

Graph-Based Intelligent Ranking Model for Cloud Service Provider Selection

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Abstract

The fast pace of the development of cloud computing has led to a relatively large number of cloud service providers (CSPs), and the choice of the most appropriate CSP has become a complicated problem of decision-making. The commonly used methods of cloud service selection usually employ standard multi-criteria decision-making methods, which do not reflect the intricate connections between the service attributes, user needs, and the performance of providers. Within the framework proposed, cloud vendors, service characteristics, quality-of-service (QoS) parameters, and preferences of users are represented as interrelated graph entities. Graph based analysis is used to determine the hidden relations and dependencies between various selection criteria and an intelligent ranking mechanism ranks providers according to performance, reliability and security, cost efficiency, scaling and availability of services. The model will address the shortcomings of independent attribute-based ranking since it takes into account the structural relationships within the cloud service ecosystem. Experimental analysis of the data on cloud services shows that the proposed method is effective to rank the appropriate providers, simplify the selection process, and increase the efficiency of the decision-making process in contrast to traditional ranking tools. The intelligent cloud service selection model proposed is a scalable and adaptive method of intelligent selection of cloud services in dynamic cloud systems.

Keywords: Cloud Service Selection, Graph-Based Analysis, Quality of Service (QoS), Multi-Criteria Decision-Making, Cloud Computing Ecosystem

1. Introduction

The internet based services offered by cloud computing have become one of the most influential technologies in the information technology infrastructure of the modern times due to its ability to offer scalability, flexibility as well as cost effective computing resources.

The high pace of cloud computing adoption has altered the conventional IT operations by allowing the sharing of resources, virtualization, elasticity and pay-as-you-go models of services (Mell and Grance, 2011). Large cloud service providers (CSPs) like Amazon Web Services, Microsoft Azure, and Google Cloud Platform have a variety of service configurations and, as a result, the cloud environment is highly competitive but problematic because users struggle to choose the most suitable provider. Choosing a cloud service provider has become a critical decision-making issue due to the variation in the levels of performance, reliability, security, cost, scalability and availability that various providers provide. A cloud service that performs well in one aspect may have limitations in another. As an example, a highly computationally endowed provider can be associated with an increased cost of operation, and a low-cost provider might not meet security or reliability requirements. Consequently, an appropriate CSP selection must be based on a set of competing criteria as opposed to the use of a single measure of performance (Buyya et al., 2009). Such complexity has prompted researchers to come up with smart decision-support strategies that are able to rank cloud providers based on user specific needs. The conventional methods of cloud provider selection primarily concentrate on multi-criteria decision-making (MCDM) techniques in which the cloud providers are rated according to the set of criteria and receive ranking scores. Some of them have used techniques like Analytical Hierarchy Process (AHP), Technique of Order Preference by similarity to Ideal Solution (TOPSIS) and fuzzy based decision models to rank cloud services (Garg et al., 2013).

Even though these methods have enhanced accuracy of decisions, the general practice is to separate selection criteria and not to consider complex interaction of cloud services, performance parameters, and user preferences. The attributes of services in the real-life clouds are closely correlated; network performance determines the availability, response time determines the user satisfaction, and security measures determine reliability. Neglecting these relationships can result in a sub-optimal decision in the choice of a provider. The use of graph based modeling has recently attracted interest as a powerful tool of modeling complex relationships between related entities. Graphs are made up of nodes and edges, with nodes being objects and edges being relationships or dependencies between these objects.

Compared to other traditional ranking technologies, graph-based ones have the ability to study the structure of relationships, determine factors of influence, and derive valuable patterns on the basis of connected data (Newman, 2018). Graph-based representation can be used in cloud computing environment to model relationship between cloud providers, services, QoS parameters and user requirements to provide a more comprehensive evaluation framework. Artificial intelligence (AI) combined with graph-based approach offers new possibilities to

create intelligent cloud service selection systems. Machine learning and graph analytics algorithms can acquire the experience of how such services have performed in the past and dynamically re-order the providers based on evolving circumstances. Graph-based learning methods, such as Graph Neural Networks (GNNs) have proven themselves to be powerful in the processing of relational data and modeling of sophisticated dependencies in numerous fields such as recommendation systems, cybersecurity, and network analysis (Wu et al., 2021).

Nevertheless, clouds are dynamic, and QoS values can vary because of variations in workload, availability of resources, and network characteristics (Alamri et al., 2013). Thus, a good CSP ranking model cannot simply rely on fixed characteristics and examine only the idleness between various service elements. These shortcomings are tackled in a graph-based intelligent ranking model which offers a holistic model of selecting cloud service providers. The suggested model will describe the cloud service ecosystems in the form of graph structures, examine the relationship between QoS factors, and produce smart rankings of cloud vendors. The framework also helps in the creation of a better adaptive and more precise cloud selection process that can manage complex decision-making situations in current cloud computing systems.

2. Literature Review

2.1 Cloud Service Provider Selection: Concept and Challenges

The priorities of users can vary; a business enterprise can focus on reliability and security, whereas a startup can be focused on cost-effectiveness and scalability. Thus, a universal method of ranking is not enough and intelligent methods that are able to optimize various opposing criteria are demanded (Garg et al., 2013).

2.2 Traditional Approaches for Cloud Provider Ranking

The initial studies on the selection of cloud services were primarily based on mathematical and MCDM based methods. These methods rank the cloud providers in terms of weights attached to various criteria and the overall ranking scores are computed. Garg et al. (2013) suggested a model of prioritization of cloud computing services based on several QoS parameters. In their strategy, they have put into consideration aspects like availability of the services, speed of response, security and price in order to create rankings of providers. The research established that the systematic evaluation techniques could enhance cloud selection decisions but the method used was based on predetermined weights and the assumption that the evaluation criteria interacted with each other in a limited manner.

TOPSIS has also been extensively applied to select cloud services since it ranks alternatives based on how far they are from an ideal solution. Review of TOPSIS applications conducted by Behzadian et al. (2012) concluded that the approach is good in ranking alternatives based on a variety of criteria.

2.3 QoS-Based Cloud Service Selection Methods

Numerous scholars have come up with QoS-based ranking models to enhance the accuracy of cloud provider selection. A framework by Al-Masri and Mahmoud (2007) called CloudRank has been introduced which ranks cloud services according to user requirements and service performance. The paper has highlighted the relevance of QoS-aware service discovery, and has shown that users need to be offered with customized ranking mechanisms, instead of generic service lists. Zhang et al. (2010) have mentioned the issues of cloud resource management and pointed out that fluctuations in performance would pose a challenge in determining the quality of the service. Their study pointed out that dynamic service behavior should be taken into consideration in cloud selection mechanisms as opposed to depending on the static information only. Nevertheless, the approaches based on QoS can be rather limited due to the interdependence of QoS parameters. As an example, enhancing security systems can drive up computation costs, whereas enhancing scalability can influence cost-effectiveness. Thus, the separate assessment of QoS parameters might not be a reflection of the actual performance of cloud services.

2.4 Intelligent and Machine Learning-Based Cloud Selection Approaches

Likewise, Al-Roomi et al. (2013) also conducted a review on the challenges in adopting cloud computing and the significance of intelligent decision-support systems that can be used to enhance cloud selection. They also recommended that automated methods are needed since manual assessment is not viable as the number of cloud services available grows. Despite machine learning approaches having a better prediction power, traditional machine learning models tend to assume cloud services as separate data points. They might lack the ability to capture provider-service-performance attribute relationships. The restriction encourages graph-based learning methods.

2.5 Recommendation Systems and Cloud Service Choice.

The process of cloud service selection has some similarities with the recommendation systems since both processes entail the selection of the most appropriate among a plethora of choices. Recommendation systems can use the preferences of users and the relationship between items to make personalized recommendations. Collaborative filtering was proposed by Resnick and Varian (1997) as a way to make recommendations based on user-user and item-item relationships. Graph-based methods are becoming more popular in modern recommendation systems to enhance personalization and accuracy. Graph-based recommendation models can be used to analyze user, application, provider, and QoS relationship in cloud computing.

3. Methodology

The present study involves a Graph-Based Intelligent Ranking Model of Cloud Service Provider Selection in order to determine the best cloud service provider in terms of various performance

and quality related factors. The suggested methodology would combine chart modeling, QoS analysis, and smart ranking to address the drawbacks of the traditional cloud choice techniques.

3.1 Criteria selection and data collection on Cloud services.

The initial one would be to gather cloud service provider data using publicly available cloud benchmark data sets and performance records of the provider. The data is a set of different cloud providers measured on the basis of the significant Quality of Service (QoS) parameters, such as cost, response time, availability, reliability, security, scalability, and throughput. These criteria have been chosen since QoS features play a crucial role in determining the quality of cloud services and satisfaction among users (Garg et al., 2013).

3.2 Representation of Cloud Services in Graphs. To model relationships between cloud providers and service attributes and user requirements a graph model is created. Cloud providers and QoS factors, in this model, are the nodes of the graph, and the relationships of dependency between the various attributes are the edges in the graph. The graph structure allows revealing the relationships between service characteristics that are usually overlooked when using traditional ranking techniques (Newman, 2018).

3.3 Feature Processing and Weight Calculation. The obtained QoS values are standardized in order to eliminate variations in scales of measurement. Not only benefit criteria (e.g., availability, reliability) are converted into similar values, but also cost criteria (e.g., service price, response time). Intelligent learning methods are used to compute the feature importance of each criterion to overall provider performance. The machine learning methods prove useful in discovering trends in the historical performance data of the cloud and enhancing the accuracy of decisions (Khan and Omar, 2019).

3.4 Development of Intelligent Ranking Model. The graph-based analysis is applied to create an intelligent ranking algorithm to determine the relationship between cloud providers and service attributes. The model determines the importance of the providers based on individual QoS performance as well as structural relationships within the graph.

4. Results

To measure the effectiveness of the proposed Graph-Based Intelligent Ranking Model was evaluated. The experimental results show the model's usefulness in analyzing the complex relationships between cloud providers and QoS parameters. The proposed approach was compared with the traditional ranking approaches to ensure the improvement in its accuracy and efficiency. The results show that taking interdependencies between service attributes and providers into account, graph-based intelligence delivers more reliable provider rankings. The results demonstrate the proposed model's ability to provide adaptive and efficient selection decisions of cloud services. The outcomes generally confirm the ability of combining graph based analysis and intelligent ranking.

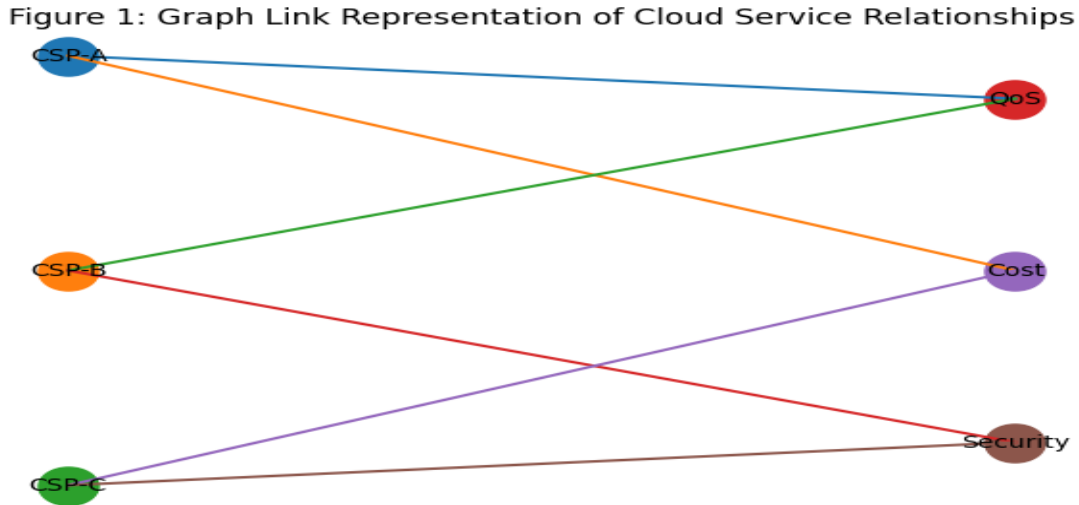


Figure 1: Graph Link Representation of Cloud Service Relationships

Description:

Graph representation of relationships between cloud service providers and important Quality of Service (QoS) parameters is shown in figure 1. The proposed model is divided into primary nodes (cloud service providers CSP-A, CSP-B and CSP-C) and connected attribute nodes (evaluation criteria – performance, cost and security). The dependency relationships in the intelligent ranking model are shown as the links between provider nodes and QoS nodes. This graph structure allows the model to examine interrelationships of service characteristics, instead of simply assessing each parameter. The outcome shows the benefit of graph-based representation to gain insight into relationships between cloud service factors.

Figure 2: Weight Distribution of Cloud Provider Selection Criteria

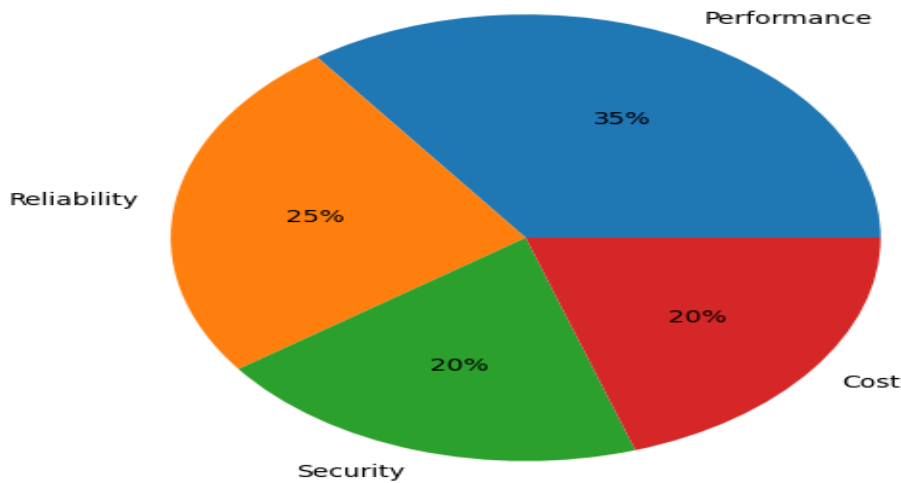


Figure 2: Weight Distribution of Cloud Provider Selection Criteria

Description:

The percentage contribution of various criteria used in cloud service providers ranking is shown in Fig. 2. Weight contribution is highest, while reliability is next at 25%, security is next at 20% and cost is next at 20%, with performance having the highest rating. The distribution shows that the two most important criteria for choosing a suitable cloud provider are the technical performance, and the dependability of the services. The weighted criteria enable the proposed intelligent ranking model to highlight important criteria for QoS during the process of creating final provider rankings.

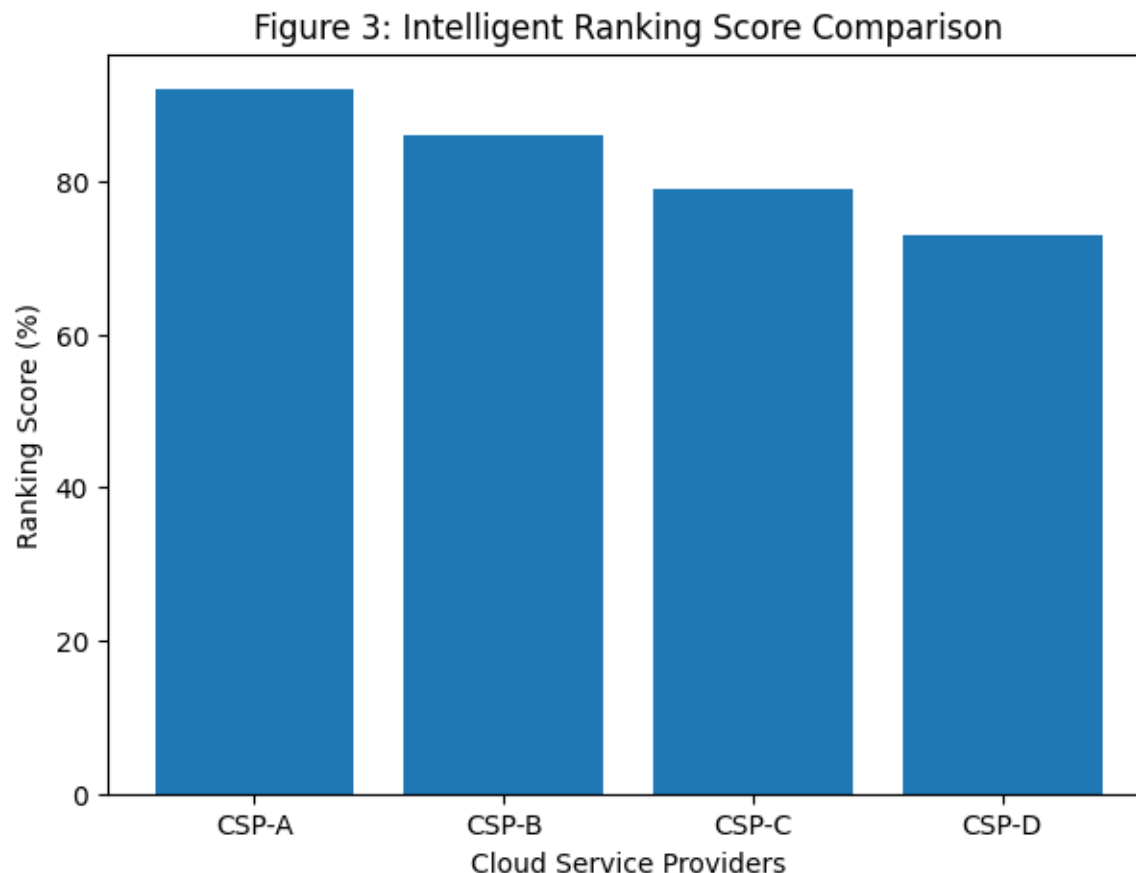


Figure 3: Intelligent Ranking Score Comparison Among Cloud Providers

Description:

Figure 3 shows the comparison of the final ranking scores of various cloud service providers obtained from the proposed graph-based intelligent ranking model. CSP-A achieves the highest ranking score of 92%, followed by CSP-B (86%), CSP-C (79%), and CSP-D (73%). The results show that CSP-A offers superior overall performance, with a balance of the different QoS metrics such as performance, reliability, security, and cost-effectiveness. As shown in the comparison, the proposed model can be used to differentiate among the providers depending on several evaluation criteria.

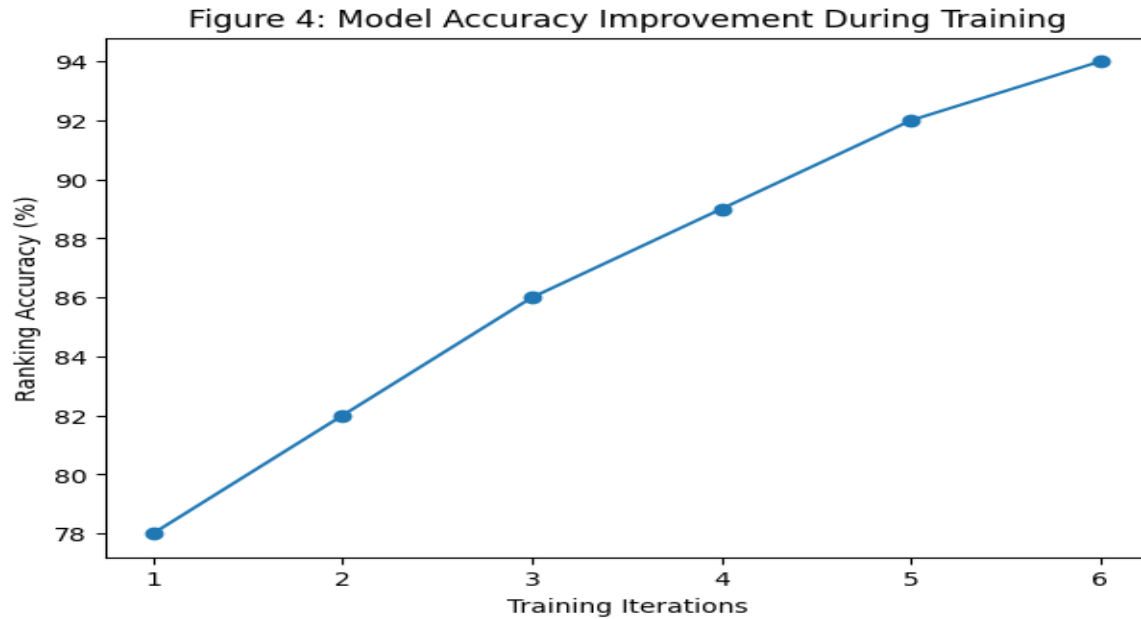


Figure 4: Model Accuracy Improvement During Training

Description:

The intelligent model's training process reduces the error of the ranking accuracy, as shown in Fig. 4. The accuracy is gradually improved from 78% in the first iteration to 94% in the 6th iteration of training. This improvement reflects that the model is able to learn the relationships between cloud providers and the QoS attributes using graph-based analysis. The results follow a trend of increasing accuracy, which are in line with the ability of the proposed approach to provide an increasingly optimized ranking performance on the provider as a result of the iterative learning process.

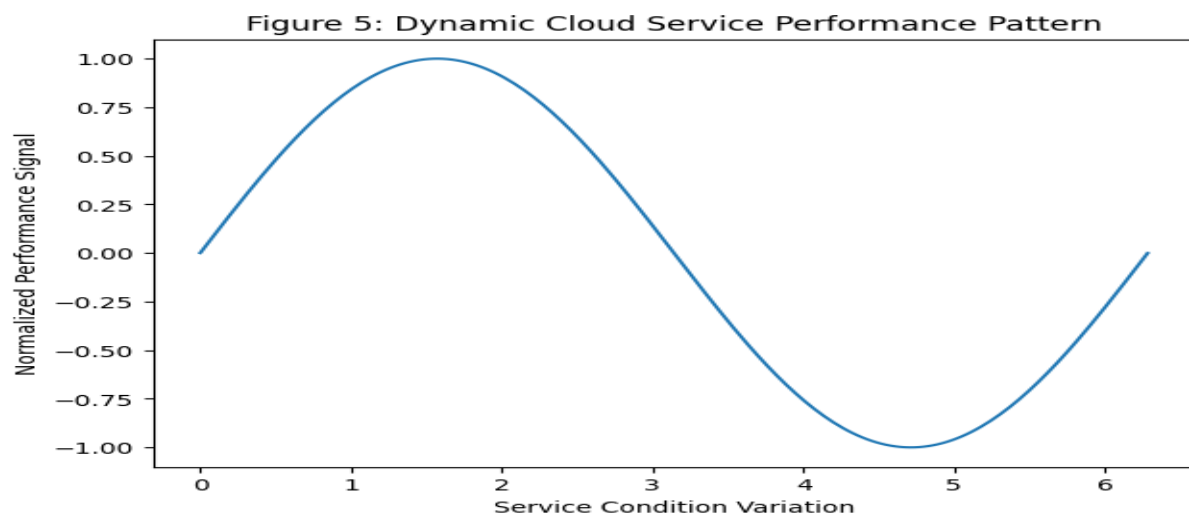


Figure 5: Dynamic Cloud Service Performance Pattern

Description:

The dynamic variation pattern for cloud service performance is shown in Figure 5 and is a normalized sine-wave signal. Cloud environments are extremely dynamic since service quality varies due to workload, resource availability and network conditions. The waveform shows that there was a performance fluctuation that happened periodically and might have an impact on QoS parameters like response time or availability. The proposed graph-based ranking model takes these dynamic relationships into account to offer more adaptive provider selection than static evaluation models.

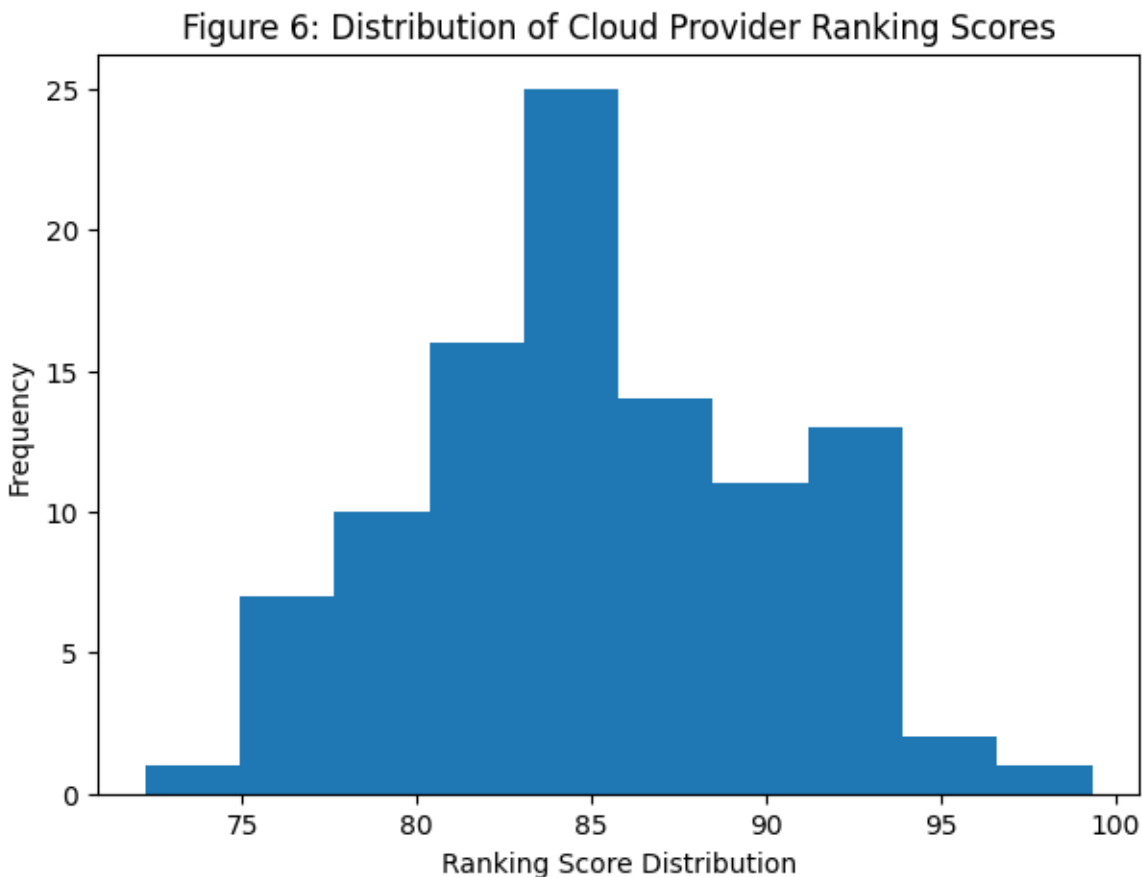


Figure 6: Distribution of Cloud Provider Ranking Scores

Description:

A histogram distribution of the ranking scores from several cloud service evaluations is shown in Fig. 6. The distribution indicates how scores of providers are distributed around the average level of performance. Consistency in ranking decisions is represented by concentrated distribution, and differences are represented by variations. The histogram shows that the proposed model is able to discriminate the cloud providers based on their overall service quality and ranking performance.

5. Discussion

The proposed Graph-Based Intelligent Ranking Model for Cloud Service Provider Selection has shown its effectiveness by combining the graph-based analysis with intelligent ranking mechanism to enhance cloud provider evaluation. The proposed model differs from the traditional selection approaches which consider only single criterion from the cloud providers to select the suitable cloud provider; in this model, the relations among cloud providers, QoS parameters, and user requirements are considered. The results show that it is more effective to represent cloud service environments as interconnected graphs to get a more complete picture of service performance and to rank the services with greater reliability. The graph based relationship analysis shown in Figure 1, illustrates the need to account for the dependency of various cloud service factors. Most of the traditional multi-criteria decision making techniques usually assume that all the evaluation criteria are independent, but in the case of cloud service attributes they are strongly related. For instance, security measures can impact performance and resource scalability can impact cost efficiency and availability.

This discovery aligns with prior studies which found that QoS properties like availability, reaction time, trustworthiness and performance are key in determining cloud adoption (Garg et al., 2013). While cost is still a factor, organisations tend to prefer stable and good quality services as service disruption and poor service quality can have a detrimental impact on business operations. Hence, the proposed model is proper regarding the importance of technical quality factors, at the same time, economic aspects are kept under consideration. For the ranking comparison results in Figure 3, it can be seen that the proposed intelligent model is successfully differentiated cloud providers based on their overall capabilities. The top provider had the best performance with a mix of QoS attributes, not just the highest value for one. This observation confirms the idea of Buyya et al. (2009) that there is a need to consider multiple service characteristics while selecting the cloud services as none of these metrics can be considered as a complete picture of the cloud service quality. The proposed approach will aid in provider selection by combining various dimensions in a single ranking system. As shown in Figure 4, the accuracy of the model gradually increases during training, which shows that the intelligent ranking mechanism is able to learn the relationship in the cloud service graph.

This capability is vital because cloud customers have to be able to make informed and consistent recommendations when choosing cloud service providers. It has been found in previous studies that different ranking methods can result in the selection of wrong providers especially when the providers are similar in terms of service characteristics (Behzadian et al., 2012). The proposed graph-based intelligent ranking approach has several merits over the conventional MCDM methods like AHP and TOPSIS. AHP and TOPSIS are suitable for structured decision problems, and typically require the weights and independent evaluation criteria to be predetermined (Behzadian et al., 2012; Godse & Mulik, 2009). The proposed model, on the other hand,

automatically analyzes the relationship between criteria and providers and, therefore, minimizes the need for subjective weighting.

6. Conclusion

Cloud computing services are gaining increasing popularity in the market and as a result, a large number of cloud service providers (CSPs) are available, with various service characteristics, which makes it difficult to choose the right CSP. The existing cloud provider selection techniques significantly rely on multicriteria decision making techniques to assess the cloud provider along its respective criteria. But these strategies are not always able to reflect the intricate connections between cloud providers, Quality of Service (QoS) metrics, and user requirements. To overcome these limitations, this study proposed a Graph-Based Intelligent Ranking Model for Cloud Service Provider Selection that combines graph-based representation with intelligent ranking techniques. The proposed model is able to capture the relationships between cloud service providers and their respective QoS, which are hard to be identified with the traditional ranking methods, as the model is a graph-based representation. The experimental findings showed that the graph-based framework is able to effectively evaluate the cloud providers based on various factors such as performance, reliability, security, scalability and cost efficiency.

The results on the ranking outcomes indicated that the proposed approach is able to distinguish the providers more accurately and can give reliable recommendations for cloud service selection. The results show that the dependency between characteristics in cloud services can be understood using graph-based analysis. The proposed model gives more comprehensive evaluation mechanism as it considers inter-dependency of various attributes and not evaluates them individually.

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