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An Integrated MCDM Approach for Cloud Service Selection Based on TOPSIS and BWM

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ABSTRACT Cloud Computing (CC) has become increasingly popular since it provides a wide variety of customized and reliable computational services. With the rapid growth of this technology, more and more IT services providers compete to offer high-quality and cost-effective cloud services that best fulfill their customers' needs. Given the vast diversity of these offers, the choice of the most appropriate Cloud Service Provider (CSP) became a dilemma that confuses most cloud customers. Many diverged criteria have to be considered to precisely evaluate services offered by several CSPs, some of these criteria cannot be quantified easily such as usability and security. The selection of the best CSP is thus a complex Multi-Criteria Decision Making (MCDM) problem that needs to be addressed efficiently. Previous studies of this problem employed MCDM methods that are either unfeasible when it is difficult or meaningless to quantify alternatives over criteria or computationally expensive and inconsistent when relative preferences of alternatives and criteria are used instead. In this paper, we propose a novel MCDM approach that is feasible, efficient and consistent using relative preferences of criteria and alternatives. The proposed approach incorporates Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and the Best Worst Method (BWM) to rank CSPs using evaluation criteria characterizing their services. The integrated approach has been tested and validated through a use-case scenario which demonstrates its effectiveness and correctness. We have also compared the proposed approach to the most commonly used MCDM approach, Analytical Hierarchical Process (AHP). The results clearly show that the proposed approach outperforms AHP in terms of computational complexity and consistency; hence, it is more efficient and reliable than AHP.

INDEX TERMS Cloud computing (CC), cloud service providers (CSPs), multiple-criteria decision-making (MCDM), best worst method (BWM), technique for order of preference by similarity to ideal solution (TOPSIS), analytical hierarchical process (AHP).

I. INTRODUCTION

Cloud Computing (CC) has become a promising choice for businesses to replace the on-premise IT infrastructure. It has changed our understanding of how to procure computing resources with high versatility, availability and minimum management effort [1]. As a result, companies can now concentrate on their core functions leaving Cloud Service Providers (CSPs) to handle their computing assets. CSPs are vendors who lease to their customers different types of services (e.g., IaaS, PaaS, SaaS) that are dynamically provisioned based on customer's demand in a pay-as-you-go basis. The relationship between the customers and CSPs is organized according to a certain contract called Service Level Agreement (SLA) [2], [3].

Due to the significant benefits offered by CC to businesses including economy of scale, investments in this technology are tremendously increasing. As a result, the number of both cloud services and CSPs who offer these services has increasingly grown [4]. Large IT companies such as Google, Microsoft, and Amazon are now competing to offer their customers reliable and cost-effective services that best fulfill their requirements. This healthy competition results in the flourishment of CC technology and prompts many IT companies to improve their Quality of Service (QoS). Each CSP offers similar services at different prices and quality levels with different set of features. While one provider might be cheap for storage services, it may be expensive

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for computation. Given this diversity of cloud services offerings, an important challenge for customers is how to select the CSP that best satisfies their requirements. This is essential to ensure future performance and maintain compliance with laws, policies, and rules [5], [6]. On the other hand, choosing the wrong CSP may lead to failure in future services delivery, compromised data confidentiality or integrity, and non-compliance for use of clouds for data storage.

Cloud service selection is typically the process of finding the most appropriate CSP by matching user requirements with the features of the available cloud services provided by the various CSPs [7]. The increasing number of CSPs together with the diverse types of service they offer on a widely varying pricing and quality schemes have led to complexities in comparing different CSPs and selecting the most appropriate one given the user preferences [8]. One example that illustrates this problem is Equinix [9], a cloud broker architecture with over 500 registered CSPs, each offering various types of cloud services, Amazon alone provides over 70 [7]. In addition, consideration must be given to a broad variety of selection criteria in order to choose the most appropriate CSP. For example, QoS criteria such as performance or reliability are essential to specify CSP characteristics. Security and privacy attributes of the services are of utmost importance for cloud customers as well. Some selection criteria are not clear to the customer, for example, CSPs show little or no transparency on how cloud resources are accessed and who access them. Others are not easy to quantify due to the nature of the cloud such as usability and security [5]. In addition, there may be trade-offs between many of these criteria such as performance and price. In order to select the CSP that best fit user preferences, a wide variety of divergent evaluation criteria that characterize several cloud services offered by many CSPs must be considered. Therefore, the selection of the right CSP is a complex Multi-Criteria Decision Making (MCDM) problem where several alternatives have to be evaluated and ranked via multiple criteria given particular user preferences (i.e., relative importance of criteria) [5], [6], [10].

Previous studies on this problem have employed MCDM methods that are either unfeasible when it is difficult or meaningless to quantify alternatives with respect to criteria (i.e., criteria cannot be quantified easily) or computationally expensive and inconsistent if relative preferences of alternatives and criteria are used instead. Thus, creating a new approach that can solve this problem more efficiently and overcome the inconsistency that characterizes other approaches became crucial. In this paper, we propose a novel MCDM approach that is feasible when scores of alternatives over criteria are not available, computationally efficient, and consistent using relative preferences of criteria and alternatives. The proposed approach integrates Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and the Best Worst Method (BWM) to rank available CSPs using evaluation criteria that characterize the services they offer. Hence, it enables customers to select the CSP that best fits their requirements. The integrated approach has been validated through a use-case scenario and compared to the most popular MCDM approach (i.e., AHP). The results clearly showed that the proposed approach outperforms AHP in terms of computational complexity and consistency; therefore, it is more efficient and more reliable than AHP.

The rest of this paper is organized as follows: in section 2, we give essential background on CC service models and MCDM methods; and in section 3, we review related work. In section 4, we describe TOPSIS method; and in section 5, we present the BWM. Section 6 describes our proposed integrated MCDM approach. In section 7, we validate our approach through a use-case scenario. In section 8, we empirically evaluate our proposed approach and compare it to AHP and discuss the results. Finally, in section 9, we give our conclusions and future work.

II. BACKGROUND

A. CLOUD SERVICES DELIVERY MODELS

CSPs deliver mainly three types of service to their customers, Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS) [2]–[4], [10]–[12]. Still many service models are available as per their functionality and service providing capabilities, which have led to the creation of Anything-as-a–Service (XaaS) delivery models. In this section, we discuss the different types of service models shown Fig. 1.

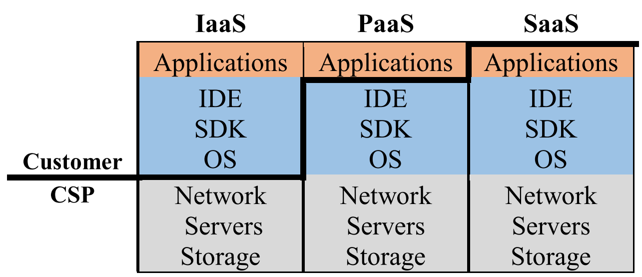

FIGURE 1. Cloud service stack.

1) INFRASTRUCTURE-AS-A-SERVICE (IaaS)

In IaaS, sometimes called Hardware-as-a-Service, a CSP supplies hardware or physical resources such as servers, storage, and network as demanded by the customers. IaaS utilizes virtualization technology to create virtual instance of physical resources such as virtual machines, storage capacity, and network bandwidth. Virtualization allows physical resources to be shared by multiple consumers (i.e., multi-tenant); however, consumers cannot see or share each other's data. Multi-tenancy results in optimal utilization of hardware and data storage mechanism. Virtual resources are location-independent in the sense that the user usually doesn't monitor or know their location. Users can access whatever resources they need without thinking about physical details. The benefit of this model include pay-per-use and resource elasticity to match computing demands. Resources can be rapidly and elastically provisioned, in some cases automatically, to quickly scale out, and rapidly released to quickly scale in. To the consumer, resources available for provisioning often appear to be unlimited and can be purchased in any quantity at any time. In IaaS, the customer does not manage or control the underlying cloud infrastructure; however, operating systems, data and applications which are run and stored on the virtual infrastructure are managed by the customer. Examples of IaaS providers include Amazon Elastic Compute Cloud (EC2), Amazon Simple Storage Service (S3), and GoGrid.

2) PLATFORM-AS-A-SERVICE (PaaS)

In PaaS, a CSP delivers services in the form of Software Development Kit (SDK), programming languages, operating systems, and Integrated Development Environments (IDE) that can be utilized by customers to develop their own applications onto the cloud infrastructure. Customers can monitor the applications; but have no means to manage the infrastructure or operating systems that underlie them. It is helpful in circumstances where multiple developers located in different physical locations need to work together as it provides them with an integrated stack for creating and deploying applications from the cloud. A popular PaaS provider is Google App Engine. It is an SDK which provides an environment that supports Python, Java, and ''Go'' programming languages. Other providers for PaaS include Salesforce and Microsoft Azure.

3) SOFTWARE-AS-A-SERVICE (SaaS)

A CSP offers ready to use applications centrally hosted in the cloud to replace applications running on local machines. Customers may access these applications simply through web browsers running on different client devices such as mobile phones. The benefits of this model include centralized configuration and hosting, software release updates without requiring reinstallation, and accelerated feature delivery. In SaaS, customers cannot manage or control the underlying cloud infrastructure, operating systems or even core functionality of applications; however, they have access to limited user-specific application configuration settings. Popular SaaS providers are Google apps and Amazon Web Services (AWS).

4) ANYTHING-AS-A-SERVICE (XaaS)

Apart from the three main services, a CSP also provides service under the term ''XaaS'', where 'X' is a variable and various entities can be associated with it, for example Data as a Service (DaaS), Monitor as a Services (MaaS), Routing as a Service (RaaS), Security as a Service (SecaaS), and Communication as a Service (CaaS)

B. MULTI-CRITERIA DECISION MAKING (MCDM)

In MCDM problems, a variety of alternatives are evaluated on the basis of different criteria characterizing these alternatives to select the best alternative(s) [13]–[16]. Different decision-makers value (weigh) criteria differently; hence, the selection of the best alternative is subject to the preferences of decision maker(s) [15]. MCDM problems are usually divided into two groups concerning problem space solution [13], [15]: continuous MCDM, also known as Multiple Objective Decision Making (MODM), and discrete MCDM, also named as Multiple Attribute Decision Making (MADM). The main difference between MODM and MADM is the number of alternatives under assessment; MODM problems have an indefinite number of alternatives; however, alternatives are confined by a set of optimal objective constraints; while in MADM problems, the number of alternatives is predetermined and limited. In existing literature; however, the term ''MCDM'' is commonly used to describe MADM [13]. Thus, we use ''MCDM'' to represent discrete MCDM or MADM.

Decision makers have suggested different ways for defining evaluation criteria, weighing them, and rating alternatives with respect to (w.r.t.) these criteria; as a result, several MCDM approaches have been introduced in literature [13], [14]. MCDM approaches can be classified into two groups: Multi-attribute Utility Theory (MAUT) methods and Outranking methods [15]. In MAUT methods, experts score (rate) alternatives over criteria to construct a decision matrix. Some aggregation functions may then be used to combine the scores of each alternative on all criteria with the weights of criteria to obtain the overall ranking of the alternatives. The typical techniques in this group include TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) [17], UTA (UTilites Additives) [18], VIKOR (VIse Kriterijumska Optimizacija kompromisno Resenje in Serbian, multiple criteria optimization compromise solution) [19], [20], MULTIMOORA (MULTIplicative Multi-Objective Optimization by Ratio Analysis) [21], [22], and MACBETH (Measuring Attractiveness by a Categorical Based Evaluation TecHnique) [23]. While these approaches are generally simple, they are difficult to apply when decision makers cannot estimate absolute scores for alternatives w.r.t. criteria (i.e., criteria cannot be quantified).

Alternatively, outranking methods estimate the relative preferences of alternatives w.r.t. each criterion based on pairwise comparisons among alternatives. The relative preferences are then aggregated to acquire the outranking relations which represent the dominance degree of one alternative over others. The widely-used outranking methods are ELECTRE (ELimination Et Choix Traduisant la REalité in French, ELimination and Choice Expressing the Reality) [24], PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations) [25], [26], GLDS (Gained and Lost Dominance Score) method [27], [28], AHP (Analytical Hierarchy Process) [29], [30] and ANP (Analytical Network Process) [31], Superiority and Inferiority Ranking (SIR) method [32], Step-Wise Weight Assessment Ratio Analysis (SWARA) [33], subjective weighting method using continuous interval scale [34], multi-attribute evaluation using Imprecise Weight Estimates (IMP) [35] and, more recently, the Best-Worst Method [13]–[15], [36]–[40]. Such approaches are effective in circumstances where it is difficult or meaningless to include the measured scores for candidate alternatives w.r.t. criteria (e.g., qualitative criteria), but it is possible to express the relative preferences of the alternatives and criteria. However, the numerous workloads of pairwise comparisons would increase the computational complexity (i.e., reduce efficiency) of these methods if there are a large number of criteria or alternatives. Moreover, the lack of consistency of the pairwise comparison matrices is a very significant challenge to the pairwise comparison methods which typical occurs in practice [13].

III. LITERATURE REVIEW

In recent years, many research efforts have been conducted to solve the problem of cloud service selection, some of them use the MAUT techniques and others use the pairwise comparison methods. Nevertheless, more hybrid approaches are being introduced using many simple MCDM techniques. Hybrid approaches improve consumer trust and help make more accurate final decisions. In this section, we review the existing approaches for cloud service selection.

Godse and Mulik [41] proposed an approach to use the AHP technique to prioritize the selection criteria for cloud services and to rank three CSPs. The study suggested the following criteria for SaaS selection based on the experience and expert opinion: functionality, architecture, usability, vendor reputation, and cost. Garg *et al.* [5], [6] proposed SMICloud framework based on the Service Measurement Index (SMI) developed by Cloud Service Measurement Initiative Consortium (CSMIC) [42]. The proposed framework measures QoS attributes in SMI and uses Key Performance Indicators (KPIs) to compare the cloud services. They ranked the cloud services via AHP method; nevertheless, they considered only CSMIC's quantifiable criteria and did not recognize the non-quantifiable QoS trustworthiness criteria for selecting CSPs.

Nie *et al.* [43] implemented a cloud service quality evaluation method based on AHP, which computes the weights of evaluation criteria. They also presented a number of qualitative models for decision making in cloud service selection. In [44] the author used the MACBETH approach to simplify the decision-making process in Cloud-based organizations. The proposed model is based on 19 criteria chosen to promote decision making among two SaaS Cloud services: Google Apps and Microsoft Office 365.

Park *et al.* [45] proposed a MCDM model the uses QoS attributes for CC service selection. The model consists of six criteria: functionality, reliability, usability, efficiency, maintainability and portability, and 25 sub-criteria. The proposed model was developed to identify the best SaaS ERP (Enterprise Resource Planning) in CC environment and provide recommendations to customers in a given priority order. In [46], Boussoualim *et al.* developed a tool to help users select the best SaaS products that meet most of their requirements based on AHP method.

Rehman *et al.* [47] proposed a parallel MCDM approach for selecting cloud services. The proposed method conducts parallel multi-criteria decision analysis to rank all cloud services in accordance with user requirements. The results are then aggregated to determine the overall rank of all available cloud services. Lee [48] described decision-making of Small and Medium Enterprises (SME) about the choice of cloud services, as well as their evaluation criteria. They proposed an AHP-based model which offers four criteria (i.e., financial, marketing, management and environment) and 14 sub-criteria. The method added values (weights) for every criterion and ranked sub-criteria by order of importance.

Papathanasiou *et al.* [49] offered a concise practical approach to choose a CSP. The authors have explored AHP and PROMETHEE and the Goal programming techniques for assessing the weights of the selection criteria. He has chosen 12 criteria to evaluate nine CSPs. Gavade [50] explores use-case scenario for different multi-criteria decision-making in CC. They analyzed various MCDM methods for different cloud services; the analyzed methods are AHP, TOPSIS, VIKOR, ELECTRE and PROMETHEE. The authors suggested the use of TOPSIS for PaaS decision-making.

Chung and Seo [51] proposes a cloud service selection model based on the Analytical Network Process (ANP). According to the proposed model, the criteria and sub-criteria for cloud service selection are identified and evaluated by weights; authors used three criteria and eight sub-criteria. Based on the chosen criteria and the ANP method, the research makes a selection out of six proposed IaaS alternatives.

Rai and Kumar [52] proposed a new decision-making model based on two methods: TOPSIS and VIKOR for IaaS cloud service selection with one method as the main method and the other as an instance method. The developed decision-making evaluation model contains three criteria; i.e., values of RAM, Bandwidth and Storage. Evaluation results showed that VIKOR has outperformed TOPSIS, in terms of evaluated criteria of memory and time.

Some authors combined fuzzy idea with basic MCDM methods to solve the uncertainty problem associated with cloud service selection [53]–[56], [65]–[68]. Supriya *et al.* [53] uses MCDM methods to rank CSPs based on their infrastructure parameters. Compared with any analytical approach alone, a mixture of analytic and fuzzy methods was found to be more trustworthy. CSP rankings are based on SMI [42] which helps organizations assess cloud-related business services on the basis of their unique business and technology needs.

In [54], the authors proposed a decisional methodology based on Fuzzy Analytic Hierarchy Process (FAHP) and PROMETHEE for comparing, ranking and selecting the most suitable CC product to accommodate and access big data. They used three criteria and 10 sub-criteria to evaluate five CC products. Wibowo *et al.* [55] has presented a fuzzy multi-criteria group decision-making method for evaluating the performance and the choice of Cloud services. Also, in [56], Sun *et al.* presented a fuzzy decision-making framework and MCDM-based approach for cloud service selection.

TABLE 1. Summary of previous work.

Publication	Year	MCDM Method
Godse et al. [41]	2009	An approach of using the AHP technique for prioritizing selection criteria and ranking Cloud services
Garg et al. [5,6]	2011	A framework that measures all the QoS attributes in SMI and then uses AHP to rank the cloud services
Nie et al. [43]	2012	An evaluation system of cloud service selection using AHP that estimates the weights evaluation criteria.
P. Costa [44]	2013	MACBETH method was used to simplify the decision-making process in organizations adopting Cloud services.
Park et al. [45]	2013	QoS model to select the best SaaS ERP in CC.
Boussoualim et al. [46]	2014	user preferences-based approach for Selecting SaaS Product using AHP
Rehman et al. [47]	2014	parallel MCDM approach based on QoS history
Lee [48]	2014	AHP method for decision-making on CC in SME
Papathanasiou [49]	2014	a concise practical approach for choosing a Cloud provider based on AHP and PROMETHEE
Gavade et al. [50]	2014	evaluate different MCDM methods for different Cloud services for selecting the most efficient method for the type of Cloud service of interest.
Chung et al. [51]	2015	a Cloud service selection model based on ANP
Rai et al. [52]	2016	Combine method of TOPSIS and VIKOR
Supriya et al. [53]	2016	AHP, Fuzzy AHP, TOPSIS and Fuzzy TOPSIS
Boutkhoum et al. [54]	2016	A decisional methodology based on Fuzzy Analytic Hierarchy Process (FAHP) and PROMETHEE
Wibowo et al. [55]	2016	A fuzzy multi-criteria group decision-making method
Sun et al. [56]	2016	A fuzzy decision-making framework and MCDM-based approach for cloud service selection.
Saroj et al. [57]	2016	Different MCDM methods
Liu et al. [58]	2016	A subjective/objective integrated MAGDM technique for decision making in cloud computing services
Kumar et al. [59,64]	2017	A framework for determining the most suitable candidate cloud service by integrating AHP and TOPSIS
Araujo et al. [60]	2018	A decision-making approach based on multiple-criteria decision analysis and stochastic models.
Nawaz et al. [7]	2018	An MCDM method for cloud service selection using a Markov chain and the BWM.
Jatoth et al. [61]	2019	A hybrid method that ranks to cloud services based a novel extended Grey TOPSIS integrated with AHP.
Al-Faifi et al. [62]	2019	A hybrid MCDM to evaluate and rank cloud service providers from smart data using k-means and DEMATEL-ANP.
Sun et al. [63]	2019	A fuzzy measure and Choquet integral to measure and aggregate non-linear relations between criteria.

Saroj and Dileep [57] provides an overview of different MCDM methods and their evaluation. The MCDM methods used are: TOPSIS, PROMETHEE, Multi-Attribute Value Theory (MAVT), Multi Attribute Utility Theory (MAUT), ELECTRE and AHP. Liu *et al.* [58] structured a multi-attribute group decision making (MAGDM) tool to help businesses decide which CSP will be more appropriate for their needs.

Kumar *et al.* [59], [64] introduced a computational framework for determining the most suitable candidate cloud service by integrating AHP and TOPSIS. They specified the architecture for the cloud services selection process and computed the weights of criteria using pairwise comparisons of AHP. Then, they obtained the final ranking of the cloud service based on overall results using the TOPSIS system.

Araujo *et al.* [60] presented an MCDM approach for selecting cloud computing infrastructures, in terms of dependability and cost that best suits both company and customer needs. Nawaz *et al.* [7] developed a cloud broker architecture for cloud service selection by finding a pattern of the changing priorities of User Preferences (UPs). In [61], Jatoth *et al.* proposed a hybrid MCDM model to select cloud services among the available alternatives using a novel extended Grey TOPSIS integrated with AHP.

Al-Faifi *et al.* [62] developed a hybrid MCDM to evaluate and rank CSPs from smart data. The hybrid method consists of two components: (i) clustering CSPs using k-means algorithm to combine them with similar features and (ii) applying MCDM methods using DEMATEL-ANP to rank clusters and make a final decision. Sun *et al.* [63] proposed a Cloud Service Selection with Criteria Interactions (CSSCI) framework that applies a fuzzy measure and Choquet integral to measure and aggregate non-linear relations between criteria.

To summarize, Table 1 shows a variety of MCDM approaches proposed in literature for CSP selection. In the analysis of these studies, we find that a great number of criteria have been used to test CSPs, resulting in additive computational complexity to the methods of pairwise comparison. Furthermore, many of such criteria are qualitative in nature (i.e. how to measure scores for alternatives w.r.t. these criteria is irrelevant or unclear), in this case, MAUT-based approaches are difficult to implement.

This work proposes a novel MCDM approach that integrates TOPSIS and BWM to evaluate available CSPs based on selection criteria characterizing their cloud services. The reason for why we integrate these two methods is that TOPSIS is a simple process, intuitive, and provides greater agility than any other MCDM methods. It is a compensatory method that allows trade-offs between criteria, where a poor result in one criterion can be negated by a good result in another criterion. It offers a more practical form of modelling than non-compensatory approaches, which include or exclude alternative solutions based on hard cut-offs. However, the construction of a decision matrix is difficult or meaningless for qualitative criteria where the scores of alternatives over criteria cannot be quantified. In addition, it is difficult to weigh criteria and keep consistency of judgments, especially with additional criteria [16].

On the other hand, BWM is a recent pairwise comparison MCDM method that is superior to other methods in that: (1) it requires less comparison data, which means that it is efficient with a large number of criteria; (2) it leads to more consistent comparisons, which means that it produces more reliable results [13]. The proposed integrated approach looks for the best of both worlds in the sense that it is feasible using relative preferences of criteria and alternatives, more efficient, and produces more consistent and reliable results.

IV. TOPSIS METHOD

TOPSIS, first proposed in [69], is known as one of the most attractive methods to deal with MCDM problem. The underlying principle behind TOPSIS is that the best alternative must be at the nearest (shortest) geometric distance from the positive ideal solution, whereas it has the farthest (longest) geometric distance from the negative ideal solution [59]. The positive ideal (i.e., best) solution represents the solution with the most advantages and lowest cost of all alternatives, whereas the negative ideal (i.e., worst) solution provides the solution with the lowest benefits and the highest cost. The main steps of TOPSIS approach are explained below.

Step 1 (Construct the Decision Matrix): Assume that we have a set A of m alternatives where: $A = \{a_1, a_2, \ldots, a_m\}$ and m is a positive integer. These alternatives have to be evaluated w.r.t. a set C of n criteria, where: $C = \{c_1, c_2, \ldots, c_n\}$ and n is a positive integer. Then, the decision maker would create a decision matrix X in which he/she quantify alternatives over criteria.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

x_{ij} : score of alternative a_i w.r.t. criterion c_j

Step 2 (Compute the Normalized Decision Matrix): The elements of the normalized decision matrix Y can be computed as follows:

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$
$$\boldsymbol{i = 1, 2, \ldots, m} \text{ and } \boldsymbol{j = 1, 2, \ldots, n} \tag{2}$$

y_{ij} : normalized score of alternative a_i w.r.t. criterion c_j

Step 3 (Compute the Weights of Criteria): The weight of criterion c_j is w_j which represents the relative importance of c_j compared to other criteria. Weights are computed using AHP method [29], [30]. The vector of weights is denoted as W where:

$$W = [w_1 w_2 \ldots w_n]$$
$$\text{such that:} \quad 0 \leq w_j \leq 1 \quad \text{and} \quad \sum_{j=1}^{n} w_j = 1 \tag{3}$$

Step 4 (Compute the Weighted Normalized Decision Matrix): The elements of the weighted normalized decision matrix Z can be computed as follows:

$$z_{ij} = w_j y_{ij} \tag{4}$$

z_{ij} : weighted score of alternative a_i w.r.t. criterion c_j

Step 5 (Find the Positive and Negative Ideal Solutions): For every criterion c_j, we define the positive ideal solution v_j^+ and the negative ideal solution v_j^-, where for beneficial criterion:

$$v_j^+ = \max\left\{z_{1j}, z_{2j}, \ldots, z_{mj}\right\} \tag{5}$$
$$v_j^- = \min\left\{z_{1j}, z_{2j}, \ldots, z_{mj}\right\} \tag{6}$$

and for non-beneficial criterion:

$$v_j^+ = \min\left\{z_{1j}, z_{2j}, \ldots, z_{mj}\right\} \tag{7}$$
$$v_j^- = \max\left\{z_{1j}, z_{2j}, \ldots, z_{mj}\right\} \tag{8}$$

The vector of positive ideal solutions is V^+ where:

$$V^+ = \left[v_1^+ v_2^+ \ldots v_n^+\right] \tag{9}$$

The vector of negative ideal solutions is V^- where:

$$V^- = \left[v_1^- v_2^- \ldots v_n^-\right] \tag{10}$$

Step 6 *(Determine the Euclidean Distance for Each Alternative From the Positive and Negative Ideal Solution):* For each alternative a_i, the Euclidian distance of a_i from the positive ideal solution V^+ is d_i^+ where:

$$d_i^+ = \sqrt{\sum_{j=1}^{n} (z_{ij} - v_j^+)^2} \tag{11}$$

and the Euclidian distance of a_i from the negative ideal solution V^- is d_i^- where:

$$d_i^- = \sqrt{\sum_{j=1}^{n} (z_{ij} - v_j^-)^2} \tag{12}$$

Step 7 (Compute the Closeness Coefficient for Each Alternative): The closeness coefficient for an alternative a_i is r_i and it can be computed as follows.

$$r_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{13}$$

The vector of all closeness coefficients is R where:

$$R = [r_1 r_2 \ldots r_m] \tag{14}$$

Step 8 (Rank R): The best alternative is the one of the highest closeness coefficient.

TOPSIS has some limitations in in step 1 and step 3. In step1, the decision matrix is commonly estimated by the decision makers. However, the construction of this matrix is difficult or meaningless for qualitative criteria (e.g., usability, portability, security, etc.) since the scores of alternatives over criteria are not available or cannot be quantified easily. In step 3, computing the weights using AHP method is computationally expensive and inconsistent especially with a large number of criteria or alternatives. We will overcome these limitations in our proposed approach.

V. THE BEST-WORST METHOD

The pairwise comparison method [70] is generally any process of comparing elements in pairs to judge which of each element is preferred with respect to some property. Pairwise comparisons (which are usually provided by an expert or a team of experts) are used to show the relative preferences of elements in situations where it is unfeasible or meaningless to provide absolute scores for these elements w.r.t. some criteria. This method has been utilized in MCDM, for instance, AHP pairwise comparison method is used to derive the relative weights of criteria against the main goal of the study and the relative scores of alternatives against criteria. The very significant challenges to AHP method stems from the inconsistency of the pairwise comparison matrices as well as the additive complexity associated with a large number of criteria or alternatives [13]. We discuss this issue below.

Suppose we want to execute a pairwise comparison between n elements w.r.t. to certain property. The pairwise comparison matrix which shows the relative preferences of the elements is an $n \times n$ matrix denoted as P where:

$$P = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{bmatrix} \tag{15}$$

The matrix, P, can be estimated using a 1/9 to 9 scale where p_{ij} shows the relative preference of element i to element j, $p_{ij} = 1$ shows that element i and element j are of the same importance, $p_{ij} > 1$ means that element i is more important than element j with $p_{ij} = 9$ showing the extreme importance of element i to element j and $p_{ij} < 1$ indicates that element i is less important than element j with $p_{ij} = 1/9$ showing the extreme less importance of element i to element j. In order for matrix P to be reciprocal, it is required that $p_{ij} = 1/p_{ji}$ for all i and j and $p_{ij} = 1$, for $i = j$.

From the above description of P, we can conclude that the number of all possible comparisons to form P is n^2, out of them, there are n comparisons for which $p_{ij} = 1$. The remainder are $n(n-1)$ comparisons, half of which are $p_{ij} > 1$, the other half being the first half reciprocals. Thus, in AHP, in order to obtain a complete matrix P for n elements, $n(n-1)/2$ comparisons must be made in pairs. The pairwise comparison matrix is said to be perfectly consistent if:

$$p_{ik} \times p_{kj} = p_{ij} \quad \forall i, j \tag{16}$$

When estimating a pairwise comparison p_{ij}, the decision-maker expresses both the direction ($p_{ij} > 1$ or $p_{ij} < 1$) and the strength (a numeric value to indicate the preference of i over j). In most cases, the decision-maker has no difficulty with the direction being conveyed. Expressing the strength; however, is a challenging job, almost the principal cause of inconsistency. In fact, when a decision maker wants to assign a number to indicate his/her decision about the comparison of two elements i and j, he/she also takes into consideration the relationships between these two elements and some other elements. Rezaei [13] discussed this issue and concluded that when considering the preference of element i over j w.r.t. some criterion, the decision-maker also considers the *Best* and the *Worst* elements w.r.t. the criterion in question while other elements have no role in this comparison. Accordingly, he divided the pairwise comparisons into two main categories: (1) reference comparisons and (2) secondary comparisons as defined below.

Definition 1: Comparison p_{ij} is defined as a reference comparison if i or j is the *Best (B)* or the *Worst (W)* element.

Definition 2: Comparison p_{ij} is defined as a secondary comparison if neither i nor j are the Best or the Worst elements.

A significant finding for the above discussion is that the relative significance of the elements can be obtained without holding the secondary comparisons. Each secondary comparison p_{ij} occurs in two relation chains, of which two members are reference comparisons, they are:

$$p_{Bi} \times p_{ij} = p_{Bj} \tag{17}$$

$$p_{ij} \times p_{jW} = p_{iW} \tag{18}$$

This is a very important result since it leads to:

1) Reduction of the required pairwise comparisons; number of required pairwise comparison = *(n-2)* Best-to-Others + *(n-2)* Others-to-Worst + *(1)* Best-to-Worst = ***2n-3*** instead of $\boldsymbol{n(n-1)/2}$. (Note that we only consider pairwise comparisons where $\boldsymbol{p_{ij}} > 1$).
2) More consistent comparisons; it is clear that secondary comparisons are more difficult, less accurate and at best redundant; they are the main source of inconsistency.

The above conclusions motivated Rezaei [13] to introduce the Best-Worst Method (BWM) for MCDM. The salient features of BWM compared to other pairwise comparison methods, are 1) it requires less computation effort since less comparison data (only reference comparisons) should be provided and processed, which means that it is more efficient; 2) it leads to more consistent comparisons since secondary comparisons are not included, which means that it produces more reliable results. The following are the steps of BWM.

Step 1: Determine a set of criteria, $\boldsymbol{C} = \{\boldsymbol{c_1}, \boldsymbol{c_2}, \ldots, \boldsymbol{c_n}\}$, n is a positive integer.

Step 2: Determine the best (e.g. most important) criterion, $\boldsymbol{c_B}$, and the worst (e.g. least important) criterion, $\boldsymbol{c_W}$.

Step 3: Determine the preference of the Best criterion over all criteria (Best-to-Others) using a number between 1 and 9. The resulting preference vector would be:

$$Best - to - Others = [p_{B1}\ p_{B2}\ \ldots\ p_{Bn}] \tag{19}$$

where: $\boldsymbol{p_{Bj}}$ indicates the preference $\boldsymbol{c_B}$ over $\boldsymbol{c_j}$. It is clear that $\boldsymbol{p_{BB}} = 1$.

Step 4: Determine the preference of all criteria over the Worst criterion (Others-to-Worst) using a number between 1 and 9. The resulting preference vector would be:

$$Others - to - Worst = [p_{1W}\ p_{2W}\ \ldots\ p_{nW}] \tag{20}$$

where: $\boldsymbol{p_{jW}}$ indicates the preference of $\boldsymbol{c_j}$ over $\boldsymbol{c_W}$. It is clear that $\boldsymbol{p_{WW}} = 1$.

Step 5: Find the optimal weights of criteria

$$\boldsymbol{W^*} = [\boldsymbol{w_1^*}\ \boldsymbol{w_2^*}\ \ldots\ \boldsymbol{w_n^*}] \tag{21}$$

The optimal weight for the criterion $\boldsymbol{c_j}$ is the one that satisfies the following conditions.

$$\frac{\boldsymbol{w_B}}{\boldsymbol{w_j}} = \boldsymbol{p_{Bj}} \quad \textbf{\textit{and}} \quad \frac{\boldsymbol{w_j}}{\boldsymbol{w_W}} = \boldsymbol{p_{jW}} \tag{22}$$

To satisfy these conditions for all j, we should solve the following formula for all j.

$$\begin{aligned} &\min_{j} \max \left(\left|\frac{\boldsymbol{w_B}}{\boldsymbol{w_j}} - \boldsymbol{p_{Bj}}\right|, \left|\frac{\boldsymbol{w_j}}{\boldsymbol{w_W}} - \boldsymbol{p_{jW}}\right|\right) \\ &\text{such that } \sum\nolimits_{j=1}^{n} w_j = 1, \quad w_j \geq 0,\ \forall j \end{aligned} \tag{23}$$

The problem in (23) can be transferred into the following problem:

$$\begin{aligned} &\min\ \boldsymbol{\xi}, \\ &\text{such that } \left|\frac{\boldsymbol{w_B}}{\boldsymbol{w_j}} - \boldsymbol{p_{Bj}}\right| \leq \boldsymbol{\xi} \quad \forall \boldsymbol{j} \\ &\qquad \left|\frac{\boldsymbol{w_j}}{\boldsymbol{w_W}} - \boldsymbol{p_{jW}}\right|| \leq \xi \quad \forall \boldsymbol{j} \\ &\qquad \sum\nolimits_{j=1}^{n} \boldsymbol{w_j} = \mathbf{1}, \\ &\qquad \boldsymbol{w_j} \geq \mathbf{0}, \quad \forall \boldsymbol{j} \end{aligned} \tag{24}$$

Solving (24), the optimal weights $(\boldsymbol{w_1^*}, \boldsymbol{w_2^*}, \ldots, \boldsymbol{w_n^*})$ and the optimal value of $\boldsymbol{\xi}$ **which is** $(\boldsymbol{\xi^*})$ can be obtained. The above procedure can also be used to find the relative scores of alternatives w.r.t. a criterion. This is a very useful property in cases where the values of alternatives w.r.t. criteria cannot be quantified.

VI. THE PROPOSED APPROACH

We propose an integrated MCDM approach based on TOPSIS and BWM that uses evaluation criteria to rank CSPs according to their fulfillment of customer's requirements. BWM is used for acquiring the weights of criteria and relative scores for alternatives w.r.t. criteria. These weights and relative scores are utilized by TOPSIS to determine the ranking order for the cloud alternatives. The following are the steps of the proposed approach.

Step 1 (Identify CSPs): Specify *S,* a set of CSPs where: $S = \{s_1, s_2, \ldots, s_m\}$, m is a positive integer. For example, *S* may contain Amazon, Microsoft, Google, HP, etc.

Step 2 (Identify Selection Criteria): Identify C, a set of selection criteria chosen by the customer to evaluate and rank S, where: $C = \{c_1, c_2, \ldots, c_n\}$, n is a positive integer. To help identify C, we refer to the Cloud Services Measurement Initiative Consortium (CSMIC) that proposes a Standard Measurement Index (SMI) [42]. The SMI framework is a hierarchical model that provides a full view of QoS characteristics (Fig. 2). All QoS metrics are broken down into seven categories: Performance, Accountability, Assurance, Agility, Cost, Security and Privacy and Usability. These categories are further divided into four and more QoS attributes [59]. In addition, we refer to the work presented in the literature review of section 3 and the work introduced in [71]–[73] which provides a wide variety of (QoS and non-QoS) criteria.

Step 3 (Compute the Relative Weights of Criteria Using BWM): Identify the Best criterion c_B and Worst criterion c_W and follow the steps of BWM described above to determine the weights of criteria $W = [w_1 w_2 \ldots w_n]$. This step requires *(2n-3)* comparisons instead of *n(n-1)/2* if we use AHP.

Step 4 (Compute the Relative Scores of CSPs w.r.t. Each Criterion Using BWM): For each criterion $\boldsymbol{c_j}$, identify the Best CSP ($\boldsymbol{s_B}$) and Worst CSP ($\boldsymbol{s_W}$), then follow the steps of BWM to find the relative scores of CSPs over this criterion. Similarly, this step requires 2m-3 comparisons (for each criterion) instead of m(m-1)/2 if we use AHP. Assume that $\boldsymbol{a_{ij}}$ is the relative score of CSP $\boldsymbol{s_j}$ over criterion $\boldsymbol{c_j}$ and $\boldsymbol{A_j}$ is the vector of relative scores of all CSPs over $\boldsymbol{c_j}$ then:

$$\boldsymbol{A_j} = [\boldsymbol{a_{1j}}\ \boldsymbol{a_{2j}}\ \ldots\ \boldsymbol{a_{mj}}] \tag{25}$$

Step 5 (Construct the Decision Matrix): The decision matrix A(mxn) is defined as follows:

$$\boldsymbol{A} = [\boldsymbol{A_1^T}\ \boldsymbol{A_2^T}\ \ldots\ \boldsymbol{A_n^T}] \tag{26}$$

Step 6 (Construct the Weighted Decision Matrix): The weighted decision matrix B(mxn) is defined as follows:

$$\begin{aligned} \boldsymbol{B} &= [\boldsymbol{w_1 A_1^T}\ \boldsymbol{w_2 A_2^T}\ \ldots\ \boldsymbol{w_n A_n^T}] \\ \boldsymbol{b_{ij}} &= \boldsymbol{w_j a_{ij}} \end{aligned} \tag{27}$$

Step 7 (Find the Positive and Negative Ideal Solutions): For every criterion c_j, find the positive ideal solution v_j^+ and the negative ideal solution v_j^-, where:

$$v_j^+ = \max\{b_{1j}, b_{2j}, \ldots, b_{mj}\} \tag{28}$$

$$v_j^- = \min\{b_{1j}, b_{2j}, \ldots, b_{mj}\} \tag{29}$$

The vector of positive ideal solutions is V^+ where:

$$V^+ = [v_1^+ v_2^+ \ldots v_n^+] \tag{30}$$

The vector of negative ideal solutions is V^- where:

$$V^- = [v_1^- v_2^- \ldots v_n^-] \tag{31}$$

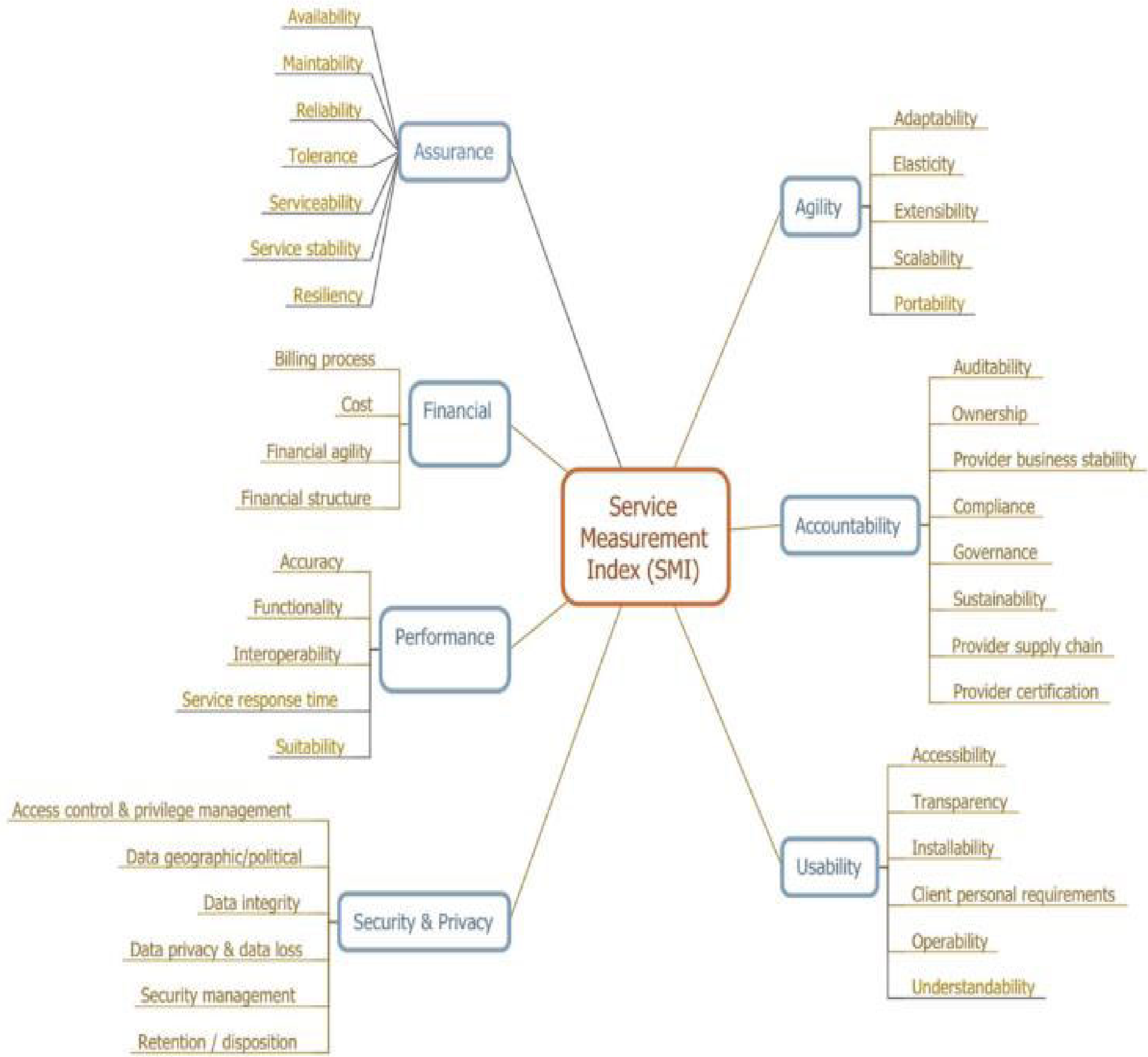

FIGURE 2. **The quality of service attributes of cloud service management (SMI) [59].**

Step 8 (Determine the Euclidean Distance for Each CSP From the Positive and Negative Ideal Solution): For each CSP, s_i, the Euclidian distance of s_i from the positive ideal solution is d_i^+ where:

$$d_i^+ = \sqrt{\sum\nolimits_{j=1}^{n} \left(b_{ij} - v_j^+\right)^2} \tag{32}$$

and the Euclidian distance of s_i from the negative ideal solution is d_i^- where:

$$d_i^- = \sqrt{\sum\nolimits_{j=1}^{n} \left(b_{ij} - v_j^-\right)^2} \tag{33}$$

Step 9 (Compute the Closeness Coefficient for Each CSP): The closeness coefficient for an alternative s_i is r_i and it can be computed from equation (13).

Step 10 (Ran R): The vector of all closeness coefficients, R, is given in equation (14). The best CSP is the one of the highest closeness coefficient.

VII. VALIDATION

The proposed approach is tested and validated through a use-case scenario which demonstrates its effectiveness and correctness.

Step 1 (Identify CSPs): We run our experiments with a set, *S*, of eight CSPs where: $S = \{s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8\}$, m = 8. CSPs could be any real service providers such as HP, Amazon, Google, GoGrid, Azure, Rackspace, Joynet, and Linode (not in any order).

Step 2 (Identify Selection Criteria): A set *C* of nine selection criteria has been chosen by the Decision Maker (DM) to evaluate and rank S where: $C = \{c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9\}$, n = 9. These selection criteria are illustrated in Table 2.

TABLE 2. Selection criteria.

Symbol	Criterion
c_1	scalability
c_2	sustainability
c_3	usability
c_4	interoperability
c_5	security management
c_6	cost
c_7	maintainability
c_8	service response time
c_9	reliability

Step 3 (Compute the Relative Weights of Criteria Using BWM): First, DM has to identify the Best (the most important) criterion c_B and Worst (the least important) criterion c_W.

$$c_B = c_5 = \textit{security management}$$
$$c_W = c_2 = \textit{sustainability}$$

DM then estimates a pair of preference vectors (i.e., pairwise comparisons of criteria) which are (c_B-to-Others) and (Others-to-c_W). The estimates for pairwise comparisons are shown in Tables 3 and 4 and the pair of preference vectors (c_5-to-c_j) and (c_j-to-c_2) are shown in Table 5. The optimal weights for selection criteria are computed as described in equations 22, 23, and 24 and are shown in Table 6 and Fig. 3.

TABLE 3. (c_B-to-Others) estimates.

c_B-to-c_j	symbol	p_{Bj}
security-to-scalability	p_{51}	3
security-to-sustainability	p_{52}	9
security-to-usability	p_{53}	4
security-to-interoperability	p_{54}	2
security-to-security	p_{55}	1
security-to-cost	p_{56}	6
security-to-maintainability	p_{57}	7
security-to-response time	p_{58}	3
security-to-reliability	p_{59}	4

Step 4 (Compute the Relative Scores of CSPs Over Each Criterion Using BWM): For *each criterion* c_j, DM has to identify the Best CSP (s_B, green) and Worst CSP (s_W, yellow) and estimate a pair of preference vectors for CSPs w.r.t. c_j, (i.e., pairwise comparisons of CSPs over c_j) which are (s_B-to-Others) and (Others-to-s_W). We have n = 9 criteria

TABLE 4. (Others-to-c_W) estimates.

c_j-to-c_W	symbol	p_{jW}
scalability-to-sustainability	p_{12}	4
sustainability-to-sustainability	p_{22}	1
usability-to-sustainability	p_{32}	5
interoperability-to-sustainability	p_{42}	6
security-to-sustainability	p_{52}	9
cost-to-sustainability	p_{62}	5
maintainability-to-sustainability	p_{72}	3
response time-to-sustainability	p_{82}	6
reliability-to-sustainability	p_{92}	7

TABLE 5. The pair of preference vectors for criteria.

p_{5j}	3	9	4	2	1	6	7	3	4
p_{j2}	4	1	5	6	9	5	3	6	7

TABLE 6. Criteria weights.

c_j	w_j
c_1	0.117582618
c_2	0.023005295
c_3	0.088186964
c_4	0.176373927
c_5	0.279897754
c_6	0.058791309
c_7	0.050392551
c_8	0.117582618
c_9	0.088186964

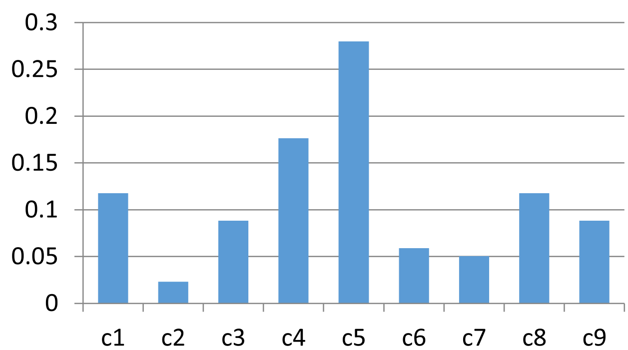

FIGURE 3. Optimal weights of selection criteria.

and m = 8 CSPs, which means that the DM has to estimate nine (s_B-to-Others) vectors (one for each criteria), each vector has eight elements which are the preferences of s_B to all others CSPs (s_B-to-s_i). These vectors are shown in a tabular form in Table 7. Each column in Table 7 represents (s_B-to-s_i) preference vector w.r.t. certain criterion c_j, for example column 1, represents (s_2-to-s_i) preference vector w.r.t. c_1.

Similarly, DM has to estimate nine (Others-to-s_W) vectors (one for each criteria), each vector has eight elements which are the preferences of all others CSPs to s_W. This can be represented in a tabular form as shown in Table 8.

TABLE 7. (s_B-to-Others) preference vectors.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9
s_1	3	2	1	6	5	2	6	9	6
s_2	1	5	3	7	2	4	9	2	7
s_3	2	4	7	4	9	6	4	4	5
s_4	4	1	6	8	1	9	3	2	4
s_5	3	9	2	1	4	8	5	5	1
s_6	9	3	3	2	3	1	4	3	2
s_7	5	6	9	9	5	5	3	1	9
s_8	6	5	5	5	6	3	1	6	5

TABLE 8. (Others-to-s_W) preference vectors.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9
s_1	4	3	9	6	6	6	5	1	6
s_2	9	4	4	3	4	2	1	4	3
s_3	5	5	3	2	1	3	4	3	2
s_4	2	9	6	8	9	1	6	2	4
s_5	6	1	5	9	5	4	3	5	9
s_6	1	6	4	4	4	9	2	7	4
s_7	3	3	1	1	3	7	5	9	1
s_8	7	2	5	5	2	5	9	6	5

TABLE 9. Pair of preference vectors for CSPs w.r.t. c_1.

p_{2i}	3	1	2	4	3	9	5	6
p_{i6}	4	9	5	2	6	1	3	7

TABLE 10. Relative scores of CSPs w.r.t. c_1.

s_i	a_{i1}	$a_{i1}\%$
s_1	0.128098023	12.81
s_2	0.292397661	29.24
s_3	0.192147034	19.21
s_4	0.096073517	9.61
s_5	0.128098023	12.81
s_6	0.022277917	2.23
s_7	0.076858814	7.69
s_8	0.064049011	6.4

Each column in Table 8 represents (s_i-to-s_W) preference vector w.r.t. certain criterion c_j, for example column 1, represents (s_i-to-s_6) preference vector w.r.t. c_1, the pair (s_2-to-s_i) and (s_i-to-s_6) are shown in Table 9.

Now, using the above pairs of preference vectors and the optimization formula (24), we can estimate the relative scores for CSPs w.r.t. each criterion. For example, the relative scores for CSPs w.r.t. criterion c_1 (i.e., vector A_1) are shown in Table 10. If we continue this way, we can estimate nine relative score vectors ($A_1, A_2, \ldots, A_9$) from which we can construct (8×9) decision matrix.

Step 5 (Construct the Decision Matrix): The decision matrix A(8×9) is defined as follows:

$$\boldsymbol{A} = [\boldsymbol{A}_1^T\ \boldsymbol{A}_2^T\ \ldots\ \boldsymbol{A}_9^T] \tag{34}$$

This matrix is shown in Table 11 (normalized to 100 instead of 1 for simplicity). An element, a_{ij}, in matrix A represents the normalized relative score of CSP s_i w.r.t. criterion c_j.

Step 6 (Construct the Weighted Decision Matrix): The weighted decision matrix B(8×9) is defined as follows:

$$\boldsymbol{B} = [w_1\boldsymbol{A}_1^T\ w_2\boldsymbol{A}_2^T\ \ldots\ w_9\boldsymbol{A}_9^T] \tag{35}$$

This matrix is shown in Table 12.

Step 7 (Find the Positive and Negative Ideal Solutions): For every criterion c_j, we find the positive ideal solution v_j^+ and the negative ideal solution v_j^- as defined in equations 28 and 29. The vectors V^+ and V^- are shown in Table 13.

Step 8 (Determine the Euclidean Distance for Each CSP From the Positive and Negative Ideal Solution): The Euclidian distance of s_i from the positive ideal solution is d_i^+ and the Euclidian distance from the negative ideal solution is d_i^- which are computed from equations (32) and (33). This is shown in Table 14.

Step 9 (Compute the Closeness Coefficient for Each CSP): The closeness coefficient for an alternative s_i is r_i and it is computed from equation (13), this is shown in Table 14.

Step 10 (Ranking): The best CSP is the one of the highest closeness coefficient. The final ranking for CSPs is shown in Table 14.

VIII. EMPRICAL EVALUATION

We compared our proposed approach to AHP in terms of computational complexity and consistency. Experiments for AHP and the proposed approach have been conducted with the same setting described in section 4 (i.e., the same criteria and the same CSPs). The steps of AHP are described in detail in [29], [59] and its computations have been performed using the tool described in [74]. Computations of BWM have been implemented using the BWM Linear Solver provided in [75].

A. COMPUTATIONAL COMPLXITY (EFFICIENCY)

We evaluated computational complexity in terms of the number of pairwise comparisons needed to estimate relative preferences of criteria and alternatives. Table 15 compares number of pairwise comparisons in AHP and the proposed approach. It shows that our proposed approach has fewer elements in the pairwise comparison matrices and a smaller number of pairwise comparisons than AHP. Fig. 4 shows how the number of pairwise comparisons changes with the number of criteria (or alternatives) in AHP and the proposed approach, it is clear that the proposed approach always needs fewer pairwise comparisons than AHP to calculate priorities or weights which means that it needs less computation effort, hence, it is more efficient than AHP.

TABLE 11. Decision matrix, A.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9
s_1	12.81	15.47	31.11	7.81	8.05	20.75	6.89	2.43	7.32
s_2	29.24	8.11	13.2	6.69	18.79	10.37	2.9	17.95	6.27
s_3	19.21	10.14	5.66	11.71	2.68	6.92	10.33	9.58	8.78
s_4	9.61	34.69	6.6	5.86	32.21	2.53	13.78	13.08	10.98
s_5	12.81	3.2	19.8	33.97	10.07	5.19	8.27	7.67	34.51
s_6	2.23	13.52	13.2	22.25	13.42	32.12	10.33	12.78	20.56
s_7	7.69	6.76	2.51	2.34	8.05	8.3	13.78	30.12	2.79
s_8	6.4	8.11	7.92	9.37	6.71	13.83	33.72	6.39	8.78

TABLE 12. Weighted decision matrix, B.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9
s_1	1.51	0.36	2.74	1.38	2.25	1.22	0.35	0.29	0.65
s_2	3.44	0.19	1.16	1.18	5.26	0.61	0.15	2.11	0.55
s_3	2.26	0.23	0.5	2.07	0.75	0.41	0.52	1.13	0.77
s_4	1.13	0.8	0.58	1.03	9.02	0.15	0.69	1.54	0.97
s_5	1.51	0.07	1.75	5.99	2.82	0.31	0.42	0.9	3.04
s_6	0.26	0.31	1.16	3.92	3.76	1.89	0.52	1.5	1.81
s_7	0.9	0.16	0.22	0.41	2.25	0.49	0.69	3.54	0.25
s_8	0.75	0.19	0.7	1.65	1.88	0.81	1.7	0.75	0.77

TABLE 13. Positive and negative ideal solutions.

c_j	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9
v_i^+	3.44	0.8	2.74	5.99	9.02	1.89	1.7	3.54	3.04
v_i^-	0.26	0.07	0.22	0.41	0.75	0.15	0.15	0.29	0.25

TABLE 14. Euclidian distances and ranking for CSPs.

s_i	d_i^+	d_i^-	r_i	r_i%	**rank**
s_1	9.46	3.54	0.272307692	27.23	**5**
s_2	7.24	5.96	0.451515152	45.15	**3**
s_3	10.25	2.84	0.216959511	21.7	**7**
s_4	6.85	8.52	0.55432661	55.43	**1**
s_5	7.4	6.9	0.482517483	48.25	**2**
s_6	7.2	5.42	0.429477021	42.95	**4**
s_7	10.05	3.69	0.268558952	26.86	**6**
s_8	9.78	2.57	0.208097166	20.81	**8**

B. CONSISTENCY (RELIABILITY)

Consistency ratio (CR) is a measurement of the reliability of the output of an MCDM method. In [13], [14], Rezaei concluded that CR in BWM can be calculated from equation (34). ξ^* is computed from equation (24) and ξ_{max} varies for different values of p_{BW} as shown in Table 16.

$$CR = \frac{\xi^*}{\xi_{max}} \tag{36}$$

TABLE 15. Comparison of the proposed approach vs. AHP in terms of computational complexity.

	AHP	Proposed approach
No. of criteria (n)	9	9
No. of CSPs (m)	8	8
No. of elements in pairwise comparison matrices	1x(9x9) for criteria comparison +9 (8x8) for CSPs comparison w.r.t. each criteria = **657**	2x(1x9) for criteria comparison +9x2x(1x8) for CSPs comparison w.r.t. each criteria = **162**
No. of pairwise comparisons	9(9-1)/2+9x8(8-1)/2 = **288**	2x9-3+9(2x8-3)= **132**

TABLE 16. Relationship between ξ_{max} and p_{BW}.

p_{BW}	1	2	3	4	5	6	7	8	9
ξ_{max}	0	0.44	1	1.63	2.3	3	3.73	4.47	5.23

In AHP, Consistency Index (CI) and Consistency Ratio (CR) are computed using equations (35) and (38), where λ_{max} denotes the largest eigenvalue of pairwise matrix (nxn) and n represents no. of criteria or alternatives. RI is the random index of consistency, the value of RI varies with n,

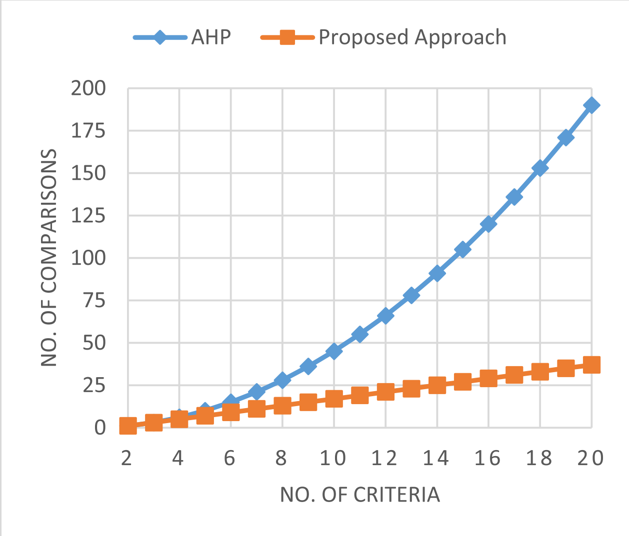

FIGURE 4. No. of pairwise comparisons needed to compute priorities in the proposed approach and AHP.

TABLE 17. Relationship between RI and n.

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

TABLE 18. Comparison of the proposed approach vs. AHP in terms of consistency (i.e., reliability of results).

Pairwise matrix	AHP		Proposed approach	
	No. of comparisons	CR%	No. of comparisons	CR%
criteria	36	44.5	15	7.29
CSPs-c_1	28	54.4	13	9.19
CSPs-c_2	28	43.5	13	5.87
CSPs-c_3	28	37.5	13	8.49
CSPs-c_4	28	55.3	13	12.88
CSPs-c_5	28	34.9	13	8.05
CSPs-c_6	28	39.4	13	9.38
CSPs-c_7	28	25	13	7.61
CSPs-c_8	28	19.5	13	8.21
CSPs-c_9	28	40.1	13	9.41
total	288		132	

as shown in Table 17 [29].

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{37}$$

$$CR = \frac{CI}{RI} \tag{38}$$

Consistency ratio ranges between 0 and 1, CR ϵ [0, 1], values close to 0 (0%) show more consistency, while values close to 1 (100%) show less consistency. If CR equals 0 then the judgments in pairwise comparison matrix are perfectly consistent. Table 18 and Fig.5 show a comparison between the proposed approach and AHP in terms of consistency. As expected, the results show that the proposed approach always gives smaller CR, thus, it is more consistent and more reliable than AHP.

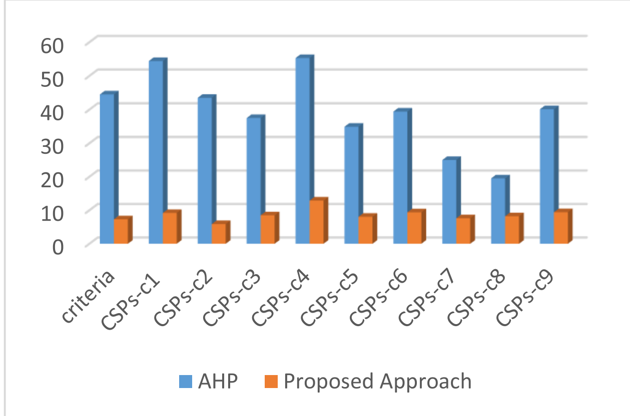

FIGURE 5. consistency ratio of the proposed approach and AHP.

C. DISCUSSION

Based on the above results, we report some important features for the proposed approach as compared to AHP considering efficiency and reliability. In the above example, we have m = 8 CSPs evaluated and ranked using n = 9 criteria chosen by the DM. For this purpose, AHP uses10 pairwise comparison matrices, 1 (9×9) matrix for criteria weights computation and 9 (8×8) matrices for computation of CSPs priorities w.r.t. criteria. DM has to make estimates for $9 \times 8.2 + 9 \times 8 \times 7.2 =$ **288** pairwise comparisons. On the other hand, the proposed approach uses 10 pairs of preference vectors (Best-to-Others and Others-to-Worst), one pair (1 × 9) for comparing criteria and nine pairs (1 × 8) for comparing CSPs w.r.t. criteria. The first pair implies $7+7+1 = 15$ (or $2\times 9.3 = 15$), while the later 9 pairs imply $9x(6 + 6 + 1) = 117$ (or $9x(2\times 8.3) = 117$), the total number of comparisons used by the proposed method $= 15 + 117 =$ **132**. Hence, AHP needs **54%** more comparisons than the proposed approach, the ratio of AHP comparisons to the proposed approach comparisons is **2.18**. If we use n = 20 criteria and m = 15 CSPs, then AHP will need **2290** comparisons and the proposed approach will imply **577** comparisons which means that AHP has approximately **75%** more comparisons than the proposed approach, and the ratio is approximately **4**. These number illustrates the additive complexity of AHP compared to the proposed approach as n and m increase. Given that the more comparisons the DM has to judge, the more inconsistency of the results, we can justify why the proposed approach has always smaller values of CR compared to AHP.

IX. CONCLUSION AND FUTURE WORK

This paper proposed a novel MCDM approach that is feasible, efficient and consistent using relative preferences of criteria and alternatives. The proposed approach integrates Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Best Worst Method (BWM) to rank

CSPs using evaluation criteria characterizing their services. BWM is used for acquiring the weights of criteria and relative scores for alternatives w.r.t. criteria. These acquired values are utilized by TOPSIS to rank the cloud services. The proposed approach has been tested and validated through a use-case scenario which demonstrates its effectiveness and correctness. We have compared the proposed method to the most commonly used MCDM method (i.e., AHP). The results clearly showed that our proposed approach outperforms AHP in terms of computational complexity and consistency; therefore, it is more efficient and more reliable. The future work may be expanded as the integration of BWM with different MCDM methods in the cloud service selection problem and other applications.

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