CLOUD ARMOR: SUPPORTING REPUTATION BASED ON TRUST MANAGEMENT FOR CLOUD SERVICES

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Abstract: In cloud computing growth, management of trust is most challenging issue. Cloud computing has several challenging issues such as privacy, security and availability by the changing of environments. Preserving consumer's privacy is not an easy task due to sensitive information involved in the interaction between consumer and the trust management service. Protecting cloud services from the malicious users is a difficult problem. The availability of trust management service is another significant challenge because of the dynamic nature of cloud environments. This paper proposes Cloud Armor, a reputation based trust management framework that provides a set of functionalities to deliver Trust as a Service(Taas), which includes i) a novel protocol to prove the credibility of trust feedbacks and preserve users' privacy, ii) an adaptive and robust credibility model for measuring the credibility of trust feedbacks to protect cloud services from malicious users and to compare the trustworthiness of cloud services, and iii) an availability model to manage the availability of the decentralized implementation of the trust management service. The benefits of the approach have been validated by a prototype and experimental studies.

Index Terms: Cloud computing, trust management, credibility, reputation, availability.

I. INTRODUCTION

The highly dynamic, distributed, and nontransparent nature of cloud services make the trust management in cloud environments a significant challenge. According to researchers at Berkeley, trust and security is ranked one of the top 10 obstacles for the adoption of cloud computing. Indeed, Service-Level Agreements (SLAs) alone are inadequate to establish trust between cloud consumers and providers because of its unclear and inconsistent clauses. Consumers' feedback is a good source to assess the overall trustworthiness of cloud services. Several researchers have recognized the significance of trust management and proposed solutions to access and manage trust based on feedbacks collected from participants. In reality, it is not unusual that a cloud service experiences malicious behaviors (e.g., collusion or Sybil attacks) from its users. This paper focuses on improving trust management in cloud environments by proposing novel ways to ensure the credibility of trust feedbacks. In particular we distinguish the following key issues of the trust management in cloud environments: Consumers' Privacy. The adoption of cloud computing raise privacy concerns. Consumers can have dynamic interactions with cloud providers, which may involve sensitive information. There are several cases of privacy breaches such as leaks of sensitive information (e.g., date of birth and address) or behavioral information (e.g., with whom the consumer interacted, the kind of cloud services the consumer showed interest, etc.). Undoubtedly, services which involve consumers' data (e.g., interaction histories) should preserve their privacy. Cloud Services Protection. It is not unusual that a cloud service experiences attacks from its users. Attackers can disadvantage a cloud service by giving multiple misleading feedbacks (i.e., collusion attacks) or by creating several accounts (i.e., Sybil attacks). Indeed, the detection of such malicious behaviors poses several challenges. Firstly, new users join the cloud environment and old users leave around the clock. This consumer dynamism makes the detection of malicious behaviors (e.g., feedback collusion) a significant challenge. Secondly, users may have multiple accounts for a particular cloud service, which makes it difficult to detect Sybil attacks. Finally, it is difficult to predict when malicious behaviors occur (i.e., strategic VS. occasional behaviors). Trust Management Service's Availability. A trust management service (TMS) provides an interface between users and cloud services for effective trust management. However, guaranteeing the availability of TMS is a difficult problem due to the unpredictable number of users and the highly dynamic

nature of the cloud environment. Approaches that require understanding of users' interests and capabilities through similarity measurements or operational availability measurements (i.e., uptime to the total time) are inappropriate in cloud environments. TMS should be adaptive and highly scalable to be functional in cloud environments.

In this paper, we overview Cloud Armor (**Clo**ud cons**u**mers cre**d**ibility Assessment & t**r**ust manage**m**ent of cl**o**ud se**r**vices): a framework for reputation-based trust management in cloud environments. In Cloud Armor, trust is delivered as a service (TaaS) where TMS spans several distributed nodes to manage feedbacks in a decentralized way. Cloud Armor exploits techniques to identify credible feedbacks from malicious ones.

II. EXISTING AND PROPOSED SYSTEMS

A. Existing System

According to researchers at Berkeley, trust and security is ranked one of the top 10 obstacles for the adoption of cloud computing. Indeed, Service-Level Agreements (SLAs). Consumers' feedback is a good source to assess the overall trustworthiness of cloud services. Several researchers have recognized the significance of trust management and proposed solutions to assess and manage trust based on feedbacks collected from participants.

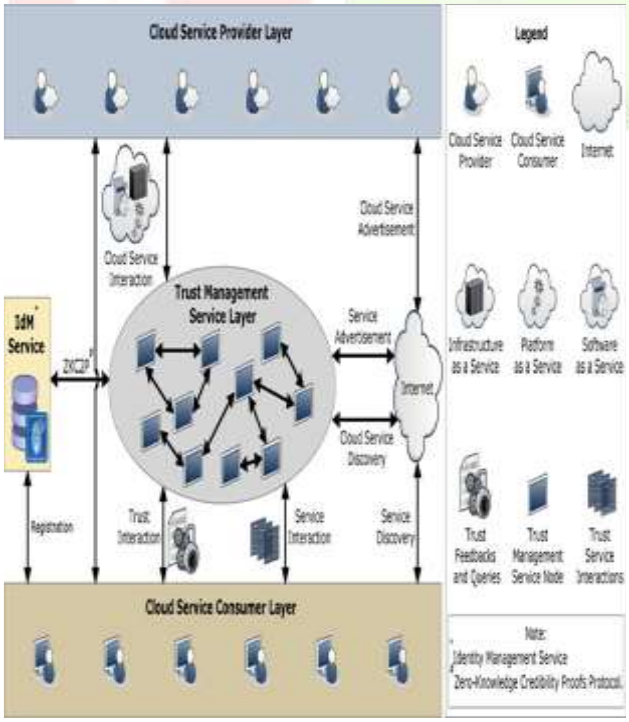


Fig.1. System Architecture

B. Proposed System

Cloud service users' feedback is a good source to assess the overall trustworthiness of cloud services. In this paper, we have presented novel techniques that help in detecting reputation based attacks and allowing users to effectively identify trustworthy cloud services as shown in Fig.1. We introduce a credibility model that not only identifies misleading trust feedbacks from collusion attacks but also detects Sybil attacks no matter these attacks take place in a long or short period of time (i.e., strategic or occasional attacks respectively). We also develop an availability model that maintains the trust management service at a desired level. We also develop an availability model that maintains the trust management service at a desired level.

III. METHODOLOGIES

A. Detection of service This layer consists of different users who use cloud services. For example, a new startup that has limited funding can consume cloud services. Interactions for this layer include: i) service discovery where users are able to discover new cloud services and other services through the Internet, ii) trust and service interactions where users are able to give their feedback or retrieve the trust results of a particular cloud service, and iii) registration where users establish their identity through registering their credentials in IdM before using TMS.

B. Trust Communication In a typical interaction of the reputation based TMS, a user either gives feedback regarding the trustworthiness of a particular cloud service or requests the trust assessment of the service 1. From users' feedback, the trust behavior of a cloud service is actually a collection of invocation history records, represented by a tuple H=(C, S, F, T f), where C is the user's primary identity, S is the cloud service's identity, and F is a set of Quality of Service (QOS) feedbacks (i.e., the feedback represent several QOS parameters including availability, security, response time, accessibility, price).

C. IDM Registration The system proposes to use the Identity Management Service (IdM) helping TMS in measuring the credibility of a consumer's feedback. However, processing the IdM information can breach the privacy of users. One way to preserve privacy is to use cryptographic encryption techniques. However, there is no efficient way to process encrypted data. Another way is to use anonymization techniques to process the IDM

information without breaching the privacy of users. Clearly, there is a trade-off between high anonymity and utility.

D. Service Announcement and Communication This layer consists of different cloud service providers who offer one or several cloud services, i.e., IaaS (Infrastructure as a Service), PaaS (Platform as a Service), and SaaS (Soft-ware as a Service), publicly on the Web (more details about cloud services models and designs can be found). These cloud services are accessible through Web portals and indexed on Web search engines such as Google, Yahoo, and Baidu. Interactions for this layer are considered as cloud service interaction with users and TMS.

IV. IMPLEMENTATION AND EXPERIMENTAL EVALUATION

In this section, we report the implementation and experimental results in validating the proposed approach. Our implementation and experiments were developed to validate and study the performance of both the credibility model and the availability model.

A. System Implementation The trust management service's implementation is part of our large research project, named Cloud Armor, which offers a platform for reputation-based trust management of cloud services [10]. The platform provides an environment where users can give feedback and request trust assessment for a particular cloud service. Specifically, the trust management service (TMS) consists of two main components: the Trust Data Provisioning and the Trust Assessment Function.

The Trust Data Provisioning: This component is responsible for collecting cloud services and trust information. We developed the Cloud Services Crawler module based on the Open Source Web Crawler for Java (crawler4j) and extended it to allow the platform to automatically discover cloud services on the Internet. We implemented a set of functionalities to simplify the crawling process and made the crawled data more comprehensive (e.g., add Seeds (), select Crawling Domain (), add Crawling Time ()). In addition, we developed the Trust Feedbacks Collector module to collect feedbacks directly from users in the form of history records and stored them in the Trust Feedbacks Database: Indeed, users typically have to establish their identities for the first time they attempt to use the platform through registering their credentials at the Identity Management Service (IdM) which stores the credentials in the Trust.

Identity Registry: Moreover, we developed the Identity Info Collector module to collect the total number of established identities among the whole identity behavior (i.e., all established identities for users who gave feedbacks to a particular cloud service).

The Trust Assessment Function: This function is responsible for handling trust assessment requests from users where the trustworthiness of cloud services are compared and the factors of trust feedbacks are calculated (i.e., the credibility factors). We developed the Factors Calculator for attacks detection based on a set of factors (more details on how the credibility factors are calculated can be found). Moreover, we developed the Trust Assessor to compare the trustworthiness of cloud services through requesting the aggregated factors weights from the Factors Calculator to weigh feedbacks and then calculate the mean of all feedbacks given to each cloud service. The trust results for each cloud service and the factors' weights for trust feedbacks are stored in the Trust Results and Factors Weights Storage.

B. Experimental Evaluation

We particularly focused on validating and studying the robustness of the proposed credibility model against different malicious behaviors, namely collusion and Sybil attacks under several behaviors, as well as the performance of our availability model.

C. Credibility Model Experiments

We tested our credibility model using real world trust feedbacks on cloud services. In particular, we crawled several review websites such as cloud-computing. findthebest.com, cloud storage provider sreviews.com, and CloudHostingReviewer.com, and where users give their feedbacks on cloud services that they have used. The collected data is represented in a tuple H where the feedback represents several QoS parameters as mentioned earlier and augmented with a set of credentials for each corresponding consumer. We managed to collect 10,076 feedbacks given by 6,982 users to 113 real-world cloud services. The collected dataset has been released to the research community via the project website. For experimental purposes, the collected data was divided into six groups of cloud services, three of which were used to validate the credibility model against collusion attacks, and the other three groups were used to validate the model against Sybil attacks where each group consists of 100 users. Each cloud service group was used to represent a different attacking behavior model, namely: Waves, Uniform and Peaks as shown in Fig.2. The behavior models represent the total number of malicious

feedbacks introduced in a particular time instance (e.g., |V(s)| = 60 malicious feedbacks.

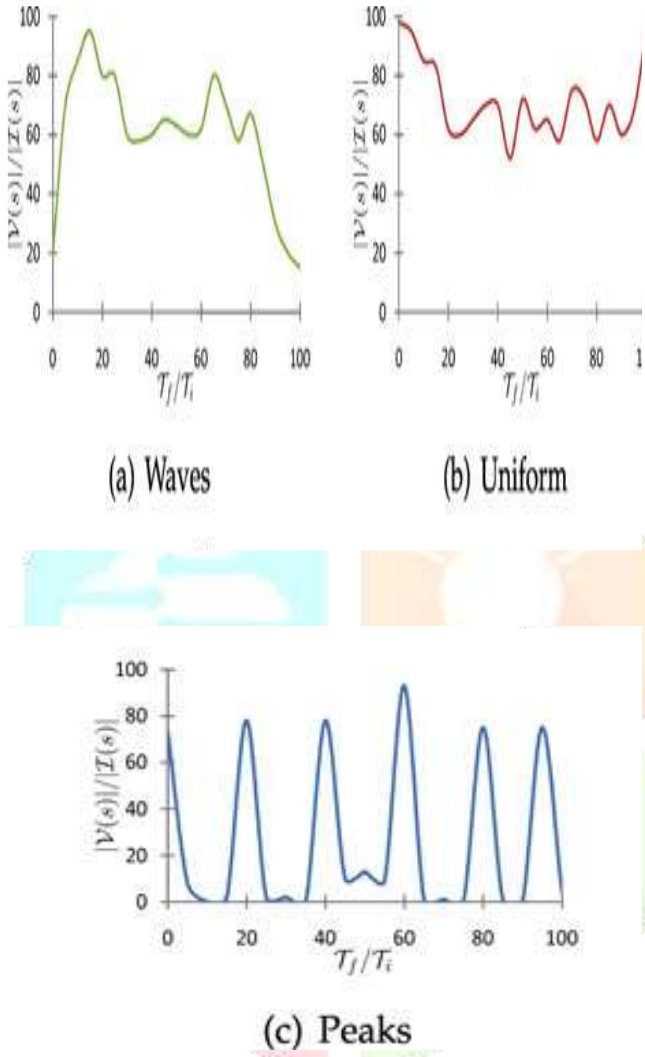


Fig.2. Attacking Behavior Models.

when Tf = 40, Fig.2(a)) when experimenting against collusion attacks. The behavior models also represent the total number of identities established by attackers in a period of time (e.g., |I(s)| = 78 malicious identities when Ti = 20, Fig.2(c)) where one malicious feedback is introduced per identity when experimenting against Sybil attacks. In collusion attacks, we simulated malicious feedback to increase trust results of cloud services (i.e., self-promoting attack) while in Sybil attacks we simulated malicious feedback to decrease trust results (i.e., slandering attack). To evaluate the robustness of our credibility model with respect to malicious behaviors (i.e., collusion and Sybil attacks), we used two experimental settings: I) measuring the robustness of the credibility model with a conventional model Con(s, t0, t) (i.e., turning Cr(c, s, t0, t) to 1 for all trust feedbacks), and II) measuring the performance of our model using two measures namely precision (i.e., how well TMS did in detecting attacks) and recall (i.e., how many detected attacks are actual attacks). In our experiments, TMS started rewarding cloud services that had been affected by malicious behaviors when the attacks percentage reached 25% (i.e., et(s) = 25%), so the rewarding process would occur only when there was a significant damage in the trust result.

We conducted 12 experiments where six of which were conducted to evaluate the robustness of our credibility model against collusion attacks and the rest for Sybil attacks. Each experiment is denoted by a letter from A to F, as shown in Table1.

Table 1

Behavior Experimental Design

Malicious Behaviors	Experimental Setting	Waves	Uniform	Peaks
Collusion Attacks	*I*	*A*	*B*	*C*
	II	*A′*	*B′*	*C′*
Sybil Attacks	*I*	*D*	*E*	*F*
	II	*D′*	*E′*	*F ′*

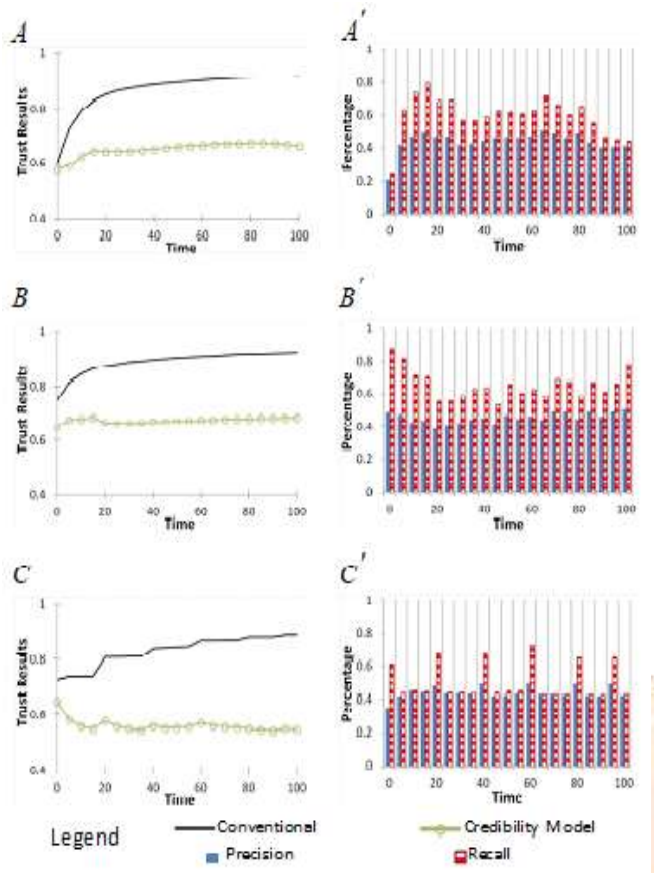


Fig.3. Robustness against Collusion Attacks.

Robustness against Collusion Attacks: For the collusion attacks, we simulated malicious users to increase trust results of cloud services (i.e., self promoting attack) by giving feedback with the range of [0.8, 1.0]. Fig.3 depicts the analysis of six experiments which were conducted to evaluate the robustness of our model with respect to collusion attacks. In Fig.3, A, B, and C show the trust result for experimental setting I, while A′, B′, and C′ depict the results for experimental setting II. We note that the closer to 100 the time instance is, the higher the trust results are when the trust is calculated using the conventional model. This happens because malicious users are giving misleading feedback to increase the trust result for the cloud service. On the other hand, the trust results show nearly no change when calculated using the proposed credibility model (Fig.3 A, B and C). This demonstrates that our credibility model is sensitive to collusion attacks and is able to detect such malicious behaviors. In addition, we can make an interesting observation that our credibility model gives the best results in precision when the Uniform behavior model is used (i.e., 0.51, see Fig.3 B′), while the highest recall score is recorded when the Waves behavior model is used (i.e., merely 0.9, see Fig.3 A′). Overall, recall scores are fairly high when all behavior models are used which indicate that most of the detected attacks are actual attacks. This means that our model can successfully detect collusion attacks (i.e., whether the attack is strategic such as in Waves and Uniform behavior models or occasional such as in the Peaks behavior model) and TMS is able to dilute the increased trust results from self-promoting attacks using the proposed credibility factors.

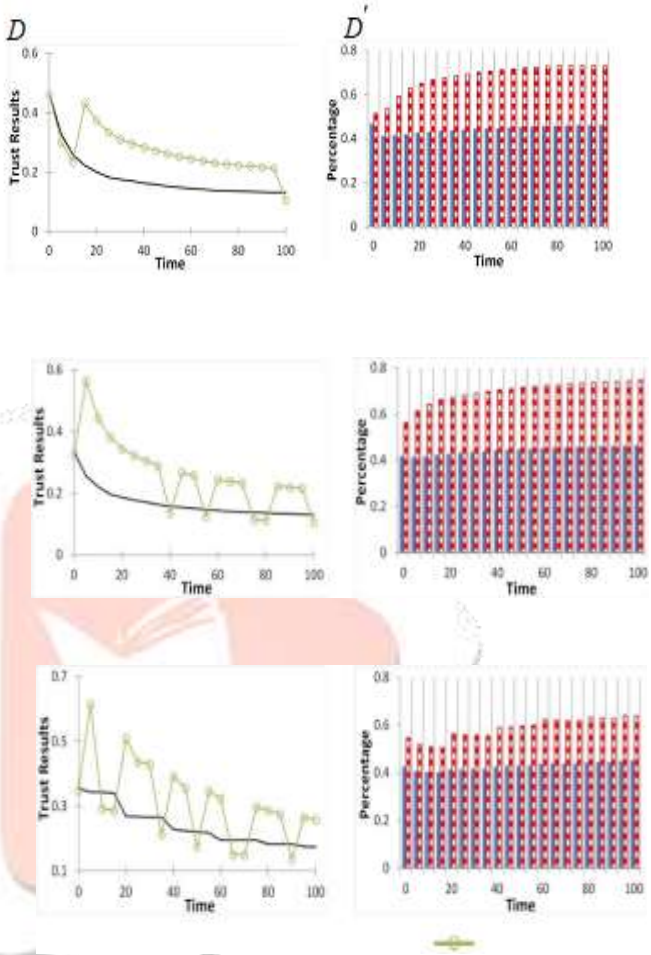
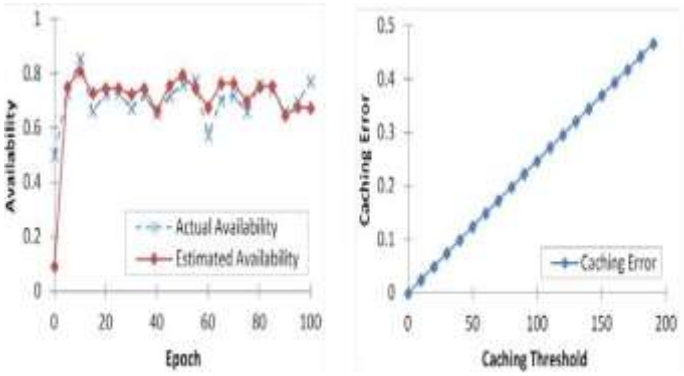


Fig.4. Robustness against Sybil Attacks.

Robustness against Sybil Attacks: For the Sybil attacks experiments, we simulated malicious users to decrease trust results of cloud services (i.e., slandering attack) by establishing multiple identities and giving one malicious feedback with the range of [0, 0.2] per identity. Fig.4 depicts the analysis of six experiments which were conducted to evaluate the robustness of our model with respect to Sybil attacks. In Fig.4, D, E, and F show the trust results for experimental setting I, while D′, E′, and F′ depict the results for experimental setting II. From Fig.4, we can observe that trust results obtained by using the conventional model decrease when the time instance becomes closer to 100. This is because of malicious users who are giving misleading feedback to decrease the trust result for the cloud service. On the other hand, trust results obtained by using our proposed credibility model are higher than the ones obtained by

using the conventional model (Fig.4 D, E and F). This is because the cloud service was rewarded when the attacks occurred.



(a)Actual Availability Vs. Estimated availability (b)Trust Result Caching Error rate

Fig.5. Availability Prediction and Caching Accuracy.

We also can see some sharp drops in trust results obtained by considering our credibility model where the highest number of drops is recorded when the Peaks behavior model is used (i.e., we can see 5 drops in Fig.4 F which actually matches the drops in the Peaks behavior model in Fig.2(c)). This happens because TMS will only reward the affected cloud services if the percentage of attacks during the same period of time has reached the threshold (i.e., which is set to 25% in this case). This means that TMS has rewarded the affected cloud service using the change rate of trust results factor. Moreover, from Fig.4 D′, E′ and F′, we can see that our credibility model gives the best results in precision when the Waves behavior model is used (i.e., 0.47, see Fig.3 D′), while the highest recall score is recorded when the Uniform behavior model is used (i.e., 0.75, see Fig.3 A′). This indicates that our model can successfully detect Sybil attacks (i.e., either strategic attacks such as in Waves and Uniform behavior models or occasional attacks such as in the Peaks behavior model) and TMS is able to reward the affected cloud service using the change rate of trust results factor.

D. Availability Model Experiments: We tested our availability model using the same dataset we collected to validate the credibility model. However, for the availability experiments, we focused on validating the availability prediction accuracy, trust results caching accuracy, and reallocation performance of the availability model (i.e., to validate the three proposed algorithms including Particle Filtering based Algorithm, Trust Results & Credibility Weights Caching Algorithm, and Instances Management Algorithm). Availability Prediction Accuracy: To measure the prediction accuracy of the availability model, we simulated 500 nodes hosting TMS instances and set the failure probability for the nodes as 3.5 percent, which complies with the findings. The motivation of this experiment is to study the estimation accuracy of our approach. We simulated TMS nodes' availability fluctuation and tracked their fluctuation of availability for 100 time steps (each time step counted as an epoch). The actual availability of TMS nodes and corresponding estimated availability using our particle filter approach were collected and compared. Fig.5 (a) shows the result of one particular TMS node. From the figure, we can see that the estimated availability is very close to the actual availability of the TMS node. This means that our approach works well in tracing and predicting the availability of TMS nodes.

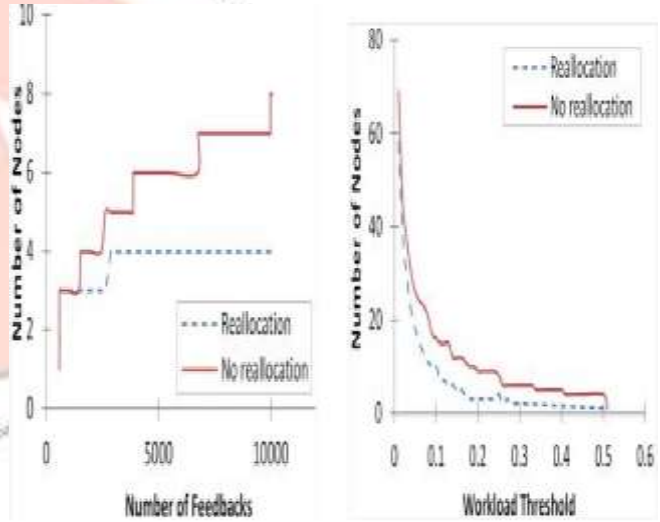


Fig.6. Reallocation Performance.

Trust Results Caching Accuracy: To measure the caching accuracy of the availability model, we varied the caching threshold to identify the optimal number of new trust feedbacks that TMS received to recalculate the trust result for a particular cloud service without having a significant error in the trust results. The trust result caching accuracy is measured by estimating the root-mean-square error (RMSE) (denoted caching error) of the estimated trust result and the actual trust result of a particular cloud service. The lower the RMSE value means the higher accuracy in the trust result caching. Fig.5 (b) shows the trust result caching accuracy of one particular cloud service. From the figure, we can see that the caching error increases almost linearly when the caching threshold increases.

The results allow us to choose the optimal caching threshold based on an acceptable caching error rate. For example, if 10% is an acceptable error margin, the caching threshold can be set to 50 feedbacks. It is worth mentioning that the caching error was measured on real users' feedbacks on real-world cloud services.

Reallocation Performance: To validate the reallocation performance of the availability model, we used two experimental settings: I) comparing the number of TMS nodes when using the reallocation of trust feedbacks and without reallocation while increasing the number of feedbacks (i.e., when the workload threshold ew (stms) = 25%); II) comparing the number of TMS nodes when using the reallocation of trust feedbacks and without reallocation while varying ew (stms). The lower the number of TMS nodes, the more cost efficient TMS is. Fig.6 (a) shows the results of experimental settings I. We can observe that the total number of TMS nodes when using the reallocation of trust feedbacks technique is fairly low and more stable than the total number of TMS nodes when reallocation is not used (i.e., even when the total number of feedbacks is high). Fig.6 (b) shows the results of experimental settings II. From the figure, we can see that the higher the workload threshold the lower the number of TMS nodes. However, the number of TMS nodes when using the reallocation of trust feedbacks technique is lower than the number of TMS nodes when reallocation is not considered. This means that our approach has advantages in minimizing the bandwidth cost by reducing the total number of TMS nodes.

V. CONCLUSION

From this Cloud Armor Supporting Reputation-based Trust Management for Cloud Services has been implemented. In cloud computing growth, the management of trust element is most challenging issue. Cloud computing has produce high challenges in security and privacy by the changing of environments. Trust is one of the most concerned obstacles for the adoption and growth of cloud computing. Although several solutions have been proposed recently in managing trust feedbacks in cloud environments, how to determine the credibility of trust feedbacks is mostly neglected. Additionally in future, we also enhance the performance of cloud as well as the security.

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