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Fire Risk Analysis in Industrial Buildings: A Qualitative Approach

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Abstract
Fires, lightning, and explosions pose significant threats to industrial enterprises, resulting in extensive material damage and potential loss of life. Effective fire risk management is crucial for minimizing these risks and optimizing insurance strategies. This study proposes a structured qualitative risk assessment model for fire, lightning, and explosion hazards, integrating probability-impact matrices with the ALARP (As Low as Reasonably Practicable) principle to enhance risk classification and insurance decision-making. The model evaluates key risk factors affecting insurability and premium adjustments, providing a systematic framework for fire risk assessment. Applied to an industrial case study, the findings demonstrate that structured risk classification enables insurers to refine premium calculations based on fire hazard levels, while industrial enterprises can implement targeted mitigation strategies to improve insurability and reduce financial exposure. This approach bridges the gap between qualitative and quantitative risk assessment, contributing to more precise underwriting decisions and enhanced industrial fire safety management.

Keywords
fire risk, qualitative risk assessment, industrial insurance, risk classification, ALARP principle, industrial safety

1. Introduction

Fire risk assessment is a fundamental component of industrial risk management, as fires and explosions can lead to severe financial losses, structural damage, and operational disruptions. While industrial enterprises implement fire prevention and suppression measures, these strategies alone are not always sufficient to mitigate potential damages. Consequently, financial risk transfer through specialized insurance policies has become a widely adopted mechanism. Industrial insurance provides coverage not only for the structural integrity of buildings but also for the assets within - such as machinery, equipment, and raw materials - ensuring financial protection in the event of fire-related incidents [1].

The evaluation of fire risks in industrial settings has been extensively analysed in academic and professional literature. Lau et al. (2015) [2] developed a fire risk assessment scorecard inspired by credit risk evaluation in the banking sector. Their research highlights the potential of machine learning techniques to significantly improve fire risk classification, leading to more accurate risk estimation for both fire departments and insurance companies. Choi & Jun (2020) [3] extended this approach by applying statistical machine learning and optimized risk indexing to refine fire risk assessment models, demonstrating that hybrid modelling techniques offer superior predictive accuracy compared to conventional methodologies.

Traditional fire risk assessment relies on probabilistic models, historical data analysis, and structured risk matrices to quantify exposure and vulnerability [4]. One of the most commonly applied methods in the insurance sector involves scoring risk factors based on probability and impact, allowing insurers to adjust premiums accordingly. A widely recognized framework for industrial insurance risk assessment uses a set of indicators to evaluate both fire hazards and vulnerability to security threats. These indicators are determined through structured questionnaires and on-site risk inspections, a methodology frequently referenced in risk evaluation models and widely implemented in insurance industry practices [5].

Although quantitative risk assessment dominates the field, existing frameworks often fail to incorporate structured qualitative risk classification. Furthermore, traditional models do not always provide a clear methodology for translating risk assessment results into concrete insurance decisions beyond numerical premium adjustments. Addressing these limitations, this study proposes a qualitative fire risk assessment model that integrates probability-impact matrices with the ALARP principle. By offering a structured and systematic framework for evaluating fire risks in industrial enterprises, the proposed model bridges the gap between qualitative and quantitative risk evaluation.

In developing this approach, the study reviews existing fire risk assessment models and insurance industry practices, formulating a qualitative classification framework based on probability and impact analysis. The model is applied to an industrial enterprise, where fire, lightning and explosion risks are assessed and compared with conventional risk evaluation methods. The findings demonstrate that structured risk classification allows insurers to refine premium adjustments based on fire hazard levels, while industrial enterprises can implement targeted mitigation strategies to improve insurability and financial resilience.

The structure of this paper follows this analytical framework, beginning with a theoretical background and a review of relevant literature, followed by the methodological foundation and the introduction of the proposed risk assessment model. The model is then applied in a case study involving an industrial enterprise, and the findings are discussed in relation to conventional risk evaluation approaches. Finally, the paper explores the implications of the model for insurance decision-making and industrial risk management, outlining key conclusions and directions for future research.

2. Literature Review

Recent advancements in fire risk assessment highlight the growing role of data-driven methodologies in improving predictive accuracy. Machine learning models have proven effective in classifying fire risks with high granularity and reliability. Ahn et al. (2024) [7] developed a stacking ensemble model that integrates predictions from 16 different machine learning algorithms, incorporating 34 variables related to building characteristics, land factors, and demographics. Their results indicate that this approach outperforms traditional models by refining risk classification at a more detailed level. Similarly, Choi & Jun (2020) [3] combined logistic regression with deep neural networks to create an optimized fire risk indexing model, demonstrating the potential of hybrid modelling techniques to address challenges related to data sparsity and overfitting.

Fire risk prediction has evolved beyond conventional statistical methods to include machine learning and catastrophe modelling techniques. Gualdi et al. (2022) [4] emphasize the significance of catastrophe loss assessment in the insurance industry, providing precise exposure and loss estimates, which are crucial for evaluating risks in industrial buildings. In a similar vein, Ghaddab et al. (2023) [8] validate the use of a Generalized Linear Model and Generalized Pareto Distributions for modelling fire insurance losses. Their findings suggest that this hybrid approach enhances predictive accuracy and prevents the underestimation of extreme losses, a particularly important factor for high-risk industrial sites. Additionally, Brazauskas & Kleefeld (2015) [1] analyse the severity of fire-related losses using parametric distributions such as Generalized Pareto, Weibull-Pareto, and Lognormal-Pareto, emphasizing the importance of extreme risk estimation through Value-at-Risk and Tail-Conditional Median methodologies.

In the context of insurance loss modelling, two-sided distributions have gained increasing relevance in capturing asymmetric loss patterns. Van Dorp & Shittu (2024) [9] propose a flexible framework using beta and Burr Type XII distributions, which improve extreme risk assessment and allow for more precise premium calibration. Further refining loss modelling approaches, Abu Bakar et al. (2020) [10] introduce a density-hazard distribution family, which simplifies loss adjustment and simulation. Their empirical analysis demonstrates a strong fit with fire-related insurance claims, supporting a more refined estimation of losses and better-informed premium structures.

Preventive measures play an essential role in fire risk assessment for industrial buildings, but their direct impact on insurance cost reduction remains ambiguous. Sølvsten & Kaiser (2022) [11] analyse data from 40 Danish municipalities and find no substantial correlation between the implementation of loss prevention measures and insurance price adjustments, suggesting that imperfect information may lead to market inefficiencies. The use of big data analytics in actuarial science has been identified as a key driver in enhancing risk modelling and premium determination. Hassani et al. (2020) [12] highlight the expanding role of predictive analytics in estimating risks associated with natural disasters, including fires. The integration of such techniques into industrial fire risk assessment could lead to more precise premium adjustments and risk mitigation strategies.

Estimating the total cost of fire incidents remains a challenge due to differences in data availability, fire service infrastructure, and regulatory frameworks. Lam & Robbins (2020) [13] compare international categorization methods for fire-related costs, identifying inconsistencies that hinder direct comparisons. A better understanding of these variations could contribute to improvements in industrial fire risk assessment and insurance premium calculations. Similarly, accurate reconstruction cost estimation is essential for fire insurance policies, as underestimation of damages can lead to inadequate indemnities. Cruz & Branco (2020) [14] develop a reconstruction cost model for housing insurance, demonstrating that traditional estimation methods often fail to capture actual damage costs. Applying similar models to industrial buildings could help ensure fair and accurate policy pricing.

Extreme risk estimation is particularly critical for industrial fire insurance, as losses and claims can be highly variable. Albrecher et al. (2021) [15] propose a tempered Pareto-Weibull distribution model, which refines high-quantile risk estimates by adjusting the tail behaviour of loss distributions. Applying such methodologies to fire insurance data could lead to more accurate premium calculations and optimized reinsurance strategies.

3. Methodology

The integration of multi-objective optimization into structural design can enhance fire prevention strategies and improve the assessment of insurable risks. Chaudhary et al. (2024) [16] propose a framework based on ALARP and probabilistic risk analysis to optimize structures exposed to fires. Their research demonstrates that considering post-fire reparability significantly influences investment decisions and risk management strategies. Similarly, Hopkin et al. (2021) [6] apply probabilistic methods and fragility analysis for steel elements in fire-exposed structures, suggesting that these techniques can guide industrial building insurance strategies by balancing initial costs with potential damage reduction.

A comprehensive fire risk evaluation must account for technical, human, and organizational factors. Tan et al. (2020) [17] develop a probabilistic model based on Bayesian networks and system dynamics modelling, illustrating that human errors and poor management can reduce the reliability of fire protection systems by up to 33%. The integration of such models into industrial risk assessments can improve fire prevention strategies and enhance insurance premium calculations.

An evaluation determines whether the global risk level is within acceptable limits for insurance. A widely used model for risk evaluation assesses insurability using two indicators (X, Y), each linked to a specific group of risk factors:

- X is associated with the group of factors referring to the risk of fire and the location's constructive and placement characteristics;
- Y is associated with the second group of factors referring exclusively to the risk of theft analysis.

These two sets of risk factors are assessed using a structured questionnaire and an on-site risk inspection. The insured party provides responses that are verified through an on-site inspection conducted by an insurance representative. Each factor receives a score based on observations, and the indicators are calculated by summing the respective scores.

The insurability decision is made after analysing these indicators, with specific threshold values guiding the final assessment. Using the obtained values for X and Y, the adjustment coefficients for the fire and theft premium quotations are computed [18]. The adjustment coefficient of the premium for fire risk (C_{aj-i}), which corrects the fire specific premium (C_{pi}), is calculated with the equation (1):

$$C_{aj-i} = 0.45 + X \tag{1}$$

The adjustment coefficient for the risk of theft (C_{aj-f}), which corrects the specific theft premium (C_{pf}), is obtained similarly with the equation (2):

$$C_{aj\text{-}f} = 0.7+Y \tag{2}$$

The final premium quotation (C_p) is calculated as the sum of the two adjusted premium quotations, according to (3):

$$C_p = C_{pi} \cdot C_{aj\text{-}i} + C_{pf} \cdot C_{aj\text{-}f} \tag{3}$$

The insurance premium (P_A) is calculated as a product between the insured amount and the premium quotation, as in (4):

$$P_A = C_p \cdot S_A \tag{4}$$

By integrating advanced probabilistic models, cost-benefit analysis, and multi-objective optimization into fire risk assessment, this methodology enhances risk classification and insurance decision-making for industrial enterprises.

4. Model for the Qualitative Analysis of the Fire, Lightning and Explosion Risks

The qualitative risk analysis process provides a structured approach to evaluating fire risks in industrial settings. This methodology facilitates risk classification, supports insurance decision-making, and enhances the implementation of targeted mitigation strategies.

A key component of this model is the definition of probability and impact scales, which establish a standardized approach to assessing the likelihood and severity of risks. By assigning predefined probability levels to fire hazards, insurers and industrial enterprises can systematically evaluate risk exposure and vulnerability. The impact scale quantifies potential losses, ensuring that risk assessment is aligned with financial and operational consequences [20].

Once probability and impact scales are established, a risk reference matrix is constructed by combining these scales into a structured classification framework. This matrix serves as a visual tool that enables a clearer understanding of risk distribution across various hazard categories [13]. The methodology proceeds with calculating risk scores, where each identified risk is assigned, a numerical value based on its likelihood and impact. The resulting risk matrix provides a comprehensive representation of risks, allowing for a systematic evaluation of fire, lightning, and explosion hazards in industrial enterprises [2].

Following the risk assessment process, risks are prioritized based on their severity and probability [3]. This ranking enables industrial enterprises and insurers to develop appropriate mitigation measures, ensuring that high-risk factors are addressed through enhanced fire safety strategies and optimized insurance policies. The prioritization framework improves decision-making, helping insurers refine premium structures while guiding enterprises in adopting risk reduction measures that enhance insurability.

4.1. Choosing the probability and impact scales

Using probability and impact in risk analysis helps in identifying those risk factors which have a high score and which must be acted upon by eliminating or excluding them from the insurance policy and by increasing the insurance premium. A risk probability scale, shown in Table 1, can be constructed using two categories of values [21]:

Table 1. Risk probability scale

Qualitative evaluation of probability	Quantitative evaluation of probability	Probability score
Very high (very probable)	Once in 5 years	5
High (probable)	Between 5 and 10 years	4
Medium	Between 10 and 20 years	3
Low (improbable)	Between 20 and 40 years	2
Very low (very improbable)	Higher than 40 years	1

- Ordinal values – these include classifications such as very low (nearly impossible), low (improbable), medium (possible), high (probable), and very high (almost certain);

- Cardinal values – each qualitative level is assigned a numerical score to facilitate quantitative analysis. The corresponding probability scores are 1, 2, 3, 4, and 5, where 1 represents a very low probability and 5 indicates a very high probability event.

By applying these scales, insurers and risk managers can systematically assess the likelihood of fire hazards and integrate them into comprehensive risk evaluation frameworks.

The risk impact scale, shown in Table 2, reflects the severity of damages when a risk is realized. It is a crucial component in risk assessment and insurance premium adjustments, as it helps quantify potential losses. The impact scale can be categorized as follows:

- Ordinal scale – classifies impact levels as very low, low, moderate, high, and very high, allowing for qualitative risk assessment.
- Cardinal scale – signs numerical values to impact levels to facilitate quantitative analysis. The corresponding scores are 1, 2, 5, 10, and 20, where 1 represents a very low impact event and 20 indicates a catastrophic loss scenario.

Table 2. Risk impact scale

Qualitative evaluation of impact	Quantitative evaluation of impact	Impact score
Very high	Damages are ≥ 20% of insured amount (SA)	20
High	Damages between 5 and 20% of SA	10
Moderate	Damages between 2 and 5% of SA	5
Low	Damages between 1 and 2% of SA	2
Very low	Damages are ≤ 1% of SA	1

The quantitative evaluation of impact is determined based on several factors, including claim capacity, availability of financial resources, and the risk appetite of the insurance company [6]. These scales are widely utilized in fire risk assessment models and provide a structured approach to decision-making in insurance underwriting and risk mitigation strategies [14].

4.2. Establishing the risk reference matrix

The risk matrix is constructed by combining the probability and impact scales presented in Tables 1 and 2. It can be represented in either an ordinal form (risk level matrix) or a cardinal form (risk score matrix). Depending on the level of detail required, the risk matrix can be designed with three, four, or five levels of probability and impact. Some models, such as those proposed by Sutton (2011) [22], use a four-level matrix.

Table 3. Risk level matrix

Very high (almost certain)	5	Low	Moderate	High	Very high	Very high
High (probable)	4	Very low	Low	Moderate	High	Very high
Medium (possible)	3	Very low	Low	Moderate	High	Very high
Low (improbable)	2	Very low	Very low	Moderate	Moderate	High
Very low (almost impossible)	1	Very low	Very low	Low	Moderate	Moderate
	Score	1	2	5	10	20
PROBABILITY		Very low	Low	Moderate	High	Very high
		IMPACT				

This study proposes a risk matrix with five levels of probability and impact, as shown in Table 3. The primary objective of this approach is to enhance the clarity of risk classification and improve decision-making processes in the insurance of industrial assets.

The risk level matrix in Table 3 is obtained by merging the ordinal probability and impact scales. It categorizes risks into five levels: very low, low, moderate, high, and very high. Each level is associated with a specific colour code for easier visualization: dark green for very low risk, light green for low risk, yellow for moderate risk, orange for high risk, and red for very high risk [23].

The risk score (RS) is a quantitative criterion used to rank risks and is calculated as the product of the probability score (PS) and the impact score (IS), as expressed in equation (5):

$$RS = PS \cdot IS \qquad (5)$$

The risk score matrix, which gives the quantitative aspect to the risk's qualitative analysis, is shown in Table 4 and is obtained in two steps [23, 24]:

- replacing the ordinal probability and impact scales from Table 3 with the cardinal scales chosen in Tables 1 and 2;
- calculating, in each cell of Table 4, the risks' score values obtained with the relation (1).

Table 4. Risk score matrix

Very high (almost certain)	5	5	10	25	50	100
High (probable)	4	4	8	20	40	80
Medium (possible)	3	3	6	15	30	60
Low (improbable)	2	2	4	10	20	40
Very low (almost impossible)	1	1	2	5	10	20
	Score	1	2	5	10	20
PROBABILITY		Very low	Low	Moderate	High	Very high
		IMPACT				

The risk score matrix is based on the same five levels as the risk level matrix and using the same colours. The score levels are as follows:

a) Level 1 – very low risk (tolerable), the risk score is between 1 and 4, sufficiently small such that the respective risk can be ignored by the industrial enterprises. Even when the probability of the risk is medium or high, which would make the risk event probable, the impact is insignificant. In this case it's almost impossible for the enterprise to suffer damages, and even if it does, they will be negligible. The risks on this level must be covered in the insurance contract.

b) Level 2 – low risk, when the risk score is between 5 and 8, sufficiently small such that the respective risk is of low importance for the industrial enterprises. If the impact is medium, it is almost impossible for the risk event to happen, and if the probability is medium, high or very high, the impact score is low or very low. If damages occur, they are negligible or very low, at most 2% of the insured amount. The risks belonging to level 2 must, also, be covered by the insurance. The level 1 and 2 risks must be monitored by both the industrial enterprises and the insurance company so as to be maintained to these values.

c) Level 3 – medium risk, when the risk score is between 10 and 20. In this case, if the risk event is almost certain, the impact is slow. It is improbable that high or very high impact events would happen. If there are damages, the value is low (at most 2% of the insured amount). High or very high value damages have a low or very low probability. For industrial enterprises these risks are tolerable only if their reduction costs surpass the obtainable results. This is the last level where the respective risks can be covered by the insurance without any measures to reduce them on the part of the industrial enterprises.

d) Level 4 – high risk, where the risk is sufficiently high, the impact score is between 25 and 40. It is almost certain that risk events with moderate or high impact will happen, possible or probable that the impact will be high, but improbable that the impact will be very high. In this case damages of between 2% and 5% of the insured amount are almost certain, damages of between 5% and 20% are possible and probable, and higher amount damages are improbable. The risks of this level must be treated adequately by the industrial enterprises, measures to reduce their probability being necessary [22]. The insurance company should cover these risks only if measures to reduce their probability are taken, otherwise an increase in the premium or their complete exclusion from the insurance policy can be decided.

e) Level 5 – very high risk, the impact score is between 50 and 100, risk events with high or very high impact being possible, probable or almost certain which would result in high and very high value damages, between 5% and 20% or even higher than 20% of the insured amount. The risks in this level are intolerable, and the industrial enterprises must take measures to eliminate them, otherwise the insurance company must exclude these risks from the policy or not sign such an insurance contract.

4.3. Determining the risk scores and building the risk matrix

For each of the identified risks or risk factors (R_i), a probability score (SP_i) and an impact score (SI_i), are established according to the chosen probability and impact scales, then the SR_i score is calculated, where i = 1, 2, …, n, using the relation (5). The global risk score is calculated with the relation (6) [25]:

$$SRM = \frac{\sum_{i=1}^{n} SR_i}{n} \tag{6}$$

where n is the number of risk factors. With the help of this data the risk matrix is built, as shown in Table 5.

Table 5. Risk matrix

Risk	**Probability**					**Impact**					**IPR**
Score	1	2	3	4	5	1	2	5	10	20	
R_1		SP_1						SI_1			$SR_1 = SP_1 \cdot SI_1$
R_2				SP_2			SI_2				$SR_2 = SP_2 \cdot SI_2$
…											…
R_i			SP_i						SI_i		$SR_i = SP_i \cdot SI_i$
…											…
R_n			SP_n					SI_n			$SR_n = SP_n \cdot SI_n$
SRM											$\sum SR_i/n$

4.4. Risk factor classification

The risk matrix described in Table 5 is ordered after the decreasing values of risks' scores. The risk factors are assigned to the corresponding level, according to the obtained score values, and are associated with the corresponding colour, according to Table 6.

Table 6. Risk classification

SR value	**Risk level**	**Associated colour**
$50 \le SR \le 100$	5 (Very high)	Red
$25 \le SR \le 40$	4 (High)	Orange
$10 \le SR \le 20$	3 (Medium)	Yellow
$5 \le SR \le 8$	2 (Low)	Light green
$1 \le SR \le 4$	1 (Very low)	Green

5. Risk Evaluation. Case Study

The risk evaluation stage necessarily follows risk analysis and plays a crucial role in determining the appropriate treatment to be applied. At this stage, the risks, whose scores and levels have been calculated, are categorized into standard intervals based on various factors, including the severity of previous incidents, established objectives, and the decision-makers' attitude towards risk. An approach frequently used in risk evaluation, known as ALARP and extensively discussed in the literature, divides risks into three areas [26, 27]:

- The unacceptable area, which includes high and very high-risk levels, associated with the red and orange colors in Table 6. The risk is deemed intolerable, regardless of the potential benefits of the economic activity. In this case, risk treatment is mandatory, irrespective of costs.
- The tolerable area, which includes medium-level risks, associated with the yellow color. The risk is considered acceptable only if its reduction is impossible or if the reduction costs outweigh the achievable benefits.
- The acceptable area, which includes low and very low-risk levels, associated with the light green and dark green colors. For these risks, no treatment measures are necessary as long as they remain within these levels.

The qualitative analyses, as well as the fire, lightning, and explosion risk evaluations, were conducted for the production section of the industrial enterprise Vioson Prodcomimpex, located in Brașov, Romania. This company specializes in the mechanical processing of metallic parts for machine building. This study considered the mechanical processing building and the goods within it as the primary assets. The risk factors for these assets were identified using the list in Table 7.

Table 7. Risk classification

No.	Risk factors	Possible situations	Observed situation	Risk
1.	Material the building was constructed from	Non-combustible materials	x	NO
		Combustible materials in reduced proportions		
		Combustible materials in increased proportions		
2.	Distance between buildings	Above 15 meters		
		Between 10 and 15 meters		
		Between 5 and 10 meters		
		Below 5 meters	x	YES
3.	Used products, substances	Non-combustible materials		
		Combustible materials in reduced proportions		
		Combustible materials in increased proportions		
		Dangerous (flammable, explosive)	x	YES
4.	Open flame	No work with open flames	x	NO
		Work with open flames		
5.	Heating system	External heating plant	x	NO
		Own, modernized heating plant		
		Other systems (radiators, stoves)		
6.	Lightning protection systems (lightning rods)	Available and periodically checked	x	NO
		Available but not checked		
		Not available, but adjacent protection available		
		Not available		
7.	Smoking rules	Smoking not allowed		
		Special smoking areas available	x	YES
		No smoking rules		
8.	Personnel discipline	Very good	x	NO
		Good		
		Satisfactory		
		Unsatisfactory		
9.	Fire detection and alerting systems	Automated		
		Manual		
		Not available	x	YES
10.	First response means	Above current regulations		
		According to current regulations	x	YES
		Below current regulations		

11.	Water sources	Own (basin and pumping installation)		
		Public	x	YES
		Not available		
12.	Automated fire extinguishing systems	Available and periodically checked		
		Available but not checked		
		Not available,	x	YES
13.	Own firefighters' squad	Available, well trained and equipped		
		Not available, not required	x	YES
		Available, partially trained and equipped		
		Available, well trained, partially equipped		
		Not available, required		
14.	Permanent guards	Available, trained		
		Available, untrained	x	YES
		Not available		
15.	Firefighting training for personnel	Very good		
		Good	x	YES
		Satisfactory		
		Unsatisfactory		
16.	Military firefighters' time to location	Under 10 minutes	x	NO
		Between 10 and 15 minutes		
		Above 15 minutes		
17.	Fire resistant compartmentalization	Available		
		Not available, not required	x	YES
		Not available, required		
18.	Electrical installations	Built according to norms	x	NO
		Improvised		
19.	Electrical installations maintenance	Very good		
		Good		
		Satisfactory	x	YES
		Unsatisfactory		

After assessing the current situation, the risk factors that can influence the probability and impact of risks, as well as those that may contribute to an increased risk of fire, lightning, and explosion, were identified and are presented in Table 8.

Table 8. Risk factors

Risk code	Risk factors
R_1	Distance between buildings
R_2	Used products, substances
R_3	Smoking rules
R_4	Fire detection and alerting systems
R_5	First response means
R_6	Water sources
R_7	Automated fire extinguishing systems
R_8	Own firefighters squad
R_9	Permanent guards
R_{10}	Firefighting training for personnel
R_{11}	Fire resistant compartmentalization
R_{12}	Electrical installations maintenance

For each risk factor, the probability and impact scores are evaluated using the corresponding scales from Tables 1 and 2. Based on this data, the risk matrix is constructed, as shown in Table 9, where the risk factor scores are determined using equation (5), and the global risk score is calculated using equation (6).

Table 9. Risk matrix

Risk	Probability					Impact					SR_i
	1	2	3	4	5	1	2	5	10	20	
R_1			3						10		30
R_2			3							20	60
R_3			3				2				6
R_4	1									20	20
R_5	1							5			5
R_6	1								10		10
R_7	1									20	20
R_8	1							5			5
R_9	1								10		10
R_{10}	1						2				2
R_{11}	1									20	20
R_{12}			3							20	60
SRM											21

To evaluate the risk factors, the risk matrix is arranged in descending order based on the risk score values, resulting in the ordered risk matrix, as shown in Table 10. In this matrix, each risk is assigned a corresponding color according to the classification in Table 6.

Table 10. Ordered risk matrix

Risk	Probability					Impact					SR_i	Risk level
	1	2	3	4	5	1	2	5	10	20		
R_2			3							20	60	5
R_{12}			3							20	60	5
R_1			3						10		30	4
R_4	1									20	20	3
R_7	1									20	20	3
R_{11}	1									20	20	3
R_6	1								10		10	3
R_9	1								10		10	3
R_3			3				2				6	2
R_5	1							5			5	2
R_8	1							5			5	2
R_{10}	1						2				2	1
SRM											21	3

A risk prioritization list is thus obtained, serving as a key component in risk management documentation and outlining the necessary treatment for each risk. A risk factor graph is constructed based on the risk levels from Table 9, where the risk factors are arranged in descending order according to their severity.

This graphical representation clearly highlights the risks, distinguishing between those above the horizontal line, referred to as the "critical level," which require treatments such as mitigation or avoidance, and those below the critical level, which can be accepted in accordance with the ALARP approach.

Thus, risk evaluation leads to the following conclusions based on Figure 1.

- Risk R_{10}, situated at level 1 with a very low value, should not be considered a concern for the industrial enterprise and can be covered by the insurance company.;
- Risks R_3, R_5, and R_8, positioned at level 2, are low risks that require minimal attention from the industrial enterprise and can also be insured;
- Risks R_4, R_7, R_{11}, R_6, and R_9, classified at level 3, are medium-level risks and are tolerable for the industrial enterprise only if the cost of risk reduction exceeds the achievable benefits. This is the highest level at which these risks can still be insured without requiring any specific treatment from the industrial enterprise.
- Risk R_1, located at level 4, is classified as high. The industrial enterprise must implement measures to reduce both its probability and impact. The insurance company may cover this risk only if appropriate mitigation measures are in place; otherwise, it may increase the premium or exclude this risk from the policy.
- Risks R_2 and R_{12}, categorized at level 5, are considered very high (unacceptable). The industrial enterprise must eliminate these risks; otherwise, the insurance company will exclude them from the policy.

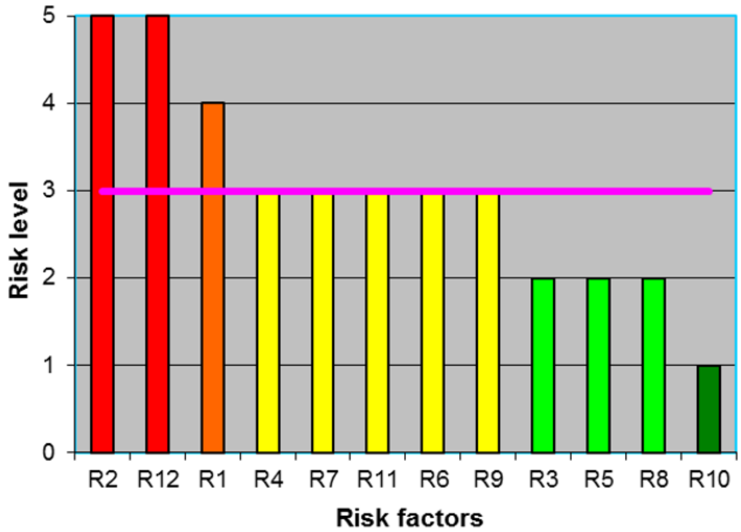

Fig. 1. Risk factor classification by severity level

6. Conclusions, Limits and Future Directions

Insuring industrial enterprises against fire, lightning, and explosion risks requires a complex risk management process, given the high insured amounts, substantial premiums, and significant potential damages. In this context, qualitative risk analysis and structured risk evaluation play an essential role in guiding insurance decision-making. This study introduces a risk matrix-based qualitative evaluation model, structured into five probability-impact levels and five risk categories, enhancing the clarity of risk classification and improving the overall risk assessment process.

Despite its strengths, the proposed methodology has certain limitations that should be acknowledged. The reliance on expert judgment in the qualitative risk assessment process may introduce a degree of subjectivity, affecting decision consistency. Additionally, the model does not fully integrate dynamic factors, such as advancements in fire prevention technologies or changes in industry regulations, which may impact the accuracy of risk classification over time. Another limitation arises from the risk matrix structure, which does not explicitly account for interdependencies between risk factors, potentially leading to overestimation or underestimation of certain scenarios.

Future research could focus on integrating machine learning and big data analytics to enhance the accuracy of fire risk classification. The application of predictive models based on artificial intelligence could automate data analysis, improving estimates of fire event probability and impact. Additionally, incorporating cost-benefit analysis and Monte Carlo simulations could provide a more detailed perspective on extreme fire risks, refining insurance premium adjustments and underwriting strategies.

From a practical perspective, the proposed model can help insurance companies optimize pricing structures and tailor insurance policies according to client-specific fire risk profiles. For industrial enterprises, this methodology serves as a risk management tool, enabling firms to identify critical vulnerabilities and prioritize investments in fire prevention measures. Ultimately, the proposed model contributes to more effective insurance decision-making, enhances fire risk classification, and strengthens industrial fire safety management through a systematic and structured evaluation approach.

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