A Fuzzy Inference-Based Warning Model for Ecological Environment Risks in Industrial Parks

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Abstract. Based on the ecological environment risk factors in industrial parks, we propose an industrial park ecological environment risk assessment model to quantify ecological environment risks and accurately identify high-risk events. The risk factors are fuzzified by using fuzzy sets, the classification criteria for risk factor levels are determined. Furthermore, we develop a fuzzy inference rule base based on expert knowledge and use fuzzy inference and hierarchical structures to build a risk early warning model across multiple dimensions. This model computes ecological environment risk values for industrial parks and simulates the occurrence and early warning of ecological environment risks in industrial parks by inputting relevant risk factor data, which provide decision support for risk prevention and ecological environment management.

1 Introduction

As industrialization accelerates in China, various industrial parks of all kinds have become key engines for regional economic development, but they have also brought increasingly severe ecological and environmental challenges. In recent years, sudden environmental incidents in industrial parks have occurred with increasing frequency, causing not only significant economic losses but also posing a serious threat to regional ecosystems and human health[1]. Xu et al. (2025) analysed 31 inorganic pollutants and 92 organic pollutants in nine representative industrial parks and found that areas classified as low-risk based on chemical analysis still exhibited significant toxic effects in biological tests, including mortality, reduced hatching rates, malformations, and behavioral toxicity[2]. The existing risk assessment methods struggle to effectively address the multi-source, dynamic, and nonlinear characteristics inherent in the complex environmental systems of industrial parks. In particular, they exhibit significant limitations in handling uncertain information, quantifying ambiguous factors, and characterizing risk transmission mechanisms[3].

To fill this research gap, this study develops a fuzzy inference-based warning model for ecological environment risk in industrial parks to improve the risk management. Fuzzy mathematics uses membership functions to characterize the gradual nature of risk factors, enabling a more accurate description of the transitional states between expert experiences and monitoring data. For example, Khan et al. (2025) have proposed a new method for dynamically optimizing the parameters of an alpha-beta filter using the Matadi Fuzzy Inference System (MFIS) for industrial applications, aiming to estimate the state of a dynamic system based on sensor measurements[4]. Chen et al. (2025) have proposed a framework that combines the Fuzzy Hierarchical Analytic Method (FAHP) with a Matani-based fuzzy inference system to address issues in the risk assessment of offshore wind turbines, such as the failure to account for the uncertainty in expert evaluations, the inefficiency of fuzzy rule generation, and shortcomings in risk classification[5]. In the field of risk assessment, the possibility theory proposed by Zadeh provides a mathematical foundation for handling imprecise information, while Mamdani fuzzy inference systems enable the transformation of qualitative knowledge into quantitative rules. The integration of fuzzy inference systems (FIS) into risk assessment has been shown to enhance infrastructure management and sustainability by reducing uncertainty in the decision-making process and simulating human decision-making[6]. Compared to traditional methods, fuzzy set theory offers distinct advantages in risk quantification: 1) It allows risk factors to simultaneously belong to multiple levels to varying degrees, which better reflects the actual characteristics of environmental systems; 2) It enables flexible integration of multi-source, heterogeneous data through the establishment of an “IF-THEN” rule base; 3) It enhances the interpretability of assessment results by expressing risk states using linguistic variables.

2 Model Building

2.1 Model Principle

Mamdani fuzzy inference can directly perform the fuzzy inference calculation process from the initial input to the final output using a set of predefined inference rules. Thus, an accurate fuzzy recognition and inference system

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can be constructed. The principle of fuzzy inference-based warning model is shown in the Figure 1.

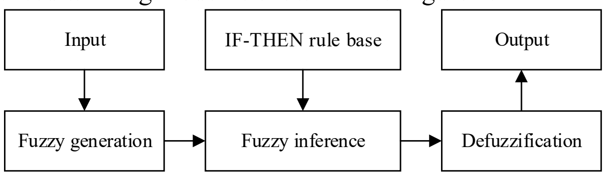

Fig. 1. The principle of fuzzy inference-based warning model.

Fuzzy inference is a method used to map given inputs to corresponding outputs, involving membership functions, logical operations, and IF-THEN rules. This model requires input and output values, and uses membership functions to determine their membership degrees in the appropriate fuzzy sets. A membership function is a curve that defines how each point in the input space is mapped to a membership value between 0 and 1. The input space is commonly referred to as the domain, while the values on the output axis are called membership degrees . The mathematical expression is:

$$A=\left\{x,\mu A\left(x\right)|\,x\in X\right\} \tag{1}$$

Where, $\mu A\left(x\right)$ denotes the membership function of x in A.

Specifically, if X denotes the domain and its elements are denoted by x, then a fuzzy set A in X can be defined as a set of ordered pairs. This definition is a key concept in fuzzy inference systems, enabling the development of effective control systems that handle uncertainty and fuzziness.

The fuzzy rule base contains rules that cover all possible fuzzy relationships between inputs and outputs. The inputs of a fuzzy operator consist of two or more membership values derived from the fuzzy input variables.

Defuzzification is the step of parsing the output values obtained in the form of fuzzy sets into a single numerical output. Among them, the center of gravity defuzzification method is one of the most commonly used and intuitive methods. The mathematical expression is as follows:

$$Z=\frac{\int \mu A\left(z\right)zdz}{\int \mu A\left(z\right)dz} \tag{2}$$

Where, $\mu\left(z\right)$ represents the membership degree of the fuzzy output set, and Z represents the precise output after defuzzification.

2.2 Ecological environment risk factors

The ecological environment of the industrial park is comprehensively affected by factors such as hazardous substances, production processes and risk management capabilities. Based on the green development requirement of industrial parks, and referencing relevant literature and expert survey findings, a total of 16 risk factors were identified. The results are shown in Table 1.

Table 1. Ecological environment risk factors.

Dimension	Indicator
Hazardous substances	Ratio of hazardous chemical storage volume to critical volume (Q value)
	Emissions concentrations of specific pollutants (e.g., VOCs, heavy metals)
	The amount of solid waste (including hazardous waste)
Production process and equipment	Process risk level
	Equipment performance
	Monitoring coverage
Sensitive targets	Biodiversity
	The distance between the enterprise and residential areas / schools / hospitals
	The distance between the enterprise and ecologically sensitive areas such as drinking water sources and wetlands
Management and Systems	Employee
	System
	Emergency management
Regional environment	Regional climate
	AQI
	Surface water quality
	Percentage of soil contamination sites exceeding standards

In hazardous substances dimension, risk factors primarily include ratio of hazardous chemical storage volume to critical volume (Q value), emissions concentrations of specific pollutants (e.g., VOCs, heavy metals), the amount of solid waste (including hazardous waste). According to "Identification of Major Hazard Sources for Hazardous Chemicals" (GB18218), the Q value is the core indicator for determining whether an enterprise constitutes a major hazard source. It directly affects the likelihood and severity of sudden environmental incidents. The control of conventional pollutants has been relatively mature, but for specific pollutants such as VOCs, there are no clear emission standards in some parks, which can lead to hidden pollution and long-term ecological accumulation risks. Problems such as mixed storage of hazardous waste and illegal dumping occur frequently. Inconsistent disposal practices will directly lead to soil and groundwater pollution.

In production process and equipment dimension, risk factors primarily include process risk level, equipment performance, monitoring coverage. If the high-risk processes get out of control, they are prone to trigger chain reactions, which is a key point where production safety and environmental pollution are intertwined. The environmental performance and related parameters of the equipment directly impact the controlled emission of pollutants and the management of potential risks. Online monitoring is the technical prerequisite for real-time risk warning, reflecting the level of intelligent management in the industrial park.

In sensitive targets dimension, risk factors primarily include biodiversity, the distance between the enterprise and residential areas / schools / hospitals, the distance between the enterprise and ecologically sensitive areas such as drinking water sources and wetlands. Biodiversity and the rate of disappearance of indicator species (such as dragonflies and frogs) are early indicators of ecosystem imbalance. Air and noise pollution have a significant impact on human health. The closer the distance, the higher the vulnerability of environmental risk receptors, and the stricter the requirements for emergency response. The water environment receptors are extremely sensitive to pollutants. Once pollution occurs, irreversible ecological damage will result.

In management and systems dimension, risk factors primarily include employee, system, emergency management. Employees are both the primary source of ecological environment risks in industrial parks and a key force in prevention and control. Operational errors, management lapses, and a lack of awareness can directly lead to pollution incidents. The system serves as the fundamental guarantee for preventing and controlling environmental risks in industrial parks. Emergency response capabilities determine the efficiency of responding to sudden environmental incidents. The absence of a contingency plan or insufficient practice will amplify the impact of the accident.

In Regional environment dimension, risk factors primarily include regional climate, AQI, surface water quality, percentage of soil contamination sites exceeding standards. Factors such as rainfall frequency and the number of days with high temperatures can have a significant impact on emissions and risk sources. AQI reflecting the atmospheric carrying capacity of the park and its surrounding areas. Since water bodies have limited self-purification capacity, if the receiving water body is nearing its functional capacity limit, enterprises must comply with stricter discharge standards. Soil pollution is characterized by its concealment and persistence. Historical legacy issues may become potential sources of future risks and hazards.

2.3 Fuzzification of risk factor

Fuzzy set theory effectively addresses the uncertainty in environmental monitoring data through membership functions. For quantitative risk indicators, piecewise linear membership functions are used to achieve precise quantification. For example, according to the Technical Guidelines for Prioritizing the Control of Air Pollution Sources, VOCs are classified into four risk levels: 1) 0.75 ≤ Pollution Source Grading Index (PGI) ≤ 1.00, the pollution source is classified as Level 1; 2) 0.50 ≤ PGI < 0.75, the pollution source is classified as Level 2; 3) 0.25 ≤ PGI < 0.50, the source is classified as Level 3; 4) 0.00 ≤ PGI < 0.25, the source is classified as Level 4. For qualitative indicators such as emergency management, a mapping relationship is established between linguistic variables and fuzzy numbers; for example, “well-developed” corresponds to [0.8, 1.0], ‘good’ corresponds to [0.7, 0.8], “basically complete” corresponds to [0.5, 0.7], and “lacking” corresponds to [0, 0.5]. The results of the risk factor fuzzification are shown in Table 2.

Table 2. The results of the risk factor fuzzification.

Indicator	I	II	III	IV
Ratio of hazardous chemical storage volume to critical volume (R value)	R ≥ 100	50 ≤ R <100	10≤ R <50	R <10
Emissions concentrations of specific pollutants (e.g., VOCs, heavy metals)	0.75 ≤ PGI ≤1.00	0.50 ≤ PGI＜0.75	0.25 ≤ PGI＜0.50	0.00 ≤ PGI＜0.25
The amount of solid waste (Annual output)	≥ 100 t	50 t ~ 100 t	10 t ~ 50 t	10 t
Process risk level	4 (Extremely hazardous process)	3 (High-risk processes)	2 (Medium-risk processes)	1 (Low-risk processes)
Equipment performance	4 (High energy consumption and high emissions)	3 (Low energy consumption, high emissions)	2 (High energy consumption, low emissions)	1 (Low energy consumption, low emissions)
Monitoring coverage	< 50%	50% ~75%	75% ~90%	≥ 90%
Biodiversity	1 (Significantly damage the ecosystem)	2 (Significantly disrupts species distribution)	3 (Slightly alter the existing ecological environment)	4 (Virtually no impact)
The distance between the enterprise and residential areas / schools / hospitals	≤ 100 m	100～300 m	300～500 m	> 500 m
The distance between the enterprise and ecologically sensitive areas such as drinking water sources and wetlands	≤ 500 m	500～1000 m	1000～2000 m	> 2000 m
Employee	1 (Low -quality employees)	/	2 (Average-performing employees)	4 (High-quality employees)
System	[0, 0.5] (Lacking)	[0.5, 0.7] (Basically complete)	[0.7, 0.8] (Good)	[0.8, 1.0] (Well-developed)
Emergency management	[0, 0.5] (Lacking)	[0.5, 0.7] (Basically complete)	[0.7, 0.8] (Good)	[0.8, 1.0] (Well-developed)

Regional climate	1 (Extremely high climate vulnerability)	2 (High climate vulnerability)	3 (Medium climate vulnerability)	4 (Low climate vulnerability)
AQI	200＜AQI	200＜AQI≤300	100＜AQI≤200	AQI≤100
Surface water quality	Class V (Poor)	Class V	Class IV	Class I, II, III
Percentage of soil contamination sites exceeding standards	≥ 30%	15% ≤ Percentage < 30%	5% ≤ Percentage < 15%	Percentage< 5%

2.4 Fuzzy rule base of ecological environment risk

We use the Mamdani fuzzy inference system to translate expert knowledge into computable semantic rules. The system constructs a rule base using "IF-THEN" conditional statements, as follows.

$$R_i : if\ x_i\ is\ A_{il}, y_i\ is\ B_{il}, then\ z\ is\ C_i\ \left(i=1.2,...,k\right) \quad (3)$$

Where, k denotes the number of rules, x_i and y_i are input variables, z is the output variable, and A_{il}, B_{il}, and C_i are the input-output membership distributions under the i th inference rule, respectively.

The number of rules involved in the 16 risk factors and the 4 risk level classifications could potentially reach 16^4. We use a hierarchical structure to reduce the number of rules to 5^4. Considering the space limitation, we only present a representative rule as follows:

IF (Hazardous substances is I) AND (Production process and equipment is II) AND (Sensitive targets is II) AND (Management and Systems is III) AND (Regional environment is II), THEN (Ecological environment risks is I).

2.5 Defuzzification of ecological environment risk

After establishing a fuzzy inference rule base, Mamdani inference is used to obtain fuzzy values, and the center of gravity method is used for defuzzification to derive the final risk values. As a defuzzification method, the center of gravity method determines precise risk values by calculating the coordinates of the center of gravity of the output fuzzy set. As shown in Table 3, the ecological risk level of the industrial park can be determined based on the total risk value, thereby enabling risk early warning.

Table 3. The ecological risk level.

Risk level	Risk description	Risk value
I	High-risk	[0.6, 1]
II	Medium risk	[0.4, 0.6]
III	Medium-low risk	[0.2, 0.4]
IV	Low risk	[0, 0.2]

As shown in Table 3, We classify risks from high to low into four risk levels: Level I is the high-risk, with the corresponding risk value range being [0.6, 1]; Level II is medium risk, with the risk value range in [0.4, 0.6]; Level III is medium-low risk, with the risk value falling within [0.2, 0.4]; and Level IV is low risk, with the risk value range being [0, 0.2].

The core advantage of the center-of-gravity method for risk management lies in its ability to convert vague risk ranges into precise numerical values, making the level of risk tangible and concrete. Through the center-of-gravity method, we can obtain a precise value that represents the overall risk level of the interval. This value comprehensively accounts for all possible risk scenarios within the interval, avoiding the one-sidedness that results from simply using the endpoints or midpoint of the interval. It more accurately reflects the actual severity of high-risk situations, helping decision-makers clearly assess the critical risk and formulate more targeted response strategies.

3 Conclusion

To improve environmental management in industrial parks, we have proposed a fuzzy logic-based environmental risk early warning model for industrial parks. This model can quickly and accurately predict ecological risks in industrial parks by comprehensively evaluating the impact of five dimension: Hazardous substances, Production process and equipment, Sensitive targets, Management and Systems and Regional environment. The research findings provide guidance for risk prevention and environmental management. Future research could supplement or adjust the risk factors based on the actual conditions of industrial parks, thereby making the model results more realistic.

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