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Artificial neural network and fuzzy rule based two-stage system for estimating mine haul road performance

This paper presents a two-stage scheme for estimating the performance of mine haul road. In the first stage, we design a feed forward artificial neural network (ANN) model to predict three important attributes (namely speed, fuel cost, and dust) of a haul road that eventually define the performance of the haul road. The ANN model is trained with eight input variables that are basically eight important parameters for determining speed, fuel cost, and dust, using gradient descent optimization technique. Moreover, a sensitivity analysis is carried out for examining the effects (or for determining the relative contribution and importance) of inputs on the outputs of the proposed ANN model. Further, the 3D response graphs are drawn for investigating the influences of inputs on the outputs of ANN. While the second stage of our method introduces a fuzzy rule based approach for estimating the performance (or condition) of a haul road. The database of two mines is used for training by back propagation and refining the model output so that prescribed error limit by the user is attained. R value obtained is 0.95. Next in a third mine using the mine database without further training the ANN model architecture the model is run and the output is compared to the target value 0.17. Average error between the predicted and the target value is. Next, ANN model output is further analysed for knowledge gain about the otherwise imprecise system by using sensitivity analysis and 3D plots being identified as a input variable with highest relative importance is a major knowledge gain. Few expert rules are then evaluated by following fuzzy rule based approach. Finally, there is some knowledge gain about the system by extraction of rules which will help in initiating timely maintenance of the haul roads so that productivity gain in the mine can be maintained.

1.0 Introduction

Mine productivity, safety, environment and mine economics are dependent *inter alia* on design and performance of a haul road. The design of a haul road for an open pit mine can significantly affect the cost associated with hauling ore and waste to the surface. Walter et al.[1] highlight that in thirty years, surface mine haulage equipment have been developed from trucks capable of moving 20 tonnes of material to 350 tonnes. Thompson et al. [2] state that with the trend in increasing truck size, haul road performance has become unpredictable and difficult to manage. Costs of both maintaining the road and operating the truck have also increased prohibitively.

Haul roads, within an opencast mine, is the major source of dust emission. Chaulya et al. [3] show that the road is the major source of emission of particulate matter. Thus prediction of dust is very much essential to minimize emission of dust from haul roads. Tannant et al. [4] state that the construction materials and design features must be examined for every stretches of haul roads due to regular increase in load transport capability of the fleet of trucks. Good haul road construction and maintenance practices are the key to minimize fuel cost of trucks, which is most important for mine economics. Because, haul roads are considered as an important asset to a mining operation. Irdemoosa et al. [5] state that fuel consumption per cycle is a valuable tool in assessing both energy costs and the resulting GHG (green house gas) generation.

Hustrulid et al. [6] define that good haul roads are essential for successful surface mining operations. Poorly designed, constructed and maintained roads are major contributors to high haulage costs and pose safety hazards. As per Sinha et al. [7] vehicular traffic on unpaved haul roads of the opencast mines has been identified as the most prolific source of fugitive dust. Thompson et al.[8] state that the structural design of public (mainly paved) roads has been focus of considerable attention from early 1920. The structural design of unpaved roads has received less attention and design guidelines having been developed only recently.

All the prediction models that are available are based on only one output that may be dust or fuel cost. But for improving haul road performance speed, fuel cost and dust are equally important. Speed is directly related to haul road performance and mine economics. Williamson [9] state that fall in speed

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indicates ultimate mechanical wear. According to Soofastaei [10] truck haulage is responsible for a majority of cost in a surface mining operation. Fuel cost has a significant importance in surface mines. Reducing diesel fuel consumption would lead to a reduction in haulage cost and greenhouse gas emissions. Kubler [11] express that fuel consumption is a key aspect of the hauling operating costs. Chaulya et al. [12] state that all major mining activities, particularly, opencast mining contributes to the problem of emission of particulate matter directly or indirectly. Therefore, assessment and prediction of dust are required to prevent and minimize the emission of particulate matter due to movement of dumpers of haul road.

The initial aim of this paper is to predict three output variables (speed, fuel cost and dust) using a feed forward artificial neural network (ANN) model. These three output variables are the important factors which measure the performance of haul road. This paper later estimates the performance of haul road using a fuzzy rule based approach.

Haul road performance is dependent on several variables. Since transporting road making material to a mine site from outside may be cost prohibitive. The common practice is to use only locally available material. There is a lack of knowledge about the strength characteristics used as sub base and base course and composite strength of the road making material. Also precise knowledge about interplay of road strength characteristics with design features of haul road and nature of fleet axle load and frequency of travel is largely absent. A brief literature review about all parameters related to mine haul road performance is undertaken. Therefore to design a performance model eight important variables (such as number of vehicles, fall and rise (gradient), curvature, compaction, subgrade strength, moisture content, axle load) are selected to response for measuring the haul road performance. Eight variables are selected based on the observations made by several researchers. As per Baek et al. [13] report that the number of vehicles passing on haul road is very much important for hauling economics. Tannant et al. [14] state that damage was caused mostly by volume of vehicle plying on the road. Haul roads with greater fall and rise (gradient) limit make it difficult to run trucks stably and increase the travel time and fuel consumption of trucks. Pankrath et al. [15] state that if a sufficient radius of curvature is obtained, a stable truck speed can be maintained and the wear of truck wheels can be reduced, thereby enabling an efficient haulage operation. Baek et al. [16] state that for good road construction, compaction contributes to material stiffness and strength. Subgrade strength in general is determined in terms of Calfifornia Bearing Ratio (CBR) values. Pankrath [17] states that CBR value is one of the most important feature for haul road performance. Pais et al. [18] state that the behaviour of a pavement depends on the one of the most important characteristics like presence of water or moisture content. They state that axle load causes significant damage to the pavements, increasing the pavement construction and rehabilitation cost. Zaghloul et al. [19] expressed in their paper that high truck loads, load configurations, and number of trucks are lead causes to pavement deterioration. Blab and LitzJw [20] state that one of the most important parameters for a technical and economical design of road pavements is the correct estimation of the expected traffic load.

However, the lack of knowledge base about the relative significance and interplay between the variables restricts the application of conventional modelling techniques (hugo 2005). Mathematical models and statistical modelling techniques require precise knowledge on interrelation amongst the variables that influences the performance of haul road, which is largely absent. Sundin et al. [21] state that ANN can be used as a modelling technique for prediction of mine haul road performance. The ANN modelling approach have several advantages. ANN is a technique that can build a model based on imprecise knowledge about the system. The modelling technique uses a learning algorithm, that is, knowledge is extracted from a system by back propagation of the input variables weights are adjusted until error between the model prediction and the actually measured value at the mine site is within the error limit prescribed by the user.

Mine haul roads are mostly designed based on empirical methodology, which will result in inappropriate haul road design. Therefore, use of prediction model for assessment of emission from mobile trucks on mine haul roads is highly essential. So far, very limited application of ANN for prediction of mine haul road performances has been made. A large number of authors have underlined their interest of using ANNs instead of linear statistical models (Paruelo and Tomasel, 1997; Ramos-Nino et al., 1997; Manel et al., 1999; Starrett and Adams, 1997; Ozesmi and Ozesmi, 1999). Lal et al. [22] describe in their deterministic and statistical based approaches that emission characteristics of dust particles are highly non-linear. They developed air pollution model for opencast mine haul road using soft computing system. They also state that such prediction model is highly essential for implementing pollution control measures.

The haul road, shown in the Fig.1 are designed to transport a few hundred tonnes of material and construction material is

Fig.1: An example image of a haul road in an open cast mine

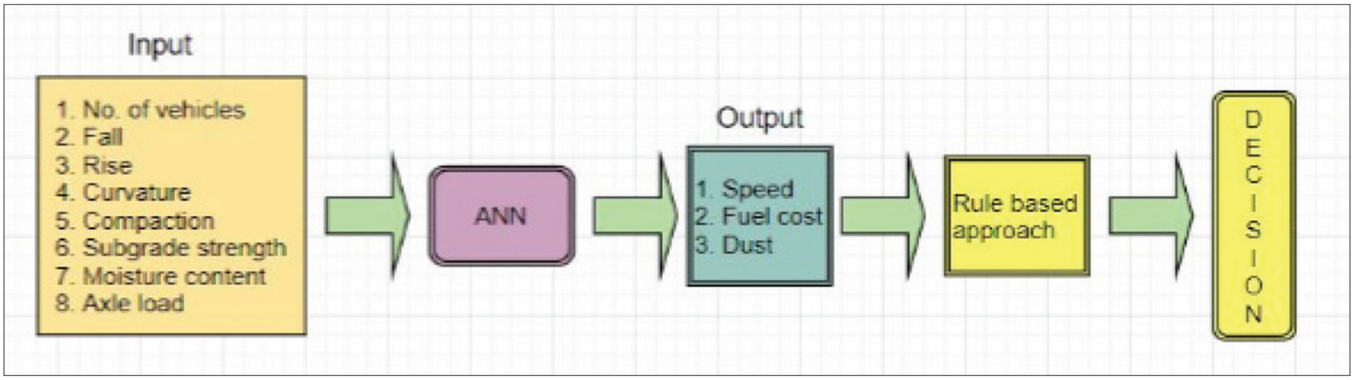


Fig.2: Flow chart of the proposed method

locally available material. Therefore, performance monitoring of these haul roads is a vital research area.

Rest of the paper is structured as follows. Section 2 describes the proposed methodology. The experiments are carried out in Section 3. Finally, Section 4 concludes the paper.

2.0 Methodology

Eight input variables are described in the previous section. They are input to the proposed model. The proposed two-stage approach first predicts three important attributes (speed, fuel cost and dust) of haul roads using an ANN based technique. With these three predicted attributes, we then estimate the performance of haul roads using an fuzzy rule based system. The process flow of the proposed scheme is presented in Fig.2

A. Predicting speed, fuel cost and dust using ANN

Artificial neural networks are being utilized for modelling the non-linear relationship between the input variables and output variables due to its capability of representing features in high dimensional space. Approximation of any non-linear function to a high degree of accuracy is one of the greatest characteristics of ANN. This is why ANN is widely used for predictions in many application areas. In this work, feed forward neural, a multi-layer perceptron is utilized in estimating the haul road performance.

Neurons are the smallest units which are grouped together in layers in order to build a neural network. There exists some variables which are the input to a neuron. On the other hand, we obtain a single output from each neuron. Each input variable is assigned to a weight which is basically a trainable/learnable parameter of the neuron. The input variables are multiplied with the corresponding weight. Then we determine the sum of the products and pass this through an activation (or transfer) function for thresholding and generating the output from the neuron. This entire procedure can be formally defined as the following.

$$\delta_i = \phi\Big(\sum_j w_{ji} o_j - \theta_i\Big) \quad \text{... (1)}$$

where δ_i is the output from the ith neuron, O_j is the jth input to the ith neuron, ϕ is the activation function, ω_{ji} is the weight of the connection from jth input to the ith neuron, and θ_i is the bias of the ith neuron.

The proposed ANN model is composed of three layers: input layer, hidden layer, and output layer. Input layer consists of eight nodes (number of input variables) while the output layer includes one/three nodes representing one/all output variables. The number of neurons/nodes in the hidden layer is varied from 5 to 15. Out of them, which yields the best result during training with the validation set of the dataset, is selected to finalize the architecture of ANN (Fig.3).

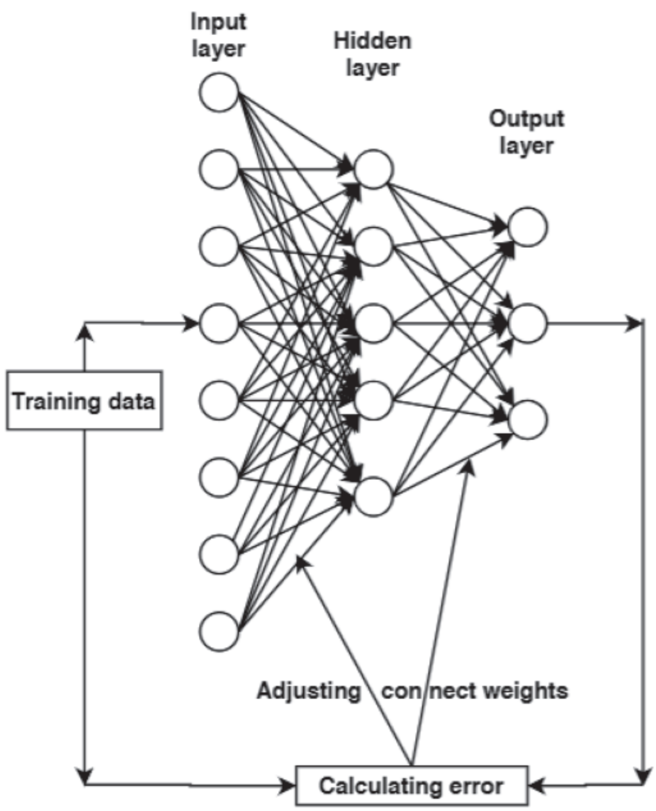


Fig.3: Schematic of the proposed ANN model

Consequently the model is tested with the test set of the dataset under consideration. A network is trained for 500 epochs using Levenberg-Marquardt back-propagation algorithm by minimizing the mean squared error. Once the network is trained, for any test data point, the output variables namely speed, fuel cost and dust are predicted using the trained ANN model. Next a sensitivity analysis is performed on these tuned weights of the ANN for determining the influences of the input variables to output variables.

B. Sensitivity analysis

Sensitivity analysis is carried out for characterizing the critical input variables and their degree of importance on the outputs from ANN. Sensitivity analysis is the method of studying the significance of each input variable on the output of the model or determining the influences of the inputs on the ANN model. Olden and Jackson determine the sensitivity of the network by utilizing connection weights used in the network architecture. Garson proposed a method later modified by Goh, for partitioning the neural network connection weights to determine the relative importance of the various inputs. Garson et al use the absolute values of the connection weights and infer a relative importance of input variables on the dependent output variable. The method proposed by Garson et al is referred to as Weights method, which is primarily a two step method as the following.

Step 1: For each hidden neuron *h*, divide the absolute value of the connection weight of the input-hidden layer by the sum of the absolute value of the connection weight of all input neurons of the input-hidden layer as follows.

For $h = 1$ to nh,
  For $i = 1$ to ni,
    $Q_{ih} = \frac{|W_{ih}|}{\sum_{i=1}^{ni} |W_{ih}|}$
  end,
end.

Step 2: For each *i*th input to the hidden layer, divide the sum of the Q_{ih} for each neuron in the hidden layer by the sum for each neuron in the hidden layer of the sum for each input to the hidden layer, multiply by 100. The relative importance (RI) of the weights of all output with respect to the given inputs is determined as the following.

In this work, we utilize this Weights method for performing the sensitivity analysis. The results of the sensitivity analysis is provided in the paragraph for Results of Sensitivity Analysis of 3.0. Next section introduces our fuzzy rule based approach taking the predicted values (using ANN) for speed, fuel cost, and dust as input for estimating the performance of haul roads in surface mines.

C. Estimating haul road performance using fuzzy rule based system

We utilize Fuzzy Inference System (FIS) for forecasting the condition of haul roads. The forecast helps in performing necessary actions like haul road maintenance and construction method in many surface mines. The entire FIS framework is built based on the concept of fuzzy set theory, fuzzy IF–THEN rules, and fuzzy reasoning (defuzzification). By critically analyzing the datasets, some important IF–THEN rules are extracted using our human expertise. We define essential components in rule base and perform fuzzy reasoning to infer the condition of a haul road. In summary, our FIS is designed by specifying the fuzzy sets, fuzzy operators and the rules extracted from data and our domain knowledge. The fuzzy inference engine uses the fuzzy IF–THEN rules for determining a mapping from fuzzy sets in the input universe of discourse to the fuzzy sets in the output universe of discourse applying fuzzy logic. The impact on some of parameters for predicting haul road performance is derived using the concept of fuzzy set theory. Lotfi A. Zadeh introduces the theory of fuzzy logic for modelling the uncertainty of the natural language. The domain experts provide the knowledge to the FIS. The knowledge is then encoded in terms of the set of IF-THEN rules within the algorithm. Subsequently, a rule based approach is constructed with the interpolative reasoning for responding to the new inputs. FIS including fuzzy sets, membership functions, fuzzy rule base are detailed next.

(1) Fuzzy inference systems

Fuzzy Inference Systems (FIS) is very close to the human perception and reasoning. The strong reasoning, intuitive handling and simplicity are the valuable factors for acceptability and usability of FIS. Using fuzzy logic, the process of determining the mapping from a given input to an output is essentially referred to as fuzzy inference. The decisions are made using this mapping. Membership functions, logical operations, and IF–THEN rules are formulated during fuzzy inference. Mamdani-type and Sugeno-type, which are two possible types of FIS, are implemented in fuzzy logic. The proposed FIS is a Mamdani-type inference engine. The Mamdani-type is chosen in our proposed scheme due the following reasons: (a) since the inputs and outputs are real valued variables, this is suitable for engineering systems like ours, (b) its framework is natural for incorporating fuzzy IF–THEN rules from human experts, and (c) this provides us so much freedom in choosing fuzzifier, fuzzy inference engine, and defuzzifier. As a result, we design most suitable fuzzy rule based system for the problem under discussion. Fig.4 illustrates the schematic of the proposed FIS.

Fuzzification interface, a fuzzy rule base (knowledge base), an inference engine (decision-making unit), and a defuzzification interface are the primary components of a FIS. First the fuzzification interface fuzzifies the input variables using the fuzzy membership functions defined on the input variables. Next the fuzzy rule base is characterized in the form of IF-THEN rules. Note that Fuzzy IF-THEN rules and fuzzy reasoning are the pillars of FIS. The rule base for the fuzzy

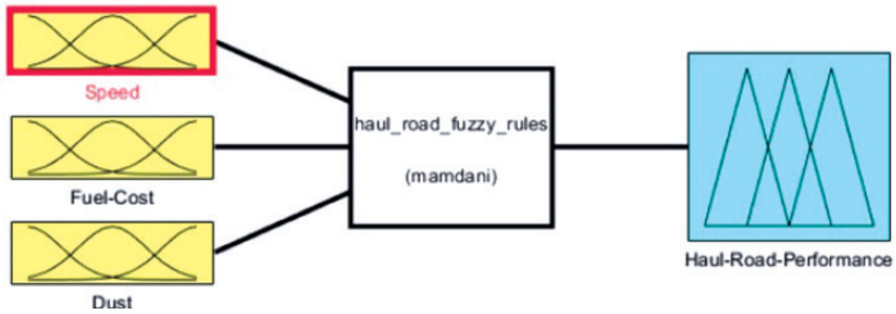


Fig.4: Block diagram of the proposed Fuzzy Inference System

logic system is created with the IF-THEN rules. The truth-value for the antecedent of each rule is computed, and applied to the consequent part of each rule using some suitable inference procedure. The result of this step is to assign one fuzzy subset to each output variable for each rule. The knowledge base is usually defined with the rule base and the dataset. All the fuzzy subsets, which are assigned to each output variable, are again combined together in order to construct single fuzzy subset for each output variable using an appropriate composition procedure. Finally, defuzzification procedure is performed to convert that fuzzy output set to a crisp output. Fuzzy sets and membership functions are described next.

(2) Fuzzy sets and membership functions

The basic idea on fuzzy sets and its membership functions is the following. If membership degree of an object is 1 then the object absolutely belongs to the set. If membership degree is 0, then the object absolutely does not belong to the set. On the other hand, if the membership value is between 0 and 1, the object partially belong to that set. The object more belongs to the set means greater is the membership degree. The parameters, that are depicted as fuzzy sets in this paper, are speed, fuel cost and dust. Table 1 presents the basic structure of the fuzzy sets that have been used in our system.

In Table 1, speed is characterized by five categories, whether the fuel cost and dust are characterized by four categories. These fuzzy sets have been created from the qualitative study of performance analysis of mine haul road and quantitatively defined by membership functions. These functions contain a specified domain of the value of the system input and have been shown in Fig.5(a)–(c) and output have been shown in Fig.5(d).

TABLE 1: STRUCTURE OF FUZZY SETS, '–' DENOTES THAT 'NO CATEGORY EXISTS'

Parameter Category	Input			Output
	Speed	Fuel Cost	Dust	Performance of Haul Road
1	Moving quickly	Extreme	Highly dusty	Good Condition
2	Moving easily	High	Moderately Dusty	Attention required
3	Moving moderately	Average	Less Dusty	Maintenance required
4	Moving Slowly	Low	Almost clean	Immediate repairing required
5	Moving Very Slowly	-	-	Worst Condition

(3) Fuzzy rule base

In a fuzzy inference system (FIS) is a set of IF-THEN rules defines a rule base of the FIS. The degree of membership of the fuzzy sets is represented by the IF part of any rule while the consequence (or the system output) is designated by the THEN part of the rule. For example, let us assume that A_1, A_2, A_3 be the different fuzzy sets (for speed, fuel cost and dust respectively) of antecedents and C is the fuzzy set (for haul road performance). The rules can be framed as:

$$\text{IF } (A_1^{(i)} \text{ and } A_2^{(j)} \text{ and } A_3^{(k)}) \text{ THEN } (C^{(l)}) \quad \text{... (2)}$$

where i, j, k and l denote the member of the fuzzy sets (i.e. the parameter categoryin Table 1). For example, in case of fuzzy set A_1 for speed, $A_1^{(3)}$ denotes the antecedent moving moderately (Table I). The total number of maximum possible rules is the product of the number of members of the fuzzy sets A_1, A_2, A_3 which is 5×4×4 = 80 in our case. But for the problem under discussion, only 12 rules, which are tabulated in Table II, are sufficient to describe the proposed system. The rules are framed such a way that all the characteristics of the system based the input parameters are considered. For example, if three parameters speed, fuel cost, and dust are moving slowly, low, and almost clean respectively then there will be a very high probability of repairing the haul road immediately.

The prediction/estimation of haul road condition depends on the membership values of the inputs (i.e., speed, fuel cost and dust) from the set of predefined rules formulated using human knowledge and expertise. Degree of membership of the inputs define the strength of the corresponding rule. In any rule, the higher degrees of membership of the inputs have more influences in the final decision.

The fuzzy logic is deployed in a rule-based system like ours by handling the operators and/or performing inferences on the rules using them. These and/or operator are applied on the rules by calculating the intersection and union of two fuzzy sets.

(4) Fuzzification, inference and defuzzification

The fuzzification, inference, and defuzzification, that are used in the proposed system, are introduced by Mamdani [32]. The inference strategy, that is used in our system, is generally known as the max-min approach. This inference procedure is a strategic plan of linking input linguistic variables to the output linguistic variable using MIN and MAX functions (as T-normand S-norm(or T-conorm respectively). Moreover,

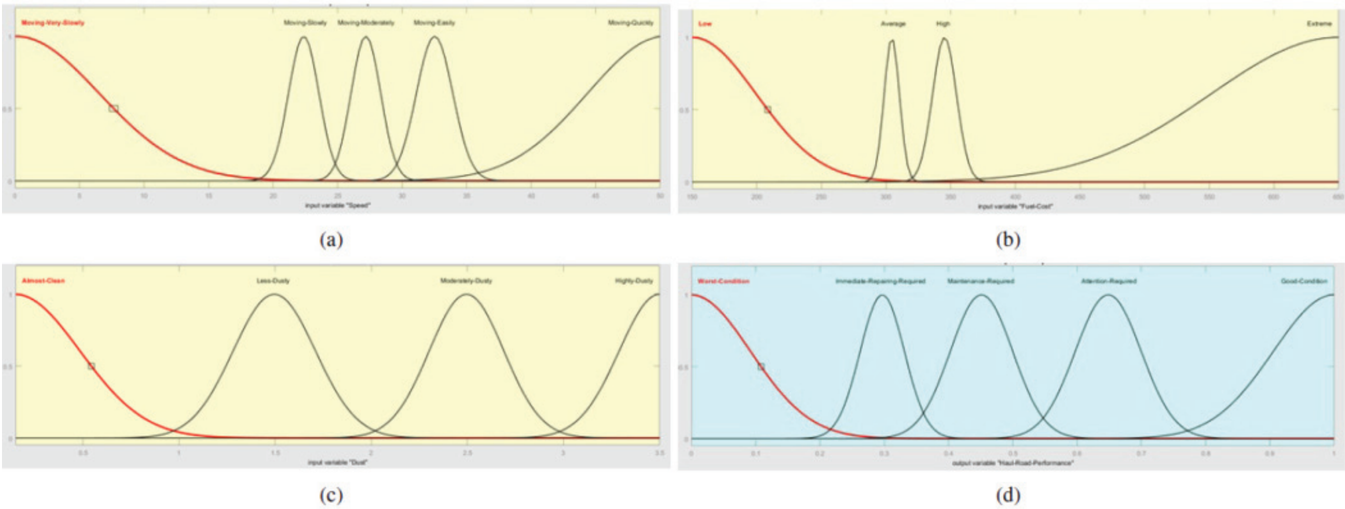


Fig.5: Membership function associated with the input (a) speed (b) fuel cost (c) dust and output (d) haul road performamce

Table 2: Fuzzy rule base, '–' denotes that 'whatever the case may be'

Rules	Speed	Fuel Cost	Dust	Performance of haul roads
1	-	-	Highly	Worst Condition
2	-	Extreme	-	Worst Condition
3	Very slow	-	-	Worst Condition
4	Moving Quickly	Low	Almost Clean	Good Condition
5	Moving Quickly	Low	Less Dusty	Good Condition
6	Moving Quickly	Low	Moderately Dust	Attention Required
7	Moving Easily	Low	Moderately Dust	Attention Required
8	Moving Easily	Average	Moderately Dust	Maintenance Required
9	Moving Moderately	Low	Less Dusty	Attention Required
10	Moving Moderately	Average	Moderately Dust	Maintenance Required
11	Moving Slowly	-	-	Immediate Repairing Required
12	-	High	-	Immediate Repairing Required

approximate reasoning (or interpolative inference) can be beautifully achieved using max-min approach. The advantage of using this kind of FIS is that the IF-THEN rules are defined as the expressions of linguistic constraints as listed in Table 2. The readers are referred to [33] for more details on Mamdani FIS. Next we present our experiments and results.

3.0 Experiments

All the methods/algorithms are implemented using MATLAB 2018b in a computing system with the following specifications: 16GB DDR4 RAM and Intel i5-8265U CPU @ 1.60GHzx4.

A. Data sets

The present study is carried out on three datasets collected from three mega opencast mines. These three datasets are representative of diverse haul road conditions in Indian coal mines. Moreover, the study areas are selected in such a way that diversity of the environmental and socioeconomic features of the entire mining region is captured. The process of mine excavation and mine loading of coal are mechanised. Keeping all these in our mind, we collect three datsets for the surface mines located at Dhanbad (study area I), Sonpur Bazari (study area II) and Sarisatoli (study area III). Block-II opencast coal project at Dhanbad, Jharkhand is a opencast mine located in the western part of Jharia coalfield that covers 3.46 sq.km. area. While Sonpur Bazari and Sarisatoli are in the Raniganj coalfield, Burdwan, West Bengal. Descriptive statistics of these three datasets collected from the above mentioned study areas. Maximum, minimum, average, and standard deviation for the input variables are denoted by max, min, mean, and standard deviation.

B. Pre-processing of data for ANN model

In order to train a deep neural network, first we need to

Table 3: Descriptive statistics of the samples collected from stury area I, study area II, and study area II, '#' denotes that 'number of'

	Study Area I					Study Area II					Study Area III				
Input Variables	#Samples	*min*	*max*	*mean*	*std_dev*	#Samples	*min*	*max*	*mean*	*std_dev*	#Samples	*min*	*max*	*mean*	*std_dev*
Number of Vehicles	34	72.00	150.00	102.50	18.29	45	456.00	720.00	648.00	85.24	35	98.00	520.00	309.00	53.86
Fall		53.40	83.20	71.91	8.67		13.92	112.23	54.78	23.43		64.00	88.20	75.35	9.65
Rise		71.66	142.32	116.65	19.60		41.97	138.62	92.86	26.45		53.90	99.20	68.42	11.59
Curvature		48.00	330.00	149.82	43.96		110.00	315.00	196.80	53.90		37.00	266.00	156.80	38.48
Compaction		1.11	3.14	1.78	0.38		1.94	2.02	1.96	0.03		1.18	3.14	1.80	0.39
Subgrade Strength		1.98	7.96	3.89	1.30		16.06	38.44	29.36	8.68		3.92	20.32	11.73	4.76
Moisture Content		3.08	15.82	9.76	3.20		9.60	12.50	11.28	1.14		2.98	15.82	9.72	3.17
Axle Load		20100.00	35000.00	26431.94	4017.89		22.11	56.95	46.75	10.06		17.80	24.53	20.31	1.68
Output Variables															
Speed	34	16.00	31.00	22.00	4.61	45	24.00	49.00	35.93	6.07	35	8	20	14.03	3.29
Fuel Cost		348.65	610.92	512.41	80.38		1430.98	3277.48	2511.04	477.43		318.54	648.95	454.28	85.89
Dust		1.11	2.30	1.59	0.37		0.18	3.06	1.42	0.59		1.12	2.34	1.60	0.38

normalize the data points in a dataset so that the dependent (or input) and independent (or output) variables exhibit particular distributional characteristics. The dependent (or input) variables must lie in the range [0,1] so that it conforms to the demands of the transfer function utilized in designing the proposed neural network. Let us assume that (x_1, $x_{2\ ...}$ x_8) be the independent variables of any data point in a dataset. Let $X_{i,}$ i = 1, 2 ... N be the collection of the values of i^{th} independent variable of N data points in the dataset. Then the i^{th} dependent variable of the j^{th} data point x_i^j is normalized as follows.

$$x'^j_i = \frac{x^j_i - min(X_i)}{max(X_i) - min(X_i)}, \quad ... (3)$$

where x'^j_i is the normalized version of *max* (.) and *min* (.) determines the maximum and minimum of a sequence of numbers. Assume $X'i$, i=1, 2 ...N be the collection of the normalized values of i^{th} independent variable of N data points in the dataset. Subsequently, the i^{th} normalized dependent variable of the j^{th} data point, x'^i_j is standardized by changing the mean of x'_i to 0 as the following.

$$x''^j_i = \frac{x'^j_i - \bar{X'}_i}{\sigma_{X'_i}} \quad ... (4)$$

where x''^i_j is the standardized version of x'_i; $\bar{X}'_i$ and $\sigma x'_i$ determines the mean and standard deviation of x'_i. It is essential to standardize the input variables so that some percentage change in the weighted sum of the inputs causes a similar percentage change in the unit output.

C. Results of predicting speed, fuel cost, and dust using ANN

In this work, a feed forward neural network model is introduced for solving the problem under discussion as described in II-A. The prediction performances of different ANN models are measured using three different evaluation metrics: mean squared error (MSE), average error of regression and correlation coefficient (R value) between the actual vs. predicted values of the output variables. Lower values of MSE/average error indicate the higher accuracy of the method. On the contrary, higher the R value is, higher is the accuracy.

However, for the jth target variable, the MSE is calculated between the targets t_i^j and o_i^j, I = 1, …, N as:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(t_i^j - o_i^j)^2. \quad ... (5)$$

For the same, the average error (AE) is derived as:

$$\text{AE} = \frac{1}{N}\sum_{i=1}^{N}|o_i^j - t_i^j|. \quad ... (6)$$

Similar the R value is determined as:

$$\text{R value} = \frac{\sum_{i=1}^{N}(t_i^j - \bar{t_j})(o_i^j - \bar{o_j})}{\sqrt{\sum_{i=1}^{N}(t_i^j - \bar{t_j})^2}\sqrt{\sum_{i=1}^{N}(o_i^j - \bar{o_j})^2}} \quad ... (7)$$

where $\bar{t_j} = \frac{1}{N}\sum_{i=1}^{N} t_i^j$ and $\bar{o_j} = \frac{1}{N}\sum_{i=1}^{N} o_i^j$ are the mean of t_j^i and o_i^j, i=1, ..., N respectively.

Our first objective for designing the proposed ANN model is to decide the optimal number of neurons in hidden layer and appropriate transfer functions in hidden and output layers. Most suitable transfer functions and the optimal number of neurons are identified using a set of experiments through trail an error approach. Different models considering different numbers of hidden nodes and different transfer functions are trained using backpropagation algorithm (as described in II-A) with the training set of our first dataset collected from study area I. The results of such experiments are tabulated in Table 4. In Table 4, logsig, tansig, and pureline are three standard activation/transfer functions that are used in ANN models. However in Table 4, this can be clearly seen that the best result is obtained using 3 number of nodes in the hidden layer (#Hidden Node in Table 4) and using tansig and pureline transfer functions in the hidden layer and output layer respectively. Once the optimal architecture of proposed ANN is determined using first dataset, the ANN model is then tested with other datasets. The complete results on three datasets are provided in Table 5.

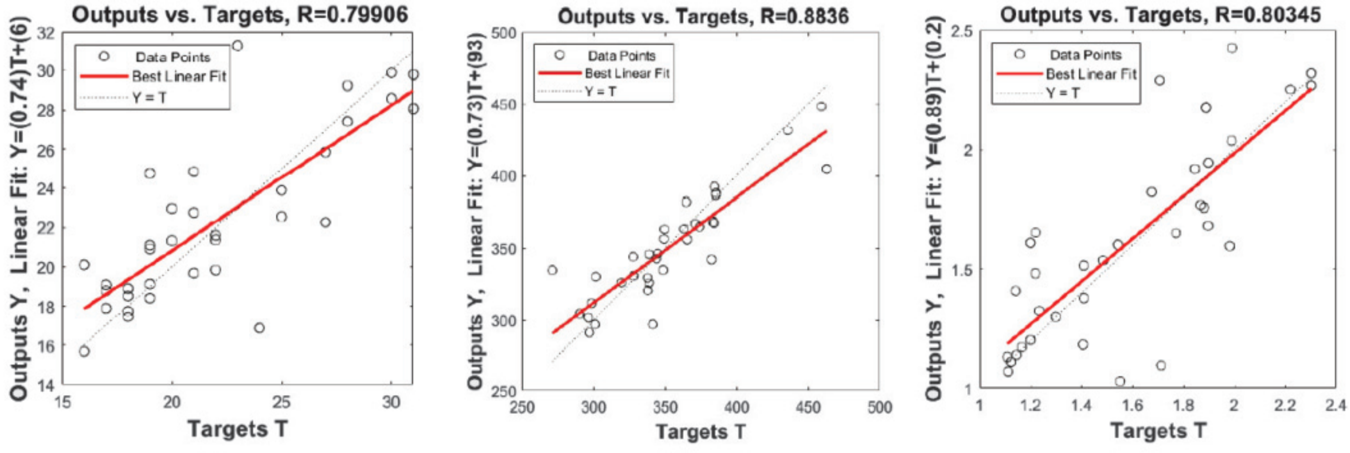
The graphical demonstration of the predictions with the plots showing predicted vs. actual values highlighting R value is presented in Fig.6. We can see through the Table 5 and Fig.6 that the R values of the predictions are from 65% to 95%. This outstanding results signifies that the proposed ANN model can be used for predicting speed, fuel cost and dust for estimating the condition or performance of haul road in opencast mines.

Next we carry out the experiments for investigating the impacts of input variables (no. of vehicles, fall, rise, curvature, compaction, subgrade strength, moisture content, axle load) on the outputs (speed, fuel cost and dust) of ANN. First we present the results of our sensitivity analysis followed by the 3D response analysis.

Results of sensitivity analysis: As described earlier in Section \ref{sensitivity}, sensitivity analysis is performed for identifying the critical input variables and their degree of

TABLE 4: COMPARATIVE STUDY USING DIFFERENT TRANSFER FUNCTION EVALUATED TO YIELD THE CRITERIA OF NETWORK PERFORMANCE, '#' DENOTES THAT 'NUMBER OF'

Exp. No.	Transfer function		#Hidden Node	R Value	MSE	AE
	Hidden layer	Output layer				
1	*logsig*	*purelin*	7	0.65	15	2.70
2	*logsig*	*logsig*	9	0.03	92	8.45
3	*logsig*	*tansig*	5	0.70	11	2.67
4	*tansig*	*logsig*	6	0.45	41191	198.00
5	*tansig*	*tansig*	7	0.30	28577	130.00
6	*tansig*	*purelin*	3	**0.90**	**5**	**1.38**
7	*pureline*	*tansig*	7	0.51	536	18.00
8	*pureline*	*logsig*	10	0.03	92	8.55



(a) (b) (c)

Fig.6: Outputs vs. targets for (a) speed, (b) fuel cost, and (c) dust predicted by ANN on the dataset collected from study area I

TABLE 5: RESULTS OF PREDICTING SPEED, FUEL COST AND DUST USING ANN ON THREE DATASETS.

Datasets	Speed			Fuel Cost			Dust		
	R	MSE	AE	R	MSE	AE	R	MSE	AE
Study Area I	0.79	7.90	2.02	0.88	437.14	14.25	0.80	0.06	0.17
Study Area II	0.85	37.58	4.98	0.95	1215	25.25	0.65	0.23	0.35
Study Area III	0.69	8.93	2.32	0.89	5057	51.54	0.80	0.13	0.31

importance on the outputs from ANN. We implement Garson's Weights [29] method for doing sensitivity analysis as discussed in Section II-B. The relative contribution and relative importance of the inputs on the outputs from ANN are provided in Table 6. This experiment is performed on our first dataset collected from study area I. However, we have seen that the results are similar for other two datasets that are collected from study areas I and II. Overall, the results of Garson's Weights method provide the information about the more sensitive variables by capturing how the network outputs are changed with the change in inputs. For the problem under consideration, we can see that subgrade strength is the most sensitive input variable in modelling an ANN architecture for predicting speed, fuel cost, and dust.

3D Response analysis

The three-dimensional ($3D$) response graphs are drawn to study the impact of a pair of input variables (out of eight variables) on one output variable (among three variables). Out of the eight variables, at a time, only values of two variables are changed and the remaining variables are kept fixed at their mean values. The 3D response graph is drawn by plotting an output variable vs. two input variables. A dataset is prepared with the input variables, varying at regular intervals, within the maximum and minimum range of values collected from the study area I. For those set of inputs, the output is determined from ANN. Subsequently, the responses (i.e. the output from ANN) for these two variables is plotted in 3-dimensions along z-axis, where x and y-axes represents two input variables. The purpose of plotting these 3D response graphs is to visualize how the output from our ANN model changes with the change of two input variables and how the proposed model supports the domain knowledge. In other words, the sensitivity of inputs on outputs is graphically captured. In Fig.7c, we see the relationship between input variable no. of vehicles and compaction with the output variable dust. We can clearly notice that if no. of vehicles increase then dust also increases and if compaction increases then also dust decreases. In Fig.7a, when no. of vehicles are at a certain limit, speed increases but after crossing the limit, speed decreases. Speed also increases with the increase of axle load. And in Fig.7b, fuel cost increases with increase of no. of vehicles and axle load, which indeed support our domain knowledge and validate the significance of our model.

TABLE 6: RELATIVE CONTRIBUTION AND RELATIVE IMPORTANCE OF INPUTS USING GARSON'S WEIGHTS [29] METHOD

Input Variables	Relative Contribution	Relative Importance
Number of Vehicles	0.19	6.42
Fall	0.37	12.18
Rise	0.61	20.24
Curvature	0.20	6.70
Compaction	0.38	12.72
Subgrade Strength	**0.91**	**30.39**
Moisture Content	0.29	9.70
Axle Load	0.05	1.66

D. RESULTS OF ESTIMATING THE CONDITION OF A HAUL ROAD USING FUZZY-RULE BASED APPROACH

As mentioned in Section II-C, the proposed fuzzy inference system (FIS) is built with the predicted speed, fuel cost and dust (using ANN) as inputs for predicting the condition/performance of a haul road in opencast mines. We have tested our proposed FIS model on all three datasets collected from study areas I, II and III. A skill score measures the accuracy of a forecast. The efficacy of the proposed FIS is evaluated using the categorical statistics such as the skill scores bias (B) and threat (T) [34] that are defined as:

$$B = \frac{F + H}{M + H} \quad \text{and} \quad T = \frac{H}{F + M + H}$$

where,

H = Number of hits (true condition is similar to the predicted condition of a haul road.),

M = Number of misses (true condition is dissimilar with the predicted condition of a haul road), and

F = Number of false alarms (predicted condition is similar to anyone of other conditions than the true one).

When M=0 and F = 0, bias B and threat T become 1. If score is less than1, the model is under-forecast else the model is over-forecast.

The skill scores along with the number of hits, misses, and false alarms of the proposed FIS for each categories of the output variable (Table 1) in each dataset are shown in Table 7. The overall skill scores are reasonably good which essentially infers that the performances of the proposed FIS are remarkably well. Similarly, the bias score indicates that the predictions of the conditions of haul roads are near perfect. In case of Attention Required and Worst Condition, the predictions are slightly under-predicted and in case of Maintenance Required, predictions are slightly over-predicted. In rest of the cases, the predictions are perfectly right. Next we conclude the paper.

TABLE 7: SKILL SCORES OF THE PROPOSED FIS ON ALL THE DATASETS

Output Category	H	M	F	Skill Score	
				Bias (B)	Threat (T)
Good Condition	4	1	1	1	0.67
Attention Required	4	3	2	0.86	0.44
Maintenance Required	9	8	12	1.2	0.31
Immediate Repairing Required	6	8	8	1	0.27
Worst Condition	59	8	5	0.96	0.82

4.0 Conclusions

This paper deals with the ways to gain knowledge about the performance of mine haul roads and also about interplay of variables that are related to haul roads. In this article, we attempted to built ANN model using three outputs which are most important to predict the performance of mine haul roads. Here ANN model is built with eight input variables in order to predict three important factors (namely speed, fuel cost and dust) of haul road performance. Subsequently these three predicted values are fed into a fuzzy rule based system to infer the condition of a haul road. Moreover, sensitivity analysis is carried out and 3D response graph is drawn for determining relative importance of input variables for the proposed artificial neural network model. In predicting speed, fuel cost and dust using the proposed ANN model, gives an outstanding R value. Consequently, we see the remarkable performance of the proposed fuzzy rule based system in predicting the condition of haul roads.

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