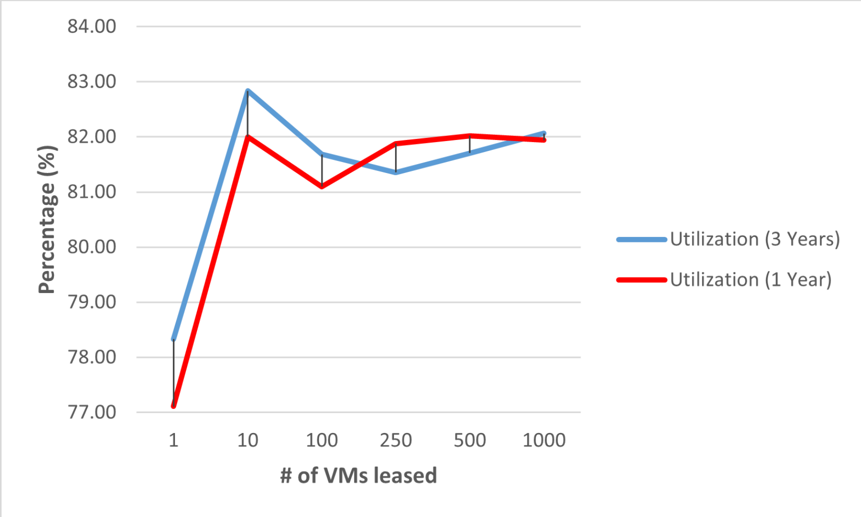


**Figure 9.** Utilization (%) of broker algorithm.

## 6. Discussion and Conclusions

In this paper, we present a cloud marketplace for medium-term instances introduced by a cloud broker. The broker sells the services by adopting an auction mechanism that considers the depreciation of cloud services over time offers. The financial viability of the investment is explored by calculating ROI and the services' utilization.

Based on the results, the broker provides significant cost reductions to users, but also enhances their profitability. Specifically, we presented that the broker can be profitable in both investment scenarios. In the 1-year scenario, the broker earns a significant profit, with an ROI of 12.89% and high resource utilization. In the 3-year scenario, ROI is further improved (23.88%), and the number of unused resources during the auction is limited.

Overall, the current study presents a new brokerage service that customizes the commitment term of a cloud service based on users' requirements and develops a dynamic auction for selling the new services. The proposed auction algorithm takes into consideration the depreciation of a cloud service, and offers significantly low-cost services to users.

Moreover, the proposed marketplace is based on the low price of reserved instances. Relevant studies [18,19,22] have also introduced brokers that lease reserved instances and sell them as on-demand instances. However, the current work diverges from these studies by transforming the leased reserved instances into reserved instances tailored for medium-term workloads. In [27,28], the authors introduced auction algorithms specifically tailored for spot instances. In contrast, our work focuses on developing an auction algorithm designed for stable instances. This distinction highlights our approach's emphasis on addressing the specific needs and characteristics of stable instances, which are better suited for medium-term workloads.

### *Managerial Implications*

Considering the managerial implications of our research, this paper can support stakeholders in the cloud industry.

Organizations can benefit from significant cost savings by leveraging medium-term instances offered through the cloud marketplace. This can lead to more efficient resource utilization and reduced expenditure on cloud services. Moreover, organizations can use the insights from this research to develop strategic plans for cloud resource procurement and utilization. By understanding the dynamics of medium-term instance leasing and auction mechanisms, organizations can make informed decisions to meet their computing demands while optimizing costs.

Additionally, cloud brokers can enhance their profitability by leasing reserved instances and selling them as medium-term instances. The auction mechanism introduced in this work enables brokers to optimize pricing strategies and maximize revenue generation.

This research paper presents several limitations that suggest directions for future research. The algorithm was evaluated using a 6-month VM commitment term. Future research could explore the algorithm's performance with different commitment duration, such as 3-month, 1-year, or longer terms, to assess its applicability across a wider range of use cases. In addition, the evaluation of the algorithm relied on data derived from Amazon. It would be valuable to expand this research by incorporating data from various cloud providers, allowing for a more comprehensive analysis of the algorithm's effectiveness and general applicability across different cloud platforms. Lastly, the algorithm's performance may vary based on diverse user preferences and requirements. It could be challenging to explore the integration of various user feedback and preferences into the auction mechanism to tailor pricing and resource allocation decisions more effectively.

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