Improving Cloud Service Provider Profits Using Repeated Ranking

Saikishor Jangiti, Hariraj Venkatesan, Praveen Kumar C, Shankar Sriram. V.S.

***Abstract:**Corporates adopt cloud computing services due to the ease of obtaining services instead of maintaining huge infrastructure. The demands of customers and services provided by Cloud Service Providers (CSP) are characterized using the Quality of Service (QoS) attributes. Each customer has different QoS requirements depending on their business and CSPs provide services with different QoS. Several multi-criteria decision frameworks exist for identifying the most suitable CSP. These mechanisms are mainly built for customers' benefits. In this paper, we propose Binary Search Cost Update (BSCU), a framework that uses AHP to increase the profits of CSPs. We compare the CSP's performance using rankings and then identify a higher price for the same set of services that are provided. The higher price will not affect the Trust value of the CSP and the rankings will remain the same even after prices are increased. Using BSCU, CSPs can increase the prices and generate more income with profits up to 19%.*

***Keywords:** Cloud computing; CSP profit maximization; Ranking of CSPs*

I. INTRODUCTION

Cloud computing facilitates small and medium enterprises (SMEs) to function more efficiently and cost-effectively using its on-demand services. The pay-per-use model is encouraging the SMEs more to migrate to the cloud [1,2] . The performance of Cloud Service Providers(CSPs) is primarily measured based on the Quality of Service(QoS) attributes. Several multi-criteria decision-making mechanisms exist to help customers choose the CSP which the most appropriate to their QoS requirements. One such popular mechanism is Analytical Hierarchy Process (AHP) [3]. AHP makes a comparison based on various attributes quantitative and simple and thus formulate the ranking of cloud service providers [3,4,5]. The importance of each parameter used for comparison can be asserted by assigning weights to each parameter appropriately which differ largely based on the company's business [6,7]. In this paper, the QoS parameters used for comparison are Availability, Technical support, Trust result and Price. We take all the parameters to have equal weights for generalisation purposes. We calculate the ranking values for each CSP using the AHP procedure and rank them based on these values.Currently,these mechanisms are mainly used by SMEs and other customers to identify the CSP that best suits their QoS requirements. However, these mechanisms can also be used by the CSPs themselves to understand the service they provide and improve accordingly. The CSPs can analyse these results and find higher prices at which customers would still be willing to use CSP's services but now at a higher price, thus increasing the monetary value of the CSP. As the CSPs have high operation costs [8] , this cost enhancement will support their sustainability The organisation of the remaining paper is as follows: Section 2 deals a case study of the current problem. The Binary Search Cost Updation (BSCU) model is defined formally in Section 3. Section 4 details results of the model and explains the related works present in Literature. Finally, Section 5 provides the conclusions and the future work.

Case Study

Cloudarmor is a research project of School of Computer Science, Faculty of Engineering, Computer and Mathematics Science, at the University of Adelaide. It aims for the protection of consumers by evaluating the Trust measure of cloud services. It provides a user-friendly interface that can be used by both consumers and CSPs. Cloud Armor detects cloud services and rates their credibility via feedbacks from experiences of past users. This data can then be used by customers to understand the trustworthiness of the specified CSP and take appropriate decisions. In this paper, we have used the data set provided by Cloud Armor and applied BSCU to identify higher prices for the same set of services provided by the CSP. Binary Search Cost Updation is a framework that can be used by Cloud service providers to compute the maximum price that can be charged for their services without having to lose out their rankings. Depending on the Trust measure, a CSP can put a higher price tag for the same instance without loss in the trust value. Hence the ranking of the CSP when compared with others will remain the same. BSCU helps in generating more income without having to lose any customers. In Section 4, an example using the data from Cloud Armor project has been used to illustrate the working of BSCU. For confidentiality, the names of CSPs are not mentioned and instead they are numbered.

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I. Proposed Model – Binary Search Cost Updation

In our proposed process, we first rank the chosen cloud service providers using the ratings given against each QoS attribute to rank the CSPs. The attributes chosen were Availability, Technical support, Trust result and Price. Table 1 defines these parameters

Table 1: Description of QoS requirement parameters used

Availability	Time taken for the service to recover after it goes down
Technical Support	Technical assistance and response provided by the CSP during periods of outages and sudden failures
Trust result	Feedback about CSP's ability to provide services as stipulated in the Service Level Agreement (SLA)
Price	Feedback about relative cost of CSPs for same set of services offered

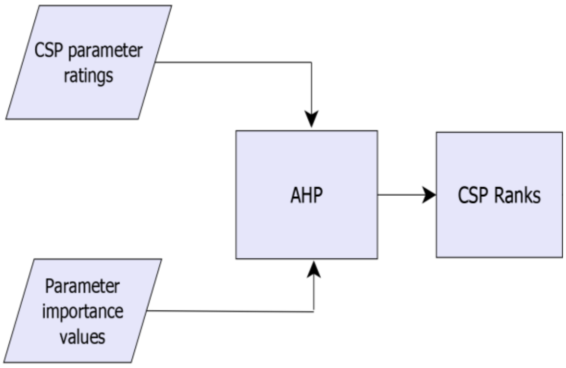

Fig. 1. CSP Rank calculation using AHP

The ratings of QoS attributes provided by customers are largely personalised and reflect their requirements and the realisations [9]. Fig. 1 depicts the service ranking process. After the Availability, Technical support, Trust result and Price rating values are obtained, Analytical Hierarchy Process (AHP) is carried out on the resulting dataset. The process is as follows:

1. From Table 2, the maximum value from each column is found and termed as MAX(Param). The MAX values are 5,5,5,4 for Availability, Technical support, Trust result and Price respectively.

Table 2: CSP v/s parameter rating dataset

CSP ID	Availability	Technical Support	Trust Result	Price
CSP 1	3	3	1	3
CSP 2	3	5	4	4
CSP 3	4	3	1	2
CSP 4	2	3	1	2.5
CSP 5	5	3	5	4

1-Very Low, 2-Low, 3-Average, 4-High, 5-Very High

2. Using the calculated MAX(Param) values and the ratings, derive the normalised matrix P, shown in Table 3. The normalised values, NORM (Param) is defined as

NORM (Param) = **Error! Reference source not found.**

Table 3: Normalized matrix P

CSP ID	Availability	Technical Support	Trust Result	Price
CSP 1	0.6	0.6	0.2	0.75
CSP 2	0.6	1	0.8	1
CSP 3	0.8	0.6	0.2	0.5
CSP 4	0.4	0.6	0.2	0.625
CSP 5	1	0.6	1	1

3. Now we need to quantify the relative importance of the attributes. We use the Saaty scale for the importance of parameters [4]. This value is named as IN(Param). For comparison purpose, we take each parameter to have equal importance [4]. Therefore, the importance of each parameter is assigned 1.

Table 4: Importance of parameters matrix M

	Availability	Technical Support	Trust Result	Price
Availability	1	1	1	1
Technical Support	1	1	1	1
Trust Result	1	1	1	1
Price	1	1	1	1
SUM	4	4	4	4

4. The importance matrix M is shown in Table 4. The values of matrix M are called IMP($Param_{xy}$). The column-wise sum of each parameter is calculated and termed as SUM(IMP ($Param_x$)).

5. a weight matrix W is prepared using importance values, The relative importance of parameters is termed as W($Param_{xy}$) and defined as

W ($Param_{xy}$) = **Error! Reference source not found.**

The weight of each parameter W (Parameter $_x$) is defined as

W ($Param_x$) = **Error! Reference source not found.**

N is the number of parameters.

The relative weights of the parameters are obtained as 0.25.

6. Using the parameter weights and the normalized rating values obtained, the ranks are calculated and the rank matrix R is formed. Each value in matrix R is called as RANK (Param) and is defined as

*RANK (Param) = W (Param) * NORM (Param)*

The final ranking value is the row-wise sum for each CSP.

7. To increase the profits, we use Binary Search Cost Updation (BSCU) shown in Algorithm 1.

Algorithm 1: Binary Search Cost Updation (BSCU)
Input : Cloud service parameters, Current cost
Output : Updated cost
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The algorithm takes the Cloud Service Parameter ratings matrix and the Current Price as input and returns the Updated Cost. A binary search technique is adopted to find the highest price. The algorithm finds higher price by decreasing the price rating and then comparing the rankings to ensure trust is maintained. The variables low, high and mid are used to change the values in a Binary Search fashion. The values in low and high are used as a reference for the minimum and maximum increase for the value of mid.

The price of the chosen CSP is increased by a **Error! Reference source not found.** % and AHP is performed again. The method Ranking (), returns 1 if there is no change in the rankings, else it returns 0. If there is no change in the rankings of the CSP, then it implies trust has been retained even after the price increase. The value of low is now assigned the value of mid and the value of mid is taken as the mean of low and high. Further iterations are performed to check whether higher prices are possible. After computing AHP, if the ranking changes, then the previous iteration's price is the maximum price possible for the current set of services. The updated cost is returned.

II. Results and Discussion

A. Results

The parameter ratings of 5 cloud service providers were chosen from the Cloud Armor data set. The CSPs were labeled as CSP 1, CSP 2, CSP 3, CSP 4, CSP 5 and the chosen QoS attributes were Availability, Technical support, Trust result and Price. The data is shown in Table 2. AHP was computed to obtain the relative rankings of the CSPs. Binary Search Cost Update (BSCU) is used to increase the prices of a CSP by decreasing the price rating to the extent that does not change the rankings of the CSP. BSCU was performed for CSP 1, and CSP 5 and the results are shown in Fig. 2. The results show that CSP 1 and CSP 5 could increase their profits by up to 6.67 % and 19.99 % respectively. Thus, the CSPs could charge more for the same instances and hence earn more profits.

B. Related Work

Many research papers describe the multi-factor criteria decision making concerning cloud service provider selection. SMICloud, a framework proposed by Saurabh et al. provides a means to measure QoS attributes and prioritise CSPs[10]. It proposes a model for evaluating QoS and hence rank the CSPs. However, it doesn't take into account the variations that may occur in the QoS attributes. Chahal et. al proposed the ranking of CSPs using AHP. TrustCom, by Somu et. al, is a framework that measures the trust of CSPs using rough set-based hypergraph technique[11]. However, it can only be used for the selection of cloud services and is not helpful in analysing the price factor for the CSP. Ma et. al, proposed on a trustworthiness ranking prediction that takes into account the fluctuating QoS values. Interval neutrosophic set (INS) theory was used for ascertaining tradeoffs among performance-cost and the risks for different periods [12]. The search-based QoS ranking prediction, proposed by Mao et al, states ranking prediction as an NP-Complete problem and uses data from neighbours to determine preference among the services [13]. At present, there exists no mechanism to specify and quantify the increase in the prices for the current service provided by the CSPs.

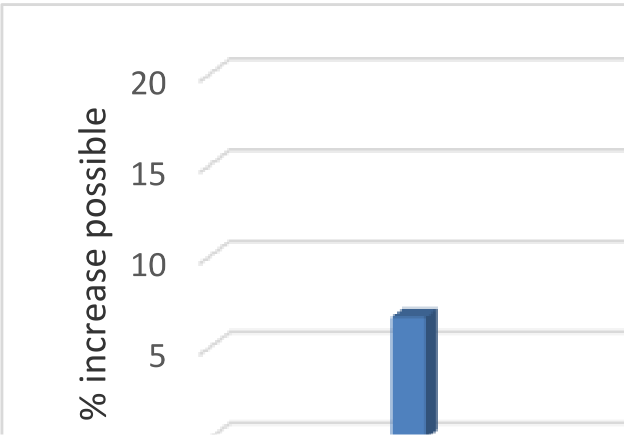

Fig. 2. Possible increase in costs for CSPs

III. Conclusion and Future work

Many of the existing multi-criteria decision-making systems are primarily targeted for customer benefits. In this paper, we have used AHP to find an increased price for the current services provided, and thus a means to gain more profit without having to change any infrastructure or services and at the same time without any change in rankings. The cloud environment is very dynamic, and the services keep changing with time. Customer demands keep evolving, and services changing with the development of technology. Hence, QoS measures will also change with time. In future works, the proposed BSCU mechanism can be scaled to accommodate QoS attributes that evolve with time.

REFERENCES

1. S. Jangiti, S.S. V S, Scalable and direct vector bin-packing heuristic based on residual resource ratios for virtual machine placement in cloud data centers, Comput. Electr. Eng. (2018). doi:10.1016/j.compeleceng.2018.03.029.
2. S. Jangiti, E.S. Ram, V.S.S. Sriram, Aggregated Rank in First-Fit-Decreasing for Green Cloud Computing, in: Cogn. Informatics Soft Comput., Springer, 2019: pp. 545–555.
3. C. López, A. Ishizaka, GAHPSort: A new group multi-criteria decision method for sorting a large number of the cloud-based ERP solutions, Comput. Ind. 92–93 (2017) 12–24. doi:10.1016/j.compind.2017.06.007.
4. R.K. Chahal, S. Singh, Information Systems Design and Intelligent Applications, 435 (2016). doi:10.1007/978-81-322-2757-1.
5. S.K. Garg, S. Versteeg, R. Buyya, A framework for ranking of cloud computing services, Futur. Gener. Comput. Syst. 29 (2013) 1012–1023. doi:10.1016/j.future.2012.06.006.
6. Y. Liu, M. Esseghir, L.M. Boulahia, Evaluation of Parameters Importance in Cloud Service Selection Using Rough Sets, Creat. Commons Attrib. Int. Licens. (CC BY). 7 (2016) 527–541.
7. N. Upadhyay, Managing Cloud Service Evaluation and Selection, in: Procedia Comput. Sci., 2017: pp. 1061–1068. doi:10.1016/j.procs.2017.11.474.
8. S. Jangiti, V.S.S. Sriram, R. Logesh, The role of cloud computing infrastructure elasticity in energy efficient management of datacenters, in: 2017 IEEE Int. Conf. Power, Control. Signals Instrum. Eng., IEEE, 2017: pp. 758–763. doi:10.1109/ICPCSI.2017.8391816.
9. G.P. Kumar, K. Morarjee, International Journal of Computer Sciences Ranking Prediction for Cloud Services from The Past Usages, (2014) 22–25.
10. S.K. Garg, S. Versteeg, R. Buyya, SMICloud: A framework for comparing and ranking cloud services, Proc. - 2011 4th IEEE Int. Conf. Util. Cloud Comput. UCC 2011. (2011) 210–218. doi:10.1109/UCC.2011.36.
11. N. Somu, K. Kirthivasan, V.S. Shankar Sriram, A rough set-based hypergraph trust measure parameter selection technique for cloud service selection, J. Supercomput. 73 (2017) 4535–4559. doi:10.1007/s11227-017-2032-8.
12. H. Ma, H. Zhu, Z. Hu, K. Li, W. Tang, Time-aware trustworthiness ranking prediction for cloud services using interval neutrosophic set and ELECTRE, Knowledge-Based Syst. 138 (2017) 27–45. doi:10.1016/j.knosys.2017.09.027.
13. C. Mao, J. Chen, D. Towey, J. Chen, X. Xie, Search-based QoS ranking prediction for web services in cloud environments, Futur. Gener. Comput. Syst. 50 (2015) 111–126. doi:10.1016/j.future.2015.01.008.