

# COVID-19 Networking Demand: An Auction-based Mechanism for Automated Selection of Edge Computing Services

Abdulsalam Yassine, *Member, IEEE*, and M. Shamim Hossain, *Senior Member, IEEE*,

**Abstract**—Network and cloud service providers are facing an unprecedented challenge to meet the demand of end-users during the COVID-19 pandemic. Currently, billions of people around the world are ordered to stay at home and use remote connection technologies to prevent the spread of the disease. The COVID-19 crisis brought a new reality to network service providers that will eventually accelerate the deployment of edge computing resources to attract the massive influx of users' traffic. The user can elect to procure its resource needs from any edge computing provider based on a variety of attributes such as price and quality. The main challenge for the user is how to choose between the price and multiple quality of service deals when such offerings are changing continually. This problem falls under multi-attribute decision-making. This paper investigates and proposes a novel auction mechanism by which network service brokers would be able to automate the selection of edge computing offers to support their end-users. We also propose a multi-attribute decision-making model that allows the broker to maximize its utility when several bids from edge-network providers are present. The evaluation and experimentation show the practicality and robustness of the proposed model.

**Index Terms**—Covid-19, Networking Demand, Edge Computing Services, Broker, Bidding, Quality of Service.

## 1 INTRODUCTION

THE Internet is witnessing unprecedented demand for network resources due to the COVID-19 pandemic. With billions of people are going online to work, communicate, and keep entertained, the overall network traffic increased by more than 50% globally [1]. In response to such demand, network and cloud service providers are optimizing their services by increasing connection and routing capacity, lowering streaming quality, and adding more cell towers to strengthen the wireless networks. While these measures are helpful, the underlying network infrastructure is not designed for this type of real-time stress that the global COVID-19 crisis has caused [2]. One solution is to include edge network computing to speed-up online services by allocating physical resource functionalities in proximity to the user [3] [4]. Edge computing [5], [6] allows network service providers to provision resources on-demand, hence avoiding over and under-provisioning, which are standard practices for networks with varying requirements due to traffic variations (e.g., on-peak and off-peak). According to a pre-COVID-19 report by IBM [7], 75% of enterprise data is going to be processed using edge computing resources by 2025 compared to only 10% today. However, the COVID-19 crisis brought a new reality to network service providers that will eventually accelerate the deployment of edge computing resources and open new avenues of competition to accommodate the massive influx of users' traffic.

On the other hand, the user (person, organization, broker, middle-ware, etc.) can elect to procure its resource needs from any edge computing provider based on a variety of attributes such as price and quality. The main challenge for the user is how to choose among the price and quality of different service providers when such offerings are changing continually. This issue is notably not a trivial prospect given the significance and varying multitude of edge computing service providers; it is not practical to optimize for the most suitable vendor manually.

In the context of the challenge mentioned above, this paper aims at investigating scalable and automated mechanisms for users to acquire the needed resource services from edge computing providers. It must be noted that, currently, standardization of edge computing services is not fully realized. Still, the providers need to address operational efficiency, security, and redundancy to monetize their offering. This effort is essential in the wake of COVID-19 pandemic because the status quo pricing strategies (e.g., pay as you go service or fixed fees) do not resonate well with users who are hungry for computing resources to meet their daily demand. Users need incentive mechanisms to adapt their consumption patterns according to the price and quality of available resources. In this paper, we propose multi-attribute bidding strategies for users to bind with an edge computing resource for application needs. The proposed bidding model allows users to control their data, lower costs, receive quicker responses, and sustain their operations. The study of multi-attribute bidding for network resource acquisition is an exciting and yet unexplored area in edge computing. The main contributions this paper is making are:

- A. Yassine with the Department of Software Engineering, Lakehead University, Ontario, Canada. E-mail: ayassine@lakeheadu.ca, M. Shamim Hossain is with the Chair of Pervasive and Mobile Computing, and the Department of Software Engineering, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia. (Email: mshossain@ksu.edu.sa).

Manuscript received April 19, 2020; revised September 22, 2020.

- Proposing an auction model for the increased net-

work connection demand and edge computing resources by users during the COVID-19 pandemic. The broker-based auction model allows users to automatically procure resources and incorporate price and QoS attribute rating to determine the best allocation of on-demand networking traffic. The significance of this model lies in the assessment and scoring functions that rank potential vendors to achieve maximum utility.

- Proposing a two-stage winner determination problem and payment allocation based on a scoring function, which provides an incentive to the providers to bid using their real valuation of price and quality attribute ratings. In the first stage, the mechanism uses the bids to qualify providers based on the broker's reservation quality and determines the cost value of various attributes. In the second stage, the broker shares the maximum score and allows the providers to increase their bids. The significance of the two-stage model is that it deters edge network service providers from deliberately submitting bids with lower quality, but instead encourages them to submit bids that meet the expectation of the broker. Furthermore, we prove that the proposed model is incentive compatible, individually rational, and computationally efficient.
- Evaluating the proposed model with extensive simulation experiments and realistic data such as those provided by Google and Amazon. We showed that the proposed solution satisfies the properties of the two-stage auction model, which makes it applicable for implementation in situations when the abnormal demand for edge computing services is present such as the case with the current COVID-19 pandemic.

The rest of the paper is organized as follows: In the next section, the related work presents the latest state-of-the-art research in the field, accompanied by a discussion of shortcoming. Section 4 provides a detail description of the model and the theoretical formulation of the problem followed by an analysis of the mechanism design in section 5. In section 6, the proposed model is evaluated with a series of experiments and discussions. Finally, in section 7, the paper is concluded with direction to future work.

## 2 RELATED WORK

The COVID-19 pandemic shows that current networking infrastructure is not ready to deal with unprecedented prolonged demand for resources. Consequently, the pricing and resource allocation models that are currently used need to be revised as well to provide flexibility beyond conventional schemes. In this section, we review some studies in the open literature related to edge computing resources allocation, bidding models, and mechanism design. The aim is to shed light on current research shortcomings and provide a comparative analysis to distinguish our work.

Existing edge computing resource providers set the cost without consultation with the users. The pricing models are mainly based on the take it or leave it scheme, which is not necessarily optimal for both parties. Furthermore, the promised QoS attributes are not contractually obligated. In

other words, it is difficult for the user to chase the provider to inquire about the delivered QoS. Therefore, several studies investigated the possibility of designing models that induce the providers to be truthful about their offerings. For example, the work presented in [8] proposes an auction model that allows users to place a bid to acquire the desired qualities. The authors proposed a two-level model where heterogeneous users compete for limited capacity. The main idea is that the model considers combinatorial auction, where users in different locations bid against each other. While helpful, the model does not consider the various qualities and ranking of these bids. The work in [9] provides a comparison of the different types of pricing structures concerning fairness; specifically, the study comments on the dynamic pricing models and their applicability to edge computing resource allocations. Similar to [9], the works in [10] [13] and [16] propose pricing mechanisms for edge computing resources [15] in highly dynamic environments. For example, [10] allowed the users to borrow credit using a double-auction model to maximize the economic benefit while [13] investigated the joint problem of network economics and resource allocation of users who are bidding for edge services. In [16], the authors focused on entertainment applications where users compete for higher quality concerning bandwidth and latency. They propose micro and macro auctions to accommodate various bidding schemes depending on the scale of the applications. Other works such as those in [17] and [18] propose auction models for resource allocation using edge computing services, but do not consider multi-attribute decision-making.

The previously discussed models do not consider the various quality attributes of the edge computing provider [14], but instead focus on the pricing and resource allocation problems. Reverse auction models were also considered in the literature where network service providers compete to attract users to purchase their services in highly dynamic environments. To this end, the work presented in [19] proposed a model by which network operators compete to provision the user requirements while minimizing the cost. The proposed model uses a reverse auction to achieve the desired resource allocation. In [20], the authors discussed a centralized strategy to induce third parties to lease unused bandwidth and storage in wireless access [11], [12] points using reverse auction models. The goal is to allow users to autonomously decide which access point they desire to use based on a set of criteria. A different model was proposed in [21], which uses an evolutionary immune mechanism to allocate resources based on market efficiency, user satisfaction, and QoS. To prevent the bidders from cheating, it implements a punishment scheme [22] to correct malicious behavior. The claimed results show that the system has the potential for better allocation of network resources in a real-world implementation. It also indicates that the model can be extended to various attributes related to user satisfaction, such as privacy. Although it is not explicitly considered but can be easily included in the negotiation process, as shown in [28] and [29].

The closest to our work are the studies in [23] [24] and [8]. In [23] and [24], the authors developed three mechanisms based on the work of [26]. Two mechanisms consider multi-attribute auctions, where one of them studies the

dominant strategic incentive-compatible scheme while the other investigates Bayesian incentive compatible. The authors show that the former mechanism provides individual rationality and allocation efficiency but not budget balanced while the latter is efficient, budget balanced but not individually rational. Also, the study proposed an optimal model where a user can decide on the preferred service provider based on price and the offered quality. In comparison to our work, we consider multi-attribute bidding, but we sacrifice budget balanced for the sake of efficiency, truthfulness, and individual rationality. The reason for this is that we did not consider an auctioneer to manage the bidding process, and payment allocation is transferred from the broker to the provider. To achieve truthfulness and to encourage the providers to bid with satisfactory quality, we implemented a two-stage approach in which only providers who meet the reserved quality of the broker are considered for final bidding. In the second stage, we followed the work in [8] and used the bid density as a factor on the scoring function. By doing so, we ensured that the providers are all treated fairly, and whoever makes the best offer wins. Thus, the difference between our work and [8] is that we do not consider satisfaction as a factor in the bidding process; instead, we implement a passing gate for providers to meet the desired quality of the broker. Table 1 provides a summary of the comparison between our work and existing studies.

Next section provides the details of the proposed model, including the parameters and utility functions of the involved parties.

### 3 SYSTEM MODEL

Before discussing the proposed model, we introduce necessary information on auctions and bidding mechanisms. Auctions are a direct application of mechanism design, which is a framework concerned with decision-making problems related to resource distribution and payment allocation of scarce resources. The main properties of mechanism design include truthfulness, individual rationality, efficiency, and budget balance. A mechanism is said to be truthful if the players have no incentive to bid values that do not represent their real types and valuation. Individual rationality means that players' outcome is non-negative. Efficient mechanism design is tractable with polynomial time complexity. Fairness ensures that the design allows all the players to have equal opportunities to participate in the auction. As mentioned earlier in section 1, we a mechanism design for multi-attribute bidding, which allows the distribution of edge network resources among competing players. Next, we describe the overall model, and in section 4, the details of the mechanism design model are introduced.

Figure 1 presents the high-level model of the proposed system and the sequence diagram of interaction among the parties during the bidding process. In this model, a broker working on behalf of users would like to procure resources from edge computing service providers. The broker informs all the providers about the resources necessary through, for example, a dedicated communication channel allocated for information sharing [27]. The providers reply with their bids, which include the price and an arbitrary number of quality attributes about the service. We consider a broker in

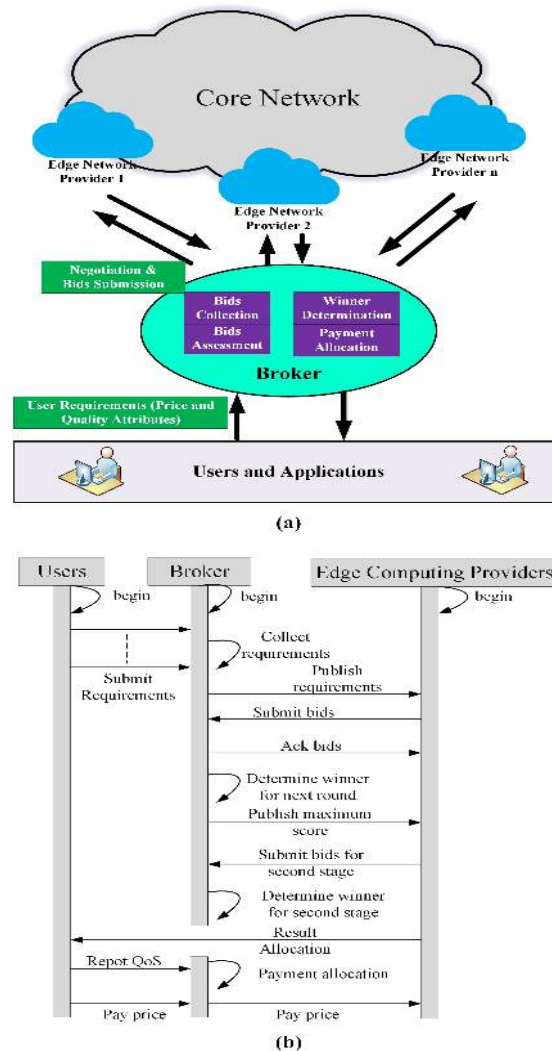


Fig. 1. (a) High Level Description of the Model with Brokers and Edge Network Providers. (b) sequence diagram describes the interaction between the parties during the bidding process

our model because it is not possible for a user to negotiate directly with a service provider. Also, when a broker is working on behalf of multiple users would be able to negotiate for a better offer that benefits everybody. By doing so, we are following a common market negotiation approach, which is far better for the user than going alone against a service provider. In this model, the broker's contract will be awarded to one winner only, i.e., we are considering an indivisible good. The broker in our model starts the auctioning process and needs to make a decision given the number of submitted bids. The providers who participate in the auction are determined to fulfill the configuration of the edge computing resources and specify that in the offers. Each quality attribute has a fixed coefficient, and the dimensions are identical for all the providers. We assume that the broker has preference over the attributes, and hence, the utility of each quality attribute is independent. For example, the broker may value bandwidth over latency in the network or vice versa, depending on the requirement of the users. The broker selects the provider who maximizes its utility based on some reservation price and quality

TABLE 1  
Comparison between our work and existing studies

Research Studies	Multi-attribute	Auction Model	Automated Selection	Utility Maximization
[10] [13]	No	Yes	No	Yes
[16]	Yes	Yes	No	No
[20] [19]	No	Yes	Yes	No
[23] [24]	Yes	Yes	Yes	No
[21]	No	Yes	No	No
Our Work	Yes	Yes	Yes	Yes

parameters. We assume that the reservation price, e.g.,  $\beta^r$ , of the broker, is private information and not shared with the providers at any stage of the auctioning process. The broker uses a scoring function of the quality attributes to evaluate the submitted bids and select the winner in the auctioning process. The scoring function is shared with all providers who use it to construct the bids that maximize their payoff. In this model, we assume that the providers are rational and have common knowledge about the auctioning process. Furthermore, the cost of allocating resources to users is private information. All providers are considered rational and strive to maximize their utility. The notations used throughout the paper are shown in Table 2.

Formally, we consider that there are  $\mathcal{P} = \{\mathcal{P}_i | i = 1, \dots, n\}$  providers of edge computing resources capable of delivering the required QoS attributes  $\mathcal{Q} = \{\mathcal{Q}_k | k = 1, \dots, m\}$ . Let  $\Lambda = \{\lambda_{ik} | i = 1, \dots, n; k = 1, \dots, m\}$  to be the set of performance ratings of provider  $i \in \mathcal{P}$  for quality attribute category  $k \in \mathcal{Q}$ . For example if quality attribute  $k = \text{"bandwidth"}$  then a possible performance rating value for provider  $i$  would be  $\lambda_{ik} = 200\text{kbps}$ . Let  $\mathcal{W} = \{w_k | k = 1, \dots, m\}$  to be the set of weights for each quality attribute  $k$ . The weights  $w_k$  are announced by the broker and denote the relative importance of the quality attributes such that  $\sum_{k=1}^m w_k = 1$ . It is also used to evaluate the providers' bids using a scoring rule.

TABLE 2  
Notations

Notation	Description
$i$	subscript player
$k$	subscript quality attribute
$\lambda_{ik}$	performance rating of attribute $k$ for provider $i$
$\beta_{ik}$	price paid to the provider
$U_{broker}$	utility function for the broker
$U_{provider}$	utility function for the provider
$w_k$	relative a=importance weight for quality attribute $k$
$\gamma_k$	single cost paramter to produce quality attribute $k$
$S$	score function for attribute ratings
$c_i$	cost value for provider $i$
$Z_i$	is the bid density
$\mathcal{P}$	set of edge computing service providers
$\mathcal{Q}$	set of quality attributes
$\Lambda$	set of performance ratings
$\mathcal{W}$	set of weights for each quality attribute

### 3.1 Utilities and Assumptions

In the proposed model, the broker's utility function is the difference of how much the broker values the quality attributes and the price it is going to pay the provider for delivering the service. The general utility function of the broker is given by:

$$U_{broker}(\beta, \lambda_{ik}) = \sum_{k=1}^m v_k(\lambda_{ik}) - \beta \quad (1)$$

where  $\beta$  is the price at which the broker is paying the provider to allocate edge computing resources according to the agreed upon quality attributes.  $v_k(\lambda_{ik})$  represents the valuation of the broker for each quality attribute. In (1), the valuation that the broker has on a certain quality attribute is derived from the users' requirements. For example, if the user values "bandwidth" more than any other quality attribute it means that the higher the performance rating of "bandwidth" is desirable as long as the utility is  $U_{broker}(\beta, \lambda_{ik}) \geq 0$ . The provider utility function is the difference between the price  $\beta$  that the broker pay for the service and the cost  $c_i = \sum_{k=1}^m \gamma_k \cdot \lambda_{ik}$  of offering the quality attributes. In general, the utility function of the provider is given by:

$$U_{provider}(\beta, \lambda_{ik}) = \beta - \sum_{k=1}^m \gamma_k \cdot \lambda_{ik} \quad (2)$$

The utility function of the provider assumes a single cost parameter  $\gamma$  to produce the quality attributes. The following are the assumptions made in the proposed mechanism.

**Assumption 1.** The providers and the broker are risk neutral individuals, the attributes  $\lambda_{ik}$  are endogenous with continuous values. Furthermore, the providers and the broker are mutually independent with respect to their preferences over the quality attributes.

**Assumption 2.** The providers' cost functions are strictly convex where the effect of  $\lambda_{ik}$  is considered to be independent and linear, when the quality increases by a unit value, the cost to the provider increases, i.e.,  $\frac{\partial c_i}{\partial \lambda_{ik}} > 0$ ,  $\frac{\partial^2 c_i}{\partial^2 \lambda_{ik}} > 0$ . Furthermore, the utility function of the broker is concave, increasing in quality while the marginal cost is not incremental, i.e.,  $\frac{\partial U_{broker}}{\partial \lambda_{ik}} > 0$ ,  $\frac{\partial^2 U_{broker}}{\partial^2 \lambda_{ik}} \leq 0$ .

To guide the providers on their offerings of quality attributes, the broker announces its scoring rule  $S_j$  as follows:

$$S_j = \sum_{k=1}^m w_k \cdot \lambda_{ik} - \beta \quad (3)$$

In (3), the term  $\sum_{k=1}^m w_k \cdot \lambda_{ik}$  is the score function for attribute ratings. A provider  $i$  is a winner if  $S_i = S_j^{max}$ ;  $1 \leq i \leq n$ . The calculation of the score function and attribute rating  $\lambda_{ik}$  for each provider is given in subsection 3.2. The objective of the providers is to respond with quality attribute parameter ratings that maximize their utility. Therefore, each provider must solve the following optimization problem to obtain the optimal best response parameter rating for each quality attribute.

$$\text{Maximize } \beta - \sum_{k=1}^m \gamma_k \cdot \lambda_{ik} \quad (4)$$

$$\text{subject to } \sum_{k=1}^m w_k \cdot \lambda_{ik} - \beta = S_i^{max} \quad (5)$$

where  $S_i^{max}$  is the current highest score. The provider might add a small increment to the maximum score only after being qualified for the next stage in order to increase its chances of winning if decided to place a new bid. If we solve (5) for  $\beta$  and then substitute it in the objective function (4), then the final problem has no constraints as follows:

$$\text{Maximize } \sum_{k=1}^m w_k \cdot \lambda_{ik} - S_i^{max} - \sum_{k=1}^m \gamma_k \cdot \lambda_{ik} \quad (6)$$

Each provider submits a bid  $\lambda_{ik}^* = \lambda_{ik}$  that yield a non-negative output, where  $\lambda_{ik}^*$  is the solution to the following first-order condition

$$\frac{\partial \sum_{k=1}^m w_k \cdot \lambda_{ik}}{\partial \lambda_{ik}} - \frac{\partial \sum_{k=1}^m \gamma_k \cdot \lambda_{ik}}{\partial \lambda_{ik}} = 0, \quad (7)$$

Notice that the term  $\sum_{k=1}^m w_k \cdot \lambda_{ik}$  is the valuation that the broker has on the quality attributes  $v_k(\lambda_{ik})$ . As in [8], the announced values of  $w_k$  may be equal or different from the actual reservation valuation of the broker. For example, if the announced values  $w_k$  are lower than the reserved valuations it means that the broker assert a lower utility from certain quality attributes. The determination of optimal  $w_k$  are not considered in this work, but we refer the reader to [30] for more details.

### 3.2 Quality Attributes Scaling

As mentioned earlier, the broker receives the performance rating values from the provider for each quality attribute. The open literature provides a wide variety of methods to compare attributes as described in [31] and [32]. In this paper, we use TOPSIS (Technique of Order Preference Similarity to the Ideal Solution) which was originally proposed by [33] to scale and normalize the various quality attributes. TOPSIS is a simple yet powerful method when there are no limits to the number of choices/alternatives and criteria in the decision making process. The information matrix that reports on the quality performance ratings can be formulated as follows:

$$\begin{pmatrix} \lambda_{11} & \lambda_{12} & \dots & \lambda_{1m} \\ \lambda_{21} & \lambda_{22} & \dots & \lambda_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{n1} & \lambda_{n,2} & \dots & \lambda_{nm} \end{pmatrix} \quad (8)$$

The parameter  $\lambda_{ik}$  represents provider  $i$ 's offer for the quality attributes where  $i = 1, \dots, n$ , and  $k = 1, \dots, m$ . It must be noted here that the quality attributes might not be expressed in numerical form, for example, "99 % reliability". It is important to assign a proper numerical value for such attributes. The TOPSIS method works only if the values of quality attributes ratings are expressed in integers. Let  $\bar{\lambda}_{ik}$  and  $\underline{\lambda}_{ik}$  be the maximum and minimum performance rating values of the quality attributes for provider  $i$ . Furthermore, the attributes are normally categorized as beneficial and non-beneficial. The former category refers to the broker's

preference for higher values of quality performance ratings while the latter category refers to the broker's preference for lower values of quality performance ratings. The first stage of the TOPSIS method is to normalize the information matrix values to a normalized decision matrix of  $\Lambda^{Norm} = [\lambda_{ik}^{Norm}]$  as follows:

$$\begin{pmatrix} \lambda_{11}^{Norm} & \lambda_{12}^{Norm} & \dots & \lambda_{1m}^{Norm} \\ \lambda_{21}^{Norm} & \lambda_{22}^{Norm} & \dots & \lambda_{2m}^{Norm} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{n1}^{Norm} & \lambda_{n,2}^{Norm} & \dots & \lambda_{nm}^{Norm} \end{pmatrix} \quad (9)$$

In (9), the value of  $\lambda_{ik}^{Norm}$  is given by

$$\lambda_{ik}^{Norm} = \frac{\lambda_{ik}}{\sqrt{\sum_{i=1}^n \lambda_{ik}^2}} \quad (10)$$

For the beneficial quality attributes,  $\lambda_{ik}^{Norm} = \frac{\lambda_{ik} - \underline{\lambda}_i}{\bar{\lambda}_i - \underline{\lambda}_i}$  and for the non-beneficial quality attributes  $\lambda_{ik}^{Norm} = \frac{\bar{\lambda}_i - \lambda_{ik}}{\bar{\lambda}_i - \underline{\lambda}_i}$ . Given the above normalization, we then calculate the weighted normalized performance ratings matrix  $S_{ik} = [s_{ik}]$  where  $s_{ik}$  is given by

$$\begin{pmatrix} w_1 \cdot \lambda_{11}^{Norm} & w_2 \cdot \lambda_{12}^{Norm} & \dots & w_m \cdot \lambda_{1m}^{Norm} \\ w_1 \cdot \lambda_{21}^{Norm} & w_2 \cdot \lambda_{22}^{Norm} & \dots & w_m \cdot \lambda_{2m}^{Norm} \\ \vdots & \vdots & \ddots & \vdots \\ w_1 \cdot \lambda_{n1}^{Norm} & w_2 \cdot \lambda_{n,2}^{Norm} & \dots & w_m \cdot \lambda_{nm}^{Norm} \end{pmatrix} \quad (11)$$

$$s_{ik} = w_k \cdot \lambda_{ik}^{Norm} \quad (12)$$

In (12)  $w_k \in [0, 1]$  and  $\sum_{x=1}^k w_x = 1$ .

## 4 MECHANISM DESIGN MODEL

The mechanism design model is composed of two stages. In the first stage, the broker receives all the bids from the providers, apply the scoring rule, and then determines the qualifying providers group for the next stage based on the reservation quality. In the second stage, the broker announces the payment function, which determines the amount of payment by the broker to the winning provider. There are a few challenges in the proposed scheme: firstly, how to determine which providers are qualified to advance to the next stage and secondly, how to ensure that the payment allocation is incentive compatible, i.e., the providers report their bid truthfully. To address these challenges, we first consider that each provider has private valuation about his bid represented by  $Bid_i = (c_i, \lambda_{ik})$  and a reported bid represented as  $\bar{B}id_i = (\bar{c}_i, \bar{\lambda}_{ik})$ . The goal is to design a mechanism that induces providers to reveal the true value about their bids. In other words, the true valuation is a dominant strategy for a provider regardless how other providers report their bids. The pseudo-code for the auction model is presented in Algorithm (1) whereas for all other stages are provided in Algorithms (2) and (3).

#### 4.1 Announcement of Score Function and Elimination of Unqualified Providers

At the beginning of the auction process, the broker announces the score function for all providers as described in (3). The providers reply with their bids  $\widehat{Bid}_i = (\widehat{c}_i, \widehat{\lambda}_{ik})$ . The bids that are less than the broker's reservation quality value are determined ineligible and cannot advance to the next stage. The broker determines the reservation quality as follows [34]:

$$v(\lambda_r^{\beta^r}) = \mu \left( \frac{1}{n} \sum_{i=1}^n \sum_{k=1}^m w_k \cdot \widehat{\lambda}_{ik}^{\widehat{c}_i} \right) \quad (13)$$

where  $v(\lambda_r^{\beta^r})$  is the broker's reservation quality at price  $\beta^r$ .  $\widehat{\lambda}_{ik}^{\widehat{c}_i}$  is the reported quality attribute performance rating for provider  $i$  at cost value  $\widehat{c}_i$ .  $\mu$  is a scaling value between  $[0, 1]$  determined by the broker. If  $\mu = 1$ , then the reservation value is exactly the average of the submitted bids, and those bids that are below average are eliminated. If  $\mu = 0$ , then the reservation value is zero and all bids are accepted. Elimination of providers using an average bid value is inspired by the work in [34] and also has been studied by [35]. Later in section (5), we discuss how such approach leads to truthful bidding when presenting the properties of the proposed auction model. Algorithm (2) describes the procedure of the elimination process.

---

#### Algorithm 1 Main Algorithm ()

---

- 1: Broker initiate the auction process ;
  - 2: Providers submit  $\widehat{Bid}_i = (\widehat{c}_i, \widehat{\lambda}_{ik})$ ;
  - 4: **foreach**  $i \in n$  **do**
    - | receive bid  $\widehat{Bid}_i = (\widehat{c}_i, \widehat{\lambda}_{ik})$
  - end**
  - 5: Elimination of Ineligible Providers
  - 6:  $(T, S_i^{max}) =$  Algorithm 2
  - 7: Winner Determination and payment allocation
  - 8:  $(i, \widehat{p}_i) =$  Algorithm 3
  - 9: Provision and allocates resources
- 

---

#### Algorithm 2 Elimination of Ineligible Providers

---

**Input** : Set of providers  $\mathcal{P} = \{\mathcal{P}_i | i = 1, \dots, n\}$ , Set of weights  $\mathcal{W} = \{w_k | k = 1, \dots, m\}$ , Score function  $\sum_{k=1}^m w_k \cdot \lambda_{ik} - \beta$ , Bid Values  $\widehat{Bid}_i = (\widehat{c}_i, \widehat{\lambda}_{ik})$

**Output**: Winning set of providers  $T \subseteq \cup_{i \in \mathcal{P}} \widehat{\lambda}_{ik}, S_i^{max}$

```

//Initialization ;
T ← ∅, S_i^{max} ← ∅
//STEP 1: Broker announces the scoring rule ;
S_j ← ∑_{k=1}^m w_k · λ_{ik} - β
//Broker determines the scaling factor for average quality value to be μ';
μ ← μ'
// Collect bids from providers;
foreach i ∈ n do
  receive bid;
  Bid_i = (c_i, λ_{ik})
  calculate v(λ_r^{β^r}) using μ';
  v(λ_r^{β^r}) ← μ' (1/n ∑_{i=1}^n ∑_{k=1}^m w_k · λ_{ik}^{c_i})
  if Bid_i ≥ v(λ_r^{β^r}) then
    | T ← T ∪ Bid_i ;
  end
else
  | Remove Bid_i
end
T ← Sort Bid_i in non-decreasing order
S_i ← S_i^{max}
return (T, S_i^{max})

```

---

#### 4.2 Wining Provider and Payment Allocation

Algorithm (3) describes the second stage of the auctioning process. It goes as follows: First, the broker announces the winning group and the maximum score from the first stage. The selected providers submit new bids which may increment the maximum score by a small amount  $\epsilon$ , such that  $S_i^{max} + \epsilon$ . Then, every provider solves the new optimization problem as in (7) to determine the optimal performance rating value of  $\widehat{\lambda}_{ik}$  that maximizes the provider's utility. The broker, on the other hand, determines the bid density of all providers and then rank them using an evaluation function  $x_i = \vartheta_i(\mathcal{Z}_i, S_i)$ , where  $\mathcal{Z}_i$  is the bid density and it is calculated as in [25].

$$\mathcal{Z}_i = \frac{\widehat{c}_i}{\sum_{k=1}^m \widehat{\lambda}_{ik}} \quad (14)$$

The broker sorts the providers' offers in the increasing order using the evaluation function  $x_i$  such that  $x_1 \leq x_2 \leq \dots \leq x_n$ . Following [25], a product function  $x_i = \vartheta_i(\mathcal{Z}_i, S_i) = \mathcal{Z}_i \cdot S_i$  is utilized for ranking. The allocation rule is then determined as follows:

$$h_i = \begin{cases} 1, & \text{if } x_i = \min(x_1, x_2, \dots, x_n). \\ 0, & \text{otherwise.} \end{cases} \quad (15)$$

After the broker determines the winner provider, a payment function known as Clark's mechanism [36] is used to calculate the amount the provider should receive to allocate the resources. The payment function is given by:

$$\widehat{p}_i = \widehat{c}_i \cdot h_i + \sum_{i \neq j} \widehat{c}_j \cdot h_j^{-i} - \sum_{i \neq j} \widehat{c}_j \cdot h_j \quad (16)$$

Basically, this payment scheme gives the winning provider  $i$  the sum of the cost and the difference between the optimal cost without provider  $i$ . For example, if  $j$  is the winner and  $l$  be the winner in the case  $j$  is not included, then the payment according to (16) is  $\widehat{p}_j = \widehat{c}_j + \widehat{c}_l - \widehat{c}_j = \widehat{c}_l$ . Let us consider the case when a provider  $g$  is not a winner. Let the winner be provider  $d$ , then the payment for  $g$  is as follows  $\widehat{p}_g = \widehat{c}_g \times 0 + \widehat{c}_d - \widehat{c}_d = 0$ . The above payment method shows that the provider that quotes the lowest cost per quality attribute receives the second lowest payment. The other providers receive no payment. Hence, this is a low-bid Vickrey auction [36].

---

**Algorithm 3** Winning Provider and Payment Allocation

---

**Input** : Set of winning providers from stage 1  $\mathcal{T}$ , Maximum Score  $S_i^{max}$ ,

**Output**: Winning provider  $i$ , payment allocation  $\widehat{p}_i$

```
//Initialization ;
//Broker announces the winning group of providers  $\mathcal{T}$ 
and the maximum score  $S_i^{max}$  ;
//Providers increment the current maximum score by  $\epsilon$  ;
// Then solve  $\sum_{k=1}^m w_k \cdot \lambda_{ik} - S_i^{max} - \epsilon - \sum_{k=1}^m \gamma_k \cdot \lambda_{ik}$  as in
(7);
// Broker collect new bids;
foreach  $i \in n$  do
    receive bids;
     $\widehat{Bid}_i = (\widehat{c}_i, \widehat{\lambda}_{ik})$ 
    Calculate bid density  $\mathcal{Z}_i$  and evaluation function
     $x_i = \vartheta_i(\mathcal{Z}_i, S_i)$  ;
     $\mathcal{Z}_i = \frac{\widehat{c}_i}{\sum_{k=1}^m \widehat{\lambda}_{ik}}$  ;
     $x_i = \mathcal{Z}_i \cdot S_i$  ;
end
Sort  $x_i$  in increasing order;
Winner provider  $i$  for  $x_1 \leq x_2 \leq \dots \leq x_n$  ;

//Payment for provider  $i$  ;
 $\widehat{p}_i = \widehat{c}_i \cdot h_i + \sum_{i \neq j} \widehat{c}_j \cdot h_j^{-i} - \sum_{i \neq j} \widehat{c}_j \cdot h_j$ 

return ( $i, \widehat{p}_i$ )
```

---

## 5 PROPERTIES OF THE PROPOSED AUCTION MODEL

The proposed auction model is evaluated based on a set of properties that describe the characteristics of computational complexity, individual rationality, and truthfulness. Before we dive in the proofs of the properties we shall introduce the following definitions.

**DEFINITION 1.** *Single-minded.* A cost function  $\mathcal{C}$  is said to be single-minded if  $\exists \lambda_{ik} \in \Lambda$  and a cost  $c$ , if  $\mathcal{C}(\lambda'_{ik}) = c$  for all  $\lambda_{ik} \in \Lambda$  and  $\mathcal{C}(\lambda_{ik}) = \infty$  for all other  $\lambda_{ik}$ . A single-minded provider bids  $(c, \lambda_{ik})$

**DEFINITION 2.** *Monotone.* If a provider wins the auction when a bid pair  $(c, \lambda_{ik})$ , and still be a winner for any  $(c', \lambda'_{ik})$  such that  $\lambda'_{ik} \subseteq \lambda_{ik}$  and with  $c' \leq c$ . Then the mechanism of selecting the winner is monotone.

**DEFINITION 3.** *Critical Payment.* There exists a critical payment  $\widehat{p}_i^c$  for a winning provide  $i$  that is independent of its asking

price. The provider  $i$  will win for any  $(c', \lambda_{ik})$ , where  $c' \leq \widehat{p}_i^c$  while the opposite leads to losing the bid.

**Lemma 1.** *The proposed auction model is computationally efficient.*

*Proof:* The computation complexity is examined in the two stages of the model. In first stage, the outer For Loop runs for all bids and then calculates the average value. The maximum complexity of the operation is bounded by  $O(\alpha)$ . The For Loop includes an If statement operation which checks for one condition and takes  $O(1)$  time to finish in the worst case scenario. Therefore, the maximum time for the For Loop to complete  $O(\alpha)$ . The sort operation in Algorithm (2) requires  $O(\phi \log \phi)$  to complete. Adding both times, we can conclude that the first stage of the auction model takes about  $O(\alpha + \phi \log \phi)$ . In the second stage in Algorithm (3), the first For Loop takes  $O(\alpha)$  time to finish and the sort operation takes  $O(\phi \log \phi)$ . Hence, the time complexity of the second stage is bounded by  $O(\alpha + \phi \log \phi)$ . Therefore, the worst case scenario for the whole acution process is to complete in twice the time of  $O(\alpha + \phi \log \phi)$  ■

**Lemma 2.** *The proposed auction model is individually rational.*

*Proof:* Individual rationality means that a participant attains a positive reward if his/her bid wins, or zero if lost. In our model, we assume that individuals are single-minded bidders and only trade if the reward is greater than their reservation cost  $c_i(\lambda_{ik})$ . Each wining provider  $i \in \mathcal{P}$  gets the Vickery payment which is more than their declared cost. Therefore, according to (2), the payoff to the provider  $U_{provider} \geq 0$ . The broker, on the other hand, will also attain a utility  $U_{broker} \geq 0$ . Since all participants receive positive utility if they win, or zero if they lose, then we conclude that our model is individually rational. ■

**Lemma 3.** *The proposed auction model is monotone.*

*Proof:* Assume provider  $i$  is a winner when bidding with pair  $(c_i, \lambda_{ik})$ . The average cost of his bid is  $\frac{c_i}{\lambda_{ik}}$ , if the provider bids with a value  $c'_i \leq c_i$  and  $\lambda_{ik}$  remains unchanged, then his bid density  $\mathcal{Z}_i$  decreases leading to a better position in the list of potential winners. Therefore, provider  $i$  remains a winner, which makes sense since the provider lowered its bidding cost  $\frac{c'_i}{\lambda_{ik}} \leq \frac{c_i}{\lambda_{ik}}$ . On the other hand, if the provider bids with a better quality attribute ratings while keeping the cost unchanged, i.e.  $(c_i, \lambda'_{ik})$  such that  $\lambda'_{ik} \supseteq \lambda_{ik}$  it will improve his score function while decreasing the bid density  $\mathcal{Z}_i$ . Therefore, provider  $i$  remains a winner and with an average cost  $\frac{c_i}{\lambda'_{ik}} \leq \frac{c_i}{\lambda_{ik}}$ . In sum, our mechanism shows that whenever the provider improves an element of his bid it remains a winner. Hence, the proposed mechanism is monotone. ■

**Lemma 4.** *The payment  $\widehat{p}$  to provider  $i$  is equal to the critical cost.*

*Proof:* According to the proposed mechanism, the payment obtained by provider  $i$  if declared a winner is  $\widehat{p}_i = \widehat{c}_i \cdot h_i + \sum_{i \neq j} \widehat{c}_j \cdot h_j^{-i} - \sum_{i \neq j} \widehat{c}_j \cdot h_j$ . Let us assume that provider  $i$  bids a value  $c_i < \widehat{p}_i$ . In this case, it will win the auction according to Lemma 3. On the other hand, if provider  $i$  bids with a cost value  $c'_i > \widehat{p}_i$ , then equation (16) becomes  $\widehat{p}'_i = c'_i \cdot h_i + \sum_{i \neq j} \widehat{c}_j \cdot h_j^{-i} - \sum_{i \neq j} \widehat{c}_j \cdot h_j > \widehat{p}_i$ . In this case, if a provider  $j$  bids with a cost value equal to  $\widehat{p}_i$  would be the first in the list because  $\widehat{p}_j = \widehat{p}_i > \widehat{p}_i$  and will be declared

winner. The above observation shows that obtaining payment exactly equal to the critical cost value for provider  $i$  is essential otherwise loses the bid. Therefore, the proposed mechanism implements the critical value. ■

**Theorem 1.** *The proposed mechanism is incentive compatible.*

*Proof:* A mechanism is said to be incentive compatible if and only if it is monotonic and implement the critical payment value. From Lemma 3 and Lemma 4 we can deduce that the proposed mechanism is incentive compatible. ■

## 6 EVALUATION

In this section, we evaluate the proposed model using multiple edge computing node providers competing to win allocation for users utilizing resource hungry application such as video streaming clients. The broker in the simulated scenario is an agent works on behalf of the clients. The interaction among the parties in this scenario is assumed to be automatic. The setup and the assumptions of the evaluation are discussed next.

### 6.1 Setup and Simulation Parameters

In real-life, edge computing providers including cloud vendors offer various price distributions for their quality of services. Currently, there is no actual bidding structure for such services and typical auctioning models are not possible. Hence, there is a need for mechanism design. Having mentioned such requirement, it is not possible to measure or enforce incentive compatibility or compare it to baseline model for benchmark. Our aim is to evaluate the proposed auction model with a dynamically generated price and quality attributes rather than a fixed formula as in [37]. Hence, we implemented our simulation using the formulation presented in this paper while taking into account realistic parameters from publically available data following [25] and [37].

To evaluate the system, we have executed a series of experiments that mimic a realistic scenario. Each edge computing node is capable of providing a range of quality attributes at different costs, however, the provider cannot place more than one bid. In other words, the provider although it can offer higher quality for the broker, it might decide to bid with lower quality at a cheaper cost. To simulate this case, we assume that there is a range of quality performance ratings and a random generator, which is applied to construct the bid for each provider. In reality, there is no limit how each provider is going to combine their quality attributes. In order to model the strategic behavior of the bidders, we assume that each provider can specify the quality ratings from various ranges (low, medium, and high) to make an offer. For the sake of simplicity, we assume that the price differs from one range of quality attribute to another, but it is constant for the same range group. The broker's initial assigned score for quality attributes is constant. Furthermore, we assume that the providers are restricted to the quality attribute performance ratings that they are capable of satisfying the broker's demand shall they win the bid. Finally, we assumed that all providers are capable of providing similar types of quality attributes, but they differ in the quality rating performance. Table (3)

shows the parameters of the quality attribute ratings and the assigned scores for each attribute. The values of the quality attribute specification for bandwidth and latency follow a normal distribution over the specified range. However, the storage capacity is a predefined amount of 50 GB increments. The cost is considered to be fixed for the duration of time (week, month etc.) of which the service is offered. This assumption is inline with acceptable current market structure of Google, Amazon, etc. All experiments are carried using a Windows 10 64-bit Operating System PC with the following specifications, Intel Core i7-6700HQCPU, 2.6 GHz, 8 GB RAM.

Each provider  $i$  selects a bid  $\widehat{bid}_i$  that maximizes its utility as described in (7). For the first round, we assume that the providers have no historical reference. Hence, the bids shown in figure (2) are randomly generated to capture the nature of the bidders. For example, provider  $i$  may bid the  $[\widehat{\lambda}_{i1} = 10Gbps, \widehat{\lambda}_{i2} = 100ms, \widehat{\lambda}_{i3} = 100GB, \widehat{c}_i = 60]$ . In figure (3), we present the varying scores for 10 providers after generating 10 random bids. The broker calculates these scores based on equation (3). As explained in the mechanism design section, the broker announces the winners for the second stage based on equation (13). In this experiment, we set the scale value  $\mu = 1$ , which means that the average value of the bidders will be used to determine the winners of the first stage. In this case, the winner set  $\mathcal{T}$  includes providers  $\{4, 5, 7, 8, 10\}$ . Each provider will be able to increase its offering for the next stage knowing that the highest score is 0.8. However, the providers do not know the price and quality attribute rating values of each others. The score increment  $\epsilon$  is affected by the choice of decreasing or increasing the offerings of beneficial and non-beneficial attributes. For this experiment, we assume that the providers can increase the beneficial value anywhere between [1-5 Gbps] for the bandwidth and decrease by [5-10ms] for non-beneficial attributes such as latency. The price/cost decrease follows a value ranges between [1-5\$].

### 6.2 Selection of the Winning Provider and the Impact of Bid Increment $\epsilon$

Figure (4) shows the updated score values for the winning providers in the second stage of the bidding process. The experiment goes for 10 iterations where various score increments are considered. In order to simulate a realistic scenario, we assumed that the winning provider in the first stage did not increase its score in the second stage while others may increase their score by a fixed amount in all iterations. Applying Algorithm (3), we noticed that the provider who may have the flexibility to offer various quality attributes is winning more iterations than those who cannot make changes. For example, in figure (5) provider 5 won six times whenever reached the second stage of the bidding. Provider 5 won most of the time because the score was increased aggressively above the maximum score from the first stage. Provider 4 was able to win 3 times while provider 7 won one time only after it raises its score to 0.98. Provider 8 and 10 did not win because as we mentioned earlier provider 8 kept the same score value from previous stage. Provider 10 increased the score by a fixed amount that was obviously below other bidders.



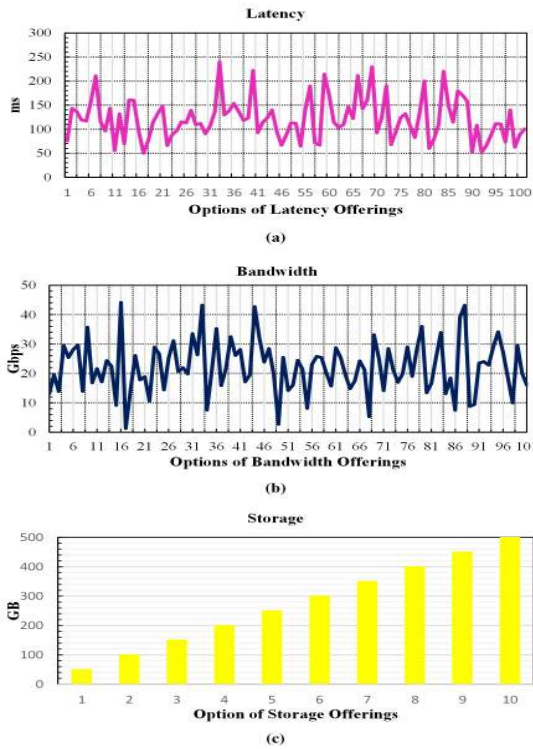


Fig. 2. Quality Attributes Ratings: (a) Latency, (b) Bandwidth, (c) Storage

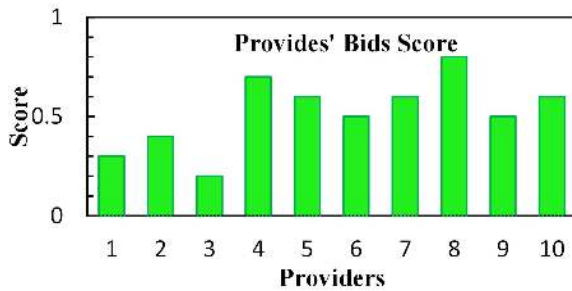


Fig. 3. Providers score for various bid offering

### 6.3 Critical Payment and Providers' Benefit

To examine the monotonicity of the proposed model, we let each winner provider in the corresponding iteration to adjust its bidding cost to enhance its position in the winning set. For this experiment, we allow each winning provider to adjust by a 2% amount. As explained earlier, the provider's average cost decreases, thus giving him a better score since his bid density decreases. For example, provider 4 in figure (6) won in iteration 4, 6 and 8 again with same benefit as in the case before making any adjustment to the cost. Similarly, provider 5 won in the same iterations 1,2,3,5,7 and 9 while provider 7 won in iteration 10. In any winning case, the benefit for providers 4,5 and 7 did not change, which means the mechanism is maintaining monotonicity. Furthermore, the winning providers are receiving the critical cost function, which concludes that the mechanism is incentive compatible. It should be noted that the providers may adjust their cost with values higher than 2%, but the final output stays the same because they would not be able

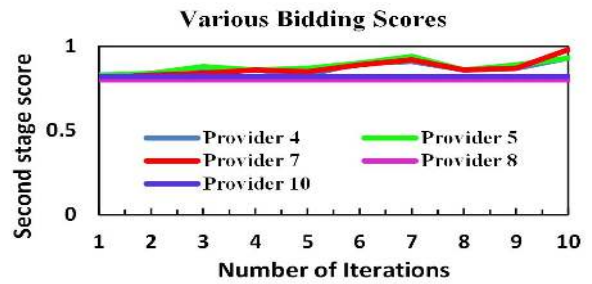


Fig. 4. Winning Providers in the second Stage with updated score values

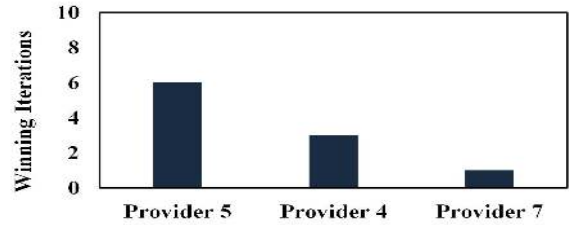


Fig. 5. Number of winning iterations for each provider

to improve their position in the winning set any further. Similarly, a smaller value than 2% would enhance their cost offering and bid density by a margin that would not affect their position score. In either case, the providers receive the critical payment. Figure 7 shows the comparison of benefits among the winning providers. Obviously, the percentage of benefit for provider 5 is much higher than those of provider 4 and provider 7 because of the winning iterations. Similarly, provider 4 has higher percentage of benefit than provider 7.

### 6.4 Computational efficiency

The computational complexity of the proposed model is affected by the overhead of the negotiation process. However, as the number of providers in the system increases the algorithms in both stages conform to the expecting execution time as shown in Lemma 1. In the simulation experiments, the average execution time of the algorithms was 2.1 ms for 10 providers. We executed the algorithms for 20 providers and the average execution time was 2.9 ms. In these results, the mechanism shows that the latency to finalize the two stage bidding process is acceptable and the delay is not significant. Furthermore, it is not common in real-life scenario to have more than 20 edge computing service providers.

TABLE 3  
Parameters and Quality Attributes Performance Ratings

Number of Providers [5-20]			
Quality Attribute	Specification	Score	Weight
Bandwidth	[1Gbps-50Gbps]	4	0.2
Latency	[50-250 ms]	3	0.3
Storage	[50GB-500GB]	3	0.1
Price/cost	[50-300\$]	5	0.4

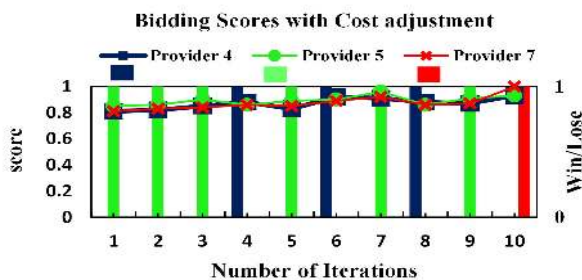


Fig. 6. Winning providers in each iteration after cost adjustment

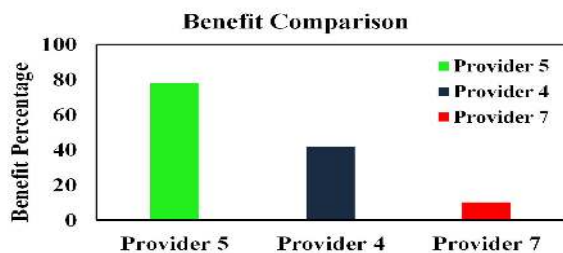


Fig. 7. Winning providers in each iteration after cost adjustment

## 7 CONCLUSION AND FUTURE WORK

This paper addresses the issue of increased demand for network resources during special times, such as the COVID-19 pandemic. We presented a model by which users can work with a broker to negotiate on their behalf to allocate network resources that satisfy their large demand. The proposed two-stage model ensures fairness and truthfulness while aiming to maximize the benefit and attain higher quality attributes. We have shown through experiments that the provider would have a higher chance of winning when bidding truthfully. This helps the broker to make an informed decision and serves the users better. As for future direction, we need to study much more complex scenarios where the cost and the score functions are not linearly additive. We also need to explore options where the quality attribute values are not continuous. Another point worth exploring is to study cases where the providers might collude or cooperate to offer bundled services. These directions may be more realistic as the development and implementation of edge network resources become widely adopted.

## ACKNOWLEDGMENT

The authors are grateful to the Deanship of Scientific Research at King Saud University, Riyadh, Saudi Arabia for funding this work through the Vice Deanship of Scientific Research Chairs: Chair of Pervasive and Mobile Computing.

## REFERENCES

[1] W. D. Heaven. *Why the coronavirus lockdown is making the internet stronger than ever*, MIT Review, April 2020. Available at <https://www.technologyreview.com/2020/04/07/998552/why-the-coronavirus-lockdown-is-making-the-internet-better-than-ever/>

[2] M. S. Hossain, G. Muhammad and N. Guizani, "Explainable AI and Mass Surveillance System-Based Healthcare Framework to Combat COVID-19 Like Pandemics," *IEEE Network*, vol. 34, no. 4, pp. 126-132, 2020.

[3] A. Yassine A., S. Singh. M.S. Hossain, G. Muhammad, "IoT big data analytics for smart homes with fog and cloud computing," *Future Gener. Comput. Syst.*, 0167-739X, 91 (2019), pp. 563-573

[4] A. Yassine, A. A. N. Shirehjini and S. Shirmohammadi, "Bandwidth On-demand for Multimedia Big Data Transfer across Geo-Distributed Cloud Data Centers," *IEEE Transactions on Cloud Computing*, 2016. doi: 10.1109/TCC.2016.2617369.

[5] M. Chen *et al.*, "Edge-CoCaCo: Toward Joint Optimization of Computation, Caching, and Communication on Edge Cloud," *IEEE Wireless Communications*, vol. 25, no. 3, pp. 21-27, JUNE 2018.

[6] Y. Hao *et al.*, "Smart-Edge-CoCaCo: AI-Enabled Smart Edge with Joint Computation, Caching, and Communication in Heterogeneous IoT," *IEEE Network*, vol. 33, no. 2, pp. 58-64, March/April 2019.

[7] S. Snyder, R. High, K. Butner, and A. Marshall. *Why organizations are betting on edge computing*, IBM Institute of Business Values, May 2020. Available at <https://www.ibm.com/downloads/cas/4EALMVGP>

[8] T. Bahreini, H. Badri and D. Grosu. *An Envy-Free Auction Mechanism for Resource Allocation in Edge Computing Systems* 2018 IEEE/ACM Symposium on Edge Computing (SEC), Seattle, WA, 2018, pp. 313-322, doi: 10.1109/SEC.2018.00030.

[9] B. Baek, J. Lee, Y. Peng and S. Park, "Three Dynamic Pricing Schemes for Resource Allocation of Edge Computing for IoT Environment," *IEEE Internet of Things Journal*, vol. 7, no. 5, pp. 4292-4303, May 2020, doi: 10.1109/JIOT.2020.2966627.

[10] Z. Li, Z. Yang, S. Xie, W. Chen and K. Liu, "Credit-Based Payments for Fast Computing Resource Trading in Edge-Assisted Internet of Things," *IEEE Internet of Things Journal*, vol. 6, no. 4, pp. 6606-6617, Aug. 2019.

[11] Y. Zhang *et al.*, "COCME: Content-Oriented Caching on the Mobile Edge for Wireless Communications," *IEEE Wireless Communications*, vol. 26, no. 3, pp. 26-31, June 2019.

[12] M. S. Hossain and G. Muhammad, "A Deep-Tree-Model-Based Radio Resource Distribution for 5G Networks," *IEEE Wireless Communications*, vol. 27, no. 1, pp. 62-67, February 2020

[13] W. Sun, J. Liu, Y. Yue and H. Zhang, "Double Auction-Based Resource Allocation for Mobile Edge Computing in Industrial Internet of Things," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 10, pp. 4692-4701, Oct. 2018.

[14] M.S. Hossain, and G. Muhammad, "Emotion Recognition Using Secure Edge and Cloud Computing," *Information Sciences*, vol. 504, no. 2019, pp. 589-601, December 2019

[15] Y. Zhang *et al.*, "Edge Intelligence in the Cognitive Internet of Things: Improving Sensitivity and Interactivity," *Network*, vol. 33, no. 3, pp. 58-64, 2019.

[16] A. G. Tasiopoulos, O. Ascigil, I. Psaras and G. Pavlou. *Edge-MAP: Auction Markets for Edge Resource Provisioning* 2018 IEEE 19th International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM), Chania, 2018, pp. 14-22.

[17] A. Yassine, M. S. Hossain, G. Muhammad and M. Guizani, "Cloudlet-Based Intelligent Auctioning Agents for Truthful Autonomous Electric Vehicles Energy Crowdsourcing," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 5, pp. 5457-5466, May 2020.

[18] A. Yassine, M. S. Hossain, G. Muhammad and M. Guizani, "Double Auction Mechanisms For Dynamic Autonomous Electric Vehicles Energy Trading," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 8, pp. 7466-7476, Aug. 2019.

[19] F. Nouri, F. Ashtiani and M. Mirmohseni. *Resource Provisioning of MVNOs in a Virtualized Wireless Network: A Procurement Auction Approach* 2018 IEEE Globecom Workshops (GC Wkshps), Abu Dhabi, United Arab Emirates, pp. 1-6, 9-13 December 2018

[20] M. Mangili, F. Martignon, S. Paris and A. Capone, "Bandwidth and Cache Leasing in Wireless Information-Centric Networks: A Game-Theoretic Study," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 1, pp. 679-695, Jan. 2017.

[21] T. Sandholm, S. Suri, A. Gilpin, and D. Levine. *CABOB: A fast optimal algorithm for winner determination in combinatorial auctions*. *Management Science*, vol. 51, no. 3, pp. 374?390, 2005.

[22] X. W. Wang, J. J. Sun, H. X. Li, C. Wu, and M. Huang. *A reverse auction based allocation mechanism in the cloud computing environment* *Appl. Math. Inf. Sci.*, vol. 7, no. 1, pp. 75?84, 2013.

- [23] G. V. Prasad and S. Rao, *A combinatorial auction mechanism for multiple resource procurement in cloud computing* in Proc. 12th Int. Conf. Intell. Syst. Des. Appl., 2012, pp. 337-344.
- [24] A. S. Prasad and S. Rao, *A mechanism design approach to resource procurement in cloud computing*. IEEE Trans. Comput., vol. 63, no. 1, pp. 177-30, 2014.
- [25] G. Baranwal and D. P. Vidyarthi, "A Truthful and Fair Multi-Attribute Combinatorial Reverse Auction for Resource Procurement in Cloud Computing," *IEEE Transactions on Services Computing*, vol. 12, no. 6, pp. 851-864, 1 Nov.-Dec. 2019.
- [26] Y. Narahari, D. Garg, R. Narayanam, and H. Prakash. *Game Theoretic Problems in Network Economics and Mechanism Design Solutions*. Springer, 2009.
- [27] X. Y. Wang and P. Ho, "Gossip-Enabled Stochastic Channel Negotiation for Cognitive Radio Ad Hoc Networks," *IEEE Transactions on Mobile Computing*, vol. 10, no. 11, pp. 1632-1645, Nov. 2011.
- [28] A. Yassine and S. Shirmohammadi. *Measuring users' privacy payoff using intelligent agents*, 2009 IEEE International Conference on Computational Intelligence for Measurement Systems and Applications, Hong Kong, 2009, pp. 169-174.
- [29] A. Yassine and S. Shirmohammadi, *Privacy and the market for private data: A negotiation model to capitalize on private data*, 2008 IEEE/ACS International Conference on Computer Systems and Applications, Doha, 2008, pp. 669-678.
- [30] T. G. Chetan, M. Jenamani and S. P. Sarmah, "Two-Stage Multi-attribute Auction Mechanism for Price Discovery and Winner Determination," *IEEE Transactions on Engineering Management*, vol. 66, no. 1, pp. 112-126, Feb. 2019.
- [31] G. Gao, Z. Fan and Y. Liu. *Determining winner in multi-attribute procurement auction: A method based on technical and business experts' evaluation information* in Journal of Systems Engineering and Electronics, vol. 26, no. 6, pp. 1244-1253, Dec. 2015.
- [32] G.H. Tzeng and Jih-Jeng Huang. *Multiple Attribute Decision Making: Methods and Applications* CRC Press, Taylor and Francis Group, June 22, 2011
- [33] C.L. Hwang and K. Yoon. *Multiple Attribute Decision Making: Methods and Applications*. 1981 Springer-Verlag, New York.
- [34] P. G. Ioannou and S.S. Leu. *Average-bid method-competitive bidding strategy* Journal of Construct. Engineering Management, vol. 119, pp. 131-147, 1993.
- [35] W.S. Chang, B. Chen, and T. C. Salmon. *An investigation of the average bid mechanism for procurement auctions* Management Science, 2014.
- [36] V.V. Vazirani, N. Nisan, T. Roughgarden, E. Tardos. *Algorithmic Game Theory* (PDF). Cambridge, UK: Cambridge University Press, 2007 ISBN 0-521-87282-0
- [37] Q. He, J. Yan, H. Jin and Y. Yang, "Quality-Aware Service Selection for Service-Based Systems Based on Iterative Multi-Attribute Combinatorial Auction," *IEEE Transactions on Software Engineering*, vol. 40, no. 2, pp. 192-215, Feb. 2014.



**Abdulsalam Yassine** Abdulsalam Yassine received the B.Sc. degree in electrical engineering from Beirut Arab University, Lebanon, in 1993, and the M.Sc. and Ph.D. degrees in electrical and computer engineering from the University of Ottawa, Canada, in 2004 and 2010, respectively. Between 2001 and 2013, he was a member of the Technical Staff in the Wireless Communication Division, Nortel Networks, and later at Alcatel-Lucent, Ottawa, Canada. From 2013 to 2016, he was a Postdoctoral Fellow at the DISCOVER Laboratory, School of Electrical Engineering and Computer Science, University of Ottawa. Currently, he is an Assistant Professor in the Department of Software Engineering, Lakehead University, Thunder Bay, Ontario, Canada. His research interests are mostly focused on behavior and predictive analytics, big data systems and networks, artificial intelligence, IoT system, smart cities, smart environments, and smart grids research and applications.

**M. Shamim Hossain** [SM-09] is a Professor at the Department of Software Engineering, College of Computer and Information Sciences, King Saud University, Riyadh, Saudi Arabia. He is also an adjunct professor at the School of Electrical Engineering and Computer Science, University of Ottawa, Canada. He received his Ph.D. in Electrical and Computer Engineering from the University of Ottawa, Canada in 2019. His research interests include cloud networking, smart environment (smart city, smart health), AI, deep learning, edge computing, Internet of Things (IoT), multimedia for health care, and multimedia big data. He has authored and co authored more than 300 publications including refereed journals, conference papers, books, and book chapters. Recently, he co-edited a book on Connected Health in Smart Cities, published by Springer. He has served as co chair, general chair, workshop chair, publication chair, and TPC for over 2 dozens of the IEEE and ACM conferences and workshops. Currently, he is the co chair of the 3rd IEEE ICME workshop on Multimedia Services and Tools for smart-health (MUST-SH 2020). He is a recipient of a number of awards, including the Best Conference Paper Award and the 2016 ACM Transactions on Multimedia Computing, Communications and Applications (TOMM) Nicolas D. Georganas Best Paper Award. He is on the editorial board of the IEEE TRANSACTIONS ON MULTIMEDIA, IEEE MULTIMEDIA, IEEE NETWORK, IEEE WIRELESS COMMUNICATIONS, IEEE ACCESS, Journal of Network and Computer Applications (Elsevier), and International Journal of Multimedia Tools and Applications (Springer). He also presently serves as a lead guest editor of IEEE Network, ACM Transactions on Internet Technology, ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM) and Multimedia systems Journal. Previously, he served as a guest editor of IEEE Communications Magazine, IEEE Network, IEEE Transactions on Information Technology in Biomedicine (currently JBHI), IEEE Transactions on Cloud Computing, International Journal of Multimedia Tools and Applications (Springer), Cluster Computing (Springer), Future Generation Computer Systems (Elsevier), Computers and Electrical Engineering (Elsevier), Sensors (MDPI), and International Journal of Distributed Sensor Networks. He is a senior member of both the IEEE, and ACM.