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A Resource Trading Framework for Cloudlets

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***Abstract*— Cloud computing has attracted a lot of interest from both industry and academia. Many business models have been proposed to bring together cloud consumers and providers. In this paper, a resource trading framework is proposed as an alternative business model for clouds. The under-utilized cloud resources are being solved to potential customers by the guidance of a broker. The applicability of the proposed theoretic model is shown on a simple but demonstrative example. This research may be considered as a preliminary business model, which will further be expanded by integrating more cloudlets that compete with each other.**

***Index Terms*— Cloud computing; cloudlet; resource trading; brokering model.**

I. Introduction

Cloud computing management supports are becoming more and more important not only in the fields of IT infrastructures for Internet applications and services, but also in the field of telecommunication services and infrastructures. The growth in the cloud computing market has had an increasing effect on the market complexity since users have to deal with different virtual machine types, pricing schemes or cloud interfaces. The role of brokering comes into the scene at this point. A brokering mechanism may be considered as an intermediary that transforms competitive cloud market into a commodity service.

The cloudlet concept is discussed in several works in literature. In one of them [1], the authors define cloudlet as a trusted, resource-rich computer or cluster of computers that is well-connected to the Internet and available for use by nearby mobile devices. They have stated the fact that using a cloudlet simplifies the challenge of meeting the peak bandwidth demand of multiple users interactively generating and receiving media such as high high-definition video and high-resolution images. One of the research questions that the authors have denoted has been our inspiration for the proposed framework: "Is deployment driven bottom-up by business owners installing cloudlets for the benefit of their customers, or is it driven top-down by service providers who share profits with the retail businesses on whose premises cloudlets are deployed?". The same cloudlet concept as the one in this paper, is proposed as a means to take advantage when mobile devices cannot or do not want to connect to the cloud [2]. The authors propose come up with an admission control policy for mobile cloud computing hotspot. They have shown that the admission control scheme can achieve a desirable performance and improve throughput of a hotspot significantly. In [3], the authors have used the same cloudlet concept, a datacenter-in-a-box, and they have used a service admission control algorithm that jointly handles radio and computing resources rather than confronting the problem as two independent resource management sub-problems.

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Related research where cloud brokering is used for resource allocation include work by Yang et al. [4]. The authors have proposed a service-oriented resource broker that has the aim to discover, select, reserve and assign best combined resources. Doing so, they have implemented a dynamic resource selection algorithm. Another research has explored the heterogeneity of cloud providers in terms of infrastructure and pricing policy in a cloud brokering approach [5]. The aim of the brokering is to optimize placement of virtual infrastructure across multiple clouds and to abstract the deployment and management of infrastructure components in these clouds. An economically viable cloud broker that sells bandwidth guarantees to video-on-demand providers individually under a certain pricing policy is presented in [6]. The broker jointly books bandwidth for them from the clouds to save reservation cost and maximize profit. They have modeled the market using a game, similar to our paper. The engineering aspects of using brokerage to interconnect clouds into a global cloud market are discussed in [7].

In this paper, the assumption is that the resources of the cloudlets (bandwidth, CPU, memory and capacity) may be under-utilized from time to time. The owners of the cloudlets may take this opportunity and sell these under-utilized resources to potential customers.

The rest of the paper is organized as follows. Section 2 represents detailed explanation of the proposed framework by giving its network elements, process flow and formulation. A simple demonstrative example is given in Section 3. Section 4 discusses the results and presents concluding remarks.

II. Proposed Resource Trading Framework

A. Network Elements and Process Flow

The brokering framework, depicted in Fig. 1, consists of three network entities: The cloudlet owner (CO), the cloudlet brokering agent (or simply the broker) and the end user. The cloudlet owner has its mobile cloud computing (MCC) hotspot. The MCC hotspot provides a wireless access and it also has a cloudlet to serve its customers running mobile applications. Thus, a cloudlet can be defined as a datacenter-in-a-box concept which is a trusted, resource-rich computer of computers, well-connected to the Internet and available for use by nearby mobile devices [1] [2] [3]. These MCC hotspots can be located in cafés, coffee shops, shopping malls, campuses, airports, libraries, etc. In this way, mobile users may receive interactive response for their real time applications by low-latency, one-hop and high-bandwidth wireless access.

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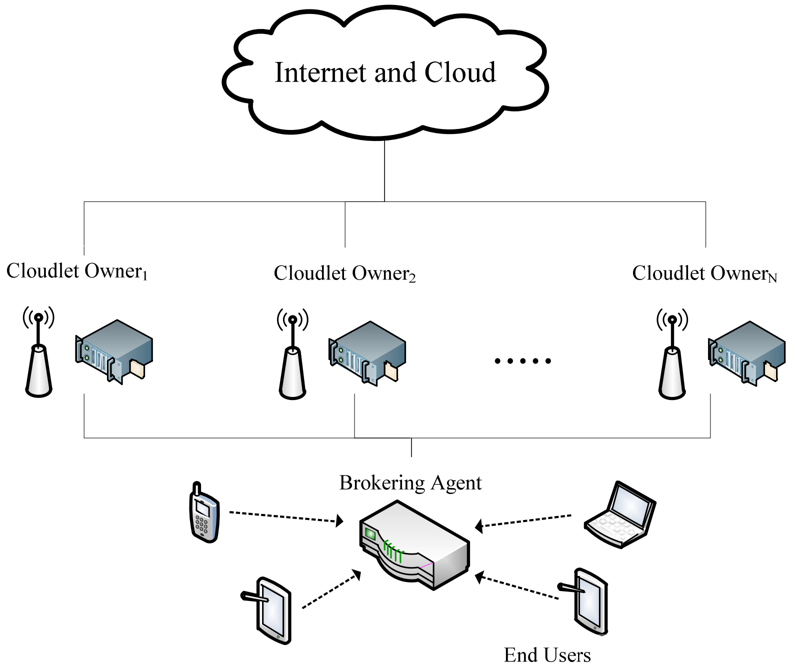

Fig. 1. System model

Mobile users request for MCC services using their mobile terminals such as smart phones, tablet PCs and laptops. Each CO has its own resources in four different forms: Bandwidth, CPU, memory, and capacity [3] to serve its customers. In this paper, we claim that these resources are not fully utilized at all times. Therefore, COs intend to sell portions of their unutilized resources to resource-seeking end users in order both obtain additional revenue and attract more customers. At this point, the broker comes into the scene as an intermediary that brings together both parties. The brokers are the regionally centralized agents that work on behalf of COs. They are responsible for the efficient and opportunistic utilization of network resources in their regions. The broker keeps track of resources of COs on regular basis to be aware of the amount and the location of the available network resources that are ready to be used. The third network entity is the end user who is defined as the potential customer who needs some resources for the mobile services.

Below is the information flow realized in one cycle of the proposed framework:

1. Cloudlet owners inform brokering agent on their available resources.
2. End users send their service requests (SR) to broker, if they have not sufficient resources. This SR is defined as a resource vector, including the amount of bandwidth, CPU, memory, and capacity separately.
3. Broker, knowing the service requirements of the requesters and currently available network resources of COs, runs Mobile Cloudlet Resources Charging Mechanism to determine equilibrium unit prices of unit resources of each CO.
4. The unit prices are offered to end users.
5. End user has two choices: Prefer one of the COs or not using any of the offered resources.

B. Problem Formulation

The framework that is considered consists of a set of N MCCs owned by N COs, denoted by I = {1, 2, …, N}. Each MCC determines two service parameters: (p, q) $\in \Re_+^{2N}$. p = {p_1, …, p_N} is the price vector where p_i is the unit price that CO_i charges the end user per unit resource demand, and q = {q_1, …, q_N} where q_i is the QoS measure of the service offered by CO_i. CO_i experiences a demand $D_i : \Re_+^{2N} \rightarrow \Re_+$. The demand to a CO depends not only on its own service parameters p_i and q_i, but also on the prices and the quality offered by its competitors. In other words, D_i depends on the entire price vector (p) and the entire quality vector (q). The utility functions of the COs are given by $U : \Re_+^{2N} \rightarrow \Re_+$. The strategy space, S_i, of CO_i with the upper and lower bound constraints is given by the subset of $\Re^2$:

$$S_i = \left\{ \left(p_i, q_i \right) : 0 \le p_{\min} \le p_i \le p^{\max} ; 0 \le q_i^{\min} \le q_i \le q_i^{\max} \right\} \quad (1)$$

Each MCC is assumed to be composed of four basic resources (bandwidth, CPU, memory and HDD capacity). Then, each new SR is expressed as a four-dimensional request vector of the form [$R_{(1,x)}$, $R_{(2,y)}$, $R_{(3,z)}$, $R_{(4,w)}$], where x, y, z, $w \in \aleph$ and $R_{(1,x)}$, $R_{(2,y)}$, $R_{(3,z)}$, $R_{(4,w)}$ are the requirements of the service for each of the four resources [3].

We assume that the average demand of CO_i, D_i (p, q), is non-linear in all prices and QoS levels. If a CO increases its price, it causes a decrease in its demand and its QoS level increase causes an increase on its own demand. Furthermore, if the prices of the competitors of CO_i increase, that results an increase on the demand of CO_i, while the increase of the QoS levels of the competitors of CO_i causes a decrease on its own demand.

Random-utility models are based on a probabilistic model of individual customer utility. It is often reasonable to

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assume that a firm has only probabilistic information on the utility function of any given customer, and this can be modeled by assuming that customers' utilities for alternatives are themselves random variables [8] [9]. Let the n alternatives be denoted as $j = 1,\ldots, n$. An end user has a utility for alternative j, denoted U_j. The probability that an end user selects alternative j from a subset S of alternatives is given by:

$$P_j(S) = P\left(U_j \geq \max\{U_i : i \in S\}\right) \tag{2}$$

The equation (2) can be defined as the probability that j has the highest utility among all the alternatives in the set S. The binary-logit model is applied to a situation where there are only two alternatives to choose from. The multinomial-logit model (MNL) is a generalization of the binary-logit model to n alternatives.

For the MNL model, the probability that an alternative j is chosen from a set $S \subseteq \{1,2, .., n\}$ that contains j is given by:

$$P_j(S) = \frac{e^{\frac{u_j}{\mu}}}{\sum_{i\in S} e^{\frac{u_j}{\mu}}} \tag{3}$$

The logit function is the inverse of the sigmoid function, or the logistic function used in mathematics, especially in statistics. The logit demand function is based on the MNL model [8]. Hence, the utility of the CO i is modeled as in (4). The no-purchase alternative is also considered with utility U_0 and u_0=0:

$$U_0 = u_0 + \xi_0 \tag{4}$$

It is common to model u_j as a linear function of several known attributes including price [10]. Assuming the representative component of utility u_j is linear in price and interpreting the choice probabilities as fractions of a population of end users of size N lead to the class of logit-demand functions. For example, if we assume that $u_1 = -bp+\beta q$, this gives the following demand function:

$$d(p,q) = N\frac{e^{-bp+\beta q}}{1+e^{-bp+\beta q}} \tag{5}$$

where N is the market size, b and β are the coefficient of the price and QoS level sensitivities, respectively. In the multiple-product case, the demand function is given by:

$$D_i(\mathrm{p},\mathrm{q}) = \frac{e^{\left(-b_i p_i + \sum_{j\in I, j\neq i} c_{ij} p_j + \beta_i q_i - \sum_{j\in I, j\neq i} \gamma_{ij} q_j\right)}}{1+\sum_{i=1}^{N} e^{\left(-b_i p_i + \sum_{j\in I, j\neq i} c_{ij} p_j + \beta_i q_i - \sum_{j\in I, j\neq i} \gamma_{ij} q_j\right)}} . a_i,\ i = 1,\ldots,N \tag{6}$$

with b_i, c_{ij}, β_i, γ_{ij} positive constants that represent to what extent the users influence from price and quality variations. Besides, these coefficients enable to unify the units by converting them to currency. The a_i is the base demand. For the simplicity, in this paper, the end user of CO_i is assumed to have the same profile. In other words, all the end users of CO_i have the same price (b_i, c_{ij}) and quality (β_i, γ_{ij}) sensitivities. Going forward, end users of a CO can be differentiated according to their sensitivities to price and quality. It is evident that one of the key driving indicators of the pricing is the user acceptance of a given service. An end user accepts to use a service only if its price is reasonable and its QoS level is satisfying. The MNL probability that an end user chooses CO_i as a function of the vector of prices (p) and quality (q) is then given by:

$$\mathrm{Prob}_i(\mathrm{p},\mathrm{q}) = \frac{e^{\left(-b_i p_i + \sum_{j\in I, j\neq i} c_{ij} p_j + \beta_i q_i - \sum_{j\in I, j\neq i} \gamma_{ij} q_j\right)}}{1+\sum_{i=1}^{n} e^{\left(-b_i p_i + \sum_{j\in I, j\neq i} c_{ij} p_j + \beta_i q_i - \sum_{j\in I, j\neq i} \gamma_{ij} q_j\right)}} \tag{7}$$

The base demand of CO_i is the sum of the resource requests coming to CO_i. Since each CO is exposed to all the SRs sending to broker by end users, a_i is the same for each CO and it can be determined as the market demand [11].

In order to differentiate SRs, we assume three classes of services: a High Demanding Service (HDS), a Low Demanding Service (LDS), ans a Best Effort Service (BES) [3]. It is assumed that the unit resource vector is given as: R_{BU} = (1 BU_1, 1 BU_2, 1 BU_3, 1 BU_4), which represent the required basic units (BU) for bandwidth, CPU, memory, and HDD capacity, respectively. The requirements of three classes of services are identified as multiples of this unit vector. Hence, the requirement of LDS is $R_{LDS} = R_{BU}$, the requirement of HDS is $R_{HDS} = 16.\ R_{BU}$, and the requirement of is $R_{BES} = 5.\ R_{BU}$. Accordingly, the market demand (a_i) can be generated by:

$$a_i = \sum_{t\in\{\mathrm{HDS,LDS,BES}\}} x_t . R_t \tag{8}$$

with x_t the number of end users requesting service class t.

For this paper, the QoS level of the given resources (q_i) is assumed to be measured by the non-blocking probability in the CO_i's network, which is in the range of [0,1].

The resource constraint needs to ensure that the resource capacity of each CO is equal or greater than the sum of the resources requested by end users (a_i). Hence, the resource constraint for a cloudlet can be expressed as:

$$a_i \leq \left[R_i(1,x_i) + R_i(2,y_i) + R_i(3,x_i) + R_i(4,w_i)\right], \forall i \in I \tag{9}$$

where

$R_i(1,x_i) + R_i(2,y_i) + R_i(3,x_i) + R_i(4,w_i)$ represents the sum of four types of resources of CO_i.

As mentioned earlier, the objective of COs in the framework is to attract potential customers by offering them available resources, by generating additional revenue. We

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assume that the revenue of CO_i is also its utility, and it is given as:

$$U_i(\mathrm{p},\mathrm{q}) = D_i(\mathrm{p},\mathrm{q}).p_i \quad (10)$$

The pricing problem solved by the broker is modeled as a non-cooperative game, where players are the COs, which compete with each other to attract maximum number of users. Their strategy is the choice of unit resource prices, subject to given QoS level. The payoffs of the players are their utility values. In analyzing the outcome of the game, as the players need to determine their unit prices independently and are influenced by the other players' decisions, the broker is interested to determine if there exists a convergence point, from which no player would deviate anymore, i.e. Nash equilibrium [12].

U_i (p,q) is the revenue of CO_i, when the vector of price set by all COs, p, and the vector of QoS parameters, q, of all COs is fixed at some point, $\hat{\mathrm{q}}$. Then a single-parameter Nash equilibrium in p at $\hat{\mathrm{q}}$ is the vector p* that solves for all *i*:

$$U_i(\mathrm{p}^*,\hat{\mathrm{q}}) = \max_{(p_i,\hat{\mathrm{q}})\in\Re_i} U_i\left(p_1^*,...,p_{i-1}^*,p_i\ ,p_{i+1}^*,...,p_N^*,\hat{\mathrm{q}}\right) \quad (11)$$

III. NUMERICAL ANALYSIS

In this section, we aim at showing the results taken by the proposed resource trading framework on a simple but demonstrative example. The framework is assumed to be composed of two cloudlet owners (CO_1 and CO_2) and six end users. Two of the end users are assumed to request HDS, one of them requests LDS and three of them request BES. Therefore, the total resource request (a_i) is equal to 48. R_{BU}. The upper and lower bound of the price values are taken 0 and 12, respectively.

The customers of CO_1 are assumed to sit for long periods and web surfing is the mostly seen mobile application. The students, who are relatively more sensitive to price, constitutes the major part of the customers. On the other hand, the customers of CO_2 are assumed to sit for shorter periods and their average age is assumed relatively higher. The customers usually make business meetings through voice over IP or video-conferencing applications. We have differentiated the customer profiles of these two COs in order to show the impact of parameter settings to the results. The parameters are identified as: b_1=0.4, b_2=0.2, c_{12}=0.25, c_{21}=0.10, β_1=1.25, β_2=1.50, γ_{12}=0.4, γ_{21}=0.75. The QoS levels of two COs are set as their non-blocking probabilities (q_1=0.8 and q_2=0.9).

The results of this given scenario are summarized in Table 1. As CO_1's customer profile has higher price sensitivity (0.4), it offers lower unit price (2.55). Together with the customers' lower quality sensitivity (1.25), CO_1 receives 44% of the market demand.

TABLE I
PRICE AND EXPECTED DEMAND VALUES AT MARKET EQUILIBRIUM

	CO_1	CO_2
Offered price (p*)	2.55	3.82
Expected percentage of end users	44%	31%
Expected demand	21.06	15.08
Unit price of HDS	40.8	61.12
Unit price of LDS	2.55	3.82
Unit price of BES	12.75	19.1
Total expected revenue of COs	111.33	

IV. THREATS TO VALIDITY AND CONCLUSION

The nonlinear structure of the objective function complicates the problem solution process. During the runtime of the code for our simple demonstrative example, we have noticed that both the initial point where the algorithm begins and the chosen algorithm have dramatic influence on the optimum points. As the optimum price values in the equilibrium are the local optimum points of the problem, it is important to be certain that the algorithm gives reliable results. Going forward, we will use heuristics to compare the results of different algorithms.

The optimum unit price values are generated by the brokering agent. The price and quality sensitivity coefficients of the cloudlet owners' customers may be determined by the broker itself, since it has sufficient information related to the end users' usage behaviors. This was not the concern of our paper, but determining the sensitivity coefficients by mining customer data would be another research area in this topic.

The proposed trading framework assumes that the cloudlet concept is adopted by many providers; moreover they tries to earn additional money from unutilized portions of its resources. Hence, this research may be considered among the propositions of business models for cloud computing. The research will be developed by considering more cloudlets and more end users to the scenario.

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