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METHODOLOGIES AND APPLICATION

Interval type-2 fuzzy logic and its application to occupational safety risk performance in industries

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Abstract In this paper, we have developed an interval type-2 fuzzy logic controller (T2FLC) approach for assessment of the risks that workers expose to at construction sites. Using this novel approach, past accident data, subjective judgments of experts, and the current safety level of a construction site are to be combined. The method is then implemented on a tunneling construction site and risk level for all type of accidents is formulated. In T2FLC assists to trace inputs and outputs in a well-organized manner for building the inferences train so that various types of risk assessment can be predicted in industry. Finally, a comparative study has been successfully performed with type-1 and type-2 fuzzy dataset for improving risk assessment that can be easily determined in the type-2 fuzzy prediction model for improving accuracy. Validity of the proposed model is done with the help of statistical analysis and multiple linear regressions.

Keywords Safety performance · Expert system · Construction safety · Risk assessment · Fuzzy inference system · Interval type-2 fuzzy logic

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1 Introduction

Small and medium-scale enterprises (SMEs) are important to almost all economies in the world, especially in the developing countries like India. The size of SMEs and its importance vary from country to country. The last few decades have seen an increasing recognition of the role of SME sector in India and due to which number of SME are increasing. In this rapidly growing SME sector, safety performance is a key issue for the industries to become a world-class competitor. Occupational accidents may lead to permanent disabilities or deaths and/or economic losses or both (Dadeviren and Yüksel 2008). As pointed out by Larcher and Sohail (1999), safety performance is a sensitive matter due to the involvement of human life, and the active resource in all aspects of life and its continuity must be ensured.

Occupational safety and health (OSH) is generally defined as the science of the anticipation, recognition, evaluation, and control of hazards arising in or from the workplace that could impair the health and well-being of workers, taking into account the possible impact on the surrounding communities and the general environment. A wide range of structures, skills, knowledge, and analytical capacities are needed to coordinate and implement all of the "building blocks" that make up national OSH systems so that protection is extended to both workers and the environment. The human, social, and economic costs of occupational acci-

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dents, injuries, and diseases, and major industrial disasters have long been the concern at all levels from the individual workplace to the national and international. Measures and strategies are designed to prevent, control, reduce, or eliminate occupational hazards and risks by good housekeeping, training, and educating the employees and better protective equipments and applied continuously over the years to keep pace with technological and economic changes. Yet, occupational accidents and diseases are still too frequent, and their cost in terms of human suffering and economic burden continues to be significant. In India, the rates of occupational fatalities and accidents are 10.4 per 100,000 for fatalities, 8700 for accidents. The economic costs of these injuries and deaths are colossal, at the enterprise, national, and global levels. The results of injury or death are compensation, lost working time, interruption of production, training and retraining, medical expenses, and so on. Estimation of these losses are routinely put at roughly 4% of global GNP every year, and possibly much more. OSH performance also varies significantly between economic sectors within countries. Statistical data show that, worldwide, the highest rates of occupational deaths occur in agriculture, forestry, mining, and construction. Generally, small workplaces have a worse safety record than large ones. It seems that the rate of fatal and serious injuries in small workplaces (defined as those with fewer than 50 employees) is twice that in large workplaces (defined as those with more than 200 employees). Workers in the informal economy are much more likely than formal workers to be exposed to poor working environments, low safety and health standards, and environmental hazards, and to suffer poor health or injury as a result. Most informal workers have little or no knowledge of the risks they face and how to avoid them. The very nature of the informal economy makes it almost impossible for governments to collect the vital statistics needed to take appropriate remedial action, and since much informal work takes place in homes, inspectorates cannot investigate working conditions or get information and advice to the people who need it.

Drivers in the transportation sector are particularly at risk. International estimates suggest that between 15 and 20% of fatalities caused by road accidents are suffered by people in the course of their work, but these deaths are treated as road traffic accidents rather than work-related fatalities. Beriha et al. (2012) have developed an artificial intelligence approach for prediction of different types of accidents in an imprecise environment. Likelihood of the occurrence of accidents in the work place in any industry is a random phenomenon, but judicious investment in various attribute such as expenses in health care, safety training, upgradation of tools and machinery, and expenses on safety equipment and apparatus may lead to reduction in accident rate.

Despite this worrying situation, international awareness of the magnitude of the problem remains surprisingly modest. The inadequate dissemination of knowledge and information hampers action, especially in developing countries. It also limits the capacity to design and implement effective policies and programs. The fatality, accident, and disease figures are alarming, but investment decisions continue to be made in disregard of safety, health, and environmental considerations. Prevention of any accident requires knowledge about how and where employees are exposed to and in which ways the risks are associated with Larsson and Field (2002). It suggests that methods of risk and safety prediction should be developed along with injury and epidemiological studies. Despite enormous studies on occupational accidents, risk assessment, or safety practices, few studies utilize a reliable methodology for prediction of different types of accidents (Chen et al. 2000; Ciarapica and Giacchetta 2009; Fang et al. 2004; Gürcanli and Müngen 2009).

In classical logic approach, an exact definition of mathematical model equations is needed to formulate a physical model, and this approach requires an exact definition of the mathematical model equations to describe the phenomenon (Naderloo et al. 2012). But in practical field where the polymer is produced, no such exact definitions have been followed, and the variables take only linguistic values rather than some crisp values. One of the best methods to make a mathematical model from it is to apply fuzzy logic approach just like how applied fuzzy programming to create an integrated model for sustainable municipal energy system planning and management in Shenzhen, China. The fuzzy logic generally allows a simple knowledge representation of the production process in terms of if–then rules (Naderloo et al. 2012). Fuzzy inference systems (FIS) can properly describe the complex and nonlinear phenomena with the precise rules. The rules are typically in if–then format with different matching degrees for a given operational situation (Amiryousefi et al. 2011). Fuzzy inference is able to handle vague situations and is built a model with words in the term of linguistic variables. Bevilacquaa et al. (2012) have developed type-1 fuzzy cognitive map (FCM) approach to explore the importance of the relevant factors in industrial plants. This is especially valuable where models are developed based on experts knowledge and individuals without a mathematical background are involved (Mendel et al. 2006; Yang et al. 2015; Cornelissen et al. 2003; Olatunji et al. 2014; Lee 1990; Valdez et al. (2008); Dey and Jana 2015; Pramanik et al. 2015; Chakraborty et al. 2015; Zhao et al. 2016). Fuzzy inference system (FIS) is one of the most efficient computational method rather than other analytical and statistical techniques. Since PP production system and technologies are quite intricate and uncertain, they can widely be applied for modeling of different components in this sector, because they can study new patterns which were not previously available in the trained datasets and they can also apprise knowledge over time as long as more training datasets are provided Khoshnevisan et al. (2014). In the context of environmental management, the use of the fuzzy logic method is strongly suggested. Khoshnevisan et al. (2014) estimated the yield of greenhouse strawberry with the help of adaptive neuro-fuzzy inference system (ANFIS). Castro et al. (2014) suggested an integrated recycling approach for GFRP pultrusion wastes using fuzzy logic. Sami et al. (2014) had done a case study in cane farms in Iran using fuzzy logic. Khoshnevisan et al. (2014) predicted the potato yield based on energy inputs by means of ANFIS. Alavi (2013) had determined the quality of Mozafati dates using Mamdani fuzzy inference system. Abghari and Sadi (2013) applied ANFIS for predicting the yield distribution of the main products in the steam cracking of atmospheric gasoil. Ertunc and Bulgurcu (2011) predicted the performance of a refrigeration system with the help of ANFIS. Wua et al. (2015) introduced a technique of measuring performance of thermal power firms in China via fuzzy enhanced Russell measure model. Similarly, Afrinaldi and Zhang (2014) proposed an alternative methods for normalization and aggregation in life cycle assessment (LCA) using a fuzzy logic-based aggregation method; Khoshnevisan et al. (2014) appraised the environmental impact on tomato and cucumber cultivation in greenhouses using life cycle assessment and ANFIS. Khoshnevisan et al. (2014) projected an environmental indices in potato production using artificial neural network; Pishgar-Komleh et al. (2012) analyzed energy consumption and CO_2 emissions analysis of potato production in Iran. Nevertheless, uses of fuzzy inference system are still in its very early stages, and there is lack of applicable models.

A type-2 fuzzy set (T2FS) is characterized by a fuzzy MF, unlike a type-1 fuzzy set (T1FS). In T1FS, the membership degree is a crisp number (Castillo and Melin 2008). Thus, a T2FS is able to model the uncertainties directly because it provides additional degrees of freedom (Mendel et al. 2006). The antecedent or consequent sets of the if–then rules for a type-2 fuzzy logic system (T2FLS) are type 2. T2FLSs have been used in many engineering applications. In spite of the above-mentioned development, we have considered the following aspects as follows:

- Interval type-2 fuzzy logic control (T2FLC) is a approach for prediction of different types of occupational safety risk in construction industry.
- T2FLC assists to trace inputs and outputs in a well-organized manner for building the inference train so that various types of risk assessment can be predicted.
- Qualitative factors responsible for improving risk assessment can be easily included in the type-2 fuzzy prediction model for improving accuracy.
- Validity of the proposed model is done with the help of statistical analysis and multiple linear regression.

The present investigation presents a comparative study on type-1 fuzzy (T1F) and type-2 fuzzy (T2F) models which give an essential indicator of parameters of safety assessment in an industry. There are so many possibilities to select functions and operators as well as inference, implication, aggregation, and defuzzification methods (Dutta and Jana 2017; Jana et al. 2017a), so the search for the perfect mathematical model can be included among the most vital topics in development of rule-based models. For this, we have made a primary investigation on the parameters controlling the safety assessment and chose the most appropriate input and output variables. A Mamdani interval type-2 fuzzy inference systems (MFT2IS) is then developed using these inputs and outputs. Depending on the membership functions (MFs), a model has been established, and by sensitivity analysis, we chose the best fitted model among them. Finally, with some graphical representation, we validate the chosen model with physical theoretical models. This study has presented a classification and prediction model based on soft computing techniques for assisting the managers to analyze occupational safety risk and planning for financial outlays in various expenses to improve industrial safety performance.

2 Notations and abbreviations

The following notations are used to describe the proposed model.

(i) FIS = fuzzy inference system.
(ii) MFIS = Mamdani fuzzy inference system.
(iii) R^2 = coefficient of determination.
(iv) RMSE = root-mean-square error.
(v) MAE = mean absolute error.
(vi) MAPE = mean absolute percentage error.
(vii) MFI = melt flow index.
(viii) MF = membership function.

2.1 Type-2 fuzzy sets

A type-2 fuzzy set (Jana et al. 2014, 2017b, c) expresses the non-deterministic truth degree with imprecision and uncertainty for an element that belongs to a set. A type-2 fuzzy set (Castillo and Melin 2008) denoted by $\tilde{\tilde{A}}$ is characterized by a type-2 membership function $\mu_{\tilde{A}}(x, u)$ where $x \in X, \forall u \in J_x^u \subseteq [0, 1]$ and $0 \leq \mu_{\tilde{A}}(x, u) \leq 1$ defined in Eq. (1)

$$\tilde{\tilde{A}} = \{(x, \mu_{\tilde{A}}(x)) | x \in X\}$$
$$\tilde{\tilde{A}} = \{(x, u, \mu_{\tilde{A}}(x, u)) | x \in X, \forall u \in J_x^u \subseteq [0, 1]\}. \qquad (1)$$

If $\tilde{\tilde{A}}$ is fuzzy type-2 (FT2) continuous variable, it is denoted in Eq. (2)

$$\tilde{\tilde{A}} = \left\{ \int_{x \in X} \left[\int_{u \in J_x^u} f_x(u)/u \right] /x \right\} \tag{2}$$

where $\int \int$ denotes the union of x and u. If A is FT2 discrete, then it is denoted and defined by Eq. (3)

$$\tilde{\tilde{A}} = \left\{ \sum_{x \in X} \mu_{\tilde{\tilde{A}}}(x)/x \right\} = \left\{ \sum_{i=1}^{N} \left[\sum_{k=1}^{M_i} f_{x_i}(u_k)/u_{ik} \right] /x_i \right\} \tag{3}$$

where $\sum \sum$ denotes the union of x and u. If $f_x(u) = 1$, $\forall u \in [\underline{J}_x^u, \overline{J}_x^u] \subseteq [0, 1]$, the type-2 membership function $\mu_{\tilde{\tilde{A}}}(x, u)$ is expressed by one type-1 inferior membership function, $\underline{J}_x^u = \mu_A(x)$ and one type-1 superior, $\overline{J}_x^u = \mu_A(x)$, then it is called an interval type-2 fuzzy set denoted by Eqs. (4) and (5).

$$\tilde{\tilde{A}} = \left\{ (x, u, 1) | \forall x \in X, \forall u \in [\underline{\mu}_A(x), \overline{\mu}_A(x)] \subseteq [0, 1] \right\} \tag{4}$$

or, it can be expressed as

$$\begin{aligned} \tilde{\tilde{A}} &= \left\{ \int_{x \in X} \left[\int_{u \in [\underline{J}_x^u, \overline{J}_x^u] \subseteq [0,1]} 1/u \right] /x \right\} \\ &= \left\{ \int_{x \in X} \left[\int_{u \in [\underline{\mu}_A(x), \overline{\mu}_A(x)] \subseteq [0,1]} 1/u \right] /x \right\} \end{aligned} \tag{5}$$

If $\tilde{\tilde{A}}$ is a type-2 fuzzy Singleton, the membership function is denoted and defined by Eq. (6).

$$\mu_{\tilde{\tilde{A}}}(x) = \begin{cases} 1/1, & \text{if } x = x' \\ 1/0, & \text{if } x \neq x' \end{cases} \tag{6}$$

Definition 1 A type-1 fuzzy set X is comprised of a domain D_X of real numbers (also called the universe of discourse of X) together with a membership function (MF) $\mu_x : D_X \to [0, 1]$, i.e.,

$$X = \int_{D_x} \mu_x(x)/x \tag{7}$$

Here $\int$ denotes the collection of all points $x \in D_X$ with associated membership grade $\mu_x(x)$.

Definition 2 (Mendel 2006) An IT2 FS $\tilde{X}$ is characterized by its MF $\mu_x(x, u)$, i.e.,

$$\begin{aligned} \tilde{X} &= \int_{x \in D_x} \int_{u \in J_x \subseteq [0,1]} \mu_x(x, u)/(x, u) \\ &= \int_{x \in D_x} \int_{u \in J_x \subseteq [0,1]} 1/(x, u) \\ &= \int_{x \in D_x} \left[\int_{u \in J_x \subseteq [0,1]} 1/u \right] /x \end{aligned} \tag{8}$$

where x, called the primary variable, has domain $D_{\tilde{X}} : u \in [0, 1]$, called the secondary variable, has domain $J_x \subseteq [0, 1]$ at each $x \in D_{\tilde{X}}$; J_x is also called the support of the secondary MF and the amplitude of $\mu_{\tilde{X}}(x, u)$, called a secondary grade of $\tilde{X}$, equals 1 for $\forall x \in D_{\tilde{X}}$ and $\forall u \in J_x \subseteq [0, 1]$. For general type-2 FSs $\mu_X(x, u)$ can be any number in [0, 1], and it varies as x and/or u vary.

Definition 3 The uncertainty about $\tilde{X}$ is suggested by the union of all its primary memberships, which is said the footprint of uncertainty (FOU) of $\tilde{X}$, i.e.,

$$\text{FOU}(\tilde{X}) = \bigcup_{\forall x \in D_{\tilde{X}}} J_x = \left\{ (x, u) : u \in J_x \subseteq [0, 1] \right\} \tag{9}$$

The size of an FOU is directly related to the uncertainty that is conveyed by an IT2 FS. So, an FOU with more area is more uncertain than one with less area.

Definition 4 The upper membership function (UMF) and lower membership function (LMF) of $\tilde{X}$ are two T1 MFs X and X that bound the FOU.

$$J_x = [\mu_{\underline{X}}(x), \mu_{\overline{X}}(x)] \tag{10}$$

Using (10), FOU $(\tilde{X})$ can also be expressed as

$$\text{FOU}(\tilde{X}) = \bigcup_{x \in D_x} [\mu_{\underline{X}}(x), \mu_{\overline{X}}(x)] \tag{11}$$

2.2 Model development and motivation

The relationship between type of accidents, severity, and current safety is difficult to establish because they do not follow any predictable rule rather associate in a nonlinear manner. In such situation, type-2 fuzzy logic assists to trace inputs and outputs in a well-organized manner for building the inference train so that various types of accidents can be easily predicted. This prediction of various types of accidents helps the managers to formulate organizational policies for improving safety performance in the construction of sight. This idea motivate us to formulate the proposed model. A block diagram of an interval type-2 fuzzy inference system is also

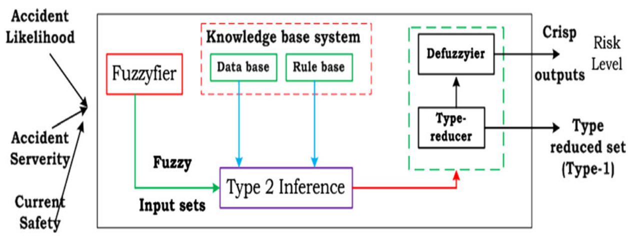

Fig. 1 Block diagram of type-2 inference fuzzy system structure

shown in Fig. 1. It is composed of five functional blocks as given in Fig. 1.

By taking into account the data gathered on pattern of risk for improving industrial safety performance and combining subjective judgment of experts, different linguistic variables are employed to develop interval type-2 fuzzy membership functions (IT2FMFs) for inputs to the proposed model. Interval type-2 fuzzy (IT2F) linguistic variables are extensions of numerical variables in the sense that they are able to represent the condition of an attributes at a given interval by taking IT2F sets as their values. Here we have considered three input parameters such as accident likelihood (AL), consequent severity (CS), and accident severity (AS). The linguistic variables of accident likelihood are very low, low, reasonably low, average, frequent, and highly frequent. For linguistic variables of consequent severity are negligible, minor, medium, severe, catastrophic which is given in Fig. 4. For linguistic variables of accident severity are poor, inadequate, average, adequate, very which is shown in Fig. 5. Similarly, the output parameter risk level (RL) is articulated as five IT2MFs denoted in linguistic terms such as high risk, substantial risk, average, low, no risk/very low as depicted in Fig. 6. The MFs in a linguistic expression for risk level uses value between 0 and 10. These MFs are commonly used to explain the parameters in assessment of risk assessment (Gürcanli and Müngen 2009).

3 Model formulation

The paper presents an interval type-2 fuzzy logic control (T2FLC) method of approach, for making prediction of various types of accidents in an environment with imprecise surroundings. Proper investment in various attributes such as expenses in health care, safety training, upgradation of tools and machinery, and expenses on safety equipment reduces possibility of occurrence of accidents which in turn reduces the accident rate. Since no predictable rule is followed in such fields, it is difficult in establishing a relation between investment and the type of accidents. Rather in other words, it is associated in a nonlinear manner. The type-2 fuzzy logics assist in a way such that the inputs and outputs are traced in a well-organized manner for building interference train for prediction of various types of accidents. The prediction of various types of accidents helps the managers in formulating policies of the organization and performs in a way such that the safety performance is increases minimizing rate of accidents.

To look into the cause of an accident and review the safety performance is known as defining. The present and the future generations of any industry face the problem of defining. The process used here develops an extension model (Gürcanli and Müngen 2009). To design a model of uncertainty in such risk-prone environments refers to the explicit quantification of probabilities and the potential results is based on the information available about risks considered. The project going on in any industry has uncertainties of risk assessment, and this may be attributed to the randomness intrinsic nature, lack of adequate data related to the probability of happening, and the possible consequences. The results which compromise such uncertainties cannot be certainly predicted. As a solution to these, the workers who have years of experience and their valuable opinions can be utilized. But contrary to these, the quantification of the knowledge they have gained is not an easy task to deal with. So the type-2 fuzzy set theory serves as a convenient tool in mathematics to solve the problem in a lucid manner. Thus, the interval type-2 fuzzy approaches are utilized to propose an efficient and systematic uncertainty modeling in this work. For the first time, it is an approach to develop safety performance model in type-2 fuzzy environment.

Firstly, the factors of accident likelihood (AL) are obtained for each type of construction accident according to various construction job sites from past data including statistical report by expert engineers. Then, the factors of accident severity (AS) for major accident cause are obtained from discussions with construction site engineers including safety experts. To mitigate or decrease these risks at construction sites which were derived from examining files, site scrutiny, and discussions with construction site engineers including safety experts, the present safety level factor was obtained by recognizing risk factors and the weighted skill of safety actions. Defining means to review safety performance and examine into their causes is one of the present and future challenges of any industry. This is an extension model of Gürcanli and Müngen (2009). Current safety level (CSL) definitions and categories are given in Table 1. The modeling of uncertainty in a risk exposure refers to the explicit quantification of probabilities and potential consequences based on all the information available about risks under consideration. In any project of any industry, uncertainties of risk assessment measures may be attributed to the randomness intrinsic in nature and to the lack of adequate data related to the probability of their happening and possible consequences from industry. As a compromise result of such uncertainties, the accidents cannot be predicted with certainty. The experts or

Table 1 Current safety level (CSL) definitions and categories

Rank	CS	Definition
1, 2, 3	Poor	No measures are taken and hazardous conditions exist
4, 5	Inadequate	Hazard prevention and abatement measures are not taken adequately and accident risk remains
6, 7	Average	Some sort of safety measures exists, but exact safety conditions are not satisfied
8, 9	Adequate	Almost all the measures are taken, and high level of safety conditions are satisfied; however, some hazardous conditions remain and could not eliminated or mitigated to a certain degree
10	Very safe	All the measures are taken, and high level of safety conditions are satisfied, and hazardous conditions eliminated or mitigated to a certain degree

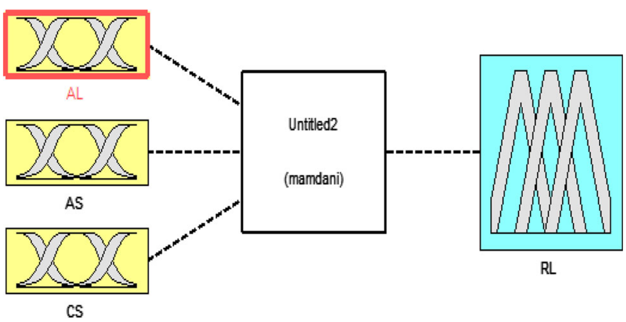

Fig. 2 The structure of Mamdani FIS

the decision makers with in-depth knowledge in such projects can provide a valuable opinion on uncertainties during risk assessment. Therefore, the opinion obtained from hundreds of experts with many years of experience needs to be utilized. On the other hand, the quantification of their valuable knowledge to estimate the uncertainties is not an easy task. The type-2 fuzzy set theory is a convenient mathematical tool that can process these linguistic terms in a lucid manner. Thus, the interval type-2 fuzzy approaches are utilized to propose an efficient and systematic uncertainty modeling in this work. We have developed this safety performance model under interval type-2 fuzzy environments for first time. The structure of the Mamdani interval type-2 fuzzy inference is shown in Fig. 2.

3.1 Accident likelihood (AL)

The types of construction work and accidents to which workers exposed are set linguistic values as given in Table 2 and are derived from investigated accident files. By using Table 2, the experts only determined the range of percentages associated with each category of likelihood (e.g., low, very low), and provided definitions, as shown in the first column of Table 2, for likelihood. Fuzzy accident likelihood set definitions are computed using these definitions, as shown in Fig. 3. The model uses the values given in Table 6 to define the linguistic expressions for accident likelihood. The users cannot change this input parameter.

3.2 Accident severity (AS)

Accident severity categories are determined by a review of the literature and rankings. Interval type-2 fuzzy consequent severity (accident severity) set definitions are calculated using these definitions as given in Table 3. Then, the subjective judgment of different groups of experts is used to determine severity of every accident. The model utilizes the average expert scores, depicted in Table 3, to define the interval type-2 fuzzy linguistic expressions. In fact, the engineers cannot change this input parameter, but if they think the severity scores given are low and decide to be at the safe side, the model can be altered to use the practitioner's judgment.

3.3 Current safety (CS) level

For every type of construction accident, first the necessary safety measures are determined and a checklist is established. This checklist is constructed using current legislation, investigated files (that shows primary faulty and negligent acts of the related parties, the ways of occurrence and the activity of victims), site inspections, and interviews with site engineers and safety experts. Then, every safety item is weighed by the experts, and checklists like Table 4 are derived (it is only for equipment accidents). The experts also determined the definitions of CS, and the interval type-2 fuzzy current safety level set definitions are computed using these definitions, as shown in Fig. 3. The users (i.e., the safety practitioners on the site) give points for the safety items on the checklist during site investigations of the construction project (daily or weekly) in linguistic expressions (Figs. 4, 5).

3.4 Risk level

The model is constructed exclusively the output parameter risk level for every type of construction accidents, and it is expressed linguistically. The interval type-2 fuzzy set definition of risk level is given in Table 5. The risk level is reported for each construction site depicted in Fig. 6.

Table 2 Linguistic variables (LVs) for input interval type-2 fuzzy values accident likelihood (AL)

LVs	IT2Fuzzy
Very low	[−0.5324, −0.03247, 0.4676, −0.3658, 0.1342, 0.6342]
Low	[−0.08333, 0.4167, 0.9167, 0.08333, 0.5833, 1.083]
Reasonably low	[0.4167, 0.9167, 1.417, 0.5833, 1.083, 1.583]
Average	[0.9167, 1.417, 1.917, 1.083, 1.583, 2.083]
Frequent	[1.417, 1.917, 2.417, 1.583, 2.083, 2.583]
High frequent	[1.831, 2.331, 2.831, 1.997, 2.497, 2.997]

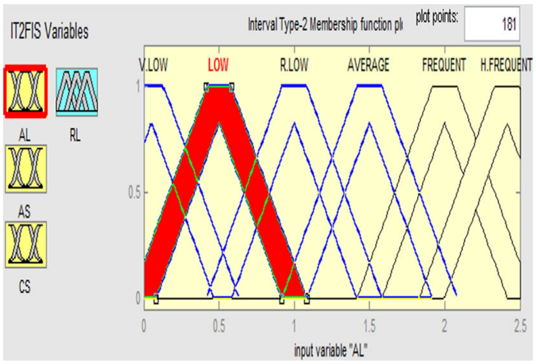

Fig. 3 MFs for accident likelihood (AL) set definition

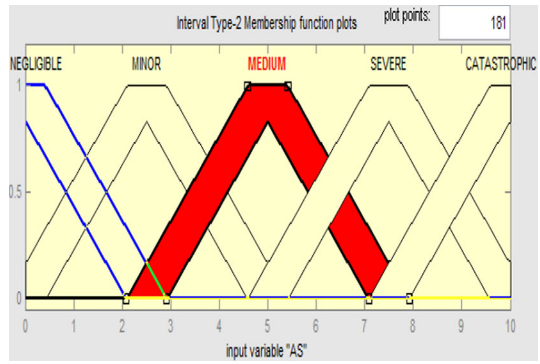

Fig. 4 MFs for consequent severity (CS) set definition

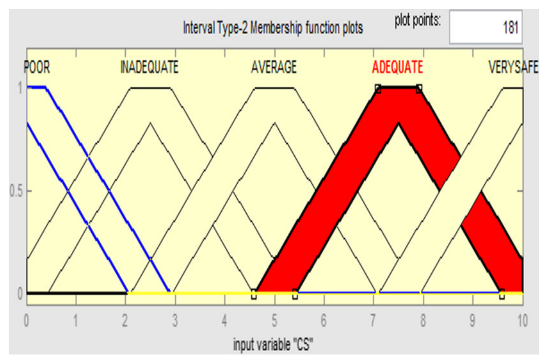

Fig. 5 MFs for accident severity (AS)

Table 3 Linguistic variables (LVs) for input interval type-2 fuzzy values accident severity (AS)

LVs	IT2Fuzzy
Negligible	[−2.917, −0.4167, 2.083, −2.083, 0.4167, 2.917]
Minor	[−0.4167, 2.083, 4.583, 0.4167, 2.917, 5.417]
Medium	[2.083, 4.583, 7.083, 2.917, 5.417, 7.917]
Severe	[4.583, 7.083, 9.583, 5.417, 7.917, 10.42]
Catastrophic	[7.083, 9.583, 12.08, 7.917, 10.42, 12.92]

Table 4 Linguistic variables (LVs) for input interval type-2 fuzzy values current safety (CS)

LVs	IT2Fuzzy
Poor	[−2.917, −0.4167, 2.083, −2.083, 0.4167, 2.917]
Inadequate	[−0.4167, 2.083, 4.583, 0.4167, 2.917, 5.417]
Average	[2.083, 4.583, 7.083, 2.917, 5.417, 7.917]
Adequate	[4.583, 7.083, 9.583, 5.417, 7.917, 10.42]
Very safe	[7.083,9.583, 12.08, 7.917, 10.42, 12.92]

Table 5 Linguistic variables (LVs) for output interval type-2 fuzzy values risk level (RL)

LVs	IT2Fuzzy
High risk	[−2.917, −0.4167, 2.083, −2.083, 0.4167, 2.917]
Substantial risk	[−0.4167, 2.083, 4.583, 0.4167, 2.917, 5.417]
Average	[2.083, 4.583, 7.083, 2.917, 5.417, 7.917]
Low	[4.583, 7.083, 9.583, 5.417, 7.917, 10.42]
No risk	[7.083, 9.583, 12.08, 7.917, 10.42, 12.92]

4 Solution procedure

Fuzzy method is a procedure that is capable of taking into account ambiguous and vague thinking. The fuzzy inference systems are recently more popular tools for solving engineering problems because of their unique features in predicting complex phenomena (Pramanik et al. 2017). The most important two types of fuzzy inference systems are Mamdani and Sugeno fuzzy inference methods (Sugeno 1985). When the output variables are also fuzzy sets with membership function, then MFIS is the most commonly used inference method. This method is introduced by Assilian (1975). The canonical structure for this system will have the following structure:

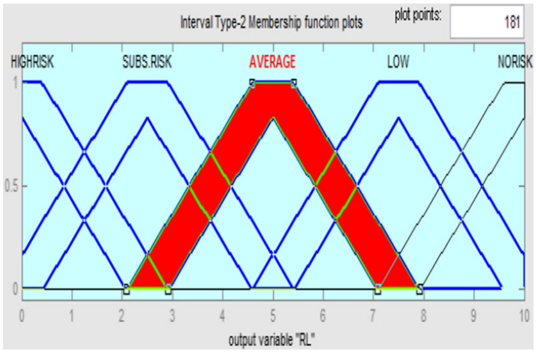

Fig. 6 MFs for risk level (RL)

If x is $\tilde{A}$ and y is $\tilde{\tilde{B}}$, then z is $\tilde{\tilde{C}}$, where $\tilde{\tilde{A}}$ and $\tilde{\tilde{B}}$ are interval type-2 fuzzy sets in the antecedent and $\tilde{C}$ is a interval type-2 fuzzy set in the consequent (Castillo and Melin 2008).

Another known inference method is the Takagi–Sugeno–Kang method of fuzzy inference process. This method was introduced by Sugeno in 1985. A typical canonical fuzzy rule for this method has the following form.

If x is $\tilde{\tilde{A}}$ and y is $\tilde{\tilde{B}}$, then $z = f(x, y)$, where $\tilde{\tilde{A}}$ and $\tilde{\tilde{B}}$ are interval type-2 fuzzy sets in the antecedent and $z = f(x, y)$ is a crisp function in the consequent. Generally, $f(x, y)$ is a polynomial in the input variables x and y (Castillo and Melin 2008). The main difference between the two methods lies in the consequent of fuzzy rules.

The next case study shows the command line editing procedure of the Mamdani interval type-2 fuzzy logic inference system structure implemented in the IT2FLS Toolbox. The proposed Mamdani type-2 fuzzy inference model with 4 input and 2 output variables is shown in Fig. 2. In this model, we have applied 4 if–then rules which are depicted in Fig. 7. Min and Max operators were employed to evaluate the logical conjunction AND and OR. We have used Min and Max operators for implication and aggregation method, respectively. Centroid method is applied for the defuzzification.

Most extensively used method is center of sets (COS)-type reduction, and Y_{COS} is given as $Y_{\text{COS}} = [y_l, y_r$. Type-reduced set gets defuzzified to crisp output. This is done by simply taking an average of the y_l and y_r points of the type-reduced set, i.e., defuzzified crisp or deterministic output is given by $Y(x) = \frac{y_l + y_r}{2}$.

4.1 Results and discussion

Corresponding to every input and output data, we have formulated a risk assessment model in IT2F environment. Considering the industry data, the model output is observed value. In order to control the risk performance of the predictive model, we have defined some statistical parameters. The prediction capability of proposed model is evaluated by using the test data in the trained data and comparing the outputs and measured values. In addition, the statistical parameters such as the root-mean-square error (RMSE) and the determination coefficient (R^2) are used to compare predicted and measured values of flexible modulus. The RMSE is defined by the following Eq. (12):

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_{\text{pred}_i} - y_{\text{obs}_i})^2}. \tag{12}$$

In addition, the determination coefficient (R^2) can be calculated using Eq. (13) that is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_{\text{pred}_i} - y_{\text{obs}_i})^2}{\sum_{i=1}^{n} y_{\text{obs}_i}^2}. \tag{13}$$

Mean absolute percentage error (MAPE) measures the average of the squares of the errors. The smaller values of MAPE ensure the better performance of the proposed models. The MAPE is calculated by the following Eq. (14):

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \frac{|(y_{\text{pred}_i} - y_{\text{obs}_i})|}{y_{\text{pred}_i}} \times 100\%. \tag{14}$$

However, the performance and efficiency of the proposed models is also analyzed using mean absolute error (MAE), which is defined by Eq. (15):

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_{\text{pred}_i} - y_{\text{obs}_i}| \tag{15}$$

where n is the number of data patterns in the dataset, y_{pred_i} indicates the predicted value of one data point i, and y_{obs_i} is the observed value of one data point i. The graphical representation of such type fuzzy logic if–then rule is shown in Fig. 7 for input and output data and IT2F controller in Fig. 8.

4.2 Error analysis by multiple linear regression

If x_i equals to process parameters and e_i denotes low predictive error that is optimization target, the multiple linear regression (MLR) can be written as

$$y_i = b_0 + b_1 x_{i1} + b_2 x_{i2} + \cdots + b_n x_{in} + e_i \tag{16}$$

Different quality measures can be used to judge the performance and accuracy of the proposed models. This is done by carrying out statistical error analysis. To evaluate and compare the performance and accuracy of the proposed model with the standard plant data, the most common statistical quality measures. The root-mean-squared error (RMSE) and correlation coefficient (R^2) have been employed by using regression in MATLAB 14.

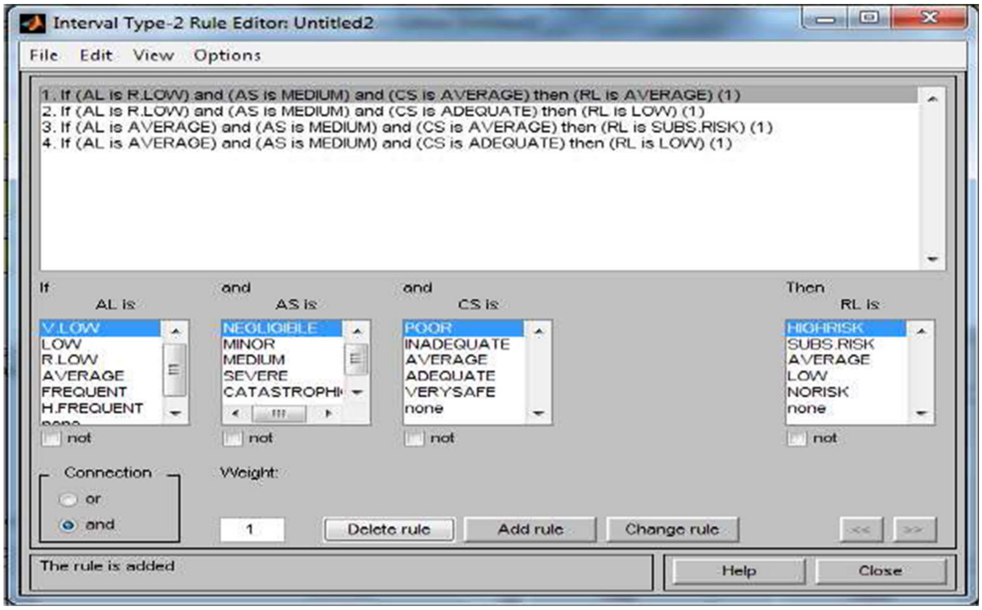

Fig. 7 If–then rule for the proposed model

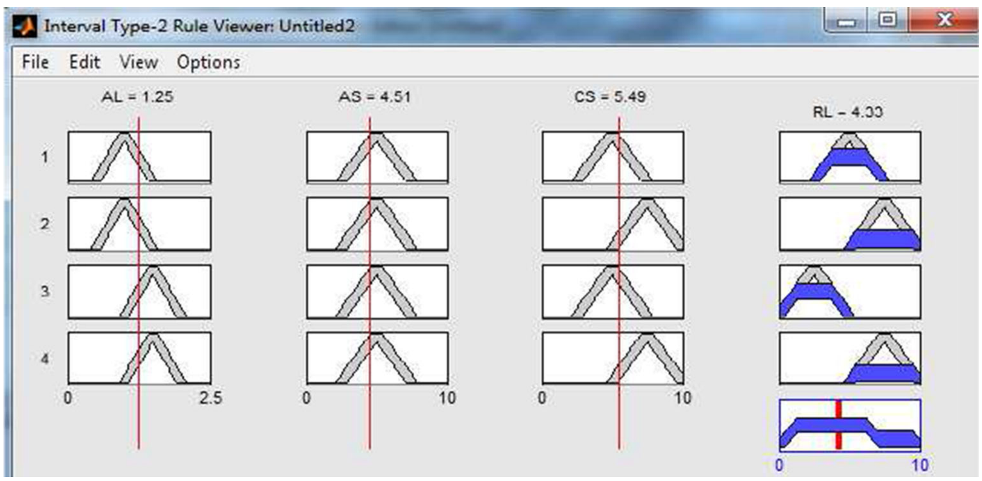

Fig. 8 Fuzzy logic controller

Corresponding to every input and output data, we have formulated a risk assessment model in IT2F environment. Considering the industry data, the model output is observed value. In order to control the risk performance of the predictive model, we have defined some statistical parameters. The prediction capability of proposed model is evaluated by using the test data in the trained data and comparing the outputs and measured values.

From Table 6, it is clear that the small value of MAPE in T2-fuzzy environment than that of T1-fuzzy data ensures the better performance of the proposed T2-fuzzy model, which is shown in Fig. 9. The determination coefficient (R^2) of T2-fuzzy environment is comparatively larger than that of T1-fuzzy data. These types of results are ensured that the T2FLC is more acceptable for occupational safety risk analysis at construction sites. The relevance of this study to industry is associated to the possibility of providing, through the use of proposed methodology, occupational

Table 6 Statistical data analysis of output using ANFIS and MLR

Model	Approach	RMSE	MAE	MAPE	R^2
Statistics					
T2-fuzzy	MLR	0.05413	0.0772	0.968	0.9714
	ANFIS	0.05187	0.0763	0.978	0.9815
T1-fuzzy	MLR	0.05873	0.0854	0.957	0.9673
	ANFIS	0.04934	0.0752	0.969	0.9684

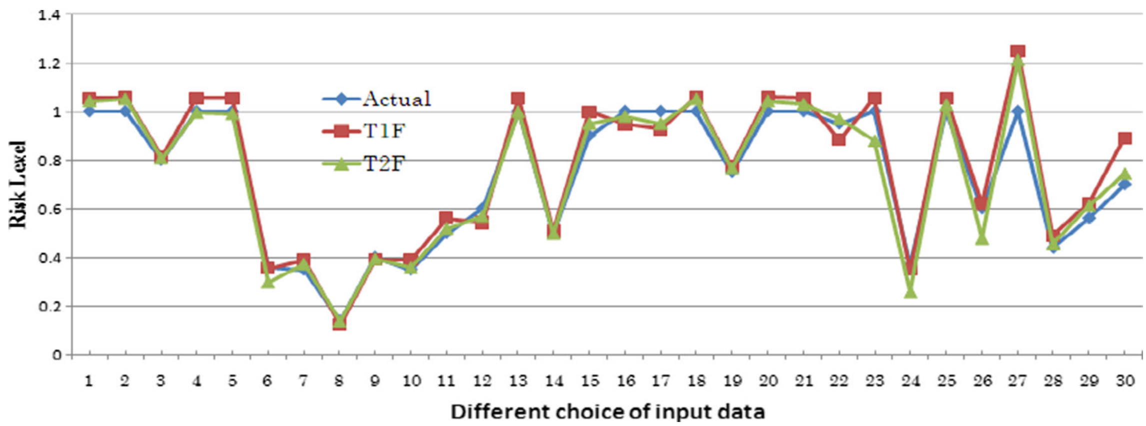

Fig. 9 Comparison of actual and predicted values from T1F and T2F controllers

safety levels for the construction sites that could result in work improvement and productivity. The application of the proposed T2FLC method can disclose which safety items and factors are most significant in improving workers safety and, therefore, decide where to concentrate resources in order to improve the safety of the work uncertain environments.

5 Conclusions and future research work

In this paper, a new risk assessment approach is proposed and utilized at a work site using an interval type-2 fuzzy logic control approach. By this approach, historical accident data from the industry are incorporated into the method. These inputs, along with subjective judgments of the experts and the current safety level of a construction site are combined by a type-2 fuzzy rule-based system. Finally, a real comparative study is shown to verify the models in the type-1 and type-2 fuzzy environments and to demonstrate its practicality and feasibility. Prediction of various types of accidents helps the managers to formulate organizational policies for improving occupational safety performance. The authors argue that the suggested T2FLC method is a new approach for construction and the checklist proposed in this paper needs to be developed, regarding safety management items that must be satisfied to establish an effective safety system in the site, such as current safety and health plans, safety and health responsibilities, fitness for duty, emergency response plans, first aid/medical requirements. The proposed method can easily incorporate the present characteristics of the site and construction conditions, by taking into account the degree of uncertainties of judgment made by safety experts that may have great effect on the results of risk assessment. Moreover, in this paper, the financial or environmental effects of the occupational accidents are not taken into account while constructing an interval type-2 fuzzy rule base. The study is only focused on daily, routine safety measures, rather than the safety management principles. Therefore, qualitative factors responsible for improving safety performance can be easily included in the fuzzy prediction model for improving accuracy. The major contribution of this research work is proposing a systematic integrated approach for modeling the accident analysis and their prediction so that occupational health and safety situation can be improved. For further research work, we will utilize and integrate other intelligent methods, such as interpretative structural modeling method, simulink, fuzzy artificial neural network, to evaluate the scale of efficiency of our current work.

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Compliance with ethical standards

Conflict of interest The authors have no conflict of interest for the publication of this paper.

Ethical approval The authors declared that this article does not contain any studies with human participants or animals performed by any of the authors.

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