Risk Assessment of Electric Vehicle Charging Stations Based on AHP Triangular Fuzzy and Variable Fuzzy Set Theories

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***Abstract*— To quantitatively evaluate the safety level during electric vehicle (EV) charging, factors inducing charging safety incidents were analyzed. Addressing limitations in existing methods for determining indicator weights, triangular fuzzy theory was employed. This method determines the weights of risk indicators based on both the likelihood of occurrence and the severity of consequences for EV battery failures, ensuring the rationality and reliability of the assessment results. Given the complex hierarchical structure and diverse attribute characteristics of this indicator system, the variable fuzzy set method was selected for a comprehensive risk assessment of EV charging station operations. A case study utilizing a charging pile in Dalian, China, was conducted for validation. This approach excels in handling fuzziness and uncertainty, enhances precision through defuzzification, and accommodates multi-level evaluation in complex systems. Charging safety was categorized into four distinct levels with defined thresholds, and trapezoidal membership functions were constructed. Analysis of operational data from a charging station confirmed the feasibility and validity of the proposed risk assessment framework. The case study demonstrates that: Triangular fuzzy theory effectively mitigates subjectivity and uncertainty in weight determination; The relative difference function-based variable fuzzy evaluation model determines membership degrees of individual factors across safety levels through parameter variation, enabling precise risk classification for each subsystem.**

***Index Terms*— Safety Engineering, Triangular Fuzzy Theory, Variable Fuzzy Sets Theory, Charging Safety, Indicator Evaluation System, Risk Evaluation**

1. INTRODUCTION

With the advancement of global energy transition and carbon neutrality goals, electric vehicles (EVs) have rapidly emerged as a key enabler for low-carbon transportation due to their zero-emission and high-efficiency advantages. According to the International Energy Agency (IEA), the global EV fleet surpassed 40 million units in 2023, accompanied by a surge in charging infrastructure scale. However, behind this rapid industrial growth, charging safety issues have become increasingly prominent: from battery thermal runaway and charging station electrical failures to grid overload risks, frequent incidents have exposed multiple hazards across technical, managerial, and environmental dimensions. Conducting a systematic safety risk assessment of the EV charging process is both an urgent necessity for safeguarding public life and property and a scientific imperative for supporting the industry's sustainable development.

Currently, EV charging safety risks exhibit characteristics of multidimensional intertwining. Technologically, the stability and compatibility of high-energy-density battery materials (such as ternary lithium and solid-state batteries) with charging protocols remain to be validated. Management-wise, responsibility boundaries among charging operators, grid companies, and users are ambiguous, with safety standards lagging behind technological iteration speeds. Environmentally, extreme conditions like high temperatures and humidity may amplify equipment failure probabilities. Additionally, emerging technologies (such as autonomous charging) may introduce novel risk scenarios. However, existing research predominantly focuses on singular risk factors (e.g., battery safety), lacking a panoramic assessment of the "human-machine-environment-management" system, thereby failing to support the optimization of risk prevention and control systems.

Based on this, this paper aims to construct a dynamic risk assessment framework for electric vehicle charging safety. By tracing technological evolution trajectories, analyzing typical accident cases, and quantifying multi-factor coupling effects, it provides a basis for formulating tiered control strategies. This research not only fills a theoretical gap in systematic assessment methods but also holds practical significance for refining industry standards and guiding equipment design and operational practices. However, existing risk assessment methods remain limited in weight determination and dynamic adaptability: traditional fuzzy comprehensive evaluation relies heavily on expert experience and is highly subjective[1]; while the Analytic Hierarchy Process (AHP) can analyze risks in layers, it inadequately addresses the multi-factor coupling effects in complex systems[2]. Furthermore, risk classification often lacks flexibility due to fixed membership functions, making it difficult to adapt to dynamic changes in charging scenarios.

To overcome these bottlenecks, this paper proposes a risk assessment framework integrating AHP triangular fuzzy theory with variable fuzzy set theory. On one hand, drawing from Panke (2018) [3]'s approach in subway operation risk assessment, triangular fuzzy quantitative indicators are introduced to capture the fuzziness of risk occurrence probability (RP) and consequence severity (RI). The comprehensive risk value (RF) is determined through composite operations (e.g., Equation (1)), thereby reducing the subjectivity of weight allocation. On the other hand, by integrating variable fuzzy set theory, the model optimizes membership functions through dynamic parameter adjustment (e.g., Equation (14)), addressing the rigid risk classification inherent in traditional approaches. This

Manuscript received September 18, 2025
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approach aligns with the subjective-objective weight fusion strategy proposed by Zhao et al. (2024) [1] while compensating for the limitations of Wang et al. (2021) [2] in dynamic assessments of complex systems. Furthermore, the AHP triangular fuzzy number method is employed to determine indicator weights. While the Analytic Hierarchy Process (AHP) leverages experts' valuable domain expertise to achieve greater realism, it overly relies on expert scoring, introducing significant subjective influence. Moreover, its judgment intervals are discontinuous, potentially undermining the objective validity of outcomes. The incorporation of triangular fuzzy numbers addresses the discontinuity issue in AHP judgments, enhancing practical applicability [4].

The innovations of this paper are: 1) Quantifying the multidimensional uncertainty of charging safety through triangular fuzzy theory to enhance the scientific rigor of weight calculations; 2) Utilizing variable fuzzy sets to dynamically map the gradual characteristics of risk levels, thereby improving the adaptability of assessment results. This research not only provides theoretical support for the safety management of charging facilities but also expands new pathways for risk assessment methods in multi-factor coupled systems.

2. Establishing an Electric Vehicle Charging Risk Evaluation System

Based on system safety principles, the key factors influencing system safety are the “Person-Vehicle-Environment-Management” framework. This framework establishes a rating system for electric vehicle charging operational risks across four dimensions: “Person,” “Machine,” “Environment,” (Equipment) - Environment - Management.“ This framework establishes a risk rating system for electric vehicle charging operations, representing the four elements through ”staff safety assessment,“ ”charging equipment safety assessment,“ ”external environment assessment,“ and ”safety management assessment." Using the Dalian Lushun Tieshan Charging Station as a case study, the framework is illustrated in Table 2.1.

Table 2.1 Risk Evaluation Index System for Automobile Charging Stations

Target Layer	Primary Indicator Layer	Secondary Indicator Layer	Indicator Description
Automotive Battery Charging Risk Level	Personnel Operation Dimension EvaluationB_1	Safety Training Coverage Rate C_1	Percentage of operations and maintenance personnel receiving specialized training on ultra-fast charging equipment operation and battery thermal runaway response.
		Certification Qualification Rate C_2	Proportion of personnel holding high-voltage electrician certification (1000V+ qualification) and charging pile operations engineer certification
		Emergency Drill Responsiveness C_3	Actual response time for liquid cooling leaks/1500V arc accidents (alarm to power disconnection ≤3 minutes)..
	Technical Equipment Dimension Evaluation B_2	Charging Peak Power Achievement Rate C_4	Ratio of measured maximum output power per gun (kW) to rated power.
		Liquid cooling system penetration rateC_5	Ratio of liquid-cooled gun lines/modules to total station equipment (liquid-cooled gun lines ≤2kg, air-cooled ≥5kg).
		V2G dispatchable capacityC_6	Total power deviation rate during station response to grid peak shaving commands (actual output/command value).
		Earth leakage protection accuracy rateC_7	Detection rate of Type B protectors for 6mA smoothed DC leakage (mandatory requirement per 2024 national standard).
	External environmental adaptability rating B_3	Salt spray protection rating C_8	Insulation resistance value of equipment metal components after 500h neutral salt spray test (≥10MΩ).
		Wide Temperature Range Output Consistency C_9	Output voltage fluctuation rate in environments from -20°C (Heilongjiang) to 50°C (Xinjiang).
		Green Power Consumption Ratio C_{10}	(Photovoltaic generation + Energy storage discharge) / Total station power consumption × 100%.
		Parking Space Management Efficiency C_{11}	Success rate of AI recognition + ground lock system in intercepting non-charging vehicles occupying spaces.
	Safety Management Evaluation B_4	Monitoring Platform Access Rate C_{12}	Percentage of charging piles uploading real-time voltage, fault codes, and charging status to government regulatory platforms.
		Insurance Coverage Completeness C_{13}	Coverage for battery puncture damage insurance + V2G reverse power transmission liability insurance, with per-incident compensation limit ≥ RMB 5 million.
		Closure Rate of Hidden Hazard Rectification C_{14}	Number of unresolved hazards past deadline / Total number of hazards × 100% (critical hazards addressed within 24 hours).
		Depth of Historical Incident Analysis C_{15}	Implementation rate of root cause analysis and improvement measures for past charging incidents.

Note:

1)The data in the table primarily references relevant evaluation factors from papers [1][2][3] and analyzes them based on corresponding assessment criteria.

2)Personnel-related indicators were determined using standards such as (GB 26860-2021) "Electric Power Safety Work Procedures" and (GB/T 29639) "Guidelines for the Preparation of Emergency Response Plans for Production Safety Accidents in Production and Business Units."

3)For technical equipment, indicators were determined using standards such as GB 26860-2021 "Electric Power Safety Work Procedures," GB/T 34657.1-2023 "Test Specification for Interoperability of Conductive Charging for Electric Vehicles," and GB 39752-2024 "Safety Requirements for Electric Vehicle Power Supply Equipment."

4)Environmental aspects adopted standards such as GB/T 18487.1-2023 Conductive Charging Systems for Electric Vehicles to determine indicators.

5)Safety management aspects adopted standards such as T/CEC 1022-2022 Technical Specification for Online Monitoring Systems of Electric Vehicle Charging Facilities.

3. Combining Triangular Fuzzy Theory with AHP and Establishing a Method for Determining Their Weights

3.1 Definition of Triangular Fuzzy Numbers

Fuzzy mathematics, based on fuzzy set theory, offers a novel approach to addressing uncertainty. It serves as a powerful tool for describing human cognitive processes and handling ambiguous information, proving particularly well-suited for describing or addressing decision-making problems involving human participation.

Definition 1 If the membership function of a fuzzy number A is:

$$\mu_A(x)=\begin{cases}\mu_A^L(x) & x\in[a,b]\\ \mu_A^R(x) & x\in[b,d]\\ 0 & x\notin[a,d]\end{cases} \tag{1}$$

式中:μ_A^L(x): [a,b] → [0,1] ,Continuous and strictly increasing;μ_A^R(x): [b,d] → [0,1] ,Continuous and strictly decreasing;a < b < d,moreovera,b,d∈ R .If

μ_A^L(x) and μ_A^R(x)are both linear functions of the form given by Equation (2), then A is termed a triangular fuzzy number and denoted as A = (a, b, d), where a is the lower bound of the possible values, b is the possible value, and d is the upper bound of the possible values.

$$\mu_A(x)=\begin{cases}\dfrac{1}{b-a}x-\dfrac{a}{b-a} & x\in[a,b]\\ \dfrac{1}{b-d}x-\dfrac{d}{b-d} & x\in[b,d]\\ 0 \quad x\in(-\infty,a]\cup[d,+\infty) & \end{cases} \tag{2}$$

Definition 2: Let the judgment matrix be defined as:

$\mathbf{A}=\left(\tilde{a}_{ij}\right)_{n\times n}$, where $\tilde{a}_{ij}=\left(a_{ij}^L,a_{ij}^M,a_{ij}^U\right),\tilde{a}_{ji}=\left(a_{ji}^L,a_{ji}^M,a_{ji}^U\right)$.

If $a_{ij}^L+a_{ji}^U=a_{ij}^M+a_{ji}^M=a_{ij}^U+a_{ji}^L=1, a_{ii}^L=a_{ii}^M=a_{ii}^U=0.5,\ a_{ij}^L..a_{ij}^M..a_{ij}^U..0,i,j\in N$, L denotes the lower bound of the value range; M denotes the possible values; U denotes the upper bound of the value range, then matrix A is termed a triangular fuzzy number complementary judgment matrix.

Let $\tilde{a}=\left(a^L,a^M,a^U\right),\tilde{b}=\left(b^L,b^M,b^U\right)$.The operation rules for triangular fuzzy numbers are as follows:

1) $\tilde{a}\oplus\tilde{b}=\left(a^L,a^M,a^U\right)\oplus\left(b^L,b^M,b^U\right)=\left(a^L+b^L,a^M+b^M,a^U+b^U\right)$.

2) $\mu\otimes\tilde{a}=\left(\mu a^L,\mu a^M,\mu a^U\right)$,where,μ≥0[4].

3) $M^{-1}=(l,m,u)^{-1}\approx\left(\dfrac{1}{u},\dfrac{1}{m},\dfrac{1}{l}\right)$.

3.2 Theory of Fuzzy Analytic Hierarchy Process

The fundamental concept of the Fuzzy Analytic Hierarchy Process (FAHP) is to decompose a multi-objective evaluation problem into hierarchical levels based on its nature and overall objectives, forming a bottom-up hierarchical structure. This process can be broadly divided into the following four steps:

Within each level (tier), pairwise comparisons are made between elements using the elements of the higher level as criteria. Their relative importance is determined based on the evaluation scale, thereby establishing a fuzzy complementary judgment matrix R = (rij). Where: The practical meaning of rij is: When comparing element ci and element cj relative to element C, ci and cj exhibit a fuzzy relationship.with a membership degree indicating "much more important than." C possesses the following properties:

$r_u=0.5,i=1,2,\cdots,n;$ (3) $r_v+r_{jn}=1,i=1,2,\cdots,n,j=1,2,\cdots,n;$ (4)

To determine the importance of element ci relative to cj, a fuzzy judgment scale ranging from 0.1 to 0.9 must be established, as shown in Table 2.1:

Table 2.1 Judgment Scale from 0.1 to 0.9

Scale	Definition	Corresponding Description
0.5	Equally important	Both factors are equally important
0.6	Slightly more important	Indicates one element is slightly more important than the other
0.7	Significantly more important	Indicates one element is significantly more important than the other
0.8	Much more important	Indicates one element is much more important than the other
0.9	Extremely more important	Indicates one element is extremely more important than the other
0.1 0.2 0.3 0.4	Contrastive	$r_{ij}+r_{ji}=1$

2 Transformation of the Fuzzy

Complementarity Judgment Matrix into a Fuzzy Consistency Matrix.Considering the subjectivity of individual evaluations, one expert is invited to provide simultaneous ratings. By applying mathematical transformations from Equations (5) and (6), complementarity judgment matrix is $\mathbf{R}=\left(r_{\mathrm{ij}}\right)_{n\times\mathrm{n}}$ converted into a fuzzy consistency matrix $\mathbf{R}^{(1)}=\left(b_{ij}{}^{(1)}\right)_{n\times\mathrm{n}}$,thereby forming the fuzzy consistency matrix . $\bar{R}=\left(\bar{b}_{ij}\right)_{n\times\mathrm{n}}$.

$$r_t=\sum_{j=1}^{n} r_{ij} \quad (i=1,2,\cdots,n) \qquad (5)$$

$$b_{ij}=\frac{r_{\mathrm{i}}-r_j}{2(n-1)}+0.5 \quad (i=1.2,\cdots,n:j=1.2,\cdots,n) \qquad (6)$$

3)Calculate the weights for each level indicator or factor using Equation (7).

$$\omega_t=\frac{\sum_{s=1}^{n}\sum_{\mathrm{i}=1}^{\mathrm{n}}\lambda_s b_y{}^n+\frac{n}{2}-1}{n(n-1)} \quad i=1,2\cdots,n \quad \text{Or } \omega_i=\frac{\sum_{j=1}^{n}\bar{b}_{ij}+\frac{n}{2}-1}{n(\bar{n}-1)},i=1.2\cdots,n \quad (7)^{[5]}$$

3.3 Applying fuzzy analytic hierarchy theory and incorporating triangular fuzzy numbers to determine weights

Based on the hierarchical relationship between evaluation indicators, as shown in Table 3-1, pairwise comparisons were conducted between factors at the criterion level and indicator level. A linguistic set I = {equally important, slightly more important, significantly more important, much more important, extremely important} was constructed. Following the calculation rules for triangular fuzzy numbers, fuzzy evaluation matrices were established for both the primary indicator level and secondary indicator level [6]. First, ten experts in the relevant field were invited to perform fuzzy semantic judgments on the electric vehicle charging evaluation indicators. Subsequently, the scores for each indicator group were statistically analyzed and normalized. Finally, triangular fuzzy number analysis was applied to obtain the l-values, m-values, and u-values for each normalized indicator score, thereby forming the triangular fuzzy numbers representing the weight ranges for each indicator. To further eliminate unreasonable subjective judgments and more accurately reflect the collective assessment results of all experts, this study employed the centroid defuzzification method to defuzzify the triangular fuzzy numbers representing each indicator's weight range, yielding a definite indicator weight value. The following formula details the calculation method.

1) The research subject group expresses their preferences using fuzzy numbers. Here, we assume three research members comparing a set of indicators (e.g., comparing C1 with C2), each obtaining a set of fuzzy numbers:$(l_1,m_1,u_1)(l_2,m_2,u_2),(l_3,m_3,u_3)$

2) Integrate the three fuzzy numbers into one.$\left(\frac{l_1+l_2+l_3}{3},\frac{m_1+m_2+m_3}{3},\frac{u_1+u_2+u_3}{3}\right)$, Repeat the above steps until all comparisons become fuzzy numbers.

3) The comprehensive fuzzy value (initial weight) of indicator i at layer K is calculated as follows:

$$\mathrm{D}_{\mathrm{i}}^{k}=\sum_{j=1}^{n}a_{ij}^{k}\div\left(\sum_{i=1}^{n}\sum_{j=1}^{n}a_{ij}^{k}\right),i=1,2,\ldots,n \qquad (8)$$

4) De-blurring, and calculating the final weights for the second-level indicator layer:

$$P\left(M_1\geq M_2\right)=\begin{cases}1 & m_1\geq m_2\\ \dfrac{l_2-u_1}{\left(m_1-u_1\right)-\left(m_2-l_2\right)} & m_1\leq m_2,u_1\geq l_2\\ 0 & \text{otherwise}\end{cases} \qquad (9)$$

5)Normalization processing:

$$\omega_i = \omega_i / \sum_{j=1}^{n} \omega_j \qquad (10)$$

After calculation, using the Dalian Lüshun Tieshan Charging Station as an example, the following data was obtained, as shown in Table 2.2,2.3,2.4,2.5,2.6:

Table 2.2 Fuzzy Judgment Matrix and Relative Weights for Factors at the Primary Indicator Level

factor	B_1	B_2	B_3	B_4	Relative Weight
B_1	(0.5,0.5,0.5)	(0.5,0.6,0.7)	(0.6,0.6,0.7)	(0.4,0.4,0.5)	0.2708
B_2	(0.3,0.4,0.5)	(0.5,0.5,0.5)	(0.5,0.6,0.6)	(0.3,0.4,0.5)	0.2336
B_3	(0.3,0.4,0.4)	(0.4,0.4,0.5)	(0.5,0.5,0.5)	(0.3,0.3,0.4)	0.2041
B_4	(0.5,0.6,0.6)	(0.5,0.6,0.7)	(0.6,0.7,0.7)	(0.5,0.5,0.5)	0.2915

Table 2.3 Fuzzy Judgment Matrix and Relative Weights for Factor B_1 in Level B_1 Secondary Indicators

factor	C_1	C_2	C_3	Relative Weight
C_1	(0.5,0.5,0.5)	(0.5,0.6,0.7)	(0.6,0.7,0.8)	0.4009
C_2	(0.3,0.4,0.5)	(0.5,0.5,0.5)	(0.5,0.6,0.7)	0.3331
C_3	(0.2,0.3,0.4)	(0.3,0.4,0.5)	(0.5,0.5,0.5)	0.2660

Table 2.4 Fuzzy Judgment Matrix and Relative Weights for Factor B_2 in Level B_2 Secondary Indicators

factor	C4	C5	C6	C7	Relative Weight
C_4	(0.5,0.5,0.5)	(0.4,0.4,0.5)	(0.5,0.6,0.6))	(0.5,0.6,0.6)	0.2629
C_5	(0.5,0.6,0.6))	(0.5,0.5,0.5)	(0.5,0.6,0.7)	(0.5,0.6,0.7)	0.2313
C_6	(0.4,0.4,0.5)	(0.3,0.4,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	0.2875
C_7	(0.4,0.4,0.5)	(0.3,0.4,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	0.2186

Table 2.5 Fuzzy Judgment Matrix and Relative Weights for Factor B_3 in Level B_3 Secondary Indicators

factor	C_8	C_9	C_{10}	C_{11}	Relative Weight
C_8	(0.5,0.5,0.5)	(0.5,0.6,0.6)	(0.4,0.4,0.5)	(0.5,0.6,0.7)	0.2629
C_9	(0.4,0.4,0.5)	(0.5,0.5,0.5)	(0.3,0.4,0.5)	(0.5,0.5,0.6)	0.2313
C_{10}	(0.5,0.6,0.6)	(0.5,0.6,0.7)	(0.5,0.5,0.5)	(0.6,0.6,0.7)	0.2875
C_{11}	(0.3,0.4,0.5)	(0.4,0.5,0.5)	(0.3,0.4,0.4)	(0.5,0.5,0.5)	0.2186

Table 2.6 Fuzzy Judgment Matrix and Relative Weights for Factor B_4 in Level B_4 Secondary Indicators

factor	C_{12}	C_{13}	C_{14}	C_{15}	Relative Weight
C_{12}	(0.5,0.5,0.5)	(0.5,0.6,0.6)	(0.5,0.6,0.7)	(0.4,0.4,0.5)	0.2629
C_{13}	(0.4,0.4,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.6)	(0.3,0.4,0.5)	0.2313
C_{14}	(0.3,0.4,0.5)	(0.4,0.5,0.5)	(0.5,0.5,0.5)	(0.3,0.4,0.4)	0.2186
C_{15}	(0.5,0.6,0.6)	(0.5,0.6,0.7)	(0.6,0.6,0.7)	(0.5,0.5,0.5)	0.2875

The absolute weight of a C-level indicator element is the product of the relative weight of the B-level indicator and the relative weight of the C-level indicator. Calculate the absolute weights based on the data in the table above. For example, C15 = 0.2875 × 0.2915 = 0.0838. Similarly, the weights for the electric vehicle charging price indicator system can be derived[6]. as shown in Table 2.7

Table 2.7 Relative and Absolute Weights of Factors at Each Level of Indicators

Overall Objective	Primary Indicator	Relative Weight	Secondary Indicator	Relative Weight	Absolute Weight

Vehicle Battery Charging Risk Level	Staff Implementation of Safety Assessment B_1	0.2708	Safety Training Coverage Rate C_1	0.4009	0.1085
			Certified Personnel Qualification RateC_2	0.3331	0.0902
			Timeliness of Emergency Drills C_3	0.266	0.072
	Charging Equipment Safety Assessment B_2	0.2336	Charging Peak Power Achievement Rate C_4	0.2589	0.0605
			Liquid Cooling System Penetration Rate C_5	0.285	0.0666
			V2G dispatchable capacity C_6	0.2281	0.0533
			Earth leakage protection accuracyC_7	0.2281	0.0533
	External environment evaluationB_3	0.2041	spray protection ratingC_8	0.2629	0.0537
			Wide Temperature Range Output ConsistencyC_9	0.2313	0.0472
			Green Power Absorption Ratio C_{10}	0.2875	0.0587
			Parking Space Management EfficiencyC_{11}	0.2186	0.0446
	Safety Management Evaluation B_4	0.2915	Monitoring Platform Access Rate C_{12}	0.2629	0.0766
			Insurance Coverage Completeness C_{13}	0.2313	0.0674
			Closure Rate of Hidden Hazard Rectification C_{14}	0.2186	0.0637
			Depth of Historical Accident Analysis C_{15}	0.2875	0.0838

4. Variable Fuzzy Evaluation Model for Risk Assessment of Electric Vehicle Charging Stations

Let the set of risk evaluation factors for charging stations be$\{B_1,B_2,\ldots,B_n\}$,where $B_1,B_2,\ldots\ldots,B_n$ represent primary indicators (e.g., personnel operations, technical equipment, etc.),each primary indicator comprises m secondary indicators. The characteristic value matrix for the subject under evaluation is $X=\left(x_{ij}\right)$, where x_{ij} the values of are determined based on the following methodology: $D(u):u|\rightarrow f_d\in[-1,1]$ primarily derived from expert scoring of the subject's actual conditions in accordance with the "Safety Evaluation Specification for Electric Vehicle Charging Stations" (GB/T 18487.1-2023) and industry standards (e.g., T/CEC 1022-2022).

4.1 Relative Difference Function Model and Fuzzying of Indicator Eigenvalues

4.1.1 Relative Subordination Function and Relative Difference Function

Let U denote the domain, and u denote any element of U. For a pair of opposing fuzzy concepts associated with element u, or two fundamental fuzzy attributes of u: A and A_C, assign the endpoints of the common-dimensional difference intermediary transition to A and A A_C with interval numbers 1, 0 and 0, 1 respectively. Form a continuum of closed intervals [1,0] and [0,1] on the number lines from 1 to 0 and from 0 to 1, respectively. For each element u in U, specify a pair of numbers f_A and f_{Ac} at any point on this continuum. Denote f_A and f_{Ac} as the relative membership degrees of u for A and A_c, respectively. Define the mapping [3] as follows:

$$\mu_A(\mu):u\ \mapsto f_A\in[0,1]$$

$$\mu_{Ac}(\mu):u\ \mapsto f_{Ac}\in[0,1] \tag{11}$$

$\mu_A(u)$ and $\mu_{Ac}(u)$ are the relative membership functions of u for A and A_c, respectively.

Let $f_d = f_A - f_{Ac}$; f_d is the relative difference degree of u for A.

Mapping

$$D(u):u|\rightarrow f_d\in[-1,1] \tag{12}$$

D(u) is the relative difference function of u with respect to A.

4.1.2 Method for Determining Relative Membership Degrees Using the Relative Difference Function

Let the set of risk evaluation factors for charging stations be $\{B_1,B_2,\ldots,B_n\}$, Assume each factor's risk domain can be divided into k levels. Based on standard specifications or evaluation objectives, the standard value interval for the hth risk level of the jth factor within the ith Level 1 indicator can be set as $[a_{ijh},b_{ijh}]$, while the upper and lower bounds for the hth risk level of this factor are $[c_{ijh},d_{ijh}]$. Here,m_{ijh} represents the point value where D(u)=1 within the interval,i.e., the most probable value of this factor at risk level h. xij denotes the numerical value at any point within the domain. Based on variable fuzzy set theory, the attraction domain I_{ab}、scope domain I_{cd} and point value matrix M fully belonging to the variable fuzzy set Iab for subway operation risk evaluation are respectively shown in Equations (13) to (15):

$$\mathbf{I}_{ab}\ =\left(\left[a_{ijh},b_{ijh}\right]\right) \tag{13}$$

$$\mathbf{I}_{cd}\ =\left(\left[c_{ijh},d_{ijh}\right]\right) \tag{14}$$

$$\mathbf{M}\ =\left(m_{ijh}\right) \tag{15}$$

In the formula, the element at row i and column h of M is m_{ijh}. The value of m_{ijh} is determined by h: When h=1, $m_{ijh}=a_{i1}$; When h=k, $m_{ijh}=b_{ik}$; When 1<h<k, $m_{ih}\in(a_{ih},b_{ih})$.

If x_{ij} falls to the left of the m_{ijh} value, the membership function of x_{ij} relative to risk level h is:

$$\mu_{Ah}\left(x_{ij}\right)=\begin{cases}0.5\left(1+\dfrac{x_{ij}-a_{ijh}}{m_{ijh}-a_{ijh}}\right), x_{ij}\in\left[a_{ijh},m_{ih}\right]\\ 0.5\left(1-\dfrac{x_{ij}-a_{ijh}}{c_{ijh}-a_{ijh}}\right), x_{ij}\in\left[c_{ijh},a_{ijh}\right]\end{cases} \tag{16}$$

Otherwise, :

$$\mu_{Ah}\left(x_{ij}\right)=\begin{cases}0.5\left(1+\dfrac{x_{ij}-b_{ijh}}{m_{ijh}-b_{ijh}}\right), x_{ij}\in\left[m_{ijh},b_{ijh}\right]\\ 0.5\left(1-\dfrac{x_{ij}-b_{ijh}}{d_{ijh}-b_{ijh}}\right), x_{ij}\in\left[b_{ijh},d_{ijh}\right]\end{cases} \tag{17}$$

Based on Equations (16) and (17), determine the relative membership degree matrix of the evaluation object's eigenvalue matrix X for each risk level, as shown in Equation (18).

$${}_{i}U=\left(\mu_{Ah}\left(x_{ij}\right)\right) \tag{18}$$

4.2 Fuzzy Variable Evaluation Model Based on Relative Membership Functions

Calculate the composite membership degree vector $U=(u_1,u_2,\ldots,u_c)$ based on the indicator weights W.:

$${}_{i}u_{h}=\left\{1+\left[\frac{\sum_{j=1}^{m}\left[\omega_{ij}\left(1-\mu_{Ah}\left(x_{ij}\right)\right)\right]^{p}}{\sum^{m}\left[\omega_{ij}\mu_{Ah}\left(x_{ij}\right)\right]^{p}}\right]^{\frac{\alpha}{p}}\right\}^{-1} \tag{19}$$

In the equation, i_{uh} denotes the non-normalized relative membership degree of the ith first-level indicator in the subway operation risk evaluation system; ω_{ij} represents the weight of the jth second-level indicator under the ith first-level indicator; α is the model optimization criterion parameter; p is the distance parameter. When p=1, equation (19) corresponds to the Hamming distance; when p=2, it corresponds to the Euclidean distance. When α=1 and p=1, equation (19) represents a fuzzy comprehensive evaluation model; when α=1 and p=2, it represents a rational model; when α=2 and p=1, it represents an S-type function; when α=2 and p=2, it represents a fuzzy preference model.

Finally, the safety level of the evaluated object can be determined based on the level discrimination criterion, defined as:

$$\begin{cases}1\le H\le 1.5,\text{Classified as Level 1}\\ h-0.5\le\overline{H}\le h,\text{Classified as Level h, leaning toward Level }(h-1)\ (h=2,3,4)\\ h\le\overline{H}\le h+0.5,\text{Classified as Level h, leaning toward Level }(h+1)(h=2,3,4)\\ 4.5\le\overline{H}\le 5,\text{Classified as Level 5}\end{cases} \tag{20}$$

4.3 Application of a Security Evaluation Model Based on Variable Fuzzy Sets

Establishing a security level domain based on fuzzy mathematical principles V={Poor,Average,Good,Excellent}, After applying fuzzy processing, the security level domain is obtained as $V=[0,70)[70,80)[80,90)[90,100]$. The risk levels are represented by the numerical values 1, 2, 3, and 4 respectively. Taking the Dalian Lushun Tieshan Charging Station as an example, within this system, assuming all indicators have consistent risk score ranges, the attractor domain of the variable fuzzy set for risk evaluation is $\mathbf{I}_{ab}=[0,70)[70,80)[80,90)[90,100]$, $\mathbf{I}_{cd}=[0,80)[0,90)[70,100)[80,100]$. Based on the attraction domain intervals of the indicators and the requirements for the point value matrix under the relative membership function, the point value matrix for the four grades of each indicator is determined as $(m_{i1},m_{i2},m_{i3},m_{i4})=(35,75,85,95)$. Through on-site investigation and inquiries, an overview of the electric vehicle charging stations in Lvshunkou District was obtained, and the project has passed mandatory inspections. Eight relevant experts scored and quantified the 15 indicators established in the evaluation system for electric vehicle charging stations in Lvshunkou District. For qualitative indicators, the average score from the eight experts served as the characteristic value. For quantitative indicators, characteristic values were determined based on actual construction standards, with judgment intervals established by reviewing relevant electric vehicle charging specifications and the regional average level. The characteristic values are shown in Table 3.1.

Table 3.1 Relative Weights and Eigenvalues of Factors at Each Level of the Indicator Hierarchy

Target Layer	Primary Indicator Layer	Relative Weight	Secondary Indicator Layer	Relative Weight	Eigenvalue
Au to mo .	Staff	0.27	Safety Training Coverage Rate C_1	0.4009	80

	Implementation of Safety Assessment B_1	08	Certified Personnel Qualification Rate C_2	0.3331	83
			Emergency Drill Timeliness C_3	0.266	56
	Charging Equipment Safety Evaluation B_2	0.2336	Charging Peak Power Achievement Rate C_4	0.2589	74
			Liquid Cooling System Penetration Rate C_5	0.285	75
			V2G Dispatchable Capacity C_6	0.2281	77
			Earth Leakage Protection Accuracy Rate C_7	0.2281	80
	External Environment Evaluation B_3	0.2041	Salt Spray Protection Rating C_8	0.2629	65
			Wide Temperature Range Output Consistency C_9	0.2313	70
			Green Power Absorption Ratio C_{10}	0.2875	72
			Parking Space Management Efficiency C_{11}	0.2186	54
	Safety Management Evaluation B_4	0.2915	Monitoring Platform Access Rate C_{12}	0.2629	55
			Insurance Coverage Completeness C_{13}	0.2313	60
			Closure Rate of Hidden Hazard Rectification C_{14}	0.2186	63
			Depth of Historical Accident Analysis C_{15}	0.2875	55

According to Equations (16)-(17), the relative membership degrees of secondary indicators C_1、C_2、C_3 under primary indicator B_1 are respectively: $\mu_{A(80)} = 0.5$ $\mu_{A(83)} = 0.8$ $\mu_{A(56)} = 0.3$

This paper calculates the comprehensive security level based on the fuzzy optimization model, where $\alpha = 1, p = 1$. The calculated $H_{B1} \approx 2.71$.

Similarly, $H_{B2}=2.90$ $H_{B3}=1.80$ $H_{B4}=2.10$

$$H_{comprehensive} = \sum\left(H_i \times \textit{Weight of Primary Indicators}\right) = 2.71\times0.2708+2.90\times0.2336+1.80\times0.2041+2.10\times0.2915\approx2.35$$

According to Equation (20), $H_{comprehensive}=2.35$ belongs to Level 2 (leaning toward Level 3).

Conclusion

This study addresses issues such as the strong subjectivity of indicator weights and inadequate handling of fuzziness in risk assessment for electric vehicle charging stations. It proposes a comprehensive evaluation method integrating AHP triangular fuzzy theory with variable fuzzy set theory. By constructing a multi-level indicator system and applying it to the Lushun Tieshan charging station in Dalian, the scientific validity and feasibility of the method were verified. Key conclusions are as follows:

1.Triangular fuzzy theory effectively enhances the objectivity of weight determination. By quantifying expert semantic judgments through dual dimensions, it significantly reduces subjective bias, making weight allocation more aligned with actual risk contributions.

2.Variable fuzzy set theory enhances the adaptability of risk classification. Its dynamic mapping mechanism based on relative difference functions flexibly handles indicator fuzziness, ensuring stable evaluation results that align with actual conditions.

3.This method combines innovation with practical value, overcoming the static limitations of traditional fuzzy evaluation. It provides comprehensive scientific support for charging station safety management and guides the formulation of targeted risk prevention measures.

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