Int. j. inf. tecnol. (August 2021) 13(4):1417–1422
https://doi.org/10.1007/s41870-021-00716-9

ORIGINAL RESEARCH

A hybrid multi-criteria decision making algorithm for cloud service selection

Munmun Saha[1] · Sanjaya Kumar Panda[2] · Suvasini Panigrahi[1]

Received: 27 November 2020 / Accepted: 20 May 2021 / Published online: 5 July 2021

Abstract In recent years, cloud computing is becoming an attractive research topic for its emerging issues and challenges. Not only in research but also the enterprises are rapidly adopting cloud computing because of its numerous profitable services. Cloud computing provides a variety of quality of services (QoSs) and allows its users to access these services in the form of infrastructure, platform and software on a subscription basis. However, due to its flexible nature and huge benefits, the demand for cloud computing is rising day by day. As a circumstance, many cloud service providers (CSPs) have been providing services in the cloud market. Therefore, it becomes significantly cumbersome for cloud users to select an appropriate CSP, especially considering various QoS criteria. This paper presents a hybrid multi-criteria decision-making (H-MCDM) algorithm to find a solution by considering different conflicting QoS criteria. The proposed algorithm takes advantage of two well-known MCDM algorithms, namely analytic network process (ANP) and VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), to select the best CSP or alternative. Here, ANP is used to categorize the criteria into subnets and finds the local rank of the CSPs in each subnet, followed by VIKOR, to find the global rank of the CSPs. H-MCDM considers both beneficial and non-beneficial criteria and finds the CSP that holds the maximum and minimum values of these criteria, respectively. We demonstrate the performance of H-MCDM using a real-life test case (case study) and compare the results to show the efficacy. Finally, we perform a sensitivity analysis to show the robustness and stability of our algorithm.

Keywords Cloud computing · Cloud service provider · Multi-criteria decision making · Service selection · Quality of service

✉ Sanjaya Kumar Panda
sanjaya@nitw.ac.in

Munmun Saha
munmunsas@gmail.com

Suvasini Panigrahi
suvasini26@gmail.com

[1] Department of Computer Science and Engineering, Veer Surendra Sai University of Technology Burla, Burla 768018, India

[2] Department of Computer Science and Engineering, National Institute of Technology Warangal, Warangal 506004, India

1 Introduction

Cloud computing is now considered as one of the leading technologies among all the emerging technologies [1–5]. It has gained much focus among the researchers due to its current issues and challenges [2, 6]. It has also gained tremendous popularity among enterprises due to its flexibility, on-demand services and cost-cutting solutions. The adoption of cloud computing is rapidly increasing, which triggers the CSPs to satisfy the QoS requirements without fail [7]. On the other hand, in order to sustain in the cloud market, CSPs are improving their services and making the services hassle-free [8, 9]. These CSPs allow their users to access the services, mainly in the form of infrastructure, platform and software, on a subscription basis [4, 10, 11].

Many CSPs have been providing similar services in the cloud market [12]. Therefore, it is difficult for cloud users to select an appropriate CSP in order to fulfill their QoS requirements [10, 11]. We refer to this as a cloud service selection problem. One of the possible reasons behind this

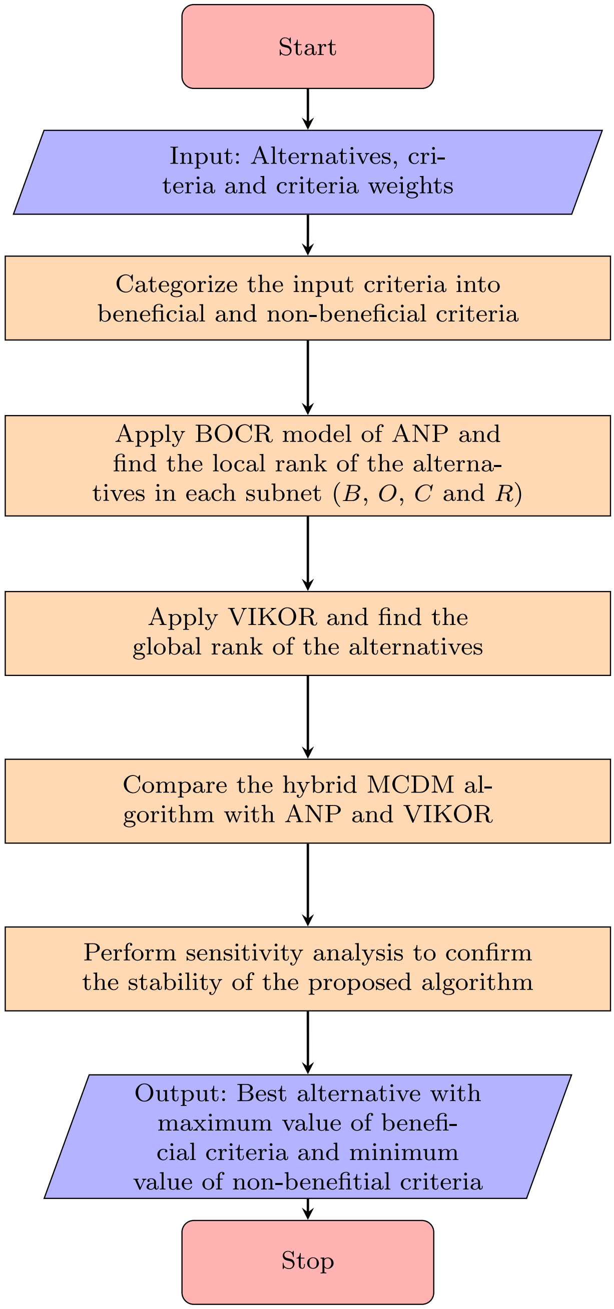

Fig. 1 Flowchart for hybrid MCDM algorithm.

is the lack of expertise of the cloud users. It may lead to vendor lock-in problems as well [5]. The cloud service selection problem can be visualized in the form of selecting the best alternative among a set of alternatives with respect to a set of common criteria. In this context, MCDM algorithms, such as the weighted sum (product) method (WSM (WPM)), preference ranking organization method for enrichment evaluations (PROMETHEE), VIKOR, multi-objective optimization on the basis of ration analysis (MOORA), technique for order of preference by similarity to ideal solution (TOPSIS), graph theory matrix approach (GTMA), analytic hierarchy process (AHP), ANP and many more, can be applied to find the possible solutions [1, 12–19]. Each MCDM algorithm has its own pros and cons. However, ANP and VIKOR are the two well-known MCDM algorithms.

In this paper, we address the cloud service selection problem and propose an algorithm, called H-MCDM, to solve the cloud selection problem by considering different conflicting QoS criteria. The proposed algorithm considers both beneficial and non-beneficial criteria, and performs a two-phase process. In the first phase, the criteria are divided into four subnets, namely benefit (B), opportunities (O), cost (C) and risk (R) and it finds the local rank of the CSPs using the ANP algorithm. In the second phase, it finds the global rank of the CSPs using the VIKOR algorithm. Alternatively, H-MCDM takes advantage of ANP and VIKOR to determine the best CSP. Note that the best CSP holds the maximum value of the beneficial criteria and the minimum value of the non-beneficial criteria. The proposed algorithm is demonstrated using a real-life test case or case study, as given in [1] and thoroughly analyzed the criteria of the alternatives. The solution of the test case is compared with ANP and VIKOR, individually, in order to show the efficacy of the proposed algorithm. At last, we perform a sensitivity analysis to check the robustness and stability of the proposed algorithm. The main contributions of this paper are as follows.

- Development of a hybrid MCDM algorithm to select the best CSP
- Determine the global rank of the CSPs based on the values that determine the local rank
- Simulation of the proposed algorithm and compare the result with the ANP and VIKOR algorithms
- Perform the sensitivity analysis to show the robustness and stability

The rest of the paper is structured as follows. Section 2 discusses the related work. Section 3 presents the proposed algorithm and its analysis. Section 4 illustrates the proposed algorithm using a real-life test case and shows the comparison of the proposed algorithm with other algorithms. Finally, Sect. 5 concludes the paper.

2 Related Work

Many MCDM algorithms have been developed for cloud service selection problem [1, 13–16, 18, 20–22]. However, these algorithms have their pros, cons and applicability. Garg et al. [1] have introduced a framework, called service measurement index (SMI) cloud, to rank the cloud services. They have used the AHP algorithm to assess the performance of cloud services by incorporating QoS

Table 1 A real-life test case [1].

Cluster	Control criteria	Level criteria	Amazon EC2	Windows Azure	Rackspace
Benefits	Accountability		4	8	4
	Agility	CPU	9.6	12.8	8.8
		Memory	15	14	15
		Disk	1690	2040	630
		Time	80–120	520–780	20–200
	Security		4	8	4
	Performance	Range	80–120	520–780	20–200
		Average Value	100	600	30
Opportunities	Availability		99.95%	99.99%	100%
	Stability	Upload Time	13.6	15	21
		CPU	17.9	16	23
		Memory	7	12	5
	Serviceability	Free Support	0.33	0.33	0.33
		Type of Support	24/7, Diagnostic Tools, Phone, Urgent Response	24/7, Diagnostic Tools, Phone, Urgent Response	24/7, Diagnostic Tools, Phone, Urgent Response
Cost	VM		$0.68	$0.96	$0.96
	Data		21	25	26
	Storage		12	15	15
Risk	Compliance		5	7	3
	Human Resource (HR)		5	6	5
	Provider		5	9	5

criteria. However, AHP considers each criterion as independent of others. Wang et al. [17] have proposed a linguistic multi-criteria group decision-making method by introducing various operators. Kumar et al. [21] have applied TOPSIS to select the best CSP. However, they have not considered the QoS criteria in terms of beneficial and non-beneficial criteria. Liu et al. [22] have considered quantitative and qualitative attributes, and provided a tool to decide an appropriate cloud vendor based on the needs of the firms. . Jatoth et al. [13] have presented a hybrid MCDM algorithm by combining extended Grey technique for order of preference by similarity to ideal solution and AHP. They have developed a framework, called SELCLOUD, which considers both functional and non-functional requirements. They have shown the performance using sensitivity analysis. Tapoglou et al. [18] have designed a framework to allocate the tasks to the manufacturing equipment based on availability, cost and capability. However, the process of selection relies on the latest information. Kheybari et al. [14] have performed a review on ANP. They have collected 456 papers and categorized them in terms of nine management applications, namely business, energy, environment, human resource, logistics, manufacturing, tourism, water, and others. They have explained the step by step process of ANP in four steps, namely model and network structure, pairwise comparison matrix and priority vectors, super matrix and weighted super matrix, and selection. Here, ANP finds the relative importance of the criteria. The main problem with ANP is that the size of super matrices depends on the number of criteria. Therefore, it is too complex when the criteria are more. Alternatively, it is sensitive to the number of criteria. Gao et al. [15] have used VIKOR by considering some new criteria, namely service year and environment, average daily traffic (ADT), and the truck's ADT. They have used VIKOR to find the solution close to the ideal solution. The problem with VIKOR is the linear normalization process. In this paper, the proposed algorithm determines the local and global rank of the alternatives using ANP and VIKOR algorithms. It considers two beneficial criteria, namely benefits and opportunities, and two non-beneficial criteria, namely cost and risk, and performs the analysis at a glance. The result shows the efficacy of the proposed algorithm in comparison to ANP and VIKOR.

Table 2 Subnet under benefits: limit matrix

Cluster node labels	Alternatives			Criteria				Goal
	Amazon EC2	Windows Azure	Rackspace	Accountability	Agility	Security	Performance	Benefits
Alternatives								
Amazon EC2	0.09151	0.09151	0.09151	0.09151	0.09151	0.09151	0.09151	0.09151
Windows Azure	0.23765	0.23765	0.23765	0.23765	0.23765	0.23765	0.23765	0.23765
Rackspace	0.08267	0.08267	0.08267	0.08267	0.08267	0.08267	0.08267	0.08267
Criteria								
Accountability	0.12222	0.12222	0.12222	0.12222	0.12222	0.12222	0.12222	0.12222
Agility	0.06382	0.06382	0.06382	0.06382	0.06382	0.06382	0.06382	0.06382
Security	0.11327	0.11327	0.11327	0.11327	0.11327	0.11327	0.11327	0.11327
Performance	0.11252	0.11252	0.11252	0.11252	0.11252	0.11252	0.11252	0.11252
Goal								
Benefits	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Table 3 Subnet under opportunities: limit matrix

Cluster node labels	Alternatives			Criteria			Goal
	Amazon EC2	Windows Azure	Rackspace	Adaptability	Flexibility	Serviceability	Opportunities
Alternatives							
Amazon EC2	0.12101	0.12101	0.12101	0.12101	0.12101	0.12101	0.12101
Windows Azure	0.12921	0.12921	0.12921	0.12921	0.12921	0.12921	0.12921
Rackspace	0.12729	0.12729	0.12729	0.12729	0.12729	0.12729	0.12729
Criteria							
Adaptability	0.13254	0.13254	0.13254	0.13254	0.13254	0.13254	0.13254
Flexibility	0.12086	0.12086	0.12086	0.12086	0.12086	0.12086	0.12086
Serviceability	0.12411	0.12411	0.12411	0.12411	0.12411	0.12411	0.12411
Goal							
Opportunities	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000

Table 4 Summary of subnets

Sl. No.	Alternatives	Benefits	Opportunities	Cost	Risk
1	Amazon EC2	0.09151	0.12101	0.14077	0.14962
2	Windows Azure	0.23765	0.12921	0.17815	0.21917
3	Rackspace	0.08267	0.12729	0.18108	0.13121

3 Proposed algorithm

The proposed algorithm, H-MCDM, is a hybrid algorithm to select the best CSP among a set of CSPs. It performs a two-phase process. The first phase considers the values of criteria with respect to the CSPs and determines the local rank of the CSPs using the ANP algorithm. The second phase considers the result of the first phase to determine the global rank of the CSPs using the VIKOR algorithm. The pseudocode for the proposed algorithm is shown in Algorithm 1 and the flow chart for the proposed algorithm is shown in Fig. 1. It takes a set of alternatives, a set of criteria and their weights, and produces the best CSP by considering both beneficial and non-beneficial criteria. Here, the beneficial criteria aim to achieve the maximum value, whereas the non-beneficial criteria aim to achieve the minimum value.

The detailed process is described as follows. Firstly, the proposed algorithm categorizes the criteria into beneficial and non-beneficial criteria. For instance, *B* and *O* are categorized as beneficial criteria, and *C* and *R* are categorized as non-beneficial criteria. Then the BOCR model of ANP is

Table 5 Simulation result of the proposed algorithm

Sl. No.	Alternatives	Combined Weight	Rank
1	Amazon EC2 (A1)	0	1
2	Windows Azure (A2)	1	3
3	Rackspace (A3)	0.5574	2

applied to these beneficial and non-beneficial criteria. Subsequently, the local rank of the alternatives is determined in each subnet with respect to *B*, *O*, *C* and *R*, respectively. Note that the local rank of the alternatives may be different with respect to subnets. Once the local rank is determined, the proposed algorithm applies VIKOR by combining the values of the alternatives of all the subents. Lastly, the global rank of the alternatives is determined. For the sake of easy understanding and completeness of this paper, the pseudocode for ANP and VIKOR is shown in Algorithm 2 and 3, respectively.

4 Case study and simulation results

We consider a real-life test case [1], as shown in Table 1. Here, we assume four criteria, namely benefits, opportunities, cost and risk, respectively, and three CSPs, namely Amazon EC2, Windows Azure and Rackspace. The weights of criteria are assumed as equal and they are equally divided among the control criteria. Similarly, the weights of control criteria are equally divided among the level criteria, if applicable, for the simplicity of illustration.

Algorithm 1 Pseudocode for hybrid MCDM algorithm

Input: Alternatives, criteria and criteria weights
Output: Select a best alternative that holds maximum value of beneficial criteria and minimum value of non-beneficial criteria

1: Categorize the input criteria into beneficial and non-beneficial criteria.
2: Apply BOCR model of ANP on the values of beneficial and non-beneficial criteria with respect to each alternative.
3: Find the local rank of the alternatives in each subnet, namely B, O, C and R from the limit matrix.
4: Apply VIKOR algorithm on the values of the alternatives by combining all the subnets.
5: Find the global rank of the alternatives.

Algorithm 2 Pseudocode for ANP

Input: Alternatives, criteria and criteria weights
Output: Local rank of the alternatives in each subnet or individual judgment of the alternatives

1: Design subnets under B, O, C and R by taking values of criteria with respect to alternatives.
2: Perform pairwise comparison using Saaty's fundamental scale and determine comparison matrix for each element of the subnet.
3: Calculate the relative priorities of the elements by calculating the eigen vector of the comparison matrix.
4: Construct super matrix for each subnet by entering the relative priorities of the elements.
5: Compute limit matrix by raising the super matrix with k^{th} power.
6: Obtain the relative value of each alternative from the respective limit matrix and find the local rank of the alternatives.

In the simulation process, we use super decision software version 2.10 [23], which is running on Windows 7, 64-bit operating system with Intel(R) Core(TM) *i*3-2330M CPU @ 2.20 GHz 2.20 GHz processor and 4 GB installed memory for the first phase of the proposed algorithm. However, the simulation is independent of the system configuration, but it is limited to Windows and Mac operating systems. In the super decision software, we consider goal, *B*, *O*, *C* and *R* as cluster and connect goal cluster with *B*, *O*, *C* and *R* clusters. Then we create subnets under clusters *B*, *O*, *C* and *R*, and add control and level criteria, followed by, the alternatives. Subsequently, we enter the values of criteria with respect to alternatives in the form of a pairwise matrix. Then we generate the limit matrices with respect to clusters, as shown in Tables 2 and

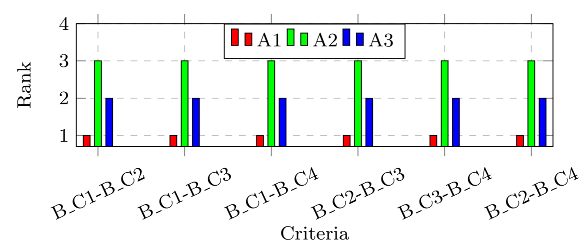

Fig. 2 Rank comparison under benefits

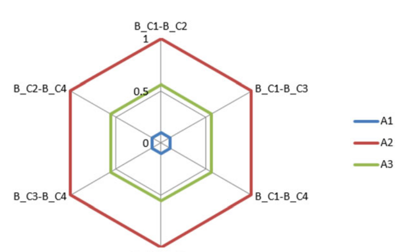

Fig. 3 Sensitivity analysis for benefits

3, respectively. The summary of subnets is shown in Table 4. Note that the local rank of the alternatives is shown in this table. This summary is given as input to the second phase of the proposed algorithm. For this, we use MATLAB R2015b to simulate this phase.

The combined weight of the alternatives are 0, 1 and 0.5574, respectively, as depicted in Table 5. It shows that Amazon EC2 > Rackspace > Windows Azure. On the other hand, in the case of ANP (VIKOR), the relative value (combined weight) of the alternatives are 0.1248, 0.1244 and 0.1256 (0.2889, 0 and 1), respectively. It shows that Rackspace > Amazon EC2 > Windows Azure (Windows Azure > Amazon EC2 > Rackspace). From the comparison, it is seen that H-MCDM provides a better solution without compromising cost and risk. We have performed the rank comparison under B and sensitivity analysis of B result, as shown in Figs. 2 and 3, respectively. Other comparisons and analyses are not shown due to space limitations. We have found that there is no variation in the result. Therefore, we conclude that the proposed algorithm is robust and stable.

5 Conclusion

In this paper, we have proposed an algorithm, H-MCDM, to find the best CSP among a set of CSPs. The proposed algorithm undergoes a two-phase process. In the first phase, it determines the local rank of the CSPs using ANP. In the second phase, it determines the global rank of the CSPs using VIKOR. The proposed algorithm has demonstrated using a real-life test case and compared it to show its efficacy. We have performed a sensitivity analysis to show the robustness and stability of the proposed algorithm. The results show that Amazon EC2 outperforms than other CSPs. In our future work, we will show the performance of the proposed algorithm using other real-life test cases.

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