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FCVM(i): Integrated FCNP-VWA-MCDM(i) Methods for On-Demand Charging Scheduling in WRSNs

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Abstract: On-demand charging schemes have been recently proposed to make efficient charging schedules of mobile chargers by introducing MCDM methods in wireless rechargeable sensor networks (WRSNs). However, most of the existing schemes use analytic hierarchy process (AHP) or fuzzy AHP (FAHP) of paired ratio scale (PRS) to exaggerate the actual paired difference between multi-criteria, thereby very likely producing misapplications such as inappropriately ranking the charging locations or inaccurately drawing the partial charging time in charging scheduling (CS) of WRSNs. In addition, in case of using FCNP of paired interval scale (PIS) for weight assignment of multi-criteria, weight compensation has not been considered. In particular, it is still unknown which is the best method for integrating FCNP with several MCDM approaches. This paper proposed novel CS methods by integrated FCNP-VWA-MCDM(i) called FCVM(i) which solves all of these problems. The proposed methods first assign the weights to multiple criteria discriminating charging request nodes (cRNs) using FCNP and make compensation of them to be relatively exact weights with VWA. Then, on the basis of these weights, MCDM(i) is used to elect the best proper next charging position. In this way, drawing up the recharging schedule, at the selected charging locations, we decide the reasonable partial charging time using the assigned weights with FCNP-VWA. Extended experiment results prove that the FCVM(1) using TOPSIS gives the best performance among FCVM(i) methods.

Keywords: wireless rechargeable sensor network, fuzzy cognitive network process, variable weight analysis, TOPSIS, on-demand CS, partial charging time

1. Introduction

In wireless rechargeable sensor networks (WRSNs), which are able to prolong the network lifetime to infinity, periodic schemes [1, 2] and on-demand schemes are used for charging sensor nodes. Unlike periodic scheme using the predetermined charging schedule, on-demand scheme has the advantages that does not make the charging schedule fixed and can deal with the change of dynamic and heterogeneous ECR of sensor nodes, hence focusing on on-demand scheme in our research, too. These on-demand schemes, which determine charging scheduling (CS) depending on charging requests that sensor nodes issue, have been widely studied since they can maximize the network lifetime by enhancing the network survival rate, and these involve most of the studies proposed so far [3–11]. In this course, intelligent CS methods in an on-demand charging scheme have been recently proposed to make charging schedules by combining multi-criteria such as distance to WCV, residual energy, node location importance degree, energy consumption rate, and neighborhood energy weightage characterizing charging request nodes (RNs) [12–15]. However, a challenge of which multi-criteria decision-making (MCDM) method is adopted to determine the best reasonable charging priority of cRNs with these conflicting criteria still remains demanding the pressing solution. The best reasonable charging priority increases survival rate of cRNs and energy usage efficiency of WCV and reduces average charging latency of cRNs, therefore maximizing the network lifetime.

MCDM-based on-demand CS schemes developed till now include schemes [14, 16] using fuzzy logic, AHP technique for order preference by similarity to ideal solution (TOPSIS)-based scheme [15], Fuzzy Q-charging schemes based on fuzzy logic and Q-Learning [12], integrated FAHP-VWA-TOPSIS-based schemes [13], an integrated FCNP-Q-Learning scheme [7], and so on. However, on-demand CS schemes which introduce existing MCDM methods use AHP or FAHP of PRS to exaggerate the actual paired disparity between multi-criteria or lack weight compensation if FCNP of PIS are used for weight assignment of multi-criteria. In particular, it remains unknown which is the best among several MCDM methods for selecting the next charging node based on the assigned weights to multi-criteria with FCNP.

Study results, which have improved the performance of decision-making by jointly considering one or more MCDM methods, continue to be reported. FCNP adopts fuzzy PIS to solve the inexact assessment result from the use of fuzzy PRS of FAHP [17]. FCNP, an ideal alternative to FAHP, can provide a very reliable decision-making compared to FAHP [17]. VWA is a method which realizes a process for adapting weights on the basis of the state variable weight vector [18]. Out of this, it can be seen

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that when we use FCNP, the relative weights of multi-criteria are assigned correctly compared to FAHP, and then moreover using VWA, weights are compensated to avoid the loss of the resolving ability when giving weights to criteria with analogous assessments, more accurate criterion-by-criterion weights can be obtained.

On the other hand, there are several methods for selecting the most proper next charging node using the weights allocated to multi-criteria, including VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [19, 20] ELimination Et Choice Translating REality (ELECTRE) [21], preference ranking organization method for enrichment evaluation (PROMETHEE) [22], in addition to TOPSIS, Q-Learning [12, 23]. However, so far, no studies on which MCDM is integrated with the FCNP-VWA to achieve the best charging and network performance have been reported.

In this paper, for on-demand CS using multi-criteria, from the inspiration that if VWA is combined with FCNP, the relative weight assignment can be proceeded more accurately, and even if various MCDM methods are combined with this, then the performance of on-demand charging schemes can be further and further improved, we comprehensively study on-demand CS schemes based on the integrated FCNP-VWA-MCDM(i).

The main objective of this study is to develop the integrated FCNP-VWA-MCDM(i) methods which improved further the charging performance by integrating FCNP-VWA with the other MCDM approaches which can be used in selecting the next cRNs and making the reasonable charging schedule so as to maximize the network lifetime of WRSNs employing on-demand and partial charging schemes [24–26].

To the best of our knowledge, this study is the first to implement the integrated FCNP-VWA-MCDM(i) for the CS in WRSN. The main contributions of our study in this paper are as follows:

We devise allocating the weights to multiple criteria distinguishing the cRNs by FCNP and making compensation of these weights by VWA and also advise adopting the exponent type state variable weight vector (E-SVWV) with penalty for performing their accommodation with VWA.

Based on the weights of multi-criteria determined by FCNP-VWA, we proposed CS methods based on the integrated FCNP-VWA-MCDM(i) which select the next charging location with MCDM(i) methods such as TOPSIS, VIKOR, ELECTRE, and PROMETHEE and calculate the partial charging time (PCT) at the chosen positions.

Through the extensive simulation, it can be seen that FCNP-VWA gives the most accurate weights of multi-criteria and that FCVM(1), that is, FCNP-VWA-TOPSIS achieves the best performance among the proposed methods.

The rest of this paper is described as follows: Section 2 gives a brief summarization of related works, and in Section 3a, preliminary consideration is described. In Section 4, the proposed methods are discussed, and Section 5 gives the analysis of the simulation results. Finally, Section 6 concludes this paper.

2. Literature Review

We briefly summarize the previous studies on on-demand CS applying MCDM and intelligent methods reported till now.

This kind of on-demand CS can be classified into schemes based on fuzzy logic [14, 16], schemes integrating AHP with TOPSIS [14], Fuzzy Q-learning-based schemes applying fuzzy logic and Q-Learning [12], and schemes based on an integrated FAHP-VWA-TOPSIS [13]. Tomar et al. [14, 16] used the distance to wireless charging vehicle (WCV), residual energy, energy consumption rate, and critical node density as multi-criteria and combined these multi-criteria to perform CS using fuzzy logic.

Nguyen et al. [12] proposed a method integrating AHP with TOPSIS, where they assigned the relative weights to multi-criteria such as distance to WCV, residual energy, ECR, and neighborhood energy weightage by AHP, and selected the next cRN by TOPSIS. Also, Priyadarshani et al. [25] evaluated the crowding distance with AHP-TOPSIS to rank the cRNs within each front using multi-criteria such as distance to depot, packet delivery rate, and number of neighboring nodes. This method used one criterion of node centrality to calculate the partial charging time of the charging positions. In the Fuzzy Q-charging scheme developed by Nguyen et al. [12], Q-Learning is employed to rank the charging locations and the partial charging time at every charging position is determined by fuzzy logic, taking into account two criteria, the minimum residual energy of the RNs and the number of charging requests within the network. Above studies using AHP-TOPSIS did not integrate the fuzzy numbers which efficiently handle the incertitude of subjective perceptions in evaluating the relative importance among multiple criteria by AHP, and moreover, did not take into account weight compensation to avoid loss of the resolving ability when giving weights to multi-criteria with approximate values.

To this end, we have developed schemes based on an integrated FAHP-VWA-TOPSIS. Ri et al. [13] developed an eIFVT scheme, focusing on the utilization of integrated FAHP-VWA-TOPSIS via the whole CS.

In this scheme, using FAHP, they first assigned the weights to four multi-criteria such as distance to WCV, residual energy, node location importance, and energy consumption rate for charging location determination, and to three multi-criteria for determining partial charging time such as energy consumption rate, residual energy, and node location importance, respectively. The assigned weights were compensated with VWA. On the basis of these weights, they select the best proper next charging position using TOPSIS and determine the partial charging time at every charging position by combinatorial optimization of three multi-criteria. In this scheme, a semi-on-demand CS with proactive charging was performed if there was a surplus for WCV's charging capability. To this end, the potential bottlenecked nodes among the non-cRNs were predicted using the relative weights of 3 multi-criteria, and among these predicted potential bottlenecked nodes, the most proper proactive charging nodes were selected using TOPSIS. Both of the above two methods assigned the weights to multiple criteria with FAHP using the PRS, thus overstating the real paired disparity and not considering the compromise of metrics including energy utilization efficiency, survival rate, and average charging latency in determining the PCT.

For settling these points, we developed a new on-demand CS method with FCNP using PIS [7]. The proposed scheme, called iFQS, first allocates the weights to five multi-criteria, including distance to WCV, residual energy, node location importance degree, energy consumption rate, and neighborhood energy weightage, and to three multi-criteria for determining the PCT such as energy severity [12], charging request issuing frequency [7], and neighborhood energy weightage [15]. Then, these five and three weights are used to design the compensation function in ranking of charging locations by Q-Learning to select the most suitable next charging locations, and the PCT at each charging

Table 1
Comparison of on-demand CS schemes

Paper	MCDM and intelligent method	Comparison scale		Weight compensation	Charging method		Partial charging time	
		Ratio	Interval		Full	Partial	fixed	variable
[14]	Fuzzy logic	No	No	No	Yes	No	Yes	No
[15]	AHP-TOPSIS	Yes	No	No	Yes	No	Yes	No
[25]	AHP-TOPSIS and NSGA-II	Yes	No	No	No	Yes	No	Yes
[12]	Fuzzy logic and Q-Learning	No	No	No	No	Yes	No	Yes
[13]	FAHP-VWA-TOPSIS	Yes	No	Yes	No	Yes	No	Yes
[7]	FCNP-Q-Learning	No	Yes	No	No	Yes	No	Yes
proposed	FCNP-VWA-MCDM(i)	No	Yes	Yes	No	Yes	No	Yes

location is determined adaptively by taking the compromise between metrics into account. The simulative results reveal that FCNP does not magnify the actual paired difference unlike FAHP of fuzzy PRS, thus very likely making the accurate decisions and greatly improving the charging performance in comparison with FAHP. FCNP uses fuzzy paired interval or differential scale to address the issue overestimating the actual paired disparity in FAHP. However, compensation of the assigned weights using FCNP was not proceeded and the combination with the several MCDM approaches was not considered.

Through the above consideration, it can be seen that most of the existing schemes use MCDM methods of PRS to overestimate the actual paired disparity between multi-criteria and FCNP of PIS for assigning weights to multi-criteria, where weight compensation has not been considered in case of latter. Especially, it is still unknown which is the best MCDM method when integrating FCNP with other MCDM methods.

In this work, we propose the integrated FCNP-VWA-MCDM(i) CS schemes where the weights assigned to multi-criteria with FCNP are compensated with VWA, and this is integrated with several MCDM methods to further improve the performance of the charging scheme. The comparison between CS schemes including our proposed schemes which use the multi-criteria and partial charging is shown in Table 1.

3. Preliminaries

3.1. Overview of the integrated FCNP-VWA-MCDM(i)

3.1.1. Weight assignment to multi-criteria by FCNP

Using the fuzzy PIS, it builds fuzzy paired opposite matrix (FPOM) with the triangular fuzzy number. Let a fuzzy utility set be $\widehat{V} = \left\{\widehat{v}_1, \cdots, \widehat{v}_n\right\}$, where the fuzzy individual utility has the form of $\widehat{v}_i = (v_i^l, v_i^\pi, v_i^u)$, and the comparison scale in fuzzy number is $\widehat{b}_{ij} \cong \widehat{v}_i - \widehat{v}_j$. By adopting this fuzzy PIS, we can denote FPOM as follows:

$$\widehat{B} = \left[\widehat{b}_{ij}\right] = \begin{bmatrix} \widehat{b}_{11} & \widehat{b}_{12} & \cdots & \widehat{b}_{1n} \\ \widehat{b}_{21} & \widehat{b}_{22} & \cdots & \widehat{b}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \widehat{b}_{n1} & \widehat{b}_{n2} & \cdots & \widehat{b}_{nn} \end{bmatrix} \quad (1)$$

where $\widehat{b}_{ij} = (b_{ij}^l, b_{ij}^\pi, b_{ij}^u) = -\widehat{b}_{ji} = (-b_{ji}^u, -b_{ji}^\pi, -b_{ji}^l)$ for $i, j = \overline{1, n}$ and $\widehat{b}_{ij} = (0, 0, 0)$ for $i = j$.

Verifying the fuzzy accordance index ($\widehat{AI}$) for $\widehat{B}$ is performed.

$$AI = (AI^l)^{1/4} \times (AI^\pi)^{1/2} \times (AI^u)^{1/4} \quad (2)$$

$\widehat{AI}$ is the weighted geometric average of (AI^l, AI^π, AI^u) for $\widehat{AI} \geq 0$. If $\widehat{AI} = 0$, then $\widehat{B}$ is definitely accordant. When $0 < \widehat{AI} \leq 0.1$, $\widehat{B}$ is satisfied and when $\widehat{AI} > 0.1$, $\widehat{B}$ is not satisfied.

From the accordance-verified FPOM $\widehat{B}$, the vector $\widehat{V} = \left\{\widehat{v}_1, \cdots, \widehat{v}_n\right\}$ of fuzzy individual utilities $\widehat{v}_i = (v_i^l, v_i^\pi, v_i^u)$ is gained from the fuzzy primitive least squares optimization model and also the fuzzy weight vector of criteria $\widehat{W} = \left\{\widehat{w}_1, \cdots, \widehat{w}_i, \cdots, \widehat{w}_n\right\}; \widehat{w}_i = (w_i^l, w_i^\pi, w_i^u)$ is obtained by normalizing the fuzzy individual utility of the fuzzy individual utility set $\widehat{V} = \left\{\widehat{v}_1, \cdots, \widehat{v}_n\right\}$.

From the fuzzy weights values, the crisp weight values are denoted by the column vectors as below.

$$w = (w_1, w_2, \cdots, w_M)^T \quad (3)$$

The following normalized decision matrix X will be input to VWA and MCDM(i).

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1M} \\ x_{21} & x_{22} & \cdots & x_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{NM} \end{bmatrix} \quad (4)$$

where the way of normalizing data dimension of criteria is the same as one in Chang et al. [27], and N and M are the number of alternatives and criteria, respectively.

3.1.2. Weight compensation by VWA

VWA is a method for fulfilling a procedure for the adaptation of the pre-assigned weights using a state variable weight vector. This method is particularly beneficial if the assignment of weights must be proceeded in advance. In CS of WRSNs, the adaptation of the pre-assigned weights based on multi-criteria values that characterize the cRNs is permitted by VWA. In other words, VWA automatically stresses significant criteria and weakens non-significant criteria.

The weight compensated by FCNP for the criterion j is computed.

$$w_j' = \frac{s(x_j)w_j}{\sum_{j=1}^{M} s(x_j)w_j}, \quad j = \overline{1, M} \tag{5}$$

In the above equation, $s(x_j)$ is E-SVWV with penalty for the criterion j and w_j is the weight for the criterion j which is allocated with FCNP. Here, we suggest the E-SVWV with penalty for criterion j. Different from FAHP, FCNP uses the E-SVWV with penalty. In FAHP adopting the PRS, it uses the E-SVWV with incentive to increase the weight of criterion as the state value is increased. However, the E-SVWV with penalty enlarges the weight of criterion when the value is decreased. That is, it satisfies the requirements for balancing criteria in decision-making in such a way as punishing the criteria with low level.

$$s(x_j) = e^{-\alpha|\overline{x}_j|\sigma_j}, \ \alpha \geq 0 \tag{6}$$

where α denotes the weights' variable level and σ is the variance which is calculated using the following equation:

$$\sigma_i = \left[\frac{1}{N}\sum_{i=1}^{N}(x_{ij} - \overline{x}_j)^2\right]^{1/2} \tag{7}$$

In the above equation, N and $|\overline{x}_j|$ denote the total number of alternatives and the absolute value of the mean, respectively.

$$|\overline{x}_j| = \left|\frac{\sum_{i=1}^{N} x_{ij}}{N}\right| \tag{8}$$

3.1.3. MCDM(i) for selecting reasonable alternatives

1) **TOPSIS**

An overview of TOPSIS follows [13, 15].

2) **VIKOR**

Step 1: For all criterion functions, the best f_j^* and the worst f_j^- values are determined using Equation (4) as follows:

$$f_j^* = \left(\left(\max_j x_{ij}\middle| j \in \overline{1, M}\right)\middle| i = \overline{1, N}\right) j = \overline{1, M} \tag{9}$$

$$f_j^- = \left(\left(\min_j x_{ij}\middle| j \in \overline{1, M}\right)\middle| i = \overline{1, N}\right) j = \overline{1, M} \tag{10}$$

Step 2: The average gap S_k and maximal gap R_k for each criterion are calculated.

$$S_k = \sum_{j=1}^{M} w_j' \left|f_j^* - x_{kj}\right| / \left|f_j^* - f_j^-\right|, \ k = \overline{1, N} \tag{11}$$

$$R_k = \max_j\left\{\left|f_j^* - x_{kj}\right| / \left|f_j^* - f_j^-\right| j = 1, 2, \cdots, m\right\} k = \overline{1, N} \tag{12}$$

where w_j' are the weights of criteria compensated by VWA, expressing their relative importance. It is calculated by Equation (5).

Step 3: The value Q_k for each criterion is calculated as follows:

$$\begin{aligned} Q_k = \nu(S_k - S^*)/(S^- - S^*) + \\ + (1-\nu)(R_k - R^*)/(R^- - R^*) \end{aligned} \quad k = \overline{1, N} \tag{13}$$

where $S^* = \min_k S_k$, $S^- = \max_k S_k$, $R^* = \min_k R_k$, $R^- = \max_k R_k$. ν denotes the weight of the strategy of "the majority of criteria", where $\nu = 0.5$.

Step 4: Sorting by the values S, R, and Q, in decreasing order, the alternatives are ranked. As a result, three ranking lists are obtained.

3) **ELECTRE-III**

Step 1: The indifference threshold $q_j(x_{ij})$ and preference threshold $p_j(x_{ij})$ are calculated using Equation (4) as follows:

$$q_j(x_{ij}) = \alpha_q + \beta_q x_{ij}, \quad j = \overline{1, M} \tag{14}$$

$$p_j(x_{ij}) = \alpha_p + \beta_p x_{ij}, \quad j = \overline{1, M} \tag{15}$$

where $p_j(x_{ij})$ and $q_j(x_{ij})$ can be solved in such a way that threshold values are one of the following cases:

1) Either constant (β equals zero and α has to be determined)
2) Proportional to x_{ij} (β has to be determined and α equals zero)
3) A form combining these two (both α and β have to be determined)

Step 2: Calculate the concordance index and discordance index. A concordance index $C(x_k, x_l)$ is computed for each pair of alternatives.

$$C(x_k, x_l) = \frac{\sum_{i=1}^{M} w_i' C_i(x_k, x_l)}{\sum_{i=1}^{M} w_i}, k = \overline{1, N}, \ l = \overline{1, N} \tag{16}$$

In the above equation, w_i' are the weights of the compensated criteria by VWA and $C_i(x_k, x_l)$ is the outranking degree of alternative x_k and alternative x_l under criterion i:

$$C_i(x_k, x_l) = \begin{cases} 0, & x_{li} - x_{ki} > p_i(x_{ki}) \\ 1, & x_{li} - x_{ki} \leq q_i(x_{ki}) \end{cases}, \quad i = \overline{1, M} \tag{17}$$

In the above equation, $0 < C_i(x_k, x_l) < 1$ when $q_i(x_{ki}) < x_{li} - x_{ki} \leq p_i(x_{ki})$.

For each criterion i, the veto threshold $v_i(x_{ki})$ is defined.

$$v_i(x_{ki}) = \alpha_v + \beta_v x_{ki}, \quad i = \overline{1, M} \tag{18}$$

Then, a discordance index $D_i(x_k, x_l)$, for each criterion i, is defined as follows:

$$D_i(x_k, x_l) = \begin{cases} 0, & x_{li} - x_{ki} \leq v_i(x_{ki}) \\ 1, & x_{li} - x_{ki} > v_i(x_{ki}) \end{cases}, \quad i = \overline{1, M} \tag{19}$$

where $0 < D_i(x_k, x_l) < 1$ when $p_i(x_{ki}) < x_{li} - x_{ki} \leq v_i(x_{ki})$.

Step 3: The outranking degree is calculated by Equation (20).

$$S(x_k, x_l) = \begin{cases} C(x_k, x_l), & D_j(x_k, x_l) \le C(x_k, x_l) \ \forall j \in J \\ C(x_k, x_l) \times \prod\limits_{j=J(a,b)} \frac{1-D_j(x_k,x_l)}{1-C(x_k,x_l)}, & D_j(x_k, x_l) > C(x_k, x_l) \end{cases} \tag{20}$$

where $J(x_k, x_l)$ represents the set of criteria which $D_j(x_k, x_l) > C(x_k, x_l)$.

Step 4: The ranking procedure used in ELECTRE-III is calculated as follows:

$$\delta_k = \sum_{l=1}^{N} S(x_k, x_l) - \sum_{l=1}^{N} S(x_l, x_k), \qquad k = \overline{1, N} \tag{21}$$

4) **PROMETHEE**

Step 1: Determine a function f_k for the normalized priority $p_k(d)$ of every criterion. There are several types of criterion such as usual criterion, quasi-one, level-one, linear one, and Gaussian one in the generalized preference functions.

Step 2: Calculate the aligning relation among the alternative x_k and alternative x_l using Equation (4) as follows:

$$\pi(x_k, x_l) = \sum_{i=1}^{M} w_i' \cdot p_i(x_{ki} - x_{li}) k = \overline{1, N}, \ l = \overline{1, N} \tag{22}$$

Here, w_i' are the weights of the criteria made compensation with VWA and calculated by Equation (5).

Step 3: Compute the leaving flow for every alternatives.

$$\Phi^+(x_k) = \frac{1}{T-1} \sum_{x_l \in A} \pi(x_k, x_l) \tag{23}$$

where T is the number of alternatives and A is a set of alternatives.

Step 4: Compute the entering flow for every alternative.

$$\Phi^-(x_k) = \frac{1}{T-1} \sum_{x_l \in A} \pi(x_l, x_k) \tag{24}$$

Step 5: Calculate the net flow for the completed ranking for each alternative.

$$\Phi^{net}(x_k) = \Phi^+(x_k) - \Phi^-(x_k) \tag{25}$$

In PROMETHEE method, the alternative with the higher the leaving flow and the lower the entering flow is better. What the alternative x_k has higher net flow compared to x_l means that x_k is better than x_l.

3.2. System model

The WRSN focused on this paper consists of sensor nodes randomly deployed in a two-dimensional plane, one WCV, and one fixed base station (BS) furnished with a rechargeable battery. Energy consumption of each sensor node with energy capacity of $E_i^{\max}$ can be classified into energy for data sensing, data transmission, and data reception. We also assume that the sensor nodes generate or relay unlike traffic and thus have unlike energy consumption rate. The WCV with energy capacity of $E_{MC}^{\max}$ goes to the place where the cRN is situated and recharges the nodes in a way recharging multiple nodes simultaneously. BS is placed at the center of the square monitoring area, collecting sensing data, communicating directly with the WCV. Time taken to exchange the battery of the WCV is negligible. It is assumed that the BS has exact information about location of each node in the whole network. Also, we assume that each node can communicated with other nodes, namely the network has not the isolated nodes. Here, the mean number of cRNs $n_{average}$ which can be charged by a WCV during a charging round is just considered as the WCV's charging capability. Using the charging capability of the WCV, the maximum allowable latency of cRNs is the time that a charging request generated in the worst case has to wait without serving in the service queue, which is set twice the duration of one charging round.

In this paper, energy model of Rault [6] is used. Energy $E_i^{receive}$ that sensor nodes receive within radius r charged by the WCV arriving at the position of sensor node i is expressed as follows:

$$E_i^{receive} = \eta \times v_{charge} \tag{26}$$

where $\eta \in (0, 1)$ denotes the efficiency of the wireless power transfer between WCV and a RN, v_{charge} is the charging rate, which is the energy rate emitted by the WCV during the unit time. Since the charging radius is usually small, all nodes within the radius r are considered to receive the same energy. On the other hand, since the WCV adopts a partial charging scheme, time taken for charging node i up to the partial charging threshold $E_i^{pc\_thre}$ is formulated as $t_i^{pc\_thre} = E_i^{pc\_thres} / E_i^{receive}$, and thus, time taken to partially charge nodes within the charging radius r (about 2.7 m) of the WCV is denoted as follows:

$$t_i^{pc\_thres} = \max_{i \in V_i^{CR}} t_i^{pc\_thres} \tag{27}$$

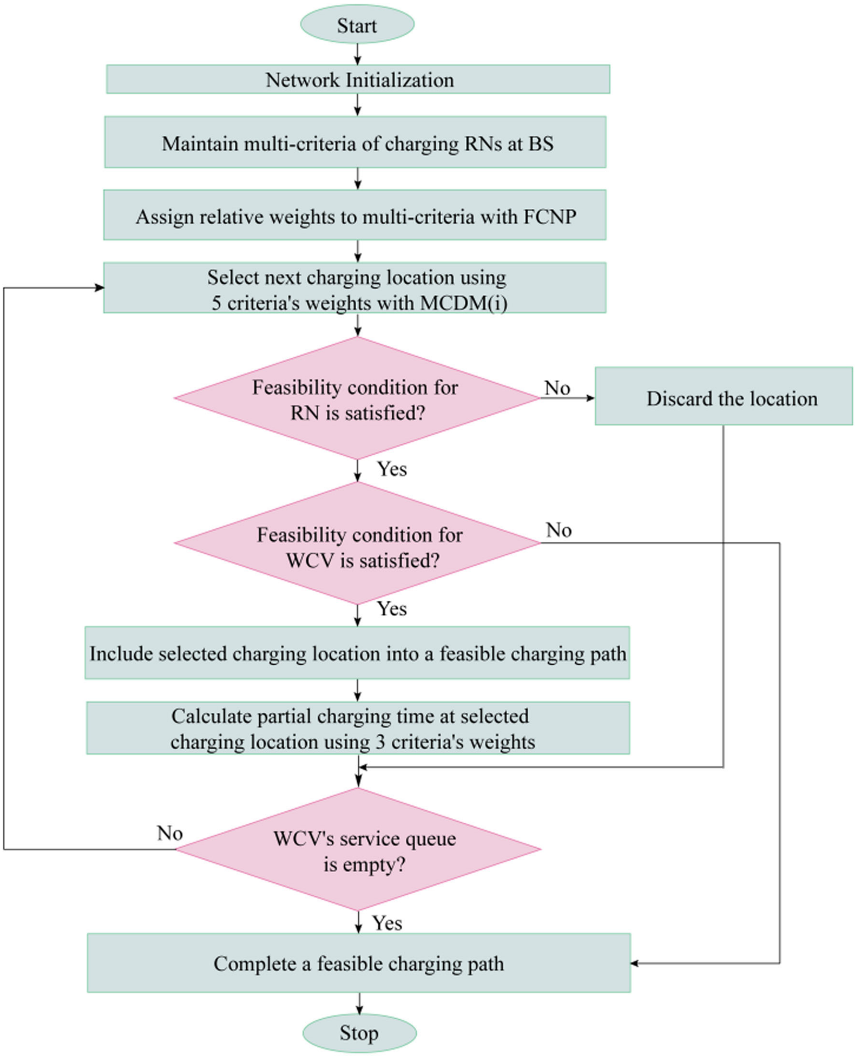
where V_i^{CR} is the set of RNs within the charging range at the charging location where a RN i is located.

The system operation is proceeded as bellow. BS holds the service requests from the nodes in its queue. If residual energy falls to a threshold, sensor nodes generate a message that requires recharging and forward it to BS either in a single hop or in a multi-hop way. Once more and more cRNs issue charging requests and the WCV's charging capability is full, the BS makes a charging schedule and passes it to the WCV. The WCV departs the BS and moves to where cRNs are located for charging them in a partial charging scheme. When recharging $n_{average}$ of sensor nodes, the WCV comes back the BS is replenished energy and is on standby for the next charging round. If more than $n_{average}$ of charging requests occur and exceed the charging capacity of one WCV, the BS lets the sensor nodes to issue charging requests when reaching the residual energy threshold defined by the increased maximum allowable waiting time.

4. Proposed Scheme

The fundamental working principles of the proposed schemes are as follows. The BS determines the relative weights for the three and five multi-criteria distinguishing cRNs using FCNP and

Figure 1
Main operation flow diagram of the proposed methods



use VWA to compensate them to acquire the correct weights relatively. As soon as the number of cRNs attains the WCV's charging capacity, the recharging schedule is made by choosing the best proper next charging locations with MCDM(i) which uses the weights of 5 multi-criteria allocated with FCNP-VWA. Here, MCDM(i) methods for selecting the next charging locations are denoted as follows, respectively.

$$MCDM(i) = \begin{cases} TOPSIS, & i = 1 \\ VIKOR, & i = 2 \\ ELECTRE, & i = 3 \\ PROMETHEE, & i = 4 \end{cases} \tag{28}$$

While drawing up the charging schedule, the PCT of every charging position is computed with the weights of 3 multi-criteria assigned using FCNP-VWA. These integrated methods take advantage of FCNP-VWA to cope with vagueness and uncertainty of assigning weights to multi-criteria and evaluating the cRNs, thereby enhancing the charging and overall network performance in comparison with using FCNP-VWA or MCDM(i) method alone.

The main operation of on-demand CS methods on the basis of the integrated FCNP-VWA-MCDM(i) is shown in Figure 1. Since CS uses multi-node charging scheme, cRNs in the radius r from the chosen charging position are eliminated from the charging schedule. While making charging schedule, two feasibility decisions are performed by the BS for the selected charging locations and WCV. At this time, the charging schedule is made in such a way that the charging locations where the conditions are all satisfied are included in the charging schedule and the BS passes it to the WCV.

4.1. Weighting multi-criteria by FCNP-VWA

4.1.1. Weighting of three criteria

The 3 multi-criteria for calculating the PCT of every cRNs include energy severity (ES) [12], charging request issuing frequency (CRIF) [7], and neighborhood energy weightage (NEW) [15]. First, relative weights are assigned to each criterion by FCNP as the triangular fuzzy number based on the fuzzy PIS as shown in Table 2.

Then, we perform the accordance conformation on the composed fuzzy paired comparison matrix. The result is $AI = 0$, thus

Table 2
The fuzzy paired comparison matrix among criteria

	ES	CRIF	NEW
ES	0	7^+	8^+
CRIF	7^-	0	3^+
NEW	8^-	3^-	0

Table 3
Criteria' weights made compensation

Criteria	Weights	Compensated weights
ES	0.4938	0.5184
CRIF	0.2840	0.2340
NEW	0.2222	0.2476

Table 4
The fuzzy paired comparison matrix between criteria

	RE	Dis	ECR	NLID	NEW
RE	0	5^+	0	6^+	7^+
Dis	5^-	0	5^-	2^+	3^+
ECR	0	5^+	0	6^+	7^+
NLID	6^-	2^-	6^-	0	2^+
NEW	7^-	3^-	7^-	2^-	0

Table 5
Compensated weight of evaluation criteria

Assessment criteria	Weights	Compensated weights
RE	0.2667	0.2749
Dis	0.1778	0.1793
ECR	0.2667	0.2121
NLID	0.1556	0.1613
NEW	0.1332	0.1724

satisfying the consistency. The allocated weights to every criterion using FCNP are normalized and then made compensation with VWA (Table 3). We set the state variable vector value as 0.1.

4.1.2. Weighting of five criteria

In charging location ranking design, the five criteria are adopted: residual energy (RE), distance to WCV (Dis), energy consumption rate (ECR), node location importance degree (NLID) [28], and neighbor energy weightage (NEW). Here, the node location importance is a criterion that indicates the importance of each grid when it is considered that we divide the entire monitoring area of the network into a number of discrete grids [13]. We define the importance of the grid as the appearance frequency of the monitored object appearing within the grid. Table 4 shows the paired comparison matrix for allocating the weights to criteria.

The accordance verification results for the constructed fuzzy paired comparison matrices are all $AI = 0$ and so the consistency is completely satisfied. The normalized weights of each of the evaluation criteria compensated by VWA are shown in Table 5.

4.2. Next charging location selection by MCDM(i)

After performing the data dimension normalization on the values of the quantitative criteria for every cRN, the decision matrix is formed. An example of criteria' values for 6 cRNs before and after normalization is shown in Table 6.

4.2.1. TOPSIS

The compensated weights of each criterion in Table 5 are used to reconstruct the decision matrix used in TOPSIS (Table 7).

From the reconstructed decision matrix in Table 7, the positive ideal solution and the negative ideal solution are calculated in Table 8.

Table 7
Reconstructed decision matrix

	RE	Dis	ECR	NLID	NEW
cRN1	0.9906	0.4616	1.7922	0.3363	0
cRN2	0.8631	0.7210	1.3940	0.6074	0.0854
cRN3	0.8267	0.6509	1.2612	0.4556	0
cRN4	0.4224	0.3507	2.0578	0.7918	0.3806
cRN5	0.9068	0.7259	1.4603	0.5098	0.1825
cRN6	1.3292	0.8858	1.5267	0.3579	0.2097

Table 8
The positive and negative ideal solutions

Ideal solution	RE	Dis	ECR	NLID	NEW
Positive ideal solution	0.4224	0.3507	2.0578	0.7918	0.3806
Negative ideal solution	1.3292	0.8858	1.2612	0.3363	0

Table 6
Criterion values of RNs

	In front of normalization					In rear of normalization				
	RE	Dis	ECR	NLID	NEW	RE	Dis	ECR	NLID	NEW
cRN1	27.2	28.3	0.0027	0.31	0	3.7146	2.5967	6.7209	2.1616	0
cRN2	23.7	44.2	0.0021	0.56	0.22	3.2366	4.0556	5.2274	3.9049	0.6408
cRN3	22.7	39.9	0.0019	0.42	0	3.1000	3.6611	4.7295	2.9286	0
cRN4	11.6	21.5	0.0031	0.73	0.98	1.5842	1.9728	7.7166	5.0903	2.8543
cRN5	24.9	44.5	0.0022	0.47	0.47	3.4005	4.0832	5.4763	3.2773	1.3689
cRN6	36.5	54.3	0.0023	0.33	0.54	4.9846	4.9824	5.7252	2.3011	1.5728

Table 9
Priorities of RNs

RN	S_i^+	S_i^-	CC_i	Priority
cRN1	0.8706	0.7593	0.4659	2
cRN2	0.9450	0.5856	0.3826	3
cRN3	1.0705	0.5674	0.3464	5
cRN4	0	1.4476	1	1
cRN5	0.9225	0.5542	0.3753	4
cRN6	1.2681	0.3390	0.2110	6

Next, the distances between the positive ideal solution and the negative one, S_i^+ and S_i^- are computed, respectively. Subsequently, based on them, the closeness to the positive ideal solution, CC_i is computed for each of RNs. Table 9 shows the priorities determined by the closeness CC_i.

4.2.2. VIKOR

From the normalized decision matrix of Table 6, we determine the best f_j^* and the worst f_j^- and using it calculate the average interval S_k and the maximum interval R_k of each cRN. Substituting S_k and R_k into Equation (13) to obtain Q_k and rank in decreasing order, the same priority as Table 10 is obtained.

Table 10
Priority of RNs

RN	S_k	R_k	Q_k	Priority
cRN1	0.6138	1	0.8713	4
cRN2	0.6334	0.8333	0.7998	3
cRN3	0.7267	1	0.9395	5
cRN4	0	0	0	1
cRN5	0.6212	0.7500	0.7507	2
cRN6	0.8266	1	1	6

4.2.3. ELECTRE-III

Table 11 represents the calculated indifference threshold q_j, preference threshold p_j, and veto threshold v_j of each criterion.

Calculation results of the paired comparison concordance and discordance from the normalized decision matrix in Table 6 are shown in Tables 12 and 13. Here, Table 13 shows the values of discordance index for NEW criterion.

Table 11
The indifference and preference thresholds

	RE	Dis	ECR	NLID	NEW
q_j	0.06	0.08	0.001	0.5	0.8
p_j	0.02	0.03	0.0005	0.3	0.5
v_j	0.005	0.006	0.0002	0.05	0.2

Table 12
Concordance

	cRN1	cRN2	cRN3	cRN4	cRN5	cRN6
cRN1	1	0.8561	0.9185	0.2124	0.7818	0.8336
cRN2	0.7439	1	1	0.1278	0.9723	0.9335
cRN3	0.7626	0.9329	1	0.0655	0.7821	0.6972
cRN4	1	1	1	1	1	1
cRN5	0.7428	0.9751	1	0.0706	1	1
cRN6	0.6956	0.6988	0.7452	0.0479	0.7941	1

Table 13
Discordance (for NEW criterion)

	cRN1	cRN2	cRN3	cRN4	cRN5	cRN6
cRN1	0	0	0	1.0000	0	0.1333
cRN2	0	0	0	0.8667	0	0
cRN3	0	0	0	1.0000	0	0.1333
cRN4	0	0	0	0	0	0
cRN5	0	0	0	0.0333	0	0
cRN6	0	0	0	0	0	0

The degree of outranking is shown in Table 14.

Table 14
Degree of outranking

	cRN1	cRN2	cRN3	cRN4	cRN5	cRN6
cRN1	1	0.8561	0.9185	0	0.7818	0.8336
cRN2	0.7439	1	1	0	0.9723	0.9335
cRN3	0.7626	0.9329	1	0	0.7821	0.6972
cRN4	1	1	1	1	1	1
cRN5	0.7428	0.9751	1	0.0057	1	1
cRN6	0.6956	0.6988	0.7452	0.0003	0.7941	1

Table 15 shows the priority of cRNs.

Table 15
Priority of cRNs

Request node	$S(x_k, x_l)$	$S(x_l, x_k)$	δ_k	Priority
cRN1	4.3899	4.9450	−0.5550	2
cRN2	4.6497	5.4629	−0.8132	4
cRN3	4.1747	5.6637	−1.4890	5
cRN4	6	1.0060	4.9940	1
cRN5	4.7236	5.3302	−0.6067	3
cRN6	3.9342	5.4643	−1.5301	6

4.2.4. PROMETHEE

Using Table 6, the paired comparison aligning relationship is obtained as shown in Table 16.

For every cRN, the "leaving flow" Φ^+ and "entering flow" Φ^- are calculated, and then, the priority of cRNs is determined based on these values as shown in Table 17.

Table 16
Aligning relation

	cRN1	cRN2	cRN3	cRN4	cRN5	cRN6
cRN1	0	0.3913	0.3913	0	0.3913	0.6663
cRN2	0.6087	0	0.5458	0	0.6155	0.6155
cRN3	0.4363	0.4542	0	0	0.4542	0.6155
cRN4	1	1	1	0	1	1
cRN5	0.6087	0.3845	0.5458	0	0	0.6155
cRN6	0.3337	0.3845	0.3845	0	0.3845	0

Table 17
Priority of cRNs

RN	Φ^{+}	Φ^{-}	Φ^{net}	Priority
cRN1	0.3681	0.5975	−0.2294	5
cRN2	0.4771	0.5229	−0.0458	2
cRN3	0.3920	0.5735	−0.1814	4
cRN4	1	0	1	1
cRN5	0.4309	0.5691	−0.1382	3
cRN6	0.2974	0.7026	−0.4051	6

4.3. PCT determination

BS calculates the PCT at every charging position with the weights of 3 multi-criteria decided with the FCNP-VWA in rear of selection of the charging position. At this time, the three multi-criteria such as energy severity (ES) Learning [12], charging request issuing frequency (CRIF) [7], and neighborhood energy weightage (NEW) Learning [15] are used for calculating the PCT. The determination method of PCT refers to Learning [13]. It is noted that lower CRIF implies that the cRNs can take longer PCT, thereby BS gives higher charging weight in comparison with the case with high CRIF and this criterion affects the desirable disparity among several metrics.

Algorithm 1 shows the pseudocode of the proposed methods.

Algorithm 1. Integrated FCVM(i)-based on-demand CS
Input: Set of RNs rn, Location coordinates of each node i ∈ rn (x_i, y_i), A feasible charging path $FCP_k \leftarrow \{BS\}$

Output: A virtual closed path FCP_k

```
BS store information of RNs in service queue;
Determine charging request threshold by maximum
    allowable latency;
Assign relative weight to each criterion with FCNP;
Compensate weights with VWA;
Select the next charging location with MCDM(i);
 if feasibility condition for selected location i is
    satisfied then
   if feasibility condition for WCV is satisfied then
     FCP_k ← FCP_k ∪ {i};
     rn ← rn * {V_i^CR}; remove request nodes falling
   within the charging radius r of node i
     Calculate PCT at selected charging location;
     Update the quantitative values of criteria for
   remaining RNs;
     i ← i + V_i^CR;
  else
     i = 0;
     return FCP_k;
  endif
else
  if i = |rn| then
    i = 0;
    return FCP_k;
  else
    i ← i + 1;
    repeat Select the next charging location;
    until |rn| ← 0;
  endif
Endif
```

5. Performance Evaluation

5.1. Simulation environment

The simulation is performed in a WRSN with nodes distributed in a 2D plane of 100 m × 100 m. The number of nodes varies from 400 to 700, and the position of BS is the center of the network. A Voronoi graph-defined polygon represents the effective monitoring area of each sensor node-the grid. The whole network area with blue dots of locations such as roads and battlefields with high location importance is shown in Figure 2.

Figure 2
Experimental environment for extensive simulation

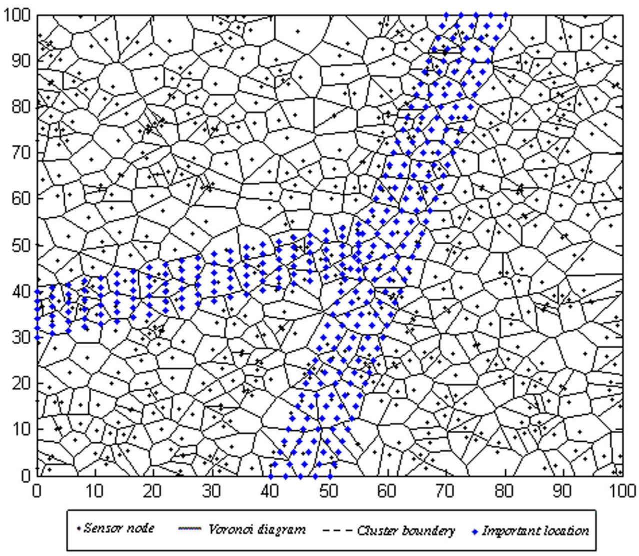


Table 18
Simulation parameters

Parameter	Value
Size of the network	100 × 100 m^2
Location of the BS	(50,50)
Number of sensor nodes	400–700
Capacity of each sensor node	200 J
Capacity of the WCV	40000 J
Moving energy consumption rate of the WCV	10 J/m
Moving speed of the WCV	1 m/s
Charging rate of the WCV	4 J/s
Charging energy efficiency rate	0.68
Simulation time	70 h

In the figure, the frequency of targets appearing in the blue regions is twice higher than in the other locations. The sensor node and the WCV have capacity of 200 J and 40000 J, respectively, and the traveling speed of the WCV is 1 m/s and the mobile ECR is 10 J/m. For a fair comparison, we present average experimental results obtained through 20 simulations. The parameters used in the experiment are shown in Table 18.

In the simulation, comparison between the proposed methods and two existing methods, AHP-TOPSIS [15] and FAHP-VWA-TOPSIS [9], are performed. According to the main objective of this study and for a fair comparison, the AHP-TOPSIS method, which operates in a full charging mode employs a partial charging mode, decides the maximal allowable latency in proportion to the number of cRNs within the network and changes the thresholds of sensor nodes accordingly. In addition, the AHP-TOPSIS and FAHP-VWA-TOPSIS methods use the same multi-criteria as the FCVM(i). On the whole, it is assumed that all the conditions for simulation for all the compared methods including the FCVM(i) are the same.

5.2. Simulation results and analysis

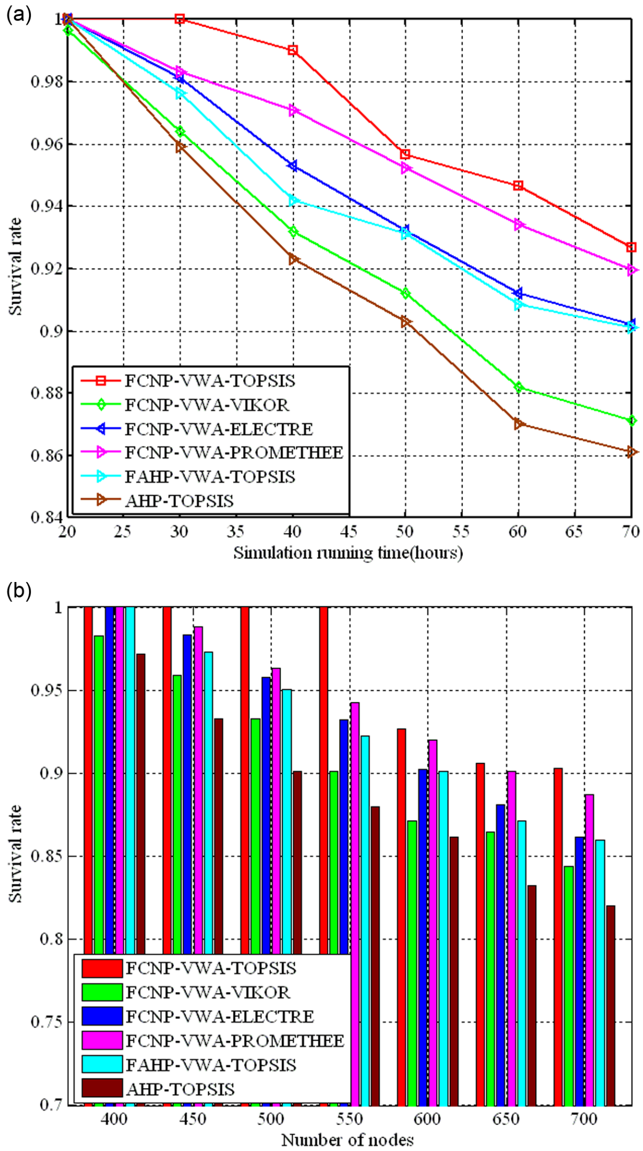
5.2.1. Survival rate

The survival rates of compared methods with varying the number of sensor nodes and simulation running time are shown in Figure 3(a) and (b), respectively.

From these results, we can see that the FCVM(1), that is, FCNP-VWA-TOPSIS method, for all cases, has the highest survival rate. This means that the TOPSIS is the best method among the MCDMs for the reasonable charging location selection which is integrated with the MCDM assigning relative weights to the multi-criteria.

Then, ranking the compared methods in order of the survival rate, the FCVP(4) is the second, the third the FCVP(3), the fourth the FAHP-VWA-TOPSIS, the fifth the FCVP(2), and the last the AHP-TOPSIS. The FAHP-VWA-TOPSIS has higher survival rate than the FCNP-VWA-VIKOR, because this method uses the TOPSIS to order the charging locations although the FAHP-VWA

Figure 3
Survival rate in various (a) simulation running time and (b) number of nodes



assigns poorer weights than the FCNP-VWA to the multi-criteria. The AHP-TOPSIS method reveals the most miserable survival rate.

It is because the AHP assigns the most exaggerated weights to the multi-criteria although the TOPSIS is the best MCDM method to select the reasonable charging locations.

Among the FCVM(i) methods, the FCVM(2), that is, FCNP-VWA-VIKOR method shows the most miserable survival rate. This indubitably indicates that no matter how correct the FCNP-VWA may assign, the VIKOR chooses the charging locations more irrationally compared to the TOPSIS, ELECTRE, and PROMETHEE methods.

5.2.2. Energy usage efficiency

The simulation results of energy usage efficiency of FCVM(i) are shown in Figure 4(a) and (b).

Among the MCDM(i) and the other two compared methods, the FCVM(4) method has the highest energy usage efficiency with varying the number of nodes and running time, and the FCVM(1) is the second. The next order in energy usage efficiency metric is the FCVM(3). The FAHP-VWA-TOPSIS method shows higher energy usage efficiency than the FCVM(2). Although the FAHP-VWA-TOPSIS method uses the FAHP-VWA which is relatively poorer than the FCNP-VWA to assign the weights, it has higher energy usage efficiency in comparison with the FCVM(2). This means that the TOPSIS significantly contributes to not only embracing more cRNs in charging path but also making the traveling distance for recharging short relatively, thereby increasing the amount of energy made over to nodes. Since the AHP-TOPSIS method assigns the most exaggerated weights to the multi-criteria, it reveals the most miserable simulation results concerning energy usage efficiency compared to other integrated MCDMs for all cases.

5.2.3. Average charging latency

Next, we compare the average charging latency for all the compared methods.

Figure 4
Energy usage efficiency in various (a) simulation running time and (b) number of nodes

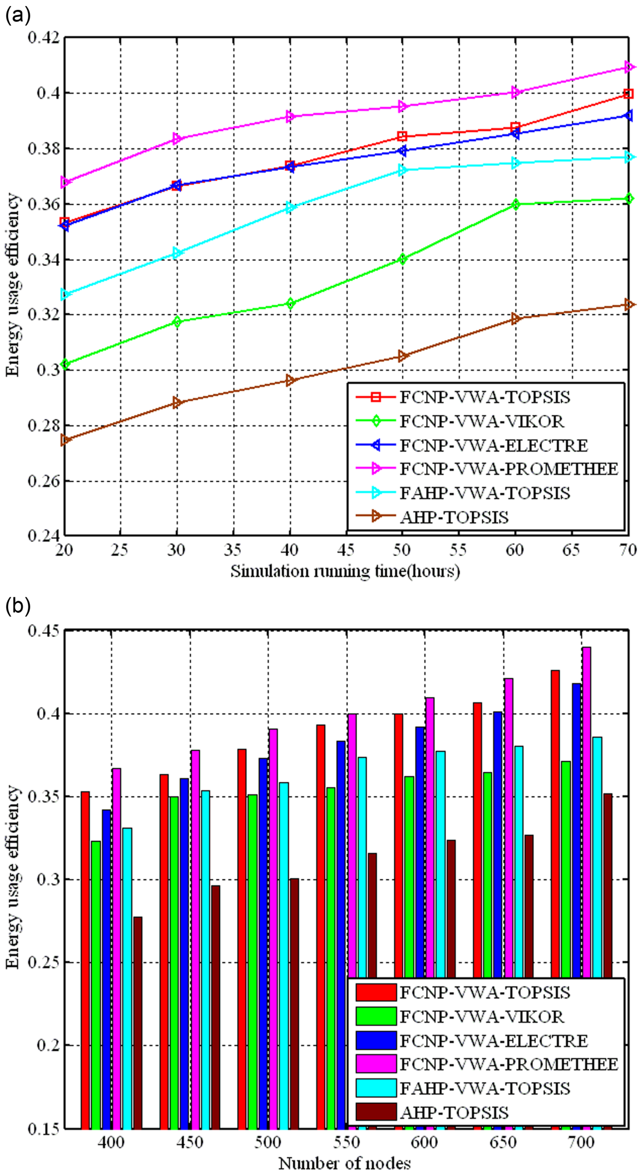
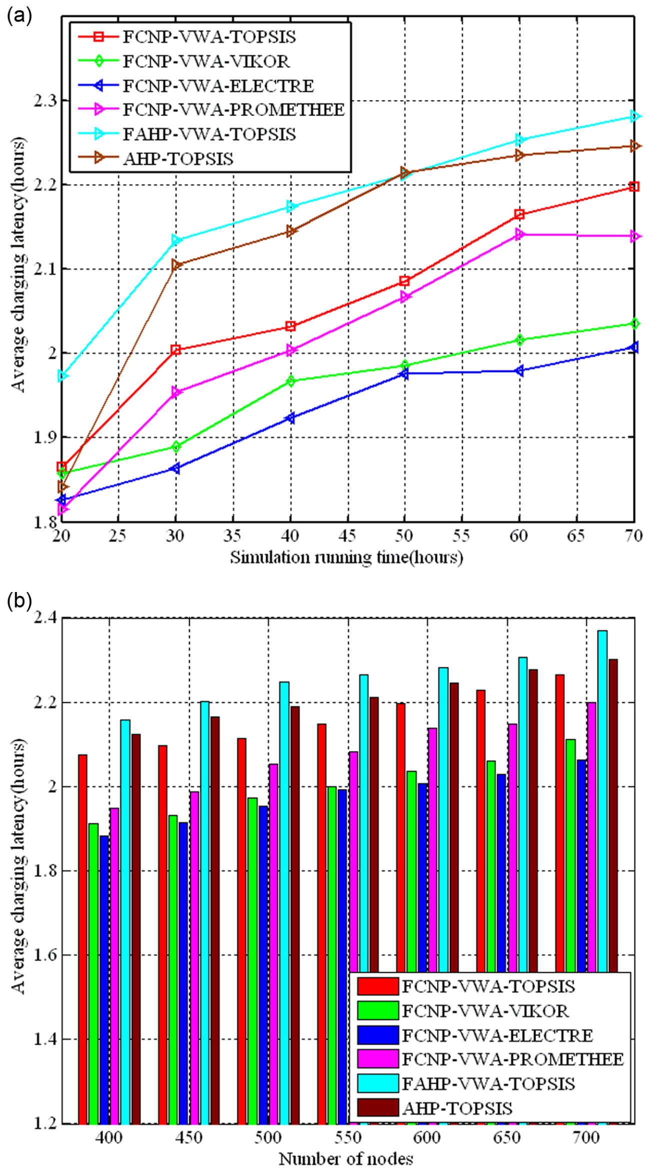


Figure 5
Average charging latency in various (a) simulation running time and (b) number of nodes



In Figure 5(a) and (b), we notice that as the running time of simulation and the number of sensor nodes increase, the average charging latency of the FCVM(3) method increases and is shorter than those of all the other methods. Namely, FCVM(3) method shows the shortest average charging latency in all cases of these simulation results. The next order concerning this metric is the FCVM(2) method. These two methods use the ELECTRE and VIKOR as the MCDMs for selecting the charging locations, respectively. As considered in the simulation analysis in terms of the survival rate metric, the VIKOR and ELECTRE choose the charging locations more irrationally than the TOPSIS or PROMETHEE, thereby resulting in the miserable survival rate. After all, since the number of surviving nodes is usually smaller than the other methods using the TOPSIS or PROMETHEE as the MCDMs for selecting the charging locations, the FCVM(3) and FCVM(2) methods result in shorter waiting time in the service queue, thus making the average charging latency relatively small.

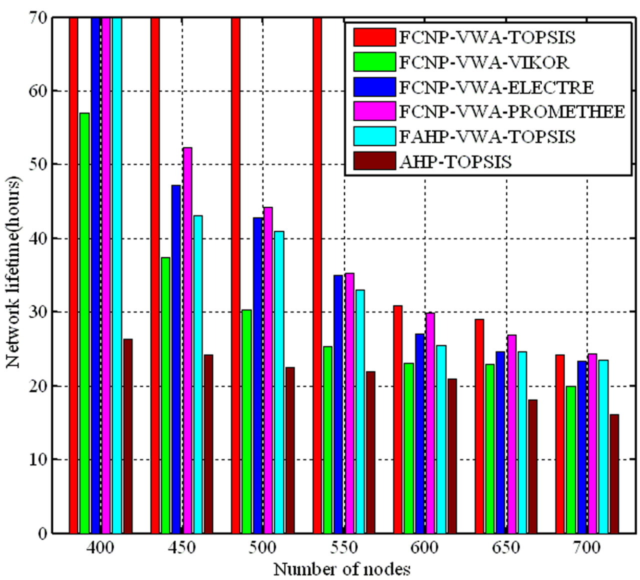
The FAHP-VWA-TOPSIS method reveals the longest average charging latency and what comes to the next is the AHP-TOPSIS. The average charging latency of FCVM(i) methods is shorter than those of the FAHP-VWA-TOPSIS and AHP-TOPSIS methods. This is because the FCVM(i) methods use the FCVP-VWA to proceed with the correct evaluation of weights compared to the FAHP-VWA using fuzzy PRS, thus reducing the waiting time in service queue and traveling distance.

5.2.4. Network lifetime

Finally, network lifetime is investigated according to varying the number of nodes.

From the simulation results in Figure 6, we can see that FCVM(1) method has the longest network lifetime. When the number of nodes is 550, the network lifetime of this method is 275.6%, 200.2%, 198.3%, 212.2%, and 318.9% longer in comparison with FCVM(2), FCVM(3), FCVM(4), FAHP-VWA-TOPSIS, and AHP-TOPSIS, respectively. The FCVM(4) is the next and is superior to the other methods for all cases of number of nodes.

Figure 6
Network lifetime in various number of nodes



Continuously, ranking the compared methods in the order of network lifetime, the FCVM(3) is the first, the FAHP-VWA-TOPSIS is the second, the FCVM(2) the third, and the AHP-TOPSIS the last. The FCVM(2) method reveals more miserable network lifetime than the FAHP-VWA-TOPSIS using fuzzy PRS, because it uses the VIKOR to select the charging locations.

On the whole, FCVM(1), that is, FCNP-VWA-TOPSIS method is the first, the second, the third (note that it has longer charging latency due to letting more nodes survive) among FCVM(i) methods in terms of three performance metrics such as energy usage efficiency, survival rate, and average charging latency, respectively, after all revealing the longest network lifetime. This finding implicates that it maximizes the network lifetime without doubt when developing on-demand CS scheme by exploiting FCVM(1) method.

From the results and analysis of the simulative experiment, it may be given a conclusion that the TOPSIS is the best method among the MCDMs integrated with the FCVP-VWA while the VIKOR method is improper for the MCDM to select the charging locations by integrating with the FCVP-VWA.

6. Conclusion

This paper proposes the novel on-demand CS methods called FCVM(i) that determines the weights of the multiple criteria discriminating cRNs using FCNP-VWA, applies these weights to determine the PCT of cRNs, and combines several other MCDM methods with FCNP-VWA to make the charging schedule. Extensive simulation results show that the TOPSIS gives the best performance among MCDM methods for next charging location selection. This FCNP-VWA-TOPSIS can be also applied in several branches of wireless sensor networks (WSNs) such as clustering including selection of cluster head (CH) node and routing effectively as well as in on-demand CS in WRSNs.

We will more and more enhance the performance by applying fuzzy logic to all MCDM methods used for charging path planning of WRSNs. In addition, the design idea of integrating FCNP-VWA with other MCDM methods will be further extended in the direction of integrating FCNP-VWA with meta-heuristic algorithms like particle swarm optimization (PSO), grey wolf optimization (GWO) and emperor penguin optimization (EPO), etc.

Abbreviations

AHP	Analytic hierarchy process
BS	Base station
cRN	Charging request node
CH	Cluster head
CRIF	Charging request issuing frequency
CS	Charging scheduling
Dis	Distance to BS
ECR	Energy consumption rate
ELECTRE	Elimination et choice translating reality
EPO	Emperor penguin optimization
ES	Energy severity
E-SVWV	Exponent type state variable weight vector
FPOM	Fuzzy paired opposite matrix
GWO	Grey wolf optimization

MCDM	Multi-criteria decision-making
NEW	Neighborhood energy weightage
NLID	Node location importance degree
PCT	Partial charging time
PIS	Paired interval scale
PROMETHEE	Preference ranking organization method for enrichment evaluation
PRS	Paired ratio scale
PSO	Particle swarm optimization
RE	Residual energy
RN	Request node
TOPSIS	Technique for order preference by similarity to ideal solution
VIKOR	VIsekriterijumska Optimizacija i Kompromisno Resenje
VWA	Variable weight analysis
WCV	Wireless charging vehicle
WRSN	Wireless rechargeable sensor network

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data used to support the finding of this study are available from the corresponding author upon request.

Author Contribution Statement

Ju Song Rim: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing – original draft, Writing – Review & Editing, Visualization, Project administration. **Man Gun Ri:** Conceptualization, Validation, Resources, Writing – Review & Editing, Supervision, Funding acquisition. **Se Hun Pak:** Validation, Investigation. **U Song Kim:** Data Curation.

References

[1] Huong, T. T., Binh, H. T. T., Le Nguyen, P., Long, D. C. T., An, V. D., & Vinh, L. T. (2020). Optimizing charging locations and charging time for energy depletion avoidance in wireless rechargeable sensor networks. In *IEEE Congress on Evolutionary Computation*, 1–8. https://doi.org/10.1109/CEC48606.2020.9185750

[2] Zhao, C., Zhang, H., Chen, F., Chen, S., Wu, C., & Wang, T. (2020). Spatiotemporal charging scheduling in wireless rechargeable sensor networks. *Computer Communications*, *152*, 155–170. https://doi.org/10.1016/j.comcom.2020.01.037

[3] Cheng, R. H., Yu, C. W., Xu, C., & Wu, T. K. (2020). A distance-based scheduling algorithm with a proactive bottleneck removal mechanism for wireless rechargeable sensor networks. *IEEE Access*, *8*, 148906–148925. https://doi.org/10.1109/ACCESS.2020.3015911

[4] Gharaei, N., Al-Otaibi, Y. D., Butt, S. A., Malebary, S. J., Rahim, S., & Sahar, G. (2021). Energy-efficient tour optimization of wireless mobile chargers for rechargeable sensor networks. *IEEE Systems Journal*, *15*(1), 27–36. https://doi.org/10.1109/JSYST.2020.2968968

[5] Han, G., Guan, H., Wu, J., Chan, S., Shu, L., & Zhang, W. (2019). An uneven cluster-based mobile charging algorithm for wireless rechargeable sensor networks. *IEEE Systems Journal*, *13*(4), 3747–3758. https://doi.org/10.1109/JSYST.2018.2879084

[6] Rault, T. (2019). Avoiding radiation of on-demand multi-node energy charging with multiple mobile chargers. *Computer Communications*, *134*, 42–51. https://doi.org/10.1016/j.comcom.2018.11.002

[7] Ri, M. G., Kim, C. H., Pak, S. H., & Pong, C. M. (2024). iFQS: An integrated FCNP-Q-learning-based scheduling algorithm for on-demand charging in wireless rechargeable sensor networks. *International Journal of Distributed Sensor Networks*, *2024*(1), 4418058. https://doi.org/10.1155/2024/4418058

[8] Ri, M. G., Kim, I. G., Pak, S. H., Jong, N. J., & Kim, S. J. (2024). An integrated MCDM-based charging scheduling in a WRSN with multiple MCs. *Peer-to-Peer Networking and Applications*. https://doi.org/10.1007/s12083-024-01705-y **AQ1**

[9] Wang, K., Wang, L., Obaidat, M. S., Lin, C., & Alam, M. (2021). Extending network lifetime for wireless rechargeable sensor network systems through partial charge. *IEEE Systems Journal*, *15*(1), 1307–1317. https://doi.org/10.1109/JSYST.2020.2968628

[10] Xu, W., Liang, W., Jia, X., Kan, H., Xu, Y., & Zhang, X. (2021). Minimizing the maximum charging delay of multiple mobile chargers under the multi-node energy charging scheme. *IEEE Transactions on Mobile Computing*, *20*(5), 1846–1861. https://doi.org/10.1109/TMC.2020.2973979

[11] Zhu, J., Feng, Y., Liu, M., Chen, G., & Huang, Y. (2018). Adaptive online mobile charging for node failure avoidance in wireless rechargeable sensor networks. *Computer Communications*, *126*, 28–37. https://doi.org/10.1016/j.comcom.2018.05.002

[12] Nguyen, P. L., La, V. Q., Nguyen, A. D., Nguyen, T. H., & Nguyen, K. (2021). An on-demand charging for connected target coverage in WRSNs using fuzzy logic and Q-learning. *Sensors*, *21*(16), 5520. https://doi.org/10.3390/s21165520

[13] Ri, M., Ko, J., Pak, S., Song, Y., & Kim, C. (2023). Notice of removal: Exploiting an integrated FAHP-VWA-TOPSIS in whole-process of on-demand charging scheduling for WRSNs. *IEEE Systems Journal*, *17*(4), 6634–6644. https://doi.org/10.1109/JSYST.2023.3302870

[14] Tomar, A., Muduli, L., & Jana, P. K. (2021). A fuzzy logic-based on-demand charging algorithm for wireless rechargeable sensor networks with multiple chargers. *IEEE Transactions on Mobile Computing*, *20*(9), 2715–2727. https://doi.org/10.1109/TMC.2020.2990419

[15] Tomar, A., & Jana, P. K. (2021). A multi-attribute decision making approach for on-demand charging scheduling in wireless rechargeable sensor networks. *Computing*, *103*(8), 1677–1701. https://doi.org/10.1007/s00607-020-00875-w

[16] Tomar, A., Muduli, L., & Jana, P. K. (2019). An efficient scheduling scheme for on-demand mobile charging in wireless rechargeable sensor networks. *Pervasive and Mobile Computing*, *59*, 101074. https://doi.org/10.1016/j.pmcj.2019.101074

[17] Yuen, K. K. F. (2014). Fuzzy cognitive network process: Comparisons with fuzzy analytic hierarchy process in new

product development strategy. *IEEE Transactions on Fuzzy Systems*, *22*(3), 597–610. https://doi.org/10.1109/TFUZZ.2013.2269150
[18] Zeng, W., Li, D., & Wang, P. (2016). Variable weight decision making and balance function analysis based on factor space. *International Journal of Information Technology & Decision Making*, *15*(5), 999–1014. https://doi.org/10.1142/S021962201650022X
[19] Falch, L., & de Silva, C. W. (2023). Improvement of VIKOR method with application to multi-objective design problems. *International Journal of Information Technology & Decision Making*, *22*(2), 777–802. https://doi.org/10.1142/S0219622022500493
[20] Khan, H. U., Ali, F., Sohail, M., Nazir, S., & Arif, M. (2024). Decision making for selection of smart vehicle transportation system using VIKOR approach. *International Journal of Data Science and Analytics*. https://doi.org/10.1007/s41060-024-00537-6
[21] Mohamadghasemi, A., Hadi-Vencheh, A., Lotfi, F. H., & Khalilzadeh, M. (2020). An integrated group FWA-ELECTRE III approach based on interval type-2 fuzzy sets for solving the MCDM problems using limit distance mean. *Complex & Intelligent Systems*, *6*(2), 355–389. https://doi.org/10.1007/s40747-020-00130-x
[22] Srivastava, A., & Mishra, P. K. (2023). Energy efficient clustering using modified PROMETHEE-II and AHP approach in wireless sensor networks. *Multimedia Tools and Applications*, *82*(30), 47049–47080. https://doi.org/10.1007/s11042-023-15378-x
[23] Cao, X., Xu, W., Liu, X., Peng, J., & Liu, T. (2021). A deep reinforcement learning-based on-demand charging algorithm for wireless rechargeable sensor networks. *Ad Hoc Networks*, *110,* 102278. https://doi.org/10.1016/j.adhoc.2020.102278
[24] Liang, W., Xu, Z., Xu, W., Shi, J., Mao, G., & Das, S. K. (2017). Approximation algorithms for charging reward maximization in rechargeable sensor networks via a mobile charger. *IEEE/ACM Transactions on Networking*, *25*(5), 3161–3174. https://doi.org/10.1109/TNET.2017.2723605
[25] Priyadarshani, S., Tomar, A., & Jana, P. K. (2021). An efficient partial charging scheme using multiple mobile chargers in wireless rechargeable sensor networks. *Ad Hoc Networks*, *113*, 102407. https://doi.org/10.1016/j.adhoc.2020.102407
[26] Wang, K., Chu, Z., Zhou, Y., Wang, K., Lin, C., & Obaidat, M. S. (2018). Partial charging scheduling in wireless rechargeable sensor networks. In *IEEE Global Communications Conference*, 1–6. https://doi.org/10.1109/GLOCOM.2018.8648027
[27] Chang, Y., Tang, H., Li, B., & Yuan, X. (2017). Distributed joint optimization routing algorithm based on the analytic hierarchy process for wireless sensor networks. *IEEE Communications Letters*, *21*(12), 2718–2721. https://doi.org/10.1109/LCOMM.2017.2756035
[28] Xiao, K., Wang, R., Deng, H., Zhang, L., & Yang, C. (2019). Energy-aware scheduling for information fusion in wireless sensor network surveillance. *Information Fusion*, *48,* 95–106. https://doi.org/10.1016/j.inffus.2018.08.005

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