



Enhanced Adaptive Learning Mechanism for Cloud Selection

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Abstract

Estimation of cloud services in a distributed computing environment is taking more interests. There is a wealth of developing cloud benefit assets that makes it difficult for the user to select the best administration related to own applications in an evolving multiple cloud environment, particularly for online processing applications. To make clients to choose their interested cloud adequately, we need a model which holds the cloud profits, and hence dynamic cloud benefit determination procedure named Dynamic Cloud Selection (DCS) is adapted. In this procedure of selected services, every cloud benefit business deals with some group of cloud administrations, and executes the DCS method. This paper studies the cloud selection and proposed a way to improve the cloud selection based on related measures. The measures are reliability, response time, throughput, availability, utilization, resilience, scalability, and elasticity. The system is contrived to enhance the cloud benefit choice powerfully and to restore the best administration result to the client. These measures are used to form best selection strategy. User memory requirement is also considered to improve the preferred task. Experimental results proved that using this new strategy, best cloud selection is made efficiently.

Keywords: Adaptive Learning Mechanism, Incentive, Forgetting, Degenerate, Remembrance, Systematic Literature Review (SLR).

1. Introduction

Working on Cloud computing process follows models called, GoGrid cloud computing services, Computing services (PaaS), Storage services(IaaS), Google App Engine, Salesforce-cloud. Hybrid cloud service is used to integrate public cloud service with local cloud service. Intelligence was implemented in brokers who play the role of an agent. This work focuses on solving distributed task problems.

To help the user to select cloud, based on their favoured cost cloud selection service is performed [1-6]. Selection [7-17] made based on metrics like availability, throughput, scalability, fault tolerance, resilience, and elasticity. But the choice is not only based on these metrics but also on reliability[19-21]. Though the process depends on the parameters presented in many papers, reliability based

selection is not performed in any of the work. Our implementation based on this new strategy enhances adaptive behaviour mechanism.

Due to the static performance, cloud selection technologies in critical situation struck at selection price, and service changes are all because of the shutdown. Cloud service broker selection model (CBRSM) is used to solve the above problem with the help of CBR and the cloud selection is dynamically done with intriguing performance, memory and price ratio. The methodology proposes an adaptive behavioural strategy activate the cloud service choice at low cost when running the system.

2. Measure to improve cloud selection efficiency

In adaptive learning mechanism, the following measures shown in fig. 1 are used to improve the cloud selection efficiency.

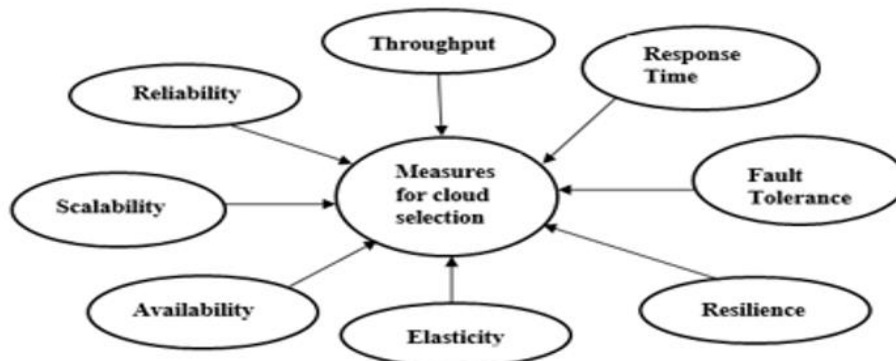


Fig. 1: Measures used for best cloud selection

The reliability plays a significant role in cloud selection in adaptive learning mechanism. It helps us select the cloud service based on the user requirement. When reliability increases, its availability also gets increased. It mainly depends on the response time value [9]. Response time is the time taken to react to a given input [10]. Throughput is the highest outcome for a particular time duration [11]. Response time is the time taken to react to a given input. Throughput is the most top outcome for a specific duration of time [13]. Availability is directly proportioning to the reliability. The cloud availability metrics contains continuity, quality, functionality, incident management, monitoring, data access, and security [14]. The scalability has summary deals with cloud users, and service providers could not determine reliable and required service level agreement studying by each one of the stakeholders. Thereby the measures for these characteristic are examined from the point of cloud users, service providers and architect of software concerning global concepts. The technique presented collects characteristic of universal ideas for metrics such as scalability, elasticity, and efficiency. These literatures differentiate all metrics [18]. Fault tolerance and resilience is used to denote reliability and availability based on user requirement [19]. It analyses fault tolerance according to every stage of failure. Elasticity plays a significant role in cloud computing. It is defined as flexible, smooth, general and straightforward to measure [20]. Resilience is used to authenticate integrity, user's response and needs of the business applicant. Testing is recreating the actual program of the user details to accept the program value for system establishment.

3. Related work

3.1. Literature survey for mediator based selection

The best cloud is selected based on the client's demand dynamically using adaptive learning method with the help of cloud broker [1]. The SLA information is provided and binding the sweep of services used to enhance the cloud computing field with spacious cost-efficient. It contains the reward for the giant, but it does not bear extra-provisioning for needed function [2]. Review between operators includes the operation setting of the administrations for the web technology in the area of agent-based and also from the field of the context-oriented concept is the major problem in [3]. Expert-based administration setting has given a faithful execution the worldview to the web structure benefits which is programmed. The distribution of planning algorithm technique had established in [4]. Arrangement of administration in the area of the multi-cloud situation must classify personal charm representatives, mechanical benefit selection and reconsider spreader administrations and classification with separated administration [5]. A design that objectifies the implemented concept which uses BPEL for finding the invite task of a web need is designed and finished in as a investigate for searching at our implemented algorithm and other gauge web need selection steps [6].

3.2. Literature survey for measures based cloud selection

Determining absolute rules is essential for calculation purpose. Systematic Literature Review (SLR) method used to calculate the perfect cloud service selection. Actions which are collected for various cloud services property to be determined, which built great determination measures list [7]. Let's see each measure in the upcoming paper. To perform a useful action under predefined conditions for a given time duration, the item's ability is SLA management, Energy management, VM management, Fault management [8]. It is used to determine the reliability of each cloud service providers [9]. Response time is the time taken to react to a given input. For each request, the time taken to respond is called response time [10]. Cerebro-It is a system which is used to evaluate statistical details of the response time of a particular application in the cloud environment [11]. In this paper problem related to choosing replica is discussed, where the user has to select model out of a large number of replica collection. Many algorithms are tried to achieve this to solve the problem [12].

Availability is directly propositional to the reliability measures. High availability terms are synchronous data mirroring, node, balanced load cluster, fail-back, cluster, asynchronous data mirroring, fail-over, [14]. Utilization mainly deals with memory, resources and task scheduling. The allocation and deallocations of the funds come under the measures of usage [15]. Corresponding user resource utilization is increased. The cost and performance are calculated using the metrics called utilization [16]. In this paper NP-Complete, Activity selection, 0/1 knapsack and resource utilization are used for determining the resource and memory utilization. [17]. This paper tells failures effect on consumer applications and analyses the fault tolerance regarding each stage of failures. [19]. This paper defines elasticity as the degree of the system enable to accept the workload variations by allocating and DE allocation of resource in an autonomic way, in such a way at each time the allocating support from available resources should have a close match with the present demand as near as possible [20].

This paper helps to determine the shared process at the design time, and it used for local needs, the selected method gives a global view, and its execution is done by various mash up engines of all working consumers. The resilience of the process is surveyed correspondingly [21]. Work [24] highlights reliability, throughput, latency, the response time for some dataset like lung cancer, balance scale, care valuation, out digits, Turkey student evaluation, and diabetic data. This paper deals with the selection of the cloud dynamically using the adaptive learning method (mechanism). It contains only three strategies for adaptive learning to optimize the cloud services for each cloud broker [25]. To increase the reliability in case of calculation, this paper uses matrix multiplication. [26]. The following table 1 & 2 shows a list of measures present in the article which we surveyed for this paper.

Table 1: Schemes based on R-Reliability, RT-Response Time, T-Throughput, and A-Availability

Schemes	R	RT	T	A
Reliability and energy efficiency in cloud computing systems: Survey and taxonomy [8]	✓	●	●	●
Service reliability modeling and evaluation of active-active cloud data center based on the IT infrastructure [9]	✓	●	●	●
Response Time for Cloud Computing Providers [10]	●	✓	●	●
Response Time Service Level Agreements for Cloud-hosted Web Applications [11]	●	✓	●	●
Cutting Tail Latency in Cloud Data Stores via Adaptive Replica Selection [12]	●	●	✓	●
Measuring network throughput in the cloud: The case of Amazon EC2 [13]	●	●	✓	●
Service availability (in the clouds) [14]	●	●	●	✓

Table 2: Schemes based on U-Utilization, S-Scalability, E-Elasticity, R-Resilience

Schemes	U	S	E	R
A Survey paper on Cloud Computing and its effective utilization with Virtualization[15]	✓	●	●	●
Resource Utilization Based Dynamic Pricing Approach on Cloud Computing Application[16]	✓	●	●	●
Resource Utilization in Cloud Computing as an Optimization Problem[17]	✓	●	●	●
Scalability, Elasticity, and Efficiency in Cloud Computing: a Systematic Literature Review of Definitions and Metrics[18]	●	✓	✓	●
Fault Tolerance and Resilience in Cloud Computing Environments[19]	●	●	●	✓
A new approach to analyze elasticity enablers of cloud services[20]	●	●	✓	●
An Analysis of Resilience of a Cloud Based Incident Notification Process[21]	●	●	●	✓

4. Proposed work

Storage service, computation service and application deployment service is provided by Cloud Service provider. Customer who needs to access web server is confused in selecting the cloud service and also expensive searching occurs. Cloud Service Broker (CBR) adds value to the cloud service, making it simple for the customer to use. User preferred task is reached by these

cloud services picking the best service integration. Finally it is difficult in the field of semantic service to tackle the choice of service in dynamic manner. CBR plays a role of middleware service effectively to set selection of cloud service simple. In addition to these, a new strategy is included in the adaptive learning mechanism to improve selection efficiency and also memory is added to the user task. The new remembrance included in finding the best selection reduces the probability of failures.



Fig. 2: Cloud service broker selection model(CBRSM)

Due to the static performance, cloud selection technologies are impacted in critical situations because of selection price and service changes. Cloud service broker selection model (CBRSM) is used to solve the above problem with the help of CBR based cloud selection, dynamically with performance, memory and price ratio. This methodology proposes adaptive behavioural strategy to activate cloud service choice at low cost when the system is running.

The CBRSM contribution adopts CBR, which runs selection process of cloud service dynamically with the help of three layers- User layer, CBR layer and Cloud service layer as shown in Fig.2. Service registration of cloud by service monitor is managed by CBR. Adaptive learning strategy contains Forgetting, Incentive, Degenerate and Remembrance. A dynamic cloud service selection algorithm is implemented and it is presented by strategy which gives methods for selection of cloud service.

4.1 Adaptive learning mechanism

Storage service, computation service and application deployment service is provided by Cloud Service provider. Customer who

needs to access web server has great confusion in selection of the cloud service and also searching is expensive. Cloud Service Broker (CBR) adds value to cloud service, making it simple for the customer to use. User preferred task is reached by picking these cloud services by service integration. Finally it is difficult in the field of semantic service to tackle the choice of service in a dynamic manner. CBR plays the role of middleware service effectively to make selection of cloud service simple. Important part of the proposed system is User Agent, Cloud Broker Agent, Adaptive Learning Mechanism and Service Monitor as shown in Fig 2.

User Agent: User sends tasks to the user agent like number of CPU, Ram speed and the price of service, and other details. User agent plays the role of a middleman placed between the user and the cloud provider and picks the services which match the user requirement. This cloud provider has link with the major agent called cloud broker agent and sends messages to the user agent which match preferred user requests.

Cloud Broker Agent: This is the major part which gets information from user agent and also from the service monitors. Based on the response received, broker agent sends messages to

the appropriate agents. This part gets information on cloud service through the service monitor who keeps all these information in the service information table (SIT). Based on the user task, CBR picks the perfect cloud service in the SIT.

Adaptive Learning: This mechanism takes place when a problem occurs in the cloud service present in the service information table of the selected CBR. The optimization of the cloud service in the SIT is done by this mechanism. Then the updated CBR is sent to the CBR cluster. The strategies are:

- a) **Third party registration based on the Incentive strategy:** The strategy is included to solve the problem based on managed cloud service failure or when service performance gets reduced. The mediator who shows interest towards the earlier registration booking. Thereby it improves the selection chance for the cloud broker and performance.
- b) **Deleting strategy for late usage:** Few cloud service which is not used for a long time is removed from the SIT which will avoid reducing the performance ratio.
- c) **Updating strategy for frequent use:** Few cloud services are repeatedly used during the period between the registered time and the time at when adaptive learning takes place, thereby minimising the performance. This strategy helps remove this problem state.
- d) **Remembrance of execution time:** If the execution time exceeds the response time limit or the threshold time then reliability becomes low. At that instant, this strategy is invoked. Let us take one pre-specified reliability R_s based on user task included in the cloud which has reliability above the R_s . Remove the cloud service with reliability below the R_s . After updation, take the cloud with low cost as the best cloud. Thereby we can reduce the probability of failure and improve the performance.
- e) **Service Monitor:** The cloud broker waits for a fresh registration message from the respective service monitor and then service monitor collects all the messages in the service information table. If any cloud service gets failed or any other problem happens, it will tell the CBR.

5. Experimental Evaluation

As a part of the experimental implementation user task is improved by adding the memory in addition to number of CPU and price. Reliability factor is added to the fourth strategy of adaptive learning for the cloud service optimization. All the experiments are executed on the JADE4.3.0 platform and computer configuration is Windows 10(64 bits) operating system, 8.0GB RAM. Here we give the experimental settings, measurement of performance, experiments conducted and the results are analysed in the comparison section.

5.1 Experimental Results

Experimental setup contains user requirement as RAM speed, processor and their preferred price. In the adaptive learning behaviour we have added four strategies and they are mentioned in Section 4.1.

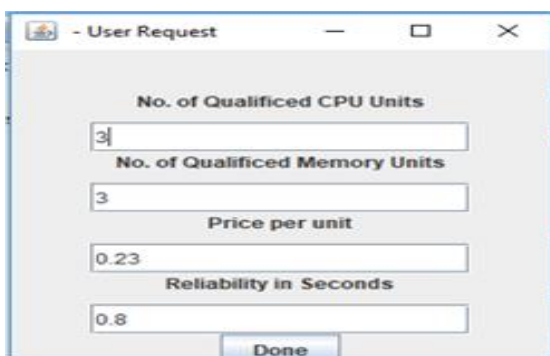


Fig. 3: Getting User Tasks

```
Agent SA started.
Row count = 70
User Calculating Ratio = 26.08695652173913
Received result 26.08695652173913
cset length=10
D[0] = 26.046456521739128
D[1] = 25.95432494279176
D[2] = 25.865527950310558
D[3] = 25.72195652173913
D[4] = 25.65195652173913
D[5] = 25.28695652173913
D[6] = 23.806956521739128
D[7] = 17.686956521739127
D[8] = 0.5830434782608727
D[9] = 48.13504347826088
-----
Selected CBR =9
-----
```

Fig.4: Selection of CBR

Fig.3 shows the details of getting user tasks for the user. Fig.4 shows how the cloud broker is clustered based on the service provider and which broker is selected based on the matching user task.

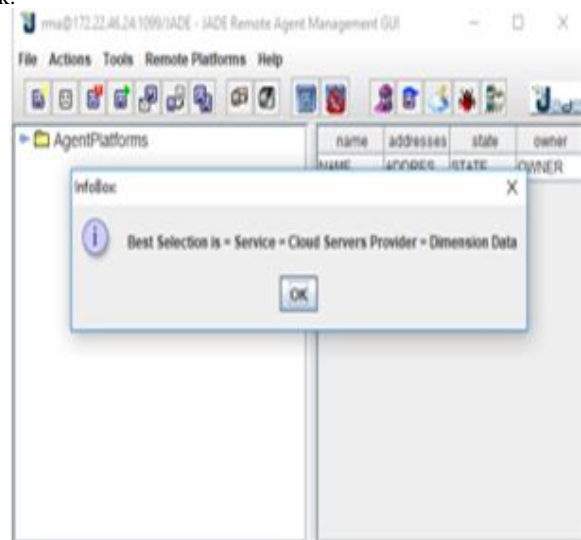


Fig. 5: Selection of Cloud service

```
-----
Table for CBR of 9
-----
Clustering Center 26.67
-----
set of registered cs :
26.67, 26.67,
The CSi of Max = 26.67
-----
```

Fig. 6: Service Information Table

Fig.5 shows the selection of cloud service in the appropriate cloud broker service information table (SIT). This table contains the details of clustered center cloud service Z_j , set of registered cloud service (CS) and CS with maximum ratio. The SIT is shown in Fig.6

```

REMEMBRANCE STRATEGY INVOKED
tri =2 tFi=16 tR=3.0 Nit =1.0
INCENTIVE STRATEGY INVOKED
Updating Table no: 4
price Ratio =151.3417119032592 Zlj=77.70142571483188
Result =5 100.0

```

Fig. 7: Remembrance strategy

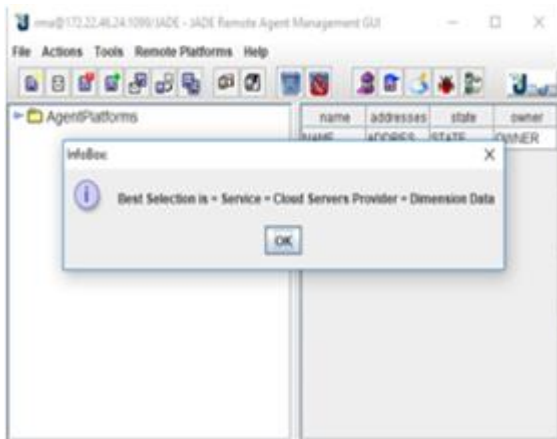


Fig. 8: Displaying Best Cloud Service for the user

The cloud broker after getting the message from the service monitor it selects the cloud service in the SIT with matching user tasks. If any CS fails, a message is given to the cloud broker from service monitor to invoke the adaptive learning method. If any managed CS fails then the incentive strategy is invoked. The strategy is included to solve the problem based on managed cloud service failure or when service performance gets reduced. The mediator shows interest towards the earlier registration booking. Thereby it improves the selection chance for the cloud broker and its performance. The cloud services that are not used for a long time are removed from the SIT to improve the performance ratio. Few cloud services are repeatedly used during the period between the registered time and time when adaptive learning takes place, thereby minimising the performance. This strategy helps to remove this problematic situation. If the execution time exceeds the response time limit or the threshold time, then reliability becomes low. At that instant, this strategy is invoked. Let us take one pre specified reliability R_s based on user task included in the cloud which has reliability above the R_s . Remove the cloud service with reliability below the R_s . After updation, take the cloud with low cost as the best cloud. Thereby we can reduce the probability of failure and improve the performance as shown in Fig.7. Finally the best cloud is selected for user as shown in Fig.8

5.2 Experimental settings

Compared to the cost and efficiency of DCS, a new strategy in adaptive learning method has been introduced. The old adaptive method does not have the knowledge about reliability but this new strategy help to improve the performance by using the knowledge about the reliability. Sample data for the purpose of testing the ratio of each cloud service is derived from already published sites like Amazon, Windows Azure, Google GAE and Force.com platform. In order to improve the fractional value, if the CPU set count is more, the cost per hour of the CPU set should also cost more. Therefore it is not essential to get large value for CPU count. If the service provider needs to give bigger ratio for the cloud service, there may be limit on the cost for the process which

is running, and update the renewed service's data into a perfect matching broker of cloud CBRj.

5.3 Measurement of performances

There may be chances for the cloud service failure when the algorithm for the execution of dynamic service selection is running or when the entire selection of the cloud service cannot be successful completed even though we utilize the successful degree of selection of cloud service as a measurement of performance.

The capability of adaptive behaviour is an essential concept for a cloud broker which uses the DCS scheme and make utilizes the fraction of full amount of adaptive behaviour use to full amount of the adaptive behaviour bonus gained by a cloud broker CBRj for every selection of cloud of UA. Thereby reliability improves the performance and efficiency by reducing the probability of failure from 0.5 to 0.3 range by adding useful knowledge in SIT when compared to SCT (Service capability table) [27]. It improves the adaptive learning behaviour utility by reducing the cost of adaptive learning process and also reduces the internal memory management cost of table information.

6. Result comparisons

Here, the degree of selection of cloud of the DCS scheme is set against the new strategy added to adaptive behaviour and changes with the growing count of cloud services prospect of failure. The number of user request (50) is used to compare selection per execution or second with the probability of failure. In Fig.9,

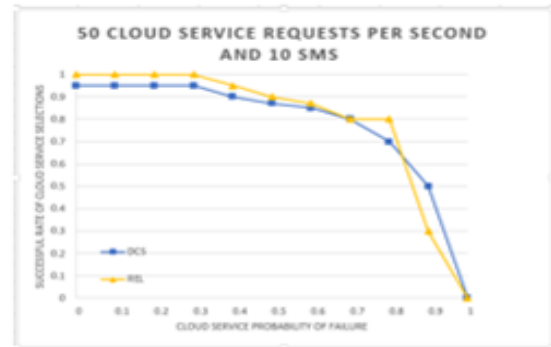


Fig. 9: Comparison of selection of cloud service in successful manner

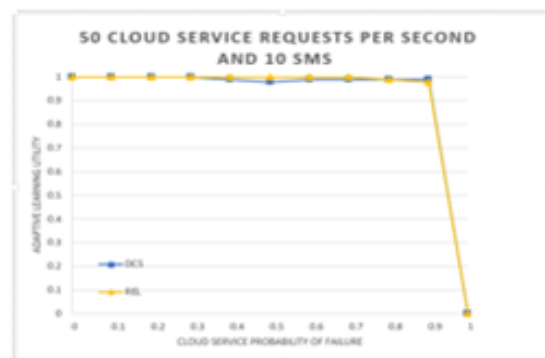


Fig. 10: Comparison of adaptive learning Utility

The degree of selection of cloud for all schemes reduces with growth of the cloud services prospect failure. When the prospect of failure is bigger than 0.6, all the successful degree get down to 0. This happens since there is a very complicated process with 0.6 cloud service prospect failure to produce the process in achieving user's task.

In Fig.9, let us see that (i) when the prospect failure is smaller or similar to 0.6, then every victorious degree is more in the REL scheme till it reaches at most 1, and (ii) if it consists of 50 cloud demand rate with medium of (10) SMs. The victorious degree for

REL scheme is mostly similar to or smaller than that of DCS scheme. When the probability of failure is smaller than 0.7 or 0.8, the adaptive behaviour has been used to decrease it. Fig.10 describes that the adaptive behaviour use of REL scheme is always more than that of the old DCS strategies. New DCS strategy is a new added strategy of adaptive method. In Fig.11, the average selection of cloud service time for all successful cases of REL scheme of new adaptive method is compared.

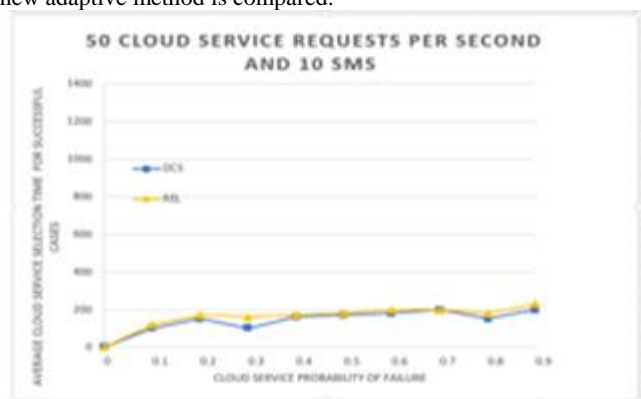


Fig. 11: Comparison of average selection of cloud service time for successful cases in REL

7. Conclusion

Our implemented work mainly concentrates on the Selection of cloud service based on the user preferred task dynamically using the model called CBRSM which contains DCS method. The implemented model assists the user to give their preferred task to the user agent and user agent select the matching cloud broker for the user to allocate the preferred cloud service. In case any problem occurs in service information table of selected broker then adaptive learning method is invoked for the optimization of the cloud and then sent to the updated cloud service to the broker layer. The added measures help us to find the best selection of cloud in multi cloud environment. Especially reliability helps us to improve the adaptive learning mechanism. Thereby reliability improves the performances and efficiency by reducing the probability of failure from 0.5 to 0.3 range by adding useful knowledge in SIT when compared to SCT (Service capability table). It improves the adaptive learning behaviour utility by reducing the cost of adaptive learning process and also reduces the management cost of internal memory of table information. Thereby it increases the performance of the selection in an efficient manner at a cheaper cost and also is experimentally verified. In future we can use fault tolerance and throughput to improve our selection process which further improves the performance.

References

- Wang X, Cao J, Xiang Y. "Dynamic Cloud Service Selection using an Adaptive Learning Mechanism in Multi-cloud Computing." *Journal of Systems and Software*, pp.195-210, 2015.
- Gupta R. "Above the Clouds: A View of Cloud Computing." *Asian Journal of Research in Social Sciences and Humanities*, pp.84-110, 2012.
- Maamar Z, Mostefaoui SK, Yahyaoui H. Toward, "An Agent-based and Context-oriented Approach for Web Services Composition", *IEEE transactions on knowledge and data engineering*, pp.686-97, 2005.
- Tong H, Cao J, Zhang S, Li M. "A Distributed Algorithm for Web Service Composition based on Service Agent Model", *IEEE Transactions on Parallel and Distributed Systems*, 2011.
- Gutierrez-Garcia JO, Sim KM, "Agent-based Cloud Service Composition." *Applied intelligence*, pp.436-64, 2013.
- Hwang SY, Lim EP, Lee CH, Chen CH, "Dynamic Web Service Selection for Reliable Web Service Composition", *IEEE Transactions on Services Computing*, pp.104-16, 2008.
- Li Z, O'Brien L, Zhang H, Cai R "On a Catalogue of Metrics for Evaluating Commercial Cloud Services", *InGrid Computing (GRID), CM/IEEE 13th International Conference*, pp. 164-173, 2012.
- Sharma Y, Javadi B, Si W, Sun D. "Reliability and energy efficiency in cloud computing systems: Survey and taxonomy", *Journal of Network and Computer Applications*, pp.66-85, 2016.
- Li X, Liu Y, Kang R, Xiao L. "Service Reliability Modeling and Evaluation of Active Cloud Data Center based on the IT infrastructure", *Microelectronics Reliability*, pp.271-282, 2017
- Mohammed Alhamad, Tharam Dillon, Chen Wu, Elizabeth Chang, "Real-Time and Stream Applications", *Response Time for Cloud Computing Providers*, 2010.
- Jayathilaka H, Krintz C, Wolski R, "Response time service level agreements for cloud-hosted webapplications", *Proceedings of the Sixth ACM Symposium on Cloud Computing*, pp. 315-328, 2015.
- Suresh PL, Canini M, Schmid S, Feldmann A, "C3: Cutting Tail Latency in Cloud Data Stores via Adaptive Replica Selection", *NSDI*, pp. 513-527, 2015.
- Persico V, Marchetta P, Botta A, Pescapé A, "Measuring network throughput in the cloud: The case of Amazon EC2", *Computer Networks*. pp. 408-22, 2015.
- Gade AH, "A Survey paper on Cloud Computing and its effective utilization with Virtualization", *International Journal of Scientific & Engineering Research*, pp. 357-363, 2013.
- Johannes A, Nanda P, He X, "Resource Utilization Based Dynamic Pricing Approach on Cloud Computing Application", *International Conference on Algorithms and Architectures for Parallel Processing*, pp. 669-677, 2015.
- Lehrig S, Eikerling H, Becker S, "Scalability, Elasticity, and Efficiency in Cloud Computing: A systematic literature review of definitions and metrics", *Proceedings of the 11th International ACM SIGSOFT Conference on Quality of Software Architectures*, pp. 83-92, 2015.
- Jhavar R, Piuri V, "Fault Tolerance and Resilience in cloud computing environments," *Computer and Information Security Handbook*, pp. 165-181, 2017.
- Beltrán M, "BECloud: A new approach to analyse elasticity enablers of cloud services." *Future Generation Computer Systems*, pp.39-49, 2016.
- De Vrieze P, Xu L, "An Analysis of Resilience of a cloud based incident notification process," *Working Conference on Virtual Enterprises*, pp. 110-121, 2015.
- Sun L, Dong H, Hussain FK, Hussain OK, Chang E, "Cloud service selection: State-of-the-art and future research directions", *Journal of Network and Computer Applications*, pp.134-50, 2014.
- Hwang K, Bai X, Shi Y, Li M, Chen WG, Wu Y, "Cloud performance modelling with benchmark evaluation of elastic scaling strategies", *IEEE Transactions on parallel and distributed systems*, pp. 130-43, 2016.
- Rahman MS, Ding C, Liu X, Chi CH, "A testbed for collecting QoS data of cloud-based analytic services," *IEEE 9th International Conference on Cloud Computing (CLOUD)*, pp. 236-243, 2016.
- Maruthi, P. Shanthi, "Efficient Dynamic Cloud Service Selection In Multi Cloud Computing Using Adaptive Learning Mechanism," *International Journal of Pure and Applied Mathematics*, 2017.
- Deng J, Huang SC, Han YS, Deng JH, "Fault-tolerant and reliable computation in cloud computing", *IEEE GLOBECOM Workshops (GC Wkshps)*, pp. 1601-1605, 2010.
- Gutierrez-Garcia JO, Sim KM, "Agent-based cloud service composition," *Applied intelligence*, pp.436-64, 2013.
- T. Padmapriya and V. Saminadan, "Utility based Vertical Handoff Decision Model for LTE-A networks", *International Journal of Computer Science and Information Security*, ISSN 1947-5500, vol.14, no.11, November 2016.
- S.V. Manikanthan and D. Sugandhi "Interference Alignment Techniques For Mimo Multicell Based On Relay Interference Broadcast Channel" *International Journal of Emerging Technology in Computer Science & Electronics (IJETCSE)* ISSN: 0976-1353 Volume- 7 , Issue 1 –MARCH 2014.