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Original Article

Safety of Workers in Indian Mines: Study, Analysis, and Prediction

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ABSTRACT

Background: The mining industry is known worldwide for its highly risky and hazardous working environment. Technological advancement in ore extraction techniques for proliferation of production levels has caused further concern for safety in this industry. Research so far in the area of safety has revealed that the majority of incidents in hazardous industry take place because of human error, the control of which would enhance safety levels in working sites to a considerable extent.
Methods: The present work focuses upon the analysis of human factors such as unsafe acts, preconditions for unsafe acts, unsafe leadership, and organizational influences. A modified human factor analysis and classification system (HFACS) was adopted and an accident predictive fuzzy reasoning approach (FRA)-based system was developed to predict the likelihood of accidents for manganese mines in India, using analysis of factors such as age, experience of worker, shift of work, etc.
Results: The outcome of the analysis indicated that skill-based errors are most critical and require immediate attention for mitigation. The FRA-based accident prediction system developed gives an outcome as an indicative risk score associated with the identified accident-prone situation, based upon which a suitable plan for mitigation can be developed.
Conclusion: Unsafe acts of the worker are the most critical human factors identified to be controlled on priority basis. A significant association of factors (namely age, experience of the worker, and shift of work) with unsafe acts performed by the operator is identified based upon which the FRA-based accident prediction model is proposed.

1. Introduction

The mining industry exists with the well-recognized fact of having the most arduous working environment, in which the safety and health of the worker are always a prime concern. Mining safety has always drawn the attention of researchers working in the field of health and safety. The metal and mining industry of India has recorded a strong expansion in the recent past, with the expectation that India is to become the second-largest steel producer from 2015. Production volumes have also grown steadily during the period 2007–2015 [1–8]. Therefore, sudden enhancement in production levels of manganese has generated an increase in concern regarding safety scenario of these mines. Nevertheless, adverse working conditions and technological advancements cannot solely be blamed for incidents taking place at the working sites. Patterson and Shappell [9] conducted a study in Queensland, Australia, considering accident data for quarries, open-cut coal mines, underground coal mines, open-cut metal mines, and underground metal mines and revealed that irrespective of the mine type, the major cause of incidents between 2004 and 2008 was skill-based errors performed by the operators, indicating the need to analyze mining accidents from a human-factor perspective in the Indian environment also. The accident analysis in the present work is performed using the modified human factors analysis and classification system (HFACS) framework. HFACS is an adaptation of Reason's swiss cheese model of accident causation. The HFACS is a general human error framework, originally developed and tested within the United States military as a tool for investigating and analyzing the human causes of aviation accidents [10]. One of the major lacuna in the model developed by Reason is a less systematic categorization of the errors. HFACS addresses a more systematic and detailed classification of human errors at four levels and many

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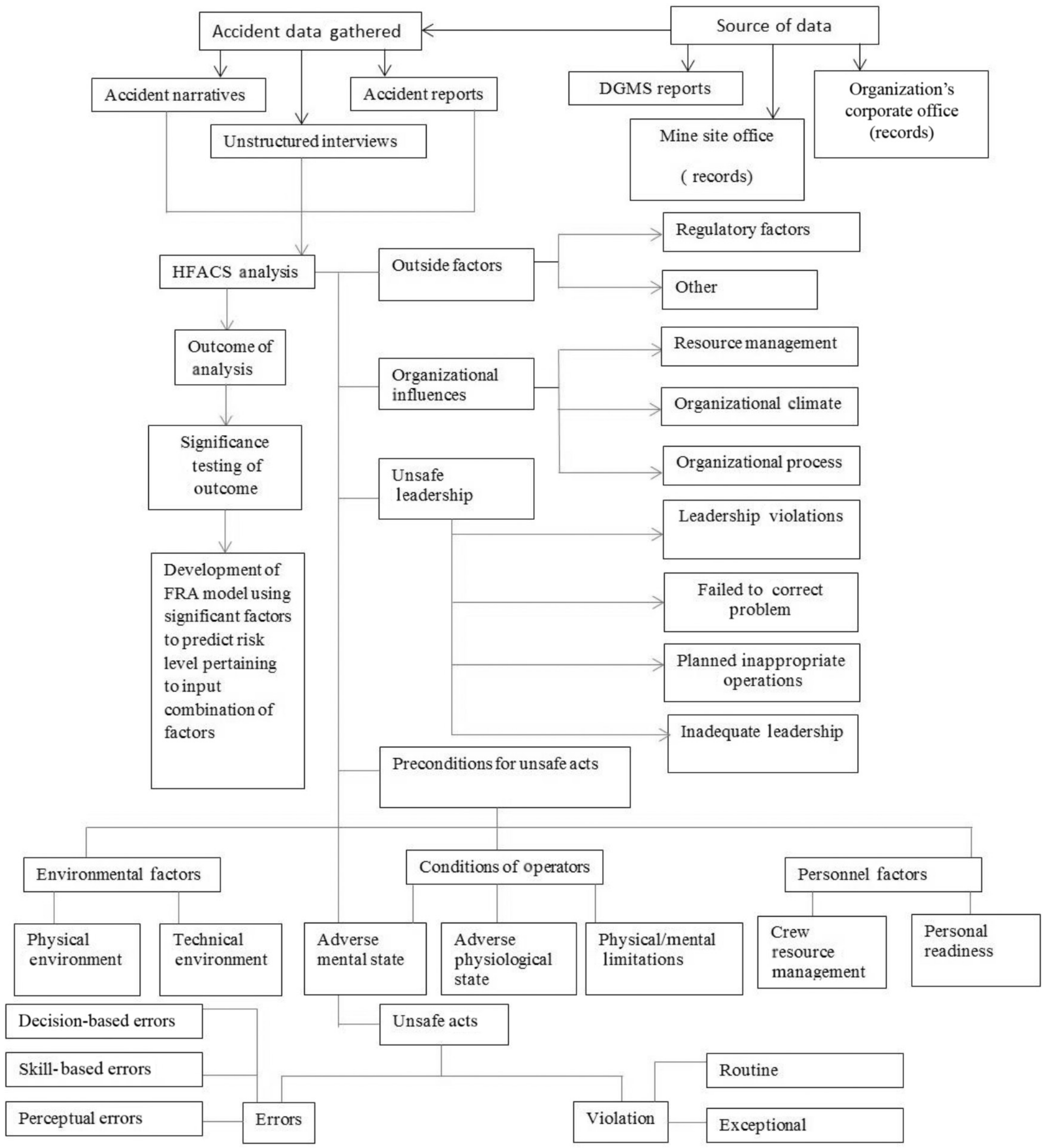

Fig.1. Modified human factors analysis and classification system framework. DGMS, Directorate General of Mining Safety; FRA, fuzzy reasoning approach; HFACS, human factors analysis and classification system.

sublevels, as shown in Fig. 1 below. The original model developed by Wiegmann and Shappell [11] in 2003 includes 19 causal categories of errors, but the framework modified by Patterson and Shappell [9] for the Australian mining industry includes 21 causal categories, including outside factors triggering unsafe consequences. This framework is an investigation model which enables the identification of human factors involved in any occurring/recurring unfavorable incident. It is believed that faulty management, work practices, and traits of the workers can be effectively controlled with an efficient safety management system. This can ultimately contribute towards a considerable reduction in incidents/accidents and aid in the development of a safe working environment. A total of 88% of incidents take place because of human error, 10% because of operating machine-related issues, and 2% because of an act of God [12]. HFACS was primarily adopted for the aviation industry [10,11,13–21], but the importance of the framework was realized and gradually adopted in other fields, such as in the analysis of marine accidents to identify the contribution of human error towards any marine mishap [22,23], in the medical industry to identify the common human mistakes made during any surgical process [24], etc. Application of this framework is not specifically for the area of manganese metal mines, although a similar kind of framework was developed for the coal and metal mining industry in Australia [9]. In 2011 another research was carried out, utilizing the accident data related to underground and surface operations in mining in Australia, to understand the human factors involved in the accidents and to highlight the impact of ill decision, policies/regulations, and leadership lacunas in the organization that eventually develops accident scenarios [25]. Because the first research [9] was conducted with the same database, the primary focus was upon Levels I and II of HFACS, meaning the factors related to the sharp end in the industry; later the focus was shifted to Levels III and IV [25], issues related to leadership practices, organizational factors, outside factors, etc. A fuzzy-based model can be used to resolve issues related to data uncertainty, vagueness, and impreciseness [26–29]. Application of the fuzzy-based approach in the area of risk and safety has gained significant importance in recent years because the data related to safety and accidents is highly uncertain and vague in nature. Analysis of such data and obtaining a robust and reliable outcome for critical issues such as safety has always been a challenge, which has evidently been resolved in the number of cases adopting this approach [30–32]. Baker et al [33] proposed fuzzy analytic hierarchy process (FAHP) approach for the assessment of risk level in the Waterloo rail depot. The criteria considered for evaluation of risk level using a fuzzy approach are "consequence" and "exposure frequency of occurrence". Grassi et al [34] applied a fuzzy technique for order of preference by similarity to the ideal solution (FTOPSIS) for risk evaluation in the Italian sausage-making industry. Gurcanli and Mungen [35] adopted fuzzy logic in a tunneling construction site for assessment of risk. Wang et al [36] proposed a fuzzy failure mode and effects analysis approach for risk assessment, the outcome of which is a fuzzy risk priority number computed based upon criteria such as occurrence, severity, and detection. Zhou [37] proposed a hybrid model of set pair analysis and fuzzy logic theory for real-time risk assessment for storing flammable gas. As an outcome, deviations from the safety levels related to hazard factors such as gas leakage, pressure of gas, etc., can be timely assessed and accidents can be predicted and prevented. Liu and Tsai [38] proposed a fuzzy risk assessment model for the construction industry. The proposed model is a hybrid model with quality function deployment (QFD), fuzzy analytic network process (FANP) (for prioritization of hazards), and failure mode effects analysis. Risk assessment in uncertain environments using triangular fuzzy numbers gives better and more reliable results, as the uncertainty and vagueness of the data can be managed with a fuzzy approach [39]. Beriha et al [40] proposed a fuzzy-based generalized risk assessment model that can be adopted irrespective of industry type. Input parameters considered in this model are the expenses involved in healthcare, safety training, upgrading process-related tools, and safety equipment and tools. Output parameters are accidents that do not cause any disability and do not involve any lost work days, accidents that caused lost work days, etc. Zheng et al [41] proposed an FAHP risk assessment model for assessment of risk in the industries where the environment is hot and humid. Factors considered for assessment of risk were working, worker, and environment, with 10 subfactors to evaluate the level of risk adopting the trapezoidal FAHP technique, and as an outcome the safety index is evaluated. Risk and safety are also assessed using this approach specifically in the mining industry and the outcome obtained is considerable in deducing significant conclusions related to safety levels in mines. Mahdevari et al [42] evaluated health and safety levels in underground coal mines in Kerman, Iran, using a fuzzy technique for order of preference by similarity to ideal solution. Altogether 86 hazards with eight hazard categories were identified. Hazard categories identified were geo-mechanical, geochemical, electrical, mechanical, chemical, environmental, personal and social, and cultural and managerial risks. Verma and Chaudhri [43] proposed a fuzzy-based risk assessment approach in which the combined output of fuzzy reasoning approach (FRA) and FAHP is considered to evaluate the level of risk associated with hazard factors. Criteria for risk evaluation identified are consequence of severity, level of exposure, and frequency of occurrence, and hazard factors identified are ground movement, winding in shaft, transportation by machinery, machinery other than transportation, explosives, electricity, and dust/gas. Verma et al [44] proposed an FRA-based risk assessment model for metal mines in India, for cause-wise and place-wise identified hazard factors. Verma and Chaudhri [45] proposed a fuzzy-based risk assessment model, the outcome of which is a risk score for the assessment of worker safety. Verma and Gupta [46] proposed a fuzzy-based risk assessment approach, the outcome of which is validated by the outcome of the conventional method of risk assessment (i.e., rapid ranking method) adopted majorly in the Indian mining industry for broad brush risk assessment. Rapid ranking method is not a robust tool for assessment of risk as it is complex; calculations need to be started from scratch so it is time consuming, continuous involvement of experts with immense experience is required, and many more lacunas have been identified by the author. But the proposed approach is found to be suitable for the case of the mining industry, with robust applicability in other industries also. The existing literature related to the application of fuzzy-based approaches is highly indicative that adoption of the same for the proposed model would be suitable. The present work focuses upon analysis of mining accidents with the perspective of the involvement of human factors as a precursor to mishaps using a modified HFACS framework. Accidents are coded as per the following categories: unsafe acts of operators, preconditions to unsafe act, unsafe leadership, organizational factors, and outside factors, which are further classified into 21 categories for detailed assessments. Subsequently an accident prediction fuzzy-based model is proposed to predict the possibility of the occurrence of mishaps based upon the age of the worker, experience of the worker, and shift timings in which the worker will be working. The research emphasizes human-based factors leading to accidents; therefore, this indicates the need to understand the chance of mishap based upon factors such as age, experience of worker, etc., considering the possibility that these are underlying reasons causing error-making behavior of an operator.

2. Materials and methods

2.1. Data

The accident data reports, summary sheets, and narratives referred for analysis were gathered from one of the major manganese ore extraction central government undertaking companies with four mining sites in Maharashtra and six mining sites in Madhya Pradesh in India. Accident data spanning from 1985 to 2015 was referred for analysis with a total of 119 case histories. Among these, 17 cases were found to be partially documented and were discarded; the remaining 102 cases were finally considered. For accidents leading to fatalities the reports were retrieved from the Directorate General of Mining Safety, because such reports were submitted to the central body in consideration of the severity of the outcome. The forms and reports referred were in standard format and uniform, as required by the Directorate General of Mining Safety. The data combined both underground and open-cast mines.

2.2. Coding process

One human factors specialist along with three seasoned experts with nearly 40 years of experience in the industry, analyzed, coded the cases, and categorized human factors. Because there was one rater the consensus classification was deemed appropriate for the analysis and the concern regarding interrater reliability was insignificant. Incidences were analyzed for each category of the HFACS framework for coding.

3. Outcome of HFACS analysis

Table 1 describes the details of causal factors. The frequency of the cases may add up to more than 100% because one incident might be associated with more than one causal category. As expected, the maximum contribution to the unsafe incident

Table 1
Frequency of cases associated with causal code categories

HFACS category	Frequency	n (102) (%)
Outside factors		
Regulatory influences	0	0
Other influences	0	0
Organizational influences		
Organizational climate	4	3.9
Organizational process	6	5.8
Resource management	4	3.9
Unsafe leadership		
Inadequate supervision	23	22.5
Planned inappropriate operations	8	7.8
Failed to correct known problems	3	2.9
Supervisory violations	2	1.9
Preconditions for unsafe acts		
Environmental conditions		
Technical environment	38	37.2
Physical environment	22	21.56
Conditions of the operator		
Adverse mental state	4	3.9
Adverse physiological state	4	3.9
Physical/mental limitations	2	1.9
Personnel factors		
Coordination and communication	18	17.6
Fitness for duty	10	9.8
Unsafe acts of the operator		
Routine disruption errors	66	64.7
Decision errors	52	50.9
Perceptual errors	4	3.9
Violations	6	5.8

HFACS, human factors analysis and classification system.

witnessed is due to unsafe acts of operator, followed by preconditions for the unsafe act and, accordingly, unsafe leadership and finally organizational influences. As far as outside factors are concerned, no case has been identified as being caused by outside factors, but this could be due to insufficiency in data compilation since it cannot be concluded that outside factors did not influence the safety conditions of the mining sites.

3.1. *Unsafe acts of operators*

This category is one of the major contributors in mishaps: there were 66 cases of routine disruption errors, 52 cases of decision errors, four cases of perceptual errors, and six cases of violations. Each of the subcategories of unsafe acts is further categorized for a comprehensive and systematic classification: (1) attention failure, postural errors, electrical errors, etc., included under skill-based errors; (2) information processing, risk assessment, and situational assessment is included under decision errors; (3) violation of usage of personal protective equipment and procedural violation is included under violation nanocodes; and (4) misjudgement, visual, and auditory errors were included under perceptual error nanocodes. The most prevailing act of the operator identified in this study is attention failure (23.53%), followed by procedural (decision) errors (14.71%), technique errors (12.75%), situational assessment (10.78%), and risk assessment (9.8%). The outcome of the HFACS analysis showed that unsafe operator acts were of maximum importance, therefore these were studied in detail in order to understand whether unsafe acts performed by the operator are influenced by factors such as age, experience, time of shift, place where operator is working, and category of work assigned to the operator. The results for the same are given in Tables 2–6 below. It is noted that in the underground mining category, 35 out of 66 incidents were found to occur because of skill-based errors; in the same category 13 out of 52 incidents occurred because of decision errors; two out of four incidents were due to perceptual errors, and

Table 2
Unsafe acts (category of working)

Category of working	Skill-based errors (n)	Decision errors (n)	Perceptual errors (n)	Violations (n)
Underground mining	35	13	2	2
Underground filling	4	8	0	1
Open-cast mining	2	6	0	1
Open-cast transportation	3	4	0	1
Open-cast mechanical/electrical	13	11	1	0
Ore cleaning floor	0	0	0	0
Surface working	0	0	0	0
Worker others (field man)	9	10	1	1

one out of six incidents occurred due to violations performed by the operator. The other tables can be interpreted in a similar way. The detailed analysis shows that skill-based errors are top priority, followed by decision errors, leaving a dominant impact upon all the factors considered below. Skill-based errors and decision errors are the top priority in all categories, similarly in all shift timing, age, and experience categories, the most common unsafe act performed leading to any incident is skill-based errors and decision error.

Further, an attempt has been made to understand if there is any significant association between two top priority unsafe acts, with the factors discussed below, because perceptions and violations did not show a considerable contribution towards mishaps.

To develop a fuzzy-based predictive system for accidents, the preliminary step is to identify input variables. These variables are identified based upon the outcome of the significance testing performed to identify the significant association between the factors of age, experience, shift, category of working, place of work, and unsafe act performed by the worker. The predictive model can analyze the factors most associated with unsafe acts and a robust outcome related to risk level can be obtained and considered for the development of intervention strategies. The association between "category of working" and "unsafe acts performed by the operator" is found to be insignificant [$P_{Test} = 0.027$ ($P_{Test} < P_{\alpha}$) *ns*]. Followed by testing for significant association between "shift of working" and "unsafe acts performed by the operator", the outcome is significant ($\mathcal{X}^2_{critical} = 7.815$ and $\mathcal{X}^2_{Test} = 1.306$, $P_{Test} > P_{\alpha}$, i.e., $P_{\alpha} = 0.727$). Thereafter, other factors such as place of work, age of worker, and experience of worker are tested to identify the existence of a significant association with unsafe acts. The outcomes obtained are: "place of work" is insignificantly associated with unsafe acts of worker ($P_{Test} < 0.001$, i.e., $P_{Test} < P_{\alpha}$); "age of the worker" is found to be significantly associated with unsafe acts performed by the operator ($\mathcal{X}^2_{critical} = 5.991$, $\mathcal{X}^2_{Test} = 0.241$, and $P_{Test} = 0.886 > P_{\alpha}$), lastly "experience of the worker" is found to be significantly associated unsafe acts performed by the operator ($\mathcal{X}^2_{critical} = 9.488$, $\mathcal{X}^2_{actual} = 4.776$, and $P_{Test} = 0.311 > P_{\alpha}$). Because unsafe acts of the operator is found to have a significant association with shift of working, age of worker, experience of worker, the FRA-based accident prediction model is developed considering these as input factors.

Table 3
Unsafe acts (shift of working)

Shift of working	Skill-based errors (n)	Decision errors (n)	Perceptual errors (n)	Violations (n)
General	22	16	2	2
I shift	28	19	2	4
II shift	11	13	0	0
III shift	5	4	0	0

Table 4
Unsafe acts (place of accidents)

Place of accidents	Skill-based errors (n)	Decision errors (n)	Perceptual errors (n)	Violations (n)
Stopping area	32	23	0	2
Tramming road	3	13	0	0
Benches	2	0	0	2
Ore cleaning floor	4	12	0	0
Other transportation road	21	0	4	0
Workshop	0	2	0	0
Stores	1	0	0	0
Above ground	3	2	0	2

3.2. Preconditions for unsafe acts

Preconditions for unsafe acts is further classified into environmental (physical and technical environment), operator's condition, and personnel factors. The mining industry is known for its dynamic and difficult environmental conditions. Issues concerned with illumination, ventilation, etc., have been a hurdle in maintaining safety at the worksite. Technical environmental factors were found to be responsible in 38 cases. Condition and maintenance of tool and operations related to tools and equipment (36.85%) were identified as being mostly responsible for mishaps; standard operating procedures (SOPs) and risk assessment were lower (10.5%) because the mines are semimechanized, so issues related to noncompliance or violating SOPs are very low and most risks associated with faulty machines are quickly assessed and handled cautiously. Under physical environment, weather is also an important factor, but it has not contributed to a great extent in leading mishaps. The rainy season is the most concerning environmental condition for the mining industry and specifically for open-cast mines. During this season, the mining site is drowned which obstructs work. Interaction of such hazardous site conditions and workers is limited, which helps to prohibit accidents; pumps are used to remove water from the site until the sites are accessible for working.

The physical environment was found to be responsible in 22 cases. Surface/road conditions (27.27%) followed by visibility (18.18%) was found to be dominant. The contribution of ergonomics was identified as being insignificant because the mines are semimechanized, so uncomfortable, unsuitable man—machine interaction or faulty workplace design is not noticed.

Condition of the operator was found to be responsible in 10 cases. Still, it is a very important factor to be considered because an operator with poor mental health will definitely underperform the task, which might lead to unsafe consequences and also poor productivity. Physical/mental limitations and adverse physiological state (40.02%) was noticed to be the priority as a causal factor for accidents under this category. Under the category of physical/mental limitations, learning ability limitations were found to be responsible to a greater extent, followed by condition-based respiratory issues; the rest of the factors were not considerably noticed, because height, weight, hearing capability, and vision tests

Table 5
Unsafe acts (age of worker)

Age of worker (y)	Skill-based errors (n)	Decision errors (n)	Perceptual errors (n)	Violations (n)
18—32	15	13	2	0
33—47	36	26	1	3
48—60	15	13	1	3

Table 6
Unsafe acts (experience of worker)

Experience of worker	Skill-based errors (n)	Decision errors (n)	Perceptual errors (n)	Violations (n)
1 mo—1y	7	13	0	3
1—5 y	14	11	1	0
6—10 y	17	11	2	3
11—20 y	19	9	1	0
$>$ 20 y	9	8	0	0

are done prior to the worker joining, which they have to clear mandatorily. If the worker eventually develops any limitation during his work then he is assigned light duty, for example, medical attendant on site, peon in office, store, etc.

With analysis, personnel factor was found to be responsible in 28 cases. It was found that the contribution of communication and coordination (64.29%) is of topmost priority, followed by fitness for duty (35.70%).

3.3. Unsafe leadership

The role of the leader is to provide adequate training and guidance to the team members to perform any task/operation efficiently and safely. In the absence of adequate leadership or leadership violations etc., unwanted consequences can come into existence. This category is further subdivided into inadequate leadership (22.55%) which was a major causal factor in incidents, followed by planned inappropriate operations (7.84%), failure to correct known problems (8.21%), and leadership violations (5.38%). As expected, leadership violations were the lowest. Under the category of inadequate leadership, training-related issues showed a major contribution (39.13%). At times it happens that less than adequate training is given to the worker to perform the task; there are a variety of mandatory trainings in order to work on a mining site, such as when there is a change in SOP, refresher training, etc. Alternatively, if the worker does not have competency to learn this can also create problems related to an unsafe working environment. Safety oversight (30.4%) had the second highest contribution in mishaps. The analysis showed that safety regulatory requirements were still not set, yet the operator was permitted to continue working which led to mishap. The timber that is used to provide roof support in underground mines has a certain specification which has to be followed, the material winding in any situation should not be used for movement of man and material together, no matter how heavy cap-lamp batteries are, it has to be carried in underground. If any kind of deviation is noticed in following such practices, an efficient leader should take immediate action to avoid any mishap. In some of the cases this was missing, leading to issues related to safety oversight.

It was noticed that in emergency circumstances, certain decisions were taken which are unconventional during normal situations/operations. The execution of such decisions with poor plan formulation will never result in the intended manner, which was also found in the analysis. Major causal factors under planned inappropriate operation were improper task or work plan (50.28%), followed by the work assignment (25.14%) nanocode. If a blaster is not available and there is an emergency, a worker who has not done blasting before cannot be assigned with the task of blasting, or a driver who has never operated or driven heavy earth moving machinery before, but has been driving jeeps/ambulances on site should not be allowed to drive loaders, dumpers, or tippers under emergency conditions. Anyone who is in job rotation and has handled such machinery can be assigned tasks during an emergency situation to avoid accidents. If an improper work assignment is made then that might lead to unfavorable events. Leadership violation was found to be negligibly responsible. Another inference can be drawn from this: leadership violation might have been responsible, but not documented or reported to overcome the drastic after effects upon the employment of the personnel responsible or vigilance inquiry issues.

3.4. Organizational influences

In a total of 14 cases, organizational factors were found to be responsible. Organizational process (42.64%) was identified as the dominant factor. Irregular reporting was found to create issues in the cases analyzed. Time pressure and shortage of staff were other important identified causal factors. As far as outside factors are concerned, these were not identified when analyzing cases. One of the reasons could be that documentation provided for analysis did not describe any outside factor responsible in mishaps.

4. Fuzzy reasoning approach

As discussed in previous sections, if any significant association exists between factors such as age of the worker, place of work, shift, or experience, then an FRA model can predict the level of risk associated with the given situation (combination of above-mentioned factors, for example prediction of risk level if "a worker of age 27 years, with 1 year of experience, working in the third shift i.e., night shift underground"). So that once the risk level can be predicted for a given situation and if a considerable risk level is reflected than changes such as in time, place, or nature of work can be made, the level of risk can be rechecked, and finally the allocation of work can be made. This can enhance preparedness against unsafe consequences and a safe working environment can be developed and maintained in the future. The outcome of the significance testing indicated a significant association between unsafe acts of the worker with the age, shift, and experience of the worker. Considering the same, and with the help of three experts with 40 years of experience in this field, a fuzzy rule base was prepared to develop in the inference engine so that risk level can be assessed.

A fuzzy set can be defined as: A fuzzy subset A of a universe of discourse U is characterized by a membership function μ: U $\rightarrow$ (0, 1) which associates with each element u of U a number μ (u) in the interval (0, 1) which represents the grade of membership of u in A. The fuzzy set A of U = u1, u2 ..... u, will be denoted:

$$A = \sum_{i=1}^{n} \mu_{A\ (u_i)/u_i} = \sum_{t} \mu_{A\ (u_i)}, \tag{1}$$

where Σ stands for the union [26].

A fuzzy number can be demonstrated with an example of the triangular fuzzy number, given as;

$$\tilde{n}_a\left(t^l{}_a\, t^m{}_a\, t^u{}_a\right) \tag{2}$$

and can be interpreted as [43]:

$$\mu_{\tilde{n}\ a}(x) = \begin{cases} 0, & x < t^l{}_a \\ \dfrac{x - t^l{}_a}{t^m{}_a - t^l{}_a} & t^l{}_a \le x \le t^m{}_a \\ \dfrac{t^u{}_a - x}{t^u{}_a - t^m{}_a} & t^m{}_a \le x \le t^u{}_a \\ 0, & x > t^u{}_a \end{cases} \tag{3}$$

The proposed FRA model was developed using MATLAB R2009a, Fuzzy Logic tool box. The FRA model is used where only a small portion of the knowledge (information) for a typical problem might be regarded as certain or deterministic. The FRA model was developed with the following steps.

4.1. Fuzzy inputs

Fuzzy inputs need to be crisp numerical values limited to the universe of discourse of the input variable. The degree to which the input belong to appropriate fuzzy sets is decided through a membership function, which is one of the critical steps in deciding and defining inputs. The output is a fuzzy degree of membership between 0 and 1.

4.2. Application of fuzzy operator

Once the inputs are fuzzified, the degree to which each part of the antecedent is satisfied for each rule is identified. The output is always a single truth value, but if there is more than one part in the antecedent, the fuzzy operator is applied to get one number that represents the result of antecedent, of that rule which is applied to the output function.

4.3. Implication

To shape up the consequent implication method is applied. Implication occurs for each rule, the number given by the antecedent is the input for implication. Each rule has a weight which is applied to the number given by the antecedent. Normally it takes 1 and it does not affect the implication process, this number may be varied from time to time from 1 in order to weigh one rule relative to another.

4.4. Aggregation

All the fuzzy sets representing the output of each rule are combined to a single fuzzy set. Aggregation occurs once for each output variable. The input for the aggregation process is the list of truncated output functions returned by the implication process for each rule. The output of the aggregation process is one fuzzy set for each output variable.

4.5. Defuzzification

The input given to the fuzzy reasoning system is crisp, similarly the output is also expected in crisp form. The defuzzification process gives a crisp form of output. The aggregate output fuzzy set is the input for this step and the output is crisp in nature.

5. Application of FRA model

For the present case the FRA model is of three inputs and one output type (Fig. 2). The three inputs are, "age of the worker", "experience of the worker", and "shift of work" and the output is "risk level". Firstly the input parameters need to be defined with qualitative descriptors and membership functions. The yardsticks developed defining qualitative descriptors are shown in detail in Table 7.

Fuzzy inference is the actual process of mapping from a given input to an output using fuzzy logic. Once the input is given to the inference system, it is mapped with the rules fed into the system and then as an outcome a defuzzified output is generated. In the present case there are three input parameters, each having a different number of qualitative descriptors based upon which the number of rules is decided. Eighty-eight rules were developed in the database, there should have been 100 (5 × 5 × 4) rules, based upon qualitative descriptors of input parameters, but few rules were discarded based upon insignificant logic, such as a fresher cannot be 57 years of age, a middle aged person cannot be a fresher, or a very young worker cannot have 20 years of experience. Such rules are not logically correct. With such screening the rule base was developed and the system was tested.

6. Results and discussion

The present work demonstrates the causal factors in the genesis of mining accidents using the HFACS framework. A total of 21 causal categories were reviewed to assess incidents with the aim to highlight the dominant participation of human error, including latent conditions leading to unacceptable consequences such as a mishap. The results are indicative, the "unsafe act" causal factor was observed to be responsible in a maximum number of cases. When this category was analyzed in detail with respect to factors such as category of working, place of accident, age of worker, experience of worker, and shift of work, skill-based errors were found to have a dominant impact and age of worker, experience of worker, and shift of work had a significant correlation with unsafe acts performed leading to accidents; this was followed by decision errors at second priority in all the cases discussed. Outside causal factors were not found to contribute to accidents, but this does not signify that these factors are dormant. It can be an outcome of partially preserved data/insufficient records pertaining to regulations or any other influences. Based upon the findings of HFACS, the proposed model has been found to work satisfactorily in identifying the level of risk associated with the given situation considering the age, experience, and shift of worker as input factors and the risk level associated with the situation as output. The accident statistics given in previous section highlights the age group, the experience slab for worker performing unsafe acts in certain time of work. These trend inference from statistical data is being utilized to test the model and predict the level of risk. To validate, the input given to the model is fresher in the category of experience, very young in the category of age and general shift (from 8:00 AM to 4:00 PM) as the time of work, then risk level obtained is 1.8 which is a low level (with reference to the yardstick for risk level given above). The outcome obtained is as expected. Thereafter the shift timing was changed to III (from 10:00 PM to 6:00 AM) and risk level came out to be 5.4, i.e., possible. This can be interpreted as follows: if this worker is to be assigned work then because he is a fresher and very young, immediately giving him a III shift should be avoided, as accident scenarios might develop. Similarly, a reverse case is tested with this model, i.e., the level of risk if the worker is middle aged with average experience of

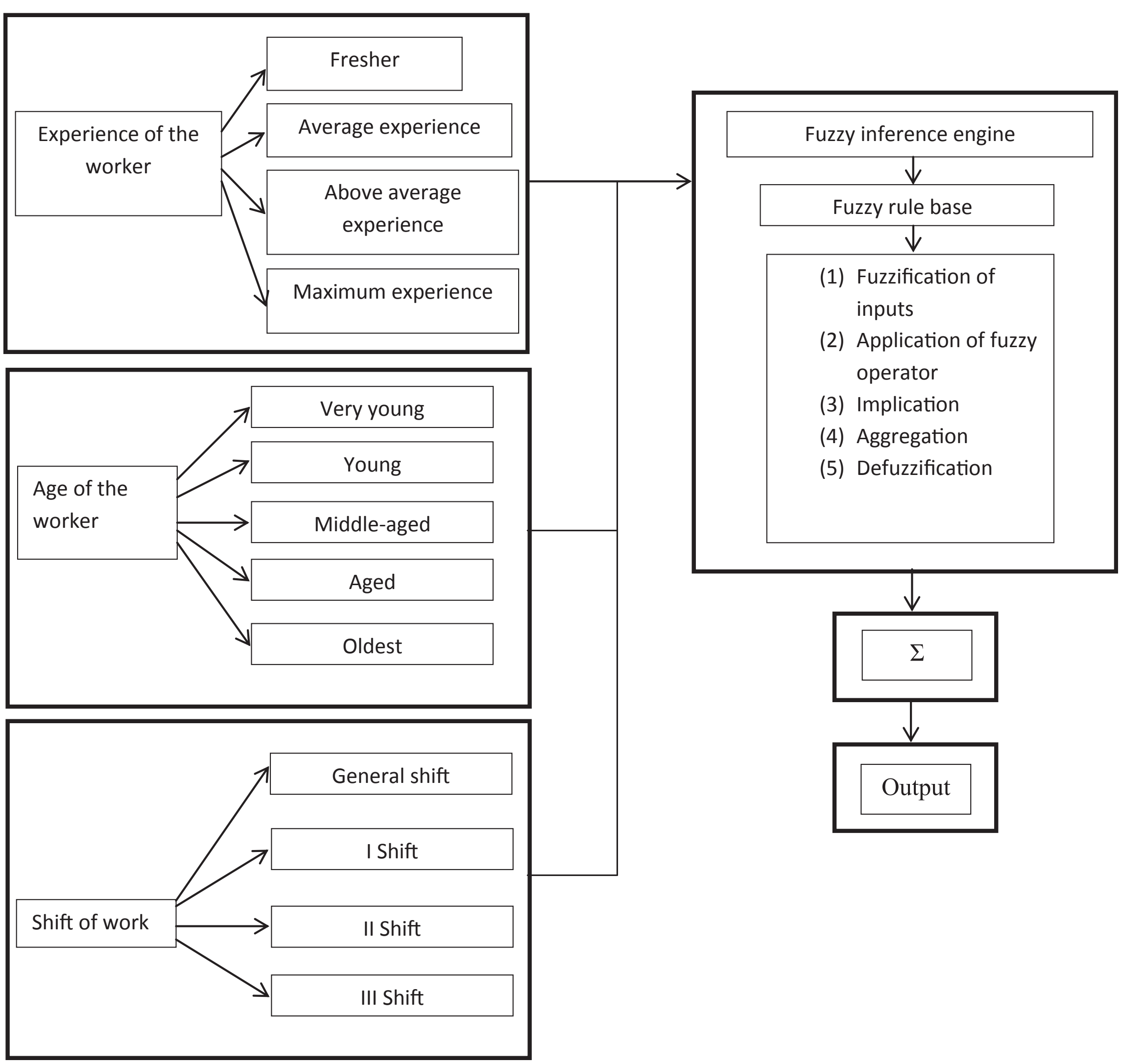

Fig. 2. Fuzzy reasoning approach model for risk assessment.

Table 7
Yardstick for input and output parameters

Qualitative descriptor	Description	Parameter
Experience of worker		
Fresher	1 mo–1 y	Trapmf [0 0 0.5 1.5]
Minimum	1–5 y	trimf [0.5 1.5 2.5]
Average	6–10 y	trimf [1.5 2.5 3.5]
Above average	11–20 y	trimf [2.5 3.5 4.5]
Maximum	> 20 y	trapmf [3.5 4.5 5 5]
Age of worker		
Very young	18–27 y	trapmf [0 0 0.5 1.5]
Young	28–37 y	trimf [0.5,1.5,2.5]
Middle aged	38–47 y	trimf [1.5 2.5 3.5]
Aged	48–57 y	trimf [3.5 3.5 4.5]
Oldest	≥ 58 y	trapmf [3.5 4.5 5 5]
Shift of work		
General	8:00 AM–4:00 PM	trapmf [0 0 1 2]
I	6:00 AM–2:00 PM	trimf [1 2 3]
II	2:00 PM–1:00 PM	trimf [2 3 4]
III	10:00 PM–6:00 AM	trapmf [3 4 5 5]
Risk level		
Low	Risk is acceptable	trapmf [0 0 3 4]
Possible	Risk is tolerable but should be further reduced if cost-effective to do so	trapmf [3 4 6 7]
Substantial	Risk must be reduced if it is reasonably practicable to do so	trapmf [6 7 9 10]
High	Risk must be reduced to safe level unless in exceptional circumstances	trapmf [9 10 12 12]

5–10 years and assigned to work in III shift, then the level of risk is 9.15 which is high, so the allocation of such workers to the III shift should be avoided under the given circumstances. In such cases the ideal combination of the worker having experience of between 1 year and 5 years and aged between 27 years and 37 years can be allocated the III shift because the risk level from the FRA model is 4.7, i.e., low. Similarly, many such input combinations can be tested and suitable allocations of the workers can be made to control unsafe working environments. In this way accident-inducing situations can be predicted in advance and prevention can be taken accordingly. Further, to control operator or worker error, the following organizational recommendations can be made. (1) Provision for repeated training modules for workers. At the time of employment initial vocational training along with refresher training within a suitable span to upgrade the workers' skill set with changing technology, and finally with changes in job special training should mandatorily be given to workers. (2) Effective supervision of work to avoid cases of noncompliance to SOPs. (3) Use of latest devices or personnel protective equipment with proper demonstration/training for the usage to the workers. (4) Mechanization of selected activities such as ore cleaning on ore cleaning floor. (5) Deployment of advanced transportation machineries with provision for rear view camera. (6) Automatic coordination of movement of man and material winding instead of manual coordination and communication. (Observation: the conventional bellman system is presently followed). (7) Mechanization of manual loading activity of ore. (8) Provision to maintain better illumination and ventilation levels in underground workings. (9) Safety week celebration to sensitize workers with the importance of safety and develop safety in their minds. (10) Quality of materials such as timber for support, explosives with appropriate shelf life, shaft winding rope, etc., should be retained as per the standard because it directly affects the safety levels in worksites. (11) The human tracking machine should be used in underground mines.

7. Conclusion

The work presents a detailed analysis of mine accidents in underground as well as open-cast manganese mines in India. The HFACS framework was adopted to perform the analysis and significant findings were obtained. Based upon the findings an FRA model was proposed to assess the risk level for a given situation and modify the same if found critical. The outcome of the research work is highlighted as follows. (1) Unsafe acts of worker found to be the most critical factor in the development of accident scenarios in mining sites, with a maximum contribution of skill-based errors performed by the workers. (2) Underground mining approach, stopping area, I shift of work, worker within the age group of 33–47 years and with 6–10 years of working experience are most critical for consideration in the development of intervention strategies. (3) Faulty behavioral traits and organizational lacunas were indicated as the outcome of HFACAS analysis and can be considered further to develop mitigation plans and intervention strategies for the industry. (4) Age, experience of the worker, and shift of work have a significant correlation with unsafe acts performed, ultimately leading to accidents. (5) The FRA-based risk prediction model proposed can be adopted by the safety analyst to predict the risk associated with a given situation and perform task allocation accordingly to prevent hazardous outcomes.

The present work demonstrates a noble approach to risk and safety assessment. In recent past significant research performed in the area of safety management has been found to be limited with respect to scope because data-based, questionnaire, and interview-based analysis of the data is not performed and the outcome indicated is merely the trend for accidents or reasons behind the mishap. But the present work is a step further in conventional research performed in this area, where the outcome of microlevel accident analysis has been utilized to develop an accident prediction model to interpret the risk levels associated with a given situation and alter them accordingly. In future, the work can further be extended for other minerals extracted for commercial purpose in India and safety levels at sites can be improved.

Conflicts of interest

The authors have no conflicts of interest to declare.

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