A Fermatean Fuzzy Decision Support Framework for Wireless Technology Selection in Disaster Management

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Abstract

Wireless technologies increasingly enable effective communication in disaster management. This study proposes a novel hybrid framework for selecting wireless technologies in disaster management. The proposed approach is called the Fermatean fuzzy (FF)–Maclaurin–Ranking Comparison Method (RANCOM)–Entropy–Alternative Ranking Using Two-Step Logarithmic Normalization (ARLON) hybrid method. FF sets capture the ambiguity and vagueness in experts' judgments. At the same time, RANCOM and Entropy determine the subjective and objective importance of the evaluation criteria, respectively. The ARLON method ranks wireless technologies based on performance. Furthermore, the Maclaurin-based aggregation operator combines expert evaluations. The study demonstrates the application through a case study in Türkiye, focusing on wireless technology selection to enhance disaster management capabilities following recent major earthquakes. A panel of nine experts with extensive knowledge of disaster management and wireless communication technologies participated in the evaluation process. The assessment considered twelve performance criteria and eight wireless technology alternatives. The results indicate that 5G RedCap is the most suitable wireless technology for the case study. In addition, the most important criterion was "ease of use/setup". Finally, sensitivity and comparative analyses confirm the proposed framework's robustness and reliability.

Keywords: Disaster Management, Wireless Technology Selection, Fermatean Fuzzy Sets, Ranking Comparison Method, Alternative Ranking Using Two-Step Logarithmic Normalization Method.

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1. Introduction

Wireless communication technologies are a main part of the modern digital ecosystems [1]. Radio frequency spectrum data transmission becomes more scalable, ensuring uninterrupted modern communication. Wireless technologies have also paved the way for many technologies (Internet of Things (IoT), artificial intelligence (AI) etc.) that have enabled digitalization [2], [3]. These technologies are used effectively in disaster management across various fields today [4], [5].

Earthquakes and similar disasters damage communication infrastructure, leading to inadequate communication aspects of disaster management [6]. Wireless communication technologies are now available to support effective disaster management. Low-Power Wide-Area Network (LPWAN) technologies, short-range protocols, and advanced cellular network capabilities are used to provide the necessary communication for rapid and effective response to disasters [7].

The selection process for wireless communication technology is as important as its use, and many parameters are used as selection criteria [8]. Among these criteria, Long Range Wide Area Network (LoRaWAN) is effective for long range and energy saving [9], while Narrowband (NB)-IoT and Long Term Evolution for Machines (LTE-M) are more effective for security and data transfer [10]. On the other hand, while mesh-based technologies excel in network resilience, hybrid communication architectures offer better connection reliability [11].

Expectations for 5G and 6G technologies are high for developing effective communication networks in disaster management, and response speed is expected to decrease [12]. IoT and autonomous systems have superior capabilities in disasters and increase situational awareness [13]. To be more mobilized in disaster management, it offers effective solutions in establishing unmanned aerial vehicles (UAVs) and mobile base stations communication network infrastructures [14]. Wireless communication technologies are also indispensable to disaster management, and their appropriate selection is critical for resilient and efficient emergency response.

The primary motivation of this research is to develop a decision support system (DSS) aimed at determining the performance of wireless technologies for disaster management. To ensure robust and reliable decision-making, an approach that incorporates both expert opinions and criteria-based wireless technology selection has been adopted. Within this framework, a hybrid model based on multi-attribute group decision making (MAGDM) under the broader multi-criteria decision making (MCDM) methodology [15] has been developed. This model is introduced as the Fermatean fuzzy (FF)–Maclaurin–ranking comparison method (RANCOM)–Entropy–alternative ranking using two-step logarithmic normalization (ARLON) model.

In this hybrid approach, the model weights experts' influence in the decision-making process is weighted according to their level of expertise, and groups them accordingly. The decision model considers both qualitative and quantitative criteria, all of which can be utilized within the proposed hybrid methodology. For subjective criteria weighting based on expert judgments, the FF-Maclaurin-RANCOM method is employed. Here, experts' linguistic assessments are converted into fuzzy logic representations using FF sets. Additionally, to aggregate expert evaluations, a Maclaurin-based aggregation operator (Fermatean fuzzy weighted partitioned dual Maclaurin symmetric mean (FFWPDMSM)) [16] is applied. The RANCOM method [17] is then utilized to conduct pairwise comparisons among criteria, facilitating their weighting process.

The FF-Maclaurin-Entropy approach is employed to derive objective criterion weights from the evaluation data. Wireless technologies are assessed FF numbers and aggregated through the FFWPDMSM operator, after which subjective and objective weights [18] are integrated to obtain the final criterion weights. The ARLON method [19] is then applied to rank the wireless technology alternatives based on its logarithmic normalization mechanism.

Methodologically, using other MCDM methods independently of fuzzy sets can lead to uncertainty and information loss in quantifying expert evaluations. In the proposed approach, however, using the methods in conjunction with FF Sets allows for better representation of uncertain and incomplete information. Calculations based on Maclaurin t-norm and t-conorm structures contribute to more precise information aggregation and reduced information loss compared to other aggregation operators. Furthermore, using both approaches together, instead of only subjective or only objective weighting, allows for more comprehensive determination of criterion weights. This integrated structure distinguishes the proposed approach from similar hybrid MCDM methods.

1.1. Research aim and contributions

This study develops a novel hybrid DSS for wireless technology selection in disaster management under uncertainty. The proposed FF-Maclaurin-RANCOM-Entropy-ARLON framework integrates subjective expert judgments and objective performance data within MAGDM environment. While FF sets allow trading under uncertainty, Maclaurin aggregation operators allow more precise calculations in aggregating expert evaluations.

The methodological contributions of this study are threefold. First, it introduces the FF-Maclaurin-RANCOM approach for subjective criterion weighting by combining expert grouping, Maclaurin-based aggregation, and the RANCOM weighting method. Second, it proposes the FF-Maclaurin-Entropy approach, which derives objective criterion weights by integrating qualitative and quantitative information within an FF environment. Third, the study combines subjective and objective weights into a unified weighting scheme and employs the ARLON method to rank wireless technology alternatives using two-step logarithmic normalization.

The proposed framework is validated through a real-world case study conducted in Türkiye, involving nine experts, twelve evaluation criteria, and eight wireless communication technologies. As a result of the research, 5G RedCap technology is more successful than other technologies in strengthening the communication success of disaster management. These results were also supported in rank-correlation with various method results. Ultimately, with this research, a reliable MCDM-based DSS for use in disaster management was developed and introduced to the literature.

The remaining part of the paper is focused on disaster management in wireless communication technologies (Section 2). FF-Maclaurin-RANCOM-Entropy-ARLON is presented as a model methodology (Section 3). Application in Türkiye has been carried out (Section 4), Application results have been presented (Section 5). Inferences based on the results were developed (Section 6). Research limitations and recommendations are presented in the Conclusion section (Section 7).

2. Overview of Wireless Communication Technologies in Disaster Management

Wireless communication technologies, which form a strong pillar of modern digital systems, are used effectively in various application areas. Disaster management is also among these areas of application [20]. Emergency response and full-time effective communication, which are indispensable in disaster management, are provided by wireless technologies. But these technologies differ and have various advantages and disadvantages.

Technological advances in IoT increase the power of wireless communication. Various studies focus on wireless technologies and evaluate them from various perspectives. Among these studies, the Land Mobile Radio System – Long Term Evolution (LMRS-LTE) hybrid structure stands out and is claimed to offer durable and secure communication solutions [20]. LMRS-LTE technology ensures secure communication between emergency response teams, transportation units, warehouses, and distribution points. It also supports more effective disaster logistics by enabling the tracking of emergency response equipment and supplies.

In addition, the long range and low energy usage provided by LoRaWAN are preferred from an environmental perspective [21]. In these strategies, NB-IoT is offered with high data transfer speed and LoRaWAN is offered with energy efficiency [22]. Thanks to its long communication range, LoRaWAN contributes to aid distribution by supporting communication between those in need and distribution points during emergency response. NB-IoT, on the other hand, supports transportation coordination by enabling the simultaneous connection of multiple devices. In addition, the long range and low energy usage provided by LoRaWAN are preferred from an environmental perspective [23]. NB-IoT, on the other hand, is preferred due to its low cost by providing massive device connectivity. It also provides reliability than unlicensed LPWAN [24]. Additionally, optimized channel structures make NB-IoT more powerful [25]. However, delays are cited as a weakness of NB-IoT [26].

Another wireless communication technology is Mesh networks. These systems, defined as "Bluemergency" systems, eliminate the need for special hardware by making use of smartphones and IoT devices [27]. Mesh networks support communication and information sharing between emergency response teams and distribution points in situations where traditional communication infrastructure is unavailable in disaster logistics. Another technology is Wi-Fi HaLow wireless technologies. This technology offers the advantage of scalability by providing a wide coverage area [28]. It also supports warehouse operations by enabling the identification of needs in disaster areas and the sharing of this information with warehouses thanks to its wide coverage. According to LoRaWAN, this technology offers longer range of connections [29], [30]. The different advantages of wireless communication technologies can meet different needs under different conditions [31]. In disaster management, the technology needed may vary depending on the type of disaster and the location where it occurs [32].

While ubiquitous sensor networks (USNs) enhance emergency coordination, hybrid architectures are explored to enhance resilience [33]. Emerging technologies (such as autonomous systems) enhance disaster response by improving connectivity. 6G networks are expected to provide more resilience [34].

Wireless communication technologies play a predominant role in disasters throughout logistics operations. Reliable communication supports the tracking of emergency supplies, thereby enhancing coordination among response teams. The diverse characteristics of wireless technologies affect these activities under rapidly changing disaster conditions. Therefore, selecting wireless communication technology is not only a technical issue but also a critical logistics issue.

Simulations conducted in the literature show that intelligent communication architectures are suitable for emergency situations [35]. Improve data security in post disaster environments [36], [37]. In addition, decentralized architectures support the networks in emergency scenarios [38].

3. Methodology Framework

The proposed hybrid framework comprises five sequential stages. First, experts are weighted based on their expertise levels. Then, the FF-Maclaurin-RANCOM and FF-Maclaurin-Entropy methods are applied to obtain subjective and objective criterion weights, respectively. These weights are integrated into a final weight vector, which is subsequently used in the ARLON method to rank wireless technologies. The overall workflow and computational steps of the FF-Maclaurin-RANCOM-Entropy–ARLON model are illustrated in Figure 1.

3.1. Fundamentals of FF sets

Definition 1. In an $\mathcal{S}$ universe consisting of elements $\mathscr{s}$, an FF set function for a $\tilde{\mathcal{R}}$ is defined as follows: $\tilde{\mathcal{R}} = \{\langle \mathscr{s}, \gimel_{\tilde{\mathcal{R}}}(\mathscr{s}), \beth_{\tilde{\mathcal{R}}}(\mathscr{s}) \mid \mathscr{s} \in \mathcal{S}\rangle\}$. Here, $\gimel_{\tilde{\mathcal{R}}}(\mathscr{s}): \mathcal{S} \to D[0,1]$ represents the membership degree function, indicating the degree to which elements belong to the set; $\beth_{\tilde{\mathcal{R}}}(\mathscr{s}): \mathcal{S} \to D[0,1]$ denotes the non-membership degree function, expressing the degree to which elements do not belong to the set; and $\daleth_{\tilde{\mathcal{R}}}(\mathscr{s}): \mathcal{S} \to D[0,1]$ signifies the indeterminacy degree function, which is computed as $\daleth_{\tilde{\mathcal{R}}}(\mathscr{s}) = \sqrt[3]{1 - \left(\gimel_{\tilde{\mathcal{R}}}(\mathscr{s})\right)^3 - \left(\beth_{\tilde{\mathcal{R}}}(\mathscr{s})\right)^3}$. The condition for the FF set function $\tilde{\mathcal{R}}$ is specified as $0 \le \left(\left(\gimel_{\tilde{\mathcal{R}}}(\mathscr{s})\right)^3\right)^3 + \left(\beth_{\tilde{\mathcal{R}}}(\mathscr{s})\right)^3 \le 1$ [39].

Definition 2. Assume two FF sets defined within the universe $\mathcal{S}$ as follows: $\tilde{\mathcal{R}}_d = \left\{\langle \mathscr{s}, \left(\gimel_{\tilde{\mathcal{R}}_d}(\mathscr{s})\right), \left(\beth_{\tilde{\mathcal{R}}_d}(\mathscr{s})\right) \mid \mathscr{s} \in \mathcal{S}\rangle\right\}; (d = 1,2)$. The operations applicable to FF sets are outlined below ($\varpi > 0$) [39].

(i) $$\tilde{\mathcal{R}}_1 \oplus \tilde{\mathcal{R}}_2 = \left\{\left(\sqrt[3]{\left(\gimel_{\tilde{\mathcal{R}}_1}(\mathscr{s})\right)^3 + \left(\gimel_{\tilde{\mathcal{R}}_2}(\mathscr{s})\right)^3 - \left(\gimel_{\tilde{\mathcal{R}}_1}(\mathscr{s})\right)^3 \left(\gimel_{\tilde{\mathcal{R}}_2}(\mathscr{s})\right)^3}, \beth_{\tilde{\mathfrak{F}}_1}(\mathfrak{f})\, \beth_{\tilde{\mathcal{R}}_2}(\mathfrak{f})\right) \mid \mathscr{s} \in \mathcal{S}\right\},$$

(ii) $$\tilde{\mathcal{R}}_1 \otimes \tilde{\mathcal{R}}_2 = \left\{\left(\gimel_{\tilde{\mathcal{R}}_1}(\mathscr{s})\, \gimel_{\tilde{\mathcal{R}}_2}(\mathscr{s}), \sqrt[3]{\left(\beth_{\tilde{\mathcal{R}}_1}(\mathscr{s})\right)^3 + \left(\beth_{\tilde{\mathcal{R}}_2}(\mathscr{s})\right)^3 - \left(\beth_{\tilde{\mathcal{R}}_1}(\mathscr{s})\right)^3 \left(\beth_{\tilde{\mathcal{R}}_2}(\mathscr{s})\right)^3}\right) \mid \mathscr{s} \in \mathcal{S}\right\},$$

(iii) $$\varpi\tilde{\mathcal{R}}_1 = \left\{\left(\sqrt[3]{1 - \left(1 - \left(\gimel_{\tilde{\mathcal{R}}_1}(\mathscr{s})\right)^3\right)^{\varpi}}, \left(\beth_{\tilde{\mathcal{R}}_1}(\mathscr{s})\right)^{\varpi}\right) \mid \mathscr{s} \in \mathcal{S}\right\} \text{ for } \varpi > 0,$$

(iv) $$\tilde{\mathcal{R}}_1^{\varpi} = \left\{\left(\left(\gimel_{\tilde{\mathcal{R}}_1}(\mathscr{s})\right)^{\varpi}, \sqrt[3]{1 - \left(1 - \left(\beth_{\tilde{\mathcal{R}}_1}(\mathscr{s})\right)^3\right)^{\varpi}}\right) \mid \mathscr{s} \in \mathcal{S}\right\} \text{ for } \varpi > 0.$$

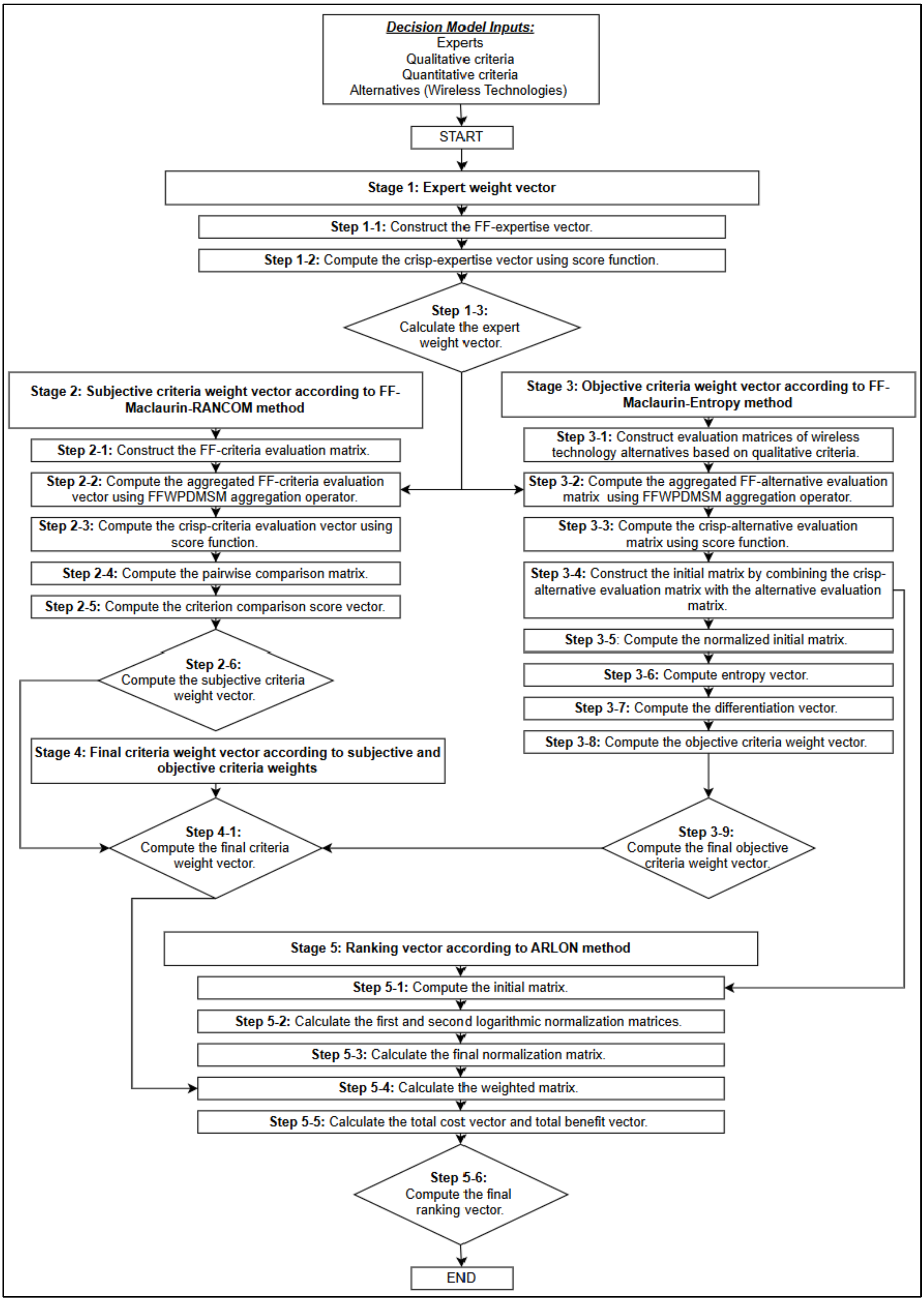

Figure 1. Flowchart of the Hybrid Method.

These are the conditions of the operations among FF numbers [39].

(i) $\tilde{\mathcal{R}}_1 \oplus \tilde{\mathcal{R}}_2 = \tilde{\mathcal{R}}_2 \oplus \tilde{\mathcal{R}}_1$,

(ii) $\tilde{\mathcal{R}}_1 \otimes \tilde{\mathcal{R}}_2 = \tilde{\mathcal{R}}_2 \otimes \tilde{\mathcal{R}}_1$,

(iii) $\varpi(\tilde{\mathcal{R}}_1 \oplus \tilde{\mathcal{R}}_2) = \varpi\tilde{\mathcal{R}}_1 \oplus \varpi\tilde{\mathcal{R}}_2$ for $\varpi > 0$,

(iv) $(\tilde{\mathcal{R}}_1 \otimes \tilde{\mathcal{R}}_2)^{\varpi} = \tilde{\mathcal{R}}_1{}^{\varpi} \otimes \tilde{\mathcal{R}}_2{}^{\varpi}$ for $\varpi > 0$,

(v) $\varpi_1\tilde{\mathcal{R}}_1 \oplus \varpi_2\tilde{\mathcal{R}}_1 = (\varpi_1 + \varpi_2)\tilde{\mathcal{R}}_1$ for $\varpi_1, \varpi_2 > 0$,

(vi) $\tilde{\mathcal{R}}_1{}^{\varpi_1} \otimes \tilde{\mathcal{R}}_1{}^{\varpi_2} = \tilde{\mathcal{R}}_1{}^{(\varpi_1+\varpi_2)}$ for $\varpi_1, \varpi_2 > 0$.

Definition 3. Assume two FF sets defined within the universe $\mathcal{S}$ as follows: $\tilde{\mathcal{R}}_d = \left\{\langle s, \left(\gimel_{\tilde{\mathcal{R}}_d}(s)\right), \left(\beth_{\tilde{\mathcal{R}}_d}(s)\right) \mid s \in \mathcal{S}\rangle\right\}; (d = 1,2)$. Crisp values are derived from FF sets through the computation of a score function $\left(\beta(\tilde{\mathcal{R}}_d)\right)$ as shown in Eq. (1) [39].

$$\beta(\tilde{\mathcal{R}}_d) = \frac{1}{2}\left(1 + \left(\gimel_{\tilde{\mathcal{R}}_d}(s)\right)^3 - \left(\beth_{\tilde{\mathcal{R}}_d}(s)\right)^3\right);\ \beta(\tilde{\mathcal{R}}_d) \in [0,1] \quad (1)$$

To analyze the interaction between two FF sets, the following set of conditions is considered:

(i) If $\beta(\tilde{\mathcal{R}}_1) > \beta(\tilde{\mathcal{R}}_2)$, then $\tilde{\mathcal{R}}_1 > \tilde{\mathcal{R}}_2$,

(ii) If $\beta(\tilde{\mathcal{R}}_1) < \beta(\tilde{\mathcal{R}}_2)$, then $\tilde{\mathcal{R}}_1 < \tilde{\mathcal{R}}_2$,

(iii) If $\beta(\tilde{\mathcal{R}}_1) = \beta(\tilde{\mathcal{R}}_2)$, then $\tilde{\mathcal{R}}_1 = \tilde{\mathcal{R}}_2$.

Definition 4. Assume a family of FF sets defined within the universe $\mathcal{S}$ as follows: $\tilde{\mathcal{R}}_{\mathrm{t}} = \left\{\langle s, \left(\gimel_{\tilde{\mathcal{R}}_{\mathrm{t}}}(s)\right), \left(\beth_{\tilde{\mathcal{R}}_{\mathrm{t}}}(s)\right) \mid s \in \mathcal{S}\rangle\right\}; (\mathrm{t} = 1,2,\ldots,l)$. The calculation of the FFWPDMSM aggregation operator is performed in accordance with Eq. (2) [16].

$$FFWPDMSM^{(l)}(\tilde{\mathcal{R}}_1, \tilde{\mathcal{R}}_2, \ldots, \tilde{\mathcal{R}}_{\mathrm{t}}, \ldots, \tilde{\mathcal{R}}_l) = \frac{1}{c}\left(\oplus_{t=1}^{c}\left(\frac{\underset{1\le k_1\le\cdots\le k_l\le o_t}{\otimes}\left(\oplus_{\mathrm{t}=1}^{l}\left(\varpi_{k_{\mathrm{t}}}\tilde{\mathcal{R}}_{k_{\mathrm{t}}}\right)\right)^{\frac{1}{(C_{o_t}^{l})}}}{l}\right)\right)$$
$$= \left(\begin{array}{c}\left(\left(\sqrt[3]{1-\left(\prod_{t=1}^{c}\left(1-\prod_{1\le k_1\le\cdots\le k_l\le o_t}\left(1-\prod_{\mathrm{t}=1}^{l}\left(1-\left(\gimel_{\tilde{\mathcal{R}}_{\mathrm{t}}}(\mathfrak{t})\right)^3\right)^{\varpi_{k_{\mathrm{t}}}}\right)^{\frac{1}{(C_{o_t}^{l})}}\right)^{\frac{1}{l}}\right)^{\frac{1}{c}}}\right)\right), \\ \left(\left(\left(\prod_{t=1}^{c}\left(\sqrt[3]{1-\prod_{1\le k_1\le\cdots\le k_l\le o_t}\left(1-\left(\prod_{\mathrm{t}=1}^{l}\left(\beth_{\tilde{\mathcal{R}}_{\mathrm{t}}}(\mathfrak{t})\right)^{\varpi_{k_{\mathrm{t}}}}\right)^3\right)^{\frac{1}{(C_{o_t}^{l})}}}\right)\right)^{\frac{1}{l}}\right)^{\frac{1}{c}}\right)\end{array}\right), \quad (2)$$

herein, $l = 1,2,\ldots,o_t$; $t = 1,2,\ldots,c$, c shows the number of partitions, o_t shows the number of elements in a group, $C_{o_t}^{l}$ shows the binomial coefficient as $C_{o_t}^{l} = \frac{o_t!}{l!(o_t-l)!}$, k_l shows all the l-tuple combinations of o_t, $\varpi_{k_{\mathrm{t}}}$ shows the weight of k_{t} ($\mathrm{t} = 1,2,\ldots,l$).

3.2. FF-Maclaurin-RANCOM-Entropy-ARLON model

In the context of disaster management, ensuring uninterrupted communication during natural disasters is crucial for both search and rescue operations and interpersonal communication among individuals. Effective communication hinges on the appropriate use of wireless technologies. This research focuses on the selection problem of wireless technologies for disaster management. The FF-Maclaurin-RANCOM-Entropy-ARLON hybrid method is proposed for this selection, incorporating expert ($\mathrm{E} = \{E_1, E_2, \ldots, E_k, \ldots, E_K\}$ $(k = 1,2,\ldots,K)$) judgment, qualitative criteria ($\mathrm{P} = \{P_1, P_2, \ldots, P_t, \ldots, P_T\}$ $(t = 1,2,\ldots,T)$), quantitative criteria ($\mathrm{B} = \{B_1, B_2, \ldots, B_v, \ldots, B_V\}$ $(v = 1,2,\ldots,V)$), overall criteria $\left(\mathrm{Z} = \{Z_1, Z_2, \ldots, Z_y, \ldots, Z_Y\}\ (y = 1,2,\ldots,Y)\right); (Y = T + V)$, and various wireless technologies ($\mathrm{H} = \{H_1, H_2, \ldots, H_d, \ldots, H_D\}$ $(d = 1,2,\ldots,D)$) into its decision model. The steps of this hybrid method are systematically detailed, presented algorithmically, and illustrated with a diagram depicting the application flow. The notation used in the proposed hybrid method is provided Table S1 in Supplementary Materials. The hybrid method comprises five stages: *Stage 1* involves determining the expert weight vector, *Stage 2* applies the FF-Maclaurin-RANCOM criteria weight method to derive a subjective criteria weight vector based on application results, *Stage 3* applies the FF–Maclaurin–Entropy criteria weight method to derive an objective criteria weight vector based on application results, *Stage 4* combines these into the final criteria weight vector, and *Stage 5* ranks wireless technologies using the ARLON alternative ranking method:

Stage 1 - Expert weight vector:

Step 1-1: The expertise levels of the experts are determined by the experts themselves based on Table 1. These levels are defined using FF numbers, forming the FF-expertise vector $\left(\tilde{\mathfrak{V}} = [\tilde{\mathfrak{V}}_k]_K\right)$.

Table 1. Expertise levels [40].

Expertise levels	*FF numbers* $\left(\lambda_{\tilde{\mathfrak{B}}_k}(s), \beth_{\tilde{\mathfrak{B}}_k}(s)\right)$
Very-poor (VP)	(0.10, 0.90)
Poor (P)	(0.30, 0.70)
Medium (M)	(0.50, 0.50)
Good (G)	(0.70, 0.30)
Very-good (VG)	(0.90, 0.10)

Step 1-2: The FF-expertise vector is converted into a crisp-expertise vector ($\mathfrak{B} = [\mathfrak{B}_k]_K$) using a score function $\left(\beta(\tilde{\mathfrak{B}}_k)\right)$ (Eq. (3)):

$$\mathfrak{B}_k = \beta(\tilde{\mathfrak{B}}_k) = \frac{1}{2}\left(1 + \left(\lambda_{\tilde{\mathfrak{B}}_k}(s)\right)^3 - \left(\beth_{\tilde{\mathfrak{B}}_k}(s)\right)^3\right);\ (k = 1,2,\dots,K)|\ \beta(\tilde{\mathfrak{B}}_k) \in [0,1] \quad (3)$$

Step 1-3: The expert weight vector ($\pi = [\pi_k]_K$) is calculated using linear normalization (Eq. (4)).

$$\pi_k = \frac{\mathfrak{B}_k}{\sum_{k=1}^{K} \mathfrak{B}_k};\ (k = 1,2,\dots,K) \quad (4)$$

Herein, the expert weight vector ($\pi_k \in [0,1]$) has a constraint as $\sum_{k=1}^{K} \pi_k = 1$.

Stage 2 - Subjective criteria weight vector according to FF-Maclaurin-RANCOM:

Step 2-1: The experts evaluate the wireless technology selection criteria (overall criteria) based on Table 2. These evaluations are organized as the FF-criteria evaluation matrix $\left(\tilde{\mathfrak{Z}} = [\tilde{\mathfrak{Z}}_{yk}]_{YK}\right)$.

Table 2. Criteria or alternative levels [40].

Criteria/alternative level	FF numbers
Exceptionally-low (ExL)	(0.05, 0.95)
Extremely-low (EL)	(0.10, 0.90)
Very-low (VL)	(0.20, 0.80)
Low (L)	(0.30, 0.70)
Below-average (BA)	(0.40, 0.60)
Average (A)	(0.50, 0.50)
Above-average (AA)	(0.60, 0.40)
High (H)	(0.70, 0.30)
Very-high (VH)	(0.80, 0.20)
Extremely-high (EH)	(0.90, 0.10)
Exceptionally-high (ExH)	(0.95, 0.05)

Step 2-2: Expert evaluations are aggregated $\left(\tilde{\mathfrak{T}}_y = \mathrm{FFWPDMSM}^{(l)}\left(\tilde{\mathfrak{Z}}_{y1}, \tilde{\mathfrak{Z}}_{y2}, \dots, \tilde{\mathfrak{Z}}_{yk}, \dots, \tilde{\mathfrak{Z}}_{yK}\right)\right)$ (Eq. (2)) to form the aggregated FF-criteria evaluation vector $\left(\tilde{\mathfrak{T}} = [\tilde{\mathfrak{T}}_y]_Y\right)$. Here, the experts are grouped. In this way, the number of partitions (c) and the number of elements (o_t) in each group are determined, and the binomial coefficient $\left(C_{o_t}^{l} = \frac{o_t!}{l!(o_t-l)!}\right)$ is calculated accordingly ($l = 2$).

Step 2-3: The FF-criteria evaluation vector is converted into a crisp-criteria evaluation vector $\left(\mathfrak{T} = [\mathfrak{T}_y]_Y\right)$ using a score function $\left(\beta(\tilde{\mathfrak{T}}_y)\right)$ (Eq. (5)):

$$\mathfrak{T}_y = \beta(\tilde{\mathfrak{T}}_y) = \frac{1}{2}\left(1 + \left(\lambda_{\tilde{\mathfrak{T}}_y}(s)\right)^3 - \left(\beth_{\tilde{\mathfrak{T}}_y}(s)\right)^3\right);\ (y = 1,2,\dots,Y)|\ \beta(\tilde{\mathfrak{T}}_y) \in [0,1] \quad (5)$$

Step 2-4: According to the RANCOM method, the criterion values are converted into a pairwise comparison matrix $\left(\mathfrak{Y} = [\mathfrak{Y}_{yy'}]_{YY}\right)$ based on binary comparisons (Eq. (6)):

$$\mathfrak{Y}_{yy'} = \begin{cases} If\ \mathfrak{T}_y > \mathfrak{T}_{y'}\ then\ 1 \\ If\ \mathfrak{T}_y = \mathfrak{T}_{y'}\ then\ 0.5 \\ If\ \mathfrak{T}_y < \mathfrak{T}_{y'}\ then\ 0 \end{cases};\ (y, y' = 1,2,\dots,Y) \quad (6)$$

Step 2-5: The pairwise comparisons are summed (Eq. (7)) to determine the criterion comparison score vector $\left(\mathfrak{U} = [\mathfrak{U}_y]_Y\right)$.

$$\mathfrak{U}_y = \sum_{y=1}^{Y} \mathfrak{Y}_{yy'};\ (y = 1,2,\dots,Y) \quad (7)$$

Step 2-6: The subjective criteria weight vector $\left(\mu = [\mu_y]_Y\right)$ is calculated using linear normalization (Eq. (8)).

$$\mu_y = \frac{\mathfrak{U}_y}{\sum_{y=1}^{Y} \mathfrak{U}_y};\ (y = 1,\dots,Y), \quad (8)$$

Stage 3 - Objective criteria weight vector according to FF-Maclaurin-Entropy method:

Step 3-1: For the evaluation matrices $\left(\tilde{\mathfrak{X}}^{(E_k)} = \left[\tilde{\mathfrak{X}}_{dt}^{(E_k)}\right]_{DT}\right)$ of wireless technology alternatives based on qualitative criteria, the experts (E_k) assess each wireless technology (H_d) according to the qualitative criteria (P_t) using Table 2. Herein, $\tilde{\mathfrak{X}}_{dt}^{(E_k)} = \left\{\langle s, \lambda_{\tilde{\mathfrak{X}}_{dt}^{(E_k)}}(s), \beth_{\tilde{\mathfrak{X}}_{dt}^{(E_k)}}(s) \mid s \in S\rangle\right\}$.

Step 3-2: The evaluation matrices are aggregated $\left(\tilde{\mathfrak{X}}_{dt} = FFWPDMSM^{(l)}\left(\tilde{\mathfrak{X}}^{(E_1)}, \tilde{\mathfrak{X}}^{(E_2)}, \dots, \tilde{\mathfrak{X}}^{(E_k)}, \dots, \tilde{\mathfrak{X}}^{(E_K)}\right)\right)$ (Eq. (2)) to form the aggregated FF-alternative evaluation matrix $\left(\tilde{\mathfrak{X}} = [\tilde{\mathfrak{X}}_{dt}]_{DT}\right)$.

Step 3-3: The FF-alternative evaluation matrix is converted into a crisp-alternative matrix ($\mathfrak{X} = [\mathfrak{X}_{dt}]_{DT}$) using a score function $\left(\beta(\tilde{\mathfrak{T}}_y)\right)$ (Eq. (9)):

$$\mathfrak{X}_{dt} = \beta(\tilde{\mathfrak{X}}_{dt}) = \frac{1}{2}\left(1 + \left(\lambda_{\tilde{\mathfrak{X}}_{dt}}(\mathcal{S})\right)^3 - \left(\beth_{\tilde{\mathfrak{X}}_{dt}}(\mathcal{S})\right)^3\right); \quad (d = 1, \dots, D; t = 1,2, \dots, T) \,|\, \beta(\tilde{\mathfrak{X}}_{dt}) \in [0,1]. \tag{9}$$

Step 3-4: The initial matrix $\left(\mathfrak{A} = [\mathfrak{A}_{dy}]_{DY}\right)$ for the Entropy method is determined by combining the crisp-alternative evaluation matrix ($\mathfrak{X} = [\mathfrak{X}_{dt}]_{DT}$) with the alternative score matrix ($\mathfrak{W} = [\mathfrak{W}_{dv}]_{DV}$) based on quantitative criteria.

Step 3-5: The normalized initial matrix $\left(\mathfrak{B} = [\mathfrak{B}_{dy}]_{DY}\right)$ is calculated using linear normalization (Eq. (10)):

$$\mathfrak{B}_{dy} = \frac{\mathfrak{A}_{dy}}{\sum_{d=1}^{D} \mathfrak{A}_{dy}}; (d = 1, \dots, D; y = 1, \dots, Y), \tag{10}$$

herein, the normalized initial matrix $(\mathfrak{B}_{dy} \in [0,1])$ has a constraint as $\sum_{d=1}^{D} \mathfrak{B}_{dy} = 1$.

Step 3-6: The entropy vector $\left(\mathrm{e} = [\mathrm{e}_y]_Y\right)$ is calculated (Eq. (11)):

$$\mathrm{e}_y = -\alpha \sum_{d=1}^{D} \left(\mathfrak{B}_{dy} \ln(\mathfrak{B}_{dy})\right); (y = 1, \dots, Y), \tag{11}$$

herein, α parameter is calculated by $\alpha = (\ln(D))^{-1}$.

Step 3-7: The differentiation vector $\left(\mathfrak{C} = [\mathfrak{C}_y]_Y\right)$ is calculated (Eq. (12)):

$$\mathfrak{C}_y = 1 - \mathrm{e}_y; (y = 1, \dots, Y) \tag{12}$$

Step 3-8: The objective criteria weights $\left(\wp = [\wp_y]_Y\right)$ is calculated using linear normalization (Eq. (13)).

$$\wp_y = \begin{cases} \wp_t = \frac{\mathfrak{C}_t}{\sum_{t=1}^{T} \mathfrak{C}_t}, & if\ y = t \\ \wp_v = \frac{\mathfrak{C}_v}{\sum_{v=1}^{V} \mathfrak{C}_v}, & if\ y = v \end{cases}; (y = 1, \dots, Y; t = 1, \dots, T; v = 1, \dots, V), \tag{13}$$

herein, the vector $(\wp_y, \wp_t, \wp_v \in [0,1])$ has a constraint as $\sum_{t=1}^{T} \wp_t = 1$ and $\sum_{v=1}^{V} \wp_t = 1$ and $\sum_{y=1}^{Y} \wp_y = 2$.

Step 3-9: The final objective criteria weights $\left(\lambda = [\lambda_y]_Y\right)$ is calculated using (Eq. (14)).

$$\lambda_y = \frac{\wp_y}{\sum_{y=1}^{Y} \wp_y}; (y = 1, \dots, Y) \tag{14}$$

herein, the final objective criteria weights $(\lambda_y \in [0,1])$ has a constraint as $\sum_{y=1}^{Y} \lambda_y = 1$.

Stage 4 **-** Final criteria weight vector according to subjective and objective criteria weights:

Step 4-1: The final criteria weight vector $\left(\delta = [\delta_y]_Y\right)$ is computed to aggregate the subjective criteria weight vector $\left(\mu = [\mu_y]_Y\right)$ with an objective criteria weight vector $\left(\lambda = [\lambda_y]_Y\right)$ (Eq. (15)):

$$\delta_y = (\Theta)\mu_y + (1 - \Theta)\lambda_y; (y = 1, \dots, Y). \tag{15}$$

herein, the final criteria weight vector $(\delta_y \in [0,1])$ has a constraint as $\sum_{y=1}^{Y} \delta_y = 1$. In addition, $\Theta \in [0,1]$ refers the parameter of the subjective criteria weight vector.

Stage 5 **-** Ranking vector according to ARLON:

Step 5-1: The initial matrix $\left(\mathfrak{A} = [\mathfrak{A}_{dy}]_{DY}\right)$, determined in *Step 3-4*, is multiplied by 100 to form the initial matrix $\left(\mathfrak{F} = [\mathfrak{F}_{dy}]_{DY}\right)$ for ARLON (Eq. (16)):

$$\mathfrak{F}_{dy} = 100 * \mathfrak{A}_{dy}; (d = 1, \dots, D; y = 1, \dots, Y) \tag{16}$$

Step 5-2: For the ARLON method based on logarithmic normalization. The first one $\left(\mathfrak{K} = [\mathfrak{K}_{dy}]_{DY}\right)$ is determined using Eq. (17), while the second one $\left(\mathfrak{L} = [\mathfrak{L}_{dy}]_{DY}\right)$ is obtained using Eq. (18).

$$\mathfrak{K}_{dy} = \begin{cases} \mathfrak{K}_{dy}^{+} = \frac{\ln(\mathfrak{F}_{dy})}{\ln(\prod_{d=1}^{D} \mathfrak{F}_{dy})}, y \in Z^{+} \\ \mathfrak{K}_{dy}^{-} = \frac{1 - \frac{\ln(\mathfrak{F}_{dy})}{\ln(\prod_{d=1}^{D} \mathfrak{F}_{dy})}}{D-1}, y \in Z^{-} \end{cases}; (d = 1, \dots, D; y = 1, \dots, Y), \tag{17}$$

$$\mathfrak{L}_{dy} = \begin{cases} \mathfrak{L}_{dy}^{+} = \frac{\log_2(\mathfrak{F}_{dy})}{\sum_{d=1}^{D}(\log_2(\mathfrak{F}_{dy}))}, y \in Z^{+} \\ \mathfrak{L}_{dy}^{-} = 1 - \frac{\log_2(\mathfrak{F}_{dy})}{\sum_{d=1}^{D}(\log_2(\mathfrak{F}_{dy}))}, y \in Z^{-} \end{cases}; (d = 1, \dots, D; y = 1, \dots, Y) \tag{18}$$

Step 5-3: The final normalization matrix $\left(\mathfrak{M} = [\mathfrak{M}_{dy}]_{DY}\right)$ is computed (Heron mean) to aggregate first matrix $\left(\mathfrak{K} = [\mathfrak{K}_{dy}]_{DY}\right)$ with second matrix $\left(\mathfrak{L} = [\mathfrak{L}_{dy}]_{DY}\right)$ (Eq. (19)):

$$\mathfrak{M}_{dy} = (1 - \phi)\sqrt{(\mathfrak{K}_{dy})(\mathfrak{L}_{dy})} + (\phi)\frac{(\mathfrak{K}_{dy}) + (\mathfrak{L}_{dy})}{2}; (d = 1, \dots, D; y = 1, \dots, Y). \tag{19}$$

herein, the final normalization matrix $(\mathfrak{M}_{dy} \in [0,1])$ has a constraint as $\sum_{d=1}^{D} \mathfrak{M}_{dy} = 1$. In addition, $\phi \in [0,1]$ refers to the parameter of the second logarithmic normalization matrix.

Step 5-4: The weighted matrix $\left(\mathfrak{O} = [\mathfrak{O}_{dy}]_{DY}\right)$ is computed (Eq. (20)):

$$\mathfrak{O}_{dy} = \delta_y \mathfrak{M}_{dy}; (d = 1, \ldots, D; y = 1, \ldots, Y). \quad (20)$$

herein, the δ_y refers to the criteria weights.

Step 5-5: The total cost vector $(\mathfrak{R}^- = [\mathfrak{R}_d^-]_D)$ is determined using Eq. (21), while the total benefit vector $(\mathfrak{R}^+ = [\mathfrak{R}_d^+]_D)$ is obtained using Eq. (22).

$$\mathfrak{R}_d^- = \sum_{y=1}^{Y} \mathfrak{O}_{dy}, y \in Z^-; (d = 1, \ldots, D), \quad (21)$$
$$\mathfrak{R}_d^+ = \sum_{y=1}^{Y} \mathfrak{O}_{dy}, y \in Z^+; (d = 1, \ldots, D) \quad (22)$$

Step 5-6: The final ranking vector $(\Omega = [\Omega_d]_D)$ for wireless technologies is computed to aggregate total cost vector $(\mathfrak{R}^- = [\mathfrak{R}_d^-]_D)$ with total benefit vector $(\mathfrak{R}^+ = [\mathfrak{R}_d^+]_D)$ (Eq. (23)):

$$\Omega_d = \left((\mathfrak{R}_d^-)^{\eta} + (\mathfrak{R}_d^+)^{(1-\eta)}\right); (d = 1, \ldots, D). \quad (23)$$

herein, $\eta \in [0,1]$ is calculated by dividing the number of benefit criteria by to total number of criteria. Also, the best value signifies the best option.

Table A1 (on Appendix) presents the detailed algorithmic steps of the proposed FF–Maclaurin–RANCOM–Entropy–ARLON model, outlining each stage of the decision-making framework.

4. Application: Performance Evaluation of Wireless Technologies for Disaster Management

4.1. Decision model

4.1.1. Expert group for evaluating wireless technologies

In this study, the performance evaluation of wireless technologies for logistics and managerial activities in earthquake disasters in Türkiye is conducted. Nine experts were identified, consisting of telecommunication and wireless technology specialists who are knowledgeable about Türkiye's seismic dynamics. The expertise levels of the experts are presented in Table 3.

Nine experts with experience in telecommunications, wireless communication technologies, disaster management, and related logistics fields were included in the study. The experts were selected based on their knowledge and experience in wireless technologies and Turkey's earthquake conditions. Their identities were kept confidential and they were coded between Specialists-1 and Specialists-9. Experts were grouped according to their professional experience: those with 0-5 years of experience were classified as "Medium," those with 5-10 years of experience as "Good," and those with more than 10 years of experience as "Very Good."

Table 3. The experts group.

Experts	Expertise level	Professions
E_1 – First Expert	Medium (M)	Specialists-1
E_2 – Second Expert	Medium (M)	Specialists-2
E_3 – Third Expert	Very-good (VG)	Specialists-3
E_4 – Fourth Expert	Good (G)	Specialists-4
E_5 – Fifth Expert	Very-good (VG)	Specialists-5
E_6 – Sixth Expert	Medium (M)	Specialists-6
E_7 – Seventh Expert	Very-good (VG)	Specialists-7
E_8 – Eight Expert	Good (G)	Specialists-8
E_9 – Ninth Expert	Good (G)	Specialists-9

4.1.2. Criteria set

The criteria consist of twelve criteria, (seven qualitative criteria and five quantitative criteria). These criteria are identified as:

i) *Robustness* $(P_1 - Z_1)$ – Robustness shows the ability of a network for operation under disaster management activities. Within resilient architecture, wireless technologies are important for effective emergency response [41], [42], [43].

ii) *Coexistence* $(P_2 - Z_2)$ – Coexistence shows the infrastructure capability of wireless technologies. Upper coexistence enables flexibility in disaster management [44].

iii) *Scalability* $(P_3 - Z_3)$ – Scalability shows the preservation capability of wireless technology. Scalable technologies are important evolving communication needs [45].

iv) *Vulnerability to Interference* $(P_4 - Z_4)$ – Interference vulnerability shows electromagnetic disturbances. Wireless technologies ensure communication performance during emergency operations when they have high level interference vulnerability [46].

v) Easy to use/setup $(P_5 - Z_5)$ – Easy setups and usability are important in disaster scenarios. Simple installation enables quick connectivity and coordination among emergency teams [47].

vi) Energy consumption $(P_6 - Z_6)$ – Energy consumption is a predominant factor in disaster environments. With low energy requirements, wireless technologies reduce constraints [7].

vii) Equipment cost $(P_7 - Z_7)$ – Equipment cost influences wireless communication networks. Lower-cost solutions enable deployment and backup capacity. So, cost efficiency is critical issue for selecting technology [48].

viii) Number of supported devices per network (Units) $(B_1 - Z_8)$ – High device capacity enables reliable connectivity, effective coordination and real-time data transfer [46]. The values reported in Table A2 represent standardized or technology-specific connection-density capabilities and are interpreted on a common devices/km² basis. For 5G RedCap, the value is based on the IMT-2020 connection-density target rather than the number of devices supported by a single network. Accordingly, the term "supported device density" is used instead of "number of supported devices per network" to avoid conflating network-scale capacity with standardized connection-density requirements.

ix) Bandwidth (Hz) $(B_2 - Z_9)$ – Bandwidth affects communication speed and quality. Higher bandwidth enables real-time coordination [49].

x) Transmission range (rural - m) $(B_3 - Z_{10})$ – Transmission range is called the maximum distance. Extended range capabilities enhance coverage in remote areas when existing infrastructure is damaged [50].

xi) Transmission range (urban - m) $(B_4 - Z_{11})$ – Transmission range shows to maintain reliable connectivity of wireless technologies. High level ranges are essential for sustaining communication in disaster management [51].

xii) Latency (ms) $(B_5 - Z_{12})$ – Latency shows delay time between data transmission and reception. Low latency provides faster effective emergency response [52].

4.1.3. Wireless Technologies set

The decision framework considers eight wireless technology alternatives, which are listed as follows:

i) LoRaWAN (H_1) – LoRaWAN is an LPWAN-based communication technology. It is suitable for disaster management under challenging conditions [53], [54].

ii) NB-IoT (H_2) – NB-IoT is a 3rd Generation Partnership Project (3GPP)-standardized LPWAN technology. It provides suitable solutions for creating secure and continuous communication [55].

iii) Bluetooth (H_3) – Bluetooth is used short-range wireless technology. It provides localized disaster communication [56].

iv) Wi-Fi HaLow (H_4) – Wi-Fi HaLow is an IoT-based technology. It makes reliable communication for suitable disaster management [57].

v) Sigfox (H_5) – Sigfox is an LPWAN technology. Its wide coverage and extended battery life make it suitable for disaster management, where reliable, low-maintenance communication is required for sensors and emergency monitoring systems [58], [59]. For the Turkish context, the relevant technical specifications are considered according to the Release Candidate 1 (RC1) regional configuration, which covers Türkiye.

vi) LTE-M (H_6) – LTE-M is a 3GPP-standardized LPWAN technology that utilizes licensed cellular spectrum to support IoT and Machine to Machine (M2M) communications. With higher data rates, lower latency, and compatibility with existing LTE infrastructure, LTE-M provides reliable and rapidly deployable connectivity for disaster logistics applications requiring efficient and secure communication [60], [61].

vii) Zigbee (H_7) – Zigbee is an IEEE 802.15.4-based low-power wireless protocol that supports reliable mesh networking through self-healing capabilities. Its energy efficiency, flexible topology, and moderate communication range make it suitable for disaster management applications requiring resilient connectivity among distributed sensors and emergency response devices [62], [63].

viii)5G (RedCap) (H_8) – 5G RedCap is an IoT-oriented 5G solution that combines enhanced data rates, low-latency communication, and scalable connectivity. Its support for massive device access, network slicing, and reliable communication makes it a promising technology for disaster management, enabling real-time coordination and resilient emergency operations [64], [65], [66].

Figure 2 presents the decision inputs.

4.2. Evaluating the wireless technologies performance using FF-Maclaurin-RANCOM-Entropy-ARLON model

This part presents the steps of the model, based on the input parameters defined for the earthquake disaster scenario. The application procedure is outlined as follows:

Stage 1 (Application) - Expert weight vector: In *Step 1-1,* the expertise levels were enabled by using Table 1, and the FF-expertise vector $\left(\tilde{\mathfrak{B}} = [\tilde{\mathfrak{B}}_k]_K\right)$ was constructed (Table S2). In *Step 1-2,* the crisp-expertise vector ($\mathfrak{B} = [\mathfrak{B}_k]_K$) (Table S2) was determined using the score function (Eq. (3)). In *Step 1-3,* the expert weight vector ($\pi = [\pi_k]_K$) (Table 4) was determined using the linear normalization (Eq. (4)).

Table 4. Expert weight vector ($\pi = [\pi_k]_K$).

	E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8	E_9
π_k	0.0824	0.0824	0.1424	0.1085	0.1424	0.0824	0.1424	0.1085	0.1085

Stage 2 (Application) - Subjective criteria weight vector according to FF-Maclaurin-RANCOM: In *Step 2-1,* the experts evaluated (Table S3) 12 criteria identified for wireless technology selection based on Table 2. The FF-criteria evaluation matrix $\left(\tilde{\mathfrak{Z}} = [\tilde{\mathfrak{Z}}_{yk}]_{YK}\right)$ is shown in Table S4. In *Step 2-2,* the aggregated FF-criteria evaluation vector $\left(\tilde{\mathfrak{T}} = [\tilde{\mathfrak{T}}_y]_Y\right)$ (Table S5) was computed by performing the FFWPDMSM aggregation operator (Eq. (2)). In this context, the experts were divided into three groups ($c = 3$) based on their expertise levels, with each group consisting of three experts ($o_t = 3$). The binomial coefficient was calculated as the combination of 3 taken 2 at a time ($l = 2$). In *Step 2-3,* crisp-criteria evaluation vector $\left(\mathfrak{T} = [\mathfrak{T}_y]_Y\right)$ (Table S5) was computed (Eq. (5)).

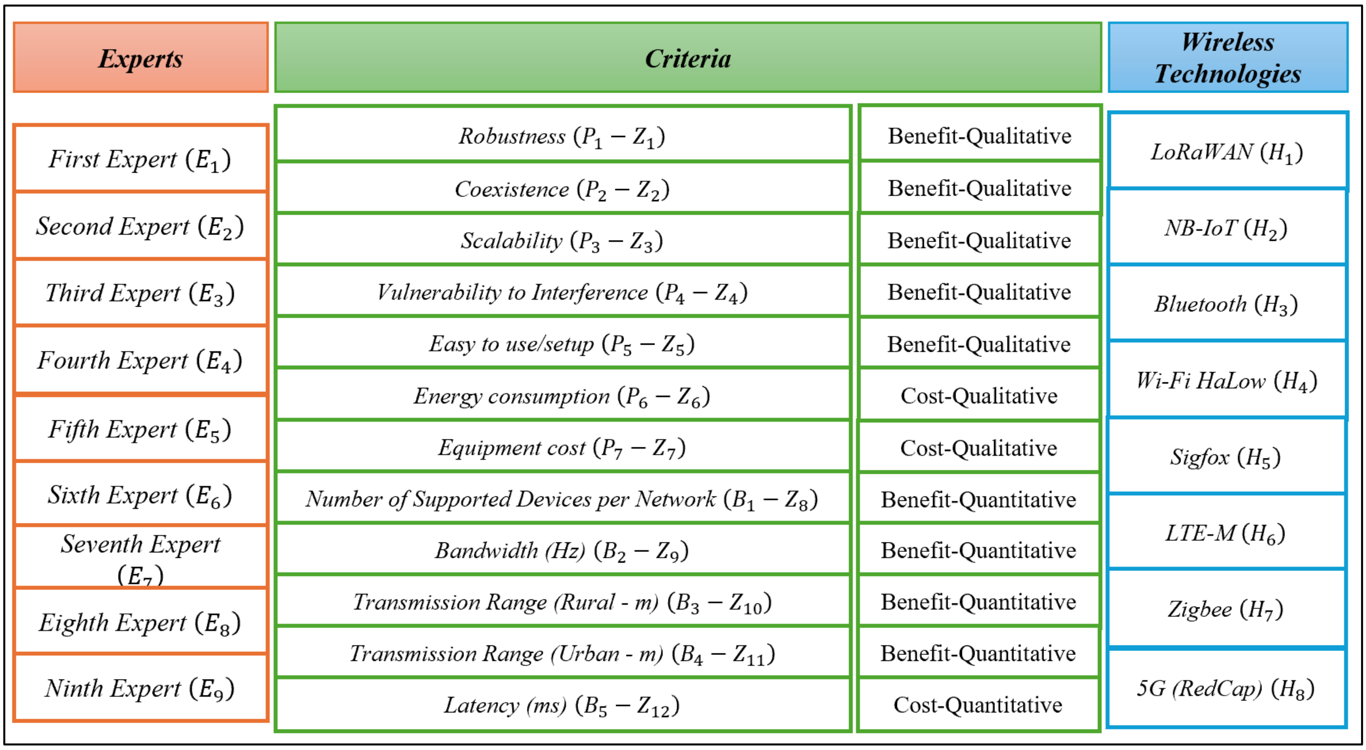

Figure 2. The Decision Inputs.

In *Step 2-4,* pairwise comparison matrix $\left(\mathfrak{Y} = [\mathfrak{Y}_{yy'}]_{YY}\right)$ (Table S6) was determined through binary comparisons (Eq. (6)). In *Step 2-5,* by performing Eq. (7), the criterion comparison score vector $\left(\mathfrak{U} = [\mathfrak{U}_y]_Y\right)$ (Table S6) was computed. In *Step 2-6,* subjective criteria weights $\left(\mu = [\mu_y]_Y\right)$ (Table 5) depending on FF–Maclaurin–RANCOM was determined using the normalization (Eq. (8)).

Stage 3 (Application) - Objective criteria weights according to FF-Maclaurin-Entropy: In *Step 3-1,* experts (E_k) evaluated the wireless technologies (H_d) based on the qualitative criteria (P_t) defined in Table 2. The evaluations are shown on Table S7. The FF-evaluation matrices $\left(\tilde{\mathfrak{X}}^{(E_k)} = \left[\tilde{\mathfrak{X}}_{dt}^{(E_k)}\right]_{DT}\right)$ converted into FF sets are presented in Table S8. In *Step 3-2,* aggregated values $\left(\tilde{\mathfrak{X}} = [\tilde{\mathfrak{X}}_{dt}]_{DT}\right)$ (Table S9) were determined using the FFWPDMSM aggregation operator (Eq. (2)). In *Step 3-3,* crisp-alternative evaluation matrix $(\mathfrak{X} = [\mathfrak{X}_{dt}]_{DT})$ (Table S10) was determined using the score function $\left(\beta(\tilde{\mathfrak{X}}_y)\right)$ (Eq. (9)). In *Step 3-4,* the initial matrix $\left(\mathfrak{A} = [\mathfrak{A}_{dy}]_{DY}\right)$ was constructed (Table S11). The values of the alternative score matrix are presented in Table A2. In *Step 3-5,* by performing normalization (Eq. (10)), the normalized values $\left(\mathfrak{B} = [\mathfrak{B}_{dy}]_{DY}\right)$ was calculated (Table S12). In *Step 3-6,* the entropy values $\left(\mathrm{e} = [\mathrm{e}_y]_Y\right)$ (Table S12) were computed (Eq. (11)). In *Step 3-7,* differentiation vector $\left(\mathfrak{C} = [\mathfrak{C}_y]_Y\right)$ (Table S12) was calculated (Eq. (12)). In *Step 3-8,* objective criteria weight vector $\left(\wp = [\wp_y]_Y\right)$ (Table S12) was computed using linear normalization (Eq. (13)). In *Step 3-9,* final objective criteria weight vector $\left(\lambda = [\lambda_y]_Y\right)$ (Table 5) depending on FF-Maclaurin-Entropy method was determined using the linear normalization (Eq. (14)).

Stage 4 (Application) - Final criteria weight vector according to subjective and objective criteria weights: The final criteria weight vector $\left(\delta = [\delta_y]_Y\right)$ (Table 5) was computed $(\Theta = 0.5)$ by aggregate subjective criteria weight vector with objective criteria weight vector (Eq. (15)).

Table 5. Criteria weights matrices.

	Z_1	Z_2	Z_3	Z_4	Z_5	Z_6	Z_7	Z_8	Z_9	Z_{10}	Z_{11}	Z_{12}
μ_y	0.1458	0.1597	0.0208	0.0347	0.0625	0.0903	0.0486	0.0069	0.1042	0.1181	0.0764	0.1319
	2nd	1st	11th	10th	8th	6th	9th	12th	5th	4th	7th	3rd
λ_y	0.0474	0.1043	0.0602	0.0742	0.0374	0.0573	0.1191	0.1283	0.1044	0.0636	0.0698	0.1339
	11th	5th	9th	6th	12th	10th	3rd	2nd	4th	8th	7th	1st
δ_y	0.0966	0.1320	0.0405	0.0545	0.0499	0.0738	0.0839	0.0676	0.1043	0.0908	0.0731	0.1329
	4th	2nd	12th	10th	11th	7th	6th	9th	3rd	5th	8th	1st

Stage 5 (Application) - Ranking vector according to ARLON: In *Step 5-1,* initial matrix $\left(\mathfrak{F} = [\mathfrak{F}_{dy}]_{DY}\right)$ (Table S13) for ARLON was constructed by employing method Eq. (16). In *Step 5-2,* first $\left(\mathfrak{K} = [\mathfrak{K}_{dy}]_{DY}\right)$ (Table S14) and second $\left(\mathfrak{L} = [\mathfrak{L}_{dy}]_{DY}\right)$ (Table S15) logarithmic normalization matrices were computed with Eq. (17) and Eq. (18), respectively. In *Step 5-3,* final normalization matrix $\left(\mathfrak{M} = [\mathfrak{M}_{dy}]_{DY}\right)$ (Table S16) was computed with Eq. (19) and $\phi = 0.5$. In *Step 5-4,* weighted matrix $\left(\mathfrak{O} = [\mathfrak{O}_{dy}]_{DY}\right)$ (Table S17) was computed (Eq. (20)). In *Step 5-5,* performing Eq. (21) and Eq. (22), the total cost vector $(\mathfrak{R}^- = [\mathfrak{R}_d^-]_D)$ and total benefit vector $(\mathfrak{R}^+ = [\mathfrak{R}_d^+]_D)$ were computed and the values are shown in Table S18. In *Step 5-6,* final ranking vector $(\Omega = [\Omega_d]_D)$ for wireless technologies is computed to aggregate total cost vector $(\mathfrak{R}^- = [\mathfrak{R}_d^-]_D)$ with total benefit vector $(\mathfrak{R}^+ = [\mathfrak{R}_d^+]_D)$ (Eq. (23)). By performing Eq. (23), the final ranking vector $(\Omega = [\Omega_d]_D)$ for the wireless technologies was computed $(\eta = 0.75)$ and shown in Table 6. 5G (RedCap) was identified as the highest-performing wireless technology for use in disaster management.

Table 6. Final ranking vector.

	H_1	H_2	H_3	H_4	H_5	H_6	H_7	H_8
Ω_d	0.7538	0.7479	0.7530	0.7484	0.7436	0.7571	0.7418	0.7691
Rank	3rd	6th	4th	5th	7th	2nd	8th	1st

4.3. Sensitivity analyses

FF-Maclaurin-RANCOM-Entropy-ARLON was employed to select the best-performing wireless technologies required in disaster management. As a result of this evaluation, 5G (RedCap) was identified as the wireless technology with the highest performance. To validate the robustness of the obtained findings, three distinct scenarios (SAS) were developed.

4.3.1. First sensitivity analysis

In the SAS-1, different values were assigned to the parameter (l), which represents the binomial coefficient in the FFWPDMSM aggregation operator used within the hybrid method. Given that the experts were divided into three groups, the l parameter was assigned values of 1, 2, and 3, and the hybrid method was reapplied accordingly. The wireless technology performance values for SAS-1 are presented in Figure 3. The corresponding performance rankings are shown in Figure 4.

4.3.2. Second sensitivity analysis

In the SAS-2, attain different values for the parameter (Θ), which is used to determine the final values by combining the weight vectors obtained from the FF–Maclaurin–RANCOM (subjective) and FF–Maclaurin–Entropy (objective) methods. This allowed the evaluation of wireless technology performance under different weighting schemes. For SAS-2, the performance values are described in Figure 5. The performance rankings are given in Figure 6.

The results indicate that as the influence of the FF–Maclaurin–RANCOM criterion weight vector (subjective expert-based approach) increases in determining the final criterion weight vector, the performance advantage of 5G (RedCap) over other technologies becomes more pronounced. Conversely, when the influence of the FF−Maclaurin−Entropy weight vector (objective, data-driven approach) increases, 5G (RedCap) maintains its leading performance, while the performance levels of the other technologies also improve. These findings confirm that 5G (RedCap) is the top-performing technology in all sub-scenarios of SAS-2, further supporting the main results.

4.3.3. Third sensitivity analysis

In SAS-3, attain different values for the parameter (ϕ), which is used to aggregate two different logarithmic normalization matrices within ARLON. This scenario evaluated the performance of wireless technologies based on various normalization schemes applied to the decision matrix. In SAS-3, the performance values are presented in Figure 7. The rankings of the wireless technology alternatives are given in Figure 8. No change was observed in the performance rankings across different final normalization vectors derived from the two logarithmic normalization matrices. 5G (RedCap) remained the highest-performing technology in all sub-scenarios. Thus, the results of SAS-3 further validate the findings of the study.

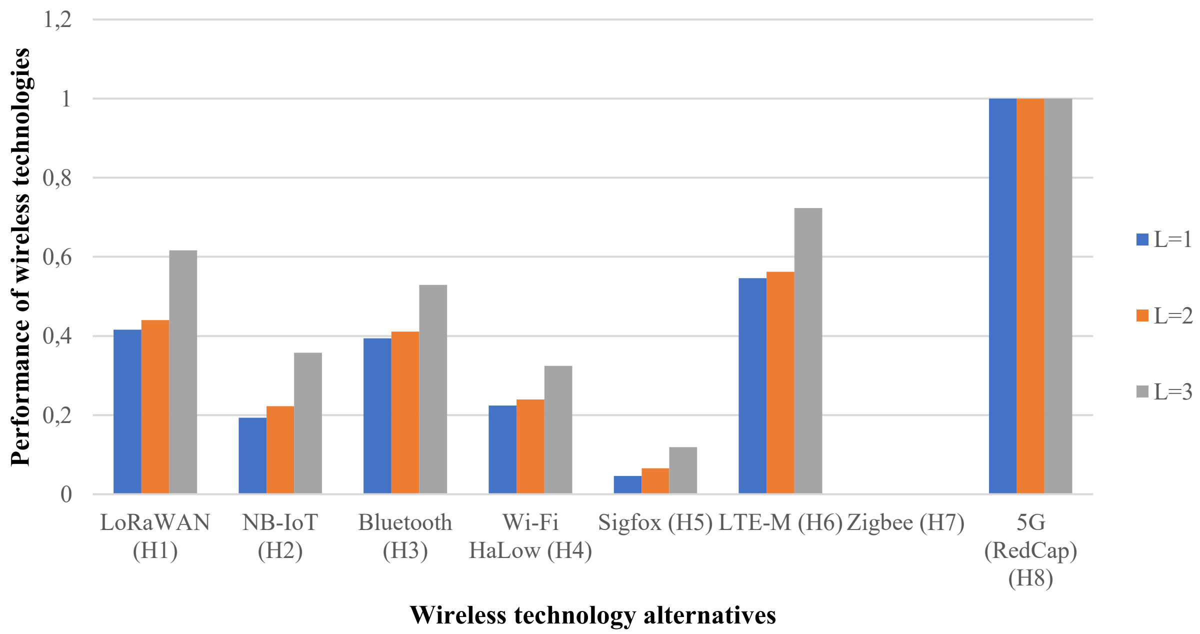

Figure 3. Wireless technology performances based on the combination value (SAS-1).

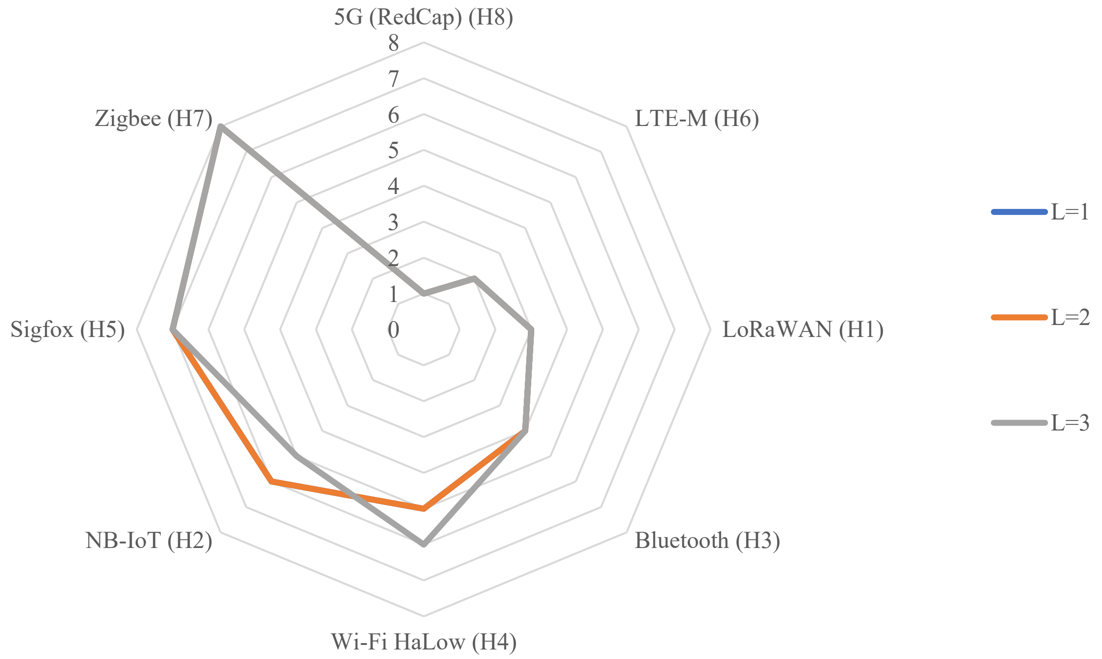

Figure 4. Wireless technology performances based on the combination value (SAS-1).

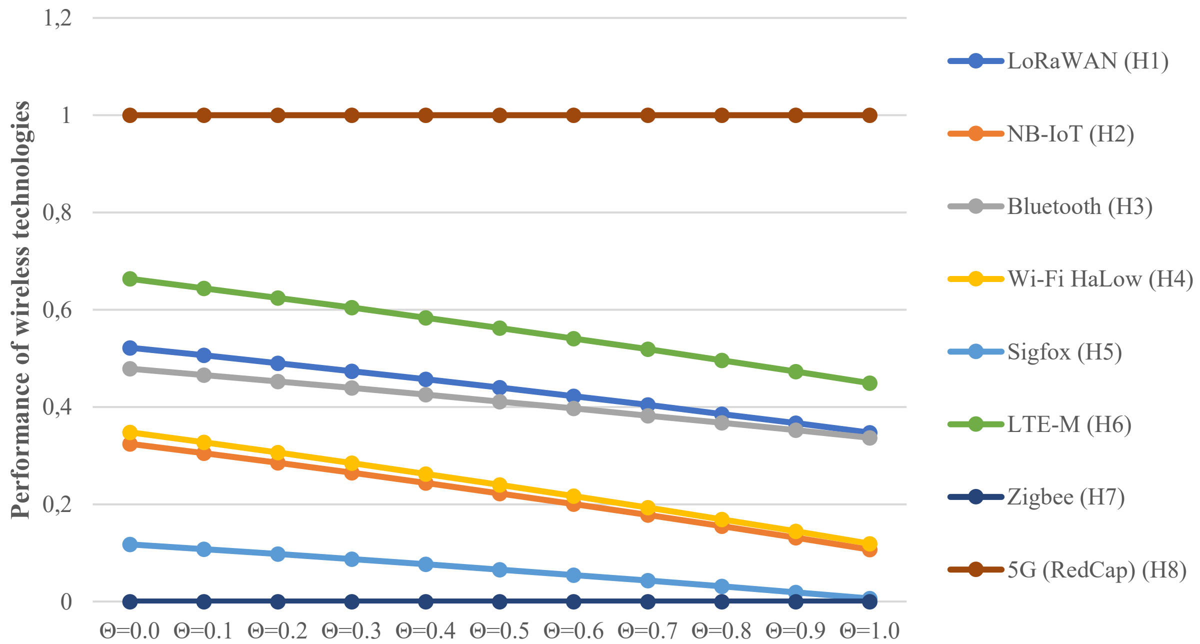

Figure 5. Wireless technology performance based on the final criterion weight vector determination parameter (SAS-2).

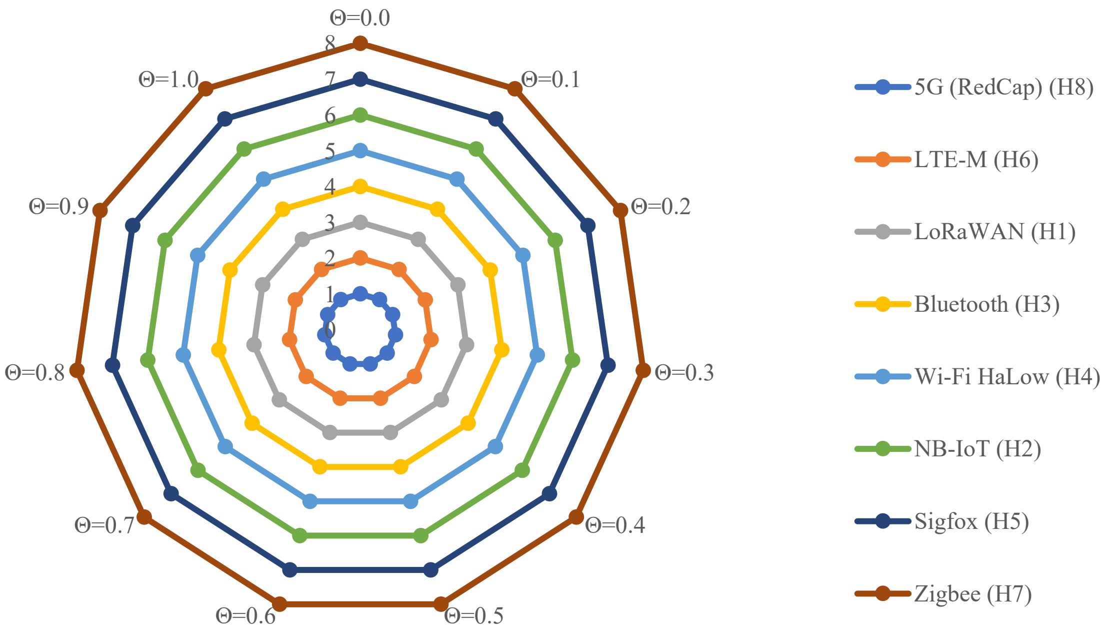

Figure 6. Wireless technology performance ranks based on the final criterion weight vector determination parameter (SAS-2).

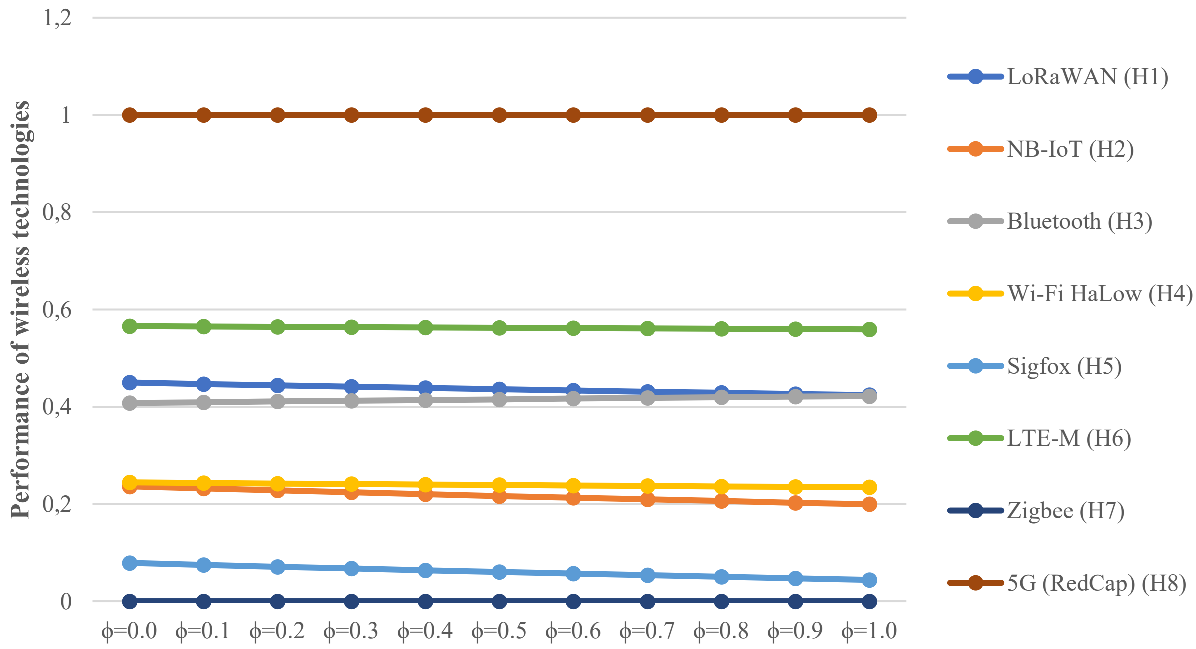

Figure 7. Wireless technology performance based on the logarithmic normalization determination parameter (SAS-3).

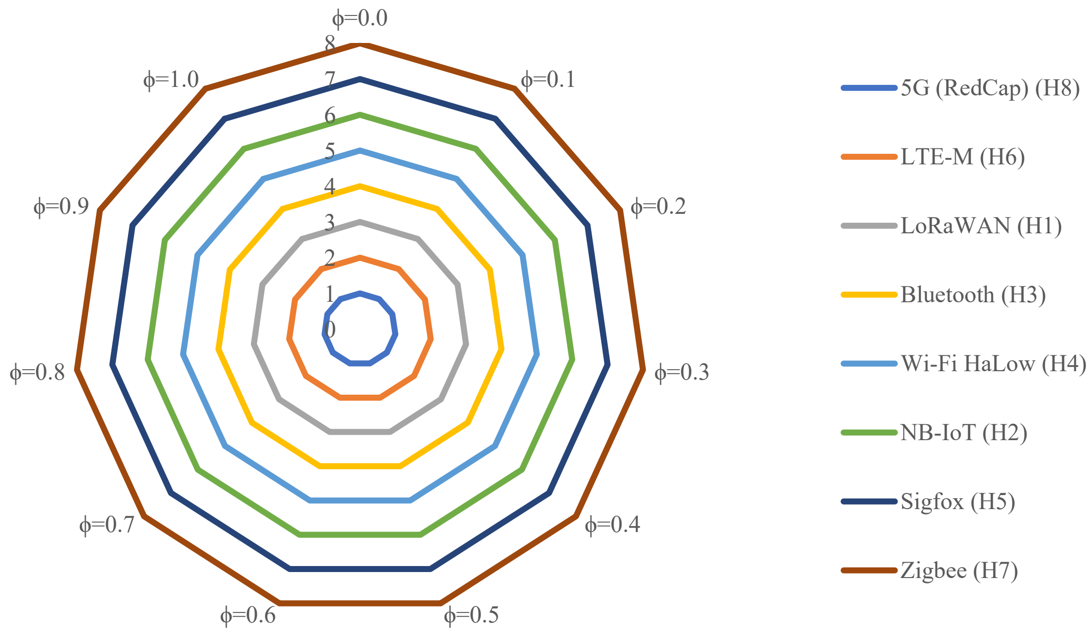

Figure 8. Wireless technology performance ranks based on the logarithmic normalization determination parameter (SAS-3).

4.4. Comparative analyses

To determine the performance of wireless technologies required within the scope of disaster management, the FF-Maclaurin-RANCOM-Entropy-ARLON model was proposed and successfully implemented. Additionally, the robustness of the results was supported through sensitivity analyses.

To further validate the consistency of the results, comparative analyses were conducted. In this context, the performances of wireless technologies were evaluated using eight different alternative ranking methods: Alternative Ranking Order Method Accounting for Two-Step Normalization (AROMAN) [67], Alternative Ranking Technique based on Adaptive Standardised Intervals (ARTASI) [68], Multi-Attributive Border Approximation Area Comparison (MABAC) [69], Measurement Alternatives and Ranking according to Compromise Solution (MARCOS) [70], Root Assessment Method (RAM) [71], Simple Additive Weighting (SAW), Weighted Aggregated Sum Product Assessment (WASPAS) [72], and Combined Compromise Solution (CoCoSo) [73]. The performance results of wireless technologies based on these methods are presented in Figure 9. Across all methods, 5G (RedCap) was consistently identified as the top-performing technology.

The performance rankings of wireless technologies according to the different methods are shown in Figure 10. While 5G (RedCap) ranked first in all methods, some variations were observed in the rankings of the other technologies.

To assess the consistency of the findings, correlation analysis was conducted, and the results are shown on Table 7. According to the correlation analysis, the results of the method showed a high level of correlation with those of the other methods, indicating that the outcomes are consistent and reliable.

Table 7. Correlation analysis among the methods.

	1	2	3	4	5	6	7	8	9
ARLON (1)	1.0	0.82	0.88	0.86	0.89	0.78	0.74	0.91	0.88
AROMAN (2)		1.0	0.99	0.99	0.69	0.92	0.75	0.88	0.94
ARTASI (3)			1.0	0.99	0.76	0.90	0.75	0.90	0.98
MABAC (4)				1.0	0.73	0.91	0.74	0.89	0.96
MARCOS (5)					1.0	0.48	0.42	0.66	0.83
RAM (6)						1.0	0.91	0.93	0.81
SAW (7)							1.0	0.93	0.65
WASPAS (8)								1.0	0.83
COCOSO (9)									1.0

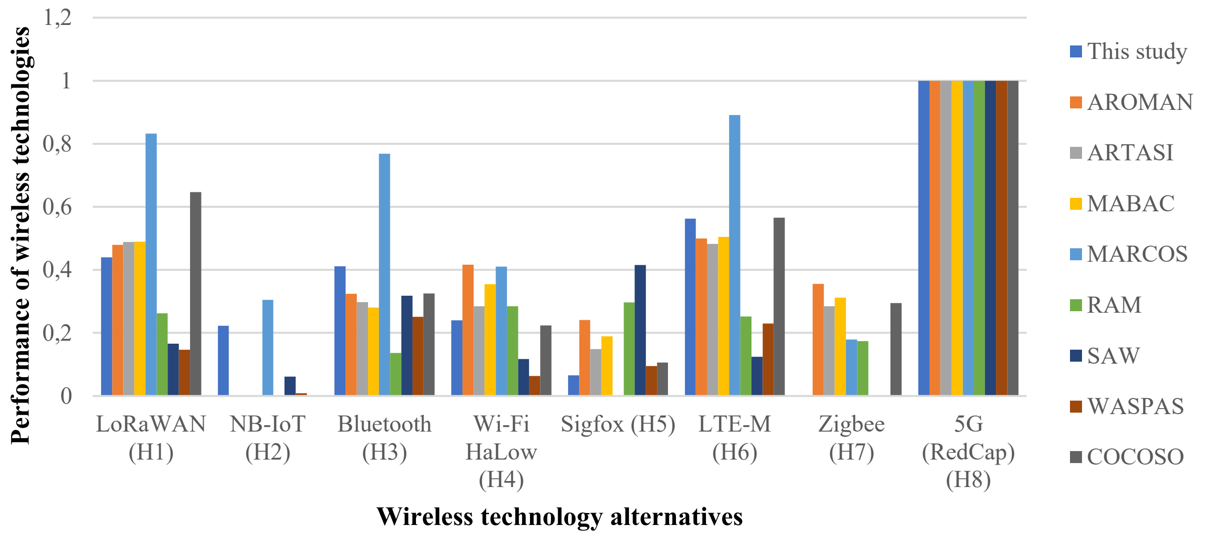

Figure 9. Wireless technology performances based on the other methods (comparative analysis).

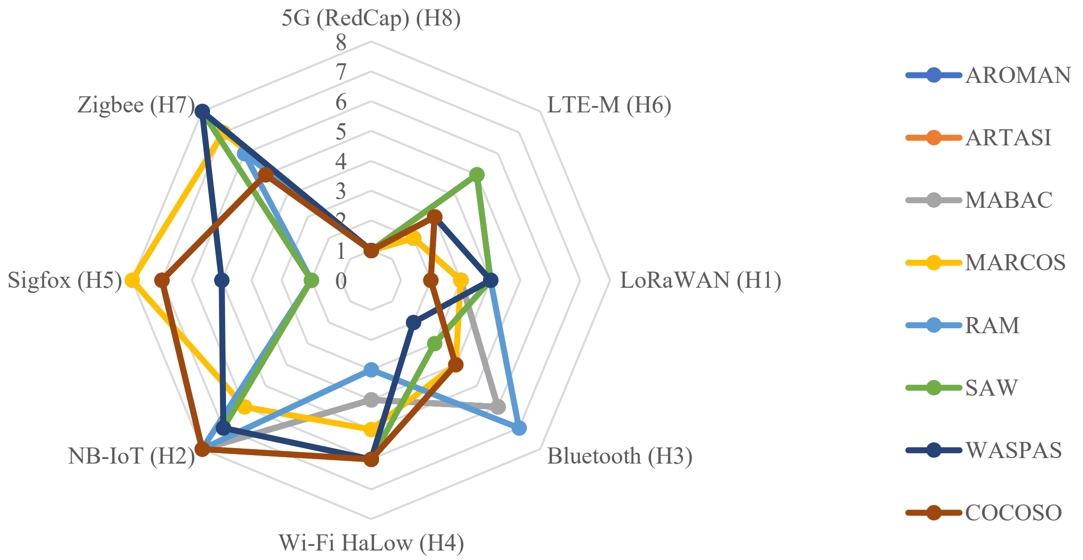

Figure 10. Wireless technology performance ranks based on the other methods (comparative analysis).

5. Results

In disaster management, communication and information exchange are indispensable elements. Wireless technologies play an effective role in the successful execution and management of these elements. This study evaluates the performance of wireless technologies in the context of disaster management. To identify the most suitable wireless technology, a novel FF–Maclaurin–RANCOM–Entropy–ARLON model was developed. This hybrid approach enables the evaluation of alternative wireless technologies. The method was applied to a case study to demonstrate its applicability, and results were obtained accordingly. The study presents five key results, which are detailed below, followed by a discussion of their implications:

i) *For experts* – Nine experts were selected for the implementation of the FF–Maclaurin–RANCOM–Entropy–ARLON model. Based on their levels of expertise, the experts were divided into three groups to enable the use of the FFWPDMSM aggregation operator. According to the derived expert weight vector, the ranking was $E_3 = E_5 =$

$E_7 > E_4 = E_8 = E_9 > E_1 = E_2 = E_6$. The experts with a "very good" expertise level (experts 3, 5, and 7) were identified as having the highest influence on the decision-making process. This demonstrates the method's ability to integrate expert judgment into both the evaluation of criteria and the assessment of wireless technologies based on qualitative parameters, making it suitable for use in DSS.

ii) For criteria – The hybrid method facilitates the use of both qualitative and quantitative criteria. In the application, 12 criteria were considered (seven qualitative and five quantitative). Based on two separate weighting approaches (i.e. FF–Maclaurin–RANCOM and FF–Maclaurin–Entropy), the importance ranking of the criteria was determined as: *latency (ms)* $(B_5 - Z_{12})$ > *coexistence* $(P_2 - Z_2)$ > *bandwidth (Hz)* $(B_2 - Z_9)$ > *robustness* $(P_1 - Z_1)$ > *transmission range (rural - m)* $(B_3 - Z_{10})$ > *equipment cost* $(P_7 - Z_7)$ > *energy consumption* $(P_6 - Z_6)$ > *transmission range (urban - m)* $(B_4 - Z_{11})$ > *number of supported devices per network (Units)* $(B_1 - Z_8)$ > *vulnerability to interference* $(P_4 - Z_4)$ > *easy to use/setup* $(P_5 - Z_5)$ > *scalability* $(P_3 - Z_3)$. Each method produced distinct weight vectors, which were then aggregated to derive the final criterion weight vector. According to FF–Maclaurin–RANCOM, the top three criteria were: "coexistence", "robustness", and "latency". According to FF–Maclaurin–Entropy, the top three criteria were: "latency", "number of supported devices per network", "equipment cost". The final criterion weights identified the top three as: "latency", "coexistence", and "bandwidth". This indicates that the FF–Maclaurin–Entropy method had a more decisive influence on the final weights due to its data-driven, quantitative nature.

iii) For wireless technology – The primary outcome of the hybrid method is the performance ranking of wireless technologies from a disaster management perspective. Based on the application results, the ranking was *5G (RedCap)* (P_8) > *LTE-M* (P_6) > *LoRaWan* (P_1) > *Bluetooth* (P_3) > *Wi-Fi HaLow* (P_4) > *Sigfox* (P_5) > *NB-IoT* (P_2) > *Zigbee* (P_7), with 5G (RedCap) identified as the top-performing wireless technology. This result is reinforced by the superior quantitative performance parameters of 5G (RedCap) compared to other technologies, as well as the expert evaluations, which also favored 5G (RedCap). Therefore, the outcome that 5G (RedCap) is the most suitable wireless technology is both logical and supported by the analysis.

iv) For robustness test – The robustness is conducted through three SASs. SAS-1 is variation in the aggregation operator parameter (binomial coefficient). SAS-2 is changing in the relative influence of subjective (FF–Maclaurin–RANCOM) and objective (FF–Maclaurin–Entropy) weight vectors. SAS-3 is an alteration in the normalization process within ARLON. In all scenarios, 5G (RedCap) consistently emerged as the top-performing technology, confirming the robustness of both the results and the proposed hybrid methodology.

v) For comparative analysis test – The performance rankings obtained from ARLON were compared with the results of eight other alternative ranking methods; i.e. AROMAN, ARTASI, MABAC, MARCOS, RAM, SAW, WASPAS, and COCOSO. Across all methods, 5G (RedCap) was consistently ranked as the top-performing wireless technology. Correlation analysis (presented in Table 7) revealed a high positive correlation between ARLON and the other methods.

6. Implications

This study contributes to MADM framework by proposing an integrated weighting framework that combines expert-based judgments and objective information through the FF-Maclaurin-RANCOM and FF-Maclaurin-Entropy approaches. The proposed hybrid model provides a robust DSS structure to disaster management for various uncertain communication problems. DSS enhances appropriate wireless technology selection approaches especially in post disasters scenarios. Proposed hybrid model covers qualitative and quantitative performance factors, as well. It also enables more systematic resource allocation, selecting best suitable wireless communication technology fitting the disaster situation.

Thanks to the advanced computational structure of the proposed model, logistics decision-makers can make more appropriate choices regarding the communication infrastructure necessary for the successful management of disaster logistics. Although 5G (RedCap) was identified as the most suitable technology in the Türkiye case study, other communication technologies may be more appropriate in different disaster scenarios and geographies. By correctly identifying the criteria and alternatives, decision-makers can use the model to effectively manage disaster logistics and increase the speed of post-disaster response. In addition, effective communication technologies contribute to the correct allocation of resources. Therefore, it is important for logistics decision-makers to benefit from the decision support offered by the model.

The findings highlight the best performing wireless technology is 5G (RedCap) for the case study. Moreover, fast and easy installation criteria have been identified as the most important criteria for wireless communication technology use. In this case, it can be said that technologies with high mobilization capacity are preferable. The proposed method also offers insights into technology developers by showing performance priorities. It also encourages all parties (technology providers, public institutions, and humanitarian organizations) to create strengthen collaboration.

7. Conclusion

This paper presents a novel algorithm to select best wireless technologies for post disaster management. The model depends on expert experience and quantitative data, providing effective decision-making under uncertainty.

The proposed framework is applied post-disaster management particular earthquake disaster case in Türkiye. Nine experts, twelve criteria, and eight wireless technologies were used for determining the best wireless communication technology. The results identified ease of use/setup as the most important criterion and 5G (RedCap) as the best-performing alternative.

The findings of this study should be interpreted considering several limitations. First, the case study focuses on earthquake scenarios in Türkiye, and the results may differ in other disaster types or geographical settings. Second, the proposed hybrid model is computationally sophisticated and may require users with knowledge of fuzzy MCDM methods. In addition, different weighting strategies may lead to slight variations in the final rankings.

Future research can extend the proposed framework by incorporating other intelligent sensing technologies. Applying the model to different disaster scenarios and including additional evaluation criteria could further improve its flexibility and decision-making capacity. Overall, the proposed DSS provides a practical and reliable framework for wireless technology selection and contributes to improving communication resilience in disaster management.

Competing Interest Statement

The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data Availability Statement

Supplementary materials and data used in this research are accessible upon request. For access, please contact the corresponding author via [vsima@korea.ac.kr].

Statement on the Ethical Use of AI Tools

Generative AI was used to improve the language and readability of the manuscript. All AI-assisted content was carefully reviewed and revised by the authors, who take full responsibility for the final version of the manuscript.

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Appendix

Table A1. Algorithm of FF–Maclaurin–RANCOM–Entropy–ARLON.

Input	*Experts* $(E = \{E_1, E_2, \dots, E_k, \dots, E_K\}\ (k = 1,2,\dots,K))$, *Qualitative criteria* $(P = \{P_1, P_2, \dots, P_t, \dots, P_T\}\ (t = 1,2,\dots,T))$, *Quantitative criteria* $(B = \{B_1, B_2, \dots, B_v, \dots, B_V\}\ (v = 1,2,\dots,V))$, *Overall criteria* $\left(Z = \{Z_1, Z_2, \dots, Z_y, \dots, Z_Y\}\ (y = 1,2,\dots,Y)\right); (Y = T + V)$, *Alternatives (Wireless Technologies)* $(H = \{H_1, H_2, \dots, H_d, \dots, H_D\}\ (d = 1,2,\dots,D))$.
Begin	
Stage 1	*Expert weight vector*
Step 1-1	*Construct the FF-expertise vector* $\left(\tilde{\mathfrak{V}} = [\tilde{\mathfrak{V}}_k]_K\right)$ *using Table 1.*
Step 1-2	*Compute the crisp-expertise vector* $(\mathfrak{V} = [\mathfrak{V}_k]_K)$ *by performing score function* $\left(\beta(\tilde{\mathfrak{V}}_k)\right)$ *(Eq. (3)).*
Step 1-3	*Calculate the expert weight vector* $(\pi = [\pi_k]_K)$ *by performing Eq. (4).*
Stage 2	*Subjective criteria weight vector according to FF–Maclaurin–RANCOM*
Step 2-1	*Construct the FF-criteria evaluation matrix* $\left(\tilde{\mathfrak{Z}} = [\tilde{\mathfrak{Z}}_{yk}]_{YK}\right)$ *by performing Table 2.*
Step 2-2	*Compute the aggregated FF-criteria evaluation vector* $\left(\tilde{\mathfrak{T}} = [\tilde{\mathfrak{T}}_y]_Y\right)$ *by performing FFWPDMSM* $\left(\tilde{\mathfrak{T}}_y = FFWPDMSM^{(l)}\left(\tilde{\mathfrak{Z}}_{y1}, \tilde{\mathfrak{Z}}_{y2}, \dots, \tilde{\mathfrak{Z}}_{yk}, \dots, \tilde{\mathfrak{Z}}_{YK}\right)\right)$ *(Eq. (2)).*
Step 2-3	*Compute the crisp-criteria evaluation vector* $\left(\mathfrak{T} = [\mathfrak{T}_y]_Y\right)$ *by performing the score function* $\left(\beta(\tilde{\mathfrak{T}}_y)\right)$ *(Eq. (5)).*
Step 2-4	*Compute the pairwise comparison matrix* $\left(\mathfrak{Y} = [\mathfrak{Y}_{yy'}]_{YY}\right)$ *by performing Eq. (6).*
Step 2-5	*Compute the criterion comparison score vector* $\left(\mathfrak{U} = [\mathfrak{U}_y]_Y\right)$ *by performing Eq. (7).*
Step 2-6	*Compute the subjective criteria weight vector* $\left(\mu = [\mu_y]_Y\right)$ *by performing Eq. (8).*
Stage 3	*Objective criteria weight vector according to FF-Maclaurin-Entropy method*
Step 3-1	*Construct evaluation matrices* $\left(\tilde{\mathfrak{X}}^{(E_k)} = \left[\tilde{\mathfrak{X}}^{(E_k)}_{dt}\right]_{DT}\right)$ *of wireless technology alternatives based on qualitative criteria using Table 2 and FF numbers.*
Step 3-2	*Compute the aggregated FF-alternative evaluation matrix* $\left(\tilde{\mathfrak{X}} = [\tilde{\mathfrak{X}}_{dt}]_{DT}\right)$ *by performing FFWPDMSM* $\left(\tilde{\mathfrak{X}}_{dt} = FFWPDMSM^{(l)}\left(\tilde{\mathfrak{X}}^{(E_1)}, \tilde{\mathfrak{X}}^{(E_2)}, \dots, \tilde{\mathfrak{X}}^{(E_k)}, \dots, \tilde{\mathfrak{X}}^{(E_K)}\right)\right)$ *(Eq. (2)).*
Step 3-3	*Compute the crisp-alternative evaluation matrix* $(\mathfrak{X} = [\mathfrak{X}_{dt}]_{DT})$ *by performing score function* $\left(\beta(\tilde{\mathfrak{T}}_y)\right)$ *(Eq. (9)).*
Step 3-4	*Construct the initial matrix* $\left(\mathfrak{A} = [\mathfrak{A}_{dy}]_{DY}\right)$ *by combining the crisp-alternative evaluation matrix* $(\mathfrak{X} = [\mathfrak{X}_{dt}]_{DT})$ *with the alternative evaluation matrix* $(\mathfrak{W} = [\mathfrak{W}_{dv}]_{DV})$ *based on quantitative criteria.*
Step 3-5	*Compute the normalized initial matrix* $\left(\mathfrak{B} = [\mathfrak{B}_{dy}]_{DY}\right)$ *by performing Eq. (10).*
Step 3-6	*Compute entropy vector* $\left(\mathrm{e} = [\mathrm{e}_y]_Y\right)$ *by performing Eq. (11).*
Step 3-7	*Compute the differentiation vector* $\left(\mathfrak{C} = [\mathfrak{C}_y]_Y\right)$ *by performing Eq. (12).*
Step 3-8	*Compute the objective criteria weight vector* $\left(\wp = [\wp_y]_Y\right)$ *by performing Eq. (13).*
Step 3-9	*Compute the final objective criteria weight vector* $\left(\lambda = [\lambda_y]_Y\right)$ *by performing Eq. (14).*
Stage 4	*Final criteria weight vector according to subjective and objective criteria weights*
Step 4-1	*Compute the final criteria weight vector* $\left(\delta = [\delta_y]_Y\right)$ *by aggregating subjective criteria weight vector* $\left(\mu = [\mu_y]_Y\right)$ *with objective criteria weight vector* $\left(\lambda = [\lambda_y]_Y\right)$ $(\Theta \in [0,1])$ *by performing Eq. (15).*
Stage 5	*Ranking vector according to ARLON*
Step 5-1	*Compute the initial matrix* $\left(\mathfrak{F} = [\mathfrak{F}_{dy}]_{DY}\right)$ *for the ARLON method by employing Eq. (16).*
Step 5-2	*Calculate the first* $\left(\mathfrak{K} = [\mathfrak{K}_{dy}]_{DY}\right)$ *and second* $\left(\mathfrak{L} = [\mathfrak{L}_{dy}]_{DY}\right)$ *logarithmic normalization matrix by performing Eq. (17) and Eq. (18).*

Table A1. Continued on next page

Table A1 (continued). Algorithm of FF–Maclaurin–RANCOM–Entropy–ARLON

Step 5-3	*Calculate the final normalization matrix* $\left(\mathfrak{M} = \left[\mathfrak{M}_{dy}\right]_{DY}\right)$ *by performing Eq. (19)* ($\phi \in [0,1]$).
Step 5-4	*Calculate the weighted matrix* $\left(\mathfrak{O} = \left[\mathfrak{O}_{dy}\right]_{DY}\right)$ *by performing Eq. (20).*
Step 5-5	*Calculate the total cost vector* ($\Re^{-} = [\Re_d^{-}]_D$) *and total benefit vector* ($\Re^{+} = [\Re_d^{+}]_D$) *by performing Eq. (21) and Eq. (22).*
Step 5-6	*Compute the final ranking vector* ($\Omega = [\Omega_d]_D$) *by performing Eq. (23)* ($\eta \in [0,1]$).
Output	*The expert weight vector* ($\pi = [\pi_k]_K$), *The subjective criteria weight vector* $\left(\mu = \left[\mu_y\right]_Y\right)$, *The objective criteria weight vector* $\left(\lambda = \left[\lambda_y\right]_Y\right)$, *The final criteria weight vector* $\left(\delta = \left[\delta_y\right]_Y\right)$, *The final ranking vector* ($\Omega = [\Omega_d]_D$).
End.	

Table A2. Score Matrix.

Wireless Tech. (H_d)	Number of Supported Devices per Network (Units) (B_1)	Bandwidth (Hz) (B_2)	Transmission Range (Rural - m) (B_3)	Transmission Range (Urban - m) (B_4)	Latency (ms) (B_5)	References
LoRaWAN (H_1)	1000	500,000	20,000	15,000	2000	[29], [74]–[77]
NB-IoT (H_2)	50,000	180,000	20,000	10,000	10,000	[26], [78], [79]
Bluetooth (H_3)	32,767	2,000,000	1000	1000	10	[80], [81], [82]
Wi-Fi HaLow (H_4)	8191	16,000,000	1000	1000	300	[28], [83], [84]
Sigfox (H_5)	500,000	600	50,000	10,000	10,000	[85], [86], [87]
LTE-M (H_6)	50,000	1,400,000	20,000	5000	150	[88]
Zigbee (H_7)	65,000	5,000,000	100	100	100	[89], [90]
5G (RedCap) (H_8)	1,000,000	20,000,000	30,000	30,000	50	[91]