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REQUIREMENT INTENSITY BASED RESOURCE PROVISIONING FOR E-LEARNING IN MULTI-CLOUD TO AVOID VENDOR LOCK-INS

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ABSTRACT

Resource allocation in cloud systems generally operates on the basis of the overall usage. Academic clouds usually have specific requirements corresponding to specific resources. This contribution presents a multi cloud resource provisioning model that operates on the basis of the intensity of the user requirements. Another major area being concentrated in the current study is the usage of e-Learning materials. These materials tend to contain information that relies on heavy bandwidth usage. Further, these materials are being accessed by external users from different geographical locations. Hence by using multiple deployment locations, access speed and usability could be improved and would also help in effective management of workload. This paper presents an effective mechanism to enable cloud package selection specifically tuned to the needs of e-Learning users. Region based user clustering is performed and cluster based quality requirements are identified by this approach. These quality parameters are used as the baseline requirements to select appropriate packages from cloud vendors. Since the process is widespread and is across several geographical barriers, multicloud based package selection is preferred over utilizing a single cloud provider to avoid vendor lock-ins.

Keywords: academic cloud, resource provisioning, multicloud, e-Learning, cloud package selection.

1. INTRODUCTION

Cloud computing is mainly considered as a platform for delivering services in terms of infrastructure, platform or software [1, 2]. The services that are provided by cloud platforms include Infrastructure as a Service (IaaS), Platform as a Service (PaaS) and Software as a Service (SaaS). Different providers offer these services at different levels and the same provider might also offer services with varied configurations described by the Service Level Agreements (SLA). Hence it becomes the responsibility of the user to identify the appropriate service suiting their needs. Optimal service selections are of paramount importance in a cloud platform. The flexibility provided by clouds for utilizing it to provide e-Learning is very sparsely explored [3]. E-learning [4,5,6] and online education models have been on raise in the current years. They provide the much required knowledge transfer transcending all boundaries. Identifying the learner's behavior is of paramount importance due to the frequently changing needs of the e-Learning system. Incorporating e-Learning in cloud provides several benefits ranging from flexibility to cost efficiency [7]. Several flexible cloud providers even assist in the reuse of components in cloud computing facilitating better e-Learning. An example is the BlueSky [8] cloud framework specifically designed for e-Learning. Initial utility of cloud in e-Learning was solely based on utilizing cloud as a storage medium [9]. Progress in technology has provided better utility for cloud in the area of e-Learning [10,11].

2. RELATED WORKS

Optimal resource identification in cloud environment is of major importance and hence several techniques have been proposed in-order to perform effective utilization of resources. This section presents some contributions on cloud provisioning and other contributions relating to e-Learning systems in cloud.

An ontology based e-Learning system in cloud is presented by Rani *et al*. in [12]. This system utilizes the cloud storage and database services in a passive manner, while utilizing the technological resources to identify the learner's learning style to incorporate efficiency in the process of e-Learning. A similar cloud utility scenario, where the cloud services are fine-tuned for Vocational, Education and Training (VET) is presented by Chao *et al*. in [13]. A comparative analysis of cloud based e-Learning is presented by Ahmed in [14]. This paper highlights the essentiality of incorporating e-Learning in cloud systems and also provides effective techniques to identify requirements of the e-Learning systems to effectively utilize cloud resources.A cloud brokerage system that provides solutions to real world service provisioning problems is presented by Khanna *et al*. in [15]. This paper deals with appropriate distribution of cloud services in a geographically distributed environment. A similar broker based architecture concentrating on QoS requirements of the user is presented by Arshad *et al.* in [16]. This paper concentrates on avoiding job denials during peak intervals and also satisfies QoS requirements effectively. A similar study on resource management in clouds is presented by Alexander et al. in [17]. A review of utilizing cloud for e-Learning is presented by Riahi in [23]. A social learning optimization model for QoS based cloud service selection is presented by Liu et al. in [24]. A learning framework that utilizes the flexibility offered by cloud to perform collaborative learning is presented by Shorfuzzaman *et al*. in [25]. This technique analyzes the user's requirements and improves the learner's experience by providing appropriate QoS requirements for the users. Academic Cloud Framework is proposed which specifies the essential components needed to construct an academic cloud in universities by Madhumathi *et al*. in [26].

3. REQUIREMENT INTENSITY BASED RESOURCE PROVISIONING FOR E-LEARNING IN MULTICLOUD TO AVOID VENDOR LOCK-INS

The requirement intensity based resource provisioning technique is specifically designed to incorporate e-Learning in academic institutes. The requirements for services within academic institutes differ considerably from the requirements on e-Learning materials. The major requirement corresponding to e-Learning is that they are accessed globally rather than in a confined environment. This leads to dynamic usage requirements and different requirements in different geographical locations based on the density and frequency of usage. Deploying such applications in cloud provides an added advantage due to the scalability associated with it. This paper presents a technique used to identify the base requirements of an e-Learning system by identifying the base requirements such that the selected packages are cost efficient and handles most of the situations without the requirements of scaling.

Vendor lock-ins remains to be a major concern when utilizing services from cloud providers. Satisfaction of all the customers is never promised, as only a part of the population would be completely satisfied. Hence the current strategy involves the inclusion of multicloud [18,19] such that the region based requirements are appropriately satisfied by specific and independent vendors, rather than utilizing a universal package from a single vendor that has several fallbacks.

The process of requirement intensity based resource provisioning for e-Learning in multicloud is carried out in two major phases (Figure-1). The first phase identifies region based requirements and groups them according to the density of usage, while the second phase identifies the QoS requirements and maps multicloud packages to appropriate groups depending on their requirements.

3.1Region based requirement identification

The input logs for the current requirement involves usage records of several users in varied geographical locations. These logs represent the access details of a single academic university pertaining to all its e-Learning materials. The logs are initially clustered based on their IP. The usage density corresponding to each IP is identified and grouped to form a cluster. Each cluster is inspected for user density and if the density is found to be lower than the minimum threshold (*minThresh*), the cluster is merged with a geographically adjacent cluster. This process is continued until the density reaches maximum threshold (*maxThresh*). If a cluster contains double or more times the *maxThresh* it is divided depending on the density levels. This process is repeated until all the IPs are moved into a cluster. Each cluster corresponds to a single requirement in that region.

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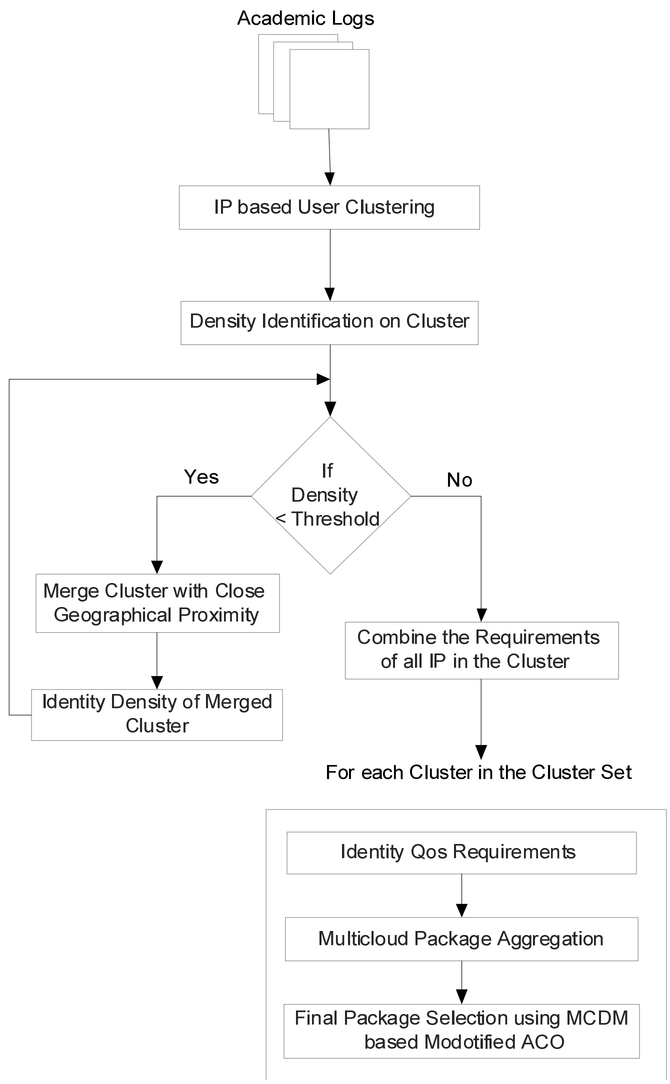

Figure-1. Requirement intensity based resource provisioning for e-Learning in multi-cloud.

3.2 QoS Identification and multicloud package mapping

Each cluster obtained in the previous phase is analyzed and its SMI parameters are identified. The other QoS requirements are obtained from the user manually. The quality parameters considered for the current evaluation and the process of identifying the parameters are presented in Table-1.

Aggregation of these parameters can be used to identify the required quality level (*QoS Requirement*). Each cloud contains a separate requirement, depending upon the level of usage. These requirements are mapped to the quality parameters provided by the cloud providers (*Provided QoS*).

Package mapping is performed using modified three-opt ACO with equal prominence provided for both exploration and exploitation. The ACO proposed by Dorigo [20, 21] utilizes two parameters namely the trail intensity and the visibility. However, the current application requires several parameters; hence the fitness function of ACO is modified as,

$$P_{ij}(t) = 1 - \left(\frac{[Bw]^{w1}.[cc]^{w2}.[Av]^{w3}.[Cr]^{w4}.[Us]^{w5}.[R]^{w6}.\left(1/[Vc]^{w7}\right)}{\sum_{j=1}^{n}[Bw]^{w1}.[cc]^{w2}.[Av]^{w3}.[Cr]^{w4}.[Us]^{w5}.[R]^{w6}.[Vc]^{w7}} \times \frac{[Sr]^{w8}.\left(1/[l]^{w9}\right).[S]^{w10}.[F]^{w11}.[Rs]^{w12}.[Db]^{w13}.[Eu]^{w14}}{\sum_{j=1}^{n}[Sr]^{w8}.[l]^{w9}.[S]^{w10}.[F]^{w11}.[Rs]^{w12}.[Db]^{w13}.[Eu]^{w14}} \right)$$

Where *Bw* is the bandwidth provided by the package, *cc* is the computational capability provided by the package, *Av* is the availability provided by the package, *Cr* is the correctness provided by the package, *Us*is the usability provided by the package, *R* is the reliability provided by the package, *Vc* is the variable computing load provided by the package, *Sr* is the serviceability provided by the package, *l* is the latency

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provided by the package, *S* is the security provided by the package, *P* is the portability provided by the package, *Rs* is the reliable storage levels provided by the package, *Db* is the data backup provided by the package and *Cu* is the customization provided by the package. Weights corresponding to the properties are represented from ω_1 to ω_{14}.

Table-1. QoS Parameters considered for evaluation.

QoS Parameters Considered for Evaluation	Obtained From
Bandwidth (Bw)=Bits/ second (B/S)	*Web Logs*
Computation Capability (CC)=Actual Usage time of the Resource/Expected Usage time of the Resource	
Availability (Av)=mean time to failure/(mean time to failure + mean time to repair)	
Correctness (Cr) =total number of failed transmissions/ (total number of failed transmissions + total number of successful transmissions)	
Usability (Us) =no of successful operations in a workload/ (total operations available in the workload)	
Reliability (Re)= mean time to failure + mean time to repair	
Variable computation load (Vc)	
Serviceability (Se) = Service Uptime/ (Service Uptime+ Service Downtime)	
Latency (l) = Time of output produced with respect to that Cloud workload - Time of input in a Cloud workload	
Security (S)	*User Input*
Portability (P)	
Reliable storage (Rs)	
Data Backup (Db)	
Customization (Cu)	

At this stage, every cluster is considered as an independent entity and the cloud providers available at their corresponding jurisdiction are considered for this process. Hence the search space varies and is to be independently built for each cluster. The ants are distributed in a single requirement node and they traverse through the search space in accordance with the probability exhibited by the packages [22]. This approach uses a transition state *S* which facilitates both exploration and exploitation of the search

$$S = \begin{cases} \arg\max\{p_{ij}(t)\} \text{ if } q \leq q_0 \text{ (exploitation)} \\ P \quad \text{otherwise (biased exploration)} \end{cases}$$

Where q is a random number distributed in [0,1], q_0 is a parameter ($0 \leqslant q_0 \leqslant 1$) that determines if the system should be explored or it should follow the already explored areas (exploitation) and *P* is the resultant value obtained by using the probability function. All the ants are made to traverse in the search space and the package containing the maximum number of ants is selected as the optimal package for the current requirement. Since this process is carried out on the basis of independent regions, it becomes a multicloud setup with different providers being assigned for different regions.

4. RESULTS AND DISCUSSIONS

The process of requirement intensity based package selection in cloud is carried out in two major phases. The initial phase of user density based clustering is carried out using the access log data. Implementation of this phase was carried out using Python. The results contain QoS parameters of each of the region groupings. These parameters are used as the requirement set to identify the appropriate packages in a multicloud. Since multiple criteria is involved in this process to identify the final package for each region, MCDM based Modified ACO is used as the selection algorithm.

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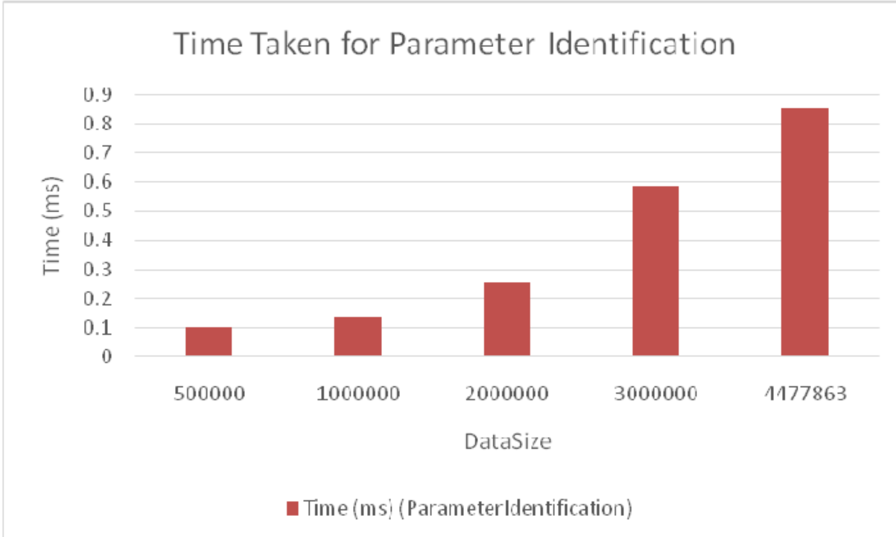

Figure-2. Time taken for parameter identification.

The Figure-2 represents the time taken for grouping and region based quality parameter identification. It could be observed from the graph that as the data size increases, the time taken for processing increases. A maximum threshold limit of 4.5 million records were analysed and it was identified that the maximum time taken remains less than 1ms. Hence this time increase becomes an acceptable limit due to its small variance increase in the range of 2ms for every 1 million record.

Figure-3. Time taken for package selection.

The Figure-3 represents the time taken for the process of package selection. It could be observed from the graph that the time taken does not depend on the data size. It remains stable in the range of 70ms to 90ms. Hence it could be concluded that the package selection time is independent of the data size.

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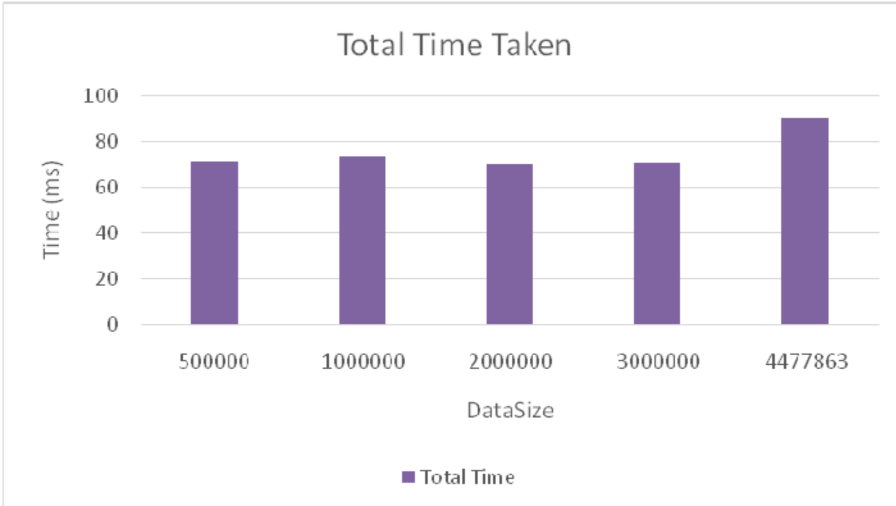

Figure-4. Total time taken.

The Figure-4 represents the total time taken for the grouping and parameter selection process. It does not show any defined variance with respect to the data set size. Hence it could be concluded that the time taken less (< 1sec) irrespective of the size of the base data. The Figure-5 presents the results obtained from modified ACO to perform package selection. It could be observed that the required and the provided QoS depicts good relationships with minimal difference.

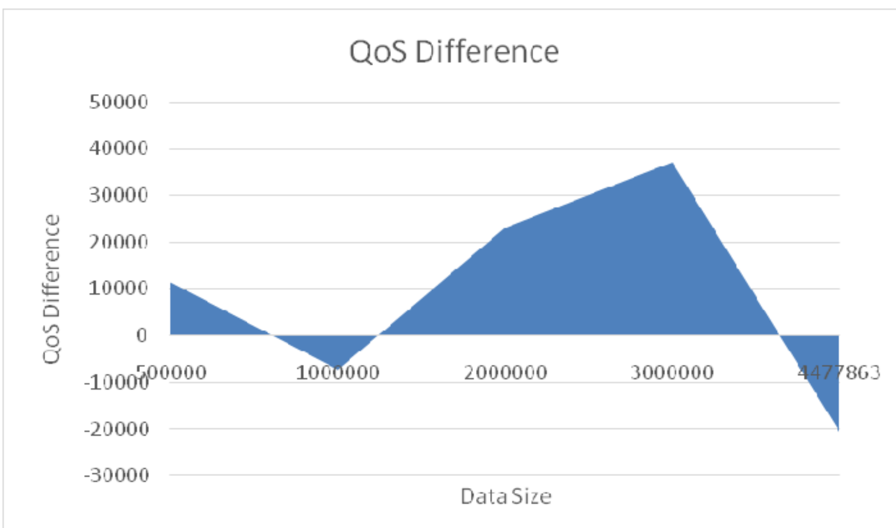

Figure-5. QoS Difference.

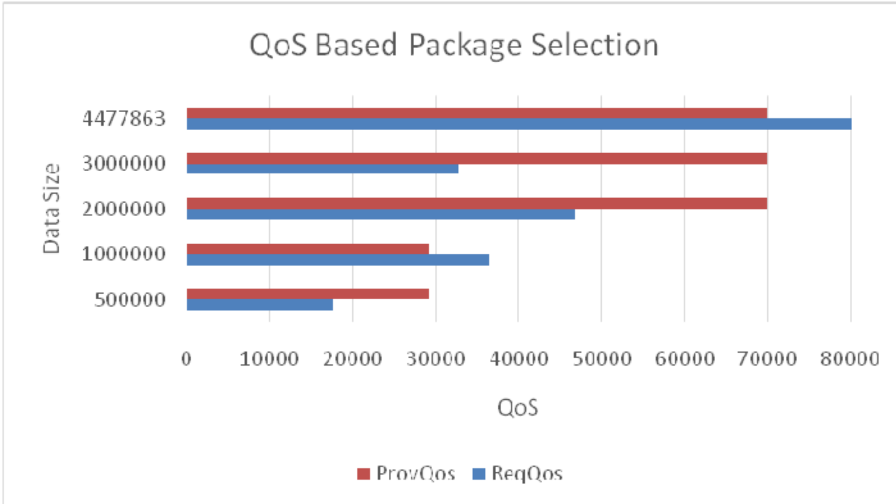

Figure-6. QoSbased package selection.

The Figure-6 presents the QoS difference between the required and the provided QoS. It could be observed that the area of difference observed is small depicting very slight variations. This circumstance of small differences is unavoidable, as perfect matching package cannot be obtained with any provider. The major objective of the selection algorithm is to provide the closest result to the requirement. Since such a scenario could be observed here, it could be concluded that the architecture presented in this study performs effectively in the process of multicloud package selection.

5. CONCLUSIONS

This paper aims at identifying the quality requirements for e-Learning and providing appropriate allocations for users based on their usage levels and geographic regions. Access logs of the e-Learning system is analysed and user based grouping is carried out. These are clustered again on the basis of regions and usage levels corresponding to each region is identified. Multi-cloud based package selection is carried out using the quality parameters obtained from the clusters.In future, the ability to handle dynamic resource requirements which arises mostly out of research divisions or departments could be included. Such dynamic requirements may require the use of an MCDM technique that could adapt for changing requirements. Also the ability to support multiple cloud providers or even cloud brokers with a high level of granularity could be provided

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