



Fuzzy based QoS prediction using bayesian network in cloud computing environment

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Abstract

The Quality of Service (QoS) is enforced in discovering an optimal web service (WS). The QoS is uncertain due to the fluctuating performance of WS in the dynamic cloud environment. We propose a Fuzzy based Bayesian Network (FBN) system for Efficient QoS prediction. The novel method comprises three processes namely Semantic QoS Annotation, QoS Prediction, and Adaptive QoS using cloud infrastructure. The FBN employs the compliance factor to measure the performance of QoS attributes and fuzzy inference rules to infer the service capability. The inference rules are defined according to the user preference which assists to achieve the user satisfaction. The FBN returns the optimal WSs from a set of functionally equivalent WS. The unpredictable and extreme access of the selected WS is handled using cloud infrastructure. The results show that the FBN approach achieves nearly 95% of QoS prediction accuracy when providing an adequate number of past QoS data, and improves the prediction probability by 2.6% more than that of the existing approach.

Keywords: WS discovery, QoS, OWL-Q, Bayesian Network, Double Exponential Smoothing, Queuing Network.

1. Introduction

With the advent of Internet and WWW, the number of available web services becomes innumerable. WSs are the primary implementation platform for Service Oriented Application (SOA) which exploits a set of standard protocols and technologies such as SOAP, UDDI, and WSDL for exchanging data between applications or systems over a network [1]. With increase in the number of WS, according to the issues also increases related to throughput, reputation, Response Time and composition of atomic services. Thus, it leads to quick development of cloud computing which has the capability to solve the WSs issues based on storage, and interoperability. Hence, the major IT organizations exploit the cloud infrastructure to publish their WS [2].

Owing to the proliferation of WSs, the process of finding a suitable WS which satisfies the user requirement for a given task becomes more critical and non-trivial task. The approach in [3] combines both the fuzzy neural networks and an online learning scheme for efficient QoS prediction. It first filters the fuzzy rules from the QoS data and online learning scheme method is applied to solve the problem. The existing mechanisms of discovery and selection must be re-examined, since the inappropriate WS usage includes the potential risk in the business applications. In order to solve this mismatched problem in WS discovery, the semantic description is annotated with the WS using OWL-S ontology. The semantically annotated WS descriptions are used to facilitate the explicit automated WS discovery and composition. However, there is no effective mechanism to describe the Web Service semantically and also this mechanism is not rich to select the appropriate Web Service from large number of Web Service with similar functionality [4]. Thus, it increases the need to include the

non-functional description. The non-functional description is also called the quality attributes such as scalability, security, availability, cost, and accuracy to differentiate the functionally similar WSs [5]. Many of the QoS attribute values are Dynamic in nature and it is not advisable to take the actual value advertised by the service provider. To overcome the issues in conventional WS discovery approaches, the proposed FBN approach utilizes the advantages of Bayesian function with fuzzy inference engine rules. To improve the QoS prediction accuracy, the Bayesian function collects the conditional probability for all possible combinations of different services from neighbor users as well as user requirements based service capability using fuzzy inference rules.

Moreover, WSs are exposed to the unpredictable spike condition. The WS management with the traditional technology is not able to handle the spike condition, as it requires costly investment for installing and setting up the infrastructure both in hardware and software. The rest of the paper is organized as follows: Section 2 includes the previous works related to the WS discovery and prediction of QoS. Section 3 describes the proposed methodology using Bayesian network, experimental results are discussed in section 4 and Section 5 concludes the work.

2. Related works

The number of web services available with the same ability to do things is the significant issue in selecting the appropriate web service for the user query.

The UDDI web service selection supports solo the keyword based search. However, the keywords are incapable to corroborate the semantically familiar concepts which conduct to the irrelevant verify for the addict query. The vital role in automatic WS

discovery is the semantic description of web services. Hence, large amount of the approaches one as QWL-S [6], and WSML [7] and have been about to be to adopt semantics to internet services which makes inconsequential the behaviour of selecting pertinent web service. However, these works provide no way to describe the user preferences of security and QoS properties for WS. Alpine, a proof-of-concept system based on Bayesian networks is proposed in [8], for cloud QoS diagnosis and prediction under uncertainty conditions. In [9] the prediction of QoS of a service is based on all the three layers of cloud computing. Lack of defining the rules and combining the QoS parameters with the resources provide uncertainty to the Bayesian results.

In [10], an uncertainty trust model is proposed which combines cloud model and Bayesian network. Guaranteed QoS is big challenge in cloud applications. Moreover, the unfair rating consideration in QoS prediction reduces the accuracy of WS discovery. To face this challenge an approach is proposed in [11] about the extension of self-tuning fuzzy control. Due to this fact the response time is assured. A two-layer QoS provisioning framework is designed for better adaptability and stability. The service provider publishes the service with the QoS attributes. The advertised QoS values changes dynamically due to uncertain environment. The QoS model in the system verifies the published QoS attributes using QoS certifier. However, the system only allows the syntactic matchmaking of offers and demands because of the usage of UDDI. With the intension of facilitating the web service discovery the QoS attributes are included with the value added services using the WSDL description [12]. Similarly, the Web Service QoS specifications are included with the WS description using an extended DAML-S. It allows the service consumers to request the web service including required QoS levels. However, the end-to-end QoS service provision needs to map the procedures of WS QoS and network infrastructure. Hence, the matchmaking between the available services and the user requirement is based on both the functional and non-functional attributes [13]. The QoS ontology and its vocabulary is modeled by the agency of the Web Services Modeling Ontology (WSMO) which annotates the WS descriptions mutually the QoS data. The quality attributes and its measurements are described with the QoS selection model which assists to select the particular service [14]. Moreover, artificial neural network model for the prediction of missing QoS-values is proposed in [15] to optimize the prediction of QoS. The limited number of artificial neural parameters impacts the accuracy of the prediction model. In [16] also exploit the QoS attributes in web service discovery. The conventional approaches emphasize the forceful nature of the QoS attributes, and they cannot find efficient web service discovery. Not any of the approaches emphasize on the forceful nature of the QoS attributes. Hence, they cannot find efficient web service discovery and QoS prediction. However the latest research considers the forceful nature QoS attributes and exploits the system to predict the QoS values.

To predict the QoS attributes the proposed system uses the Bayesian Network Model for efficient WS discovery and QoS prediction. It predict the capability of web services in different user requirements QoS attributes based on the past invocation experiences [17].

3. Proposed methodology

With the increasing proliferation of WSs, the optimal WS discovery becomes a challenging and overwhelming task. To address this problem, the FBN approach is proposed which includes three techniques of Semantic QoS Annotation, QoS Prediction, and Adaptive QoS using cloud infrastructure.

3.1 Semantic QoS Annotation with WS

With the ever increasing number of available WSs, the optimal WS discovery with the required functionality and appropriate

quality characteristics is more critical and significant task. The traditional WS discovery approaches follow the syntactic matching using the standards UDDI and WSDL, hence it leads the users to provide accurate query [11]. Lack of details in user query returns high false positive values, and thus it leads to the inefficient automatic service discovery with unmatched results. The proposed system, model the WS description as formal declarative model using OWL-S ontology that makes more expressive and meaningful WS description. Only with the semantic description of web services is not enough to choose the appropriate services, since many number of web services available with the similar functionality. Among them, the system exploits the OWL-Q ontology considering QoS static and dynamic attributes to select best available Web service. QoS factor is discriminated from the functional characteristics by a set of attributes such as response time, availability, reliability, etc. Even though all the WS are functionally equivalent, it is discriminated by the QoS attributes. The OWL-Q ontology extends the OWL-S to describe the QoS attributes and their constraints [24]. With the help of OWL-Q the complete QoS specifications defined with the WS description are stored in ontological service profile advertisements and thus, it enables the semantic matchmaking of QoS advertisements and offers.

Semantic matchmaking is method which takes the input as the query submitted by the user and checks for all possible ontological service profile in UDDI to match the given input. It returns a set of matching advertisements sorted according to the degree of match. The degree of the match is determined from the level of matching between the user submitted query and service advertisements from the service provider. The lists of functionally similar WSs are obtained and the QoS of each WS is modeled as Bayesian network (BN).

3.2 Bayesian network model

BN based QoS assessment model is used in the proposed system to correctly predict the service provider's capability in various combinations of user's QoS requirements. After obtaining a list of functionally similar WSs, the BN based QoS prediction model evaluates the probability value of each service. And the services are arranged according to the high probability and user selects any one of the WS from this optimal WS. The proposed FBN system for predicting the QoS of WS using BN is shown in Fig. 1.

The naive BN is a simple BN model which is created separately for each services in the format of CPT. CPT which refers the Conditional Probability Table defines the conditional probabilities of all possible combinations of different service capability values of similar users. It is constructed for all QoS attributes like reliability, response time, availability, and throughput.

The values of CPT tables are filled with the compliance factor of the QoS attributes. Compliance is the performance metric which measures the difference in the delivered and projected value of QoS property. Let, R is the Response time property, RR is Required Response time of user and the DR is the Delivered Response time. Compliance value (represented as C) is calculated using the following Eq. (1),

$$C = (DR - RR) / DR \quad (1)$$

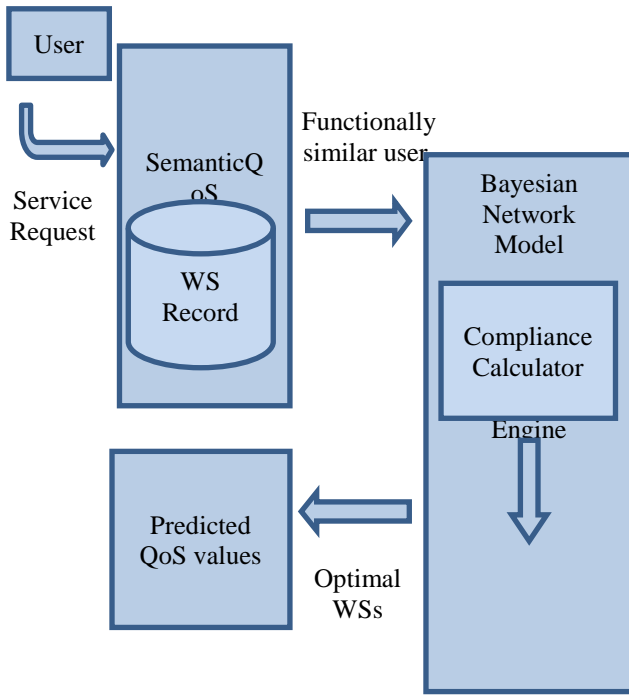


Fig. 1: Bayesian network model with fuzzy inference engine

The compliance value C_x [-1 to 1] which can be easily classified as low, good, and excellent according to the positive, zero and negative value of compliance. But in order to achieve a more reasonable and fine grained estimation of compliance, fuzzy representation is exploited. Based on the conditions, five levels of compliance values are classified and described in Eq. (2). According to the property or user need, the number of levels can be varied.

$$C_x = \begin{cases} \text{Verylow} & \text{if } -1 \leq C_x < -0.5 \\ \text{Low} & \text{if } -0.5 \leq C_x < 0 \\ \text{Moderate} & \text{if } C_x = 0 \\ \text{Good} & \text{if } 0 < C_x < 0.5 \\ \text{Excellent} & \text{if } 0.5 \leq C_x < 1 \end{cases} \quad (2)$$

Moreover, the QoS attributes have different user tendency like "Higher the Better" and "Lower the Better". The attributes such as Response Time, Cost, Latency and Number of failures have the tendency of Lower the Better meanwhile; the attributes such as Security, Reliability, and Availability have the tendency of Higher the Better. For "Lower the Better" attributes the compliance factor is considered in inverse.

If all the entries of the CPT table for QoS attributes are completed, the probability of the service capability can be predicted. The service capability is defined according to the user requirement which may depend on one or more QoS attributes. For example, some users may concentrate on security not in response time and others may need both security and response time. For the first requirement if the service provides high security then the service capability is considered as excellent. But for the second requirement if the service provides high security and low response time then only the service will be considered as excellent. Due to this different combination of QoS requirement of users, the service capability is identified by applying the rules called biased inference rules shown in Fig. 2. Finally, with the help of identified compliance and service capability values the Bayes rule identifies the probability of the overall service capacity. The WS are arranged based on the high probability value and provided to the user. Now the user can select the optimal WS among these according to their needs.

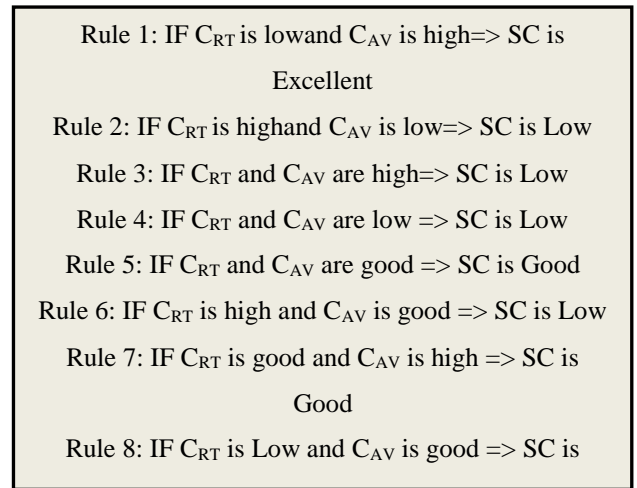


Fig. 2: Biased inference rules

Let us consider the following scenario: WS1 and WS2 are functionally similar input WSs. User1, User2, and User3 are similar users of WS1 and User4, User5, and User6 are similar users of WS2. The past QoS values for WS1 and WS2 are given in Table 1 and 2 respectively. The required QoS attributes of user is: Response Time (RT) = 0.3ms and Reputation (RP) = 0.9. The compliance factor is calculated and its values are classified according to the Eq.(3).

$$C_x = \begin{cases} \text{Low} & \text{if } -1 \leq C_x < 0 \\ \text{Good} & \text{if } C_x = 0 \\ \text{High} & \text{if } 0 < C_x \leq 1 \end{cases} \quad (3)$$

Table 1: QoS prediction of web service (WS1)

WS User	WS1			
	RT	C_{RT}	AV	C_{AV}
User1	0.25	-0.2	0.91	0.01
User2	0.2	-0.5	0.9	0
User3	0.3	0	0.95	0.05

Table 2: QoS prediction of web service (WS2)

WS User	WS2			
	RT	C_{RT}	AV	C_{AV}
User4	0.45	0.33	0.86	-0.05
User5	0.3	0	0.8	-0.13
User6	0.6	0.5	0.92	0.022

From the Table 1 and 2 it is obvious that the WS1 has the highest probability value hence, it is selected as the optimal WS for the user query.

3.3 Adaptive QoS using Cloud Infrastructure

The selected optimal WS is provided to the user and it should guarantee the predicted QoS attributes even the extreme access of WS. In general, before using the WS, the service user enter into the Service Level Agreement (SLA) which is an agreement between a service provider and service user about the QoS attributes [19]. The system assumes the predicted QoS values as the SLA between the selected WS and user. However, the unpredictable load conditions and fluctuating demands of the WS make difficulties in maintaining the defined SLA. Managing the WS with the obsolete intelligence requires heavy cost and the lack of programming imparts more CPU cycles to execute the task. Dynamic resource provisioning of the cloud overcomes these difficulties and it creates several virtual machines and WS

replication that reduces the request queue length and waiting time [20]. Moreover, an elastic infrastructure of the cloud provides the WS application with the ability to exploit parallelization in a cost-effective manner. This leads to guarantee the expected SLA and improves the user satisfaction. Hence, the proposed FBN system exploits the cloud infrastructure with the help of DES and QN model. DES predicts the future arrival rate and QN model estimates the resource utilization for scaling the virtual machines and resources.

3.3.1 Double exponential smoothing

DES is a computationally cheap, smoothing and forecasting time series technique. It is capable of providing short term prediction for any sequence of observations based on the trend which exist over the time series [21]. This system exploits the DES to predict the future request rate using the monitored service rate and response time. The forecast value at $t+n$ time in time series X_t is show in Eq. (4).

$$X_{t+n} = L_t + B_t \quad (4)$$

Where, L_t represents the level of the time series at time t and its value is given by Eq.(5), and the Eq. (6), represents B_t , the trend of the time series at time t .

$$L_t = \alpha X_t + (1 - \alpha)(L_{t-1} + B_{t-1}) \quad (5)$$

X_t is the actual request rate at the current time t and α is the smoothing constant for the level $0 \leq \alpha \leq 1$

$$B_t = \beta(L_t - L_{t-1}) + (1 - \beta)B_{t-1} \quad (6)$$

β is the smoothing constant for trend $(0 \leq \beta \leq 1)$.

3.3.2 Queuing network model

QN is the system model and it provides the analytical performance [22]. The system effectively predicts the response time of a system under various request load conditions which assists in decision making of whether resources have to scaling up or scaling down. It is operated based on two parameters such as Request load (λ) and Response Time (RT). The average RT on the machine i is calculated based on the following Eq.(7), and Eq. (8).

$$RT = \sum_{i=1}^K \frac{RT_i}{1-U_i} \quad (7)$$

$$U_i = \lambda_i \times SD_i \quad (8)$$

Where K = total number of machines which have replicas for the selected WS, and

U = Utilization of physical host,

SD = Service Demand.

3.3.3 Cloud framework

The cloud framework comprises two important services namely monitoring and controlling to effectively guarantee the defined SLA. In this system, the cloud monitoring service monitors the arrival request rate for every virtual machine which comprises the selected WS replica at each 30 seconds. DES is applied on the collected data to predict the next 90 seconds of request rate for each virtual machine. The predicted request rate is fed into the controller which is the responsible for resources scaling up and scaling down. After receiving the request rate, the controller utilizes the QN to identify the utilization of virtual machines. If all the allocated virtual machines reached the above or equal to 90% of utilization then the new virtual machine is allocated with the WS replica to the WS is known as resource scaling up. Similarly, if the virtual machine has below or equal to 30% utilization then

the virtual machine is free from the WS is called as resource scaling down. Thus, with the help of the DES and QN, the system achieves the guaranteed WS even the extreme demand and with the facility of resource scaling up and scaling down algorithm in cloud it achieves the effective resource utilization.

4. Performance evaluation

The performance of the deployment architecture depends on the software and hardware settings. The experiments are implemented with JDK1.7, Netbeans 8.0.1, Glass Fish Application Server, MySQL 5.0, Eucalyptus and Apache Benchmark tool. They are conducted on a PC with Pentium (R) Dual Core Processor, 3.20 GHz CPU, 1.96 GB of RAM, running a Ubuntu 12.04 operating system.

4.1 Implementation scenario

This section runs an experiment with the objective of measuring the prediction accuracy and QoS management of the proposed system. The experiments are conducted based on a publicly available QoS dataset of real-world Web services [23] which is collected in [9]. The dataset was collected in August 2009, providing a total of 1,974,675 response time and throughput records of service invocations between 339 users and 5,825 Web services. The 339 users are simulated by PlanetLab2 nodes distributed at 30 countries, while the 5,825 real-world Web services are crawled from the Internet and are deployed at 73 countries. The system randomly extracts 150 users and 100 Web services and uses the invocation records between them as the experimental data. Moreover, the private cloud was set with the help of open source Eucalyptus software for Infrastructure as a service (IaaS) cloud. Four physical machines are exploited in this experiment. The Glassfish Application Server assists to virtualize the selected WS in cloud. The cloud provides different virtual machine types up to 64 GB of main memory. Xen is also a open source software used as a VMM hypervisor which exists on every physical machine. Apache Benchmark was used to generate the required load requests to show the impact of cloud infrastructure.

4.2 Result analysis

The simulated results of the proposed FBN system are discussed. To determine the performance of the novel system, various performance metrics are evaluated.

4.2.1 Impact of Past QoS

A. Accuracy

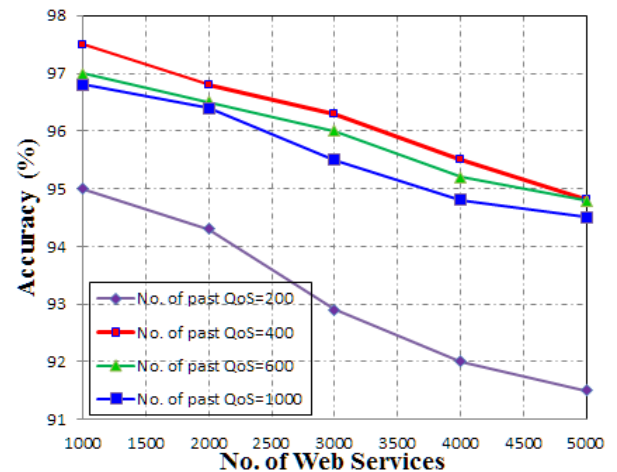


Fig. 3: No. of Web Services vs. Accuracy

The prediction capability of the system is indicated by the accuracy was then evaluated by varying the past QoS data while increasing the number of WSs. The numbers of WSs are varied from 1000 to 5000 and the numbers of past QoS data are varied from 200 to 1000. This scenario shows the impact of exploiting more and less QoS in WS discovery. According to the assumption, for a optimal WS discovery 400 past QoS data are enough. When the service discovery is performed using 400 past QoS data then the accuracy is consistent and linear (94.82).

The process of increasing the number of QoS may include inaccurate QoS data, thus resulting in decreases the prediction accuracy. Hence, as shown in Fig.3 for 1000 QoS data, the system obtains 94.5 accuracy. Similarly, the process of considering less QoS explode the relevant QoS data, thus also reduces the prediction accuracy. For 200 QoS data, it obtains only 91.5 accuracy.

B. Execution Time

Fig. 4 shows the performance of the system in terms of execution time by increasing the number of WSs and its past QoS data. From the Fig. 4, it is acceptable when the number of WSs and its past QoS data are increase the execution time of the system also increases. When a service discovery is performed using enough 400 past QoS data among 5000 WSs the system obtain 140ms for execution.

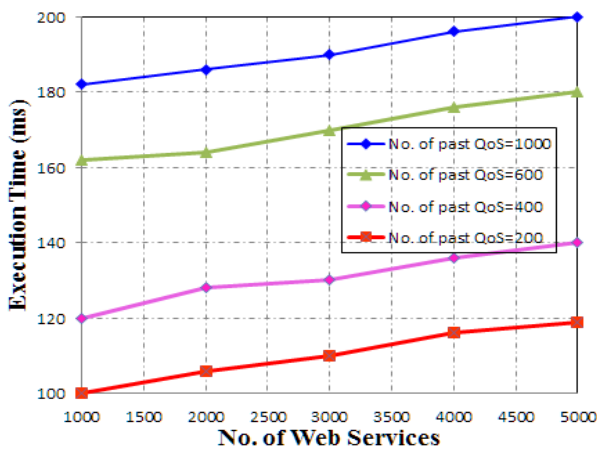


Fig. 4: No. of Web Services vs. Execution time

While, when the number of past QoS data are 200 the system obtain only 119ms for execution and for the 1000 past QoS data the system obtain 199.5ms for execution. Hence, the enough past QoS data should be exploited in service discovery.

4.2.2 Prediction Probability

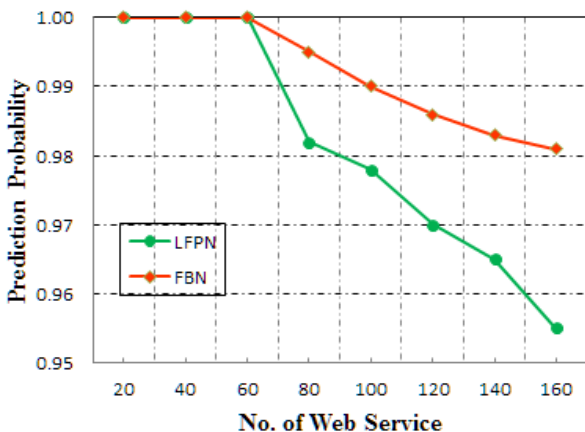


Fig. 5: No. of Web Services vs. Prediction Probability

In this scenario, the performance of the system is evaluated in term of optimal WS Prediction capability by comparing with the existing LFPN system [18]. As shown in Fig.5 the proposed FBN system performs better than the existing LFPN. Similar to the system the LFPN system figures out the different service functional descriptions to predict the QoS with the support of Petri Net model. But, it does not take into the fact of different users get different QoS for the similar WS according to their network conditions. This is achieved by the proposed system with the help of Fuzzy based QoS prediction using Bayesian network. Hence, the system optimal service prediction probability as 0.983% and the LFPN capability is 0.954%.

4.2.3 Impact of Cloud Infrastructure

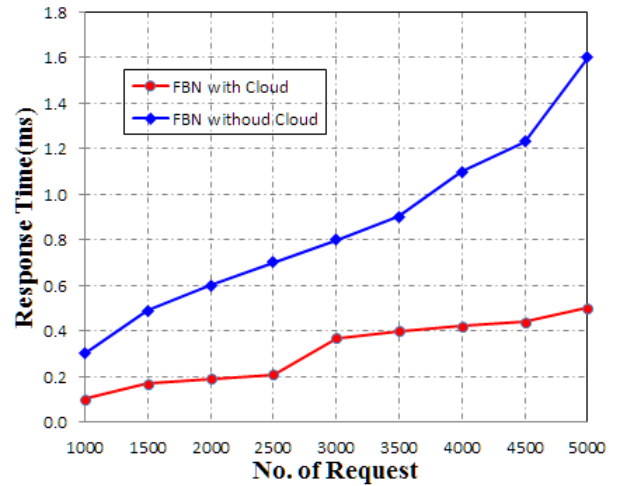


Fig. 6: No. of Request vs. Response Time

The Fig. 6 shows the performance impact brought by the cloud infrastructure in the proposed FBN system and it shows that the QoS management in this particular cloud environment was even greater than the single WS host environment. The experiment is based on number of concurrent user request varying from 1000 to 5000 and the expected RT is 0.4 to 0.5ms. The proposed framework with cloud successfully managed to keep the response time with in the defined SLA while increasing the user request. For example, as shown in Fig. 6 with the number of request 4000, the FBN system with cloud achieves 0.42 ms but without cloud infrastructure even for the number of request 3000 the system obtains 0.6ms.

5. Conclusion

The proposed architecture and its corresponding infrastructure provide an optimal WS discovery over the huge number of available WSs with the help of effective QoS prediction. Semantic QoS incorporation, QoS prediction and adaptive QoS are the steps involved in the proposed FBN system. The semantic QoS incorporation utilizes OWL-Q ontology to successfully include the semantic as well as QoS description with the WS description and it overcomes the inaccurate WS discovery in syntax based WS techniques. The exploitation of Bias rules and compliance factor improves the prediction accuracy of the proposed FBN system and assist to achieve the user satisfaction. User preference assisted fuzzy inference rules to tend the FBN to attain 95% of prediction accuracy. According to the maintenance of the conditional probability table for all combinations of service capability, the Bayesian function reduces the uncertainty and improves the accuracy of FBN approach. Finally, the fluctuating demands of the WS is handled effectively using the cloud infrastructure with the DES and QN techniques. The short term prediction technique DES predicts the future arrival time and QN estimates the resource

utilization. The experimental evaluation gives the evidential result of the performance, and it shows the proposed FBN system achieves better performance than the existing system. In future, the Bayesian function is extended to adapt high dimensional data. To improve the prediction accuracy, it is planned to develop domain-level ontologies and effectively support WS discovery under complex scenarios.

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