

Prediction of Blast-Induced Airblast, Ground Vibration and Rock Fragmentation Using
Machine Learning Methods in Debswana Diamond Mine

By

Kesalopa Gaopale

Reg No: 17100152

BSc (Mining Engineering)

Department of Mining and Geological Engineering

College of Engineering and Technology

Botswana International University of Science and Technology

Email: Kesalopa.gaopale@studentmail.biust.ac.bw, Tel (+267) 72591144

A Dissertation/Thesis Submitted to the College of Engineering and Technology in Fulfilment
of the Requirements for the Award of the Degree of Master of Science in Mining Engineering

Supervisor: Associate Professor Rodrigo S. Jamisola Jr

Department of Mechanical, Energy and Industrial Engineering

College of Engineering and Technology, BIUST

Email: jamisolar@biust.ac.bw

Office No.: +267-493-1649 Mobile: +267-7571-6329

Signature:  Date: 06/03/2019

Co-Supervisor: Dr Itumeleng Seitshiro

Debswana

Email: ITSeitshiro@debswana.bw

Tel : +267 72986995

Signature:

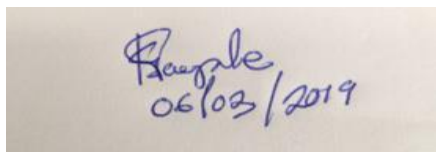
 06/03/2019

March/2019

DECLARATION AND COPYRIGHT

I Kesalopa Gaopale declare that this dissertation/thesis is my own work and that it has not been presented and will not be presented to any other university for a similar or any other degree award.

Signature

A photograph of a handwritten signature in blue ink. The signature appears to be 'Gaopale' with a stylized initial. Below the name, the date '06/03/2019' is written.

This dissertation/thesis is copyright material protected under the Bene Convention, the Copyright Act of 1999 and other international and national amendments, on that behalf, on intellectual property. It must not be reproduced by any means, in full or in part, except for short extracts in fair dealing; for researcher private study, critical scholarly review or disclosure with an acknowledgement, without the written permission of the office of the Provost, on behalf of the author and the BIUST.

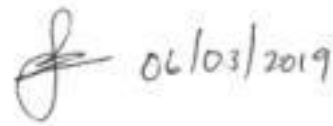
CERTIFICATION

The undersigned certifies that he/she has read and hereby recommends for acceptance by the College of Engineering and Technology a dissertation/thesis titled Prediction of Blast-Induced Airblast, Ground Vibration and Rock Fragmentation Using Machine Learning Methods in Debswana Diamond Mine in fulfilment of the requirements for the degree_of Master of Science in (Mining Engineering) of the BIUST.



06/03/2019

Associate Professor Rodrigo S. Jamisola Jr
(Supervisor)



Dr Itumeleng Seitshiro
(Co-Supervisor)

ABSTRACT

This work presents machine learning methods, particularly artificial neural networks (ANN) and multivariate regression analysis (MVRA) to create a mathematical model that will be used to predict the blasting effects in a Debswana diamond mine. These effects include airblast, ground vibration and rock fragmentation. We compare results from ANN, MVRA and empirical formulas using coefficient of determinant (R^2) and root mean square error (RMSE). The ANN model with one hidden layer, 14 nodes and Levenberg Marquardt algorithm had optimum results compared to MVRA and empirical formulas. This study uses eight input parameters and three output parameters. Sensitivity analysis was conducted to evaluate the influence of each input parameters to the resulting values of the output parameters. Lastly, this work claims the following three contributions. Firstly, to the best of the author's knowledge, this is the first machine learning study conducted on blast-induced effects in a diamond mine. Secondly, it is among the largest input to output parameter ratio at 8-to-3 on any other blast-induced study. And thirdly, the sensitivity study conducted in the input-to-output parameter effects can lead to the design of input parameters to predict possible expected effects in the output parameters.

ACKNOWLEDGMENTS

I would like to thank the all mighty God for guidance and strength he has given me to finish this research work. Also, I would like to further thank my supervisors Associate Professor Rodrigo.S Jamisola Jr and Dr Itumeleng Seitshiro for their continuous advice and help to do this research paper. I am grateful to Debswana Diamond Company especially Mr Eddie Mosware and Mr Moses Serojane for allowing us to visit the Orapa mine and share the blasting records with me to do my research work.

Lastly, I would like to be thankful to my parents, Mr and Mrs Gaopale, my sisters, Boitumelo, Opelo and Gaolapelwe for their support and prayers during my research work.

TABLE OF CONTENTS

DECLARATION AND COPYRIGHT.....	i
CERTIFICATION	ii
ABSTRACT.....	iii
ACKNOWLEDGMENTS	iv
LIST OF FIGURES	vii
LIST OF TABLES	ix
CHAPTER 1: INTRODUCTION.....	1
1. Background	1
1.1.Statement of the problem	2
1.2.Project objectives	3
1.3. Mine information.....	3
1.3.1. location	3
1.3.2. mine geology	4
1.3.3. mine operations.....	4
1.4.Contribution of this study.....	5
1.5. Summary	6
CHAPTER 2: LITERATURE REVIEW	7
2.1. Blasting.....	7
2.2. Air over pressure/ airblast	10
2.3. Ground vibration	15
2.4. Rock fragmentation	21
2.5. Artificial neural network	23
2.6. Summary	29
CHAPTER 3: METHODOLOGY	30
3.1 Data collection.....	30
3.2. Blasting data sets.....	31
3.3. Artificial neural model network architecture	32
3.4. Multivarite regression analysis (mvra).....	39
3.5. Empirical formulas for ground vibration (ppv).....	42
3.6. Empirical formulas for air-overpressure (aop) / airblast.....	47
3.7. Sensitivity analysis	50
3.8. Summary	52
CHAPTER 4: RESULT ANALYSIS AND DISCUSSION	53

4.1. ANN and mvra evaluation	53
4.2. Emprical predictors and ann.....	54
4.3. Sensitivity analysis	55
4.4. Summary	55
CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS.....	56
5.1. Conclusions	56
5.2. Recommendations	57
APPENDIX A.....	58
Creation of artificital neural network model	58
APPENDIX B	63
Models tested with different articteture and transfer function	63
REFERENCES.....	79

LIST OF FIGURES

	Page
Figure 1. 1. Environmental effects of blasting.....	9
Figure 1. 2. Map of Botswana showing the location of Orapa mine.....	12
Figure 1. 3. Ariel view of Orapa open pit mine.....	13
Figure 2. 1. Blast pattern design 845-830IO32-37.....	15
Figure 2. 2. Charged and stemmed blast holes before blasting pattern 845-830IO32-37.....	16
Figure 2. 3. Muck pile distribution after blasting pattern 845-830IO32-37.....	17
Figure 2. 4. Mining Cycle.....	18
Figure 2. 5. Graphical representation of ANN network.....	31
Figure 3. 1. Image of blasted rock fragments.....	36
Figure 3. 2. Bench 890-875 Split desktop Fragmentation Analysis.....	37
Figure 3. 3. MATLAB window for ANN.....	39
Figure 3. 4. Training of back propagation neural network.....	40
Figure 3. 5. Optimum model network architecture.....	41
Figure 3. 6. Regression plots of ANN during training, testing and validation.....	42
Figure 3. 7. Relation between Predicted Airblast by ANN and measured values.....	43
Figure3. 8. Relation between predicted Ground Vibration by ANN and measured values....	44
Figure 3. 9. Relation between predicted rock fragmentation by ANN and measured values.....	44
Figure 3. 10. Relation between predicted by MVRA and measured values.....	46
Figure 3. 11. Relation between predicted ground vibration by MVRA and measured values	47
Figure 3. 12. Relation between predicted rock fragmentation by MVRA and measured values.....	47
Figure 3. 13. Ground vibration (PPV) and Scaled distance on log–log scale for Duvall and Petkof.....	49
Figure 3. 14. Ground vibration (PPV) and Scaled distance on log–log scale for Langefors and Kihlstrom.....	49
Figure 3. 15. Ground vibration (PPV) and Scaled distance on log–log scale for BIS.....	50
Figure 3. 16. Ground vibration (PPV) and Scaled distance on log–log scale for Ambraseys and Hendron.....	50
Figure 3. 17. Predicted PPV by Duvall and Petkof formula and Measured PPV.....	51
Figure 3. 18. Predicted PPV by Langefors and Kihlstrom formula and Measured PPV.....	52

Figure 3. 19. Predicted PPV by BIS formula and Measured PPV.....	52
Figure 3. 20. Predicted PPV by Ambraseys and Hendron formula and Measured PPV.....	53
Figure 3. 21. Measured Airblast and predicted Airblast by National Association of	
Figure 3. 22. Measured Airblast and predicted Airblast by McKenzie.....	55
Figure 3. 23. Measured Airblast and predicted Airblast by Persson et al.....	55
Figure 3. 24. Sensitivity analysis quantifying the influence of each input parameter on Airblast.....	56
Figure 3. 25. Sensitivity analysis quantifying the influence of each input parameter on Ground vibration.....	57
Figure 3. 26. Sensitivity analysis quantifying the influence of each input parameter on Rock fragmentation.....	57

LIST OF TABLES

	Page
Table 1. Comparison of previous studies with my study.....	5
Table 2. 1. Various Researchers Empirical Models.....	19
Table 2. 2. Air overpressure levels and their impacts	24
Table 2. 3. Empirical formulas developed by Researchers.....	25
Table 2. 4. Site Constant, H and β for different blasting condition.....	26
Table 3. 1. Ranges of Input and Output parameters.....	38
Table 3. 2. Different ANN models.....	41
Table 3. 3. Results of Measured and Predicted Output.....	43
Table 3. 4. Ground vibration empirical formulas.....	48
Table 3. 5. Calculated site constants.....	51
Table 3. 6. Air overpressure empirical models.....	54
Table 4. 1. R2 and RMSE values for ANN and MVRA models.....	60
Table 4. 2. R2 and RMSE values of PPV using ANN and empirical predictors.....	61
Table 4. 3. R2 and RMSE values of airblast using ANN and empirical predictors.....	62

CHAPTER 1: INTRODUCTION

1. BACKGROUND

Blasting is the most common method of rock breakage in mining operations and civil engineering works such as tunnelling and road construction. When an explosive detonates, it generates a huge amount of energy and only a small fraction of energy breaks the rock whereas the rest results in undesirable environmental events. About 20-30% of explosive energy generated breaks the rocks whereas the rest results in ground vibrations, air blast, dust and flyrock (Monjezi and Bahrami et al., 2009; Cheng and Huang 2000; Hakan and Konuk, 2008). The main concern areas of blasting operation are safety, productivity and environmental effects as shown in Figure 1. Therefore it is vital for a blast engineer to develop an optimum blasting design that will result in a best rock fragmentation and environmental safe blasting.

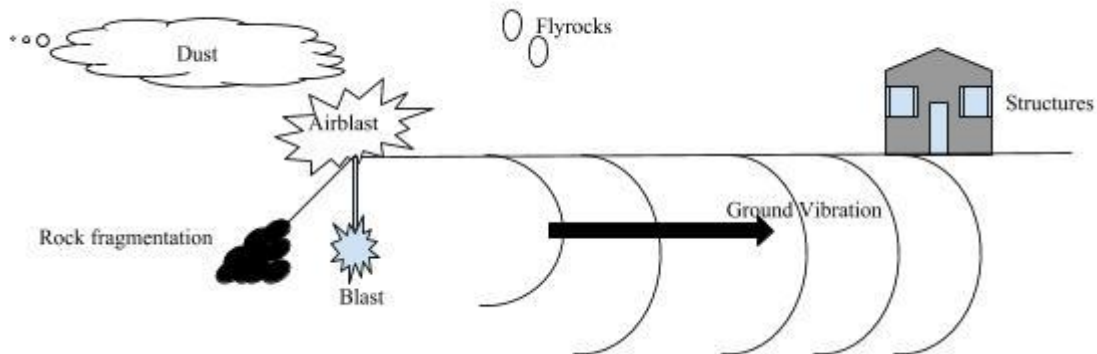


Figure 1. 1. Environmental effects of blasting

Several researchers have developed some empirical formulas as a guide to design the blast. However, these empirical formulas do not incorporate as many factors that affect the outcome of the blast as compared to Artificial Neural Network (ANN). The ability of ANN to incorporate many factors gives it more advantage over other prediction methods. Also, the ANN model generated is site specific and it can be expanded by including other parameters such as rock hardness, and rock strength etc.

Therefore, for this research the ANN model will be developed to predict blast induced airblast, ground vibration and rock fragmentation.

Artificial neural network (ANN) is a branch of artificial intelligence that operates the same way as a human brain works. It is a highly interconnected structure that consists of neurons that perform massive parallel computation for knowledge representation and data processing.

1.1. STATEMENT OF THE PROBLEM

Rock fragmentation is one of the vital stages of blasting operations that are carefully looked at than the resulting after-effects of blasting in the environment. A good designed blast will result in optimum rock fragmentation and displacement of rock mass because of the efficient use of the explosive energy from the detonation of explosives in the blast hole whereas a poor blast results in poor rock fragmentation and undesirable environmental effects such as ground vibrations, fly rock, backbreak etc. Ground vibrations are the main worry for blast engineers as they may result in undesirable effects in nearby buildings, roads , etc. On the other hand, the noise generated during the blast can result in complaints from nearby local inhabitants and impact the personnel negatively psychologically. Poor rock fragmentation can affect the mining cycle thereby leading to lower production and increasing overall mining costs as secondary blasting will be needed. Also, poorly fragmented rocks may damage the mining equipment used for processing the material such as the crusher.

This is a case study based in Debswana Orapa mine in Botswana. Currently blast designers in Debswana Orapa mine have no predictive methods that they use to predict the blast induced airblast, ground vibration and rock fragmentation prior to blasting. Having predictive methods will enable blast engineers to develop a blast design that will have optimum rock fragmentation and minimum environmental effects. Also, the use of ANN to develop a predictive model will enable more input parameters to be used as compared to other empirical methods that have limited outputs.

1.2. PROJECT OBJECTIVES

A well-designed blast should produce a desired rock fragmentation and reduced environmental effects such as ground vibration, flyrock and airblast in the nearby communities. This study will emphasize on the following objectives to reduce ground vibrations and achieve desired rock fragmentation.

- Develop MATLAB-based ANN predictive model for blast induced airblast, ground vibration and rock fragmentation
- Compare developed ANN predictive model results to existing empirical methods and multivariate regression analysis.
- Quantify the influence of each input parameter on the airblast, ground vibration and rock fragmentation by conducting sensitivity analysis.

1.3. MINE INFORMATION

1.3.1. Location: Orapa mine is located in Botswana, Southern Africa. It is situated 240 km west of Francistown in the Central District of Botswana as shown in Figure 1.2. It is positioned between the latitude and longitude of $21^{\circ} 18' 30''$ S and $25^{\circ} 22' 10''$ E respectively.



Figure 1. 2. Map of Botswana showing the location of Orapa mine

1.3.2. Mine Geology: The mine lies on igneous rocks known as kimberlite which bears diamonds and it was intruded about 92 million years ago. The Orapa kimberlite has two coalescing diatremes with preserved crater sedimentary facies named southern and northern lobes which lie on an ground area of 1.18 square kilometres. The northern lobe was the first to be intruded and it is a regularly shaped, steep-sided diatreme. The top part of the northern lobe is packed with lustrous pyroclastic kimberlite distinguished by fragments of up to ten meters in diameter. The lustrous pyroclastic kimberlite grades diminish into monotonous, massive tuff isitic kimberlite breccia downwards. The southern lobe is irregularly shaped, steep sided with carter zone above it filled with epiclastic and volcanoclastic kimberlite. The epiclastic kimberlite occupies the top part of the carter while the volcanoclastics the bottom part of the carter. There are two main types of the epiclastic deposits which are mass flow and talus deposits.

1.3.3. Mine Operations: Orapa mine is a conventional open mine as shown in Figure 1.3. The mine operates a four-shift system with 8 hours per shift. The mine operations start with drilling of the blastholes, charging blastholes with explosives and detonating blastholes. The resulting rock fragments from the blasting are loaded into dump trucks using hydraulic excavators. The waste material is hauled to waste dumps while the ore is transported directly to the crusher or to the stockpile. Dewatering is one of the processes that is also done as mining progresses to control water inflows thus creating workable dry conditions and reducing pore water pressure which affects slopes significantly.



Figure 1. 3. Ariel view of Orapa open pit mine

1.4.CONTRIBUTION OF THIS STUDY

In the Table 1 below, present four previous works that are very closely related to our work. Comparison of these studies is based on the following items : number of input and output parameters, type of mineral, and number of blasting events modelled.

Table 1: Comparison of previous studies with my study

Author	Paper	Number of Input Parameters	Number of Output Parameters	Number of Blasting events	Mineral Excavated and Location
Manoj Khandelwal and T.N. Singh (2009)	Prediction of blast-induced ground vibration using ANN	10	2	104	Coal mine in India
Kazem Oraee and Bahareh Asi (2006)	Prediction of rock fragmentation in open pit mines , using Neural Network Anal	11	1	54	Iron ore mine in Iran
Hajihassani et al (2014)	Prediction of air-overpressure induced by blasting using Hybrid artificial neural network and particle swarm optimization	9	1	62	Granite quarry in Malaysia
Parida, A and Mishra, M.K (2015)	Blast Vibration analysis by different predictor Approaches-A comparison	5	1	9	Iron ore mine in India
My Research	Prediction of Blasting effects, i.e., Airblast, Ground Vibration and Rock Fragmentation using Machine Learning Methods in a Debswana Diamond Mine	8	3	104	Diamond mine in Botswana

Compared to previous studies, we claim the following contributions:

1. To the best of our knowledge, this is the only study conducted in a diamond mine related machine learning modelling of blasting.
2. We are among the biggest ratio of input to output parameters at $8/3 = 2.67$
3. Our sensitivity study allows assessment of input parameters that has the biggest influence in the output parameters. This will guide in the design of blasting with a more realistic prediction of its physical effects.

1.5. SUMMARY

This research work is to develop an ANN predictive model that will result in optimum rock fragmentation and minimum airblast and ground vibration. Optimized rock fragmentation will increase the overall crusher output and minimize its wear and tear. In addition, it will prevent the need for secondary blasting hence minimising the overall mining cost. Optimum blast will minimize the levels of airblast and ground vibration hence less damage to mine structures, community buildings and less annoyance to personnel and inhabitants near the mine. Chapter 2 is a conducted literature review on blasting and artificial neural network.

CHAPTER 2: LITERATURE REVIEW

2.1. BLASTING

Blasting is the most common method of rock fragmentation in mining operations and civil engineering works. Blast designing is the first step that is done before the actual blasting. Blast pattern design is shown in Figure 2.1. There are many factors that are taken into consideration when designing blasting pattern. These factors include geology, physico-mechanical properties of the rock, pit geometry, explosive characteristics, spacing of the holes, burden distance, depth of holes, diameter of holes, stemming length, powder factor, blasting technique, angle of drilling, vibration level, presence of water, required muck pile profile and size of rock fragments wanted.

Key:

Red dots:- As drilled above holes

Blue circles:- As designed holes

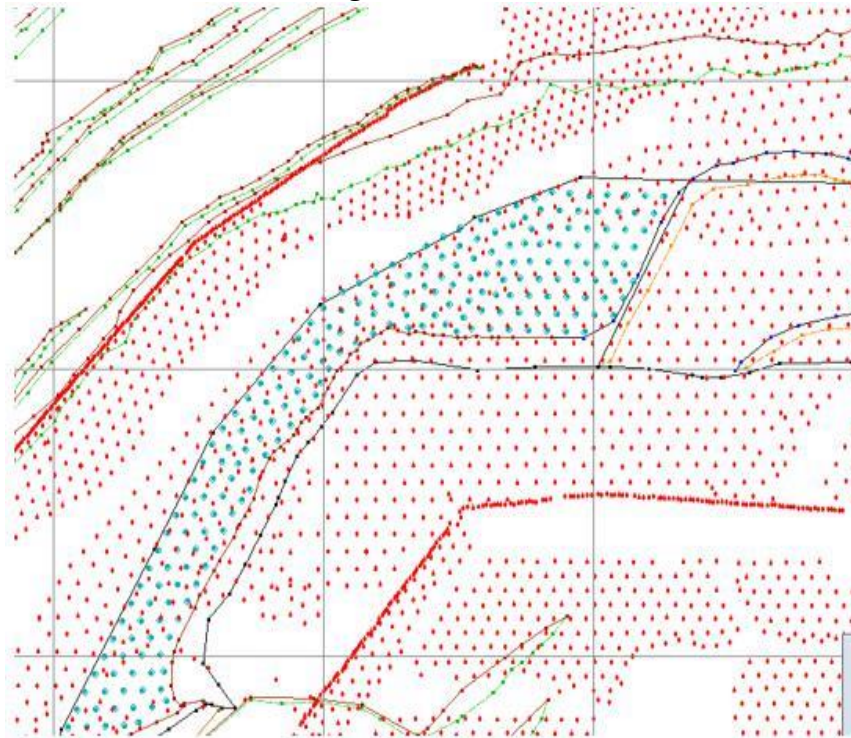


Figure 2. 1. Blast pattern design 845-830IO32-37

The second step before the actual blasting is to send the designed blast for actual drilling in the site. The blastholes will be drilled to actual depth and loaded with appropriate explosives. Then the explosive gets triggered by a detonator. Detonators can be mechanically, chemically and electrically initiated. When an explosive in the blasthole detonates, it generates detonation wave which acts on the confined medium surrounding it and further induces blast wave which impacts the surrounding rock of the blasthole. The surrounding rock of the blasthole gets crushed when its compressive strength is exceeded. The blast waves lessen to stress wave beyond the crushed zone during the process of propagation and inflict tensile damage on the surrounding rock beyond the crushed zone and forms hoop and radial cracks at a certain distance from the blasthole (Yang 2005 and Li 2011).



Figure 2. 2. Charged and stemmed blast holes before blasting pattern 845-830IO32-37.



Figure 2. 3. Muck pile distribution after blasting pattern 845-830IO32-37

Blasting is an essential part in mining cycle. It is commonly used for rock breakage in open pits, quarries, surface and underground mining works. Figure 2.4 shows different stages of mining cycle.

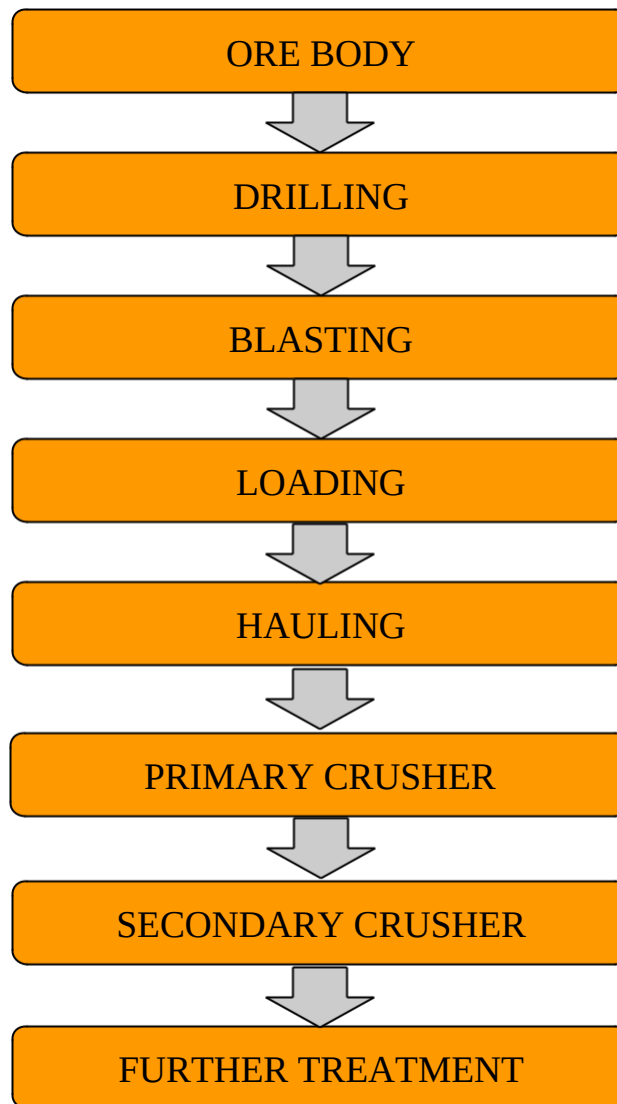


Figure 2. 4. Mining Cycle

2.2. AIR OVER PRESSURE/ AIRBLAST

Airblast or air overpressure is the one of the most hazardous effects of blasting operation on the environment. The noise generated during the blast can result in complaints from nearby local inhabitants and impact the personnel negatively psychologically. When an explosive detonates in the blasthole , it generates a great amount of energy in terms of temperature and pressure. A small fraction of energy is used for rock breakage and displacement and this results in negative environmental effects such as airblast, ground vibration, flyrock etc.

During blasting, airblast is generated when explosive gases get released into the atmosphere and create air pressure waves. These generated explosive gases have energy that leads to the rise of air pressure level above the normal atmospheric pressure. Atmospheric pressure wave can be subcategorized into two: audible and sub-audible (Bhandari, 1997). Audible pressure waves are those with high frequency sound while sub-audible pressure waves have low frequency sound. Blast induced airblast is a shock wave which is refracted horizontally by density variations in the atmosphere and gradually dies out with distance and time.

The minimum frequency of sound that a human being can hear is 20 Hz and below that it cannot be heard. Also, the maximum sound the human can hear is 85 Hz and above that the hearing gets damaged. Airblast is measured in terms of Pascal (Pa) and Decibels (dB) (Kuzu et al., 2009). Air blast results in inhabitants' annoyances and potential structural damage when air overpressure waves energy is higher than the atmospheric pressure. Table 2.3 below shows the types of impacts that different levels of air overpressure can cause (Griffiths et al., 1978; Morhard, 1987 and Rodriguez et al., 2010).

Table 2.1. Air overpressure levels and their impacts

Air Overpressure level	Impacts
<110 dB	Non
110-130 dB	Window Vibration
130-150 dB	Glass Break
180 dB	Structural damage

In blasting operation, air overpressure is mainly a resultant of the following (Morhard, 1987; Wiss and Linehan, 1978; Siskind et al., 1980) :

- Air pressure pulse (APP): displacement of the rock at bench faces as the blast progresses.
- Stemming release pulse (SRP): escape of gases from the blasthole when the stemming is ejected.

- Gas release pulse (GRP): escape of gases through rock fractures.
- Rock pressure pulse (RPP): induced by ground vibration.

Air overpressure is influenced by many factors; blast design parameters such as burden and spacing, charge depth, stemming, maximum charge per delay, detonator accuracy and direction of initiation. Other factors that influence air overpressure include atmospheric conditions, weak strata, overcharging and conditions caused by secondary blasting (Bhandari, 1997; Rodriguez et al., 2007; Siskind et al., 1980 and Dowding, 2000). Several researchers have developed empirical formulas to predict air over pressure as shown in Table 2.4.

Table 2.2. Empirical formulas developed by Researchers

No	Researchers	Empirical formula	Description
1	National Association of Australian State (1983)	$P = \frac{140 \sqrt[3]{\frac{E}{200}}}{d}$	P is overpressure in kPa, E is charge mass in kg, and d is distance from blasthole center to the monitoring point in meters.
2	McKenzie (1990)	$dB = 165 - 24 \log(D/W^{1/3})$	dB is the decibel reading D is distance in meter, and W is the maximum charge weight per delay (in kg)
3	Persson et al (1994)	$P = 0.7(W^{1/3}/D)$	P is Air Overpressure in mbar; W is Cooperating Charge in kg; and D is Distance in meter

Also, cube-root scaled distance factor (SD) can be used to predict air overpressure when there is no monitoring equipment. SD is formulated as below;

$$SD=DW^{-0.33}$$

Where D is the distance (m) to the explosive charge and W is the explosive charge weight (kg) and SD is the scaled distance factor ($m\ kg^{-0.33}$). Therefore, the relationship between air overpressure and scaled distance gives the following formula:

$$P=H (SD)^{-\beta}$$

Where P is air overpressure measured in dB or Pa, H and β are site constant are the site factors. Table 2.5 gives H and β of specific site and different blasting condition.

Table 2. 3. Site Constant, H and β for different blasting condition

Source	Description	H	β
Hustrulid	Detonations in air	261.54	0.706
USBM	Quarry blasts, behind face	622	0.515
	Quarry blasts, direction of initiation	19,010	1.12
	Quarry blasts, front of face	22,182	0.966
Kuzu et al	Quarry blasts in competent rocks	1833.8	0.981
	Quarry blasts in weak rocks	21,014	1.404
ISEE	Confined blasts for AOp suppression	1,906	1.1
	Blasts with average burial of the charge	19,062	1.1

Wu and Hao (2007) found that airblast level generally determines the structural response and damage when they investigated the impact of simultaneous airblast forces and ground shock on structures.

Kuzu et al. (2009) established the relationship between air overpressure and the weight of the explosive and distance between the monitoring point and blast face. This enabled them to generate practical results.

Segarra et al. (2010) developed a new air overpressure prediction formula when they investigated the propagation of pressure waves or airblast in air generated by bench blasting that is rock breakage towards free vertical face by detonating explosives in a row of blasthole.

Artificial intelligence methods like ANN, fuzzy logic and support vector machine (SVM) have been applied to predict blast induced AOp by a number of researchers. Khandelwal and Singh (2005) predicted blast induced air overpressure (AOp) in an opencast limestone mine using artificial neural network (ANN). A total number of 56 blasting events were investigated. The distance between the blast face and monitoring point were incorporated as input parameters for ANN model development whereas AOp was regarded as output parameters. Conventional statistical methods and empirical formulas prediction were used to assess the effectiveness of the ANN model. The findings show that the ANN model had the most accurate predictions as compared to conventional statistical methods and empirical formulas. The Mean Absolute Percentage Error (MAPE) and correlation co-efficient were used to evaluate the performance of ANN models and predictors. ANN, statistical analysis and empirical formula (MAPE) were 2.7437, 69179 and 8.6957 respectively.

Sawmliana et al (2013) used artificial neural network to predict blast induced air overpressure (AOp). A total number of 110 blasting events were investigated. For construction of the model, 70 datasets were used for training, 25 datasets were used for validation and 15 datasets were used for testing the model. Also for construction of the model, the most effective parameters on blast induced AOp namely; total charge, depth of the burial charge, maximum charge per delay and the distance between the blast face and the monitoring point were regarded as input parameters whereas AOp was the output parameter. To prove the effectiveness of the ANN model, the predicted values of the ANN model were compared with those predicted by the empirical formulas. Each predictor performance was evaluated using correlation coefficient and ANN (correlation coefficient: 0.931) thus showing a logical relationship between the measured and predicted values of air overpressure.

Also, sensitivity analysis was conducted based on the ANN results and it demonstrated that the most effective parameters on AOp are maximum charge per delay and depth of burial of charge.

Hybrid artificial neural network (ANN) and particle swarm optimization (PSO) were used to predict airblast-overpressure at granite quarry site in Malaysia by Hajihassani et al. (2014). 62 blasting events were monitored for a period of six months. Blasting parameters namely hole depth, stemming length, rock quality designation (RQD), powder factor, spacing and burden were measured during data collection while airblast was monitored in each blasting event. The PSO-ANN optimum model was achieved after training and testing several models using data collected. For checking the effectiveness of the PSO-ANN model, the results were compared with the results of multivariate regression analysis (MVRA) and conventional formulas. The results show that the PSO-ANN model is the most effective and highly accurate when predicting airblast with correlation of coefficient of 0.94 proving that it is better as compared to other predictive methods.

Armaghani et al (2015) used a hybrid AI-based predictive model to predict blast induced air overpressure (AOp). This study used ANN optimized by imperialist competitive algorithm (ICA) to predict blast-induced AOp at granite quarry site in Malaysia. A total 95 blasting event were investigated and the most effective parameter were measured and used to develop the ICA-ANN model. The input parameters for model development were the distance between the monitoring point and the blast point and the maximum charge per delay whilst AOp was regarded as the output parameter. Conventional predictors were also used and their results were compared with the results of the developed ICA-ANN model. The ICA-ANN model predictive results were highly accurate as compared to conventional predictors.

2.3. GROUND VIBRATION

Ground vibration is the motion of waves that are generated after the explosive detonates and propagates outward from the blast. The level of vibration is measured in mm/s (peak particle velocity). As ground vibration propagates, it changes the rock

behaviour of the site and surrounding areas thus affecting the stability and integrity of the site and the nearby surrounding structures. Uncontrollable levels of ground vibration will eventually lead to structures damage or failure. When an explosive detonates within a blasthole, a large amount of chemical energy is released at high pressure thereby forming a hot gas (Hopler 1998). After detonation, two forms of energy are generated; gas pressure energy and shock wave energy (Djordjevic 1995). The shock wave energy greatly affects the walls of the blasthole and crushes it up. The damaged area surrounding the blasthole is called the crushed zone. Fracturing will result beyond the crushed zone caused by elastic and plastic waves and form what is called nonlinear zone (Mortazavi 1999). Elastic waves propagate beyond this zone while plastic waves lessen in this zone. As the elastic wave propagates beyond the nonlinear zone, this motion is referred to as peak particle velocity.

Ground vibrations are influenced by controllable parameters and uncontrollable parameters. Controllable parameters are those that are man-made, mostly associated with explosive characteristics and blast design parameters such as explosive energy, charge per delay, blasthole diameter, blasthole depth, stemming etc. Uncontrollable parameters are those that are naturally occurring such as rock characteristics and geological conditions. The magnitude of the ground vibration at any locations is influenced by the following;

- Frequency: is the number of oscillations per second the wave undergoes.
(measured in(Hz))
- Wave displacement : The distance a wave moves before returning to its
original position (measured in mm)
- Wave velocity: the rate of change of displacement (measured in mm/s).
- Wave acceleration: This is the rate of change of velocity (measured in mm/s^2)

Ground vibrations are measured by the particle velocities at certain ground locations (Parida and Mishra, 2015). Several researchers had developed empirical formulas to predict the peak particle velocity. The following Table 2.4 shows some empirical formulas that some researchers came up with.

Table 2. 4. Various Researchers Empirical Models

No	Researchers	Empirical Models
1	Duvall and Petkof (1959)	$v = k(R/Q^{1/2})^{-b}$
2	Langefors and Kihlstrom (1963)	$v = k(Q/R^{2/3})^{b/2}$
3	Ambraseys and Hendron (1968)	$v = k(R/Q^{1/3})^{-b}$
4	IS 6922 (1973)	$v = k(Q^{2/3}/R)^{1.25}$

The empirical formulas in table 2.4 have no uniformity in the PPV predicted. The non-uniformity is mainly because there are site specific and include one or two blasting parameters such as charge per delay and the distance between the blasting point and the monitoring point. Also, these empirical models are not able to predict other blast induced effects such as flyrock, air over pressure and frequency (Monjezi et al., 2011) Furthermore, this empirical prediction model cannot incorporate many blast design parameters that affect the blast outcome hence paving the way for other techniques that can incorporate many blast design parameters such as artificial intelligence methods. Artificial intelligence methods such as Support Vector machines (SVM), artificial neural network (ANN), Maximum likelihood classification and Genetic Algorithm (GA) are robust techniques that are currently used to build prediction models (Khandelwal and Singh, 2007).

Khandelwal and Singh (2007) used the ANN technique to predict blast-induced ground vibration and frequency in a coal mine in India. A three-layer, feed-forward back-propagation neural network with 15 hidden neurons, 10 input parameters and two output parameters were trained using 154 blast datasets. The ANN prediction model results were compared MVRA predictions and conventional predictors. The PPV and frequency results of the ANN prediction model were closer to that of the field datasets as compared to that of MVRA predictions and conventional predictors.

Kamali and Ataei (2010) predicted blast induced PPV in the structures of the Karoun III power plant and dam by using Artificial neural networks (ANN), Multi-variate regression analysis (MVRA) and empirical analysis. The ANN prediction model was the best as compared to the other two because its results were closer to that of the measured data. This work only predicts one parameter, i.e. ground vibration.

Ground vibration was predicted in Siahbisheh project, Iran using ANN by Monjezi et al. (2011). The ANN was constructed using 162 datasets and 20 were picked randomly to validate the ANN model. Input parameters were hole depth, stemming, maximum charge per delay, distance between the monitoring point and the blast face while PPV was regarded as an output parameter. The performance of the ANN model was compared with regression analysis and empirical formulas using coefficient of determination. The ANN model results were better than those of other proposed models. Additionally, it was that the distance between the blasting point and the monitoring point that was the most effective on the PPV while stemming was the least effective after conducting sensitivity analysis on each parameter that influences PPV. This study predicts one parameter, ground vibration.

Armaghani et al. (2013) predicted blast induced ground vibration and flyrock using the ANN based on particle swarm optimization (PSO). PSO algorithm was used with the ANN than the traditionally BP-ANN combination. A trial and error method and sensitivity method were used to determine PSO parameters and ANN optimal architecture. 44 datasets were used to train and test the model. The model results showed that PSO-ANN combinations were able to predict blast induced PPV and flyrock at high accuracy. Again, sensitivity analysis showed that charge per delay and blastability index has great influence on flyrock distance whereas charge per delay and sub-drilling has great influence on the PPV.

Kostic et al (2013) predicted ground vibrations induced by blasting using artificial neural network (ANN) and empirical formulas. The ground vibrations were monitored at the limestone quarry near Kosjeric, located in Serbia. The ANN model was built using four input parameters namely hole depth, maximum charge per delay, total charge and the distance between the blast face and the monitoring point whereas peak particle velocity (PPV) was regarded as output parameter. The models performance

was evaluated using MAPE, RMSE VARE, VAF and MEDAE. The ANN had the most precise prediction accuracy of the highest value of VAR and lowest value of MAPE, RMSE VARE and MEDAE, in comparison with empirical formulas.

Saadat et al. (2014) used the ANN approach to predict blast induced ground vibration of Gol-E-Gohar iron ore mine, Iran. Levenberg–Marquardt algorithm was used to train a four-layer feed-forward back propagation multilayer perceptron (MLP). 69 datasets were used to develop the model, stemming, hole depth and the distance between the blast face and monitoring point were regarded as inputs parameters whereas the PPV was considered as the output parameter. A network with architecture 4-11-5-1 was developed and mean square error (MSE), Coefficient of determination (R^2) were used to measure the performance of the optimum developed network. It was found that the ANN optimum model results were better as compared to multiple linear regression (MLR) analysis and four common empirical models.

Kostic et al (2014) assessed the blast induced ground vibration using artificial neural network at limestone quarry in central Serbia. A three feed-forward three-layer back-propagation ANN model was built with three main inputs parameters considered (total charge, distance between the blast face and the monitoring point and maximum charge per delay) and only the PPV was considered as the output parameter. The results of the built ANN model were compared to conventional predictors using coefficient of determinant (R^2) to evaluate the performance of the predictors. The ANN model forecasting gave a high prediction accuracy ($R^2 > 0.9$) while conventional predictors gave an acceptable prediction accuracy ($R^2 > 0.7$).

Hajihassani et al (2015a) used a particle swarm optimization-based artificial neural network approach to predict blast induced ground vibration and airblast. 88 datasets were used to construct the ANN model using PSO algorithm. The results of the constructed model were compared with results of empirical formulas as well as the measured values. The constructed model results indicated that it can predict blast induced airblast and ground at a high degree of accuracy.

Hajihassani et al (2015b) used imperialist competitive algorithm (ICA) to optimize ANN to predict blast induced ground vibration in quarry site in Malaysia. 95 datasets

were used for training and testing ANN model and optimized using ICA. The ICA-ANN model results were compared to measured results as well as other empirical methods. The proposed ICA-ANN results indicated a high degree of accuracy as compared to other empirical methods.

Parada and Misha (2015) compared different blast-induced ground vibration predictors at iron mine located at Koria in India. A total of 9 blasting events were used for comparing different predictors. Blast design parameters such as maximum charge per delay, distance between the blast face and the monitoring point and peak particle velocity (PPV) were recorded. MVRA, ANN, USBM and Ambrsdris-Hendron models were used as predictors and each model performance was evaluated by R^2 and RMSE. The ANN model had the highest predicted accuracy with R^2 , RMSE of 0.898 and 0.908 respectively as compared to MVRA, USBM and Ambrsdris-Hendron models.

Classification and regression tree (CART), multivariate regression analysis (MVRA) and conventional methods were used to predict blast induced ground vibrations in the Miduk copper mine, Iran by Hasanipanah et al (2016). A total number of 86 blasting events were monitored and two influential parameters on ground vibration namely: the maximum charge and distance between the monitoring face and blast face were measured. The CART model and predictors performance was evaluated using root mean square error (RMSE), coefficient of correlation (R^2) and Nash and Sutcliffe (NS). The results showed that the CART technique had the best prediction accuracy with RMSE = 0.17, NS = 0.17 and R^2 = 0.95 when compared to MVRA and empirical models.

Faradonbeh et al (2016) used gene expression programming (GEP) to predict blast induced ground vibration in a granite quarry, Malaysia. A total number of 102 blasting events were monitored. The most effective parameters on ground vibration were used for construction of the GEP model, i.e., hole depth, powder factor, stemming, burden-to-spacing ratio, distance between the blast face and the monitoring point and maximum charge per delay. Nonlinear multiple regression (NLMR) technique was also used to predict the blast induced ground vibration using the same datasets. The results showed that the GEP model had more accurate readings

as compared to NLMR technique. The performance of the GEP model and NLMR technique were evaluated using coefficient of determination (R^2). GEP model had $R^2 = 0.914$ for training and $R^2=0.874$ thus showing superiority over NLMR model which had R^2 of 0.829 and 0.790 for training and testing respectively.

Ragam and Nimaje (2018) used different predictors to assess blast-induced ground. The study was conducted at IDL Explosive Limited at Sonaparnat area, Rourkela, India and fourteen blasting events were monitored at various distances from the monitoring point to the blast face in relation to the maximum charge per delay. The generalized regression neural network (GRNN) and conventional models were used to predict peak particle velocity (PPV). The conventional models applied were Langefors-Kihlstrom, United States Bureau of Mines (USBM), Central Mining Research Institute (CMRI) predictor, Ambraseys-Hendron, and Bureau of Indian standard. The results obtained performance was evaluated using mean square error (MSE) and coefficient of determinant (R^2). The GRNN model had the lowest MSE = 0.0001 and highest $R^2 = 0.9988$ as compared to other conventional models.

2.4. ROCK FRAGMENTATION

Rock fragmentation is one of the vital aspects of mining as the degree of rock fragmentation plays a critical role in cost control and reduction of loading, hauling and crushing of the material. Mining operations are divided into 5 categories which are drilling, blasting, loading, hauling and crushing. 30% of the total mining operational cost is constituted by drilling and blasting and the cost will be increased by 50% if oversized fragments are generated requiring secondary blasting (Kazen and Bahareh, 2006). Therefore, size and shape of rock fragments determines the efficiency of the crushing and grinding phases. Hence it is important to measure and analyse the rock fragments of the blasted rock.

There are many methods that can be used for rock fragmentation analysis. This methods include sieving analysis method, experimental, observational, image analysis methods and shovel loading rate (Hosseini and Alireza, 2017; Monjezi et al., 2010). Shovel loading rate and Split desktop technology (image analysis method) will be used in this research for rock fragmentation analysis. Shovel loading rate uses the

principle of the faster the mucking, the satisfactory the rock fragmentation (Cho et al., 2003). In this method the loading rate of particular muck pile by the shovel is pivotal. Split desktop technology involves the use for software. Image of muck pile or stockpile are captured using high quality digital camera. The images are then downloaded from the camera and fed to the software for analysis. The software then depicts the fragments size of each image then size distribution graphs are plotted. Advantages of Split desktop technology over other methods are that it provides real-time measurement results, which can be used quickly to control systems.

Several researchers such as Kuz-Ram, Larson Rosin-Rammler and et al have developed empirical formulas to predict rock fragmentation. However, this empirical formulas are inconsistent due to changing geological conditions or presence of underground waters and also, there do not incorporate most blast design parameters that affect the outcome of the blast. Therefore the use of artificial intelligence methods such as ANN, SVM or fuzzy logic is vital to fill the incompletes of the empirical formulas, because there are versatile and incorporate most factors that affect the blast outcome.

Ho Co et al. (2003) found out that numerical simulation and digital image analysis were better than sieve analysis using image analysis method for determining rock fragmentation.

Monjezi et al. (2009) used fuzzy logic to predict rock fragmentation due to blasting in Gol-E-Gohar iron mine and compared the results with statistical methods. Input parameters were as follows; spacing, burden, stemming length, specific drilling, hole depth, charge per delay, powder factor and rock density while fragmentation was the output parameter. They observed that the predicted results by fuzzy logic were much better than statistical methods.

Bahrami et al. (2011) predicted blast induced rock fragmentation using ANN. 220 datasets which were used to develop and train the model using back propagation algorithm. The optimum model obtained had four-layered ANN with 10-9-7-1 architecture. Furthermore, sensitivity analysis was carried out and showed that burden

blastability index, powder factor ,charge per delay and SMR and powder factor are most influential parameters on rock fragmentation.

Sayadi et al (2013) conducted a comparative study on the application of various artificial neural networks to simultaneous prediction of rock fragmentation and backbreak. For simulation , radial basis function neural network (RBFNN) and back propagation neural network (BPNN) were adopted. Also, dependent and independent variables were used to perform regression analysis. They observed that BPNN was the most effective one with minimum error and maximum accuracy. Further, they carried out sensitivity analysis and found the most influential parameters were burden and stemming on fragmentation while specific charge was the least influential.

Hosseini and Elahi (2017) used digital image processing to analyze the blasted rocks fragmentation from limestone quarry of Abyek Cement Company. The results from the Split Desktop were closer to the measured as compared to the results of the Kuz-Ram experimental model.

Murlidhar et al (2018) used neural network and imperial competitive algorithm (ICA) to predict blast induced rock fragmentation in a limestone quarry at Thailand. 8 inputs namely block size, maximum charge per delay, powder factor, burden to hole diameter ratio, spacing to burden ratio, ratio of bench height to burden, stemming height to burden and one output parameter which is rock fragmentation were used to build hybrid ICA-ANN model. The coefficient of determination (R^2) was used to evaluate the performance of the ANN and ICA-ANN models. The results showed that ICA-ANN model ($R^2 = 0.949$) can be applied to improve the performance of the ANN ($R^2 = 0.941$) in predicting rock fragmentation.

2.5. ARTIFICIAL NEURAL NETWORK

Artificial neural network (ANN) is a branch of artificial intelligence that depicts the same way how the human brain works. The ANN is a data processing tool that is used to model the complex systems into simulation in science, engineering, finance and medicine approximation problems. It is a highly interconnected multilayer structure that consists of neurons that perform massive parallel computation for knowledge

representation and data processing. ANN systems are able to predict proposed output pattern when presented with new input datasets because of its versatile ability to recognize similarities.

The ANN has three components that are vital; transfer function, network architecture and learning law (Simpson, 1990). The ANN system is usually divided into three basic layers which are the input layer, output layer and hidden or intermediate layers as shown in Figure 2.5. The number of neurons and hidden layers is determined by the complexity of the problem (Simpson, 1990). Each layer is interconnected by neurons and has one or more nodes.

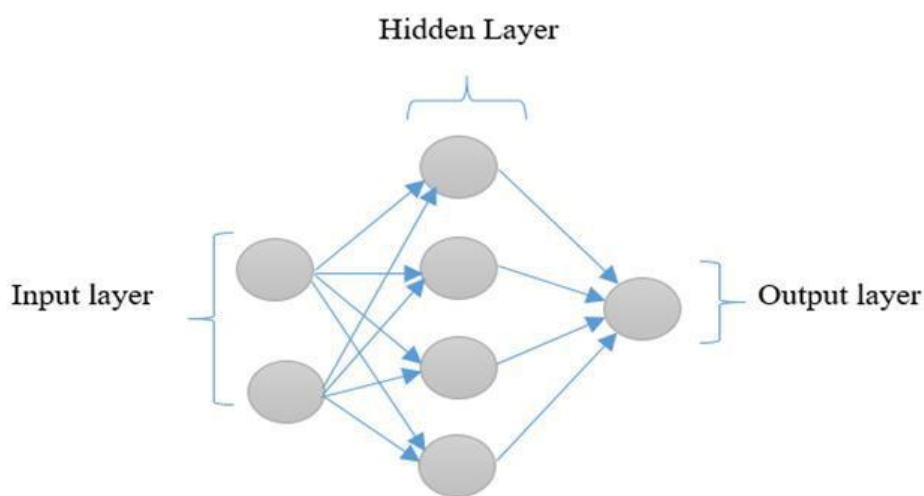


Figure 2. 5. Graphical representation of ANN network

The input layer receives the information, then transmits it through neurons to the hidden layer, also the hidden layer transmits it to the output layer through neurons. The input/output relationship does not need to be known prior to ANN processing (Shahin et al., 2001). All, it needs is to be presented with data examples and it will use this data to depict the relationship between inputs and corresponding outputs by adjusting their weights in the network. This ability makes it to be excellent in the interpolation of data, especially when the input data is not exact. Neural networks can be used as direct substitute for multivariable regression, autocorrelation, trigonometric, linear regression and other statistical analysis techniques.

The ANN system is first trained with large numbers of data to develop the relationship between the input data and output data. There are several algorithms that can be used to train the model however we are going to use the back propagation algorithms. Back propagation algorithms is the most efficient and robust technique that is used for multiple layer neural networks and capable of solving predictive problems. Once the network model is trained successfully, the trained model has to be validated using an independent testing data set. Unsatisfactory network performance can be improved by retraining, using a larger training dataset or increasing the number of neurons.

McCulloch and Pits (1943) were the first to originally introduce the ANN and showed its ability to predict any logical or arithmetic functions. Werbos (1975) further developed the neural networks capability to solve non-linear functions. He introduced the use of backpropagation algorithm that made the training of multi-layer networks feasible and efficient. Backpropagation distributes the error term back up through the layers, by modifying the weights at each node until the network is able to perform the task for which it is being trained. Rumelhart and McClelland (1986) popularized the artificial neural networks by applying it in various fields because of its prevailing tools for estimation of unknown non-linear functions.

The ANN system has being used recently to solve mining and environmental problems mainly prediction, pattern recognition and optimisation (Khandelwal and Singh, 2005; Monjezi et al., 2010). Bahrami et al., 2011; Enayatollahi et al., 2014; Hajihassani et al., 2014 used the AAN system to predict blast-induced rock fragmentation, airblast and ground vibration.

Eren et al. (1997) applied the ANN system to predict densities and particle size distributions in mineral processing industry. The ANN system results were found to be in a close range with experimental results than the results of statistical prediction methods. This proved that the ANN system is the future in prediction separation efficiencies. Also, this paved the way for the use of ANN systems in common circumstance in mineral processing industry.

Kalogirou and Bojic (2000) used the ANN system to predict energy consumption of passive solar building. Two Buildings with a one-side wall masonry insulated and other walls partially thermal and masonry insulated were investigated. A masonry only wall building faced north in summer whilst the same kind of building faced south in winter. The thickness, insulation of the masonry and the season determined the energy consumption. The ANN system was trained using simulated data to determine the relationship between the measurable inputs and desired output. Back-propagation algorithm was applied and the results yielded a coefficient of multiple determinations (R^2 value) equal to 0.9985. New datasets were used for other cases than the ones used in training the network for predictions of energy consumption and yielded R^2 value equal to 0.9991, which is acceptable.

Zhao and Chen (2011) utilized artificial neural network to predict ground subsidence in a metal mine. The measured datasets of the roof subsidence from November 2009 to August 2010 of metal mine was used to develop a time series ANN prediction model. The first seven months datasets were used for learning processing while the last three datasets were used for testing the developed ANN model. The ANN model prediction results were highly accurate and consistent with the measured values. The ANN system proved it can used to monitor mine ground subsidence.

Sharma and Panigrahi (2011) predicted customer loyalty using the ANN approach in cellular network services. A total of 2427 customers' information with 20 variables was used for the ANN model development. The results show that the developed ANN model predicted customers' loyalty with overall accuracy of 92%. Moreover, sensitivity analysis was conducted and it was found out that customer service call was the most effective parameter on customers' loyalty whereas the area code was the least effective parameter.

Lal and Tripathy (2012) predicted dust concentration using artificial neural network in an open cast coal mine in Jharkhand, India. The dust concentration predicted used three models at different locations from the source of the dust. The learning of the models was done using back-propagation feedback algorithm. Meteorological data such as rain fall, cloud cover, dispersion coefficients, wind speed and temperature and geographical data such as the rate of data emission and the receptor distance

perpendicular to the direction of the wind were regarded as inputs parameters. Inputs for model 1, model 2, and model 3 were 6, 7 and 9 respectively. The dust concentration was used as the output parameter for all the models. The ANN models performance was evaluated using RMSE and compared Gaussian-Plume model. The ANN model 3 outperformed other models. Further ,the ANN models predicted better than the Gaussian-Plume model. This study shows that artificial intelligence techniques such as ANN can be used as predictive tool across various fields.

Rezaei et al. (2012) used geomechanical properties of rocks to develop the ANN model to predict burden in a gold mine. Cohesive strength, density, rock quality designation (RQD), blastability index (BI) and unconfined compressive strength (UCS) were regarded as input parameters whereas burden was the output parameter. The ANN model results were compared with the MVRA model results. The results show that the ANN prediction was accurate as compared to the MVRA prediction. In addition, sensitivity was conducted and it showed that RQD and BI were the most influential input parameters while cohesive strength was the least influential input parameter on burden.

Litta et al. (2013) predicted Meteorological Parameters during Premonsoon Thunderstorms using the ANN system. The ANN system was used to predict severe thunderstorms that occurred over Kolkata/India during May 3, 11, and 15, 2009. The thunderstorms affected surface parameters; relative humidity and temperature were able to be predicted in 1, 3, and 24 h advanced using Levenberg-Marquardt algorithm. This developed ANN model provided real time thunderstorm forecast which can be useful for meteorologists when predicting weather forecasts.

Singh (2013) used the ANN system approach to predict and control ground vibrations in mines. Ground vibrations produce peak particle velocity which was used for risk assessment damage that might be caused by ground vibration induced by blast. It was found that the ANN system had better accuracy than conventional regression analysis based on error estimates and correlation coefficient.

Trivedi et al (2014) used artificial neural networks (ANN) and multivariate regression analysis (MVRA) to predict blast induced flyrock in a limestone mine at India. A total

95 blasting events were monitored. Geological and blast design parameters namely; rock quality designated (RQD), unconfined compressive strength (UCS), stemming length, specific charge, burden and linear concentration were regarded as input parameters while flyrock distance was the output parameter. The results show that the ANN model with two hidden layers and log-sigmoid transfer function had the highest predictive accuracy when compared to the MVRA model. The ANN model had the highest R^2 and lowest RMSE as well as MAE. Sensitivity analysis was carried out and it was found out that specific charge and linear concentration are the most effective parameters on flyrock distance while UCS, RQD, burden and stemming length bear least impact on flyrock distance.

Jang et al (2015) used the ANN and MVRA models to predict unplanned dilution and ore loss prediction in longhole stoping mines. 1067 datasets with 10 most influential parameters were used to develop the ANN and MVRA models. The performance of both models was evaluated using coefficient of determinant (R^2). R^2 obtained were 0.419 and 0.719 for MVRA and ANN respectively. The ANN model performed better than the MVRA and it shows that it can be used as a predictive tool. Patra et al (2015) predicted particulate matter concentration profile using the ANN in an opencast copper mine. Meteorological parameters such as temperature, wind speed and relative humidity were input parameters while particulate matter was the output parameter. The ANN model performance was evaluated using correlation coefficient between the model results and the real datasets. The ANN model showed a strong correlation with the real datasets.

Suitability assessment of artificial neural network to approximate surface subsidence due to rock mass drainage was conducted by Hejmanowski and Witkowski (2015). They found out that the ANN system can be successfully used in predicting changes caused by the carried out rock mass drainage in surface subsidence

Yeng et al (2016) applied artificial neural network to predict small folds and faults in coal seams at China. Two factors were selected as input parameters for construction of the ANN model namely coal seam thickness change (CSTK) and coal seam dip angle (CSDA). The output parameters were the risk levels of the structural change (folds and faults) in front of the working faces. A total of 23 test data used the ANN

model development whereas 3 was used for validating the developed model. The ANN model results were highly accurate as there was no significant difference when compared with the measured field test results. This accurate prediction of small folds and faults enables coal mines to control hazards caused by water and gases in working faces.

Dhene et al (2017) used artificial neural network in prediction of boulder as a result of rock blasting in four limestone quarries in India. A total number of 300 blasting events were monitored. The optimum ANN model was developed using MATLAB software and 191 data sets were used for training the model while 32 and 77 data sets were used for testing and validating the developed ANN model. The new developed ANN model was compared to the statistical model (MVRA) for checking effectiveness of each approach for prediction. The Coefficient of determinant (R^2) was used for evaluation of each model performance. The ANN model had the highest prediction accuracy with R^2 of 0.96 while statistical model had R^2 of 0.9. Sensitivity analysis shows that burden, spacing and stemming length have the most effective influence on the number of boulders whereas the number of rows and type of explosive had the least influence.

2.6. SUMMARY

The literature review shows that there are statistical methods and ANN models that have been used before to predict airblast, ground vibration and rock fragmentation. Furthermore it shows empirical formulas do, not incorporate the most input parameters that affect the blasting outcome and their prediction is limited to one output only. Therefore, the ANN models can be used to address the limitation of empirical formulas. The next chapter discusses the methodology of the research.

CHAPTER 3: METHODOLOGY

A total number of 104 blasting data sets were extracted from the Debswana mining company records. The most influential parameters according to literature were used for development of the ANN model. The ANN model consists of eight input parameters which are interrelated and three output parameters. The input parameters are hole depth, hole diameter, burden, spacing, distance between the blast face and monitoring point, stemming length, powder factor and maximum charge per delay. The output parameters were airblast, ground vibration and rock fragmentation. The optimum ANN model was built using MATLAB-based ANN system.

3.1 DATA COLLECTION

Seismograph device is placed on locations based on the area to be blasted. It was used to measure the ground vibrations and airblasts at various distances from the blast face ranging from 438m to 1500m. The seismograph device is placed on levelled ground. The microphone and geophone are then connected to it. Ground vibrations are measured with a geophone while airblasts are measured with a microphone. The seismograph device is switched on and the trigger level is set. The recording of the readings is automatic as long as the trigger level is exceeded and only stop when the readings are below the trigger level after blasting. The device is then taken to the office after blasting to download readings into a computer for analysis.



Figure 3. 1. Image of blasted rock fragments

Rock fragmentation starts with the drilling and blasting. Images of the muck pile were taken using a digital camera and downloaded into a computer with split desktop technology for analysis of fragments size distribution as shown in Figure 3.1 and Figure 3.2. This technology was adapted because it is user-friendly and provides real-time measurement results, which can be used quickly to control systems.

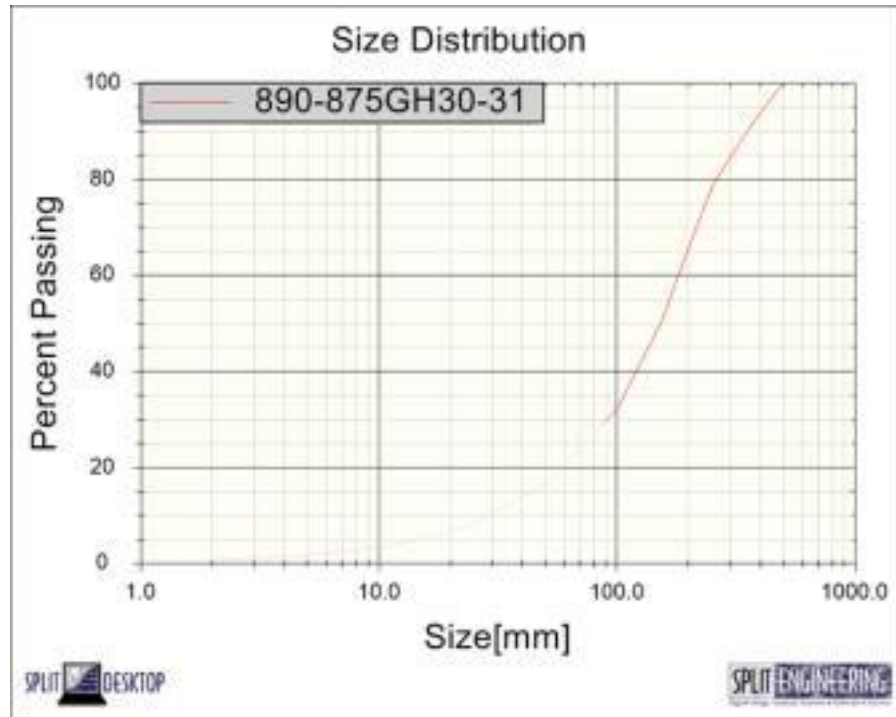


Figure 3. 2. Bench 890-875 Split desktop Fragmentation Analysis

Drilling and blasting are the first stages of rock fragmentation. AtlasCo hydraulic rigs were used for drilling the blastholes to different depths. Priming was done using electric detonators. The blastholes were stemmed appropriately. On average per blast round, about 50 to 200 holes are blasted.

3.2. BLASTING DATA SETS

A total number of 94 blast datasets were retrieved from the Debswana (Orapa Mine) records for development of the ANN model. Eight input parameters were chosen based on the literature to have the most influence on ground vibration, airblast and rock fragmentation. This input parameters are (i) Hole depth, (ii) Hole diameter, (iii)

Burden, (iv) Spacing, (v) Distance between the blast face and monitoring point, (vi) Stemming length, (vii) Powder factor and (viii) Maximum charge per delay. Therefore, the ANN model was developed using eight input parameters and their corresponding outputs for the 104 different blasting events. The range of these input and output parameters are shown in the following Table 3.1.

Table 3. 1. Ranges of Input and Output parameters

Type of data	Parameters	Range
Input	Hole depth (m)	6.54 -18.43
	Hole diameter (mm)	150 – 250
	Spacing (m)	4-7
	Burden (m)	4-8
	Stemming length (m)	4-8
	Distance (m)	438 - 1500
	Powder factor (kg/m^3)	0.3 - 61.4
	Maximum charge per delay (kg)	27- 61.4
Output	Rock fragmentation (%)	65-83
	Ground vibration (PPV), mm/s	0.12 – 5.65
	Airblast (dBL)	91.5 – 126.7

3.3. ARTIFICIAL NEURAL MODEL NETWORK ARCHITECTURE

A three layer feed-forward back-propagation ANN model was developed to predict ground vibration, airblast and rock fragmentation. Once the ANN model is developed, any similarities will be detected in the new pattern, thus giving the interpolation technique. These three-layer ANN model composed of the input layer, hidden layer and output layer. Layers are made up of basic processing units called neurons which interconnect these layers to each other using appropriate weight. The output analyses the rock fragments of the blasts that were carried out in the area. Also, this neurons in the input layer connect to a hidden layer while the output neurons in the hidden layer connect to the output layer.

The ANN model was developed by (i) converting the blasting data sets in a csv file (ii) importing the csv file with blast data sets into MATLAB software (iii) developing the ANN model using the built in MATLAB nntool function and (iv) training, testing and validating.

A total number of 94 blasting data sets were used for this research. 70% of the blasting data sets have been used to train the network while 15% have being used to test the network and the remaining 15% were used for validations of the neural network. Feed-forward back-propagation was used for training the ANN model because it is a gradient descent system which moves down the gradient of the error curve in order to minimize the mean squared error (MSE) and it is good for non-linear fittings. Levenberg-Marquardt algorithm was adopted for optimization of the training ANN models using Trainlm as the training function. Learngdm was the learning function used because of its ability to import a number of inputs. To create a network, the following were selected accordingly (i) performance function, (ii) number of neutrons, (iii) transfer function and (iv) number of layers. The next steps after creating a network is to train, test and validate the network. Examples of MATLAB window to create network and architecture of the neural network are shown in Figure 3.3 and 3.4 respectively.

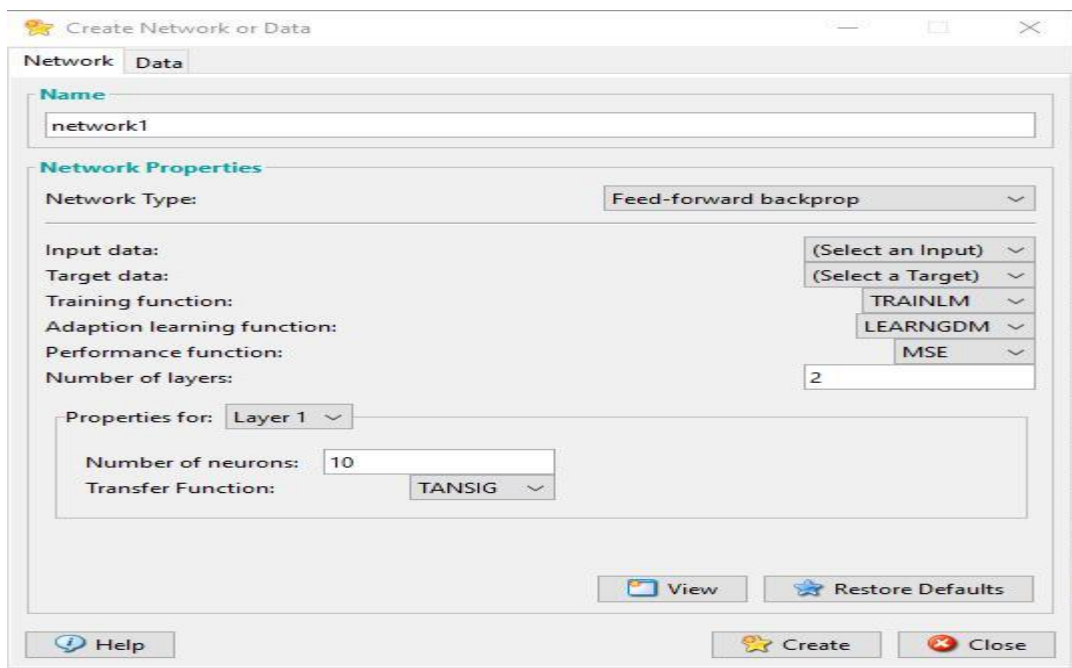


Figure 3. 3. MATLAB window for ANN

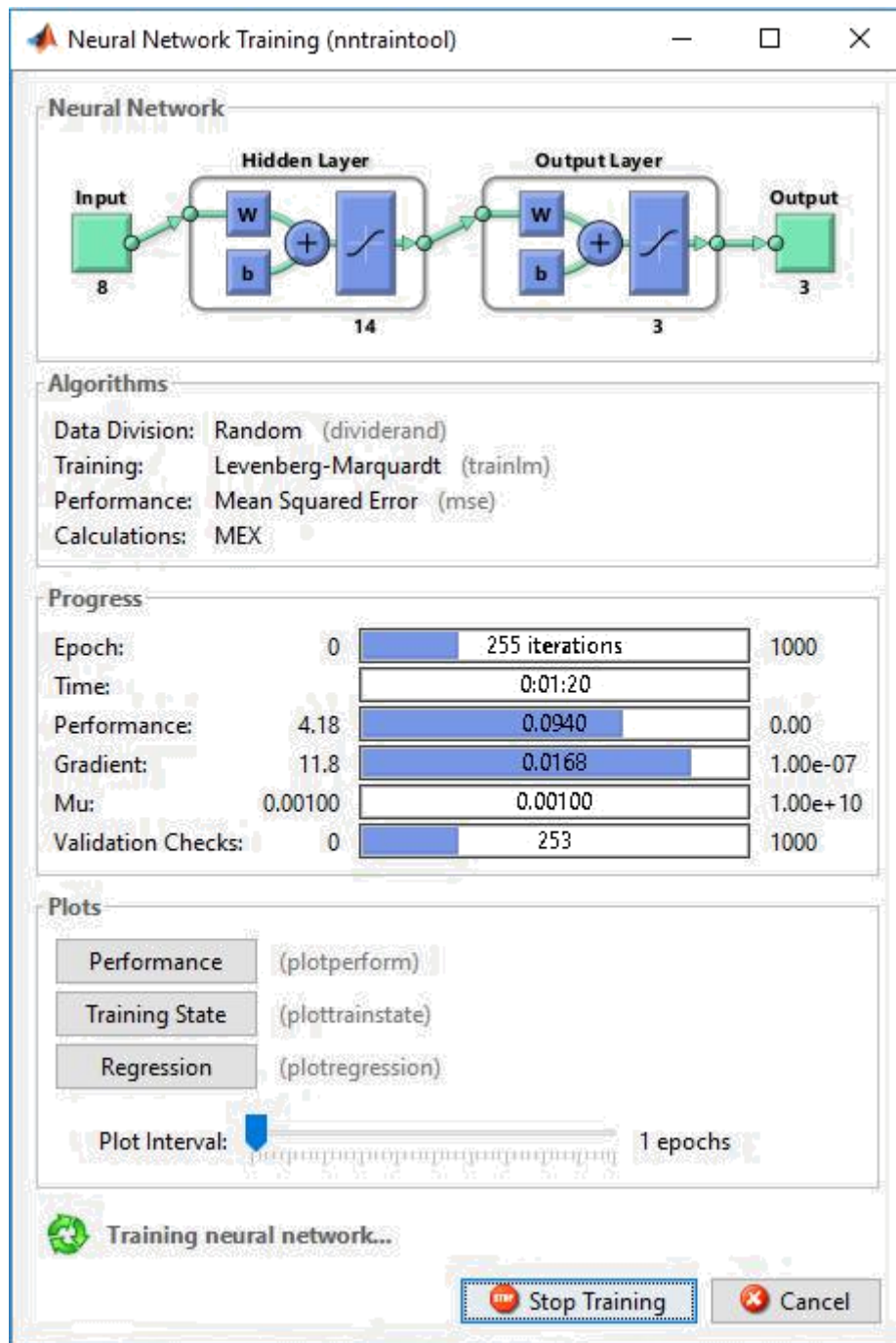


Figure 3. 4. Training of back propagation neural network

After building several ANN models with different architectures as shown in Table 3, the optimum ANN model is selected. Its selection was based on the ANN models performance evaluation using determinant of coefficient (R^2) and the root mean square error (RMSE). A model network architecture of 8-14-3 (8 input parameters, 14

hidden neurons and 3 output parameters) as shown in Table 3.2 with transfer function of transig was found to be the optimum model.

Table 3. 2. Different ANN models

Model	Transfer function	Network architecture	(R ²)	(RMSE)
1	Logsig	8-12-3	0.99721	1.78
2	Logsig	8-10-3	0.99596	1.41
3	Logsig	8-11-3	0.99192	1.45
4	Transig	8-12-3	0.99620	1.69
5	Transig	8-14-3	0.99827	1.02
6	Transig	8-15-3	0.98290	1.54

Table 3.2 shows that model 5 was chosen to be the optimum model because it has lower RMSE and higher R². The optimum model architecture is shown in Figure 4 and regression plots of the optimum model during training, testing and validation indicating the excellence of the optimum model is illustrated in Figure 3.5

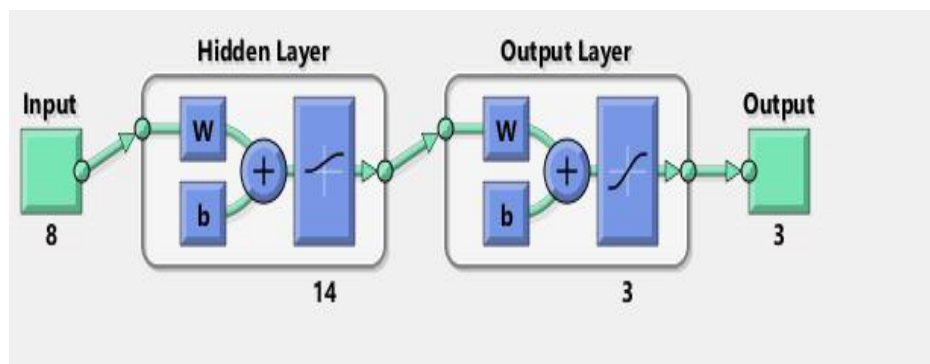


Figure 3. 5. Optimum model network architecture

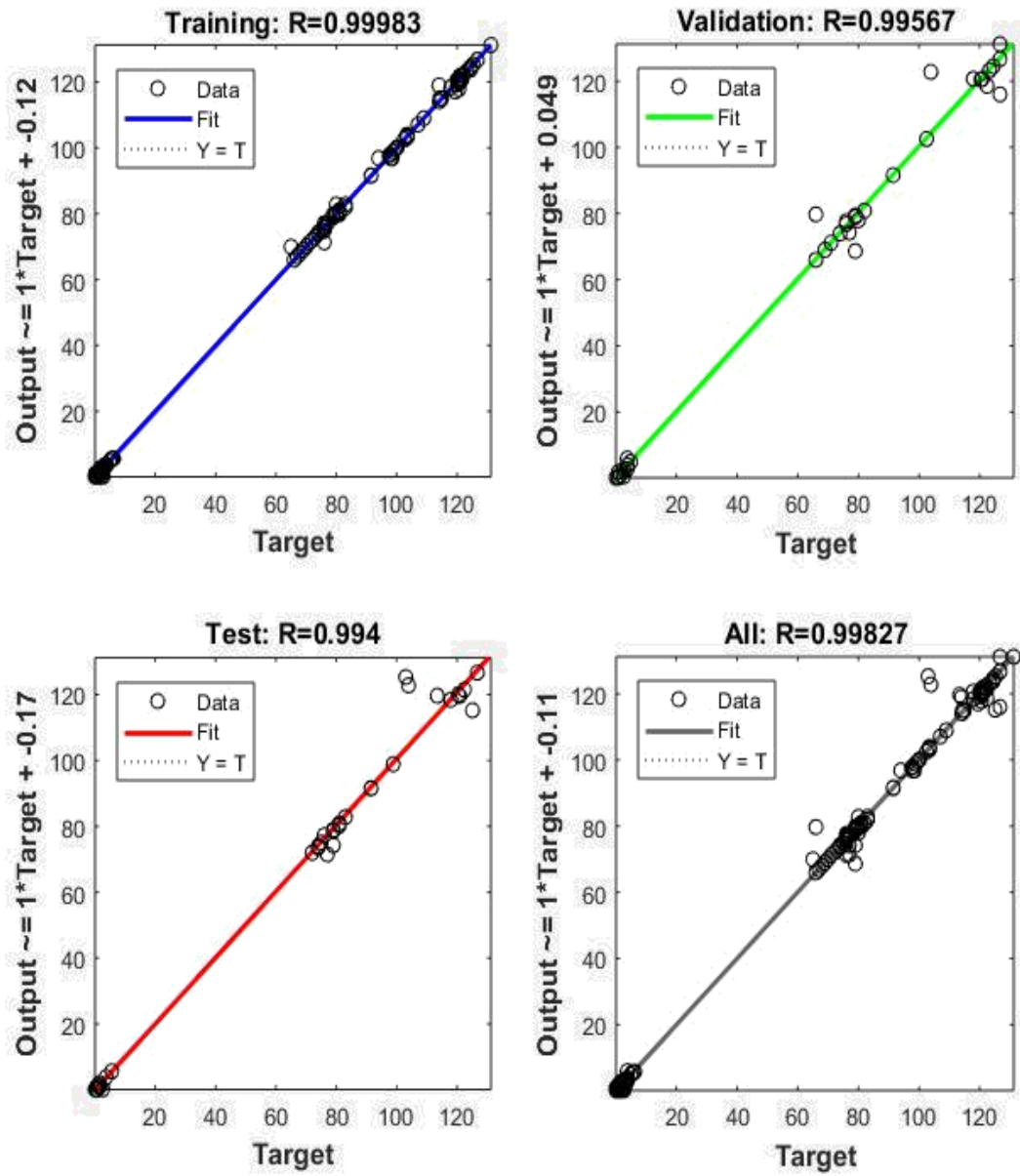


Figure 3. 6. Training, testing and validation regression plots of ANN model

Figure 3.6 shows a strong correlation between the output and target datasets during training, testing and validation of the optimum model considering R^2 . The regression plots of tested different ANN models are listed in Appendix A and B.

The optimum ANN model was presented with 10 new datasets to evaluate its accuracy in predicting the rock fragmentation, airblast and ground vibration. The results of the optimum ANN model was compared with measured outputs as shown in Table 3.3.

Table 3. 3. Results of Measured and Predicted Output

Measured Rock fragmentation (%)	Predicted Rock fragmentation (%)	Measured Ground Vibration (mm/s)	Predicted Ground Vibration (mm/s)	Measured Airblast (dBL)	Predicted Airblast (dBL)
75	74.99	5.65	5.67	98.84	98.84
76	75.72	0.145	1.02	103.50	103.17
66	66.01	4.93	4.88	123.3	123.31
80	82.80	0.17	0.14	121	121.91
80	80.03	3.24	3.25	97.5	97.64
81	81.01	3.51	3.51	97.98	97.97
69	68.95	1.48	0.91	114.90	114.86
74	73.98	3.23	3.63	91.48	91.61
79	78.98	1.66	2.67	99.6	99.57
68	68.03	2.95	2.84	131.2	131.19

Figures 3.7, 3.8, and 3.9 shows graphs a comparison between the predicted and measured airblast, ground vibration and rock fragmentation respectively.

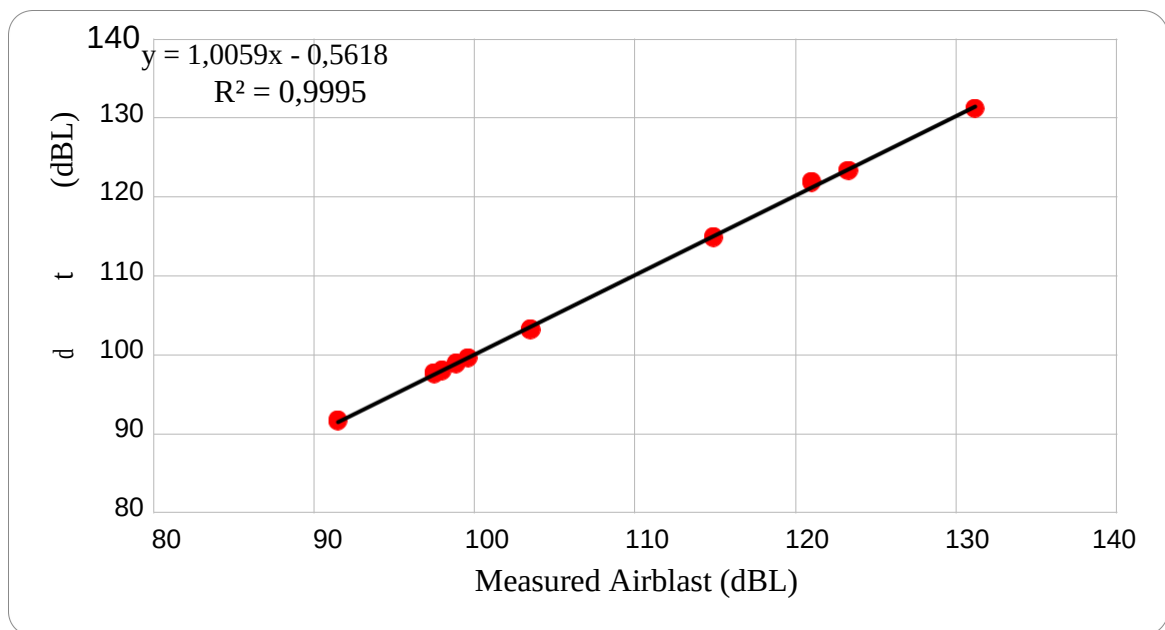


Figure 3. 7. Relation between Predicted Airblast by ANN and measured values

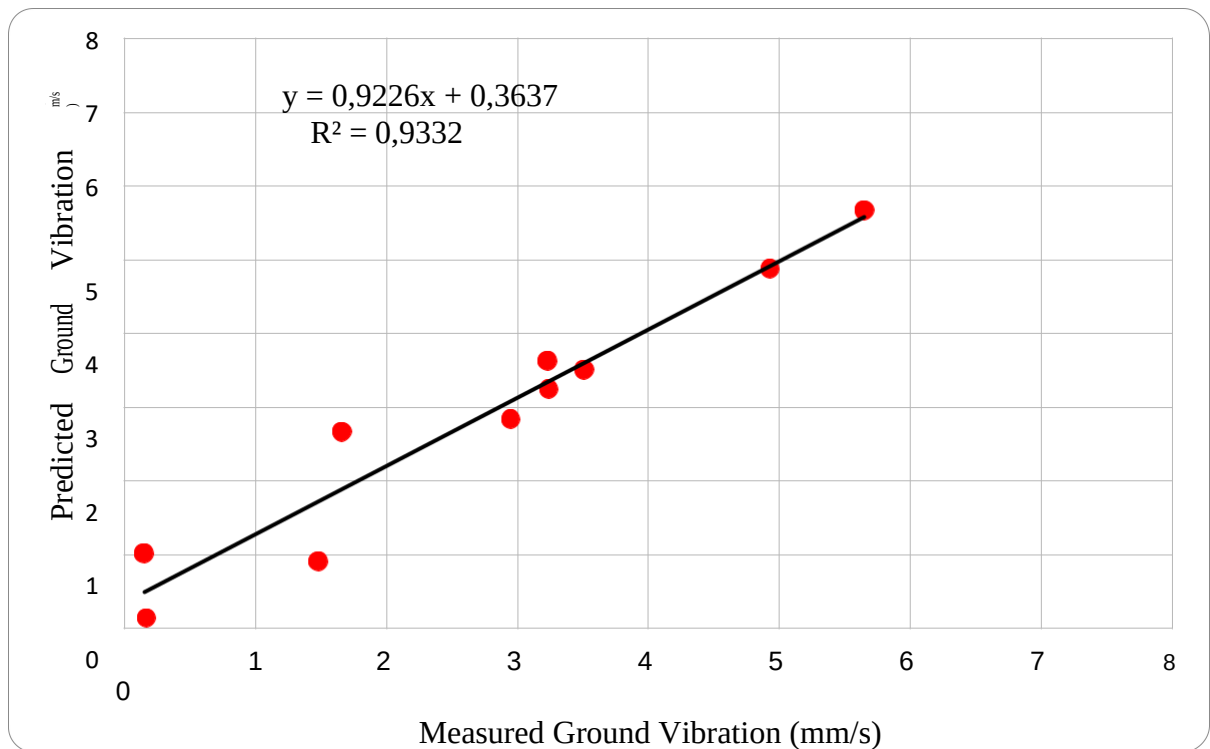


Figure 3. 8. Relation between predicted Ground Vibration by ANN and measured values

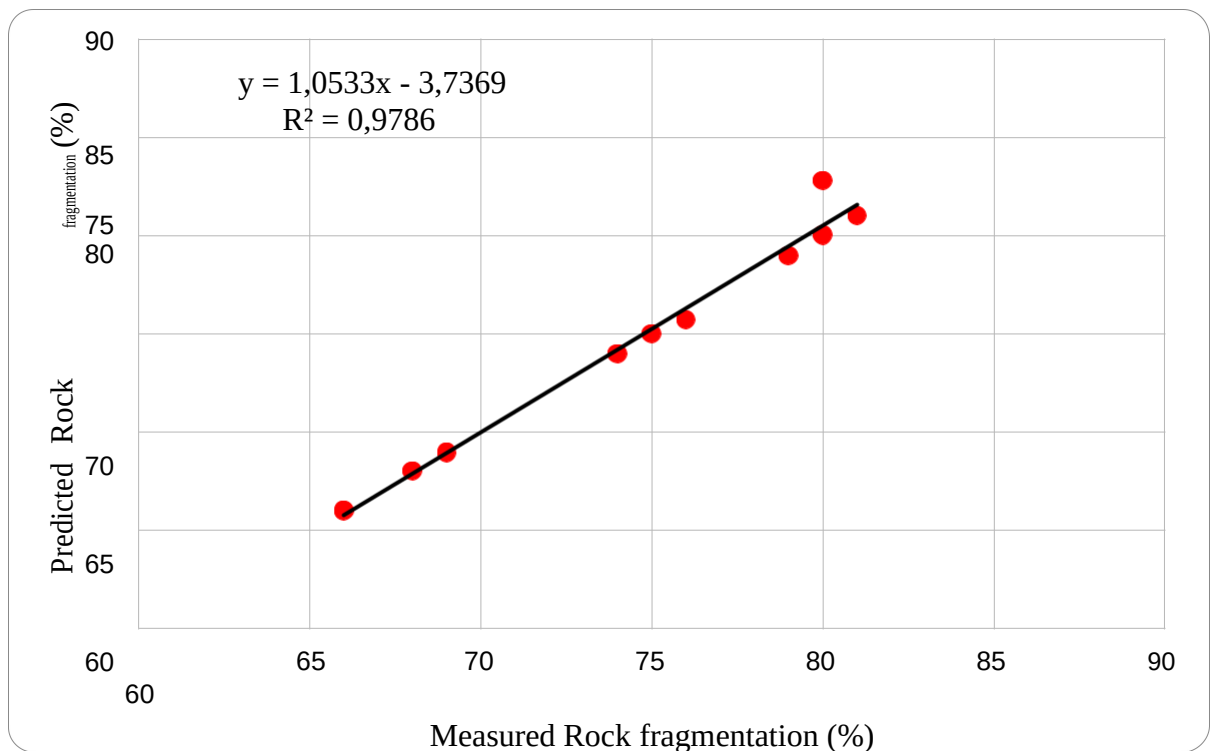


Figure 3. 9. Relation between predicted rock fragmentation by ANN and measured values

The predicted output parameters values by the optimum artificial neural network (ANN) tool and measured output parameters show a strong correlation between them as shown by the coefficient of determination (R^2) for figures 3.7, 3.8 and 3.9 above are closer to 1. This shows that the optimum ANN model can be used to predict airblast, ground vibration and rock fragmentation based on the known input data set.

3.4. MULTIVARITE REGRESSION ANALYSIS (MVRA)

This is one of the statistical tools that can incorporate multiple inputs to predict outputs. It uses the same concept of ANN by using input-independent variables (known values) to predict output-dependent variables. The MVRA equation is expressed as follows:

$$Z = b_0 + b_1X_1 + b_2X_2 + b_3X_3 + \dots + b_kX_k \quad (3.1)$$

whereby Z is the predicted output value from X_i , b_0 (intercept) and b_i (regression coefficients). The predictive ability of MVRA equation is evaluated using coefficient of determinant (R^2) (Enayatollahi et al., 2014). The MVRA prediction model is accurate when its R^2 is closer to one and its accuracy reduces as R^2 decreases to zero.

From the above equation (3.1), the derived equations of airblast, ground vibration, and rock fragmentations are as follows:

$$\begin{aligned} \text{Airblast (dBL)} = & -1.093 [\text{Hole depth}] + 0.078[\text{Hole diameter}] - 8.944[\text{Burden}] + \\ & 14.152[\text{Spacing}] + 0.792[\text{Stemming length}] + 0.005[\text{Distance}] + 5.876[\text{Powder Factor}] \\ & - 0.462[\text{Maximum charge per delay}] + 81.476 \end{aligned} \quad (3.2)$$

$$\begin{aligned} \text{Ground vibration (mm/s)} = & -0.379 [\text{Hole depth}] + 0.01[\text{Hole diameter}] - \\ & 0.234[\text{Burden}] - 1.44[\text{Spacing}] + 0.218[\text{Stemming length}] - 0.005[\text{Distance}] \\ & + 1.8[\text{Powder Factor}] - 0.067[\text{Maximum charge per delay}] + 13.7 \end{aligned} \quad (3.3)$$

$$\begin{aligned} \text{Rock Fragmentation (\%)} = & 0.83 [\text{Hole depth}] - 0.039[\text{Hole diameter}] + 0.29[\text{Burden}] - \\ & 0.831[\text{Spacing}] + 1.678[\text{Stemming length}] - 0.011[\text{Distance}] - 0.116[\text{Powder Factor}] - \\ & 0.0616[\text{Maximum charge per delay}] + 72.993 \end{aligned} \quad (3.4)$$

A total of ten new datasets that was used to check the prediction accuracy of the optimum ANN model were used also to predict airblast, ground vibration and rock fragmentation using the generated MVRA models. MVRA prediction results were compared to measured ones for correlation. The correlation between the measured and MVRA predicted airblast, ground vibration and rock fragmentation are shown in Figures 3.10, 3.11, and 3.12 respectively.

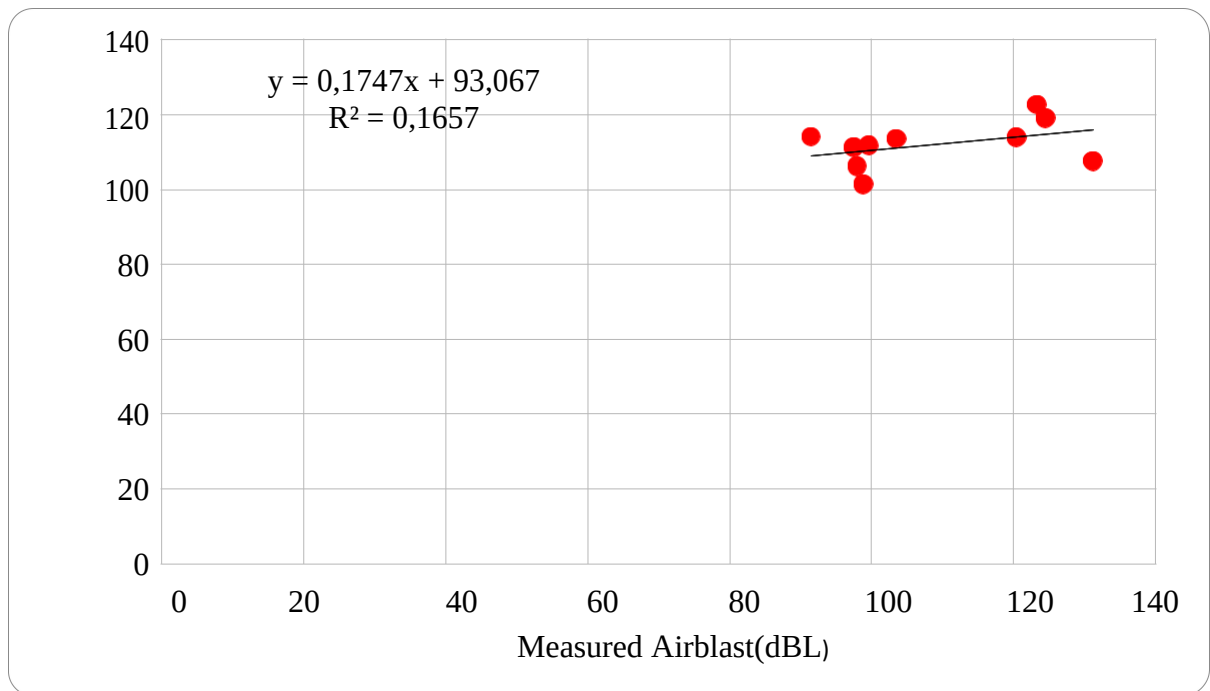


Figure 3. 10. Relation between predicted by MVRA and measured values

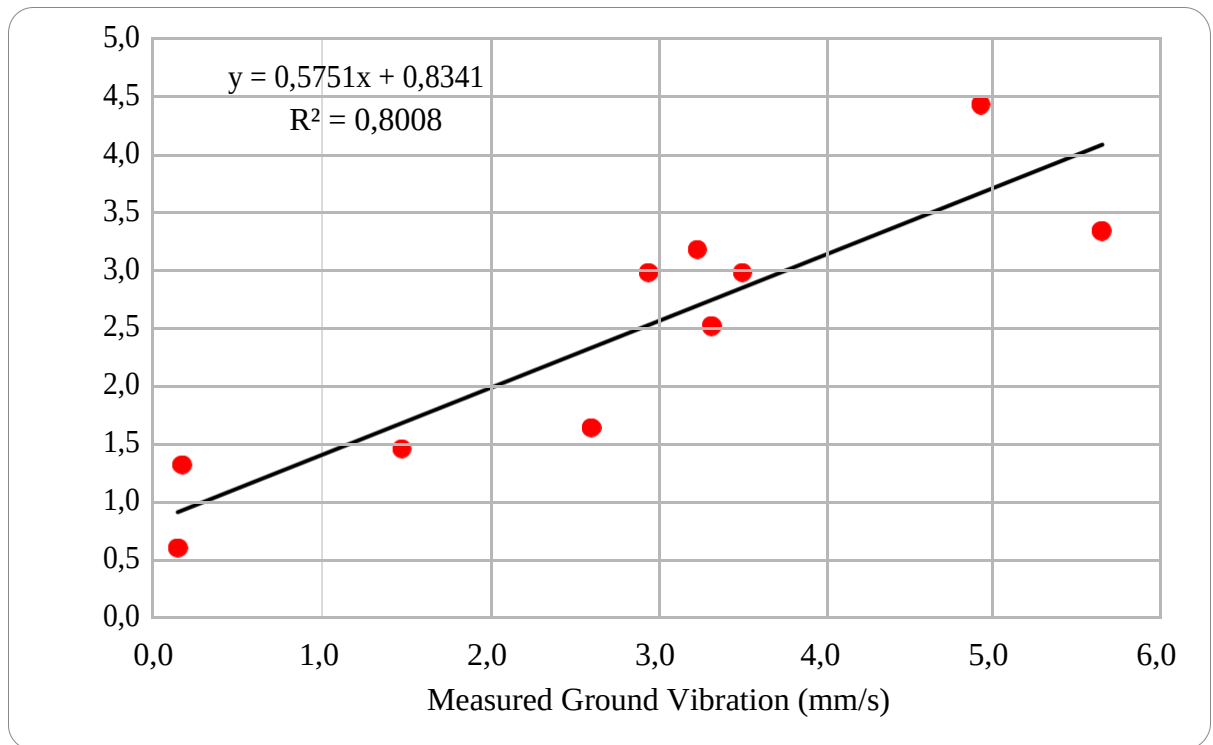


Figure 3. 11. Relation between predicted ground vibration by MVRA and measured values

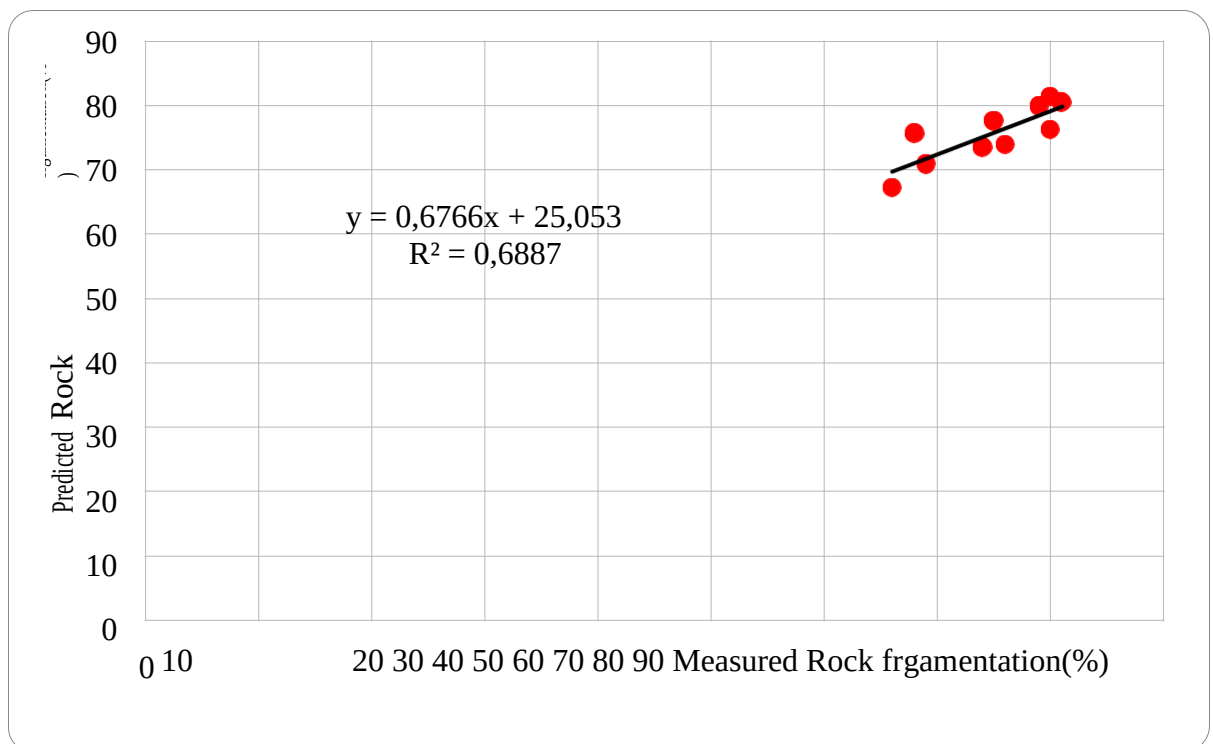


Figure 3. 12. Relation between predicted rock fragmentation by MVRA and measured values

The predictions accuracy by MVRA as illustrated in Figure 3.10, 3.11 and 3.12 were poor with the better correlation between predicted and measured ground vibrations in Figure 3.11. The poor prediction performance by MVRA makes it not applicable in predicting complicated blasting problems hence the need to use ANN.

3.5. EMPIRICAL FORMULAS FOR GROUND VIBRATION (PPV)

Several researchers have developed empirical formulas that are used for prediction of peak particle velocity (PPV). Those researchers include Duvall and Petkof (1962), Langefors and Kihlstrom (1963), Ambraseys and Hendron (1968), Bureau of Indian Standards, BIS (1973). Table 3.4 summarizes each empirical formula. The distance between the blast face and the monitoring point and maximum charge per delay are used to scale blasts to equivalent distances. The site constants K and B are determined by plotting scaled distances and PPV on log-log scale as shown in Figures 3.13, 3.14, 3.15 and 3.16. The generated site constant for each research empirical formula is presented in Table 3.5.

Table 3. 4. Ground vibration empirical formulas

No	Researchers	Empirical Models	Description
1	Duvall and Petkof (1962)	$v = k(R/Q^{1/2})^{-b}$	V is the Peak Particle Velocity k and b site constants R is the ratio of distance from charge point Q is the charge mass
2	Langefors and Kihlstrom (1963)	$v = k(Q/R^{2/3})^{b/2}$	V is the Peak Particle Velocity k and b site constants R is the ratio of distance from charge point Q is the charge mass
3	Ambraseys and Hendron (1968)	$v = k(R/Q^{1/3})^{-b}$	V is the Peak Particle Velocity k and b site constants R is the ratio of distance from charge point Q is the charge mass
4	BIS (1973)	$v = k(Q^{2/3}/R)^{1.25}$	V is the Peak Particle Velocity k is the site constant R is the ratio of distance from charge point Q is the charge mass

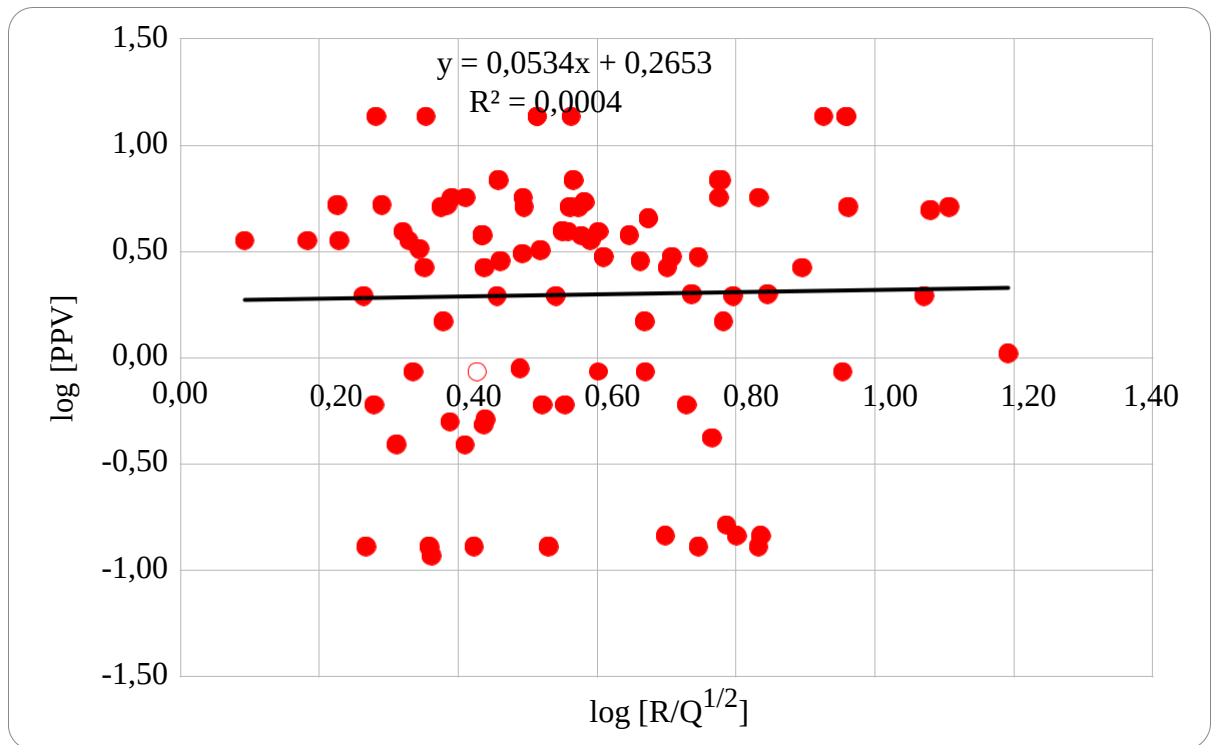


Figure 3. 13. Ground vibration (PPV) and Scaled distance on log–log scale for Duvall and Petkof

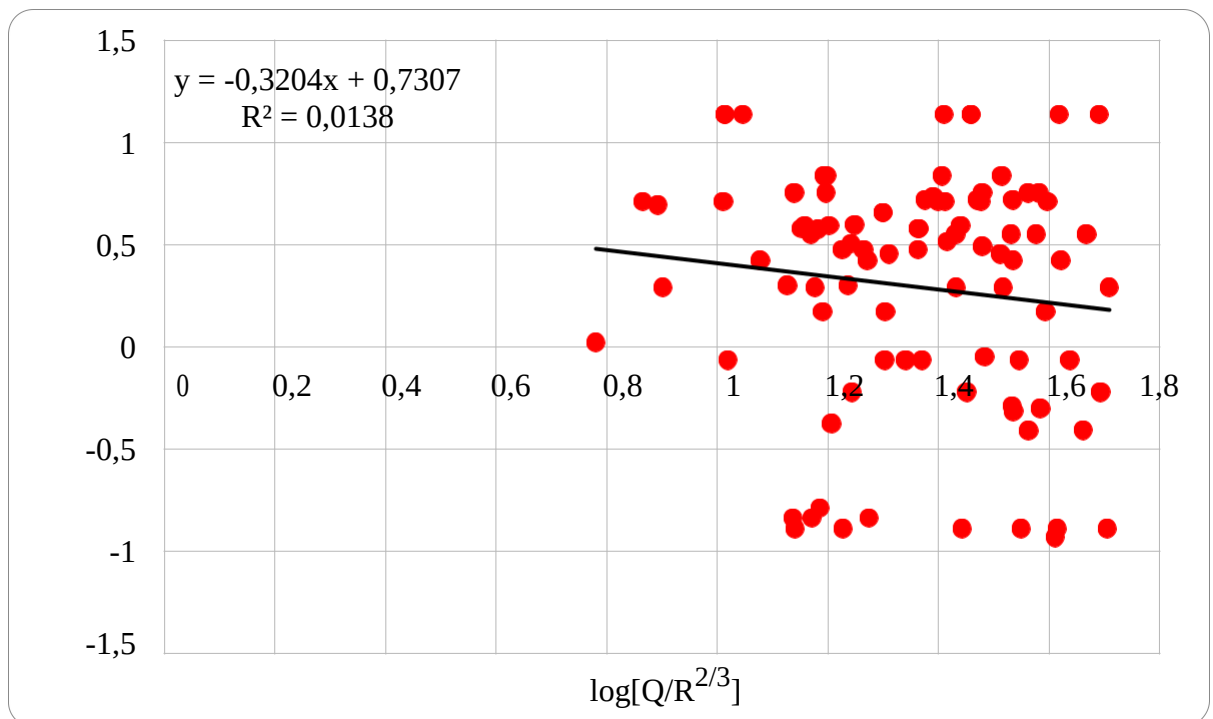


Figure 3. 14. Ground vibration (PPV) and Scaled distance on log–log scale for Langefors and Kihlstrom

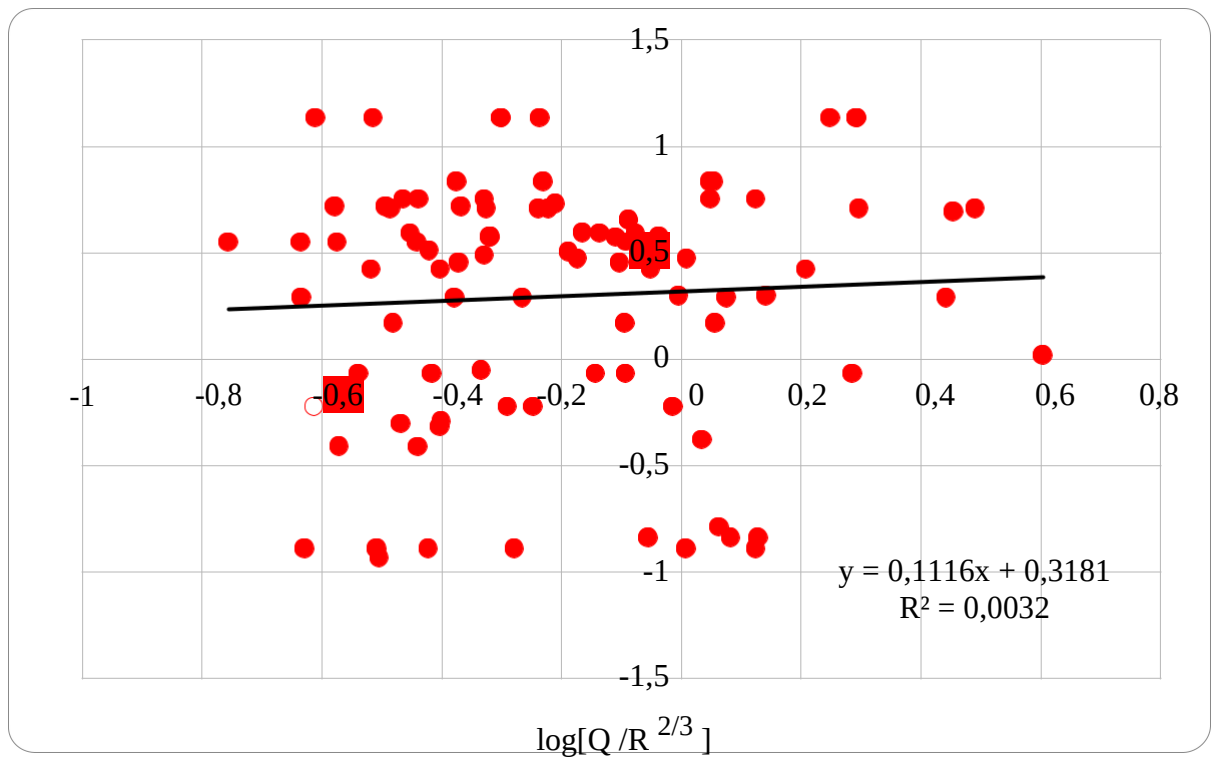


Figure 3. 15. Ground vibration (PPV) and Scaled distance on log-log scale for BIS

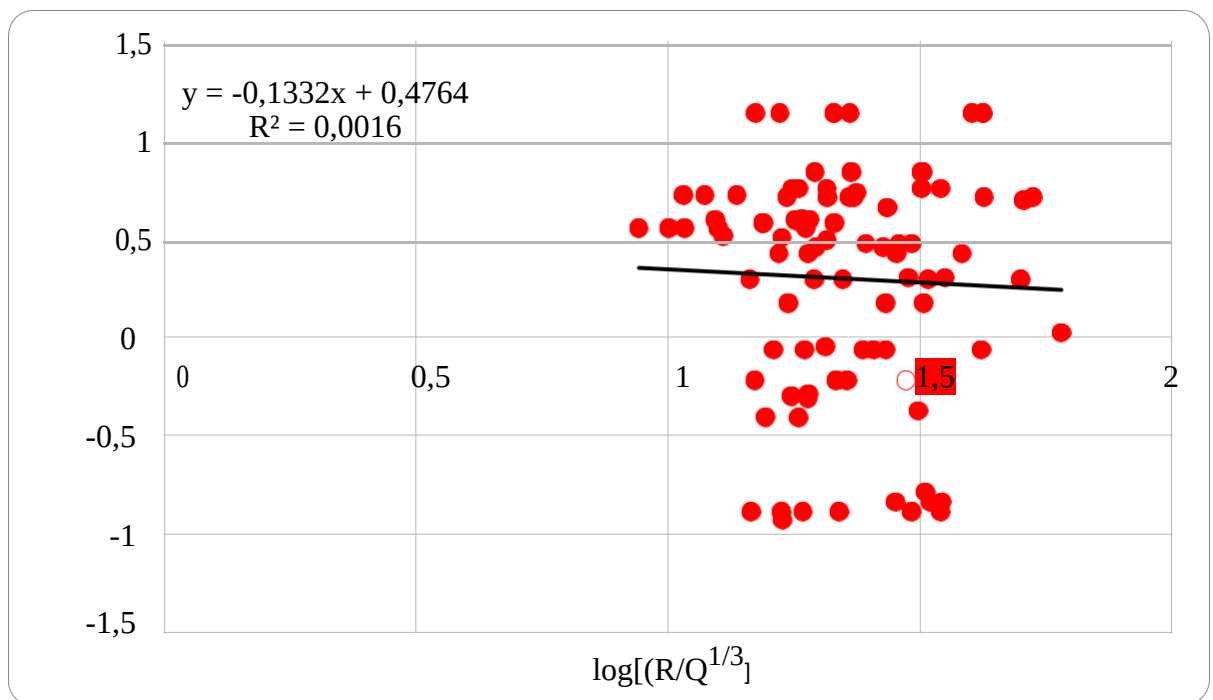


Figure 3. 16. Ground vibration (PPV) and Scaled distance on log-log scale for Ambraseys and Hendron

The plots shown in Figure 3.13, 3.14, 3.15 and 3.16 illustrate the relationship between the PPV and scaled distance using the developed empirical formulas. The correlation is very weak as indicated by a very small coefficient of determinant values (R^2).

The specific site constants (K and B) generated from plots in Figure 3.13, 3.14, 3.15 and 3.16 are shown in Table 3.5 below.

Table 3. 5. Calculated site constants

PREDICTORS	SITE CONSTANTS	
	K	B
DUVALL AND PETKOF	1.841	0.053
LANGFORS AND KIHLSROM	5.383	-0.32
AMBRASEYS AND HENDRON	2.992	-0.133
INDIAN STANDARD PREDICTORS	2.079	0.112

10 new datasets have been used for predicting the ground vibration using the empirical models that had being formulated as in Table 1. Figures 3.17, 3.18, 3.19 and 3.20 show the comparison between the predicted PPV by different empirical formulas and measured PPV.

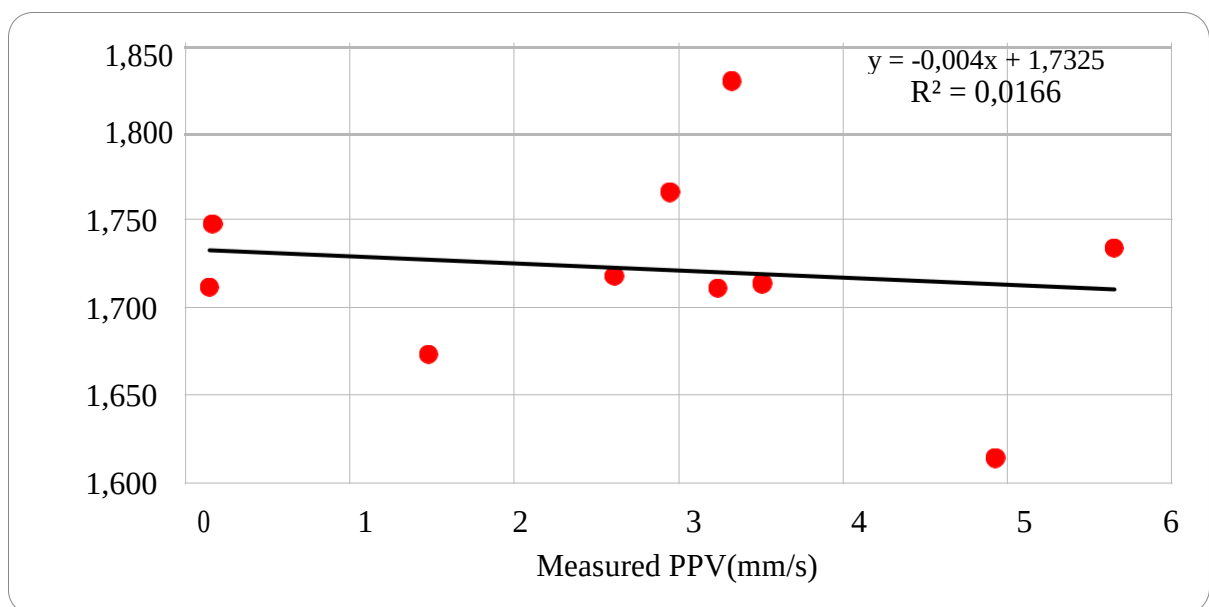


Figure 3. 17. Predicted PPV by Duvall and Petkof formula and Measured PPV

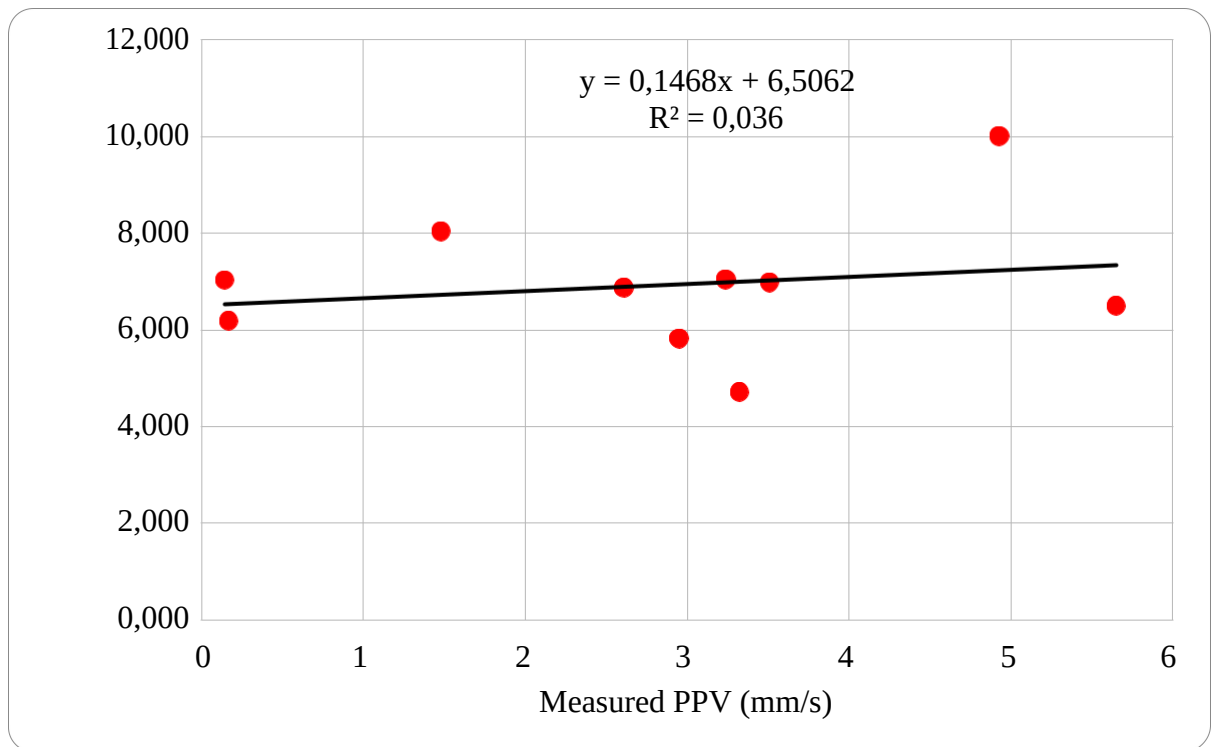


Figure 3. 18. Predicted PPV by Langefors and Kihlstrom formula and Measured PPV

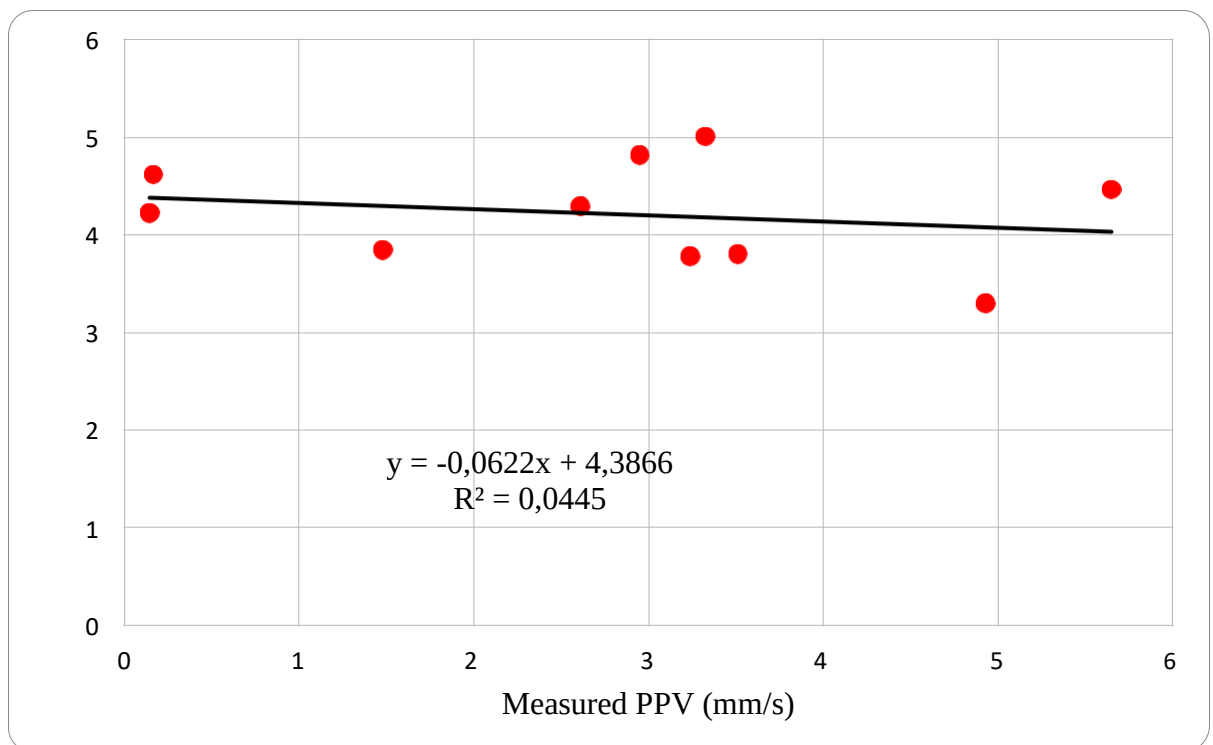


Figure 3. 19. Predicted PPV by BIS formula and Measured PPV

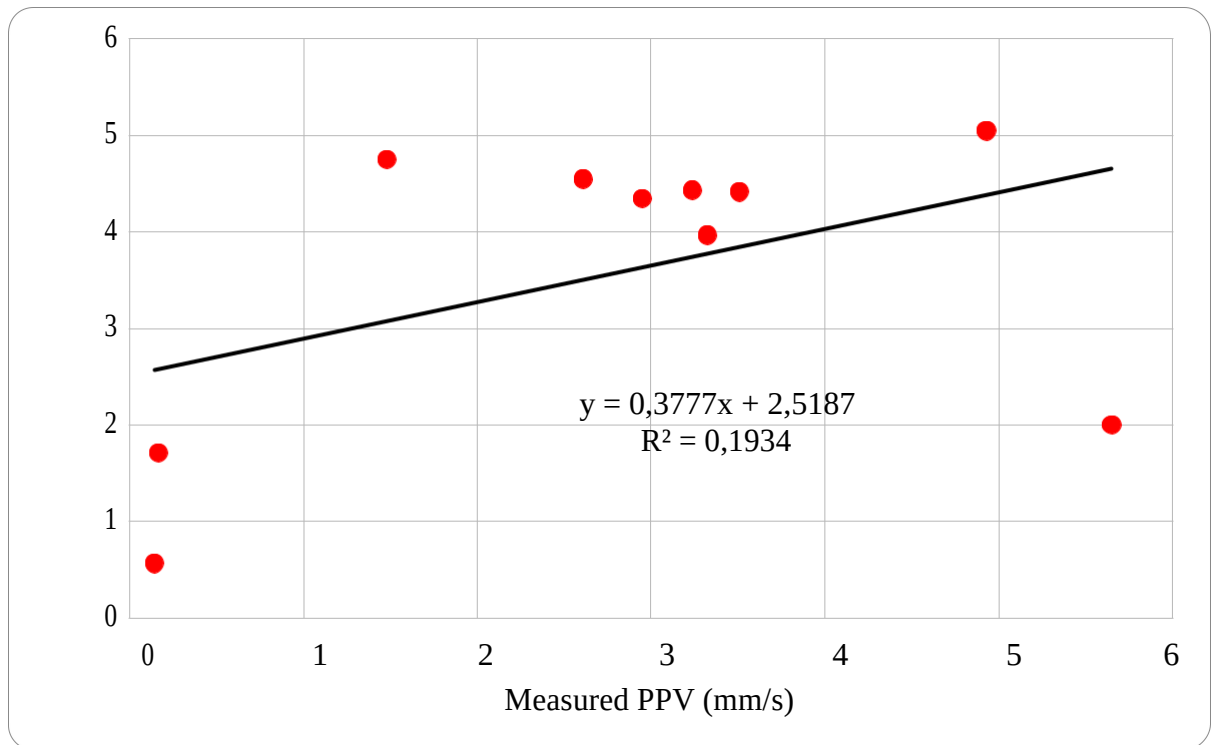


Figure 3. 20. Predicted PPV by Ambraseys and Hendron formula and Measured PPV

Figures 3.17, 3.18, 3.19 and 3.20 illustrate the relationship between the predicted PPV by different empirical formulas and the measured PPV. The plots have weak correlation between the predicted and the measured PPVs as indicated by a lower determinant of coefficient (R^2) values. Therefore their prediction accuracy is at the lowest and there cannot be used to predict complex blasting problems because of its limit input parameters hence the ANN should be applied. The ANN incorporates many input parameters that affect the blast outcome.

3.6. EMPIRICAL FORMULAS FOR AIR-OVERPRESSURE (AOp) / AIRBLAST

Some researchers have formulated empirical predictors for the prediction of airblast such as National Association of Australian State (1983), McKenzie (1990) and Persson et al (1994). Table 3.6 summarizes each empirical formula. To test the prediction accuracy for the airblast empirical formulas, 10 new datasets used for validating the ANN and MVRA models were applied. Figures 3.21, 3.22 and 3.23 shows the relation between the airblast predicted by different empirical formulas and measured airblast values.

Table 3. 6. Air overpressure empirical models

No	Researchers	Empirical formula	Description
1	National Association of Australian State (1983)	$P = \frac{140 \sqrt[3]{\frac{E}{200}}}{d}$	P is air overpressure in kPa, E is charge mass in kg, and d is distance in meters
2	McKenzie (1990)	$dB = 165 - 24 \log(D/W^{1/3})$	dB is the decibel reading D is distance in meter, and W is the maximum charge weight per delay (in kg)
3	Persson et al (1994)	$P = 0.7(W^{1/3}/D)$	P is Air Overpressure in mbar; W is Cooperating Charge in kg; and D is Distance in meter

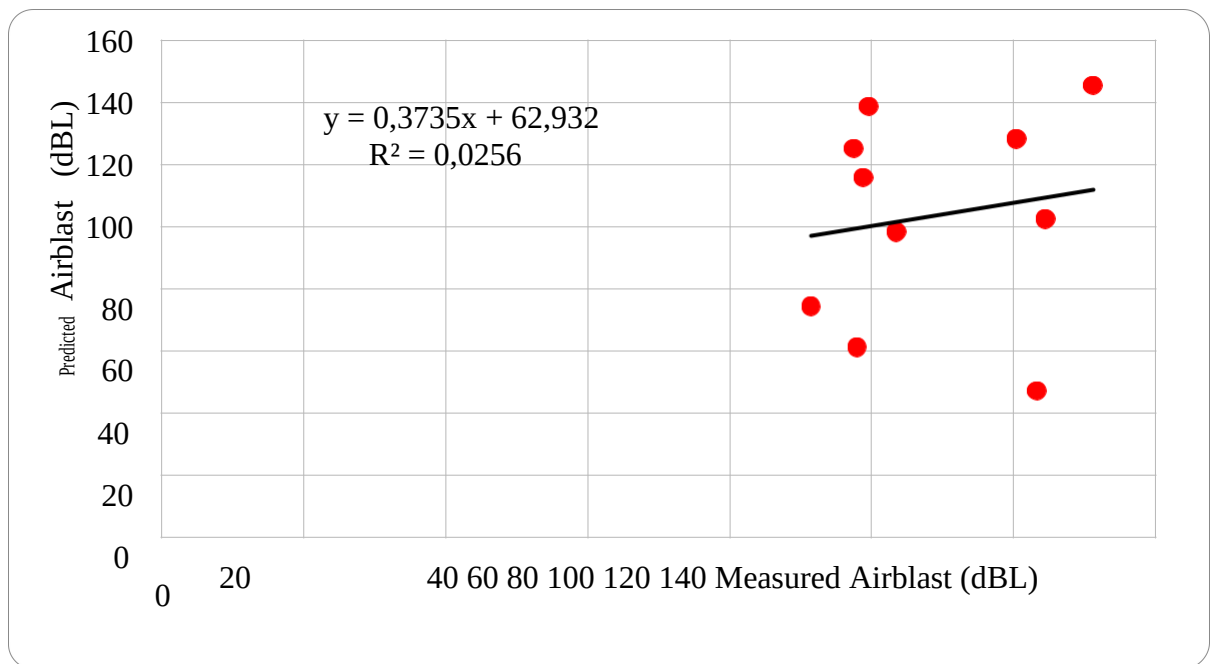


Figure 3. 21. Measured Airblast and predicted Airblast by National Association of Australian State

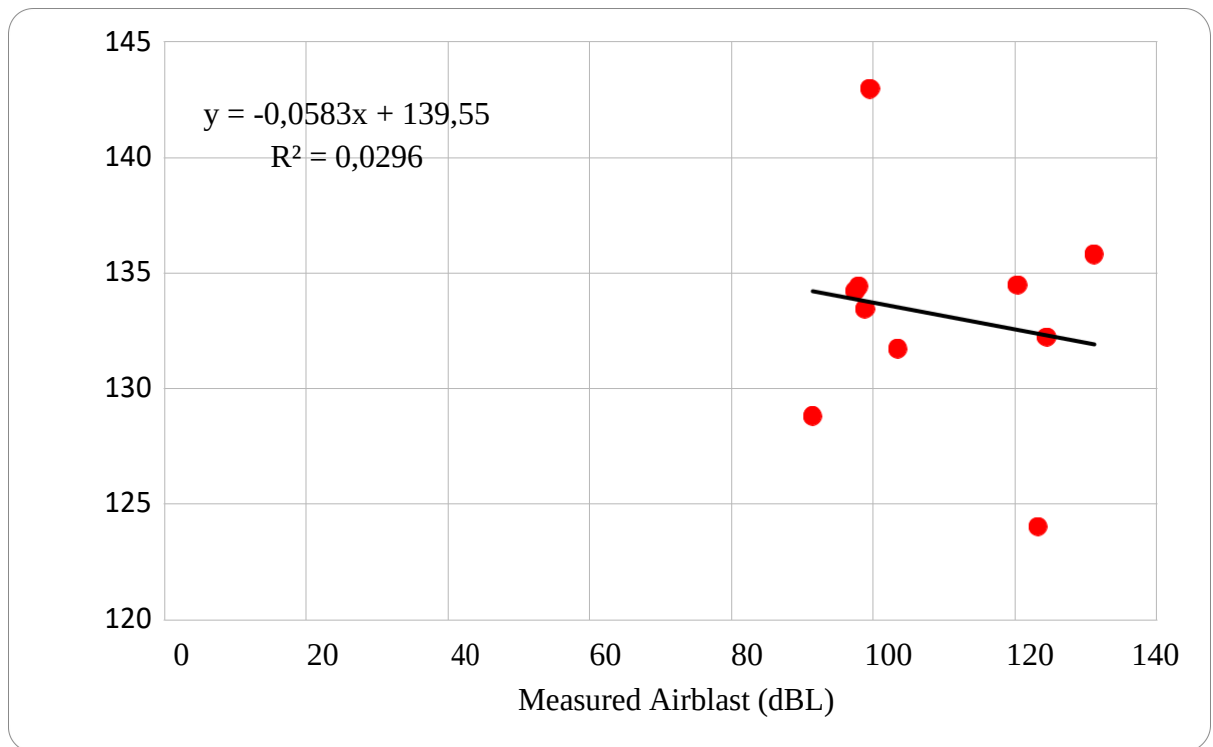


Figure 3. 22. Measured Airblast and predicted Airblast by McKenzie

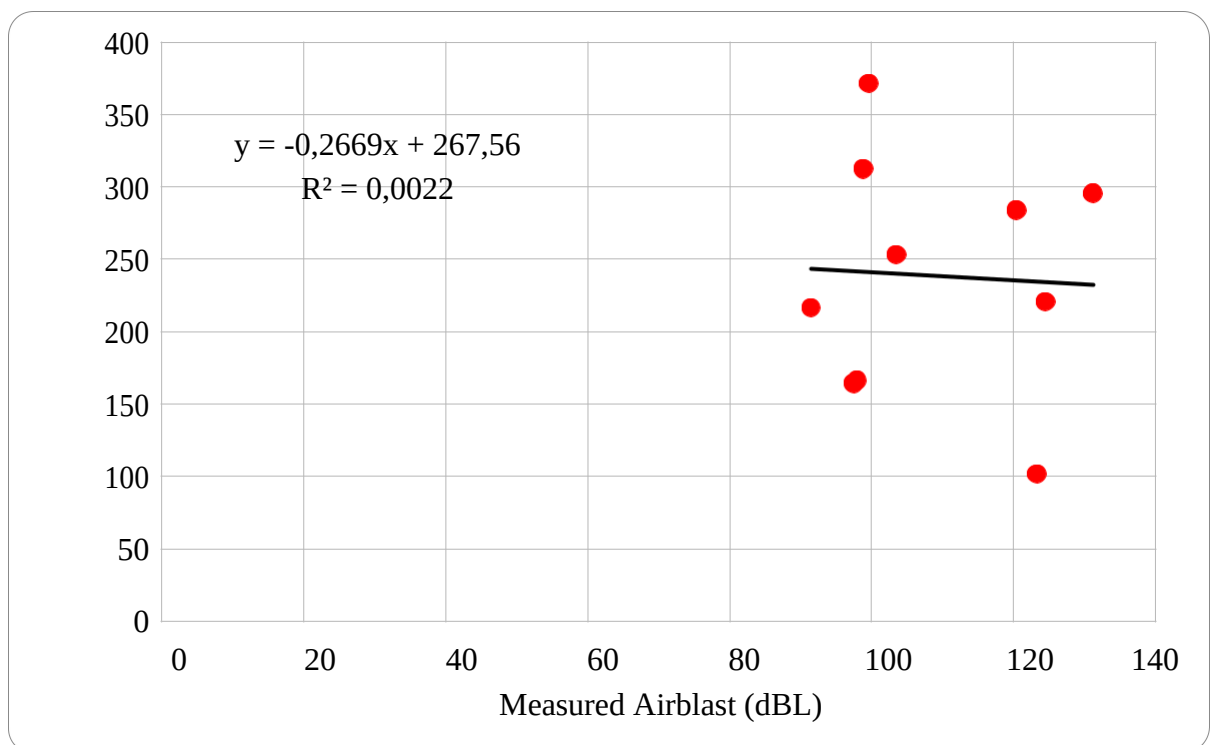


Figure 3. 23. Measured Airblast and predicted Airblast by Persson et al

Figures 3.21, 3.22 and 3.23 above shows a poor correlation between the measured and the predicted airblast by different empirical formulas as indicated by the plots R^2 values which are very lower and closer to zero. Therefore, the formulated empirical equations cannot be used to predict airblast because of its prediction accuracy which is very lower and does not incorporate many parameters that affect blasting outcomes, hence the ANN should be applied.

3.7. SENSITIVITY ANALYSIS

Sensitivity analysis is method that is conducted to quantify each input parameter influence on the output parameters. Sensitivity analysis was conducted separately for (i) airblast, (ii) ground vibrations and (iii) rock fragmentation. The input parameters was hole depth, hole diameter, burden, spacing, stemming length, distance (between the blasting face and monitoring point), powder factor and charge. The output parameters were airblast, ground vibration and rock fragmentation. The following cosine amplitude equation was used to quantity each input parameter influence on the output parameters (Lu. 2005):

$$= \frac{\sum_{i=1}^n (x_i \times y_i)}{\sqrt{\sum_{i=1}^n x_i^2} \sqrt{\sum_{i=1}^n y_i^2}} \quad (3.4)$$

where by indicate input parameters data sets while indicates output parameters datasets. The influence of each parameter on airblast, ground vibration and rock fragmentation is shown in Figure 3.24, Figure 3.25 and Figure 3.26 respectively.

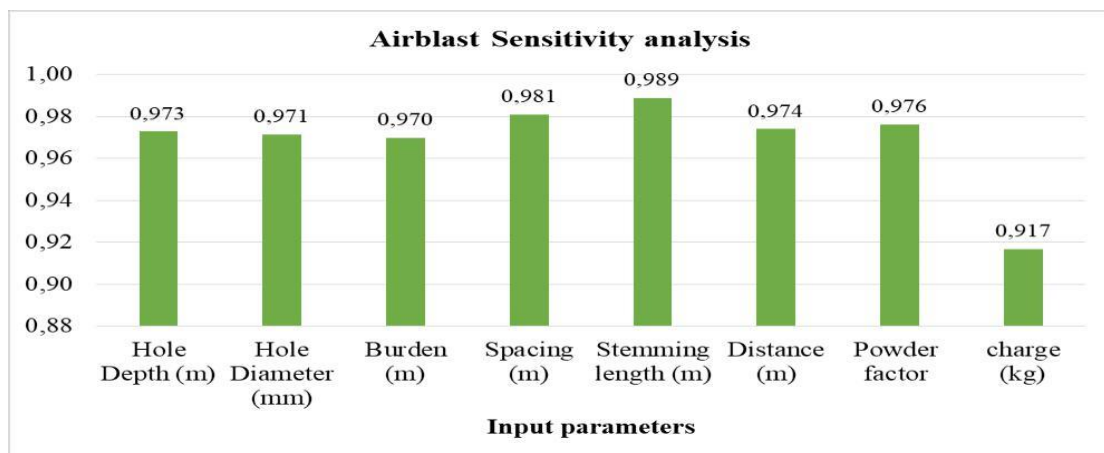


Figure 3. 24. Sensitivity analysis quantifying the influence of each input parameter on Airblast

From Figure 3.24, it can be noted that spacing and stemming length have the greatest effect on the amount of airblast whereas, hole depth, hole diameter, burden, distance and powder factor significantly affect airblast. Charge has the least sensitive factor.

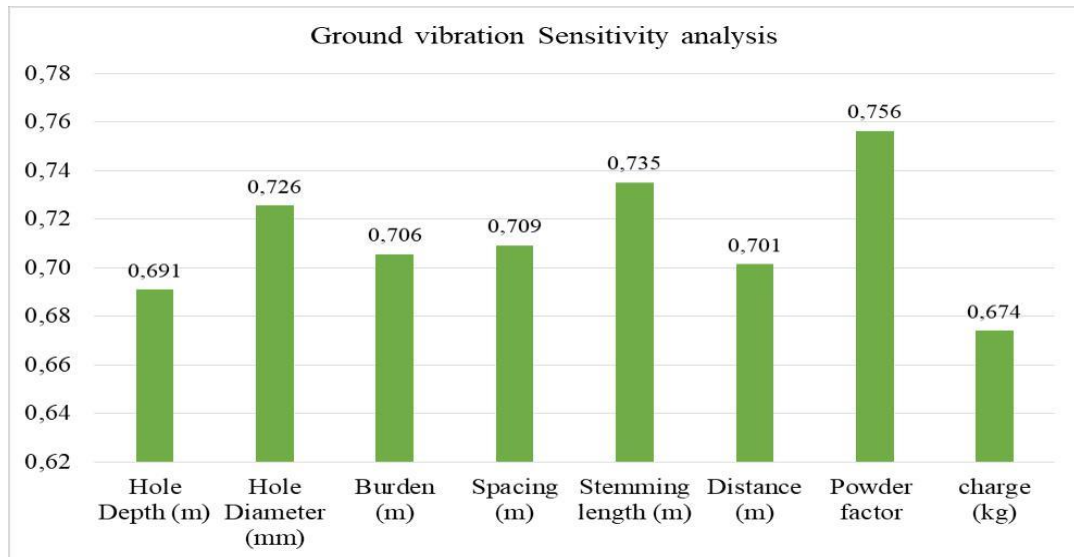


Figure 3. 25. Sensitivity analysis quantifying the influence of each input parameter on Ground vibration

Powder factor has the greatest effect on the amount of ground vibration as shown in Figure 3.25 whereas, charge has the least sensitive factor.

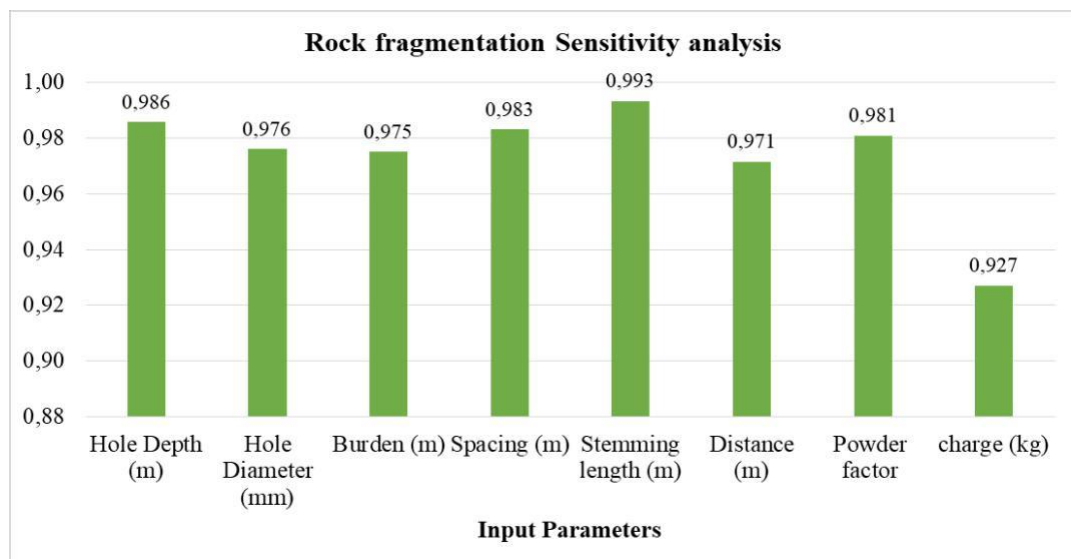


Figure 3. 26. Sensitivity analysis quantifying the influence of each input parameter on Rock fragmentation

Based on Figure 3.26, it can be said that stemming length has a very significant effect on the amount of rock fragmentation, as compared to hole depth, hole diameter, burden, spacing, distance and powder factor which have a great impact on the rock fragmentation. Charge shows a lower sensitive factor compared to other input parameters.

3.8. SUMMARY

The ANN predictive model was developed using MATLAB. The input parameters were hole depth, hole diameter, burden, spacing, stemming length, distance, powder factor and maximum charge per delay whereas airblast, ground vibration and rock fragmentation were regarded as output parameters. These inputs and outputs were fed into a MATLAB-based ANN system to attain the best model by, training, testing and validating the model respectively. Ninety four (94) data sets were used for training and testing the model while 10 new datasets were used to validate the developed optimum model. The optimum ANN model has the highest R^2 and least RMSE. The results from the ANN model has high accuracy as compared to the measured outputs, hence making the ANN model a robust predictive tool.

MVRA equations prediction results of ten (10) new datasets did not have accuracy as compared to the measured outputs. Also, empirical formulas for airblasts and ground vibrations are used to predict the new 10 datasets and the predicted results did not have the level of accuracy desired. The big difference between the predicted outputs and measured outputs make this two not to be useful for prediction of both airblasts and ground vibrations.

Most of the actual and predicted outputs plots show linear relationship. This makes interpretation and analysis easy to depict. Lastly, sensitivity analysis of the optimum ANN model have better performance in quantifying the influence of each input parameter on airblast, ground vibration and rock fragmentation.

CHAPTER 4: RESULT ANALYSIS AND DISCUSSION

4.1. ANN AND MVRA EVALUTION

The optimum ANN model and MVRA performance were evaluated using R^2 and RMSE in table 4.1 below. Figure 1, 2 and 3 demonstrate that ANN model was highly accurate in prediction than MVRA in Figure 4, 5 and 6. The strongest relationship in the ANN model was between the predicted and measured airblast with R^2 and RMSE of 0.9995 and 0.2931 respectively. MVRA prediction results of output parameters was poor as compared with the measured outputs as shown by Figure 4, 5 and 6 with the better prediction in ground vibration with R^2 and RMSE of 0.8001 and 0.4918 respectively.

Table 4. 1. R2 and RMSE values for ANN and MVRA models

Model	Parameter	R^2	RMSE
ANN	Airblast	0.9995	0.2931
	Ground vibration	0.9332	0.4307
	Rock fragmentation	0.9786	0.8083
MVRA	Airblast	0.1657	5.3309
	Ground vibration	0.8001	0.4918
	Rock fragmentation	0.6887	2.3617

As demonstrated in Table 4.1, the MVRA model is less accurate than the ANN model since the RMSE for various output parameters is large as compared to the ANN model which was smaller. Also, it can be noted that the R^2 of MVRA model is relatively smaller as compared to that of the ANN model which is closer to 1, thus making the ANN model reliable and accurate in the prediction field. As seen in Table 4.1 the best prediction by the ANN model is airblast with R^2 of 0.9995 and with regards to MVRA model, it is ground vibration of R^2 of 0.8001.

4.2. EMPIRICAL PREDICTORS AND ANN

Empirical formulas developed by several researchers as shown in Table 3.4 and Table 3.6 were used to predict PPV and airblast respectively. R^2 and RMSE are used to evaluate the performance of empirical formulas against the ANN model. From Table 4.2 it shows ANN model has a higher R^2 of 0.9332 which is closer to one and a relative smaller RMSE of 0.4307 compared to empirical formulas for PPV prediction. This shows the ANN model is better in predictions as compared to empirical predictors.

Table 4. 2. R^2 and RMSE values of PPV using ANN and empirical predictors

Predictor	R^2	RMSE
Duvall and Petkof (1959)	0.0166	0.0528
Langefors and Kihlstrom (1963)	0.0360	1.3039
Ambraseys and Hendron (1968)	0.1934	1.3226
BIS (1973)	0.0445	0.4944
ANN	0.9332	0.4307

As for airblast prediction, Table 4.3 shows that the ANN model performed better as compared to empirical model. The ANN model has a R^2 and RMSE of 0.9995 and 0.2931 respectively. A R^2 closer to one indicates the strongest relationship between the predicted and measured output, as well as a RMSE closer to zero. Therefore, ANN is a better prediction model as compared to empirical formulas.

Table 4. 3. R^2 and RMSE values of airblast using ANN and empirical predictors

Predictor	R^2	RMSE
National Association of Australian State (1983)	0.0256	31.3380
McKenzie (1990)	0.0296	4.5428
Persson et al (1994)	0.0022	96.4270
ANN	0.9995	0.2931

4.3. SENSITIVITY ANALYSIS

Sensitivity analysis was conducted to quantify the effect of all the input parameters on the airblast, ground vibration and rock fragmentation. As shown by Figure 3.24, the greatest parameters that influence airblast are stemming length and spacing while charge and burden are the least influential parameters. Powder factor has the most influence on the ground vibration as compared to other input parameters as illustrated in Figure 3.25 whereas charge is the least effective parameter. From Figure 3.26, stemming length and hole depth are the most effective parameters on rock fragmentation while charge bears least influence on rock fragmentation.

4.4. SUMMARY

The ANN prediction model has proved that it is the best when compared to empirical models and multivariate regression analysis equations. The ANN model produced highly accurate outputs readings as compared to the measured ones with coefficient of determinant (R^2) closer to one and a relatively smaller root mean square error. Stemming length and spacing are the most influential parameters on airblast and charge was the least influential. Moreover, powder factor proved to be the input parameter with the most influence in ground vibration while linear charge was the least sensitive input parameter. The least effective input parameter on rock fragmentation was found to be charge whilst, stemming length and hole depth were the most effective parameters.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1. CONCLUSIONS

The study examined blast induced airblast, ground vibration and rock fragmentation using artificial neural network, multivariate regression analysis and empirical formulas. The conducted analysis showed that the developed optimum artificial neural network has a higher predictive precision. The results from this study are summed up below:

1. The developed optimum model has:
 - Coefficient of determinant (R^2) of 0.9983.
 - Network architecture of 8-14-3 (8 input parameters, 14 hidden neurons and 3 output parameters) with transfer function of transig.
2. The ANN model showed excellent conformity between the measured and predicted outputs as compared to MVRA and empirical formulas.
3. The empirical formulas are either over estimating or under estimating airblast, ground vibrations and rock fragmentation.
4. According to sensitivity analysis, the most effective parameters on airblast are stemming length and spacing.
5. Powder factor was the most influential input parameter on ground vibration.
6. Stemming length and hole depth proved to be the most sensitive parameter on rock fragmentation.
7. Maximum charge per delay was found to be the least effective input parameter on airblast, ground vibration and rock fragmentation.

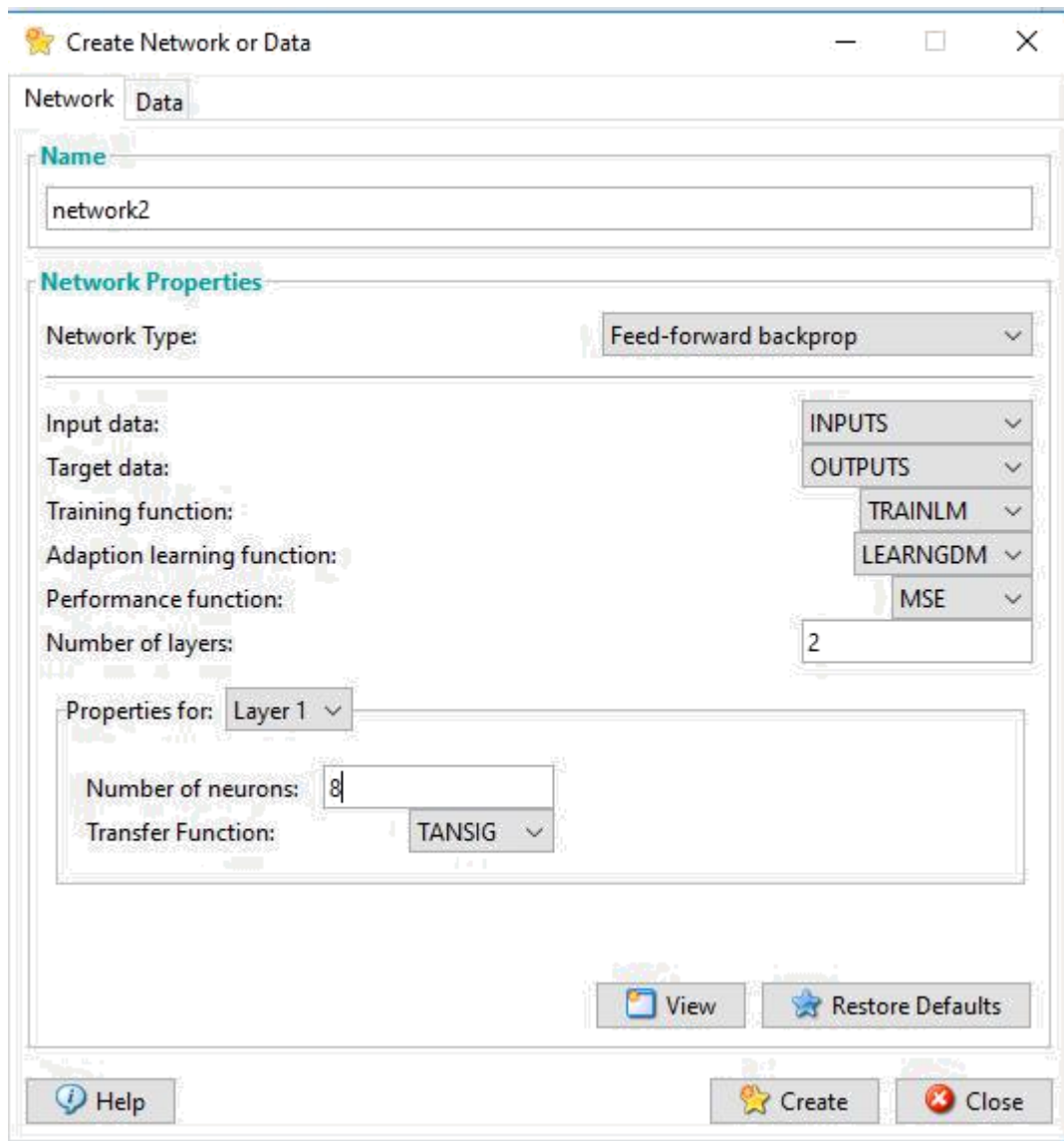
An optimum ANN model is developed and can be used to predict blast induced airblast, ground vibration and rock fragmentation. This can be used by mining companies to predict blast-induced effects in blasting operations. This prediction model will enable blast designers to know ahead of time the amount of blast-induced effects that will be generated when the actual blast is carried out. It can help in minimizing the undesirable blast-induced environmental effects such as airblast, ground vibration, flyrocks etc.

5.2. RECOMMENDATIONS

This study has shown that ANN models can be applicable in predicting blast induced airblasts, ground vibrations and rock fragmentation. More studies are needed to be carried out to improve the research work done in this study. These improvements include the following:

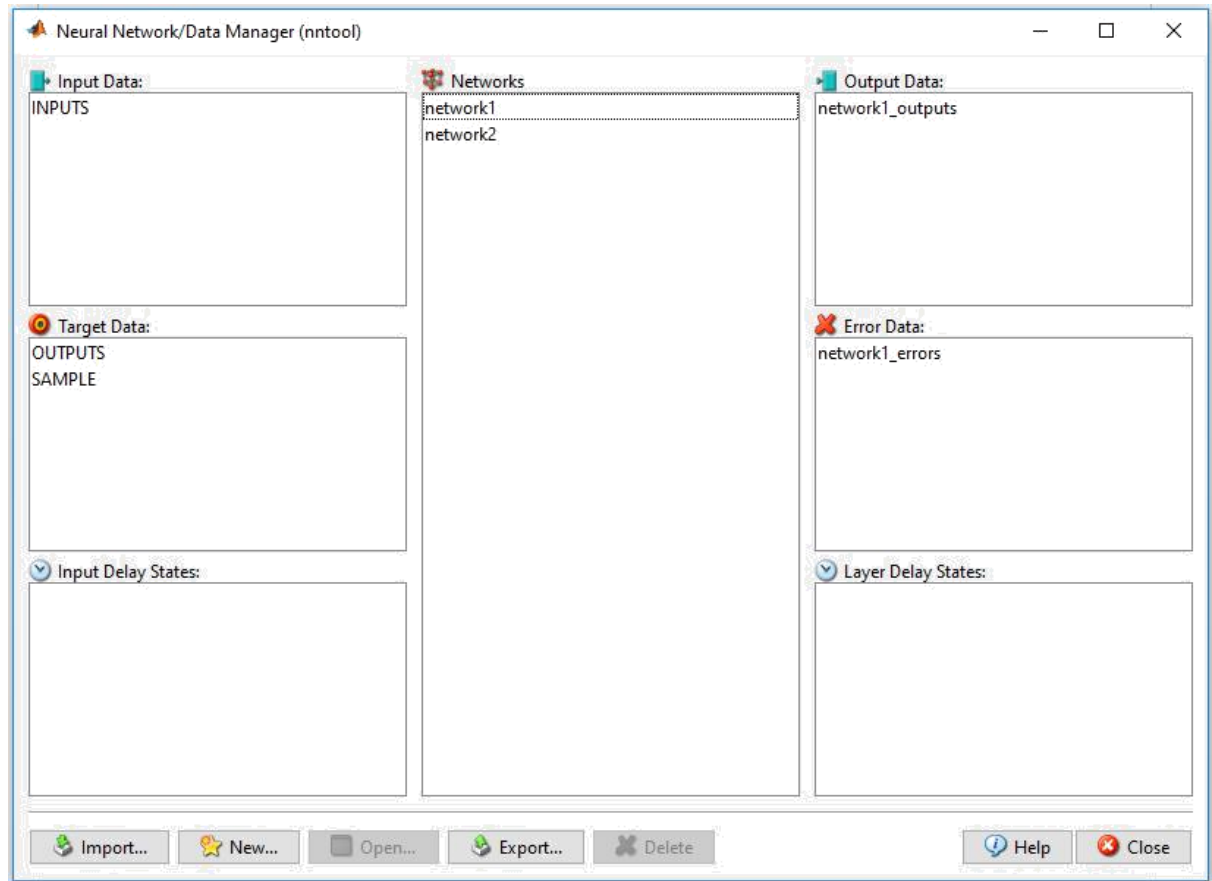
1. Increase in number of input parameters affecting the blasting outcomes. This may include rock hardness, rock strength or rock quality designated.
2. Other blast induced effects such as backbreaks, overbreaks and flyrock could be included as output parameters.
3. The developed ANN performance could be improved by using it with algorithms such as hybrid imperialist competitive algorithm and particle swarm optimization algorithm etc.

APPENDIX A
CREATION OF ARTIFICIAL NEURAL NETWORK MODEL



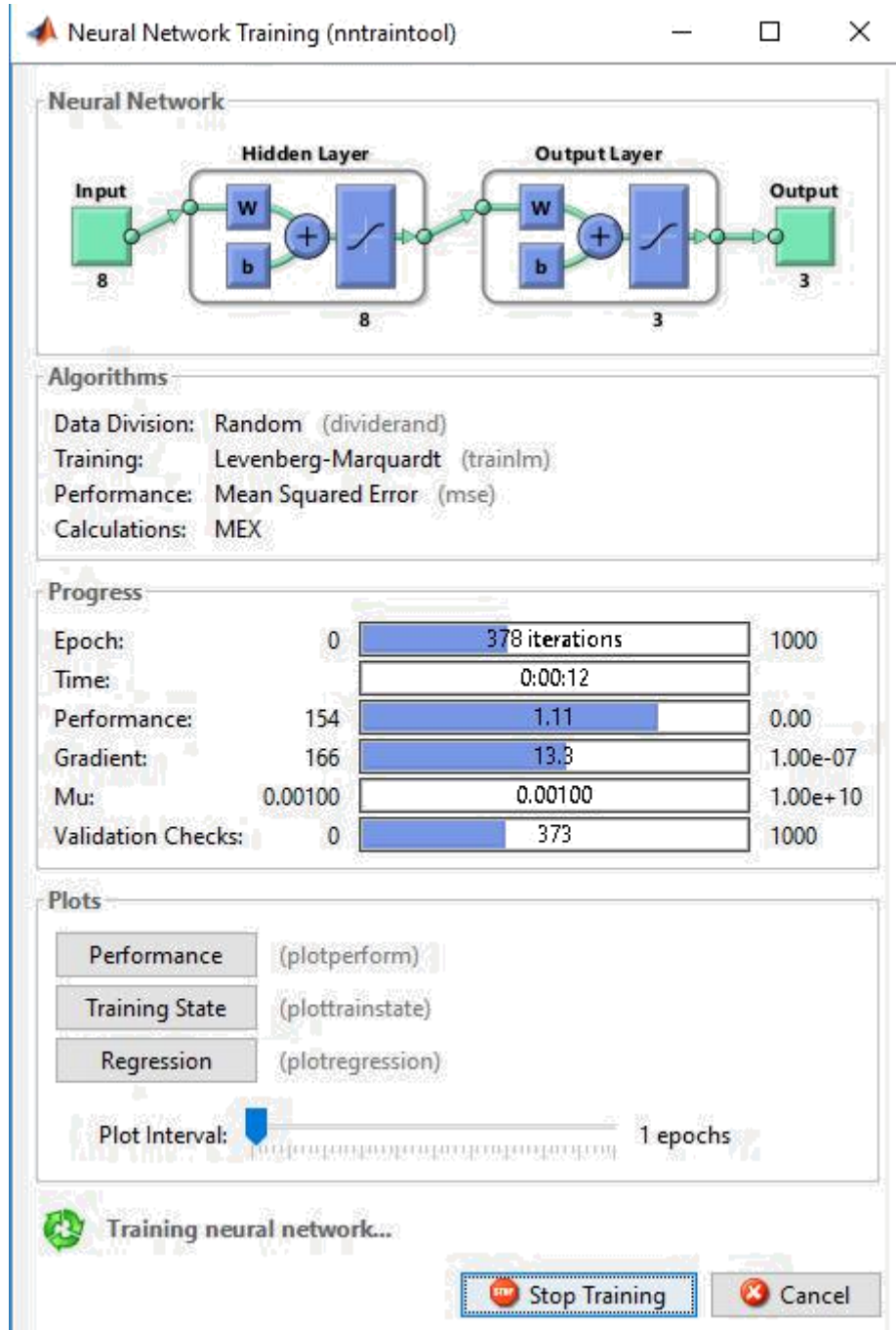
MATLAB interface for creation of the ANN network

Certain parameters are defined before training the network. Those parameters are the learning function, training function, number of neurons and number of layers among others.

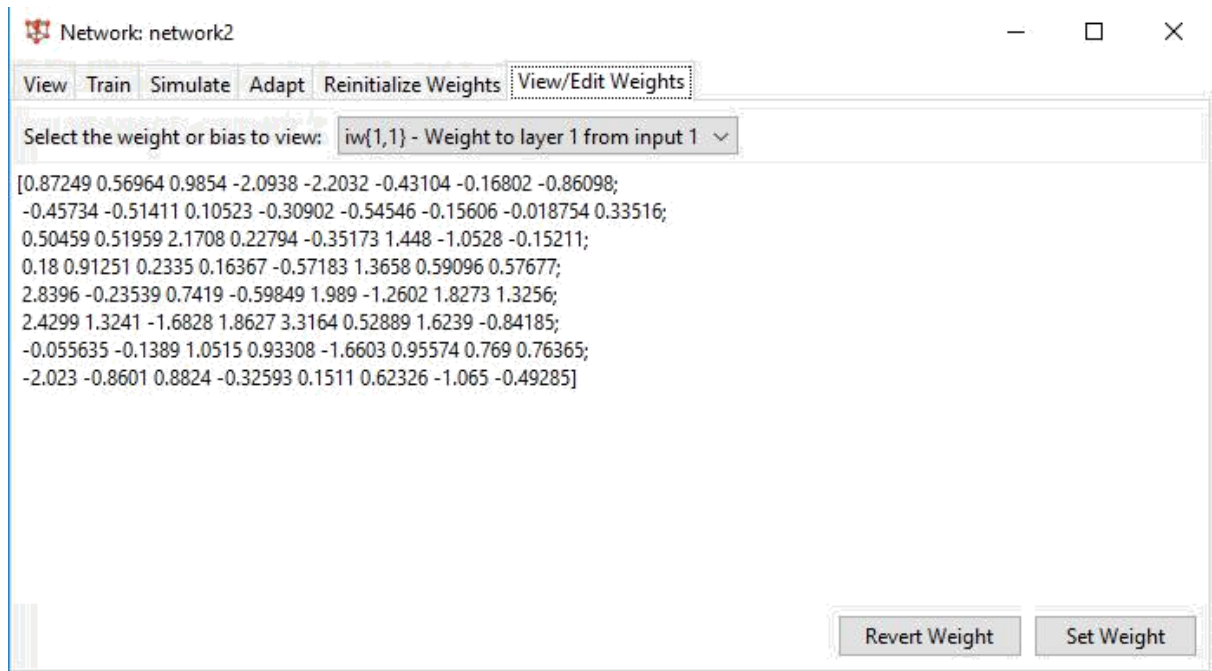


MATALAB Data manager interface for neural network

All the datasets used for building the network are displayed here before further processing.
Also networks built are shown here.



Training of back propagation neural network.

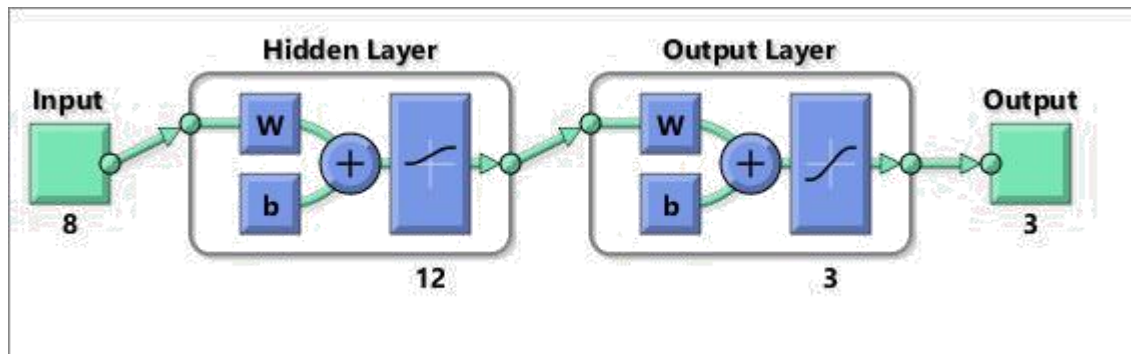


MATLAB Tab for editing weights

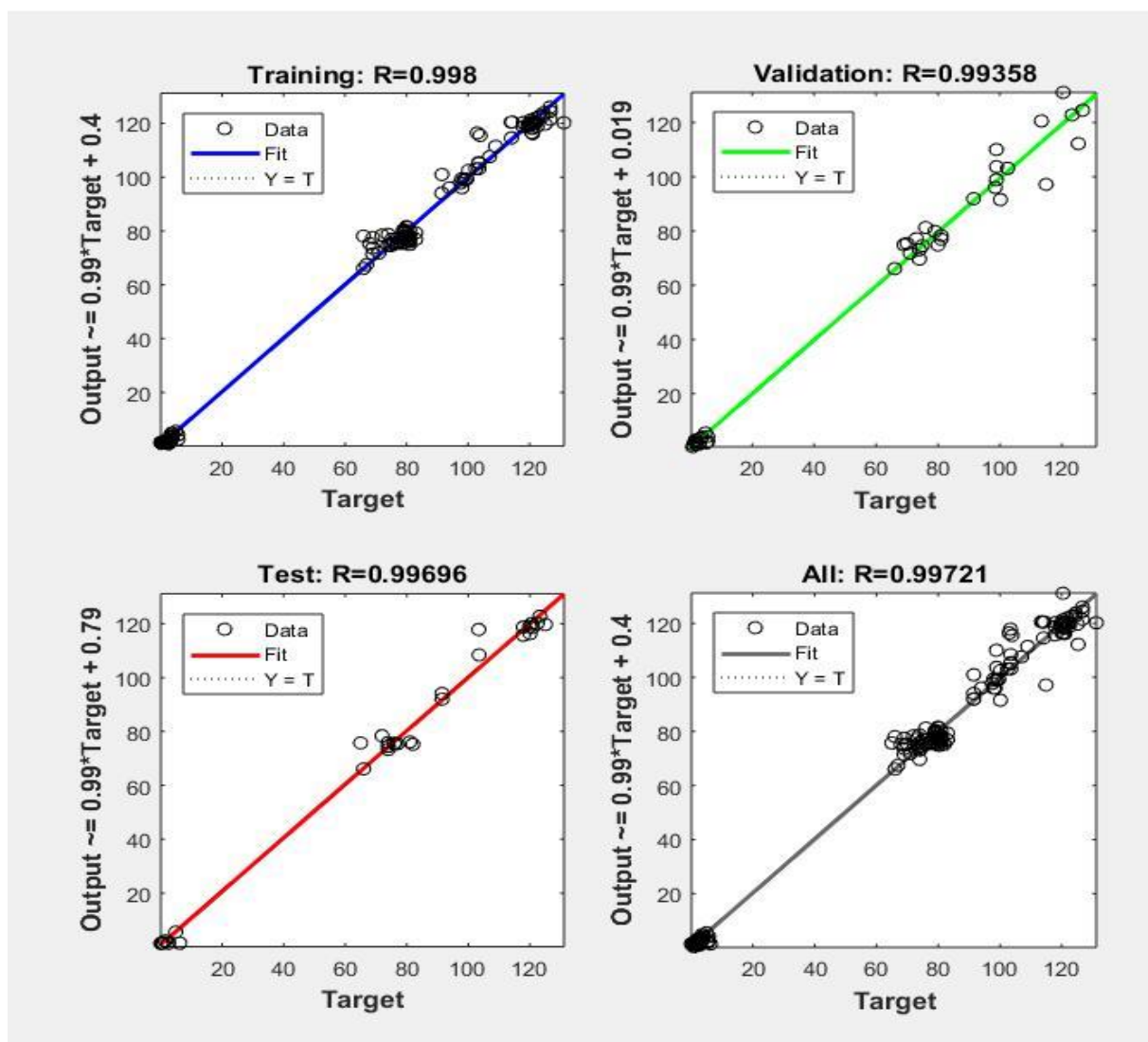
These weights can be edited to better the performance of the ANN model created.

APPENDIX B

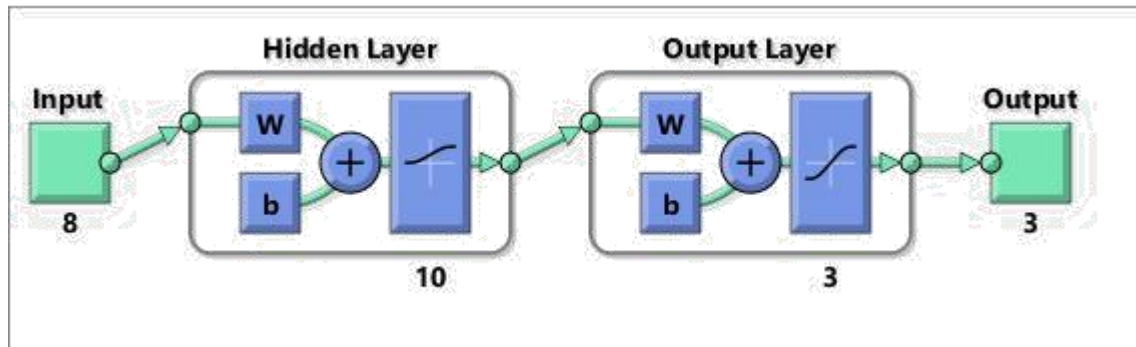
MODELS TESTED WITH DIFFERENT ARTICTETURE AND TRANSFER FUNCTION



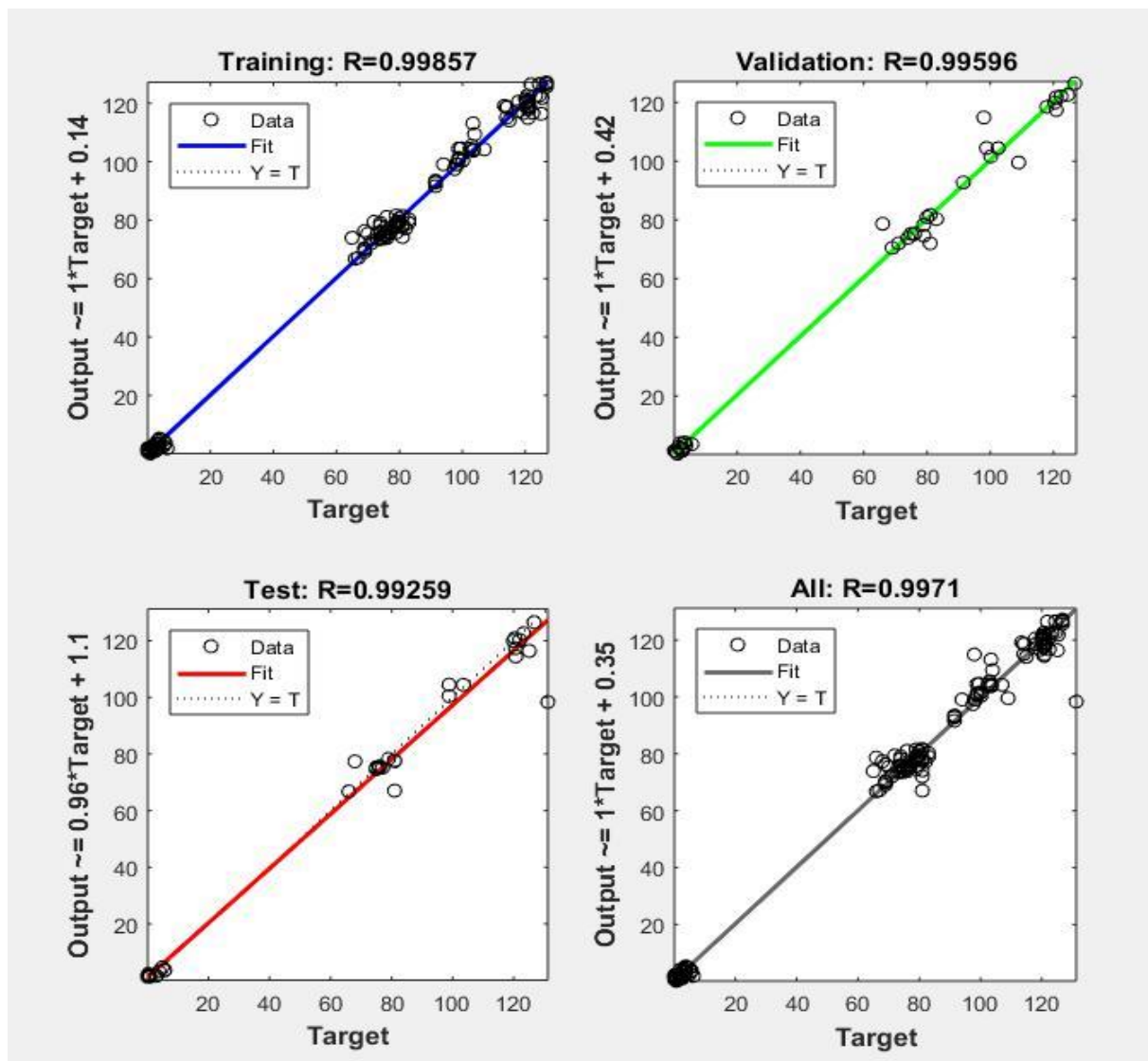
Network architecture of (8-12-3) with LOGSIG as a transfer function



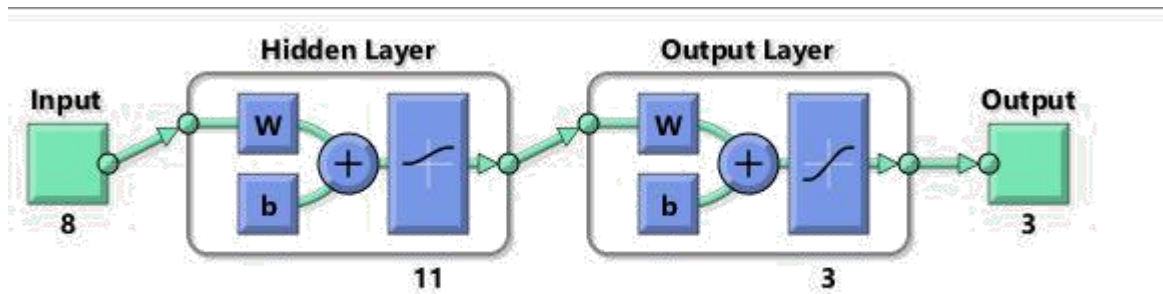
Regression plot of Network architecture of (8-12-3) with LOGSIG as a transfer function



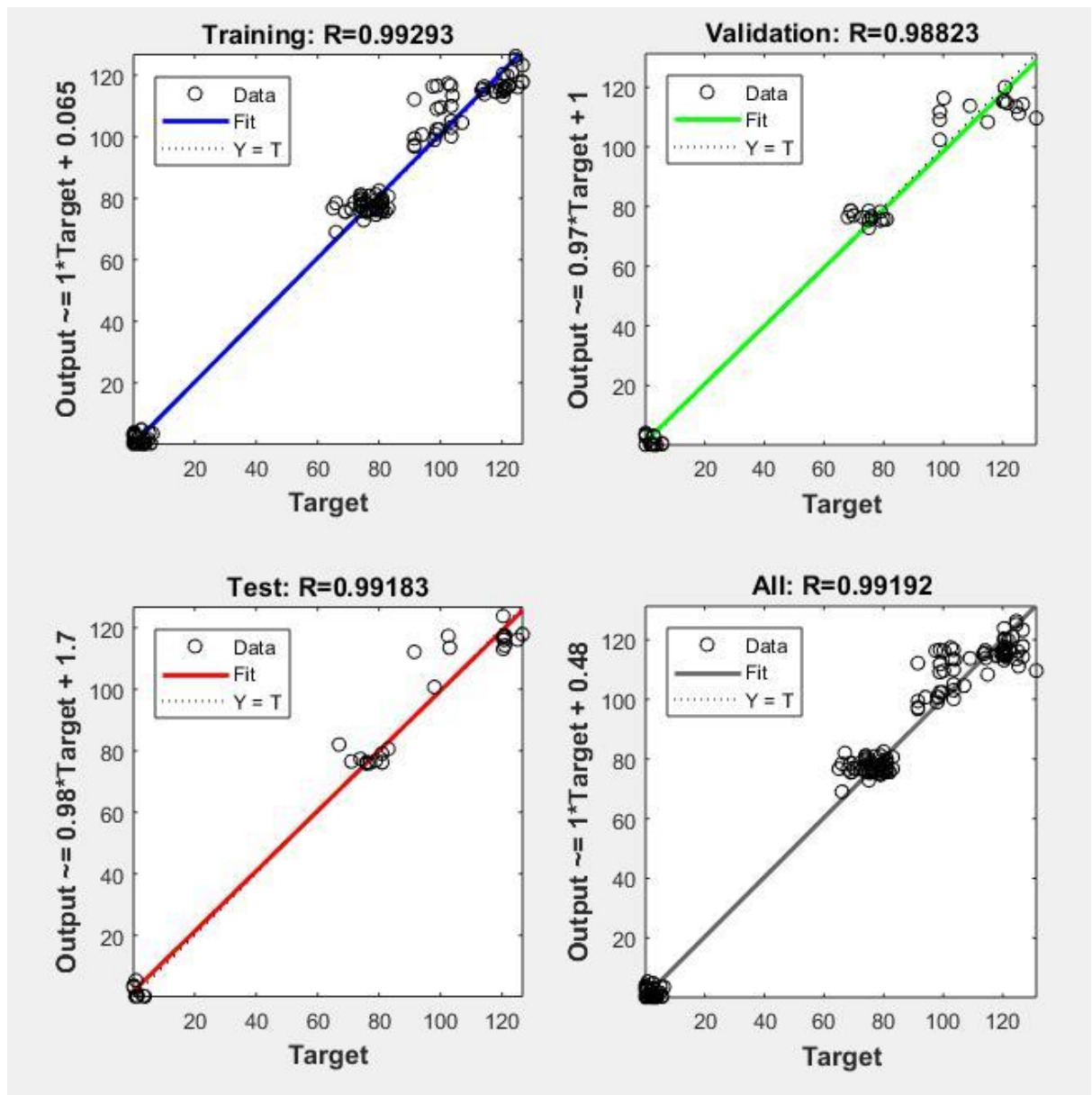
Network architecture of (8-10-3) with LOGSIG as a transfer function



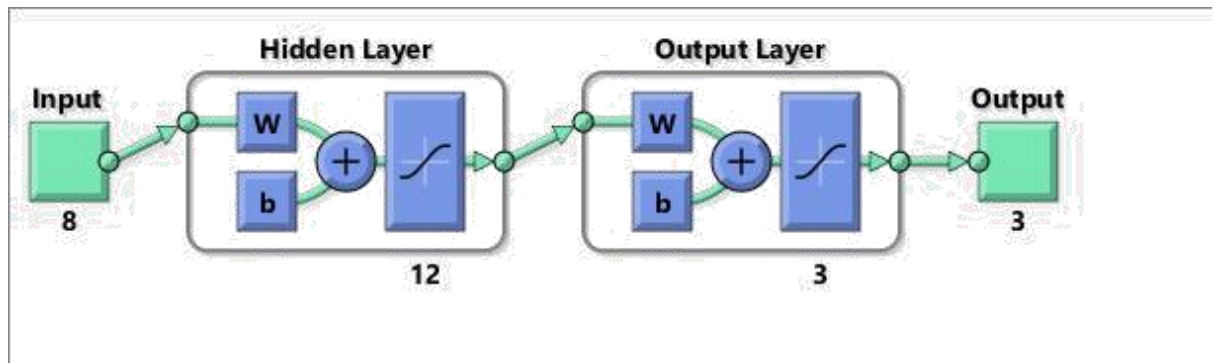
Regression plot of Network architecture of (8-10-3) with LOGSIG as a transfer function



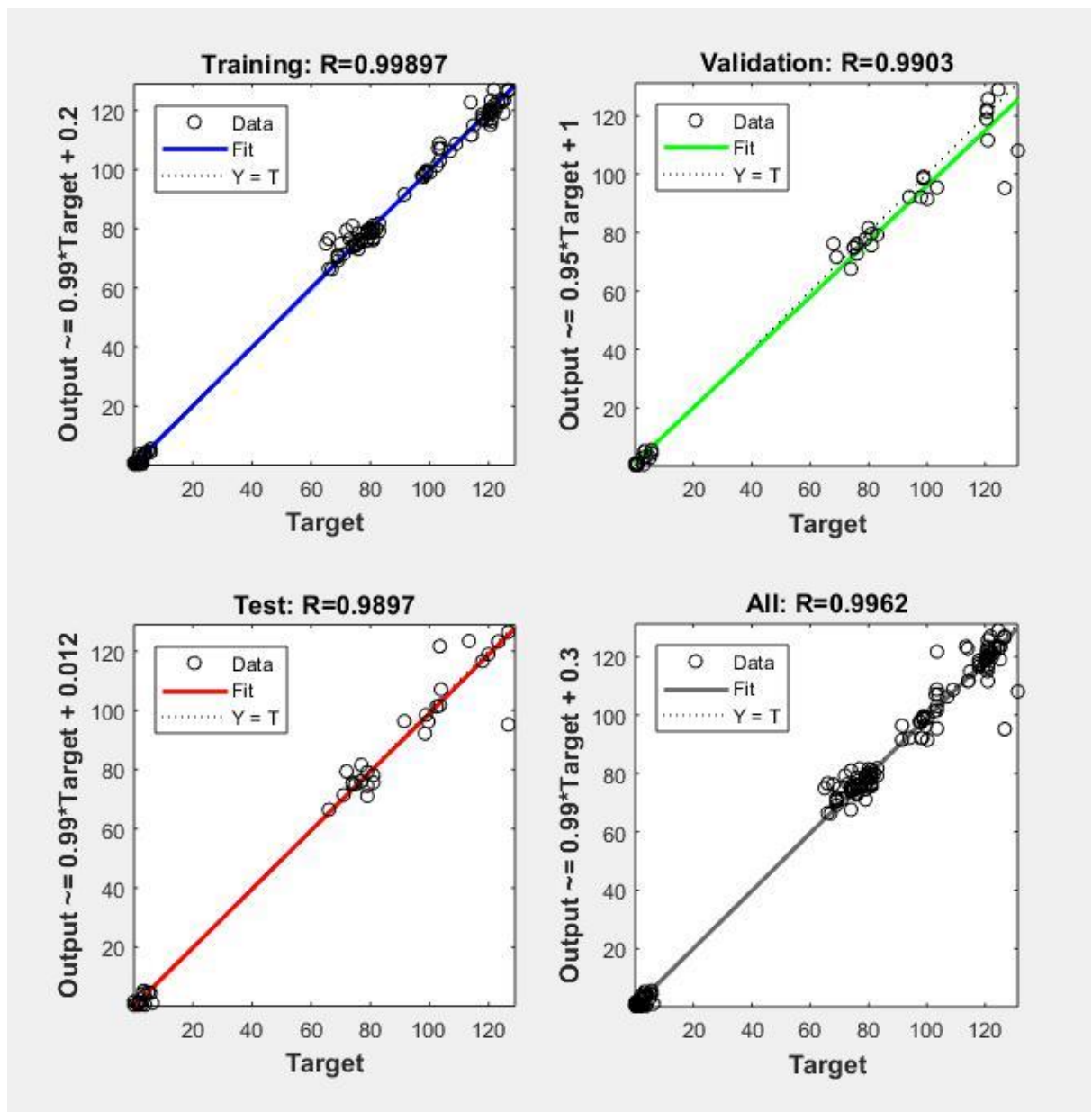
Network architecture of (8-11-3) with LOGSIG as a transfer function



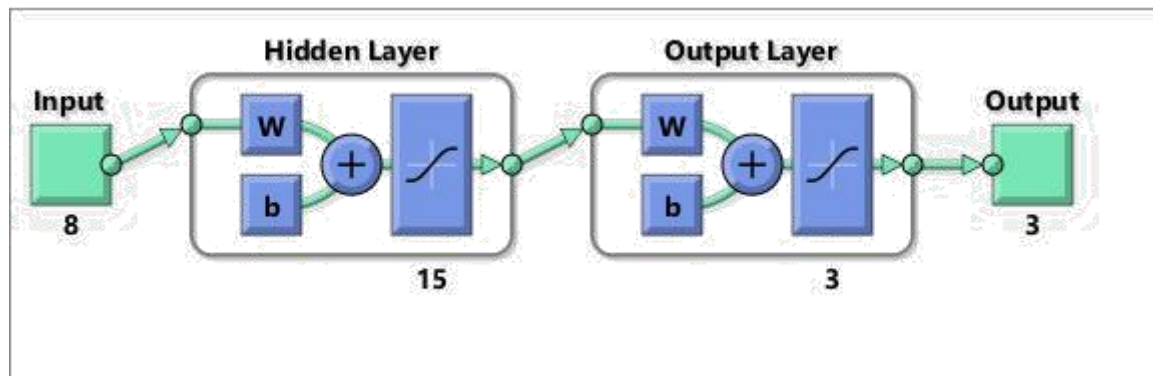
Regression plot of Network architecture of (8-11-3) with LOGSIG as a transfer function



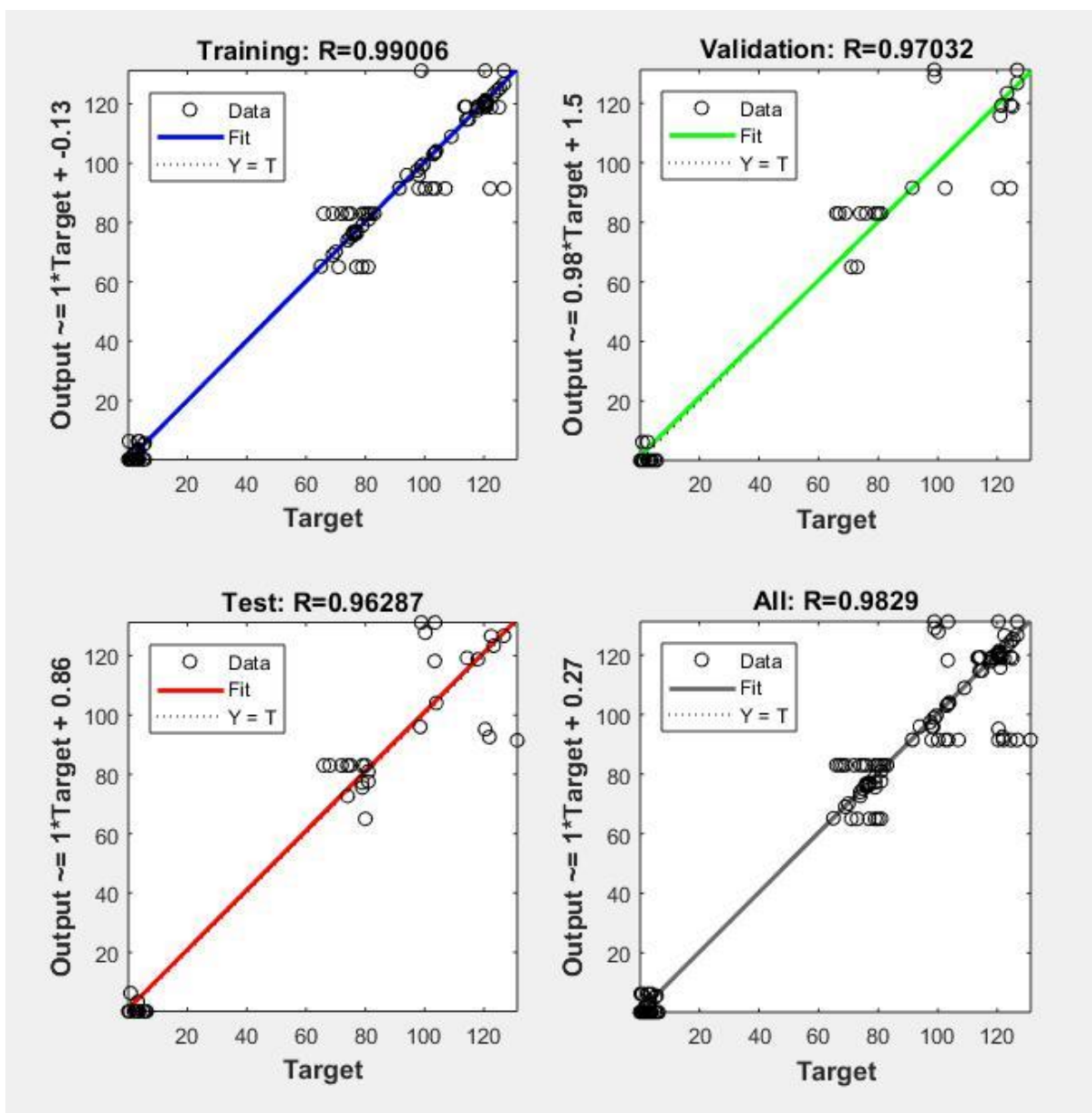
Network architecture of (8-12-3) with TRANSIG as a transfer function



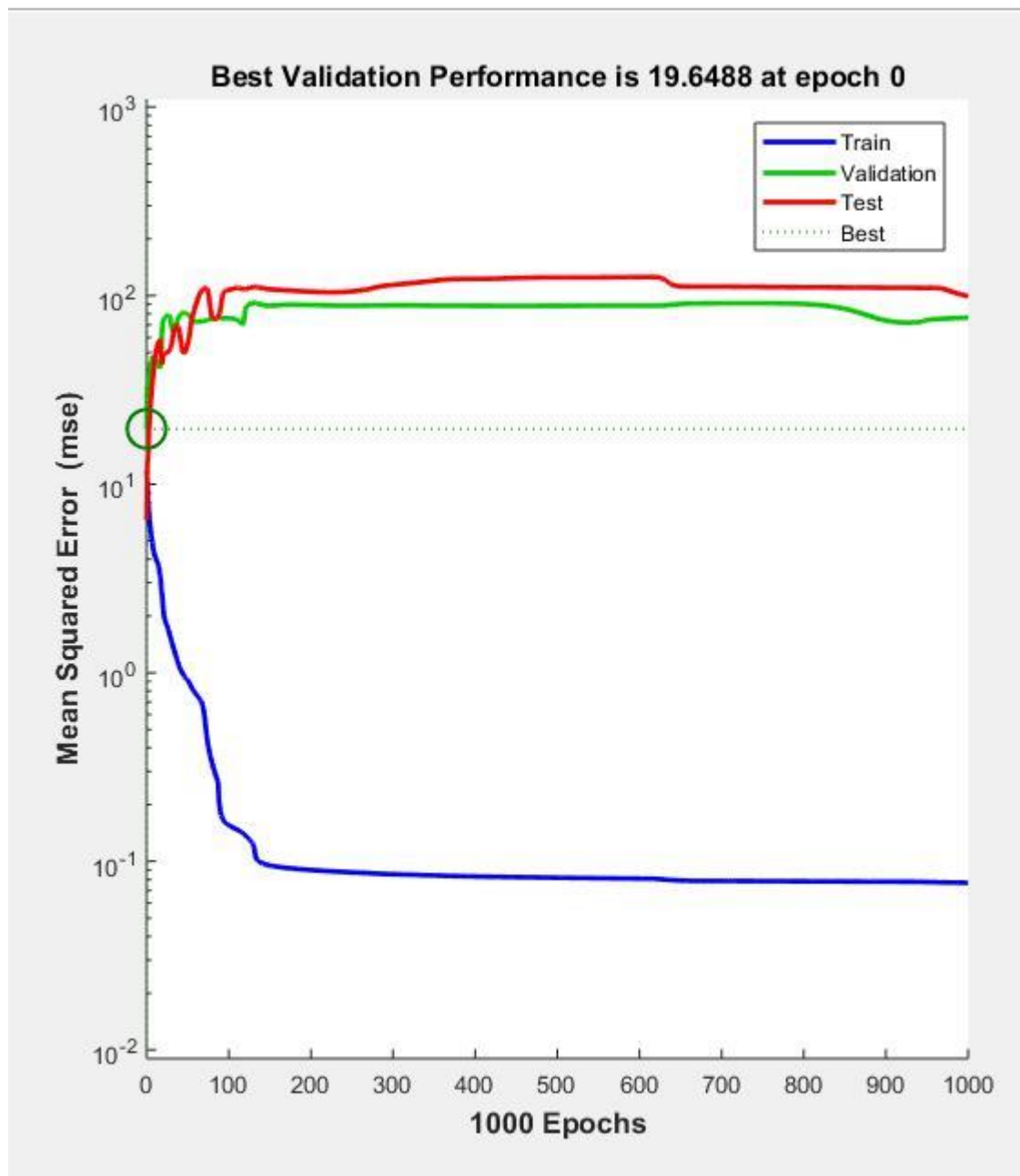
Regression plot of Network architecture of (8-12-3) with TRANSIG as a transfer function



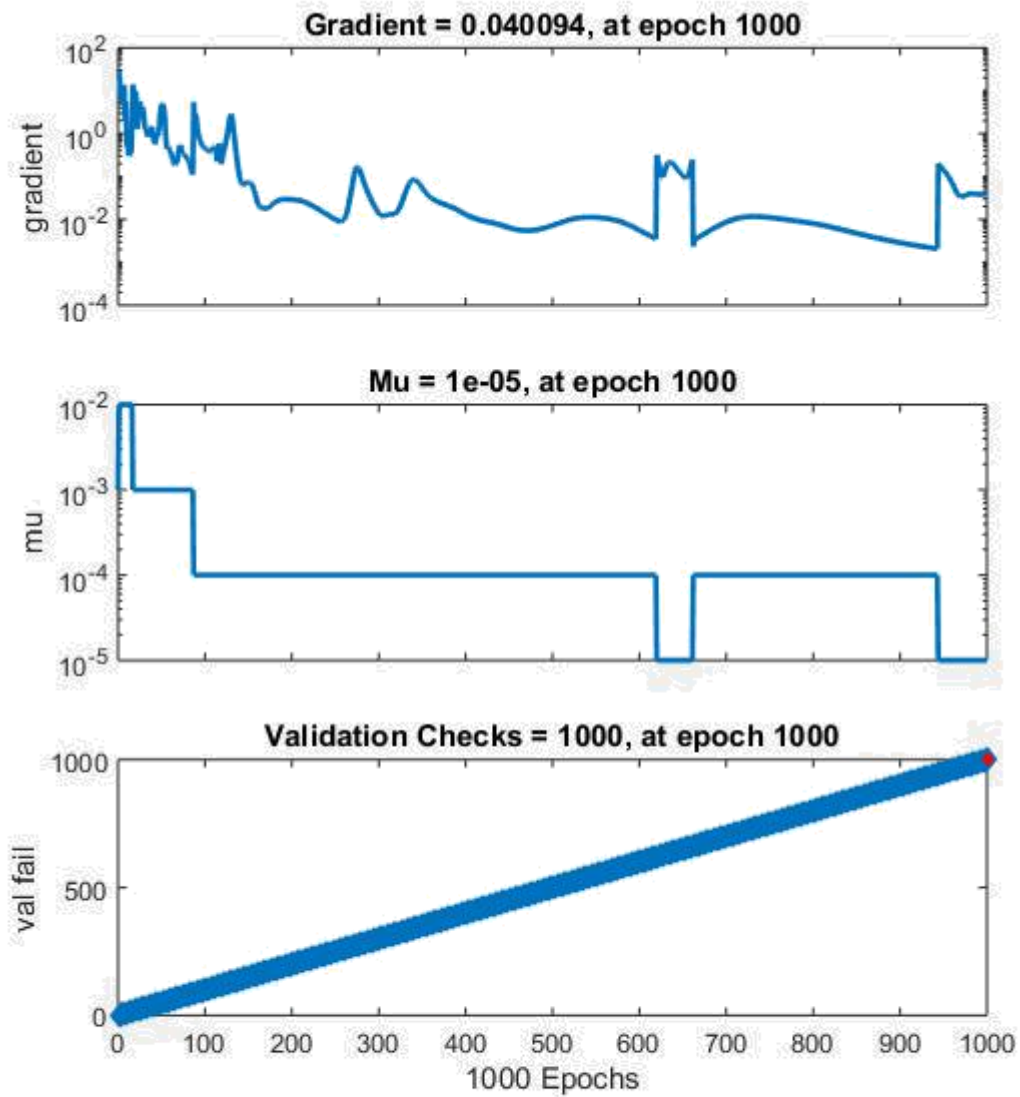
Network architecture of (8-15-3) with TRANSIG as a transfer function



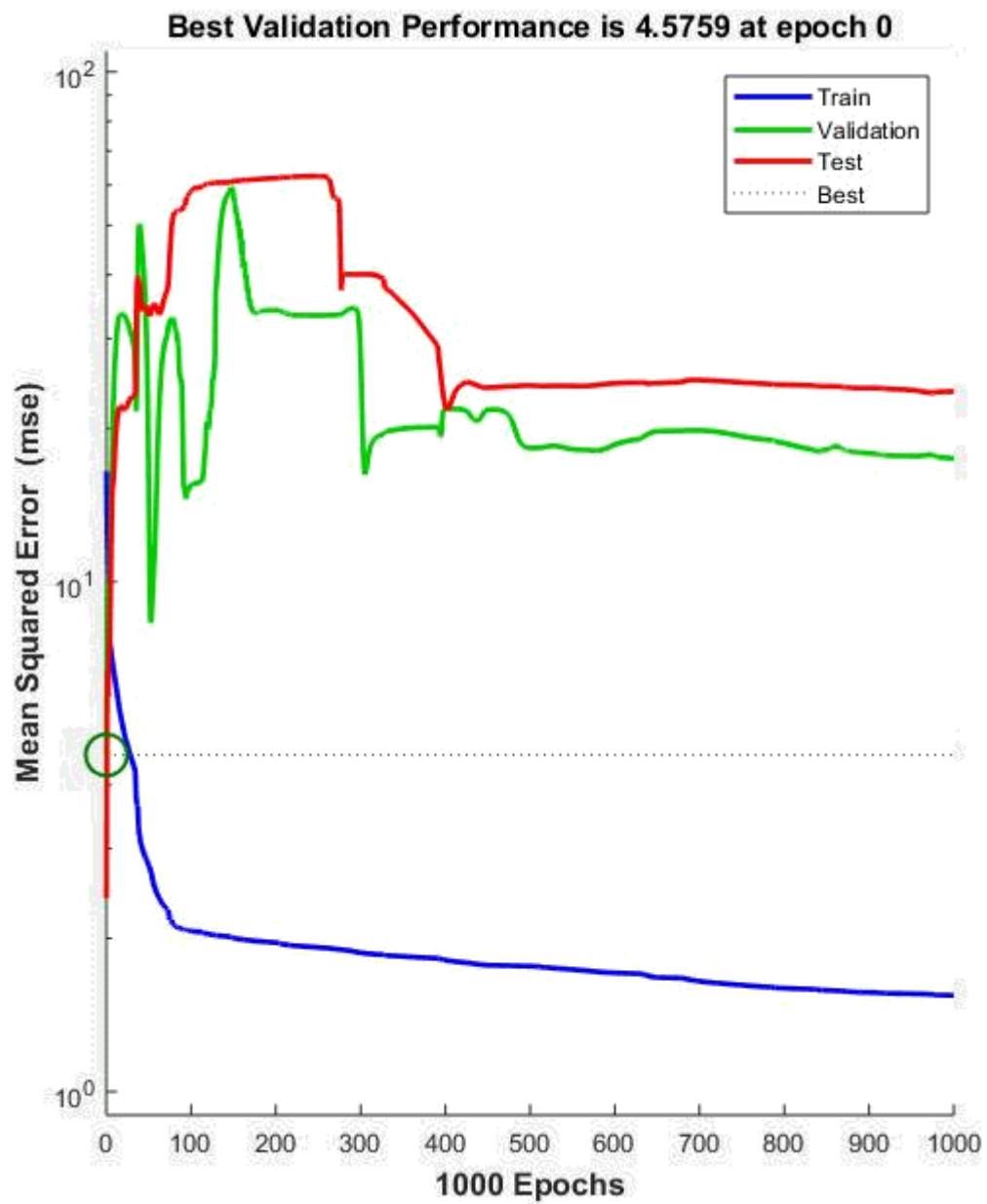
Regression plot of Network architecture of (8-15-3) with TRANSIG as a transfer function



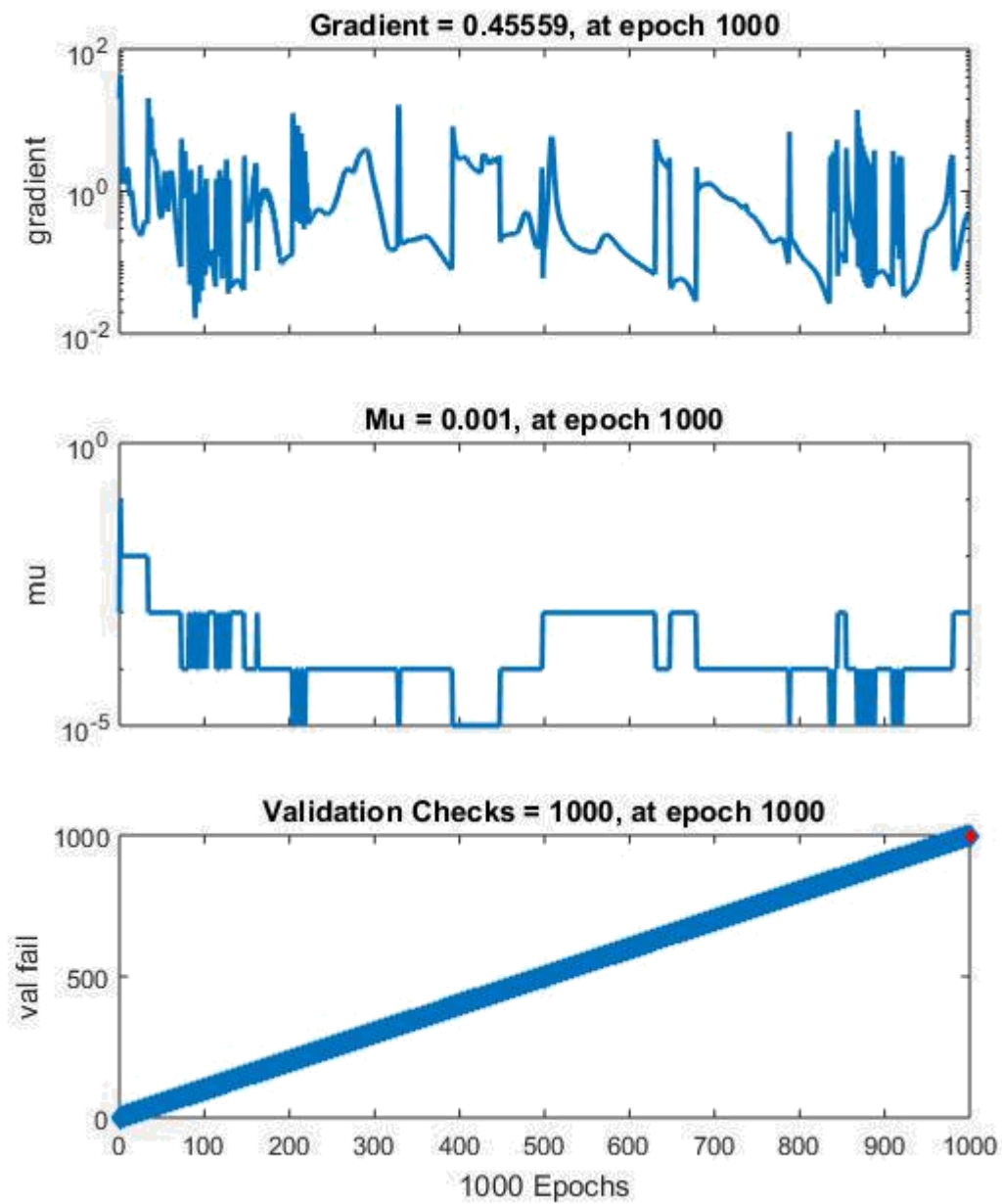
Performance plot of network architecture of (8-12-3) with LOGSIG as a transfer function



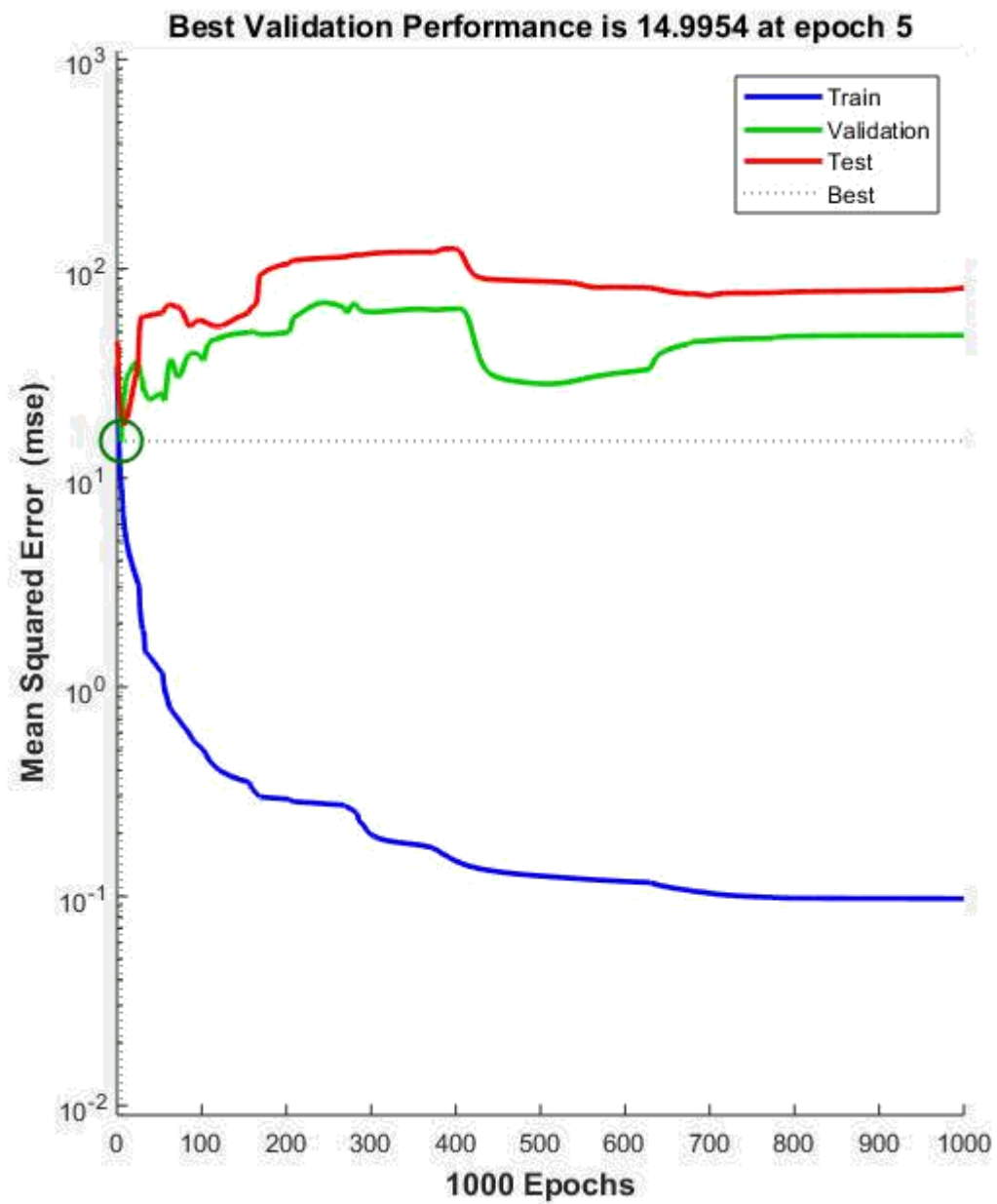
Training state plot of network architecture of (8-12-3) with LOGSIG as a transfer function



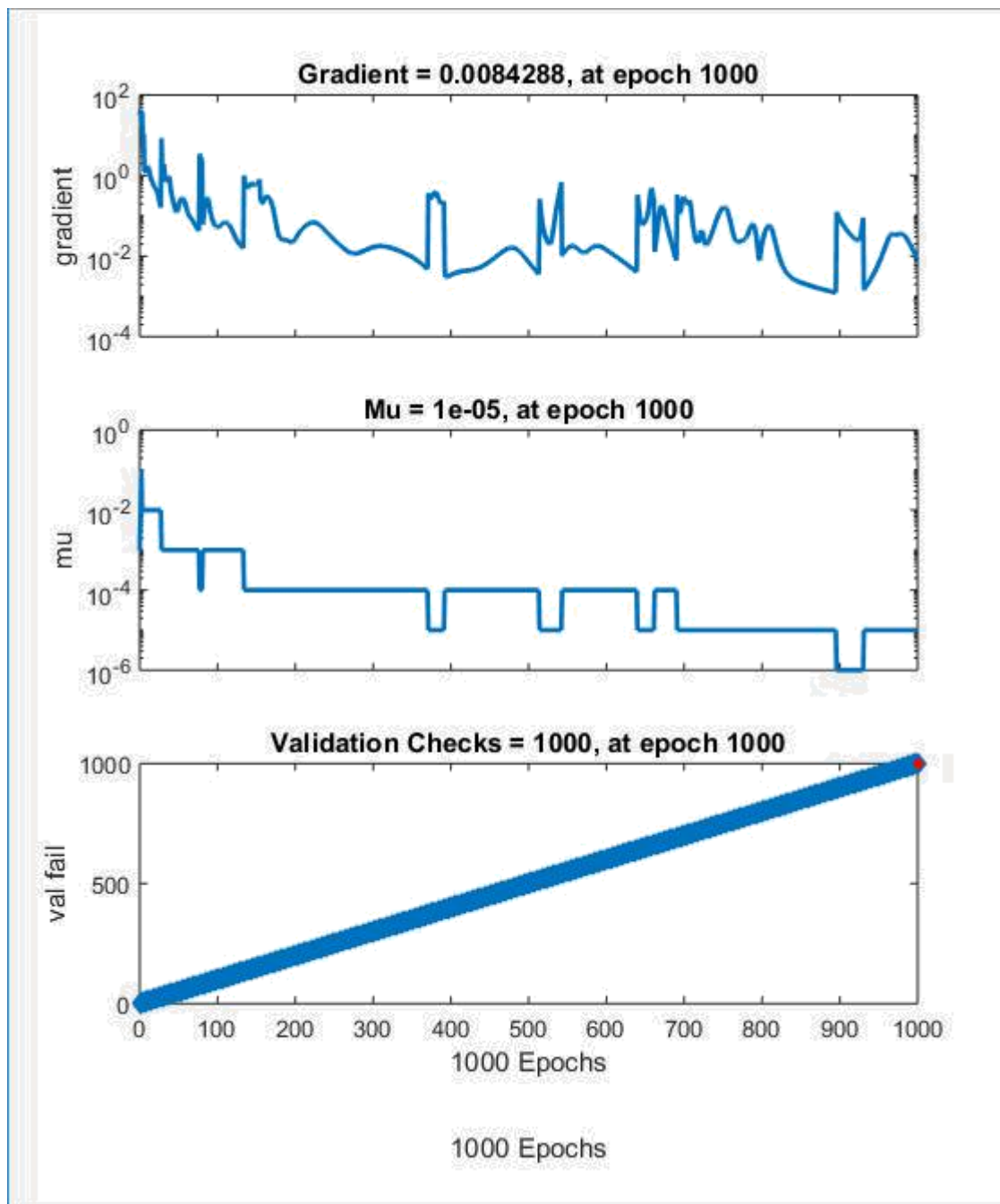
Performance plot of network architecture of (8-10-3) with LOGSIG as a transfer function



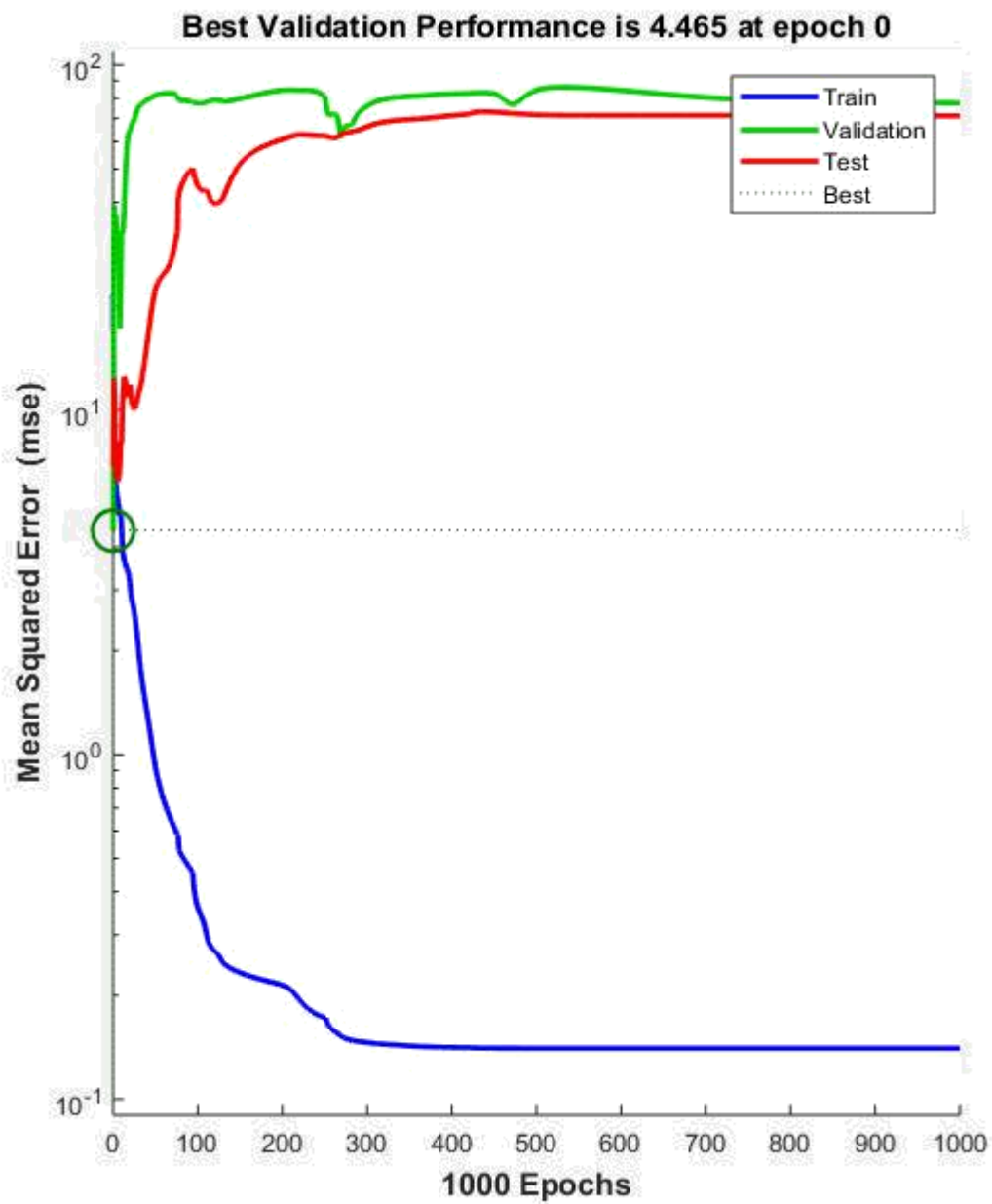
Training state plot of network architecture of (8-10-3) with LOGSIG as a transfer function



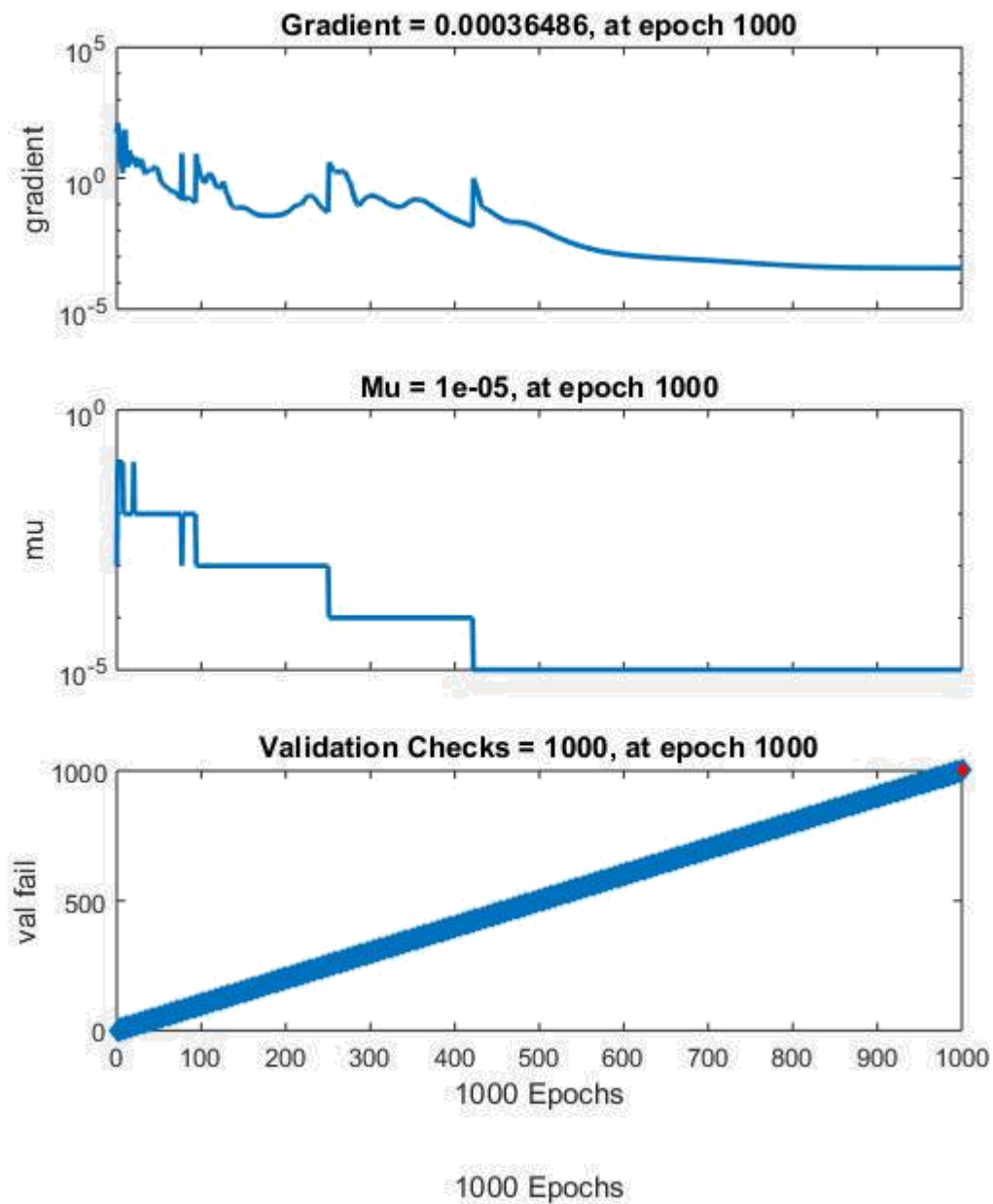
Performance plot of network architecture of (8-11-3) with LOGSIG as a transfer function



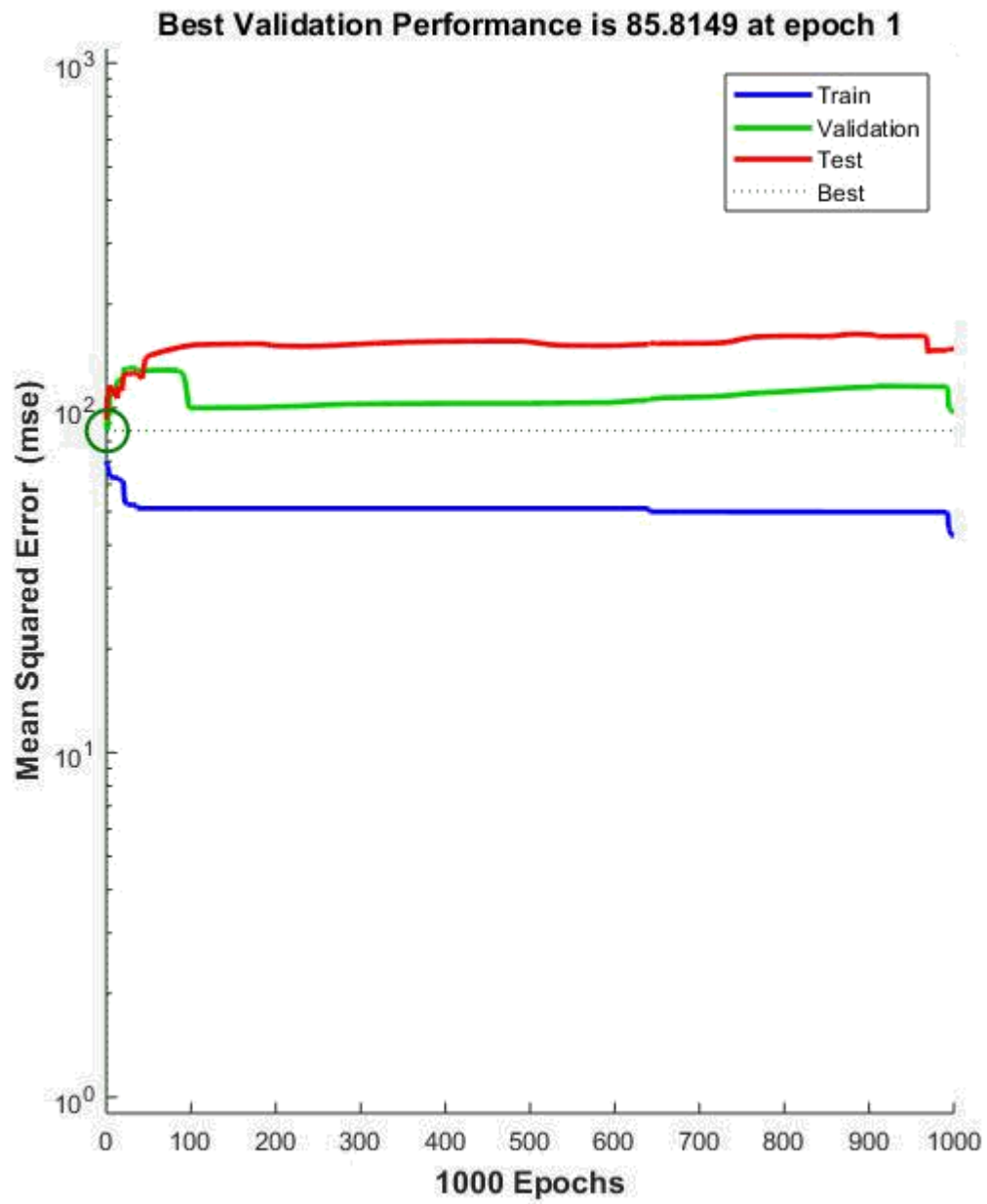
Training state plot of network architecture of (8-11-3) with LOGSIG as a transfer function



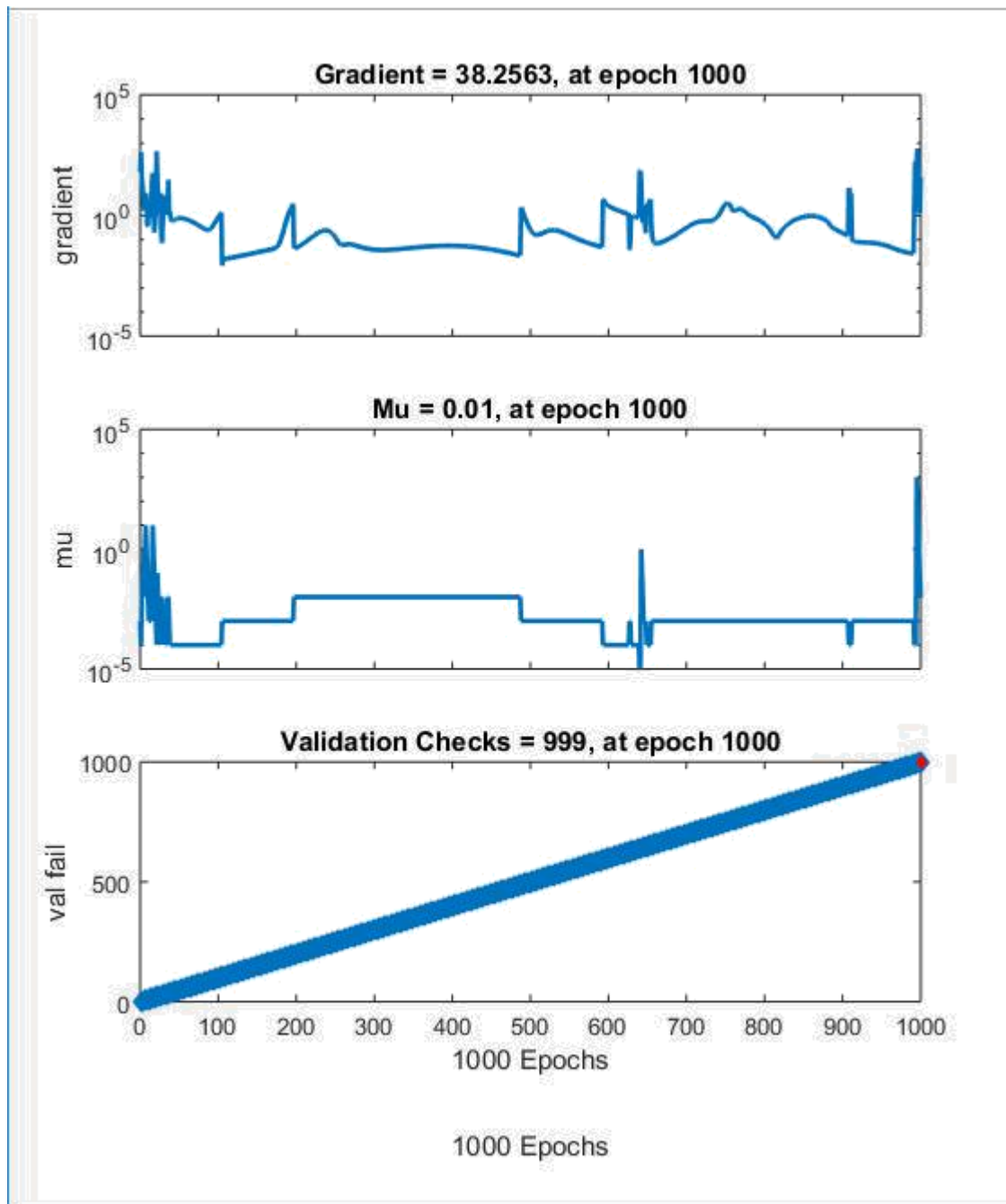
Performance plot of network architecture of (8-12-3) with TRANSIG as a transfer function



Training state plot of network architecture of (8-12-3) with TRANSIG as a transfer function



Performance plot of network architecture of (8-15-3) with TRANSIG as a transfer function



Training state plot of network architecture of (8-15-3) with TRANSIG as a transfer function

REFERENCES

1. Singh TN, Singh V (2005) An Intelligent approach to prediction and control ground vibration in mines. *Geotech Geolog Eng* 23:249–262
2. Rezaei M, Monjezi M, Yazdian Varjani A (2011) Development of a fuzzy model to predict flyrock in surface mining. *Safety Sci* 49(2):298–305
3. Hajihassani M, Jahed Armaghani D, Sohaei H, Tonnizam Mohamad E, Marto A (2014) Prediction of airblast-overpressure induced by blasting using a hybrid artificial neural network and particle swarm optimization. *Appl Acoust* 80:57–67
4. Li XB. Rock drilling and blasting engineering. Changsha: Central south University Press; 2011
5. Yang J, Chen PW, Hu G. Modern blasting techniques. Beijing: Press of Beijing Institute of Technology; 2005
6. Hopler, R.B. (Ed.) (1998) *Blasters' Handbook*, 17th ed., International Society of Explosives Engineers, Cleveland, OH.
7. Djordjevic, N.M. (1995) A Study on the Blast Induced Ground Vibrations and their Effects on Structures, PhD Thesis, Julius Kruttschnitt Mineral Research Centre, The University of Queensland, Brisbane, Australia
8. Mortazavi, A. (1999) Modelling of Rock Blasting in Jointed Media using Discontinuous Deformation Analysis, PhD Thesis, Mining Engineering department, Queen's University, Canada
9. Parida A, Mishra, M.K. (2015) Blast Vibration Analysis by Different Predictor Approaches-A Comparison. *Procedia Earth and Planetary Science* 11; 337-345
10. Monjezi, M., M. Ghafurikalajahi, and A. Bahrami, 2011. Prediction of blast-induced ground vibration using artificial neural networks. *Tunnelling and Underground Space Technology* 26.1, 46-50.
11. Khandelwal, Manoj, and T. N. Singh, 2007. Evaluation of blast-induced ground vibration predictors. *Soil Dynamics and Earthquake Engineering*, pp. 116-125.
12. Kamali M. and Ataei M., 2010. Prediction of blast induced ground vibrations in Karoun III power plant and dam: a neural network. *Journal of the South African institute of mining and metallurgy*, ISSN 0038-223X, Volume 110, Issue 8, pp. 481 – 490
13. D. Jahed Armaghani, M. Hajihassani, E. Tonnizam Mohamad, A. Marto, and S. A. Noorani. (2013), flyrock and ground vibration prediction through an expert artificial neural network based on particle swarm optimization, *Arabian Journal of Geosciences*, Volume 7, Issue 12, pp 5383–5396

14. Saadat,M., Khandelwal., Mojenzi, M. (2014). An ANN-based approach to predict blast-induced ground vibration of Gol-E-Gohar iron ore mine, Iran .*Journal of Rock Mechanics and Geotechnical Engineering*. Volume 6, Issue 1, pp 67-76
15. Hajihassani M, Jahed Armaghani D, Sohaei H, Tonnizam Mohamad E, Marto A (2014) Prediction of airblast-overpressure induced by blasting using a hybrid artificial neural network and particle swarm optimization. *Appl Acoust* 80:57–67
16. Hajihassani M, Jahed Armaghani D, Marto A, Tonnizam Mohamad E (2015b) Ground vibration prediction in quarry blasting through an artificial neural network optimized by imperialist competitive algorithm. *Bulletin of Engineering Geology and the Environment*, Volume 74, Issue 3, pp 873–886
17. Bhandari S. *Engineering rock blasting operations*. Netherlands: A.A. Balkema;1997
18. Kuzu C, Fisne A, Ercelebi SG. Operational and geological parameters in the assessing blast induced airblast-overpressure in quarries. *Appl Acoust* 2009;70:404–11
19. Rodríguez R, Lombardía C, Torno S. Prediction of the air wave due to blasting inside tunnels: approximation to a ‘phonometric curve’. *Tunn Undergr Sp Technol* 2010;25:483–9
20. Griffiths MJ, Oates JAH, Lord P. The propagation of sound from quarry blasting. *J Sound Vibration* 1978;291:358–70
21. Morhard RC, editor. *Explosives and rock blasting*. Atlas Powder Company; 1987
22. Siskind DE, Stachura VJ, Stagg MS, Koop JW. In: Siskind DE, editor. *Structure response and damage produced by airblast from surface mining*. United States Bureau of Mines; 1980
23. Wiss JF, Linehan PW. *Control of vibration and blast noise from surface coal mining*. Northbrook, IL (USA): Wiss, Janney, Elstner and Associates Inc; 1978
24. Bhandari S. *Engineering rock blasting operations*. Netherlands: A.A. Balkema;1997
25. Rodríguez R, Toraño J, Menéndez M. Prediction of the airblast wave effects near a tunnel advanced by drilling and blasting. *Tunn Undergr Sp Technol* 2007;22:241–51
26. Dowding CH. *Construction vibrations*. In: Dowding, editor; 2000. p. 204–207
27. National Association of Australian State Road Authorities, *Explosives in Roadworks - A Users Guide*, NAASRA, Sydney, 1983.
28. McKenzine C. Quarry blast monitoring: technical and environmental perspective. *Quarry Manage* 1990;17:23–9
29. Persson PA, Holmberg R, Lee J. *Rock blasting and explosives engineering*, 1994. In: editors, C.R.C. Press; pp. 375–86, 515.

30. M. Hajihassani; D. Jahed Armaghani; H. Sohaei; E. Tonnizam Mohamad; A. Marto., 2014. Prediction of airblast-overpressure induced by blasting using a hybrid artificial neural network and particle swarm optimization. *Applied Acoustics*, Volume 80, pp. 57–67
31. Segarra, P., et al., 2010. Prediction of near field overpressure from quarry blasting. *Applied Acoustics* 71(12), 1169-1176
32. Wu, Chengqing and Hao, Hong, 2007. Modeling of simultaneous ground shock and airblast pressure on nearby structures from surface explosions. *International Journal of Impact Engineering*, ISSN 0734-743X, Volume 31, Issue 6, pp. 699 – 717
33. 40. Kazem O. and Bahareh A., 2006. Prediction of Rock Fragmentation in Open Pit Mines, using Neural Network Analysis; Msc Thesis. University of Stirling, UK
34. Monjezi, M; Bahrami, A; Yazdian Varjani, A., 2010. Simultaneous prediction of fragmentation and flyrock in blasting operation using artificial neural networks. *International Journal of Rock Mechanics and Mining Sciences*, Volume 47, Issue 3, pp. 476–480.
35. Hosseini M. and Alireza .E., 2017. Analysis of blasted rocks fragmentation using digital image processing (case study: limestone quarry of Abyek Cement Company). *International Journal of Geo-Engineering*. 8:16
36. Ho Cho, S ; Masaaki, N ; Masaaki, Y ; Katsuhiko, K., (2003). Fragment Size Distribution in Blasting. *The Mining and Materials Processing Institute of Japan*, Volume 44, Issue. 5, pp. 951 to 956
37. Monjezi, M., Rezaei, M., Varjani, A., (2009). Prediction of rock fragmentation due to blasting in Gol-E-Gohar iron mine using fuzzy logic. *International Journal of Rock Mechanics & Mining Sciences* , Volume 46, Issue 8, pp. 1273–1280
38. Sayadi, A., Monjezi, M., Talebi, N., and Khandelwal, M., 2013. A comparative study on the application of various artificial neural networks to simultaneous prediction of rock fragmentation and backbreak. *Journal of Rock Mechanics and Geotechnical Engineering*, 5(4), 318-324.
39. Simpson, P.K., 1990. *Artificial Neural Systems. Foundation, Paradigms, Applications, and Implementations*. Pergamon Press, New York, NY.
40. Shahin, Mohamed A., Mark B. Jaksa, and Holger R. Maier, 2001. Artificial neural network applications in geotechnical engineering. *Australian Geomechanics*, Volume 36. Issue 1, pp. 49-62.

41. McCulloch WS, Pitts W. A logical calculus of the ideas immanent in nervous activity .Bull Math Biophys ,Volume 3. Issue 5.pp 115-33
42. Eren H., Fung, CC.,Wong, KW., (1997). An application of Artificial Neural Network for prediction of densities and particle size distributions in mineral processing industry. IEEE Instrumentation and Measurement. Technical Conference. Ottawa, Canada,
43. Kalogirou, AS and Bojic, M. 2000.Artificial neural networks for the prediction of the energy consumption of a passive solar building. Science Direct.Volume 25, Issue 5,pp.479-491
44. Litta, JA., Idicula, SM., Mohanty.,CU.(2013). Artificial Neural Network Model in Prediction of Meteorological Parameters during Premonsoon Thunderstorms. International Journal of Atmospheric Sciences. Volume 2013, (525383):14pp
45. Zhao, K and Chen, S (2011). Study on artificial neural network method for ground subsidence prediction of metal mine. Science Direct. Volume 2. pp 177-182
46. Kostic····.
47. Hasanipanah, M., Faradondeh, SR., Amnienh, BH., Armaghani, JD., and Monjezi, M., (2016). Forecasting blast-induced ground vibration developing a CART model. Engineering with Computers. Volume 33. pp 307-316
48. Parida, A., and Mishra M.K., (2015). Blast vibration analysis by different predictor approaches- A comparison. Procedia Earth and Planetary Science. Volume 11. pp 337-345.
49. Ragam, P., and Nimage, D.S., (2018). Assessment of Blast-induced Ground Vibration using Different Predictor Approaches- A Comparison. Chemical Engineering Transactions. Volume 66.pp 487-492.
50. Kostic, D., Perc, M., Vasovic, N., and Trajkovic, S., (2013). Predictions of Experimentally Observed Stochastic Ground Vibrations Induced by Blasting. Plosone. Volume 12. Pp 1-13
51. Faradonbeh, SR., Armaghani, JD., Majid, AM., Tahir, M., Murlidhar, RB., Monjezi,M., and Wong, MH., (2016). Prediction of ground vibration due to quarry blasting based on gene expression programming: a new model for peak particle velocity prediction. Int. J. Environ. Sci. Technol., Volume. 13, no. 6, pp. 1453-1464
52. Sawmliana,C., Roy, P., Singh, KR., and Singh, TN., (2013). Blast induced air overpressure and its prediction using artificial neural network. Mining Technology. Volume 116. Pp 41-48.

53. Khandelwal, M., and Singh, TN., (2005). Prediction of Blast Induced Air Overpressure in Opencast Mine.....
54. Hajihassani, M., Armaghani, JD., Sohaei, H., Mohamad, TE., and Marto, A., (2014). Prediction of airblast-overpressure induced by blasting using a hybrid artificial neural network and particle swarm optimization. *Applied Acoustics*. Volume 80. Pp 57-67
55. Armaghani, JD., 54. Hajihassani, M., Marto, A., Faradonbeh, SR and Mohamad, TE., (2015). Prediction of blast-induced air overpressure: a hybrid AI-based predictive model.
56. Murlidhar, RB., Armarghani, JD., Mohamad, TE and Changthan, S., (2018). Rock Fragmentation Prediction through a New Hybrid Model Based on Imperial Competitive Algorithm and Neural Network. *Smart Construction Research*. Volume 3. Pp 1-12
57. Trivedi, R., Singh, TN and Raina, AK., (2014). Prediction of blast-induced flyrock in Indian limestone mines using neural networks. *Journal of Rock Mechanics and Geotechnical Engineering*. Volume 6. Pp 447-454
58. Zeng, Y., Liu, S., Zhang, W and Zhai, Y., (2016). Application of artificial neural network technology to predicting small faults and folds in coal seams, China. *Sustain. Water Resource Management* Volume 2. Pp 175-181
59. Dhekne, YP., Pradhan, M., Jade, KR., and Mishra, R., (2017). Boulder prediction in rock blasting using artificial neural network. *ARPJ Journal of Engineering and Applied Sciences*. Volume. 12, No. 1.Pp 47-61
60. Zhao, K and Chen, S., (2011). Study on artificial neural network method for ground subsidence prediction of metal mine. *The Second International Conference on Mining Engineering and Metallurgical Technology*. *Procedia Earth and Planetary Science*. Beijing, China. pp. 177-182
61. Duvall WI, Johnson CF, Meyer AVC, 1963. Vibrations from instantaneous and millisecond delay quarry blasts. RI. 6151. US, Bureau of Mines, United States Department of Interior, Washington.
62. U. Langefors, B. Kihlstrom, 1963. *The modern technique of rock blasting*. Wiley, New York.
63. N.R. Ambraseys, A.J. Hendron, 1968. *Dynamic behaviour of rock masses: rock mechanics in engineering practices* Wiley, London.
64. Rumelhart, D.E; James McClelland, 1986. *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*. Cambridge: MIT Press.

65. Bureau of Indian Standard, 1973. Bureau of Indian Standard. Criteria for safety and design of structures subjected to underground blast. ISI Bulletin IS-6922.
66. Lu Y. 2005. Underground blast induced ground shock and its modelling using artificial neural network. *Comp Geotech*. Volume 32. Pp 164-178
67. Werbos, P.J., 1975. *Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences*.
68. Rezaei, M., Monjezi, M., Moghaddam, S. G., & Farzaneh, F., 2012. Burden prediction in blasting operation using rock geomechanical properties. *Arabian Journal of Geosciences*, 5(5), 1031-1037.
69. Enayatollahi, Iman; Aghajani Bazzazi, Abbas; Asadi, Ahamad, 2014. Comparison between Neural Networks and Multiple Regression Analysis to Predict Rock Fragmentation in Open-Pit Mines. *Rock Mechanics and Rock Engineering*, Volume 47, Issue 2, Pp. 799 – 807.
70. Lal, B and Tripathy, S. (2012) Prediction of dust concentration in open cast coal mine using artificial neural network. *Atmos Pollut Res* , Volume 3, Pp 211–218.
71. Jang H, Topal E and Kawamura Y. (2015). Unplanned dilution and ore loss prediction in longhole stoping mines via multiple regression and artificial neural network analyses. *J S Afr I Min Metall*. Volume 115: Pp 449–456.
72. Patra, A.K., Gautam, S., Majumdar, S., Kumar, P., 2015. Prediction of particulate matter concentration profile in an opencast copper mine in India using an artificial neural network model. *Air Qual. Atmos*. Volume 9, Issue 6, Pp 697 – 711