Prediction of Riser Base Pressure in a Multiphase Pipeline-Riser System Using Artificial Neural Networks

A. B. Ehinmowo[1], S. A. Bishop[2], N. M. Jacob[1]
[1]Chemical and Petroleum Engineering Department, University of Lagos, Lagos, Nigeria
[2]Mathematics Department, Covenant University, Ogun, Nigeria
Email: aehinmowo@unilag.edu.ng

Abstract
In the multiphase flow of oil and gas in pipeline-riser systems, reliable pressure measurements and monitoring is of utmost importance for flow assurance. These measurements are usually obtained using remote pressure measuring gauges and other devices. They are employed in the automatic slug flow control technique. However, these devices are quite expensive and often require calibration at intervals to guarantee accuracy and precision. There is therefore, the need for suitable alternatives. In this study, a feed-forward back propagation artificial neural network (ANN) for predicting riser base pressure in offshore pipeline riser systems is presented. A total of 16,870 experimental data sets were used to develop the ANN model. The results show near perfect predictions with an average mean square error of 0.00207197 and regression correlation coefficient, R values as high as 0.99919. The models obtained from this work can be pivotal to the development of data driven control of slug in pipeline-riser systems.

Keywords: *ANN, multiphase flow, pipeline-riser, riser base pressure, slug flow*

1.0 INTRODUCTION

Multiphase flow of fluid in pipeline-riser systems is a common practice in the oil and gas industry and has its attendant problems. One of such challenges is slug flow which usually poses significant threat to production facilities. Many solutions have been proposed to attenuate slugging but among them, automatic control of topside valve, an active slug control, has been reported to be more production and economic friendly (Ogazi *et al.,* 2010; Ehinmowo, 2015). Riser base pressure has been identified as one of the best controlled variables for this type of active slug control in multiphase flow systems (Storkaas, 2005). However, such measurements are usually expensive, difficult to get and when they are available, their reliability might be of concern. Also, additional challenges are associated with down-hole and subsea pressure measurements as any equipment to be deployed would need to be able to withstand the higher temperature and pressure conditions. Their operations in this harsh environment necessitate periodic maintenance and calibration. This lack of dependability, along with the cost (including production deferment) associated with frequently calibrating and/or replacing the down-hole gauges makes this a less-preferred alternative (Awadalla *et al.*, 2016).

To address issues like this, several empirical correlations and mechanistic models have been proposed over the last seven decades but their applicability doesn't cover wide range of data and due to the complexities of problems encountered, it has become imperative to go beyond the standard mathematical techniques and incorporate soft computing techniques and artificial intelligence (Mohammadpoor *et al.*, 2010). These provide an efficiently robust and cost-effective alternative that can tolerate imprecision and uncertainty to demonstrate superior performance.

The use of artificial neural networks (ANNs) and other forms of artificial intelligence, such as Fuzzy Logic to resolve various engineering problems has gained increasing popularity in recent years (Al-Shammari, 2011). ANNs have been used to satisfactorily predict bottom hole pressure as shown in the works of Ternyik *et al.* (1995), Osman *et al.* (2005), Mohammadpoor *et al.* (2010), Al-Shammari (2011) and in conjunction with multiphase correlations as reported by Li *et al.* (2014). ANNs have been found to achieve better performance over the conventional solution methods. Artificial neural networks can be said to be biologically-inspired adaptive systems with the ability to acquire, store, recall and utilize experiential knowledge (Mohaghegh *et al.*, 1999). The idea is to train a computer program to recognize patterns and predict output values from given input values.

There are two types of Artificial Neural Networks (ANN): static and dynamic. In a static ANN, the model is not modelled again if any error exists whereas in a dynamic ANN, the weights and biases are updated for better optimization using a suitable algorithm (Kumar, 2012). Dynamic model is more frequently used because of its better prediction property.

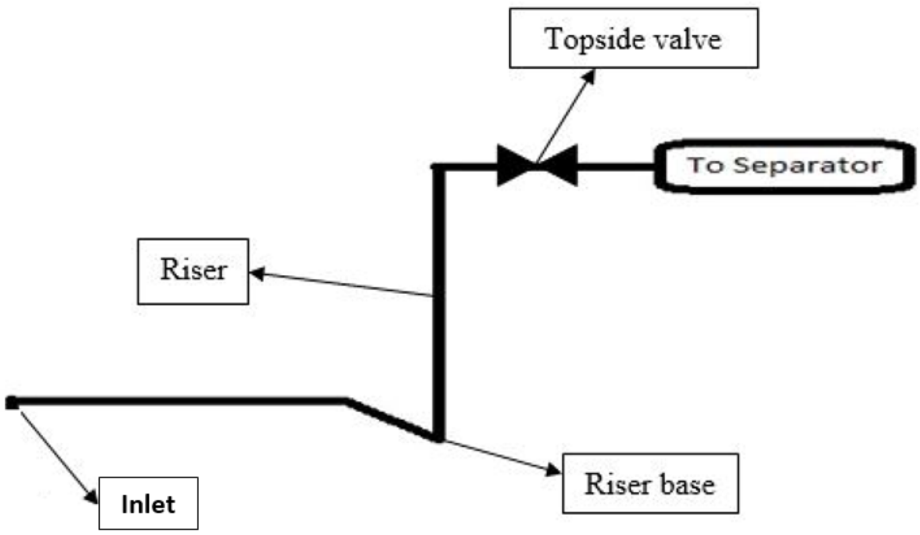

Figure 1: An Illustration of the Experimental Setup of the Pipeline Riser System

Many authors including Di Meglio *et al.* (2012) have proposed model-based approaches to acquire variables for control in a multiphase pipeline-riser system. Cao *et al.* (2013) for example applied a data driven approach to circumvent this difficulty of sub-surface pressure measurements. Despite the advancement made in data driven approaches to modelling pipeline-riser systems, artificial neural network has not been applied to predict this very important variable - riser base pressure. This study seeks to employ artificial neural networks to predict riser base pressure in a multiphase pipeline-riser system based on superficial velocity of flowing fluid materials, size of valve opening and topside pressure measurements. The models are based on experimental data and different training algorithms and network sizes were tested and the results obtained from these scenarios were evaluated and compared. The pipeline-riser system adopted for this study is shown in Figure 1.

2.0 METHODOLOGY

Many factors can be considered for the calculation of riser base pressure, some of which could be redundant and of little effects. In this study, the critical factors such as liquid flow rates, gas flow rates, and other available topside measurements (topside pressure, and valve openings) were combined in various ways to predict the riser base pressure. The proposed functions of these factors can be presented in the following mathematical forms.

$$P_{RB} = f(V_{SL}, V_{SG}, P_{RT}, Z) \qquad (1)$$

Where P_{RB} is the riser base pressure, V_{SL} is the superficial liquid velocity, V_{SG} is the superficial gas velocity, P_{RT}, is the riser top pressure and Z is the riser top valve opening.
When the flow rates were kept constant, Eqn. 1 reduces to Eqn. 2.

$$P_{RB} = f(P_{RT}, Z) \qquad (2)$$

Here, the riser base pressure was modelled as a function of the topside pressure and valve openings. A total of twelve neural network models were developed, three each for the low flow rate, medium flow rate, high flow rate regions following mathematical model presented in Eqn. 2 as well as three for the combined analysis of all three regions following the model presented in Eqn. 1.

In each of these regions, three training algorithms (Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient) were tested and the results from all twelve scenarios are documented. The number of hidden neurons in each case was set as twice the number of input parameters. For each of the individual flow regions, topside pressure and riser top valve opening were used as input parameters with four hidden neurons while the combined analysis utilized superficial velocity of water and air in addition to the topside pressure and riser top valve opening as input parameters with eight hidden neurons.

2.1 Model Training, Testing and Validation

In this study, various feed-forward back-propagation artificial neural networks, incorporating three different training algorithms, were developed and trained with experimental data using the Artificial Neural Network toolbox of MATLAB to predict riser base pressure. A total of 16,870 experimental data sets adapted from the experimental work of Ehinmowo (2015) were used to develop the ANN model. The training stopped after the required number of iterations in each case achieving MSE values as low as 0.001062 and regression values as high as 0.99919.

The neural network models were trained using 70% of the data while 15% each was used for validation and testing. This data division is such that each data subset is representative of the entire range of data sets and is thus valid for all regions.

The performance of the network is judged based on the average mean square error and regression correlation coefficient values. The lower the mean square error, the more accurate the neural network model, thus, a mean square error of 0 represents a perfect model. Regression Values, on the other hand, measure the correlation between the neural network outputs and targets. Regression values, R values, are numerical values between 0 and 1 with an

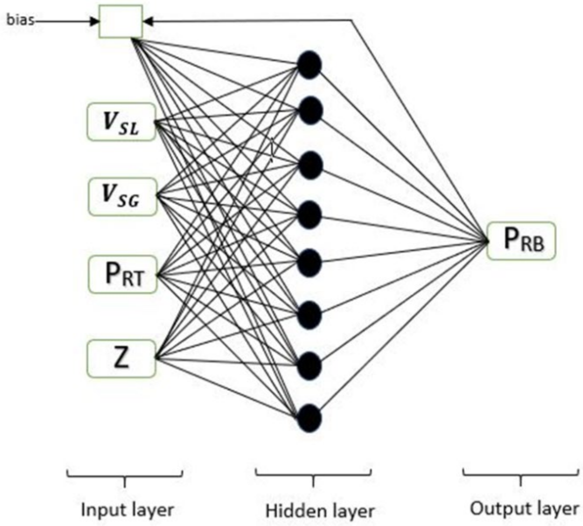

Figure 2: Neural network Architecture for the Developed Model

R value of 1 signifying a close relationship while an R value of 0 represents an absolutely ill-fitted relationship. Other factors or measurement could be added to these factors. However, the factors considered in this study were observed to be sufficient in predicting the riser base pressure.

2.2 The Experimental Data

In this study, the data used was obtained from one of the 2-inch multiphase facility of Cranfield University, United Kingdom. The details of these experimental works have been documented in Ehinmowo (2015). Table 1 shows the summary of the data used in this work while Figures 3, 4 and 5 show the plot of the riser base and riser top pressures against valve openings for the various flow regions.

Table 1: Range of Experimental Data used

	V_{SL} (m/s)	V_{SG} (m/s)	P_{RT} (bar)	Z (%)	P_{RB} (bar)
Min	0.25	0.71	0.97	23.00	1.44
Max	1.72	3.38	1.95	100.00	4.67

2.2.1 Low Flow Rate Region

In this region, the flow rate of the two phases in the conduit is kept constant at 7 standard m^3/hr of air with 0.5 kg/s of water (0.71 m/s and 0.25 m/s superficial velocities of air and water, respectively). The transient pressure values measured against various valve openings is as shown in Figure 3.

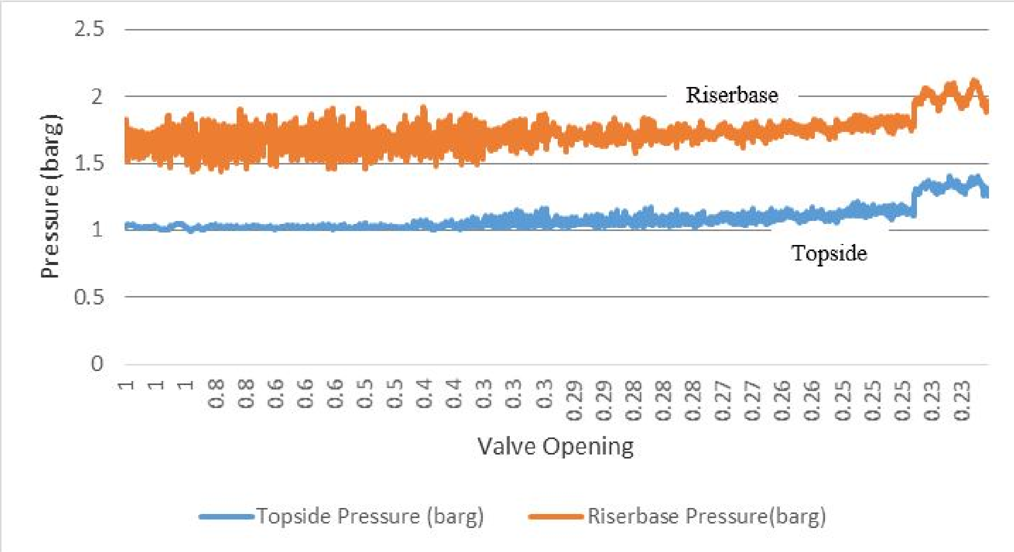

Figure 3: Topside and Riser Base Pressure (barg) per seconds Against Valve Openings for Low Flow Rate

2.2.2 Medium Flow Rate Region

In this region, the flow rate of the two phases in the conduit is kept constant at 30 standard m^3/hr of air with 2.0 kg/s of water (1.95 m/s and 1.0 m/s superficial velocities of air and water, respectively). The transient pressure values measured against various valve openings is as shown in Figure 4.

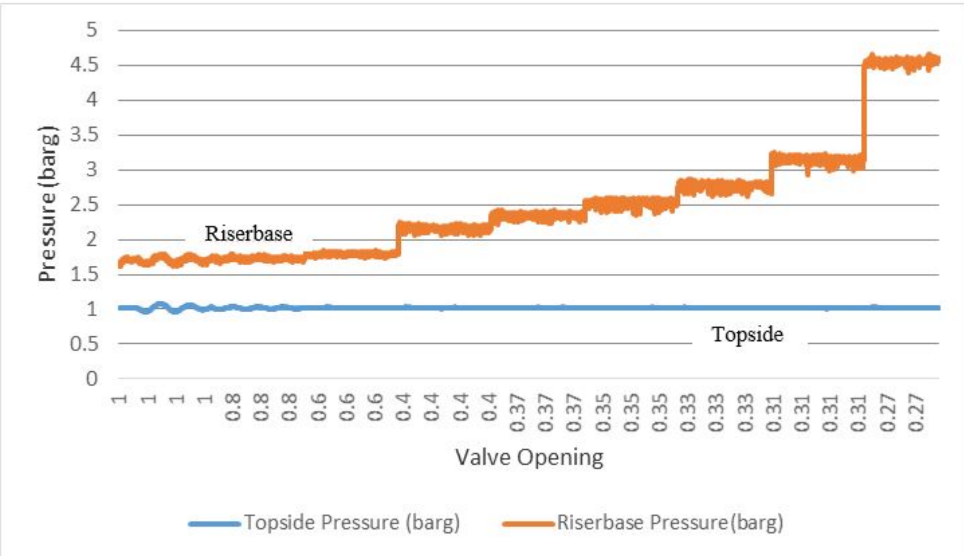

Figure 4: Topside and Riser Base Pressure (barg) per seconds Against Valve Openings for Medium Flow Rate

2.2.3 High Flow Rate Region

In this region, the flow rate of the two phases in the conduit is kept constant at 75 standard m^3/hr of air with 3.5 kg/s of water 3.5 kg/s (3.38 m/s and 1.72 m/s superficial velocities for air and water, respectively). The transient pressure values measured against various valve openings is as shown in Figure 5.

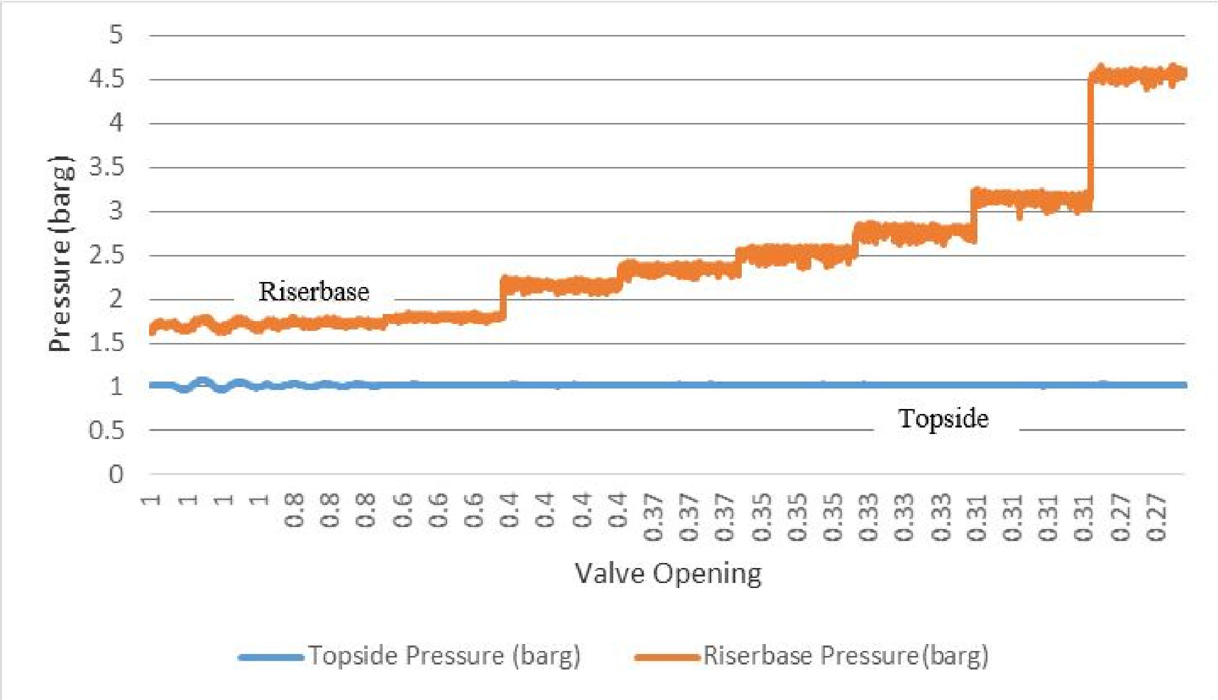

Figure 5: Topside and Riser Base Pressure (barg) per seconds Against Valve Openings for High Flow Rate

3.0 RESULTS AND DISCUSSION

The data used in this study cover three distinct flow rate regions representing low, medium and high flow rate regions. The topside pressures used in this study ranged from 0.936358 to 1.9494 bar gauge while the riser base pressure values ranged from 1.44223 to 4.66663 bar gauge and the valve opening ranged from 23% to the fully open 100% condition.

The ANN models in this study tested three different training algorithms, Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient algorithms, for each of the flow rate regions as well as for the entire data range. Figure 6 shows a plots of regression values

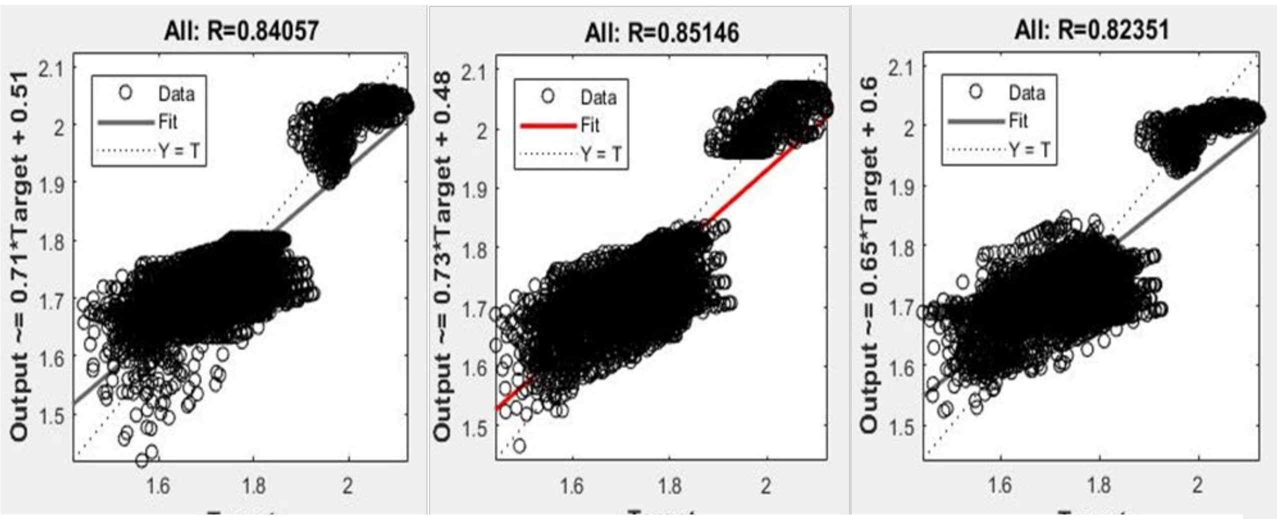

Figure 6: Regression Plots Using Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient, respectively for Low Flow Rate Region

obtained for the low flow region.

The results show that the Levenberg-Marquardt and Bayesian Regularization algorithm predicted the riser base pressure at similar level with R-value of about 85% while a lower value of 82% was obtained for the Scaled Conjugate Gradient algorithm. The developed ANN models were tested using different training algorithms. The best average MSE of 0.001062 was

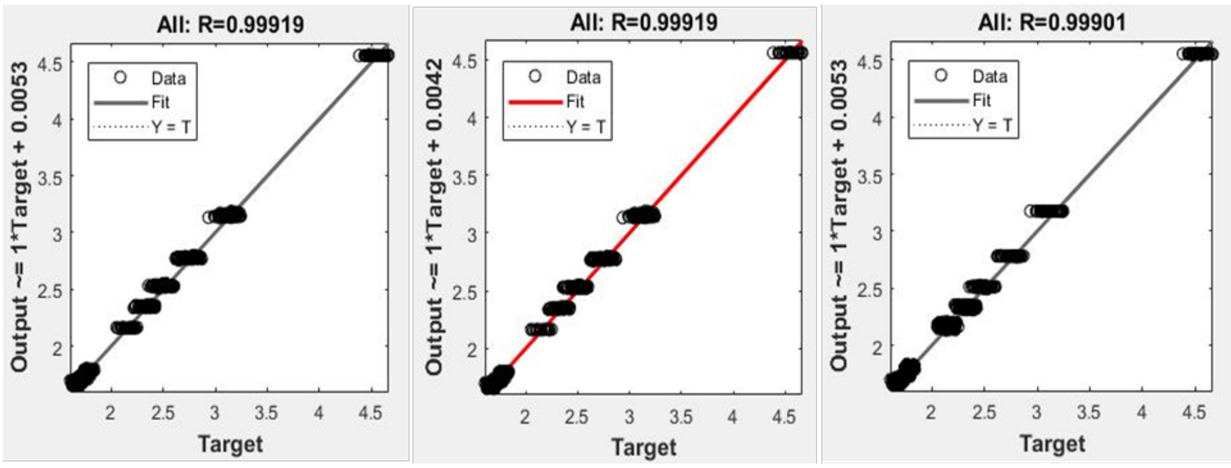

Figure 7: Regression Plots Using Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient, respectively for Medium Flow Rate Region

obtained using Bayesian Regularization.

Figure 7 shows the plots of regression values obtained for the medium flow region. The excellent regression values obtained in this region demonstrate a very close relationship between the inputs (topside pressure and valve opening) and the output (riser base pressure). Unlike the results obtained in the low flow region, each valve opening change presents a well-defined change in the pressure values as demonstrated by the presence of distinct data cluster groups in the regression plots in Figure 7. Thus, in this region, the dependence of the riser base pressure on the topside pressure and valve opening is significant and the two-stream correlate near to perfection. Figure 8 shows the plots of regression values obtained for the high flow

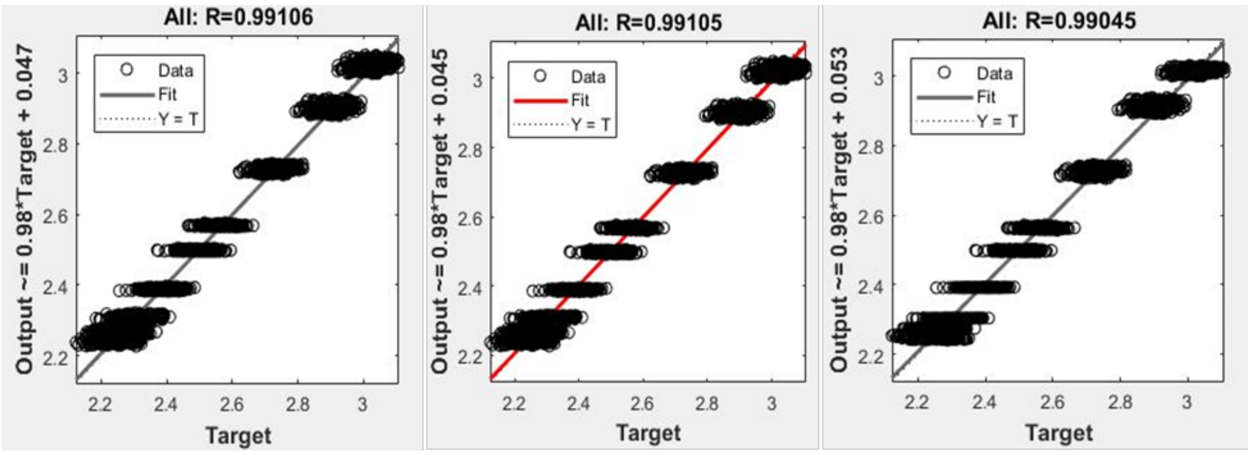

Figure 8: Regression Plots Using Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient, respectively for High Flow Rate Region

region.

Similar to the medium flow rate region results, the results here show a close relationship between the output and input parameters. The clusters are well differentiated and represent different valve opening sizes.

The training, validation and testing of the neural network incorporating all three flow regions was also done using the three different algorithms. This includes the combined flow rates of 7, 30 and 75 standard m3/hr of air with 0.5, 2.0 and 3.5 kg/s of water, respectively. The best average MSE of 0.0020694 was obtained using Bayesian Regularization.

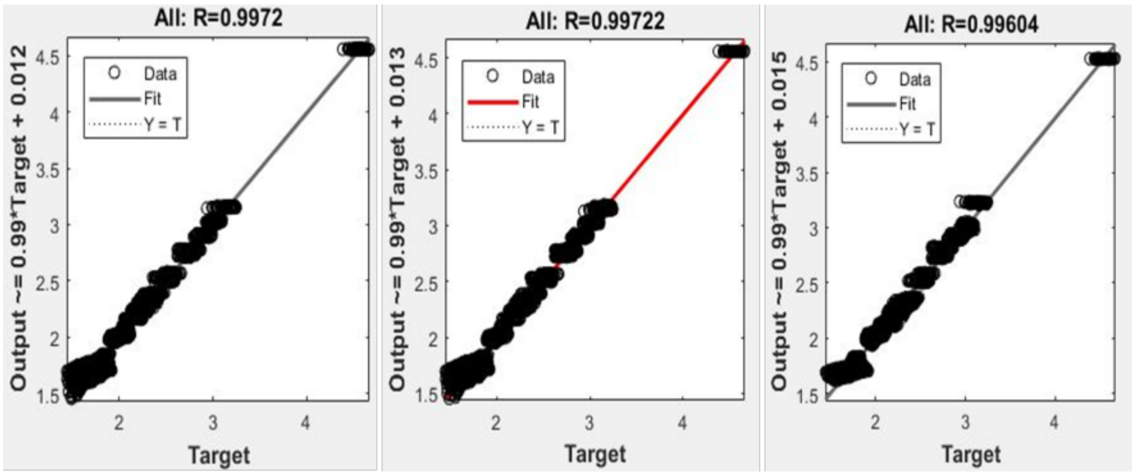

Figure 9: Regression Plots Using Levenberg-Marquardt, Bayesian Regularization and Scaled Conjugate Gradient, respectively for Combined Analysis of Low Medium and High Flow Regions

Figure 9 shows the regression plots obtained from the training algorithms. Again, similar trend observed for the degree of accuracy for the results earlier presented are revealed. Levenberg-Marquardt and Bayesian Regularization algorithm predicted the riser base pressure at similar level with R-value of about 99.7% while a lower value of 99.6 % was obtained for the Scaled Conjugate Gradient algorithm. An illustration of the MSE and Regression values obtained under each of the tested scenarios is shown in Figure 10

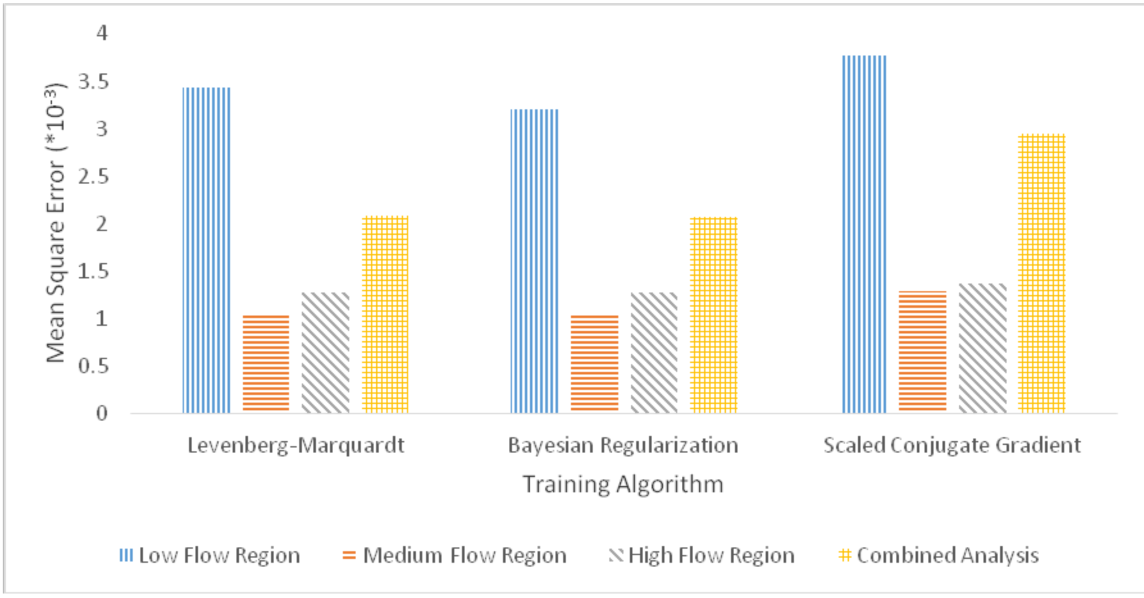

Figure 10: Mean Square Error Values for Each of the Scenarios Considered

From Figure 10, it is evident that the Scaled Conjugate Gradient algorithm consistently achieved the highest mean square error value for each of the flow regions and it is therefore the least accurate for this study. The Bayesian Regularization algorithm achieved the most ideal MSE values, however, the disparity compared to the results obtained using the Levenberg-Marquardt algorithm is very minimal. Thus, any of the two algorithms would give a more excellent result compared with the Scaled Conjugate Gradient algorithm. Figure 11 shows the regression values obtained under the various scenarios considered. Again, the Bayesian regularization method outperforms the Levenberg-Marquardt very marginally.

It is also worthy of note that, in the low flow rate region, the regression values obtained are considerably lower than those obtained in other flow regions as well as in the combined analysis. This indicates that the type of flow observed in this region is significantly different from other regions (Ehinmowo *et al.*, 2016). This also suggests that the pressure in this region may need more factors for the prediction of riser base pressure than proposed in model 2 (Equation 2). This is supported by the excellent results obtained for model 1 (Equation 1) for all the regions.

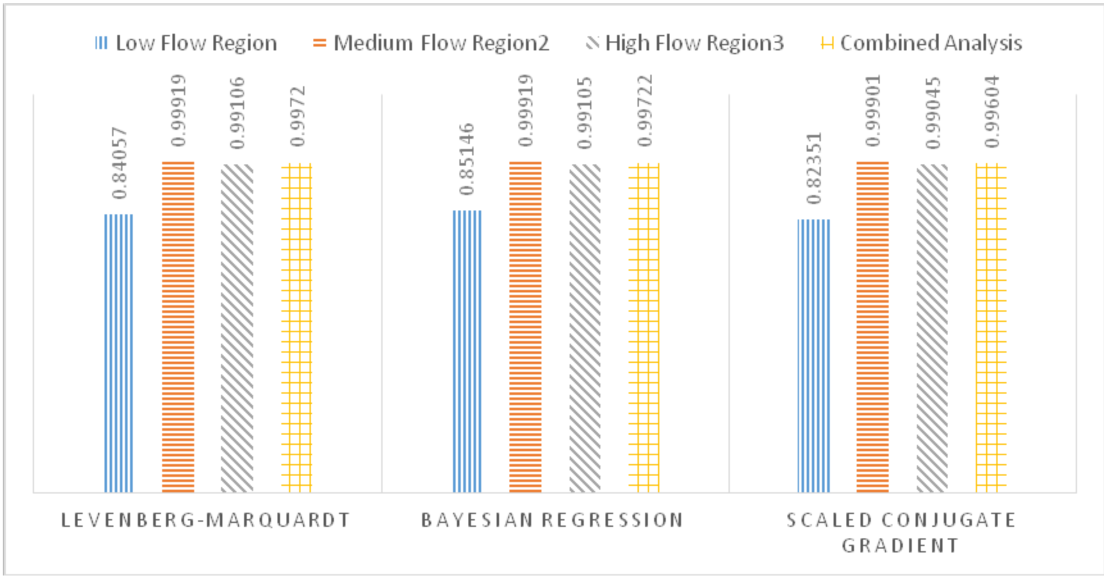

Figure 11: Regression Values for the Different Scenarios Considered

After testing several network configurations, and the three training algorithms, it was found that a neural network of 8 neurons in the hidden layer, utilizing the Bayesian Regularization training algorithm performed best with an average mean squared error of 0.00205947 and 0.00211559 on the training and testing data respectively. An excellent agreement was found between the values predicted by the neural network and the measured experimental pressure values.

4.0 CONCLUSION

Artificial neural network models for the prediction of riser-base pressure in pipeline-riser system has been developed and its applicability was validated using experimental data. Several network configurations were considered and the results obtained from the developed models compared well with the experimental data. The following conclusions can be drawn.

(i) The use of artificial neural networks in this manner would significantly reduce operating costs, in field and laboratory scenarios, as fewer pressure gauges would be required.

ANN usage in pressure prediction would also eliminate the avoidable pressure losses due to the intrusions of pressure measuring devices.

(ii) The proposed models can be used to predict riser base pressure in pipeline-riser systems. However, model 1 performed better than model 2 for all the regions investigated.

(iii) For the riser base prediction in pipeline-riser system, both Bayesian regularization and the Levenberg-Marquardt algorithms can be used to obtain excellent results.

(iv) The results obtained from this study can be pivotal to data driven control of slug flow in pipeline-riser systems. This is a subject of further studies.

(v) Further studies may also be carried out using field data to investigate pipeline-riser systems at higher pressure conditions. Other factors such as pipeline geometry, pipe diameter, pipeline materials, not considered in this study can also be investigated.

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