Prediction of Oil Well Flowing Bottom-hole Pressure in Petroleum Fields

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***Abstract*—Installation of down-hole gauges in oil wells to determine Flowing Bottom-Hole Pressure is a dominant process especially in wells lifted with electrical submersible pumps. However intervening a well is occasionally an exhaustive task, associated with production risk, and interruption. The empirical correlations and mechanistic models failed to provide a satisfactory and reliable tool for estimating pressure drop in multiphase flowing wells. This paper proposes Feed-Forward Neural Network with back-propagation algorithm to predict the flowing bottom-hole pressure in vertical oil wells using real measured data from different oil fields. Intensive experiments have been conducted and the standard statistical analysis has been accomplished on the achieved results to validate the models' prediction accuracy. The obtained results show that the proposed artificial neural network is capable of estimating the Flowing Bottom-Hole Pressure with high accuracy.**

Keywords*— *Flowing Bottom-Hole Pressure, Forward Neural Network, back-propagation algorithm

I. INTRODUCTION

With the increased utilization and deployment of permanent down-hole gauges, measuring flowing bottom-hole pressure (FBHP) gets relaxed and faster. However, these gauges require continuous maintenance and calibration to avoid erroneous readings. Also by intervening a well from time to time to measure FBHP is an expensive task, associated with production risk and interruption. For these reasons, the motivation of the prediction of FBHP has been argued.

Flowing bottom hole pressure prediction in gas wells is an old petroleum engineering problem. There is a long history of attempts to develop empirical correlations to predict the pressure drop in pipes. Some of these attempts have produced correlations that provide good prediction in some cases [1-3]. However, their general applicability is questionable. Correlations that address only a specific class of problems exist. These types of correlation usually perform better than those which attempt to meet the need of a variety of problems. Usually, the higher the number of variables in the model the lesser the reliability and general applicability of the correlations. This is the result of using methodologies such as conventional regression analysis [4]. In such methodologies, the chances of correctly and completely capturing the relationship between variables decreases as the number of variables increases. Many parameters could be involved in these types of problems, such as gas-oil ratios in two-phase systems, water flow in three phase systems, and inclination angles of the pipe. Models proposed by the investigators are based on empirical wells contained modest amounts of gas and oil production rates correlations developed from laboratory studies.

Most of the existing methods for predicting FBHP require one or more assumptions [5-7] (e.g., steady state flow, ideal gas of constant viscosity, small and constant compressibility and constant viscosity fluid) be applied. These methods appear to be subject to appreciable error unless better limits of applicability are defined.

Recently, neural networks (NN) have been employed in the petroleum industry [8-9], but their potential has not been fully investigated. In areas where a pattern exists between sets of data, a successful correlation can be developed with an artificial neural network (ANN). The pattern recognition capability of NN makes it a desirable tool to employ under a variety of conditions. When the data contains a relationship that is implicit in nature, a network such as Kohonen, Probabilistic, or Back-propagation may discover that relationship despite the complexity. Most applications of artificial neural networks (ANNs) in multi-phase flow are confinedto pipes. Authors in [10] found fairly good bed heights estimationsusing an ANN. Flow pattern and frictional pressure drop were predicted [11-13] using an ANN. Neural networks (NNs) estimated the flow pattern Bottom Hole Pressure Prediction with less than 5% error and frictional pressure drop with less than 30%. Satisfactory results have been found for three phase relative permeability compared with experiments using adopted a PSO model to train the perceptron and to predict pollutant levels in gas wells [14-15]. The approach was proved to be feasible and effective by applying to some real air-quality problems

and by comparison with a simple back-propagation (BP) algorithm. Support vector machine approach have been also used in training ANNs for predicating flow bottom hole pressure [16].

The aim of this paper is to enhance the accuracy achieved of artificial neural work and optimize the number of neurons in single and double hidden layers and determine the minimum data samples required to train the neural networks.

In this paper, an intelligent scheme for estimating FBHP in oil fields is developed. The proposed scheme utilize the capabilities of the artificial neural networks (ANN) to predict the FBHP. Practical sets of data available from an oil field are used for learning, testing, and validation of the designed schemes. To prove the effectiveness of the proposed neural networks in estimation of the FBHP, extensive performance analysis is carried out for the FFNN.

This paper is organized as follows: Section two shows the literature review. Section three presents the proposed techniques. Section 4 illustrates the conducted experiments and discussions. Section 5 concludes the paper.

II. Flowing Bottom-hole Pressure Importance and Electrical Submersible Pump (ESP) Well System

Electric Submersible Pumping (ESP) is the second most commonly used method of well production/fluid lifting in the oil and gas industry. It is responsible for the highest amount of total fluids produced (oil and water) by any artificial lift method and an ideal method for high water cut wells. Centrifugal pumps can be single-stage or multi-stage units. Single-stage pumps are mainly used when low to medium discharge pressure is required, while multi-stage pumps are designed to overcome higher discharge pressures. This is the case of ESP used in the petroleum industry where fluids must be lifted from deep formations.

Figure-1: ESP Well System

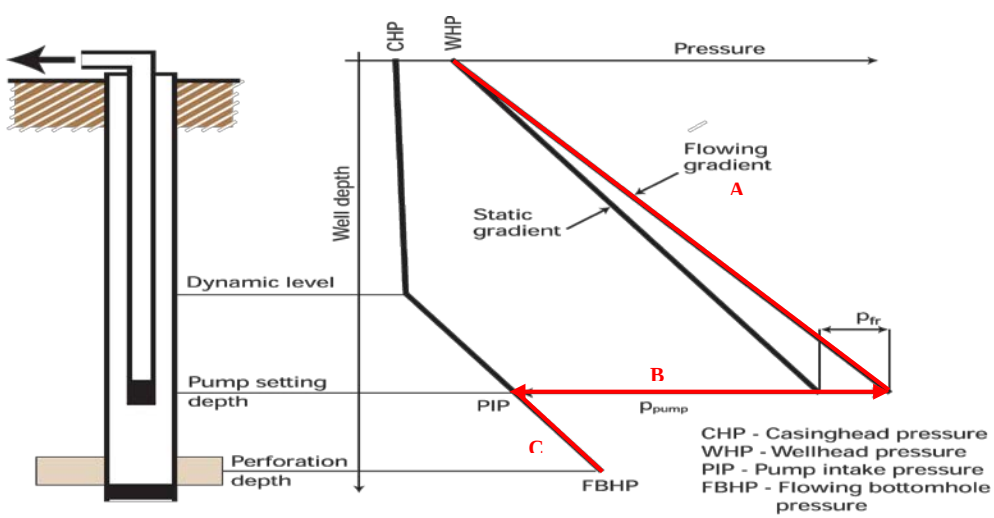

Fig. 2. Typical Pressure Drop Profile Diagram

An ESP is normally installed at the end of the production tubing string, which is inserted inside a bigger piping called casing. Normally the ESP installation depth is shallower than the formation (producing zone) depth. The pressure drop schematic of flowing oil well with ESP is shown in Fig. 1 and Fig. 2. The pressure drop lines of interest in this study are the lines drown in red and labeled as A, B &C. The pressure at the top of line A is the well head pressure and the end of it is the pressure of the pump discharge. This line A represents the drop in pressure due to the hydrodynamic multiphase flowing column and the frictional losses in the tubing. The line B is the line difference between the discharge and intake pressures of the pump. Simply it represents the total pressure developed by the ESP. The line C represents the drop in pressure between the pump intake and the perforations at the producing formation due to the hydraulic column and frictional loss in the casing below the pump. Its top end is the pump intake pressure and its lower end is the well flowing bottom-hole pressure. It is a normal practice to have online pressure measurements at, well-head, pump discharge and pump intake. In fields of the study these measurements are recorded every 15 minutes. In this project re-sampled data for daily records have been used.

The pressure measurements for the pump discharge and intake are normally obtained by permanent pressure gauges installed within the ESP assembly. Unfortunately, the FBHP at the perforations has no permanent measurements and in our case we almost have no records for the FBHP of an ESP well due to difficulties of access and other restrictions. Therefore, the scope of the project is limited to the estimation of the pressure drop along the lines A and B only. The estimation of the pressure drop along the line C (i.e. estimation of the pressure drop from the FBHP to the pump intake pressure) is less complex compared to drop in pressure along line A due to better homogenous flow and negligible friction. Hence, this pressure drop is out of the project scope. Also, it would be very difficult to evaluate this estimation due to unavailability of the FBHP records.

Flowing bottom-hole pressure of a well is the pressure that is measured or calculated at or near the producing formation at the bottom of the well while the well is flowing or producing hydrocarbons. Refer to Fig. 3. It will always be higher than the flowing pressure at the surface, but lower than the shut in bottom-hole pressure.

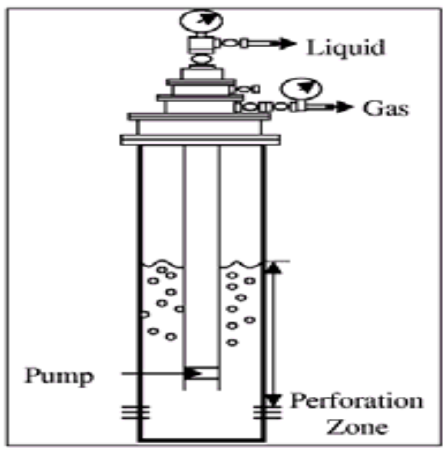

Fig. 3. Schematic of Oil Well with ESP

Knowing the bottom-hole pressure of an oil well can help forecasting the well potential during the life cycle of the well. In other words, well production monitoring and artificial lifting optimization can be performed, which is a key objective for oil production maximization and operational cost reduction [12]. Bottom-hole pressure data also can be used to provide information on pore pressure that can be calculated for safety while drilling development wells in the area. It is critical for drilling operations especially underbalanced drilling. This also provides valuable data to select accurate kill fluid weight. The data also can be used to improve accurate under- or over-balance before perforation.

Tubing pressures and casing pressures of flowing wells have always been important factors in operating wells and under restricted production their importance is increased. Changes in these pressures, correlated with age or with rate of production, have been considered as giving important information as to the quality of the well, sand conditions, conditions of the bore hole through the sand, and whether the equipment in the hole is operating properly. A general study of bottom-hole pressures throughout an entire field has a direct application to the operation of a particular lease or an individual well. Bottom-hole pressure surveys of the field will provide data which will assist in making a more accurate estimate, much earlier in the life of the field, of the time when wells must be produced by artificial lift and of the amount of fluid that will have to be handled. It is of considerable value to know within reasonable limits when the wells will have to be pumped.

III. BASICS OF FEED FORWARD NEURAL NETWORKS

Typically, FFNN consists of a set of sensory units (source nodes) that constitute the input layer, one or more hidden layers of computation nodes, and an output layer. The source nodes in the input layer of the network supply respective elements of the activation pattern (input vector), which constitute the input signals applied to the neurons (computation nodes) in the second layer (i.e., the first hidden layer). The output signals of the second layer are used as an input to the third layer, and so on for the rest of the network. The set of output signals of the neurons in the output (final layer) constitute the overall response of the network to the activation pattern supplied by the source nodes in the input (first) layer. A multilayer FFNN with one input, two hidden and one output layers is shown in Fig. 4

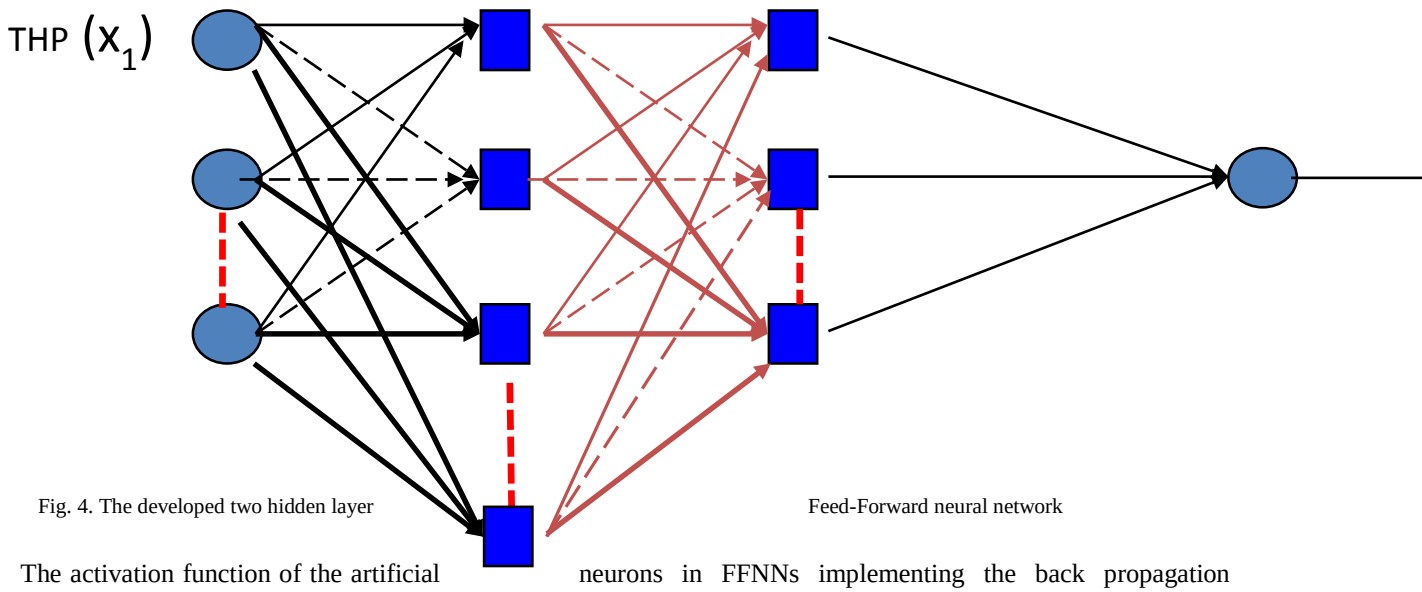

Fig. 4. The developed two hidden layer Feed-Forward neural network

The activation function of the artificial neurons in FFNNs implementing the back propagation algorithm is a weighted sum (the sum of the inputs x multiplied by their respective weights w_{ji}):

$$A_j(\bar{x},\bar{w}) = \sum_{i=0}^{n} x_i w_{ji} \qquad (1)$$

The activation function depends only on the inputs and the weights. If the output function would be the identity (output=activation), then the neuron would be called linear. But it has severe limitations and the most common output function is the sigmoidal function:

$$O_j(\bar{x},\bar{w}) = \frac{1}{1+e^{A(\bar{X},\bar{W})}} \qquad (2)$$

The output depends only on the activation, which in turn depends on the values of the inputs and their respective weights. Now, the goal of the training process is to obtain a desired output when certain inputs are given. Since the error is the difference between the actual output $O_j(\bar{x},\bar{w})$and the desired output d_j, the error depends on the weights, and we need to adjust the weights in order to minimize the error. The error function for the output of each neuron can be defined as:

$$E_j(\bar{x},\bar{w},d) = \left(O_j(\bar{x},\bar{w}) - d_j\right)^2 \qquad (3)$$

The error of the network will simply be the sum of the errors of all the neurons in the output layer:

$$E(\bar{x},\bar{w},d) = \sum_j \left(O_j(\bar{x},\bar{w}) - d_j\right)^2 \qquad (4)$$

Using the gradient descent to minimize the error (4), one can obtain the following adjustment rule for the weights

$$\Delta w_{ji} = -\eta \frac{\partial E}{\partial w_{ji}} \qquad (5)$$

Equation (5) is used to get the updated weights as:

$$w_{ji}(k+1) = w_{ji}(k) + \Delta w_{ji} \quad (6)$$

IV. NEURAL NETWORK DEVELOPMENT AND OPTIMIZATION

To estimate FBHP, realistic data sets available from Oman oil fields, specifically from oil production wells lifted with ESP are used. The data were collected from three different fields, Field-A, Field-B and Field-C. All three fields have water injection as reservoir pressure support and all of them have well production with two different artificial lifting; namely ESP and gas-lift. There are twelve different input variables and one output variable for the ANN to be constructed. The motor current and pressures data are obtained from online-meters measurements that record samples every 15 minutes in a data base historian system. The measurement frequency is every one to three months, depending on the well oil production rate. The data pertaining to fluids properties is obtained from laboratory analysis that is done once for every well or field.

Fifteen minutes frequency data is re-sampled to daily frequency records to reduce number of samples while keeping reasonable representative variation in the data. Since the study scope is to estimate FBHP, and then the data sets for well static conditions (i.e. when the well is not flowing) were excluded. Also, incomplete data sets and sets with readings over the meters range are removed. Then monthly production data is aligned with the daily data by replicating the monthly data daily until next month sample. The well (field) fluid data is then aligned with the daily data sets for each well (field). Before training neural network model, the data is normalized.

A. FFNN with a single hidden Layer Structure

A very basic structure of FFNN with one hidden layer is considered. To reach to the optimal number of hidden neurons, a testing of the network is started with 4 neurons in the hidden layer and then increased the number of neurons in a multiple of four until 80. For each case, the network is trained to a specified training error goal of 0.005. The data used for the neural network model are taken from Field-A. The network performance statistical factors are recorded.The main performance metric considered is the relative root mean square error (RMSE) and standard deviation (STD). Also, the percentages of the test data attaining 95% and 90% accuracy of FBHP estimation is used as a secondary performance metric. Figure-5 shows the network performance against the number of neurons in the hidden layer. The results indicate that the optimal number of neurons that achieves minimum RMSE is 68. Also, this result is supported from the overall accuracy of both 95% and 90% accuracy trends. Table 1 summarizes all statistical indicators of the network performance. It indicates that a remarkable performance of single hidden layer is achieved with 68 neurons where the RMSE is 2.53% and the STD is 2.44%. Also the percentage of the test data that showed intake pressure estimations within the 5% and 10% error from the actual intake pressure measurements are 94.4% and 99.8% respectively. The selected structure above is addressed again with different training mean square error goals and the performance is analyzed. The network is trained and tested for twenty different training mean square error goals within the range of 0.0001 to 0.04. Table 1 and Figure 5 illustrate the achieved results in terms of RMSE and accuracy for the twenty runs.

TABLE-I. PERFORMANCE ANALYSIS OF 68-NEURONS SINGLE LAYER NEURAL NETWORK

	Relative Error (Test Data)	**Relative Error (Training Data)**
Root Mean Square Error	**2.5264**	1.6958
STD of Error	2.4378	1.6130
Correlation Coefficient	0.9921	0.9953
% of Data >95% Accuracy	0.9437	0.9870
% of Data >90% Accuracy	0.9969	0.9982
Error Avg	0.6650	0.5240
Abs Error Avg	1.8276	1.0998
Error min	0.0003	0.0004
Error max	16.9147	20.1590

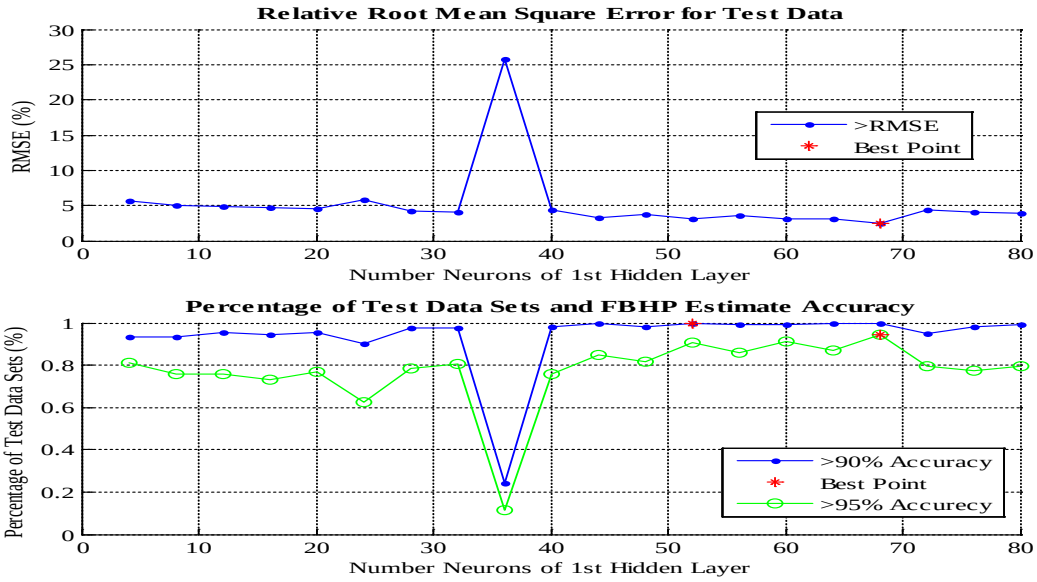

Fig.5. RMSE and Accuracy vs. Number of Neurons of single Hidden Layer

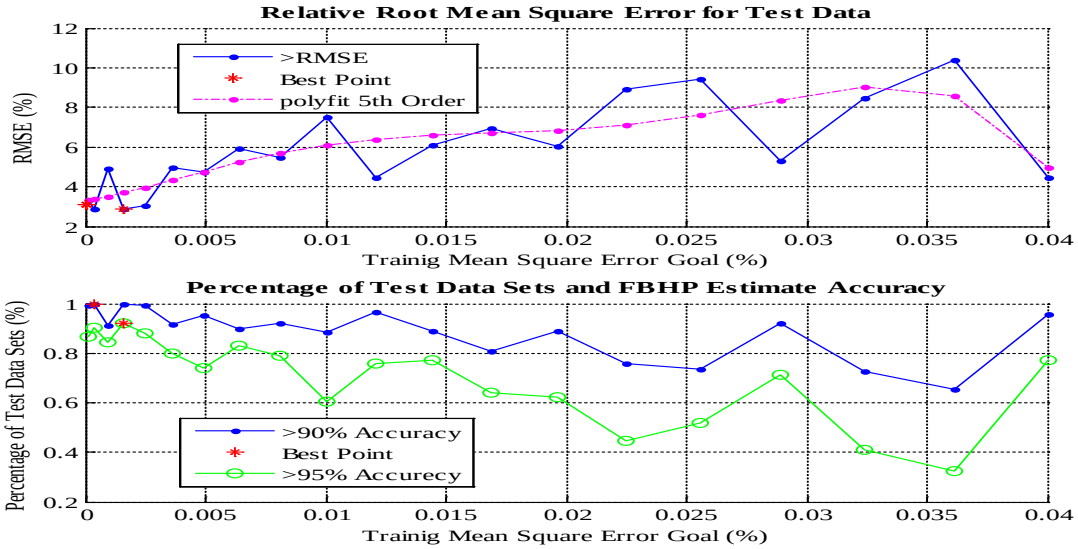

Fig. 6. RMSE and Accuracy of FF with BPNN {68} vs. Training Error Goal

B. FFNN with Two Hidden Layers Structure

Two hidden layers structure of FFNN is investigated. The objective of the investigation is to select the number of hidden neurons for each hidden layer that yields the best network performance. To start, a rule of thumb is used to select 15 neurons for the second hidden layer. Then, the network is trained and tested for different numbers of neurons for the first hidden layer staring from 4 neurons and increasing the number of neurons in multiple of four until 40 neurons. The obtained RMSE and the accuracy are shown in Fig. 6. It is found that the best RMSE is about

3.6% when 20 neurons in the first hidden layer are used. This is also supported by good accuracy points of 99% of test data fall within the 10% error band and 85% fall within the 5% error band. So the number of neurons in the first hidden layer is selected to be 20 neurons. The network is trained and tested again for different numbers of neurons in the second hidden layer. Performance analysis for different number of neurons in the second hidden layer were accomplished starting with 2 neurons for the second hidden layer and then increasing the number of neurons in multiple of two until reached 40 neurons. The achieved results are shown in Fig. 7.

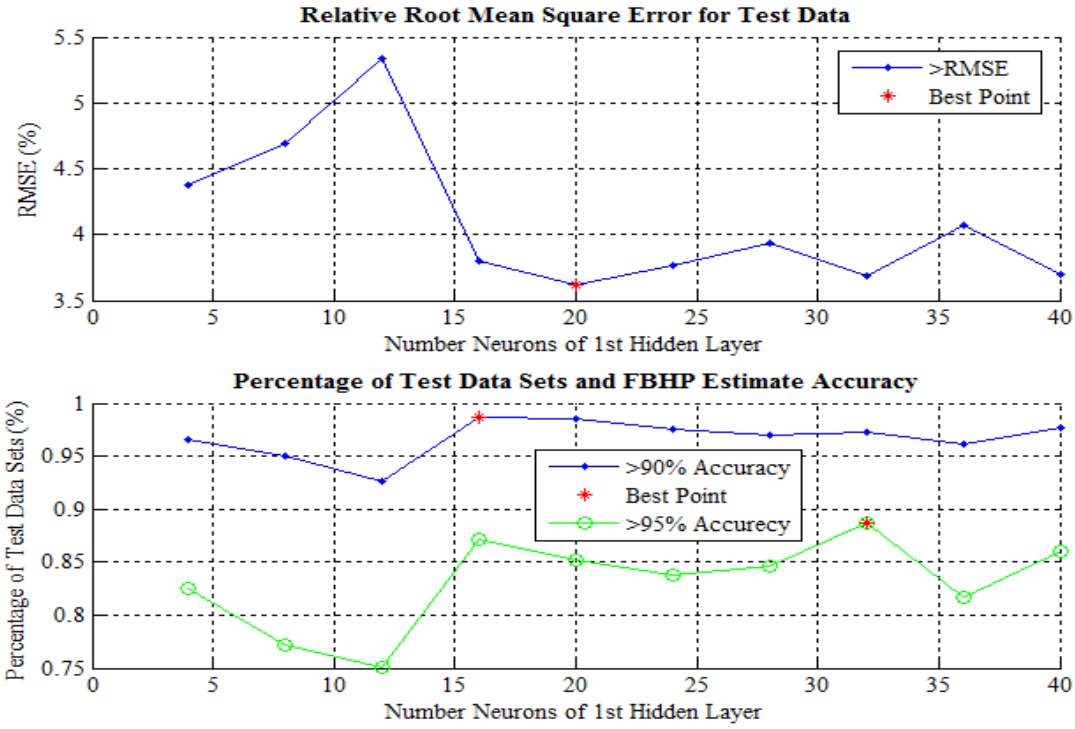

Fig. 6. RMSE and Accuracy of FFNN vs. number of neurons in the firsthidden layer

Fig. 7. RMSE and Accuracy of FFNN vs. number of neurons in the secondhidden layer

From Fig. 7, it is clear that the best RMSE is about 2.6% when 24 neurons in the second hidden layer are used. This is also supported by the good accuracy points of 99% of test data fall within the 10% error band and 92% fall within the 5% error band. As a final check, the tuning of the number of neurons for the first hidden layer is repeated with 24 neurons for the second hidden layer. Figure 8 indicates the achieved results.

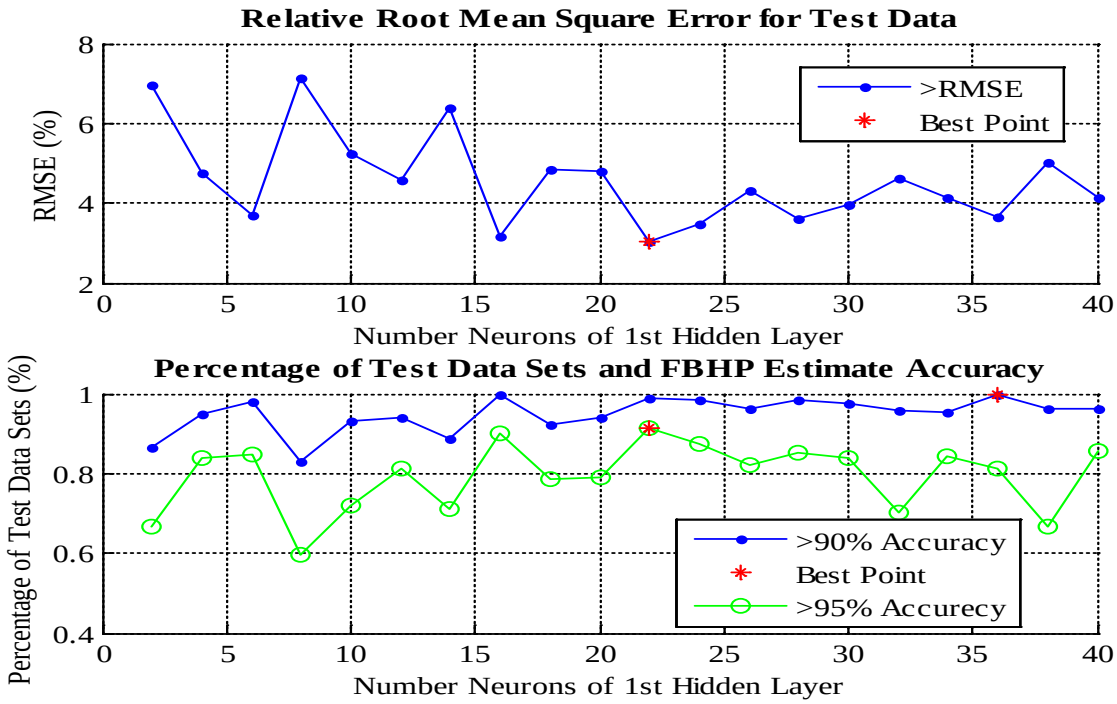

Fig. 8 RMSE and Accuracy of FFNN vs. number of neurons in the first hidden layer

It is shown that the best RMSE is about 2.9% when 22 neurons in the first hidden layer are used.

This is also supported by the good accuracy points of 99% of test data fall within the 10% error band and 91% fall within the 5% error band. Therefore, the selected number of neuronsfor the first layer is 22 and for the second hidden layer is 24 .Therefore the final feed forward neural network structure with two hidden layer is the {22 24} neurons and 0.001training mean square error goal.

V. FBHP ESTIMATION RESULTS USING THE DESIGNED NEURAL NETWORK

In this section, the results and performance analysis of the proposed single-layer FFNN and multilayer FFNN are illustrated.

A. Intake Pressure Estimation using FFNN with Two Hidden Layers for Field-A

The analysis in this section is performed for the data collected from 15 wells in the Field-A. Below are the results for FFNN with two hidden layer, 22 neurons in the first layer and 24 neurons in the second layer {22 24} and 0.001 training mean square error goal. The number of data points used is 6000 with 60%, 20%, and 20% used for training, validation and testing respectively and the maximum number of epochs is 100. An additional 2560 new data sets are also used for further testing the model after FFNN is trained.Table-2 shows the summary of some statistical performance parameters, RMSE, STD of the error and the correlation coefficient of the relative error. These values after the testing phase are 2.16%, 2.07% and 0.993 respectively.

TABLE-II. FIELD-A PERFORMANCE RESULTS USING FF WITH BPNN {22 24} MODEL

	Abs Error KPa(Test Sets)	%Relative Error (Test Sets)	Abs Error KPa (Train sets)	%Relative Error (Train Sets)
Root Mean Square Error RMSE	**149.554**	**2.164**	**121.516**	**1.872**
STD of Error	140.727	2.067	121.290	1.864
Avg. Error	50.695	0.643	-7.563	-0.180
Abs. Error	103.290	1.481	76.001	1.153
Error min	0.009	0.000	0.004	0.000
Error max	1554.999	19.040	1398.879	19.620
Correlation Coefficient R	-	0.993	-	0.995

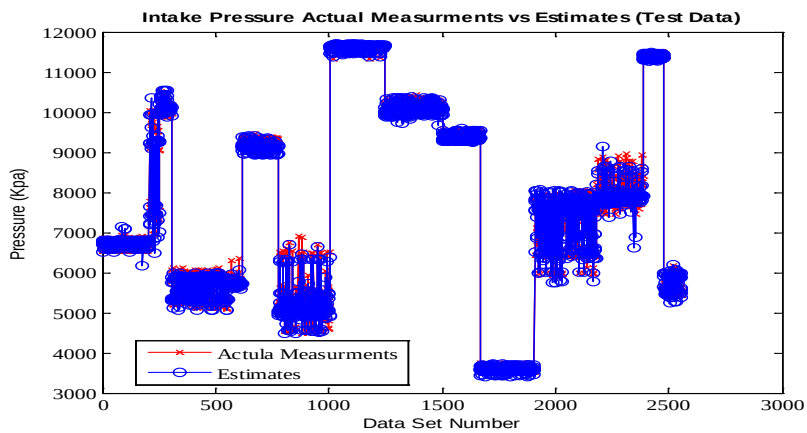

Fig. 9. Actual and Estimated Intake Pressure with FFNN {22 24}

The actual intake pressure and the corresponding estimates from FFNN {22 24} model is shown in Fig. 9. It is clear that the model estimates are superbly close to the actual measurements with minor error at cases where the intake pressure of the well is fluctuating sharply due to unstable well flow. These cases can be seen at data sets in the range of 900-1000 and from 2200-2400. Therefore, we could mention that the model accuracy slightly decreases under unstable well flow conditions.

B. Intake Pressure Estimation using FFNN with Single Hidden Layer of Field-A

Table 3 shows the achieved results for a single layer with 68 neurons and training mean square error goal is 0.001. The values of RMSE, STD of error and the correlation coefficient of the relative error are 2.3, 2.3 and 0.0993 respectively. These values are comparable to that obtained from the two hidden layers model.

TABLE III. FIELD-A PERFORMANCE RESULTS USING SINGLE HIDDEN LAYER FF {68} MODEL

	Abs ErrorKPa (Test Sets)	%Relative Error (Test Sets)	Abs Error KPa(Train sets)	%Relative Error (Train Sets)
Root Mean Square Error RMSE	**142.5**	**2.3**	**116.1**	**1.8**
STD of Error	142.6	2.3	91.5	1.5
Avg. Error	1.4	0.1	-71.5	-1.1
Abs Error	111.7	1.7	85.2	1.3
Error min	0.1	0	0	0

Error max	1047.6	15.2	1915.2	20.4
Correlation Coefficient R	-	0.9927	-	0.9945

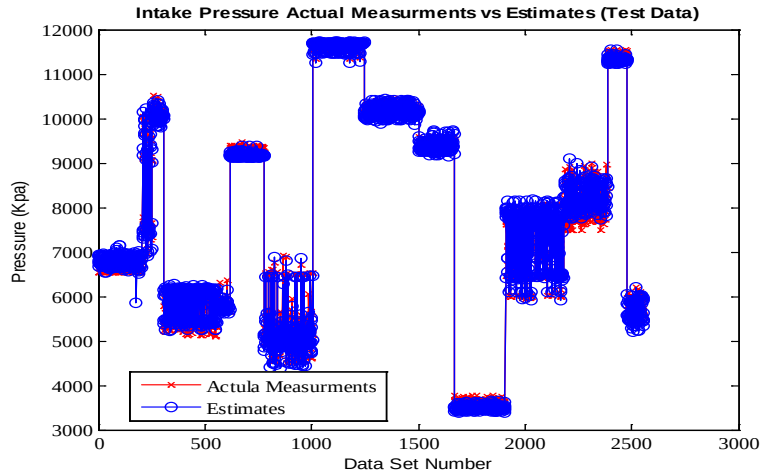

Fig.10. Intake Pressure Measurements and FFNN {68} Model Estimations

Fig. 10 above shows the actual intake pressure and the corresponding estimates from the model. These data were rearranged into well by well intake pressure sets for the purpose of analysis and clear illustration. It is clear seen that the model estimates are superbly close to the actual measurements with minor error at cases where the intake pressure of the well is fluctuating sharply which could be due unstable well flow. These can be seen at data sets number 2200-2400. Therefore, we could stat that the model accuracy slightly decreases under unstable well flow conditions.

VI. CONCLUSION

Estimating FBHP of well is a challenging and very complex system. The empirical and mechanistic models were not able to estimate the FBHP with a suitable accuracy. The developed neural network model has shown exceptionally accurate FBHP performance estimation that significantly outperforms the empirical model. The number of neural network layers and the number of neurons per layer have been addressed to find the optimum neural network structure. The paper shows that the accuracy of FBHP estimation using FFNN with two hidden layers model is better than the FFNN with single hidden layer model in terms of data set used, mean square error, and the correlation coefficient error.

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