An Adaptive Neuro-Fuzzy Inference System for Predicting Survivability Rate in Underground Mining Accident

Mary Opokua Ansong[1] and Samuel King Opoku[1]

[1, 2] *Computer Science Department, Kumasi Technical University, Ghana*

Corresponding Contacts: ansongm@yahoo.com, +233-208-145-025

Abstract

Underground mining has been characterized by high accidental rates over the years. Many efforts have been put in place to decrease the response time in evacuation situations after accidents. These efforts are reactive mechanisms rather than proactive mechanisms. Reactive mechanisms eventually end up losing valuable lives and properties. There is a need to develop a proactive mechanism to reduce the impact of underground mining accidents. This paper developed an Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict the survivability rate of fall of ground in underground mining site using AngloGold Ashanti as a case study. Fuzzy rules were formulated by training Artificial Neural Network using such parameters like working shifts, types of rocks, nature of the rock, rock roof thickness and nature of stope to predict the rate of survivability as either high or low in accidental situations. These parameters were normalized by assigning them values between 0 and 1 to train the ANFIS model. The model's predictions were compared with some recorded data for verification which proved to be 90% accurate. The implemented model will help policy-makers to plan for an inevitable accident to reduce the impact of the accident.

Keywords: ANFIS, Fuzzy, Mining, Neural Network, Occupational Accident

1.0 Introduction

One of the dangerous environmental jobs in the world is underground mining which has been characterized by high accidental rates over the years. An underground accident can be classified as near-miss, minor injuries, disabling injuries, serious injuries and fatalities (Amegbey, Ndur, & Adjei, 2009). These accidents usually occur through the operational activities of the mining site. The common causes of underground mining accidents are fall of ground, machinery operations, slipping and falling, and electrocution. Unfortunately, the fall of the ground accounts for more than half of the total accidents (Emery, Canbulat, & Zhang, 2020). Many efforts have been put in place to decrease the response time in evacuation situations after accidents. These efforts are reactive mechanisms rather than proactive mechanisms. Amegbey et al. (2009) studied the causes and effects of underground accidents of AngloGold Ashanti. Their work revealed that the major cause of fatalities in underground mining site is the fall of ground.

Similarly, Stemn (2019) analyzed 10-year records to develop interventions to improve safety at mining sites. He concluded that some of the items that can cause accidents at the mining sites are the mining equipment and the task being performed. Other researchers devise means to enhance rescue operations. A typical example is the use of sensor networks attached to robots in the works of Ansong et al (2013) and Ansong et al (2015). Interestingly, the work of Emery et al (2020) focused on the geological nature of the mining grounds to reduce the number of accidents at mines. He proposed a proactive ground control management system which minimized unplanned delays. This paper developed an Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict the survivability rate of fall of ground in underground mining site using AngloGold Ashanti as a case study. Fuzzy rules were formulated by training Artificial Neural Network using such parameters like working shifts, types of rocks, nature of the rock, rock roof thickness and nature of stope to predict the rate of survivability as either high or low in accidental situations

One of the powerful mechanisms of Artificial Intelligence for solving problems is the fuzzy logic proposed by Zadeh in 1965 (Zadeh, 1965). Certain situations in our daily lives are best explained using uncertain terms. For example, to say that the weather is hot raises a question, "How hot is hot?" This question about temperature is best answered using the range of values measured in degree Celsius or Fahrenheit. The range of values that each member can belong based on a certain degree is called membership functions. The fuzzy inference system handles uncertain situations using rules to make decisions. However, in some situations, the rules are not known before the start of a study. One helpful mechanism to determine the rules is through an artificial intelligence technique called artificial neural networks. Combining the neural network architecture with the fuzzy inference systems in an adaptive manner gives the Adaptive Neuro-Fuzzy Inference System (ANFIS) (Jang, 1993). ANFIS generates rules through learning. The best ANFIS model is obtained when the error value is the lowest after successive training and testing. Training an ANFIS model involves using either a gradient-descent backpropagation algorithm or least-square method or both. Research works have demonstrated that the hybrid method performed better than the single method (Méndez et al, 2014). Thus, this study employed the hybrid method

2.0 Materials and Methods

2.1 ANFIS Structure

An ANFIS structure usually consists of five layers. The first layer is the premise parameter set that defines the membership functions. This study employs the gradient descent algorithm in the first layer to define the membership functions. This helps the ANFIS model to obtain the required minimum functions with ease without using a brute force mechanism. ANFIS tries to determine the membership functions from the training dataset. The model updates the premise parameters when the error obtained is greater than the threshold. The fourth layer is the consequent parameter set that defines the coefficient of the output equation. The model aims at generating the line of best fit between the input and output variables. Thus the least square method was employed at the consequent parameter set. The hybrid mechanism of training ANFIS models is available in Matrix Laboratory (MatLab) software (Sivanandam et al, 2007) and therefore, it was adopted for developing the model in this study. A typical ANFIS structure is illustrated in Figure 1.

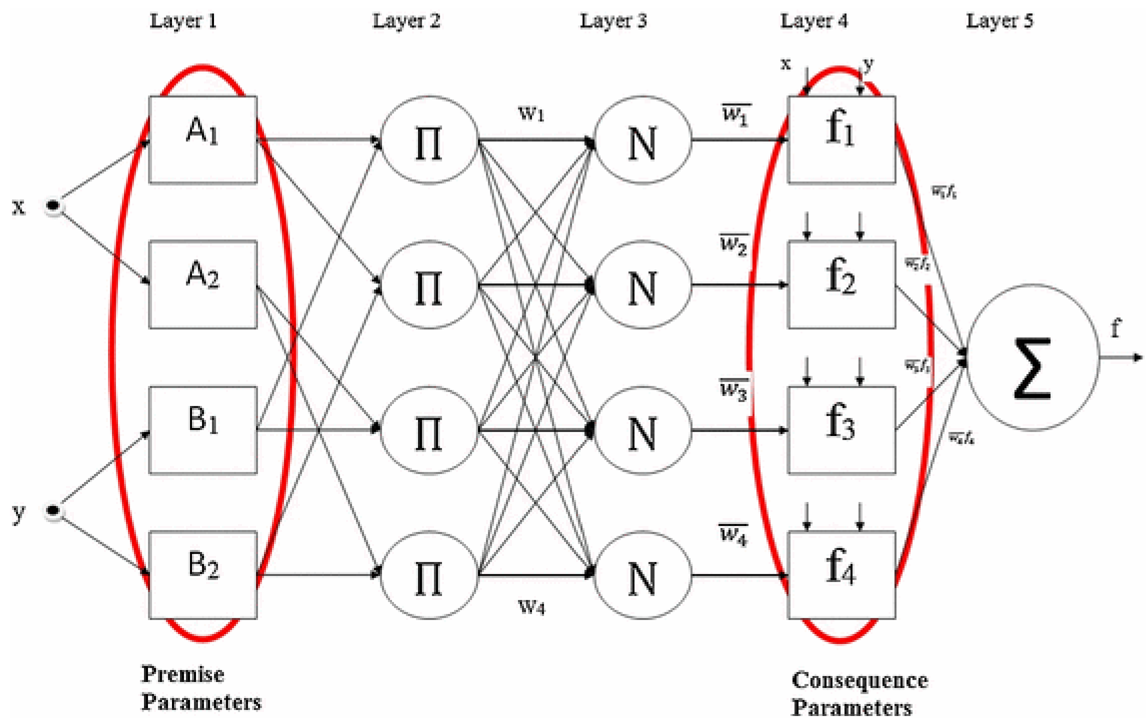

Figure 1: Basic ANFIS Structure with Two Inputs and One Output

Figure 1 has two input variables denoted by x and y, and one output variable denoted by f. There are four membership functions and four rules. Consider the premise parameters such that given a node i, with x as input and a linguistic label A_i, the membership function O_i^1 of A_i is given by

$$O_i^1 = \mu_{A_i}(x) \text{ ------------------------------ } (1)$$

Where $\mu_{A_i}(x)$ is a continuous differentiable function. This study used the Gaussian function. Other membership functions are trapezoidal and triangular-shaped. The Gaussian function uses the standard deviation and the mean of the data. This takes into account every item of the distribution and also neutralizes the effect of instabilities of sampling (Rashid & Ahmed, 2012). Thus, given that σ and c are the standard deviation and mean respectively, the Gaussian function is expressed as:

$$\mu_{A_i}(x, \sigma, c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \text{ ---------------------------------- } (2)$$

After obtaining the premise parameters, nodes in layer 2 produce the firing strength of a rule by multiplying the incoming signal as shown in equation (3) below

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \forall i = 1, 2 \text{ ------------------------------- } (3)$$

In layer 3, the normalized firing strength or the firing ratio of every node is determined. Thus, given a node t with a firing ratio $\overline{w_t}$, equation (4) gives the mechanism to compute its firing ratio as

$$\overline{w_t} = \frac{w_t}{\sum w_{k,t}} \text{ ------------------------------------ } (4)$$

Where w_t is the firing strength of node t and $w_{k,t}$ are the firing strengths from the other nodes in the network that connects to node t such that $k \in \mathbb{Z}^+$ and $k \geq 1$ representing the number of rules.

Layer 4 determines the consequent parameters. Thus, given the parameter set $\{p_t, q_t, r_t\}$ and the outputs, $\overline{w_t}$, from layer 3, the output of the nodes in layer 4 is given by equation (5) as

$$O_t^4 = \overline{w_t} \times f_t = \overline{w_t}\,(p_t x + q_t y + r_t) \text{ ------------------------- } (5)$$

The last layer calculates the final output by adding the outputs from layer 4 as

$$O^5 = \sum(O_k^4) \text{ -------------------------------- } (6)$$

Where $k \in \mathbb{Z}^+$ and $k \geq 1$ representing the number of rules

2.2 Data Collection

This study focused on underground hard rock mining but not soft rock mining. Hard rock mining focuses on unearthing such hard minerals as gold and silver. Soft rock mining, however, looks at digging softer minerals such as salt, coal or oil sands. This study used AngloGold Ashanti (AGA), Ghana, as the case study. AGA is among the largest underground gold mines in the world. Though AGA is involved in surface mining, about 90% of its activities employ underground mining methods. Between the period of 2005 and 2008, there were a total of 1502 accidents of which 58% was due to the fall of ground. This data is similar to the data used by Amegbey et al (2009). Thus a total of 871 records were obtained for this study.

2.3 Data Pre-processing Method

To ensure that the system did not get trapped in the local minima, repeated records and missing values were removed (Thomas, 2020). This reduced the data to 198 unique records. 70% of the data (139 records) was used for training and 30% of the data (59 records) was used for testing. Attribute features were also filtered to get rid of unproductive attributes. Attributes from the employees like age, gender, accident history and hospital bills were ignored as they had little to no effect on the survivability rate of the employee. The algorithm below was used for the data pre-processing method

1. Begin
    2. The four types of measurement scale (nominal, ordinal, interval and ratio) were grouped into two in this study as categorical (consisting of nominal and ordinal scales) and numerical (consisting of interval and ratio scales) based on whether the degree of quantity can be determined.
    3. Since the survivability rate is a categorical attribute, it implies a classification model was developed in this study
    4. Given a 95% confidence level, the alpha value was set to 0.05 in this study.

5. The probability of obtaining results at least as extreme as the observed results of a statistical hypothesis test assuming the null hypothesis is correct (p-value) was determined as:

    5.1 Get the first attribute

    5.2 If the attribute is categorical then

        5.2.1 Conduct a Chi-square test and determine the p-value

        5.2.2 The null hypothesis is the test for independence between the attribute under consideration and the survivability rate

        5.2.3 When the p-value ≤ 0.05, reject the null hypothesis and add the attribute to the list of input variables of the ANFIS model to be developed in this study.

        5.2.4 When the p-value > 0.05, accept the null hypothesis and reject the attribute as an input variable for the ANFIS model to be developed in this study

    5.3 If the attribute is numerical then

        5.3.1 Conduct a one-way analysis of variance (ANOVA) and determine the p-value

        5.3.2 The null hypothesis is the test for no difference in means of the attribute under consideration and the survivability rate

        5.3.3 When the p-value ≤ 0.05, reject the null hypothesis and add the attribute to the list of input variables of the ANFIS model to be developed in this study.

        5.3.4 When the p-value > 0.05, accept the null hypothesis and reject the attribute as an input variable for the ANFIS model to be developed in this study.

5.4 Get the next attribute

5.4.1 If end of attribute then go to step 6

5.4.2 If not end of attribute then go to step 5.2

6. End

At the end of the pre-processing method, five attributes or parameters were selected for the model. These were the type of rock, nature of the rock, working shifts, the thickness of rock roof and the nature of stope. A rock type can be siltstone, phyllite, greywackes, schists or volcanic. The nature of rock can be soft, normal or hard depending on the general type of rock as either sedimentary, metamorphic or igneous respectively. A working shift is usually morning, afternoon or night. A stope is an opening of large underground rooms by the diggings of ore. This requires that the surrounding rock is strong enough to permit drilling, blasting, and removal of ore without caving. A stope can be uniform or non-uniform and/or with its walls being supported with pillars. These parameters constitute the input variables. These variables were used to determine the survivability rate during an accident. The survivability rate constituted the target output of the training data set. Five different types of accidents were obtained from the data collection. They were near-miss, minor injuries, disabling injuries, severe injuries and fatalities. This work grouped the survival rates into two: high rate of survival when an accident is classified as near-miss or minor injuries and low rate of survival when the accident is classified as disabling injuries, severe injuries or fatalities. The data was normalized by assigning numeric values to all the variables so that they could be used by ANFIS. The normalized values were between 0.00 and 1.00. Table 1 shows the various codes assigned to the various variables of the categories

Table 1: Normalization of the Various Variables

Categories of Variables	Parameters	Coding/Values
Types of Rock	Siltstones	0.20
	Phyllites	0.40
	Meta-greywackes	0.60
	Schists	0.80
	Meta-volcanic	1.00
Nature of Rock	Soft	0.25
	Normal	0.50
	Hard	0.75
Working Shifts	Morning Shift	0.25
	Afternoon Shift	0.50
	Night Shift	0.75
Nature of Stope	Non-uniform and unsupported	0.25

	Non-uniform but supported	0.50
	Uniform but unsupported	0.75
	Uniform and supported	1.00
Survivability Rate	High	0.00
	Low	1.00

From Table 1, the values in the third column for each category were evenly coded. When the category has three items, then the codes were 0.25, 0.50 and 0.75. For a four-item category, the codes were 0.25, 0.50, 0.75 and 1.00 and for a five-item category, the codes were 0.20, 0.40, 0.60, 0.80 and 1.00. ANFIS during training may devise a different coding system to create membership functions for each category as demonstrated under the result section.

The following mechanism was used to normalize the thickness of the roof of rock. Given T_i as the thickness of the roof of rock i and T_{max} be the highest value of all the $T_i's$, then R_i is the normalized value of the thickness of the roof of rock i

$$R_i = \frac{T_i}{T_{max}}, \forall i \geq 1 \; such \; that \;\; i \in \mathbb{Z} \;\; and \; R_i \in \mathbb{R}^+$$

Thus, when $R_i < 0.25$, the roof is considered as light. When $0.25 \leq R_i < 0.75$, it is considered as normal otherwise the roof is thick.

3.0 Results and Findings

With 100 epochs, training ended successfully with a minimal training Root Mean Square Error (RMSE) of 0.0101 and a minimal testing RMSE of 0.0109. There were a total of 524 nodes and 273 parameters. The total number of fuzzy rules generated by the model was 243. Figure 2 illustrates the architecture obtained at the end of the training

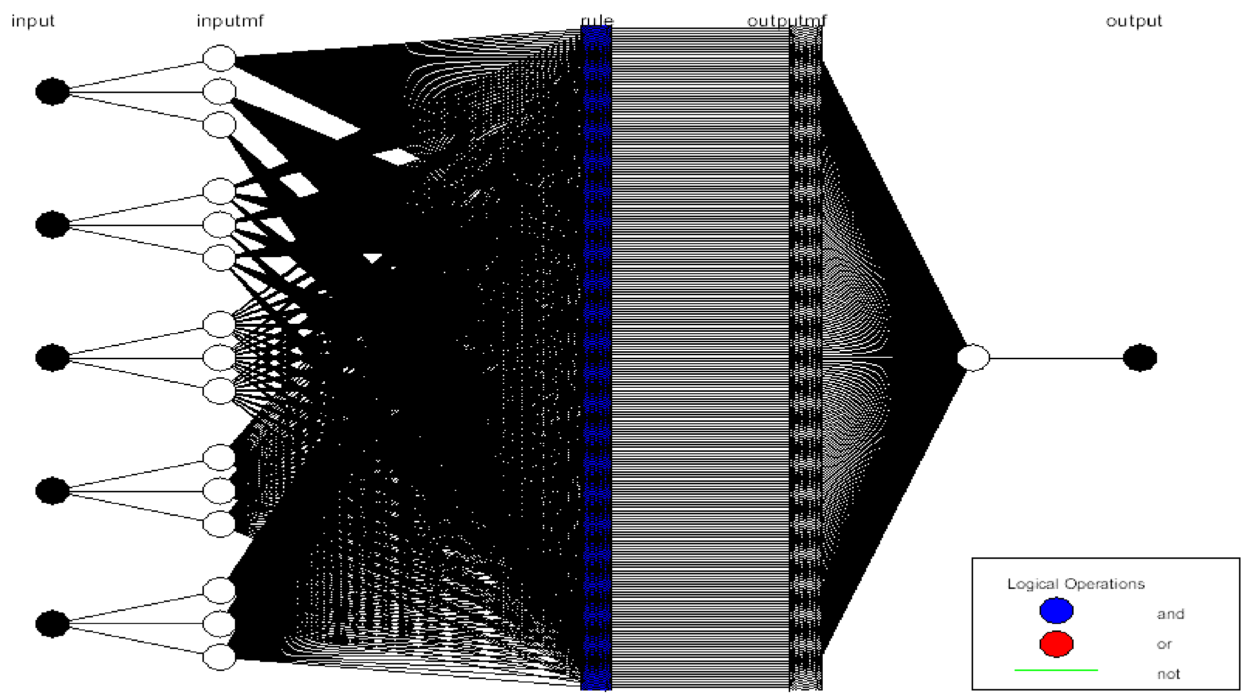

Figure 2 Architecture of the ANFIS Model (Authors' model)

From Figure 2, there are five inputs. All the inputs were designated with three membership functions. The inputs were arranged from top to down as working shifts, type of rock, nature of the rock, thickness of roof rock and nature of stope respectively. All the rules were generated using the AND logical operator. The surface graph shown in Figure 3 depicts the relationship between some of the input variables and the output variable.

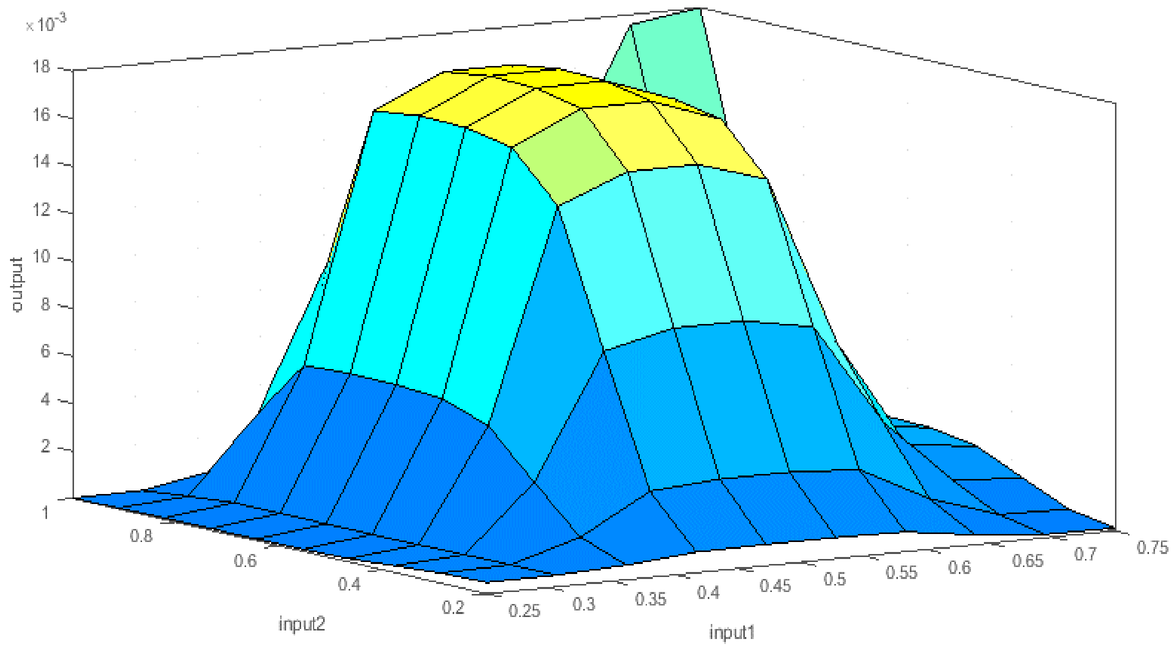

Figure 3 Surface of the Model

The surface graph represents the three-dimensional view between two inputs and the output. Input 1 represents the working shifts, input 2 on the other hand represents the type of rock and the output represents the survivability rate. Figure 4 illustrates the rules of the model. The output values can be meaningful when they are approximated to the nearest whole number which can either be 0 or 1. If the output is 0 then the survivability is high otherwise the survivability is classified as low, therefore the organization should institute a survival plan.

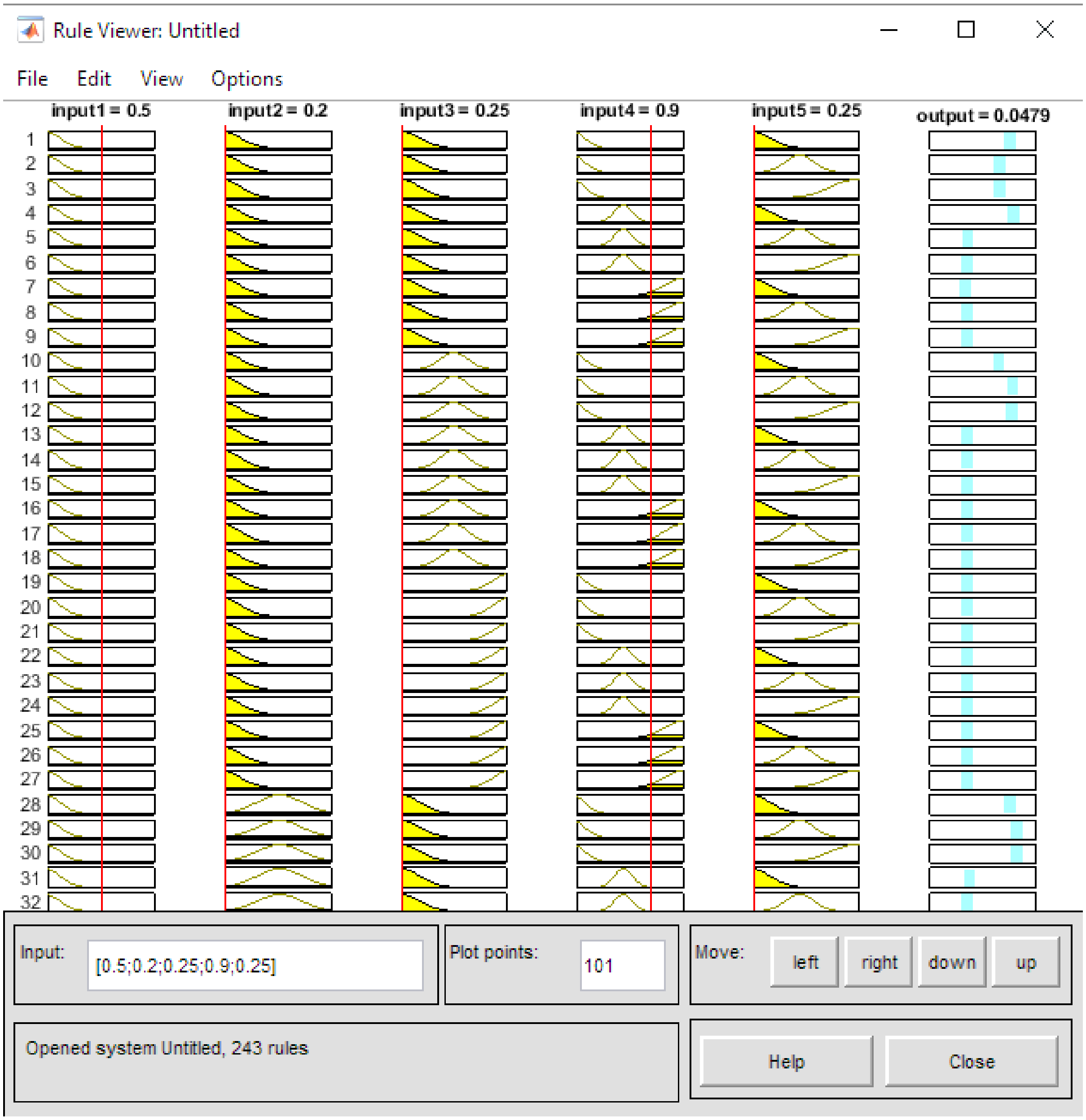

Figure 4 Rule System of the Model

Data can be entered using the input section of the rules interface. From Figure 4, the input data is given at the input section as [0.5; 0.2; 0.25; 0.9; 0.25]. The value of the output generated is displayed on top of the output bars as 0.0479. Table 2 gives the interpretation of the data for us to appreciate what they mean.

Table 2: Interpretation of Input Data from Figure 4

Category of Inputs	**Rule Value**	**Representation**
Working Shifts	0.5	Afternoon
Type of Rock	0.2	Siltstones
Nature of Rock	0.25	Soft
Thickness of Rock Roof	0.9	Thick
Nature of Stope	0.25	Non-uniform and unsupported
Survivability Rate	$0.0479 \cong 0$	High

Thus with the coded information provided in Table 2, a mining organization can predict the survivability rate should an accident occur in a particular section.

4.0 Conclusions and Recommendations

An intelligent system for predicting the rate at which an employee of an underground mining site can survive during an accident has been developed by using a combination of fuzzy logic and artificial neural network concepts. A major limitation of this model is how it classified certain parameters different from known ones. For instance, five types of rocks were identified in this study but the model classified them into three types. Similarly, four parameters were identified for the nature of stope in the mining site but the model classified them into three. Fortunately, the strength of the model lies in the coded system used for this study. Irrespective of how the parameters were classified by the model, the coded system worked for all parameters. The model only looked at one type of accident which is the fall of ground. There are other types of accidents which were not considered in this study. Future study should develop a model to include the other types of accidents not considered in this study. Since human life and other organizational property are valuable, organizations are therefore urged to put prudent measures in place to reduce the impact of accidents in the mining sites.

References

Amegbey, N., Ndur, S., & Adjei, R. K. (2009). Analysis of Underground Mining Accidents at AngloGold Ashanti Limited, Obuasi Mine. *Ghana Mining Journal, 10*(1), 25-29.

Ansong, M. O., Huang, J. S., Yeboah, M. A., Dun, H., & Yao, H. (2015). Non-Gaussian hybrid transfer functions: memorizing mine survivability calculations. *Mathematical Problems in Engineering, 2015.*

Ansong, M. O., Yao, H.-X., & Huang, J. S. (2013). Radial and sigmoid basis function neural networks in wireless sensor routing topology control in underground mine rescue operation based on particle swarm optimization. *International Journal of Distributed Sensor Networks, 9*(9), 376931.

Emery, J., Canbulat, I., & Zhang, C. (2020). Fundamentals of modern ground control management in Australian underground coal mines. *International Journal of Mining Science and Technology*, 1-10.

Jang, J. S. R. (1993). ANFIS: adaptive-network-based fuzzy inference system. *IEEE Trans Systems, Man, Cybernetics, 23*, 665-685.

Méndez, G. M., Martinez, J. C., & Rendón-Espinoza, F. J. (2014). Orthogonal-least-squares and backpropagation hybrid learning algorithm for interval A2-C1 singleton type-2 Takagi-Sugeno-Kang fuzzy logic systems. *International Journal of Hybrid Intelligent Systems, 11*(2), 125-135.

Rashid, T. A., & Ahmed, H. A. (2012). Revised General Test/Gross Point Average System Via Fuzzy Logic Techniques. *Journal Of Computer Science And Engineering, 16*(1), 1-9.

Sivanandam, S. N., Sumathi, S., & Deepa, S. N. (2007). *Introduction to fuzzy logic using MATLAB* (Vol. 1). Berlin: Springer.

Stemn, E. (2019). Analysis of injuries in the Ghanaian mining industry and priority areas for research. *Safety and health at work, 10*(2), 151-165.

Thomas, S., 2020. *Data Cleaning In Machine Learning: Best Practices and Methods.* [online] Einfochips.com. Available at: <https://www.einfochips.com/blog/data-cleaning-in-machine-learning-best-practices-and-methods/> [Accessed 21 September 2020].

Zadeh, L. A. (1965). Fuzzy sets. *Inf Control, 8*, 338-353.