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A CRITIC-CODAS Approach for Ranking Wireless Communication Technologies in Precision Agriculture: Application to Irrigation System

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Abstract—This study evaluates and ranks wireless communication technologies for agricultural irrigation systems using the CRITIC-CODAS multi-criteria decision-making method. WSN, LPWAN, LoRa, 5G, IoT, and NB-IoT are compared based on range, power consumption, data rate, coverage, latency, battery life, and device density. The CRITIC method objectively determines criteria weights, with data rate, latency, and battery life emerging as the most critical factors. 5G ranks highest with its superior data rate and device density, but its high-power needs may limit suitability for remote agriculture. IoT offers a balanced option across multiple criteria, while WSN excels in power efficiency and battery life. Despite lower data rates, LPWAN, LoRa, and NB-IoT provide excellent range and battery life for wide-area, low-power applications. The analysis offers a framework for stakeholders to select appropriate technologies based on specific agricultural requirements. Matching wireless technologies to irrigation needs can enhance agricultural sustainability and productivity. Further research could explore technology combinations, cost factors, and real-world testing. This systematic evaluation approach can be extended to other intelligent agriculture applications to optimize technology adoption.

Keywords—*Wireless communication technologies, Agricultural irrigation systems, CRITIC-CODAS method, Multi-criteria decision-making, Precision agriculture*

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1 Introduction

The agricultural sector is crucial to the global economy. It faces increasing challenges such as food security, climate change, and resource management [1]. To overcome these challenges, innovative approaches are needed. One area that requires attention is irrigation systems. They are essential for providing crops with the correct amount of water at the appropriate time, leading to higher yields and less wastage. However, Traditional irrigation methods such as surface irrigation (including flood and furrow irrigation), sprinkler irrigation (overhead sprinklers), manual irrigation (watering cans and hoses), basin irrigation, and border strip irrigation are often inefficient, leading to significant water loss through evaporation, runoff, and uneven distribution (Anjum et al., 2023). These methods are unsuited to adapt to varying water availability and climatic conditions, underscoring the need for more advanced and efficient irrigation technologies [2]. As a result, there has been a growing interest in using advanced technologies to improve irrigation techniques in agriculture.

Wireless communication technologies are changing the game in modern agriculture, especially regarding irrigation systems. They have the power to transform how we approach irrigation completely. With these technologies, farmers can now monitor and control their irrigation processes in real-time, using data to guide their actions. This ability to make informed decisions based on accurate information is crucial for optimizing water usage and maximizing crop yields [3].

The use of wireless communication technologies in agricultural irrigation systems is a key aspect of precision agriculture. Precision agriculture is all about making farming more efficient, productive, and sustainable [4]. One of the main pillars of precision agriculture is collecting, transmitting, and analyzing data from different sources like soil moisture sensors, weather stations, and crop monitoring devices. And that's where wireless communication technologies come in and play a crucial role in a data-driven approach by ensuring smooth connectivity and coordination among the various components. One of the key advantages of wireless communication in irrigation systems is its flexibility. These systems can adapt and respond to the specific needs of different crops, soil conditions, and weather patterns by utilizing wireless sensors and devices. For example, suppose a particular area of the field requires more water due to dry soil or high temperatures. In that case, the system can automatically increase irrigation in that specific zone while reducing water flow in other areas where it is not needed as much. This targeted approach ensures that each plant receives the right amount of water at the right time, minimizing waste and promoting healthy growth [5].

There are several wireless communication technologies accessible for use in agriculture, each having unique features, benefits, and drawbacks. Many agricultural contexts have seen extensive research and application of technologies like Wi-Fi, Zigbee, LoRa (Long Range), and NB-IoT (Narrowband Internet of Things) [6]. Wi-Fi has a restricted range and increased power consumption, but it can handle big data and delivers high data transfer rates [7]. Conversely, Zigbee can enable mesh networking and is intended for low-power, low-data-rate applications, which qualifies it for dispersed sensor networks [8]. NB-IoT has great coverage and penetration, supporting enormous numbers of low-power devices, LoRa delivers long-range communication at low power consumption, making it perfect for isolated agricultural areas [9]. Because these technologies have such different features, choosing the best wireless communication technology for agricultural irrigation systems needs a methodical assessment based on several factors. Careful consideration of factors including range, power consumption, data transfer rate, cost, and dependability is necessary to ensure the selected technology satisfies the needs of the irrigation system and the agricultural environment [10].

Multi-criteria decision-making (MCDM) methods offer a systematic strategy for assessing and prioritizing choices by considering various factors. The CRITIC (CRiteria Importance Through Intercriteria Correlation) and CODAS (COmbinative Distance-based ASsessment) approaches are reliable frameworks for this purpose, among the several existing MCDM methods [11], [12]. The CRITIC approach is employed to ascertain the weights of the criteria by evaluating the contrast intensity and correlation among them. The method considers the variability of each criterion as well as the redundancy among them, guaranteeing that criteria with more information and less duplication are given greater weights. The CODAS technique evaluates the options by measuring their distance from the negative-ideal solution, considering both the Euclidean and Taxicab distances. The utilization of this dual-distance strategy amplifies the ability to differentiate between options, resulting in a more precise evaluation of the choices.

JDFEWS 5 (1): 134-145, 2024
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The objective of this study is to evaluate and prioritize wireless communication solutions for agricultural irrigation systems using the CRITIC-CODAS approach. Through a systematic assessment of technologies using essential performance criteria, our objective is to determine the most appropriate technology for improving the efficiency and efficacy of irrigation systems. The findings of this study will offer essential knowledge for farmers, agricultural engineers, and legislators, enabling them to make well-informed choices on the adoption and integration of wireless communication technology in agriculture.

2 Literature Review

This section provides a discussion on Wireless Communication Technologies Used in Agriculture and Previous Studies on the Evaluation and Ranking of Wireless Communication Technologies.

2.1 Review of Wireless Communication Technologies Used in Agriculture

Wireless communication technologies have transformed agricultural practices, particularly through precision agriculture and smart irrigation systems. This section reviews key wireless communication technologies used in agriculture, including Wireless Sensor Networks (WSN), Low Power Wide Area Networks (LPWAN), LoRa, 5G, Internet of Things (IoT), and Narrowband Internet of Things (NB-IoT). Wireless Sensor Networks (WSN) consist of spatially distributed sensors that monitor and record environmental conditions and transmit the collected data wirelessly. These networks are essential in precision agriculture for monitoring soil moisture, temperature, humidity, and other critical parameters. For instance, accurate soil moisture data in crop farming ensures optimal irrigation scheduling, reducing water usage while maintaining crop health [13]. Horticulture benefits from temperature and humidity monitoring to create optimal growing conditions in greenhouses [14]. Viticulture relies on precise environmental monitoring to enhance grape quality and vineyard management [15].

WSNs provide real-time data, enabling farmers to make informed decisions about irrigation and crop management [6]. Despite their effectiveness, WSNs often face challenges related to power consumption and network scalability. Low Power Wide Area Networks (LPWAN) are designed for long-range communication with low power consumption, making them suitable for agricultural applications that require connectivity over vast areas. These networks support low data rates, which are adequate for transmitting sensor data. LPWAN technologies include LoRa, and Sigfox. Their ability to cover large distances with minimal power makes them ideal for remote monitoring and control in agriculture [16]. LoRa (Long Range) is a type of LPWAN that offers long-range communication and low power consumption. It is particularly suitable for agricultural applications in remote areas where traditional communication infrastructure is unavailable. LoRa technology enables data transmission over several kilometers, making it ideal for monitoring large agricultural fields and optimizing irrigation systems [17]. Its robustness and reliability in varying environmental conditions further enhance its agricultural applicability.

The fifth generation of wireless technology, 5G, delivers high data transfer rates, low latency, and massive connectivity. These features make 5G a potential game-changer for smart agriculture, enabling real-time data transmission and advanced applications such as autonomous machinery and drone-based monitoring [18], [19], [20], [21], [22]. However, deploying 5G infrastructure in rural and agricultural areas remains challenging due to high costs and the need for extensive network coverage. Internet of Things (IoT) refers to the interconnection of physical devices through the Internet, allowing them to collect and exchange data. In agriculture, IoT enables the integration of various sensors, devices, and systems, facilitating real-time monitoring and control of irrigation, soil conditions, and crop health [7]. IoT technologies enhance decision-making and operational efficiency, contributing to sustainable agricultural practices. Narrowband Internet of Things (NB-IoT) is a LPWAN technology specifically designed for IoT applications. It offers excellent coverage, low power consumption, and support for many devices. NB-IoT is well-suited for agricultural applications that require reliable connectivity over long distances and in challenging environments [23], [24], [25], [26]. Its ability to penetrate obstacles and cover large areas makes it an effective solution for monitoring and controlling agricultural processes.

JDFEWS 5 (1): 134-145, 2024
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Table 1. Comparison of various wireless communication technologies in agricultural applications

Technology	Range (meters)	Power Consumption	Data Rate (kbps)	Coverage (meters)	Latency (ms)	Battery Life (years)	Device Density (devices/km²)
WSN (Wireless Sensor Networks) [27]	10 - 1,000	Low	10 - 1,000	10 - 1,000	10 - 1,000	1-5	1,000 - 10,000
LPWAN (Low Power Wide Area[28] Networks)	1,000 - 15,000	Very low	0.3 - 50	1,000 - 15,000	1,000 - 10,000	5-10	10,000 - 100,000
LoRa (Long Range)[29]	1,000 - 15,000	Very low	0.3 - 50	1,000 - 15,000	1,000 - 10,000	5-10	10,000 - 100,000
5G[30]	1,000 - 10,000	Moderate to high	20,000,000	1,000 - 10,000	1-10	1-3	1,000,000 - 10,000,000
IoT (Internet of Things)[31]	10 - 10,000+	Low to moderate	10 - 1,000	10 - 10,000+	50 - 500	1-5	1,000 - 100,000
NB-IoT (Narrowband IoT)[32]	1,000 - 10,000	Very low	0.1 - 250	1,000 - 10,000	1,500 - 10,000	5-10	50,000 - 100,000

2.2 Examination of Previous Studies on the Evaluation and Ranking of Wireless Communication Technologies

Several studies have evaluated and ranked wireless communication technologies based on various criteria such as range, power consumption, data transfer rate, cost, and reliability. These evaluations provide insights into the suitability of different technologies for specific agricultural applications. Ref [6] conducted a comprehensive review of wireless sensors and networks' applications in agriculture, highlighting the advantages and limitations of various technologies. The study emphasized the importance of selecting the right technology based on the application's specific needs, such as field size, crop type, and environmental conditions. Ref [7] evaluated the performance of Wi-Fi-based remote sensing and control systems for irrigation. The study found that while Wi-Fi offers high data transfer rates, its limited range and higher power consumption could be mitigated using repeaters and optimizing power management strategies. Ref [10] proposed a Smart Irrigation Decision Support System (SIDSS) that uses soil measurements and climatic data to manage irrigation in agriculture. Using PLSR and ANFIS machine learning techniques, the system adapts to local conditions and is validated on citrus plantations in Spain, outperforming human expert decisions.

Ref [8] evaluated the performance of Zigbee in agricultural sensor networks. They highlighted Zigbee's low power consumption and mesh networking capabilities, making it an efficient solution for continuously monitoring and controlling extensive farm fields. Ref [33] discussed the potential of NB-IoT in supporting IoT-based agricultural applications. They emphasized NB-IoT's ability to support many devices with low power consumption, making it suitable for large-scale deployments in agriculture. Ref [34] presented a comprehensive survey on the transformative impact of 5G technology on the agricultural sector, emphasizing its role in enhancing crop yields and quality while reducing labor requirements. The authors highlight how smart and precision farming, enabled by the superfast 5G network, will make farmers more informed and productive. The survey underscores that 5G will not only revolutionize agricultural practices but also significantly change the nature of jobs in farming.

3 Methodology

This section provides an overview of the methods applied in this study. It discusses the methods of CRITIC (Criteria Importance Through Intercriteria Correlation) and CODAS (Combinative Distance-based Assessment).

JDFEWS 5 (1): 134-145, 2024
ISSN 2709-4529

3.1 CRITIC (Criteria Importance Through Intercriteria Correlation) Method

The CRITIC approach (Criteria Importance Through Intercriteria Correlation) is employed to calculate objective weights for criteria in the context of multi-criteria decision-making (MCDM) [35]. It is especially beneficial when there is a lack of subjective weights or when an objective evaluation is necessary. The CRITIC approach consists of several phases, each with its corresponding mathematical representations:

Step 1: Normalize the Decision Matrix

Given a decision matrix $X = [x_{ij}]$ where x_{ij} represents the performance of the $i-th$ alternative on the $j-th$ criterion, normalizes the decision matrix to make the criteria comparable.

$$r_{ij} = \begin{cases} \dfrac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})} & beneficial \\ \dfrac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} & non-beneficial \end{cases}$$

where r_{ij} is the normalized value.

Step 2: Calculate Standard Deviation for Each Criterion

The standard deviation σ_j of each criterion $j-th$ is calculated as:

$$\sigma_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(r_{ij} - \bar{r}_j)^2}$$

where $\bar{r}_j$ is the mean of the normalized values for the $j-th$ criterion, and m is the number of alternatives.

Step 3: Compute the Correlation Coefficient Matrix

Calculate the correlation coefficient ρ_{jk} between each pair of criteria j and k:

$$\rho_{jk} = \frac{\sum_{i=1}^{m}(r_{ij} - \bar{r}_j)(r_{ik} - \bar{r}_k)}{\sqrt{\sum_{i=1}^{m}(r_{ij} - \bar{r}_j)^2}\ \sqrt{\sum_{i=1}^{m}(r_{ik} - \bar{r}_k)^2}}$$

Step 4: Calculate the Contrast Intensity

The contrast intensity C_j for each criterion j is computed by considering both the standard deviation and the correlation coefficients:

$$C_j = \sigma_j \sum_{k=1}^{n}(1 - \rho_{jk})$$

where n is the number of criteria.

Step 5: Determine Criteria Weights

Normalize the contrast intensity values to obtain the weights w_j for each criterion

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j}$$

3.2 CODAS (Combinative Distance-based Assessment)

The CODAS (Combinative Distance-based Assessment) method is a multi-criteria decision-making (MCDM) technique used to evaluate and rank alternatives based on multiple criteria. This method is particularly useful in scenarios where decision-makers need to consider both the distance from an ideal solution and the distance from an anti-ideal solution. Here are the key steps involved in the CODAS method [36]:

Step 1: Criteria Weighting

Let w_j be the weight of the $j-th$ criterion, where $j = 1,2,\ldots,n$.

Step 2: Normalization
Normalize the decision matrix matrix $X = [x_{ij}]$ where x_{ij} represents the performance of the $i-th$ alternative on the $j-th$ criterion. The normalization can be done using different methods, such as linear normalization:

$$r_{ij} = \begin{cases} \dfrac{x_{ij}}{\max(x_{ij})} & beneficial \\ \dfrac{\min(x_{ij})}{x_{ij}} & non-beneficial \end{cases}$$

where r_{ij} is the normalized value.
Step 3: Euclidean and Taxicab Distances
Calculate the Euclidean distance D_i^+ from the ideal solution and the Taxicab distance D_i^- from the non-ideal solution for each alternative i.
Ideal solution $A^+ = (r_1^+, r_2^+, r_3^+ \ldots, r_n^+)$
$r_j^+ = \max(r_{ij})$
Non-ideal solution $A^- = (r_1^-, r_2^-, r_3^- \ldots, r_n^-)$
$r_j^- = \min(r_{ij})$
Euclidean distance D_i^+:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} w_j \left(r_{ij} - r_j^+\right)^2}$$

Step 4: Assessment Score Calculation
Combine the Euclidean and Taxicab distances to compute the assessment score for each alternative i

$$S_i = D_i^+ - \theta D_i^-$$

where θ is a parameter that adjusts the influence of the distances. Commonly, θ is set to 0.5, but it can be adjusted based on the decision-maker's preference.
Step 5: Ranking
Rank the alternatives based on their assessment scores S_i. The alternative with the highest score is considered the best choice.

$$Rank\ (A_i) = \text{order of } S_i$$

By following these steps, the CODAS method systematically evaluates and ranks alternatives based on multiple criteria, considering both their proximity to the ideal solution and their distance from the anti-ideal solution.

4 Results and discussion

The CRITIC technique offers a systematic approach to determining criteria weights by considering their variability and interconnections. The weights obtained from this method provide valuable information about the relative significance of each criterion in distinguishing between the technologies being evaluated.

The normalization of the decision matrix (Table 2) ensures that all criteria are on a comparable scale. This step is crucial for the subsequent calculations as it allows for a fair comparison between different criteria, which may initially have different units or ranges of values. The mean and standard deviation (Table 3) provide insights into each criterion's central tendency and dispersion. For instance, the mean value for Data Rate is significantly lower (0.167) than other criteria, indicating that most technologies have relatively low data rates. The high standard deviation for the Data Rate (0.399) suggests a significant variability, which is confirmed by its high coefficient of variation.

JDFEWS 5 (1): 134-145, 2024
ISSN 2709-4529

Table 2. Normalized Decision Matrix

Technology	Range	Power Consumption	Data Rate	Coverage	Latency	Battery Life	Device Density
WSN	0.067	0.8	0.00005	0.067	0.1	0.5	0.001
LPWAN	1	1	0.0000025	1	1	1	0.01
LoRa	1	1	0.0000025	1	1	1	0.01
5G	0.667	0.2	1	0.667	0.001	0.3	1
IoT	0.667	0.6	0.00005	0.667	0.05	0.5	0.01
NB-IoT	0.667	1	0.0000125	0.667	1	1	0.01

Table 3. Mean and Standard Deviation for Each Criterion

Criterion	Mean	Standard Deviation
Range	0.678	0.389
Power Consumption	0.767	0.327
Data Rate	0.167	0.399
Coverage	0.678	0.389
Latency	0.692	0.434
Battery Life	0.717	0.379
Device Density	0.173	0.395

The coefficient of variation (Table 4) highlights the relative variability of each criterion. Data Rate and Device Density have the highest coefficients of variation (2.391 and 2.282, respectively), indicating that these criteria have the most variability relative to their means. This high variability suggests that Data Rate and Device Density are critical factors in distinguishing between the technologies. The correlation matrix (Table 5) reveals the relationships between criteria. For instance, the negative correlation between Data Rate and Range (-0.402) indicates that technologies with higher data rates tend to have shorter ranges. This trade-off is common in wireless communication technologies. The positive correlations among Range, Power Consumption, and Coverage suggest that technologies with greater range and coverage also tend to have higher power consumption.

Table 4. Coefficient of Variation

Criterion	Coefficient of Variation
Range	0.574
Power Consumption	0.426
Data Rate	2.391
Coverage	0.574
Latency	0.627
Battery Life	0.529
Device Density	2.282

JDFEWS 5 (1): 134-145, 2024
ISSN 2709-4529

Table 5. Correlation coefficient

Criterion	Range	Power Consumption	Data Rate	Coverage	Latency	Battery Life	Device Density
Range	1	0.267	-0.402	1	0.217	0.185	-0.235
Power consumption	0.267	1	-0.467	0.267	0.278	0.353	0.139
Data Rate	-0.402	-0.467	1	-0.402	-0.386	-0.148	0.625
Coverage	1	0.267	-0.402	1	0.217	0.185	-0.235
Latency	0.217	0.278	-0.386	0.217	1	0.15	-0.378
Battery Life	0.185	0.353	-0.148	0.185	0.15	1	-0.059
Device Density	-0.235	0.139	0.625	-0.235	-0.378	-0.059	1

The information content (Figure 1) measures the importance of each criterion based on its variability and correlation with other criteria. Data Rate has the highest information content (0.411), indicating that it is the most important criterion in distinguishing between the technologies. Latency (0.349) and Battery Life (0.326) also have high information content, reflecting their significant roles in ensuring system responsiveness and longevity.

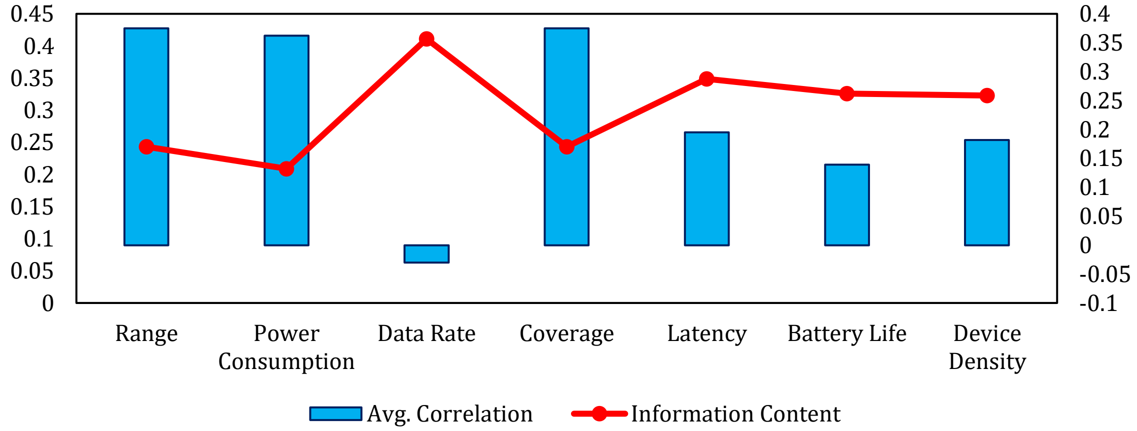

Figure 1. Average correlation and information content of the criteria

The final weights, derived by normalizing the information content (Figure 1), represent the relative importance of each criterion in differentiating between technologies. Data Rate, with the highest weight of 0.1954, is crucial for applications requiring real-time data transmission, underscoring its significant variability and impact. Latency (0.1658) and Battery Life (0.1549) also have high weights, highlighting their roles in ensuring responsive and long-lasting systems, which are vital for effective and efficient technology performance. Range and Coverage, with equal weights of 0.1156, emphasize their combined importance in maintaining communication over large areas, which is essential for widespread connectivity. With a moderate weight of 0.0993, power consumption points to the necessity of energy-efficient solutions, particularly in remote areas where power resources might be limited. Device Density, with a significant weight of 0.1535, indicates its critical role in supporting many devices per unit area, which is particularly important for large-scale IoT deployments where numerous devices must operate simultaneously without performance degradation.

JDFEWS 5 (1): 134-145, 2024
ISSN 2709-4529

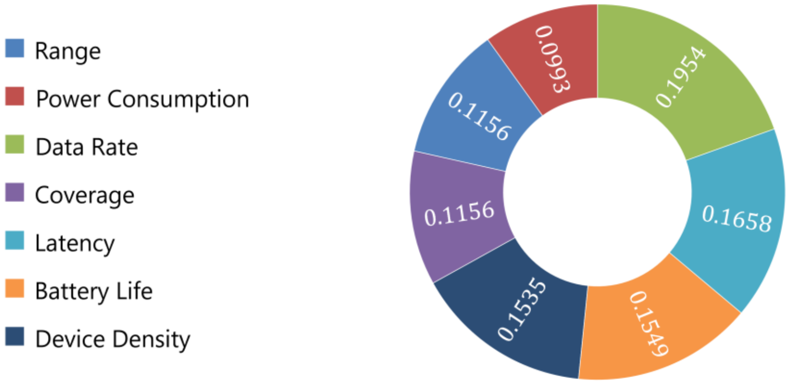

Figure 2. Weights of the criteria

The CODAS method's ranking reveals 5G as the top wireless communication technology for agricultural irrigation systems, with a utility value of 1.000. This ranking is due to its unmatched data rate and device density, making it ideal for high-density, data-intensive applications. However, its higher power consumption and lower battery life might be less suited for remote agricultural environments where energy efficiency is critical. IoT, ranked second with a utility value of 0.982, offers a balanced performance with moderate data rates and extensive coverage, making it a versatile option for various agricultural needs. WSN, positioned third with a utility value of 0.934, excels in power efficiency and battery life, making it suitable for long-term deployments in extensive agricultural fields. LPWAN and LoRa, which share the fourth rank with utility values of 0.674, are notable for their excellent range and battery life, making them highly suitable for large-area coverage with minimal power consumption despite their lower data rates and higher latency. NB-IoT, also ranked fourth with a utility value of 0.674, shares similar strengths and limitations as LPWAN and LoRa. These rankings suggest that while 5G is superior for real-time, high-data applications, IoT and WSN provide more balanced solutions for typical agricultural needs. LPWAN, LoRa, and NB-IoT are best for wide-area, low-power deployments. These insights can guide stakeholders in selecting the most appropriate technology based on specific requirements, balancing performance, efficiency, and cost, ultimately enhancing the sustainability and productivity of agricultural irrigation systems.

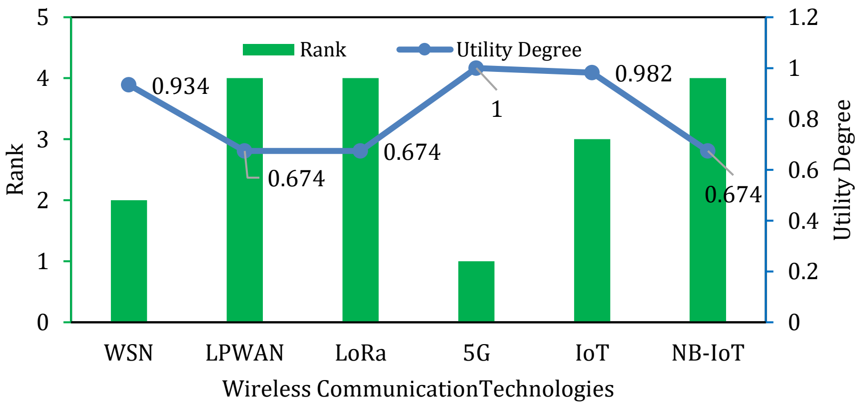

Figure 3. The Utility degree and ranking of the wireless and communication technologies

5 Implication of results

The ranking based on COPRAS indicates that 5G is the best wireless communication technology of all candidate solutions for agricultural irrigation systems under investigation, with a utility value of 1.000. This can be explained by the data rate and unmatched device density offered by 5G, which makes it very suitable for high-density and data-intensive applications such as real-time monitoring and advanced analytics. The high data rate in the case of 5G implies that there will be a fast transfer of large amounts of data from several sensors spread

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over the agricultural field. The ability to render accurate and timely decisions gives efficiency and effectiveness to irrigation systems. 5G's high data rate facilitates the real-time monitoring of soil moisture levels, weather conditions, and crop health, ensuring optimal water usage and preventing over- and under-watering.

Moreover, the high density of devices supported under 5G can accommodate many sensors and devices deployed in a field for monitoring and management purposes, making irrigation very zone-specific. With low latency, 5G enables the automation of irrigation systems, allowing quick adjustments to water delivery based on sensor data, improving responsiveness and accuracy, and reducing the need for manual intervention. Furthermore, advanced data analytics can become possible with the high throughput offered by 5G through the integration of various sources of data to help drive informed decisions on irrigation scheduling for efficient water use and improved crop management. This, of course, will enhance food security through increased crop output, water resource conservation, waste reduction, and scalable solutions for both large commercial and smallholder farms. This adaptability ensures sophisticated irrigation technologies are realized at different agriculture production scales, improving food production in various settings. While 5G performs better for high-data applications, its high-power needs might limit its suitability for remote agricultural environments. IoT and WSN have more balanced solutions for typical agricultural requirements; LPWAN, LoRa, and NB-IoT are the best in wide-area and low-power deployments.

6 Conclusions and future studies

This study employed the CODAS method, guided by CRITIC-derived weights, to evaluate and rank various wireless communication technologies for agricultural irrigation systems. The analysis identified 5G as the top-performing technology with a utility value of 1.000 due to its superior data rate and device density, making it ideal for high-density, data-intensive applications. However, its higher power consumption and lower battery life may limit its suitability for remote agricultural environments where energy efficiency is paramount. IoT, with a utility value of 0.982, emerged as a versatile option, offering a balanced performance across range, power consumption, and coverage, making it suitable for various agricultural needs. WSN, ranking third with a utility value of 0.934, excels in power efficiency and battery life, making it ideal for extensive agricultural fields requiring long-term deployments. LPWAN, LoRa, and NB-IoT, each with utility values of 0.674, demonstrated their strength in providing excellent range and battery life, making them suitable for large-area coverage with minimal power consumption, although with lower data rates and higher latency. These findings highlight that while 5G is advantageous for real-time, high-data applications, IoT and WSN offer more balanced solutions for typical agricultural requirements, and LPWAN, LoRa, and NB-IoT are optimal for wide-area, low-power deployments. The study's comprehensive evaluation provides critical insights for stakeholders, guiding the selection of appropriate technologies based on specific agricultural needs, thereby enhancing the sustainability and productivity of agricultural irrigation systems.

Future research can be directed toward investigating the integration of multiple wireless communication devices for optimum performance. For instance, research can investigate the integration of 5G and IoT, balancing high data rates for effectiveness, and assessing the cost-effectiveness for small-scale farmers. The power-saving features that WSNs offer excellent performance for the system when combined with the wide-area coverage provided by LPWAN and LoRa. Therefore, field-testing in the real world and long-term studies will be instrumental in establishing this selection framework in terms of practical applicability and long-term impact on crop yield and sustainability. This would enable the development of solutions tailored to meet diversified agricultural requirements. Also, further studies should investigate the integration of technology, cost factors, and optimization in precision agriculture technology adoption.

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