

A framework to evaluate underground mine safety performance by using Bayesian structural equation modelling

This paper proposed an approach of a quantitative analysis to evaluate the accident causation in underground coal mines in India. The Bayesian structural equation modelling (SEM) is the best multivariate analysis to comprehend the safety measures for reducing accidents in underground coal mines in India. In this paper, an accident causation model have been proposed and developed for structural equation modelling with Bayesian inferences by using workers response on the basis of their perception of the parameters of several hazards which has to be measured by considering mine, miners and management variables and to achieve zero accident potential (ZAP), identification of hazards and actual cause of accident analysis is crucial. Moreover, Bayesian inferences in structural equation modelling has to be applied to identify the hazards and Markov Chain Monte Carlo sampling in the form of Gibbs sampling has to be applied for parameter estimation.

Keywords: Hazards, occupational safety, Bayesian SEM

1. Introduction

Mining of minerals is considered to be one of the most hazardous occupations and the safety of miners is a major social responsibility to ensure zero incidents all over the world (Katiyar and Sinha, 2008). It entails constant struggle of human being with reasons and resources against the changing forces of nature. The hazardous nature of coal mine operations can easily be depicted from the national statistics of mine accident and injuries. For example, the fatality and serious bodily injury rates per 1000 persons employed for the years 2014 and 2015 are 0.26, 0.32 and 1.79, 1.38 respectively (DGMS Standard Note, 2016). In addition to that loss of human lives and sufferings, the costs of mine accidents are substantial. On an average, the total economic cost of an injury in the mining industry is approximately \$7,000 (Regan et al., 2014). The cost of the job related injuries to the USA economy was estimated at more than \$27 billion annually (NSC, 2004). In Britain, the estimated total cost of work place injuries to employers for the year 2005–2006 was between £1.2 and

£1.3 billion (Pathak, 2008). Hence, reducing the accidents and injuries is of paramount importance to the industries in particular and society in general. In safety research, emphasis is placed on identifying the safety risk factors, analyzing the underlying accident mechanisms, developing improvement strategies and their implementation, and monitoring for reduction of accidents/injuries in industries.

2. Literature review of quantitative analysis on safety

Accidents and injuries are the result of interacting events occurring in mines. Presence of hazards is the primary condition for occurrence of injury/accident event. Causal factors are responsible for transformation of injury risk into injury incident. Based on availability of different literature, books, journals, conference proceedings, injury/accident literature can be categorized in several divisions. A literature review is performed at international and national level for mining as well as a non-mining sector based on injury experience and questionnaire based data in safety engineering.

QUANTITATIVE ANALYSIS OF SAFETY ENGINEERING BASED ON INJURY EXPERIENCE AND QUESTIONNAIRE SURVEY BASED DATA (NATIONAL AND INTERNATIONAL STATUS)

A variety of methodological techniques have been applied to analyse mine injury data. The statistical models are applied by researchers to have primarily relied on the nature of the parameters and various methodological issues associated with the data, as discussed previously. The parameters of existing statistical model are typically may be binary or multiple response outcomes. However, some researchers have investigated the severity of mine accident by considering injury severity level of the accident involved and non-accident involved individual. However, research on quantitative analysis in mine safety perspective is highly inculcated to the improvement of miners' safety. A literature review is executed, which can be classified as follows:

1. Classification-based analysis
2. Correlation and Bivariate regression analysis
3. Cost-benefit analysis
4. Reliability analysis

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5. Risk analysis
6. Time series analysis
7. Multivariate analysis

CLASSIFICATION BASED ANALYSIS

Classification based analysis plays a significant role in statistics and can be used in a wide range of other domain such as education, industry, business and defence. The goal of this analysis is to accurately analyze the accident data based on several factor, such as sources of injury, body parts injured, mining equipment involved, and work system. Bahn (2013) used Safe Performance Index (SPI) to assess risk of injury severities to prevent accident in underground coal mines in United States and Australia. As per mine equipment injuries data, Na et al. (2011) established Safety Information Management System (SIMS) to obtain the actual cause of mine equipment related injuries and its' prevention. In the non-mining sector, to achieve the target zero disaster potential Liu et al. (2015) characterized the various chemicals to determine the sources of the harmful effects for better safety practices.

CORRELATION AND BIVARIATE REGRESSION ANALYSIS

The studies explored the relationships between parameters and measures of mine safety by injury experience data. Basically, these studies are mainly conducted to evaluate cause and effect relationship and factors affecting the safety of mines. The regression based analyses are cost effective and that can be used for cross sectional designs. Correlation analysis is used to generate relationship with several mine safety variables, prior injury rates and workforce size. Cheng et al. (2010) carried out a cost effective analysis of underground mine mechanization to forecast the occupational injuries, the same patterns (rules) analysis was created by Verma et al. (2014) to determine the main hindrance of safety related accidents in Indian mines. To explore the relationships between demographic, organizational variables and safety performance. Autenrieth et al. (2016) conducted a correlational analysis to resolve the strength and significance of injury rates, workforce size and occupational health and safety management system for dairy operations in United States.

COST BENEFIT ANALYSIS

Economic analysis in mining industry for injury prevention and safety control is an incredibly significant topic for the researchers. The eminent researcher does not apply this analysis due to non-availability of data. Generally, they are using Markov Decision Model for cost benefit analysis to prevent injury in mines. However, Tan et al. (2012) introduced safety indexes to enhance the safety level of mining industry in China and Biddle (2013) and Lebeau et al. (2014) analysed overall costs of occupational injuries and syndromes to improve injury prevention in Québec. Cost worksheets has been evaluated by Dembe et al. (2005)

to analyse the impact of occupational injuries and illnesses among workers in the United States and further Ibarrondo-Dávila et al. (2015) emphasized the weaknesses of current managerial accounting systems on the cost of measures to ensure health and safety in the workplace of a mine.

RELIABILITY ANALYSIS

In mine safety context the definition of reliability is a simple word which is defined as a kind of measurement which is reliable if it reflects mostly accurate score and most comparative to the error. However, the application of reliability analysis in the context of mine safety is very limited. Kinilakodi et al. (2011) examines the potentiality of injuries by event tree analysis in United States and concurrently, Lee and Park (2013) constructed a decision tree to predict occupational risk in an underground coal mine. In non-mining sector, a regression tree analysis has been applied by Wang et al. (2010) to predict the occurrence of occupational injuries for construction project in Taiwan.

RISK ANALYSIS

Risk analysis of injury prevention programme is a topic of great importance in mine safety studies. These studies were basically conducted to recognize the risk and several factors that affect the safety in mines. A roof fall accident in an underground coal mine has been quantified by Duzgun (2005) through risk assessment techniques and further Pinto et al. (2011) evaluated the occupational risk based on failure mode effect and analysis (FMEA) and Mandal and Maiti (2014) analyzed the risk of failure of underground mining machinery in coal mines. A weibull distribution based hazard mitigation scheme has been recommended by Khanzode et al. (2011) for better planning and control of hazards. A questionnaire survey has been conducted by Naderpour et al. (2015) to scrutinize the factors related to human risk analysis interface of system activities in underground mines.

TIME SERIES ANALYSIS

Mine accident data analysis (MADA) was conducted by a very few researcher in the globe through time series analysis. To achieve a goal of zero accident potential (ZAP), Kohler (2015) described lost time injuries, fatality rate and fatal accidents from 1983 to 2012 in coal mines of United States which is followed by Unsar and Sut (2009) and they observed the upward fluctuation of fatal and serious bodily injury curve which resulting from occupational injuries of coal mines in Turkey from 2000 to 2005. For miners perceptual skills improvement, Kowalski Trakofler and Barrett (2003) stated that hazard recognition training which has to transfer potential for improving miners' ability to recognize hazards in underground coal mines and Morillas et al. (2013) carried out an exploratory comparative study to reduce risk of workplace accidents through time series analysis.

The influence of several causal factors on the severity of injury in mines and the effect of each of the factors is determined by various multivariate models. Though, accident analysis of injury experience data by statistical model are very few, but recent trends shows that statistical modelling techniques are the best for the analysis of better injury prevention and safety control for mine safety studies. Several factors such as miner's age, job experience, shift timing, occupation, degree of injury has already been discussed through multinomial logit model by Maiti et al. (1999) and more specifically, Bhattacharjee et al. (2013) applied logistic regression model and a conditional logistic regression model has been carried out by Kunar et al. (2014) based on questionnaire survey to identify the relationship between several environmental and social factors for miners. In France, Chau et al. (2010) constructed a variety of logistic regression models through miners' response. In the later 2000, the most popular loglinear model was applied by Ghosh and Bhattacharjee (2009) to emphasize the relation between significant safety measures. A sensitivity analysis was conducted by Palei and Das (2008) by Monte Carlo simulation to correlate the parameters on support safety factor. In the application of path model, structural equation modelling is well known for linearity testing which is frequently adopted in accident analysis, safety management and other fields and it should be constructed in the area of research to examine the interaction among all endogenous and the exogenous latent parameters. First of all, for Indian mine safety context, Maiti and Bhattacharjee (2000) presented a SEM considering the exogenous strings such as work exposure, absenteeism; etc. and production, violation, etc. as endogenous. By amalgamating all personal and socio-technical parameters of mine workers. Paul and Maiti (2008) developed a SEM and result shows that the all variables are the major concerns for safety improvement in the mines under study. In Indian mine safety scenario, Maiti (1999), Paul (2004), Ghosh et al. (2004), Palei (2006), Kunar (2008), Khanzode (2010) have established numerous relationship based on multivariate analysis which address various issues in mine safety management. The literature review revealed that, although the studies mentioned above point out various causal factors mainly personal, social and behavioural for mine accident analysis and prevention which was investigated separately through quantitative model.

3. Materials and methods

The study was conducted in two neighbouring underground coal mines within a large public sector organisation in the eastern part of India. The mines were selected because the work injury rates of these mines are high. Data were

collected through accident/injury reports available at the mines and through a questionnaire survey. Interviews were conducted with individual miner through a random sampling from different categories of workers from both of the mines. The workers were approached individually at the mines. Two groups, namely, a non-accident group (NAG) and an accident group (AG) of workers were identified to study the influence of different factors contributing to mine accident/injury amongst the workers. AG workers were defined as workers in the mine who had sustained a prior mine-related injury during the last five years, while NAG workers were defined as those with no history of a prior mine-related injury during the last five years. In this study, AG workers are treated as cases and NAG workers as controls. Initially, a random selection amongst the cases was done for interview. A few interested, experienced mine workers, who were fluent in reading and writing, were asked to help in conducting the questionnaire survey for others. Questionnaires for most of the mine workers who were not fluent in reading and writing were read out. It took 45 - 60 minutes to fill in the questionnaire forms for an individual participant. Out of 175 participants from the case group, 150 miners' answers matched the inclusion criteria of the study. Inclusion criteria consist of proper identifying information and a proper response to each of the questions. Through frequency matching, 150 participants were chosen randomly from the participants in the control group, whose answers matched the inclusion criteria of the survey. Overall, of the 435 participants, 295 miners participated from the case group and 140 miners participated from the control group with an overall response rate of 80%. Of the 295 cases, 185 workers were from Mine 1 and 110 were from Mine 2.

4. Analysis

The model depicted in Fig. 1 will be tested in LISREL 9.2 (Joreskog and Sorbom, 1998) by employing the two stage approach suggested by Anderson and Gerbing (1988). In this approach, the first step involves testing a measurement model via confirmatory factor analysis and the second involves testing a series of structural models including the hypothesised model. The purpose of a measurement model is to describe how well the observed or measured variables serve as measurement instruments for the underlying latent variables (Sumer, 2003). The measurement model also estimates the non-directional relationships (correlations) among the latent variables. The purpose of a structural model is to test a general model that prescribes the relationships among the latent variables. The relationships between the exogenous and endogenous variables are denoted by gamma (γ) parameters and between endogenous variables are denoted by beta (β) parameters. Zeta (ζ) parameter represents the residual variance (Hansen, 1989).

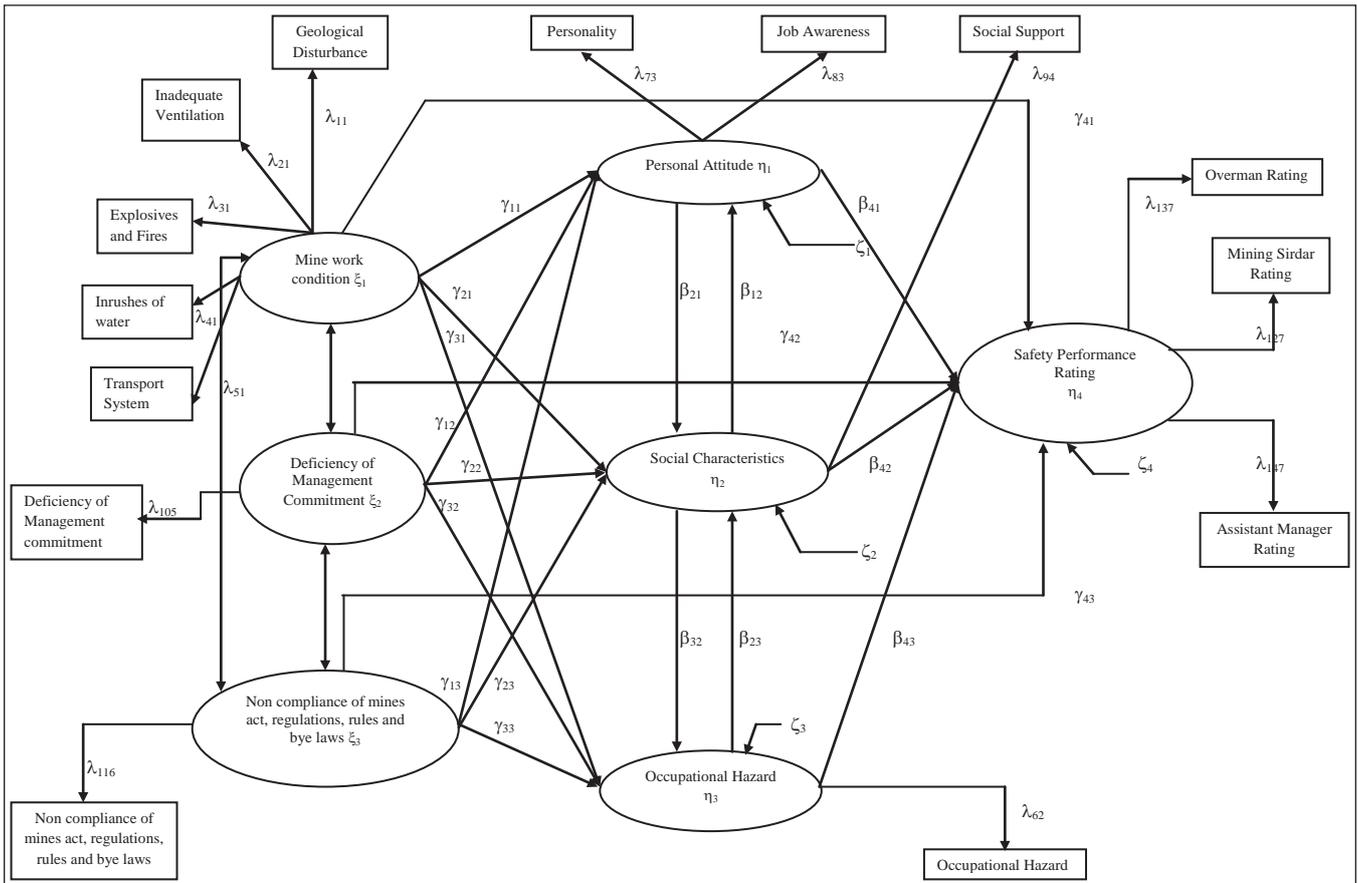


Fig. 1: Hypothesised accident model path diagram

5. Bayesian inferences in SEM

In the traditional approach to statistical inference, the probability of an event is interpreted as the relative frequency of an event given an infinite sequence of samples from an identical (i.e. fixed) probability distribution. This notion is made explicit in Null hypothesis significance testing (NHST), where the researcher asks how likely it is to observe the estimated parameter values (i.e. the data), if a Null hypothesis (which defines the assumed sampling distribution) were true. If this likelihood is below a certain threshold α (e.g. 0.05), the researcher rejects the Null hypothesis.

Selected variables which are measured by multiple observed variables are common in substantive research. SEM which can be regarded as path model is useful models to assess interrelationships among variables and have been widely applied to many fields. When applied with data augmentation and recent techniques in statistical computing, the Bayesian approach has been found to be a powerful tool for analysing many important extensions of the basic structural model. We are going to introduce a basic SEM, present a brief discussion on the Bayesian approach and illustrate it with a simulation study, and review some recent extension.

Bayesian approach is based on exact posterior distributions for the parameters and variables estimated by MCMC.

The Bayesian estimation views parameters as variables and estimates the posterior distributions by combining the likelihoods of the data with prior distributions (Muthen, 2010). As sample sizes increases, Bayesian and standard estimators of the parameters should converge. However, an appealing feature of the Bayesian approach is that posterior distributions are obtained both for the parameters and variables.

The posterior distribution of parameters is computed by the complete data likelihood multiplied by the prior and divided by the marginal likelihood. The data likelihood and priors can be easily calculated; however, the calculation of the marginal likelihood is very challenging, because it typically involves a high-dimensional integration of the likelihood over the prior distribution. In this paper, instead of calculating the marginal likelihood mathematically, MCMC techniques were applied to numerically obtain the marginal likelihood values by generating random draws from the posterior distribution. Due to the conditional normality structure of the loglinear model, MCMC computation can be performed by Gibbs sampling algorithm (Gelfand and Smith, 1990; Geman and Geman, 1984).

Once all the full conditional posteriors are computed, the following Gibbs sampling algorithm can be implemented.

The Gibbs sampling is an iterative algorithm by initialising the parameters and updating all posteriors and to converge the parameter values. The number of iterations for the Gibbs sampler was determined using an extension of the Raftery Lewis diagnostic (Raftery and Lewis, 1992) for multiple chains, which determines the number of iterations necessary to estimate a quantile of the parameters with a given accuracy, as well as the number of 'burn-in' iterations to discard (Warnes, 2005).

6. Conclusions

This paper presents an approach of Bayesian inference in SEM considering mine, miners and management variables as exogenous and endogenous variables to reduce the errors in the statistics. Through respondents response the model is established to identify the root causes of accident which has to be a role model for the underground coal mines in India. The Bayesian structural equation model is iteratively solved in Bayesian context and the sample is randomly sampled from the posterior distribution using Gibbs sampling. The results reveal a better result in terms of number of statistical significant parameters and moreover, the error statistics by reducing error also identifies the actual cause of mine accident. It is observed that the introduction of Bayesian statistics in traditional SEM for questionnaire survey data can improve the model performance by reducing the error. The results also demonstrated that the Bayesian inference in SEM is less sensitive with number of sample size. The Bayesian SEM is a robust approach than classical SEM since it does not need any assumption of the distribution function like normality.

References

- Katiyar, S. N., Sinha, V. K. (2008): "Mine Disaster Prevention - A Human Approach". In: Proceedings of the 19th national convention and seminar on 'Disaster in mines' organized by Institution of Engineers, Dhabad local centre in association with Department of Mining Engineering, I.S.M. Univesity, Dhanbad, India, 10 – 11 March, pp.113–119.
- Directorate General of Mines Safety, (2016): "Standard Note", Office of Directorate General of Mines Safety, Ministry of Labour and Employment, Dhanbad, Hirapur, 826001, Jharkhand, India.
- Regan T. L., Xing Liu, E. A. Lutz and Jefferey L. (2014): "Age, Injuries, and Costs: A Case Study for U.S. Gold and Coal Mines", 6th Biennial Conference on New Frontiers in Health Policy and Health Care, held in the University of Pennsylvania, during June, 12-15, 2014.
- National Safety Council (NSC), (2004): Estimating the Costs of Unintentional Injuries. Retrieved from <http://www.nsc.org>. [Last accessed 14/10/2016]
- Pathak, M. (2008): Discussion Paper Series No. 002, HSE, United Kingdom.
- Bahn S. (2013): "Workplace hazard identification and management: The case of an underground mining operation", *Safety Science*, vol. 57, pp. 129 – 137.
- Na G., Longzhe J., Peng W., Ling L. (2011): "The Study and Application of Safety Information Management System of the Coal Mines", *Procedia Engineering*, vol. 26, pp. 2051 – 2058.
- Liu Q., Li X., Hassall M. (2015): "Evolutionary game analysis and stability control scenarios of coal mine safety inspection system in China based on system dynamics", *Safety Science*, vol. 80, pp. 13 – 22.
- Cheng C., Lin C., Leu S. (2010): "Use of association rules to explore cause effect relationships in occupational accidents in the Taiwan construction industry", *Safety Science*, vol. 48, pp. 436 – 444.
- Verma A., Khan S. D., Maiti J., Krishna O. B. (2014): "Identifying patterns of safety related incidents in a steel plant using association rule mining of incident investigation reports", *Safety Science*, vol. 70, pp. 89 – 98.
- Autenrieth D. A., Brazile W. J., Sandfort D. R., Douphrate D. I., Román-Muñiz I. N., Reynolds S. J. (2016): "The associations between occupational health and safety management system programming level and prior injury and illness rates in the U.S. dairy industry", *Safety Science*, vol. 84, pp. 108 - 116.
- Tan H., Wang H., Chen L., Ren H. (2012): "Empirical analysis on contribution share of safety investment to economic growth: A case study of Chinese mining industry", *Safety Science*, vol. 50, pp. 1472 – 1479.
- Biddle E. A. (2013): "Is the Societal burden of fatal occupational injury different among NORA industry sectors?", *Journal of Safety Research*, vol. 44, pp. 7 - 16.
- Lebeau M., Duguay P., Boucher A. (2014): "Costs of occupational injuries and diseases in Québec", *Journal of Safety Research*, vol. 50, pp. 89 – 98.
- Dembe A. E., Erickson J. B., Delbos R. G., Banks S. M. (2005): "The impact of overtime and long work hours on occupational injuries and illnesses: new evidence from the United States", *Occupational and Environmental Medicine*, vol. 62, pp. 588 – 597.
- Ibarrondo-Dávila M. P., López-Alonso M., Rubio-Gámez M. C. (2015): "Managerial accounting for safety management. The case of a Spanish construction company", *Safety Science*, vol. 79, pp. 116 – 125.
- Kinilakodi H., Grayson R. L. (2011): "A methodology for assessing underground coal mines for high safety-related risk", *Safety Science*, vol. 49, pp. 906 – 911.
- Lee S., Park I. (2013): "Application of decision tree model for the ground subsidence hazard mapping near abandoned underground coal mines", *Journal of Environmental Management*, vol. 127, pp. 166-176.
- Wang, Y. R., and Gibson, G. E. (2010): "A study of pre project planning and project success using ANNs and regression models", *Automation in Construction*, vol. 19, no. 3, pp. 341–346.
- Duzgun H. S. B. (2005): "Analysis of roof fall hazards and risk assessment for Zonguldak coal basin underground mines", *International Journal of Coal Geology*, vol. 64, pp. 104 – 115.
- Pinto A., Nunes I. L., Ribeiro R. A. (2011): "Occupational risk assessment in construction industry – Overview and reflection", *Safety Science*, vol. 49, pp. 616–624.

22. Mandal S., Maiti J. (2014): "Risk analysis using FMEA: Fuzzy similarity value and possibility theory based approach", *Expert Systems with Applications*, vol. 41, pp. 3527 – 3537.
23. Khanzode V. V., Maiti J., Ray P. K. (2011): "Injury count model for quantification of risk of occupational injury", *International Journal of Injury Control and Safety Promotion*, vol. 18, no. 2, pp. 151 - 162.
24. Naderpour M., Lu J., Zhang G. (2015): "A human-system interface risk assessment method based on mental models", *Safety Science*, vol. 79, pp. 286 – 297.
25. Kohler J. L. (2015): "Looking ahead to significant improvements in mining safety and health through innovative research and effective diffusion into the industry", *International Journal of Mining Science and Technology*, vol. 25, pp. 325 – 332.
26. Unsar S., Sut N. (2009): "General assessment of the occupational accidents that occurred in Turkey between the years 2000 and 2005", *Safety Science*, vol. 47, pp. 614 – 619.
27. Kowalski-Trakofler K. M., Barrett E. A. (2003): "The concept of degraded images applied to hazard recognition training in mining for reduction of lost-time injuries", *Journal of Safety Research*, vol. 34, pp. 515 – 525.
28. Morillas R. M., Rubio-Romero J. C., Fuertes A. (2013): "A comparative analysis of occupational health and safety risk prevention practices in Sweden and Spain", *Journal of Safety Research*, vol. 47, pp. 57–65.
29. Maiti J., Bhattacharjee A. (1999): "Evaluation of risk of occupational injuries among underground coal mine workers through multinomial logit analysis", *Journal of Safety Research*, vol. 30, no. 2, pp. 93 - 101.
30. Bhattacharjee, A., Kunar, B., M Baumann M, Chau N. (2013): "The role of occupational activities and work environment in occupational injury and interplay of personal factors in various age groups among Indian and French coalminers", *International Journal of Occupational Medicine and Environmental Health*, vol. 26, no. 6, pp. 910 - 929.
31. Kunar, B. M., Bhattacharjee, A., Samanta B., Mitra A. (2014): "Relationship of individual and work related factors with obstructive type lung function disorder of underground coal miners: A spirometry study", *Journal of Geology and Mining Research*, vol. 6, no. 5, pp. 57 - 63.
32. Chau N., Wild P., Dehaene D., Benamghar L., Mur J. M., Tournon C. (2010): "Roles of age, length of service and job in work-related injury: a prospective study of 446 120 person-years in railway workers", *Occupational and Environmental Medicine*, vol. 67, pp. 147-153.
33. Ghosh A. K., Bhattacharjee A. (2009): "Loglinear model for assessment of risk factors of occupational injuries in underground coal mines", *Journal of Geology and Mining Research*, vol. 1, no. 2, pp. 25–33.
34. Palei S. K., Das S. K. (2008): "Sensitivity analysis of support safety factor for predicting the effects of contributing parameters on roof falls in underground coal mines", *International Journal of Coal Geology*, vol. 75, pp. 241 – 247.
35. Maiti J., Bhattacharjee A. (2000): "A causal model for evaluation of mine safety", *Mining Technology: Transactions of the Institutions of Mining and Metallurgy: Section A*, vol. 109, no 1, pp. 55 - 59.
36. Paul P. S., Maiti J. (2008): "The synergic role of sociotechnical and personal characteristics on work injuries in mines", *Ergonomics*, vol. 51, no. 5, pp. 737 – 767.
37. Maiti. J. (1999). "An Investigation of Multivariate Statistical Models to Evaluate Mine Safety Performance". Unpublished Ph.D. Thesis, Department of Mining Engineering, Indian Institute of Technology, Kharagpur, 217 pp.
38. Paul P. S. (2004): "Mine Safety Management - an Application of Personal and Sociotechnical Characteristics of Work Injury in Mines", unpublished Ph.D. dissertation, Department of Mining Engineering, Bengal Engineering and Science University, Shibpur, pp. 231.
39. Ghosh A.K., Bhattacharjee A., Chau N. (2004): "Relationships of working conditions and individual characteristics with occupational injuries: A case-control study in coal miners", *Journal of Occupational Health*, 46, pp. 470 - 478.
40. Palei S. K. (2006): "Development of Risk Analysis Model for Roof Fall Hazards in underground coal from Eastern South mine India", unpublished Doctoral dissertation, Indian Institute of Technology, Kharagpur, Midnapore, 721302, West Bengal, India, pp. 152.
41. Kunar B. M. (2008): "Impact of Occupational and Individual Characteristics in Underground Coal Miner's Injuries: Matched Analysis in a Case-Control Study", unpublished Doctoral dissertation, Indian Institute of Technology, Kharagpur, Midnapore, 721302, West Bengal, India, pp. 147.
42. Khanzode V. V. (2010): "Modeling Risk of Occupational Injury", unpublished Doctoral dissertation, Indian Institute of Technology, Kharagpur, Midnapore, 721302, West Bengal, India, pp. 220.
43. Joreskog, K. G. and Sorbom, D. (1998): "LISREL 9.2: Structural equation modelling with the SIMPLIS command language", Hillsdale, NJ: Erlbaum.
44. Anderson, J.C. and Gerbing, D. W. (1988): "Structural equation modelling in practice: a review and a recommended two step approach", *Psychological Bulletin*, vol. 103, pp. 411–425.
45. Sumer, N. (2003): "Personality and behavioral predictors of traffic accidents: testing a contextual mediated model", *Accident Analysis and Prevention*, vol. 35, pp. 949–964.
46. Hansen, C. P. (1989): "A causal model of the relationship among accidents, biodata, personality and cognitive factors", *Journal of Applied Psychology*, vol. 74, pp. 81–90.
47. Muthen, B.O. (2010). Bayesian analysis in Mplus: A brief introduction. Retrieved from <http://www.statmodel.com> [Last accessed 11/10/2016].
48. Gelfand, A.E., and Smith, A.F.M. (1990). Sampling-based approaches to calculate marginal densities. *Journal of the American Statistical Association*, 85, 398–409.
49. Geman, S., and Geman D. (1984). Stochastic relaxation, Gibbs distributions and the Bayesian restoration of images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 6, 721–741.
50. Raftery, A., and Lewis, S. (1992): "How many iterations in the Gibbs sampler", *Bayesian Statistics*, vol. 4, no. 2, pp. 763 – 773.
51. Warnes, G. R. (2005): "MCGibbsit: Warnes and Raftery's MCGibbsit MCMC diagnostic" (R package version).