湖南大学学报（自然科学版） 第 51 卷 第 5 期
Journal of Hunan University (Natural Sciences） 2024 年 5 月

Available online at http://jonuns.com/index.php/journal/index

Vol. 51 No. 5
May 2024

Open Access Article https://doi.org/10.55463/issn.1674-2974.51.5.4

Comparative Analysis of the IoT Architectures for Smart Agriculture: Methodological Study Using the AHP and COPRAS

Othmane Aitlmoudden[1]*, Abdellah Bakhouyi[2], Nisrine Safeh[1], Mohammed Aitdaoud[1], Nawal Sael[1]

[1] Laboratory of Modeling and Information Technology, Faculty of Sciences Ben M'Sik, Hassan II University of Casablanca, Morocco

[2] Laboratory of Information Processing, Faculty of Sciences Ben M'Sik, Hassan II University of Casablanca, Morocco

* Corresponding author: othmane.aitlmoudden-etu@etu.univh2c.ma

Received: February 10, 2024 / Revised: March 13, 2024 / Accepted: April 18, 2024 / Published: May 30, 2024

Abstract: Global population growth, coupled with the depletion of natural resources and agricultural land and the increasing unpredictability of environmental conditions, has raised significant concerns regarding food security worldwide. These challenges have prompted the adoption of smart farming practices in the agricultural sector, leveraging the internet of things (IoT) and big data solutions to enhance operational efficiency and productivity. The IoT encompasses various advanced technologies such as wireless sensor networks, self-organizing cognitive radio networks, cloud computing, big data analytics, and end-user applications. This article presents a comparative study using multi-criteria analysis to evaluate different proposed architectures for the IoT technology-based smart agriculture. To find the best architecture based on predetermined criteria, this study uses the analytic hierarchy process (AHP) and complex proportional assessment (COPRAS) techniques. By employing these decision-making methodologies, this research contributes to the selection and optimization of IoT-based solutions for smart agriculture, thereby addressing the imperative need for sustainable and efficient food production systems.

Keywords: smart farming, the internet of things, complex proportional assessment, analytic hierarchy process.

智能农业物联网架构的比较分析：使用层次分析法和椰枣的方法研究

摘要：全球人口增长，加上自然资源和农业用地的枯竭以及环境条件越来越不可预测，引起了全世界对粮食安全的严重担忧。这些挑战促使农业部门采用智能农业实践，利用物联网(物联网)和大数据解决方案来提高运营效率和生产力。物联网涵盖各种先进技术，如无线传感器网络、自组织认知无线电网络、云计算、大数据分析和最终用户应用程序。本文介绍了一项使用多标准分析的比较研究，以评估基于物联网技术的智能农业的不同架构。为了根据预定标准找到最佳架构，本研究使用了层次分析法(层次分析法)和复杂比例评估(椰枣)技术。通过采用这些决策方法，本研究有助于选择和优化基于物联网的智能农业解决方案，从而满足对可持续和高效粮食生产系统的迫切需求。

关键词：智能农业、物联网、复杂比例评估、层次分析法。

1. Introduction

Agriculture holds significant importance in human society, playing a crucial role in providing sustenance throughout history. From ancient times to the Agricultural Revolution in England and Great Britain, farming has been the primary means of cultivating and consuming crops. Advancements in agricultural technologies, such as harvesters, seeders, and other machinery, have revolutionized the industry, reduced labor, and saved time. The idea of “smart farming” has evolved recently, integrating numerous IT technologies, tools, protocols, and paradigms to provide farmers with ground-breaking remedies [1].

Agricultural innovation, sometimes known as the “digital farming revolution,” is expected to fundamentally alter all facets of farming by introducing more effective, productive, sustainable, inclusive, transparent, and resilient systems. However, aspects including the complexity and maturity of mobile devices, precision agriculture, remote sensing, big data, cloud computing, analytics, cyber-security, and intelligent systems have a role in how well technology is integrated within the agricultural industry [2].

Smart farming, also known as intelligent agriculture, is an evolving domain of the internet of things (IoT) [3] that offers novel avenues for enhancing the adaptability, efficiency, and resilience of agricultural production systems. The IoT, a term that has gained prominence in recent years, connects billions of devices and individuals, serving as a powerful tool for generating, modifying, and sharing vast amounts of information. Its purpose lies in enabling seamless communication between devices and people. The IoT includes cloud computing, wireless sensor networks, and artificial intelligence and provides real-time processing, remote access, online analysis, and management capabilities. The IoT applications are found in a variety of industries, such as automation, transportation, the environment, and agriculture, and have a wide range of advantages, from smart cities and smart industries to healthcare.

In the context of smart farming, the IoT brings forth advantages like improved service quality and enhanced user experiences achieved through automation. However, it also poses unique security concerns associated with the integration of the IoT, cellular, and wireless technologies. In addition, smart agriculture faces unique security difficulties related to data and device integrity, data quality, and data availability. In smart agriculture, devices (sensors and actuators) and communication systems are exposed to environmental factors like climatic variations (sun, rain, snow), natural occurrences (lightning, hail), motor use in agriculture, power line transmissions (common in rural areas), interactions with animals, people, and farm equipment, and more. These elements render smart agriculture vulnerable to difficulties never seen in other situations.

With this understanding, it becomes essential to explore and analyze the IoT architectures in smart agriculture, evaluating their effectiveness and comparative advantages through comprehensive methodologies such as the analytic hierarchy process (AHP) and complex proportional assessment (COPRAS). Such research endeavors aim to identify optimal IoT-based architectures that address the evolving needs of the agricultural sector, ensuring sustainability, efficiency, and resilience in food production systems.

The remainder of this essay is divided into the following sections: Section 2 highlights the existing research gaps and provides a thorough evaluation of related work on IoT technologies-based smart agriculture. Section 3 presents an overview of smart agriculture, exploring its key components, advantages, and challenges. In Section 4, the concept of the IoT in agriculture is discussed, examining the integration of various technologies and their applications in enhancing agricultural processes. Section 5 focuses on the process of selecting architectures for IoT technologies-based smart agriculture, presenting the criteria and methodology employed for comparative analysis. Furthermore, in Section 6, the COPRAS method is applied to select the best architecture among the analyzed options. The empirical results and their implications are discussed in detail.

Finally, Section 7 concludes the research paper, summarizing the key findings and their significance for advancing smart agriculture practices. The conclusion also offers recommendations for policymakers and highlights potential areas for future research to foster continuous improvements in IoT technology-based smart agriculture and its overall sustainability.

2. Related Works

In today's fast-paced world, the rapid advancement of smart systems and emerging technologies has created a wealth of new opportunities across various industries. Two notable fields that have been revolutionized by the integration of the IoT and big data technologies are smart farming and architecture.

The proposed technology is anticipated to be beneficial to farmers in operating an irrigation system in a better and more precise way according to [4].

In contrast to the traditional trash collection framework, an exploratory study [5] offered a framework that would reduce transportation distance by 30% on average in a typical case. By enabling continuous observation and an optimized route, it reduces the cost of fuel and human labor, thus upgrading and improving the system.

Several comparative studies were conducted in the same fields. These studies included tests utilizing IEEE 802.11 g (Wi-Fi 2.4 GHz), IEEE 802.15.4 (Zigbee), and Long-Range Wireless Area Network (LoRaWAN) [6] to evaluate the performance of each technology in different environmental settings.

Another contribution discusses the implementation of various IoT strategies and intelligent decision support systems in agriculture [7]. This research provides a comprehensive analysis of techniques, technologies, predictions generated by the PLSR and ANFIS models, and insights into the challenges faced.

Furthermore, the challenges encountered by DL and IoT are addressed in [8]. Additionally, a bootstrapping method of transfer learning for pest identification is proposed, which involves combining fine-tuned VGG16 with enhanced and improved fully connected layers.

3. Overview of Smart Agriculture

Agriculture plays a significant role in national economic growth and sustains human populations by providing a crucial source of food. Moreover, it has been an integral part of the development of human civilization. According to the Food and Agriculture Organization of the United Nations, by 2050, there will be an additional 2.3 billion people to feed. This will require a 70% increase in global food production [9].

One of the pressing challenges faced by agriculture today is the impact of climate change and global warming, which leads to uncertainties in weather forecasting. Farmers struggle to make informed decisions to mitigate the potential damage caused by unpredictable climate. To address this issue, the adoption of IoT-based weather forecasting models offers a solution. These models enable farmers to make timely decisions by forecasting rainfall and optimizing pesticide usage. Consequently, the advancement of sophisticated irrigation and fertigation systems that consider environmental factors is achievable, leading to the promotion of sustainable and efficient agricultural practices.

In response to the growing demand for food, a concerted effort has been made to enhance the efficiency of food production. The integration of new technologies into agriculture is seen as a strategic approach to achieve this objective. To optimize agricultural processes, smart farming uses a wide range of computing technologies, tools, protocols, and paradigms. Considering the large amount of data generated by many components, it is noteworthy that big data, artificial intelligence, cloud computing, and edge computing offer opportunities and solutions for effective data preservation, storage, and analysis. However, smart farming is still in its infancy and currently lacks effective security features.

Data availability and accuracy will be crucial components of future smart farming solutions that will help farmers while ensuring the installation of reliable and secure systems. Smart farming uses a wide range of resources; therefore, security considerations include compatibility, resource scarcity, and massive data management. Traditional IoT [10] settings' use of conventional protection measures may not be sufficient for agricultural systems, leading to new requirements and possibilities.

A typical agricultural monitoring IoT system entails the deployment of various sensor types, including environmental and soil sensors. The collected data from IoT sensors, such as CO2 levels, rainfall, temperature, humidity, soil moisture [11], and plant health [10], can be utilized to devise strategies for enhancing productivity and economic profitability in Morocco. Subsequently, the gathered data are transmitted to cloud servers through gateways using the communication protocols employed within the system.

Overall, smart agriculture represents a promising approach to address the challenges faced by the agricultural sector. By leveraging the potential of IoT technologies and data-driven decision-making, farmers can enhance productivity, optimize resource utilization, and adapt to changing environmental conditions, thereby contributing to the advancement of sustainable and resilient agricultural systems [12].

4. Concept of IoT in Agriculture

Using the IoT in agriculture presents a revolutionary approach to not only meet the increasing food demands but also foster sustainability. By lever-aging IoT, crop monitoring is enhanced, resulting in maximum yield from plants. The impact of IoT and connected devices in various sectors is undeniable in today's modern world, including homes, healthcare, smart cities, fitness, and industry. Agriculture is no exception. The IoT and connected devices can bring about significant transformations in farming practices, liberating farmers from traditional reliance on manual labor. While the IoT is commonly associated with consumer-connected devices, its applications in agriculture are gaining traction.

The integration of the IoT technology into agricultural operations offers several benefits, such as reduced reliance on manual labor through automation, accelerated machinery control through remote and real-time monitoring, and improved resource utilization through predictive maintenance and environmental forecasting. By adopting these advancements, farmers can scale up their revenues and effectively manage larger areas of land. Smart agricultural technology empowers farmers with greater control over crop growing and livestock rearing processes, leading to increased efficiency, cost savings, and conservation of scarce resources like water.

Implementing an IoT solution for farming and agricultural purposes requires careful selection of appropriate sensors. The choice of sensors depends on the specific information to be collected and the intended use of the data. Ensuring the quality of sensors is vital for the success of the IoT solution as the accuracy and reliability of the collected data are crucial factors. The IoT simplifies the collection and management of large volumes of data from sensors by using cloud storage, farmland maps, and real-time monitoring to enable seamless connectivity and widespread distribution of experiments and relevant details.

In the realm of smart farming, the IoT is regarded as a crucial component. Experts assert that farmers could increase yields by 72% by 2050 through the precise use of sensors and smart devices. Embracing IoT can significantly reduce costs while enhancing productivity and overall sustainability. It facilitates improved resource efficiency by optimizing the use of water, soil, fertilizers, pesticides, and other essential inputs [13].

By harnessing the potential of the IoT in agriculture, farmers can revolutionize their practices, achieve higher yields, minimize waste, and promote sustainable agricultural systems that meet future food demands.

5. Choosing Architectures for IoT Technologies in Smart Agriculture

The implementation of various designs and efforts for smart farming using various technologies and systems enables farmers to make informed decisions and enhances nearly every element of their work.

Table 1 displays various IoT-based smart farming and agriculture architectures we chose for our comparative analysis.

Table 1 IoT-based smart farming and agricultural architectures (The authors)

References	Architecture	Protocol	Technologies
[7]	Short Supply Circuit Internet of Things (SSCIoT)	5G-MEC/LoRa/WSN Wi-Fi/3GPP	Edge, fog, and cloud computing
[8]	5-layer sensor edge-fog-cloud terminal system architecture	LoRa/nRF Wi-Fi/AVR	Edge and fog computing LPWAN
[9]	IoT Edge-Fog-Cloud Architecture	nRF24L01/HTTP	Edge, fog, and cloud computing and AI
[10]	SmartDairyTrace platform based on Global Edge Computing Architecture (GECA)	ZigBee/Wi-Fi/HTTP/MQTT/CoAP	Edge and Fog Computing AI Blockchain
[11]	WALLeSMART architecture	LoRa/Wi-Fi Bluetooth/EMQ	Apache Kafka, Storm, and Hadoop
[12]	MARS Architecture	LoRaWAN	WSN UAV cloud computing machine learning
[13]	Overall architecture of the PA platform	6LoWPAN/MQTT/Co AP CPS	NFV FIWARE edge computing
[14]	Precision farming system architecture	ZigBee/LoRa 6LoWPAN/Wi-Fi/UAV	WSN
[15]	GECA 2.0 improved with SDN/NF	ZigBee/Wi-Fi/HTTP/MQTT	Blockchain SDN/NFV edge, fog computing, AI
[16]	SEnvironodes	MQTT/HTTP/2G/3G/AM QP/STOMP	RabbitMQ, Microservices, Mu, Influx, and Firebase
[17]	High-level system architecture	nRF24L01/12C/SPI/Zigbee	WSN ATmega32 8P MCU

Utilizing distributed edge architecture enables the efficient processing and storage of multimedia and IoT data in close proximity to the data generators. This proximity allows rapid response times from current applications due to the immediate access to media items by data providers [14].

The Short Supply Circuit IoT architecture, which is built upon short supply chains in agriculture, enhances efficiency by removing unnecessary intermediaries between IoT data generators and end users. Utilizing CNNs and LoRa, this architecture showes an edge and fog computing-based system for smart farming procurement [15]. The architecture includes a sensor layer, where a set of sensor nodes collects data and sends it to the edge gateway. The edge layer processes and compresses the data via nRF and sends them to the fog gateway via LoRa.

Fog gateways connected to the cloud through Wi-Fi, Ethernet, or 4G are found in locations with old but dependable internet connections. The end user layer is made up of mobile applications and websites that access the data from the cloud layer, which uses sophisticated algorithms to store, process, and analyze data.

Based on Edge-Fog IoT cloud, intelligent agriculture architecture and outcome analysis [16]. The architecture consists of three layers: the IoT data collection and transmission layer, which is made up of sensor nodes that gather and send data to the Edge through nRF24L01, the processing and intelligence layer, where the EDGE acts as an intermediary layer between the IoT sensor network and the cloud, and finally placed in the user application layer where farmers can access the results.

Architecture based on edge computing (GECA) [17] consists of three layers: the IoT layer, which is made up of various sensors, the edge layer, which is administered by edge nodes or form edge gateways and serves as an IoT device and business solution, and the middle layer. The gateway between levels examines and analyzes the gathered data before sending it through HTTP, MQTT, or AMQP to the application layer, where it is then sent to the business solution layer, from where the end user can view and control the data from the comfort of his own backyard.

Three Lambda layers make up the WALLeSMART architecture, which is based on the Lambda architecture [18]. Data is gathered from two main sources, Eleveo for information on cattle behavior and Pameseb5 for information on the weather, and is then transferred over Wi-Fi, EMQ, or the LoRa data processing layer. The data access layer leverages multiple technologies, such as graphQL, to create interfaces and re-ports, while the data processing layer uses Apache Hadoop for batch data processing before storing it in Cassandra or PostgreSQL.

Other architecture [19] has been designed to leverage the latest technological advancements in drones, cameras and WSNs for an integrated crop protection and tree protection architecture. The best level of accuracy in the analysis and processing of agricultural data will be achieved by combining computer vision and machine learning techniques. Any adaptable soilless cultivation platform needs a circulating green-house with acceptable salinity [20].

Powered by a three-tier open-source software platform at the local edge and cloud levels, it is based on cheap swappable hardware. Cyber-physical systems (CPS) inter-act with cultural objects locally, gather real-time data, and carry out atomic control operations. Dashboard In order to increase the system's reliability against network access failures, this platform is in charge of controlling and monitoring access points close to the access network. Finally, the cloud platform stores the data analysis module for the FIWARE deployment and gathers both recent and old information. The Next Generation Services Interface (NGSI) is utilized for north-south access to the cloud, whereas IoT protocols such Message Queuing Telemetry Transport (MQTT) or Constrained Application Protocol (CoAP) are used to interface with the CPS.

A contribution has been created for the generic reference architectural model [21], taking into account the energy consumption restriction, a very significant non-functional need. It aims to address the lack of smart agriculture architecture by proposing a “precision agriculture” approach. The primary components of a precision agriculture system are the collection of agricultural parameters, the identification of data collection locations, the transmission of data from the cultivation field to the control station for decision-making, the actuation and control of decisions based on detected data, and the visualization of results to the farmer through an application.

Based on the prior GECA design, this architecture [22] has been modified with the following changes: Two sub-layers make up the edge layer. Existing components are inherited by edge sub layers. Edge gateways contain internal storage and data preprocessing, from the IoT layer to the application layer and Fog sub layer, starting with the prior GECA.

Fog reverse doors can be found on this new ground floor. Similar to edge gate-ways, packet fog forwarding gates in the edge sub layer have tables of routes that can be reconfigured remotely from SDN. The virtual network management sub layer, which is the control plane, and the application sub layer-layer of the SDN architecture are both sub layers of the business solution layer that are separated by Southern API control. The functionality from GECA’s Business Solutions layer is completely pre-sent in this sub layer.

The two domains of the architecture [23] are physical and network. The network and perception layers make up the physical domain, which comprises IoT devices and represents hardware devices.

There are two main layers in the network domain: cloud and client. The first layer is the Internet of Things platform, which is made up of two layers: data and services, and the second layer is made up of applications/business apps which support the IoT platform.

The most recent architecture consists of three levels: the access layer, gateway layer, and application layer [24]. The access layer handles data traffic, data processing, and data trafficking. The gateway layer's function is to collect data from the access layer and store it locally on a server. Data processing and end-user display are managed by the application layer.

6. Methodology

6.1. Choosing Evaluation Criteria

To compare 23 criteria and characteristics of IoT technologies in smart agriculture, research and development activities were centered on the IoT Technologies designs used in the industry, which list more than 100 items. The crite-ria were chosen with the intention of identifying and resolving the limitations and issues related to IoT technologies in smart agriculture. We develop eight alternative analysis criteria that we will use in the multi-criteria study to enable better analysis and optimization.

The following are the criteria:

- *Protocol (C1):* a communication protocol that defines how multiple digital devices communicate, which are grouped into different categories based on their role in the network. Among many other protocols, there are protocols for connecting infrastruc-ture, such as “6LowPAN”, communications “Wi-Fi, ZigBee, Bluetooth”, data trans-mission “CoAP, MQTT, XMPP”, security “DTLS” and many more.
- *Interoperability (C2):* the ability for one object to communicate with other different objects.
- *Resilience (C3):* the ability of a system or one of its components to continue its activity in the event of a failure.
- *Accessibility (C4):* This means you can access the information you need anywhere, on any network, and in any environment.
- *Scalability (C5):* IT resources can be increased or decreased as needs change.
- *Latency (C6):* the time it takes for data to travel from the source to the destination.
- *Cost (C7):* related to infrastructure and equipment.

6.2. AHP Methodology

Thomas Saaty created the AHP [25], a multi-criteria decision-making technique. By displaying the connections between the aim, objectives (criteria), and options in a hierarchical structure, AHP enables decision-makers to represent complicated problems. AHP includes a number of elements, including pairwise comparisons, judgments, an eigenvector approach for determining weights, and consistency concerns. It also includes hierarchical structure of complexity.

The steps in the analytical hierarchy process (AHP) are as follows:

6.2.1. Defining Decision Criteria in the Form of a Hierarchy of Objectives

The pairwise comparisons done in the indices using “Criteria 1-9 Proportion” by AHP for the relative relevance given in Table 2 employ a normalized comparison scale.

Table 2 Attribute pair-wise comparison scale (The authors)

Intensity of importance	Definition
1	Equal importance (no preference)
2	Intermediate between 1 and 3
3	Moderately more important
4	Intermediate between 3 and 5
5	Strongly more important
6	Intermediate between 5 and 7
7	Very strongly important
8	Intermediate between 7 and 9
9	Extremely strongly more important
1/2, 1/3, 1/4, 1/5, 1/6, 1/7, 1/8, 1/9	Reciprocals of 2, 3, 4, 5, 6, 7, 8, and 9

– Take 1 if they are both equally significant;

– If the former is significantly more significant than the latter, the former should be given three points (3) and the latter one-third (1/3);

– If the former is significantly more important than the latter, the former should be given five points (5) and the latter one-fifth (1/5);

– If the former is significantly more important than the latter, the former should be given seven points (7) and the latter one-seventh (1/7);

– If the former is significantly more important than the latter, the former should be given nine points (9) and the latter one-ninth (1/9);

– The values between them are 2, 4, 6, and 8.

6.2.2. Developing Judgment Matrices A by Pairwise Comparisons

$$A = \{a_{ij}\} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \cdots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2n} \\ a_{31} & a_{32} & a_{33} & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & a_{n3} & \cdots & a_{nn} \end{bmatrix} \quad (1)$$

A priority vector is created after a judgment matrix to weigh the matrix's components.

$$W_i = \frac{\sqrt[n]{\prod_{j=1}^{n} a_{ij}}}{\sum_{i=1}^{n} \sqrt[n]{\prod_{j=1}^{1} a_{ij}}} (\mathrm{i, j} = 1, 2, \ldots, \mathrm{n}) \quad (2)$$

Inconsistency in pair-wise comparison following priority vector construction may arise as a result of subjective human judgment error.

As a result, it is crucial to use the consistency index (CI) in the following equation to assess the consistency of the response.

$$CI = (\lambda_{max} - n)/(n - 1) \quad (3)$$

Inconsistency in pair-wise comparison following priority vector construction may arise as a result of subjective human judgment error.

As a result, it is crucial to use the consistency index (CI) in the following equation to assess the consistency of the response.

$$CR = CI/RCI \quad (4)$$

Table 3 Random consistency index (The authors)

Matrix Rank	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
R1	0,00	0,00	0,58	0,90	1,12	1,24	1,32	1,41

If CR<0.10, the judging matrix, in our opinion, exhibits sufficient consistency.

If not, we should make changes to the matrix members and run a consistency test to ensure that the comparison matrices are consistent.

In our analysis, we discovered that the comparison is consistent because the consistency rate (CR) was CR=0,09, which is smaller than 0,1.

The AHP approach can be used to determine the weights of the hierarchical structure for the interoperability assessment of smart agriculture technologies [26]. The precise weights of the criteria are determined and displayed in Table 4.

Table 4 Matrices of criteria (The authors)

Criteria	**Weight**
Protocol	0,286
Interoperability	0,188
Security	0,129
Resilience	0,118
Accessibility	0,113
Scalability	0,084
Latency	0,082
Cost	0,080

7. Results and Discussion

7.1. Selection of Optimal IoT Architecture for Smart Agriculture Using the COPRAS Method

Zavadskas and Kaklauskas present the COPRAS approach [27].

The COPRAS technique assumes that the relevance and priority of the studied alternatives are directly and proportionally dependent on a set of criteria [28], [29]. By putting the following phases into practice, the COPRAS method's determination of relevance and priority of alternatives can be expressed succinctly [28-30]:

- *The normalized decision-making matrix R is constructed using a specific formula in the COPRAS method for normalization:*

$$R = r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}} \quad (5)$$

where r_{ij} is the normalized value, a_{ij} is the performance of the ith option in relation to the jth criterion, and m is the number of alternatives.

Forming of the weighted normalized decision matrix

$$V = \left[v_{ij}\right]_{mxn} \quad (6)$$

Weighted normalized value v_{ij} is calculated using the formula:

$$v_{ij} = w_j . r_{ij} \ , i = 1, \dots, m \ ; \ j = 1, \dots, n \quad (7)$$

where w_j represents the weight/importance of the j-th criteria/attributes, and $\sum_{j=1}^{n} w_j = 1$.

The normalized decision-making matrix R is constructed using the following formula in the COPRAS method for normalization:

$$P_i = \sum_{j=1}^{n} v_{ij} \mid j \in j^{max} , i = 1, \dots, m \quad (8)$$

$$R_i = \sum_{j=1}^{n} v_{ij} \mid j \in j^{min} , i = 1, \dots, m \quad (9)$$

where j^{max} represents a set of revenue criteria/attributes, and j^{min} a set of expenditure criteria/attributes.

- *Weighing each possibility according to its relative relevance*

The following formula is used to determine the relative weight Q_i of the i-th alternative:

$$Q_i = P_i + \frac{\min R_i \sum_{i=1}^{m} R_i}{R_i \sum_{i=1}^{m} \frac{\min R_i}{R_i}} \quad (10)$$

Formula (10) can also be written in simplified form as follows:

$$Q_i = P_i + \frac{\sum_{i=1}^{m} R_i}{R_i \sum_{i=1}^{m} \frac{1}{R_i}} \quad (11)$$

The weighted relative relevance Q_i of the i-th alternative is determined as follows:

$$A^* = \{A_i \mid \max Q_i\} \quad (12)$$

7.2. The Choice of the Best Architecture for IoT Technology in Smart Agriculture by Applying the COPRAS Method

Table 5 Results from judgment matrices of criteria (The authors)

Alt	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
Weight	0,286	0,188	0,129	0,118	0,113	0,084	0,082
A01	10	11	14	16	15	2	2
A02	9	13	14	16	13,5	7	8
A03	9	16	17	16	13	4	6
A04	10	12	13	15	16	2	2

Continuation of Table 5

A05	8	14	14	16	14	6	4
A06	16	15	12	13	12	10	9
A07	10	12	13	15	13	4	6
A08	8	14	14	16	14	6	4
A09	10	11	12	15	13	4	4
A10	10	9	9	5,5	6	16	15
A11	9	9,5	8,5	5n	7	17,5	18

The process for deciding on the most suitable approach utilizing the COPRAS method will be described in the steps below:

Developing a normalized decision matrix:

$$R = \begin{bmatrix} 0,030 & 0,136 & 0,060 & 0,031 & 0,781 & 0,938 & 0,313 \\ 0,030 & 0,042 & 0,188 & 0,469 & 0,625 & 1,094 & 1,094 \\ 0,015 & 0,006 & 0,063 & 2,031 & 0,938 & 0,625 & 0,625 \\ 0,114 & 0,060 & 0,094 & 2,500 & 0,313 & 0,313 & 0,313 \\ 0,129 & 0,036 & 0,031 & 0,375 & 0,063 & 0,688 & 0,688 \\ 0,023 & 0,018 & 0,125 & 0,094 & 0,469 & 0,094 & 0,094 \\ 0,083 & 0,024 & 0,031 & 2,031 & 0,469 & 0,625 & 0,625 \\ 0,379 & 0,120 & 0,094 & 2,188 & 0,244 & 0,938 & 0,938 \\ 0,023 & 0,120 & 0,125 & 0,719 & 0,563 & 0,719 & 0,719 \\ 0,008 & 0,102 & 0,125 & 0,938 & 0,125 & 0,031 & 0,031 \\ 0,061 & 0,120 & 0,094 & 0,250 & 0,469 & 0,375 & 0,375 \end{bmatrix} \quad (13)$$

Developing a weighted, normalized decision matrix:

$$W = [0,038 \quad 0,155 \quad 0,058 \quad 0,068 \quad 0,165 \quad 0,110 \quad 0,186 \quad 0,220] \quad (14)$$

$$V = W * R \quad (15)$$

$$V = \begin{bmatrix} 0,009 & 0,026 & 0,008 & 0,004 & 0,088 & 0,079 & 0,026 \\ 0,052 & 0,006 & 0,005 & 0,022 & 0,053 & 0,053 & 0,090 \\ 0,013 & 0,003 & 0,001 & 0,007 & 0,230 & 0,079 & 0,051 \\ 0,039 & 0,021 & 0,008 & 0,011 & 0,283 & 0,026 & 0,026 \\ 0,022 & 0,024 & 0,005 & 0,004 & 0,042 & 0,005 & 0,056 \\ 0,013 & 0,004 & 0,002 & 0,015 & 0,011 & 0,039 & 0,008 \\ 0,035 & 0,016 & 0,003 & 0.004 & 0,230 & 0,039 & 0,051 \\ 0,004 & 0,071 & 0,015 & 0.011 & 0,247 & 0,020 & 0,077 \\ 0,026 & 0,004 & 0,015 & 0,015 & 0,081 & 0,047 & 0,059 \\ 0,013 & 0,001 & 0,013 & 0,015 & 0,106 & 0,011 & 0,003 \\ 0,061 & 0,011 & 0.015 & 0.011 & 0.028 & 0,039 & 0,031 \end{bmatrix} \quad (16)$$

Calculating P and R's values:

$$P = \begin{bmatrix} 0,134 \\ 0,138 \\ 0,254 \\ 0,362 \\ 0,097 \\ 0,045 \\ 0,287 \\ 0,349 \\ 0,142 \\ 0,148 \\ 0,127 \end{bmatrix} \quad (17)$$

$$R = \begin{bmatrix} 0,104 \\ 0,142 \\ 0,130 \\ 0,052 \\ 0,062 \\ 0,047 \\ 0,091 \\ 0,097 \\ 0,106 \\ 0,013 \\ 0,070 \end{bmatrix} \quad (18)$$

Assessing the performance of each smart agriculture solution and selecting the optimal alternative:

$$Q_i = \begin{array}{c} A_1 \\ A_2 \\ A_3 \\ A_4 \\ A_5 \\ A_6 \\ A_7 \\ A_8 \\ A_9 \\ A_{10} \\ A_{11} \end{array} \begin{bmatrix} 14,00 & 8 \\ 10,32 & 11 \\ 11.39 & 10 \\ 28.26 & 3 \\ 23.58 & 4 \\ 30.79 & 2 \\ 16.25 & 6 \\ 15.21 & 7 \\ 13.77 & 9 \\ 110,93 & 1 \\ 20.76 & 5 \end{bmatrix} \quad (19)$$

Based on the values of Q_i, the most suitable IoT technology for smart agriculture is A10 (LoRa technology).

Fig. 1 displays the distribution of the four curves that represent the ultimate performance of each IoT technology-based smart agriculture system in relation to the comparison criteria.

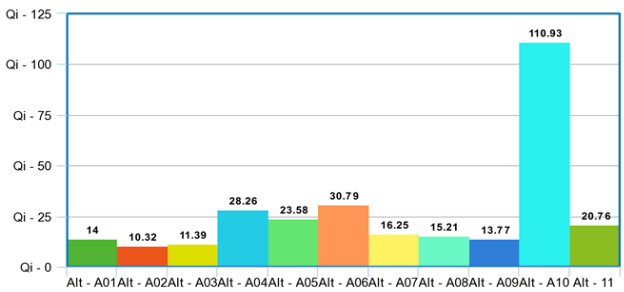

Fig. 1 Resulting performance of each IoT architecture in smart agriculture (The authors)

Q = 110,93 is the performance score that is best. According to this comparative analysis, we can say that none of these IOT technologies was able to achieve a perfect score.

The study's findings show that, with an overall score of Q = 110,93, the LORA Protocol, which is the best option under the circumstances and consistently achieves the highest scores on all of the chosen criteria, is superior to other smart agricultural systems.

The other protocols, such as the 5G-MEC protocol with a score of Q=10,32 and the ZigBee protocol with a score of Q=30,79, respectively, come last and are followed by other IOT technologies.

8. Conclusion

The advancement of farming practices through smart farming is crucial for achieving increased production rates while preserving natural resources. By incorporating efficient control of actuators, optimization of resource usage, streamlined production management, and cost reduction, smart farming can significantly enhance agricultural operations. However, to fully realize these benefits, intelligent systems must possess enhanced computational capabilities, including edge computing, effective big data management, access to artificial intelligence resources, and robust security features.

In this research, we proposed a methodology combining the AHP and COPRAS methods for the selection and evaluation of the IoT technology architectures used in smart agriculture. The AHP method facilitated the determination of criteria weights, while the COPRAS method aided in identifying the optimal solution among the analyzed options. By employing these methodologies, we achieved a more objective and consistent approach to selecting the IoT technology architectures for smart agriculture.

It is important to note that this methodology can be extended to evaluate and rank combinations of other types of IoT technologies-based solutions in smart agriculture. Additionally, the selection of appropriate smart agriculture solutions can be based on diverse criteria beyond those utilized in this study, thereby allowing for more comprehensive assessments tailored to specific needs.

Moving forward, future research efforts should focus on expanding the scope of criteria and considering additional aspects to further enhance the decision-making process in selecting the IoT technology architectures for smart agriculture. Furthermore, investigations into the integration of emerging technologies, such as edge computing and artificial intelligence, should be explored to unlock their potential in optimizing agricultural practices. Overall, the findings of this study contribute to the ongoing development of sustainable and efficient smart agriculture systems, advancing the transformation of the agricultural sector and ensuring global food security.

References

[1] DALENS T. *Learnable factored image representations for visual discovery*. Doctoral thesis, Ecole Normale Superieure de Paris-ENS Paris, 2019. https://inria.hal.science/tel-02296150/

[2] TRENDOV N. M., VARAS S., and ZENG M. *Digital technologies in agriculture and rural areas – Status report.* Food and Agriculture Organization of the United Nations, Rome, 2019. https://openknowledge.fao.org/server/api/core/bitstreams/0bb5137a-161c-4b7c-9257-3d4d5251b4bf/content

[3] RAY P. P. Internet of things for smart agriculture: Technologies, practices and future direction. *Journal of Ambient Intelligence and Smart Environments,* 2017, 9(4): 395-420. https://doi.org/10.3233/AIS-170440

[4] DEEPA B., ANUSHA C., and CHAYA DEVI P. Smart Agriculture Using IOT. In: SATAPATHY S., BHATEJA V., JANAKIRAMAIAH B., and CHEN Y. W. (eds.) *Intelligent System Design. Advances in Intelligent Systems and Computing,* Vol. 1171. Springer, Singapore, 2021: 11–19. https://doi.org/10.1007/978-981-15-5400-1_2

[5] SENTHIL KUMAR A., SURESH G., LEKASHRI S., BABU LOGANATHAN G., and MANIKANDAN R. Smart Agriculture System with E–Carbage Using IoT. *International Journal of Modern Agriculture,* 2021, 10(1): 928-931. http://www.modern-journals.com/index.php/ijma/article/view/690

[6] SEKARAN K., MEQDAD M. N., KUMAR P., RAJAN S., and KADRY S. Smart agriculture management system using internet of things. *TELKOMNIKA (Telecommunication Computing Electronics and Control),* 2020, 18(3): 1275-1284. https://doi.org/10.12928/telkomnika.v18i3.14029

[7] SRILAKSHMI A., RAKKINI J., SEKAR K. R., and MANIKANDAN R. A comparative study on Internet of Things (IoT) and its applications in smart agriculture. *Pharmacognosy Journal,* 2018, 10(2): 260-264. https://doi.org/10.5530/pj.2018.2.46

[8] SARANYA T., DEISY C., SRIDEVI S., and ANBANANTHEN K. S. M. A comparative study of deep learning and Internet of Things for precision agriculture. *Engineering Applications of Artificial Intelligence,* 2023, 122: 106034. https://doi.org/10.1016/j.engappai.2023.106034

[9] DAWSON T. P., PERRYMAN A. H., and OSBORNE T. M. Modelling impacts of climate change on global food security. *Climatic Change,* 2016, 134: 429-440. https://doi.org/10.1007/s10584-014-1277-y

[10] SINHA B. B., & DHANALAKSHMI R. Recent advancements and challenges of Internet of Things in smart agriculture: A survey. *Future Generation Computer Systems,* 2022, 126: 169-184. https://doi.org/10.1016/j.future.2021.08.006

[11] BOURSIANIS A. D., PAPADOPOULOU M. S., DIAMANTOULAKIS P., LIOPA-TSAKALIDI A., BAROUCHAS P., SALAHAS G., KARAGIANNIDIS G., WAN S., and GOUDOS S. K. Internet of things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review. *Internet of Things,* 2022, 18: 100187. https://doi.org/10.1016/j.iot.2020.100187

[12] HASAN M. Real-time and low-cost IoT based farming using raspberry Pi. *Indonesian Journal of Electrical Engineering and Computer Science,* 2020, 17(1): 197-204. http://doi.org/10.11591/ijeecs.v17.i1.pp197-204

[13] PRIYADHARSHINI M. J. G., HARIHARASUDHAN B., NEELAKANDAN R., and ARVIND R. K. Review on IoT based smart agriculture monitoring system. *International Journal of Research and Analytical Reviews,* 2022, 9(2): 38-43. https://ijrar.org/papers/IJRAR1COP007.pdf

[14] DEBAUCHE O., MAHMOUDI S., and GUTTADAURIA A. A new edge computing architecture for IoT and multimedia data management. *Information*, 2022,

13(2): 89. https://doi.org/10.3390/info13020089
[15] GIA T. N., QINGQING L., QUERALTA J. P., ZOU Z., TENHUNEN H., and WESTERLUND T. Edge AI in smart farming IoT: CNNs at the edge and fog computing with LoRa. Proceedings of the IEEE AFRICON, Accra, 2019, pp. 1-6. https://doi.org/10.1109/africon46755.2019.9134049
[16] DAHANE A., BENAMEUR R., KECHAR B., and BENYAMINA A. An IoT based smart farming system using machine learning. Proceedings of the International Symposium on Networks, Computers and Communications, Montreal, 2020, pp. 1-6. https://doi.org/10.1109/isncc49221.2020.9297341
[17] PÉREZ-PONS M. E., ALONSO R. S., PARRA-DOMÍNGUEZ J., PLAZA-HERNÁNDEZ M., and TRABELSI S. An Edge-IoT Architecture and Regression Techniques Applied to an Agriculture Industry Scenario. In: CORCHADO J. M., & TRABELSI S. (eds.) *Sustainable Smart Cities and Territories. SSCTIC 2021. Lecture Notes in Networks and Systems,* Vol. 253. Springer, Cham, 2022: 92–102. https://doi.org/10.1007/978-3-030-78901-5_9
[18] ROUKH A., FOTE F. N., MAHMOUDI S. A., and MAHMOUDI S. Big data processing architecture for smart farming. *Procedia Computer Science,* 2020, 177: 78-85. https://doi.org/10.1016/j.procs.2020.10.014
[19] KAKAMOUKAS G., SARICIANNIDIS P., LIVANOS G., ZERVAKIS M., RAMNALIS D., POLYCHRONOS V., KARAMITSOU T., FOLINAS A., and TSITSIOKAS N. A multi-collective, IoT-enabled, adaptive smart farming architecture. Proceedings of the IEEE International Conference on Imaging Systems and Techniques, Abu Dhabi, 2019, pp. 1-6. https://doi.org/10.1109/ist48021.2019.9010236
[20] ZAMORA-IZQUIERDO M. A., SANTA J., MARTÍNEZ J. A., MARTÍNEZ V., and SKARMETA A. F. Smart farming IoT platform based on edge and cloud computing. *Biosystems Engineering,* 2019, 177: 4-17. https://doi.org/10.1016/j.biosystemseng.2018.10.014
[21] TRIANTAFYLLOU A., TSOUROS D. C., SARIGIANNIDIS P., and BIBI S. An architecture model for smart farming. Proceedings of the 15th International Conference on Distributed Computing in Sensor Systems, Santorini, 2019, pp. 385-392. https://doi.org/10.1109/dcoss.2019.00081
[22] ALONSO R. S., SITTÓN-CANDANEDO I., CASADO-VARA R., PRIETO J., and CORCHADO J. M. Deep reinforcement learning for the management of software-defined networks in smart farming. Proceedings of the International Conference on Omni-Layer Intelligent Systems, Barcelona, 2020, pp. 1-6. https://doi.org/10.1109/coins49042.2020.9191634
[23] TRILLES S., GONZÁLEZ-PÉREZ A., and HUERTA J. An IoT platform based on microservices and serverless paradigms for smart farming purposes. *Sensors,* 2020, 20(8): 2418. https://doi.org/10.3390/s20082418
[24] FAID A., SADIK M., and SABIR E. IoT-based low cost architecture for smart farming. Proceedings of the International Wireless Communications and Mobile Computing, Limassol, 2020, pp. 1296-1302. https://doi.org/10.1109/iwcmc48107.2020.9148455
[25] SAATY T. L. Fundamentals of the Analytic Hierarchy Process. In: SCHMOLDT D. L., KANGAS J., MENDOZA G. A., and PESONEN M. (eds.) *The Analytic Hierarchy Process in Natural Resource and Environmental Decision Making. Managing Forest Ecosystems,* Vol. 3. Springer, Dordrecht, 2001: 15–35. https://doi.org/10.1007/978-94-015-9799-9_2
[26] DARKO A., CHAN A. P. C., AMEYAW E. E., OWUSU E. K., PÄRN E., and EDWARDS D. J. Review of application of analytic hierarchy process (AHP) in construction. *International Journal of Construction Management,* 2019, 19(5): 436-452. https://doi.org/10.1080/15623599.2018.1452098
[27] KAKLAUSKAS A., ZAVADSKAS E. K., RASLANAS S., GINEVICIUS R., KOMKA A., and MALINAUSKAS P. Selection of low-e windows in retrofit of public buildings by applying multiple criteria method COPRAS: A Lithuanian case. *Energy and Buildings,* 2006, 38(5): 454-462. https://doi.org/10.1016/j.enbuild.2005.08.005
[28] BAKHOUYI A., DEHBI R., and TALEA M. Multiple criteria comparative evaluation on the interoperability of LMS by applying COPRAS method. Proceedings of the Future Technologies Conference, San Francisco, California, 2016, pp. 361-366. https://doi.org/10.1109/ftc.2016.7821635
[29] DEHBI A., BAKHOUYI A., DEHBI R., and TALEA M. MOOCs in smart education: Comparative study by applying AHP and COPRAS method. *International Journal of Emerging Technologies in Learning,* 2022, 17(8): 61-74. https://doi.org/10.3991/ijet.v17i08.27871
[30] ALINEZHAD A., & KHALILI J. New methods and applications in multiple attribute decision making (MADM). Springer, Cham, 2019. https://doi.org/10.1007/978-3-030-15009-9

参考文:

[1] DALENS T. 可学习的分解图像表示用于视觉发现。博士论文，巴黎高等师范学院，2019年。https://inria.hal.science/tel-02296150/
[2] TRENDOV N. M.、VARAS S. 和 ZENG M. 农业和农村地区的数字技术——现状报告。联合国粮食及农业组织，罗马，2019年。https://openknowledge.fao.org/server/api/core/bitstreams/0bb5137a-161c-4b7c-9257-3d4d5251b4bf/content
[3] RAY P. P. 物联网用于智能农业：技术、实践和未来方向。环境智能与智能环境杂志，2017年，9(4)：395-420。https://doi.org/10.3233/AIS-170440
[4] DEEPA B.、ANUSHA C. 和 CHAYA DEVI P. 使用物联网实现智能农业。在：SATAPATHY S.、BHATEJA V.、JANAKIRAMAIAH B. 和 CHEN Y. W.（编辑）智能系统设计。智能系统和计算的发展，第1171卷。施普林格，新加坡，2021年：11-19。https://doi.org/10.1007/978-981-15-5400-1_2
[5] SENTHIL KUMAR A.、SURESH G.、LEKASHRI S.、BABU LOGANATHAN G. 和 MANIKANDAN R.

使用物联网实现电子垃圾智能农业系统。国际现代农业杂志，2021年，10(1)：928-931。http://www.modern-journals.com/index.php/ijma/article/view/690

[6] SEKARAN K.、MEQDAD M. N.、KUMAR P.、RAJAN S. 和 KADRY S. 使用物联网的智能农业管理系统。电信公司（电信计算电子与控制），2020年，18(3)：1275-1284。https://doi.org/10.12928/telkomnika.v18i3.14029

[7] SRILAKSHMI A.、RAKKINI J.、SEKAR K. R. 和 MANIKANDAN R. 物联网（物联网）及其在智能农业中的应用的比较研究。生药学杂志，2018年，10(2)：260-264。https://doi.org/10.5530/pj.2018.2.46

[8] SARANYA T.、DEISY C.、SRIDEVI S. 和 ANBANANTHEN K. S. M. 深度学习与物联网在精准农业中的比较研究。人工智能工程应用，2023年，122：106034。https://doi.org/10.1016/j.engappai.2023.106034

[9] DAWSON T. P.、PERRYMAN A. H. 和 OSBORNE T. M. 模拟气候变化对全球粮食安全的影响。气候变化，2016年，134：429-440。https://doi.org/10.1007/s10584-014-1277-y

[10] SINHA B. B.，& DHANALAKSHMI R. 物联网在智能农业中的最新进展和挑战：一项调查。未来一代计算机系统，2022年，126：169-184。https://doi.org/10.1016/j.future.2021.08.006

[11] BOURSIANIS A. D.、PAPADOPOULOU M. S.、DIAMANTOULAKIS P.、LIOPA-TSAKALIDI A.、BAROUCHAS P.、SALAHAS G.、KARAGIANNIDIS G.、WAN S. 和 GOUDOS S. K. 物联网(物联网)和农业无人机(无人机)在智能农业中的应用：全面回顾。物联网，2022，18：100187。https://doi.org/10.1016/j.iot.2020.100187

[12] HASAN M. 使用树莓派实现基于物联网的实时低成本农业。印度尼西亚电气工程与计算机科学杂志，2020，17(1)：197-204。http://doi.org/10.11591/ijeecs.v17.i1.pp197-204

[13] PRIYADHARSHINI M. J. G.、HARIHARASUDHAN B.、NEELAKANDAN R. 和 ARVIND R. K. 基于物联网的智能农业监测系统综述。国际研究与分析评论杂志，2022，9(2)：38-43。https://ijrar.org/papers/IJRAR1COP007.pdf

[14] DEBAUCHE O.、MAHMOUDI S. 和 GUTTADAURIA A. 一种用于物联网和多媒体数据管理的新型边缘计算架构。信息，2022年，13(2)：89。https://doi.org/10.3390/info13020089

[15] GIA T. N.、QINGQING L.、QUERALTA J. P.、ZOU Z.、TENHUNEN H. 和 WESTERLUND T. 智能农业物联网中的边缘人工智能：边缘的美国有线电视新闻网和使用洛拉的雾计算。电气电子工程师学会非洲分会论文集，阿克拉，2019年，第1-6页。https://doi.org/10.1109/africon46755.2019.9134049

[16] DAHANE A.、BENAMEUR R.、KECHAR B. 和 BENYAMINA A. 一种基于物联网的机器学习智能农业系统。国际网络、计算机和通信研讨会论文集，蒙特利尔，2020年，第1-6页。https://doi.org/10.1109/isncc49221.2020.9297341

[17] PÉREZ-PONS M. E.、ALONSO R. S.、PARRA-DOMÍNGUEZ J.、PLAZA-HERNÁNDEZ M. 和 TRABELSI S. 一种应用于农业行业场景的边缘物联网架构和回归技术。引自：CORCHADO J. M. 和 TRABELSI S. (编辑) 可持续智慧城市和地区。南海海事科技信息中心2021。网络和系统讲义，第253卷。施普林格，占婆，2022年：92–102。https://doi.org/10.1007/978-3-030-78901-5_9

[18] ROUKH A.、FOTE F. N.、MAHMOUDI S. A. 和 MAHMOUDI S. 智能农业的大数据处理架构。普罗塞迪亚计算机科学，2020年，177：78-85。https://doi.org/10.1016/j.procs.2020.10.014

[19] KAKAMOUKAS G.、SARICIANNIDIS P.、LIVANOS G.、ZERVAKIS M.、RAMNALIS D.、POLYCHRONOS V.、KARAMITSOU T.、FOLINAS A. 和 TSITSIOKAS N. 一种多集体、支持物联网的自适应智能农业架构。电气电子工程师学会国际成像系统和技术会议论文集，阿布扎比，2019年，第1-6页。https://doi.org/10.1109/ist48021.2019.9010236

[20] ZAMORA-IZQUIERDO M. A.、SANTA J.、MARTÍNEZ J. A.、MARTÍNEZ V. 和 SKARMETA A. F. 基于边缘和云计算的智能农业物联网平台。生物系统工程，2019年，177：4-17。https://doi.org/10.1016/j.biosystemseng.2018.10.014

[21] TRIANTAFYLLOU A.、TSOUROS D. C.、SARIGIANNIDIS P. 和 BIBI S.

智能农业架构模型。第15届传感器系统分布式计算国际会议论文集，圣托里尼，2019年，第385-392页。https://doi.org/10.1109/dcoss.2019.00081

[22] ALONSO R. S.、SITTÓN-CANDANEDO I.、CASADO-VARA R.、PRIETO J. 和 CORCHADO J. M. 深度强化学习用于智能农业中软件定义网络的管理。全层智能系统国际会议论文集，巴塞罗那，2020年，第1-6页。https://doi.org/10.1109/coins49042.2020.9191634

[23] TRILLES S.、GONZÁLEZ-PÉREZ A. 和 HUERTA J. 基于微服务和无服务器范式的物联网平台，用于智能农业。传感器，2020，20(8)：2418。https://doi.org/10.3390/s20082418

[24] FAID A.、SADIK M. 和 SABIR E. 基于物联网的低成本智能农业架构。国际无线通信和移动计算会议论文集，利马索尔，2020年，第1296-1302页。https://doi.org/10.1109/iwcmc48107.2020.9148455

[25] SAATY T. L. 层次分析法基础。引自：SCHMOLDT D. L.、KANGAS J.、MENDOZA G. A. 和 PESONEN M.（编辑）层次分析法在自然资源和环境决策中的应用。森林生态系统管理，第3卷。3. 施普林格，多德雷赫特，2001：15–35。https://doi.org/10.1007/978-94-015-9799-9_2

[26] DARKO A.、CHAN A. P. C.、AMEYAW E. E.、OWUSU E. K.、PÄRN E. 和 EDWARDS D. J. 回顾分析层次分析法(层次分析法)在建筑中的应用。国际建筑管理杂志，2019年，19(5)：436-452。https://doi.org/10.1080/15623599.2018.1452098

[27] KAKLAUSKAS A.、ZAVADSKAS E. K.、RASLANAS S.、GINEVICIUS R.、KOMKA A. 和 MALINAUSKAS P. 应用多标准方法椰枣选择公共建筑改造中的低辐射窗户：立陶宛案例。能源与建筑，2006年，38(5)：454-462。https://doi.org/10.1016/j.enbuild.2005.08.005

[28] BAKHOUYI A.、DEHBI R. 和 TALEA M. 应用椰枣方法对语言管理系统互操作性的多标准比较评估。未来技术会议论文集，加利福尼亚州旧金山，2016年，第361-366页。https://doi.org/10.1109/ftc.2016.7821635

[29] DEHBI A.、BAKHOUYI A.、DEHBI R. 和 TALEA M. 智能教育中的大规模在线课程：应用层次分析法和椰枣方法的比较研究。国际新兴学习技术杂志，2022年，17(8)：61-74。https://doi.org/10.3991/ijet.v17i08.27871

[30] ALINEZHAD A. 和 KHALILI J. 多属性决策(多模态多目标决策)中的新方法和应用。施普林格，占婆，2019年。https://doi.org/10.1007/978-3-030-15009-9