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RESEARCH ARTICLE

A User-Priorities-Based Strategy for Three-Phase Intelligent Recommendation and Negotiating Agents for Cloud Services

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ABSTRACT As the field of information technology expands, there is a huge need for cloud service providers (CSP). CSP's vast solutions and services support Cloud, IoT, Fog, and Edge computing. In today's competitive cloud market, customer satisfaction is critical more than ever. CSP and consumer satisfaction with service level agreement (SLA) fulfillment have always been given more attention. As a result of signing SLA and CSP agreements to supply resources in high demand, customers are now experiencing issues with resource delivery. Cloud and heterogeneous environments necessitate an intelligent recommender and negotiation agent model (IRNAM) to handle responsibilities in the current system. The Recommender system recommends CSP as per users' priorities, which eases the filtration process. The negotiation process provided by IRNAM ensures that users' choices are prioritized with maximum jobs to CSP. IRNAM keeps track of the most critical metrics and can reach decisions quickly and for the best possible deal. It uses an analytical concession algorithm that analyzes consumer and CSP choices to find a reliable, secure server with the simplest solution. The negotiation process uses user's and CSP choice metrics, performance factors, evaluation measures, and success factors in the best execution time to decide. IRNAM provides a flexible and valuable way for selecting CSP and negotiating for services on the user's terms while considering CSP satisfaction.

INDEX TERMS Agent, cloud management, cloud services, cloud computing, intelligent system, negotiation; recommender system, SLA, SLA life cycle.

I. INTRODUCTION

Cloud computing is an internet-based service to support users in computing, storing data, designing software, and using the software as a service [1], [2], [3]. Cloud computing is evolving with significant features like full virtualization, elastic resources, reliable and secure services, and a low-cost on-demand computing paradigm on a subscription-based model [4]. Cloud service provider (CSP) offers maintenance-free services, flexible model, and pay-per-use schemes, which has gained popularity in academia and industry. Thousands of CSPs come into the business with various schemes; with

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the increase of this business, the revenue of the cloud market reached $312 billion in 2021, and it is expected to increase to $850 billion by 2025 [3], [4], [5], [6]. Due to the pandemic crisis, all industries are looking forward to cloud solutions, increasing the demand for cloud solutions [2], [7]. Companies need modern and quick solutions to overcome the crisis [8].

Due to the availability of cloud services and its cost-effective model, many micro industries to significant major enterprises are attracted and looking forward to utilizing cloud facilities [9], [10]. Due to CSP's maximum availability of services, it looks easy to adopt cloud services [9], [11], [12], [13]. However, it is challenging to find preferred services as per demand from available options [14], [15]. Some CSPs have robust, secure, reliable, and functional services, while others may have more miniature, cheap cost models with com-promising service quality [9], [13], [16], [17]. For users, selecting CSP with authentic services from the available group of CSPs is challenging. Concerning this problem, an intelligent agent may assist users in selecting a matching cloud service provider (CSP) from a pool of CSPs [18], [19], [20], [21]. An agent acts as a mediator that considers the user preferences and recommends a suitable CSP per the demand [17], [22], [23].

Another challenge is that there may be a contradiction over service level agreement (SLA) between them after the recommendation of CSP to the consumer. Since cloud consumers and CSPs are contradictory regarding requirements and demands, negotiation can provide a solution to establish a stable SLA between both parties [9], [15], [24], [25], [26]. Negotiation is a process between the consumer and CSP to define a mutually acceptable agreement that leads to a final SLA. Negotiation may help obtain essential services with maximum benefits for consumers and CSP, which further settle on an SLA contract to satisfy the quality of service (QoS) as per requirements [27], [28], [29], [30]. This study proposes a solution for meeting the demands of users who require prioritized service attributes in cloud computing. The proposed solution utilizes an agent framework with a novel analytical technique for managing service level agreements (SLAs). The aim is to develop a three-phase intelligent agent technique that can effectively address the challenges associated with SLA management in the cloud, including the recommendation of CSP.

We proposed an Intelligent Recommender and Negotiation Agent Model (IRNAM) to select matching CSP in cloud environments and provide negotiation for selected services to overcome these challenges. IRNAM is a compact recommendation and negotiation model that could help entities make decisions by considering the market demands and supply. It also considers the user and provider QoS satisfaction before finalizing the SLA, making the IRNAM more efficient, satisfactory, and reliable. The proposed study uses an optimized negotiation solution to recommend CSPs based on the user's preferences and choices. This approach offers a more personalized and efficient recommendation system that can improve user satisfaction with the recommended CSP.

The significant contributions of this article are as mentioned below:

1. To design the three-phase interaction system between the user and provider for obtaining cloud services in real-time.
2. To develop a recommender system that helps users find CSP from the pool of cloud service providers per the particular cloud service requirements.
3. To develop a negotiation system that could benefit users to obtain on-demand cloud services and select CSP to deliver the maximum load.
4. To develop an aggregated system, which helps finalize the SLA to achieve consensus based on the satisfaction level for both cloud users and CSP.

The rest of the article continues with related work in section II, followed by methods of the model in section III. Section IV includes an illustration of IRNAM by case study, section V analyses results and discusses obtained results, and concludes the article in section VI.

II. RELATED WORK

As network and Cloud technology have evolved in recent years, so has the demand for Cloud services [31], [32], [33]. More cloud service providers (CSPs) are joining the market. Each CSP advertises itself based on attributes that give it a competitive edge. Some CSPs have substantial functioning properties, while others have more flexible payment options. Some CSPs give more service management services, while others provide exceptional dependability and strong SLAs [6, 9, 11-13]. Furthermore, CSPs often offer the same services with varying performance and functionality and variable pricing. As a result, the same type of Cloud services differs in service quality when evaluated collectively [25].

When it comes to cloud computing, it is all about the network. Market-oriented cloud computing is a theory proposed by some researchers to improve the efficiency and profitability of cloud systems [34], [35], [36]. CSP and its services selection are an essential issue in market-oriented cloud systems, growing exponentially in recent years [24], [25]. While a good service agent-based system can help users save time and be more satisfied with their service, it can also maximize the profits of users and cloud service providers. Most people prefer the agent-based model when looking at different ways to match different types of services in CSPs [16], [28], [31]. For example, article [15] proposed a cloud computing framework consisting of users, service agents, and resource providers, in which resource agents aid in collaboration between cloud users and cloud service providers.

Similarly, a concept proposed by the author is the cloud services agent intermediary, which connects users and providers through the auction mechanism [9], [13], [37], [38]. Discussed methods allow clouds to operate in a market-oriented manner. Still, many challenges remain in developing an efficient cloud service market, particularly in meeting users' quality of service requirements [15], [39], [40].

The author employed a 15-quality-of-service-attribute methodology to evaluate and rank public Cloud infrastructure services (IaaS) [25], [41], [42]. To model the overall performance of an IaaS, the authors adopted a tiered analytical process [9], [25].

The author's [32] research project is focused on developing an energy-efficient recommendation system for cloud service providers. The suggested effort generally is a step toward reducing energy consumption in cloud servers and creating an efficient cloud service selection and ranking system [24], [43]. The research left scope to consider multiple attributes, trust including reliability, and recommendation matching with more satisfaction value.

According to Zheng et al. [42], [44], an algorithm based on the quality of service (QoS) rankings can uncover appropriate cloud services and anticipate quality of service (QoS) values by looking for customers with comparable characteristics. In another Zhang et al. [42] article, the principal objective function can be sorted out efficiently, and the other objectives can be ignored.

Cloud services and cloud technologies have advanced significantly in recent years. Because of this, the number of Cloud service providers (CSPs) is growing [15]. Each CSP promotes itself by highlighting the features that give it an advantage over the competition. The functional qualities of certain CSPs are robust, while the payment plans of other CSPs are more lenient [16], [22], [43], [45], [46], [47]. Service level agreements (SLAs) vary widely among CSPs, with some providing more comprehensive service management capabilities than others (SLA). CSPs offer various degrees of performance and durability, meaning varied pricing. The same cloud services differ regarding service qualities [40], [43]. To overcome these issues recommendation of CSP is also needed to negotiate over multiple attributes. For recommendation, author [25] develop the analytical magiq method by considering key performance indicators of users and CSP.

After the recommendation process, a user and CSP might negotiate to agree on essential bar-gained attributes from the standpoints of both trading parties. When incorporating utility considerations in the hybrid environment, the author's [13] automated negotiation method displays good negotiating speed under a limited set of circumstances. In another paper [12], the negotiation three-phase process is discussed with a recommendation strategy. They have used four significant attributes price, response time, availability, and reliability. They left the scope to add more negotiable parameters to get a satisfied SLA [48], [49], [50], [51].

The paper [27] proposes the AFCN model for negotiation in cloud computing using a third-party agent as a moderator. The authors introduce the degree of satisfaction for users and CSP. Their experiment results explored the negotiation speed and successful negotiation success rate.

An adaptive neuro-fuzzy model [52] considers the utility value for successful negotiation. The success rate of the model depends upon the number of negotiation rounds. Another adaptive probabilistic model [29] proposed a bilateral negotiation strategy using the fuzzy method, which mentions the success rate after negotiation, considering user preferences.

In the TSLAM model [15], the authors introduce a three-layered architecture for cloud trading. The restricted model with the number of CSPs with limited resources, less reliable broker management, also the satisfaction of users and CSPs not considered. TSLAM model considers trust mechanisms that help users and CSP to identify honest candidates in the market, which helps to increase the success rate of the process [15].

TABLE 1. The table represents the review summary of the recommendation and negotiation method proposed in the articles.

Article	Recommendation Method	Negotiation Method
[10]	--	√
[15]	√	--
[13]	--	√
[12]	--	√
[24]	√	--
[26]	--	√
[32]	√	--
[25]	√	--
[53]	--	√
[42]	--	√
[27]	--	√
[21]	√	--
IRNAM	√	√

According to the research that was carried out, the current approaches used to promote Cloud Service Providers (CSP) cannot consider user preferences and only provide a restricted number of options. Because these approaches do not consider individual users' one-of-a-kind needs and preferences, the resulting cloud service provider (CSP) may not meet the consumers' expectations. Compared to more conventional CSP recommendation approaches, the utilisation of mediating agents provides several distinct benefits. It offers a more individualized and custom approach to suggestion, considering the specific needs and interests of each user [15], [40]. This can boost user satisfaction with the suggested CSP and the chance they will continue using the service. The suggestion procedure's efficacy and efficiency may be improved due to the optimum negotiating solution that the mediating agents utilized. The agents can swiftly determine the CSP that is best suited for the user by taking into account the user's preferences as well as the offers of the CSP. This helps to reduce the amount of time and effort necessary for the process of making recommendations. Our proposed model IRNAM mediates between user and CSP, which helps users to find CSP as per choice with negotiated SLAs. The proposed study introduces mediating agents that use an optimized negotiation solution to recommend CSPs based on the user's preferences and choices. This approach offers a more personalized and efficient recommendation system that can improve user satisfaction with the recommended CSP.

III. METHODOLOGY

The technologies representing cloud service providers are upgraded due to the evolution of the market and its demand. However, the commercial solution of the business architecture of cloud computing is still not up to the mark due to a lack of business management strategies [4], [25]. The cloud is a booming market, and it needs a model which supports the system [19]. We introduce the IRNAM (Intelligent Recommender and Negotiation Agent Model), an intelligent agent model designed to support the cloud market structure.

IRNAM provides a recommendation system with negotiation features for cloud services. As per the market, cloud consumers face trouble when selecting cloud service providers (CSP) from the cloud market. Most consumers' primary concern is getting the maximum required services at a low price from a reliable CSP with minimum delays. IRNAM considers all these issues and recommends the best CSP out of the market over negotiated attributes. In this methodology of IRNNAM, we explained with communication between the cloud user and CSP via the agent, then described the framework of IRNAM, detailed architecture, and functioning of IRNAM.

A. IRNAM FRAMEWORK

The simplest way of communication is that the consumer interacts with CSP to negotiate and deliver services [10]. Sending a communication request is the first step in the process, and CSP accepts or rejects it. The procedure begins if the request is approved. After a proposal is approved or refused, the CSP and the consumer acknowledge the agreement. Figure 1 depicts a three-way handshake communication diagram for establishing the consumer-CSP connection. This three-way handshake diagram helps to set up communication in agent IRNAM.

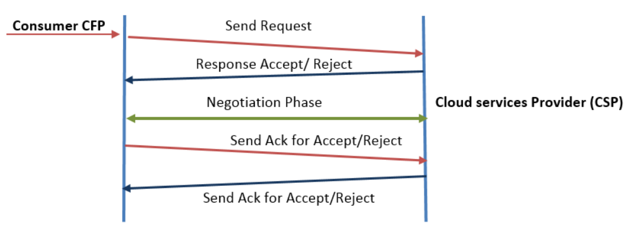

FIGURE 1. Three-way communication between consumer and CSP [13].

In this instance, introducing IRNAM between both parties helps create a safe and speedy negotiation process between clients and CSPs. It streamlines the process and reduces risk, allowing the consumer to choose from various CSPs.

IRNAM help in matching and negotiating services between users and providers. The cloud market has many cloud users and CSPs, resulting in low efficiency in recommending and providing negotiation over SLA with CSPs. As a result, IRNAM serves as an intermediaries and coordinator between cloud users and CSP.

IRNAM framework explains the interactions between cloud users, agent IRNAM and CSP. Cloud users first submit requests for required cloud resources, individual services, prices, and details of the required range of attributes defined in SLA. IRNAM accepts the request and process as per the functioning of the system architecture. Different CSPs provide counter SLA as per user requirements to get the agreement.

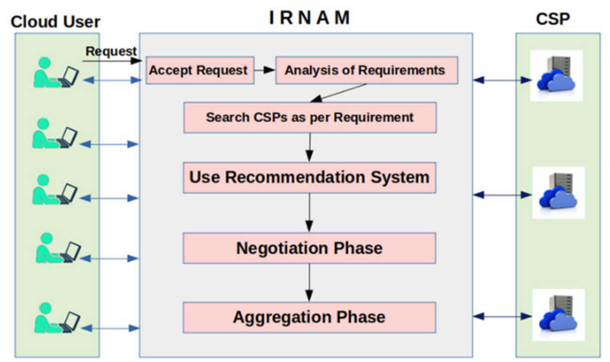

FIGURE 2. IRNAM Framework: Communication between cloud user and CSP via IRNAM.

The main reason to obtain a broker between user and provider is that users have complex requirements with multiple attributes to consider with quality of service (QoS). IRNAM analyzes the requirement and recommends the optimal available CSP for the user. The proposed agent organized the list of CSPs according to the requirement of users and as per market performance. Later, negotiation parameters for cloud services are considered, which leads to the negotiation process with recommended CSP. After the negotiation process, the resulting parameters are aggregated in the aggregation phase. Based on the negotiation phase, the aggregation phase verifies whether the user and provider satisfaction has been met. Overall, IRNAM's primary concern is to satisfy the user and provider's quality of service.

B. IRNAM ARCHITECTURE

The IRNAM architecture is divided into three phases that include the recommendation phase, the negotiation phase, and the aggregation phase. In the recommendation phase, the process starts with identifying the requirements proposed by the user, which searches CSPs in the repository with matching attributes. With the help of recommender system algorithm 2, a suitable CSP is recommended to IRNAM then the process moves to the negotiation phase. In the negotiation phase, priority attributes consider for negotiation. As mentioned in algorithm 3, negotiation continues until the user's aggregated value is satisfied. In the aggregation phase, analyze the user's and CSP's degree of satisfaction. If the offer is accepted, the SLA contract is established, and cloud services are operationalized.

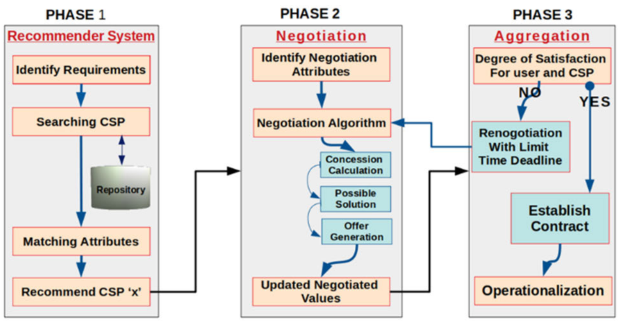

FIGURE 3. The three-phase architecture of IRNAM.

All three phases are explained in the below sections, including the functioning of phases, algorithms performed for the execution of each phase, and later, in chapter 4, an illustrated example explaining the working of IRNAM architecture.

Functioning of IRNAM Architecture: The process starts with the user request to IRNAM, where the user requests multiple cloud services with some predefined attributes, for example, price of services, reliability of CSP and cloud services, response time each and individual cloud services, availability of cloud and its services during peak time.

Algorithm 1 illustrated the user request to IRNAM. Requested SLA identified and analyzed by agent and filtered down its attributes. The algorithm recognizes the user's preferences, filters the CSP, and updates the sorted list (SORT_list).

The updated sorted list is sent to the recommender system as explained in algorithm 2. The first distribution of attribute weight (W^{U}_{attr}) in the recommendation generation process is computed according to the user's preferences. With the help of a sort_list, the agent computes the CSP weightage (W^{CSP}_{attr}) according to attributes. In step 2.3, the evaluation score (Es) is calculated, where Es(W^{CSP}_{attr}, W^{U}_{attr}) represents the evaluated score of the weight of CSP concerning the defined attribute and the weight of the user's defined attribute. Step 2.4 calculates the overall evaluation score (Oes) by obtaining the sum of Es of CSP with all attributes. In step 2.5, based on Oes, the recommender system selects the CSP and recommends it to the user for the negotiation phase [25].

Algorithm 2 shows the execution steps of the recommender system.

In the negotiation system, the second phase of IRNAM. Once the first phase is completed, and one CSP is recommended to cloud users, both parties negotiate in the second phase of IRNAM, i.e., the negotiation system. At the beginning of algorithm 3, recommended CSP calls its SLA and proposes against the user's proposal. User's and CSP attributes have been filtered out, and their values with priorities are identified by algorithms 1 and 2. The deadline time (t) was assigned for the negotiation process from 0 to t', stating that the negotiation must finish within this defined time limit. In step 4.1, the value of attributes is normalized

TABLE 2. Algorithm 1: User request (UREQ) to IRNAM.

Algorithm 1: User Request (UREQ) to IRNAM

Begin:
1. REQ → IRNAM #User sends SLA request to IRNAM
2. SLA analysis begins:
2.1 Check attributes #user's defined attributes (1,2,3…...n)
2.2 Check user's preference #for example Price>Security>ResponseTime>Availability>Reliability
2.2.1 list available CSPs #IRNAM calls all available CSPs
2.2.2 SORT_list(CSPs) #IRNAM sort CSPs according to the user's attribute preference
2.3 SORT_list(CSPs) → Recommender_system() #refer to Table 1
END

TABLE 3. Algorithm 2: Recommender systems.

Algorithm 2: Recommender Systems

Begin:
1. Receive SORT_list(CSPs) #step 2.3 from Algorithm 1 REQ
2. RECOMMENDATION GENERATION
2.1 Compute Attribute weight for user SLA

$$Weight, W^{U}_{attr} = \sum_{i=1}^{k} \frac{\left(\frac{1}{i}\right)}{k}$$

#Refer to section 3, Step 2
Where, W^{U}_{attr} is the single attribute weightage of the user
k is the number of attributes, i represents the preference order of attributes
2.2 Compute CSP weight in order of SORT_list(CSPs) #Refer to Table II

$$Weight, W^{CSP}_{attr} = \sum_{j=1}^{m} \frac{\left(\frac{1}{j}\right)}{m}$$

Where, W^{CSP}_{attr} is the single CSP weightage according to Attributes
m is the number of CSPs, j represents the rank order of CSPs for each attribute
2.3 Compute Evaluation Score (Es) #Refer to Table 3

$$Evaluation\ Score, Es(W^{CSP}_{attr}, W^{U}_{attr}) = \prod_{k=1} Weight\ (W^{CSP}_{attr}, W^{U}_{attr})$$

2.4 Compute Overall Evaluation Score (Oes) #Refer to Table 4

$$Overall\ Evaluation\ Score, Oes = \sum_{CSP=1}^{n} Es(W^{CSP}_{attr}, W^{U}_{attr})$$

2.5 Selection of CSP
if (Oes (X) = Oes (Y))
Select the user SLA preference attribute from Algorithm 1
Select(Oes(CSP))
Else
Select MAX(Oes(CSP))
2.6 Recommend Oes(CSP) → Negotiation System
END

and stored in η^{Party}_{Attr}. In step 4.2, the aggregated evaluation score ($\bar{Æ}_{party}$) calculated for the user and CSP by taking the sum of the number of attributes and the product of the normalized value of attributes η^{Party}_{Attr} and weight of attributes W^{party}_{attr}. It is used to evaluate the satisfaction value of an offer to reach an agreement or make a concession in the negotiation phase. $\bar{Æ}_{UA}$ and $\bar{Æ}_{PA}$, represents aggregated evaluated values of cloud users and cloud service providers. Calculate the concession (θ) in step 4.3, in which the degree of negotiation (ρ)

TABLE 4. Algorithm 3: Negotiation system.

Algorithm 3: Negotiation System

Begin:
1. Receive Oes(CSP)
#step 2.6 from Algorithm 2
2. Call User_Attributes & $Weight, W_{attr}^{U}$ #Values obtain from Algorithms 1&2
3. Call CSP_Attributes & $Weight, W_{attr}^{CSP}$ #Values obtain from Algorithms 1&2
4. NEGOTIATION PROCESS (t=0 to t')
4.1 Compute Normalized value of User_Attributes & CSP_Attributes,

$$\boldsymbol{\eta}_{\boldsymbol{Attr}}^{\boldsymbol{Party}} = \frac{x_{attr} - \min(x_{attr})}{\max(x_{attr}) - \min(x_{attr})}$$

Where, $\boldsymbol{\eta}_{\boldsymbol{Attr}}^{\boldsymbol{Party}}$ represents the normalized value of the party's attribute
x is the range value of the attribute defined in SLA by both parties
party, can be user(U) and CSP
4.2 Compute Aggregated Evaluation Score ($\bar{\text{Æ}}_{Party}$),

$$\bar{\text{Æ}}_{\boldsymbol{party}} = \frac{1}{k}\sum_{attr=1}^{k}(\eta_{attr}^{party} \bullet W_{attr}^{party})$$

4.3 Compute Concession (θ),

$$\textbf{Degree of difference}, \ \alpha = \left[1 - \left(\frac{D(X_{n-1}, Y_n) - D(X_n, Y_n)}{D(X_{n-1}, Y_n)}\right)\right],$$

where, $D(X_n, Y_n)$ The Euclidean distance between offer X and offer Y in the nth negotiation round, and the n value ranges from 0 to n.

$$\text{Concession}, \ \theta = \left[\frac{t+\frac{\alpha}{2}}{2}\left(1 - \bar{\text{Æ}}_{UA}(\mathrm{X})\right)\right]^{\rho}$$

Where t = negotiation time, α = degree of difference from the latest offer,
$\bar{\text{Æ}}_{UA}$(X) = Aggregated evaluated Value of cloud user from offer X,
ρ = degree of negotiation, Compute θ for ρ
4.4 Compute

$$\rho = \begin{cases} \rho > 1, \text{Collaborative} \\ \rho \ = 1, \ \text{Win} - \text{Win} \\ \rho < 1, \text{Competitive} \end{cases}$$

select BestCase (θ)
4.5 Compute new offer on (X& Y)
£ = θ* - θ
Where θ* is defined as the threshold from the previous negotiation.
4.6 Compute offer,
If $\bar{\text{Æ}}_{U}(X) * k \geq$ £,
Offer (X) Accepted
If Else
renegotiation until t=t'
Go to step 4
else
Recommend New_CSP(Oes_list)
Go to the negotiation system ()
5. Offer (X) → Aggregation System
END

TABLE 5. Algorithm 4: Aggregation phase.

Algorithm 4: Aggregation Phase

Begin:
1. Receive Offer (X)
2. Analyze Utility Satisfaction (Ûs),
At t = (0 to t')
If Ûs = $\bar{\text{Æ}}_{USER}(X) \geq \bar{\text{Æ}}_{CSP}(X)$
Offer (X) → Accepted
If Else
Offer (X) → Rejected
Else
Go to Renegotiation → Negotiation System (until t=t')
#Renogotiation in Algorithm 3
3. Accepted,
Initialize SLA Signing
Operationalization ()
END

TABLE 6. Algorithm 5: Pseudocode for irnam.

ALGORITHM 5: PSEUDOCODE FOR IRNAM

1. User offer → IRNAM
2. Start timer, T=0
3. IRNAM (UREQ)
4. IRNAM receives SORT_List(CSPs)
5. SORT_Lists → Recommender System
6. Recommend (CSP) → Negotiation System
7. Offer (X) → Aggregation Phase
8. **If** offer (X) → Accepted
9. IRNAM initialize operationalization
10. **Elseif** Renegotiation back to Step 6
11. **Elseif** NEW_CSP from Step 5
12. **Else** Terminate Deadline, t' finished
13. **Endif**
14. **Count** Total Timer value, T

TABLE 7. The table exemplifies the user's attributes choices and IRNAM order of CSP as per the attribute.

Priority order by the user → CSP Order ↓	Price	Security	Response Time	Availability	Reliability
1	CSP1	CSP5	CSP3	CSP2	CSP5
2	CSP2	CSP4	CSP4	CSP4	CSP1
3	CSP3	CSP3	CSP5	CSP1	CSP2
4	CSP4	CSP2	CSP1	CSP3	CSP3
5	CSP5	CSP1	CSP2	CSP5	CSP4

decides that the SLA negotiation finalizes on collaborative, win-win or competitive condition. The value of concession (θ) directly depends upon the degree of negotiation (ρ). During the evaluation, the best case of concession value is considered. After the concession, the new offer is generated, and SLA is finalized when the user's aggregated evaluation score exceeds the new offer values. Else, go for renegotiation. If the deadline time (t) is over, IRNAM offers a new CSP to the cloud user [12], [13], [27], [28].

Algorithm 3 shows the execution steps of the negotiation system.

After successfully executing the negotiation system within the negotiation deadline, CSP SLA and cloud user SLA forwarded to the aggregation phase, as mentioned in algorithm 4. A new offer (X) is generated in algorithm 3 and sent to the aggregation phase. In the aggregation phase, IRNAM analyzes the utility satisfaction under the condition that $\bar{\text{Æ}}_{USER}(X) \geq \bar{\text{Æ}}_{CSP}(X)$, it leads to acceptance of the offer, or the user rejects it after acceptance of SLA, and the operationalization of requested services is delivered.

Algorithm 4 shows the execution steps of the aggregation phase.

TABLE 8. The table exemplifies the weight of attributes.

W(User, Attributes)	$Weight, W_{attr} = \sum_{i=1}^{n} \left(\frac{1}{i}\right)/n$	W_{attr}
Weight of Price, W(Pr)	(1+1/2+1/3+1/4+1/5)/5	0.46
Weight of Security, W(Se)	(0+1/2+1/3+1/4+1/5)/5	0.26
Weight of Response Time, W(Rt)	(0+0+1/3+1/4+1/5)/5	0.15
Weight of Availability, W(Av)	(0+0+0+1/4+1/5)/5	0.09
Weight of Reliability, W(Rel)	(0+0+0+0+1/5)/5 = 0.04	0.04

TABLE 9. The table exemplifies the attributes and CSP rank as per the attribute.

W(CSP ,Attributes)	Price	Security	Response Time	Availability	Reliability
CSP1	0.46	0.04	0.09	0.15	0.26
	0.26	0.09	0.04	0.46	0.15
CSP2					
CSP3	0.15	0.15	0.46	0.09	0.09
CSP4	0.09	0.26	0.26	0.26	0.04
CSP5	0.04	0.46	0.15	0.04	0.46

TABLE 10. The table exemplifies the attributes and evaluates the score per attribute.

Evaluated Score(Es)	Price	Security	Response Time	Availability	Reliability
Es(CSP1,Attributes)	0.21	0.01	0.02	0.02	0.01
Es(CSP2, Attributes)	0.12	0.03	0.01	0.04	0.006
Es(CSP3, Attributes)	0.07	0.04	0.07	0.01	0.004
Es(CSP4, Attributes)	0.04	0.07	0.04	0.02	0.002
Es(CSP5, Attributes)	0.02	0.12	0.02	0.01	0.02

The model's functioning begins with the user's offer proposing the requirements of cloud services in SLA. IRNAM receives the offer and starts processing the offer, and initiates a timer to count the time and finish the task before the deadline. The pseudocode of the proposed IRNAM is shown in algorithm 5. The user's SLA is analyzed per the priority of QoS and filters the CSP as per requirements in a sorted list. The CSP's sort list send to the recommender system phase as described in algorithm 2.

Further, one CSP is recommended to the user, and IRNAM initiates the negotiation phase between the user's SLA and CSP SLA. If the negotiation process is finished successfully, an offer is generated, renegotiation occurs until the deadline meets, or a new CSP is recommended from the sort_list. Once the offer is generated, the process moves to the aggregation phase, which finalizes the SLA and starts operationalization, including delivering the user's required cloud services. In the end, the timer stops before operationalization, and IRNAM calculates the overall time duration of the whole process.

IV. ILLUSTRATION BY CASE STUDY

This section is going to illustrate the working of IRNAM with an example. Suppose the user requested an offer with given priorities of cloud services' attributes, and IRNAM has five CSPs to sort the list for the given user.

According to the user's requirement, let us consider the user's priority choices for selecting CSP and negotiation: price, security, response time, availability, and reliability of services provided by CSP. It is possible to specify that just one of the two available priority levels can be set to "high" if only two QoS characteristics exist. If there are three characteristics, there should be three numerical priority orders for those characteristics 1, 2, and 3. Here, as per the user's requirement, we have five attributes. The proposed algorithm is assigned ranked to all attributes as per priority.

In algorithm 1, attributes are sorted as per the user's choice, such as Price > Security > response time > availability > reliability. IRNAM sorted out the order of CSP according to each attribute. For example, if the price is the attribute, CSP1 has a higher rank in providing cloud services at a better cost, followed by CSP2, CSP3, CSP4, and CSP5. Similarly, each attribute and its highest order of CSP are mentioned in Table 2. Table 2 and the user's choice are forwarded to algorithm 2 in table 3.

In algorithm 2, i.e., recommendation phase, receive a sort_list of CSP per user's choices. In the next step of recommendation generation, first compute the attribute weight for the user, which is defined for n attributes by the given formula: $Weight, W_{attr} = \sum_{i=1}^{n} \left(\frac{1}{i}\right)/n$.

Step 1 of Algorithm 2: Call order of attributes as stated in the above example: price (Pr) > Security (Se) > Response Time (Rt) > Availability (Av) > Reliability (Rel).

Step 2 of Algorithm 2: Compute the weight of CSPs with each attribute. The CSP order concerning each attribute is determined per the order produced by IRNAM in table 2. For example, for CSP1, the order of attributes is price, security, response time, availability, and reliability is 1,5,4,3,2, respectively, as per table 2.

Step 3 of Algorithm 2: In this step, IRNAM evaluated the score of CSP and user's attribute by the product of the weight of CSP and user with each attribute, as mentioned in table 6. For example, if the weight of CSP1 with the price is 0.46 and the weight of price by the user is 0.46, the value of Es(CSP1, price) is 0.21 (round off till two decimal places). The given equation evaluates it:

$$Evaluation\ Score, Es\left(W_{attr}^{CSP}, W_{attr}^{U}\right) = \prod_{k=1} Weight\left(W_{attr}^{CSP}, W_{attr}^{U}\right)$$

Step 4 of Algorithm 2: In step 4, compute the Overall evaluated score of CSP by adding all values of the evaluated score. Its formula is given by:

$$Overall\ Evaluation\ Score,\ Oes = \sum_{CSP=1}^{n} Es\left(W_{attr}^{CSP}, W_{attr}^{U}\right)$$

Step 5 of Algorithm 2: Based on the overall evaluated score (Oes) of CSPs, CSP1 has a higher rank value, which IRNAM recommends to the cloud user. If CSP(X) and CSP(Y) Oes values are identical, select based on priority from Table 7.

In algorithm 3, i.e., the negotiation phase, once the CSP1 is recommended to the user, it recalls the user's SLA and extracts the user's negotiable prior attributes and their weight from algorithms 1 &2. IRNAM call CSP1 for SLA and asks for the values of attributes and their weights from the priority rank in table 7. Here is the list of variables used by cloud user (UA) as per prioritized attributes for negotiation:

η_{Pr}^{UA} = Normalized Value of User attribute (U.A.) for Price (Pr)

w_{Pr}^{UA} = Priority weightage of User attribute (U.A.) for Price (Pr)

η_{Se}^{UA} = Normalized Value of User attribute (U.A.) for Security (Se)

w_{Se}^{UA} = Priority weightage of User attribute (U.A.) for Security (Se)

η_{Rt}^{UA} = Normalized Value of User attribute (U.A.) for Response Time (Rt)

w_{Rt}^{UA} = Priority weightage of User attribute (U.A.) for Response Time (Rt)

η_{Av}^{UA} = Normalized Value of User attribute (U.A.) for Availability (Av)

w_{Av}^{UA} = Priority weightage of User attribute (U.A.) for Availability (Av)

η_{Rel}^{UA} = Normalized Value of User attribute (U.A.) for Reliability (Rel)

w_{Rel}^{UA} = Priority weightage of User attribute (U.A.) for Reliability (Rel)

Here are the Variables used by the cloud service provider (PA) as per prioritized attributes for negotiation:

η_{Pr}^{PA} = Normalized Value of Provider attribute (P.A.) for Price (Pr)

w_{Pr}^{PA} = Priority weightage of Provider attribute (P.A.) for Price (Pr)

η_{Se}^{PA} = Normalized Value of Provider attribute (P.A.) for Security (Se)

w_{Se}^{PA} = Priority weightage of Provider attribute (P.A.) for Security (Se)

η_{Se}^{PA} = Normalized Value of Provider attribute (P.A.) for Response Time (Rt)

w_{Se}^{PA} = Priority weightage of Provider attribute (P.A.) for Response Time (Rt)

η_{Av}^{PA} = Normalized Value of Provider attribute (P.A.) for Availability (Av)

w_{Av}^{PA} = Priority weightage of Provider attribute (P.A.) for Availability (Av)

η_{Rel}^{PA} = Normalized Value of Provider attribute (P.A.) for Reliability (Rel)

w_{PA}^{Av} = Priority weightage of Provider attribute (P.A.) for Reliability (Rel)

As mentioned in step 2 of algorithm 3, we call the weight of attributes for user and CSP1, given below in table 10.

In table 13, the normalized value, η_{Attr}^{Party}, is obtained by formula,

$$Normalized\ Value,\ \eta_{Attr}^{Party} = \frac{x_{attr} - min(x_{attr})}{max(x_{attr}) - min(x_{attr})}$$

Table 9 calls the range value defined by the user and provider for cloud services for each attribute. All values are measured as common units, as a unit. For example, security measures in percentage explain that this value of the security percentage is demanded by the user and provided by the consumer. In table 10, users and providers normalized initial values for negotiation. Users value (x_{attr}) price, security, response time, availability, and reliability are 100, 90, 15, 95, and 98, respectively. Provider values for the price, security, response time, availability, and reliability are 125, 75, 25, 93, and 98, respectively.

In Step 4.2, Aggregated Evaluated Value ($\bar{Æ}$) computed by the given method,

$$\bar{Æ}_{UA} = \frac{1}{5}\left\{\eta_{UA}^{Pr} \bullet w_{UA}^{Pr} + \eta_{UA}^{Se} \bullet w_{UA}^{Se} + \eta_{UA}^{Rt} \bullet w_{UA}^{Rt} + \eta_{UA}^{Av} \bullet w_{UA}^{Av} + \eta_{UA}^{Rel} \bullet w_{UA}^{Rel}\right\}$$

Value of $\bar{Æ}_{UA}$, = 0.366/5 = 0.0732

Similarly,

$$\bar{Æ}_{PA} = \frac{1}{5}\left\{\eta_{PA}^{Pr} \bullet w_{PA}^{Pr} + \eta_{PA}^{Se} \bullet w_{PA}^{Se} + \eta_{PA}^{Rt} \bullet w_{PA}^{Rt} + \eta_{PA}^{Av} \bullet w_{PA}^{Av} + \eta_{PA}^{Rel} \bullet w_{PA}^{Rel}\right\}$$

Value of $\bar{Æ}_{PA}$, = 0.6192/5 = 0.124

In Step 2 of computing concession Calculation, let us consider the cloud user offers that offer X and Y are offered by CSP1.

Degree of difference, $\alpha = 1 - (\frac{D(X_{n-1}, Y_n) - D(X_n, Y_n)}{D(X_{n-1}, Y_n)})$

Let us consider $D(X_{n-1}, Y_n) = 1$, and after calculation, $D(X_n, Y_n) = 0.481$. Value of degree of difference α = 0.48. We have considered initializing values with '1' from all previous offerings and considering the maximum range from 0 to 1. After doing the above calculation, the value of concession, $\theta = \left[\frac{t + \frac{\alpha}{2}}{2}\left(1 - \bar{Æ}_{UA}(\mathrm{X})\right)\right]^{\rho}$, $\theta = [0.575]^{\rho}$, now it depends upon IRNAM and the user to go for collaborative, win-win, or competitive ρ values, as described in Algorithm 3 and explained results tables 9 & 10, or renegotiation takes place until time 't'. In Step4.7, if $\bar{Æ}_{PA}(X) * 5 \geq £$ than accepted.

In the aggregation phase of algorithm 4, the IRNAM rectifies the negotiation phase and accepts the offer X only if the overall satisfaction score of the user is equal to or greater than the provider, CSP1. After acceptance of the offer, the process initializes the SLA establishment and signing. After confirming SLA, cloud services operationalization continues.

CSP delivered cloud services as per negotiated in the negotiation phase.

V. RESULTS AND DISCUSSION

To validate and verify the negotiation process and overall performance of IRNAM, we simulate the case mentioned above with more combinations. Simulation of IRNAM carried out on ubuntu 16 edition on i3 1.9 GHz processor, 4GB RAM computer.

IRNAM processing takes two primary algorithms, i.e., the recommender and negotiation phases. In the first setup of the experiment, as stated in the case study, the recommender system delivered CSP 1 for negotiation. After the negotiation phase, the final phase concession depends upon the type of negotiation strategies, whether competitive, collaborative, or win-win. The proposal is acceptable if the user selects competitive, as mentioned in Table 9, at 0.9, θ value. Similarly, in collaborative strategy, at value 2.0, the proposal is close to the user's choice. For a win-win situation, the process must do renegotiation. For a win-win strategy, the value of θ is 0.575.

A. PERFORMANCE OF IRNAM

We have considered samples to determine the execution time of each algorithm IRNAM. For sampling, we have considered four sets of attributes, each consisting of 3, 5, 7 & 10 attributes. Similarly, we have considered two sets of CSP groups for negotiation and recommendation, with 5 & 10 CSPs.

To calculate the execution run-time of the recommender system, we are using time complexity on the algorithm. We have tested the maximum possible combination of attributes vs. a set of CSPS, the execution time of algorithm 2 mentioned in table 13. In table 13, the execution time of IRNAM represents that when the number of attributes and CSP increases, the total time for IRNAM processing also increases.

Measuring the execution time of the negotiation phase depends upon the number of attributes for negotiation and the number of negotiation rounds until the process finishes before the deadline. Let us consider the deadline, t = 2500; IRNAM gave good results when the number of attributes is less than 10 vs. 10 number of CSP. Considering our case study, the execution time for five attributes averages 200 units in a win-win strategy situation.

After the negotiation phase, the success rate has analyzed the success of the negotiation after the number of renegotiation attempts. Here, we have three situations from the negotiation phase, i.e., collaborative, win-win and competitive. In the first round of collaboration, we can see at value 2.0 in table 14 that the aggregation value is almost below the user's demand, so negotiation is successful. Whereas in competitive, it accepts a value at 0.9 in table 11, the success rate is high. In a win-win situation, it takes multiple negotiation rounds to reach success, as seen in table 15. Our results are prominent if we compare our success rate [8], [22], [33], [47] work with previous work. We have set some preliminary exceptions; our results have shown positive outcomes under those conditions.

The overall performance of the proposed model of IRNAM depends upon the number of attributes and the number of

TABLE 11. The table exemplifies the attributes and evaluates the score per attribute.

Overall evaluated score (Oes)	Price	Secu rity	Response Time	Availa bility	Relia bility
Oes(CSP1)	0.21	0.01	0.02	0.02	0.01
Oes (CSP2)	0.12	0.03	0.01	0.04	0.006
Oes (CSP3)	0.07	0.04	0.07	0.01	0.004
Oes (CSP4)	0.04	0.07	0.04	0.02	0.002
Oes (CSP5)	0.02	0.12	0.02	0.01	0.02

TABLE 12. The table exemplifies the weights of attributes for user and provider.

W_{Attr}^{Party}	Price	Secu rity	Response Time	Availa bility	Relia bility
w_{Attr}^{UA}	0.46	0.26	0.15	0.09	0.04
w_{Attr}^{PA}	0.46	0.04	0.09	0.15	0.26

TABLE 13. The table exemplifies the attribute range value for user and provider.

Attributes Range value	Price	Secu rity	Response Time	Availa bility	Relia bility
USER	95-120	85%-95%	10-20	95-100	95-100
PROVIDER	105-130	70%-80%	20-30	90-95	95-100

TABLE 14. The table exemplifies the attribute range value for user and provider.

Normalized Value, η_{Attr}^{Party}	Price	Secu rity	Response Time	Availa bility	Relia bility
η_{Attr}^{UA}	0.20	0.5	0.5	0.5	0.6
η_{Attr}^{PA}	0.67	0.5	0.5	0.6	0.6

TABLE 15. The table exemplifies the value of θ for competitive strategy.

Value of θ	**Competitive, $\rho < 1$**
0.10	0.946
0.20	0.895
0.30	0.847
0.40	0.801
0.50	0.758
0.60	0.717
0.70	0.679
0.80	0.641
0.90	**0.607**
0.10	0.575

TABLE 16. The table exemplifies the value of θ for collaborative strategy.

Value of θ	Collaborative, $\rho > 1$
1.0	0.575
2.0	**0.331**
3.0	0.1901
4.0	0.109
5.0	0.063
6.0	0.036
7.0	0.021
8.0	0.012
9.0	0.007
10.0	0.004

TABLE 17. The table exemplifies the execution time of the recommender phase.

Possible Combinations	Execution Time (unit of time)
3x5	55
3x10	140
5x5	75
5x10	160
7x5	130
7x10	188
10x5	160
10x10	245

TABLE 18. The table exemplifies the execution time of the negotiation phase.

Number of attributes for the negotiation phase	Execution Time (unit of time) after Negotiations rounds				
	1	5	10	25	50
3	23	58	115	288	575
5	45	112	225	562	1125
7	75	187	375	937	1875
10	135	337	675	1687	3375

TABLE 19. The table exemplifies the success rate of IRNAM after the negotiation round.

Negotiation Strategy IRNAM VS Others		Success Rate after negotiation round				
		1	5	10	25	50
IRNAM	Collaborative	1	1	1	1	1
	Win-Win	0	0	1	1	1
	Competitive	1	1	1	1	1
Linear [10, 31, 52]		0	0	0	0	0
Conservative [10, 27, 29, 52]		0	0	0	0	1
Conciliatory [10, 26-29, 52, 54]		0	0	0	1	1

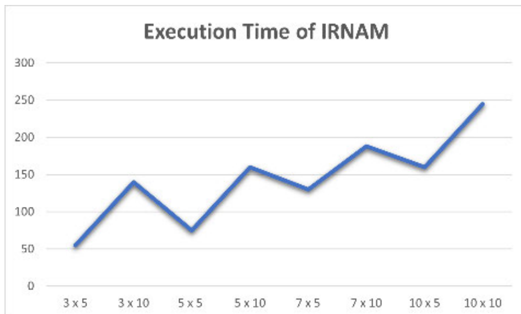

FIGURE 4. Showing the overall execution time of IRNAM.

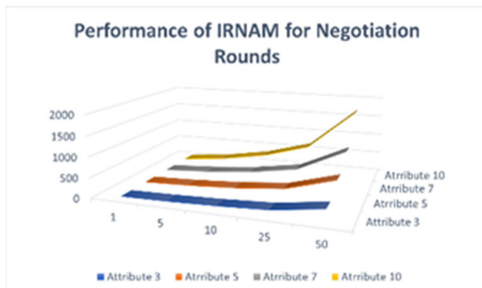

FIGURE 5. Performance of IRNAM during the negotiation.

CSPs participating in providing services. In figure 4, the first figure represents the execution time of IRNAM during the whole process and shows that execution time depends directly upon the number of attributes and CSP. Similarly, in figure 4, the second figure shows how performance time increases when the number of negotiation rounds increases with the number of attributes.

The proposed IRNAM model supports QoS in optimal execution time while using user and CSP satisfaction values. IRNAM shows efficient performance on minimum negotiation rounds. The success rate is very promising in collaborative and competitive negotiation. The recommendation algorithm follows the user's priority and recommends the maximum utility of CSP. Hence, the IRNAM model is a proficient mediator agent that helps users recommend CSP to negotiate SLA over prioritized attributes.

VI. CONCLUSION AND FUTURE SCOPE

The research proposes IRNAM, a mediator between the user and cloud service provider. It has two significant functions: recommending the CSP per user requirement and negotiating SLA between users and CSP. The main objective of IRNAM is to provide a straightforward way to find CSP as per the user's prioritized attributes and negotiate to get the best out of the CSP. This study proposes an innovative solution to the problem of managing SLAs in the cloud. The three-phase intelligent agent technique offers a robust platform for managing SLAs and provides better insights into the SLA management process. By employing this agent methodology, cloud service providers can meet the demands of users who require prioritized service delivery and improve the overall efficiency and fulfillment of the service delivery process. IRNAM provides flexibility to adapt both recommendation of CSP and negotiation on desired cloud services on the degree of satisfaction for both parties. In this article, we proposed the analytical method of IRNAM and proved it with the case study mentioned above. As per obtained results, we can predict IRNAM's success rate on fewer negotiation rounds is impressive. In the future scope of IRNAM, we can introduce a behavior learning algorithm and a new approach of quantum computing algorithm for the recommendation to monitor the operationalization and final billing processes. We can test IRNAM on composite attributes from multiple CSPs. There is a scope to investigate the model on more complex cloud services scenarios, or it can be tested on intra-cloud and inter-cloud services. Blockchain can play a vital role in monitoring and securing the process.

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