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An Effective Model for Selecting the Best Cloud Platform for Smart Farming in Smart Cities: A Case Study

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Abstract

Cloud computing has become an essential technology for various industries, including smart farming and smart city initiatives. Integrating smart farming into smart city initiatives can bring numerous benefits, such as increased food production, resource efficiency, environmental sustainability, and improved quality of life for urban residents. Smart cities and smart farming are two interconnected concepts that aim to improve the efficiency and sustainability of urban areas. Smart cities use technology and data to optimize infrastructure, services, and resources, while smart farming applies these same principles to agriculture. Smart farming with cloud computing involves the use of cloud computing technologies to optimize agricultural processes and improve crop yields. By using cloud computing technologies, farmers can collect, store, and analyze large amounts of data, access advanced analytics and machine learning tools, collaborate with agricultural experts, and benefit from scalability and flexibility. In this paper, we propose a novel MEREC-MAIRCA method to select the best cloud platform that helps decision-makers use smart farming in smart cities. By leveraging technology and data, smart farming can enable new business models, create new jobs, and foster social connections around food production and consumption.

Keywords: Cloud Computing; Multi-Criteria Decision Making; Smart Cities; Smart Farming.

1 | Introduction

Cloud computing refers to the delivery of computing services—including servers, storage, databases, networking, software, and more—over the internet ("the cloud") to offer faster innovation, flexible resources, and economies of scale. Cloud computing enables users to access and use computing resources without the need for physical hardware or infrastructure ownership. Cloud computing has transformed the way organizations build and deploy IT infrastructure, enabling agility, scalability, and cost-efficiency in managing computing resources. It has become a foundational technology for businesses of all sizes, driving innovation and digital transformation across industries. Cloud computing has become a foundational technology for businesses of all sizes, driving innovation and digital transformation across industries. From smart farming to

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smart city applications, cloud computing is enabling new possibilities and opportunities for organizations to improve their operations, reduce costs, and enhance customer experiences.

The concept of a smart city revolves around the integration of information and communication technologies (ICT), Internet of Things (IoT) devices, software solutions, user interfaces (UI), and communication networks to optimize city operations and services. A smart city can be defined as a high-tech, advanced metropolitan region where a variety of electrical devices and sensors are interconnected and specific data is gathered together [1]. Cloud computing is an essential technology for smart cities, enabling governments to deliver connected, secure, and reliable services to residents and businesses. Cloud applications could help smart cities that contain information gathered from citizens, devices, homes, and other things. [2]

One of the most important projects in smart cities is agriculture. Emerging technologies such as fog computing, cloud computing, artificial intelligence (AI), and the Internet of Things (IoT) connect machines or end devices to the Internet, facilitating data collection and processing and driving the agricultural cutting-edge innovation known as Agriculture 4.0 [3].

Smart cities and smart farming can benefit from each other in the context of cloud computing. Smart cities can provide the necessary infrastructure for smart farming, such as high-speed internet connectivity, data storage, and processing power. This can help farmers collect, analyze, and act on data in real time, improving crop yields, reducing waste, and increasing efficiency. On the other hand, smart farming can contribute to the sustainability goals of smart cities by reducing the environmental impact of agriculture, improving food security, and creating new economic opportunities. By using IoT devices, sensors, and data analytics, farmers can optimize their operations, reduce water and energy consumption, and minimize the use of chemical fertilizers and pesticides. Cloud computing platforms can facilitate the integration of smart city and smart farming systems, enabling seamless data exchange, interoperability, and collaboration. For example, smart city sensors can detect environmental conditions, such as temperature, humidity, and air quality, and share this data with smart farming systems to optimize crop growth and reduce the impact of extreme weather events.

Smart farming, also known as smart agriculture, is an evolving system that applies information and communication technologies such as the Internet of Things (IoT) to agriculture [4]. Smart farming in smart cities involves the integration of urban agriculture with advanced technologies such as data science, IoT, AI, and automation. This approach enables the development of smart urban farms in, on, and around buildings, which not only increases food security but also addresses other urban challenges such as natural disaster resilience, air pollution reduction, social interaction, education, and pollinator support. While urban agriculture cannot provide for all of humanity's consumption needs, it is an essential tool for cities and local communities to make their food systems more resilient. Some estimates suggest that 5–10% of the global supply of fruits and vegetables could be provided by urban AgTech alone, with 30–70% of a city's needs potentially grown nearby in peri-urban areas. Cities worldwide are recognizing this potential and are implementing policies and programs to encourage urban agriculture, such as Paris with its Parisculteurs program, Singapore with its local food production goals and innovation centers, New York City with its Office of Urban Agriculture and Urban Agriculture Advisory Board, and Dallas with its urban agriculture master planning techniques. However, there is a need for data-driven innovation and entrepreneurship to accelerate the transition towards truly Smart Cities with agriculture at their center.

Smart farming with cloud computing involves the integration of IoT devices, data analytics, and cloud computing to optimize agricultural processes. By using cloud computing, farmers can access real-time data, monitor crop health, and automate irrigation and fertilization systems. This approach not only increases crop yield and quality but also reduces resource waste and labor costs. In a smart farming system with cloud computing, IoT sensors and devices are used to collect data on various environmental factors, such as temperature, humidity, soil moisture, and light intensity. This data is then transmitted to a cloud platform, where it is stored and analyzed using data analytics tools and machine learning algorithms. The insights gained from this analysis can be used to make informed decisions about crop management, such as when to irrigate, fertilize, or harvest. Moreover, cloud computing provides scalability and flexibility for smart farming systems.

As the amount of data generated by IoT devices increases, cloud computing platforms can easily scale up to handle the increased data volume. This allows farmers to expand their smart farming systems as needed without having to worry about infrastructure limitations Figure 1.

Smart Farming (SF) refers to applying Information and Communication Technologies to agriculture. [5]. SF aims at increasing the quality of products, improving crop production, and optimizing agriculture yield with minimum human intervention [6]. In a smart city, smart farming can help address food security and sustainability challenges by enabling the development of urban agriculture systems. These systems can range from small-scale rooftop gardens to large-scale vertical farms and can be integrated with other smart city infrastructure, such as energy and water systems. Smart farming in smart cities can also contribute to other urban goals, such as reducing greenhouse gas emissions, improving air quality, and enhancing biodiversity. By using precision agriculture techniques, smart farming can optimize resource use and reduce waste while also providing fresh, locally grown produce to urban residents.

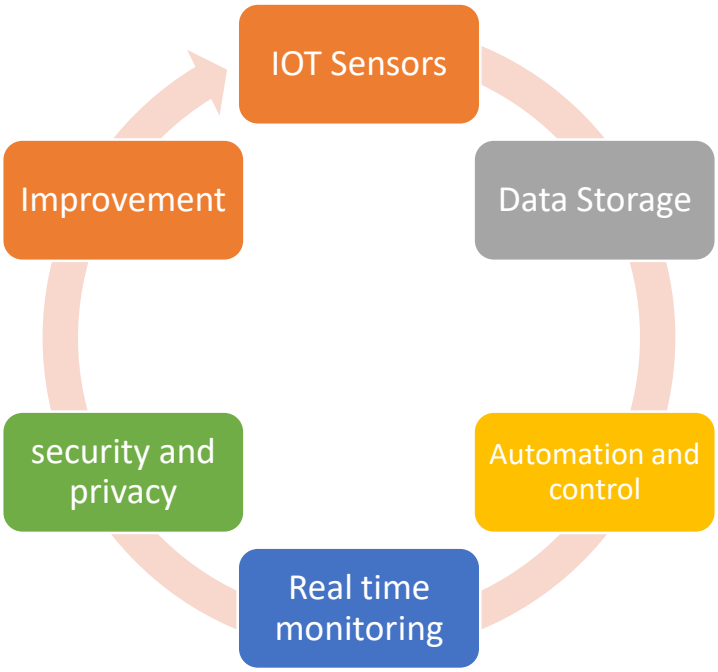

Figure 1. Cloud phases.

Multi-criteria decision-making (MCDM) methods are used in cloud computing research to aid decision-makers in selecting the best alternative among several options. These methods help in resolving issues. Various MCDM methods have been proposed and compared in terms of time complexity and robustness for cloud service selection. Frameworks like Fuzzy-ETDBA have been developed for selecting cloud deployment models, which is also considered a multi-criteria decision-making problem. MCDM techniques are also used to evaluate and rank the performance of different cloud service providers (CSPs) based on multiple criteria. A new method called the best-only method (BOM) has been proposed for CSP selection, which is efficient and consistent. [7]. This paper aims to show a new hybrid method to help decision-makers select the best city. The first MEREC method (method based on the removal effects of criteria) is used for determining criteria weights [8]. The MAIRCA method is used to rank alternatives based on the MEREC weight [9]. Additionally, the proposed approach is presented in the type-2 neutrosophic number (T2NN). Hence, the T2NN-MEREC method is used to calculate the weight of each criterion, and then the T2NN-MAIRCA method is used to evaluate and rank alternatives.

2 | Related Work

In this section, a literature review of studies related to this subject is presented. This section is divided into two parts. The first one presents studies related to smart cities, smart farming, and cloud computing. The second part introduces the studies related to the T2NN environment and hybrid method MEREC- MAIRCA.

2.1 | Related Studies

New trends in agriculture seek to manage crops in controlled environments such as greenhouses, which enable the recreation of the quasi-optimal parameters that plants need to improve production or duplicate the environmental conditions of specific geographical areas to locally obtain products that are usually imported [10]. Hang Thanh Bui et al (2024) assess the applicability of existing cyber threat intelligence (CTI) techniques within smart farming infrastructures (SFIs) [11] Anil V. Turukmane et al. [12] propose a general intelligent agriculture cloud-based platform that supports administration, academics, and producers in running their farms and reaching educated choices. Ana Isabel Montoya-Munoz et al. (2020) introduce an optimization model for providing reliability and, consequently, service continuity to the IoT-Fog-Cloud continuum-based smart farms. This paper proposes a smart irrigation system based on cutting-edge technologies like the embedded system, Internet of Things (IoT), and cloud computing as a groundbreaking strategy to improve food security through the implementation of advanced agricultural technology [13].

Tahir Mahmood et al. [14] providing decision-making approaches for the assessment and selection of cloud computing using bipolar complex fuzzy Einstein power aggregation operators. Tanweer Alam et al (2022) review the Sustainable Development of Smart Cities Through Cloud Computing [15]. Lubna Ansari et al. identify the factors that contribute to the slow performance of e-governance systems when compared to the use of cloud technology in supporting e-governance implementation; it also examine the main factors influencing cloud computing technology adoption and argue that cloud computing technology can be recommended as a new avenue to support smart governance implementation with various cloud techniques [16].

2.2 | T2NN-MEREC-MAIRCA

Type-1 neutrosophic number (T1NNS) is a mathematical concept introduced by Florentin Smarandache in the early 1990s as a generalization of fuzzy numbers. Fuzzy set theory is a research approach that can deal with problems relating to ambiguous, subjective, and imprecise judgments, and it can quantify the linguistic facet of available data and preferences for individual or group decision-making (Shan et al., 2015a). The theory seeks to deem uncertain data that can be related to the existent fuzziness of peoples' observations and perceptions. Neutrosophic is an extension of the fuzzy theory and intuitionistic fuzzy set (IFS). Smarandache proposed the neutrosophic sets in [17]. Type-2 neutrosophic number (T2NNS) is an extension of the concept of a T1NN to a higher level of indeterminacy. The neutrosophic sets proved to be a valid workspace in describing incompatible and indefinite information. z(T, I, F) is a Type-1 Neutrosophic Number. But z((T_t, T_i,T_f), (I_t, I_i,I_f), (F_t, F_i, F_f)) is a Type-2 Neutrosophic Number, which means that each neutrosophic component T, I, and F is split into its truth, indeterminacy, and falsehood subparts [18]. then T2NN has become a preferred tool by scholars and researchers in recent times. Görçün et al. (2023) presented research for extending the version of the Weighted Aggregated Sum Product Assessment (WASPAS) technique under T2NNs based on the Bonferroni function (WASPAS'B) for selecting the suitable Ro-Ro vessel that has been used in the second-hand vessel market.

Mehdi Keshavarz-Ghorabaee et al. [19] presented a new method based on the Removal Effects of Criteria (MEREC). This method is used for determining criteria weights [19]. Mohamad Shahiir Saidin et al. [20] mentioned that MEREC can solve fuzzy Multi-Criteria Decision-Making Problems. Shanmugasundar et al. (2022) introduce Application of MEREC in Multi-Criteria Selection [21]. The multiattribute ideal–real

comparative analysis (MAIRCA) compares both theoretical and empirical alternative ratings [22]. Dragan S. Pamucar et al, introduce a New hybrid multi-criteria decision-making DEMATEL-MAIRCA model [23].

3 | Methodology

This section introduces the methodology for each study in this paper. This section is also divided into three parts. First, some basic concepts and definitions of T2NN. Second, use the MEREC method to evaluate weights. Finally, the MAIRCA method for ranking the best alternatives.

3.1 | Preliminaries

In this part definitions and some concepts and operations associated with T2NN are given below:

Definition 1. [18] We consider that Z is a limited universe of discourse and F [0,1] is the set of all triangular neutrosophic numbers on F [0,1].

A Type 2 neutrosophic number set (T2NNS) $\widetilde{U}$ in Z is represented by

$$\widetilde{U} = \left\langle \left(T_{T_{\widetilde{U}}}(z), T_{I_{\widetilde{U}}}(z), T_{F_{\widetilde{U}}}(z)\right), \left(I_{T_{\widetilde{U}}}(z), I_{I_{\widetilde{U}}}(z), I_{F_{\widetilde{U}}}(z)\right), \left(F_{T_{\widetilde{U}}}(z), F_{I_{\widetilde{U}}}(z), F_{F_{\widetilde{U}}}(z)\right)\right\rangle \quad (1)$$

Where $\breve{T}_{\widetilde{U}}(z) : Z \rightarrow F[0,1]$, $\tilde{I}_{\widetilde{U}}(z) : Z \rightarrow F[0,1]$, $\breve{F}_{\widetilde{U}}(z) : Z \rightarrow F[0,1]$. The type -2 neutrosophic number set $\breve{T}_{\widetilde{U}}(z) = \left(T_{T_{\widetilde{U}}}(z), T_{I_{\widetilde{U}}}(z), T_{F_{\widetilde{U}}}(z)\right)$, $\tilde{I}_{\widetilde{U}}(z) = \left(I_{T_{\widetilde{U}}}(z), I_{I_{\widetilde{U}}}(z), I_{F_{\widetilde{U}}}(z)\right)$, $\breve{F}_{\widetilde{U}}(z) = \left(F_{T_{\widetilde{U}}}(z), F_{I_{\widetilde{U}}}(z), F_{F_{\widetilde{U}}}(z)\right)$ defined as the truth, indeterminacy, and falsity of member-ships of z in $\widetilde{U}$.

Definition 2. [18] Suppose that

$\widetilde{U}_1 = \left\langle \left(T_{T_{\widetilde{U}_1}}(z), T_{I_{\widetilde{U}_1}}(z), T_{F_{\widetilde{U}_1}}(z)\right), \left(I_{T_{\widetilde{U}_1}}(z), I_{I_{\widetilde{U}_1}}(z), I_{F_{\widetilde{U}_1}}(z)\right), \left(F_{T_{\widetilde{U}_1}}(z), F_{I_{\widetilde{U}_1}}(z), F_{F_{\widetilde{U}_1}}(z)\right)\right\rangle$ and $\widetilde{U}_2 = \left\langle \left(T_{T_{\widetilde{U}_2}}(z), T_{I_{\widetilde{U}_2}}(z), T_{F_{\widetilde{U}_2}}(z)\right), \left(I_{T_{\widetilde{U}_2}}(z), I_{I_{\widetilde{U}_2}}(z), I_{F_{\widetilde{U}_2}}(z)\right), \left(F_{T_{\widetilde{U}_2}}(z), F_{I_{\widetilde{U}_2}}(z), F_{F_{\widetilde{U}_2}}(z)\right)\right\rangle$

Are two T2NNs then the following equations describe some T2NN operators.

$$1: \widetilde{U}_1 \oplus \widetilde{U}_2 = \left\langle \begin{array}{c} \left(\begin{array}{c} T_{T_{\widetilde{U}_1}}(z) + T_{T_{\widetilde{U}_2}}(z) - T_{T_{\widetilde{U}_1}}(z).T_{T_{\widetilde{U}_2}}(z),\ T_{I_{\widetilde{U}_1}}(z) + T_{I_{\widetilde{U}_2}}(z) - T_{I_{\widetilde{U}_1}}(z).T_{I_{\widetilde{U}_2}}(z), \\ T_{F_{\widetilde{U}_1}}(z) + T_{F_{\widetilde{U}_2}}(z) - T_{F_{\widetilde{U}_1}}(z).T_{F_{\widetilde{U}_2}}(z) \end{array}\right), \\ \left(I_{T_{\widetilde{U}_1}}(z).I_{T_{\widetilde{U}_2}}(z), I_{I_{\widetilde{U}_1}}(z).I_{I_{\widetilde{U}_2}}(z), I_{F_{\widetilde{U}_1}}(z).I_{F_{\widetilde{U}_2}}(z)\right), \\ \left(F_{T_{\widetilde{U}_1}}(z).F_{T_{\widetilde{U}_2}}(z), F_{I_{\widetilde{U}_1}}(z).F_{I_{\widetilde{U}_2}}(z), F_{F_{\widetilde{U}_1}}(z).F_{F_2}(z)\right) \end{array} \right\rangle \quad (2)$$

$$2: \widetilde{U}_1 \otimes \widetilde{U}_2 = \left\langle \begin{array}{c} \left(\left(T_{T_{\widetilde{U}_1}}(z).T_{T_{\widetilde{U}_2}}(z), T_{I_{\widetilde{U}_1}}(z).T_{I_{\widetilde{U}_2}}(z), T_{F_{\widetilde{U}_1}}(z).T_{F_{\widetilde{U}_2}}(z)\right)\right), \\ \left(\left(I_{T_{\widetilde{U}_1}}(z) + I_{T_{\widetilde{U}_2}}(z) - I_{T_{\widetilde{U}_1}}(z).I_{T_{\widetilde{U}_2}}(z)\right), \left(I_{I_{\widetilde{U}_1}}(z) + I_{I_{\widetilde{U}_2}}(z) - I_{I_{\widetilde{U}_1}}(z).I_{I_{\widetilde{U}_2}}(z)\right), \left(\begin{array}{c} I_{F_{\widetilde{U}_1}}(z) + I_{F_{\widetilde{U}_2}}(z) - \\ I_{F_{\widetilde{U}_1}}(z).I_{F_{\widetilde{U}_2}}(z) \end{array}\right)\right) \\ \left(\left(F_{T_{\widetilde{U}_1}}(z) + F_{T_{\widetilde{U}_2}}(z) - F_{T_{\widetilde{U}_1}}(z).F_{T_{\widetilde{U}_2}}(z)\right), \left(F_{I_{\widetilde{U}_1}}(z) + F_{I_{\widetilde{U}_2}}(z) - F_{I_{\widetilde{U}_1}}(z).F_{I_{\widetilde{U}_2}}(z)\right), \left(\begin{array}{c} F_{F_{\widetilde{U}_1}}(z) + F_{F_2}(z) - \\ F_{F_{\widetilde{U}_1}}(z).F_{F_2}(z) \end{array}\right)\right) \end{array} \right\rangle \quad (3)$$

3: T2NNWA to aggregate T2NN decision matrices:

Let $\widetilde{U}_p = \left\langle \left(T_{T_p}(z), T_{I_p}(z), T_{F_p}(z)\right), \left(I_{T_p}(z), I_{I_p}(z), I_{F_p}(z)\right), \left(F_{T_p}(z), F_{I_p}(z), F_{F_p}(z)\right)\right\rangle$ is a group of T2NN where p =1, 2, ……. , then the aggregate value will be obtained using Eq.(4).

$$\text{T2NNWA} = \left\langle \begin{matrix} \left(1-\prod_{p=1}^{n}(1-T_{T_p}(z)^w, 1-\prod_{p=1}^{n}(1-T_{I_p}(z)^w, 1-\prod_{p=1}^{n}(1-T_{f_p}(z)^w\right), \\ \left(\prod_{p=1}^{n}(I_{T_p}(z)^w, \prod_{p=1}^{n}(I_{I_p}(z)^w, \prod_{p=1}^{n}(I_{f_p}(z)^w\right), \\ \left(\prod_{p=1}^{n}(F_{T_p}(z)^w, \prod_{p=1}^{n}(F_{I_p}(z)^w, \prod_{p=1}^{n}(F_{f_p}(z)^w\right) \end{matrix} \right\rangle \tag{4}$$

3: Score Function:

$$S(\widetilde{U}) = \frac{1}{12}\left\langle 8+\left(T_{T_{\widetilde{U}_1}}(Z)+2\left(T_{I_{\widetilde{U}_1}}(Z)\right)+T_{F_{\widetilde{U}_1}}(Z)\right)-\left(I_{T_{\widetilde{U}_1}}(Z)+2\left(I_{I_{\widetilde{U}_1}}(Z)\right)+I_{F_{\widetilde{U}_1}}(Z)\right)-\left(F_{T_{\widetilde{U}_1}}(Z)+2\left(F_{I_{\widetilde{U}_1}}(Z)\right)+F_{F_{\widetilde{U}_1}}(Z)\right)\right\rangle \tag{5}$$

Definition 3. [18]To Build the evaluation matrix $A_i \times Œ_{ip}$ to assess the classification of alternatives to each criterion.

$$\check{R} = \begin{array}{c} \\ Alt_1 \\ \vdots \\ Alt_m \end{array} \begin{array}{c} \begin{array}{ccc} Œ_{ip} & \cdots & Œ_{in} \end{array} \\ \begin{bmatrix} \check{Z}_{11} & \cdots & \check{z}_{1n} \\ \vdots & \ddots & \vdots \\ \check{Z}_{m1} & \cdots & \check{Z}_{mn} \end{bmatrix} \end{array} \tag{6}$$

3.2 | MEREC Method

In this section, the following steps present the MEREC method that is used to evaluate the weights of criteria in MCDM problems as mentioned in Figure 2 [8].

Step 1: First, construct the decision matrix. The elements of this matrix are denoted by x_{ij}. Suppose that there are n alternatives and m criteria, and the form of the decision matrix is as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{im} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{nm} \end{bmatrix} \tag{7}$$

Step 2. Then, Normalize the decision matrix (N). The elements of the normalized matrix are denoted by n^x_{ij}. B shows the set of beneficial criteria, and H represents the set of non-beneficial criteria, we can utilize the following equation for normalization:

$$n^x_{ij} = \begin{cases} \dfrac{\min_k x_{kj}}{x_{ij}}, & if\ j \in B \\ \dfrac{x_{ij}}{\max_k x_{kj}}, & if\ j \in H \end{cases} \tag{8}$$

Step 3. Calculate the overall performance of the alternatives (S_i). According to the normalized values obtained from the previous step, we can ensure that smaller values of n^x_{ij}. yield greater values of performances (S_i).

$$S_i = \ln\left(1+\left(\frac{1}{m}\ \sum_j \left|\ln(n^x_{ij})\right|\right)\right) \tag{9}$$

Step 4. Calculate the performance of the alternatives by removing each criterion. The difference between this step and Step 3 is that the alternatives' performances are calculated based on removing each criterion separately. Let us denote by $\grave{S}_{ij}$ the overall performance of ith alternative concerning the removal of the jth criterion. The following equation is used for the calculations of this step:

$$\hat{S_{ij}} = \ln\left(1 + \left(\frac{1}{m} \sum_{k,k\neq j} |\ln(n_{ik}^{x})|\right)\right) \tag{10}$$

Step 5. Compute the summation of absolute deviations. In this step, we calculate the removal effect of the jth criterion based on the values obtained from Step 3 and Step 4. Let E_j denote the effect of removing the jth criterion. We can calculate the values of E_j using the following formula:

$$E_j = \sum_i \left| \hat{S_{ij}} - S_i \right| \tag{11}$$

Step 6: Finally, determine the final weights of the criteria. In this step, each criterion's objective weight is calculated using the removal effects (E_j) of Step 5. In what follows, w_j stands for the weight of the jth criterion.

$$W_j = \frac{E_j}{\sum_k E_k} \tag{12}$$

3.3 | MAIRCA Method

To Rank alternatives based on some function [21].

Step 1: Building the initial matrix according to the following equation:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1j} & \cdots & x_{im} \\ x_{21} & x_{22} & \cdots & x_{2j} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i1} & x_{i2} & \cdots & x_{ij} & \cdots & x_{im} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nj} & \cdots & x_{nm} \end{bmatrix} \tag{13}$$

where m is the number of options; n is the number of criteria.

Step 2: Determining the priority for an indicator. When the decision maker is neutral, the role of the indicators is the same (no priority is given to any). Then the priority for the criteria is the same and is calculated as follows:

$$p_{A_j} = \frac{1}{m'} \qquad j = 1, 2\ldots, n. \tag{14}$$

Step 3: Calculating the quantities t_{pij} according to the equation:

$$t_{pij} = p_{A_j} \cdot w_{j,} \qquad i = 1,2,\cdots,m; j = 1,2\cdots,n \tag{15}$$

Where w_j is the weight of the jth criterion.

Step 4: Calculating the quantities t_{rij} according to the equations:

$$t_{rij} = t_{pij} \cdot \left(\frac{x_{ij} - x_i^-}{x_i^+ - x_i^-}\right) \quad \text{for beneficial} \tag{16}$$

$$t_{rij} = t_{pij} \cdot \left(\frac{x_{ij} - x_i^+}{x_i^- - x_i^+}\right) \quad \text{for non} - \text{beneficial} \tag{17}$$

Step 5: Calculating the quantities gij according to the equation:

$$g_{ij} = t_{pij} - t_{rij} \tag{18}$$

Step 6: Summing the gj values according to the equation:

$$Q_i = \sum_{i=1}^{m} g_{ij} \tag{19}$$

Ranking the options according to the principle that the one with the smallest Qi is the better.

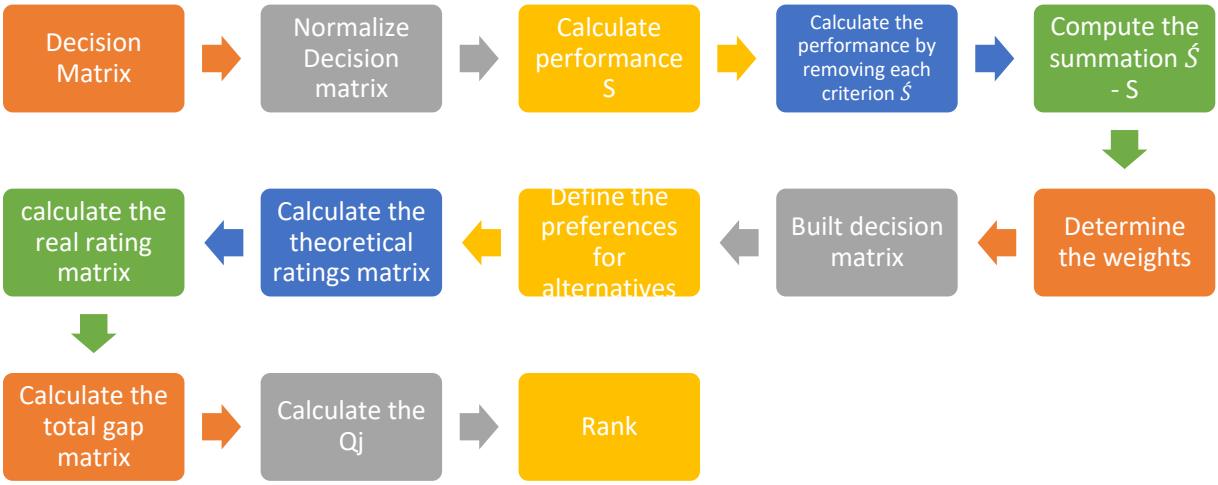

Figure 2. Phases of the hybrid MEREC–MAIRCA model.

4 | Case Study

4.1 | Problem Definition

The problem definition of smart farming using cloud computing is the application of cloud computing technology to improve the efficiency, productivity, and sustainability of agricultural practices. By leveraging the power of cloud computing, farmers can access and analyze large amounts of data from various sources, including sensors, drones, satellites, and weather forecasts, to make informed decisions about crop management, irrigation, and pest control. Cloud computing also enables farmers to use advanced analytics, machine learning, and artificial intelligence to optimize their operations and reduce waste. Additionally, cloud-based platforms can provide real-time monitoring and automation of farm equipment, reducing the need for manual labor and increasing efficiency. However, there are also challenges in implementing cloud computing in smart farming, such as the need for reliable and high-speed internet connectivity in rural areas, the lack of technical expertise among farmers, and the high cost of implementing and maintaining cloud-based systems. Therefore, the problem definition also includes addressing these challenges and finding solutions that can help farmers adopt and benefit from cloud computing technology cost-effectively and sustainably.

Smart cities and smart farming are two complementary concepts that can help create more sustainable, resilient, and livable urban areas. By integrating agriculture into the fabric of the city, smart farming can contribute to a range of urban goals, from food security and sustainability to innovation and community engagement. Smart cities and smart farming are two interconnected concepts that aim to improve the efficiency and sustainability of urban areas. Smart cities use technology and data to optimize infrastructure, services, and resources, while smart farming applies these same principles to agriculture. Smart farming with cloud computing is a powerful approach to optimizing agricultural processes and improving crop yields.

4.2 | Description of Alternatives and Criteria

In the context of smart farming using cloud computing, there are several alternatives and criteria to consider.

- Alternatives:

Cloud service providers, such as Amazon Web Services, Microsoft Azure, and Google Cloud Platform, offer various services for data storage, processing, and analytics.

IoT platforms, such as AWS IoT, Microsoft Azure IoT, and Google Cloud IoT, provide connectivity, device management, and data processing for IoT devices.

Data analytics tools, such as Apache Hadoop, Apache Spark, and TensorFlow, enable data processing, machine learning, and AI applications. here we introduce four alternatives.

- Criteria:

(i). Cost C1: The total cost of ownership, including upfront and ongoing costs, such as subscription fees, data transfer, and storage costs.

(ii). Scalability C2: The ability to handle increasing amounts of data and users without degrading performance.

(iii). Security C3: The measures taken to protect data and systems from unauthorized access, theft, and damage.

(iv). Reliability C4: The availability and uptime of the system, including backup and disaster recovery options.

(v). Integration C5: The ease of integrating the cloud computing solution with existing systems and tools.

(vi). Performance C6: The speed, responsiveness, and latency of the system, including data processing and analytics.

(vii). Usability C7: The user-friendliness and accessibility of the system, including mobile and remote access options.

(viii). Support C8: The availability and quality of technical support, documentation, and training resources.

The decision matrix is built by applying the Linguistic terms that are found in Table 1.

Table 1. Linguistic terms.

Linguistic terms	The Type 2 Neutrosophic numbers
Very Bad (VB)	((0.20,0.20.0.10), (0.65,0.80,0.85), (0.45,0.80,0.70))
Bad (B)	((0.35,0.35,0.10), (0.50,0.75,0.80), (0.50,0.75,0.65))
Medium Bad (MB)	((0.40,0.30,0.35), (0.50,0.45,0.60), (0.45,0.40,0.60))
Medium (M)	((0.50,0.45,0.50), (0.40,0.35,0.50), (0.35,0.30,0.45))
Medium Good (MG)	((0.60,0.45,0.50), (0.20,0.15,0.25), (0.10,0.25,0.15))
Good (G)	((0.70,0.75,0.80), (0.15,0.15,0.25), (0.10,0.10,0.15))
Very Good (VG)	((0.95,0.90,0.95), (0.10,0.10,0.05), (0.05,0.05,0.05))

4.3 | Applying the Hybrid Method to the Case Study

Step 1:

- In our problem we have four decision makers, their opinions are represented in Table 2 as linguistic terms presented in Table 1.
- Then, using Eq. (4) to aggregate the decision makers' opinions to build a decision matrix for Eq. (6) to get Table 3.
- After that use Eq (5) score function to convert T2NN into crisp numbers as shown in Table 4.

Table 2. DMs matrix.

Alternatives	DMs	C1	C2	C3	C4	C5	C6	C7	C8
Alt1	DM1	VG	M	G	B	MB	M	M	M
	DM2	VG	M	G	MB	MB	MG	MG	MG
	DM3	VG	M	G	B	MB	G	G	G
	DM4	VG	M	G	MB	MB	VG	VG	VG
Alt2	DM1	G	MG	G	M	B	B	M	B
	DM2	G	MG	G	M	MB	MB	M	MB
	DM3	G	MG	G	M	B	B	M	B
	DM4	G	MG	G	M	MB	MB	M	MB
Alt3	DM1	G	MB	VG	VB	VB	MB	MB	MB
	DM2	G	MB	VG	VB	VB	MB	MB	MB
	DM3	G	MB	VG	VB	VB	MB	MB	MB
	DM4	G	MB	VG	VB	VB	MB	MB	MB
Alt4	DM1	G	B	VG	MB	M	MG	VB	B
	DM2	G	MB	VG	MB	M	MG	B	B
	DM3	G	M	VG	MB	M	MG	MB	B
	DM4	G	MG	VG	MB	M	MG	M	B

Table 3. Aggregated matrix.

	Criteria	
	$C_1 \in H$	$C_2 \in B$
A_1	$\langle(0.95,0.90,0.95);(0.10,0.10,0.05);(0.05,0.05,0.05)\rangle$	$\langle(0.50,0.45,0.50);(0.40,0.35,0.50);(0.35,0.30,0.45)\rangle$
A_2	$\langle(0.70,0.75,0.80);(0.15,0.15,0.25);(0.10,0.15,0.15)\rangle$	$\langle(0.40,0.30,0.35);(0.50,45,0.60);(0.45,0.40,0.60)\rangle$
A_3	$\langle(0.70,0.75,0.80);(0.15,0.15,0.25);(0.10,0.15,0.15)\rangle$	$\langle(0.38,0.32,0.26);(0.50,0.55,0.67);(0.47,0.51,0.62)\rangle$
A_4	$\langle(0.70,0.75,0.80);(0.15,0.15,0.25);(0.10,0.15,0.15)\rangle$	$\langle(0.47,0.38,0.37);(0.37,0.35,0.48);(0.28,0.39,0.39)\rangle$
	Criteria	
	$C_3 \in B$	$C_4 \in H$
A_1	$\langle(0.70,0.75,0.80);(0.15,0.15,0.25);(0.10,0.15,0.15)\rangle$	$\langle(0.38,0.32,0.26);(0.50,0.55,0.67);(0.47,0.51,0.62)\rangle$
A_2	$\langle(0.70,0.75,0.80);(0.15,0.15,0.25);(0.10,0.15,0.15)\rangle$	$\langle(0.50,0.45,0.50);(0.40,0.35,0.50);(0.35,0.30,0.45)\rangle$
A_3	$\langle(0.95,0.90,0.95);(0.10,0.10,0.05);(0.05,0.05,0.05)\rangle$	$\langle(0.20,0.20,0.10);(0.65,0.80,0.85);(0.45,0.80,0.85)\rangle$
A_4	$\langle(0.95,0.90,0.95);(0.10,0.10,0.05);(0.05,0.05,0.05)\rangle$	$\langle(0.40,0.30,0.35);(0.50,0.45,0.60);(0.45,0.40,0.60)\rangle$
	Criteria	
	$C_5 \in B$	$C_6 \in H$
A_1	$\langle(0.40,0.30,0.35);(0.50,0.45,0.60);(0.45,0.40,0.60)\rangle$	$\langle(0.78,0.71,0.78);(0.19,0.16,0.18);(0.11,0.15,0.14)\rangle$
A_2	$\langle(0.38,0.32,0.26);(0.50,0.55,0.67);(0.47,0.51,0.62)\rangle$	$\langle(0.38,0.32,0.26);(0.50,0.55,0.67);(0.47,0.51,0.62)\rangle$
A_3	$\langle(0.20,0.20,0.10);(0.65,0.80,0.85);(0.45,0.80,0.70)\rangle$	$\langle(0.40,0.30,0.35);(0.50,0.45,0.60);(0.45,0.40,0.60)\rangle$
A_4	$\langle(0.50,0.45,0.50);(0.40,0.35,0.50);(0.35,0.30,0.45)\rangle$	$\langle(0.60,0.45,0.50);(0.10,0.15,0.25);(0.10,0.25,0.15)\rangle$
	Criteria	
	$C_7 \in H$	$C_8 \in H$
A_1	$\langle(0.78,0.71,0.78);(0.19,0.16,0.18);(0.11,0.15,0.14)\rangle$	$\langle(0.78,0.71,0.78);(0.19,0.16,0.18);(0.11,0.15,0.14)\rangle$
A_2	$\langle(0.50,0.45,0.50);(0.40,0.35,0.50);(0.35,0.30,0.45)\rangle$	$\langle(0.38,0.32,0.26);(0.50,0.55,0.67);(0.47,0.51,0.62)\rangle$
A_3	$\langle(0.40,0.30,0.35);(0.50,45,0.60);(0.45,0.40,0.60)\rangle$	$\langle(0.40,0.30,0.35);(0.50,0.45,0.60);(0.45,0.40,0.60)\rangle$
A_4	$\langle(0.37,0.34,0.28);(0.50,0.56,0.68);(0.43,0.53,0.59)\rangle$	$\langle(0.35,0.35,0.10);(0.50,0.75,0.80);(0.50,0.75,0.65)\rangle$

Table 4. Crisp numbers.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8
Alt1	0.929	0.575	0.8125	0.408	0.458	0.8117	0.8117	0.8117
Alt2	0.8125	0.458	0.8125	0.575	0.408	0.408	0.575	0.408
Alt3	0.8125	0.408	0.929	0.2375	0.2375	0.458	0.458	0.458
Alt4	0.8125	0.55	0.929	0.458	0.575	0.708	0.4125	0.308

Step 2: Using the MEREC method to get weight:

- First, normalize the matrix using Eq. (8) we consider that C1 is non-beneficial and the rest of the criteria are beneficial the normalized matrix is represented in Table 5.
- Then using Eq. (9), we calculate the overall efficiency of the alternatives as shown in Table 6.
- Then calculate the performance of the alternatives by removing each criterion to get $Sij^{`}$ as Table 7 using Eq. (10).
- Using eq (11) to calculate the absolute value of the deviations using Ej then Eq. (12) to get weight as shown in Table 8.

Table 5. Normalized matrix.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8
Alt1	1	0.709	1	0.582	0.519	0.503	0.508	0.379
Alt2	0.875	0.89	1	0.413	0.582	1	0.717	0.755
Alt3	0.875	1	0.875	1	1	0.891	0.9	0.672
Alt4	0.875	0.742	0.875	0.519	0.413	0.576	1	1

Table 6. The overall efficiency.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	Si
Alt1	1	0.709	1	0.582	0.519	0.503	0.508	0.379	0.395
Alt2	0.875	0.89	1	0.413	0.582	1	0.717	0.755	0.252
Alt3	0.875	1	0.875	1	1	0.891	0.9	0.672	0.105
Alt4	0.875	0.742	0.875	0.519	0.413	0.576	1	1	0.287

Table 7. The performance of the alternatives.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8
Alt1	0.395	0.366	0.395	0.348	0.338	0.335	0.336	0.309
Alt2	0.239	0.240	0.252	0.162	0.198	0.252	0.219	0.224
Alt3	0.105	0.105	0.089	0.105	0.105	0.092	0.093	0.059
Alt4	0.274	0.258	0.274	0.223	0.200	0.234	0.287	0.287

Table 8. The final weight.

Criteria	Removal effect	Weight
C1	0.026	0.028
C2	0.07	0.077
C3	0.029	0.032
C4	0.201	0.219
C5	0.198	0.217
C6	0.126	0.138
C7	0.104	0.114
C8	0.16	0.175

Step 3: Use the MAIRCA method to rank alternatives.

- The initial matrix is the aggregate of four DMs as Table 4. Use Eq. (14) to get preference as $Pj = ¼$
- Then apply Eq. (15) to get the theoretical ratings matrix Tp as Table 10.
- Using Eqs. (16) and (17) to get real ratings matrix Tr as Table 11.
- Calculate the total gap matrix (G) using Eq. (18).
- Use Eq. (19) to the final values of criteria functions (Qi) then rank as Table 12.

Table 10. The theoretical rating matrix.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8
Alt1	0.02743	0.02743	0.02743	0.02743	0.02743	0.02743	0.02743	0.048
Alt2	0.02743	0.02743	0.02743	0.02743	0.02743	0.02743	0.02743	0.048
Alt3	0.02743	0.02743	0.02743	0.02743	0.02743	0.02743	0.02743	0.048
Alt4	0.02743	0.02743	0.02743	0.02743	0.02743	0.02743	0.02743	0.048

Table 11. The real ratings matrix.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8
Alt1	0	0.02743	0	0.01386	0.01792	0.02743	0.02743	0.048
Alt2	0.02743	0.00821	0	0.02743	0.01386	0	0.01117	0.00953
Alt3	0.02743	0	0.02743	0	0	0.0034	0.00313	0.01429
Alt4	0.02743	0.02332	0.02743	0.01792	0.02743	0.02038	0	0

Table 12. Final rank.

Alternatives	C1	C2	C3	C4	C5	C6	C7	C8	Qi	Rank
Alt1	0.02743	0	0.02743	0.01357	0.00951	0	0	0	0.07793778	4
Alt2	0	0.01922	0.02743	0	0.01357	0.02743	0.01626	0.03847	0.14237953	2
Alt3	0	0.02743	0	0.02743	0.02743	0.02403	0.0243	0.03371	0.16432523	1
Alt4	0.02743	0	0.02743	0.01357	0.00951	0	0	0	0.0960889	3

5 | Sensitivity Analysis

This section introduces the sensitivity analysis, which proposes various criteria weights to rank the alternatives under different cases to show the stability of the rank. This study proposed nine cases with different criteria weights, as shown in Figure 3. Table 13 shows the score values of each alternative under sensitivity analysis, and Table 14 shows the rank of alternatives.

In case one, alternative 3 is the best, followed by alternative 2 and alternative 1. Alternative 4 is the worst. In case two, alternative 3 is the best, followed by alternative 2 and alternative 1. Alternative 4 is the worst. In case three, alternative 3 is the best, followed by alternative 2 and alternative 4. Alternative 1 is the worst. In case four, alternative 3 is the best, followed by alternative 2 and alternative 1. Alternative 4 is the worst. In case five, alternative 3 is the best, followed by alternative 2 and alternative 1. Alternative 4 is the worst. In case six, alternative 3 is the best, followed by alternative 2 and alternative 1. Alternative 4 is the worst. In case seven, alternative 3 is the best, followed by alternative 2 and alternative 4. Alternative 1 is the worst. In case eight, alternative 3 is the best, followed by alternative 2 and alternative 4. Alternative 1 is the worst. In case nine, alternative 3 is the best, followed by alternative 2 and alternative 4. Alternative 1 is the worst.

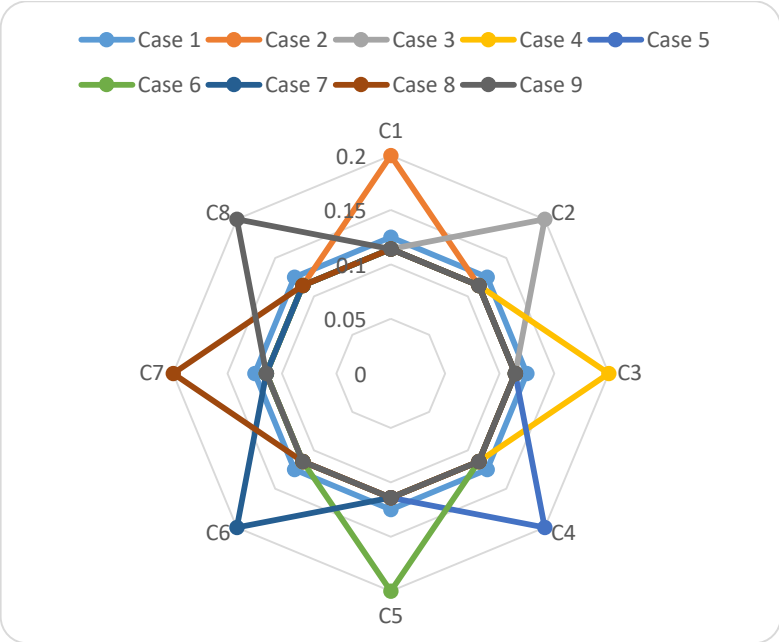

Figure 3. The nine cases in criteria weights change.

Table 13. The score values of alternatives under sensitivity analysis.

Alternatives	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9
Alt1	0	0	0.008	0.0271	0.0188	0	0	0	0.0539
Alt2	0.007	0.0133	0.008	0	0.0268	0.0345	0.0169	0.035	0.1415
Alt3	0.007	0.019	0	0.0547	0.0542	0.0302	0.02525	0.0307	0.22105
Alt4	0.007	0.003	0	0.019	0	0.0089	0.0285	0.0437	0.1101

Table 14. The rank of alternatives under sensitivity analysis.

Alternatives	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9
Alt1	4	3	3	4	3	3	3	4	4
Alt2	2	2	2	2	2	2	2	2	2
Alt3	1	1	1	1	1	1	1	1	1
Alt4	3	4	4	3	4	4	4	3	3

6 | Conclusions

Integrating smart farming into smart cities can yield numerous benefits for urban residents, agricultural producers, and city authorities. Smart farming technologies, including precision agriculture, IoT sensors, and data analytics, enable more efficient use of resources such as water, land, and energy. By optimizing irrigation, fertilization, and pest control practices, smart cities can minimize resource wastage and environmental impact while maximizing agricultural productivity. Smart farming practices prioritize environmental sustainability by minimizing chemical inputs, reducing greenhouse gas emissions, and preserving natural ecosystems. By adopting agroecological principles and sustainable farming techniques, smart cities can mitigate the environmental footprint of agricultural activities and promote ecosystem health. The MEREC-MAIRCA method is a decision-making framework that combines the MEREC (Multi-Attribute Decision Making based on Evaluation of Ranking and Exploratory Complexities) method with the MAIRCA (Multi-Attribute Ideal-Real Comparative Analysis) method. This approach facilitates a systematic evaluation of alternatives based on multiple attributes or criteria. By applying the MEREC-MAIRCA method, stakeholders can systematically evaluate cloud computing platforms for smart farming applications, considering multiple criteria and ensuring alignment with the objectives of the initiative. This approach helps make informed decisions that optimize performance, efficiency, and cost-effectiveness in deploying smart farming solutions on cloud infrastructure.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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