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A Multi-Criteria Decision-Support Framework for Evaluating Fog Computing Challenges and Service Models

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ABSTRACT

Fog computing extends cloud computing by bringing processing, storage, and networking resources closer to end devices and data sources. This architecture can reduce latency, improve response times, decrease bandwidth consumption, and support applications that require rapid decision-making and the processing of large volumes of data. However, its adoption is affected by technological, operational, economic, and security-related challenges. This study develops a multi-criteria decision-making model to evaluate the principal challenges of fog computing and identify the most suitable fog computing service model. Seven criteria are considered: latency requirements, bandwidth efficiency, security and privacy, scalability and flexibility, energy efficiency, cost effectiveness, and network reliability. Six service models are evaluated as alternatives: Infrastructure-as-a-Service, Platform-as-a-Service, Software-as-a-Service, Data-as-a-Service, Communication-as-a-Service, and Edge-as-a-Service. The proposed framework integrates the Entropy and CoCoSo methods within a crisp decision-making environment. The Entropy method is used to determine objective criteria weights, while the CoCoSo method is employed to prioritize the alternatives. The results indicate that network reliability is the most influential criterion, with a weight of 0.2636, followed by energy efficiency with a weight of 0.2343. Security and privacy receives the lowest weight of 0.0360. Among the evaluated alternatives, Software-as-a-Service achieves the highest ranking, followed by Data-as-a-Service and Infrastructure-as-a-Service. Comparative analysis using the WASPAS and TOPSIS methods and sensitivity analysis under five scenarios are conducted to examine the robustness and stability of the findings. The results provide practical guidance for researchers, service providers, and policymakers involved in fog computing adoption and implementation across distributed, data-intensive, and time-sensitive computing environments in practice.

1. Introduction

Fog computing [1] is very much suitable for IoT, autonomous systems and smart cities, which is extremely versatile as it enables real-time data processing in proximity to the source. It supports various kinds of applications by minimizing latency, reinforcing security and boosting efficiency. Moreover,

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several difficult challenges [2] impede the adoption of fog computing. The challenges of managing distributed infrastructure are increasing, requiring robust security and network management processes. Linkage with existing cloud systems and high deployment costs are some of the hurdles faced by organizations. Regulatory compliance and ensuring data privacy are other crucial issues. Scalability remains a significant challenge, as expansion of fog nodes requires substantial resources. In addition, energy consumption can increase due to ongoing data processing at the edge. Standardization causes further complications in the interoperability between several fog computing environments. Advancements in Artificial Intelligence (AI) [3] and 5G [4] are expected to increase fog computing efficiency and adoption despite the above barriers. The combination of Entropy [5] and CoCoSo [6] provides a more reliable decision-making framework than many conventional MCDM methods. In general, the Entropy and CoCoSo methods reduce subjective bias to a large extent by determining the weight of the adopted criteria and the correct ranking of the alternatives based on the inherent variability of the model data. Moreover, unlike other conventional methods such as AHP [7], TOPSIS [8] or COPRAS [9], the Entropy-CoCoSo combination improves the consistency of the decision by increasing the ability to distinguish between alternatives. We have used these two special decision-making methods in this paper because these methods are computationally flexible, efficient, and can solve various complex real-world decision problems with high accuracy and reliability. The following paragraphs discuss cloud computing, edge computing, and fog computing and outline their services.

Cloud computing [10] provides access to different computing resources, i.e., servers, storage and software over the internet. It actually comes from the development of computer networks, internet technologies and virtualization. Professor John McCarthy proposed the concept of utility computing in 1960 and then Joseph Carl Robnett Licklider started to explore this idea globally in 1962. Utilizing these concepts, in the 2000s, modern cloud computing initially developed with different companies, like Microsoft Office, Amazon and Google on large-scale cloud infrastructures. It was prompted by the need to replace traditional on-premise hardware with flexible, budget-friendly and scalable solutions.

Cloud computing services provide on-demand access to computing resources, including storage, processing capacity, and networking, over the internet. These services include Infrastructure-as-a-Service, Platform-as-a-Service, Software-as-a-Service, Data-as-a-Service, Communication-as-a-Service, and Edge-as-a-Service [11], thereby addressing diverse commercial and personal requirements. Users can scale resources up or down according to their needs, which provides greater flexibility and helps control costs. Cloud-based backup and security solutions also support data protection, disaster recovery, and remote access. These services are widely used in business, education, healthcare, entertainment, and other fields to improve productivity and operational efficiency.

In the 1990s, edge computing [12] originated from the initial concept of Content Delivery Network (CDN). By processing the required data nearer to its main source, this localized computing process minimizes delay and allows for real-time response capabilities. By holding sensitive data regionally, it raises safety and privacy while optimizing bandwidth utilization by reducing the necessary bandwidth for cloud data transactions.

For smarter decision-making, edge analytics and Artificial Intelligence enable instant data processing and IoT edge services and also effectively handle connected devices. Currently, 5G edge computing is available on the market, which enhances internet speed and performance and supports a seamless mobile experience. CDNs increase content distribution by caching data near consumers. It has a crucial role in manufacturing automation, autonomous systems, and smart cities by promoting real-time control and supervision. The reason for completely trusting Edge Computer is that it provides unwavering internet service reliability. Its use enhances user experience and efficiency across several industries, including healthcare, retail and smart homes. After considering all perspectives, edge computing transforms digital ecosystems by bringing evaluation closer to the data source for faster, more efficient operations and remakes.

Fog computing [13] comes from the need to process required data closer to its source, reducing latency and improving efficiency in distributed systems. It was introduced by Cisco in 2012 as

an extension of cloud computing to support real-time applications, particularly for the Internet of Things (IoT). The idea emerged from the drawbacks of conventional cloud computing, such as high latency and bandwidth constraints, which posed challenges for applications requiring fast processing, including smart cities and driverless cars. It acts as a middle layer between the cloud and the edge devices, enhancing performance, security and reliability in modern computing environments. Fog computing services provide storage facilities, data processing and networking closer to end devices, lowering bandwidth usage and delays. It enables real-time analytics for IoT applications, improving decision-making speed. Security services in fog computing improve data privacy by rectifying sensitive information locally. It also supports resource management by optimizing computational power across distributed nodes. These services are widely used in modern cities, health services, industrial automation and self-contained systems to improve efficiency and performance.

Fog computing balances processing between local edge devices and organized cloud servers and minimizes latency while maintaining flexibility, making it more necessary than cloud and edge computing. Fog computing processes data closer to the source, whereas cloud computing depends on remote data centres. This helps provide real-time responses in applications such as health management and autonomous vehicles. Edge computing is actually a device-specific system, but fog computing provides a proper distributed network that boosts effectiveness and resource management. It eliminates network congestion by limiting needless data communication to the cloud. In industrial automation, it guarantees uninterrupted performance with real-time monitoring and maintenance. It enables rapid diagnosis and supports healthcare by securely processing patient information. Fog computing is applied in smart cities for energy management, traffic control, and surveillance. Thus, fog computing offers a balanced, sage and productive approach to modern digital requirements.

1.1 Motivation of this research

The motivation for this research arises from the expanding use of fog computing in real-time data analysis and Internet of Things (IoT) applications, which require reliability, security, and interoperability. Identifying these challenges will improve productivity, cost-effectiveness, and seamless integration with cloud and edge computing environments. By implementing MCDM methods, this research aims to address the adaptability and barrier issues associated with fog computing. Ultimately, the research results will help users address these challenges successfully.

1.2 Novelties of the study

This section describes the novelties of the paper. Scientifically examining the adoption of fog computing and its various challenges is a complex task. The novelties of the study are as follows:

1. Various challenges to adopting fog computing are analyzed and discussed.
2. Various services of fog computing are considered for adopting this technology.
3. Two MCDM methods are used to evaluate the proposed model: the Entropy method determines the criteria weights, and the CoCoSo method evaluates the ranking of the alternatives.
4. Multiple DMs are considered for the fair and unbiased data collection process.
5. Sensitivity analysis is conducted to check the stability of the proposed system.

1.3 Structure of this paper

The structure of this study is presented in this section, as follows: First, the introduction to the adaptability and challenges of fog computing is explained in Section 1. Then, Section 2 presents a literature survey on this study and the proposed MCDM methodologies. The mathematical processes of the proposed decision-making MCDM methodologies are presented in Section 3. Further, Section 4 and Section 5 outline the procedures for criteria selection and alternative sorting for this adaptation and challenge issues, respectively. The overall formulation of the model and data collection technique of this proposed research are structured in Section 6. Furthermore, the numerical illustration and discussion for this research study are presented in Section 7. The comparative and sensitivity analyses of this model are presented in Section 8. Ultimately, the research implications of this empirical study are discussed in Section 9. Finally, conclusions and future research scope are analyzed in Section ??.

2. Literature survey of this study

This section presents a brief literature survey of recent studies on fog computing adoption challenges and multi-criteria decision-making (MCDM) methods.

2.1 Background of Application

Implementation complexity, high infrastructure costs, and integration with existing systems are the main obstacles to the adoption of fog computing [14]. Privacy and security issues [15] arise because data are processed across several distributed nodes. The primary challenge remains ensuring interoperability across diverse IoT platforms and devices. Widespread acceptance is hindered by a lack of standards and skilled professionals. For large-scale implementations, power consumption and resource management are also important issues. Despite these barriers, technological advancements and industry collaboration are driving the adoption of effective fog computing solutions [16]. To provide a clearer understanding, Table 1 presents a literature survey of several studies on fog computing.

Table 1

Some recent literature on fog computing model

Author	Year	Methodology	Application Area
Khaledian <i>et al.</i> , [17]	2025	MOAOA and TOPSIS	A two-stage approach to task scheduling in a fog-cloud environment
Mehta <i>et al.</i> , [18]	2025	TOPSIS	An optimization technique to schedule real-time IoT applications in Fog Computing
Ahmed <i>et al.</i> , [19]	2025	Real-time data processing	A review to identify the challenges and opportunities in IoT networks
Alsadie <i>et al.</i> , [20]	2024	PRISMA method	Application of AI techniques to secure the Fog Computing environments
Li <i>et al.</i> , [21]	2024	Optimization Method	High offloading service based fog computing
Jeyarama <i>et al.</i> , [22]	2024	Artificial intelligence	Applications of fog computing in healthcare services
Zavieh <i>et al.</i> , [23]	2024	FIMDEAP	Increased the productivity of fog computing
Alfakeeh <i>et al.</i> , [24]	2023	Stable matching algorithm	Resource allocation in fog-computing-based IoT networks
Hosseinzadeh <i>et al.</i> , [25]	2023	Scheduling algorithm	Fog computing with the help of task scheduling mechanisms
Aliyu <i>et al.</i> , [26]	2023	Discounts, congestion and the relative distance	Smart shopping with the help of fog computing-supported path planning
Qian <i>et al.</i> , [27]	2022	Federated Learning (FL) with Machine Learning (ML)	Analytics required data for Fog Computing
Saurabh <i>et al.</i> , [28]	2021	Integration	To solve problems with identifying the challenges during integration of cloud with IoT for fog computing paradigm
Movahedi <i>et al.</i> , [14]	2021	OppoCWOA	A multi-objective task evaluation model of fog computing system analysis
This article	2026	Entropy & CoCoSo	Adaptation and challenges of fog computing model

2.2 Literature of MCDM methodologies

The MCDM [29, 30] is a method for making decisions when multiple, conflicting criteria are presented. In real life, there are many types of decision-making methods [31] for assigning weights to different criteria in different problems. Also, the primary function of some MCDM [32] is to determine the order of alternatives. In this paper, we have applied the entropy method [6] and the CoCoSo method [33]. The entropy method is a popular MCDM technique used for finding criteria weight and the CoCoSo method is very effective for ranking alternatives in an uncertain environment. These MCDM methodologies are applied in numerous fields, including education [34], technology [35], supply chain [36], industries, risk assessment [37], medicine [38], data analysis [3], disaster management [39] and so on. Some of the recently published papers on the entropy method and the CoCoSo method are listed in Table 2 and Table 3, respectively.

3. Proposed MCDM Methodology

For problems involving multiple criteria, MCDM processes [59, 60, 61] provide a structured means of determining the best feasible solution. These methods are widely applied to real-world problems. In this study, the overall problem is evaluated through two processes: the Entropy weighting method and the CoCoSo ranking method. This section first presents the Entropy method and then the CoCoSo method.

3.1 Entropy Weighted Method (EWM)

In 1948, C. E. Shannon [62] proposed a mathematical procedure called the Shannon method, or entropy-weighting method. It is one of the most useful decision-making methods for determining criteria weights. It plays a crucial role in balancing conflicting criteria and quantifying their relationships [6]. The graphical framework of the entropy-weighting methodology [47] is shown in Figure 1. The stepwise procedure of the Entropy Weighting Method (EWM) is presented below.

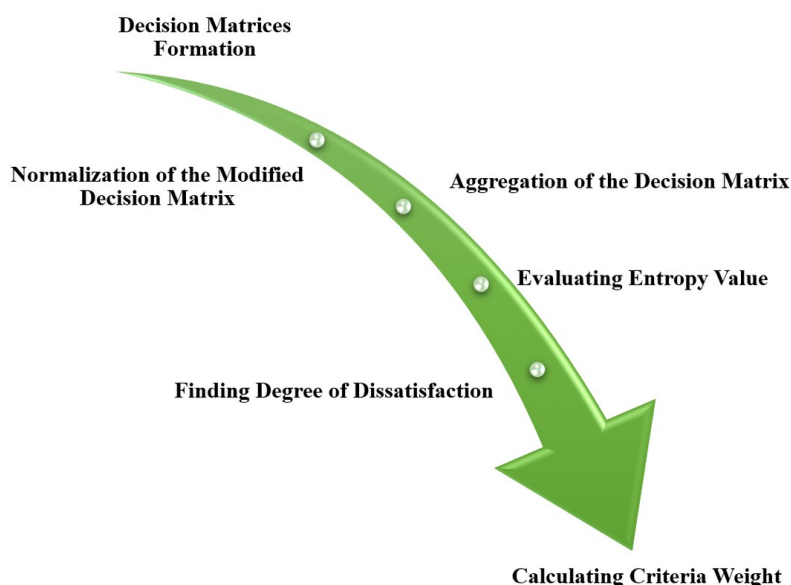


Fig. 1. Structural flowchart of the entropy weighted method

Step I: Decision Matrices Formation:

In this study, we choose P number of criteria, i.e., $(C_1, C_2, \dots, C_P)$ and Q number of alternatives, i.e., $(A_1, A_2, \dots, A_Q)$. Here, R number of decision makers (DMs) make viewpoints based on their wise skills and knowledge. Now, we have established a decision matrix based on the DMs' opinion. We can also say that there are total R number of decision matrices. Now, the

Table 2
Literature of the latest studies on the entropy method

Author	Year	Optimization Tools	Uncertainty taken	Application Area
Lakshmi <i>et al.</i> , [40]	2025	FAHP, ENTROPY, TOPSIS, PROMETHEE, VIKOR & ELECTRE	Triangular Fuzzy Number (TFN)	Selecting portfolio in the post-COVID Indian mutual fund market
Pan, L., [41]	2025	TOPSIS & ENTROPY methods	Crisp number	Assessment of the level of energy security of China
Ren <i>et al.</i> , [42]	2025	AHP & Entropy methods	Crisp number	Identifying the factors which are influencing spatial demand of EVs public charging stations
Liang <i>et al.</i> , [43]	2025	Entropy method	fuzzy number	Diagnosing fault of battery systems in electric vehicles
Kumar <i>et al.</i> , [44]	2023	Entropy method	Picture fuzzy sets and fuzzy measures	A new measure for managing ambiguity in MCDM with picture fuzzy entropy
Öztürk <i>et al.</i> , [45]	2023	Anti-Entropy Weighting method and TOPSIS method	Fuzzy number	A particular case of the scientific and technological research council of Türkiye
Thakur <i>et al.</i> , [46]	2022	Entropy method	Pythagorean fuzzy sets	Application to group decision-making with complex proportional assessment
Cao <i>et al.</i> , [29]	2022	Entropy & TOPSIS methods	Fuzzy number	Application on the investment decision optimization of large-scale projects
Kumar <i>et al.</i> , [47]	2021	Entropy & TOPSIS methods	Pythagorean fuzzy number	Application in inclination of the advertising company
Aldring <i>et al.</i> , [48]	2021	CRITIC & Entropy methods	Fuzzy sets	A systematic analysis based on fuzzy MCDM
Reddy <i>et al.</i> , [49]	2019	Entropy & TOPSIS methods	Trapezoidal fuzzy number	Selection for the sustainable building material
Garg <i>et al.</i> , [50]	2015	Entropy method	Fuzzy triangular number	Application on MCDM Method under uncertain environment with unknown attribute weights

decision matrix formed by β^{th} decision maker is denoted by $(\mathcal{G})_{\beta}$. So, the decision matrices are

Table 3
Literature of the latest studies on the CoCoSo method

Author	Year	Optimization Tools	Uncertainty taken	Application Area
Zhai <i>et al.</i> , [33]	2025	CoCoSo method	Interval Neutrosophic Sets	Evaluating the quality of Higher Education Management
Thinh <i>et al.</i> , [51]	2024	CoCoSo method	Crisp number	Selecting Copper electrical wire
Lai <i>et al.</i> , [52]	2020	CoCoSo method	Crisp number	Selection of Cloud Service provider
Liang, J., [53]	2024	CoCoSo & CRITIC method	Double-Valued Neutrosophic Sets	Evaluating the teaching effectiveness
Abdolshah, M., [54]	2025	CoCoSo method	Crisp number	Comparative analysis of evaluation of BPM regarding digital transformation
Mukherjee <i>et al.</i> , [55]	2025	CoCoSo & WASPAS method	Fuzzy number	A review of two alternative ranking methods
Taghizadeh <i>et al.</i> , [35]	2025	CoCoSo method	Crisp number	Ranking of innovative strategies in the digital economy
Ahmad <i>et al.</i> , [36]	2024	CoCoSo method	Circular spherical fuzzy sets	Optimization of logistics in oil and gas supply chain
Bhanutej <i>et al.</i> , [56]	2024	GRA-TOPSIS & CoCoSo method	Crisp number	Assessing the efficacy of healthcare organizations
Xiao <i>et al.</i> , [57]	2025	TOPSIS & CoCoSo method	Triangular Fuzzy Neutrosophic Sets	Evaluating the effect of intelligent technology for empowering Physical Education teaching
Lai <i>et al.</i> , [58]	2022	CoCoSo method	Hesitant Fermatean Fuzzy Set	Evaluating Blockchain Platform

represented as,

$$(\mathcal{G})_{\beta} = \left[(\mathcal{J}_{\alpha\delta})_{\beta} \right]_{Q \times P} = \begin{bmatrix} (\mathcal{J}_{11})_{\beta} & (\mathcal{J}_{12})_{\beta} & \cdots & (\mathcal{J}_{1P})_{\beta} \\ (\mathcal{J}_{21})_{\beta} & (\mathcal{J}_{22})_{\beta} & \cdots & (\mathcal{J}_{2P})_{\beta} \\ \vdots & \vdots & \ddots & \vdots \\ (\mathcal{J}_{Q1})_{\beta} & (\mathcal{J}_{Q2})_{\beta} & \cdots & (\mathcal{J}_{QP})_{\beta} \end{bmatrix} \quad (1)$$

where $\beta = 1, 2, \dots, R$; $\alpha = 1, 2, \dots, Q$ and $\delta = 1, 2, \dots, P$. Here, each decision matrix $(\mathcal{G})_{\beta}$ is of order $Q \times P$ and all elements of the decision matrix are crisp numbers.

Step II: Aggregation of the Decision matrix:

The decision matrices are aggregated into a single decision matrix by using Equation (2), as

follows:

$$\mathcal{J}_{\alpha\delta} = \left(\prod_{\beta=1}^R \{(\mathcal{J}_{\alpha\delta})_{\beta}\} \right)^{\frac{1}{R}} \quad (2)$$

Now, the Aggregated decision matrix ($\mathcal{G}_A$) defined as,

$$\mathcal{G}_A = [(\mathcal{J}_{\alpha\delta})]_{Q \times P} \quad (3)$$

where $\mathcal{J}_{\alpha\delta}$ are evaluated by using the Formula 2 where $\alpha = 1, 2, \dots, Q$ and $\delta = 1, \dots, P$.

Step III: Normalization of the modified Decision matrix:

Normalize the aggregated decision matrix by using Equation (4), as follows:

$$\mathcal{J}_{\alpha\delta}^N = \frac{\mathcal{J}_{\alpha\delta}}{\sum_{\alpha=1}^Q \mathcal{J}_{\alpha\delta}} \quad (4)$$

and the normalized decision matrix can be represented as,

$$\mathcal{G}_A^N = [(\mathcal{J}_{\alpha\delta}^N)]_{Q \times P} \quad (5)$$

where $\delta = 1, 2, \dots, P$ and $\alpha = 1, 2, \dots, Q$.

Step IV: Evaluating Entropy value:

The Entropy value ($\mathcal{E}'_{\delta}$) of each criteria will be evaluated in this step with the help of the following Equation (6),

$$\mathcal{E}'_{\delta} = -\frac{1}{\log Q} \times \sum_{\alpha=1}^Q \{ \mathcal{J}_{\delta\alpha}^N \times \log (\mathcal{J}_{\delta\alpha}^N) \} \quad (6)$$

where $\delta = 1, 2, \dots, P$ and $\alpha = 1, 2, \dots, Q$.

Step V: Finding degree of Dissatisfaction:

For each criteria δ , the degree of dissatisfaction $\mathcal{I}_{\delta}$ is calculated by applying the following formula,

$$\mathcal{I}_{\delta} = (1 - \mathcal{E}'_{\delta}) \quad (7)$$

for $\delta = 1, 2, \dots, P$.

Step VI: Calculating criteria weight:

Finally, the criteria weight ($\mathcal{W}_{\delta}$) of each criteria will be evaluated as follows,

$$\mathcal{W}_{\delta} = \frac{\mathcal{I}_{\delta}}{\sum_{\delta=1}^P \mathcal{I}_{\delta}} \quad (8)$$

From equation (8), we will obtain the weight ($\mathcal{W}_{\delta}$) of each criteria which will be used for further calculation, where $\delta = 1, 2, \dots, P$.

3.1.1 Advantages of taking Entropy method

Entropy methodology is a very beneficial MCDM method and its key advantages are:

1. The Entropy approach minimizes subjectivity in MCDM by providing required weights based on the given data.
2. The entropy methodology is executed based on Shannon's entropy theory and it ensures the system's consistency and reliability.
3. Unlike individual methodologies like AHP, it relies solely on data, but it avoids human bias.
4. This method seamlessly processes large datasets and tackles several criteria.
5. Higher variability in a criterion means a higher value, which guarantees logical weight distribution.
6. The entropy methodology ensures that selected criteria with distinct differences are given greater relevance.

3.1.2 Disadvantages of taking Entropy method

While the Entropy method in MCDM has many advantages, it also has some limitations, such that

1. Errors or inconsistencies in the data received during entropy processing can lead to misleading weighting. This method converts the linguistic term to numerical input for further processing.
2. The entropy process determines that every criterion influences choices equally, which may not always be the case. If they are extremely correlated, the process may overstate or understate their significance.
3. Although manageable, this process can become difficult for very large datasets and therefore requires pre-processing.
4. The entropy method does not adjust to changing preferences or real-world circumstances unless recalculated with fresh data.

3.2 Combined Compromise Solution (CoCoSo) Method

The CoCoSo method is an MCDM technique for ranking alternatives developed by Yazdani *et al.*, [63] in 2019. Here, we provide a detailed description of the CoCoSo method [6]. The graphical flowchart of the CoCoSo method is depicted in Figure 2. Here, P criteria and the opinions of R decision makers are considered to rank Q alternatives.

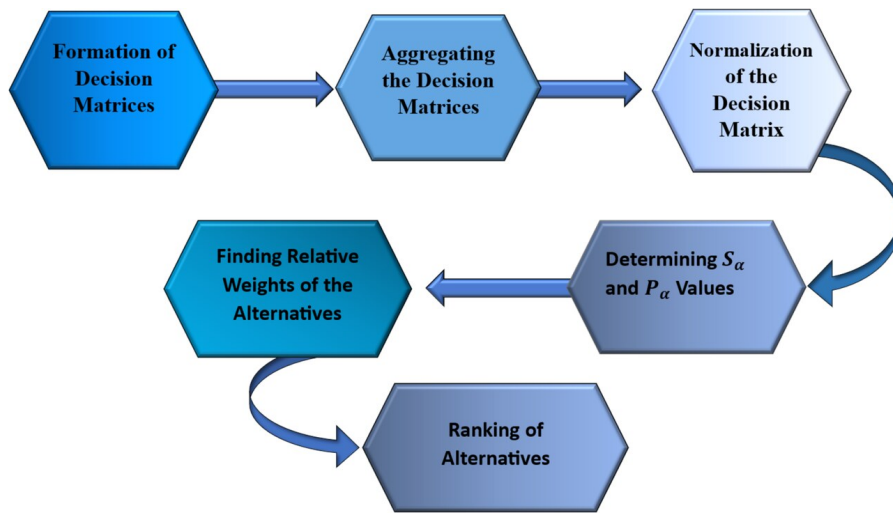


Fig. 2. Flowchart of the MCDM-based CoCoSo method

(i) Formation of Decision Matrices:

In this step, we will construct the decision matrices $(\mathcal{G})_\beta$ where $\beta = 1, 2, \dots, R$ in a similar way as we have mentioned in step I of the Entropy method and it is represented in the same way as we mentioned in Equation (1). i.e,

$$(\mathcal{G})_\beta = \left[(\mathcal{J}_{\alpha\delta})_\beta \right]_{Q \times P} \quad (9)$$

where $\beta = 1, 2, \dots, R$, $\alpha = 1, 2, \dots, Q$ and $\delta = 1, \dots, P$. Here, each decision matrix is of order $Q \times P$ and all elements of the matrices are crisp numbers.

(ii) Aggregating the Decision Matrices:

In this step, we will aggregate these decision matrices into a single matrix called Aggregated Decision Matrix $(\mathcal{G}_A)$ using Equation (2). It is defined in a similar way, which is given in Equation (3) of step II of the Entropy method.

(iii) Normalization of the Decision Matrix:

In this step, we will normalize the decision matrix by using the following formula,

$$\begin{cases} \mathcal{J}_{\alpha\delta}^N = \frac{\mathcal{J}_{\alpha\delta} - \min_{\alpha} \mathcal{J}_{\alpha\delta}}{\max_{\alpha} \mathcal{J}_{\alpha\delta} - \min_{\alpha} \mathcal{J}_{\alpha\delta}} ; \text{ for benefit Criterion} \\ \mathcal{J}_{\alpha\delta}^N = \frac{\max_{\alpha} \mathcal{J}_{\alpha\delta} - \mathcal{J}_{\alpha\delta}}{\max_{\alpha} \mathcal{J}_{\alpha\delta} - \min_{\alpha} \mathcal{J}_{\alpha\delta}} ; \text{ for cost Criterion} \end{cases} \quad (10)$$

where $\delta = 1, 2, \dots, P$. The normalized matrix is of the form

$$\mathcal{G}_A^N = [(\mathcal{J}_{\alpha\delta}^N)]_{Q \times P} \quad (11)$$

(iv) Determining $\mathcal{S}_{\alpha}$ and $\mathcal{P}_{\alpha}$ values:

Here, for each alternatives, we will consider the total of the weighted comparability sequence and the whole of the Power weight of comparability sequences. The sum of the weighted comparability sequence is denoted by $\mathcal{S}_{\alpha}$ and defines as,

$$\mathcal{S}_{\alpha} = \sum_{\delta=1}^P (\mathcal{W}_{\delta} \mathcal{J}_{\alpha\delta}^N) \quad (12)$$

where $\alpha = 1, 2, \dots, Q$. The $\mathcal{S}_{\alpha}$ values are evaluated depending on relational generation approach. The sum of the power weight of comparability sequences is denoted by $\mathcal{P}_{\alpha}$ and defined as,

$$\mathcal{P}_{\alpha} = \sum_{\delta=1}^P (\mathcal{J}_{\alpha\delta}^N)^{\mathcal{W}_{\delta}} \quad (13)$$

where $\alpha = 1, 2, \dots, Q$. The $\mathcal{P}_{\alpha}$ values are evaluated based on the WASPAS multiplication attribute.

(v) Finding Relative Weights of the alternatives:

In this step, we will calculate the relative weights of the alternatives by applying 3 appraisal score strategies, which are discussed as follows:

$$\mathcal{H}_{\alpha a} = \frac{(\mathcal{P}_{\alpha} + \mathcal{S}_{\alpha})}{\sum_{\alpha=1}^Q (\mathcal{P}_{\alpha} + \mathcal{S}_{\alpha})} \quad (14)$$

which represents the Arithmetic mean of the sums of WSM and WPM scores.

$$\mathcal{H}_{\alpha b} = \frac{\mathcal{S}_{\alpha}}{\min_{\alpha} \mathcal{S}_{\alpha}} + \frac{\mathcal{P}_{\alpha}}{\min_{\alpha} \mathcal{P}_{\alpha}} \quad (15)$$

which represents the sum of the relative scores of WSM and WPM compared to the best.

$$\mathcal{H}_{\alpha c} = \frac{\xi \mathcal{S}_{\alpha} + (1 - \xi) \mathcal{P}_{\alpha}}{\xi \max_{\alpha} \mathcal{S}_{\alpha} + (1 - \xi) \max_{\alpha} \mathcal{P}_{\alpha}} ; \text{ where } 0 \leq \xi \leq 1 \quad (16)$$

which represents a balanced compromise between the WSM and WPM model scores. Here, the value of ξ depends entirely on the DM's choice.

(vi) Ranking of alternatives:

Lastly, we will calculate the value of $\mathcal{H}_{\alpha}$ corresponding to each alternative.

$$\mathcal{H}_{\alpha} = (\mathcal{H}_{\alpha a} \mathcal{H}_{\alpha b} \mathcal{H}_{\alpha c})^{1/3} + \frac{(\mathcal{H}_{\alpha a} + \mathcal{H}_{\alpha b} + \mathcal{H}_{\alpha c})}{3} \quad (17)$$

Using the Equation (17), we can find the value of $\mathcal{H}_{\alpha}$. The alternative which possesses more value of $\mathcal{H}_{\alpha}$ will receive a better ranking.

3.2.1 Advantages of taking CoCoSo method

CoCoSo method is a very effective MCDM method. Some advantages of using these methods are mentioned as follows:

1. The numerical calculations of the CoCoSo methods are easier than those of other complex MCDM methodologies.
2. It can address both beneficial and non-beneficial criteria.
3. This method included diverse approaches rather than a single approach and thus the generated result became more reliable and balanced.
4. This method can be used effectively in a flexible environment with either subjective or objective weights.

3.2.2 Disadvantages of taking the CoCoSo method

Despite the various benefits of the CoCoSo method, there are some disadvantages of this method, such as:

1. The result obtained from this method can differ if the normalization technique is changed.
2. In some decision-making problems where so many criteria and alternatives are considered, the mathematical calculations of this method become too lengthy to tackle.
3. The result obtained from this method relies on the quality of the considered data set.
4. To use this method, it is essential to have some previous understanding of the basic concepts of MCDM calculations.

3.3 Pseudo-Code of the Proposed Model

In this fog computing model, build the structure with P criteria, Q alternatives and R decision-makers, and the decision matrix of order $m \times n$. Two MCDM methods are used for this numerical computation. The pseudo code of this model is as follows:

INPUT: R number of $Q \times P$ order decision matrix

OUTPUT: Compute criteria weight and rank the alternatives

INITIALIZE: Linguistic terms and crisp numbers

OPERATION: Entropy and CoCoSo

1. **MERGE** aggregate the R number of decision matrices
 2. **NORMALIZATION** normalize the aggregated decision matrix
 3. **FOR Entropy**
 4. **FIND** determine the logarithmic sum for every criteria
 5. **CALCULATE** find out the entropy value and degree of dissatisfaction value
 6. **FIND** determine the weights of the criteria
 7. **END Entropy**
 8. **BEGIN CoCoSo**
 9. **COMPUTE** determine the $\mathcal{S}_\alpha$ and $\mathcal{P}_\alpha$ values
 10. **FIND** evaluate the $\mathcal{K}_{\alpha a}$, $\mathcal{K}_{\alpha b}$ and $\mathcal{K}_{\alpha c}$ for alternatives
 11. **RANKING** rank the alternatives based on the value of $\mathcal{K}_\alpha$
 12. **END CoCoSo**
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4. Criteria Selection for Challenges of Fog Computing

Fog computing is an advanced technology that extends cloud computing. It is suitable for applications in which a quick response or rapid decision-making is required. This supports the development of faster and more effective systems, giving fog computing broad applications across different technologies. Its challenges can therefore be treated as criteria in this problem. We reviewed numerous research articles and consulted decision experts. Finally, we selected seven key factors as criteria for this decision-making problem: Latency Requirements ($\mathcal{C}_1$), Bandwidth Efficiency ($\mathcal{C}_2$), Security and

Privacy (C_3), Scalability and Flexibility (C_4), Energy Efficiency (C_5), Cost Effectiveness (C_6), and Network Reliability (C_7). The following subsections briefly discuss these criteria.

4.1 Latency Requirements (C_1)

Latency Requirements [64] Latency is an important criterion in fog computing. Latency is measured by the delay between receiving a request and receiving a response. In networking and computing, it helps us understand the amount of time it takes for data to travel from source to destination and vice versa. In traditional cloud computing, there was a long distance between the server and the user, which caused delays in data transmission. In addition, it is recommended to include things like bandwidth utilization, latency threshold, compute capacity, and scalability parameters to improve technical depth. In fog computing, servers are usually located very close to end users, which also helps in reducing response time and jitter. Latency is also affected by various factors such as network congestion, data transmission speed, distance to fog nodes, and processing power. There are many areas such as smart healthcare, automated industries, self-driving vehicles, etc., where even a small delay can cause major problems and low latency is required in these areas. Therefore, latency is a key factor in providing high-quality services through fog computing. The analysis will be further enhanced and strengthened by explicitly linking the criteria of IaaS with measurable impacts within the fog-based architecture.

4.2 Bandwidth Efficiency (C_2)

Bandwidth Efficiency [65] is a crucial criteria of fog computing. In fog computing, bandwidth efficiency quantifies the effective use of network resources and the smooth transmission of data without jamming the system. Fog computing reduces the need to send large amounts of data to distant cloud servers, as the data is closer to end users and thus saves bandwidth. This is particularly useful in cases where large amounts of data are generated continuously, such as healthcare monitoring, industrial automation, smart cities and video surveillance. Good bandwidth ensures faster data transfer, reduced costs and a stable network connection.

4.3 Security and Privacy (C_3)

Security and privacy are among the main criteria of fog computing [64]. Fog computing is very effective because it helps in reducing the distance between cloud services and users and thereby bringing them closer to each other. Protecting sensitive data processed in distributed edge nodes of fog computing makes it more vulnerable than in centralized cloud environments. Therefore, some security issues arise, such as unauthorized access, malware attacks, data theft, etc. Therefore, strong encryption and an authentication mechanism are very important to protect such sensitive data. Maintaining confidentiality is also a very important issue to keep personal confidential information safe. Having complete control over the access and techniques used to protect personal information on the server is essential, as the data is processed in multiple locations. Sometimes, a problem arises in which hackers try to listen to or modify data in transit, which can be solved by implementing secure communication protocols. Regular updates and patch management are required to mitigate the flaws of fog devices. Strong encryption and intrusion detection techniques help maintain secure communication between fog nodes and cloud servers while maintaining data integrity and confidentiality. Therefore, a proper security and privacy plan helps ensure compliance with data protection regulations. Therefore, strong security and privacy measures are essential to ensure reliable, trustworthy, and real-time fog computing operations.

4.4 Scalability and Flexibility (C_4)

Scalability and Flexibility [66] are very important criteria of fog computing. Fog computing intensifies the scalability through helping the system to address the tasks properly by sharing the work among many nearby devices. Thus, it reduces the dependency of systems on one large centralized cloud system. Sometimes, issues arise, such as difficulty in identifying which resource can be used for operating a work or the quantity of resources needed for working effectively. However, fog computing can adaptively use and allocate different types of resources as needed, depending on the workload.

The decentralized design of fog computing makes it more flexible and efficient for the execution of applications and services closer to end-users. It also helps to add new nodes without hampering the existing system. Due to its flexibility, it helps process real-time data and make decisions quickly across diverse situations. Thus, the characteristics of scalability and flexibility of fog computing make it more applicable in smart devices, IOT, automated industries, etc.

4.5 Energy Efficiency (C_5)

Energy Efficiency [64] is a crucial criteria of fog computing. Fog computing reduces energy consumption during data processing as it helps to diminish the distance between the source and the cloud. It assists in lessening network congestion and minimizing the utilization of power in data centres. In Fog computing, data is processed locally, which enables it to utilize the resources optimally and reduce energy waste during data transmission. Efficient power sharing among fog nodes is balanced through adaptive load balancing. The durability of the battery of edge devices can be extended by including an energy-saving algorithm. Fog computing mitigates energy costs and environmental impact, thereby helping achieve sustainability.

4.6 Cost Effectiveness (C_6)

In fog computing, cost effectiveness [67] is a vital criteria. Fog computing reduces the reliance on expensive cloud resources and thus it helps to minimize the cost related to data transmission. In fog computing, data are processed locally, which diminishes bandwidth usage and thus helps to lessen the network costs. It eliminates the need for additional hardware by leveraging existing edge devices. The cost of maintenance and operation is reduced by proper resource allocation. Thus, fog computing helps manage real-time data processing for IoT systems in an affordable and cost-effective manner.

4.7 Network Reliability (C_7)

Network Reliability [68] is one of the main criteria of fog computing. In fog computing, data are processed closer to the source, thereby increasing network reliability. It also decreases the dependency on centralized cloud services during data processing, which helps to reduce the delay during data transmission. It also supports the system to continue the operations even if there is a technical fault that arises and its distributed design assists in this case. This method minimizes network traffic and reduces data loss as it tackles the data locally and processes the system smoothly. Thus, fog computing helps provide services all the time and maintains the stability of the system.

5. Alternative for Adaptation of Fog Computing Model

Fog nodes provide various types of services in a network system, which are known as Fog computing service models [69, 70]. These models also assist us in recognizing the approach of interaction among these services with cloud and edge environments. Here, we have considered six fog computing service models as alternatives, based on a comprehensive literature review and consultation with decision experts. Alternatives are discussed as follows,

5.1 Infrastructure-as-a-Service (IaaS) ($\mathcal{A}_1$)

Infrastructure-as-a-Service (IaaS) [11] is a model where a fog node provides the infrastructure for virtual computing. It differs from traditional cloud IaaS mainly in terms of architecture, latency, and data processing location. It also provides some resources such as servers, storage, networking, and operating systems to end users. To manage their workloads and build their own applications, they can rent these resources from a cloud provider instead of purchasing them. Again, fog IaaS brings computing resources closer to edge devices and users, whereas cloud IaaS relies on centralized data centers located far from end users. Additionally, Fog IaaS reduces network congestion by processing data locally before sending it to the cloud to support location-aware services. This further streamlines this process by reducing layer storage, thereby automatically helping to achieve faster responses.

5.2 Platform-as-a-Service (PaaS) ($\mathcal{A}_2$)

In fog computing, developers are provided with the gadgets and atmosphere to set up, examine and run applications neighboring to devices despite, depending on remote cloud servers with the

help of Platform-as-a-Service (PaaS) [11]. Developers can concentrate on application areas without requiring to set up hardware or complicated infrastructure, as PaaS in fog computing includes ready-made software, management tools and security features. This model is highly applicable in areas where rapid responses are required, such as smart cities, sensor fusion, self-driving cars, and industrial machinery.

5.3 Software-as-a-Service (SaaS) ($\mathcal{A}_3$)

In fog computing, the Software-as-a-Service (SaaS) model [11] provides software applications over the fog framework. Users can operate these applications wherever they want without installing and updating them on their devices. Depending on fog nodes, this software is operated and some services like management of IoT devices, processing of data, prediction of trends, etc., are provided through this software. As rapid response and local data processing are very crucial for some real-time services such as advanced healthcare systems, smart cities, tracking vehicles, etc., this model is best suited for such circumstances.

5.4 Data-as-a-Service (DaaS) ($\mathcal{A}_4$)

In the Data-as-a-Service (DaaS) model, instant access to raw or already analyzed data is offered to users through the fog nodes. Here, users can retrieve the data directly from the source, thereby reducing the need to transmit it to central cloud servers. In some scenarios where swift access to a huge amount of data is needed, then this model becomes very effective. This model is applicable in some situations, such as tracking environmental changes, smart grid operations and sensor data in industry.

5.5 Communication-as-a-Service (CaaS) ($\mathcal{A}_5$)

In fog computing, Communication-as-a-Service (CaaS) is a model that provides communication services over the fog network. It enables devices and sensors to operate smoothly by providing low-latency, highly reliable connectivity. Fog nodes help manage network routes, move data, and follow communication rules, thereby assisting fast data sharing among edge devices, IoT systems, and cloud resources. In emergency response systems, this model becomes very effective.

5.6 Edge-as-a-Service (EaaS) ($\mathcal{A}_6$)

In fog computing, deployment and accessibility of edge computing resources are given to users through the Edge-as-a-Service (EaaS) model. Thus, organizations are allowed to operate applications close to the source of data, using fog computing, which has some inherent attributes like fast processing, real-time analysis, and prompt decision-making. The EaaS model simplifies managing edge hardware and software services, making it easier to set up and maintain edge-based services. This model is particularly well-suited to large-scale IoT systems.

6. Model Formulation and Data Collection

6.1 Model formulation

In this section, we will discuss model formulation. Seven criteria are considered to evaluate the adaptability and challenges of fog computing, which are mentioned in section 4. And, six different services are also taken as alternatives, which are discussed in Section 5. Therefore, the order of the decision matrix is 6×7 . We have also considered the opinions of three decision-making experts who are experienced in this field. Figure 3 conveys the hierarchical structure of the proposed research model.

6.2 Data collection

This section discusses the sources of information for this study. The data are collected in an unbiased way from three decision-makers (DMs). All DMs are professional, experienced and knowledgeable in their fields. The brief details on DMs are given as follows

DM_1 : A cybersecurity expert who evaluates privacy protection and data integrity within the fog computing framework.

DM_2 : An energy management expert professor in the MBA department of a university.

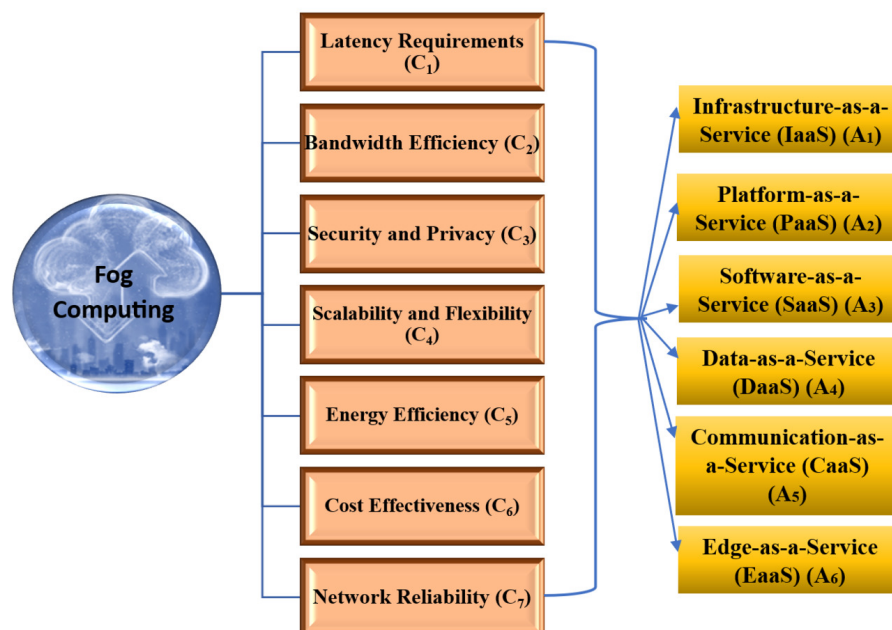


Fig. 3. Hierarchical Structure of the Suggested Fog Computing model

DM_3 : A network administrator with expertise in network infrastructure management, latency optimization and resource allocation.

Table 4 presents the linguistic terms associated with their crisp values. The decision-makers provided their decision in linguistic terms. Thus, we have three decision matrices, which are shown in Table 6. For our subsequent calculations, we have converted these linguistic terms into equivalent crisp values using Table 5.

Table 4

The comparison table between linguistic terms and the set of considered numbers

Linguistic terms	Crisp numbers
Absolutely Significant Inference (ASI)	13
Strongly Significant Inference (SSI)	11
More Significant Inference (MSI)	9
Equally Significant Inference (ESI)	7
Less Significant Inference (LSI)	5
Below Significant Inference (BSI)	3
Weakly Significant Inference (PSI)	1

Remark 1. Justification for using "Crisp environment" instead of "Fuzzy sets": The Crisp environment has been used in studies on the adaptability and challenges of fog computing because it makes the available data and evaluation criteria measurable and explicit. In this environment, Crisp values provide an easy interpretation of the results with the help of calculations in the decision-making process. However, the complexity of the calculations increases because fuzzy sets [71] usually operate in an uncertain environment. As a result, in the Crisp environment, decision makers can analyze the

model very quickly based on quantitative information in the considered problem. Therefore, the Crisp environment is suitable for achieving effective and reliable decision-making results.

Table 5

Decision matrix constructed by linguistic terms by three DMs

DM	Alternative	C_1	C_2	C_3	C_4	C_5	C_6	C_7
DM_1	Infrastructure-as-a-Service (IaaS) ($\mathcal{A}_1$)	ASI	SSI	SSI	ASI	MSI	SSI	ASI
	Platform-as-a-Service (PaaS) ($\mathcal{A}_2$)	ASI	MSI	MSI	SSI	ESI	MSI	SSI
	Software-as-a-Service (SaaS) ($\mathcal{A}_3$)	SSI	ASI	SSI	SSI	SSI	ASI	ASI
	Data-as-a-Service (DaaS) ($\mathcal{A}_4$)	SSI	ASI	MSI	SSI	SSI	SSI	SSI
	Communication-as-a-Service (CaaS) ($\mathcal{A}_5$)	ASI	SSI	SSI	MSI	MSI	MSI	ASI
	Edge-as-a-Service (EaaS) ($\mathcal{A}_6$)	SSI	SSI	ASI	SSI	ASI	ESI	MSI
DM_2	Infrastructure-as-a-Service (IaaS) ($\mathcal{A}_1$)	SSI	ASI	MSI	SSI	MSI	MSI	SSI
	Platform-as-a-Service (PaaS) ($\mathcal{A}_2$)	ASI	SSI	SSI	SSI	MSI	SSI	MSI
	Software-as-a-Service (SaaS) ($\mathcal{A}_3$)	MSI	SSI	ASI	ASI	ESI	MSI	ASI
	Data-as-a-Service (DaaS) ($\mathcal{A}_4$)	SSI	ASI	ASI	ESI	ASI	SSI	SSI
	Communication-as-a-Service (CaaS) ($\mathcal{A}_5$)	ASI	SSI	SSI	MSI	SSI	SSI	ASI
	Edge-as-a-Service (EaaS) ($\mathcal{A}_6$)	SSI	ASI	SSI	SSI	SSI	MSI	ESI
DM_3	Infrastructure-as-a-Service (IaaS) ($\mathcal{A}_1$)	ASI	ASI	SSI	SSI	ESI	SSI	ASI
	Platform-as-a-Service (PaaS) ($\mathcal{A}_2$)	SSI	SSI	ASI	ASI	SSI	MSI	SSI
	Software-as-a-Service (SaaS) ($\mathcal{A}_3$)	SSI	ASI	SSI	SSI	MSI	MSI	SSI
	Data-as-a-Service (DaaS) ($\mathcal{A}_4$)	MSI	SSI	ASI	MSI	SSI	ASI	ASI
	Communication-as-a-Service (CaaS) ($\mathcal{A}_5$)	ASI	MSI	MSI	SSI	MSI	SSI	ASI
	Edge-as-a-Service (EaaS) ($\mathcal{A}_6$)	ASI	SSI	SSI	MSI	SSI	MSI	MSI

7. Numerical Illustration and Discussion

First, we applied the entropy method to evaluate the weight of each criterion. For this purpose, we first converted the decision matrices given in Table 5 into their corresponding crisp values. After that, we have applied Equation (2) to aggregate these three decision matrices into a single decision matrix. Further, we have normalized the aggregated decision matrix using Equation (4). Afterwards, we have evaluated the entropy value and the degree of dissatisfaction corresponding to each criterion using Equation (6) and Equation (7), respectively. Lastly, we have applied Equation (8) to calculate the weight for each criterion. The weights corresponding to each criterion are shown in Table 6.

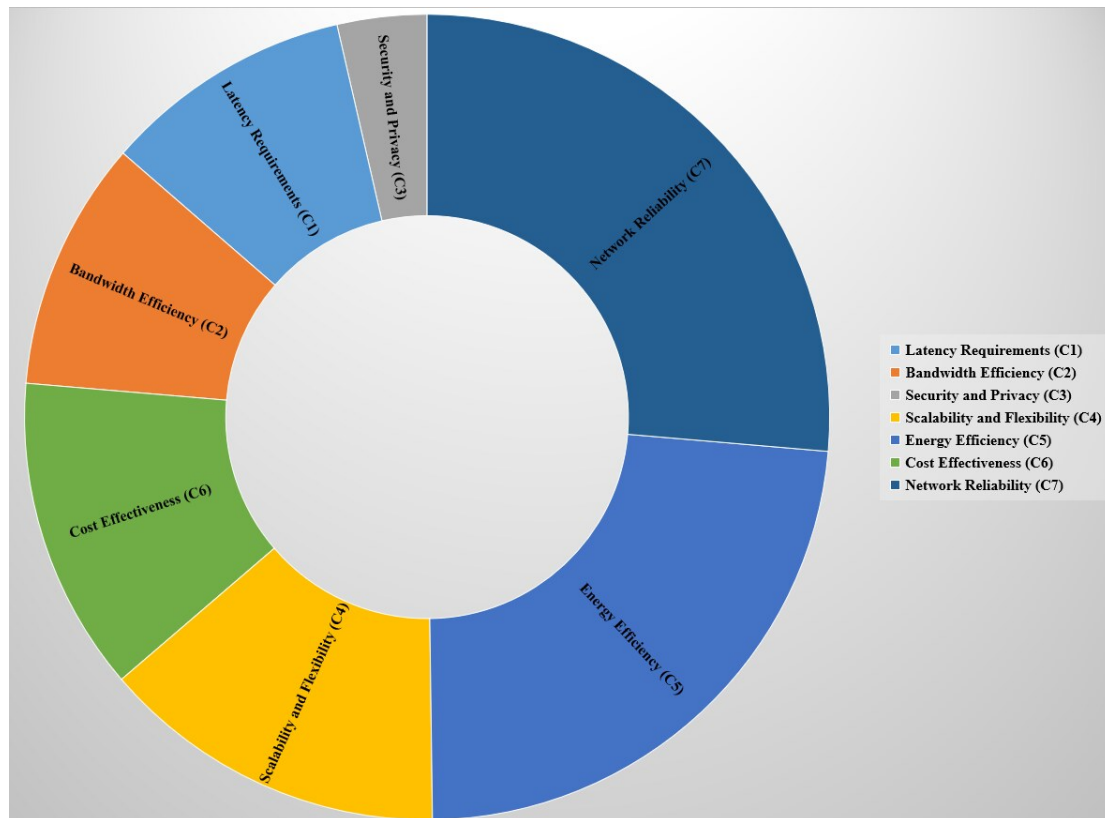
Remark 2. Figure 4 represents the criteria weights in a pie chart. From the above table, we can see that the highest weight is 0.2636, which is obtained by the criterion Network Reliability (C_7) and the lowest weight is 0.0360, which is obtained by the criterion Security and Privacy (C_3).

We will use these weights associated with the criterion in our subsequent analysis. Now, we have applied the CoCoSo method for evaluating the ranking of alternatives. Here, we have used the Aggregated decision matrix, which we have already obtained in Step II of the Entropy method. In the CoCoSo method, we have applied Equation (10) for normalizing the aggregated decision matrix. Further, we have used Equation (12) and Equation (13) for calculating the values of $\mathcal{S}_\alpha$ and $\mathcal{P}_\alpha$ respectively. After that, we have calculated the relative weights in three ways, namely $\mathcal{H}_{\alpha a}$, $\mathcal{H}_{\alpha b}$ and $\mathcal{H}_{\alpha c}$ using the Equations (14), (15) and (16) respectively. Here, for finding the value of $\mathcal{H}_{\alpha c}$, the value of ξ is taken as

Table 6

Criteria weight evaluated by the Entropy approach

Criterion	Weight
Latency Requirements (C_1)	0.1003
Bandwidth Efficiency (C_2)	0.1003
Security and Privacy (C_3)	0.0360
Scalability and Flexibility (C_4)	0.1393
Energy Efficiency (C_5)	0.2343
Cost Effectiveness (C_6)	0.1262
Network Reliability (C_7)	0.2636

**Fig. 4.** Criteria Weight of Fog Computing Model with Associated Data (using Entropy Method)

$\xi = 0.5$. Lastly, we have evaluated the ranking of alternatives by applying Equation (17). The values of $\mathcal{I}_\alpha$, $\mathcal{P}_\alpha$, $\mathcal{K}_{\alpha a}$, $\mathcal{K}_{\alpha b}$, $\mathcal{K}_{\alpha c}$ and $\mathcal{K}_\alpha$ along with the ranking of alternatives are shown in Table 7.

Figure 5 depicts the bar diagram along with the $\mathcal{K}_\alpha$ value of each alternative of the fog computing-based proposed model. From Table 7, we came to know that the alternative "SaaS" has obtained the 1st position, the alternative "DaaS" has obtained the 2nd position, the alternative "IaaS" has obtained the 3rd position and so on.

8. Comparative Analysis and Sensitivity Analysis

Comparative analysis and sensitivity analysis are conducted in this section to assess the stability of the results. First, perform the comparative analysis and followed by a sensitivity analysis of the proposed fog computing model as follows:

Table 7
Calculating the value of $\mathcal{K}_\alpha$ and Rank for Alternatives

Alternatives	$\mathcal{S}_\alpha$	$\mathcal{P}_\alpha$	$\mathcal{S}_\alpha + \mathcal{P}_\alpha$	$\mathcal{K}_{\alpha a}$	$\mathcal{K}_{\alpha b}$	$\mathcal{K}_{\alpha c}$	$\mathcal{K}_\alpha$	Rank
IaaS ($\mathcal{A}_1$)	0.588	4.836	5.424	0.163	2.415	0.875	1.853	3
PaaS ($\mathcal{A}_2$)	0.432	5.292	5.724	0.172	2.155	0.923	1.783	4
SaaS ($\mathcal{A}_3$)	0.585	5.520	6.105	0.184	2.559	0.985	2.016	1
DaaS ($\mathcal{A}_4$)	0.680	4.910	5.590	0.168	2.646	0.902	1.976	2
CaaS ($\mathcal{A}_5$)	0.572	4.582	5.154	0.155	2.324	0.831	1.773	5
EaaS ($\mathcal{A}_6$)	0.442	4.776	5.218	0.157	2.064	0.841	1.669	6

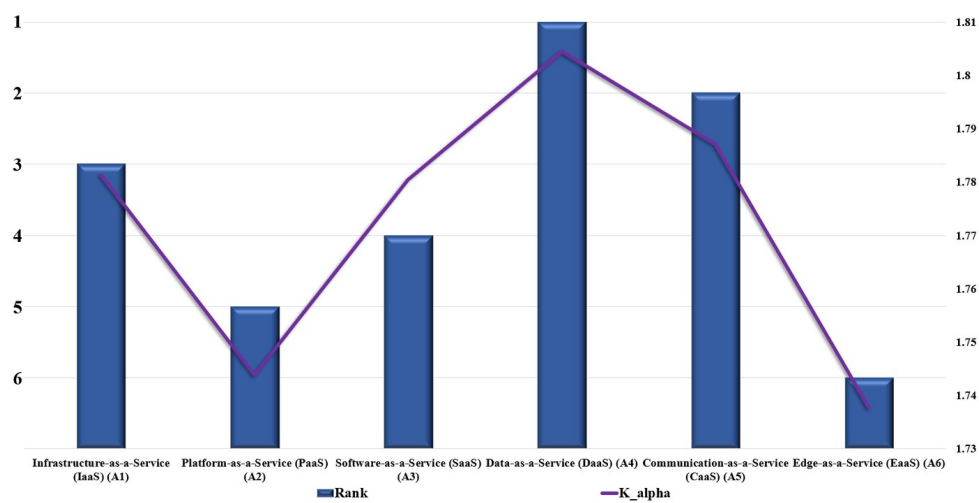


Fig. 5. Alternative ranking by CoCoSo method

8.1 Comparative analysis

Comparative analysis is conducted in this section to assist in the flexibility and robustness of the results. There are various methodologies that can be used to perform this. However, in this study, we analyzed using two MCDM methods as follows:

The comparative analysis is conducted using two MCDM methods: the WASPAS method proposed by Zavadskas *et al.*, [72] and the TOPSIS method introduced by Hwang *et al.*, [73]. The ranking of the alternatives is determined by these two methods and compared with the main CoCoSo ranking. The results are presented in Table 8.

Table 8
Alternative ranking through different MCDM methods

Alternative	WASPAS	TOPSIS	CoCoSo
Infrastructure-as-a-Service (IaaS) ($\mathcal{A}_1$)	3	3	3
Platform-as-a-Service (PaaS) ($\mathcal{A}_2$)	5	5	5
Software-as-a-Service (SaaS) ($\mathcal{A}_3$)	4	4	4
Data-as-a-Service (DaaS) ($\mathcal{A}_4$)	1	1	1
Communication-as-a-Service (CaaS) ($\mathcal{A}_5$)	2	2	2
Edge-as-a-Service (EaaS) ($\mathcal{A}_6$)	6	6	6

The evaluated results by the three MCDM methods are shown in Table 8 and graphically depicted

in Figure 6, respectively. Based on the above results, all alternatives rank the same regardless of the MCDM methods. This implies that our main results are flexible and robust.

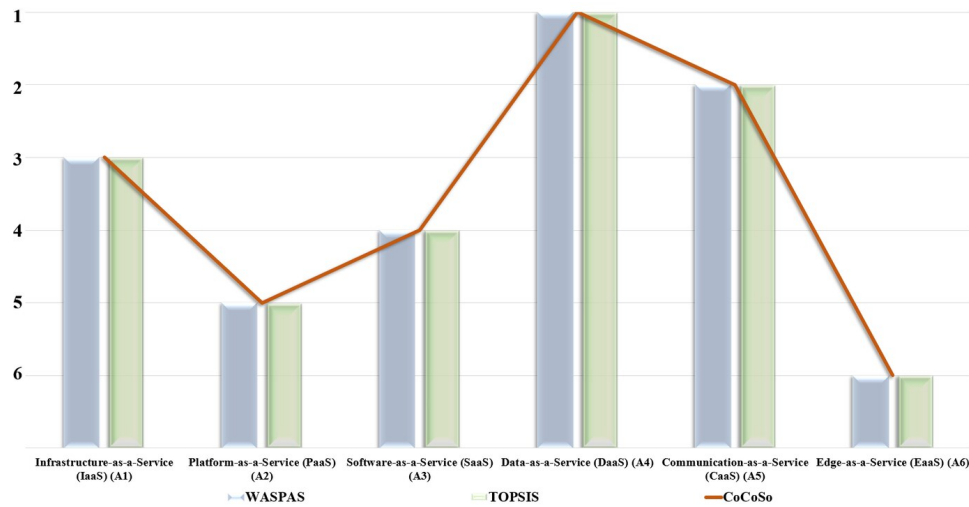


Fig. 6. Alternative ranking analysis through comparative study

8.2 Sensitivity analysis

This subsection discusses the sensitivity analysis. Sensitivity analysis is a mathematical process used to verify the stability of the results. This means we want to check how the result will be affected by a small variation in input data. There are many ways to perform sensitivity analysis, such as small variations in the criterion weights, removing some criteria, or interchanging the criterion weights. In this paper, we have performed five cases for sensitivity analysis, which are discussed as follows:

Case 1. Removing the criterion Security and Privacy (C_3):

In the first case, a sensitivity analysis is conducted by removing criteria Security and Privacy (C_3) and evaluating the weights of the criteria in the modified model. Then, the ranked alternatives based on the updated weighted and ranking of the alternatives are presented in Table 9.

Case 2. Removing the criterion Scalability and Flexibility (C_4):

In the second case, sensitivity analysis is performed by removing criteria Scalability and Flexibility (C_4) and determining the weights of the criteria in the revised model. Further, ranked the alternatives on the basis of the modified model and ranking of the alternatives shown in Table 9.

Case 3. Removing the criterion Energy Efficiency (C_5):

In this case, another sensitivity analysis is conducted by removing the criteria Energy Efficiency (C_5) and evaluating the weights of the criteria in the modified model. After that, the ranking is calculated by the CoCoSo method and the rankings of the alternatives are shown in Table 9.

Case 4. Removing the criterion Cost Effectiveness (C_6):

In the fourth case, a sensitivity analysis is conducted by removing the criteria Cost Effectiveness (C_6) and determining the weight of the criteria in the revised model. Furthermore, the ranking of the alternatives is evaluated by the proposed method and the results are shown in Table 9.

Case 5. Interchanging the weights of the criterion Latency Requirements (C_1) and Security and Privacy (C_3):

In the last case, a sensitivity analysis is performed by interchanging the weights of the two criteria, Latency Requirements (C_1) and Security and Privacy (C_3). The evaluated results are presented in Table 9.

The ranking of the alternatives is based on five scenarios and evaluated using the CoCoSo method under this sensitivity analysis section. The results in all five cases are presented in Table 9. The more stable case is Case 1, followed by Case 2, Case 4 and Case 5, respectively. The most unstable case is

Case 3 in this sensitivity analysis of the proposed fog computing model. The graphical representation of the ranking fluctuation of the fog computing services as alternatives is presented in Figure 7.

Table 9

Different fog computing service prioritization by sensitivity analysis

Alternative	Case 1	Case 2	Case 3	Case 4	Case 5
Infrastructure-as-a-Service (IaaS) ($\mathcal{A}_1$)	3	3	1	4	4
Platform-as-a-Service (PaaS) ($\mathcal{A}_2$)	5	6	5	6	5
Software-as-a-Service (SaaS) ($\mathcal{A}_3$)	4	4	2	3	2
Data-as-a-Service (DaaS) ($\mathcal{A}_4$)	1	1	4	1	1
Communication-as-a-Service (CaaS) ($\mathcal{A}_5$)	2	2	3	2	3
Edge-as-a-Service (EaaS) ($\mathcal{A}_6$)	6	5	6	5	6

From Figure 7 through sensitivity analysis, we conclude that Case 1 is the most stable case among all. Further, Data-as-a-Service (DaaS) ($\mathcal{A}_4$) is a fog computing service as an alternative, which is the optimal consistent alternative. This analysis shows that a slight change can cause an alternative result to fluctuate. Then the optimal result is sensitive and stable.

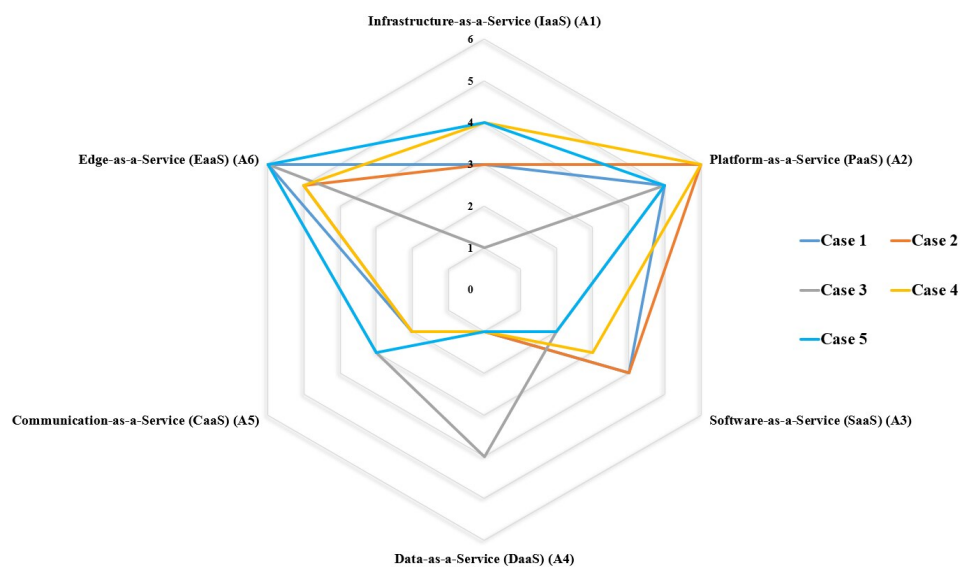


Fig. 7. Graphical diagram of the alternative ranking through sensitivity analysis

9. Conclusions

Fog computing extends cloud computing by processing data closer to users and connected devices, thereby reducing latency and supporting faster communication and decision-making. In this study, an Entropy-CoCoSo-based model was developed in a crisp environment to evaluate the challenges of fog computing and identify the most suitable fog computing service model. The model included seven criteria and six alternatives. The Entropy results showed that Network Reliability ($\mathcal{C}_7$) was the most important criterion, with a weight of 0.2636, followed by Energy Efficiency ($\mathcal{C}_5$). According to the CoCoSo results, Software-as-a-Service (SaaS), Data-as-a-Service (DaaS), and Infrastructure-as-a-Service (IaaS) ranked first, second, and third, respectively. The robustness of these findings was further examined through comparative analysis and five sensitivity-analysis scenarios.

These results provide a clearer understanding of how Latency Requirements, Bandwidth Efficiency, Security and Privacy, Scalability and Flexibility, Energy Efficiency, Cost Effectiveness, and Network Reliability affect fog computing adoption. The proposed framework can therefore assist researchers,

service providers, and policymakers in evaluating fog computing services and developing policies related to data transmission, data storage, and distributed computing infrastructure. Such guidance is particularly relevant to healthcare, transportation, smart cities, and other applications that depend on reliable and time-sensitive data processing.

Despite these contributions, the study also offers several opportunities for further research. Future studies may apply other MCDM methods, such as MEREC, SWARA, PROMETHEE, ELECTRE, and MACBETH, and compare their results with those obtained using the proposed framework. The model could also be extended by incorporating fuzzy or neutrosophic information instead of crisp values. Moreover, involving a larger and more diverse panel of decision experts and introducing additional criteria, sub-criteria, and service alternatives could improve the comprehensiveness and generalizability of the analysis.

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Conflicts of Interest

The authors declare no conflicts of interest.

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