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A Hybrid Multi Criteria Decision Method for Cloud Service Selection from Smart Data

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Abstract

Cloud computing refers to providing computing services and resources over the Internet. The cloud provider is an organization or company which offers the services to the consumer at different levels of features and characteristics. However, as the growth of cloud services as well as cloud service providers are increasing rapidly, it is becoming a challenge for consumers to choose the best service provider based on their requirements. In this paper, we propose a method to help the consumer to answer this question. A hybrid multi criteria decision method (MCDM) is developed to evaluate and rank cloud service providers from Smart Data. Furthermore, this method considers the interdependencies and relations between the performance measurements. The hybrid method consists of two components: (i) clustering the providers using k-means algorithm to consolidate cloud service providers with similar features and (ii) applying MCDM methods using DEMATEL-ANP to rank clusters and make a final decision. The proposed method also considers the existing workloads of the organization as well as assigns different importance and weights for a set of criteria by clustering the cloud service providers using k-means algorithm. A simulation on the MATLAB was performed to evaluate the proposed method, and the results indicate how the proposed hybrid approach can provide an accurate and efficient way to select the best providers.

Keywords— Cloud service selection, Smart data, Multi criteria decision method, DEMATEL, *K*-means, Analytical network process

1. Introduction

Cloud computing is emerging technology in computing resources allocation over the Internet. This model of computing provides important benefits to the organizations by relieving them of low-level tasks related to setting up IT infrastructure as well as allowing organizations to begin small resources and increase these resources on demand, thus enabling more time for innovation and the creation of business value.

This technology is a model for providing a pool of on demand resources like software as a service SaaS, infrastructure as a service IaaS, and platform as a service PaaS [1].

Nowadays, migrating the applications, data, and/or infrastructure to a cloud is a confirmed challenging process. Certain obstacles prevent cloud computing from offering its full features. Those obstacles are related to the fact that current applications, data, and/or infrastructure have specific needs and configurations that must be realized by the cloud provider [1, 2]. From an organization's perspective, each system has its own configuration performance and factors that affect workload parameters. Furthermore, each cloud service provider offers its services with various features such as performance, cost, and security. Therefore, it is challenging for organizations to choose the most appropriate cloud service provider in the presence of these multiple features.

By examining related research, we found that many studies that have proposed methods for vendor selection. One of these methods is MCDM, which is used for structuring and making a decision for problems containing multiple criteria. Majority of the reviewed studies have not considered the interdependencies and relations between criteria and parameters. While some research has been identified guidelines and instructions for the readers to evaluate and rank cloud service providers, the organization's systems and workloads are not considered. When MCDM has been applied in studies, researchers assume that the importance and weight of each criterion is equal. Therefore, it is essential to consider these limitations and provide the hybrid method, KD-ANP, which aims to supplement MCDM within a context of addressing interdependencies and relations between the criteria. Moreover, our proposed KD-ANP method is distinguished from other published approaches since it considers an organization's existing workload and by clustering the cloud service providers using *k*-means algorithm, assigns various degrees of importance and weight for a set of criteria. In summary our contributions are as follows:

- In this paper, we have proposed a cloud service selection using hybrid MCDM to select the best provider.
- We benefit from our earlier work that was proposed in [1] to build a comprehensive method by employing the performance prediction model to obtain the required performance for the organization considering the existing workloads.

The rest of the paper is organized as follows: Section 2 describes the related works. Section 3 presents the problem formulation and proposed hybrid MCDM approach. Section 4 describes the experimental results and finally Section 5 concludes the paper.

2. Related work

The issue of cloud service provider selection is comparatively old. The best selection of provider is one of the main goal for enhancing the efficiency of the organizations, which effects on the growing, competitiveness and performance of the organization. Recently, some researched have been conducted to address and proposed the solutions for this issue. In this section we will explore the most relevant studies to our own.

In [3] they proposed a decision making method for MCDM based on integrating analytical network process ANP and DEMATEL to select best cloud service provider in uncertain conditions. They used these techniques to handle the issue of assigning weights to indexes for obtaining the interdependencies between the criteria. They also used service measurement index SMI to measure and evaluate the services. In [4] the authors proposed a cloud service selection framework using ANP to determine the best service provider for IaaS. The proposed study was applied for ICT resources. They also defined some criteria and sub-criteria and evaluate the alternatives based on that. In [5] they proposed a framework to measure and evaluate the quality of service in cloud. They used SMI measurements along with analytical hierarchal process (AHP) to rank and evaluate the cloud service providers according to their SLA.

In [6] the researchers proposed a framework for choosing the suitable cloud service provider using service metrics such as SMI measurements. They used Ranked Voting Method to evaluate and rank the cloud providers. In [7] they explored the several MCDA methods and they provided a comprehensive analysis of these methods for general researchers. They also presented a taxonomy from their surveyed literature. In [8] the authors reviewed the cloud service selection methods using multi criteria decision analysis (MCDA). They gathered an information about the selection and adoption of Cloud services using MCDM methods for cloud service types (IaaS, PaaS and SaaS).

In [9] they proposed a framework for cloud service selection on the fuzzy environment using (AHP) and fuzzy technique for order preference by similarity to ideal solution (fuzzy -TOPSIS). The authors defined performance metrics to compare and evaluate the performance of cloud service providers. The Authors also proposed in [10] a framework for selecting the best cloud service provider by applying (AHP) and (TOPSIS) and the study was proven by conducting a case study. In [11] the researchers proposed a framework using MCDM methods to rank the cloud service providers based on their infrastructure parameters. They combined various methods such as AHP, fuzzy-AHP, TOPSIS, and fuzzy-TOPSIS. The parameters prioritized based on three criteria: performance, cost and security.

In [12] they explored the application of (MCDM) methods for cloud computing and big data. Moreover, they proposed a MCDM framework by combining the interpretive structure modeling (ISM) and fuzzy-ANP based method to handle the interrelationship among evaluation criteria and to handle data uncertainties. In [13] the authors proposed a hybrid MCDM framework for cloud service selection based on the Balanced Scorecard (BSC), fuzzy-Delphi method and fuzzy-AHP. They applied this model on selecting an infrastructure service in cloud computing. The BSC technique is used to form the hierarchy that contains four perspectives: financial, customer, internal processes, and learning and growth. Fuzzy-Delphi method is used to determine the important decision making factors within each perspective. A Fuzzy-AHP method is also used to compares the criteria and the factors and determine the importance of them to choose the best cloud service from the cloud service providers. In [14] they proposed a hybrid method for MCDM by using AHP and reference Ranking Organization METHod for Enrichment Evaluations (PROMETHEE). AHP method is applied to form the hierarchy of the service ranking issue and to find the weights of the selected criteria, as well as PROMETHEE method is used for the final decision.

In [15] the researcher proposed a fuzzy hybrid MCDM method. Fuzzy-ANP is used to calculate the pairwise comparison matrices. Fuzzy-TOPSIS is applied to calculate the weights of the criteria. Fuzzy-ELECTRE methods is also used to rank the alternatives.

The researchers used SMI measurements to evaluate the alternatives. In [16] they proposed a model using MCDM methods to select the cloud service provider. They applied fuzzy AHP to evaluate and rank cloud service providers. They also proved their work by applying IaaS provider selection case study. In [17] they proposed a MCDM method framework to for ranking the cloud providers and selecting the best one. They applied Interval Valued Intuitionistic Fuzzy (IVIF) set with Multi-Objective Optimization on the basis of Ratio Analysis (MULTIMOORA) approach to optimize complex systems with conflicting criteria and focuses on the selection and ranking of distinct alternatives among a set of other choices.

Although many various supplements of MCDM have been implemented in related work so far, most of the reviewed researches did not consider the interdependencies and relations between the criteria and parameters. While some have been identified a guidelines and instructions to the readers when they need to evaluate and rank cloud service providers. Therefore, in our proposed method we aim to supplement MCDM within the context of its ability handle the interdependencies and relations among the criteria by applying DEMATEL and ANP methods. Moreover, our proposed method also has its competence that distinguishes it from other published approaches while we assigning different importance and weights for a set of criteria by clustering the cloud service providers using k-means algorithm.

3. Problem Formulation

Since cloud service providers offer services with different features and characteristics, their services can greatly vary based on performance and cost. Because some features and characteristics are interdependent, ANP is a helpful solution since it engages with element interdependency.

To apply ANP, we assess the importance and weight of criteria since ANP assumes an equal weight for all involved. In our case, however, we need to provide different importance weight for each criterion. It may not make sense to give equal weight to performance and cost; for example, if the provider offers services of low performance and high cost, the weight of the performance will be less than the weight of the cost. Meanwhile, if another provider offers services of high performance and low cost, the weight of the cost will be less than the weight of the performance. Furthermore, the importance and weight can vary from sector to sector and person to person.

Additionally, if we assume there is a large number of service providers and a large number of criteria and sub-criteria, the calculating and forming the super-matrix will be complicated and time consuming. To resolve this issue, we perform clustering and then apply the ANP with same weight to each cluster. Thus, we obtain the highest quality representative from each cluster and, finally, select from those representatives.

To carry out this process, we use an efficient clustering algorithm. We utilize the *k*-means clustering algorithm as a simple and efficient tool to monitor the progression of a provider's performance. Meanwhile, to address and confirm interdependency and relations between criteria, we use the DEMATEL method [18, 19, 20]. We provide a detailed description of the *k*-means algorithm and DEMATEL method in Sections 3.1 and 3.2. Figure 1 below shows the structure of proposed methods.

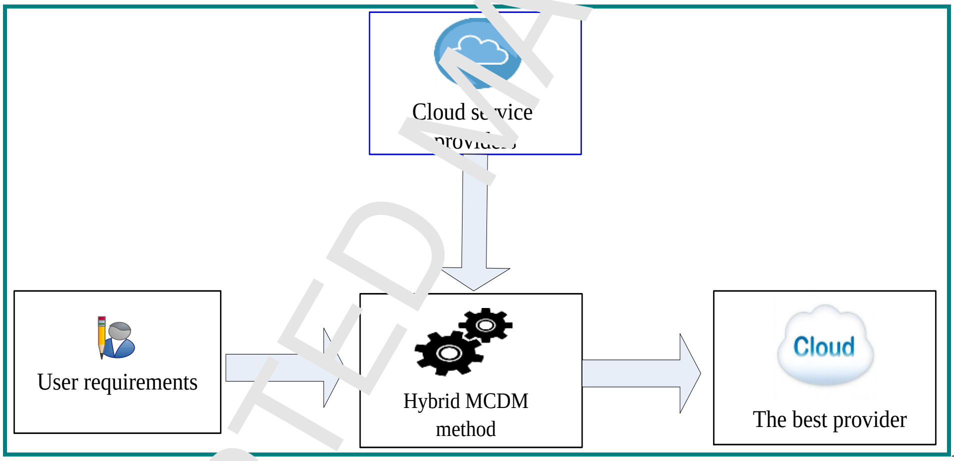

Figure 1: Structure of hybrid multiple-criteria decision-making method

Our proposed method, KD-ANP, is designed as follows:

1. Apply *k*-means algorithm to cloud service providers. The output is *k* clusters. In each cluster, all providers have similar features.
2. For each cluster, we apply DEMATEL and ANP in order to obtain one representative from each. The output is *k* representatives.

3. We apply standard ANP on the defined criteria, with respect to *k* alternatives. The output is the most appropriate alternative. Below, Figure 2 presents the structure of KD-ANP.

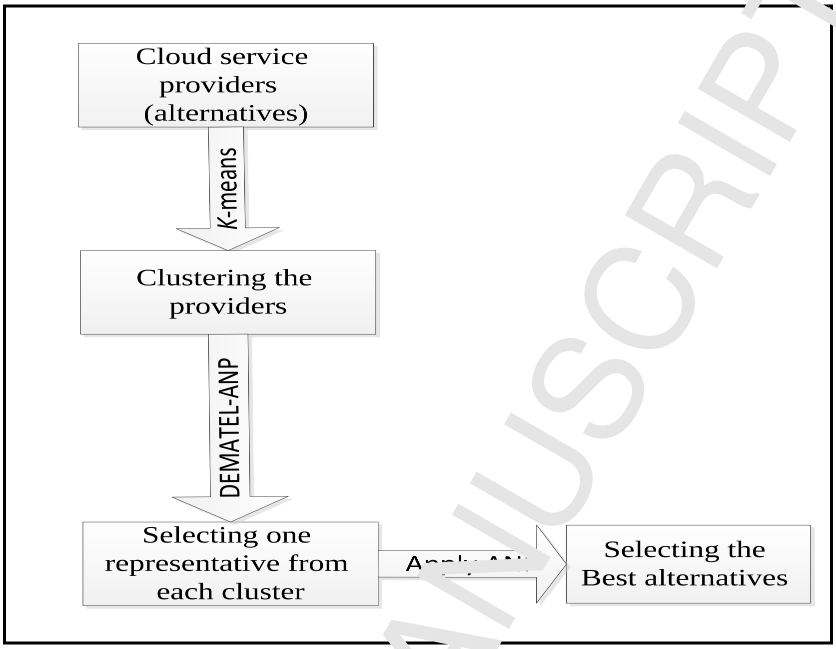

Figure 2: Workflow of KD-ANP

3.1 Analytical Network Process (ANP)

As a comprehensive MCDM approach, ANP can successfully manage multiple interactions between quantitative and qualitative criteria [3]. By capturing dependencies between decision attributes, ANP allows a more systematic analysis [2][21]. Thus, ANP has been used to make complex decisions related to energy policy planning, product design, and equipment replacement [22]. ANP contains clusters, known as components, nodes, or criteria, and elements, known as sub-criteria factors, that populate the clusters [4]. Figure 3 depicts the network structure.

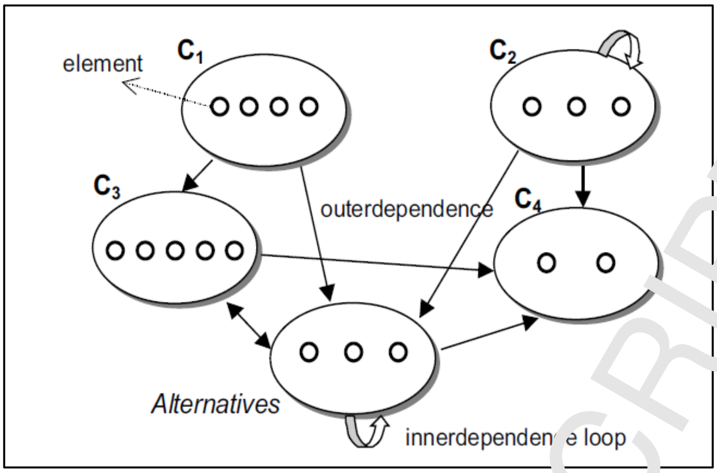

Figure 3: Network structure [99]

3.2 Measurement Attributes

In this section, we define a set of attributes to assess cloud service providers. In fact, we use the same measurements proposed in our earlier work [1]. Those measurements, including memory utilization, CPU utilization, response time in milliseconds, and cost, are explained as follows:

Memory utilization: The measure of how well available memory space is used

CPU utilization: The measure of how well available computer resources are used

Response time: The average amount of time a system or function needs to respond to a service request

Cost: The cost of each service in the cloud, taking into account cloud configurations and workload

3.3 ANP Phases

Seven phases constitute ANP. They are listed as follows [4, 23]:

Phase 1: Model development and problem formulation

Breaks down the decision problem into components and organizes it into a hierarchy of goal, main criteria, sub-criteria, elements, and alternatives.

Phase 2: Pairwise comparison of determinants

The decision-maker evaluates each component's importance. In this phase, a series of pairwise comparisons are made, wherein a ratio of Saaty scale [24] from 1 to 9 is used to compare any two elements. The denotations follow: equal importance (1), weak or slight (2), moderate importance (3), moderate plus (4), strong importance (5), strong plus (6), very strong or demonstrated importance (7), very, very strong (8), and extreme importance (9).

Phase 3: Pairwise comparison of dimensions

Obtain the relative importance of each dimension for a determinant through a pairwise comparison matrix.

Phase 4: Calculating the relative local weights

Accumulates the relative local component weights and summarizes them into global weights, which explain the significance of alternatives by using the eigenvector derivation procedure.

Phase 5: Additional clusters of elements are formed

Continues to make supplementary clusters of components and perform dependency examinations among components within a cluster, or inner-interdependencies. Additionally, carries out dependency examinations between components of one cluster and those of other clusters, or outer-interdependencies.

Phase 6: Networks of clusters are pooled into block matrices

Pools networks into block matrices to form a super matrix. Then, computes weights and obtains the weighted stochastic super matrix. Finally, the decision-maker determines strategic criteria and selects the most appropriate alternative with a top ranked priority. Figure 4 describes the model of this problem using MCDM.

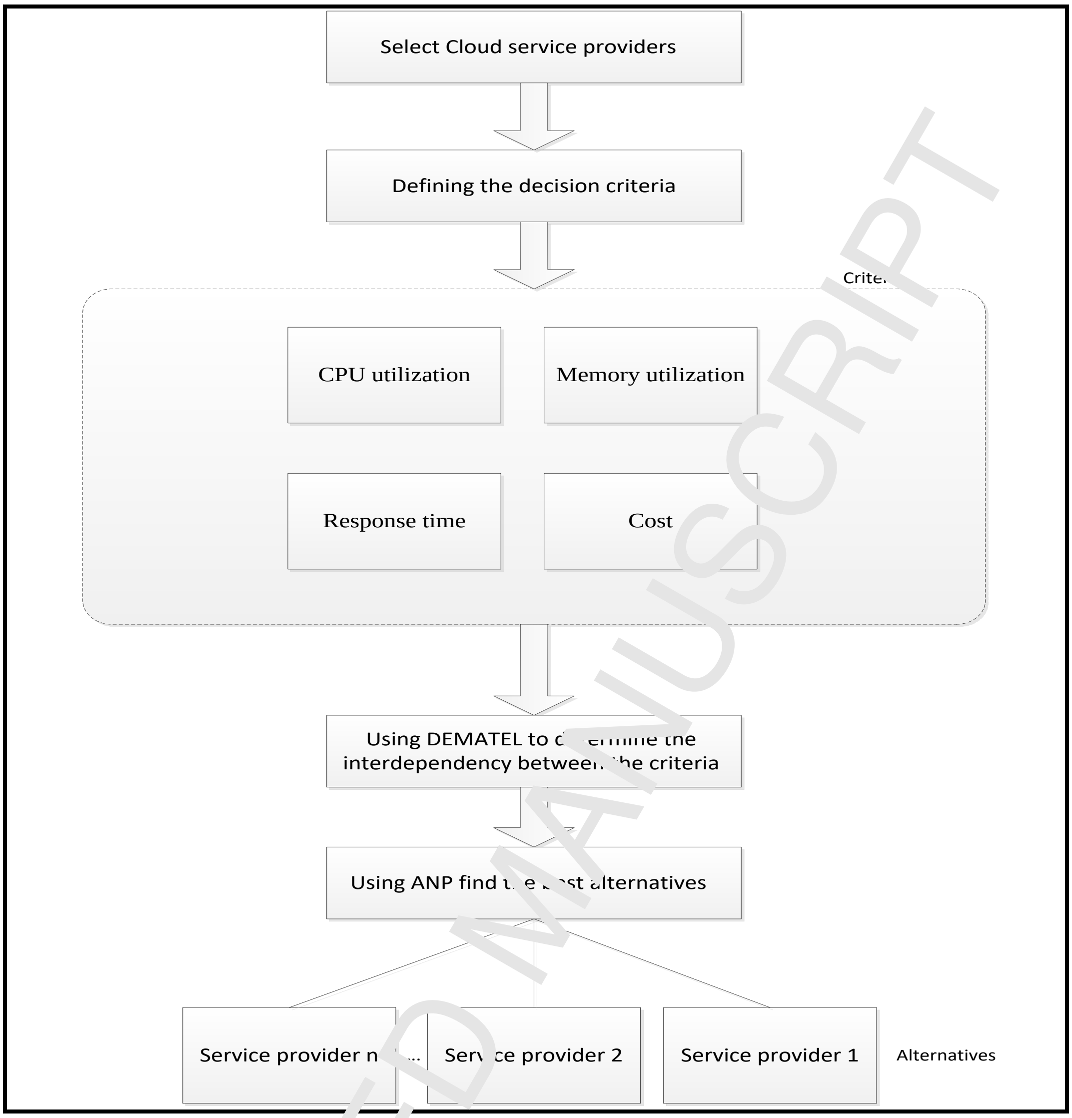

Figure 4: Detailed workflow of the proposed method

3.4 *K*-means Algorithm

The *k*-means algorithm is a popular and effective clustering technique which clusters observations into a specific number of disjoint clusters. This method is used in many practical applications. It works by specifying an initial number of *k* clusters and initial centroids [25, 26, 27] and then following the steps below:

Step 1: Select the number of *k* clusters, and for each point, place it in the cluster whose current centroid it is nearest.

Step 2: After all points are assigned, update the centroid locations of the k clusters.

Step 3: Reassign all points to their closest centroid.

Step 4: Repeat steps 2 and 3 until points do not move between clusters and centroids stabilize.

The equation (1) below describes the steps

$$J = \sum_{j-1}^{k} \sum_{i=1}^{k} \| x_i^{\,j} - c_j \|^2 \qquad (1)$$

where $\| x_i^{\,j} - c_j \|^2$ is a chosen distance measure between a data point ($x_i^{\,j}$) and the cluster center (c_j), is an indicator of the distance of the n data points from their respective cluster centers [28].

To calculate the distance *d* from (*a* to *b*) or (*b* to *a*) is given by the equation (2) below [27]:

$$d(a,b) = d(b,a) = \sqrt{(b_1 - a_1)^2 + (b_2 - a_2)^2 + \ldots + (b_n - a_n)^2} = \sqrt{\sum_{1}^{n} (b_i - a_i)^2} \qquad (2)$$

3.5 DEMATEL method

Proposed by the BMI Institute in Switzerland, the DEMATEL method was applied to construct interrelationships and feedback that occur in the criteria and sub-criteria and to find the central criteria for represent factor effectiveness. The DEMATEL method can be used to find solutions for complicated and intertwined problems by building an impact relation map (IRM) of the criteria [19, 20, 29].

Many fields have successfully applied DEMATEL for projects such as marketing strategy, research and development, electronic learning evaluation, global manager competency development, group decision-making, and airline safety [30, 31]. The following steps further detail the nuances of DEMATEL:

Step 1: Calculate the initial average matrix using scores

In this step, a group of experts are asked to indicate their perception of the direct influence that each element/factor *i* exerts on each factor/element *j*, as presented by *aij*.

The experts are then asked to use the scale from 0 to 4, where no influence is 0, low influence is 1, medium influence 2, high influence is 3, and very high influence is 4, respectively. Each expert generates a direct matrix, and an average matrix *A* is then obtained through the mean of the same factors/elements in the various direct matrices of the experts (see matrix 3 below) [29][30].

$$A = \begin{pmatrix} a_{11} & a_{1j} & a_{1n} \\ \vdots & \vdots & \vdots \\ a_{i1} & a_{ij} & a_{in} \\ \vdots & \vdots & \vdots \\ a_{n1} & a_{nj} & a_{nn} \end{pmatrix} \tag{3}$$

Step 2: Calculate the initial influence matrix

The normalizing matrix *A* is calculated to obtain the initial direct influence matrix in this step. Equations 4 and 5 are used to obtain the matrix *X* [29, 30].

$$X = s \times A \tag{4}$$

$$\text{Where } s = \min\left[\frac{1}{\max_i \sum_{j=1}^{n} |a_{ij}|}, \frac{1}{\max_j \sum_{i=1}^{n} |a_{ij}|}\right] \tag{5}$$

Step 3: Create the full direct / indirect influence matrix

In this step, the powers *X* reveal a continuous decrease of indirect effects. Equations 6, 7, and 8 are create the full direct and indirect influence matrix *T*,

$$\lim_{k \to \infty} X^k = [0]_{n \times n} \tag{6}$$

$$r = (r_i)_{n \times 1} = \left[\sum_{j=1}^{n} t_{ij}\right] \tag{7}$$

$$c = (c_j)_{n \times 1} = (c_j)'_{n \times 1} = \left[\sum_{i=1}^{n} t_{ij}\right]'_{1 \times n} \tag{8}$$

Where r_i presents the row sum of the *i*-the row of matrix *T* and offers the sum of direct and indirect effects of factor/element *i* on the other factors/elements. Similarly, c_j

presents the column sum of the *j*-th column of matrix *T* and provides the sum of direct and indirect effects that factor/element *j* has received from the other factors/ criteria [29, 30].

Step 4: Set the threshold value (α) and generate the impact relation map (IRM)

This step develops the threshold (α) to filter the miner effect on the matrix *T* that was created in step 3. Regarding the matrix *T*, each factor t_{ij} of matrix *T* gives information about how factor *i* affects factor *j*. The threshold is defined using a scale from 1 to 9, where 1 means equal importance and 9 means extreme inequality in importance, in order to reduce complexity. Equation 9 provides the result of matrix *T* [29, 30].

$$T = \begin{pmatrix} t^{\alpha}{}_{11} & t^{\alpha}{}_{1j} & t^{\alpha}{}_{1n} \\ \vdots & \vdots & \vdots \\ t^{\alpha}{}_{i1} & t^{\alpha}{}_{ij} & t^{\alpha}{}_{in} \\ \vdots & \vdots & \vdots \\ t^{\alpha}{}_{n1} & t^{\alpha}{}_{nj} & t^{\alpha}{}_{nn} \end{pmatrix} \qquad (9)$$

4. Experiments and Results

4.1 Dataset Collection

We collected a large workload dataset, containing 28147 instances from 13 cloud nodes, from the Saudi Ministry of Finance [1, 32]. The set was recorded in continuous time slots from March 1, 2016, to February 20, 2017. The different periods of data collection provide more diversity, enabling a fair classifier test and more accurate work. In the model, nodes 1 and 5 are HP RP 4440, nodes 24 and 6 are HP RP 7420, and nodes 713 are HP DL 380 G5. The number of instances collected for specific nodes may differ if they were out of service during the data recording period. Therefore, we gathered 2427 instances from node 1, 2426 instances from nodes 2–5, 2232 instances from nodes 6 and 8–13, and 392 instances from node 7. Below, Table 1 provides a description of the dataset.

Table 1: Dataset description

Number of Requested Services	28147
Number of Service Attributes	9
Number of Criteria	4
Number of Cloud Service Providers	13
Types of Cloud Service Providers Model	Nodes 1 and 5 are HP RP 4440. Nodes 2–4 and 6 are HP RP 7420. Nodes 7–13 are HP DL 380 G5

The description of criteria used in this dataset and their associated symbols are listed in Table 2.

Table 2. The four criteria used, with associated symbols

Criteria	**Description**	**Symbol**
CPU Utilization	The CPU utilization of the cloud service.	C1
Memory Utilization	The memory utilization of the cloud service.	C2
Response Time	The response time to execute the cloud service.	C3
Cost	The cost of cloud service depending on resources requested in the service attributes and estimated by the standard of cloud services report [33].	C4

4.2 Tool Description

The experiment was conducted using MATLAB R2015a on a laptop with Intel Core i7-3632QM processors at 2.20 GHz, using 12 GB of RAM memory on a 64-bit Windows 10 operating system.

4.3 Experiment Results

In this section, we present the results of the proposed methodology for selecting the most appropriate service provider based on the four criteria used in the study. Below, we present the main steps of the research methodology together with the results.

4.3.1 Pairwise Comparison of Criteria Interdependencies

In this step, cloud computing experts follow the five steps of the DEMATEL method, as explained in the research methodology. First, experts are asked to provide an evaluation grade, ranging from 0 to 4, to represent the degree of effects between the selected criteria. The evaluation grade is 0 represents no influence, 1 represents low influence, 2 for medium influence, 3 for high influence, and 4 for very high influence. The evaluation matrix is called the initial direct-relation matrix, R. Table 3 provides the initial direct-relation matrix for the four criteria used in our dataset.

Table 3. Initial direct-relation matrix (R) of the four criteria

	CPU Utilization	Memory Utilization	Response Time	Cost
CPU Utilization	0	2	3	3
Memory Utilization	2	0	3	3
Response Time	3	3	0	2
Cost	3	3	3	0

In step two, the normalized initial direct-relation matrix is computed using equations (4– 8). Table 4 indicates the normalized initial direct-relation matrix, N.

Table 4. Normalized initial direct-relation matrix (N) of the four criteria

	CPU Utilization	Memory Utilization	Response Time	Cost
CPU Utilization	0	0.222	0.333	0.333
Memory Utilization	0.222	0	0.333	0.333
Response Time	0.333	0.333	0	0.222
Cost	0.333	0.333	0.333	0

Next, the indirect effects in the matrix N are reduced by a continuous reduction along the powers to lead to a steady state of the matrix inverse. The total relation matrix, T is computed using equation (9) and is provided in Table 5.

Table 5. Total relation matrix (T) of the four criteria

	CPU Utilization	Memory Utilization	Response Time	Cost
CPU Utilization	0.210293	0.225902	0.25058	0.229698
Memory Utilization	0.225902	0.210293	0.25058	0.229698
Response Time	0.229698	0.229698	0.227378	0.222738
Cost	0.25058	0.25058	0.271462	0.227378

In the fourth step, we obtain the network relations map (NRM) matrix based on a threshold value (p), set to be 0.226 by consultation with the experts. This threshold value is the most appropriate value to represent the strong relationship of trying a value under or above this value. A value under 0.226 reflects a weak relationship between these criteria; thus, values below this value are set to zero. Table 6 presents the NRM matrix and Figure 5 displays the impact-diagraph map of the four criteria. In the pairwise comparison criteria step, the NRM matrix is used to cancel out the four criteria weights from the unweighted super matrix.

Table 6. NRM of the four criteria

	CPU Utilization	*Memory Utilization*	*Response Time*	*Cost*
CPU Utilization	*0*	*0*	*0.25058*	*0.229698*
Memory Utilization	*0*	*0*	*0.25058*	*0.229698*
Response Time	*0.229698*	*0.229698*	*0*	*0*
Cost	*0.25058*	*0.25058*	*0.271462*	*0*

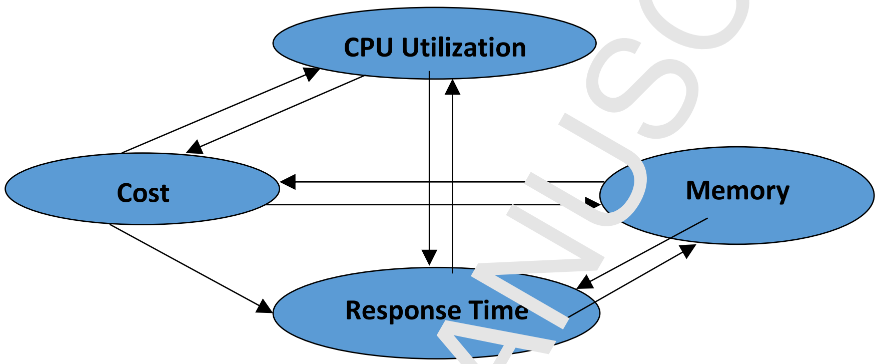

Figure 5. The impact-diagraph map of the four criteria

Lastly, utilizing the NRM for criteria, we compute the sum of indices in each row (D) to represent the degree of effect given by that criterion on other criteria in the NRM matrix. We also compute the sum of each column (R) to represent the degree of effect received by that criterion on other criteria in the NRM matrix. Using D and R, we calculate (D+R), which known as the prominence and represents the relative degree of importance for each criterion. If a specific criterion has a higher (D + R) value, then that criterion has more interaction with other criteria in the total relation matrix of the criteria. Moreover, we calculate (D-R), which allocates criteria in cause and effect groups. Thus, if the value of (D-R) is positive, then that specific criterion is a net causer. If the (D-R) value is negative, then that specific criterion is a net receiver. Table 7 indicates the values of (D+R) and (D-R). Using these values, a DEMATEL scatter graph is provided in Figure 6.

Table 7. The causal diagram for the four criteria

	D	R	D+R	D-R
CPU utilization	0.916473	0.916473	1.832947	0
Memory utilization	0.916473	0.916473	1.832947	0
Response time	0.909513	1	1.909513	-0.09049
Cost	1	0.909513	1.909513	0.090487

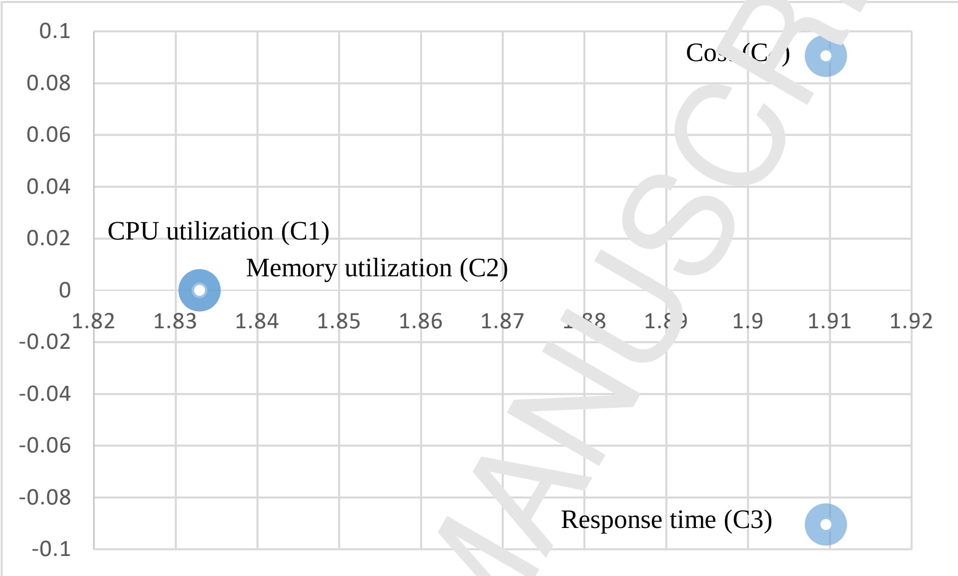

Figure 6. Scatter graph of DEMATEL for the used criteria

Based on the values of D in Table 7, cost has the most effect, CPU and memory utilization have the same effect, and response time has the least effect. Based on the values of R in the same table, response time reveals the greatest effect received by other criteria and cost reveals the least. Figure 6 evidences cost as the user criteria and response time as the receiver criteria.

4.3.2 *K*-means Algorithm for Cloud Provider Clustering

After discerning the interdependencies between cloud service provider criteria using the expert evaluated initial direct-relation matrix (M), we cluster providers based on the cloud service criteria collected in our dataset. We assume each provider's criteria values to be in a Gaussian distribution. The main clustering step objective is to join cloud providers with similar selected service criteria in order to reduce the number of evaluation matrices for candidate cloud provider selection, especially when there are many service providers. In this step, we only require a small number of evaluation matrices to correspond to the number of clusters. To cluster the cloud providers in the collected dataset, we use the *k*-means algorithm since it is a simple clustering method that yields meaningful results. The *k*-means clustering algorithm is implemented for a number of clusters, where *K* equals 5. First, the algorithm arbitrarily chooses the initial *K* cluster centers of the cloud providers. Second, it reassigns each cloud provider to the cluster wherein the cloud provider is most similar, based on the main cloud provider criteria value mean, and updates the cluster mean. The reassignment and update end when the cluster mean no longer changes. Euclidean distance is used as a measure for reassigning cloud providers to each cluster. Figure 7 visualizes the results of the *k*-means clustering method for dataset cloud providers. Moreover, using the four criteria, Table 8 offers the service provider clustering method results.

Table 8. Service providers (SP) in each cluster based on clustering method

Cluster 1	SP1	SP2	SP3	SP4	SP5	SP7	-
Cluster 2	SP1	SP8	SP9	SP10	SP11	SP13	-
Cluster 3	SP1	SP2	SP3	SP6	SP8	SP12	-
Cluster 4	SP1	SP2	SP3	SP5	SP6	SP12	-
Cluster 5	SP1	SP2	SP3	SP4	SP5	SP6	SP7

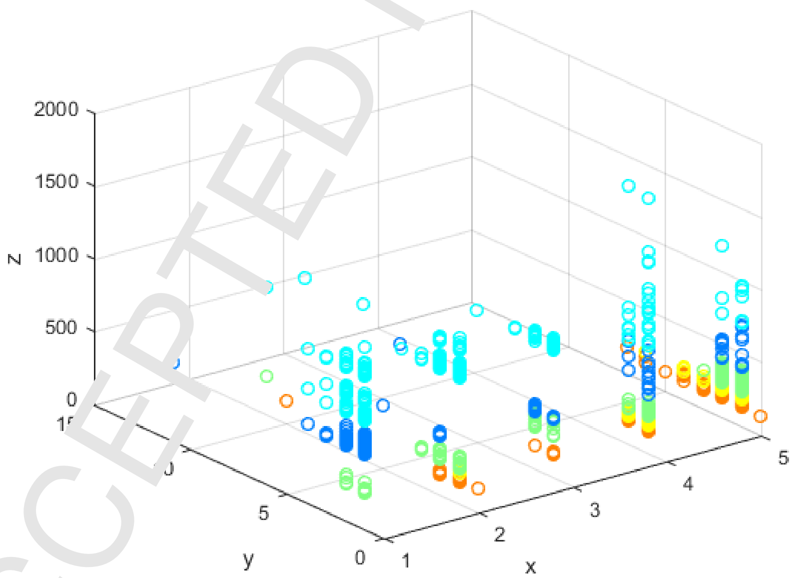

Figure 7. Service providers clustered using k-means algorithm

4.3.3 Pairwise Comparison of the Criteria Based on the Goal

After we define the selected criteria interdependencies and cluster cloud service providers, we utilize the ANP method to compute the criteria weight of each cluster, including the cloud service providers. Initially, the cloud provider experts evaluate the matrices of all criteria corresponding to the *K=5* clusters for pair-wise comparisons. The assessment value for each criterion is scaled from 1 to 9, thus representing criteria importance in a hierarchical manner. An assessment of 1 denotes equal importance, while an assessment of 9 indicates extreme importance of one criteria over another. When the weights of the pairwise comparisons are computed, the consistency ratio (CR) values are also computed to validate if the weights' suitability for entering the super matrix. Table 9 presents the pairwise comparison of the four criteria corresponding to each cluster goal. Additionally, the weights of service providers, with regard to the criteria of and between each cluster, are expressed as an unweighted super matrix. Tables 10, 13, 16, 19, and 22 present the values associated with the unweighted super matrix, M of all service providers in each cluster.

The unweighted super matrix of candidate service providers from all clusters is provided in Table 3.25. Because these unweighted super matrices include interactions between service providers and clusters, there are inner dependences among criteria. Thus, each cluster is weighted to a relative importance corresponding to the component in that row. The weights of "goal," ‘‘criteria," and ‘‘alternatives" for the "goal" and ‘‘criteria" columns are multiplied by 0.50. Tables 11, 14, 17, 20, and 23 offer the weighted super matrix, M^W for service providers in each cluster. Table 26 demonstrates the weighted super matrix of candidate service providers selected from all clusters. To capture the interactions and obtain a steady-state of outcomes, the weighted super matrices are raised to limiting powers to produce the limit super matrix, M^L. The limit super matrices are presented in Tables 12, 15, 18, 21, 24, and 27. The candidate service providers selected from cluster 1, cluster 2, cluster 3, cluster 4, and cluster 5 are SP4, SP8, SP12, SP5, and SP4, respectively. Furthermore, from Table 27 we noted the best cluster is cluster 1, which means that the selected service provider based on candidate service providers is (SP4).

Table 9. Pairwise comparison of the main criteria with respect to

With respect to Selecting service provider (SSP) goal

	C1	C2	C3	C4	W1
C1	1	4	0.2	0.333	0.154051
C2	0.25	1	0.25	0.2	0.062363
C3	5	4	1	0.17	0.265077
C4	3	5	6	1	0.518509

CR= 0.029321634 (desirable value to be less than 0.100)

With respect to CPU utilization (C1)

	C1	C2	C3	C4	W2
C1	1	6	0.14	0.17	0.143726
C2	0.17	1	0.25	0.2	0.059549
C3	7	4	1	0.17	0.247427
C4	6	5	6	1	0.549297

CR= 0.045291648 (desirable value to be less than 0.100)

With respect to Memory utilization (C2)

	C1	C2	C3	C4	W3
C1	1	1	0.1667	0.2	0.084666
C2	1	1	0.5	0.2	0.09937
C3	6	2	1	0.25	0.252936
C4	5	5	4	1	0.563027

CR= 0.00964 (desirable value to be less than 0.100)

With respect to Response time (C3)

	C1	C2	C3	C4	W4
C1	1	0.5	0.2	0.2	0.073012
C2	2	1	0.5	0.2	0.120106
C3	5	2	1	0.25	0.236716
C4	5	5	4	1	0.570166

CR= 0.00645 (desirable value to be less than 0.100)

With respect to Cost (C4)

	C1	C2	C3	C4	W5
C1	1	0.333	0.143	0.143	0.051498
C2	3	1	0.333	0.2	0.113713
C3	7	3	1	0.2	0.248591
C4	7	5	5	1	0.586198

CR= 0.01084 (desirable value to be less than 0.100)

Table 10. The unweighted super matrix, M for Cluster 1

		Goal	Criteria				Alternatives					
		SP	C1	C2	C3	C4	SP1	SP2	SP3	SP4	SP5	SP7
Goal	SP	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.154	0.000	0.000	0.073	0.051	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.062	0.000	0.000	0.120	0.114	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.265	0.247	0.253	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.519	0.549	0.563	0.570	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.100	0.180	0.171	0.108	1.000	0.000	0.000	0.000	0.000	0.000
	SP2	0.000	0.253	0.222	0.169	0.115	0.000	1.000	0.000	0.000	0.000	0.000
	SP3	0.000	0.160	0.188	0.154	0.168	0.000	0.000	1.000	0.000	0.000	0.000
	SP4	0.000	0.222	0.153	0.193	0.201	0.000	0.000	0.000	1.000	0.000	0.000
	SP5	0.000	0.116	0.118	0.160	0.174	0.000	0.000	0.000	0.000	1.000	0.000
	SP7	0.000	0.149	0.136	0.154	0.233	0.000	0.000	0.000	0.000	0.000	1.000

Table 11. The weighted super matrix, M^W for Cluster 1

		Goal	Criteria				Alternatives					
		SP	C1	C2	C3	C4	SP1	SP2	SP3	SP4	SP5	SP7
Goal	SP	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.077	0.000	0.000	0.037	0.026	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.031	0.000	0.000	0.060	0.057	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.133	0.124	0.126	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.259	0.275	0.282	0.285	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.050	0.090	0.085	0.054	1.000	0.000	0.000	0.000	0.000	0.000
	SP2	0.000	0.126	0.111	0.084	0.058	0.000	1.000	0.000	0.000	0.000	0.000
	SP3	0.000	0.080	0.094	0.077	0.084	0.000	0.000	1.000	0.000	0.000	0.000
	SP4	0.000	0.111	0.077	0.097	0.101	0.000	0.000	0.000	1.000	0.000	0.000
	SP5	0.000	0.058	0.059	0.080	0.087	0.000	0.000	0.000	0.000	1.000	0.000
	SP7	0.000	0.075	0.068	0.077	0.117	0.000	0.000	0.000	0.000	0.000	1.000

Table 12. The limit super matrix, M^L for Cluster 1

		Goal	Criteria				Alternatives					
		SP	C1	C2	C3	C4	SP1	SP2	SP3	SP4	SP5	SP7
Goal	SP	0.100	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.008	0.000	0.000	0.004	0.003	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.003	0.000	0.000	0.006	0.006	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.015	0.014	0.014	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.035	0.038	0.039	0.040	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.005	0.010	0.009	0.006	1.000	0.000	0.000	0.000	0.000	0.000
	SP2	0.000	0.014	0.013	0.009	0.006	0.000	1.000	0.000	0.000	0.000	0.000
	SP3	0.000	0.009	0.010	0.008	0.009	0.000	0.000	1.000	0.000	0.000	0.000
	SP4	0.000	0.013	0.008	0.011	0.011	0.000	0.000	0.000	1.000	0.000	0.000
	SP5	0.000	0.006	0.006	0.009	0.010	0.000	0.000	0.000	0.000	1.000	0.000
	SP7	0.000	0.008	0.007	0.008	0.013	0.000	0.000	0.000	0.000	0.000	1.000

Table 13. The unweighted super matrix, M for Cluster 2

		Goal	Criteria				Alternatives					
		SP	C1	C2	C3	C4	SP1	SP8	SP9	SP10	SP11	SP13
Goal	SP	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.154	0.000	0.000	0.073	0.051	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.062	0.000	0.000	0.120	0.114	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.265	0.247	0.253	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.519	0.549	0.563	0.570	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.133	0.169	0.09[illegible]	0.163	1.000	0.000	0.000	0.000	0.000	0.000
	SP8	0.000	0.169	0.262	0.274	0.190	0.000	1.000	0.000	0.000	0.000	0.000
	SP9	0.000	0.154	0.159	0.160	0.177	0.000	0.000	1.000	0.000	0.000	0.000
	SP10	0.000	0.169	0.196	0.18[illegible]	0.188	0.000	0.000	0.000	1.000	0.000	0.000
	SP11	0.000	0.154	0.082	0.161	0.117	0.000	0.000	0.000	0.000	1.000	0.000
	SP13	0.000	0.221	0.13[illegible]	0.130	0.165	0.000	0.000	0.000	0.000	0.000	1.000

Table 14. The weighted super matrix, M^W for Cluster 2

		Goal	Criteria				Alternatives					
		SP	C1	C2	C3	C4	SP1	SP8	SP9	SP10	SP11	SP13
Goal	SP	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.077	0.000	0.000	0.037	0.026	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.031	0.000	0.000	0.060	0.057	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.133	0.124	0.126	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.259	0.275	0.282	0.285	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.067	0.084	0.046	0.081	1.000	0.000	0.000	0.000	0.000	0.000
	SP8	0.000	0.084	0.131	0.137	0.095	0.000	1.000	0.000	0.000	0.000	0.000
	SP9	0.000	0.077	0.080	0.080	0.089	0.000	0.000	1.000	0.000	0.000	0.000
	SP10	0.000	0.084	0.098	0.092	0.094	0.000	0.000	0.000	1.000	0.000	0.000
	SP11	0.000	0.077	0.041	0.080	0.059	0.000	0.000	0.000	0.000	1.000	0.000
	SP13	0.000	0.110	0.067	0.065	0.082	0.000	0.000	0.000	0.000	0.000	1.000

Table 15. The limit super matrix, M^L for Cluster 2

		Goal	Criteria				Alternatives					
		SP	C1	C2	C3	C4	SP1	SP8	SP9	SP10	SP11	SP13
Goal	SP	0.100	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.008	0.000	0.000	0.004	0.003	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.003	0.000	0.000	0.006	0.006	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.015	0.014	0.014	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.035	0.038	0.039	0.040	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.007	0.009	0.005	0.009	1.000	0.000	0.000	0.000	0.000	0.000
	SP8	0.000	0.009	0.015	0.016	0.011	0.000	1.000	0.000	0.000	0.000	0.000
	SP9	0.000	0.008	0.009	0.009	0.010	0.000	0.000	1.000	0.000	0.000	0.000
	SP10	0.000	0.009	0.011	0.010	0.010	0.000	0.000	0.000	1.000	0.000	0.000
	SP11	0.000	0.008	0.004	0.009	0.006	0.000	0.000	0.000	0.000	1.000	0.000
	SP13	0.000	0.012	0.007	0.007	0.009	0.000	0.000	0.000	0.000	0.000	1.000

Table 16. The unweighted super matrix, M for Cluster 3

		Goal	Criteria				Alternatives					
		SP	C1	C2	C3	C4	SP1	SP2	SP3	SP6	SP8	SP12
Goal	SP	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.154	0.000	0.000	0.073	0.051	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.062	0.000	0.000	0.120	0.114	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.265	0.247	0.253	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.519	0.549	0.563	0.570	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.120	0.223	0.186	0.101	1.000	0.000	0.000	0.000	0.000	0.000
	SP2	0.000	0.170	0.133	0.219	0.179	0.000	1.000	0.000	0.000	0.000	0.000
	SP3	0.000	0.142	0.168	0.159	0.163	0.000	0.000	1.000	0.000	0.000	0.000
	SP6	0.000	0.208	0.156	0.155	0.180	0.000	0.000	0.000	1.000	0.000	0.000
	SP8	0.000	0.167	0.160	0.174	0.154	0.000	0.000	0.000	0.000	1.000	0.000
	SP12	0.000	0.193	0.160	0.107	0.224	0.000	0.000	0.000	0.000	0.000	1.000

Table 17. The weighted super matrix, M^W for Cluster 3

		Goal	Criteria				Alternatives					
		SP	C1	C2	C3	C3	SP1	SP2	SP3	SP6	SP8	SP12
Goal	SP	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.077	0.000	0.000	0.037	0.026	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.031	0.000	0.000	0.060	0.057	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.133	0.124	0.126	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.259	0.275	0.282	0.285	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.060	0.112	0.093	0.050	1.000	0.000	0.000	0.000	0.000	0.000
	SP2	0.000	0.085	0.066	0.110	0.089	0.000	1.000	0.000	0.000	0.000	0.000
	SP3	0.000	0.071	0.084	0.080	0.081	0.000	0.000	1.000	0.000	0.000	0.000
	SP6	0.000	0.104	0.078	0.077	0.090	0.000	0.000	0.000	1.000	0.000	0.000
	SP8	0.000	0.084	0.080	0.087	0.077	0.000	0.000	0.000	0.000	1.000	0.000
	SP12	0.000	0.096	0.080	0.053	0.112	0.000	0.000	0.000	0.000	0.000	1.000

Table 18. The limit super matrix, M^L for Cluster 3

		Goal	Criteria				Alternatives					
		SP	C1	C2	C3	C3	SP1	SP2	SP3	SP6	SP8	SP12
Goal	SP	0.100	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.008	0.000	0.000	0.004	0.003	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.003	0.000	0.000	0.006	0.006	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.015	0.014	0.014	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.035	0.038	0.039	0.040	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.006	0.013	0.010	0.005	1.000	0.000	0.000	0.000	0.000	0.000
	SP2	0.000	0.009	0.007	0.012	0.010	0.000	1.000	0.000	0.000	0.000	0.000
	SP3	0.000	0.008	0.009	0.009	0.009	0.000	0.000	1.000	0.000	0.000	0.000
	SP6	0.000	0.012	0.008	0.008	0.010	0.000	0.000	0.000	1.000	0.000	0.000
	SP8	0.000	0.009	0.009	0.010	0.008	0.000	0.000	0.000	0.000	1.000	0.000
	SP12	0.000	0.011	0.009	0.006	0.013	0.000	0.000	0.000	0.000	0.000	1.000

Table 19. The unweighted super matrix, M for Cluster 4

		Goal	Criteria				Alternatives					
		SP	C1	C2	C3	C3	SP1	SP2	SP3	SP5	SP6	SP12
Goal	SP	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.154	0.000	0.000	0.073	0.051	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.062	0.000	0.000	0.120	0.114	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.265	0.247	0.253	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.519	0.549	0.563	0.570	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.114	0.184	0.213	0.171	1.000	0.000	0.000	0.000	0.000	0.000
	SP2	0.000	0.215	0.162	0.090	0.186	0.000	1.000	0.000	0.000	0.000	0.000
	SP3	0.000	0.174	0.191	0.155	0.112	0.000	0.000	1.000	0.000	0.000	0.000
	SP5	0.000	0.158	0.158	0.199	0.209	0.000	0.000	0.000	1.000	0.000	0.000
	SP6	0.000	0.145	0.182	0.177	0.205	0.000	0.000	0.000	0.000	1.000	0.000
	SP12	0.000	0.193	0.123	0.166	0.118	0.000	0.000	0.000	0.000	0.000	1.000

Table 20. The weighted super matrix, M^W for Cluster 4

		Goal	Criteria				Alternatives					
		SP	C1	C2	C3	C3	SP1	SP2	SP3	SP5	SP6	SP12
Goal	SP	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.077	0.000	0.000	0.037	0.026	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.031	0.000	0.000	0.060	0.057	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.133	0.124	0.126	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.259	0.275	0.282	0.285	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.057	0.092	0.107	0.085	1.000	0.000	0.000	0.000	0.000	0.000
	SP2	0.000	0.108	0.081	0.045	0.093	0.000	1.000	0.000	0.000	0.000	0.000
	SP3	0.000	0.087	0.096	0.077	0.056	0.000	0.000	1.000	0.000	0.000	0.000
	SP5	0.000	0.079	0.079	0.099	0.104	0.000	0.000	0.000	1.000	0.000	0.000
	SP6	0.000	0.072	0.091	0.088	0.102	0.000	0.000	0.000	0.000	1.000	0.000
	SP12	0.000	0.097	0.062	0.083	0.059	0.000	0.000	0.000	0.000	0.000	1.000

Table 21. The limit super matrix, M^L for Cluster 4

		Goal	Criteria				Alternatives					
		SP	C1	C2	C3	C3	SP1	SP2	SP3	SP5	SP6	SP12
Goal	SP	0.100	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.008	0.000	0.000	0.004	0.003	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.003	0.000	0.000	0.006	0.006	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.015	0.014	0.014	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.035	0.038	0.039	0.040	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.006	0.010	0.012	0.009	1.000	0.000	0.000	0.000	0.000	0.000
	SP2	0.000	0.012	0.009	0.005	0.010	0.000	1.000	0.000	0.000	0.000	0.000
	SP3	0.000	0.010	0.011	0.008	0.006	0.000	0.000	1.000	0.000	0.000	0.000
	SP5	0.000	0.009	0.009	0.011	0.012	0.000	0.000	0.000	1.000	0.000	0.000
	SP6	0.000	0.008	0.010	0.010	0.011	0.000	0.000	0.000	0.000	1.000	0.000
	SP12	0.000	0.011	0.007	0.009	0.006	0.000	0.000	0.000	0.000	0.000	1.000

Table 22. The unweighted super matrix, M for Cluster 5

		Goal	Criteria				Alternatives						
		SP	C1	C2	C3	C3	SP1	SP2	SP3	SP4	SP5	SP6	SP7
Goal	SP	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.154	0.000	0.000	0.073	0.051	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.062	0.000	0.000	0.120	0.114	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.265	0.247	0.253	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.519	0.549	0.563	0.570	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.136	0.119	0.132	0.148	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	SP2	0.000	0.105	0.160	0.168	0.168	0.000	1.000	0.000	0.000	0.000	0.000	0.000
	SP3	0.000	0.162	0.166	0.143	0.158	0.000	0.000	1.000	0.000	0.000	0.000	0.000
	SP4	0.000	0.136	0.198	0.140	0.190	0.000	0.000	0.000	1.000	0.000	0.000	0.000
	SP5	0.000	0.135	0.101	0.104	0.099	0.000	0.000	0.000	0.000	1.000	0.000	0.000
	SP6	0.000	0.134	0.182	0.185	0.104	0.000	0.000	0.000	0.000	0.000	1.000	0.000
	SP7	0.000	0.193	0.074	0.128	0.133	0.000	0.000	0.000	0.000	0.000	0.000	1.000

Table 23. The weighted super matrix, M^W for Cluster 5

		Goal	Criteria				Alternatives						
		SP	C1	C2	C3	C3	SP1	SP2	SP3	SP4	SP5	SP6	SP7
Goal	SP	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.077	0.000	0.000	0.037	0.026	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.031	0.000	0.000	0.060	0.057	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.133	0.124	0.126	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.259	0.275	0.282	0.285	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.068	0.059	0.066	0.074	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	SP2	0.000	0.052	0.080	0.084	0.084	0.000	1.000	0.000	0.000	0.000	0.000	0.000
	SP3	0.000	0.081	0.083	0.071	0.079	0.000	0.000	1.000	0.000	0.000	0.000	0.000
	SP4	0.000	0.068	0.099	0.070	0.095	0.000	0.000	0.000	1.000	0.000	0.000	0.000
	SP5	0.000	0.068	0.051	0.052	0.050	0.000	0.000	0.000	0.000	1.000	0.000	0.000
	SP6	0.000	0.067	0.091	0.093	0.052	0.000	0.000	0.000	0.000	0.000	1.000	0.000
	SP7	0.000	0.096	0.037	0.064	0.067	0.000	0.000	0.000	0.000	0.000	0.000	1.000

Table 24. The limit super matrix, M^L for Cluster 5

		Goal	Criteria				Alternatives						
		SP	C1	C2	C3	C3	SP1	SP2	SP3	SP4	SP5	SP6	SP7
Goal	SP	0.100	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.008	0.000	0.000	0.004	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.003	0.000	0.000	0.006	0.006	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C3	0.015	0.014	0.014	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.035	0.038	0.039	0.040	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	SP1	0.000	0.007	0.006	0.007	0.008	1.000	0.000	0.000	0.000	0.000	0.000	0.000
	SP2	0.000	0.006	0.009	0.009	0.009	0.000	1.000	0.000	0.000	0.000	0.000	0.000
	SP3	0.000	0.009	0.009	0.008	0.009	0.000	0.000	1.000	0.000	0.000	0.000	0.000
	SP4	0.000	0.007	0.011	0.008	0.010	0.000	0.000	0.000	1.000	0.000	0.000	0.000
	SP5	0.000	0.007	0.005	0.005	0.005	0.000	0.000	0.000	0.000	1.000	0.000	0.000
	SP6	0.000	0.007	0.010	0.010	0.006	0.000	0.000	0.000	0.000	0.000	1.000	0.000
	SP7	0.000	0.011	0.004	0.007	0.007	0.000	0.000	0.000	0.000	0.000	0.000	1.000

Table 25. The unweighted super matrix, M for All Clusters

		Goal	Criteria				Alternatives				
		SP	C1	C2	C3	C3	CSPC1	CSPC2	CSPC3	CSPC4	CSPC5
Goal	SP	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.154	0.000	0.000	0.074	0.051	0.000	0.000	0.000	0.000	0.000
	C2	0.062	0.000	0.000	0.120	0.114	0.000	0.000	0.000	0.000	0.000
	C3	0.265	0.247	0.253	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.519	0.549	0.563	0.570	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	CSPC1	0.000	0.216	0.237	0.244	0.218	1.000	0.000	0.000	0.000	0.000
	CSPC2	0.000	0.172	0.203	0.178	0.194	0.000	1.000	0.000	0.000	0.000
	CSPC3	0.000	0.194	0.214	0.201	0.271	0.000	0.000	1.000	0.000	0.000
	CSPC4	0.000	0.193	0.153	0.220	0.155	0.000	0.000	0.000	1.000	0.000
	CSPC5	0.000	0.225	0.192	0.157	0.162	0.000	0.000	0.000	0.000	1.000

Table 26. The weighted super matrix, M^W for All Clusters

		Goal	Criteria				Alternatives				
		SP	C1	C2	C3	C3	CSPC1	CSPC2	CSPC3	CSPC4	CSPC5
Goal	SP	0.500	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.077	0.000	0.000	0.037	0.026	0.000	0.000	0.000	0.000	0.000
	C2	0.031	0.000	0.000	0.060	0.057	0.000	0.000	0.000	0.000	0.000
	C3	0.133	0.124	0.126	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.259	0.275	0.282	0.285	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	CSPC1	0.000	0.108	0.119	0.122	0.109	1.000	0.000	0.000	0.000	0.000
	CSPC2	0.000	0.086	0.101	0.089	0.097	0.000	1.000	0.000	0.000	0.000
	CSPC3	0.000	0.097	0.107	0.101	0.135	0.000	0.000	1.000	0.000	0.000
	CSPC4	0.000	0.097	0.077	0.110	0.078	0.000	0.000	0.000	1.000	0.000
	CSPC5	0.000	0.112	0.096	0.078	0.081	0.000	0.000	0.000	0.000	1.000

Table 27. The limit super matrix, M^L for All Clusters

		Goal	Criteria				Alternatives				
		SP	C1	C2	C3	C3	CSPC1	CSPC2	CSPC3	CSPC4	CSPC5
Goal	SP	0.100	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Criteria	C1	0.008	0.000	0.000	0.004	0.003	0.000	0.000	0.000	0.000	0.000
	C2	0.003	0.000	0.000	0.006	0.006	0.000	0.000	0.000	0.000	0.000
	C3	0.015	0.014	0.014	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.035	0.038	0.039	0.040	0.000	0.000	0.000	0.000	0.000	0.000
Alternatives	CSPC1	0.000	0.012	0.013	0.014	0.012	1.000	0.000	0.000	0.000	0.000
	CSPC2	0.000	0.009	0.011	0.010	0.011	0.000	1.000	0.000	0.000	0.000
	CSPC3	0.000	0.011	0.012	0.011	0.016	0.000	0.000	1.000	0.000	0.000
	CSPC4	0.000	0.011	0.008	0.012	0.008	0.000	0.000	0.000	1.000	0.000
	CSPC5	0.000	0.013	0.011	0.009	0.009	0.000	0.000	0.000	0.000	1.000

4.4 Discussion

This work introduced the study results of applying the *k*-means algorithm together with the DEMATEL and ANP methods to form a hybrid method, KD-ANP. This hybrid method is used for selecting the appropriate cloud service provider to meet customer requirements. Indeed, appropriate provider selection is a primary step in enhancing an organization's efficiency and performance. Our study focuses on four criteria related to appropriate cloud service provider selection: CPU utilization, memory utilization, response time, and cost. The proposed KD-ANP method aims to make multi-criteria decisions for considering interdependencies and relations between criteria. In fact, the proposed KD-ANP has a competence that distinguishes it from other published approaches. After clustering cloud service providers using the *k*-means algorithm, KD-ANP considers current organization workloads and assigns them different weights based on a set of criteria. Cloud service provider clustering is critical for grouping service providers with similar features and reducing the number of evaluation matrices used by the DEMATEL and ANP methods. A MATLAB simulation evaluated the proposed method using a collected dataset. The evaluation results indicates how MCDM provides an accurate and efficient method for appropriate service provider selection.

In the DEMATEL method, cloud experts give an evaluation grade, between 0 and 4, representing the degree of affects between the selected criteria. An evaluation grade of

0 denotes “No influence,” 1 equals “Low influence,” 2 for “Medium influence,” 3 reveals “High influence,” and 4 shows “Very high influence.” The evaluation matrix is known as the initial direct-relation matrix. After applying the DEMATEL method, D, R, D + R, and D - R values are computed, as listed in Table 7. The interrelations between criteria are presented in Figure 5. Based on the values of D, cost has the most effect whereas CPU and memory utilization have the same effect. Response time has least effect. Based on the values of R, response time has the greatest effect received by other criteria, and cost has the least effect received from other criteria. As depicted in Figure 6, cost is the cause criteria and response time is the effect criteria.

When the ANP method is used to compute the weights of the pairwise comparisons, CR values are also computed and are always less than 0.100. The latter computation proves the weight validation for entering the super matrices. Using the super matrices, the unweighted super matrix of all candidate service providers in the clusters is also computed. Finally, the weighted super matrices are raised to limiting powers for producing the limit super matrices. In our study, the cluster number of the *k*-means algorithm is fixed to 5. Therefore, the candidate service providers selected from cluster 1, cluster 2, cluster 3, cluster 4, and cluster 5 are SP4, SP8, SP12, SP5, and SP4, respectively, while the best cluster from Table 27 is cluster 1, the selected service provider from candidate service providers is (SP4).

4.5 Comparisons with Previous Works

Selection of cloud services is an important task for different IT needs of individuals, organizations and companies. A large number of cloud providers offer a diverse set of services in clouds environment with different SLAs and QoS. The decision making to select the cloud services based on a set of criteria is a challenge for the upper management since it needs operational and financial views, determining the performance of the organizations in the long-term. Consequently, selecting a service provider is a multi-criteria decision problem. These criteria and sub-criteria may be correlated or relevant and have some interdependencies.

There are few methods of multi criteria decision making have been proposed to select the cloud services or alternatives, such as the previous works in [3,5,7,9,34]. In this section, we compare the proposed method of multi criteria decision making with previous works in [3, 34, 35, 36, 37] that used the ANP or ANP and DEMATEL methods for selecting cloud services. However, one of the most important differences between the proposed method and these works is the number of evaluation matrices of the pre-defined criteria used to compare a large number of cloud providers and determine relative impacts and strengths of them. Therefore, the comparison will be based on the number of matrices required for evaluation versus the number of service providers or alternatives and criteria. Figure 7 shows how the proposed method reduces the number of evaluation matrices used for pairwise comparison compared to the previous works in [3, 34].

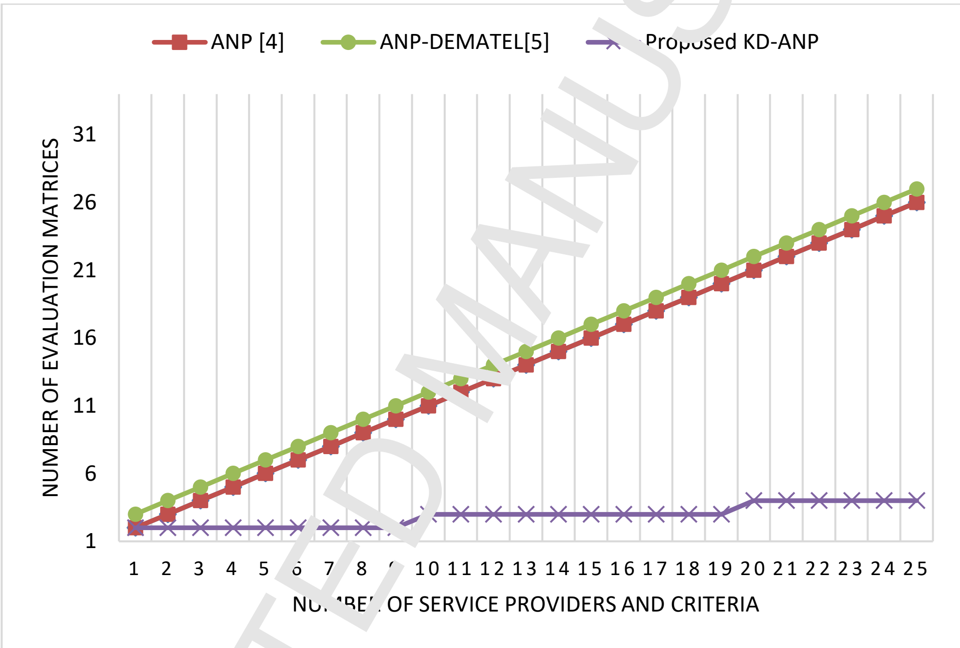

Figure 8. Proposed KD-ANP method against some other methods for cloud service selection.

The proposed method clusters the service providers according to the similarity of the criteria used using K-means algorithm. Thus, the number of evaluation matrices of the proposed method is small and increases gradually depending on the number of clusters as shown in the Figure 8. While, the number of evaluation matrices of the methods in [3, 34] is increased exponentially with increasing the number of service providers or alternatives and criteria

5. Conclusions

Our proposed work provides a simple method to select an appropriate cloud service provider that meets consumer requirements. In this paper, we proposed a method for the consumer to identify workload and predict required performance and configurations from historical data. We developed a hybrid MCDM method, KD-ANP, for cloud service selection using *k*-means, DEMATEL and ANP. By implementing the KD-ANP method, consumers can select the best provider and consider the interdependencies and relations between criteria. Moreover, by clustering providers using the *k*-means algorithm, the consumer can assign different weight and importance to the criteria. We evaluated KD-ANP using the performance prediction model data proposed in [1] In future, we plan to define more criteria as well as to find out how to automate the expert's preferences using machine learning.

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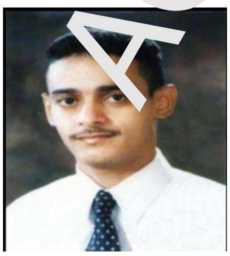

Abdu Gumaei

Highlights

* A hybrid MCDM method is developed for cloud service selection from Smart data

* A k-means clustering is used to consolidate cloud service providers with similar features

* Applied MCDM methods using DEMATEL-ANP to rank clusters and make a final decision