Game theoretical approach for a fair and effective pricing strategy in cloud computing

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Abstract: The most proven pricing models for the healthy competition are based on game theory techniques that ensure equal consideration of interests for both clients and providers. However, user's preferences and price's sensitivity have a direct influence on the acceptance of new services, an issue that has been relatively neglected by previous research in this area. Thus, we formulate a mathematical model that takes into consideration users' behaviour and at the same time increases the marginal profit. The objective of this work is to improve the revenue for cloud providers as well as users' satisfaction. Experimental results show that the proposed approach is an optimal solution to obtain a reasonable price strategy in a competitive cloud market. More importantly, client's satisfaction has a considerable influence on pricing policy and the expected payoff. In this context, cloud providers compete with each other to maximise their expected utility even when they offer services at a reasonable price.

Keywords: cloud computing; game theory; Nash equilibrium; non-cooperative game; duopoly market; price competition; consumer's preference; price's sensitivity; profit margin.

Reference to this paper should be made as follows: Ait Temghart, A., Ait Omar, D., Baslam, M. and Marwan, M. (2021) 'Game theoretical approach for a fair and effective pricing strategy in cloud computing', *Int. J. High Performance Systems Architecture*, Vol. 10, No. 1, pp.43–55.

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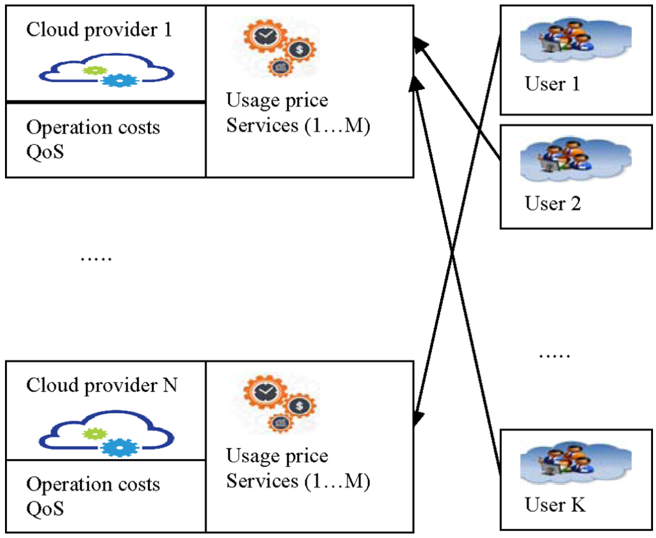
1 Introduction

Cloud computing has emerged as a new alternative to traditional data centres due to the various advantages it provides, including cost saving, scalability and availability. A cloud provider is responsible for providing remote tools and services, including platform-as-a-service (PaaS), infrastructure-as-a-service (IaaS) and software-as-a-service (SaaS). This is typically accessed through the web or an application programming interface (API). Despite its great potential, there still some major hurdles to overcome, most notably the challenges related to security (Zhang et al., 2018; Kong et al., 2017), energy-efficiency and pricing mechanisms. Compared to other problems, less attention has been paid to users' satisfaction and fair pricing policy and resources scheduling optimisation (Shen et al., 2016; Zhang et al., 2017; Li et al., 2018). Game theory was initially developed in economic studies for strategic decision making and pricing policy (Allon and Gurvich, 2010; Lin and Sibdari, 2009). Currently, it has been widely used as an important approach to analyse and model the competition among cloud providers and the behaviour of customers in order to reduce costs and maximise profits. In doing so, an appropriate mathematical model is formulated to make a better pricing strategy in cloud markets according to various parameters, like price, quality of service (QoS), security, user satisfaction, etc. Of course, the price needs to be adjusted based on new information about competitors' behaviour and consumers' preferences and willingness-to-pay (WTP) for cloud services. Obviously, the best pricing policy for optimising profits is calculated based on the key factors affecting the future growth of the cloud market and consumers' changing needs. On the one hand, cloud providers would set a pricing policy that attracts new customers and increases their revenue regardless of the eventual reactions of other providers and clients. Such situation would create a market dominated by only a few large cloud service providers, and this can lead to unhealthy competition. Globally, the vast majority of existing game-theoretic analyses on cloud markets focus on a model of decision making under bounded rationality or the non-cooperative game model. The central issue of non-cooperative game is that each cloud provider determines the pricing strategy without knowing the strategy chosen by other public cloud vendors. For that reason, several parameters are generally used to attract the target customers in accordance with service-level agreement (SLA), among them: response time, price, security, reliability, costs, and reputation. On the other hand, cloud consumers would opt for a pricing model that satisfies their expectations and ensures maximum payoffs with high probability. In dealing with the users' behaviour, we suppose that their preferences are represented by a probabilistic model. The real challenge in cloud computing is finding an optimal way to form a stable market and reach equilibrium between the customers' satisfaction and the providers' expectations.

It is important to note that a fair and healthy competition between various cloud providers implies a detailed analysis of the players' payoffs and the interaction among the various players in the market. In this regard, the cloud service takes care of, among other things, the user's preferences, processing power, user's behaviours and user experience (UX). Figure 1 illustrates the key concepts of a cloud market and the interaction between the clients and the providers.

Figure 1 Basic model of competition in cloud market (see online version for colours)



In general, security issues and sophisticated pricing models must be properly addressed to make this new concept viable and extremely successful. Fortunately, security concerns have been addressed in the literature, and several cryptographic techniques are suggested for preventing the outsourced data from the unauthorised access and modification. In contrast, the competition in a non-competitive market can give rise to a variety of managerial issues, including those related to potential pricing policies and the billing management system. Specifically, price competition can be fierce, especially in markets with similar cloud-based services. It is important to note that a situation with imperfect competition would undoubtedly lead to a oligopolistic or monopolistic market (Laatikainen et al., 2013). Intuitively, a higher price for cloud services risks losing users as well as decreasing sales revenue. In the same line, cloud providers that opt for low pricing models to attract more users may face overwhelming demands accompanied by a dramatic decrease in the quality of cloud services. In light of this fact, we need to develop the most appropriate pricing strategy that will attract a large number of potential customers as well as able to generate much more revenue.

Although considerable research has been devoted to price strategy, only a few studies have explored the users' behaviour when making decisions about the adoption of cloud services. This work aims at addressing the potential impacts of users' preferences and users' price sensitivity on the overall cloud services market. Furthermore, it shows how cloud providers can take the advantage of those types of bounded rationality to enhance their reputation and increase profit margins. The contribution of this paper is threefold. First, we show that we can achieve a fair pricing model by doing a thorough analysis of both cloud providers' needs and users' expectations. Second, we suggest a non-cooperative game theoretical model to build an effective pricing strategy (Osborne, 2004) that ensures economic benefits for both cloud providers and clients. Third, we conduct a deeper analysis on the impact of the users' preferences and users' price sensitivity on the optimal competitive strategy, and the potential effect of these factors on the pricing schemes in the cloud computing market.

The remainder of this paper is organised as follows. In Section 2, we highlight the contribution of this study to the subject of research we are concerned with in this paper and the gaps it aims to fill in with respect to the existing literature. Sections 3 and 4 formulate the research problem with regard to the users' behaviour and the utility model. In Section 5, we present the theory of non-cooperative games study and the proposed model to find the Nash equilibrium, as well as determining the robust best-response strategies. Section 6 presents the numerical analysis concerning the verification and validation of the proposed model along with the subsequent results. In Section 7, we end this study by some concluding remarks and recommendations for further research.

2 Related work

The challenges of the cloud computing can have two dimensions:

- an intra-provider that deals with internal factors that affect operational expenses such as load balancing, energy, hardware and so on
- an inter-provider that is associated with market competition among providers including price, QoS and reputation.

Optimisation models are vastly used in job scheduling strategies and in the optimal utilisation of cloud resources (Sangaiah et al., 2019a, 2019b, 2020). Recent years have seen a tremendous rise in the number of researches related to the second research direction concerns. In this context, a review of related works in pricing policy and resource allocation, using game theory models, is presented here.

In Hammoud et al. (2020), the authors proposed a genetic algorithm to improve the total payoffs in federated clouds. Additionally, evolutionary game theory is used for minimising the difference between profits among cloud providers so as to achieve a stable strategy that guarantees fairness between providers. However, the authors do not take into consideration of the user's behaviour. Kishor et al. (2020) suggested game-theoretic model for an effective load-balancing mechanism in distributed systems. The proposal guarantees equitable response time to all consumers by reducing both the processing time and the price of a service. Nevertheless, this work do not take into account two parameters, i.e., energy cost and server availability. In Swathy et al. (2020), the authors rely on available CPU and memory resource to create Stackelberg game model in order to allocate tasks to each host according to resource requirement, price strategy, resource availability and performance. Despite its success in creating an effective tasks scheduling, the proposal did not specifically deal with issues related to the priority of jobs and the queue of waiting jobs. In Ghobaei-Arani et al. (2019), the authors propose an powerful solution to manage cloud elasticity. They use an adaptive neuro-fuzzy inference system (ANFIS) model for load prediction, and fuzzy decision tree (FDT) algorithm for resources allocation. However, although its objectives are ambitious, the proposed system does not ensure a fair and equitable competition within the cloud providers market. Anglano et al. (2019) proposed a cooperative game for coalition formation in fog computing providers. This would help fog infrastructure providers (FIPs) to share their resources so as to increase their profits. Despite this model reduces costs and meets QoS requirements, it does not ensure a fair competition among fog providers.

Chen et al. (2020) propose a Stackelberg game-based framework to address the problem of fair resource allocation in a mobile edge computing system. This solution helps find the best resource demand strategy and an equilibrium price. However, it clearly does not take into consideration users' preferences. In Dibaj et al. (2020), double auctions are proposed to define an appropriate pricing mechanism and support the dynamic nature of cloud environments. The proposal is an efficient online cloud auction method for a sustainable pricing model and resource allocation. Despite the fact that this solution ensures both cost effective and fair competition between cloud providers, the research does not analyse the impact of users' behaviours and characteristics on competition in the cloud computing sector. In this context, the authors in Feng et al. (2014) proposed a model to help each cloud provider to select its optimal prices to compete with the other IaaS. The primary objective is to find an equilibrium price in the duopoly and oligopoly market. This study shows that improving resource capacity is less profitable than other performance parameters. However, this work does not consider the impact of the consumers' preferences on the profitability of remote services. In light of this fact, the authors in Vengerov (2008) and Xu and Li (2013) provide a game theoretical analysis of the relationship between profitability and the users' behaviour. The results show that there is a significant level of connection between these items so as to find the price in competitive markets. Despite its importance, this work does not take into consideration the competition among cloud providers. The authors propose in Truong-Huu and Tham (2014) a discrete choice model to represent the users' choice behaviour so as to create a dynamic price policy. In this case, an optimal cooperation structure is used for selecting the right client's requests for each cloud provider. However, the impact of the users' preference was not well explored during the competition among cloud providers. In Xu et al. (2015), the authors analyse the market that consists only of one proactive cloud provider. The latter determines the type of pricing strategy that need to be adopted by other competitors. In the same line, the work in Chen and Frank (2004) aims at determining the optimal profit and efficient pricing in a monopoly market. Often, it can be expected that the equilibrium is socially efficient if the users' preferences are linear. Another example demonstrating these concepts is that services with the higher value generate high profit and take a larger market share, as illustrated in Chen and Wan (2003). However, adopting this approach to cloud market is not as good as it was in the case of the model based on make-to-order business. In Daoud et al. (2008, 2009), and Shu and Varaiya (2003), the authors propose a pricing model for maximising the revenue of their data centres and users' utilities as well. To provide a deeper analysis of the cloud competition, Yeo et al. (2010) suggested a game theoretical approach to model the advantages and disadvantages of fixed, variable and autonomic pricing mechanism. Accordingly, autonomic pricing would help cloud providers to achieve higher revenue than other models. Similarly, Taghavi et al. (2020) proposed a two-stage game theoretical framework to build a fair pricing strategy for the cloud market, especially in the case of IaaS. First, they use the Stackelberg game to build an ideal pricing strategy that captures the users' needs to ultimately increase the cloud demands and the profitability. Second, they built a differential game model based on price and quality to preserve a fair competition in the cloud market. However, authors neglect the fact that customers' satisfaction plays a central role in creating a healthy cloud market.

Although many efforts have been made to encourage a fair and effective competition among cloud providers, many options are possible and there are still improvements in order to respond to the changing requirements of users and the increasing demands of cloud services. Besides the quality and affordable services, we propose a model that takes into consideration the users' preferences as well as price sensitivities. Table 1 summarises the existing works and the one we propose.

Table 1 Summary of our work compared to existing works

Work	*Techniques and tools*	*Advantages*	*Disadvantages*
Hammoud et al. (2020)	• Genetic algorithms • Evolutionary game theory • Cloud harmony	• It increases the profit and assures market stability	• They neglect the impact of bounded rational users
Kishor et al. (2020)	• Game-theoretic model • Load balancing game	• It minimises response time and minimises cost	• They did not take into account security level and availability
Swathy et al. (2020)	• Stackelberg game theory • They rely on price and parameters (CPU and memory)	• It reduces number of task failures in load balancing for cloud computing	• They did not consider the computational complexity of each job
Ghobaei-Arani et al. (2019)	• Adaptive Neuro Fuzzy Inference System (ANFIS) predictor • Fuzzy Decision Tree	• It guarantees the QoS requirements in a dynamic environment	• They did not take into account response time and privacy
Anglano et al. (2019)	• Game-theoretical framework	• It creates a fair cooperation among Fog providers	• Their approach does not distinguish the ratings for each node's QoS
Chen et al. (2020)	• Stackelberg game in a mobile edge computing system	• It maximises revenue and ensures high utility for users	• This work deals only with static environment
Dibaj et al. (2020)	• Dynamic online double auction mechanism	• It obtains sustainable pricing scheme for cloud market	• They did not take into account QoS requirements
Feng et al. (2014)	• Game theoretical techniques in monopoly, duopoly and oligopoly market	• It defines optimal price for cloud services	• It does not take into account the brand and reputation of the cloud providers
Vengerov (2008)	• Reinforcement learning approach	• It enables to set dynamic pricing policies	• It neglects the case of cooperative markets
Xu and Li (2013)	• Stochastic dynamic program	• It maximises revenue when using dynamic cloud pricing	• It neglects competitive among cloud providers
Truong-Huu and Tham (2014)	• Non-cooperative stochastic game	• It helps create an optimal cooperation strategy for cloud	• It does not take into account consumers' brand preferences
Xu et al. (2015)	• Game theory for dynamic cloud pricing	• It maximises the cloud provider's revenue	• It does not take into account users' behaviours
Chen and Frank (2004)	• Game theory in a monopoly market • Social welfare	• It defines an optimal price that takes into account service's delays	• It neglects others some factors that attract consumers such as quality and brand
Daoud et al. (2009)	• Stackelberg game	• It provides an optimal pricing policy for uplink power	• It does not take into account users' preferences

Table 1 Summary of our work compared to existing works (continued)

Work	*Techniques and tools*	*Advantages*	*Disadvantages*
Shu and Varaiya (2003)	• Game theory	• It provides a solution for congestion control	• It does not take into account quality of service (QoS)
Yeo et al. (2010)	• Autonomic pricing mechanism	• It used autonomic metered pricing to self-adjust prices and increase revenue	• It does not take into account the impact of competition and users' preferences on price strategy
Taghavi et al. (2020)	• Stackelberg game • Differential game	• It creates a healthy competition among clouds	• They neglect the impact of users' preferences
The proposed approach	• Game-theoretic model	• It takes into consideration customers' preferences	• Some parameters are ignored such as QoS and security

3 Users utility model

The competition among cloud providers is formulated as a non-cooperative game. Besides, we rely on the multinomial logit (MNL) approach to describe the user's discrete choice models. The primary objective is to find the probability of a cloud user to choose the best strategic option among a set of alternatives (Train, 2003). This study aims to develop an effective pricing strategy for cloud providers, especially for IaaS services. In this concept, needed resources are dynamically allocated to a client over the Internet without installing them on promises. Moreover, users pay for the consumption of remote services based on storage use, computing power and bandwidth.

We consider cases involving N providers actively competing against each other for K users. Each cloud computing delivers M different types of IaaS services with various capabilities and performance. When using fixed-pricing strategy, each remote cloud resource has an associated cost, set by the cloud provider i, typically expressed as $P_i = (p_{i,1}, p_{i,2}, p_{i,3}, \ldots, p_{i,M})$. In this sense, K users choose the provider that is able to fully satisfy their requirements in terms of price and performance. This selection depends heavily on the quality and properties of each online resource as well as the user's preferences.

In light of this context, the proposed framework is composed of the following core modules: Client (or a broker acting on its behalf), Master and Execution. After successful authentication, the Master module determines the optimal pricing strategy based on the user's requirements and their preferences. Next, Execution module is designed to distribute the users' requests across several data centres so as to achieve the optimal resource scheduling and promote the healthy competition among cloud providers. Figure 2 provides the principle and the key elements of the proposed solution.

For an effective resource management system, computational overhead, which is associated with the decision-making process, is automatically distributed across multiple cloud servers. Figure 3 shows the interaction between the user/broker and the cloud providers.

Figure 2 Fundamental elements of the proposed framework (see online version for colours)

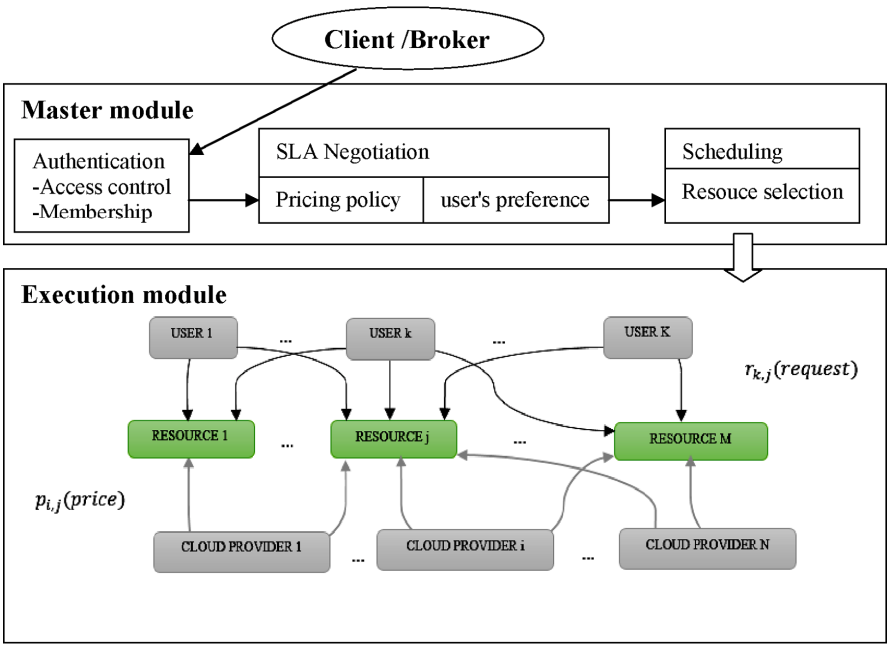
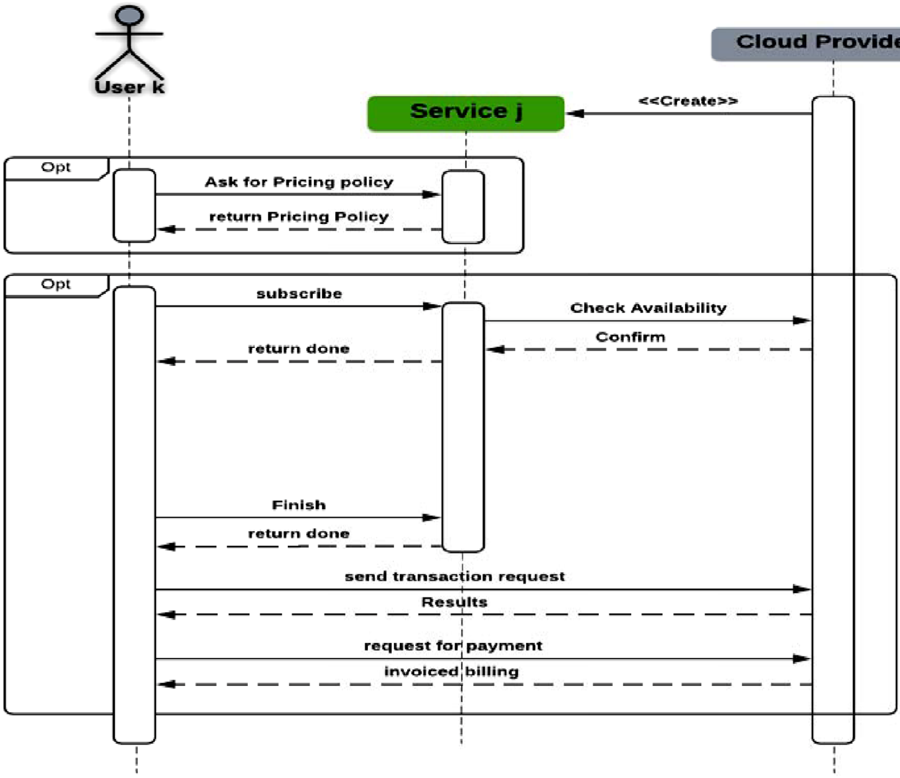


Figure 3 Flow diagram of price negotiation for cloud resource provisioning (see online version for colours)



Definition 1 (Request matrix)**:** Let r_k be a set of requests sent by the user k to use different M services delivered by cloud providers. Formally, the request matrix can be represented as a $K \times M$ dimensional matrix. In this case, the arrows refer to the cloud resources required by a user, while columns show available remote resources.

$$r_k = (r_{k,1}, r_{k,2}, \ldots, r_{k,j}, \ldots, r_{k,M}) = \begin{pmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,M} \\ r_{2,1} & r_{2,2} & \cdots & r_{1,M} \\ \vdots & \vdots & \ddots & \vdots \\ r_{k,1} & r_{k,2} & \cdots & r_{k,M} \end{pmatrix}.$$

Definition 2 (User's price sensitivity)**:** Let $\beta_{k,i}$ denote price sensitivity of the user k on price of resource offered by the cloud provider i (CP_j). Generally speaking, customers compare the costs and benefits of a given cloud service. Indeed, the users show their reactions to changes in price levels so as to obtain maximum benefits from their investments. In reality, high price sensitivity means that users will easily refuse to subscribe on a service based on its price. In contrast, low price sensitivity means that they are usually willing to pay more for high quality services.

Concretely, we use the following formula to calculate the total costs of resources offered by the cloud provider i to the user k.

$$C_{k,i} = \sum_{j=1}^{M} r_{k,j} \beta_{k,i} p_{i,j} \tag{1}$$

Where, $p_{i,j}$ refers to the price of resource $r_{i,j}$.

Definition 3 (User's preference)**:** The user's choices are affected by psychological factors such as comfort, flexibility and brand loyalty (Train, 2003). The user-defined preference function is commonly denoted by $\eta_{k,i}$.

In this paper, we rely on the multinomial logit (MNL) model to describe the users' discrete choice for the modelling of their political preferences in a probabilistic way. In doing so, users are able to independently select the cloud provider that maximises their payoffs and reduce the cost of their utility with higher probability.

As For instance, the user k uses ready-to-use services offered by the cloud provider i. Basically, the utility function of the user k is often expressed as in equation (2).

$$U_{k,i} = \alpha_{k,i} - C_{k,i} + \eta_{k,i} \tag{2}$$

In this case, $\alpha_{k,i}$ refers to the total benefits received when using IT resources from the cloud provider i. This parameter is obtained using equation (3):

$$\alpha_{k,i} = \sum_{j=1}^{M} r_{k,j} \lambda_{i,j} \tag{3}$$

$\lambda_{i,j}$ is the benefit per unit of the resource j offered by the cloud provider i. It reflects the relative capacity to satisfy the user's requirements.

$C_{k,i}$ is the total cost that a user k needs to pay for using the resources offered by the cloud provider i.

As shown in equation (2), the utility function is decomposed into two parts. The first one, which is expressed as $\alpha_{k,i} - C_{k,i}$, must be established ahead of time by the cloud provider i. The second part refers to the user's preference $\eta_{k,i}$, which is usually unknown to the cloud providers. Formally, this unknown part is a random variable that can take any numeric value in a specified range. In light of this fact, we suppose that $\eta_{k,i}$ is independent and identically distributed (Train, 2003). The most common approach to representing the probability distribution is the extreme value type I distribution, which is also called Gumbel distribution (Gumbel, 1961). Accordingly, the density of unobserved component of the utility $\eta_{k,i}$ can be expressed as follows:

$$f\ (\eta_{k,i}) = e^{-\eta_{k,i}} e^{-e^{-\eta_{k,i}}} \tag{4}$$

Similarly, the cumulative distribution is calculated as:

$$F\ (\eta_{k,i}) = e^{-e^{-\eta_{k,i}}} \tag{5}$$

The following equation gives the probability that the user k chooses the cloud provider i, which is denoted as $\rho_{k,i}$:

$$\begin{aligned}\rho_{k,i} &= \text{prob}(U_{k,i} > U_{k,i'}, \quad \forall i \neq i' \\ &= \text{prob}(\alpha_{k,i} - C_{k,i} + \eta_{k,i} > \alpha_{k,i'} - C_{k,i'} + \eta_{k,i'}, \quad \forall i \neq i' \\ &= \text{prob}(\eta_{k,i'} < \eta_{k,i} + (\alpha_{k,i} - C_{k,i}) - (\alpha_{k,i'} - C_{k,i'}), \quad \forall i \neq i')\end{aligned}$$

Therefore, the probability $\rho_{k,i}$ is:

$$\rho_{k,i} = e^{-e^{\eta_{k,i} + (\alpha_{k,i} - C_{k,i}) - (\alpha_{k,i'} - C_{k,i'})}} \tag{6}$$

Taking into account that $\eta_{k,i}$ is independent, the cumulative distribution for all $i \neq i'$ is normally the product of the individual cumulative distribution, as shown in equation (7).

$$\rho_{k,i} \mid \eta_{k,i} = \prod_{i \neq i'} e^{-e^{-(\eta_{k,i} + (\alpha_{k,i} - C_{k,i}) - (\alpha_{k,i'} - C_{k,i'}))}} \tag{7}$$

In general, finding the closed-form of the probability that the user k opts for the cloud provider i implies the utilisation of both the density function and the cumulative distribution (Train, 2003). The expression of this choice is given by formula (8)

$$\rho_{k,i} = \frac{\exp^{U_{k,i}}}{\sum_{i'=1}^{N} \exp^{U_{k,i'}}} \tag{8}$$

Likewise, the probability of not choosing the provider i is given as:

$$1 - \rho_{k,i} \tag{9}$$

In this study, we assume that each user must select no more than one cloud provider Thus, users have the possibility to choose a cloud provider with an equal probability among all the $N + 1$ alternatives. Consequently, the probability that a user chooses the cloud provider i is expressed by:

$$\rho_i = \frac{\exp^{U_i}}{1 + \sum_{i'=1}^{N} \exp^{U_{i'}}} \tag{10}$$

Where U_i is the utility of each user when choosing at most one online resource offered by the cloud provider i. This parameter is expressed in this competitive market model as:

$$U_i = \lambda_i - \beta_i p_i + \eta_i \tag{11}$$

4 Monopoly pricing analysis

In this case study analysis, we assume that each cloud provider offers infrastructure as a service. Therefore, the market is composed primarily of N cloud providers serving K users. The demand function is the expected value of demands for online resources, which can be written as in (Baslam et al., 2012).

$$d_i(p) = K.\rho_i.p_i \tag{12}$$

We formulate the expected profit, denoted π_i, to help a cloud provider determine the usage price pi that maximises his profit. Concretely, the utility function of CP is the total revenue d_i minus the operating expenses $\gamma_i(\mu_i)$, which is directly related to software and hardware maintenance agreements, security measures and salaries. It is commonly calculated using equation (13):

$$\begin{aligned}\pi_i(p) &= d_i(p) - \gamma_i(\mu_i) \\ \pi_i(p) &= K.\rho_i.p_i - \gamma_i(\mu_i)\end{aligned} \tag{13}$$

In other words, each provider needs to pay the cost per unit of cloud services (Adams et al., 2009), denoted as μ_i. It reflects the amount of money spent to offer a specific cloud resource. In order to calculate the operating costs $\gamma_i(\mu_i)$, we use equation (14).

$$\gamma_i(\mu_i) = K.\rho_i.\mu_i \tag{14}$$

Therefore, the profit function of the cloud provider i is formulated as follows:

$$\begin{aligned}\pi_i(p) &= K.\rho_i.p_i - K.\rho_i.\mu_i \\ \pi_i(p) &= K.\rho_i.(p_i - \mu_i) \\ \pi_i(p) &= \frac{K.\exp^{U_i}}{1 + \sum_{i'=1}^{N} \exp^{U_{i'}}}(p_i - \mu_i)\end{aligned} \tag{15}$$

5 Price competition in the duopoly case

Competitive pricing is the process of selecting the strategic price that will assist in satisfying customers' requirements and achieving high revenues as well. In the Duopoly case, only two IaaS cloud providers compete with each other to attract potential customers and gain market share. Usually, users act in a selfish fashion to maximise their payoffs. In this respect, we calculate the Nash equilibrium to obtain optimal outcome and maximise the expected payoff.

Definition 1 (Nash equilibrium)**:** We consider a strategic form game composed of N different cloud providers (CPs) $\Gamma = \{N, p_1, ..., p_N, \pi_1, ..., \pi_N\}$, where p_i and π_i are the price strategy and utility set of each cloud provider *i* respectively. The existence of a Nash equilibrium in pure strategies for the vector price $p^* = (p_1^*, \ldots, p_N^*)$ implies the existence of a utility function that maps a vector with a value for each objective, as in equation (16).

$$\pi_i(p^*) = \max_{p_i \in P_i} \pi(p_1^*, \ldots, p_{i-1}^*, p_i, p_{i+1}^*, \ldots, p_N^*) \tag{16}$$

5.1 Price competition in a duopoly case

In the case of duopoly market, the primary objective of the Nash equilibrium price is to define a model so that efficient and reasonable profit margins can be reached and sustained in a non-cooperative setting. In other words, each price policy is associated with expected payoffs. Moreover, the outcome of a game clearly depends on the reaction of the other cloud providers and all cloud users.

We assume that $\pi_i(p_1; p_2)$ refers to the estimated profit of the cloud provider *i* when the cost associated with remote services is p_i. Meanwhile, the other cloud provider i' choose the price p_i, where $i \neq j$ and i, $i' = 1, 2$.

Now let us consider a pair of price $(p_1^*; p_2^*)$, one can easily check that the equilibrium set satisfies the following condition, as in equation (17).

$$\begin{aligned} &\pi_1(p_1^*; p_2^*) \geq \pi_1(p_1; p_2^*), \quad \forall\, p_1 \geq 0 \\ &\pi_2(p_1^*; p_2^*) \geq \pi_2\,(p_1^*; p_2), \quad \forall\, p_2 \geq 0 \end{aligned} \tag{17}$$

Since Nash equilibrium aims at determining the best response for each cloud service provider, the intersection of these two most favourable outcomes represents the Nash equilibrium point of the cloud market.

We denote $p_i = BR(p_{i'})$ to indicate the optimal price of the cloud provider *i* when the cloud provider i' chooses the usage price $p_{i'}$. In the duopoly competition market, we consider a pair of prices (p_1, p_2) such that $p_1 = BR(p_2)$ and $p_2 = BR(p_1)$ as a Nash equilibrium.

Formally, we rely on Algorithm 1 to find the Nash equilibrium in the duopoly case.

Algorithm 1 Compute the best response

1: Initiation.
Every cloud provider selects its own pricing scheme to create a price vector.

2: Iterative step.
For each $\mathrm{CP_i}$ /i∈ N at iteration t
$$\mathrm{BR_i^{t+1}} = \mathrm{argmax}_{\mathrm{p_i \in P}}\ (\pi_\mathrm{i}\ (\mathrm{p_i}))$$

In the same line, we use Algorithm 2, which is a graphical method, to determine the Nash equilibrium price in case it exists.

Algorithm 2 Graphic Nash equilibrium

1: Initiate the strategy vector of price p_1 and p_2;
2: Find the best response vector $BR_1(p_2)$ for all p_2;
3: Find the best response vector $BR_2(p_1)$ for all p_1;
4: Intersections of BR_1 and BR_2 are the set of Nash equilibria.

5.2 The price equilibrium

As discussed above, the primary objective of a non-cooperative game theoretical model is to find the optimal pricing strategy that ensures a fair competition between two cloud providers. One obvious challenge is that whether a price strategy is the best response or not depends entirely on the existence of a Nash equilibrium.

This section provides necessary and sufficient conditions that guarantee the existence and uniqueness of Nash equilibria. This implicitly determines the best-response function (Ait Omar et al., 2019). In this context, Lemma 1 defines the first-order necessary condition for the existence of such equilibrium.

Lemma 1 (Existence of equilibrium)**:** *The (necessary) first-order condition for a given price p_i to be a Nash equilibrium price implies that the following condition must be satisfied.*

$$p_i > \mu_i - \frac{2}{\beta_i(2\rho_i - 1)} \tag{18}$$

Proof: The condition to prove the concavity of the utility function is

$$\frac{\partial^2 \pi_i(p_i)}{\partial p_i^2} < 0$$

In this respect, the first derivative of function (15) is:

$$\frac{\partial \pi_i(p_i)}{\partial p_i} = -k\beta_i(p_i - \mu_i)\rho_i(1 - \rho_{k,i}) + k\rho_i \tag{19}$$

Note that $\frac{\partial \rho_i}{\partial p_i} = -\beta_i\rho_i + \beta_i\rho_i^2 = -\beta_i\rho_i(1 - \rho_i)$.

Hence, the 2nd derivative of utility function is:

$$\begin{aligned} \frac{\partial^2 \pi_i(p_i)}{\partial p_i^2} &= -k\beta_i^2(p_i - \mu_i)\rho_i(1 - \rho_i)(2\rho_i - 1) \\ &\quad -2\beta_i k\rho_i(1 - \rho_i) \end{aligned} \tag{20}$$

Then

$$-k\beta_i^2(p_i - \mu_i)\rho_i(1 - \rho_i)(2\rho_i - 1) - 2k\beta_i\rho_i(1 - \rho_i) < 0.$$

We conclude that

$$p_i > \mu_i - \frac{2}{\beta_i(2\rho_i - 1)}. \tag{21}$$

Lemma 2 (Uniqueness of equilibrium)**:** *Let f be Nash equilibrium for a given price competition. This equilibrium is unique in this game if only if the price satisfied this condition:*

$$p_i > \mu_i - \frac{3}{2\beta_i(2\rho_i - 1)}. \tag{22}$$

Proof: We rely principally on the methodology used in Ait Omar et al. (2019) to prove the uniqueness of Nash equilibrium price. In this case, we suppose the conditions given by Rosen (1965) and Gabay and Moulin (1980). Accordingly, a concave game satisfies the dominance solvability condition (Lasaulce et al., 2009). This is illustrated in equation (23).

Thus

$$\frac{\partial^2 \pi_i(p_i)}{\partial p_i^2} + \sum_{j,j\neq i} \frac{\partial^2 \pi_i(p_i)}{\partial p_i \partial p_j} \geq 0 \tag{23}$$

We have

$$\sum_{j,j\neq i} \left| \frac{\partial^2 \pi_i(p_i)}{\partial p_i \partial p_j} \right| = \left| \beta_i k(p_i - \mu_i)(2\rho_i - 1) + \beta_i k \right| \rho_i (1 - \rho_i) \tag{24}$$

From equations (20) and (23), knowing that $\beta_i k(p_i - \mu_i)(2\rho_i - 1) + \beta_i k \leq 0$, we find that:

$$\begin{aligned} &\frac{\partial^2 \pi_i(p_i)}{\partial p_i^2} + \sum_{j,j\neq i} \frac{\partial^2 \pi_i(p_i)}{\partial p_i \partial p_j} \\ &= -k\beta_i \rho_{k,i}(1 - \rho_i)\left((4\beta_i\rho_i - 2\beta_i)(p_i - \mu_i) + 3\right) \geq 0 \end{aligned} \tag{25}$$

Then

$$p_i > \mu_i - \frac{3}{2\beta_i(2\rho_i - 1)} \tag{26}$$

Consequently, Nash equilibrium price is unique if the following equation is satisfied.

$$p_i > \mu_i - \frac{3}{2\beta_i(2\rho_i - 1)} \tag{27}$$

Algorithm 3 Compute the optimal price

1: Initialization
Each cloud provider i sets the usage price to be $p_i = 1$.
2: Iterative step
Each cloud provider i updates the usage price p_i when his profit margin is increased ($\pi_i < \pi_{i+1}$) and also satisfied the following conditions:
$p_i > \mu_i - \frac{2}{\beta_i(2\rho_i - 1)}$ Or $p_i > \mu_i - \frac{3}{2\beta_i(2\rho_i - 1)}$
3: Convergence criterion
Repeat the iterative step until (Err (p_i) = the present value - previous value) is less than a predetermined value.

Concretely, we use Algorithm 3 as an iterative method to compute the optimal price for each cloud provider in a duopoly market. Note that the convergence to Nash or approximate Nash equilibrium is not likely to be correct in some practical situation.

6 Numerical simulation and results

In this section, we provide a proof-of-concept of the proposed model through some numerical simulation. The main objective of study is to prove that game theory models may be used as a tool to create a fair and effective price strategy in cloud markets. More importantly, we examine the impact of users' preferences on pricing competition. Table 2 represents the most commonly used parameters in the case of duopoly.

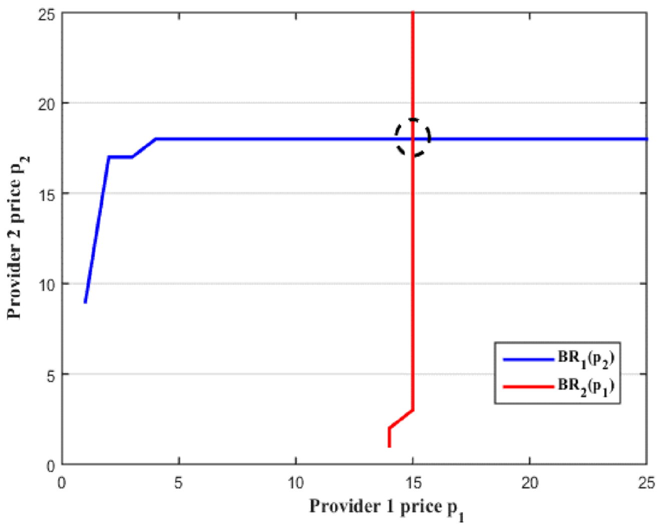
Table 2 Parameters used in the numerical simulations

n	k	$p_1 = p_2$	λ_1	λ_2	μ_1	μ_2	η_1	η_2	β
2	100	[1:1000]	30	23	6.2	11.95	10	12	1

6.1 Equilibrium state of the cloud market

In this section, we conduct numerical simulation of the proposed game-theoretic model. Specifically, we compute the best response strategies in a market composed of two cloud providers, as shown in Figure 4.

Figure 4 Nash equilibrium points of a 2-player game (see online version for colours)

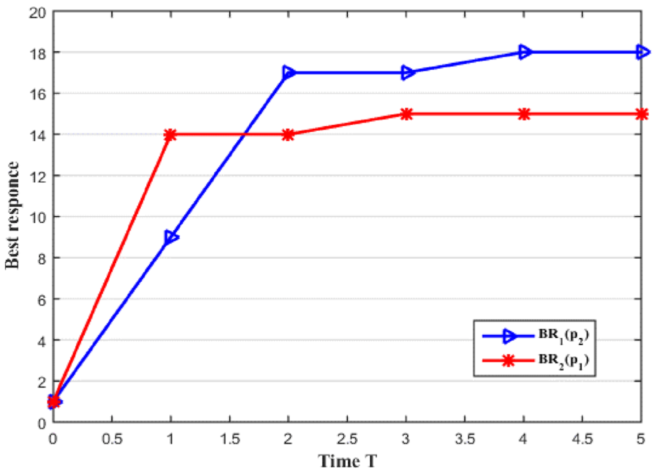


We then draw two curves where we identify the intersection point through Algorithm 2. This procedure is used to determine the best response, which produces the most favourable outcome for both cloud providers. Interestingly, we notice that there exists an intersection between the curve of vector BR_1 and that of BR_2. Therefore, the experimental result proves the existence and the uniqueness of the

Nash equilibrium in the case of duopoly where there are just two cloud providers for a price competition game. In the same vein, we show that the best-response algorithm can be iterated to find the corresponding Nash equilibrium. The simulation results prove the convergence properties of the proposed iterative best-response algorithm at the equilibrium prices. This point satisfies the equation $BR_1(p_2) = BR_2(p_1)$, as illustrated in Figure 5. In this case, the pricing policy for each cloud provider is determined by contrasting its best response function with the other provider's strategy.

More importantly, the best dynamic response algorithm converges to a unique Nash equilibrium within a small number of iterations. Such equilibrium gives the best payoff in response to a given action by an opponent. In other words, this price strategy allows cloud providers to find the most profitable combination that not only satisfies the needs of the customers but also maximises the cloud provider's expected payoff.

Figure 5 Convergence to the Nash equilibrium (see online version for colours)



6.2 *Impact of the cost per unit of a service on the equilibrium price*

In this study, we consider the pricing model in which a user pays a static price for a used unit, often per hour, GB, etc. In the subscription-based pricing model, service quality and customer satisfaction are the most important criteria to consider when opting for a reputable cloud provider. Although low cost can contribute to attract more customers, it is more expensive and difficult to keep existing and loyal clients, especially regarding the preferences for the new clients. Therefore, the pricing scheme is a critical factor for organisations offering remote services and hence has a significant impact on Nash equilibrium price, as illustrated in Figure 6.

Accordingly, the best response increases when the cost per unit of a cloud service increases. This implies that cloud providers can increase their profit margins if they can raise the prices of delivered services. In a highly competitive environment, excessive pricing maximises short-term profit but will result in a loss of customers' confidence. Thus, the cloud provider will select their optimal price to maintain equilibrium between their expectations and those of the clients. Consequently, engaging in an inappropriate pricing strategy cannot last for long, as competitors soon launch rival services, which put pressure on the adopted pricing policy, as shown in Figure 7.

Figure 6 Best response with respect to the cost per unit of a service (see online version for colours)

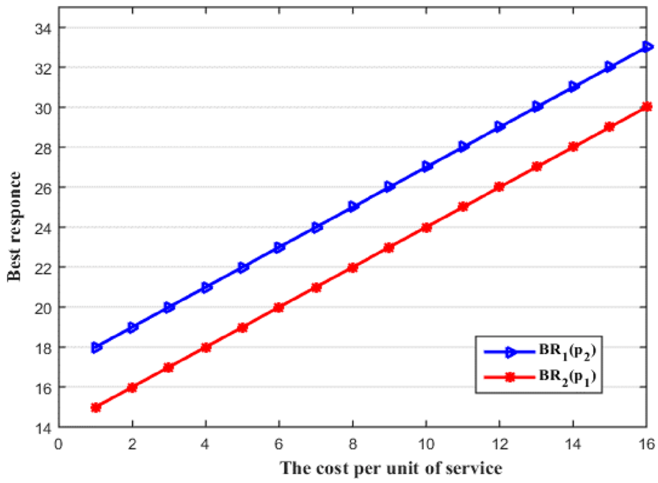
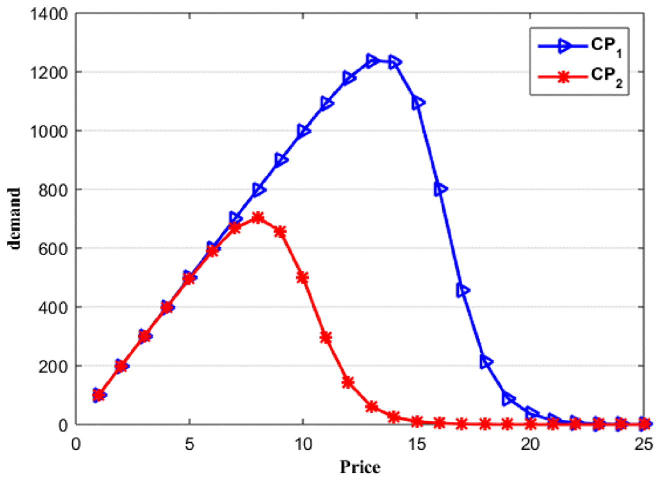


Figure 7 Price vs. demand on cloud market (see online version for colours)



6.3 *Impact of the user's price sensitivity on the equilibrium price*

The user's price sensitivity known also as price response coefficient refers to the degree of importance that a user places on a service price. In fact, the user's sensitivity to price has a significant impact on user's choice. In this part, we focus on the influence of the user's price sensitivity or the user's price reaction to the cloud revenue in the cloud market. From Figure 8, it appears that the best response for the price strategy is influenced by the user's price sensitivity of each service offered by the cloud provider. More specifically, we notice that the predictions for cloud revenues increase greatly in markets characterised by consumers with a low level of price sensitivity (close to 0).

In the same line, we analyse the impact of operating costs on the overall cloud profitability. To this aim, we use different functions to calculate the operating costs, among them linear and exponential functions. As shown in Figure 9, markets in which customers have higher price sensitivity (close to 1) usually have a low profit margin compared to other markets. Certainly, the less sensitive users are to the price, the higher the providers' revenue is.

In light of this fact, the rational providers are strongly encouraged to reduce the cost of delivered services to attract more consumers. For example, Figure 10 indicates that cloud providers that opt for a low-cost price policy will undoubtedly attract more users. Unlike the case of perfect competition, the higher prices of cloud services can cause a decrease in demand.

Figure 8 Impact of user's price sensitivity on best-response (see online version for colours)

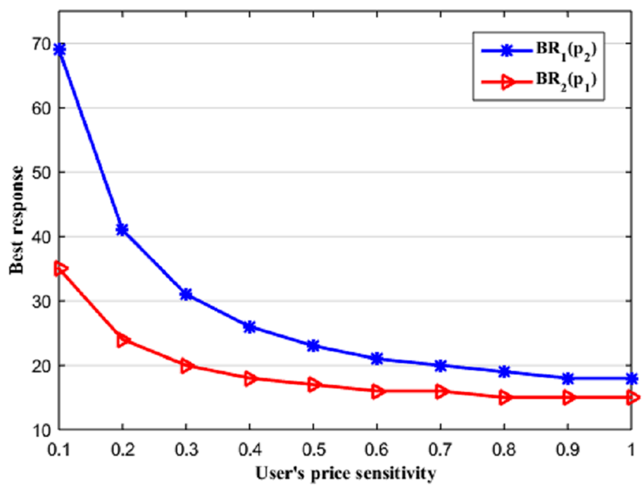


Figure 9 Effect of user's price sensitivity on expected profit with different operating costs functions (a = 10, b = 5, c = 0.7) (see online version for colours)

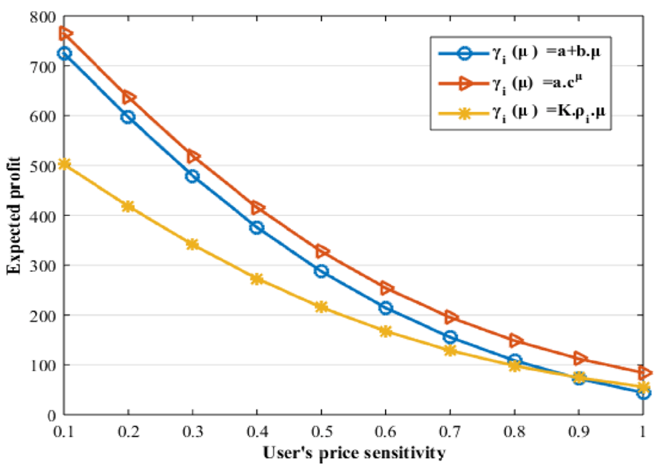
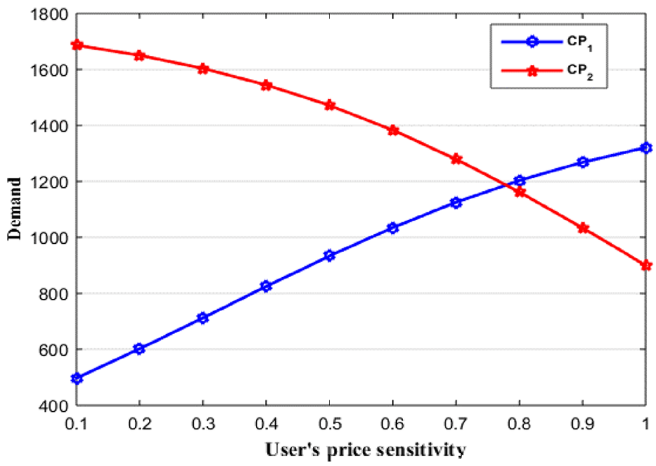


Figure 10 Demand vs. user's price sensitivity (see online version for colours)



6.4 *Impact of users' preferences on the equilibrium pricing structure*

We also analyse the impact of the users' preferences on the competition among cloud providers, especially in the revenue growth. In general, there are two possibilities: either a fixed or variable user's preferences, as shown in Figure 11.

From Figure 11, one can clearly see that there is a highly significant negative correlation between profit and users' preferences. In this sense, the profit was negatively impacted by fixed preferences, whereas an increase in the users' preferences leads to much higher profits for all cloud providers. Moreover, from Figure 12 we can see that high demand for ubiquitous cloud services is mainly due to an increased in customers' preferences. Subsequently, users are more willing to subscribe to cloud services even after the price has considerably increased.

Figure 11 Impact of user's preference on best response (see online version for colours)

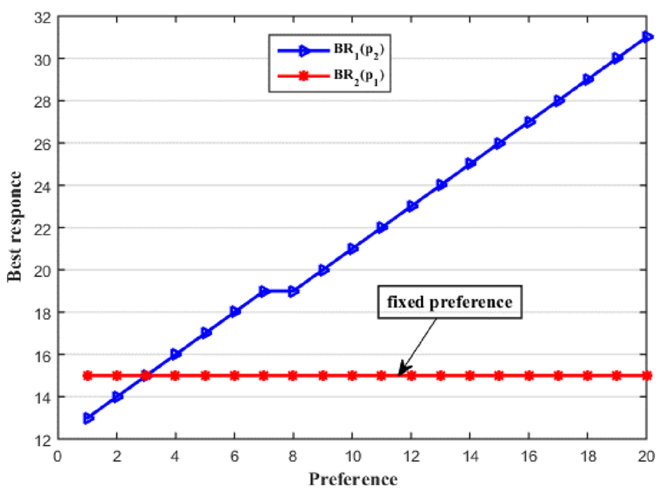
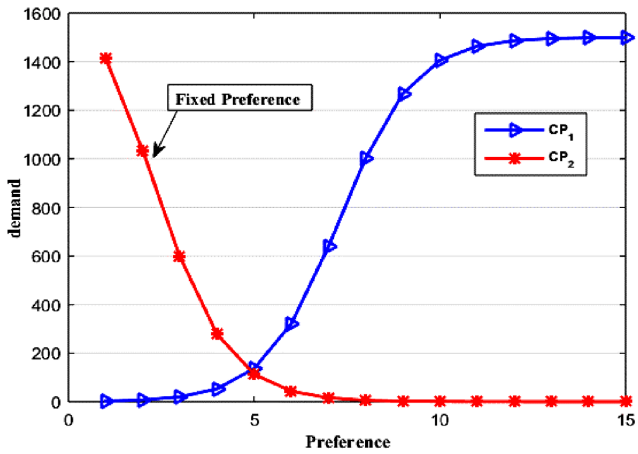


Figure 12 Demand vs. preference in cloud market (see online version for colours)



7 Conclusions

This study has dealt with the problem of price competition in a duopoly cloud market. In particular, we have focused on the non-cooperative game model to find the optimal pricing strategy that attracts more users and maximises profit margins as well. In this respect, we rely on a game theory model to analyse the users' choice behaviour and their impact on the strategic decisions among the cloud providers. The proposed model, when implemented properly, yields to the existence and the uniqueness of Nash equilibrium. Thus, the proposed model can be implemented as a useful and reliable tool to ensure a trade-off between profit and customers' satisfactions. More importantly, we show that the convergence to Nash equilibrium can be found quickly in the case of a duopoly cloud market. Furthermore, extensive research that has been under taken in the theoretical issues underpinning the proposed models and its practical application to determine the most effective pricing strategy for the cloud market. This study demonstrates the positive impact of the users' preference and the price sensitivity on the cost of remote services as well as the profitability of cloud providers.

In the future work, we plan to use a number of factors that contribute to the brand and reputation of the cloud provider. In particular, we intend to use the QoS and data security to develop a fair and effective pricing strategy for the cloud market to meet both customers and cloud providers' needs.

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