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Article

A Fuzzy Logic-Enhanced Risk Assessment Framework for Battery Locomotive Maintenance in Underground Coal Mines

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Abstract

Battery locomotives used in underground coal mining operations require continuous maintenance, and failures occurring during these operations pose significant occupational safety and health (OSH) risks. Traditional Risk Assessment Methods (TRAMs), particularly the Risk Matrix Method (RMM), often fail to capture the uncertainty and subjectivity inherent in complex mining environments. This study develops a fuzzy logic-based risk assessment framework to improve the evaluation of accident risks associated with maintenance and repair activities in battery locomotive workshops of an underground coal mine in Turkey. Two fuzzy inference models (FL-Basic and FL-Advanced) based on expert knowledge and linguistic variables were designed using Mamdani-type inference with centroid defuzzification. The mathematical formulation of the fuzzy inference and defuzzification steps is presented explicitly, and a six-step algorithm formalises the proposed framework. The rule base of FL-Advanced systematically upweights the severity dimension relative to RMM through reassignment of 16 of the 25 consequent categories. The outputs of these models were compared with RMM to analyse their effectiveness in identifying critical hazards. Application results from Karadon Hard Coal Company show that the proposed FL-Advanced model significantly reduces ambiguity, prioritises high-severity risks more realistically, and provides a more consistent decision-making structure for OSH specialists. The study highlights the advantages of fuzzy logic for modelling uncertain, incomplete, and human-dependent data in hazardous underground mining conditions.

Keywords: fuzzy logic; traditional risk assessment methods; risk matrix method; coal mining; battery locomotive; Mamdani inference; decision making

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1. Introduction

The coal mining industry is divided into two main methods: surface mining and underground coal mining. Underground coal mining is typically chosen when surface mining is either technically or economically unfeasible. The necessity for Occupational Safety and Health (OSH) Risk Assessment Methods (RAMs) and practices in underground coal mining, which constitutes 60 percent of the world's coal production, has been increasing [1–3].

Occupational accidents in underground coal mining encompass dangers that result in serious injuries, occupational diseases, and fatalities due to hazardous working conditions [4–8]. Consequently, underground coal mining is among the most dangerous sectors in terms of occupational safety and health [9]. Occupational accidents in coal mining bring profound grief to both the families of the victims and society at large. Despite economists conceptualising the risk of death similarly to that of non-fatal occupational accidents and attempting to assign a monetary value to life [2,10,11], the existence of fatal accidents complicates matters, making it considerably more difficult to assign a price to life and death [12].

Various factors influence occupational accidents [10,13], including mining methods, geological conditions, natural gas leakage, mine collapse, dust explosions, flooding, and general mechanical hazards arising from misused or malfunctioning mining equipment [14–16]. The majority of deaths resulting from occupational accidents occur in developing countries [17]. From a mining occupational accidents perspective, fatal accidents—especially in coal mining—are prevalent in China, which accounts for 35% of global coal production [18]. Examining the number of fatal coal-mining accidents in China between 2000 and 2008 reveals that the number of deaths peaked in the early 2000s and started to decrease afterwards. When comparing death numbers in the USA, China, and Turkey, the death toll is highest in China. However, when evaluating fatality rates per million tons of coal produced, Turkey exhibits higher rates than China, with significant fluctuations over the years. This situation may be attributed to challenges in practical implementation despite robust legislation aimed at preventing work-related accidents in Turkey. In addition to legislation, risk assessment and management remain compulsory in Turkish industry, with the selection of the applicable Traditional Risk Assessment Method (TRAM) overseen by Occupational Safety Specialists [19–22].

Table 1 below provides a historical comparative overview of fatalities and fatality rates in coal mining across China, the USA, and Turkey for the period 2000–2008.

Table 1. Comparative number of fatalities in coal mining in three countries [19,23].

Year	Deaths (China)	Deaths (USA)	Deaths (Turkey)	Deaths per Mt (China)	Deaths per Mt (USA)	Deaths per Mt (Turkey)
2000	5798	18	17	5.71	0.03	7.10
2001	5670	13	18	5.07	0.02	7.22
2002	4640	19	14	4.64	0.04	6.04
2003	6995	19	19	3.71	0.04	9.23
2004	6702	14	10	3.08	0.03	5.14
2005	5986	7	12	2.84	0.01	5.51
2006	4746	33	6	2.04	0.06	2.59
2007	3786	20	20	1.49	0.04	8.02
2008	3092	9	19	1.18	0.02	7.22

Although Table 1 covers a historical period, publicly available statistics from sources such as the International Labour Organization and the US Mine Safety and Health Administration confirm that Turkey's coal-mining fatality rate per million tons of coal produced has remained substantially higher than that of the United States in the years following 2008, indicating that the safety problem motivating the present study has not been resolved in the intervening period.

In Turkey, it is of paramount importance to utilise equipment that complies with the latest legislation, implemented within the last quarter-century, to identify risks in the adaptation process and implement necessary measures [21,22]. The Explosive Atmosphere directive [24] has been implemented voluntarily since 1 March 1996, and has been mandatory since 1 June 2003. The "Equipment and Protective Systems Intended for Use in Potentially Explosive Atmospheres Regulations" (94/9/AT) came into force on 27 October 2002, and was completely revised on 30 December 2006. The second regulation, the "Regulation on the Protection of Employees from the Hazards of Explosive Environments (99/92/EC)", was implemented in Turkey on 26 December 2003. The ATEX directives comprise two groups: the Equipment directive (94/9/EC), designed for use in potentially explosive equipment and containing protective systems instructions, and the Workplace Directive (99/92/EC), which includes minimum requirements for improving the safety and health of employees potentially at risk. These regulations serve as the criteria for assessing explosion risk in explosive atmospheres and protection from explosion.

In underground mining, locomotives are critical equipment affected by ATEX criteria. Trolley locomotives, battery locomotives, and diesel locomotives are used for underground and above-ground transportation in coal mines [25,26]. Trolley locomotives receive their electrical energy from overhead lines through current collectors, with the railway serving as the return path for the electric current. Consequently, trolley locomotives cannot be used in coal mines with coal dust or methane ratios exceeding 0.3% or in sulfur mines with sulfur dust. Diesel locomotives are avoided due to the risk of poisoning from exhaust smoke, fire, and fire-damp explosions. Battery locomotives, on the other hand, draw electrical energy from onboard batteries, making them suitable for various purposes in underground mining, such as transporting coal, stone, equipment, and emergency evacuation [27].

In Turkey, elevators are used in coal mines to transport coal, materials, and personnel. However, locomotives are also indispensable for transportation in coal mines. Battery locomotives, compliant with ATEX directives, have a broad range of applications in underground mining and are expected to be increasingly utilised with advancements in alternative battery cells and efficiency improvements [25,26].

The use of battery locomotives in underground mining is on the rise due to measures taken to prevent occupational accidents within the framework of OSH. These locomotives require routine mechanical maintenance and battery charging. Operator experience and breakdown maintenance are crucial for occupational health and safety, as accidents occurring while the locomotive is in motion pose significant risks and may cause disruptions due to breakdowns [15,16,18,23,25–27]. This study aims to develop a RAM for the maintenance and repair of battery locomotives using Fuzzy Logic (FL) to reduce occupational accidents during maintenance and repair.

FL is widely used in safety analysis and risk assessment to deal with uncertain and insufficient data [19,20,28–30]. In the coal mining sector, FL is applied to enhance health and safety, take appropriate precautions against risky situations, and mitigate unexpected hazards [6,14,31]. FL-based risk assessments offer several advantages over Traditional Risk Assessment Methods (TRAMs), including better management of uncertainty, the ability to address problems affected by multiple parameters—particularly those centred on human factors [32,33]—and superior modelling of real-life behaviours using linguistic labels rather than rigid mathematical models [2,34].

Indeed, fuzzy logic finds extensive application in the mining sector. Table 2 illustrates various applications of fuzzy logic in mining, including predicting mine roof collapse rates, mine explosions, fatal mine accidents, early detection of mining machinery failures, reclamation of mining areas, and the development of early warning models for mining risk sources. As evidenced by the examples in Table 2, fuzzy logic effectively addresses many issues in the mining sector.

Table 2. Research on fuzzy logic and mining occupational accidents.

Subject of Research	Conclusion	Ref.
Estimating the rate of roof collapse in coal mines	Fuzzy logic is a useful and powerful tool to improve the safety of underground coal mines.	[35]
Comparative analysis of mortality rates in coal mines in Pakistan, China and India (2010–2018).	Fuzzy logic is used to accurately understand sudden death rates. Effective safety recommendations are made to reduce fatalities in Pakistani coal mines.	[3]
Post-mining pit area reuse via fuzzy analytical hierarchy processing.	Fuzzy AHP for post-mining reclamation gives more reliable results than alternative techniques.	[36]
Coal-fire prediction from gas monitoring data using FL.	FL is more reliable than alternatives in handling non-linearities and imprecision in the data.	[37]
Risk assessment in underground coal mines using FL under uncertainty (India).	The methodology supports prioritisation and stepwise risk improvement in mines.	[38]
Risk-based maintenance management of mining machinery with safety considerations.	Maintenance personnel can make faster and more effective decisions; serious events such as operator harm are avoided.	[39]
Stability control of mine geotechnical systems via FL.	The developed model can be embedded in digital safety systems to assess stability and prevent emergencies.	[40]
Failure-severity expert assessment of mining machinery in FL.	The model observes and evaluates failure severity through harmful effects, reducing repair costs and production delays.	[41]
Safety early-warning model using Fuzzy AHP in coal mining.	Risk sources and hidden hazards are identified in a timely manner; effective in accident prevention.	[42]
Coal-explosion probability via combined fuzzy theory and fault-tree analysis.	Self-initiated and remotely triggered probabilities are 0.9% and 11.6%; critical pathways are identified.	[43]

Synthesising the body of work catalogued in Table 2 reveals three persistent limitations of existing fuzzy risk-assessment approaches in mining. First, most studies retain the multiplicative likelihood × severity structure of RMM at the rule-base level, so that combinations whose product is identical (e.g., P = 1, S = 5 versus P = 5, S = 1) are still treated equivalently, despite the very different operational implications of each. Second, the literature has paid limited attention to severity-dominant maintenance environments in which low-frequency, high-consequence events demand earlier intervention than a multiplicative score would justify. Third, fuzzy risk assessment specifically targeting battery-locomotive maintenance workshops in underground coal mines has not, to the best of our knowledge, been reported.

Beyond Mamdani-type inference, recent work in linguistic decision-making has explored large-group consensus and cloud-model formulations, including rough integrated asymmetric cloud models in multi-granularity linguistic environments [44]. These approaches address granularity and group heterogeneity in linguistic information when the number of decision-makers is large and the linguistic vocabulary itself varies between participants. The present study addresses a distinct decision context: a focused panel of certified Occupational Safety Specialists operating under a single regulatory taxonomy. For this context, a Mamdani-type framework with explicit severity weighting offers a parsimonious and operationally tractable formulation while remaining directly interpretable by the personnel who will use the results.

In direct response to the limitations identified above, this study makes the following contributions. (i) We propose FL-Advanced, a Mamdani-type fuzzy inference model whose rule base systematically upweights severity through the reassignment of consequent categories—explicitly correcting the severity-blindness of the multiplicative risk score. (ii) We instantiate the framework for battery-locomotive maintenance workshops, an application context that has not previously been studied in the FL risk-assessment literature. (iii) We compare RMM, FL-Basic, and FL-Advanced against a defined set of evaluation criteria, supported by computational-cost analysis demonstrating real-time feasibility. The effectiveness of the proposed framework is assessed through a case study at the Battery Locomotive Maintenance Workshop of Karadon Hard Coal Company in Turkey.

2. Materials and Methods

2.1. Characteristics of the Study Area

Turkey Hard Coal Enterprises (TTK) (Turkey, Zonguldak) was established in accordance with Turkey's general industry and energy policy to effectively assess the country's coal reserves and significantly contribute to the national economy by meeting Turkey's coal needs. TTK operates in the Western Black Sea Region of Turkey and is responsible for exploring all types of coal mines, land and sea transportation, commercial transactions such as purchases and sales, and the establishment and operation of new plants and factories. TTK comprises Armutçuk, Amasra, Üzülmez, Karadon, and Kozlu Hard Coal Companies (Turkey, Zonguldak), all of which are actively engaged in their activities. The Çatalağzı Thermal Power Plant (Turkey, Zonguldak), with an installed power of 2 $\times$ 150 MW in the regions near the TTK basin, plays a crucial role in the economy of the Western Black Sea Region, meeting the entire coal requirement and contributing significantly to the coking coal needs of Kardemir (Turkey, Karabük) and Erdemir (Turkey, Zonguldak), the first two integrated iron and steel factories in Turkey (data were obtained from TTK enterprises). Karadon Hard Coal Company (Turkey, Zonguldak), one of the five hard coal establishments under the General Directorate of TTK, conducts production operations on 18 coal seams of various thicknesses, with vein thicknesses ranging between 100 and 300 cm. As of the end of 2015, the total length of underground openings, including drifts, shafts, and production panels, amounted to 128 km. The coal extracted from the mine is transported to the Çatalağzı Enrichment Plant for processing. Following processing at the plant, the final product is sold to the steel industry and the local market for heating purposes. On average, Karadon Hard Coal Company produced 581,502 tons of coal between 2011 and 2020. Table 3 illustrates the production amounts during this period. The company employs 200 civil servants, 2265 underground workers, and 332 surface workers (data were obtained from Karadon company).

Table 3. Coal production amounts in Karadon Hard Coal Company (Turkey, Zonguldak) by year.

Year	Tonnes
2011	803,067
2012	805,871
2013	756,596
2014	680,215
2015	468,896
2017	427,921
2018	434,818
2019	465,863
2020	390,271

A total of 54 battery locomotives employed at Karadon Hard Coal Company were specifically designed considering the working conditions within the charging and mainte-

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nance workshops. Table 4 presents the specifications of the battery locomotives utilised in Karadon Hard Coal Company.

Table 4. Data on the battery locomotives used in Karadon Hard Coal Company.

Feature	Capacity (17 t)	Capacity (9 t)	Capacity (6 t)
Number of battery locomotives	11	20	23
Weight (kg)	16,964	7257	7257
Battery (V)	128	96	80
Number of waggons towed	15 coal/8 stone	8 coal/5 stone	5 coal/5 stone

In Karadon Hard Coal Company, two distinct workshops are utilised for the maintenance of battery locomotives: a Battery Charging Station (BCS) and a mechanical maintenance workshop. When the charge of the batteries used in locomotives drops below 20%, they are transported to the above-ground charging station. This process involves removing the battery from the locomotive, transferring it to a separate locomotive, and transporting it to the charging station. At the charging station, cranes are used to position the batteries onto the charging points. Once charging is completed, the batteries are reinstalled into the respective locomotives. Figure 1 depicts the entrance of the Battery Locomotive Maintenance Workshop in panel Figure 1a; the 9-ton batteries situated at the charging points in panel Figure 1b; the interior of the Battery Locomotive Maintenance Workshop in panel Figure 1c; and a maintenance operation in which the oxides on the battery terminals are being cleaned in panel Figure 1d, which is one of the routine maintenance activities included in the risk inventory analysed in Section 3.

Figure 1. View of the battery locomotive service and charging unit at Karadon Hard Coal Company: (**a**) entrance of the maintenance workshop; (**b**) 9-ton batteries at the charging points; (**c**) interior of the maintenance workshop; (**d**) cleaning the battery oxides.

Within the mechanical workshop, all essential maintenance tasks such as electric motor maintenance, wheel upkeep, and waggon repairs are conducted. Figure 2 illustrates the layout plan of the charging station at Karadon Hard Coal Company. The locomotive battery charging station is equipped with 6 charging units for 17-ton batteries, 11 charging units for 9-ton batteries, and 8 charging units for 6-ton batteries. These charging stations in the workshop can accommodate the simultaneous charging of up to 17 batteries.

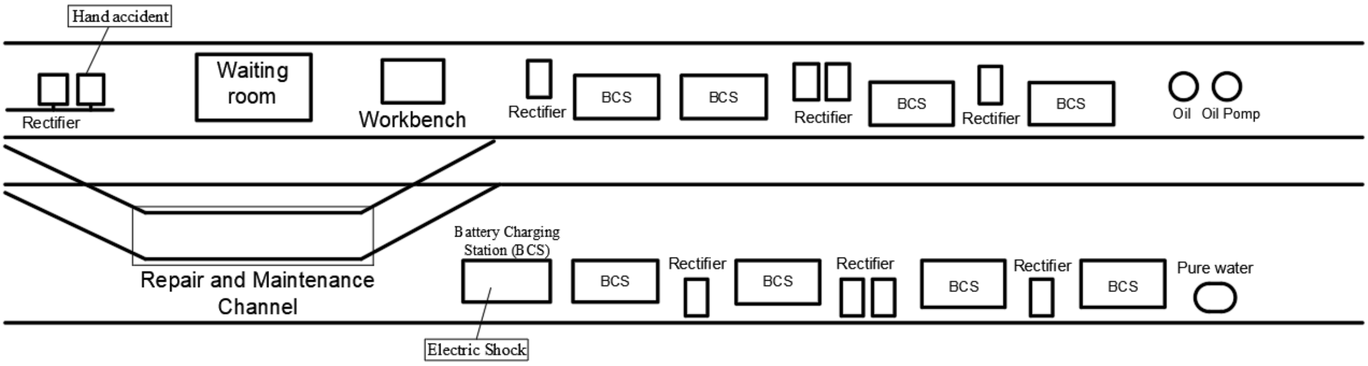

Figure 2. Battery charging station layout plan.

2.2. Traditional Risk Assessment Methods and the Risk Matrix Method

The concept of risk can be viewed both positively and negatively, defined as the "chance of something happening that will have an impact upon objectives" or as something that poses a negative effect on health and safety. Risk assessment involves evaluating the risk associated with a hazard, assessing the effectiveness of existing controls, and determining the acceptability of the risk.

Assessing risk involves considering both the likelihood of an event occurring and the severity of its consequences. This process is integral to risk assessment, allowing for a comprehensive understanding of potential hazards [45]. Among Traditional Risk Assessment Methods, the risk matrix stands out as a widely accepted practice in OSH [20,45]. Use of the RMM is valuable for prioritising risk management efforts and setting appropriate safety measures [46].

Risk Matrix Method (RMM)

A risk matrix is utilised to determine the level of risk by considering the severity of the consequences in a particular occupational accident scenario and its likelihood. In the risk matrix, the likelihood and consequences are assessed together, avoiding the use of complex mathematical manipulations [47]. When employing a quantitative risk method, risk is defined as the product of hazard probability and hazard severity [28]. Hence, the risk score R is calculated as $R = S \times P$ [20], where S represents the severity of an occurrence and P represents the likelihood of the occurrence.

In assessing hazard severity, the potential impact of the hazard on people and equipment is initially identified. The worst possible outcome that can be reasonably expected is considered as the basis for assessing the severity of the hazard. After identifying the accident probability, the parameters in Tables 5 and 6 are used to determine severity and likelihood ratings [20]. These parameters can be described as insignificant, minor, moderate, major, and catastrophic for severity, while rare, unlikely, possible, likely, and almost certain are used for likelihood.

Table 5. Severity of consequences ratings (S) [20].

Rating (Linguistic)	Numerical	Description
Insignificant	1	No loss of working hours; requires first aid
Minor	2	No loss of working days; outpatient treatment without lasting impact
Moderate	3	Minor injury, requiring inpatient treatment
Major	4	Major injury, requiring long-term treatment and therapy; occupational disease
Catastrophic	5	Death; permanent total disability

Table 6. Hazard likelihood ratings (P) [20].

Rating (Linguistic)	Numerical	Description
Rare	1	Hardly ever
Unlikely	2	Remote (once a year), only in abnormal conditions
Possible	3	Occasional (a few events per year)
Likely	4	Frequent (monthly)
Almost certain	5	Very frequent (once a week or daily), under normal working conditions

Accident probability and accident severity are typically divided into five ranks. The 5×5 risk matrix depicted in Table 7 is employed to represent the final comprehensive risk assessment. In the final assessment, risk is categorised as intolerable, significant, intermediate, acceptable, and insignificant. Table 8 is employed to interpret the acceptability level of the risk. In this process, the first step involves controlling or minimising the highest risk levels (i.e., the most severe consequences and highest likelihood of occurrence) [48]. There are some drawbacks of the RMM. Firstly, the RMM never assumes values of 7, 11, 13, 14, 17, 18, 19, 21, 22, 23, and 24. The most notable shortcoming of TRAM is that identical values for the risk index may be generated by various sets of P and S.

Table 7. Risk assessment decision matrix [20].

Severity (S) ↓/Likelihood (P) →	Rare (1)	Unlikely (2)	Possible (3)	Likely (4)	Almost Certain (5)
Insignificant (1)	1	2	3	4	5
Minor (2)	2	4	6	8	10
Moderate (3)	3	6	9	12	15
Major (4)	4	8	12	16	20
Catastrophic (5)	5	10	15	20	25

The arrows indicate severity (↓) and likelihood (→), while the numbers in parentheses represent the corresponding rating scores from 1 to 5.

In TRAM, risk assessment is score-oriented, calculated by multiplying the likelihood P by the severity S. However, a significant issue arises from the large number of variations that yield the same result. For example, the combinations (P, S) = (1, 5) and (P, S) = (5, 1) produce the same score of 5, leading to identical assessments. Yet the risk profiles differ significantly: when severity is catastrophic (5) but likelihood is rare (1), failing to differentiate from the inverse case may result in insufficient precautions. Treating these two parameters as equally important may therefore lead to inaccurate risk assessments [34,49,50].

In addition, since the RMM relies on subjective evaluations, it is important to consider the margin of error. The outcome of this TRAM application can vary depending on the knowledge and experience of the person conducting it. As the severity of potential occupational accidents increases, so does the likelihood of “long-term incapacity,” “permanent incapacity,” and “death.” This escalation necessitates more serious measures, such as increased costs and broader scopes [28,51]. Consequently, the subjective approach of the RMM directly influences the sensitivity of the obtained risk scores.

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Table 8. Risk categories and suggested events [20].

Risk Category (Linguistic)	Numerical	Suggested Event
Intolerable	25	Work should not start until the risk reaches an acceptable level. Ongoing activity must be stopped. If risks cannot be reduced despite precautions, the activity must be avoided.
Significant	15, 16, 20	Work should not start until the risks are addressed; ongoing activity should be stopped. Emergency precautions are mandatory if the risk endangers continuation of the work.
Intermediate	8, 9, 10, 12	Actions should be initiated to reduce the identified risks. Reduction may take time.
Acceptable	2, 3, 4, 5, 6	No control plan is required to eliminate the identified risks; existing controls must be maintained and monitored.
Insignificant	1	No control plan is required; no records of the activity need to be kept.

The numerical values represent the risk scores obtained by multiplying the severity and likelihood ratings.

In this study we attempt to address this limitation of RMM through an FL approach. Fuzzy logic is integrated into the decision-making process to handle scenarios with complex, ambiguous, incomplete, and difficult-to-interpret data, particularly in crucial decision-making processes such as OSH measures.

2.3. Fuzzy Logic

The notion of fuzzy sets was first introduced by Lotfi A. Zadeh in 1965 as a mathematical theory representing linguistic vagueness [52,53]. Classical set-theoretic methods are inadequate when dealing with problems that involve human judgement in the real world. To address this, Zadeh introduced the definition of fuzzy sets, in which membership is expressed by a continuous membership function rather than a sharp 0/1 indicator [54,55]. In classical sets, an element either belongs or does not belong to a set; the transition between membership and non-membership is abrupt. In a fuzzy set, the degree of membership can take any value in the interval [0, 1], allowing partial membership. The fuzzy-logic approach lets machines process linguistic and experience-based information [56], using symbolic expressions whose semantics are encoded through Fuzzy Sets Theory.

The correspondence between inputs and outputs is realised by a Fuzzy Inference System (FIS). Mamdani and Takagi–Sugeno are the two methods most widely used [2,47,57–64]. Sugeno outputs depend functionally on the inputs, whereas Mamdani outputs are linguistic fuzzy sets that are subsequently defuzzified. An FIS comprises three phases (Figure 3): fuzzification, rule-based inference, and defuzzification [59,65].

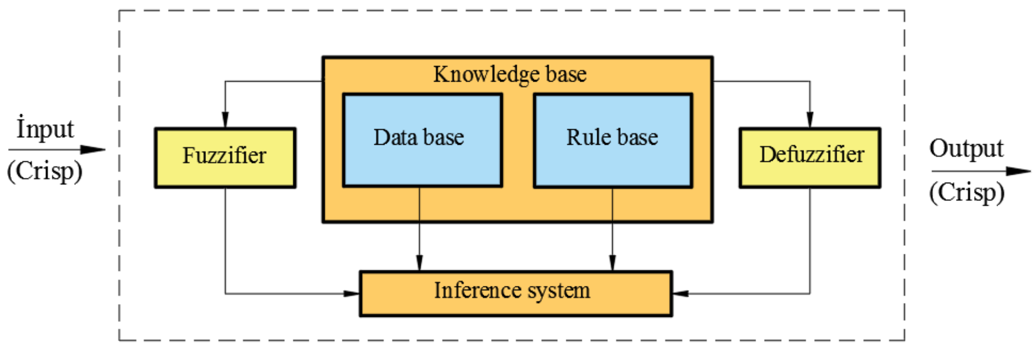

Figure 3. Fuzzy rule-based system [56].

The full mathematical formulation of the Mamdani-type inference adopted in this study is given below. Each crisp input $x \in X$ is fuzzified through membership functions μ: $X \to [0, 1]$. We employ triangular and trapezoidal membership functions, which are the most common choices in rule-based fuzzy modelling. The triangular membership function with parameters (a, b, c), $a \leq b \leq c$, is defined as:

$$\mu\_tri(x; a, b, c) = max(min((x - a)/(b - a), (c - x)/(c - b)), 0) \tag{1}$$

and the trapezoidal membership function with parameters (a, b, c, d), $a \leq b \leq c \leq d$, is defined as:

$$\mu\_trap(x; a, b, c, d) = max(min((x - a)/(b - a), 1, (d - x)/(d - c)), 0). \tag{2}$$

The rule base consists of R IF–THEN rules of the form:

$$Rk\text{: } IF\ x1\ is\ A1, k\ AND\ x2\ is\ A2, k\ THEN\ y\ is\ Bk, k = 1, \ldots, R \tag{3}$$

where x1 (likelihood) and x2 (severity) are the inputs, y is the output (risk score), A1,k and A2,k are the antecedent fuzzy sets of the k-th rule, and Bk is the consequent fuzzy set. The firing strength αk of the k-th rule is computed by the min (T-norm) operator:

$$\alpha k = min(\mu\_\{A1,k\}(x1), \mu\_\{A2,k\}(x2)). \tag{4}$$

Each rule contributes a truncated consequent set μ_{B′k}(y) = min(αk, μ_{Bk}(y)). The aggregate output fuzzy set μ_{B*}(y) is obtained by the max (T-conorm) operator over all R rules:

$$\mu\_\{B^*\}(y) = max\ over\ k\ of\ min(\alpha k, \mu\_\{Bk\}(y)). \tag{5}$$

Finally, the crisp output y* is obtained by the Centre of Area (centroid) defuzzification:

$$y^* = \int y \cdot \cdot \cdot \mu\_\{B^*\}(y)\, dy / \int \mu\_\{B^*\}(y)\, dy. \tag{6}$$

Equations (1)–(6) fully specify the Mamdani inference used in both the FL-Basic and FL-Advanced models. The two models share the same operators and membership functions; they differ only in the consequent sets Bk attached to the rules. The integrals in Equation (6) are evaluated numerically on a discretisation of the output universe with N = 101 sample points, which is the MATLAB 2017b default and provides sub-percent accuracy for the membership-function shapes used here.

People often encounter decision-making scenarios in their personal and professional activities. Decision-making entails selecting the most suitable alternative from various options, aligning with predetermined criteria and objectives [66]. Traditional decision-making approaches that rely on instinct and subjectivity prove inadequate in handling uncertain or ambiguous scenarios. Hence, Fuzzy Decision-Making Methods become pertinent in such contexts; in particular, Fuzzy Multi-Criteria Decision Making methods address the uncertainty inherent in verbal evaluations made by decision-makers [64,67].

2.4. Computational Results for FL Model

Expert evaluation procedure: The construction of the rule base for both FL-Basic and FL-Advanced relies on expert knowledge. The rule base and the risk ratings of the 82 hazards listed in Section 4 were elicited from certified Occupational Safety Specialists of Turkish Hard Coal Enterprises (TTK) through field visits and structured interviews conducted at the Karadon Hard Coal Company site and the affiliated TTK operating units

(Kozlu, Üzülmez, and Armutçuk). Hazard identification was performed first, on the basis of direct on-site observation of the maintenance and repair activities in the battery-locomotive workshop. The likelihood and severity ratings of each hazard, and subsequently the consequent categories of the FL-Advanced rule base, were then refined through iterative discussions with the specialists until a shared judgement was reached for each entry. We acknowledge that the precise number of participating specialists and the formal procedure for aggregating individual judgements were not systematically documented during the field campaign; this is stated explicitly as a limitation in Section 4, and the adoption of more formal consensus protocols (e.g., Delphi or weighted aggregation) is identified as a direction for future work in Section 4.

In this research, FL-based models (FL-Basic and FL-Advanced) were devised to assess the risks associated with occupational accidents in the Maintenance Workshops of Battery Locomotives used in underground coal mines. An FIS model utilising the Mamdani method was developed using the FL toolbox within MATLAB. A rule-based table comprising 25 rules was constructed to yield precise outputs. The "Linguistic Value" and "input range" intervals outlined in Tables 5 and 6 were considered. The inputs of the model are the two parameters likelihood (P) and severity (S); the output is the risk of the occupational accident. Table 9 summarises the characteristics of the developed FL models.

Table 9. FL parameter configuration.

Parameter	Value
Inference type	Mamdani
AND method	min
OR method	max
Implication method	min
Aggregation method	max
Defuzzification method	Centroid
Number of inputs	2
Number of outputs	1
Number of rules	25

Triangular and trapezoidal membership functions were chosen because they are the most commonly used in rule-based fuzzy modelling and they admit the simple analytical forms given in Equations (1) and (2). The fuzzification ranges of the inputs are listed in Table 10 as fuzzy sets overlapping with linguistic terms. Membership functions are tailored with these fuzzification ranges; the input membership functions are illustrated in Figure 4 and the output membership functions in Figure 5.

Table 10. Factors affecting occupational accident risk.

Linguistic Value for Likelihood	Numeric Range (a, b, c)	Linguistic Value for Severity	Numeric Range (a, b, c)
Rare	[0, 0.5, 1.25]	Insignificant	[0, 0.5, 1.25]
Unlikely	[0.5, 1.25, 2]	Minor	[0.5, 1.25, 2]
Possible	[1.5, 2.25, 3]	Moderate	[1.5, 2.25, 3]
Likely	[2.5, 3.25, 4]	Major	[2.5, 3.25, 4]
Almost certain	[3.5, 4.25, 5]	Catastrophic	[3.5, 4.25, 5]

As noted in Section 2.2, RMM assigns the same numerical risk score to combinations of likelihood and severity whose product is identical, regardless of which factor is dominant. For example, in Table 11, rule 5 (P = Rare, S = Catastrophic, $P \times S = 1 \times 5 = 5$) and rule 21 (P = Almost certain, S = Insignificant, $P \times S = 5 \times 1 = 5$) both receive a Traditional RS of 5 and are classified as "Acceptable" by RMM. The proposed FL-Advanced model addresses this asymmetry: rule 5 is reassigned to the "Significant" category because of its catastrophic severity, while rule 21 remains "Acceptable" because the severity is insignificant. This is the central mechanism by which FL-Advanced corrects the severity-blindness of the multiplicative risk score.

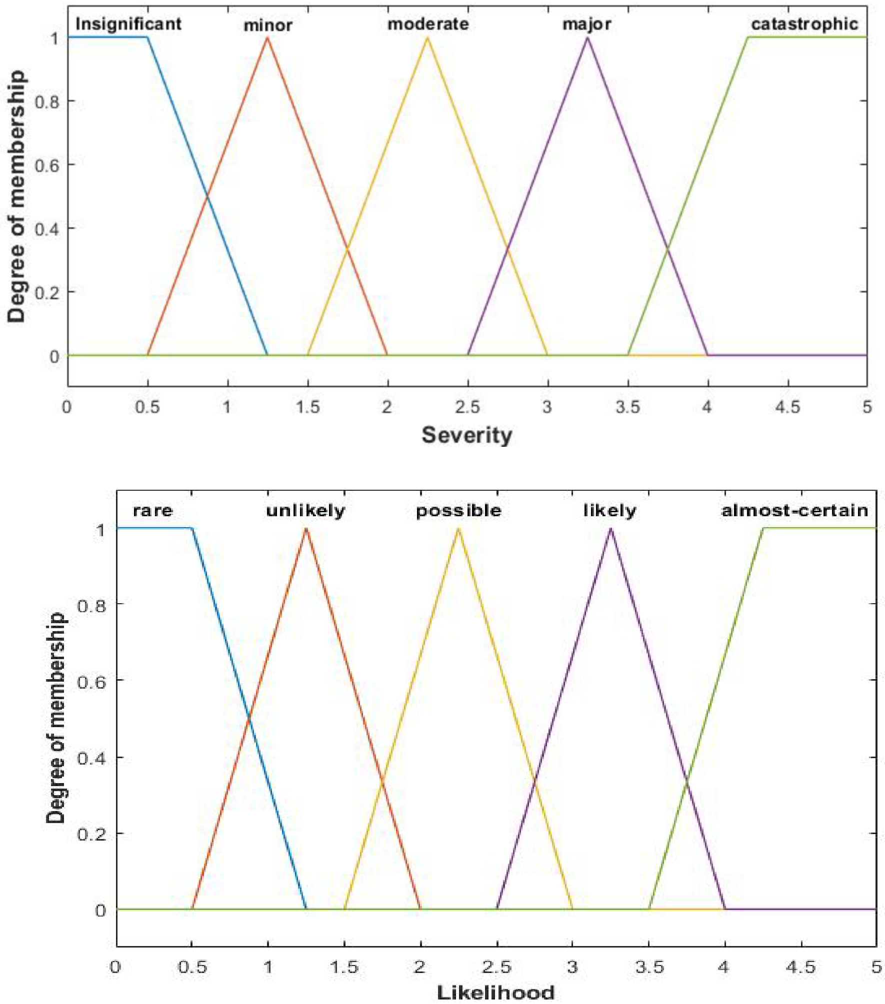

Figure 4. Input membership functions of the fuzzy inference system.

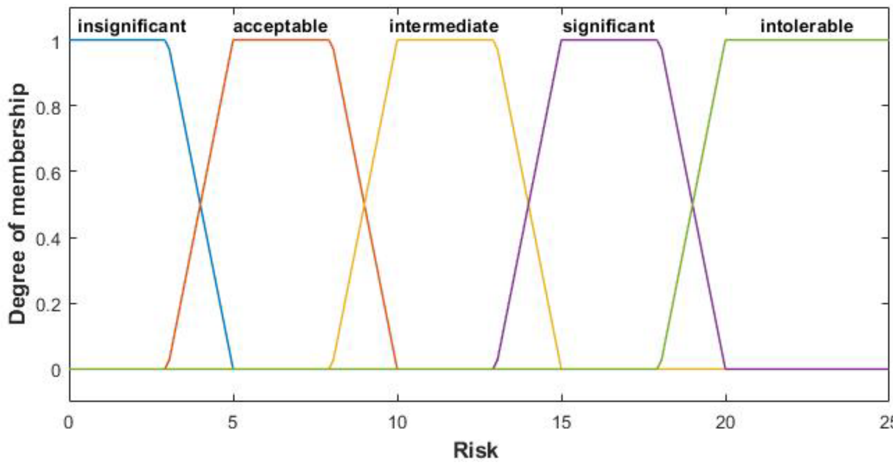

Figure 5. Output membership functions of the fuzzy inference system.

Table 11. Comparison of Traditional Risk Score (RS) and Proposed Risk Score (RS).

No	P	S	Likelihood	Severity	RS	Traditional RS	Proposed RS
1	1	1	Rare	Insignificant	1	Insignificant	Insignificant
2	1	2	Rare	Minor	2	Acceptable	Acceptable
3	1	3	Rare	Moderate	3	Acceptable	Intermediate
4	1	4	Rare	Major	4	Acceptable	Significant
5	1	5	Rare	Catastrophic	5	Acceptable	Significant
6	2	1	Unlikely	Insignificant	2	Acceptable	Acceptable
7	2	2	Unlikely	Minor	4	Acceptable	Acceptable
8	2	3	Unlikely	Moderate	6	Acceptable	Intermediate
9	2	4	Unlikely	Major	8	Intermediate	Significant
10	2	5	Unlikely	Catastrophic	10	Intermediate	Significant
11	3	1	Possible	Insignificant	3	Acceptable	Acceptable
12	3	2	Possible	Minor	6	Acceptable	Acceptable
13	3	3	Possible	Moderate	9	Intermediate	Significant
14	3	4	Possible	Major	12	Intermediate	Significant
15	3	5	Possible	Catastrophic	15	Significant	Intolerable
16	4	1	Likely	Insignificant	4	Acceptable	Acceptable
17	4	2	Likely	Minor	8	Acceptable	Intermediate
18	4	3	Likely	Moderate	12	Acceptable	Intermediate
19	4	4	Likely	Major	16	Intermediate	Significant
20	4	5	Likely	Catastrophic	20	Significant	Intolerable
21	5	1	A-C	Insignificant	5	Acceptable	Acceptable
22	5	2	A-C	Minor	10	Intermediate	Significant
23	5	3	A-C	Moderate	15	Significant	Significant
24	5	4	A-C	Major	20	Significant	Intolerable
25	5	5	A-C	Catastrophic	25	Intolerable	Intolerable

A-C: Almost certain.

Table 11 displays the values of occupational accident probability, accident severity, and risk score, presented both numerically and through linguistic labels. The "Traditional RS" column shows the conventional risk score derived from "likelihood × severity" and its linguistic expression. This column represents the rule base of the FL-Basic Model. The "Proposed RS" column was formulated by considering the limitations of classical risk assessment and following the consensus discussions with the expert panel. This column represents the rule base of the FL-Advanced Model. Although the rule bases of FL-Basic and FL-Advanced differ, their inference characteristics remain the same (Table 9).

Rule-base differences between FL-Basic and FL-Advanced: The FL-Advanced rule base differs from the FL-Basic (RMM-equivalent) rule base in 16 of the 25 rules. The pattern of these modifications is systematic: whenever severity (S) is rated Moderate, Major, or Catastrophic, the consequent category is raised by one level relative to its RMM-equivalent counterpart, regardless of the likelihood value. For instance, rule 5 (P = Rare, S = Catastrophic) is upgraded from "Acceptable" to "Significant"; rule 13 (P = Possible, S = Moderate) is upgraded from "Intermediate" to "Significant"; and rule 22 (P = Almost Certain, S = Minor) is upgraded from "Intermediate" to "Significant". Conversely, all nine rules whose severity is Insignificant or Minor remain unchanged, since these scenarios do not warrant severity-driven escalation. This systematic rule modification produces the upward curvature along the severity axis visible in the FL-Advanced surface, and ensures that low-likelihood, high-severity events receive the operational attention they merit in a maintenance context.

Nomenclature: The mathematical symbols used in this manuscript are summarised in Table 12.

The flowchart of the two FL models developed in the proposed study is shown in Figure 6. The flowchart corresponds one-to-one to the six steps of Algorithm 1: hazard identification, linguistic rating, fuzzification, rule-base inference, centroid defuzzification, and risk categorisation.

Table 12. Nomenclature.

Symbol	Meaning
X	Universe of discourse
A, B	Fuzzy sets (antecedent and consequent, respectively)
μ_A(x)	Membership function of fuzzy set A evaluated at x
μ_tri, μ_trap	Triangular and trapezoidal membership functions
(a, b, c)	Parameters of a triangular membership function
(a, b, c, d)	Parameters of a trapezoidal membership function
x1, x2	Crisp input variables (likelihood, severity)
P, S	Linguistic likelihood and severity
R	Number of fuzzy rules (R = 25)
k	Rule index, k = 1, . . ., R
αk	Firing strength of the k-th rule
Bk, B*	Consequent fuzzy set of rule k; aggregated output fuzzy set
y*	Crisp output (risk score) after defuzzification
N	Number of discretisation points on the output universe
RS	Risk score (numerical)
RMM, FL-B, FL-A	Risk Matrix Method, FL-Basic, FL-Advanced

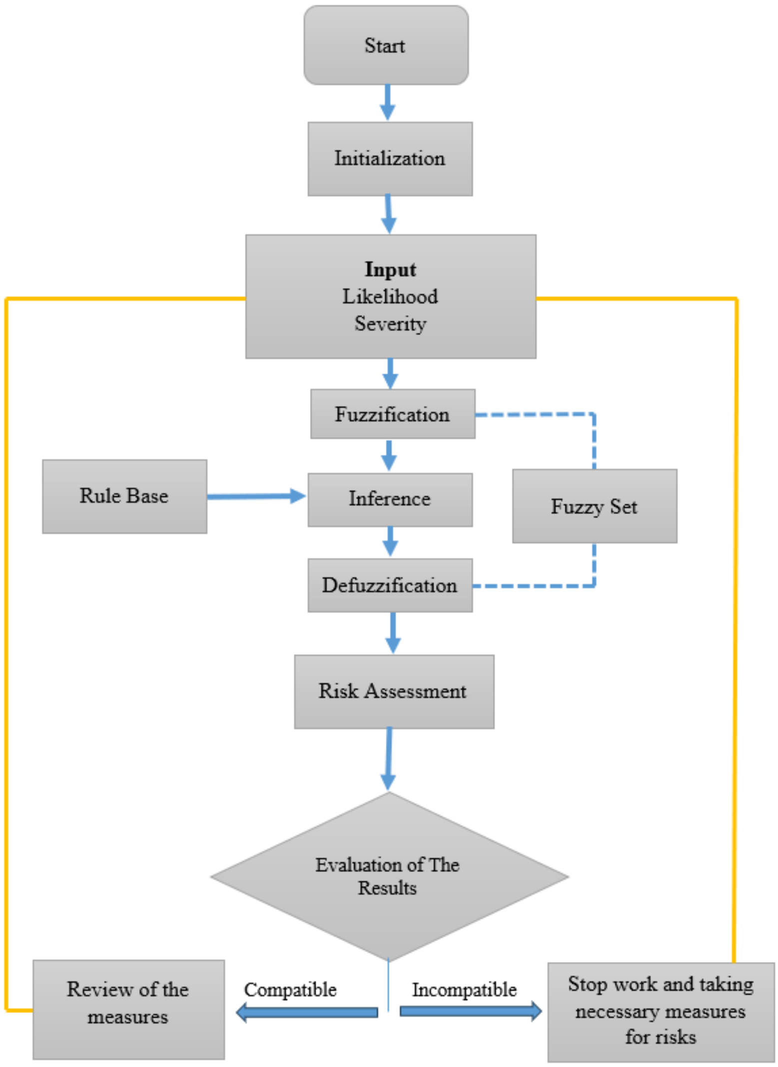

Figure 6. Flowchart of the FL models (Basic and Advanced), aligned with the six steps of Algorithm 1.

Algorithm 1 Proposed FL-Advanced risk-assessment procedure

Step 1. Hazard identification. Enumerate the maintenance activities performed in the battery-locomotive workshop and identify the associated hazards (in this study, 82 hazards were identified at the Karadon site).
Step 2. Linguistic rating. The expert panel rates each hazard's likelihood (P) and severity (S) on the five-point linguistic scale (Tables 5 and 6) through the field-visit and consensus procedure described above.
Step 3. Fuzzification. Apply Equations (1) and (2) using the membership-function parameters of Table 10 to map crisp ratings into fuzzy sets.
Step 4. Rule-base inference. Evaluate each of the R = 25 rules of the FL-Advanced rule base ("Proposed RS" column of Table 11) using Equations (3) and (4); aggregate the consequents via Equation (5).
Step 5. Centroid defuzzification. Compute the crisp risk score y^* using Equation (6).
Step 6. Categorisation and reporting. Map y^* onto the five risk categories of Table 8 and report the result together with the recommended action.

3. Results and Discussion

The RMM described in Table 7 was applied to the maintenance and repair of battery locomotives at Karadon Hard Coal Company, in line with the six steps of Algorithm 1. The RMM, FL-Basic, and FL-Advanced models were used to determine probability and severity scores for 82 risk events resulting from the hazards identified in maintenance and repair activities. The results are presented in Table 13.

Table 13. Risk assessment results for 82 risk events (RMM, FL-Basic, FL-Advanced). [The full Table 13 listing all 82 risk events—preserved from the original manuscript—appears at this position. Columns: No, Activity, Possible accident, P, S, RS, Existing Controls.]. (RMM application in Battery Locomotive Maintenance Workshop, P: Likelihood, S: Severity, RS: Risk score).

Event	Activity	Possible Accident	P	S	RS	Existing Controls
1	Removing the armature	Slip and fall	5	4	20	Periodic check-up
2	Removing the windings	Slip and fall	5	4	20	Periodic check-up
3	Combining the gearbox with the drive motor	Slip and fall	4	4	16	Control
4	Connecting the battery to charge	Hand accident	4	4	16	Periodic check-up
5	Opening the locomotive controller covers	Slip and fall	5	3	15	Periodic check-up
6	Separating the transmission from the drive motor	Slip and fall	3	5	15	Control
7	Demounting the covers	Slip and fall	5	3	15	Periodic check-up
8	Removing the battery connector plug	Injury	3	5	15	Control
9	Removal of the battery from the locomotive	Y	3	5	15	Control
10	De-energizing the rectifier	Worker injury	3	5	15	Periodic check-up
11	Detection of rectifier failure	Hand accident	3	5	15	Periodic check-up
12	Testing by energizing the rectifier	Worker injury	3	5	15	Periodic check-up
13	General follow-up and fault detection of the installation	Shock, injury	3	4	12	Periodic check-up

Table 13. *Cont.*

Event	Activity	Possible Accident	P	S	RS	Existing Controls
14	Testing the locomotive by energizing	Shock, injury	3	4	12	Periodic check-up
15	Closing the locomotive's controller doors	Slip and fall	4	3	12	Control
16	Removing the malfunctioning gears of the gearbox with a press	Slip and fall	3	4	12	Control
17	Mounting the solid gear to the gearbox with press	Slip and fall	3	4	12	Control
18	Collecting the gearbox	Slip and fall	4	3	12	Control
19	Removing the battery connector plug	Hand accident	4	3	12	Periodic check-up
20	Cleaning the battery's oxides	Hand and Eye Injury	4	3	12	Periodic check-up
21	Adding distilled water to battery elements	Hand and Eye Injury	4	3	12	Periodic check-up
22	Closing the battery covers	Slip and fall	4	3	12	Periodic check-up
23	Transport (shipping) of batteries	Slip and fall	3	4	12	Control
24	Removing the damaged transformer	Slip and fall	3	4	12	Periodic check-up
25	Installing the new transformer	Slip and fall	3	4	12	Periodic check-up
26	Transmission removal and cleaning	Slip and fall	2	5	10	Control
27	Replacing the faulty part	Slip and fall	5	2	10	Periodic check-up
28	Removing the faulty element from the battery with the help of a hoist	Slip and fall	2	5	10	Control
29	Mounting the new element to the battery with the help of the calascal	Slip and fall	2	5	10	Control
30	Connecting the battery to charge	Hand accident	2	5	10	Control
31	Battery case cover repair	Hand accident	2	5	10	Control
32	Battery case apparatus handle repair	Slip and fall	2	5	10	Control
33	Separating the drive motor from the transmission	Injury	2	5	10	Control
34	Removing the armature	Slip and fall	3	3	9	Staff education
35	To send the faulty armature for repair	Slip and fall	3	3	9	Staff education
36	Removal and installation of drive motor power cables	Injury	3	3	9	Control
37	Closing the drive engine covers	Slip and fall	3	3	9	Control
38	Removing the bandage bolts	Injury	3	3	9	Control
39	Taking the faulty bandage from the locomotive	Injury	3	3	9	Control
40	Loading the battery to the locomotive	Slip and fall	3	3	9	Control
41	Spare material transportation for locomotives	Slip and fall	3	3	9	Control
42	Applying 550 volts to the primary windings	Electric shock	3	3	9	Periodic check-up
43	Measuring voltage from secondary windings with a measuring device	Hand accident	3	3	9	Periodic check-up

Table 13. *Cont.*

Event	Activity	Possible Accident	P	S	RS	Existing Controls
44	Opening the rectifier covers	Hand accident	3	3	9	Periodic check-up
45	Closing the rectifier covers	Hand accident	3	3	9	Periodic check-up
46	Replacing the faulty part	Injury	4	2	8	Control
47	Making the cable connections of the replaced element	Injury and Burning	2	4	8	Control
48	Pulling the locomotive into the canal	Injury	2	4	8	Control
49	Measuring the armature	Slip and fall	3	2	6	Staff education
50	Sending the repaired armature to the workshop	Slip and fall	3	2	6	Staff education
51	Replacing the faulty bearings of the gearbox	Slip and fall	2	3	6	Control
52	Removing the faulty patagresin	Slip and fall	2	3	6	Periodic check-up
53	Mounting the repaired patagresin	Slip and fall	2	3	6	Periodic check-up
54	Mounting the heated pulley to the bandage	Slip, fall and burning	2	3	6	Control
55	Opening the battery covers	Slip and fall	2	3	6	Control
56	Detection of the faulty element	Slip and fall	2	3	6	Control
57	Disconnecting the cables of the faulty element	Injuries and Burn	2	3	6	Control
58	Control and completion of the element's distilled water	Slip and fall	2	3	6	Control
59	Closing the battery covers after charging	Slip and fall	2	3	6	Control
60	Loading the new bandage to the locomotive	Injury	2	3	6	Control
61	Connecting the drive motor to the gearbox	Injury	3	2	6	Control
62	Mounting the bandage bolts	Injury	3	2	6	Control
63	Transportation of gearbox	Slip and fall	2	3	6	Control
64	Transport of pure waters	Slip and fall	3	2	6	Control
65	Transporting drive motors	Slip and fall	2	3	6	Control
66	Transporting transformers to the test site	Slip and fall	3	2	6	Periodic check-up
67	Transporting the transformer in the test site to the required place	Slip and fall	3	2	6	Periodic check-up
68	Removing the battery connector plug	Hand accident	1	5	5	Control
69	Transferring the battery to the truck through the locomotive	Slip and fall	1	5	5	Control
70	Dismounting the locomotive cabin	Slip and fall	1	5	5	Control
71	Loading the dismounted cabinet to the carrier	Slip and fall	1	5	5	Control
72	Loading the 6/9 ton locomotive to the carrier	Slip and fall	1	5	5	Control

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Table 13. *Cont.*

Event	Activity	Possible Accident	P	S	RS	Existing Controls
73	Installation of the transported locomotive cabin on the locomotive	Slip and fall	1	5	5	Control
74	Uploading the transported 6/9 ton locomotive from the carrier	Slip and fall	1	5	5	Control
75	Loading the battery on the locomotive	Slip and fall	1	5	5	Control
76	Connecting the battery connector plug	Hand accident	1	5	5	Control
77	Loading the locomotive to the other carrier	Hand accident	1	5	5	Control
78	Mounting the bandage bridge bolts	Slip and fall	2	2	4	Control
79	Removing the locomotive from the canal	Slip and fall	2	2	4	Control
80	Inserting the battery connector plug	Slip and fall	2	2	4	Control
81	Cutting worn pulleys	Slip, fall and burning	1	3	3	Control
82	Heating the machined pulley	Slip, fall and burning	1	3	3	Control

Table 13 presents the RS values obtained from the RMM and the linguistic outputs of FL-Basic and FL-Advanced for the 82 risk events. As an example, taking case 5 from Table 13 ("OSH risks of the worker working on the locomotive in the workshop"), severity is rated 5 (S = Catastrophic) and likelihood is rated 1 (P = Rare). The RMM produces an RS = 5 categorised as Acceptable; the FL-Basic Model returns the same Acceptable category; however, the FL-Advanced Model classifies this risk as Significant. This reflects the rule-base modifications listed in Table 11: the elevated severity dimension is upweighted in FL-Advanced, producing a more cautious risk evaluation that matches expert judgement for catastrophic-severity scenarios.

According to Figure 7, RMM classified 16 risks as Insignificant, 9 risks as Acceptable, 13 risks as Intermediate, 39 risks as Significant, and 5 risks as Intolerable. The FL-Basic Model produced 0 Insignificant, 23 Acceptable, 9 Intermediate, 21 Significant, and 29 Intolerable categorisations. Notably, the FL-Basic Model categorised more risks as both Acceptable and Intolerable than RMM. The FL-Advanced Model, with its severity-weighted rule base, produced an even larger group of Intolerable risks, prioritising high-consequence events that RMM and even FL-Basic might overlook.

Figure 8 depicts the comparison results between the FL-Advanced Model and RMM. Unlike the FL-Basic Model, the FL-Advanced Model's risk scores vary depending on severity. For example, examining the risk scores of Risk Event 47, it is classified as "Intermediate" according to RMM (RS: 8), while in the FL-Basic Model (RS: 16.85) it is regarded as "Significant," and in the FL-Advanced Model (RS: 21.89) it is considered "Intolerable." These differing results stem from the fact that RMM assessments are outcome-oriented, whereas the FL-Advanced Model also incorporates severity into its evaluations.

Table 14 and Figure 9 illustrate the disparities in "Risk Scores" (RS) when compared across RMM, FL-Basic Model, and FL-Advanced Model. In Figure 9a, the "Risk Scores" derived from RMM are presented. One drawback of RMM is the infrequent occurrence of extreme values such as 1×1 and 5×5, representing the most severe measures (e.g., "decision to stop working"), which are obtained only when both Probability (P) and Severity (S) are at maximum, resulting in RS = 25. Another limitation of RMM is that RS results, in many cases (e.g., $P \times S$ 1×4 or 4×1), cannot be practically applied to different approaches, thus hindering the generation of alternative solutions.

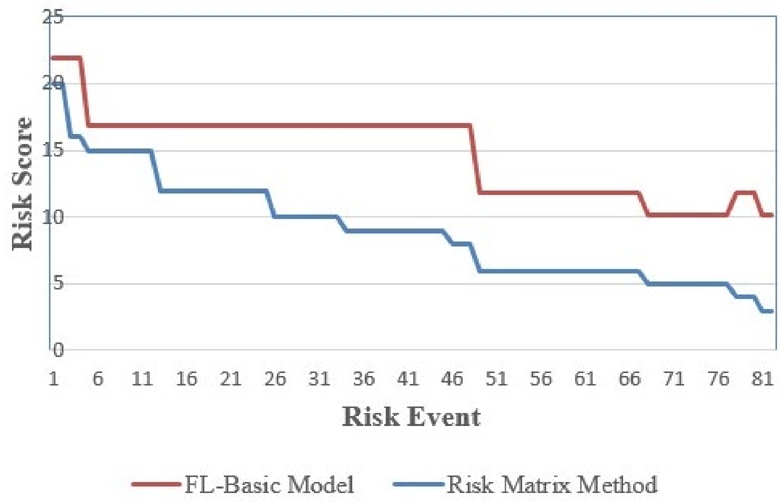


Figure 7. Comparison of RMM and FL-Basic Model results.

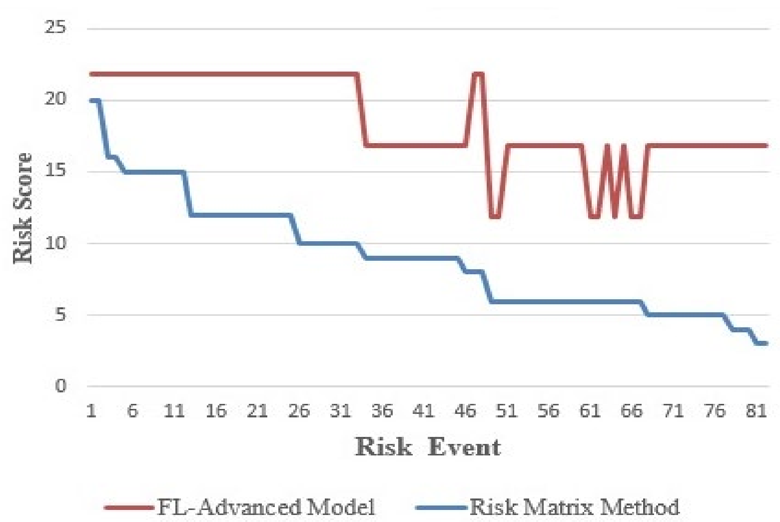
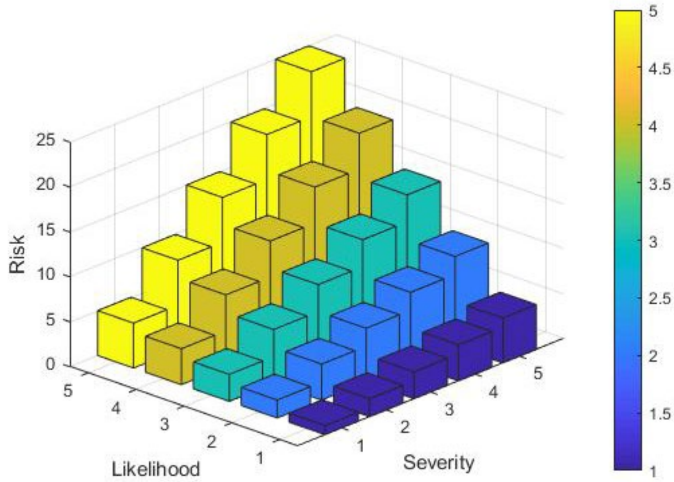


Figure 8. Comparison of RMM and FL-Advanced Model results.

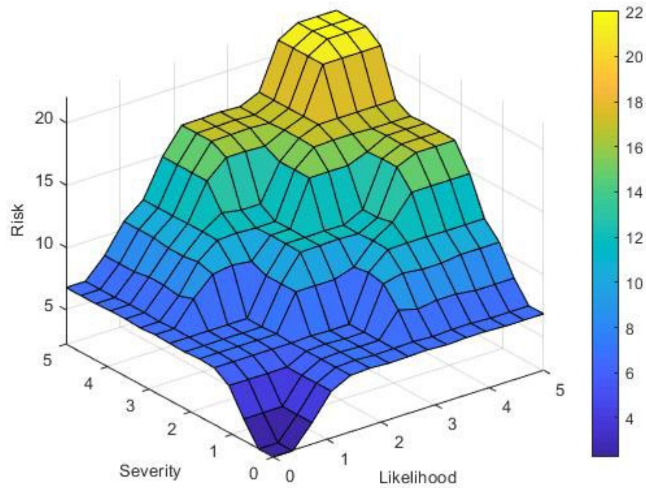
Table 14. Comparison of the risk scores in the application (according to some selected Risk samples).

RE	P	S	RMM RS	Linguistic	FL-Basic RS	Linguistic	FL-Advanced RS	Linguistic
47	2	4	8	Intermediate	16.85	Significant	21.89	Intolerable
60	2	3	6	Acceptable	11.85	Intermediate	16.85	Significant
68	1	5	5	Acceptable	10.15	Intermediate	18.44	Significant
72	1	5	5	Acceptable	10.15	Intermediate	18.44	Significant
77	1	5	5	Acceptable	10.15	Intermediate	18.44	Significant

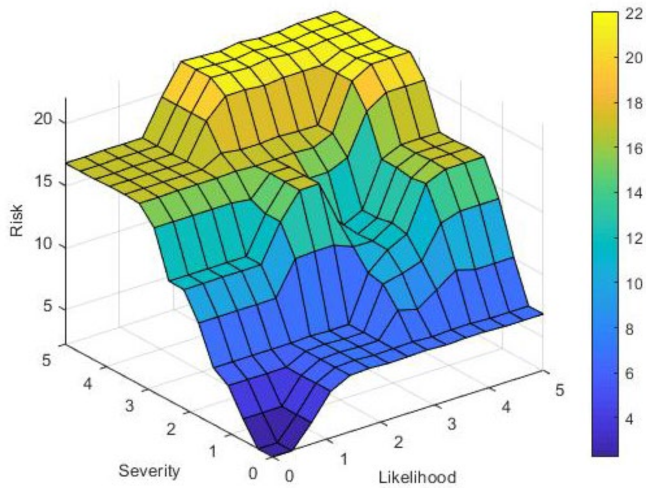
In Figure 9b, the “Risk Scores” of the FL-Basic Model are presented. Compared to Figure 9a, it is evident that the “intolerable” region, especially for RS values near the extremum (e.g., RS = 16 – RS = 25), is enlarged. Additionally, RS values start from 5 in the FL-Basic Model, which is a more realistic representation compared to RMM. However, RS values (P × S and S × P combinations) remain the same in this FL-Basic Model. Hence, the FL-Advanced model was developed in this study to address this limitation.



(**a**) Possible risks scores of Risk Matrix Method



(**b**) Possible risks scores of FL-Basic Model



(**c**) Possible risks scores of FL-Advanced Model

Figure 9. Possible risk scores in the RMM, FL-Basic Model and FL-Advanced Model.

In Figure 9c, the "Risk Scores" of the FL-Advanced Model are depicted. As the most refined model developed, it exhibits a non-linear characteristic, unlike the linear nature of

RMM. In the FL-Advanced Model, the severity value plays a more decisive role than the likelihood value in calculating RS, thereby yielding more realistic results. Consequently, Figure 9c showcases a considerably wider intolerable region in RS values (e.g., P $\times$ S combinations like 5×5, 4×5, 3×5, 2×5, and 3×4), depending on the severity.

The control-surface comparison of Figure 9 provides a direct visualisation of the input–output relationship of each model. The surface of FL-Basic (Figure 9b) is approximately linear in the P $\times$ S product, reproducing the RMM logic with smoothing at the category boundaries. In contrast, the surface of FL-Advanced (Figure 9c) is markedly non-linear and curves upward along the severity axis, which is the geometric expression of the severity-weighted rule reassignment described in Section 2.4. The two surfaces share the same shape on the likelihood axis (the operator structure is identical) but diverge as severity grows, which is precisely the regime in which the multiplicative RMM score becomes operationally misleading.

3.1. Selection Criteria for the Reasoning Approach

The comparison of RMM, FL-Basic, and FL-Advanced raises a practical question for occupational-safety specialists: which of the three reasoning approaches is most appropriate in a given setting? We propose four selection criteria.

(i) Data availability and quality of likelihood estimates. When event-frequency data are scarce or uncertain, the smoothing provided by fuzzy inference is advantageous; FL-Basic and FL-Advanced are preferable to RMM in this regime.

(ii) Tolerance for severity-driven prioritisation. When the operational context tolerates—and indeed benefits from—treating high-severity, low-frequency events as critical, the FL-Advanced rule base is the natural choice. This applies to maintenance environments in underground coal mining, where rare but catastrophic events dominate the long-run risk profile.

(iii) Computational and software resources. All three methods are computationally light; this criterion rarely discriminates. RMM requires only a spreadsheet, while FL-Basic and FL-Advanced require a fuzzy-inference toolbox; modern computing environments support all three.

(iv) Regulatory acceptance and interpretability. When the regulator mandates a particular method (often RMM in legacy frameworks), the legal choice is constrained. Where regulators accept equivalent or improved methods, FL-Advanced offers superior interpretability through its explicit linguistic rule base.

The recommendation that emerges is that FL-Advanced is the most appropriate choice when severity dominates the operational risk profile (as in battery-locomotive maintenance), FL-Basic is preferable when the rule base must mirror a regulatory RMM structure while gaining the smoothing benefits of fuzzy inference, and RMM remains acceptable for low-severity, well-characterised hazards where regulatory simplicity is the priority.

3.2. Strengths, Weaknesses, and Computational Complexity

Strengths of the FL-Advanced model: (a) Methodologically, FL-Advanced explicitly addresses the severity-blindness of the multiplicative RMM score through systematic rule reassignment, while preserving the interpretability of a linguistic rule base. (b) Operationally, it is well suited to severity-dominant maintenance contexts in which low-frequency, high-consequence events drive the long-run safety profile. (c) Computationally, it is light enough for real-time decision support (see complexity analysis below). (d) Practically, it integrates with existing OSH workflows because its outputs are reported on the same five-category linguistic scale used by Turkish OSH legislation.

Weaknesses: (a) The quality of the inference depends on the quality of the rule base, which in turn depends on the expert panel. (b) The linguistic granularity is fixed at five levels for both inputs and the output; finer-grained discrimination would require a larger rule base. (c) The membership-function design is data-independent, fixed by expert consensus; data-driven tuning could in principle further reduce subjectivity. (d) Likelihood and severity are treated as independent inputs; weak couplings between them are not modelled.

Computational complexity: For a Mamdani-type inference system with R rules, n inputs, and a discretisation of N points on the output universe, the dominant computational cost of one inference is $O(R \cdot N)$. In the proposed model, R = 25 and N = 101, yielding on the order of 2500 elementary operations per evaluation. This is a negligible computational load on any modern personal computer or industrial embedded controller; the evaluation of all 82 hazards is therefore completed virtually instantaneously, which confirms that the framework is compatible with real-time decision-support deployment at the workshop level.

3.3. Robustness Considerations

Although a formal sensitivity analysis under controlled parameter perturbations is left for future work, the structural design of the proposed framework already offers a degree of robustness against small variations in the membership-function parameters. The five overlapping triangular membership functions on each axis (Table 10) are constructed so that adjacent linguistic values share a non-trivial transition region; combined with the centroid defuzzification of Equation (6), which integrates over the smooth aggregated set μ_{B*}(y), small displacements of the membership-function vertices produce continuous, rather than discontinuous, changes in the crisp risk score. Sensitivity to membership-function design is therefore concentrated near the category boundaries of Table 8, which is the expected and intended behaviour of any well-designed fuzzy classifier. A systematic empirical assessment of this property, employing controlled parameter perturbations and alternative membership-function shapes (e.g., Gaussian or π-functions), is identified in Section 4 as a primary direction for future work.

3.4. Limitations and Applicability Conditions

The applicability of the proposed framework to other production facilities is subject to several limitations and conditions. (i) The rule base reflects the consensus of Occupational Safety Specialists from a single national context and may need re-elicitation when transferred to facilities operating under different regulatory regimes or organisational cultures. (ii) The linguistic granularity is fixed at five levels for both inputs and the output, which suffices for the Turkish OSH framework but may be insufficient for finer-grained risk discrimination in other settings. (iii) The model treats likelihood and severity as independent inputs; weak couplings between them are not modelled. (iv) The precise number of participating specialists and the formal protocol for aggregating their individual judgements were not systematically documented during the field campaign; we openly acknowledge this and identify the adoption of more formal consensus protocols (e.g., Delphi or weighted aggregation) as future work. (v) Validation has so far been performed on a single industrial site (Karadon Hard Coal Company).

Subject to these limitations, the framework is applicable to other facilities meeting the following conditions: (a) operation under a five-point linguistic risk taxonomy or one compatible with it; (b) availability of OSH specialists with field experience for the rule-base elicitation, ideally spanning more than one site; (c) discrete identifiability of hazards as maintenance activities, as is typical of mechanical workshops; and (d) willingness to adopt severity-driven prioritisation, which may increase the number of hazards flagged for immediate action.

3.5. Operational Recommendations

On the basis of the field visits and interviews conducted with Occupational Safety Specialists, and informed by the risk prioritisation produced by the FL-Advanced model, the following recommendations were identified for the Battery Powered Locomotive Maintenance Workshop. These recommendations are the operational corollary of the methodological contribution of this study.

1. Ensure Availability of Ambulance Waggons: Battery-powered locomotives are extensively used for transporting coal, stone, and underground support materials. To facilitate swift response in emergencies, it is crucial to allocate special waggons as ambulances, ensuring they are readily available at all times.
2. Address Battery Transportation Risks: As the charging stations for battery-powered locomotives are prohibited underground, batteries with a charge level of 20% are removed and transported to above-ground charging stations using carrier locomotives. The frequent transportation of these heavy batteries (weighing about 7 tons to 17 tons) poses Occupational Safety and Health (OSH) risks. It is recommended to expedite technological research and development (R&D) efforts to develop longer-lasting batteries, thereby reducing the need for frequent transportation.
3. Review OSH Focus for Above-Ground Workshops: Since the workshop is situated above ground, it tends to receive less attention in terms of OSH compared to underground facilities, resulting in higher risk events. It is advisable to reconsider this perception and allocate appropriate resources and attention to mitigate risks effectively.
4. Revise Workshop Facility Planning: The workshop conducts machining, welding, and maintenance operations, involving various manufacturing methods, making the combinations complex. Therefore, it is beneficial to review the facility planning by potentially dividing the workshop into sections to streamline operations and enhance safety measures.

Implementing these recommendations can significantly improve safety standards and mitigate risks in the Battery Powered Locomotive Maintenance Workshop.

4. Conclusions

Coal is a strategic resource for many economies; in Turkey it remains essential to industrial production. However, the OSH risk profile of coal mining—and especially of underground coal mining—is severe. The maintenance and repair of underground battery locomotives is one of the activities in which careful, consistent risk assessment is most needed, because failures during these operations combine multiple low-frequency hazards with potentially catastrophic consequences.

In this study we developed and validated a fuzzy logic-enhanced risk assessment framework for battery-locomotive maintenance in underground coal mines. Two Mamdani-type FL models—FL-Basic, which mirrors the RMM rule base, and FL-Advanced, whose rule base systematically upweights severity through reassignment of 16 of the 25 consequent categories—were compared with the conventional RMM on 82 risk events at Karadon Hard Coal Company.

Main findings. (i) The FL-Advanced model expands the Intolerable category to include low-likelihood, high-severity events that RMM and FL-Basic classify as Acceptable or Intermediate, in agreement with the consensus expert judgement that catastrophic-severity events warrant elevated prioritisation regardless of frequency. (ii) FL-Basic eliminates the artificial sharpness of RMM at category boundaries through fuzzy smoothing, but inherits

its severity-blindness; FL-Advanced is therefore the model that meaningfully improves over RMM. (iii) The proposed framework is computationally light (per-inference cost of order 2500 elementary operations) and is therefore compatible with real-time decision support in the field.

Mechanism of subjectivity reduction. FL-Advanced mitigates the subjectivity inherent in RMM through three mechanisms. First, overlapping triangular membership functions translate each discrete linguistic rating into a continuous fuzzy set, replacing the sharp transitions of RMM with smooth boundary behaviour and reducing the impact of small differences in expert judgement near category boundaries. Second, the min–max inference followed by centroid defuzzification produces a single crisp output that integrates the contributions of all fired rules, rather than relying on the single point estimate $P \times S$ of RMM, thereby averaging out individual rater biases. Third, the severity-weighted rule reassignment encodes a transparent and reproducible policy decision (severity dominates at high values), displacing the implicit and inconsistent subjective adjustments that OSH specialists otherwise apply when using RMM in severity-critical contexts. The criteria used to evaluate this advantage were: the spread of risk scores produced for nominally equivalent $P \times S$ inputs, the consistency of the output category with expert post hoc judgement, and the reproducibility of the assessment when re-run on the same data—all three of which are met by FL-Advanced in the case study reported.

Limitations. We acknowledge that the framework depends on the quality of the expert elicitation (the precise panel size and consensus protocol of which were not formally documented), that its linguistic granularity is fixed by the five-point taxonomy used in the case study, and that validation has so far been performed at a single industrial site.

Future work. Four concrete directions are proposed: (a) a systematic sensitivity analysis under controlled perturbations of the membership-function parameters, together with comparisons across alternative membership-function shapes (triangular, trapezoidal, Gaussian, π-functions); (b) adoption of more formal expert-elicitation protocols, such as Delphi or weighted aggregation, with a larger and explicitly documented expert panel; (c) extension to type-2 fuzzy sets to model expert disagreement explicitly within the inference, and integration with real-time condition-monitoring sensor data from battery packs; and (d) replication of the case study across other TTK companies and, in due course, across underground coal-mining facilities in other countries to assess cross-site generalisability.

In summary, this study demonstrates that a carefully designed Mamdani-type fuzzy inference system, with a severity-weighted rule base, provides a more consistent and decision-relevant risk-assessment framework for battery-locomotive maintenance in underground coal mining than the conventional Risk Matrix Method, while retaining computational efficiency and operational interpretability.

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