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Location Selection of Electric Vehicle Charging Stations Through Employing the Spherical Fuzzy CoCoSo and CRITIC Technique

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Abstract. Energy conservation and emission reduction are important policies vigorously promoted in China. With the continuous popularization of the concept of green transportation, electric vehicles have become a green transportation tool with good development prospects, greatly reducing the pressure on the environment and resources caused by rapid economic growth. The development status of electric vehicles has a significant impact on urban energy security, environmental protection, and sustainable development in China. With the widespread application of new energy vehicles, charging piles have become an important auxiliary infrastructure necessary for the development of electric vehicles. They have significant social and economic benefits, so it is imperative to build electric vehicle charging piles. There are many factors to consider in the scientific layout of electric vehicle charging stations, and the location selection problem of electric vehicle charging stations is a multiple-attribute group decision-making (MAGDM) problem. Recently, the Combined Compromise Solution (CoCoSo) technique and CRITIC technique have been utilized to deal with MAGDM issues. Spherical fuzzy sets (SFSs) can uncover the uncertainty and fuzziness in MAGDM more effectively and deeply. In this paper, on basis of CoCoSo technique, a novel spherical fuzzy number CoCoSo (SFN-CoCoSo) technique based on spherical fuzzy number cosine similarity measure (SFNCSM) and spherical fuzzy number Euclidean distance (SFNED) is conducted for dealing with MAGDM. Moreover, when the attribute weights are completely unknown, the CRITIC technique is extended to SFSs to acquire the attribute weights based on the SFNCSM and SFNED. Finally, the SFN-CoCoSo technique is utilized for location selection problem of electric vehicle charging stations to prove practicability of the developed technique and compare the SFN-CoCoSo technique with existing techniques to further demonstrate its superiority.

Key words: multiple-attribute group decision-making (MAGDM), spherical fuzzy sets (SFSs), CoCoSo technique, CRITIC technique, location selection.

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1. Introduction

Traditional cars consume energy and cause pollution, so electric vehicles have become a key focus of industry development (Wang *et al.*, 2013; Zhang *et al.*, 2014). A survey shows that the concern of users about the range of electric vehicles greatly hinders the development of electric vehicles. In order to promote the development of electric vehicles, we need to establish sufficient and reasonably arranged electric vehicle charging facilities (Lin and Hua, 2015; Kong *et al.*, 2017). In 2009, the planning and layout of charging facilities in the United States began construction projects in multiple states. In February 2022, the US Department of Energy announced that it would spend $5 billion to build a charging network for electric vehicles. In order to significantly promote the development of the electric vehicle industry, Japan is expected to reach 30000 fast charging stations by 2030 (Zhang and Wei, 2023; Zhao *et al.*, 2023). According to data from the National Energy Administration, the annual growth of charging facilities in China in 2022 is about 2.6 million units, a year-on-year increase of nearly 100%. New energy electric vehicle charging stations refer to various charging facilities that provide charging services for electric vehicles, mainly including dedicated charging stations, public charging stations, and personal charging stations (Zhang and Shi, 2023; Sisman, 2023). Among them, dedicated charging stations are mainly used for passenger car services and provide fast charging services to meet the travel needs of car owners; public charging stations mainly provide services for public transportation such as buses, taxis, and shared cars; personal charging stations are mainly used for private cars, personal taxis, and personal ride hailing services (Zu and Sun, 2022; Banegas and Mamkhezri, 2023). Currently, developing a low-carbon economy has become a trend in global economic development and an inevitable way to achieve sustainable development. A low-carbon economy is an economic form based on low energy consumption, low pollution, and low emissions. Its core lies in the innovation of energy-saving and emission reduction technologies, as well as the innovation of industrial structure and system (Seikh and Mandal, 2022; Wang *et al.*, 2022; Wei *et al.*, 2022). At present, China is in a period of accelerated industrialization and urbanization, and the demand for energy is constantly increasing. At the same time, China's energy intensive and high emission industries account for a large proportion of the entire industry, and there is a rough development model (Liang *et al.*, 2022). Therefore, in the process of developing a low-carbon economy, it is necessary to focus on energy conservation and emission reduction. In the process of developing a low-carbon industry, more attention should be paid to "industrial carbon reduction" in order to save energy, reduce pollution, and alleviate pressure on resources, energy, environment, and other aspects. The automotive industry is a high energy consuming industry, and while the number of motor vehicles continues to grow, the exhaust gases it produces are a major source of pollution (Li *et al.*, 2022a, 2022b). Compared with traditional fuel vehicles, electric vehicles have advantages such as high efficiency, low environmental pollution, and low noise. Therefore, it is an inevitable trend to transform the energy drive system of vehicles (Bian *et al.*, 2022). Electric vehicles are a transportation vehicle with great development prospects, and their development is of great strategic significance for ensuring energy security, achieving energy conservation and emission reduction, and comprehensively promoting the transformation of economic development mode. This is an important historical opportunity for China to revitalize the automotive industry and build a strong automotive country (Yazdekhasti *et al.*, 2021; Asna *et al.*, 2022).

Since 2015, the sales of new energy vehicles in China have continued to rise. In 2018, the sales of new energy vehicles reached 1.256 million units, a year-on-year increase of 61.7%. In 2022, the production and sales of new energy vehicles reached 7.058 million and 6.887 million, respectively, with year-on-year growth of 96.9% and 93.4%, maintaining the world's first place for 8 consecutive years (He *et al.*, 2022; Huang *et al.*, 2022). Meanwhile, the construction of charging facilities is also accelerating. According to data from the Ministry of Industry and Information Technology, as of the end of 2022, a total of 5.21 million charging stations and 1973 swapping stations have been built nationwide. Among them, 2.593 million new charging stations and 675 swapping stations were added in 2022, and the construction speed of charging and swapping infrastructure has significantly accelerated. In order to ensure the safety of electric vehicle charging in China, the National Development and Reform Commission and 10 other departments have clearly stated that by the end of the 14th Five Year Plan, China's charging infrastructure system can meet the charging needs of over 20 million electric vehicles (Li *et al.*, 2021; Rani and Mishra, 2021; Wang *et al.*, 2021). It is expected that by 2025, the number of new energy vehicles in China will reach 26.72 million, pure electric vehicles will reach 23.24 million, and the total number of charging stations in China will reach 6.543 million. The relevant factors involved in the site selection process of charging piles mainly include the construction cost, construction period, and operation and maintenance cost of charging piles, and other factors need to be considered, such as market demand, power supply situation, transportation convenience, etc. (Karasan *et al.*, 2020; Liu *et al.*, 2020; Luo *et al.*, 2020; Bao and Xie, 2021). Therefore, the selection of charging station locations needs to comprehensively consider multiple factors, and then determine the optimization plan for charging station locations based on the relationship between each factor (Yang and Cao, 2019; Yi *et al.*, 2019; Jiang and Wan, 2020). The main evaluation indicator in optimizing the location of charging stations is the demand of new energy electric vehicles for existing charging infrastructure. In addition, it is necessary to consider multiple aspects such as power supply, transportation convenience, parking charging, and operation and maintenance costs (Ju *et al.*, 2019; Kizhakkan *et al.*, 2019). The evaluation indicators for the demand for charging infrastructure construction mainly include the number of public parking lots, the number of charging stations in public parking lots, the number of taxi charging stations, and the number of bus charging stations. The number of public parking lots is generally determined based on the actual situation of the city, but can also be obtained through survey statistics, while the number of charging stations is calculated based on the number of new energy electric vehicles in the city. The number of charging stations in public parking lots needs to take into account the construction cost of charging facilities, power supply, and operation and maintenance costs. The number of taxi charging stations can be determined based on the existing number of taxis. Bus charging stations are generally set up in bus stops to meet the charging needs of new energy electric buses. Based on the evaluation indicators for the construction needs of charging piles, the optimization plan for the site selection of charging piles can be determined, and corresponding conclusions can be drawn (Liu *et al.*, 2018; Ahn *et al.*, 2019; Fredriksson *et al.*, 2019). For the optimization problem of charging station location, multiple methods such as fuzzy comprehensive evaluation, analytic hierarchy process, and expert consultation can be combined to obtain the optimal solution (Li *et al.*, 2017; Cui *et al.*, 2018; Erbas *et al.*, 2018). With the development of the national new energy vehicle industry and the continuous progress of electric vehicle technology, charging stations have become a key link and infrastructure in the development of the electric vehicle industry, and also an important infrastructure to promote the rapid development of the electric vehicle industry. As one of the key links in the construction of new energy electric vehicle charging stations, reasonable site selection planning plays a decisive role in the construction of charging stations. It can not only reduce resource waste, but also lower investment costs, improve service quality and efficiency, and increase user stickiness (Liu *et al.*, 2019; Wang *et al.*, 2019).

In practical life, people often face various decision-making problems, ranging from personal clothing, food, housing, and transportation to national policies and guidelines (Chen *et al.*, 2021; Dong *et al.*, 2021; Verma and Alvarez-Miranda, 2023; Saghari *et al.*, 2023). Multiple-attribute group decision-making (MAGDM), as an important branch of modern decision science, refers to the process, where a group of experts is sorting and selecting a finite number of options under the consideration of multiple attribute constraints (Garg, 2021; Garg *et al.*, 2021a; Liao *et al.*, 2021). The theory and methods of MAGDM have been widely applied in various fields such as engineering design, economics, management, medicine, and military, such as investment decision-making, project evaluation, factory site selection, medical diagnosis, supply chain selection, and weapon system performance evaluation (Shabu *et al.*, 2023; Sankar *et al.*, 2023; Palanikumar *et al.*, 2023). In order to portray the fuzzy information, in 1965, Zadeh (1965) put forward the fuzzy sets (FSs) to portray the ambiguity of things. As a new extended form of FSs, spherical fuzzy sets (SFSs) (Mahmood *et al.*, 2019; Gundogdu and Kahraman, 2019) combined the advantages of PFSs (Yager and Abbasov, 2013) and picture fuzzy sets (Cuong, 2014), expressing the ambiguity of things from four aspects. The location selection problem of electric vehicle charging stations could be solved as MAGDM. Mahmood *et al.* (2019) and Gundogdu and Kahraman (2019) used the spherical fuzzy sets (SFSs) which could consist of the uncertainty and fuzziness during the location selection problem of electric vehicle charging stations. Yazdani *et al.* (2018) put forward the CoCoSo technique for MADM issues. Compared with other techniques, the main advantages of CoCoSo technique consisted of high efficiency and low computational complexity. More and more scholars have studied the CoCoSo technique based on different uncertain MAGDM (Yazdani *et al.*, 2019; Peng and Smarandache, 2020; Torkayesh *et al.*, 2021; Kharwar *et al.*, 2022; Lai *et al.*, 2022; Turskis *et al.*, 2022). Unfortunately, we have not been able to find efficient research works for CoCoSo technique (Yazdani *et al.*, 2018) based on the cosine similarity measure (Ye, 2016) and Euclidean distance under SFSs in the existing MADM and MAGDM. Therefore, it is of great significance to investigate the novel CoCoSo technique based on the cosine similarity measure (Ye, 2016) and Euclidean distance based on the CRITIC technique (Diakoulaki *et al.*, 1995; Badi *et al.*, 2023; Narang *et al.*, 2022; Pamucar *et al.*, 2022) under SFSs. The basic main goal of this research is to put forward the spherical fuzzy number CoCoSo (SFN-CoCoSo) technique based on the cosine similarity measure and Euclidean distance that can address MAGDM based on the CRITIC technique (Diakoulaki *et al.*, 1995) under SFSs more efficiently. Finally, a numerical example is presented to demonstrate the SFN-CoCoSo technique and several comparative analyses are utilized to verify the advantages of SFN-CoCoSo technique. Therefore, the research motivations and aims of this research work are outlined: (1) the CRITIC technique (Diakoulaki *et al.*, 1995) is utilized to derive the attribute's weight; (2) the novel CoCoSo technique is extended to the SFSs environment; (3) the novel spherical fuzzy number CoCoSo (SFN-CoCoSo) technique based on the Cosine similarity measure and Euclidean distance is put forward to solve the MAGDM; (4) a numerical example for location selection problem of electric vehicle charging stations is presented to demonstrate the SFN-CoCoSo technique and several comparative analyses are utilized to verify the advantages of SFN-CoCoSo technique.

The remaining framework of this paper proceeds as follows. The SFSs are used in Section 2. The SFN-CoCoSo technique is put forward to solve the MAGDM in Section 3. A numerical example for location selection problem of electric vehicle charging stations and several comparative analysis are utilized to verify the advantages of SFN-CoCoSo technique in Section 4. Lastly, a useful conclusion is presented in Section 5.

2. Preliminaries

Mahmood *et al.* (2019) and Gundogdu and Kahraman (2019) used the SFSs.

Definition 1 (Mahmood *et al.*, 2019; Gundogdu and Kahraman, 2019). The SFSs EE in Θ are used:

$$EE = \{(\theta, ET(\theta), EI(\theta), EF(\theta)) | \theta \in \Theta\}, \tag{1}$$

where $ET(\theta), EI(\theta), EF(\theta)$ is the truth-membership, indeterminacy-membership and falsity-membership, $ET(\theta), EI(\theta), EF(\theta) \in [0, 1]$ and satisfies $0 \leqslant ET^2(\theta) + EI^2(\theta) + EF^2(\theta) \leqslant 1$. The spherical fuzzy number (SFN) is used as $EE = (ET, EI, EF)$, where $ET, EI, EF \in [0, 1]$, and $0 \leqslant ET^2 + EI^2 + EF^2 \leqslant 1$.

Definition 2 (Mahmood *et al.*, 2019; Gundogdu and Kahraman, 2019). Let $EA = (ET_A, EI_A, EF_A)$ be the SFN, a score value is determined:

$$SV(EA) = (ET_A - EI_A)^2 - (EF_A - EI_A)^2, \quad SV(EA) \in [0, 1]. \tag{2}$$

Definition 3 (Mahmood *et al.*, 2019; Gundogdu and Kahraman, 2019). Let $EA = (ET_A, EI_A, EF_A)$ be the SFN, an accuracy value is determined:

$$AV(EA) = (ET_A)^2 + (ET_A)^2 + (EF_A)^2, \quad AV(EA) \in [0, 1]. \tag{3}$$

Mahmood *et al.* (2019) and Gundogdu and Kahraman (2019) determined the order relation for SFNs.

Definition 4 (Mahmood *et al.*, 2019; Gundogdu and Kahraman, 2019). Let $DA = (DT_A, DI_A, DF_A)$ and $DB = (DT_B, DI_B, DF_B)$ be SFNs, let $SV(EA) = (ET_A - EI_A)^2 - (EF_A - EI_A)^2$ and $SV(EB) = (ET_B - EI_B)^2 - (EF_B - EI_B)^2$, and let $AV(EA) = (ET_A)^2 + (ET_A)^2 + (EF_A)^2$ and $AV(EB) = (ET_B)^2 + (ET_B)^2 + (EF_B)^2$, respectively, then if $SV(EA) < SV(EB)$, then $EA < EB$; if $SV(EA) = SV(EB)$, then (1) if $AV(EA) = AV(EB)$, then $EA = EB$; (2) if $AV(EA) < AV(EB)$, then $EA < EB$.

Definition 5 (Gundogdu and Kahraman, 2019; Sharaf, 2021). Let $EA = (ET_A, EI_A, EF_A)$ and $EB = (ET_B, EI_B, EF_B)$ be two SFNs, the basic operations are conducted:

(1) $EA \oplus EB = (ET_A + ET_B - ET_A ET_B, EI_A EI_B, EF_A EF_B)$;
(2) $EA \otimes EB = (ET_A ET_B, EI_A + EI_B - EI_A EI_B, EF_A + EF_B - EF_A EF_B)$;
(3) $\lambda EA = \big(1 - (1 - ET_A)^\lambda, (EI_A)^\lambda, (EF_A)^\lambda\big), \quad \lambda > 0$;
(4) $(EA)^\lambda = \big((ET_A)^\lambda, (EI_A)^\lambda, 1 - (1 - EF_A)^\lambda\big), \quad \lambda > 0$.

The SFN weighted averaging (SFNWA) technique and SFN weighted geometric (SFNWG) technique are used.

Definition 6 (Mahmood *et al.*, 2019; Gundogdu and Kahraman, 2019). Let $EA_j = (ET_j, EI_j, EF_j)$ $(j = 1, 2, \dots, n)$ be a family of SFNs, the SFNWA technique is used:

$$\mathrm{SFNWA}_{e\omega}(EA_1, EA_2, \dots, EA_n) = \bigoplus_{j=1}^{n} (e\omega_j EA_j)$$
$$= \left(\begin{array}{l} \sqrt{1 - \prod_{j=1}^{n} \big(1 - ET_j^2\big)^{e\omega_j}}, \\ \sqrt{\prod_{j=1}^{n} \big(1 - ET_j^2\big)^{e\omega_j} - \prod_{j=1}^{n} \big(1 - ET_j^2 - EI_j^2\big)^{e\omega_j}}, \\ \prod_{j=1}^{n} (EF_j)^{e\omega_j}, \end{array} \right), \tag{4}$$

where $e\omega = (e\omega_1, e\omega_2, \dots, e\omega_n)^T$ is the weight of EA_j $(j = 1, 2, \dots, n)$ and $e\omega_j > 0$, $\sum_{j=1}^{n} e\omega_j = 1$.

Definition 7 (Mahmood *et al.*, 2019; Gundogdu and Kahraman, 2019). Let $EA_j = (ET_j, EI_j, EF_j)$ $(j = 1, 2, \dots, n)$ be a family of SFNs, the SVNNWG technique is used:

$$\mathrm{SFNWG}_{e\omega}(EA_1, EA_2, \dots, EA_n) = \bigotimes_{j=1}^{n} (EA_j)^{e\omega_j}$$

$$= \left(\begin{array}{l} \prod_{j=1}^{n} (ET_j)^{e\omega_j}, \\ \sqrt{\prod_{j=1}^{n} \left(1 - EF_j^2\right)^{e\omega_j} - \prod_{j=1}^{n} \left(1 - EF_j^2 - EI_j^2\right)^{e\omega_j}}, \\ \sqrt{1 - \prod_{j=1}^{n} \left(1 - EF_j^2\right)^{e\omega_j}} \end{array} \right), \tag{5}$$

where $e\omega = (e\omega_1, e\omega_2, \dots, e\omega_n)^T$ is the weight of EA_j $(j = 1, 2, \dots, n)$ and $e\omega_j > 0$, $\sum_{j=1}^{n} e\omega_j = 1$.

Definition 8 (Aydin and Kahraman, 2020). Let $EA = (ET_A, EI_A, EF_A)$ and $EB = (ET_B, EI_B, EF_B)$, then the SFN cosine similarity measure (SFNCSM) between $EA = (ET_A, EI_A, EF_A)$ and $EB = (ET_B, EI_B, EF_B)$ is constructed:

$$\begin{aligned} & SFNCSM(EA, EB) \\ & = \frac{1}{2} \left(\begin{array}{l} \cos\left[\frac{\pi}{6}\left(\left|ET_A^2 - ET_B^2\right| + \left|EI_A^2 - EI_B^2\right| + \left|EF_A^2 - EF_B^2\right|\right)\right] \\ \quad + \cos\left[\frac{\pi}{2} \max\left(\left|ET_A^2 - ET_B^2\right|, \left|EI_A^2 - EI_B^2\right|, \left|WF_A - WF_B\right|\right)\right] \end{array} \right), \\ & SFNCSM(EA, EB) \in [0, 1]. \end{aligned} \tag{6}$$

Definition 9 (Kutlu Gündoğdu and Kahraman, 2021). Let $EA = (ET_A, EI_A, EF_A)$ and $EB = (ET_B, EI_B, EF_B)$, then the SFN Euclidean distance (SFNED) between $EA = (ET_A, EI_A, EF_A)$ and $EB = (ET_B, EI_B, EF_B)$ is computed:

$$SFNED(EA, EB) = \sqrt{\frac{1}{2}\left(\left|ET_A^2 - ET_B^2\right|^2 + \left|EI_A^2 - EI_B^2\right|^2 + \left|EF_A^2 - EF_B^2\right|^2\right)}. \tag{7}$$

3. SFN-CoCoSo Technique for MAGDM Based on the CRITIC with SFNs

In this section, SFN-CoCoSo technique is used for MAGDM. Let $EA = \{EA_1, EA_2, \dots, EA_m\}$ be alternatives. Let $EG = \{EG_1, EG_2, \dots, EG_n\}$ be attributes with weight information $e\omega = \{e\omega_1, e\omega_2, \dots, e\omega_n\}$, where $e\omega_j \in [0, 1]$, $\sum_{j=1}^{n} e\omega_j = 1$. Assume $EE = \{EE_1, EE_2, \dots, EE_l\}$ be a family of DMs with weight values $ew = \{ew_1, ew_2, \dots, ew_l\}$, where $ew_k \in [0, 1]$, $\sum_{k=1}^{l} ew_k = 1$. And $EE^{(k)} = (EE_{ij}^{(k)})_{m\times n} = (ET_{ij}^{(k)}, EI_{ij}^{(k)}, EF_{ij}^{(k)})_{m\times n}$ is the SFN-matrix, $EE_{ij}^{(k)} = (ET_{ij}^{(k)}, EI_{ij}^{(k)}, EF_{ij}^{(k)})$ means the SFNs of EA_i for the attribute EG_j through EE_k. Subsequently, the calculating steps are carried out (see Fig. 1).

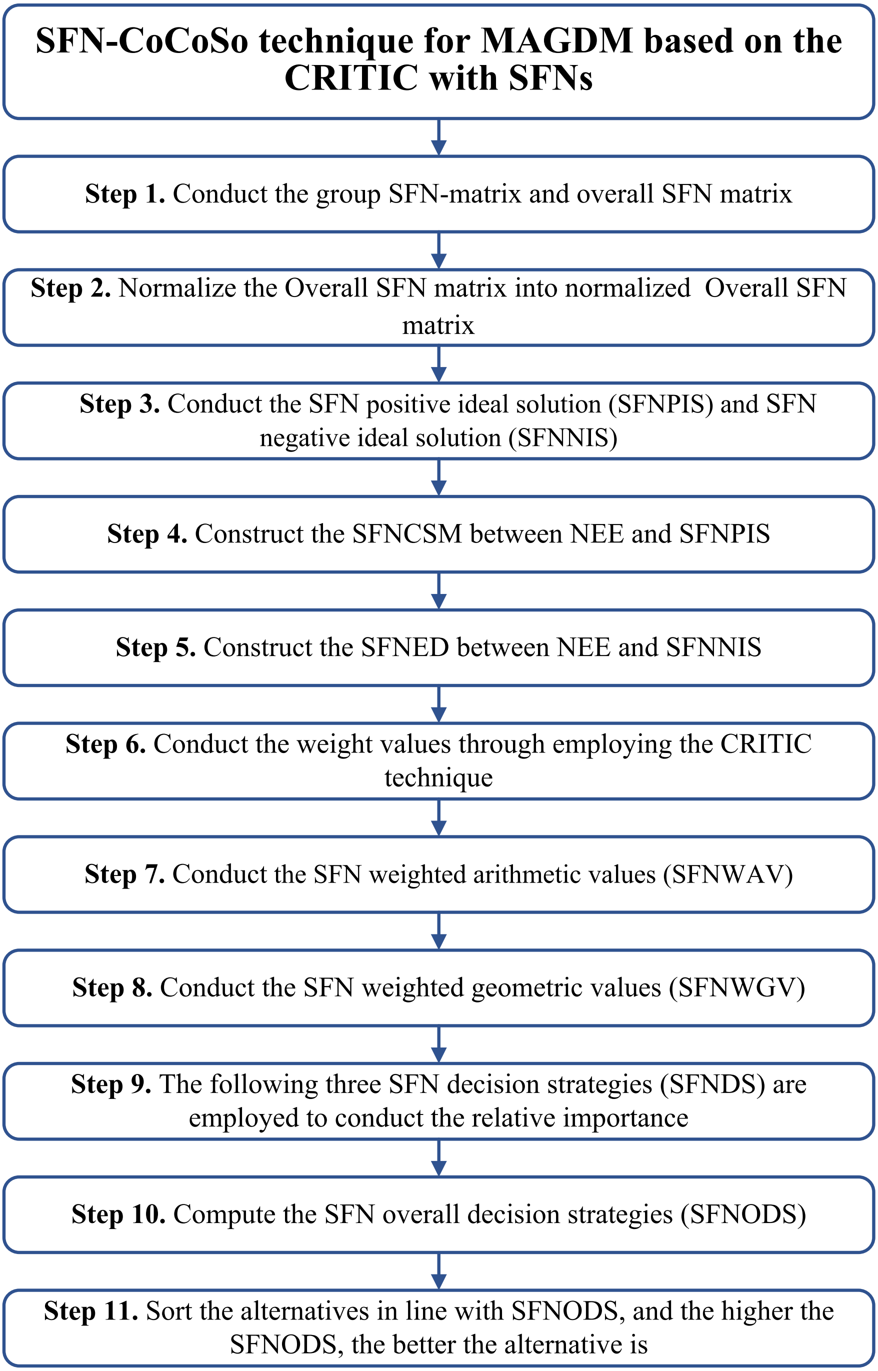

Fig. 1. SFN-CoCoSo technique for MAGDM based on the CRITIC with SFNs.

Step 1. Determine the group SFN-matrix $EE^{(k)} = (EE_{ij}^{(k)})_{m\times n} = (ET_{ij}^{(k)}, EI_{ij}^{(k)}, EF_{ij}^{(k)})_{m\times n}$ and the overall SFN matrix $EE = (EE_{ij})_{m\times n}$ using the SFNWG technique.

$$EE^{(k)} = \left[EE_{ij}^{(k)}\right]_{m\times n} = \begin{bmatrix} EE_{11}^{(k)} & EE_{12}^{(k)} & \dots & EE_{1n}^{(k)} \\ EE_{21}^{(k)} & EE_{22}^{(k)} & \dots & EE_{2n}^{(k)} \\ \vdots & \vdots & \vdots & \vdots \\ EE_{m1}^{(k)} & EE_{m2}^{(k)} & \dots & EE_{mn}^{(k)} \end{bmatrix}, \tag{8}$$

$$EE = [EE_{ij}]_{m\times n} = \begin{bmatrix} EE_{11} & EE_{12} & \dots & EE_{1n} \\ EE_{21} & EE_{22} & \dots & EE_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ EE_{m1} & EE_{m2} & \dots & EE_{mn} \end{bmatrix}, \tag{9}$$

$$\begin{aligned} EE_{ij} &= (ET_{ij}, EI_{ij}, EF_{ij}) \\ &= \left(\begin{array}{l} \prod_{k=1}^{l} \left(\left(ET_{ij}^{(k)}\right)^2\right)^{ew_k}, \\ \sqrt{\prod_{k=1}^{l} \left(1 - \left(EF_{ij}^{(k)}\right)^2\right)^{ew_k} - \prod_{k=1}^{l} \left(1 - \left(EF_{ij}^{(k)}\right)^2 - \left(EI_{ij}^{(k)}\right)^2\right)^{ew_k}}, \\ \sqrt{1 - \prod_{k=1}^{l} \left(1 - \left(EF_{ij}^{(k)}\right)^2\right)^{ew_k}} \end{array} \right). \end{aligned} \tag{10}$$

Step 2. Normalize the $EE = (EE_{ij})_{m\times n}$ to $NEE = [NEE_{ij}]_{m\times n}$.

$$\begin{aligned} NEE_{ij} &= (NET_{ij}, NEI_{ij}, NEF_{ij}) \\ &= \begin{cases} (ET_{ij}, EI_{ij}, EF_{ij}), & EG_j \text{ is a benefit criterion}, \\ (EF_{ij}, EI_{ij}, ET_{ij}), & EG_j \text{ is a cost criterion}. \end{cases} \end{aligned} \tag{11}$$

Step 3. Determine the SFN positive ideal solution (SFNPIS) and SFN negative ideal solution (SFNNIS):

$$SFNPIS_j = \left(NET_j^+, NEI_j^+, NEF_j^+\right), \tag{12}$$

$$SFNNIS_j = \left(NET_j^-, NEI_j^-, NEF_j^-\right), \tag{13}$$

$$SV(SFNPIS_j) = \max_i SV(NET_{ij}, NEI_{ij}, NEF_{ij}), \tag{14}$$

$$SV(SFNNIS_j) = \min_i SV(NET_{ij}, NEI_{ij}, NEF_{ij}). \tag{15}$$

Step 4. Construct the SFNCSM between $NEE_{ij} = (NET_{ij}, NEI_{ij}, NEF_{ij})$ and $SFNPIS_j = (NET_j^+, NEI_j^+, NEF_j^+)$.

$$SFNCSM(NEE_{ij}, SFNPIS_j) = \frac{1}{2}\left(\begin{array}{l}\cos\left[\dfrac{\pi}{6}\left(\begin{array}{l}\left|(NET_{ij})^2-\left(NET_j^+\right)^2\right|+\left|(NEI_{ij})^2-\left(NEI_j^+\right)^2\right|\\ \quad +\left|(NEF_{ij})^2-\left(NEF_j^+\right)^2\right|\end{array}\right)\right]\\ +\cos\left[\dfrac{\pi}{2}\max\left(\begin{array}{l}\left|(NET_{ij})^2-\left(NET_j^+\right)^2\right|,\left|(NEI_{ij})^2-\left(NEI_j^+\right)^2\right|,\\ \quad \left|(NEF_{ij})^2-\left(NEF_j^+\right)^2\right|\end{array}\right)\right]\end{array}\right). \tag{16}$$

Step 5. Construct the SFNED between $NEE_{ij} = (NET_{ij}, NEI_{ij}, NEF_{ij})$ and $SFNNIS_j = (NET_j^-, NEI_j^-, NEF_j^-)$.

$$SFNED(NEE_{ij}, SFNNIS_j) = \sqrt{\frac{1}{2}\left(\begin{array}{l}\left|(NET_{ij})^2-(NET_j^-)^2\right|+\left|(NEI_{ij})^2-(NEI_j^-)^2\right|\\ \quad +\left|(NEF_{ij})^2-(NEF_j^-)^2\right|\end{array}\right)}. \tag{17}$$

Step 6. Compute the weight values through employing the CRITIC technique.

The CRITIC technique (Diakoulaki *et al.*, 1995) is employed to compute the weight values.

(1) The SFN correlation coefficient values (SFNCCV) are determined.

$$SFNCCV_{jt} = \frac{\sum_{i=1}^{m}(\varphi(SFN_{ij})-\varphi(SFN_j))(\varphi(SFN_{it})-\varphi(SFN_t))}{\sqrt{\sum_{i=1}^{m}(\varphi(SFN_{ij})-\varphi(SFN_j))^2}\sqrt{\sum_{i=1}^{m}(\varphi(SFN_{it})-\varphi(SFN_t))^2}},$$
$$j, t = 1, 2, \dots, n, \tag{18}$$

where

$$\varphi(SFN_j) = \frac{1}{2m}\sum_{i=1}^{m}\big(SFNCSM(NEE_{ij}, SFNPIS_j) + SFNED(NEE_{ij}, SFNNIS_j)\big),$$
$$\varphi(SFN_t) = \frac{1}{2m}\sum_{i=1}^{m}\big(SFNCSM(NEE_{it}, SFNPIS_t) + SFNED(NEE_{it}, SFNNIS_t)\big),$$
$$\varphi(SFN_{ij}) = \frac{1}{2}\big(SFNCSM(NEE_{ij}, SFNPIS_j) + SFNED(NEE_{ij}, SFNNIS_j)\big),$$
$$\varphi(SFN_{it}) = \frac{1}{2}\big(SFNCSM(NEE_{it}, SFNPIS_t) + SFNED(NEE_{it}, SFNNIS_t)\big).$$

(2) Compute the SFN standard deviation values (SFNSDV).

$$SFNSDV_j = \sqrt{\frac{1}{m-1}\sum_{i=1}^{m}\big(\varphi(SFN_{ij})-\varphi(SFN_j)\big)^2}. \tag{19}$$

(3) Compute the attribute weight values.

$$e\omega_j = \frac{SFNSDV_j \sum_{t=1}^{n}(1 - SFNCCV_{jt})}{\sum_{j=1}^{n}(SFNSDV_j \sum_{t=1}^{n}(1 - SFNCCV_{jt}))}, \tag{20}$$

where $e\omega_j \in [0, 1]$, $\sum_{j=1}^{n} e\omega_j = 1$.

Step 7. Compute the SFN weighted arithmetic values (SFNWAV).

$$SFNWAV_i = \sum_{j=1}^{n} e\omega_j \times \left(\frac{1}{2}\begin{pmatrix} SFNCSM(NEE_{ij}, SFNPIS_j) \\ + SFNED(NEE_{ij}, SFNNIS_j) \end{pmatrix}\right). \tag{21}$$

Step 8. Compute the SFN weighted geometric values (SFNWGV).

$$SFNWGV_i = \sum_{j=1}^{n} \left(\frac{1}{2}\begin{pmatrix} SFNCSM(NEE_{ij}, SFNPIS_j) \\ + SFNED(NEE_{ij}, SFNNIS_j) \end{pmatrix}\right)^{e\omega_j}. \tag{22}$$

Step 9. The following three SFN decision strategies (SFNDS) are employed to compute the relative importance:

$$SFNDS_{ia} = \frac{SFNWAV_i + SFNWGV_i}{\sum_{i=1}^{m}(SFNWAV_i + SFNWGV_i)}, \tag{23}$$

$$SFNDS_{ib} = \frac{SFNWAV_i}{\min_i SFNWAV_i} + \frac{SFNWGV_i}{\min_i SFNWGV_i}, \tag{24}$$

$$SFNDS_{ic} = \frac{\lambda SFNWAV_i + (1 - \lambda)SFNWGV_i}{\lambda \max_i SFNWAV_i + (1 - \lambda)\max_i SFNWGV_i}, \quad 0 \leqslant \lambda \leqslant 1, \tag{25}$$

where $SFNDS_{ia}$ is the arithmetic sum of $SFNWAV_i, SFNWGV_i$; $SFNDS_{ib}$ is the relative score of $SFNWAV_i, SFNWGV_i$, and $SFNDS_{ic}$ is the computed compromise of $SFNWAV_i, SFNWGV_i$.

Remark 1. λ (usually $\lambda = 0.5$) is chosen by DMs. The higher the λ, the higher the each alternative.

Step 10. Compute the SFN overall decision strategies (SFNODS).

$$SFNODS_i = \sqrt[3]{SFNDS_{ia}SFNDS_{ib}SFNDS_{ic}} + \frac{SFNDS_{ia} + SFNDS_{ib} + SFNDS_{ic}}{3}. \tag{26}$$

Step 11. Sort the alternatives in line with $SFNODS_i$ $(i = 1, 2, \dots, m)$, and the higher the $SFNODS_i$, the better the alternative is.

4. Numerical Example and Comparative Analysis

4.1. *Numerical Example*

The traditional operation mode of vehicles driven by energy sources such as gasoline and diesel has drawbacks such as high energy consumption and pollution. With the increasing accessibility of urban transportation and the significant increase in the proportion of vehicles in transportation, a large amount of exhaust from fuel powered vehicles will exacerbate air pollution in urban areas, leading to the depletion of non-renewable energy sources. The electric energy resources used by new energy vehicles have good cleanliness and renewability, and the energy consumption cost and pollution gas volume generated during vehicle operation are relatively small, which is an important direction for the transformation and upgrading of the automotive industry. The new energy charging station is a workstation that provides electricity replenishment for new energy vehicles. With the increase of the proportion of new energy electric vehicles in the total ownership of vehicles, the planning, construction, and later operation and maintenance management of new energy charging piles are directly related to the operating income of new energy charging piles and their contribution to new energy vehicles. The charging piles for new energy electric vehicles are mainly electronic products. They are located in the external environment for a long time and have a high frequency of use, which can easily lead to aging or damage to the charging pile equipment and facilities. It is necessary to promptly investigate and repair the fault problems to avoid insufficient operation and maintenance time, which may affect the use of new energy electric vehicle owners. At the same time, limited human resources for inspection, operation, and maintenance make it difficult to monitor the charging piles of new energy electric vehicles 24/7, and there is a lag in emergency response and fault maintenance. In addition, in many regions, the operation and maintenance of electric vehicle charging piles are the responsibility of manufacturers, who arrange on-site inspection personnel to discover defects and faults in the operation of the charging piles. Under the constraints of operation and maintenance labour costs, the inspection strength of manufacturers is weak, and the real-time and timely management of operation and maintenance is insufficient. On the contrary, the operation and maintenance management costs of new energy electric vehicle charging piles have increased. The operation and maintenance management of new energy electric vehicle charging piles mainly includes daily operation status inspection of charging piles, defect detection feedback, defect maintenance and fault handling, etc. Through daily operation status inspections, they can comprehensively and timely grasp the operation status and abnormal situations of new energy electric vehicle charging piles, discover defects in charging pile equipment and facilities, as well as safety hazards timely, so that maintenance personnel can promptly go to the site to handle defects and eliminate hidden dangers, and improve the safety of the operation of new energy electric vehicle charging piles. The defect repair and troubleshooting of charging piles require the charging pile manufacturer to arrange personnel to the site for defect confirmation and equipment maintenance. The process involves many engineering task orders, such as defect dispatch forms, maintenance confirmation forms, process control forms, etc. Through standardized and procedural management, it promotes the operation and maintenance management of new energy electric vehicle charging piles to form an organic whole. The traditional operation and maintenance management of new energy electric vehicle charging piles is mainly manual, and there is a certain time lag in the closed-loop management of the process from discovering faults or defects during daily inspections of new energy electric vehicle charging piles to reporting faults or defects, arranging maintenance personnel for review and repair by manufacturers, and providing feedback on maintenance situations. By utilizing information technology and information management systems, the process of closed-loop management for the operation and maintenance of new energy electric vehicle charging piles is commercialized. Real time online filling of inspection and discovery of faults or defects, online approval and dispatch of defective orders, acceptance and on-site maintenance of defective orders, and feedback on defective order maintenance are utilized to promote closed-loop management of the operation and maintenance process of new energy electric vehicle charging piles. The closed-loop management of the operation and maintenance of new energy electric vehicle charging piles can avoid equipment failures or defects found during daily inspections that are not repaired in a timely manner. It can also improve the efficiency of the operation and maintenance of new energy electric vehicle charging piles. By leaving traces in intermediate processes such as dispatching orders, maintenance, and feedback, it ensures that each process task is clearly decomposed and responsibilities are assigned to individuals, achieving online traceability of relevant responsible persons and work effectiveness. The location selection problem of electric vehicle charging stations could be deemed as the MAGDM problem. In this section, an empirical example for location selection problem of electric vehicle charging stations is provided using SFN-CoCoSo technique. In order to choose the most suitable electric vehicle charging stations, some traffic departments invite three experts (transportation department officials, transportation department management personnel, university professors) $EE = (EE_1, EE_2, EE_3)$ to evaluate the five electric vehicle charging stations EA_i $(i = 1, 2, 3, 4, 5)$ in line with four attributes: EG_1 is the demand for charging infrastructure construction, EG_2 is the urban transportation convenience, EG_3 is the construction cost of electric vehicle charging stations, EG_4 is the urban power supply situation. Among them, only EG_3 is cost attribute. Furthermore, $hw = (0.2346, 0.3233, 0.4421)^T$ denotes experts' weight information. The evaluation information from $EE = (EE_1, EE_2, EE_3)$ with linguistic scale (see Table 1, Gundogdu and Kahraman, 2019) are displayed in Tables 2–4. Then, the SFN-CoCoSo technique is utilized to help the traffic management department select the best electric vehicle charging station.

Step 1. Put forward the group SFN matrix $EE^{(k)} = (EE_{ij}^{(k)})_{5\times4}$ $(k = 1, 2, 3)$ as in Tables 2–4. The overall SFN-matrix is calculated by SFNWG technique. The results are calculated in Table 5.

Step 2. Normalize the SFN-matrix $EE = [EE_{ij}]_{5\times4}$ to $NEE = [NEE_{ij}]_{5\times4}$ (see Table 6).

Step 3. Obtain the SFNPIS and SFNNIS (Table 7).

Step 4. Conduct the SFNCSM between $NEE_{ij} = (NET_{ij}, NEI_{ij}, NEF_{ij})$ and $SFNPIS_j = (NET_j^+, NEI_j^+, NEF_j^+)$ (Table 8):

Table 1
Linguistic scales and their corresponding SFNs.

Linguistic terms	SFNs
Exceedingly Terrible-EET	(0.9, 0.1, 0.1)
Very Terrible-EVT	(0.7, 0.3, 0.3)
Terrible-ET	(0.6, 0.4, 0.4)
Medium-EM	(0.5, 0.5, 0.5)
Well-EW	(0.4, 0.4, 0.6)
Very Well-EVW	(0.3, 0.3, 0.7)
Exceedingly Well-EEW	(0.1, 0.1, 0.9)

Table 2
Linguistic scale from EE_1.

	EG$_1$	**EG$_2$**	**EG$_3$**	**EG$_4$**
EA$_1$	EVT	EM	EW	EVW
EA$_2$	EM	EVT	EVT	EVW
EA$_3$	EM	ET	EVW	EVT
EA$_4$	EVT	EVW	EW	EM
EA$_5$	EVW	EW	EM	ET

Table 3
Linguistic scale from EE_2.

	EG$_1$	**EG$_2$**	**EG$_3$**	**EG$_4$**
EA$_1$	EVT	EM	EVW	EW
EA$_2$	EVT	EVW	EM	EW
EA$_3$	EVW	EW	EM	ET
EA$_4$	EVW	ET	EVT	EM
EA$_5$	EM	EVW	ET	EW

Table 4
Linguistic scale from EE_3.

	EG$_1$	**EG$_2$**	**EG$_3$**	**EG$_4$**
EA$_1$	ET	EM	EM	EW
EA$_2$	ET	EM	EW	EVW
EA$_3$	EM	EW	EVT	EVT
EA$_4$	EVW	EW	EM	ET
EA$_5$	EVT	ET	EW	EVW

Step 5. Conduct the SFNED between $NEE_{ij} = (NET_{ij}, NEI_{ij}, NEF_{ij})$ and $SFNNIS_j = (NET_j^-, NEI_j^-, NEF_j^-)$ (Table 9).

Step 6. Conduct the weight values utilizing the CRITIC technique (Table 10).

Step 7. Conduct the SFNWAV (Table 11).

Step 8. Conduct the SFNWGV (Table 12).

Step 9. Conduct the $SFNDS_{ia}$, $SFNDS_{ib}$, $SFNDS_{ic}$ (see Table 13).

Table 5
Overall SFNs information.

	$\mathbf{EG_1}$	$\mathbf{EG_2}$
$\mathbf{EA_1}$	(0.3712, 0.1436, 0.4287)	(0.4376, 0.3418, 0.4276)
$\mathbf{EA_2}$	(0.4328, 0.1425, 0.4324)	(0.3778, 0.1659, 0.4398)
$\mathbf{EA_3}$	(0.4434, 0.1618, 0.3584)	(0.4736, 0.1658, 0.3549)
$\mathbf{EA_4}$	(0.4497, 0.2436, 0.2564)	(0.4325, 0.1857, 0.2439)
$\mathbf{EA_5}$	(0.4315, 0.2775, 0.3435)	(0.3217, 0.2513, 0.4439)
	$\mathbf{EG_3}$	$\mathbf{EG_4}$
$\mathbf{EA_1}$	(0.2143, 0.2657, 0.5443)	(0.54547, 0.3524, 0.3376)
$\mathbf{EA_2}$	(0.3354, 0.2276, 0.5635)	(0.3473, 0.4564, 0.5476)
$\mathbf{EA_3}$	(0.3354, 0.2875, 0.5536)	(0.2576, 0.1958, 0.5324)
$\mathbf{EA_4}$	(0.5347, 0.3764, 0.3349)	(0.6426, 0.3369, 0.3873)
$\mathbf{EA_5}$	(0.3725, 0.4126, 0.5347)	(0.3724, 0.4376, 0.5213)

Table 6
The $NEE = [NEE_{ij}]_{5\times 4}$.

	$\mathbf{EG_1}$	$\mathbf{EG_2}$
$\mathbf{EA_1}$	(0.3712, 0.1436, 0.4287)	(0.4376, 0.3418, 0.4276)
$\mathbf{EA_2}$	(0.4328, 0.1425, 0.4324)	(0.3778, 0.1659, 0.4398)
$\mathbf{EA_3}$	(0.4434, 0.1618, 0.3584)	(0.4736, 0.1658, 0.3549)
$\mathbf{EA_4}$	(0.4497, 0.2436, 0.2564)	(0.4325, 0.1857, 0.2439)
$\mathbf{EA_5}$	(0.4315, 0.2775, 0.3435)	(0.3217, 0.2513, 0.4439)
	$\mathbf{EG_3}$	$\mathbf{EG_4}$
$\mathbf{EA_1}$	(0.2143, 0.2657, 0.5443)	(0.54547, 0.3524, 0.3376)
$\mathbf{EA_2}$	(0.3354, 0.2276, 0.5635)	(0.3473, 0.4564, 0.5476)
$\mathbf{EA_3}$	(0.3354, 0.2875, 0.5536)	(0.2576, 0.1958, 0.5324)
$\mathbf{EA_4}$	(0.5347, 0.3764, 0.3349)	(0.6426, 0.3369, 0.3873)
$\mathbf{EA_5}$	(0.3725, 0.4126, 0.5347)	(0.3724, 0.4376, 0.5213)

Table 7
The SFNPIS and SFNNIS.

	SFNPIS	SFNNIS
$\mathbf{EG_1}$	(0.4497, 0.2436, 0.2564)	(0.3712, 0.1436, 0.4287)
$\mathbf{EG_2}$	(0.4736, 0.1658, 0.3549)	(0.3217, 0.2513, 0.4439)
$\mathbf{EG_3}$	(0.5347, 0.3764, 0.3349)	(0.2143, 0.2657, 0.5443)
$\mathbf{EG_4}$	(0.6426, 0.3369, 0.3873)	(0.3473, 0.4564, 0.5476)

Table 8
The SFNCSM between $NEE_{ij} = (NET_{ij}, NEI_{ij}, NEF_{ij})$ and $SFNPIS_j = (NET_j^+, NEI_j^+, NEF_j^+)$.

Alternatives	$\mathbf{EG_1}$	$\mathbf{EG_2}$	$\mathbf{EG_3}$	$\mathbf{EG_4}$
$\mathbf{EA_1}$	0.5820	0.5722	0.5685	0.7699
$\mathbf{EA_2}$	0.8563	0.7917	0.7875	0.4265
$\mathbf{EA_3}$	0.6916	1.0000	0.5899	0.6578
$\mathbf{EA_4}$	1.0000	0.7155	1.0000	1.0000
$\mathbf{EA_5}$	0.8175	0.5401	0.8091	0.7496

Table 9
The SFNED between $NEE_{ij} = (NET_{ij}, NEI_{ij}, NEF_{ij})$ and $SFNNIS_j = (NET_j^-, NEI_j^-, NEF_j^-)$.

Alternatives	**EG$_1$**	**EG$_2$**	**EG$_3$**	**EG$_4$**
EA$_1$	0.4016	0.2476	0.0000	0.3188
EA$_2$	0.0000	0.3282	0.3611	0.0000
EA$_3$	0.3672	0.3739	0.3245	0.2942
EA$_4$	0.4524	0.2765	0.5322	0.4404
EA$_5$	0.4239	0.0000	0.3880	0.3972

Table 10
The attribute weight.

	EG$_1$	**EG$_2$**	**EG$_3$**	**EG$_4$**
Weight	0.1760	0.3281	0.2751	0.2208

Table 11
The SFNWAV.

	EA$_1$	**EA$_2$**	**EA$_3$**	**EA$_4$**	**EA$_5$**
SFNWAV	0.4194	0.4642	0.5494	0.6603	0.4891

Table 12
The SFNWGV.

	EA$_1$	**EA$_2$**	**EA$_3$**	**EA$_4$**	**EA$_5$**
SFNWGV	0.4074	0.4346	0.5410	0.6491	0.4596

Table 13
Three aggregation strategies.

	$SFNDS_{ia}$	$SFNDS_{ib}$	$SFNDS_{ic}$
EA$_1$	0.1630	2.0000	0.6315
EA$_2$	0.1771	2.1733	0.6864
EA$_3$	0.2149	2.6377	0.8328
EA$_4$	0.2581	3.1674	1.0000
EA$_5$	0.1870	2.2942	0.7245

Step 10. Conduct the assessment value $SFNODS_i$ (see Table 14).

Step 11. In line with the $SFNODS_i$ $(i = 1, 2, 3, 4, 5)$, the order is $EA_4 > EA_3 > EA_5 > EA_2 > EA_1$ and the optimal electric vehicle charging station is EA_4.

Table 14
The $SFNODS_i$.

	EA$_1$	**EA$_2$**	**EA$_3$**	**EA$_4$**	**EA$_5$**
SFNODS	1.5219	1.6540	2.0071	2.4101	1.7459

Table 15
Order results for these different techniques.

Techniques	Ranking order
SFNWA technique (Gundogdu and Kahraman, 2019)	$EA_4 > EA_3 > EA_5 > EA_2 > EA_1$
SFNWG technique (Gundogdu and Kahraman, 2019)	$EA_4 > EA_3 > EA_2 > EA_5 > EA_1$
SFPWA technique (Garg *et al.*, 2021b)	$EA_4 > EA_3 > EA_5 > EA_2 > EA_1$
SFPWG technique (Garg *et al.*, 2021b)	$EA_4 > EA_3 > EA_2 > EA_5 > EA_1$
SFGWMSM technique (Liu *et al.*, 2019)	$EA_4 > EA_3 > EA_5 > EA_2 > EA_1$
SFN-VIKOR technique (Aydogdu and Gul, 2020)	$EA_4 > EA_3 > EA_5 > EA_2 > EA_1$
SFN-GRA technique (Zhang *et al.*, 2022)	$EA_4 > EA_3 > EA_5 > EA_2 > EA_1$
SFN-TODIM technique (Zhang *et al.*, 2023)	$EA_4 > EA_3 > EA_5 > EA_2 > EA_1$
SFN-CoCoSo technique	$EA_4 > EA_3 > EA_5 > EA_2 > EA_1$

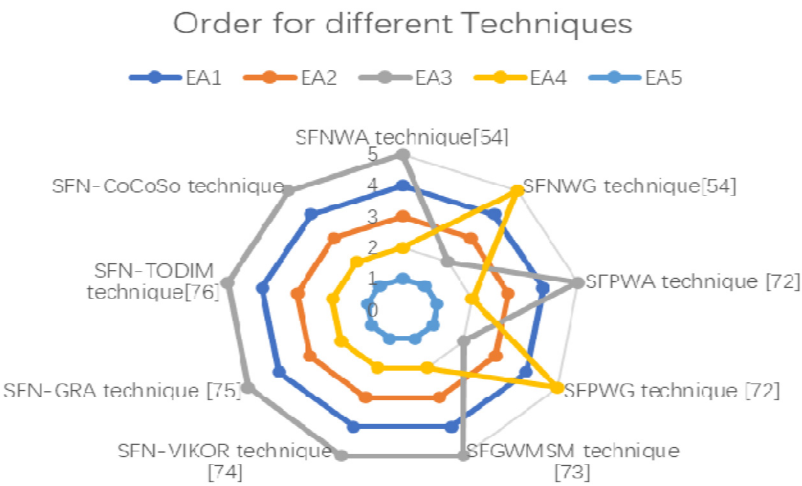

Fig. 2. Order for different techniques.

4.2. *Comparative Analysis*

The SFN-CoCoSo technique is compared with some existing techniques, such as SFNWA technique (Gundogdu and Kahraman, 2019), SFNWG technique (Gundogdu and Kahraman, 2019), spherical fuzzy power weighted averaging (SFPWA) technique (Garg *et al.*, 2021b), spherical fuzzy power weighted geometric (SFPWG) technique (Garg *et al.*, 2021b), spherical fuzzy generalized weighted MSM (SFGWMSM) technique (Liu *et al.*, 2019), SFN-VIKOR technique (Aydogdu and Gul, 2020), SFN-GRA technique (Zhang *et al.*, 2022) and SFN-TODIM technique (Zhang *et al.*, 2023). Then, the results of these techniques are depicted in Table 15 and Fig. 2.

In accordance with WS coefficient technique (Sałabun and Urbaniak, 2020; Sałabun *et al.*, 2020), the WS coefficient information between the SFNWA technique (Gundogdu and Kahraman, 2019), SFNWG technique (Gundogdu and Kahraman, 2019), SFPWA technique (Garg *et al.*, 2021b), SFPWG technique (Garg *et al.*, 2021b), SFGWMSM technique (Liu *et al.*, 2019), SFN-VIKOR technique (Aydogdu and Gul, 2020), SFN-GRA technique (Zhang *et al.*, 2022), SFN-TODIM technique (Zhang *et al.*, 2023) and the proposed SFN-CoCoSo technique is 1.0000, 0.7266, 1.0000, 0.7266, 1.0000, 1.0000, 1.0000, 1.0000, respectively. Therefore, the proposed SFN-CoCoSo technique is effective and reliable MAGDM model. The main advantages of SFN-CoCoSo technique combined the weighted arithmetic technique and weighted geometric technique to construct the compromise solution of combining different fused decision strategies, then ranked the alternatives based on the SFNCSM and SFNED. *The main limits of the results obtained in this paper hasn't mentioned the psychological behaviour of DMs.*

5. Conclusion

New energy electric vehicles use electricity as their energy source, and the use of clean energy can reduce the pollution caused by the operation of new energy electric vehicles. The new energy electric vehicle charging station is a device that provides electrical energy supply for new energy electric vehicles. In the current stage of rapid development of new energy electric vehicles, the operation and maintenance management level of the charging station is directly related to the practicality of new energy electric vehicles. At present, there are problems with uneven regional distribution and untimely operation and maintenance management of new energy electric vehicle charging piles, which affect the actual usage rate and operation and management costs of charging piles. In view of this, it is necessary to introduce computer technology, digital technology, and information technology to innovate the operation and maintenance management mode of new energy electric vehicle charging piles, sort out and digitize the operation and maintenance management process and content, achieve all-weather monitoring of the operation status of new energy electric vehicle charging pile equipment, equipment inspection and maintenance process control, fault or defect diagnosis and early warning, and extend the service life of new energy electric vehicle charging piles. The location selection problem of electric vehicle charging stations could be deemed as the MAGDM problem. In this paper, on basis of CoCoSo technique, a novel SFN-CoCoSo technique based on SFNCSM and SFNED is conducted for dealing with MAGDM. Moreover, when the attribute weights are completely unknown, the information entropy technique is extended to SFSs to acquire the attribute weights. Finally, SFN-CoCoSo technique is used for location selection problem of electric vehicle charging stations to prove practicability of the developed technique and compare SFN-CoCoSo technique with existing techniques to further demonstrate its superiority. Hence, the main research achievements are obtained: (1) the CRITIC technique is extended to SFSs to acquire the attribute weights; (2) the novel CoCoSo technique is extended to the SFSs environment; (3) the novel SFN-CoCoSo technique based on the SFNCSM and SFNED is used to deal with MAGDM; (4) a numerical example for location selection problem of electric vehicle charging stations is presented to verify the SFN-CoCoSo technique and several comparative analysis are utilized to verify the advantages of SFN-CoCoSo technique.

There may be some possible limitations for location selection problem of electric vehicle charging stations, which could be further managed in our future research for location selection problem of electric vehicle charging stations: (1) It is a worthwhile research work to manage consensus (Wu *et al.*, 2023; Xu *et al.*, 2023; Zhang and Dai, 2023) to deal with location selection problem of electric vehicle charging stations under SFSs; (2) It is also a worthwhile research to manage regret theory to deal with the location selection problem of electric vehicle charging stations under SFSs (Tian *et al.*, 2021; Lin *et al.*, 2017).

References

Ahn, N., Jo, S.Y., Kang, S.J. (2019). Constraint-aware electricity consumption estimation for prevention of overload by electric vehicle charging station. *Energies*, 12(6), 1000.

Asna, M., Shareef, H., Muhammad, M.A., Ismail, L., Prasanthi, A. (2022). Multi-objective quantum atom search optimization algorithm for electric vehicle charging station planning. *International Journal of Energy Research*, 46(12), 17308–17331.

Aydin, S., Kahraman, C. (2020). A spherical fuzzy multi expert MCDM method based on the entropy and cosine similarity. In: *Developments of Artificial Intelligence Technologies in Computation and Robotics*. World Scientific, pp. 157–164.

Aydogdu, A., Gul, S. (2020). A novel entropy proposition for spherical fuzzy sets and its application in multiple attribute decision-making. *International Journal of Intelligent Systems*, 35(9), 1354–1374.

Badi, I., Alosta, A., Elmansouri, O., Abdulshahed, A., Elsharief, S. (2023). An application of a novel grey-CODAS method to the selection of hub airport in North Africa. *Decision Making: Applications in Management and Engineering*, 6(1), 18–33.

Banegas, J., Mamkhezri, J. (2023). A systematic review of geographic information systems based methods and criteria used for electric vehicle charging station site selection. *Environmental Science and Pollution Research*, 30, 68054–68083.

Bao, Z.Y., Xie, C. (2021). Optimal station locations for en-route charging of electric vehicles in congested intercity networks: a new problem formulation and exact and approximate partitioning algorithms. *Transportation Research Part C: Emerging Technologies*, 133, 103447.

Bian, H.H., Zhou, C.G., Guo, Z.Y., Wang, X.M., He, Y., Peng, S. (2022). Planning of electric vehicle fast-charging station based on POI interest point division, functional area, and multiple temporal and spatial characteristics. *Energy Reports*, 8, 831–840.

Chen, X., Ding, Z., Dong, Y., Liang, H. (2021). Managing consensus with minimum adjustments in group decision making with opinions evolution. *IEEE Transactions on Systems Man Cybernetics-Systems*, 51(4), 2299–2311.

Cui, F.B., You, X.Y., Shi, H., Liu, H.C. (2018). Optimal siting of electric vehicle charging stations using Pythagorean fuzzy VIKOR approach. *Mathematical Problems in Engineering*, 2018, 9262067.

Cuong, B.C. (2014). Picture fuzzy sets. *Journal of Computer Science and Cybernetics*, 30(4), 409–420.

Diakoulaki, D., Mavrotas, G., Papayannakis, L. (1995). Determining objective weight in multple criteria problems: the CRITIC method. *Computers & Operations Research*, 22(7), 763–770.

Dong, Y., Li, Y., He, Y., Chen, X. (2021). Preference-approval structures in group decision making: axiomatic distance and aggregation. *Decision Analysis*, 18(4), 273–295.

Erbas, M., Kabak, M., Ozceylan, E., Cetinkaya, C. (2018). Optimal siting of electric vehicle charging stations: a GIS-based fuzzy multi-criteria decision analysis. *Energy*, 163, 1017–1031.

Fredriksson, H., Dahl, M., Holmgren, J. (2019). Optimal placement of charging stations for electric vehicles in large-scale transportation networks. *Procedia Computer Science*, 160, 77–84.

Garg, H. (2021). Multi-attribute group decision-making process based on possibility degree and operators for intuitionistic multiplicative set. *Complex & Intelligent Systems*, 7, 1099–1121.

Garg, H., Naz, S., Ziaa, F., Shoukat, Z. (2021a). A ranking method based on Muirhead mean operator for group decision making with complex interval-valued q-rung orthopair fuzzy numbers. *Soft Computing*, 25, 14001–14027.

Garg, H., Ullah, K., Mahmood, T., Hassan, N., Jan, N. (2021b). T-spherical fuzzy power aggregation operators and their applications in multi-attribute decision making. *Journal of Ambient Intelligence and Humanized Computing*, 12, 9067–9080.

Gundogdu, F.K., Kahraman, C. (2019). Spherical fuzzy sets and spherical fuzzy TOPSIS method. *Journal of Intelligent & Fuzzy Systems*, 36(1), 337–352.

He, J., Yang, X.L., Deng, C.H., Liu, G.G., Huang, W.T., Zhu, L.W. (2022). Expansion planning of electric vehicle charging stations considering the benefits of peak-regulation frequency modulation. *IET Generation, Transmission & Distribution*, 16(7), 1400–1415.

Huang, M.F., Shen, H., Peng, J.J., Zhang, L. (2022). Research on fault recovery method of AC/DC hybrid distribution network with electric vehicle charging station. *Energy Reports*, 8, 273–279.

Jiang, Y., Wan, J.P. (2020). Research on location of electric vehicle charging station based on Voronoi diagram and improved particle swarm algorithm. In: *19th Annual Wuhan International Conference on E-Business (WHICEB)*, Wuhan, China, pp. 450–460.

Ju, Y.B., Ju, D.W., Gonzalez, E., Giannakis, M., Wang, A.H. (2019). Study of site selection of electric vehicle charging station based on extended GRP method under picture fuzzy environment. *Computers & Industrial Engineering*, 135, 1271–1285.

Karasan, A., Kaya, I., Erdogan, M. (2020). Location selection of electric vehicles charging stations by using a fuzzy MCDM method: a case study in Turkey. *Neural Computing and Applications*, 32, 4553–4574.

Kharwar, P.K., Verma, R.K., Singh, A. (2022). Neural network modeling and combined compromise solution (CoCoSo) method for optimization of drilling performances in polymer nanocomposites. *Journal of Thermoplastic Composite Materials*, 35(10), 1604–1631.

Kizhakkan, A.R., Rathore, A.K., Awasthi, A. (2019). Review of electric vehicle charging station location planning. In: *2019 IEEE Transportation Electrification Conference (ITEC-India)*, Bengaluru, India, pp. 1–5. https://doi.org/10.1109/ITEC-India48457.2019.ITECINDIA2019-226.

Kong, C.Y., Jovanovic, R., Bayram, I.S., Devetsikiotis, M. (2017). A hierarchical optimization model for a network of electric vehicle charging stations. *Energies*, 10(5), 675. https://doi.org/10.3390/en10050675.

Kutlu Gündoğdu, F., Kahraman, C. (2021). Optimal site selection of electric vehicle charging station by using spherical fuzzy TOPSIS method. In: Kahraman, C., Kutlu Gündoğdu, F. (Eds.), *Decision Making with Spherical Fuzzy Sets. Studies in Fuzziness and Soft Computing*, Vol. 392. Springer, Cham, pp. 201–216. https://doi.org/10.1007/978-3-030-45461-6_8.

Lai, H., Liao, H.C., Long, Y.L., Zavadskas, E.K. (2022). A hesitant fermatean fuzzy CoCoSo method for group decision-making and an application to blockchain platform evaluation. *International Journal of Fuzzy Systems*, 24, 2643–2661.

Li, S.W., Fan, X.L., Gao, S., Sun, Q., Bai, X.Z. (2017). Research on two-stage planning method of electric vehicle charging station based on immune algorithm. In: *2017 IEEE Conference on Energy Internet and Energy System Integration (EI2)*, Beijing, China, 2017, pp. 1–6. https://doi.org/10.1109/EI2.2017.8245441.

Li, Y.J., Pei, W.H., Xu, D. (2021). Electric vehicle charging station planning based on immune algorithm and Voronoi diagram. In: *2021 40th Chinese Control Conference (CCC)*, Shanghai, China, 2021, pp. 1532–1537. https://doi.org/10.23919/CCC52363.2021.9549436.

Li, J.L., Liu, Z.B., Wang, X.F. (2022a). Public charging station localization and route planning of electric vehicles considering the operational strategy: a bi-level optimizing approach. *Sustainable Cities and Society*, 87, 104153.

Li, Y.J., Pei, W.H., Zhang, Q. (2022b). Improved whale optimization algorithm based on hybrid strategy and its application in location selection for electric vehicle charging stations. *Energies*, 15(19), 7035.

Liang, D.C., Li, F.S., Wang, M.W., Xu, Z.S. (2022). Two-stage assignment classification model based on an improved AHPSort II with heterogeneous criteria for location selection of electric vehicle charging stations. *IEEE Transactions on Engineering Management*, 71, 2241–2254.

Liao, H.C., Kuang, L.S., Liu, Y.X., Tang, M. (2021). Non-cooperative behavior management in group decision making by a conflict resolution process and its implementation for pharmaceutical supplier selection. *Information Sciences*, 567, 131–145.

Lin, W.T., Hua, G.W. (2015). The flow capturing location model and algorithm of electric vehicle charging stations. In: *2015 International Conference on Logistics, Informatics and Service Sciences (LISS)*, Barcelona, Spain, 2015, pp. 1–6. https://doi.org/10.1109/LISS.2015.7369788.

Lin, Y., Wang, Y.M., Chen, S.Q. (2017). Hesitant fuzzy multiattribute matching decision making based on regret theory with uncertain weights. *International Journal of Fuzzy Systems*, 19, 955–966.

Liu, A.J., Zhao, Y.X., Meng, X.G., Zhang, Y. (2020). A three-phase fuzzy multi-criteria decision model for charging station location of the sharing electric vehicle. *International Journal of Production Economics*, 225, 107572.

Liu, C.C., Xiang, X., Zhang, C.R., Wang, Q., Zheng, L. (2018). A column generation based distributed scheduling algorithm for multi-mode resource constrained project scheduling problem. *Computers & Industrial Engineering*, 125, 258–278.

Liu, H.C., Yang, M.Y., Zhou, M.C., Tian, G.D. (2019). An integrated multi-criteria decision making approach to location planning of electric vehicle charging stations. *Ieee Transactions on Intelligent Transportation Systems*, 20(1), 362–373.

Liu, P.D., Zhu, B.Y., Wang, P. (2019). A multi-attribute decision-making approach based on spherical fuzzy sets for Yunnan Baiyao's R&D project selection problem. *International Journal of Fuzzy Systems*, 21(1), 2168–2191.

Luo, Q.Y., Tian, W.L., Jia, H.F. (2020). Location and capacity model of charging station for electric vehicles based on commuting demand. *IEEJ Transactions on Electrical and Electronic Engineering*, 15(7), 1089–1099.

Mahmood, T., Ullah, K., Khan, Q., Jan, N. (2019). An approach toward decision-making and medical diagnosis problems using the concept of spherical fuzzy sets. *Neural Computing & Applications*, 31, 7041–7053.

Narang, M., Joshi, M.C., Bisht, K., Pal, A. (2022). Stock portfolio selection using a new decision-making approach based on the integration of fuzzy CoCoSo with Heronian mean operator. *Decision Making: Applications in Management and Engineering*, 5(1), 90–112.

Pamucar, D., Žižović, M., Đuričić, D. (2022). Modification of the CRITIC method using fuzzy rough numbers. *Decision Making: Applications in Management and Engineering*, 5(2), 362–371.

Palanikumar, M., Kausar, N., Garg, H., Kadry, S., Kim, J. (2023). Robotic sensor based on score and accuracy values in q-rung complex diophatine neutrosophic normal set with an aggregation operation. *Alexandria Engineering Journal*, 77, 149–164.

Peng, X.D., Smarandache, F. (2020). A decision-making framework for China's rare earth industry security evaluation by neutrosophic soft CoCoSo method. *Journal of Intelligent & Fuzzy Systems*, 39(5), 7571–7585.

Rani, P., Mishra, A.R. (2021). Fermatean fuzzy Einstein aggregation operators-based MULTIMOORA method for electric vehicle charging station selection. *Expert Systems with Applications*, 182, 115267.

Saghari, A., Budinská, I., Hosseinimehr, M., Rahmani, S. (2023). A robust-reliable decision-making methodology based on a combination of Stakeholders' preferences simulation and KDD techniques for selecting automotive platform benchmark. *Symmetry*, 15(3), 750.

Sałabun, W., Urbaniak, K. (2020). A new coefficient of rankings similarity in decision-making problems. In: *20th Annual International Conference on Computational Science (ICCS)*, Amsterdam, Netherlands, 2020, Springer, Cham, pp. 632–645.

Sałabun, W., Wątróbski, J., Shekhovtsov, A. (2020). Are MCDA methods benchmarkable? A comparative study of TOPSIS, VIKOR, COPRAS, and PROMETHEE II methods. *Symmetry*, 12(9), 1549.

Sankar, S.M.U., Kumar, N.J., Elangovan, G., Praveen, R. (2023). An integrated Z-number and DEMATEL-based cooperation enforcement scheme for thwarting malicious nodes in MANETs. *Wireless Personal Communications*, 130, 2531–2563.

Seikh, M.R., Mandal, U. (2022). Multiple attribute group decision making based on quasirung orthopair fuzzy sets: application to electric vehicle charging station site selection problem. *Engineering Applications of Artificial Intelligence*, 115, 105299.

Shabu, S., Yadav, K., Kariri, E., Gola, K.K., AnulHaq, M., Kumar, A. (2023). Trajectory clustering and query processing analysis framework for knowledge discovery in cloud environment. *Expert Systems*, 40(4), e12968.

Sharaf, I.M. (2021). Spherical fuzzy VIKOR with SWAM and SWGM operators for MCDM. In: Kahraman, C., Kutlu Gündoğdu, F. (Eds.), *Decision Making with Spherical Fuzzy Sets. Studies in Fuzziness and Soft Computing*, Vol. 392. Springer, Cham, pp. 217–240. https://doi.org/10.1007/978-3-030-45461-6_9.

Sisman, A. (2023). Identification of suitable sites for electric vehicle charging stations; a geographical information systems based multi criteria decision making approach. *Energy Sources Part A: Recovery, Utilization, and Environmental Effects*, 45, 4017–4030.

Tian, X.L., Xu, Z.S., Gu, J., Herrera, F. (2021). A consensus process based on regret theory with probabilistic linguistic term sets and its application in venture capital. *Information Sciences*, 562, 347–369.

Torkayesh, A.E., Pamucar, D., Ecer, F., Chatterjee, P. (2021). An integrated BWM-LBWA-CoCoSo framework for evaluation of healthcare sectors in Eastern Europe. *Socio-Economic Planning Sciences*, 78, 101052.

Turskis, Z., Bausys, R., Smarandache, F., Kazakeviciute-Januskeviciene, G., Zavadskas, E.K. (2022). M-generalised q-neutrosophic extension of CoCoSo method. *International Journal of Computers Communications & Control*, 17(1), 4646.

Verma, R., Alvarez-Miranda, E. (2023). Group decision-making method based on advanced aggregation operators with entropy and divergence measures under 2-tuple linguistic Pythagorean fuzzy environment. *Expert Systems with Applications*, 231, 120584.

Wang, M., Liu, K., Zhao, S.H. (2013). Evaluation of electric vehicle charging station sitting based on fuzzy analytic hierarchy process. In: *2013 Fourth International Conference on Digital Manufacturing and Automation (ICDMA)*. Shinan, China, 2013, pp. 568–571. https://doi.org/10.1109/ICDMA.2013.134.

Wang, J.M., Liu, Y., Yang, Y.F., Cai, W., Wang, D.X., Jia, Z.W. (2019). The location of electric vehicle charging stations based on FRLM with robust optimization. *International Journal of Pattern Recognition and Artificial Intelligence*, 33(8), 1959027.

Wang, Y., Tang, K.W., Lai, K.X., Chen, T., Wu, X. (2021). Optimal planning of charging stations for an electric vehicle fleet in car-sharing business. *International Transactions on Electrical Energy Systems*, 31(11), e13098.

Wang, Y., Zhou, J.X., Sun, Y.Y., Wang, X.W., Zhe, J.Y., Wang, H.Z. (2022). Electric vehicle charging station location-routing problem with time windows and resource sharing. *Sustainability*, 14(18), 11681.

Wei, G.W., Lin, R., Lu, J.P., Wu, J., Wei, C. (2022). The generalized dice similarity measures for probabilistic uncertain linguistic MAGDM and its application to location planning of electric vehicle charging stations. *International Journal of Fuzzy Systems*, 24, 933–948.

Wu, P., Li, F.G., Zhao, J., Zhou, L.G., Martfnez, L. (2023). Consensus reaching process with multiobjective optimization for large-scale group decision making with cooperative game. *IEEE Transactions on Fuzzy Systems*, 31(1), 293–306.

Xu, X.X., Gong, Z.W., Herrera-Viedma, E., Kou, G., Cabrerizo, F.J. (2023). Consensus reaching in group decision making with linear uncertain preferences and asymmetric costs. *IEEE Transactions on Systems Man Cybernetics-Systems*, 53(5), 2887–2899.

Yager, R.R., Abbasov, A.M. (2013). Pythagorean membership grades, complex numbers, and decision making. *International Journal of Intelligent Systems*, 28(5), 436–452.

Yang, R.Z., Cao, Q.N. (2019). Time-satisfaction of data series based on computer original genetic algorithm gradually covers the location and algorithm of electric vehicle charging station. *Journal of Intelligent & Fuzzy Systems*, 37(5), 5993–6001.

Yazdani, M., Zarate, P., Zavadskas, E.K., Turskis, Z. (2018). A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems. *Management Decision*, 57(9), 2501–2519.

Yazdani, M., Wen, Z., Liao, H.C., Banaitis, A., Turskis, Z. (2019). A grey combined compromise solution (CoCoSo-G) method for supplier selection in construction management. *Journal of Civil Engineering and Management*, 25(8), 858–874.

Yazdekhasti, A., Jazi, M.A., Ma, J.F. (2021). Electric vehicle charging station location determination with consideration of routing selection policies and driver's risk preference. *Computers & Industrial Engineering*, 162, 107674.

Ye, J. (2016). Similarity measures of intuitionistic fuzzy sets based on cosine function for the decision making of mechanical design schemes. *Journal of Intelligent & Fuzzy Systems*, 30(1), 151–158.

Yi, T., Cheng, X.B., Zheng, H., Liu, J.P. (2019). Research on location and capacity optimization method for electric vehicle charging stations considering user's comprehensive satisfaction. *Energies*, 12(10), 1915.

Zadeh, L.A. (1965). Fuzzy sets. *Information and Control*, 8, 338–353.

Zhang, H.M., Dai, Y.Y. (2023). Consensus improvement model in group decision making with hesitant fuzzy linguistic term sets or hesitant fuzzy linguistic preference relations. *Computers & Industrial Engineering*, 178, 14.

Zhang, H., Shi, F.F. (2023). A multi-objective site selection of electric vehicle charging station based on NSGA-II. *International Journal of Industrial Engineering Computations*, 15, 293–306.

Zhang, H.Y., Wei, G.W. (2023). Location selection of electric vehicles charging stations by using the spherical fuzzy CPT-CoCoSo and D-CRITIC method. *Computational and Applied Mathematics*, *42*(60). https://doi.org/10.1007/s40314-022-02183-9.

Zhang, Z.H., Huang, Q.X., Huang, C., Yuan, X.G., Zhang, D.W. (2014). The layout optimization of charging stations for electric vehicles based on the chaos particle swarm algorithm. In: *6th Chinese Conference on Pattern Recognition (CCPR)*, Changsha, China, 2014. Springer-Verlag, Berlin, pp. 565–574.

Zhang, H., Wei, G., Chen, X. (2022). SF-GRA method based on cumulative prospect theory for multiple attribute group decision making and its application to emergency supplies supplier selection. *Engineering Applications of Artificial Intelligence*, 110, 104679.

Zhang, H.Y., Wang, H.J., Wei, G.W. (2023). Spherical fuzzy TODIM method for MAGDM integrating cumulative prospect theory and CRITIC method and its application to commercial insurance selection. *Artificial Intelligence Review*, 56, 10275–10296.

Zhao, H., Gao, J., Cheng, X. (2023). Electric vehicle solar charging station siting study based on GIS and multi-criteria decision-making: a case study of China. *Sustainability*, 15(14), 10967. https://doi.org/10.3390/su151410967.

Zu, S.D., Sun, L.J. (2022). Research on location planning of urban charging stations and battery-swapping stations for electric vehicles. *Energy Reports*, 8, 508–522.

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