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Fuzzy inference model for assessing occupational risks in construction sites

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ABSTRACT

Occupational risk assessment is a key measure to reach safety in construction industries. The assessment process is involved with many parameters which are difficult to assess, due to inadequate data or imprecise information. So, traditional quantitative approaches fail, frequently, to assess risk levels and to identify adequate preventive measures. A Takagi-Sugeno type fuzzy inference system is developed in this article to overcome these lacunas. In the model formulation process, the risk factors and controlling factors for accidental injuries are considered as input parameters. Safety levels of each type of injury prone body parts are evaluated by using analytical hierarchy process. Subtractive clustering technique is used to reduce the number of rules and thereby an initial fuzzy inference system is generated. Finally, the initial model is updated by tuning all the parameters corresponding to the input variables using a hybrid learning process. The developed methodology has been applied to few selected construction sites in India. The derived results validate the applicability of the developed model for assessing risks in construction sites and also identifies the pertinent progress of existing safety strategies.

1. Introduction

Withstanding with mechanization, it is established that the occupational risk factors increase (Lyons and Skitmore, 2004) and their systematic amelioration became challenging to the safety professionals and researchers (Paulmann, 1997). It is very much important to appraise the risk level of the industries frequently and develop remedial strategy to reduce occupational injuries (Mazumdar et al., 2007). Occupational injuries not only affect human resources, but also caused financial losses due to disruptions in industrial processes, damages to production machinery and harm firm's reputation. So, various safety management processes based on a hierarchy of hazard control, viz., elimination, substitution, engineering, administration, and use of personal protective equipment (OHS642 Hierarchy of Risk Controls, 2007) were introduced and implemented in the organized sectors as safety policies in the past. Again, different companies adopted different scales for measuring safety levels based on its resources (Tam et al., 2002). Cagno et al. (2014) developed a systemic and interpretive model for measuring safety performances of small and medium-sized enterprises. An approach for classifying jobs by assessing occupational risk levels was suggested by Aneziris et al. (2010). Dejoy et al. (2004) reported that employees' attitudes play a vital role in safety issues. It was also conveyed that due to lack of safety awareness, workers are involved in unsafe activities (Choudhry and Fang, 2008). It is to be noted here that proper precautions for preventing accidents on job sites cannot be taken in a justified way through most of the models developed earlier due to unavailability of non-reportable accidents.

Again, it is very often observed that risk analysis deals with unforeseen situations, i.e., with situations in which there is no previous and accurate knowledge about the state of the system. So, there is a constant need to introduce uncertainty factors in risk analysis as adequately as possible. In this context, fuzzy set theoretic analysis (Zadeh, 1965; Zimmerman, 1996) and fuzzy logic (Gupta et al., 1988; Yen and Langari, 1999) appeared as efficient tools for assessing risks due to their abilities to capture uncertainties in an imprecise decision making situation. The study of

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fuzzy logic began with the pioneering work of Zadeh (1965) with the inception of fuzzy set theory. In 1970s, fuzzy logic was combined with expert systems to become a fuzzy logic system that was then implemented in industrial (Blockley, 1980), medical (Vila and Delgado, 1983) and environmental (Cao and Chen, 1983) sectors.

Several methods have been introduced using fuzzy principles for analyzing risks (Azadeh et al., 2008; Cuny and Lejeune, 1999; Rafat, 1995). Blockley (1975) made a breakthrough in the study of structural safety in structural engineering using fuzzy concepts. Fujino (1994) demonstrated the applicability of fuzzy fault tree analysis to case studies of construction site accidents in Japan. Cho et al. (2002) and Choi et al. (2004) analysed the risk assessment process for underground construction projects using a model based on fuzzy concepts.

Occupational accidents are not only limited to large scale industries, but also to informal construction sectors. In assessing determinants and roles of safety climate, Gurcanli and Mungen (2009) proposed a Mamdani model to assess risks of workers who are exposed in construction sites by using uncertain and inadequate data. A review work on occupational risk assessment in construction sites using traditional methods and fuzzy set theoretic approaches for reducing subjectivity in estimating occupational accident severity was performed by Pinto et al. (2011, 2012). Beriha et al. (2012) proposed a risk assessment technique based on a Mamdani fuzzy inference model by considering expenses in health care, safety training, upgrading the machines and safety tools. Arunraj et al. (2013) derived a technique by integrating fuzzy set theory with Monte Carlo simulation for modelling uncertainty in risk assessment. Neumann et al. (2001) proposed a method that was able to identify low-back pain risk factors properly.

All research works involving fuzzy techniques developed so far are either based on simple fuzzy set theoretic concepts or Mamdani type inference model. In those models there was no scope for tuning the membership functions (MFs) so as to minimize the output error. In this perspective, adaptive neuro FIS (ANFIS) (Venugopal et al., 2010) appeared as an efficient tool for constructing a set of fuzzy if-then rules with appropriate MFs to generate the stipulated input-output pairs. Also, Takagi-Sugeno (TS) type fuzzy control system has its greater applicability for deriving inference by minimizing output errors in different real life decision making situations in which the rules and parameters are ambiguously defined.

In this paper, risk assessment has been performed by giving priorities to accidents related to all body parts, their corresponding safety measures and expenses in maintaining the safety protection together to deal with the inconsistency in the number of non-reportable accidents. An ANFIS based on TS fuzzy control system is developed in a systematic manner to assess risk in construction sites from the viewpoint of minimizing the number of fuzzy IF-THEN rules due to unavailability of standard methodology for transforming the knowledge of experts into rule base or database of FIS and also, to tune the parameters of MFs so as to minimize output error or maximize performance index.

2. The proposed methodology

The risk level of each type of body part wise injuries due to accidents is determined with the help of the previous data available in a construction industry, subjective judgements and site inspections. The opinions of ten experts who are actively involved in occupational safety of construction industries are taken into consideration. Those experts exerted their opinions on the basis of their experimental knowledge and the knowledge acquired thorough the process of consultation with several safety personnel of that concerned industry to analyse the current scenario and to assess the risk levels. The knowledge of the experts were mapped into the database of the rules for the ANFIS model to generate a unique base of knowledge to be used to assess the risk in the job sites (as desired output). In model formulation process, the risk factors and controlling factors for accidental injuries to different body parts are identified as input parameters. Among the factors, safety levels of each type of accidents are evaluated by analytical hierarchy process (AHP) introduced by Saaty and Vargas (1980). Collected data are divided into two sets: 70% of them are used for training purposes and rest 30% are used for testing purposes. Subtractive clustering method is applied to develop the initial FIS. After that the membership parameters of the initial FIS are tuned using a hybrid learning algorithm (Jang, 1993) by setting the error tolerance at zero in order to generate the optimum model. The final model thus obtained is employed on the testing dataset so as to compare the achieved output values corresponding to the inputs under consideration with the desired outputs determined by the experts. Finally, a framework is specifically presented to provide guidance for the prevention of injuries as well as promotion of safety in a wider sense.

2.1. Selection of input variables

The risk factors for the occurrence of injuries to different body parts due to accidents are identified first. Based on a case-control study, the neuro fuzzy technique is then put forward by selecting the identified risk factors and protective measures. By a thorough observation of the raw data and judgements of the experts the following four key input parameters are selected to develop the proposed model.

Accident Percentage (AP): AP signifies the percentage of occurrence of accidents on any type of body parts. It is evaluated in the usual manner by calculating the percentage score.

Accident Severity (AS): Severity of an accident signifies the extent of harm it causes due to injury; and it is usually manifested by the extent or degree of injury caused to one or more persons. Depending on the extent of damages caused by the accidents, AS is measured by adopting a preference scale. For example, if the outcome of an accident is permanent disablement or death, the accident is considered as very serious and the maximum score is allotted. In the current context, AS has been classified as negligible, minor, severe, serious and very serious. To determine AS of any type of accidents, a judgement is made on the basis of a preference scale based on the steps taken after the occurrence of such kind of accidents. The preference scales for AS with score values are presented in the following Table 1.

It is to be noted here that LTI cases are considered in the context when a worker is absent for more than 2 days and the accidents are reportable to the Government.

Safety Level (SL): SL of each type of accidents is derived using AHP (Gurcanli and Mungen, 2009; Saaty and Vargas, 1980; Saaty, 1990, 2003). In the proposed process the weights of different types of safety measures which are taken in respect of each type of accidents are evaluated by pairwise comparison matrices. The process of evaluation is described below.

Let $C_1, C_2, \ldots C_n$ be a set of n activities. The quantified judgements on the pairs of activities C_i, C_j are represented by $n \times n$ matrix $A = (a_{ij})$, $(i, j = 1, 2, 3, \ldots n)$. The entries a_{ij} are defined by the following rules.

- ➢ If $a_{ij} = \beta$ then $a_{ji} = 1/\beta$, $\beta \neq 0$.
- ➢ If C_i is judged to be equally relative important as C_j, then the value of a_{ij} as well as a_{ji} are considered as 1; in particular, $a_{ii} = 1$ for all i. Thus A is of the form