A Review Of Artificial Neural Network Applications In Petroleum Exploration, Production And Distribution Operations

Angella Nwachukwu, Henry O. Omoregbee, Modestus O. Okwu, Lagouge K. Tartibu, Dolor Roy Enarevba, Adedoyin Adesuji

Abstract: The energy business thrives with in-depth knowledge and awareness of the subsurface in the oil and gas operations. Strategists have attempted to solve the problem of uncertainties which exist as a result of the complex nature of the subsurface in a variety of ways; nevertheless, the traditional approaches used have failed to provide a reliable guide to apposite decisions on the exploitation of these reservoirs. Artificial intelligence techniques, specifically artificial neural networks (ANN) have been discovered as a possible tool for unravelling the uncertainties experienced during exploration and production (E&P) operations. This research is an exposition and demonstration of the ANN capabilities in E&P operations. Firstly, the nitty-gritties of ANN were discussed. Secondly, information on AI applications in the oil and gas operations was divulged. Then the application of ANN in reservoir characterization, drilling operation, exploration and production were detailed. Finally, a case study was presented focusing on ANN application in drilling operations by considering simple speed in rpm, feed rate in mm/rev, drill size in mm and depth of cut in mm as input variables. The output target is the surface roughness obtained via experiment. The system was trained by using nineteen (19) samples representing 70%of the dataset for training and 30% for testing and validation. The close values of the experimental and predicted results demonstrate the capability of ANN to effectively fine-tune the values of input and output variables and parameters to obtain a good solution.

Index Terms: Artificial intelligence, Artificial neural networks, Drilling operations, Petroleum Exploration, Reservoir characterization.

1 INTRODUCTION

Artificial neural networks is a system based on the same principle of the functionality and organization of biological neural systems for information processing. ANN is a computer algorithm that broadly categorizes and solve several types of problems, including pattern classification, pattern recognition, pattern completion, function approximation, filtering, [47]. The mimicking of human attributes of solving a complex problem that is difficult to imitate is the basic attribute of ANN via using the analytical and logical techniques of expert systems [13]. Kohli and Arora [40] listed some advantages of ANN to include: effective computation where data availability is less adequate; possessing of great potential in computing results that would otherwise be irrelevant for analysis from historical data; Solve fundamental problems from well log responses with high accuracy such as permeability prediction. ANNs' greatest advantages over other modelling techniques are its' capability of modelling non-linear complex processes without the input and output variables relationship assumption [13]. Other advantages of ANN are: Its' ability to outperform other models with the availability of high-quality data; Its' relative learning algorithm is simple; Its' ability to approximate any function regardless its linearity; It finds application readily in problems which are impractical or difficult to formulate a non-linear relationship.

- Nwachukwu A.has a PhD degree in Petroleum engineering from Federal University of Technology Oweri, Nigeria. PH-01123456789. E-mail: angella.nwachukwu@futo.edu.ng
- Henry O. Omoregbee has a PhD degree in Mechanical engineering from University Pretoria, South Africa, PH-+2348035809083. E-mail: omoregbeeho@gmail.com
- Modestus O. Okwu name has a PhD degree in Mechanical engineering from Federal University of Technology Oweri, Nigeria. PH-01123456789. E-mail: mechanicalmodestus@yahoo.com
- Lagouge K. Tartibu has a PhD degree in Industrial Engineering from University of Johannesburg, South Africa, PH-01123456789. E-mail: itartibu@uj.ac.za

Neural network development usually requires informative data sets to ensure large enough spanning area for an application. A crucial feature of the neural network is the ability to be trained and to compute by use of parallel computation [17]. This can produce a suitable outcome, results and to handle many inputs [49], [63]. ANN is regarded as a black boxes technology which attempts to raise concerns regarding the ability of the tool to generalize to situations and also to map the relationship between input and output variables based on a training data set which is one of its major drawbacks [22], [45]. The other disadvantage is its' susceptibility to overtraining that is, they are not capable of generalization as they only memorize the training data fed into it. One proposed solution to the black box problem according to [47] is the use of hybrid systems (e.g combining neural networks with fuzzy logic to form a neuro-fuzzy system or combining ANN with traditional solution systems such as Bayesian classifiers). Some features adapted to neural networks makes them particularly appropriate for solving certain classes of problems in the petroleum industry. Firstly, they provide a powerful technique for solving complex problems in image analysis, pattern recognition and classification. Secondly, ANN "learn" to solve problems through examples and they are specifically suited for interpretative and subjective processes that humans can easily perform intuitively, which especially cannot be described in terms of a set of equations or algorithm [48].

2. Details of Neural Network Operation

An artificial neural network comprises the collection of neurons which are grouped into layers and arranged in specific formations. Where we have an input layer, one or more hidden layers and an output layer then we are referring to a multilayer network. In the input layer, the number of parameters that are being presented to the network as input corresponds to the number of neurons which also applies to the output layer. In the hidden layer, the neurons provide increased dimensionality and are responsible for feature extraction. They accommodate such tasks as pattern recognition and classification. A schematic of fully a connected, three-layer neural network is shown in Fig. 1. Neural networks are classified in different ways with the most popular classification been based on training method. Training is the process of updating a neural network by modifying its weight, biases and other parameters that may be available. ANNs generalizes an output based upon the learned patterns and once they are trained, the network can implicitly classify new patterns [44], [21], [65], [64]. The training methods are divided into two major categories: supervised and unsupervised. The supervised training process permits learning on a feedback basis while on the other hand, the unsupervised training of the neural networks, known also as self-organizing maps mainly involves the classification and clustering algorithms. Where no feedback is provided to the network such is referred to as unsupervised and such network is usually asked to classify the input vectors into groups and clusters. They have found large application in the oil and gas industry in interpreting well logs and in identifying lithology. However, in the oil and gas industry most neural network applications are based on supervised training algorithms [50]. Several artificial neural networks architectures are commonly used such as back-propagation (BP), multilayer perception (MLP), recurrent neural network (RNN) and radial basis function network (RBF) [36].

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3. Recent Research Work on AI in Oil and Gas Operations

Artificial intelligence technology is a global technique which has been used vastly for analysis of systems. It is useful in the diverse area of engineering field. The superiority and strength of AI have been demonstrated in the work of [55], [29], [9], [31], [79], [61], [81], [82]. ANN specifically has been used in the work of [11], [32], [68], [56], [30], [57], [69], [78], [89], [90], [81], [82]. Trifonov et al. [86] viewed ANN as a good intelligent system with self-governing optimal topology. Ahamad et al. (2018) discussed the strength of backpropagation neural network (BPNN) especially for the prediction of heat transfer and other stochastic processes. Wenliang et al. [88] equally demonstrated the effectiveness of ANN in coating operations. Equally, Sun et al. [80] considered Bayesian regularized (BR) artificial neural network (ANN) in optics forecasting. Zhang et al [94] in their study examined the superficial gooeyness of crude oil in a waxy form which was treated using pour point depressant (PPD). They looked at the history (shear and thermal) and its effect on superficial viscosity of the crude oil conveyed using a pipeline. In conclusion, they noted the most significant variable in viscosity prediction, which was as a result of viscous flow rate. Quite a good number of researchers have used ANN for the prediction and analysis of oil recovery (OR) in oil and gas operations. One interesting research in this field is a research conducted by [55], in their work, they used different artificial intelligence (ANN, RNN, ANFIS-SC and SVM) to estimate ORF for sandy reservoir system. ANN was considered the best of four AI in predicting ORF based on analysis of the system using thirty-eight (38) reservoir system. ANN solution gave the highest R^2 value of 0.94 and the lowest AAPE of 7.92%. ANN is, therefore, a vital technique for analysis of systems especially in the oil and gas operations. Some of the areas of its application include reservoir characterization, drilling operation, exploration and production etc.

3.1 Reservoir Characterization Applications

Reservoir characterization (RC) is the process of quantitative assignment of reservoir properties such as permeability, porosity, fluid contact, saturation etc. [52], [40]. The petroleum industry always aims at achieving a good reservoir characterization because it reduces uncertainty which translates to better field development and improved oil recovery. Characterization of the reservoir is most times complicated and challenging due to the nonlinear, heterogeneous physical properties of the well formation especially when conventional analysis techniques are applied. For instance, the use of conventional methods for reservoir characterization in a case of distribution of reservoir properties using core data gathered at selected locations or using pressure transient analysis based on volumetrically averaged permeability will be almost impossible [52]. In recent times, however, the use of artificial intelligence-based techniques such as artificial neural networks has helped to address these issues as recorded in the literature. Artificial neural is preferred over other artificial intelligence techniques because of its prediction and generalization capabilities [20]. Information for reservoir characterization comes from different sources such as seismic surveys, cores, well logs, well test and other various sources. A review of available literature reveals the applications of ANN in these major areas: for example, neural networks have been used for gas chromatography analysis, microfossil identification, gravity/magnetics modeling, seismic horizon picking, satellite imagery resource analysis and several applications in seismic data processing (first break refraction picking, data compression, wavelet extraction, trace editing, inversion and spike filtering) [48]. Nwaoha used computational intelligence for risk analysis in LNG operations. Thararoop et al., [85] used ANN to map production data, completion information, interference effects and reservoir characteristics from seismic data. Neural network has also found application in the detection of some geologic features from seismic such as gas chimney, salt, fracture, fault, sand thickness lithology, dynamic changes in the reservoir and hydrocarbon probability [6], [7]. Petroleum reservoirs are best characterized and evaluated with the aid of core samples taken from such reservoirs. However, due to the cost of taking core samples, it is not feasible to core all wells. Artificial neural network has been applied to extract information from uncored but logged wells. Some researchers have used neural network to predict geological lithofacies classification and geo-mechanical failure parameters from well logs [46], [7], [66], [83], [84], [3]. ANN has also been used to predict petrophysical properties such as porosity and permeability from well log data and/or seismic data [46], [41], [40], [53] as well as prediction of water saturation [2]. Another tool which is often used to characterize oil and gas reservoirs is the pressure transient well test analysis. When well are tested, they provide a description of the reservoir in dynamic conditions as opposed to well log and geological data. According to Earlougher [25], interpretation of rate/pressure data of typical well test yields information about damage and improvement, wellbore volume, permeability, reservoir pressure, reserves, porosity, fluid discontinuities, reservoir and other related data. The basis of well test interpretation is model identification. Conventionally this has been done using linear, log-log and semi-log plots of time and pressure to calculate various reservoir parameters. The selection of the correct reservoir model for the calculation of reservoir parameters with these diagnostic plots was always not obvious from the well test data [27]. This uncertainty leads to trial and error in model identification. The problem has been greatly reduced by the use of pressure derivative plots [16]. The derivative plots also have their challenges. Because they depend heavily on visual inspection, derivative plots sometimes lead to incorrect results which are very sensitive to noise [75], [24]. Artificial neural networks provide better alternative means of analyzing pressure transient tests due to the properties of noise insensitive and nonlinear mapping [24]. ANN has been applied successfully in parameter estimation and model identification [42], [75], [24], [4]. It is important to note that ANN also has its weakness but has mostly been addressed [38], [93]. Artificial neural network is, therefore, a great asset to integrated reservoir characterization because it helps to integrate different types of data with its application to geological, geophysical and engineering data analysis. It could be advantageous in data mining activities in large exploration and production (E&P) databases and has the potential to drive future research on how to apply the information generated for enhanced reservoir management of existing fields.

3.2. ANN in Drilling Operations

Drilling operations is one of the most important aspects of oil and gas industry operations because it is the only means of producing hydrocarbons and remaining in business. The profitability of E&P business rests on successful completion of a useable hole at a minimum cost in a safe manner. The drilling industry is highly technology-driven and always seeking ways and means to achieve its basic objectives. In recent times, artificial intelligence (AI) techniques particularly artificial neural network has been identified as a tool that is very useful in achieving some of these objectives. The drilling industry is well known for its large database in form of offsets records and is, therefore, a good candidate for data-driven techniques such as ANN. Bello et al. [13] list major artificial intelligence solutions for specific drilling processes and system design (Fig. 1). Well planning, drilling optimization, well integrity, troubleshooting, problem detection and quick decision making are critical to drilling operations. ANN has been applied successfully in some of these areas where other techniques are lacking.

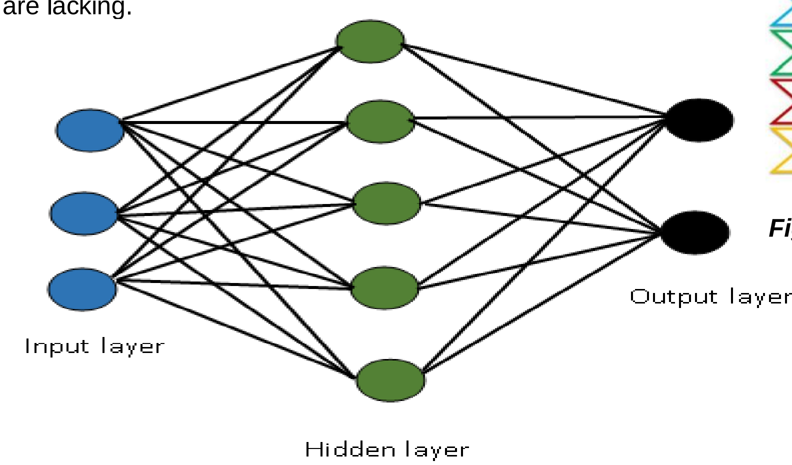

Fig. 1: Three-layer neuron network (Mohaghegh, 2000).

Artificial neural networks more than the other AI techniques are commonly used in providing solutions to the various specific drilling processes listed in fig. 2. When planning a new oil or gas well there is often the need for the selection of hardware components such as bits and casings. Bit selection is also critical in designing and planning a new gas or oil well. Proper selection of bit is a difficult task which affects the complex relationships between formation properties, bit hardware design and operational parameters that reflects on the factors affecting bit performance [15]. The conventional methods of bit selection are not designed to incorporate the large number of variables that should be considered to select the best bit. Artificial neural networks in the last decades are used in identifying complex relationships when sufficient data exists and has been used successfully to select bits for new sections [8], [14], [23], [15], [92], and casing prediction [71]. Artificial neural networks have also been applied to cement quality/ performance estimation [34]. Improved monitoring of downhole parameters is primarily related with optimization of drilling process (BHA response, ROP, bit performance, DS vibrations, etc) for reducing drilling uncertainty and enhanced confidence [13]. To help rig-site personnel a new methodology is required in the industry to help make informed drilling parameters decision based on real-time offset data analysis which increases the efficiency of reducing drilling costs and neural networks have filled that gap [35]. In optimization of the drilling process, ANN model has been applied in bottom-hole assembly (BHA) monitoring [23], Rate of penetration (ROP) prediction [54], [19], [5]; Bit wear control [35], Drag and slack-off load prediction [73], Drill string (DS) vibration control [28], pump pressure prediction [87]. In some petroleum-producing regions, maintaining a stable wellbore while drilling is difficult due to complex lithology and abnormal pore pressure values. It is important to know ahead of time if such problems are likely to be encountered to be prepared to address it. ANN has been applied in predicting wellbore instability [37], [62]. Fig. 3 is a demonstration of how the wellbore instability prediction technique may work using the ANN model (Jahanbakhshi and Keshavarzi, 2012).

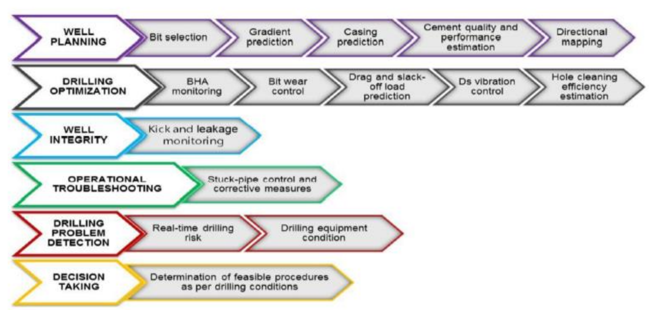

Fig. 2: AI solutions for specific drilling processes and system design (Bello et al., 2016)

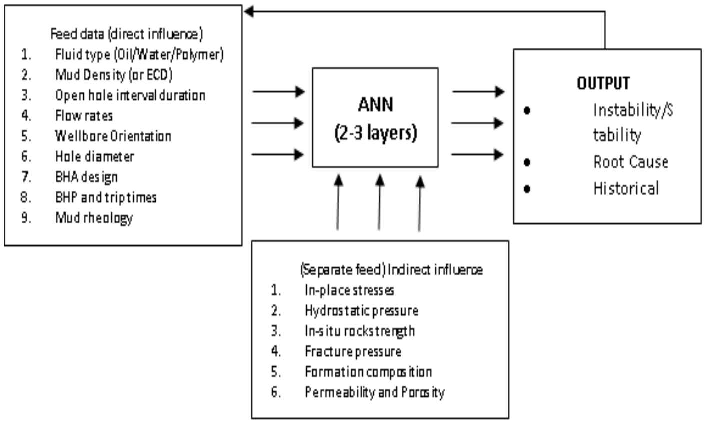

Fig. 3: Predicting wellbore instability by ANN (Jahanbakhshi and Keshavarzi, 2012)

Drilling problems are highly undesirable because of the level of damage in terms of loss of life, equipment, investment and environmental pollution whenever they occur. The deep-water horizon drill rig explosion of April 20, 2010, in the Macondo field is still very fresh in our minds. Hence predicting drilling problems before they occur is desirable as it will help operators to take the necessary measures to avoid it. Artificial neural network has helped in predicting drilling problems [43], prediction of pipe sticking while drilling [76], [51], [1]. Other applications include mud rheological properties determination [26]. ANN like other artificial intelligence techniques is the technology for the future as they have the potential to solve most complex nonlinear problems mostly encountered in E&P operations. Drilling operations rely heavily on historical and offset drilling data and fortunately, the industry has such data in abundance, ANN potentials should be exploited in optimizing our drilling processes with the database.
The output target is the surface roughness obtained via experiment. The system was trained by grouping the dataset into three. Nineteen (19) representing seventy percent (70%) of the dataset was used for training, four (4) representing fifteen percent (15%) was used for testing and validation respectively.

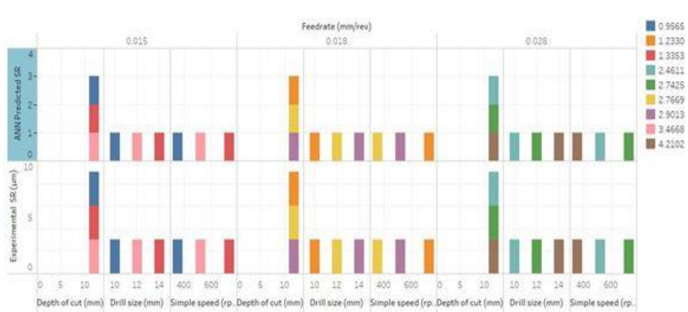

Fig. 4: Graphical representation of the data set in relation to surface roughness in drilling operation

3.3. Applications of Artificial Neural Network in E&P Operations.
Artificial neural network has been applied in other areas such as optimal well operations. For instance, artificial neural network-based tools have assisted in identifying sweet spots by predicting optimal well location/completion parameters and production profiles [39], gas lift optimization [67], Grave pack design [33], production optimization [77], field optimization [72], identification of re-stimulation candidate [74], optimal completion design [12], diagnosis of formation damage mechanism [18], waterflood recovery predictions [58], [65]. Literature shows that the applications of ANN in E& P operations are wide and vast. Recovery enhancement and optimization of field development will be the main drivers of future research on ANN capabilities in the future.

4. Application of ANN in Drilling Operations
The capability of the computational strength of ANN is described in this section. ANN model is a necessary technique to facilitate the solution to the complex stochastic problem. The classical methods of solving such a problem are rigorous and computationally intensive. MATLAB 2019 software is applied to demonstrate the effectiveness of ANN toolbox in-network fitting and prediction. Data used in Fig. 4 are programmed as input and output expressions. The input expressions are simple speed in rpm, feed rate in mm/rev, drill size in mm and depth of cut in mm. The output target is the surface roughness obtained via experiment. The system was trained by grouping the dataset into three. Nineteen (19) representing seventy percent (70%) of the dataset was used for training, four (4) representing fifteen percent (15%) was used for testing and validation respectively.

Several training runs were established for each precise set of weights as well as the neurons of the hidden layer which was adjusted in a number of anticipation in the convergence of the training algorithm which occurred at the seventeenth (17^{th}) trial in the hidden layer. The error and R-value of the training process were monitored continuously as the training process continues until a point where the error on the validation set was noticed to have reduced to the barest minimum and R-value close to unity. This occurred at the seventeenth iteration where the training was stopped automatically. The result of the ANN training in Fig. 5 shows a good agreement between the predicted values and the experimental values for surface roughness in a drilling operation. The experimental values and the predicted values are quite close to each other. The closeness of the values revealed that the developed neural network model was able to generalize between the input variables and the output variables.

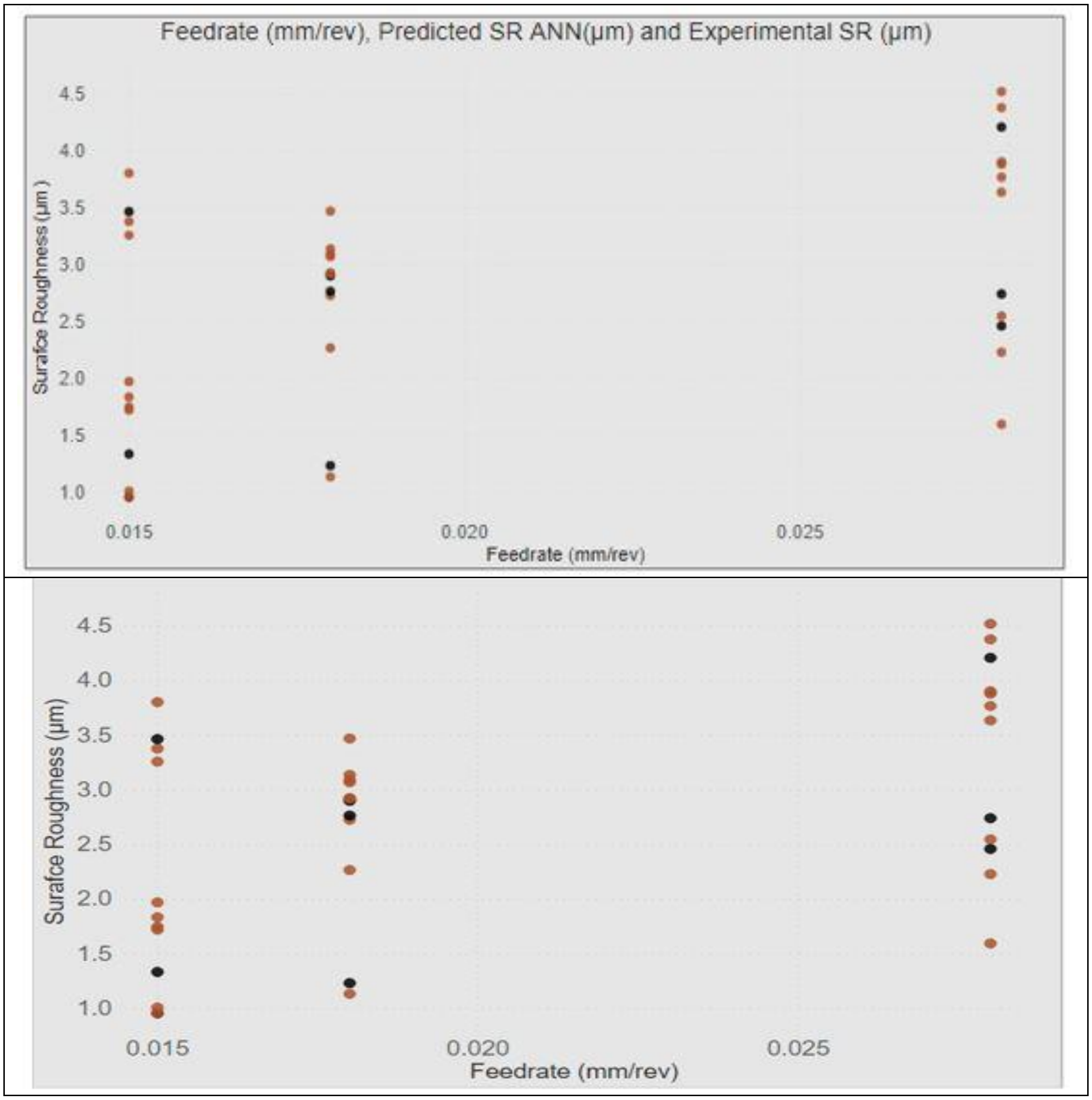

Fig. 5 a) and b): Result of the experimental versus the predicted ANN

Conclusions

Artificial neural network has been applied widely in the diverse field of operation. This study is focused on its application in the oil and gas industry. Its application has resulted in time savings, risk reduction, cost minimization and improved efficiency in E&P operations. Artificial neural network modeling using the existing abundant historical data could provide the useful insight necessary for oil recovery and enhancement through a better understanding and description of the reservoir. It is important to demonstrate the expressive power of the wizard ANN in the petroleum industry, especially in exploration, production, characterization and distribution operations. Its' application in drilling operation has been demonstrated in this research. The full potentials of ANN are yet to be fully exploited in oil and gas operations, hence there is the need for intensive research focused in the field of artificial neural network in particular and artificial intelligence in general. ANN is highly recommended for analysis of non-deterministic systems in E&P operations.

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