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Fire Risk Assessment Method of Energy Storage Power Station Based on Cloud Model

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Abstract: - In response to the randomness and uncertainty of the fire hazards in energy storage power stations, this study introduces the cloud model theory. Six factors, including battery type, service life, external stimuli, power station scale, monitoring methods, and firefighting equipment, are selected as the risk assessment set. The risks are divided into five levels. Membership function is constructed using cloud model. The forward generator is responsible for calculating the complete coefficient matrix and the comprehensive evaluation matrix, while the reverse generator handles the same calculations separately. By utilizing fuzzy synthesis operators and cloud computing, the numerical attributes of the evaluation cloud model are derived, resulting in the creation of a visual representation that illustrates the fire hazard level for energy storage power stations. The results show that the cloud model can be used for fire risk assessment in energy storage power stations. Fuzzy variables can be accurately and clearly represented and corresponded to different safety levels. The effectiveness and feasibility of this assessment method have been verified through case analysis.

Keywords: Energy Storage Power Station, Fire, Cloud Mode, Battery Failure, Safety Assessment.

I. INTRODUCTION

New energy technologies like wind energy and solar energy have given rise to the emergence of large-scale energy storage plants. As of the end of 2022, the cumulative installed capacity of the global power storage projects has reached 237.2 gigawatts, indicating a yearly growth rate of 15%. The cumulative installed capacity of new energy storage, at 45.7 GW, had doubled compared to the previous year, with an annual growth rate of 80%. However, as the number of energy storage power stations continues to increase, fire and explosion incidents have become frequent. Overcharging, overdischarging, and overcurrent can lead to thermal runaway, further resulting in catastrophic explosions and casualties [1]. Just since August 2017, South Korea has experienced nearly 30 incidents of fire accidents in lithium battery energy storage projects. In China, incidents of energy storage fires and explosions have occurred in places such as Shanxi, Jiangsu, Guangdong, and Beijing [2]. For example, on April 16, 2021, a fire broke out at the Nansihuan Energy Storage Power Station in Fengtai District, Beijing, resulting in casualties. Currently, energy storage technology and industry are still in the early stages of large-scale application, lacking effective regulation, technical support for fire safety, and mature performance indicators, planning designs, technologies, and management. Therefore, this poses significant challenges to the assessment of fire hazards in energy storage power stations. Gao et al. [3] focused on the reliability and safety of current energy storage systems. Based on previous research on safety-related technologies, they proposed measures to improve the reliability and safety of energy storage systems, including establishing reasonable management systems and standards, enhancing the inherent safety of batteries, implementing module control technology, early accident prediction and alarm

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technology, and efficient firefighting technology. The causes of fires in energy storage power stations were analyzed by Kang [4] from the perspectives of battery technology, types of accidents in electrochemical energy storage power stations, and the stages of project engineering. Xiao et al. [5] established a risk assessment system from six aspects: battery basic information, battery operating conditions, external stimuli, operating environment, safety monitoring and protection systems, and human factors. The analytic hierarchy process and the entropy weight method are used to identify the subjective and objective weights of the indicators in the risk evaluation system and to evaluate the risk level of the energy storage power station. Wang et al. [6] selected 43 charging stations and conducted a comprehensive assessment of their overall situation using the analytic hierarchy process. Based on the results, they made improvements and provided supervision to ensure charging safety. Liang Yunhua et al. [7] analyzed the causes of lithium battery thermal runaway based on relevant accident cases of chemical energy storage power stations, and summarized the deficiencies and fire safety risks of current fire protection systems in chemical energy storage power stations. Fang et al. [8] provided safety risk suggestions for energy storage power stations, covering aspects like site selection, energy storage battery systems, environmental control systems, monitoring systems, protection systems, fire alarm and extinguishing systems, equipment selection, and installation and commissioning. Xu et al. [9] summarized various accidents in battery energy storage power stations and analyzed the primary safety risk factors, including fire, explosion, poisoning, electric shock, burns, etc., within battery energy storage power stations. From the above analyses, it becomes evident that accidents in energy storage power stations persist, and scholars have developed a relatively comprehensive understanding of the factors affecting fires in such stations. However, there has been limited systematic and comprehensive evaluation of the numerous influencing factors. This limitation primarily stems from the complexity of energy storage power stations themselves and the variability of factors that impact batteries, resulting in significant fuzziness surrounding these influencing factors. Uncertainty exists in the risk assessment process, whether it is the selection of the risk set, calculation of weight coefficients, or the formation of comprehensive judgment matrices [10], making it difficult to express using quantitative methods. Traditional methods such as the analytic hierarchy process and fuzzy mathematics have been widely applied in coal mining engineering practice and theoretical research, but these evaluation methods have inherent fuzziness. Cloud model theory, with its strong visual and quantitative representation, has been widely applied in various aspects of risk assessment, combining qualitative and quantitative approaches, and has shown good effectiveness.

II. Basic Theory of Cloud Model

A. *Definition and Numerical Characterization of Cloud Models*

The distribution of x over a domain U is called a cloud if the quantitative value $x \in U$ is a stochastic realization of the qualitative concept C and the determinism of x with respect to C, $\mu(x) \in [0, 1]$, is a stable trend, and each x is called a cloud droplet (x, μ(x)). In cloud modeling, the qualitative concepts are represented by three numerical features: expectation (E), entropy (N) and hyper entropy (H). The expected value E in the cloud model represents the most representative point of the qualitative concept. The entropy N quantifies the uncertainty of the qualitative concept, reflecting not only the dispersion of the cloud droplets, but also the range of values that are acceptable as part of the concept within the domain. The hyper entropy H reflects the degree of aggregation of cloud droplets in the cloud model.

B. *Cloud Generator*

This study primarily employs forward and reverse cloud generators [11]. Forward cloud generator is a direct process of transforming qualitative concepts into quantitative values. By inputting the expectation, entropy, hyper-entropy, and the number of cloud droplets into the generator, the quantitative value in the domain of the characterized cloud droplets and the degree of conceptual representation are obtained. The forward cloud generator satisfies the conditions that the distribution follows a normal distribution with a mean of μ and a variance of. For a normally distributed random number, the distribution satisfies a normal distribution with a mean of μ and a variance of, and it also satisfies the degree of concept representation for the qualitative concept [12].

$$\mu = exp\{-(x-E)^2/[2(N')^2]\} \tag{1}$$

In contrast to the forward cloud generator, the reverse cloud generator is an indirect process that converts quantitative values into qualitative concepts [13]. The generator utilizes statistical cloud drops to compute the expectation, entropy, and superentropy of a cloud model, providing an effective method for fuzzy synthesis and evaluation. If the sample size of x is n, the operation mechanism of the generator consists of two steps: firstly, the mean and variance of the sample x are calculated, and then the expectation, entropy and superentropy of the cloud model are obtained as follows:

$$\begin{cases} E = \bar{X}; \\ N = \frac{\sqrt{\pi/2}}{n} \sum_1^n |x - E| \\ H = \sqrt{s^2 - N^2} \end{cases} \quad (2)$$

III. CLOUD MODEL CONSTRUCTION

A. *Risk Set Factors are Determined*

The evaluation results of energy storage power stations crucially depend on the selection of risk factors in the risk assessment. Based on engineering practical experience and relevant literature [14,15], this study selects six risk factors: battery type, service life, external stimuli, power station scale, monitoring methods and means, and firefighting equipment (as shown in Figure 1) to constitute the set of fire hazard factors for energy storage power stations and they are categorized into four levels of hazard.

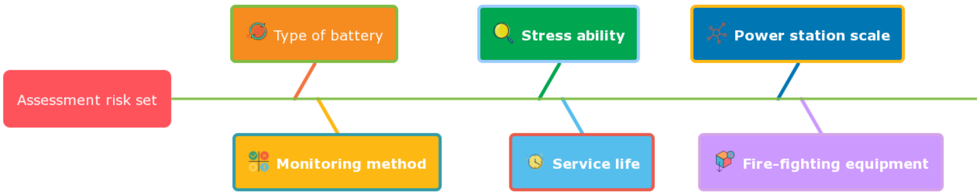

Figure1: Set of Risk Factors for Energy Storage Power Stations

The risk assessment of energy storage power plant fires based on cloud model can be divided into three steps (as shown in Figure 2):

Step 1: Select risk factors (Table 1) for the evaluation of the energy storage power plant as the assessment object and clarify the evaluation criteria. Then, establish the set of fire risk factors and the set of risk level comments for energy storage power plants.

Table 1: Risk Factors of Energy Storage Power Station

Primary index	Secondary index	Pointer code
Type of battery A	Lithium ion cobalt acid battery	A1
	Ternary lithium battery	A2
	Lithium iron phosphate battery	A3
	Too acidic lithium-ion batteries	A4
Charge and discharge frequency B	0~500 times	B1
	500~1200 times	B2
	1200~2000 times	B3
	2000~25000 times	B4
Stress ability C	Temperature resistance	C1
	Extrusion degree	C2
	Voltage interval	C3
	Current interval	C4
Power station scale D	Installed capacity	D1
	Battery management system	D2
	Plant cost	D3
Monitoring method E	Cell voltage monitoring	E1
	Cell temperature monitoring	E2
	Gas concentration monitoring	E3
	Optical fiber pressure detection	E4
	Insulation detection	E5
	Ultrasonic inspection and measurement	E6
Fire-fighting equipment F	Fire sensor	F1
	Fire pipe	F2
	Fire sprinkler	F3
	Fire power distribution	F4

Step 2: Combine historical data, literature, and on-site surveys to obtain a set of weights corresponding to the risk factor set using the expert scoring method. Then, each factor in the risk set is scored and the inverse cloud

generator is used to obtain the coefficient matrix and the combined evaluation matrix represented by the numerical features of the cloud model.

Step 3: Fuzzy synthesis operators and cloud computing are employed to obtain the digital features of the evaluation cloud model from the coefficient matrix and comprehensive evaluation matrix. Clouds of various evaluation comments and “cloud droplets” diagrams of the evaluation cloud model are generated using the forward cloud generator for intuitive comparative analysis, thereby determining the level of fire hazard for the energy storage power plant.

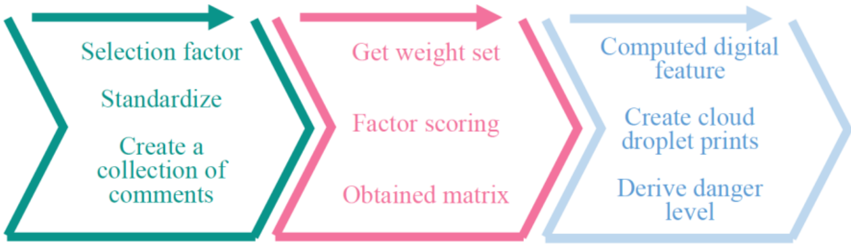

Figure 2: Fire Risk Assessment Steps of Energy Storage Power Station Based On Cloud Model

B. The Fire Risk Evaluation Cloud Model of Energy Storage Power Station was Established

First, the energy storage power plant is described in terms of risk levels using the cloud model, assigning a set of comments. Each comment is assigned a value within a bilateral boundary [Amin, Amax], and the digital features of each comment’s cloud model can be calculated as follows:

$$\begin{cases} E = (Amax + Amin)/2 \\ N = (Amax - Amin)/6 \\ H = k \end{cases} \tag{3}$$

In Equation (3), Amin and Amax represent the lower and upper limits of the comment values for a certain risk level, respectively. The constant k is adjusted based on the fuzzy threshold of the risk factor set [16].

Considering the distribution of the total risk values of fire hazards in different sections and the level of risk acceptance, the risk levels of the energy storage power plant fire hazards are divided based on the accumulated experience of decision-makers [17]. Then, evaluation comments and evaluation ranges are assigned to different risk levels as follows:

Extremely Safe (Level 1): The evaluation range is [0, 2), indicating that the probability of fire occurrence in the energy storage power plant is almost nonexistent, and no measures need to be taken to reduce the risk.

Relatively Safe (Level 2): The evaluation range is [2, 5), indicating that the probability of fire occurrence in the energy storage power plant is low and acceptable, but the risk is not significant. Mainly periodic inspections, standardized electricity usage, and other measures are taken to address the risk.

Moderately Unsafe (Level 3): The evaluation range is [5, 7), indicating that there is a probability of fire occurrence in the energy storage power plant, which is allowed to exist. Proper protection measures such as identifying and eliminating hazards and improving equipment are needed to reduce the risk.

Extremely Unsafe (Level 4): The evaluation range is [7, 8), indicating that the probability of fire occurrence in the energy storage power plant is extremely high and unacceptable. Due to the ambiguity and uncertainty of accidents, the consequences of the risk are severe. The probability must be reduced to a reasonable and acceptable range. Measures such as equipment replacement and timely cessation of use are necessary to address the risk.

Based on this, the cloud model is used to represent these four levels of fire hazard for the energy storage power plant, replacing constants to construct the membership functions. Table 2 presents the evaluation cloud model concerning the risk levels of fire hazards in the energy storage power plant, which is derived from the categorization of risk levels and Equation (1).

Table 2: Cloud Model for Evaluation of Fire Risk Level of Energy Storage Power Station

Risk grade	Parameter	
	(E,N)	H
Extremely low	(1,0.333)	0.1
Low	(3,0.333)	0.1
Medium	(5,0.333)	0.1
High	(7,0.333)	0.1
Extremely high	(9,0.333)	0.1

The cloud map of fire risk level of the energy storage power station is obtained by using the forward cloud generator, as shown in the Figure 3:

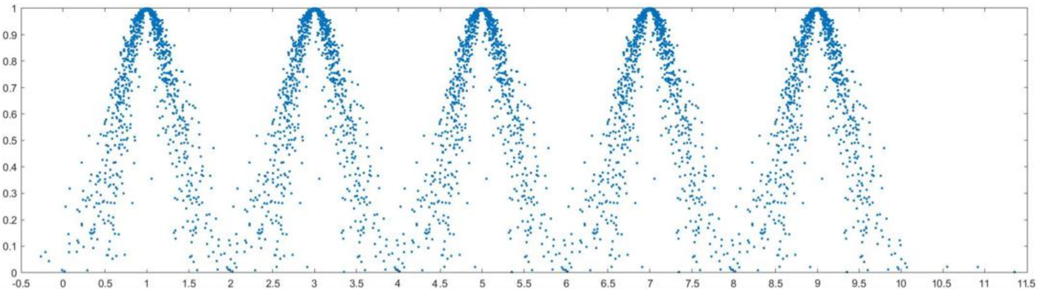

Figure 3: Cloud Diagram of Fire Risk Level of Energy Storage Power Station

C. The Weight Coefficient Matrix and Comprehensive Evaluation Matrix are Calculated

The risk set M is established as $= [m_1, m_2, \ldots, m_q]$, where q is the number of risk factors for energy storage power plant fires. The corresponding weight set and evaluation matrix for the risk set are $A = [a_1, a_2, \ldots, a_q]$ and $R = [r_1, r_2, \ldots, r_q]^{\tau}$, respectively. In this approach, the cloud model is used to calculate the coefficient matrix and the comprehensive evaluation matrix instead of the membership function. The weights are determined by consulting domain experts and assigning scores to determine the importance of each factor. Similarly, based on the evaluation criteria for the fire factor risk level of the energy storage plant, the inverse cloud generator is utilized to solve the comprehensive evaluation matrix and calculate the expected value, entropy, and hyper entropy of the cloud model.

The following are the coefficient matrices and comprehensive evaluation matrices for the fire risk factors of the energy storage plant:

$$A = [a_1, a_2, \ldots, a_q] = \begin{bmatrix} E_{a1} & N_{a1} & H_{a1} \\ E_{a2} & N_{a2} & H_{a2} \\ & \cdots & \\ E_{aq} & N_{aq} & N_{aq} \end{bmatrix} \mathrm{T} \tag{4}$$

$$R = [r_1, r_2, \ldots, r_q] = \begin{bmatrix} E_{r1} & N_{r1} & H_{r1} \\ E_{r1} & N_{r2} & H_{r2} \\ & \cdots & \\ E_{rq} & N_{rq} & H_{rq} \end{bmatrix} \mathrm{T} \tag{5}$$

The interpretation of the coefficient parameters a_i (E_{ai}, N_{ai}, H_{ai}) can be understood based on the significance of the cloud model feature parameters. Due to the randomness and uncertainty involved in obtaining the weight coefficients [18], the assigned score E_{ai} for the i-th specific risk factor m_i of the energy storage power plant may vary. Due to the influence of subjective factors, different experts' assessment scores for the same factor generally fall within the range [E_{ai}-$3N_{ai}$, E_{ai}+$3N_{ai}$]. Conversely, H_{ai} more intuitively reflects the randomness of the evaluation [19].

D. Generate Evaluation Clouds and "Cloud Droplet" Graphs for Each Evaluation Cloud

The digital feature B of the cloud model for fire risk assessment of energy storage power station is obtained through fuzzy synthesis operators and cloud computing, namely:

$$B = A\mathrm{o}R = (E, N, H) \tag{6}$$

Where o is the comprehensive computing operator and the symbol of cloud computing, there are:

$$E = E_{a1}E_1 + E_{a2}E_2 + \ldots + E_{aq}E_q \tag{7}$$

$$N = \left\{ \left| E_{a1}E_1[(N_{a1}/E_{a1})^2 + (N_1/E_1)^2]^{1/2} \right|^2 + \left| E_{a2}E_2[(N_{a2}/E_{a2})^2 + (N_2/E_2)^2]^{1/2} \right|^2 + \ldots \left| E_{aq}E_q\left[\left(N_{aq}/E_{aq}\right)^2 + \left(N_q/E_q\right)^2 \right]^{1/2} \right|^2 \right\}^{1/2} \tag{8}$$

$$H = \left\{ \left| E_{a1}E_1[(H_{a1}/E_{a1})^2 + (H_1/E_1)^2]^{1/2} \right|^2 + \left| E_{a2}E_2[(H_{a2}/E_{a2})^2 + (H_2/E_2)^2]^{1/2} \right|^2 + \ldots \left| E_{aq}E_q\left[\left(H_{aq}/E_{aq}\right)^2 + \left(H_q/E_q\right)^2 \right]^{1/2} \right|^2 \right\}^{1/2} \tag{9}$$

In conclusion, "cloud droplets" diagrams for the evaluation cloud and each comment cloud model are generated using the positive cloud generator, facilitating a comparative analysis. The comment cloud model that best matches the evaluation cloud model is chosen as the outcome of the risk assessment, determining the fire hazard risk level in the energy storage power plant.

IV. EXPERIMENTAL VERIFICATION

A. Instance Selection

A large-scale shopping mall in Beijing, with a total floor area of approximately 154,000 square meters, is an internationally standardized one-stop shopping center. The mall has over 400 merchants. Due to its extensive floor area and diverse range of merchants, the shopping center has various energy storage power systems, all of which have certain fire hazards. Moreover, the mall experiences a high volume of foot traffic, so any accidents such as fires would result in severe casualties and economic losses. Given this background, this paper selects the shopping mall as the research subject and adopts the expert scoring method to analyze the risk level of fire hazards in its energy storage power systems.

B. Risk Level Assessment of Fire Hazards in Energy Storage Power Plants Based on Cloud Model

Since the selected factors have different impacts on the risk levels of fire hazards, it is necessary to assign weights to each risk factor. After collecting samples for risk assessment of fire hazards in energy storage power plants, expert opinions are consulted to score each factor based on their importance, obtaining the weight set corresponding to each risk. The generation of weight clouds for each risk factor and the calculation of the coefficient matrix *A* are carried out using the inverse cloud generator. Combining the evaluation criteria for the risk levels of fire hazards in energy storage power plants, on-site investigations, and consultations with relevant experts, evaluation vectors for each factor in the risk set are obtained through value assignment and scoring. The inverse cloud generator is used to compute the expected value, entropy and hyper entropy for each risk factor to derive the comprehensive evaluation matrix R.

By using fuzzy synthesis operators [20] and cloud computing, the digital features B of the evaluation cloud model for fire risk in energy storage power plants are obtained. With the help of positive cloud generator, six risk assessment levels and assessment results are represented using MATLAB [21] as shown in Figure. From the results in the figure, it can be concluded that the risk level of fire hazards in the energy storage power plant of the shopping mall aligns closely with the low-risk level, indicating that the risk level is categorized as low risk (Level 2, as is shown in Figure 4).

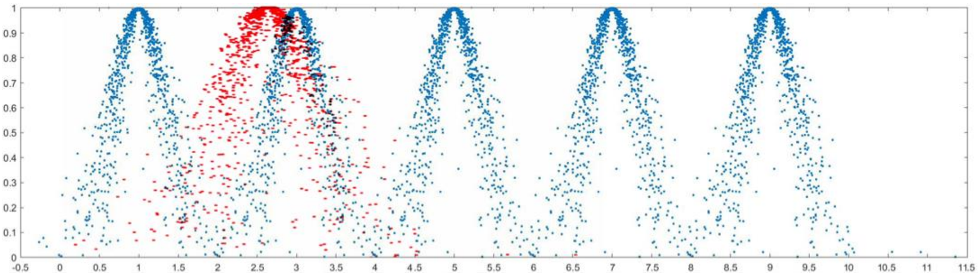

Figure 4: Case evaluation results

V. CONCLUSION

In this study, cloud modeling was used to analyze the fire risk of energy storage stations. The conclusions are as follows:

(1) The risk of energy storage stations can be analyzed in terms of battery type, service life, external stimuli, station scale, monitoring methods and means, and fire protection equipment.

(2) Using fuzzy synthesis operator and cloud computing, we extracted numerical features for evaluating the cloud model. Subsequently, a positive cloud generator was employed to create evaluation clouds and “cloud droplets” that represent the assessment of fire risk in energy storage stations, offering an intuitive visualization of the risk levels.

(3) Cloud modeling can be applied in the field of fire risk assessment for energy storage stations. Fuzzy variables can be accurately represented by intervals, corresponding to different safety levels. The reliability of this method was also verified through case studies.

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