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RESEARCH PAPER

Prediction of Accident Occurrence Possibility by Fuzzy Rule-Based and Multi-Variable Regression (Case Study: Lift Trucks)

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Abstract

Uncertain and stochastic conditions of accidents could affect the risk and complexity of decisions for managers. Accident prediction methods could be helpful to confront these challenges. Fuzzy inference systems (FIS) have developed a new attitude in this field in recent years. As lift truck accidents are one of the main challenges that industries face worldwide, this paper focuses on predicting the possibility of these types of accidents. At first, the data collection is done by using interviews, questionnaires, and surveys. An FIS approach is proposed to predict the possibility of lift truck accidents in industrial plants. Furthermore, our approach is validated using data from many real cases. The results are approved by the multivariate logistic regression method. Finally, the output of the fuzzy and logit models is compared with each other. The re-validation of the fuzzy control model and high consistent of the output of these two models is presented.

Keywords:
Accident Prediction;
Fuzzy Inference System (FIS);
Multivariate Logistic Regression;
Lift Truck Accident

Introduction

An accident is an unwanted and unexpected event that may interrupt the production process. It includes irreparable injuries, death, facilities destruction, and the environment [1]. Although many safety procedures have been created for accident prevention in process industries, the domino effect phenomenon might occur. Furthermore, a danger exists that the accident may extend to other units in an industrial plant [2].

Accidents can be occurred by various factors, and these factors should be identified to prevent their occurrence. Attwood et al. have announced that the causes of an accident can be divided into the operator's error and inefficiency of safety procedures. They have introduced insufficient operator training, incorrect and incomplete operating manual and procedures, inefficient organization and lack of previous data, and insufficient control room design as a root cause of operator's error [3]. In another study, a bibliometric analysis of process system failure and reliability engineering was conducted. The results showed that despite the vital role of this subject in the industry, the collaboration between industry and academia is rare [4].

Lift trucks have one of the highest levels of occupational fatalities. It is estimated that 1 in 6 workplace deaths involve a lift truck [5]. Kim et al. analyzed the characteristics of lift truck accidents by employment type and work process, and the experience of the lift truck driver was one of the most critical factors in accident occurrence [6].

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Fuzzy logic is applied in order to realize effective and efficient accident prediction in industrial plants. The fuzzy logic approach is proved to be a convenient model for dealing with uncertainty phenomena. Many dynamic Factors like the weather conditions and the static factors like the geometry of the factory could cause accidents. So we defined a Fuzzy Inference System that is more consistent than human experts. This system can also minimize human expertise needed at several locations simultaneously, especially in industrial plants, that accidents can happen simultaneously in different sections of industrial plants.

So, This paper uses an FIS approach to predict lift truck accidents in industrial plants by considering the most critical variables based on Fuzzy sets. After explaining the research goals, a literature review section has discussed different accident prediction methods. Following that, a fuzzy rule-based approach is introduced in the materials and method section for lift truck accidents. Finally, in the conclusion section, the main results of the study have been described.

Literature review

Gajendran et al. compared three types of accident prediction models. They show that the dynamic system model is used on complex and nonlinear data, and its flexibility is advantageous. The next technique is the Bayesian method, which helps display and convey the problem comprehensively and understandably. Another method is fuzzy logic, which is advantageous compared to the other methods due to its simple reasoning based on mathematics [7]. The principles of fuzzy logic, fuzzy clustering, and fuzzy modeling can analyze the level of complexity of the involved factors and model relations between physical and psychophysical measures [8]. One of the Fuzzy logic's most prominent features is that it uses professional experts' discrimination by linguistic expressions. This process started with transforming the linguistic expressions into Fuzzy numbers and then aggregating them into one Fuzzy number called “Fuzzy Possibility” [9]. Fuzzy logic is a reliable method for unavailability, scarcity, or uncertainty in data [10]. Some researchers have used the logical model and Bow-Tie technique in quantitative evaluation and accident prediction of crane overturning, the collapse of objects and loads, dropping down altitude, and falling from the ladder [11].

Several types of research have been done on real data to perform practical projects using fuzzy logic for accident prediction. Maraj et al. developed a fuzzy logic model to predict road accidents in Albania using four different inputs [12]. Another research developed a fuzzy logic traffic system on two-way intersections by considering Kuwait's delay and traffic situation levels [13]. Xiang et al. created a fuzzy logic prediction model with 41 effective urban traffic accidents in a Chinese city [14]. Driss et al. conducted a study on one of the roads in Alegria to propose a traffic accident prediction system based on fuzzy logic. They focused on the effect of environmental factors rather than on drivers and vehicles [15]. Ghousi et al. used the Fuzzy approach for risk evaluating and lift truck accident prediction in industrial plants. They consider all effective variables in different accident scenarios to reduce the uncertainty [16].

Materials and method

This article studies the possibility of lift truck accidents in a prominent Iranian automotive manufacturing company. First, a Fuzzy logical methodology for predicting the possibility of an accident is developed. In addition, a real accident scenario and a multivariate logistic regression model are used for validation. Finally, all variables are assumed to be triangular and trapezoidal fuzzy numbers. These two types of fuzzy numbers are the most used in the literature [16].

In order to predict a factor, it is necessary to divide and break it down into the main, basic, and constituent variables. Therefore, in this study, the factor of the possibility of lift truck accidents as a research problem is broken down and divided into four basic and main variables at the level of one. In level two, similar to the previous level, the four criteria are broken down into the eleven main and basic criteria. Obviously, using the input variables, the output criteria can be predicted and evaluated.

Recognizing of effective variables

At first, we conducted frequent surveys of lift truck operations to identify effective variables in lift truck accident occurrence. Then we used a hierarchical structure to determine the input and output variables and then divide them into three levels: zero, one, and two.

Eleven input variables have been considered in level two, and then four variables have been determined in level one as the outputs, as is shown in Fig. 1. We implemented these four variables to predict lift truck accident occurrence as an output variable at zero levels in the next stage. Conventional rule-based expert systems use human expert knowledge to solve real-world problems that generally would require human intelligence. Depending upon the problem requirement, these rules and data can be recalled to solve problems. Our study's approach has been using real data to increase the reliability of the results. During six months, experts applied the defined scale of variables to express the level of intellectual items by using questionnaires and surveys. In this way, we have the ability to capture and preserve irreplaceable human experiences. The name of variables and their scales has shown in Fig. 1 and Table 1, respectively.

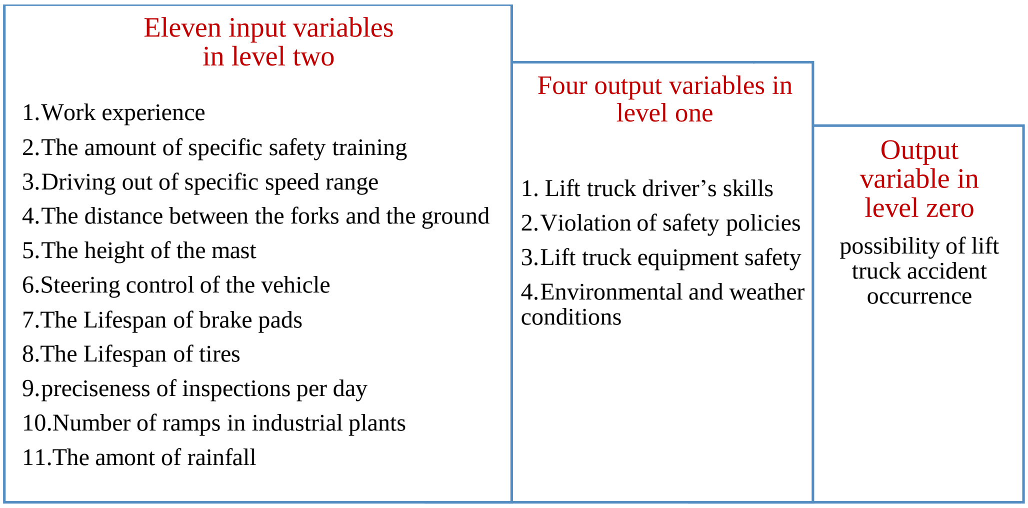

Fig. 1. Variables name in each level

Table 1. Determining the scale of variables [16]

Variable name	scale
Work experience	0 to 10
The amount of specific safety training	0 to 200
Driving out of specific speed range	0 to 1
The distance between the forks and the ground	0 to 4.5
The height of the mast	0 to 4.5
Steering control of the vehicle	0 to 1
The lifespan of brake pads	0 to 200
The lifespan of tires	0 to 300
the preciseness of inspections per day	0 to 10
Number of ramps in industrial plants	0 to 0.15
The amount of rainfall	0 or 1

Categorizing variables through linguistic variables

The main and basic variables in the research problem are defined using linguistic variables. For example, the lift truck driver's skills are categorized into four groups: very low, low, medium, and high. Likewise, the environmental and weather condition is also divided into four groups: very good, good, bad, and very bad.

Describing linguistic variables through fuzzy sets

Linguistic variables are defined by using triangular and trapezoidal fuzzy numbers. As an example, consider the skill variable illustrated in Fig. 2.

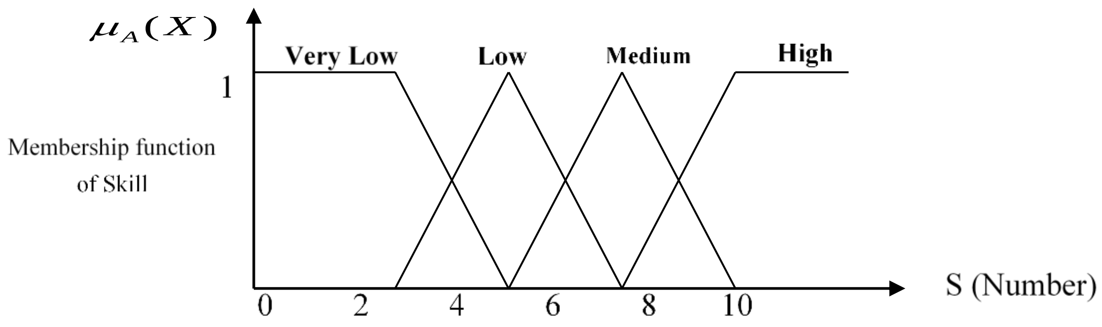

Fig. 2. Skill Membership Function

Using fuzzy rules for achieving the fuzzy inference system

We simulate all possible lift truck accidents using fuzzy if-then rules, and 208 fuzzy rules are created. **Fig. 3** shows one of them. All rules in the fuzzy inference model are defined as conjunction rules [17]. The fuzzy inference model must use the t-norms operator to implement the minimum operator [18].

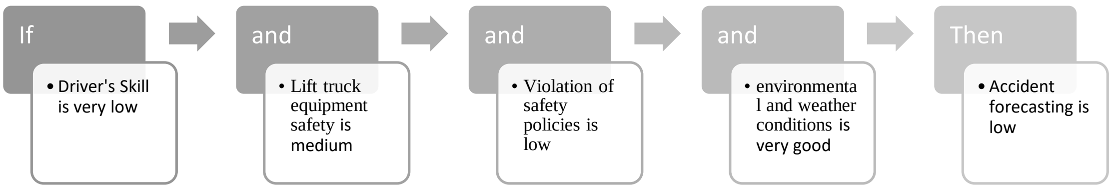

Fig. 3. One rule of the fuzzy control model

Describing crucial rules of the fuzzy inference system

The fuzzy if-then rules by screening or filtering among All possible accident conditions are processed. It should be noted that the preparation of fuzzy if-then rules is based on negotiating and brainstorming and using the opinions of automotive industry experts.

Aggregating of Fuzzy rules as an output of the fuzzy inference system

We considered all objective rules of the fuzzy control model with high likelihood and aggregated their results. The S-norm is necessary as the max operator to use [19].

Results

After defining the principles of our model, the results will be explained. In this section, the results will also validate with a logistic regression model.

Defuzzification and numerical estimation of the output variables

After the defuzzification process, crisp numbers can be obtained and show the possibility of lift truck accident occurrence. The proposed model considers 13 scenarios leading to a real lift truck accident and then simulates five different scenarios to validate the fuzzy inference model. The obtained results and the details of the accident scenarios are presented in Tables 2 and 3. As can be seen, the proposed model can predict that all 13 real situations will lead to accident occurrence.

The accident possibility for the collision between lift trucks and workers' feet is more than others, so it is essential to provide all employees with adequate information about the risks in the industrial plants. The two other causes with the most possibility are falling of the second pallet and collision in the downward-sloping places.

Fitting the results obtained by the fuzzy control model through the sequential regression

In this section, we use a Cumulative Logit model about sequential response variables. This model is obtained based on cumulative probabilities. The cumulative probability is the probability that the Y response is placed in category J or less. The cumulative probability of j^{th} can be determined according to Eq. 1:

$$P(y \leq j) = \pi_1 + \pi_2 + \ldots . + \pi_j j = 1, \ldots \ldots . , J \tag{1}$$

When we fitted a sequential regression, we assumed that the relationship between independent variables and all logits is the same. Then, according to Eqs. 2 and 3, cumulative probability and response probability, respectively, can be measured:

$$P(y \leq j) = \frac{1}{1 + \exp^{(-(\propto_j - \beta X))}}. \tag{2}$$

$$P(y = j) = P(y \leq j) - P(y \leq j - 1) \tag{3}$$

In the Logit model, unlike the fuzzy inference system, the type and order of the numerical amounts of the scenarios should not be the same since it may lead to errors in the multi-variable regression approach. This can cause the exclusion of similar scenarios. In Table 4, the information of twelve scenarios fitted by the sequential regression model is presented. The results of Tables 5 and 6 show that the model is well fitted.

Table 2. Fuzzy inference system validation results with details of accident scenarios (real accidents)

Row	Cause of the accident	Variables' Value				Lift truck accident prediction in high situation
		Lift truck driver's skills	Lift truck equipment safety	Violation of safety policies	Environmental Condition	(Possibility, Membership degree)
1	Driver's imprudence in Shifting the pallets by lift truck	1	6.5	0.5	0.5	(0.6, 0.5)
2	Reverse motion without allowed speed	1.5	6.5	0.85	0.5	(0.7, 1)
3	Overloading with reverse motion	1	6.5	0.5	0.5	(0.6, 0.5)
4	Falling of the second pallet on because of high speed and uneven path	1	3.5	0.5	0.5	(0.8, 0.5)
5	Collision between the lift truck and the pallets	1	6.5	0.85	0.5	(0.7,1)
6	Falling of pallets on others because of insufficient driver's eyesight	1	6.5	0.5	0.5	(0.6,0.5)
7	The collision between the lift truck fork and the other workers	1	6.5	0.8	0.5	(0.7,1)
8	The collision between lift truck and other workers because of carrying two pallets of cars' doors	1	6.5	0.5	0.5	(0.6,0.5)
9	The collision between lift truck and other workers because of brake pads defection	5	0.5	0.8	0.9	(0.9,1)
10	The collision between lift truck and workers' feet because of driver's imprudence in high speed	2.5	6.5	0.8	0.5	(0.7,1)
11	Driver's imprudence in carrying the unstable pallets	4	6.5	0.79	0.5	(0.7,1)
12	Driver's imprudence in delivering to other drivers in a downward-sloping place	1.5	6.5	0.5	3.5	(0.7,1)
13	The collision between lift truck and workers in the downward-sloping places	5	0.5	0.85	3.5	(0.8,0.5)

Table 3. Fuzzy inference system validation results with details of accident scenarios (simulated accidents)

Row	Cause of the accident	Variables' Value				Lift truck accident prediction in a low situation
		Lift truck driver's skills	Lift truck equipment safety	Violation of safety policies	Environmental Condition	(Possibility, Membership degree)
1	Simulated situation without accident	7	8	0.1	1	(0.302, 1)
2	Simulated situation without accident	3	8	0.1	1	(0.4, 0.5)
3	The simulated situation with an accident	3	5	0.1	1	(0.495, 1)
4	Simulated situation with accident	2	5	0.7	1	(0.8, 0.5)
5	Simulated situation with accident	3	5	0.7	7	(0.9, 1)

Table 4. The information of twelve fitted accident scenarios through a sequential regression model (Parameter estimation)

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[y = 1.00]	-15.482	1.806	73.465	1	.000	-19.023	-11.942
	[y = 2.00]	-12.253	1.483	68.269	1	.000	-15.160	-9.346
	[y = 3.00]	-6.458	1.025	39.663	1	.000	-8.468	-4.448
	[y = 4.00]	.108	.758	.020	1	.887	-1.378	1.594
Location	[x1=1.00]	5.379	.769	48.955	1	.000	3.872	6.886
	[x1=2.00]	5.305	.771	47.334	1	.000	3.794	6.816
	[x1=3.00]	2.044	.571	12.825	1	.000	.925	3.163
	[x1=4.00]	0[a]	.	.	0	.	.	.
	[x2=1.00]	8.637	1.066	65.688	1	.000	6.548	10.725
	[x2=2.00]	8.023	1.009	63.266	1	.000	6.046	10.001
	[x2=3.00]	2.656	.603	19.429	1	.000	1.475	3.837
	[x2=4.00]	0[a]	.	.	0	.	.	.
	[x3=1.00]	-10.888	1.280	72.307	1	.000	-13.398	-8.378
	[x3=2.00]	-10.100	1.217	68.823	1	.000	-12.486	-7.714
	[x3=3.00]	-5.648	.905	38.916	1	.000	-7.422	-3.873
	[x3=4.00]	0[a]	.	.	0	.	.	.
	[x4=1.00]	-6.079	.851	50.978	1	.000	-7.748	-4.410
	[x4=2.00]	-5.672	.827	47.055	1	.000	-7.293	-4.051
	[x4=3.00]	-2.660	.681	15.243	1	.000	-3.995	-1.325
	[x4=4.00]	0[a]	.	.	0	.	.	.

Table 5. The goodness of fit test result

	Chi-Square	df	Sig.
Pearson	333.232	816	1.000
Deviance	178.734	816	1.000

Table 6. R-Square test results

Cox and Snell	.817
Nagelkerke	.886
McFadden	.664

As mentioned before, in sequential regression fitness, it is assumed that the relation between the independent variables and logit is the same for all Logits. According to Table 7, this assumption is examined by using the test of parallel lines. As a result, the null hypothesis is strongly accepted.

Table 7. Parallel lines test results

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	178.734			
General	165.487[a]	13.247[b]	36	1.000

prediction of the probability of the response variable and categorical response variable for twelve accident scenarios

An example for one of the observations in Table 4 is calculated to clarify the probability of the categorical response variable. X_1 and X_4 values are in level one in the sample observation, and X_2 and X_3 values are in level three. According to Table 4, the estimated coefficients of the model in this observation are as follows:

$$X_1 = 1, X_2 = 3, X_3 = 3, X_4 = 1 \tag{4}$$
$$\beta_1 = 5.379, \beta_2 = 2.656, \beta_3 = -5.648, \beta_4 = -6.079 \tag{5}$$

Following that, by applying the coefficients in Eq. 6, we obtained the cumulative distribution function for the sample observation.

$$P(y \le j) = \frac{1}{1 + exp(-(\alpha_j - \beta X))} \tag{6}$$
$$P(y \le 1) = \frac{1}{1 + exp^{(15.482+(5.379+2.656-5.648-6.079))}} = 7.579923 \times exp^{-6} = 0.0000075799 \tag{7}$$
$$P(y \le 2) = \frac{1}{1 + \exp^{(12.253+(5.379+2.656\_5.648\_6.079))}} = 0.0001913911 \tag{8}$$
$$P(y \le 3) = \frac{1}{1 + exp^{(6.458+(5.379+2.656\_5.648-6.079))}} = 0.05918937 \tag{9}$$
$$P(y \le 4) = \frac{1}{1 + exp^{(0+(5.379+2.656-5.648-6.079))}} = 0.975683 \tag{10}$$

Now by applying Eq. 11, prediction of the response probability is determined for the sample observation:

$$P(y = j) = p(y \le j) - p(y \le j - 1) \tag{11}$$
$$P(y = 1) = p(y \le 1) - p(y \le 0) = 7.579923\ exp^{-6} = 0.0000075799 \tag{12}$$
$$P(y = 2) = p(y \le 2) - p(y \le 1) = 0.0001913911 - 7.579923\ exp^{-6} = 0.0001838112 \tag{13}$$
$$P(y = 3) = p(y \le 3) - p(y \le 2) = 0.05918937 - 0.0001913911 = 0.05899798 \tag{14}$$
$$P(y = 4) = p(y \le 4) - p(y \le 3) = 0.9756839 - 0.05918937 = 0.9164945 \tag{15}$$
$$P(y = 5) = 1 - p(y = 1) - p(y = 2) - p(y = 3) - p(y = 4) = 0.02431611 \tag{16}$$

Now by comparing the predicted response probabilities, it can be seen that the maximum probability is related to the response variable of level four. Thus, as can be seen, the probability of the sample observation in level 4 equals 0.92. Meanwhile, we can use the same procedure for other accident scenarios.

Comparison of results obtained from the fuzzy control model and sequential logistic regression

The results of the fuzzy control and logistic regression models for categorical response variables of twelve independent accident observations are presented in Table 8.

Table 8. The results of the response variable of fuzzy and logit models for twelve accidents

The Categorical response variable of the Sequential regression model	The Predicted categorical response variable by the Fuzzy model
High	High
Very High	Very High
Very High	Very High
Very High	Very High
Very High	Very High
High	Very High
Very High	Very High
Very Low	Very Low
Medium	Low
Medium	low
High	High
High	Very High

According to Tables 9 and 10 that show the chi-square-Pearson test results, the independence hypothesis between the results of the two proposed models is rejected. It illustrates that the answers for the accident prediction in fuzzy and logistic regression methods are almost identical and show that our results could be reliable.

Table 9. The presented information for Chi-square Tests

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	28.286[a]	9	.001
Likelihood Ratio	21.305	9	.011
Linear-by-Linear Association	9.281	1	.002
N of Valid Cases	12		

a. 16 cells (100.0%) have expected count less than 5. The minimum expected count is .08.

Table 10. The presented information for Symmetric Measures

		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.[c]
Ordinal by Ordinal	Spearman Correlation	.871	.095	5.604	.000[c]
N of Valid Cases		12			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

Discussion

Although most accident prediction studies have focused on car road accidents, there has not been enough research on lift truck accidents. The lift truck is one of the most important and widely used equipments to lift and transport materials for short distances. Lift trucks are often involved in severe accidents and injuries since they are essential equipment in warehouses or construction sites. Rodwics et al. evaluated the effect of using a rear operator guard on the overall safety of a lift truck in working environments [20]. C Ull et al. described injury patterns, treatment, and outcome after lift truck accidents in the context of the employers' liability insurance association [21]. None of the previous studies did work on finding the accident scenarios and predictions simultaneously. Contrary to others, this study focused on using fuzzy inference systems to develop a DSS for predicting lift truck accidents in industrial plants.

Another unique aspect of this study is that all the results have been obtained based on real data. The lack of real datasets in this area was a critical challenge. The data for creating our model have been collected in six months from one of Iran's most significant car factories.

We validated our results with a logistic regression model to increase the validation of our results. The close convergence of the answers in these two methods was one of the significant points for future studies.

Conclusion

Risk and accident concepts are tightly related to uncertainty. Compared with the classical binary situation, Fuzzy logic can better identify various accident scenarios for decision-makers. Fuzzy logic is an effective and computational intelligence technique to handle reasoning under uncertainty, which is a significant concern in accident prediction model design. It also can combine the knowledge of multiple human experts.

In this study, a fuzzy inference system for identifying the possible accident scenarios is developed. At first, a hierarchical structure for identifying the input and output variables and their ranges is prepared. Then using linguistic variables and fuzzy sets system, the variables are described. Following that, using fuzzy rules, 208 possible accident scenarios are defined. At last, the scenarios that can lead to the accident are identified. After the defuzzification step, accident probability is calculated as a number in the range of zero to one. In the next stage, the fuzzy control model is validated by thirteen real accident scenarios. After estimating all variables of levels one and two and the output variable to predict an accident scenario, the model predicts the possibility of an accident in all thirteen real scenarios.

The result of the fuzzy control model is used as inputs for a multivariate logistic regression software, and the response variable's likelihood and the response variable's category are predicted. Finally, the output of the fuzzy and logit models is compared. The re-validation of the fuzzy control model and high consistent of the output of these two models is presented.

Using the fuzzy control model as a decision support system (DSS) to identify possible accident scenarios and urgent decision-making can provide the best guidance for senior manufacturing plant managers. It is necessary to explain that the results of this research were used in one of the Iranian car companies and had a significant impact on reducing lift truck accidents.

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