The Use of Artificial Neural Networks and Genetic Algorithms for Effectively Optimizing Production from Multiphase Flow Wells

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ABSTRACT

Bottom-hole pressure (BHP) and separator pressure (SEPP) are playing an important role in defining the general fashion of production from upstream and downstream systems. The need for accurate prediction of these parameters is a key factor in clearly understanding multiphase flow in tubing. Prediction of pressure drop in multiphase flow is quite difficult and complicated due to the complex relationships between the various parameters involved. As they considered very hard obtaining parameters, bottom-hole pressure and separator pressure are selected for prediction using Artificial Neural Networks. The latter will be utilized in attempt at this study to generate a generic model for predicting bottom-hole and separator pressures in multiphase flow tubing that accounts for all angles of inclination. Artificial Neural Networks provide an easy and trustable means for predicting these parameters with high degree of confidence. Moreover, the output from the ANNs will be utilized plus selected other input parameters as controlling variables for optimizing the production from a multiphase producing field using Genetic Algorithms (GA).

Keywords
Petroleum Production System Optimization, Genetic Algorithms Artificial Neural Networks, Multiphase flow in tubing.

INTRODUCTION

Two phase flow; namely liquid and gas, or what is alternatively called Multiphase flow, occurs in almost all oil production wells, in many gas production wells, and in some types of injection wells.
The phenomenon of multiphase flow is governed mainly by bubble point pressure; whenever the pressure drops below bubble point, gas will evolve from liquid, and from that point to surface, gas-liquid flow will occur. Furthermore, certain flow patterns will develop while the pressure decreases gradually below the bubble point. The flow patterns depend mainly on the gas and liquid velocities, and gas/liquid ratio. Pressure drop estimation in multiphase flow wells is of a paramount importance. This pressure drop needs to be estimated with good precision in order to implement certain design and optimization considerations. Such considerations include tubing sizing and operating wellhead pressure in a flowing well; well completion or re-completion schemes; artificial lift during either gas-lift or pump operation in a low energy reservoir; direct input for surface flow line and equipment design calculations. In addition to the abovementioned considerations, determination of these pressures can aid in optimizing production from a multiphase producing fields in which petroleum production could be boosted using genetic algorithms.

AIMS OF THE RESEARCH

The aim of this research as follows:

- To construct an ANN model for predicting pressure drop in multiphase flow for all angles of inclination (vertical, horizontal and inclined pipes).
- To test and validate the constructed model against real field data.
- To optimize the Petroleum Production System (PPS) under multiphase flow conditions using Genetic Algorithms (GA) through constructing an ANN model that provides the necessary controlling variables.
- To convert the generated model into a complete production optimization tool using GA.

LITERATURE REVIEW

Investigators and researchers in the field of multiphase flow came up with two general approaches to resolve the problem of getting accurate pressure drop estimation; those are through empirical correlations or mechanistic models. The recent applied approach was the application of artificial neural networks in the area of multiphase flow.

This part of the research deals with the revision of the most commonly used correlations and mechanistic models and evaluates their drawbacks in estimating pressure drop in multiphase flow. Special emphasis will be given to Beggs & Brill correlation (Ref. [2]) and OLGAS 2000 software (Ref. [3]) correlations because they were designed originally to be working for all angles of inclination. The concepts of artificial neural network and genetic algorithms are, in brief, being presented along with their applications in multiphase flow and production optimization areas.

Empirical Correlations

Numerous correlations have been developed since the early 1940s on the subject of multiphase flow. It has been noticed that most of these correlations were developed under laboratory conditions and are, consequently, inaccurate when scaled-up to oil field conditions (Ref. [1]).
The most commonly used correlation for all angles of inclination reported in the literature is Beggs & Brill (Ref. [2]), while OLGAS version 2000 (from Scandpower) is the most recommended mechanistic model that works perfectly for hilly terrain environments (Ref. [3]). The correlation and mechanistic model have been evaluated and studied carefully by several investigators to validate their applicability under different ranges of data (Ref. [4 - 9]).
Most researchers agreed upon the fact that no single correlation was found to be applicable over all ranges of variables with suitable accuracy (Ref. [1]).

Artificial Neural Networks

Artificial neural networks are collections of mathematical models that imitate some of the observed properties of biological nervous systems and draw on the analogies of adaptive biological learning.

Artificial Neural Networks in Multiphase Flow

Recently ANN has been applied in the multiphase flow area and achieved promising results compared to the conventional methods (empirical correlations and mechanistic models). With regard to this field, a few researchers have applied Artificial Neural Networks technique to resolve some problems associated with multiphase problems including flow patterns identification, liquid hold up, and gas and liquid superficial velocities (Ref. [10 - 14]).
As stated by different authors and researchers, the empirical correlations and mechanistic models failed to provide a satisfactorily and a reliable tool for estimating pressure in multiphase flow tubing. High errors are usually associated with these models and correlations which provoked a new approach to be investigated for solving this problem. Artificial neural networks gained wide popularity in solving difficult and complex problems, especially in petroleum engineering. This new approach will be utilized as a tool for estimating bottom-hole and separator pressures for multiphase flow at all angles of inclination.

Genetic algorithms

Genetic Algorithm is a search technique to find approximate solutions to optimization problems. It is a global search technique and a particular class of evolutionary algorithms. From biological sciences, evolutionary processes have been translated to efficient search and design strategies. Genetic Algorithms use these strategies to find an optimum solution for any multi-dimensional problems (Ref. [15]). Genetic Algorithms are search algorithms that mimic the behavior of natural selection.
Genetic Algorithms attempt to find the best solution to a problem by generating a collection (population) of potential solutions (individuals) to the problem. The best solution is the maximum of a function. A flowchart (Ref. [16]) of genetic algorithm is presented hereunder (Fig. 1).

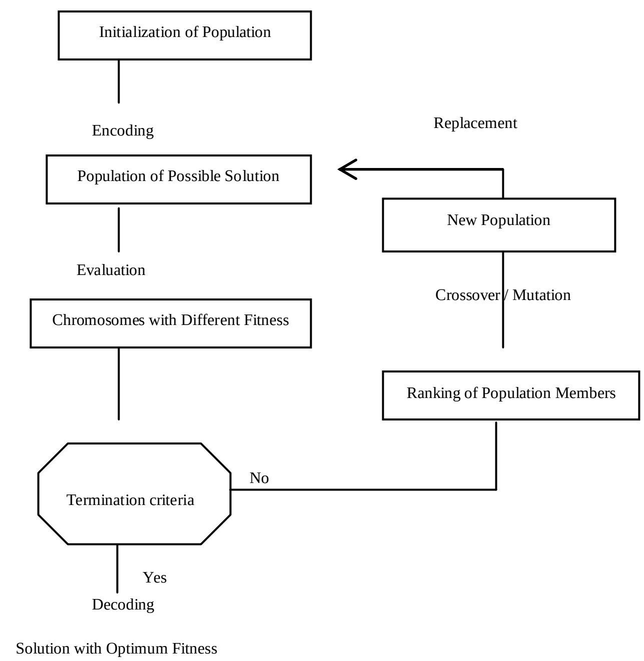

Figure 1. Genetic algorithms in production optimization

Genetic Algorithm (GA), a most robust searching and optimizing technique, that requires no previous knowledge about the problem at hand, has been used to design and optimize the operations of multi-well production well (Ref. [17]). The authors noted that multiple decisions and solution might exist for multiphase network flow problem. Although guaranteed solution for such problem is difficult to obtain, the robustness of the technique was assured.
They (Ref. [18]) also evaluated three different search techniques (a derivative-based method, the polytope method, and the GA) as applied to the optimization of a networked production system by varying parameters such as separator pressure, diameters of tubing, pipeline versus surface choke.
A similar approach has been followed when a Newton-type algorithm, a polytope method, and genetic algorithm to a

compositional model of a single well system. The decision variables included in that study contained tubing diameter, separator pressure, and volume of gas injected. It has been concluded that when the tubing diameter is included in the analysis, the prediction of the objective function can not produce a smooth surface (as usually expected). Thus the gradient-based algorithms report failure to solve the optimization problem at hand. Eventually, the authors recommended the application of GA to solve such problems (Ref. [19]).

An interesting study has been done to optimize production using GA (Ref. [20]). The authors of that study investigated the effectiveness of GA technique in optimizing the performance of hydrocarbon producing wells. The technique has been applied initially for well and surface facilities. The production facilities consist of tubing, choke and separator. The model has the ability to consider single or dual sized tubing and to determine the optimum number of separators. The method has been applied to the production system of real oil and gas condensate field and the results have been compared with Prosper simulator. It's been found that GA is successfully effective for handling such problems with high number of non-linear parameters.

RESEARCH METHODOLOGY

The research methodology involves constructing the best Artificial Neural Network model to predict the bottom-hole and separator pressures. The contribution of each input parameter to the total output will be assessed and reported for further usage. After determining the most influential parameters to the predicted output, decision variables will be added to the objective function to create a GA that deals with optimizing the production system under multiphase flow in terms of boosting oil production.

RESEARCH PLAN

The research plan will be focusing in addressing the best available correlations used by the industry in estimating pressure drop in MPF. A comprehensive model for predicting bottom-hole and separator pressures is more essential in order to be linked to the final optimization model. The Matlab (Ref. [21]) software ANN and GA toolboxes will be utilized in generating the specified models from the scratch. A complete statistical and graphical sensitivity analyses will be carried to ensure the robustness of the developed models.

RESULRS & DISCUSSION

The following section deals with presenting part of the accomplished research results.

ANN technique has been used successfully for developing a model for predicting bottom-hole & separator pressures in multiphase flow in oil wells, which deals with all angles of inclination. The new model has been developed using the most robust learning algorithm (back-propagation scheme). A total number of 337 data sets; collected from Middle East fields; have been used in developing the model. The data used for developing the model covers an oil rate from 2200 to 24900 BPD, water cut up to 59.6%, and gas oil ratios up to 988 SCF/STB. A ratio of 3:1:1 between training, validation, and testing sets yielded the best training/testing performance.

ANN model has been generated and optimized to have 13-4-2 neurons configuration (input-hidden-output) in which bottom-hole and separator pressures are served as outputs.

Simple statistical and graphical analyses were carried out to show the model robustness.

STATISTICAL ERROR ANALYSIS

This error analysis is utilized to check the accuracy of the models. The statistical parameters used in the present work are: average percent relative error, average absolute percent relative error, minimum and maximum absolute percent error, root mean square error, standard deviation of error, and the correlation coefficient.

Table (1) shows a summary of the model results for both bottom-hole and separator pressures.

Table 1. Statistical Analysis Results of one-hidden layer Artificial Neural Network model

parameter	E_a (AAPE)	E_r (APE)	E_{Max}	E_{Min}	RMSE	R%	STD
BHP	0.0005	-0.0003	0.0076	0.0001	0.0011	100.0	0.021
SEPP	0.2704	0.0813	3.5488	0.0012	0.6034	99.98	2.83

GRAPHICAL ERROR ANALYSIS

Graphical tools aid in visualizing the performance and accuracy of a model. Three graphical analysis techniques are employed; those are crossplots, error distribution, and residual analysis.

Crossplots

In this graphical based technique, all estimated values are plotted against the measured values and thus a crossplot is formed. A 45° straight line between the estimated versus actual data points is drawn on the crossplot, which denotes a perfect correlation line. The tighter the cluster about the unity slope line, the better the agreement between the experimental and the predicted results. Figs. 2 & 3 present crossplots of simulated bottom-hole and separator pressures versus their actual values.

Investigation of these two Figs clearly shows that the developed ANN model giving accurate prediction for the two properties despite the low range of investigated data.

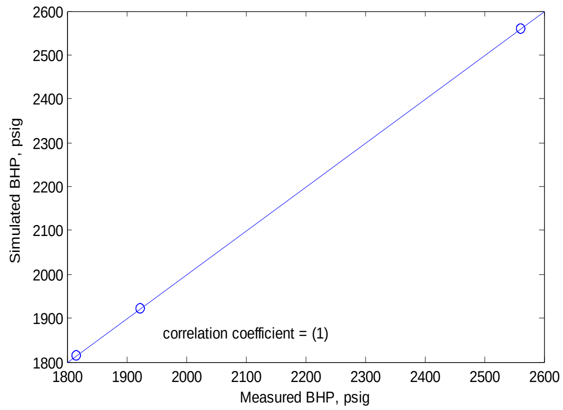

Figure 2. Crossplot of Simulated vs. Measured BHP (ANN model)

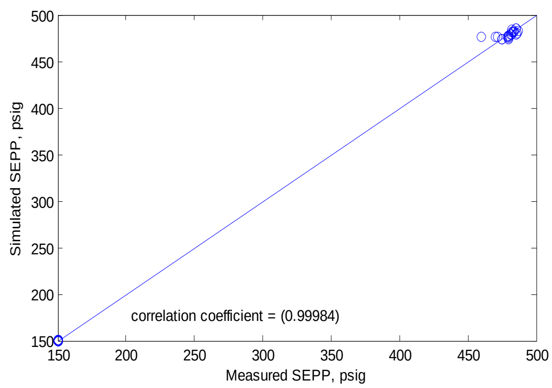

Figure 3. Crossplot of Simulated vs. Measured SEPP (ANN model)

Error Distribution

Figs. 4 & 5 show the error distribution histograms for the neural network model. Normal distribution curves are fitted to each one of them.

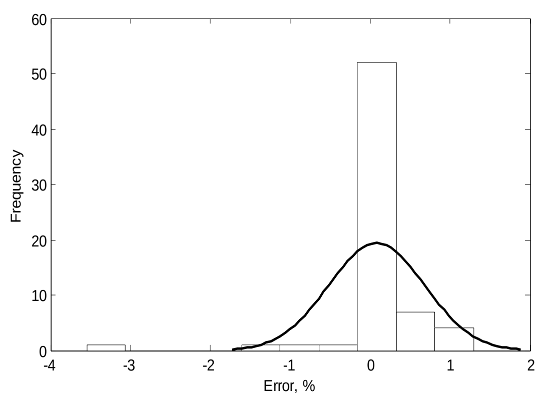

Figure 4. Error Distribution for Testing Set of BHP

The errors are said to be normally distributed with a mean around the 0%. Hence, models for both properties show normal error distribution. Thus, normal distribution of errors can be visualized as perfect prediction (neither overestimating nor underestimation).

The range of errors also is an important parameter for detecting the accuracy of each model. A range of -1.7% to 1.89% is calculated for separator pressure. However a range of -0.0034% to 0.0029% is calculated for bottom-hole pressure, which indicates the superiority of the new developed model.

If the correlation coefficient is used as a main criterion for selecting the best overall performance, the new developed model could be selected based on this feature. Because standard deviation is one of the measures of scattering tendencies, it is included as a measure of how points are distributed and scattered. Based on this criterion, both models performed well (refer to Table 1).

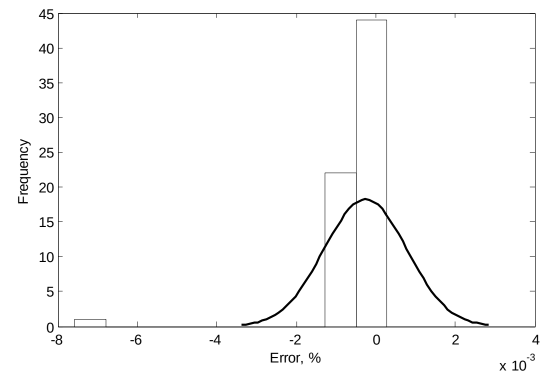

Figure 5. Error Distribution for Testing Set of SEEP (ANN model)

Residual Analysis

According to the data partitioning scheme, the test set contains 68 sets, which were utilized to perform all statistical and graphical tests. The relative frequency of deviations between estimated and actual values is depicted in Figs. 6 & 7 for the tested properties (BHP & SEPP).

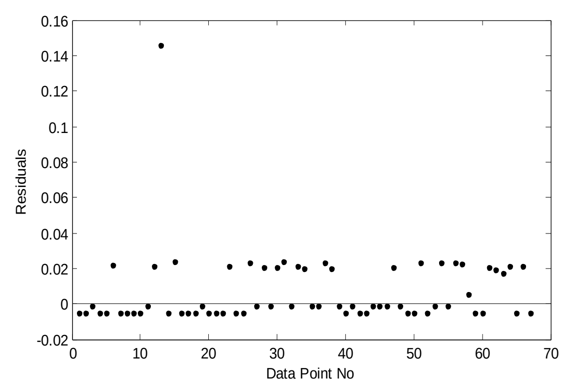

Figure 6. Residual graph of BHP (ANN model).

These Figs. showed the error distribution around the zero line to verify whether models and correlation have error trends. Analysis of residual, i.e. simulated BHP minus the actual BHP is an effective tool to check model deficiencies. Residual limits of each property are shown in Table 2.

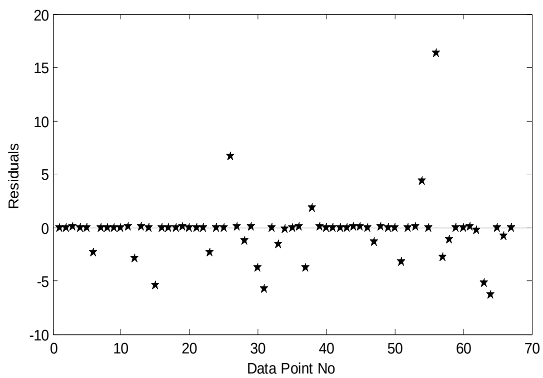

Figure 7. Residual graph of SEPP (ANN model).

Table 2. Residual limits of the New ANN Model

Model Name	**Minimum**	**Maximum**
BHP	0.0001	0.0076
SEPP	0.0001	3.3993

Table 3. illustrates the relative importance of each input parameter to the total output using Garson model (Ref. [22]).

Table 3. Relative Importance of each input parameter to the output

Parameter	Relative Importance %
Wellhead Temperature	4.84
Separator Temperature	14.44
Wellhead Pressure	5.57
Oil rate	6.14
Water Rate	5.00
Diameter of the pipe	3.74
API	22.90
Gas-Oil-Ratio	9.81
Water Specific Gravity	5.74
Gas Specific Gravity	10.34
Length	5.05
Angle of deviation	6.41

FUTURE WORK

The results obtained by ANN model will be further verified by applying the same data used for testing ANN in Beggs & Brill correlation and OLGAS 2000 software. An ANN model will be utilized to optimize production from Petroleum Production System. Genetic Algorithm will be exploited to achieve the desired objective. The research work is going on towards extracting an objective function from ANN model to be inserted in GA model.

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