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An Approach for Accident Forecasting Using Fuzzy Logic Rules: A Case Mining of Lift Truck Accident Forecasting in One of the Iranian Car Manufacturers

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Risk assessment,
Safety analysis

ABSTRACT

Fuzzy Logic is one of the concepts that has created different scientific attitudes by entering into various professional fields nowadays and in some cases has made remarkable effects on the results of the practical researches. However, the existence of stochastic and uncertain situations in risk and accident field, affects the possibility of the forecasting and preventing the occurrence of the accident and the undesired results of it.

In this paper, fuzzy approach is used for risk evaluating and forecasting, in accidents caused by working with vehicles such as lift truck. Basically, by using fuzzy rules in forecasting various accident scenarios, considering all input variables of research problem, the uncertainty space in the research subject is reduced to the possible minimum state and a better capability of accident forecasting is created in comparison to the classic two-valued situations. This new approach helps the senior managers make decisions in risk and accident management with stronger scientific support and more reliably.

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1. Introduction

According to the nature of industrial processes in car manufacturing plants and also high frequency of utilizing transport facilities, especially various kinds of lift trucks, a considerable part of working accidents is caused by these vehicles. So, after necessary checks, frequent visits of production departments, extracting the opinion of experts, analyzing historical data and related accident statistics, the topic has been defined as an industrial project and this paper is that result of the project.

Using new technologies has improved production process while various industries such as air traffic control, telecommunications, nuclear plants, oil process industries and chemicals are strongly turning towards complexity and consequently we are faced the potentially dangerous and catastrophic defects [1].

On the other hand, there are so many raw materials at industrial plants that during their production or storage process, while keeping potential accidents inside the system, different types of pseudo-accidents in the form of chain reactions and causes Domino model [2]. Accident can be defined as an undesired and unintended event that may interrupt industrial operation, including various unfavorable results such as injuries, death and destruction of property, machines and environment.

Famous accidents and well known disasters like Bhopal toxic gas tragedy (India, 1984), the Chernobyl disaster (Ukraine, 1986), the Hindustan petroleum refinery fire (India, 1997), the Queen of the sea rail disaster (Sri Lanka, 2004), the Electrical Transformer explosion (Dhaka- Bangladesh, 2010) and the British petroleum deepwater horizon explosion (Gulf of Mexico, 2010) are clear examples caused by systematic

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defects in complicated systems resulting heavy costs and life loss [1, 3].

2. Literature Review

The two terms “risk” and “safety” are related fields between which the conceptual relation has been established practically based on accident.

In a scientific point of view, risk is probability of occurrence of an event, while the safety field can be meaningful in case of absence of risk [4].

Using various quantitative and qualitative methods of risk assessment such as safety audit, fault tree analysis, HAZOP, what-if analysis and the risk matrix, aware experts of safety situation in manufacturing and industrial environments and in some cases notify them before occurrence of accident. In fact, accident forecasting can assist experts in making decisions and necessary plans before occurrence of unpleasant outcomes [3, 5].

On the other hand, as a trustworthy approach, designing probable scenarios of accident can also help safety professionals to assess properly industrial environments and production departments regarding identification and classification danger focuses.

The object of the research in ARAMIS project was establishing an integrated methodology of risk assessment of industrial accidents. To forecast accidents, Bow-Tie technique has been utilized in this methodology. Actually, the relation between accident and its possible causes is studied by fault tree. The relation between accident and outcomes of event or probable results of critical event is checked by event tree. Identification of important accidents, identification of safety protective barriers and their function assessment, safety management function assessment of reliability of barriers, identification of scenarios of reference accidents, assessment and mapping of risk intensity of reference scenarios and vulnerability of factory environment, have been studied in this research [6, 8].

A logical model has been studied in another research, defined by Ministry of Social Affairs and Employment in Netherlands, to estimate job risks quantitatively in chemical and nuclear plants. Probable internal and logical relations between various events involved in occurrence of industrial accidents and also their outcomes have been simulated in this model Bow-Tie technique has been used in preparation of these models to estimate job accidents quantitatively [9].

Logical models have been used in another part of the above mentioned study in quantitative estimation of job risks according to forecasting of accidents caused by crane reversal, collapse of objects and loads, dropping down of altitude and falling from ladder.

Inspired by this technique and the mentioned model and using top-down approach, which leads to divide events to simpler components, duty block diagram has been considered as a completely compatible model with probability theory [10-12].

Scenario analysis can also be mentioned as other way of accident forecasting. This method can predict different scenarios of accident and assign each of them the probability of occurrence and identify factors causing accident as well [13].

Regression method is one of accident forecasting models. Dependant variable is modeled using independent variable function, corresponding parameters and fault factor. In time series analysis, future outcomes can be estimated and forecasted using previous time series data as historical data. Various approaches have recently been developed to forecast events using time series during past decades. The ARMA modeling approach has been more considered among them. This model has two parts -autoregressive and moving average- in majority of cases. Another model that is utilized in this field is called ARIMA.The ARIMA stands for Autoregressive Integrated Moving Average. Some researchers have used ARIMA to correct fault cases in accident forecasting field whereas other researchers have suggested the combination of regression models and ARIMA in this field [13].

For instance, in a part of a suggested methodology of a huge project in coal mines of Turkey, time series has been used to forecast accidents and job risks. Markov chain model is one of the other ways of accident and risk forecasting. Markov chain is, in fact, stochastic processes which can estimate quantitatively by using practical estimation of probability between discrete states of observed systems. The main feature of Markov chain is that, regarding current state, it illustrates future states which are independent of previous state [13]. Neural network is another forecasting method which can identify complicated nonlinear relations between input and output variables unlike previously mentioned models that define and predict relations and interactions between dependant and independent variables in advance, neural network is used for complicated accidents and may cause wrong estimation of probability of occurrence of accident.

This method is a very powerful tool for accident forecasting. The two forms of application of artificial neural network in accident forecasting are procedure forecasting and causality forecasting. Bayesian network is another method of accident forecasting as well. It is a probability graphical model designed on the basis of Bayesian inference.

In this method by planning probability relation network, Bayesian network can analyze and quantitatively determine complicated cause and effect relations and interactions between various factors [13].

Regarding uncertainty situations in accident domain, many researchers have worked in the field of quantitative estimation of risk and accident forecasting, and have tried to compensate this deficiency as possible, and predict probable scenarios in accident domain more than ever and prevent their occurrence by providing appropriate corrective actions.

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Applying quantitative estimation of risk in domain of different industrial activities, they have considered various effective factors in happening of an accident and then considering all possible events regarding to classical binary conditions, have evaluated degree of accident occurrence according to different situations.

In some other researches performed in this field, probability of occurrence of critical event has been determined by means of estimation of conditional probability of all existent events provided that the desired industrial activity has been accomplished.

For instance, Bow-Tie quantitative model uses relation 1 to estimate probability of critical event occurrence of falling from ladder.

$$Pr(CE)=Pr(l).Pr\ (p\ /l) \tag{1}$$

Where "I" is the event of working with ladder- and "p" is the event of preventing from occurrence of falling. By the way, according to relation 2, preventive event can be categorized to primary approaches (measures) and supportive approaches.

Preventive event can be decomposed to different sub-factors such as ability of consumer (A), put and protect (PP), type of ladder (TL), and strength of ladder (SL), ladder stability (LS), user stability (US).

$$Pr\ (CE)\ =Pr\ (l)\ Pr\ \{A.PP.TL.SR.LS.US\ /l\} \tag{2}$$

Where Pr (l) is the probability of working with ladder and Pr {A.PP.TL.SR.LS.US /l} is the probability of total estimation and compound result of all considered sub-factors provided that the industrial operation is performed [11]. High frequency of mortality and injuries in job accidents, especially through transportation of equipment in the world, such as lift truck, large number of trips performed by these equipments (due to nature of production process in industrial factories especially car manufacturers) and case mining of study, show the necessity of research in this paper [9, 15, 16].

In this research, there have been attempts to study and analyze possibility of occurrence of lift truck accident as a case mining in a car manufacturing industry. The aim of the proposed approach is to predict this significant event by using fuzzy logic and its related rules. However, once instead of studying problems in binary states, fuzzy logic and if-then rules are utilized, more effective variables can be considered and all probable scenarios are studied in occurrence of event and finally, accident is forecasted with more precision. Considering a set of variables in classic concepts, they can be studied by means of a membership function accepting two values zero and one. But the fact is that variables getting value 1 in this function may differ from each other.

Therefore, it seems necessary to consider partial or fuzzy membership and to keep on researching from this perspective. Some researchers have used control rules (if-then) of fuzzy sets in changing and correcting risk chart method [17]. Whereas some others have introduced a new model for risk estimation by using fuzzy control rules. They have introduced new factors in this model so that researchers and experts of this field can estimate effects of human behavior and environment on risk level [18].

Some other researchers have provided a new method of risk estimation for workers of construction projects by means of application of fuzzy control rules according to existence of uncertain situations in risk domain and insufficient historical statistics of accidents [16].

Since it is necessary to use fuzzy concepts and linguistic variables to describe all variables of research problem, triangular and trapezoidal fuzzy numbers are introduced in this section before describing stages of research.

2.1 Triangular and Trapezoidal Fuzzy Numbers

The main reason of using triangular and trapezoidal fuzzy numbers in this paper is their frequent application in published research papers.

In classic logic a member can belongs to a set of data or not. This can be considered in binary states, zero and one. In contrast, when fuzzy logic is used, degree of belonging of a member may be selected from a set of fuzzy numbers defined as fuzzy membership function [19- 21]. Triangular fuzzy number x with membership function in real numbers set is studied according to relation 3 and fig 1 [21].

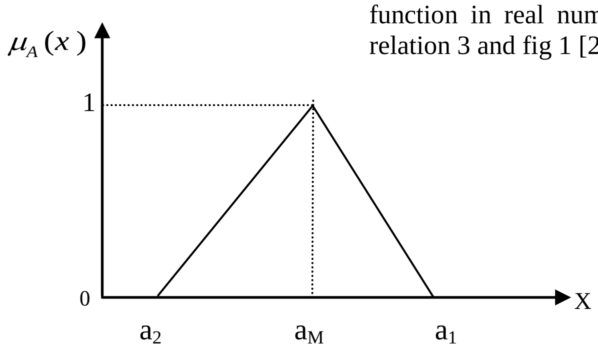

Fig.1. Triangular fuzzy number [21]

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$$A\Delta\mu_A(x)=\begin{cases}\dfrac{x-a_1}{a_M-a_1} & a_1\le x\le a_M\\ \dfrac{x-a_2}{a_M-a_2} & a_M\le x\le a_2\\ \mathbf{0} & Other\ points\end{cases} \quad (3)$$

Fuzzy numbers have supporting interval [a_1,a_2] and point is the peak (a_M, 1). In some states and applications of triangular fuzzy numbers, a_M point is located in the middle of fulcrum which is measured by relation $a_M=\dfrac{a_1+a_2}{\mathbf{2}}$.

In case of occurrence of such these states, in order to estimate triangular fuzzy numbers, relation 4 can be used:

$$A\Delta\mu_A(x)=\begin{cases}\mathbf{2}\dfrac{x-a_1}{a_2-a_1} & a_1\le x\le\dfrac{a_1+a_2}{\mathbf{2}}\\ \mathbf{2}\dfrac{x-a_2}{a_1-a_2} & \dfrac{a_1+a_2}{\mathbf{2}}\le x\le a_2\\ \mathbf{0} & \end{cases} \quad (4)$$

Unlike triangular fuzzy numbers which have one point in the peak, trapezoidal fuzzy numbers have supporting interval [a_1, a_2] and a same level part of flat segment which have b_1 and b_2 on X axis.

By the way, this level has membership degree of 1, the same as point is the peak of triangular fuzzy numbers. Trapezoidal fuzzy number x is studied with membership function $\mu_A(x)$ in real numbers set according to equation 5 and fig 2.

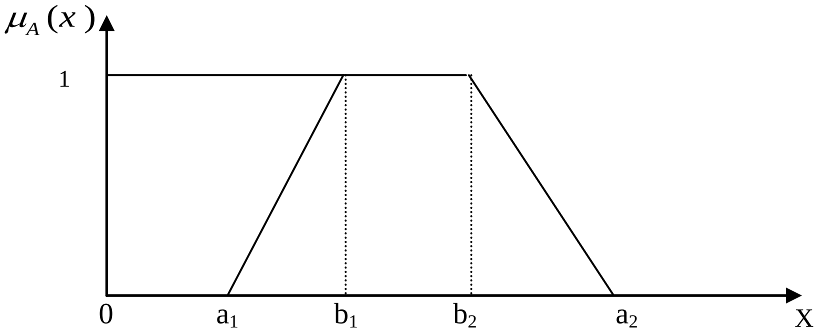

Fig. 2. Trapezoidal fuzzy number [21]

$$A\Delta\mu_A(x)=\begin{cases}\dfrac{x-a_1}{b_1-a_1} & a_1\le x\le b_1\\ x=\mathbf{1} & b_1\le x\le b_2\\ \dfrac{x-a_2}{b_2-a_2} & b_2\le x\le a_2\\ \mathbf{0} & \text{Other point}\end{cases} \quad (5)$$

3. Research Methodology

In this paper, we try to forecast probability of occurrence of lift truck accidents in different scenarios regarding to variables of research problem by using fuzzy logic approaches and utilizing a rule based methodology.

3.1. Identification of Effective Variables in Occurrence of Lift Truck Accidents

First it is necessary to elaborately identify all effective variables in occurrence of accident of working with lift truck. Due to lack of accessibility to precise information, especially in accident statistics and historical data in the research domain and absence of clear and exact information in the accident record sheets, about 20 hours negotiations with industry experts such as production managers and engineers, production planning and safety management units are held finally, according to fig 3, input and output variables of problem have been taken into consideration in three levels zero, one and two.

According to fig 3, in level two of input variables, eleven input variables have been considered. By which four output variables of level one can be estimated and evaluated. In the next stage by means of four input variables of level one, output variable of level zero is estimated, by which the rate of lift truck accident can be forecasted. To forecast a factor, it is necessary to divide the desired parameter to its major variables. Therefore, in this research, at first, lift truck accident has been divided to its four basic variables i.e. skill of lift truck operator, break of safety procedure for lift truck, lift truck equipment safety and environmental and weather condition. According to fig 3, these are considered as variables of level one of input variables.

In level two, eleven input variables including work experience, rate of hours of specialized training of safety, unauthorized speed, distance between fork and the ground, height of mast rate of control and steering, useful life of brake hoof, useful life of tires, rate of precision of daily inspections, percentage of slope of existent ramps in factory workplace and rate of rainfall by means of which output variables of level one can also be determined.

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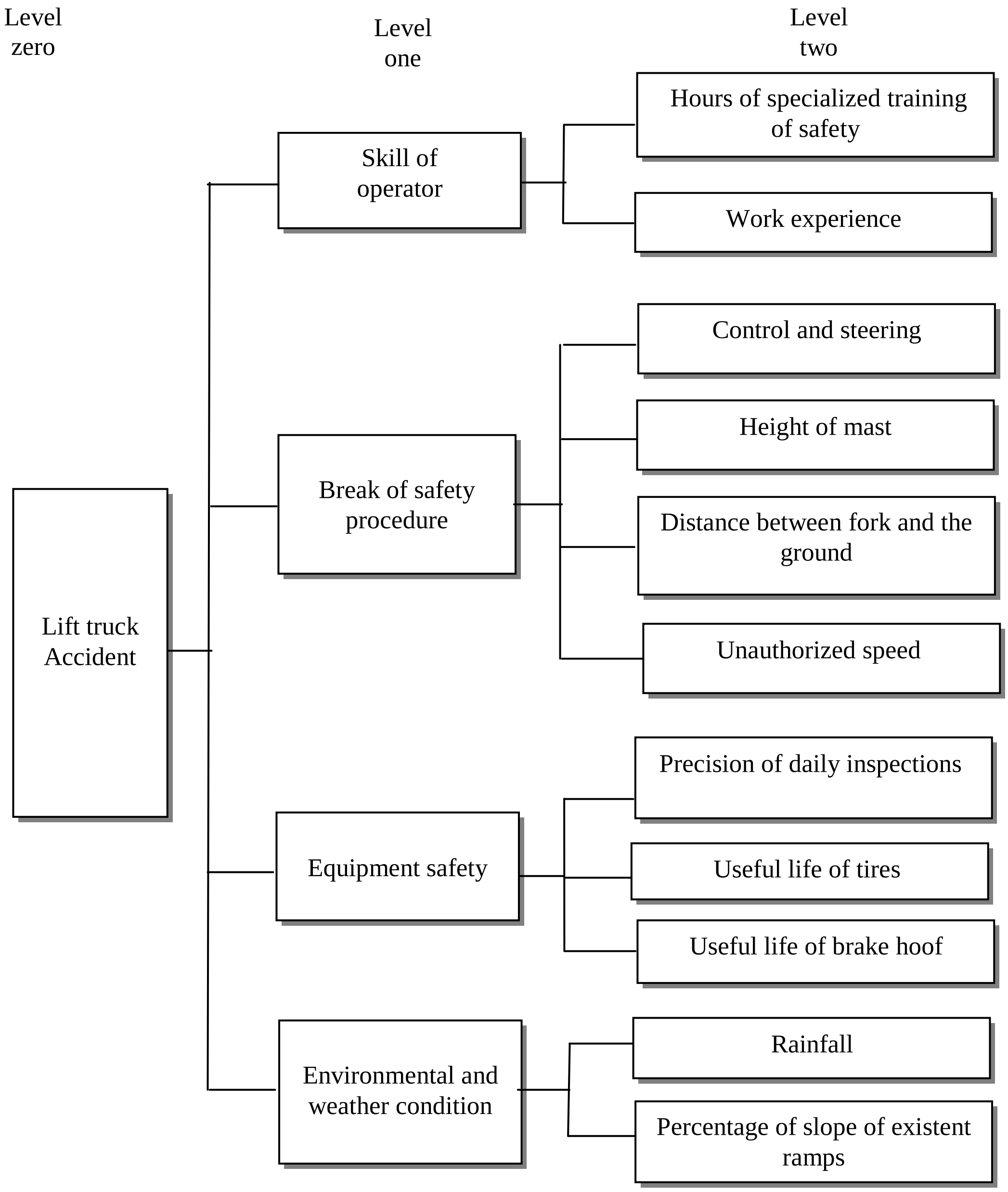

Fig 3. Input Variables of research problem

3.2. Determining the Scale of Input Variables

In this section, measurement range of all effective variables are determined within this order: skill of operator of lift truck(0 to 10), break of safety procedure(0 to 1), lift truck equipment safety(0 to 10), environmental condition(0 to 10), work experience(0 to 10), rate of hours of specialized training for lift truck safety(0 to 200), unauthorized speed (0 to 10), distance between fork and the ground(0 to 4.5), height of mast (0 to 4.5), rate of control and steering (0 to 1), useful life of brake hoof (0 to 200), useful life of tire (0 to 300), rate of precision of daily inspections (0 to 10), percentage of slope of existent ramps in factory workplace(0 to 0.15) and rate of rainfall(0 or 1).

3.3. Categorizing Input Variables by Means of Linguistic Variables

In this stage, for instance, input variables, skill of operator and environmental condition, are categorized into four groups: very low, low, medium and high, also very good, good, bad and very bad. Likewise, all input variables are categorized by means of linguistic variables.

3.4. Describing Linguistic Variables by Means of Fuzzy Sets

We describe linguistic variables, which are mainly in qualitative form, by using triangular and trapezoidal fuzzy number sets.

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As instances of linguistic variables related to input variables, skill variable from variables of level 1 and work experience and rate of hours of specialized training of safety from level 2 have been described by means of fuzzy sets, which are illustrated in figs 4 to 6.

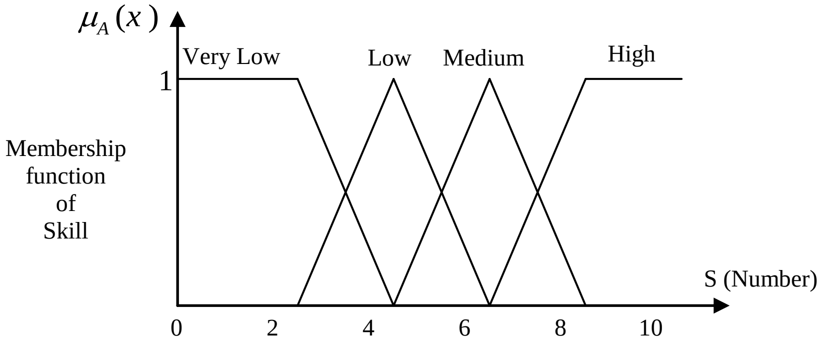

Fig. 4. Describing basic variable, skill of lift truck operator

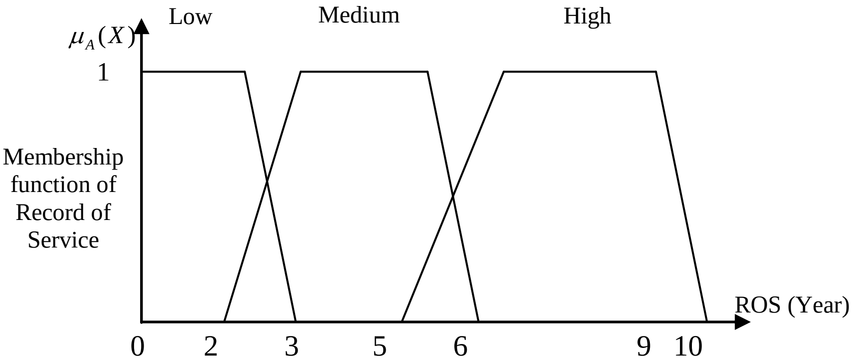

Fig. 5. Describing work experience variable

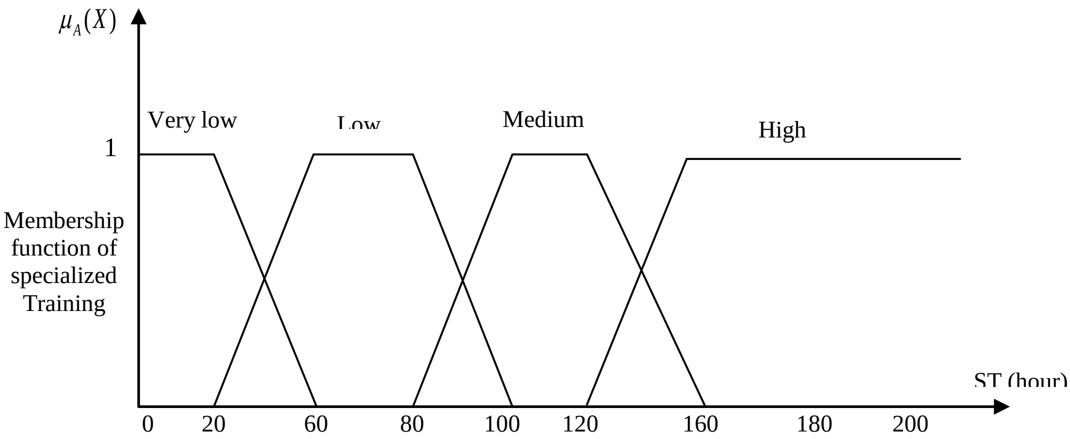

Fig. 6. Describing specialized safety training

3.5. Using Fuzzy Rules in Preparation of Fuzzy Control model

Using fuzzy logic rules enables us to simulate various scenarios of accident by considering input variables and then identify critical situations which may lead to certain accidents.

In this section of paper, by using of input variables, 208 fuzzy rules are made, and for instance 4 of them are presented.

Rule1: If (Skill is very low) and (Lift truck equipment safety is medium) and (Break of safety procedure is very low) and (Environmental condition is very good) Then (Accident forecasting is low).

Rule 2: If (Skill is very medium) and (Lift truck equipment safety is low) and (Break of safety procedure is very low) and (Environmental condition is good) Then (Accident forecasting is medium)

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Rule3: If (Skill is very low) and (Lift truck equipment safety is low) and (Break of safety procedure is medium) and (Environmental condition is good) Then (Accident forecasting is high)
Rule4: If (Skill is very low) and (Lift truck equipment safety is low) and (Break of safety procedure is high) and (Environmental condition is good) Then (Accident forecasting is very high)
As can be seen above, in the research problem, each of input variables of the problem is described by means of linguistic variables and is defined in form of fuzzy numbers by using triangular and trapezoidal fuzzy numbers. Consequently, in simulation of accident scenarios, all existent states and conditions of reality are considered and practically, each of 208 regarded rules in this case mining can simulate a real state of possibility of accident occurrence. By this way, non-deterministic states in space of accident occurrence can be reduced to the possible minimum rate.
According to relation 6, the mentioned if-then fuzzy rule in it is a conditional sentence which shows truth of P_i and q_j as pre-condition or introduction.
Since Mamdani approach has been selected for this research, deduction rules which are used for the research have been defined as conjunction rules and are illustrated as minimum and r_k is considered as the result.

$$\text{if } P_i \text{ and } q_j \text{ then } r_k \text{، } r_k = r_{ij} \tag{6}$$

It is necessary to mention that according to relations 7 and 8 , the above conjunction provides the truth of the rule which is the result of minimum operation on membership functions of A,B, and C fuzzy sets in U1,U2 and U3 universal sets[21, 23].

$$p_i \wedge q_j \wedge r_k = \min\left(\mu_{Ai}(x)\right),\left(\mu_{Bj}(x)\right),\left(\mu_{Cij}(x)\right), r_k = r_{ij} \tag{7}$$

$$i = 1,\dots,n;\ j = 1,\dots m;\ k = 1,\dots,l;\ and\ (x,y,z) \in A \times B \times C \subseteq U_1 \times U_2 \times U_3 \tag{8}$$

3.6. Evaluating Fuzzy Rules in Accessing Major Rules of Fuzzy Control Model

In this section, all recognized created fuzzy rules are processed. So certain cases of accident are gained by Screening among all possible states of accident and then objective rules of fuzzy control model are practically determined.
It seems that if managers of organizations want to make decisions in the field of risk evaluation and industrial accidents, the processed fuzzy rules, as certain rules of fuzzy control model of accident, can assist them to make better decisions.

According to figure 7, certain value of an input variable in comparison with different terms, may have correspondent numbers regarding to fuzzy membership function which can be called fuzzy readable inputs. If the estimated numerical value of “skill of lift truck operator” input variable equals to 6.5, this number will be considered as an input variable, which has membership degree 0.25, in comparison with High state and has membership degree 0.75, in comparison with Medium state.

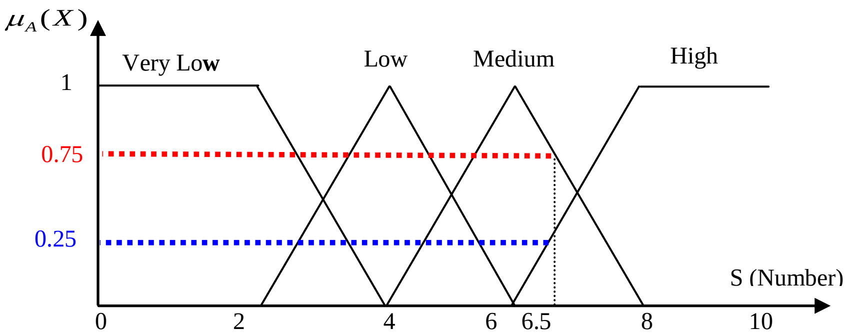

Fig. 7. Describing “skill of lift truck operator” input variable, by fuzzy sets

3.7. Defuzzification and Numerical Estimation of Output Variable

Defuzzification stage is the process by which outcomes of control models in the form of fuzzy numbers can be converted to precise output numbers.
Therefore, in this stage, fuzzy outcomes of fuzzy control model, including effects of all input variables of problem, and considering integrated effects of them by accessing various scenarios of accident by fuzzy rules, are undergone fuzzy removing process and rate of occurrence is determined as an exact number in the interval of zero to one.
To forecast lift truck accident, it is necessary to estimate four output variables of level one.
So we can estimate the only output variable of level zero quantitatively as the main output of the model in

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the next stage. According to figure 8, the value of the main variable “skill” has been estimated 5 (in the scale of 0 to 10), variable “lift truck safety equipment” has been estimated 0.5 (in the scale of 0 to 1), variable “break of safety procedure” has been estimated 5(in the scale of 0 to 10) and finally, variable “environmental condition” has been estimated 5(in the scale of 0 to 10). After considering effects of input variables and integration of all values and existent conditions, at the end of the process of defuzzification forecasting of possibility of lift truck accident occurrence is obtained in the format of a precise number as the outcome of the model.

In fact, according to fig 8, the number 0.7 as the estimation of the output variable of the model, forecasts possibility of accident occurrence.

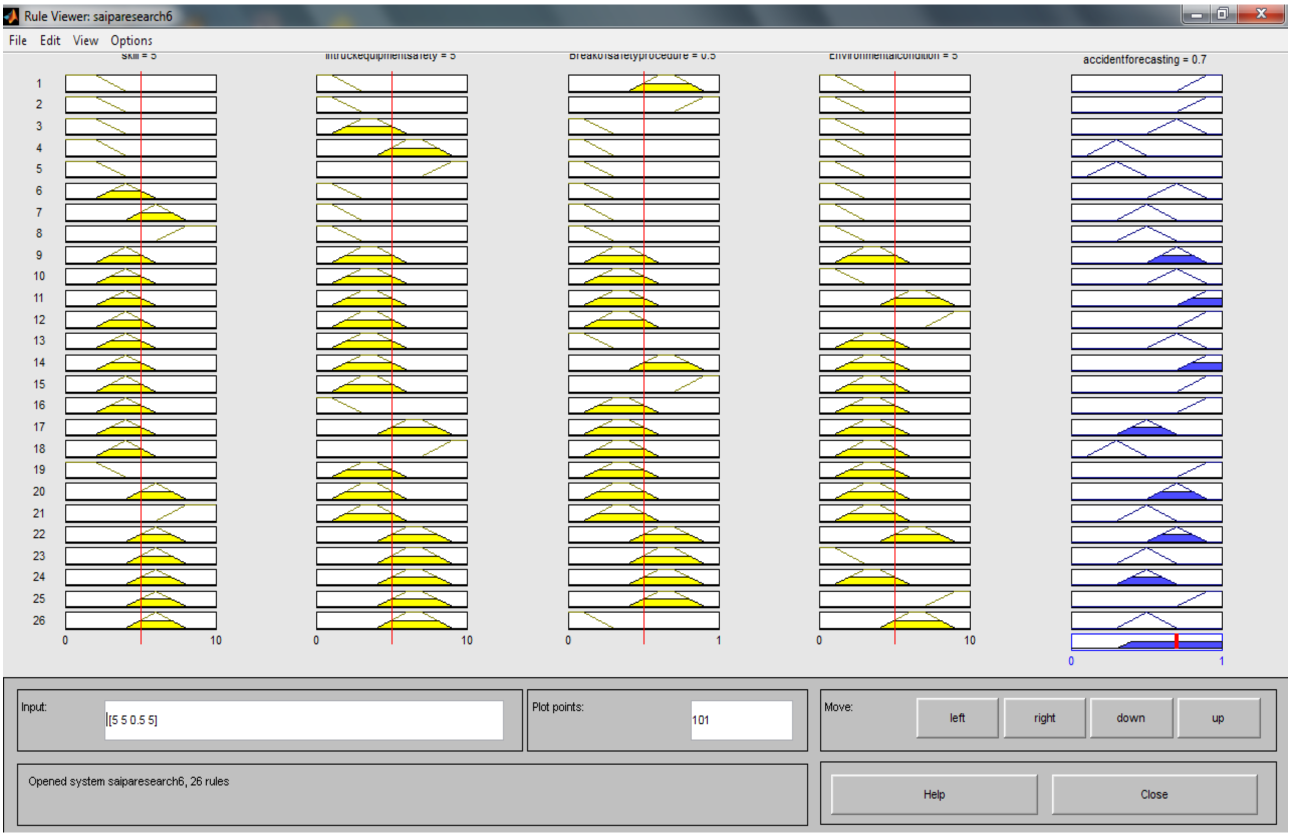

Fig. 8. The process of defuzzification to estimate the output variable

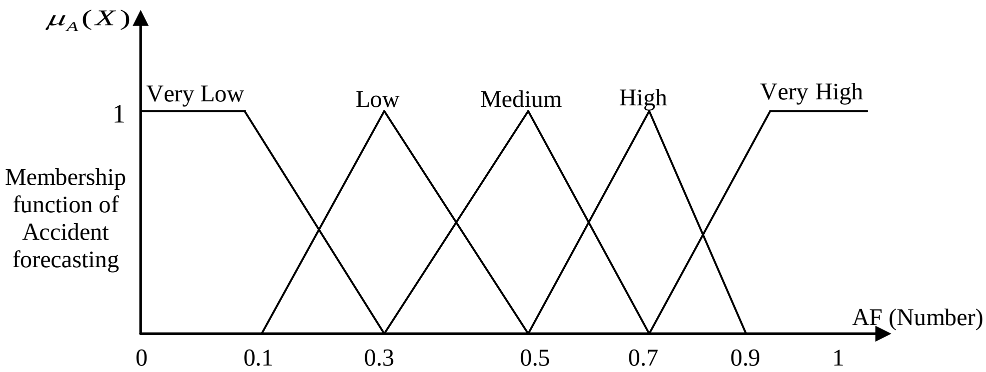

Fig. 9. Describing output variable by forecasting lift truck accident

Using fig 9 to describe the output variable and forecasting lift truck accident, it can be observed that the number 0.7 as the output of the defuzzification chart mentioned in figure 8, is located in High state with the membership degree 1 that shows high possibility of accident occurrence regarding all current variables and conditions.

3-8. Fuzzy Deduction Model

According to fig 10, the fuzzy deduction model of the research problem is briefly provided:

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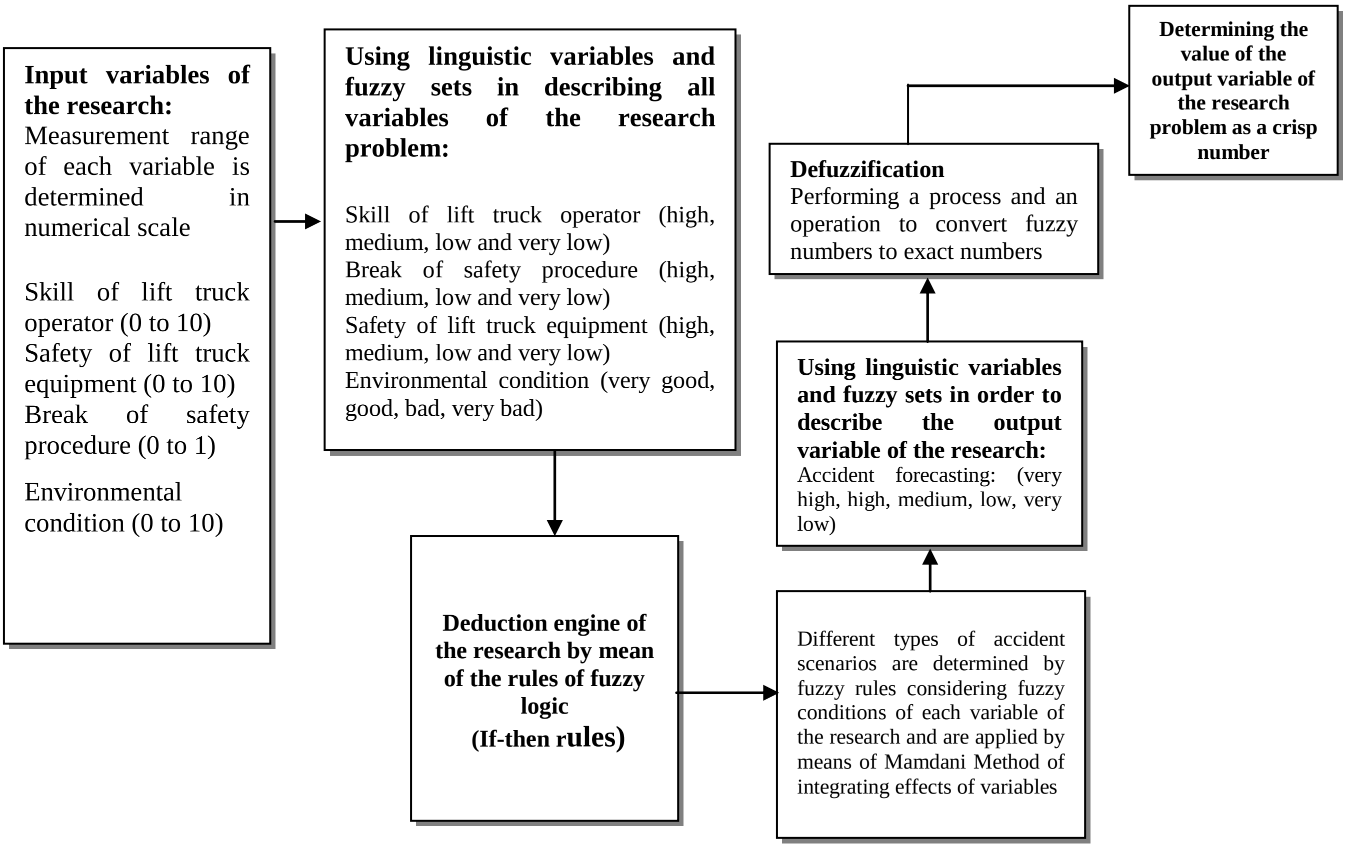

Fig. 10. The fuzzy deduction model

As can be seen in figure 10, the fuzzy deduction model of the research problem has been initiated from identifying the input variables of the problem and determining measurement range of them and then has been described by means of linguistic variables and has been defined by means of triangular and trapezoidal fuzzy numbers. Next, by using fuzzy rules, all scenarios of the research problem have been simulated and after processing all rules, the most important scenario among them is determined as the main rules or objective of fuzzy control model and at last, after defuuzification, output of model is determined in the form of a crisp number as lift truck accident forecasting.

4. Model Validation

In this section of the paper, 14 scenarios which had leaded to real lift truck accident in the industrial unit of the research, 3 simulated scenarios without any accident and 2 simulated scenarios leading to accident by fuzzy model have been studied.

Tab. 1. Model Validation's Tabel

Row	Cause of accident	Value of variable Skill	Value of Safety of Lift Truck Equipment	Value of variable Break of safety procedure	Value of variable Environmental Condition	Lift truck accident forecasting
1	Indiscretion of operator in relocating pallet by lift truck	1	6.5	0.5	0.5	0.6 In high situation and membership degree equal 0.5
2	Reverse movement of lift truck with unauthorized speed	1.5	6.5	0.85	0.5	0.7 In high situation and membership degree equal 1
3	Reverse movement of lift truck with overloading	1	6.5	0.5	0.5	0.6 In high situation and membership degree equal 0.5
4	Downfall of the second pallet on worker because of unauthorized speed and inequality of path of lift truck	1	3.5	0.5	0.5	0.8 In very high situation and membership degree equal 0.5

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Row	Cause of accident	Value of variable Skill	Value of Safety of Lift Truck Equipment	Value of variable Break of safety procedure	Value of variable Environmental Condition	Lift truck accident forecasting
5	Crash of lift truck with pallet box and crash of pallet with injured worker	١	6.5	0.85	0.5	0.7 In high situation and membership degree equal 1
6	Crash of lift truck along with its carried pallet with injured worker because of sufficient vision of operator	1	6.5	0.5	0.5	0.6 In high situation and membership degree equal 0.5
7	Sliding of lift truck carrying shield pallet with injured worker	1	6.5	0.8	0.5	0.7 In high situation and membership degree equal 1
8	Carrying two pallet of car doors and lack of front vision and crash with injured worker	1	6.5	0.5	0.5	0.6 In high situation and membership degree equal 0.5
9	Defect of brakes of lift truck and crash with injured worker	5	0.5	0.8	0.9	0.9 In very high situation and membership degree equal 1
10	Crash of tire of lift truck with injured worker's foot because of unauthorized speed and indiscretion of operator	2.5	6.5	0.8	0.5	0.7 In high situation and membership degree equal 1
11	Indiscretion of operator and unbalanced carriage of pallet and crash with injured worker	4.0	6.5	0.79	0.5	0.7 In high situation and membership degree equal 1
12	Indiscretion of operator in delivering lift truck to his colleague in downhill of new assemblage hall and crash with injured worker	1.5	6.5	0.5	3.5	0.695 In high situation and membership degree equal 1
13	Crash of lift truck with injured worker in downhill of factory workplace	5	0.5	0.85	3.5	0.8 In very high situation and membership degree equal 0.5
14	Reverse movement of lift truck and overloading	1	6.5	0.5	0.5	0.6 In high situation and membership degree equal 0.5
15	Situations without accident	7	8	0.1	1	0.302 In low situation and membership degree equal 1
16	Situations without accident	3	8	0.1	1	0.4 In low situation and membership degree equal 0.5
17	Situations without accident	3	5	0.1	1	0.495 In medium situation and membership degree equal 1
18	Situations without accident	2	5	0.7	1	0.8 In very high situation and membership degree equal 0.5
19	Situations without accident	3	5	0.7	7	0.9 In very high situation and membership degree equal 1

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As it can be seen, in each of 14 states of real accident scenarios, the research model also forecasted the accident situation by considering all conditions of variables. By the way, forecasted the results with minimum error. Regarding to 3 simulated scenarios without accident and 2 simulated scenarios with accident, the model has studied different states and after integrating values of all variables of level 1 and 2, according to the mentioned table, has declared its estimation of probability of accident forecasting as the only output variable of the model, the same as forecasting in 14 real accident scenarios along with inserting related category and its membership degree.

5. Conclusion

Uncertainty is a very significant topic in the field of risk and accident management and is always considered along with them.

Using fuzzy logic and its related sets can dramatically reduce uncertainty in comparison with the classic binary state so that determiner managers can reduce uncertainty of the domain by identifying different accident scenarios more effectively and can more successfully reduce accidents and prevent their future outcomes by means of output values of the model as fuzzy model forecasting.

The application of fuzzy logic rules for better identifying possible scenarios of accident have been considered in this research.

By the same token, after introducing input and output variables of the research problem by means of the hierarchy approach, measurement ranges of input variables were determined and then all variables of the problem were described by means of linguistic variables and fuzzy sets and all possible scenarios of accident were determined and processed by fuzzy rules.

Finally, the scenarios leading to accident were identified and after defuzzification process, the value of output variable of the research model was declared in the form of a precise number in the interval of zero to one. In fact, the output of this model can apprise senior managers of industrial and manufacturing systems of these items so that they can prevent early occurrence of accidents by applying corrective approaches. It seemed necessary to validate the fuzzy model.

Therefore, 14 real accident scenarios were studied by using statistics and historical reports of case mining and after estimation all variables of the level one and zero, and accessing the estimation of the output variable of the accident forecasting model, like all real states of accident, the model itself forecasted 14 real scenarios of the problem as well. The related category of each accident has been declared along with its membership degree in the mentioned charts.

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