Application of Fuzzy and RBF Neural Networks in the Prediction of Distribution of Coal Seams

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Abstract— *A prediction approach through fuzzy logic and RBF neural networks were proposed to determine the distribution of coal seam terrains. A triangular fuzzy set was selected as the fuzzification basis for this work. The triangular fuzzy sets was created for each factor involved in the experiment, and are divided according to the levels of factors used in the experiment. The fuzzy membership functions and rule bank were based on observations during cutting experiments using the shearer drum operations and the measurements from the electrical conductance sensor for sensing the variations in the electrical conductance value in the coal mines. Also an efficient output can be obtained by RBF neural network with trained set of data. Then data set training is being done and the mining process can be established.*

Keywords— ANFIS, FIS Editor, Fuzzy logic, RBF Neural Networks.

I. INTRODUCTION

In order to overcome the problems such as low visibility, high coal dust and narrow space and difficulties of the shearer operator an effective method such as prediction of the distribution of the coal seam terrain can be done. This will increase the quality of coal and high mining efficiency. The coal seam prediction is of two methods, indirect prediction and direct prediction. The coal –rock recognition technology is the former method to predict the distribution of coal seams [2]. But this method is not able to meet the requirement of industrial production. The direct prediction is by different forecast methods based on the historical records of terrain data and this method can sufficiently provide local characteristics of coal seams. By depending on the performance of these forecast methods the prediction precision of coal seam terrain get changed [3] and [4]. In this paper the prediction is done through fuzzy logic method with wide range acceptance and the RBF neural network which is used to train the fuzzified range of the parameters.

II. RELATED WORKS

Several researches have been done over the field of coal seam terrain prediction. A particular prediction approach is mainly done based upon a theory or on the basis of the measurements and instrumentation. Also, the advanced or recent approach is based upon the intelligent algorithms such as the neural network algorithms. In the field of coal seam terrains the application of fuzzy approach is used for the selection of underground mining method. The selection process is done based upon the physical parameters such as geology and the geotechnical properties of ore, properties of the long wall coal mines and environmental and economical effects are being established with field and lab tests together with the determination of other qualitative variables. The selection process is being undertaken with fuzzy multiple attribute decision making. Under the principle of the Dempster – Shafer evidence theory the prediction of coal seam terrains and the safety evaluation model for the coal roof and in coal mines were determined [10].The Dempster – Shafer theory is being combined with the information from the multi-sensors used in the coal seam terrains. The Dempster- Shafer theory and information evidence fusion method provides accurate and effective methods throughout the evaluation of the model. The BPAs functions are constructed based upon the trained and training weights from the specific neural networks. The neural networks which dealt with coal seam terrain prediction approaches are Elman and Probabilistic neural networks.

Other methods also are being proposed for the recognition of coal from the coal-rock interface for getting a better result during the caving processes in underground coal mines. The recognition was done using the Mel-frequency Cepstrum coefficient (MPCC) and BP neural network [14].The noise frequency for the acoustic signal which is given through the top coal caving process id determined and compared. Also the ultrasonic wave reflection method and the torsional vibration signal method are being used for the coal-rock recognition and fusion of image based feature information.

III. PROPOSED WORK

3.1 Shearers with measuring sensors.

With high powered ranging arms and haulage units, shearers cut and load according to the respective tons ranges per hour more, based upon the mining conditions.

Nowadays a modernized shearer consists different components such as the cutting drum, the main frame ,innovative trapping shoe, power for the toughest mining conditions, strong arm, down drive, modular haulage system, coal sizer, visualisation for not only the currently working parameters but also for the history of the operated parameters. The schematic diagram of a shearer is given in Fig.1.The seam with thickness in the range of 1.5m to 6.0m is being mined with shearers.

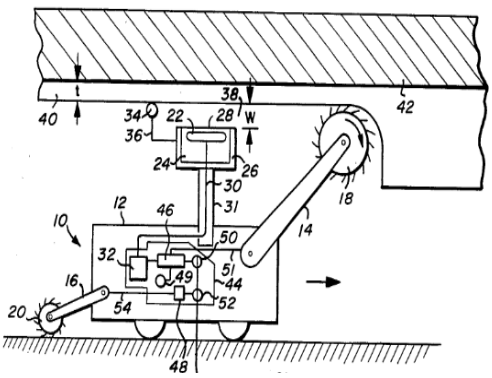


Fig.1: Schematic diagram of a shearer cutting a coal seam

Shearers while operating in many cases cut additional floor or roof or both due to the reason they are being operated at higher cutting heights than the thickness of the coal seams. This leads to additional contents of the rock in the coal which is mined out and the production costs get increased. The sensors are placed over the shearer arm for measuring the speed of the cutting drum, vibration of the drum, coal seam thickness. Also the electrical conductance sensor which is used for the detection of the presence of the coal is also placed on the shearer's arm.

3.2 Fuzzy Logic Approach.

In this system, the Mamdani inference model is used for the fuzzy logic implementation with the help FIS Editor in MATLAB software as shown in Fig 2. Here, five input variables are used; they are coal thickness, shearer drum speed, detection of coal, dip angle of the shearer arm and the vibration caused during the cutting of the shearer arm. The output variable is the coal density rate. A triangular fuzzy set was selected as the fuzzification basis for this work. The triangular fuzzy set was created for each factor involved in the experiment such as the shearer arm speed and the input sensor reading, and divided according to the levels of factors used in the experiments. There are five input variables and one output variable, the output variable in this prediction approach is the density of the coal. The membership functions are divided equally in three ranges such as Low, Medium and High.

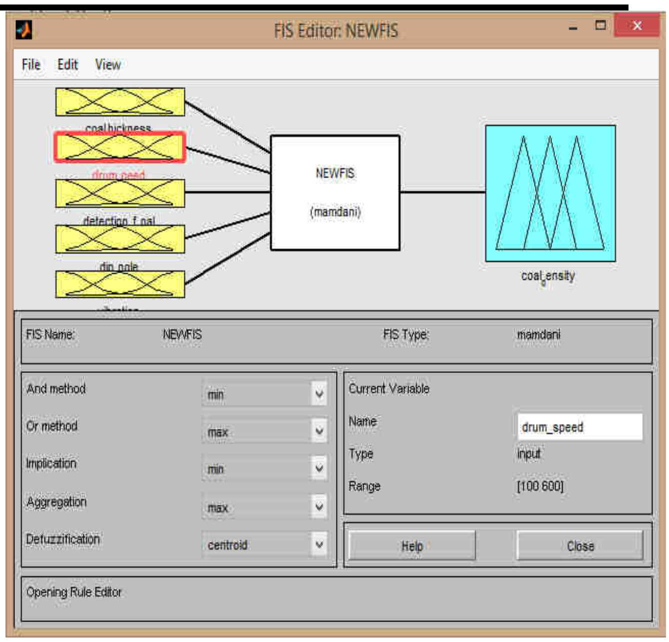


Fig.2 :FIS Editor with input variables

3.3 RBF Neural Networks

The Radial Basis Function (RBF) is a classification of neural network developed by M .J .D Powell which deals with functional approximations. The network uses the most common nonlinearities such as sigmoid and Gaussian kernel functions [9]. The Gaussian function is generally defined as in: f(y)=e^{-y^2}(1) .

The entire network develops a linear combination of the nonlinear basis function. The comparison of relative error with other neural networks in the prediction of coal seam terrains is shown in Fig.3 and the architecture of a RBF neural network is shown in Fig.4.A set of [1x5] matrix with trained weights are constructed as input matrix and a [1x1] matrix is constructed as output matrix. Also, since the fuzzy logic approach is also combined with neural network for this prediction purpose, a matrix for the rule bank is also constructed in the order of [1x 17].

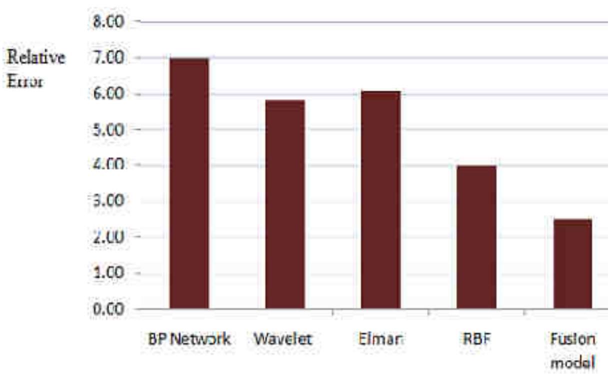


Fig.3:Comparison of prediction with various neural networks

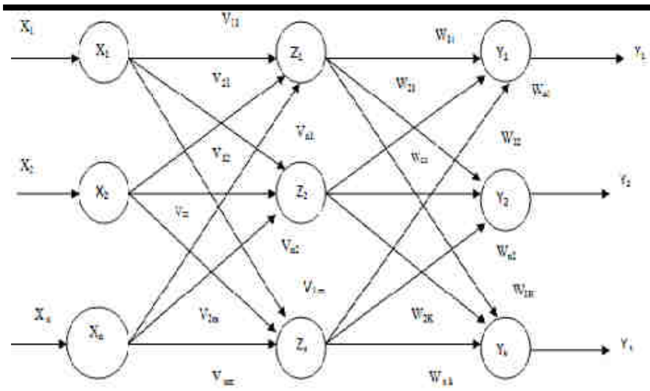


Fig.4:Architecture of a RBF neural network

The ANFIS Editor is used to compute the neural network suggested. The proposed type of neural network in this project is the RBF Neural model. The training data and the testing data is being trained and tested by using the MATLAB's ANFIS Edit Toolbox. The compared output of the generated FIS and the trained data is being obtained.

IV. PROPOSED APPROACH

Several sensors are being proposed in this set up for measuring the various input parameters present in the coal mines which helps to predict the distribution of the coal seams [6]. An opto-tactile sensor is to used to detect the presence of the coal. The thickness of the coal seam is being measured using an electrical conductance sensor. A thermal inclinometer is used to measure the dip angle of the shearer arm and the rate of vibrations caused during the cutting by the shearer drum is being measured with a vibration sensor [1].

Based upon the data from the sensors and the cutting drum speed the fuzzy decision making table is being created as shown in Fig.5.

Coal detection / Dip angle, Vibration	LOW	MEDIUM	HIGH
LOW	LOW	LOW	LOW
MEDIUM	LOW	LOW	MEDIUM
HIGH	LOW	MEDIUM	MEDIUM

Coal thickness / Drum Speed	LOW	MEDIUM	HIGH
LOW	LOW	LOW	MEDIUM
MEDIUM	LOW	MEDIUM	HIGH
HIGH	LOW	MEDIUM	HIGH

Fig.5:Fuzzy decision making tables for the input parameters for the prediction of coal seams

The table consists of three levels of the input factors. If-then rules is created based upon this table. The rules are created such as:-

1. If dip angle, vibration and coal detection is low, then coal density is low.
2. If dip angle and vibration is low, and coal detection is medium then coal density is low.
3. If dip angle and vibration is low, and coal detection is high then coal density is low.
4. If dip angle and vibration is high, and coal detection is medium then coal density is medium.
5. If drum speed and coal thickness is low, then coal density is low.
6. If drum speed is medium and coal thickness is low, then the coal density is low.
7. If drum speed is high and coal thickness is medium, then coal density is medium.
8. If drum speed is high and coal thickness is high, then coal density is high.
9. If drum speed and coal thickness is medium ,then coal density is medium.

After building the rules with the help of the decision table, the rules can be graphically seen with the help of rule viewer as in Fig. 6. The rule viewer consists of the input plots and the output plots and an output plot which combines all the output plots.

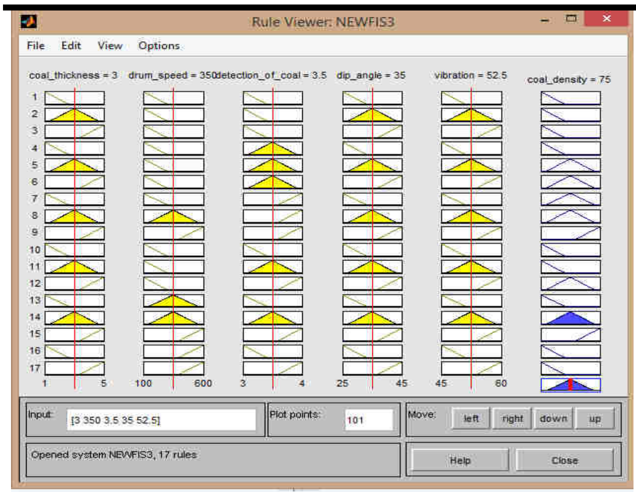


Fig.6:Output for the input parameters being analyzed through a rule viewer

After analyzing the plots it can be concluded that when the input sensors reading are in the range of high and the cutting drum speed is in the range of medium, then the output is in the range of high which means the density of coal will be high. The fuzzified output can also be viewed using the surface viewer as in Fig.7 .In the surface viewer, it consists of three axes, where the x-axis for the input sensor reading ,y-axis for the shearer arm speed and the z-axes for the output variable ,i.e. for the coal density.
The rule viewer gives better and efficient output when the input parameters are in the range of medium for the given membership functions.

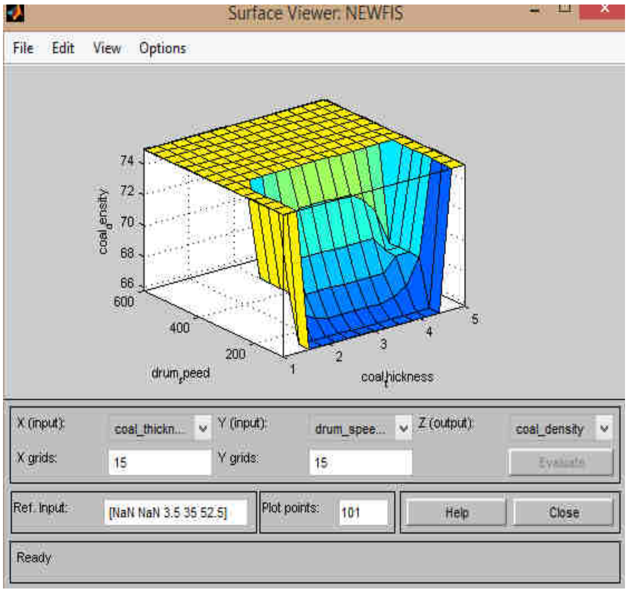
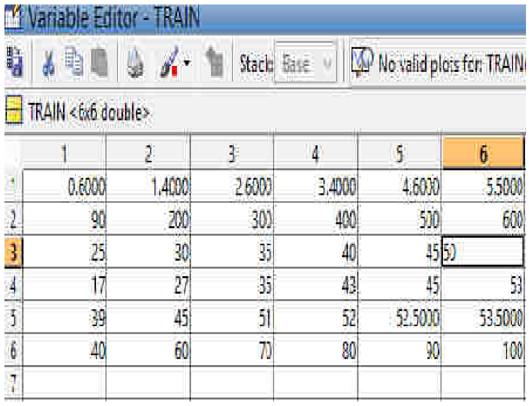


Fig.7:Surface viewer for the input parameters

After finishing the fuzzy logic approach, the experiment is preceded by using the ANFIS model. The ANFIS model helps to acquire the most accurate data set from the given input range. So from the generated FIS's data set, a data set is being trained and tested by compared with the generated FIS. Some of the samples of the trained data set is given in Fig. 8.



Variable Editor - TRAIN

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	1	2	3	4	5	6
1	0.6000	1.4000	2.6000	3.4000	4.6000	5.5000
2	90	200	300	400	500	600
3	25	30	35	40	45	50
4	17	27	35	43	45	53
5	39	45	51	52	52.5000	53.5000
6	40	60	70	80	90	100
7						

Fig.8: Table showing the trained data set

With the help of the ANFIS Editor, the graph between the trained and the generated FIS structure is being obtained. The output for the trained data set and the respective generated FIS data set is being shown in Fig.9. From the RBF model the value of the respective sensors can be achieved precisely such that,

Coal thickness= 4.65m

Drum speed = 455 rpm

Coal detection =3.81 κ/m^2

Dip angle =41.8 degree Celsius

Vibration =56.1 Hz

According to this values, finally the density of coal can be calculated as 81.2 %.

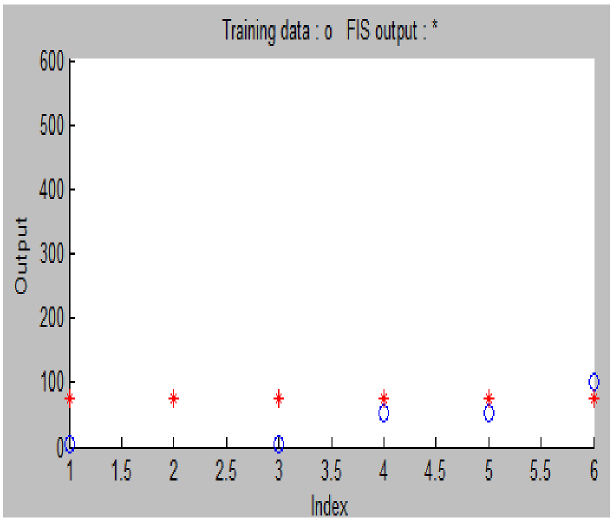

Fig.9:Graph for the trained and training data set using ANFIS Editor.

V. CONCLUSION

By studying the simulation results it is very clear that the output depends upon a wide range acceptance of the input parameters. By analyzing the plots it can be concluded that when the input sensors reading are in the range of high and the cutting drum speed is in the range of medium, then the output is in the range of high, i.e. the density of coal will be high. The difficulties in the model will occur during the stage of training the data set, ones it's cleared the achieved result will be more comfortable. In future, GA optimization can be done in this paper which will help to increase the efficiency of the designed model for the prophecy of the distribution of the coal seams. GA optimization is chosen because it helps to do the optimization more reliable with the environment.

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