AVEEK MANGAL
and
P. S. PAUL

Bayesian inference of structural equation modelling in mine accident and safety research – an approach

This paper proposed an approach of Bayesian inference in structural equation modelling (SEM) to evaluate the accident causation in underground coal mines in India. The statistics on accident events and reportable incidents has not shown the corresponding levels of improvement. In the area of major hazards control, the mining industry has emphasized mainly on past experiences and lessons learnt. However, the conventional risk management processes are not able to achieve the goal of zero accident potential (ZAP) due to a tonne of reasons. Bayesian inference SEM is necessary to develop the models and the coefficient of parameter estimation. The Markov Chain Monte Carlo sampling in the form Gibbs sampling was applied for sampling from the posterior distribution. The results revealed that all coefficients of SEM parameters are statistically significant. The Bayesian error statistics reveals that this model provides an approach to reduce accidents in underground coal mines of India.

Keywords: *Mine safety, structural equation modelling, Bayesian inferences.*

Introduction

The safety of mine workers and employees is a major social responsibility and it is a challenging task to ensure zero incidents at mines all over the world. Though, hazard, accident and injury are related but it is totally different concepts. Every accident need not necessarily result in injury, but every injury is a result of an accident. The Mines Act, 1952 is fragmented 'injury' in three divisions such as 'fatal injury', 'serious bodily injury', and 'reportable injury'. A large number of diverse literatures are available on mine safety, injury and accident research in mining and non-mining sector and the available literature has segregated in different bodies of knowledge such as injury control, accident analysis, safety engineering, industrial psychology and socio-technical theory, human engineering and law (Paul, 2008; Maiti, 2010).

Present status of Indian coal mine safety

With about 500 coal mines, 80 oil projects and 5000 metalliferous mines of different sizes employing over one million persons on daily average basis, the mine safety problems in India create many challenges. The principal statute The Mines Act, 1952, technical statute The Coal Mines Regulations 1957, welfare statute The Mines Rules 1955, the Workmen's Compensation Act 1923 and Mines Vocational Rule 1966 were framed to enhance safety of Indian mining work personnel. Various types of measures such as formation of Pit Safety Committee, Safety Talk, Annual Mine Safety Week, Bi-partite and Tri-partite Safety Committee and Internal Safety Organisation were taken in order to diminish accident rates and improve safety performance after the nationalization of coal industry in 1975.

Although the acquiescence of stern mine safety act, regulations, rules, bye-laws and circulars issued by Directorate General of Mines Safety, Indian coal mining industry still continues to generate threat to accidents/ injuries to miners. A methodical study of accident statistics emphasizes the impact of accident/injury in the coal mining industry. According to the Directorate General of Mines Safety (DGMS) report of accident statistics, there were fatalities and serious injuries for the year 2014-15 (DGMS Standard Note, 2015). The national level fatalities, injuries and their rates per thousand persons employed since 1901 (ten yearly average) are shown in Figs.1 and 2.

From Fig.1, it is seen that the number of fatalities as well as injuries has no evidence since 1985. Fig.2 reveals that the fatality and injury rates excluding disasters progressively came downwards; however, there have been fluctuations over the year up to 1960, then decreasing tendency up to 1980 and it remains more or less stagnant ever since 1983. The last ten years accident statistics of fatal and serious injuries and their rates in Indian coal mines are shown in Table 1.

On an average, there are 83 fatal and 653 serious accidents in coal mines. The average death rate per 1000 persons employed per year is around 0.258 and that of serious injury rate is around 1.793. The accident/injury experience data evidently state that for the last 30 years there is no enhancement in terms of accident/injury occurrences in Indian coal mines. Perhaps, traditional approaches of safety culture and training have accomplished saturation limit of effectiveness for accident reduction. A fresh approach is

Messrs. Aveek Mangal, PhD Scholar and P. S. Paul, Assistant Professor, Department of Mining Engineering, Indian Institute of Technology (Indian School of Mines), Dhanbad, 826 004, Jharkhand, India

TABLE 1: TREND IN FATAL AND SERIOUS ACCIDENTS IN COAL MINES FOR THE PERIOD 2005-2014

Year	Number of accidents		Number of persons		Rate per 1000 persons employed		Death rate/Mt
	Fatal	Serious	Killed	Seriously injured	Death rate	SI Rate	
2005	96	1106	117	1138	0.29	2.85	0.28
2006	78	861	137	891	0.36	2.31	0.32
2007	76	923	78	951	0.21	2.51	0.16
2008	80	686	93	709	0.25	1.92	0.18
2009	83	636	93	660	0.25	1.76	0.17
2010	97	480	118	511	0.32	1.39	0.20
2011	65	533	67	556	0.18	1.52	0.11
2012	83	512	87	523	0.24	1.43	0.14
2013	82	456	87	468	0.24	1.28	0.14
2014	84	337	87	353	0.24	0.96	0.14

(Source: Standard Note, 2015; Directorate General of Mines Safety, Dhanbad)

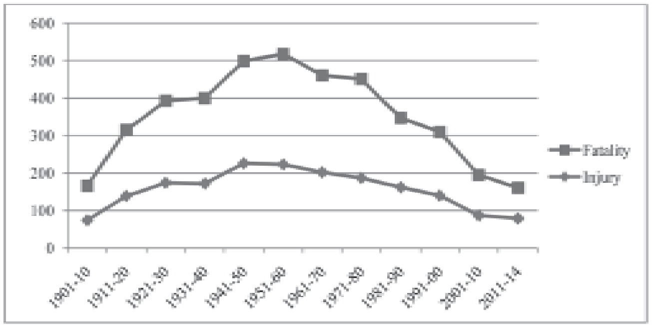

Fig.1 Number of fatalities and injuries for ten yearly averages since 1901 to 2014

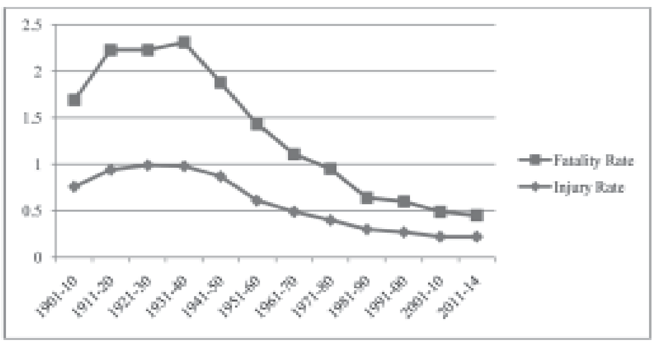

Fig.2 Number of fatalities and injuries rates per thousand persons employed for ten yearly averages since 1901 to 2014

supposed to obligatory for further diminution of accidents/ injuries in coal mines.

Taxonomy of literature

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. This literature can be classified as injury experience based, questionnaire survey based. Based on availability of different literature, books, journals, conference proceedings, injury/accident literature can be categorized in seven categories such as classification based analysis, correlation and bivariate regression analysis, reliability analysis, risk analysis, cost benefit analysis, time series analysis, multivariate analysis which is given in Table 2.

Materials and methods of structural equation modelling (SEM)

Structural equation modelling (SEM) is frequently adopted in accident analysis, safety management, and other fields and it will be investigated in this research to examine the interaction among the endogenous and the exogenous latent parameters. According to Palomo et al. (2007), an accident is the result of the interaction between latent and active failures. Active failures are the immediate observable causes which are easily identified. Root cause analysis can diagnose the root cause and then predict the future outcome of an accident in an application. The direct cause segregates a number of categories (i.e. geological, technical, personal and social factors) simultaneously indirect cause has been attributed as non-compliance of mines act, rules, and regulation and bye laws. Hence a structural equation modelling will be investigated by considering the non-compliance of mines act, rules, regulations, and bye laws as latent parameter while analyzing the mine injury/experience data and the various causative factors responsible for accidents/injuries occurrences in coal mines which affect the safety of mining personnel including consideration of working environment, mining methods, geological conditions, and individual characteristics of miners.

For this SEM, the cause of coal mine accidents of different categories are subdivided into several subcategories and also subcategories are classified into indicators. Indicators are in essence possible contraventions of provisions behind the accident occurrence in underground mines which have been formulated through methodically design of integers. These

TABLE 2: SELECTED REFERENCES ON QUANTITATIVE ANALYSIS OF SAFETY ENGINEERING STUDIES IN MINING SECTOR (AFTER BHATTACHARJEE AND MAITI (2000) AND PAUL (2012))

Quantitative analysis	References	
	Injury experience data	Questionnaire survey based data
Classification based analysis	Bahn (2013) Cagno et al. (2014) Khanzode (2010) Maiti and Bhattacharjee (2000) Saleh and Cummings (2011)	
Correlation and bivariate regression analysis	Liu et al. (2015)	
Reliability and tree analysis	Khanzode et al. (2011) Kinilakodi et al. (2011) Lee and Park (2013)	
Risk analysis	Castro et al. (2016) Kumar et al. (2016) Mandal and Maiti (2014)	Burlet-Vienney et al. (2015) Naderpour et al. (2015)
Cost benefit analysis	Biddle (2013) Ibarrondo-Dávila et al. (2015) Lebeau et al. (2014)	
Time series analysis	Kohler (2015) Morillas et al. (2013)	Cappelletto and Merler (2003)
Multivariate analysis	Basha and Maiti (2016) Chen et al. (2014) Khanzode et al. (2010) Song et al. (2014) Tawiah et al. (2013)	Kunar et al. (2014) Maiti et al. (2004) Paul (2013) Paul and Maiti (2007; 2008) Rahman et al. (2014)

integers are used to assess each and every accident occurred in the mines to be studied. Based on the content analysis method, two steps must be conducted to analyze coal mine accidents. Step 1 is the development of the coding scheme. The coding scheme has been discussed by the research team who came from university and the coal mine company, including two coders. We attributed the indirect causes in the standards of "non compliance of mines act, rules, regulations and bye laws", the direct cause to five such as "mine work condition", "occupational hazards", "personal attitude", "social characteristics" and "deficiency of management commitment". The parameters such as "mine work condition", "deficiency of management commitment" and "non compliance of mines act, rules, regulations and bye laws" are considered as exogenous parameters and "personal attitude", "social characteristics" and "occupational hazards" are considered as endogenous parameters. The following conceptual hypothesized research framework of this study is proposed based on the root cause analysis and the injury experience data which is given in Fig.3.

The model depicted in Fig.3 is going to test 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 indicators serve as measurement instruments for the underlying latent constructs (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 parameters. The relationships between the exogenous and endogenous variables are denoted by gamma (γ) parameters and between endogenous parameters are denoted by beta (β) parameters. Zeta (ζ) parameter represents the residual variance (Hansen, 1989).

Bayesian inference in structural equation modelling

Parameters which are measured by multiple observed variables are common in substantive research. Structural equation model, which can be regarded as nested model, is largest useful statistical models to assess inter-relationships among all parameters 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 classical structural equation model. We are going to introduce a SEM and 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

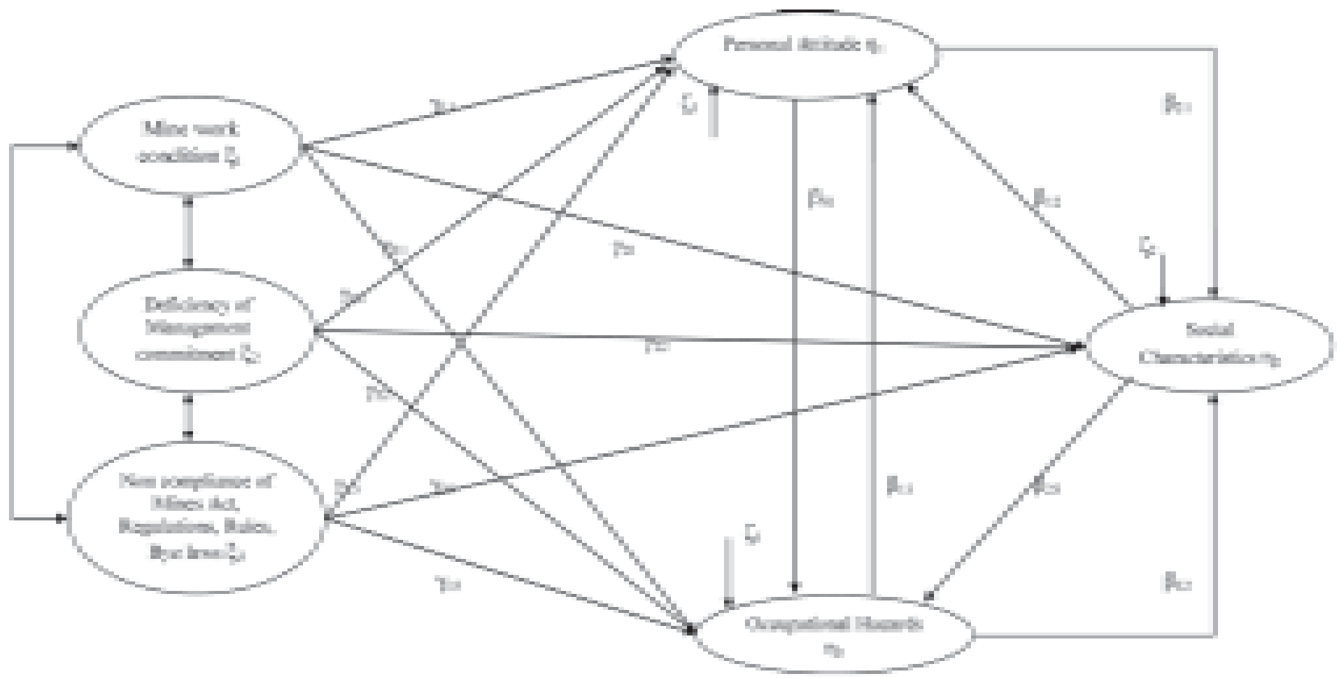

Fig.3 Hypothesised accident model path diagram

Markov chain and Monte Carlo (MCMC) simulation. 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 increase, 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 are applied to numerically obtain the marginal likelihood values by generating random draws from the posterior distribution. Due to the conditional normality structure of the SEM, 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

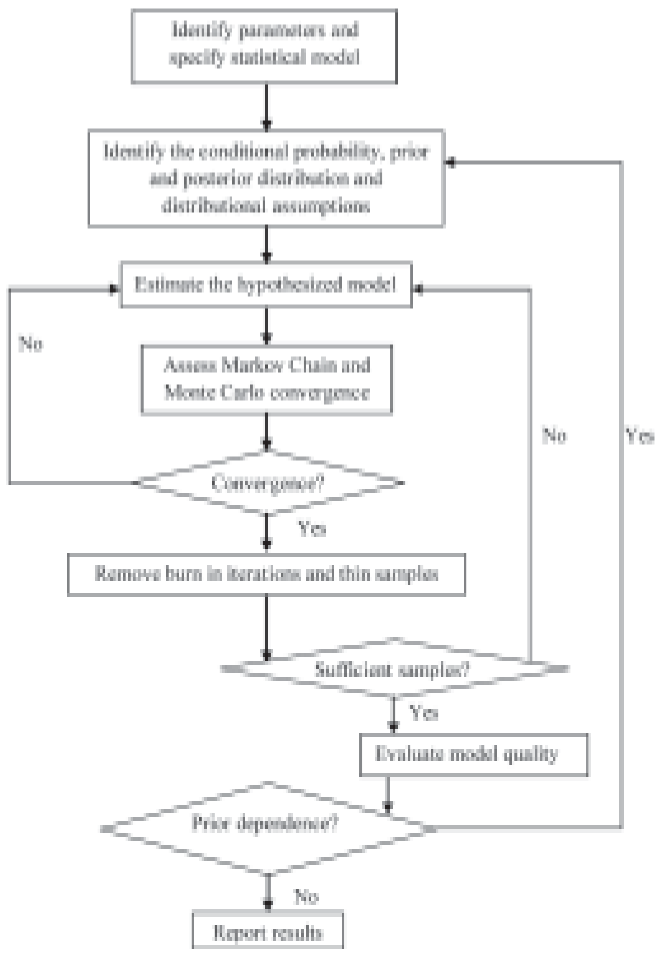

Fig.4 Proposed process for Bayesian estimation of structural equation modelling

to estimate a quantile of the parameters with a given accuracy, as well as the number of ‘burn-in’ iterations to discard (Warnes, 2005).

In the Bayesian SEM, the posterior distribution of model parameters and latent variables were estimated using Gibbs sampling algorithm. Since, most of the accident causation materials, not much information is available other than the observed data, and fixed random priors are generally selected (Paul and Maiti, 2007; Chatterjee, 2014). Therefore, the fixed priors for the parameters are selected. For fixed prior based Bayesian SEM, the initial values of the prior means are set randomly within -1 to +1 for all factor loading parameters and for the structural parameters and with large variance (102). The WinBUGS software is used for posterior calculation and Gibbs sampling and a flow chart is recommended for Bayesian estimation of structural equation modelling and has been given in Fig.4.

The algorithm is run for several chains of more than 5000 iterations each using initial random values from the assumed prior distributions. The Raftery Lewis algorithm indicates 82,000 iterations are adequate to estimate the 2.5% and 97.5% posterior quantiles to within ± 0.011 with 95% probability, after discarding a number of iterations from each chain for 'burn in'. Finally, goodness of fit statistics and test of significance have to be done. Especially, comparison between the values of goodness of fit indices (GFI), mean absolute error (MAE), root mean squared error (RMSE) for classical SEM and Bayesian SEM should be compared. The value of GFI which is developed by using Bayesian approach can provide better fit model than the standard classical SEM.

Conclusion

This paper presents the accident causation model using structural equation model within the Bayesian framework. The coefficient of parameters has to be estimated and also test of significance has to be done. 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 was randomly sampled from the posterior distribution using Gibbs sampling.

The results reveal a better result in terms of a number of statistical significant parameters and more over, 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 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

1. 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.
2. Bahn, S. (2013): “Workplace hazard identification and management: The case of an underground mining operation,” *Safety Science*, vol. 57, pp. 129-137.
3. Basha, S. A. and Maiti, J. (2016): “Assessment of work compatibility across employees' demographics: a case study,” *International Journal of Injury Control and Safety Promotion*, pp. 1-14.
4. 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.
5. Burlet-Vienney, D., Chinniah, Y., Bahloul, A. and Roberge, B. (2015): “Design and application of a 5 step risk assessment tool for confined space entries,” *Safety Science*, vol. 80, pp. 144-155.
6. Cagno, E., Micheli, G. J. L., Jacinto, C. and Masi, D. (2014): “An interpretive model of occupational safety performance for Small and Medium sized Enterprises,” *International Journal of Industrial Ergonomics*, vol. 44, pp. 60-74.
7. Cappelletto, F. and Merler, E. (2003): “Perceptions of health hazards in the narratives of Italian migrant workers at an Australian asbestos mine (1943-1966),” *Social Science and Medicine*, vol. 56, pp. 1047-1059.
8. Castro, C., Ventsislavova, P., Peña-Suarez, E., Gugliotta, A., Garcia-Fernandez, P., Eisman, E. and Crundall, D. (2016): “Proactive Listening to a Training Commentary improves hazard prediction,” *Safety Science*, vol. 82, pp. 144-154.
9. Chatterjee, S. (2014): “Development of uncertainty-based work injury model using Bayesian structural equation modelling,” *International Journal of Injury Control and Safety Promotion*, vol. 21, no. 4, pp. 318-327.
10. Chen, J., Ma, L., Wang, C., Zhang, H. and Ha, M. (2014): “Comprehensive evaluation model for coal mine safety based on uncertain random variables,” *Safety Science*, vol. 68, pp. 146-152.
11. Directorate General of Mines Safety (2015): “Standard Note”, Office of Directorate General of Mines Safety, Ministry of Labour and Employment, Dhanbad, Hirapur, 826 001, Jharkhand, India.
12. 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.
13. 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.
14. 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.

15. Ibarrondo-Dávila, M. P., López-Alonso, M. and Rubio-Gámez, M. C. (2015): "Managerial accounting for safety management. The case of a Spanish construction company," *Safety Science*, vol. 79, pp. 116-125.
16. Joreskog, K. G. and Sorbom, D. (1998): "LISREL 9.2: Structural equation modelling with the SIMPLIS command language," Hillsdale, NJ: Erlbaum.
17. Khanzode V. V. (2010): "Modeling Risk of Occupational Injury," unpublished Doctoral dissertation, Indian Institute of Technology, Kharagpur, Midnapore, 721302, West Bengal, India, pp. 220.
18. Khanzode, V. V., Maiti, J., Ray, P. K. and Tewari, V. K. (2010): "Injury severity assessment for underground coalmine workers," *Applied Ergonomics*, vol. 41, pp. 242-250.
19. Kinilakodi, H. and Grayson, R. L. (2011): "A methodology for assessing underground coal mines for high safety-related risk," *Safety Science*, vol. 49, pp. 906-911.
20. 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.
21. Kumar, P., Gupta, S., Agarwal, M. and Singh, U. (2016): "Categorization and standardization of accidental risk-criticality levels of human error to develop risk and safety management policy," *Safety Science*, vol. 85, pp. 88-98.
22. Kunar, B. M., Bhattacherjee, A., Samanta B. and 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.
23. Lebeau, M., Duguay, P. and Boucher, A. (2014): "Costs of occupational injuries and diseases in Québec," *Journal of Safety Research*, vol. 50, pp. 89-98.
24. Lee, S. and 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.
25. Liu, Q., Li, X. and 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.
26. Maiti, J. (2010): "Development of worksystem safety capability index (WSCI)," *Safety Science*, vol. 48, pp. 1369-1379.
27. Maiti, J. and 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.
28. Maiti, J., Chatterjee, S. and Bangdiwala, S. I. (2004): "Determinants of work injuries in mines - an application of structural equation modelling," *Injury Control and Safety Promotion*, vol. 11, no. 1, pp. 29-37.
29. Mandal, S. and Maiti, J. (2014): "Risk analysis using FMEA: Fuzzy similarity value and possibility theory based approach," *Expert Systems with Applications*, vol. 41, pp. 3527-3537.
30. Morillas, R. M., Rubio-Romero, J. C. and 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.
31. Muthen, B. O. (2010): Bayesian analysis in Mplus: A brief introduction. Retrieved from http://www.statmodel.com (Last accessed September 30, 2016)
32. Naderpour, M., Lu, J. and Zhang, G. (2015): "A human-system interface risk assessment method based on mental models," *Safety Science*, vol. 79, pp. 286-297.
33. Palomo, J., Dunson, D. and Bollen, K. (2007): Bayesian structural equation modeling. In S. Lee (Ed.), Handbook of latent variable and related models. Amsterdam: North Holland, pp. 163-188.
34. Paul, P. S. (2012): "Safety in Indian Coal Mines - Where Do We Go from Here," *International Journal of Ecology and Conservation*, vol. 2, pp. 33-55.
35. Paul, P. S. (2013): "Investigation of the role of personal factors on work injury in underground mines using structural equation modelling," *International Journal of Mining Science and Technology*, vol. 23, pp. 815-819.
36. Paul, P. S. and 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. Paul, P. S. and Maiti, J. (2007): "The role of behavioral factors on safety management in underground mines," *Safety Science*, vol. 45, pp. 449-471.
38. Raftery, A. and Lewis, S. (1992): "How many iterations in the Gibbs sampler," *Bayesian Statistics*, vol.4, no.2, pp.763-773.
39. Rahman, N. A. A., Ismail, A. R. and Mansor, M. A. (2014): "Analysis of the perception of occupational accident in mining and quarry sector towards safe and healthy working environment," *International Journal of Current Research and Academic Review*, ISSN: 2347-3215, Special Issue-1, pp. 95-102.
40. Saleh, J. H. and Cummings, A. M. (2011): "Safety in the mining industry and the unfinished legacy of mining accidents: Safety levers and defense-in-depth for addressing mining hazards," *Safety Science*, vol. 49, pp. 764-777.
41. Song, Z., Zhu, H., Jia, G. and He, C. (2014): "Comprehensive evaluation on self-ignition risks of coal stockpiles using fuzzy AHP approaches," *Journal of Loss Prevention in the Process Industries*, vol. 32, pp. 78-94.
42. Sumer, N. (2003): "Personality and behavioral predictors of traffic accidents: testing a contextual mediated model," *Accident Analysis and Prevention*, vol. 35, pp. 949-964.
43. Tawiah, K. A., Jain, A., Leka, S., Hollis, D. and Cox, T. (2013): "Examining psychosocial and physical hazards in the Ghanaian mining industry and their implications for employees' safety experience," *Journal of Safety Research*, vol. 45, pp. 75 - 84.
44. Warnes, G. R. (2005): "Mcgibbsit: Warnes and Raftery's MCGibbsit MCMC diagnostic." (R package version 1.0.5).