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Developing a new fuzzy inference model for warehouse maintenance scheduling under an agile environment

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Abstract

Today, the military bodies of different countries have identified the existence of a condition assessment system in order to optimize the process of maintenance and repair of military buildings and equipment as a need and are looking for a suitable answer. The issue of less and/or outright lack of knowledge and uncertainty in modeling and decision making plays a crucial part in many engineering and especially military difficulties, resulting in designers and engineers being unable to obtain definitive solutions for the problems under discussion. This study develops a fuzzy logic application for representing the uncertainty inherent in the problem of warehouse maintenance scheduling. The relative risk score (RRS) approach, one of the most prevalent methodologies for maintenance assessment, is combined with fuzzy logic to achieve the goal. Based on expert knowledge, the suggested model is run on the MATLAB® fuzzy logic toolbox using the Mamdani algorithm. A representative case study is used, and a comparison is made between the traditional risk assessment technique and the suggested model. The findings show that the suggested model produces more accurate, exact, and certain results, allowing it to be used as an intelligent risk assessment tool in many engineering settings.

Keywords: risk assessment, fuzzy logic, warehouse maintenance, Mamdani algorithm
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1 Introduction

Maintenance activities may have a significant impact on an asset's usable life and overall performance. As a result, both asset operators/owners and asset service providers are always attempting to devise the most effective strategy for this critical activity. Currently, billions of dollars are spent each year to manufacture various types of facilities for use in the construction and industry sectors. The competitive global economy is driving managers to identify the best ways to increase their competitiveness in order to compete with other organizations in the global marketplace, such as by enhancing their performance in terms of quality, flexibility, delivery time, and cost [25].

Incapacity or destruction of such infrastructures would have a crippling effect on national security and economic stability, public health and safety, or any combination of these issues. As a result, risk assessment may assist authorities

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in identifying riskier components and developing an appropriate reaction and strategy to decrease and/or eliminate them. To achieve the goal, a good approach is required that can analyze the current risks more precisely, accurately, and confidently. According to the importance of warehouses, several researches are conducted to analyze risks connected with agile maintenance.

Dziubinski et al. [9] provided a risk assessment technique for dangers connected with dangerous drug transportation. Han and Weng [15] suggested a method for integrating quantitative risk analysis in natural networks. The approach consists of assessing the likelihood of accidents, analyzing the effects, and assessing risk. Brito et al. [5] introduced a multicriteria approach for assessing risk based on Utility Theory and the ELECTRE TRI technique for dividing sections into risk categories. Jo and Ahn [18] proposed a simpler technique for quantitative risk assessment and introduced the fatal length and cumulative fatal length parameters. Liang et al. [20] suggest using self-organizing maps (SOMs) to assess the risk of third-party intervention and identify their risk patterns. The fault tree is employed initially in this work to build the risk assessment index system, and then SOM is used in the multi-parameter risk pattern classification technique.

Cagno et al. [6] developed a strong Bayesian technique to support replacement policies by assessing their failure probability. Shahriar et al. [30] used fuzzy logic to calculate fuzzy probabilities (likelihood) of fundamental events in a fault tree and estimate fuzzy probabilities (likelihood) of output event outcomes. The research also investigates how the interdependence of numerous elements may impact analytical outcomes.

Soszynska [31] used a multi-state technique to analyze and evaluate system dependability and risk. Gharabagh et al. [11] created an algorithm that uses probabilistic and indexing models to overcome the majority of the models' constraints, which is an effective approach for comprehensive risk assessment and management. Breton et al. [4] developed a Bayesian probabilistic technique to identifying and forecasting failure types. Yuhua and Datao [34] used expert elicitation in conjunction with fuzzy set theories to assess the likelihood of occurrences.

Often, the research stated above only used two key characteristics to determine the degree of risks: likelihood and effects; nevertheless, these two elements cannot cover all aspects of the hazards. On the other hand, uncertainty is such an essential feature of real-world systems that Boolean logic is incapable of dealing with it. Existing ambiguity stems from two sources [10]: (1) uncertainty in subjective judgements and (2) uncertainty owing to a lack of data or insufficient information. Fuzzy logic is an effective technique for dealing with ambiguity and solving situations that lack defined limits and exact values. This strategy is used to address many areas of risk concerns. Table 1 shows numerous applications of fuzzy logic in risk modeling.

Often above-mentioned studies only applied two main parameters likelihood and consequences in order to assess the level of risks; while, these two factors cannot cover all aspects of the risks [13]. On the other hand, uncertainty is an inseparable part of real life systems that Boolean logic is not able to handle this inherent uncertainty and complexity. The existing uncertainty is created by two parts [10]: (1) uncertainty in subjective judgments (2) uncertainty due to lack of data or incomplete information. Fuzzy logic is a powerful tool for facing with uncertainty and solves problems where there are no sharp boundaries and precise values. This method is used to solve different aspects of risk problems. Table 1 lists several applications of fuzzy logic in modeling risk.

Table 1: Several applications of fuzzy logic in risk analysis

Proposed by	Application
Yuksel and Atmaca [35]	A system for driver risk assessment using machine learning and fuzzy logic
Milton-Thompson et al [24]	A fuzzy logic-based risk assessment for groundwater contamination from well integrity failure during hydraulic fracturing
Aalipour Erdi et al [1]	Risk zoning of land subsidence
Abdollahi et al [2]	Prioritization of effective factors in the occurrence of land subsidence
Chanapathi et al [7]	Fuzzy-based approach for evaluating groundwater sustainability
Meshram et al [23]	Assessing erosion prone areas in a watershed
Plebankiewicz et al [28]	Modelling of time, cost and risk of construction

From Table 1, it can be seen that fuzzy logic has demonstrated its capabilities and efficiencies as a practical engineering and problem-solving tool.

The primary goal of this study is to offer a novel technique based on relative risk score (RRS) and fuzzy inference system for providing a systematic framework for developing a more certain, precise, and robust model for controlling warehouse risks and hazards. The plan's major goal is to guarantee that the planning program under consideration is robust, safe, and capable of swiftly detecting and mitigating faults. To demonstrate the capacity and efficacy of the suggested model, the outputs of the proposed model are compared to the outputs of the conventional technique.

The rest of the paper is organized as follows. Next section describes the basic structure of traditional relative risk score. In section 3, Fuzzy inference system is briefly illustrated, including fuzzy theory, fuzzification, knowledge base, fuzzy inference system, and defuzzification. The proposed model is introduced in Section 4. The implementation of the proposed model is presented in section 5. A real case study is illustrated in section 6. Comparison between the proposed model and traditional RRS is summarized in section 7. In the last section, conclusions are discussed.

2 Traditional RRS framework

The relative risk score (RRS) is a logical instrument for measuring maintenance based on warehouse system failure. This model is used not only for complete maintenance assessment, but also to get comprehensive information for inspection, modification, or risk management [11]. This approach has lately been employed by several researchers to assure warehouse safety and dependability.

3 Fuzzy inference system

In many practical challenges, assessors are confronted with a dearth of information or inadequate data when modeling real-world occurrences; hence, ambiguity and uncertainty are integral parts of knowledge. Zadeh's [36] fuzzy logic is a valuable tool for dealing with such circumstances. This method makes use of language concepts to offer an inference structure for modeling sophisticated and complicated systems. A fuzzy set is a generalized variant of a crisp set with values between 0 and 1, where 1 represents complete membership and 0 represents non-membership [33]. Crisp sets, on the other hand, can only accept 0 or 1.

A typical fuzzy inference system (FIS) is schematically depicted in Fig. 1. As shown in Fig. 1, an FIS includes four main parts (1) fuzzification, (2) Knowledge base, (3) fuzzy inference system, and (4) defuzzification.

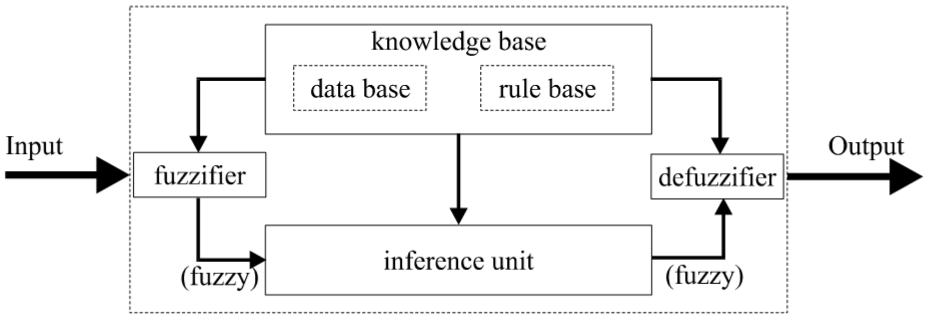

Figure 1: Fuzzy inference systems

3.1 Fuzzification

The initial step of FIS is fuzzification, which involves mapping linguistic variables and membership functions by converting the input vector into fuzzy If-Then rules. In other words, input vectors (crisp values) may be converted into language variables like very high, high, medium, low, and very low. This procedure is carried out with the assistance of the membership function (MF). These functions have various linear and nonlinear forms. The MF type is determined by the modeled problem, expert knowledge, and circumstances [14].

3.2 Knowledge base

The database and rule base create the knowledge base, and the MFs of the fuzzy sets used in creating the fuzzy rules are specified by the database, while fuzzy if-then rules build the rule base. Expert judgements, engineering knowledge, and experience are used to generate the fuzzy if-then rules [12].

Fuzzy conditional functions, often known as fuzzy "if-then" rules, establish the input-output connections. A fuzzy conditional rule is often composed of a premise (antecedent) and a conclusion (conclusion), such as "if x is high (premise), then y is low (consequent)," where the words high and low can be represented by membership functions [17].

3.3 Fuzzy inference system

The fuzzy inference unit employs these fuzzy If-Then rules in this stage to allocate a map from fuzzy inputs to fuzzy outputs based on fuzzy composition rules [19]. This is the key portion of a fuzzy expert system that combines the facts acquired from the fuzzification process with the rule bases established in the previous phase and models them.

Several FISs have been used in various fields of research and engineering applications. One of the most prominent algorithms is the Mamdani fuzzy model, which employs the principles of fuzzy sets and fuzzy logic to convert a fully unstructured set of linguistic heuristics into an algorithm [21]. The following is the generic "if-then" rule form of the Mamdani algorithm (Fig. 2):

$$\text{If } x_1 \text{ is } A_{i1} \text{ and } x_2 \text{ is } A_{i2} \text{ and } \cdots\ x_r \text{ is } A_{ir} \text{ then } y \text{ is } B_i \text{ (for } i = 1, 2, \cdots, k) \tag{3.1}$$

where x_i is the input variable,A_{ir} and B_i are linguistic terms,y is the output variable, and k is the number of rules. Different fuzzy composition methods can be applied to establish the Mamdani fuzzy model. In this paper, max–min composition, the most commonly used method [29], is utilized. This technique is mathematically defined as follows [26]:

$$\mu_{C_K}(Z) = \max\left[\min[\mu_{A_K}(input(x)), \mu_{B_K}(input(y))]\right] \quad K = 1, 2, \cdots, r \tag{3.2}$$

where μ_{C_K}, μ_{A_K}, and μ_{B_K} are the membership functions of output "z" for rule "k", input "x", and "y", respectively.

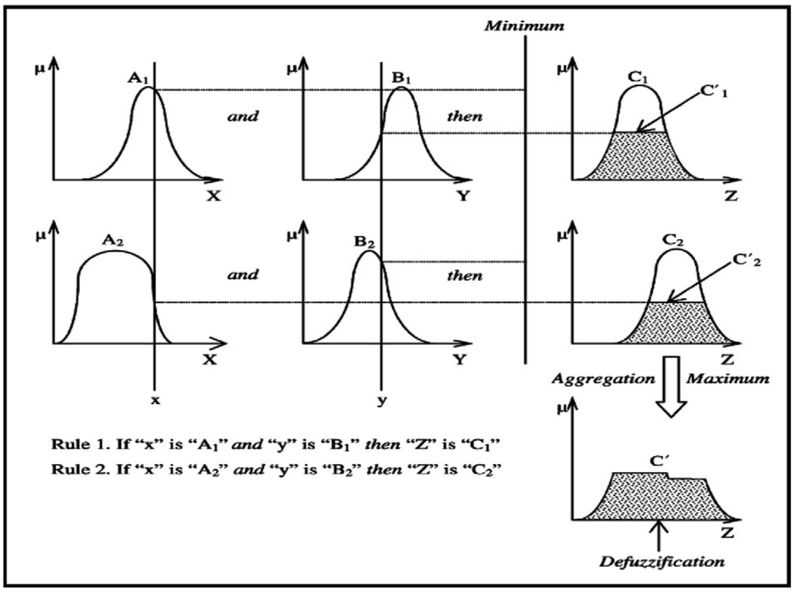

Figure 2: A typical Mamdani inference mechanism [21]

3.4 Defuzzification

Finally, the defuzzifier is used to transfer fuzzy sets into crisp value. There are several defuzzifier methods in the literature. Centroid of area (COA) is one of the most popular methods for defuzzification process. The advantage of the COA method is that all activated membership functions of the conclusions (all active rules) take part in the defuzzification process ([8]. The COA method applies the following equation for transferring fuzzy scheme into a crisp value [16]:

$$Z^{\star}_{\mathrm{COA}} = \frac{\int_z \mu_A(z) z dz}{\int_z \mu_A(z) dz} \tag{3.3}$$

where $Z^{\star}_{\mathrm{COA}}$ is the crisp value for the "z" output and $\mu_A(z)$ is the aggregated output membership function.

4 Proposed model for maintenance assessment of warehouses under agile environment

The fuzzy risk analysis method proposed in this study contains of three phases vulnerability, probability, and consequences. Fuzzy logic is applied to handle the uncertainty involved in process of modeling. A specific feature of the proposed model is an integrated model based on qualitative and quantitative techniques for agile maintenance assessment. This can result in a complete and more accurate assessment of risks connected with hazard sources [3]. The framework of the proposed method is schematically depicted in Fig. 3.

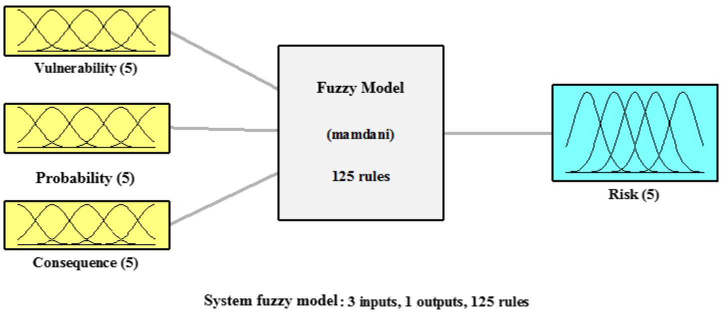

Figure 3: Schematic diagram of the proposed model

The first phase focuses on the overall vulnerability, which is caused by damage, corrosion, design, and incorrect operation. This phase calculates the potential for a particular failure mechanism to be active and is subtly different from the likelihood of failure [27].

The second phase concentrates on the probability of a failure. The third phase concentrates on the overall consequence of a failure, including product hazard, leak volume, dispersion, and receptors.

The last phase computes the final risk score to evaluate the level of risk in order to determine the proper mitigation strategy for activity continuity. After computing the risk values, these values are ranked in descending order. In the last step of the phase, riskier sections are highlighted to be improved by appropriate strategies.

5 Modeling fuzzy risk assessment

The procedure of the proposed model is presented by a stepwise process in the following part.

Probability refers to the potential for an exacting failure mechanism to be happened, and is induced by the influence of internal parameters. In order to composite fuzzy relations, the max–min composition method, most popular applied technique, is selected [29]. The variables are fuzzified with membership functions presented in Table 2 as shown in Fig. 4. As seen in the figure, the Gaussian type of membership functions are employed because of being the most natural [22], smooth and nonzero at all points [32]. The Gaussian membership function is based on two parameters and can be represented by Eq. (5.1):

$$\text{Gaussion}(x; c, \sigma) = e^{-\frac{1}{2}}(\frac{x-c}{\sigma})^2 \tag{5.1}$$

where c and σ are the center and width of the membership function, respectively. The authors adjusted parameter σ so that every membership function has 50 percent overlapping. This causes the risk of introducing a “hole” in the input domain be eliminated [17]. Based on the basic descriptions of Mamdani model, both input and output variables are fuzzy propositions.

The next step is the construction of the fuzzy if–then rules. These rules represent the fuzzy relations between input and output variables. Based on experts’ knowledge, the rule base of fuzzy model is constructed. A sample of the fuzzy if–then rules including 20 rules of the model established in MATLAB® software package is listed in Fig. 5.

Table 2: Definition of fuzzy and crisp ratings

Factors	Linguistic term	Crisp rating	Fuzzy ratings	Universe of discourse (X)
Vulnerability	Very High (VH)	5	$3.5 < V \leq 5$	$X_V \in (1,5)$
	High (H)	4	$3 \leq V < 5$	
	Medium (M)	3	$2 \leq V \leq 4$	
	Low (L)	2	$1 \leq V \leq 3$	
	Very Low (VL)	1	$1 \leq V < 2.5$	
Probability	Very High (VH)	5	$3.5 < P \leq 5$	$X_P \in (1,5)$
	High (H)	4	$3 \leq P < 5$	
	Medium (M)	3	$2 \leq P \leq 4$	
	Low (L)	2	$1 \leq P \leq 3$	
	Very Low (VL)	1	$1 \leq \mathrm{P} < 2.5$	
Consequence	Very High (VH)	5	$3.5 < C \leq 5$	$X_C \in (1,5)$
	High (H)	4	$3 \leq C < 5$	
	Medium (M)	3	$2 \leq C \leq 4$	
	Low (L)	2	$1 \leq C \leq 3$	
	Very Low (VL)	1	$1 \leq C < 2.5$	
Risk	Very High (VH)	5	$3 \leq R \leq 5$	$X_R \in (0,5)$
	High (H)	4	$2 \leq R < 5$	
	Medium (M)	3	$1 \leq R < 4$	
	Low (L)	2	$0 < R \leq 3$	
	Very Low (VL)	1	$0 \leq R < 2.5$	

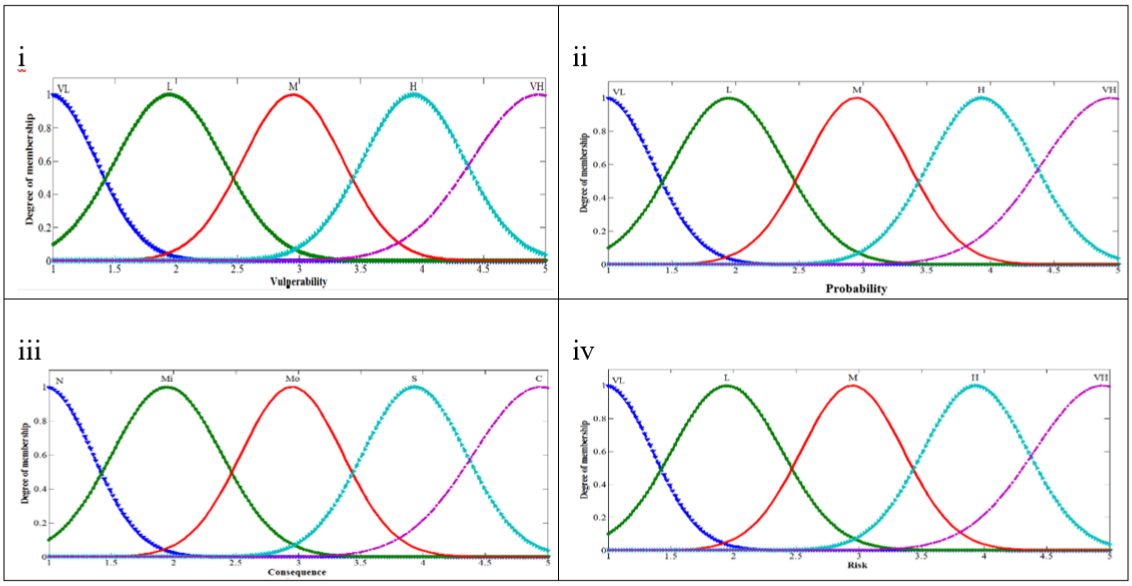

Figure 4: Membership functions of input variables involved in the model

In the last step, the defuzzification process is applied to fuzzy values be converted into a crisp ones. In this paper, the COA method, one of the most common methods, is employed for defuzzification process.

The interdependency of input and output parameters derived from the rules generated in the fuzzy IS model can be shown by using control surface as depicted in Fig. 6.

6 Case study

A numerical case study as an illustration of the application of the proposed model for warehouse maintenance assessment is illustrated. This application is based on information taken from a typical warehouse. The process of risk assessment is performed by using the proposed model to rank the 8 sections according to the RSS values in descending order and the section with the lowest score is selected as the riskiest section. This process helps authorities to take into account the suitable strategies in order to reduce or mitigate the levels of risk of each section. The results of the proposed model for risk assessment of the 5 sections are listed in Table 3.

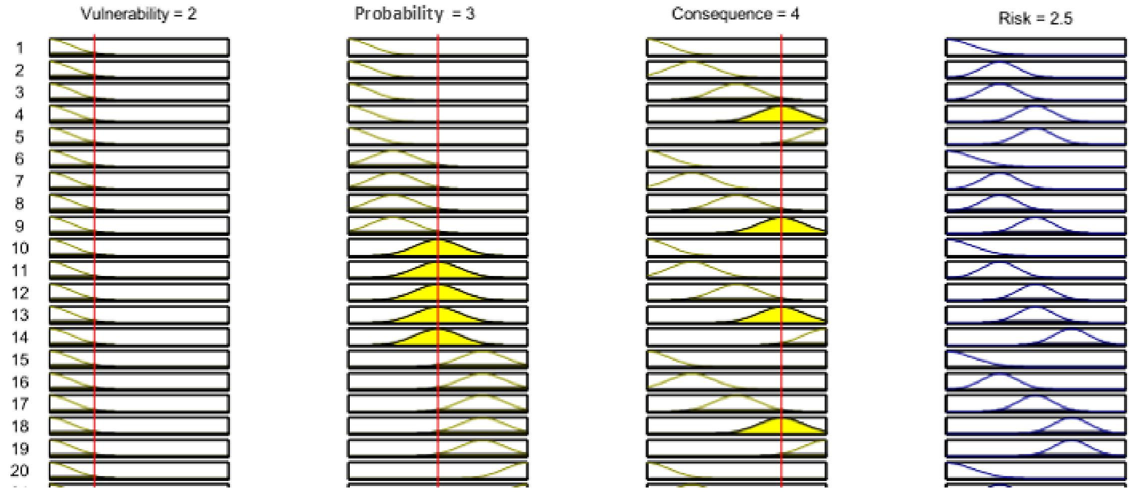

Figure 5: Graphical indication of fuzzy reasoning mechanism

7 Comparison with traditional RSS

In order to compare between the results obtained by the proposed model and traditional RSS, the outputs from two methods are presented in Table 3. The main drawback of the traditional RSS is that different datasets of input variables may generate a same value, and consequently a similar value of risk index. However, the risk implication may not essentially be the same. This problem may impose a waste of time and finance.

Another limitation of the traditional RRS is that it cannot consider the relative importance among input variables. This problem results in the outputs of the traditional RRS be inaccurate in real-life problems. Whereas, the proposed model takes into account the relative importance among the variables. Therefore, the output of the proposed model for risk assessment is more sure, precise, and accurate.

Table 3: Output of the proposed model

ASSETS	INPUT						OUTPUT			
	CRIPS			FUZZY			CRIPS	RANK	FUZZY	RANK
	V	P	S	V	P	S				
A1	5	1	2	4.38	1.06	2.37	10	8	2.12	7
A2	3	2	4	3.02	2.53	3.96	24	3	3.05	4
A3	2	3	4	2.57	3.15	4.05	24	3	3.11	3
A4	4	3	5	3.84	3.22	4.53	60	1	3.78	1
A5	3	2	4	2.65	2.33	3.69	24	3	2.84	5
A6	2	3	2	1.69	3.14	2.21	12	7	1.79	8
A7	2	4	3	1.87	4.00	3.63	24	3	2.75	6
A8	3	3	4	2.95	2.84	4.07	36	2	3.27	2

8 Conclusions

In this paper, an integrated methodology based on fuzzy logic and relative risk score (RRS) for hazards connected with warehouses is proposed. A specific feature of the proposed model is a combination of qualitative (RSS) and quantitative (fuzzy inference system) techniques. The merit of using fuzzy logic is to handle often associated with RSS components. This improves the possibility of a complete risk assessment for warehouses. Therefore, it helps to assign more risky items in order to allocate the limited time and resources. The results demonstrate that the proposed model is capable to remove the main shortcomings of the traditional RRS. The advantages of the proposed model are, but not limited to, as follows:

(1) The output of the proposed model is more accurate, precise, and sure than the traditional RRS.

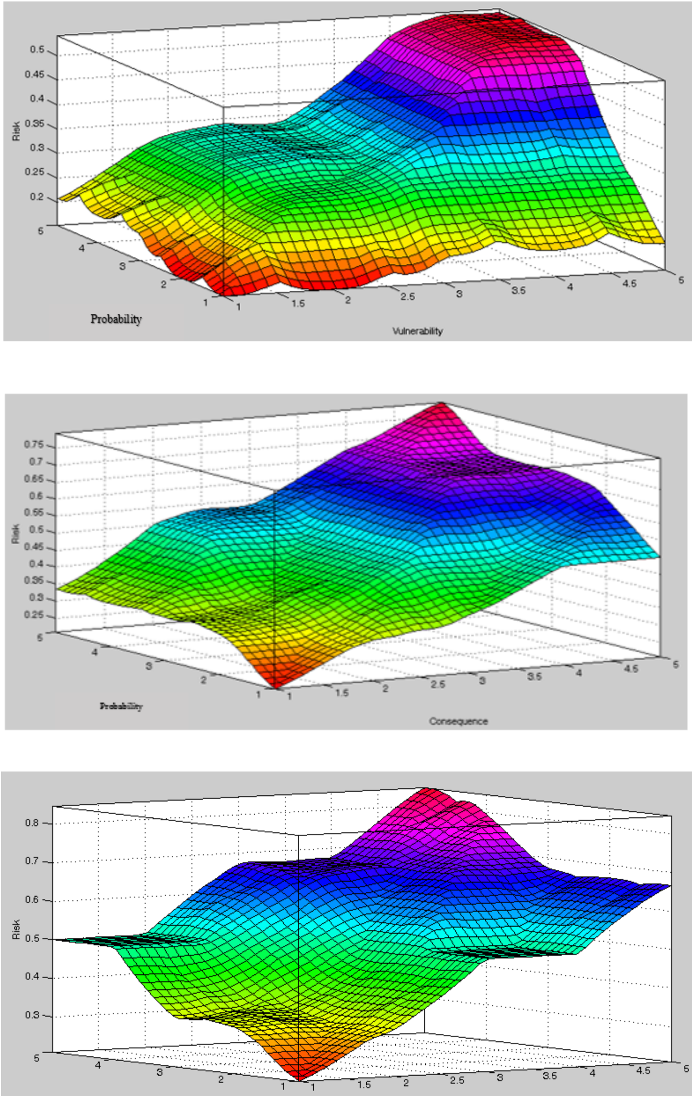

Figure 6: Control surface

(2) The relation between input and output information in the fuzzy proposed system is described as linguistic variables, which are more flexible and realistic in reflecting real situations.

(3) In contrast with the traditional RRS, the proposed model is able to take into account the relative importance among the parameters influenced on risk index.

The risk patterns in this research can be used in warehouse maintenance software and models, in which the application of the obtained results will emerge. Regarding the advantage of fuzzy inference in determining the pattern of conditions compared to determining the pattern based on probabilities, it can be said that both methods receive the same input value of risk parameters, however, despite the similar values, the fuzzy method will provide a more realistic output [24]. The fuzzy method will have more advantages in areas where human error may be involved, such as maintenance. In this research, based on the experiences of people who have experienced various conditions of warehouse maintenance, the conditions model has been defined, the difference of which is in the table 3 is displayed. On the other hand, if an error occurs in determining the pattern, the fuzzy method will show more sensitivity and will lead to a larger error [12]. In general, it can be said that if the field of study is very specific and there are not enough experts, the fuzzy method is more suitable and will provide better results, and on the other hand, if there are enough experts to provide unbiased opinions, a method based on probabilities is suggested [25].

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