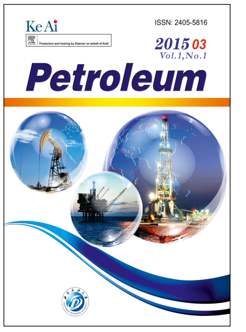
Accepted Manuscript



Bottom hole pressure estimation using hybridization neural networks and grey wolves optimization

Menad Nait Amar, Nourddine Zeraibi, Kheireddine Redouane

PII: S2405-6561(17)30127-X

DOI: 10.1016/j.petlm.2018.03.013

Reference: PETLM 205

To appear in: *Petroleum*

Received Date: 1 July 2017

Revised Date: 7 March 2018

Accepted Date: 19 March 2018

Bottom hole pressure estimation using hybridization neural networks and grey wolves optimization

NAIT AMAR Menad [1*], ZERAIBI Nourddine [1] and **REDOUANE Kheireddine [1]**

[1] Laboratoire Génie Physique des Hydrocarbures, Faculty of Hydrocarbons and Chemistry, University M'hamed Bougara of Boumerdes, Avenue de l'Indépendance, 35000, Boumerdes, Algeria

[*] Corresponding Author: Email: manad1753@gmail.com

m.naitamar@univ-boumerdes.dz

Bottom hole pressure estimation using hybridization neural networks and grey wolves optimization

NAIT AMAR Menad [1*], ZERAIBI Nourddine [1] and **REDOUANE Kheireddine [1]**

[1] Laboratoire Génie Physique des Hydrocarbures, Faculty of Hydrocarbons and Chemistry, University M'hamed Bougara of Boumerdes, Avenue de l'Indépendance, 35000, Boumerdes, Algeria

[*] Corresponding Author: Email: manad1753@gmail.com

m.naitamar@univ-boumerdes.dz

Abstract

An effective design and optimum production strategies of a well depend on the accurate prediction of its bottom hole pressure (BHP) which may be calculated or determined by several methods. However, it is not practical technically or economically to apply for a well test or to deploy a permanent pressure gauge in the bottom hole to predict the BHP. Consequently, several correlations and mechanistic models based on the known surface measurements have been developed. Unfortunately, all these tools (correlations & mechanistic models) are limited to some conditions and intervals of application. Therefore, establish a global model that ensures a large coverage of conditions with a reduced cost and high accuracy becomes a necessity.

In this study, we propose new models for estimating bottom hole pressure of vertical wells with multiphase flow. First, Artificial Neural Network (ANN) based on back propagation training (BP-ANN) with 12 neurons in its hidden layer is established using trial and error. The next methods correspond to optimized or evolved neural networks (optimize the weights and thresholds of the neural networks) with Grey Wolves Optimization (GWO), and then its accuracy to reach the global optima is compared with 2 other naturally inspired algorithms which are the most used in the optimization field: Genetic Algorithm (GA) and Particle Swarms Optimization (PSO). The models were developed and tested using 100 field data collected from Algerian fields and covering a wide range of variables.

The obtained results demonstrate the superiority of the hybridization ANN-GWO compared with the 2 other hybridizations or with the BP learning alone. Furthermore, the evolved neural networks with these global optimization algorithms are strongly shown to be highly effective to improve the performance of the neural networks to estimate flowing BHP over existing approaches and correlations.

Keywords: flowing bottom hole pressure (BHP), BHP correlations & mechanistic models, Artificial Neural Network, neural network training, BP (back propagation), GWO, GA, PSO.

1. Introduction

Bottom hole pressure (BHP) is a crucial parameter for a well during its various stages of life. It is used to establish the development strategies and the design of completions. As the estimation of this parameter technically i.e. using gauge or well testing is so expensive, numerous empirical correlations and semi empirical (mechanistic) models based on the known surface measurements have been developed since the early 1940s. The most commonly used correlations are those of: Hagedorn and Brown [1], Duns and Ros [2], Orkiszewski [3], Beggs and Brill [4], Aziz and Govier [5], Mukherjee and Brill correlation [6]; the commonly used mechanistic models are those of Ansari et al [7], Chokshi et al [8], Gomez et al. [9] and Gray [10]. Most of these correlations and models were developed under a range of conditions; consequently, when their applications are out of these domains, their performances became poor and mediocre.

Recently, Artificial Intelligence (AI) based methods have been widely applied in petroleum engineering to solve many conventional and unconventional problems [11]. Among AI methods, artificial neural networks (ANNs) is the famous tool thanks to its effectiveness. ANNs create models that can recognize highly complex and non-straight-forward problems, and since the prediction of bottom hole pressures in multiphase flow belongs to these problems, this tool, i.e. ANNs, provides an integrated approach for the estimation of a such key parameter (BHP). The results from some papers suggest a better BHP prediction performance of ANN than multiphase correlations [12]. Given sufficient actual field data sets or lab measurements, the neural network can be trained to predict pressure values much closer to the measured values than those from the established correlations.

The main problem that ANN models suffer from, is the presence of some inaccuracies which caused by the defaulted training algorithms (like backpropagation BP) that trap in local minima. Hence, in this paper, we propose to optimize the weights and thresholds of the neural networks (on other words minimize the neural network error function and achieving global convergence) with Grey Wolves Optimization (GWO), and then its accuracy to reach the global optima is compared with 2 other naturally inspired algorithms which are the most used in the optimization field: Genetic Algorithm (GA) and Particle Swarms Optimization (PSO). The models were developed and tested using 100 field data collected from Algerian fields and covering a wide range of variables. There are three differences between this work and other research works in this field (such as in [13], and [14]): (1) the developed models considered in our study are to estimate BHP in vertical wells with multiphase flow during the production (and not during the drilling as in [13], and [14]), (2) the interval of the used data covers a big variety, this gives an excellent generalization of the established models, and (3) besides the application of two algorithms frequently used in global optimization (GA and PSO), this study shows the efficiency and the robustness of the GWO algorithm in the optimization of the weights and the biases of ANNs to estimate BHP.

Fig. 1 illustrates the main workflow of this study.

2. BHP roles and methodologies of calculation

BHP is a key parameter either in the production process or in the reservoir studies. Its accurate prediction affects on one hand the effectiveness and economical design of well's completion and strategies of development (which allows to reach the well best potential), and in the other one, the right characterization of hydrocarbon reservoirs and their models identification (such through well test analysis). Several valuable articles shed light this last point such as in [15–20].

Because of the complexity of multiphase flows, the calculation of the BHP is complicated [21,22]. One of the applied methods to determine BHP is the deployment of pressure down-hole gauges (PDG) which can record a huge amount of bottom-hole pressure data [20]. Although the value of this advantage, this method presents two limitations: it's cost and the handling of its data which are noisy [20].

The available correlations and mechanistic models (for estimating BHP) insure an alternate method that is practicable on the slightest costs. These models and correlations are based on the surface measurements. However, almost of these approaches have been developed under laboratory condition and specific ranges of variables. As a result, when scaling up these correlations to the field condition, they fail to provide the desired accuracy. Table 1 shows some examples of the intervals of application and ranges of development of these models. Another problem to apply these models is the difficulty to choose the appropriate one during the calculation.

The paper is focused on building robust, fast and cheap approaches to monitor BHP through vertical production wells with multiphase flow by applying hybridization of three naturally inspired algorithms with artificial neural networks.

3. Theory background

3.1. Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is an efficient algorithm to approximate any function with finite number of discontinuities by learning the relationships between input and output vectors. Its mathematical model is inspired by the biological neural networks. It is a non-linear mapping model and has been successfully applied in many domains such as in: biology and biomedicine [23–25]; finance [26,27]; engineering, modeling and design [28–30]; petroleum and reservoir engineering [11,31,32]. It consists of many calculating units called nodes, which are inside the layers: input data enter the first layer and output data exit the last layer. The layers between input and output layers are called hidden layers. For modeling purposes, the commonly used feed-forward ANN architecture namely multi-layer perceptron (MLP) may be employed. MLP involves an input layer, an output layer, and one (or more) hidden layer (s) with different roles. Each connecting line has an associated weight. MLP training consists in adjusting the connection weights, so that the calculated outputs may be approximated by the desired values. The output from a given neuron is calculated by applying a transfer function to a weighted summation of its input to give an output, which can serve as input to other neurons, as follows [11]:

$$\boldsymbol{a_{jk} = g_k\left(\sum_{i=1}^{N_{k-1}} w_{ijk} a_{i(k-1)} + b_{jk}\right)} \quad (1)$$

Where a_{jk} are jth neuron outputs from kth layer and $b_{jk}$is the bias weight for neuron j in layer k. The model fitting parameters w_{ijk} are the connection weights. The nonlinear activation transfer functions g_k may have many different forms. The classical ones are threshold, sigmoid, Gaussian and linear function [33–35].

3.2. Back propagation training (BP)

MLP training procedure aims at obtaining an optimal weight set $\mathbf{w_{ijk}}$ and biases that minimizes a pre-specified error function such as average absolute relative deviation percent (AARD %). The back propagation learning algorithm is the most commonly used learning algorithm, and among its methodologies: the quasi-Newton backpropagation (BFGS), the Powell -Beale conjugate gradient, the Levenberge-Marquardt Algorithm (LMA) and others. During the training, both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. Errors are then propagated back through the system, causing the system to adjust the weights that control the network. This process occurs over and over as the weights are continually tweaked.

According to [36,37], the convergence of the BP algorithm is highly dependent on the initial values of weights and biases. In the literature, using novel heuristic optimization methods or evolutionary algorithms (which are naturally inspired algorithms) is a popular solution to enhance the problems of BP-based learning algorithms.

3.3. Naturally Inspired algorithms and their hybridization with ANN

Recently, several naturally inspired algorithms such as Particle Swarm Optimization, and Genetic Algorithms are becoming very powerful in solving hard optimization problems. These methods are suitable for global search due to their capability of exploring and finding promising regions in the search space at an affordable computational time. In this section, a brief theory of the employed algorithm in our study (GA, PSO and GWO) and the manner of their hybridization with ANN (to optimize the weights and thresholds of a pre-established BP-ANN) are given.

3.3.1. Genetic Algorithm (GA)

Genetic algorithm (GA) is a global heuristic, stochastic optimization technique based on evolution theory and genetic principles developed by Holland (1975) [38]. The algorithm begins with a randomly generated population that consists of chromosomes, and applies three kinds of genetic operators: selection, crossover and mutation operators to find the optimal solutions. GA processes the population of chromosomes by replacing unsuitable candidates according to the fitness function. In this study, the considered fitness function is the absolute average deviation between expected and predicted values of BHP. The selection operator of GA is implemented by using the linear ranking selection algorithm to determine which population members are chosen as parents that will create offspring for the next generation. Crossover is a mechanism of randomly exchanging information between two chromosomes. Mutation operation can change the values of randomly chosen gene bits, and this process continues until some predefined termination criteria are fulfilled. Mutation operation aims to make genetic algorithm obtain local random research capability through varying certain genes of chromosome. In the current work, GA is used to optimize the weights and thresholds of the ANN. Fig. 2 summarizes the followed steps to implement GA in the ANN's training.

3.3.2. Particle Swarms Optimization (PSO)

PSO is a population based meta-heuristic algorithm inspired from the nature social behavior and dynamic movements with communications of insects, birds and fish. It was proposed and developed by James Kennedy & Russell Eberhart (1995) [39]. Like evolutionary algorithms, PSO performs searches using a population (called a swarm) of individuals (called particles) that are updated from iteration to iteration. Each particle represents a candidate position (i.e., solution) as a point in a dimensional space, and its status is characterized according to its position and velocity [39,40]. The D-dimensional position and velocity for the particle i at iteration t can be represented as:

$$\boldsymbol{x_{i,t} = \{x_{i1,t}, x_{i2,t}, \dots, x_{iD,t}\}} \quad (2)$$

$$\boldsymbol{v_{i,t} = \{v_{i1,t}, v_{i2,t}, \dots, v_{iD,t}\}} \quad (3)$$

In the partial PSO, the speed and position of each particle change according the following equality [40]:

$$\boldsymbol{v_{iD,t+1} = v_{iD,t} + c_1 r_1 (pbest_{iD,t} - x_{iD,t}) + c_2 r_2 (gbest_{D,t} - x_{iD,t})} \quad (4)$$

Each particle then moves to a new potential solution based on the following equation:

$$\boldsymbol{x_{iD,t+1} = x_{iD,t} + v_{iD,t+1}} \quad (5)$$

In this equality, $v_{iD,t}$ and $x_{iD,t}$ stand for separately the velocity of the particle i at its t iteration and the D-dimension quantity of its position; $pbest_{D,t}$ represents the D-dimension quantity of the individual i at its most optimist position at its t times. $gbest_{D,t}$ is the D-dimension quantity of the swarm at its most optimist position. c_1 indicates the cognitive learning factor; c_2 indicates the social learning factor, r_1 and r_2 are random numbers from [0;1].

A new parameter called inertia weight ω (introduced by Shi and Eberhart in 1998 [41]) was incorporating to the Eqt 4 to enhance its convergence and to slowly reduce the velocity of the particles to keep the swarm under control:

$$\boldsymbol{v_{iD,t+1} = \omega * v_{iD,t} + c_1 r_1 (pbest_{iD,t} - x_{iD,t}) + c_2 r_2 (gbest_{D,t} - x_{iD,t})} \quad (6)$$

The later version of PSO is the version developed by (Clerc M,1999) [42], where a convergence agent is introduced in the speed changing formula:

$$\boldsymbol{v_{iD,t+1} = \chi * \left((v_{iD,t} + c_1 r_1 (pbest_{iD,t} - x_{iD,t}) + c_2 r_2 (gbest_{D,t} - x_{iD,t})\right)} \quad (7)$$

$$\boldsymbol{\chi = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}}$$

where χ is called the convergence factor, $\varphi = c_1 + c_2 > 4$. Generally, φ is equal to 4.1, so χ is equal to 0.729.

In terms of the search for minimization problems, the individual best solution of the particle at the next time step (t+1), is given as follows:

$$\boldsymbol{pbest_{iD,t+1}} = \begin{cases} \boldsymbol{pbest_{iD,t}}, \boldsymbol{if} \ \boldsymbol{f}(\boldsymbol{pbest_{iD,t}}) \leq \boldsymbol{f}(\boldsymbol{x_{iD,t+1}}) \\ \boldsymbol{x_{iD,t+1}}, \ \boldsymbol{otherwise} \end{cases}$$
(8)

where f is the objective function to minimize.

$$\boldsymbol{gbest_{D,t+1}} = \mathbf{min}\{\boldsymbol{f}(\boldsymbol{pbest_{iD,t+1}})\} \tag{9}$$

In this paper, the Clerc's approach is used. Fig. 3 shows the procedure of optimizing the BHP ANN's weights and biases using PSO.

3.3.3. Grey Wolves Optimization (GWO)

GWO is a recently proposed swarm-based metaheuristic [43]. It was proposed and developed by Seyedali Mirjalili [43]. It is inspired from the social leadership and hunting behavior of grey wolves in nature. In this algorithm, the population is divided into four groups: alpha (α), beta (β), delta (δ), and omega (ω). The first three fittest wolves are considered as α, β, and δ who guide other wolves (ω) toward promising areas of the search space. During optimization, the wolves update their positions around α, β, or δ as follows:

$$\vec{\boldsymbol{D}} = |\vec{\boldsymbol{C}}.\overrightarrow{\boldsymbol{X_p}}(\boldsymbol{t}) - \vec{\boldsymbol{X}}(\boldsymbol{t})| \ \boldsymbol{and} \ \vec{\boldsymbol{X}}(\boldsymbol{t}+\mathbf{1}) = \overrightarrow{\boldsymbol{X_p}}(\boldsymbol{t}) - \vec{\boldsymbol{A}}.\vec{\boldsymbol{D}} \tag{10}$$

where t indicates the current iteration, $\vec{A} = 2a.\overrightarrow{r_1} - a$, $\vec{C} = 2\overrightarrow{r_2}$; $\overrightarrow{X_p}(t)$ is the position vector of the prey, X ⃗(t) indicates the position vector of a grey wolf, a is linearly decreased from 2 to 0 (generally), and $\overrightarrow{r_1}, \overrightarrow{r_2}$ are random vectors in [0,1].

In GWO algorithm, it is always assumed that α, β, and δ are likely to be the position of the prey (optimum) [43]. During optimization, the first three best solutions obtained are assumed as α, β, and δ respectively. Then, other wolves are considered as ω and able to re-position with respect to α, β, and δ. The mathematical model proposed to re-adjust the position of ω wolves are as follows [43]:

$$\overrightarrow{\boldsymbol{D_\alpha}} = |\overrightarrow{\boldsymbol{C_1}}.\overrightarrow{\boldsymbol{X_\alpha}}(\boldsymbol{t}) - \vec{\boldsymbol{X}}(\boldsymbol{t})|; \ \overrightarrow{\boldsymbol{D_\beta}} = |\overrightarrow{\boldsymbol{C_2}}.\overrightarrow{\boldsymbol{X_\beta}}(\boldsymbol{t}) - \vec{\boldsymbol{X}}(\boldsymbol{t})|; \ \overrightarrow{\boldsymbol{D_\delta}} = |\overrightarrow{\boldsymbol{C_3}}.\overrightarrow{\boldsymbol{X_\delta}}(\boldsymbol{t}) - \vec{\boldsymbol{X}}(\boldsymbol{t})|$$
(11)

where $\overrightarrow{X_\alpha}(t)$ shows the position of the alpha, $\overrightarrow{X_\beta}(t)$ shows the position of the beta, $\overrightarrow{X_\delta}(t)$ is the position of delta, $\overrightarrow{C_1}$, $\overrightarrow{C_2}$, and $\overrightarrow{C_3}$ are random vectors and $\vec{X}(t)$ indicates the position of the current solution.

These three last equations calculate the approximate distance between the current solution and alpha, beta, and delta respectively. After defining the distances, the final position of the current solution is calculated or updated as follows:

$$\overrightarrow{\boldsymbol{X_1}} = \overrightarrow{\boldsymbol{X_\alpha}}(\boldsymbol{t}) - \overrightarrow{\boldsymbol{A_1}}.\overrightarrow{\boldsymbol{D_\alpha}}; \ \overrightarrow{\boldsymbol{X_2}} = \overrightarrow{\boldsymbol{X_\beta}}(\boldsymbol{t}) - \overrightarrow{\boldsymbol{A_2}}.\overrightarrow{\boldsymbol{D_\beta}}; \ \overrightarrow{\boldsymbol{X_3}} = \overrightarrow{\boldsymbol{X_\delta}}(\boldsymbol{t}) - \overrightarrow{\boldsymbol{A_3}}.\overrightarrow{\boldsymbol{D_\delta}} \tag{12}$$

$$\vec{\boldsymbol{X}}(\boldsymbol{t}+\mathbf{1}) = \frac{\overrightarrow{\boldsymbol{X_1}}+\overrightarrow{\boldsymbol{X_2}}+\overrightarrow{\boldsymbol{X_3}}}{\mathbf{3}} \tag{13}$$

The general steps of the GWO algorithm are [43]:

- Initialize a population of wolves randomly.
- Evaluate the corresponding objective value for each wolf.
- The first three best wolves are saved as α, β, and δ.
- Update the position of the rest of the population (ω wolves) using equations discussed above.
- Update parameters a, A, and C.
- Return the position of α as the best approximated optimum.
- These steps are repeated till the termination criterion will be satisfied.

Fig. 4 illustrates the implementation of GWO to train the BHP ANN.

4. Methodology

4.1. DATA acquisition, pre-fitting and pre-processing

A total of 125 data sets was collected from different Algerian fields. Ten parameters were utilized as inputs of the developed ANN models to predict bottom-hole pressure (BHP) in vertical wells with multiphase flow. The input variables are illustrated in the following sequence: Oil flow rate (Q_{oil}) expressed in (bbl/day), Gas flow rate (Q_{gas}) in (scf/day), Water flow rate (Q_{water}) in (bbl/day), Oil gravity, gas gravity, Depth in (ft), inside pipe diameter (ID) expressed in (inch), well head temperature (WHT) in (°F), well head pressure (WHP) expressed in (Psia) and the gas oil ratio (GOR) in (bbl/scf). The data used for developing the models cover the ranges illustrated in the Table 2.

To check the validity of the collected data and remove the suspected outliers, empirical correlations and mechanistic models were used to predict the bottom-hole flowing pressures and compare them with the measured values. Data sets which consistently resulted in poor predictions by all correlations and mechanistic models were considered to be invalid, and therefore removed. A cut-off-error percentage (relative error) of 20% was implemented for the whole data. After such a screening, a total 100 data sets were used to develop the ANN models: 80% of the filtered data are used to build (training) the ANNs, and the other 20% are used to check the accuracy of the ANNs developed (predictive test).

To improve the convergence conditions of ANN models, the used data are normalized at the interval [-1, 1] according to the following equation:

$$\boldsymbol{x_{normalized}} = \frac{2(x_i - x_{min})}{(x_{max} - x_{min})} - \mathbf{1} \qquad (14)$$

where $x_{normalized}$ is the normalized value of x_i, x_{max} *and* x_{min} are the maximum and minimum values of the variable *x*, respectively (as shown in Table 2).

To demonstrate the correlation between BHP and the used independent variables, the correlation matrix was implemented [44,45]. This matrix illustrates the power of a linear relationship between two different variables in multi-variables system [44,45]. The coefficient between two variables x and y is defined by the following formula:

$$\boldsymbol{r_{xy}} \frac{\sigma_{xy}}{\sigma_x \sigma_y} \qquad (15)$$

where σ_x *and* σ_y are the sample standard deviations, and σ_{xy} is the sample covariance.

Its values are between [-1 1]. Two variables are said to be positively linearly related if their correlation coefficient is close to 1 and negatively linearly if it is close to -1. For values nearby zero, it would indicate a weak linear relationship between the variables.

The obtained correlation matrix between independent variables and BHP is presented in Table 3. The c_{ij} element of the correlation coefficient matrix presents the linear relation between i^{th} and j^{th} variable. According to Table 3, WHP has the maximum degree of linear relation with BHP. In addition, BHP follow the fairly linear tendency with the depth and don't have direct relation with any of the 3 flow rates (oil, water and gas).

4.2. ANN models development

The first step to establish and develop the different models with the cited three algorithms consists to achieve to an ANN topology with BP learning. One hidden layer was employed in our study (it is proven in the literature [46] that a MLP network having only one hidden layer can estimate most of nonlinear systems) and its number of neurons was established using trial and error method (after a series of optimization processes by monitoring the performance of the network until the best network structure was accomplished). The Sigmoid activation function was used as the transfer function from input layer to hidden layer, and the Linear function was taken as the activation function in the last layer. Then, the weights and the biases of the elaborated ANN structure were optimized using evolutionary and metaheuristic algorithms discussed in the theory background part. Table 4 shows the setting parameters of the used algorithms.

4.3. Statistical and graphical error analysis

To evaluate the developed models and their predictive performances, the new models must be compared against existing correlations and models. This is done through cross plots (all predicted values are sketched against the experimental values and therefore across plot is created and compared against a unit slope line which shows the perfect model line: the closer the plotted data to this line, the higher is the reliability of the model) and a group error analysis, using the average absolute percent error (AARD%), standard deviation (SD), and the correlation factor (R^2) as indicators. These statistical indexes can be mathematically expressed by the Eqs (16) through (18).

$$AARD\% = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{BHP_i^{exp}-BHP_i^{cal}}{BHP_i^{exp}}\right| \times 100 \tag{16}$$

$$SD = \sqrt{1/(N-1)\sum_{i=1}^{N}\left(\frac{BHP_i^{exp}-BHP_i^{cal}}{BHP_i^{exp}}\right)^2} \tag{17}$$

$$R^2 = 1-\frac{\sum_{i=1}^{N}\left(BHP_i^{exp}-BHP_i^{cal}\right)^2}{\sum_{i=1}^{N}\left(BHP_i^{cal}-\overline{BHP}\right)^2} \tag{18}$$

where N represents the number of the measured information, BHP_i^{exp} is the observed bottom hole pressure values while BHP_i^{cal} is the calculated BHP values which is predicted by the developed models. Average value of the BHP data is shown by $\overline{BHP}$.

4.4. Leverage approach

Outlier diagnostics (or detection) are of much importance in developing the mathematical models/correlations since it allows to detect the applicability domain of a model and identify suspect data [47–50]. Several approaches have been proposed for this purpose of which Leverage approach is one of the most well-known [47,48]. This approach is based on the calculation of the values of the residuals that represent the deviations of a model results from the experimental data, and a matrix known as Hat matrix composed of the experimental data and the predicted values obtained from a model. Then, the Leverage or Hat indices are calculated based on Hat matrix (H) according to the following expression:

$$H = X(X^t X)^{-1} X^t \tag{19}$$

where X is a two-dimensional $(N \times k)$ matrix composing N data points (rows) and k parameters of the model (columns), and X^t is the transpose of matrix X. The diagonal elements of the H matrix represent the hat values of the data in the feasible region of the model. Once this matrix is calculated, the applicability domain and the outlier detection is done through Williams plot which sketches the correlation of hat indices vs. standardized residuals (R). A warning Leverage (H^*) is generally fixed at the value equal to $3(k+1)/N$, in which N is the number of data points and k is the number of model parameters. A cut-off value (standardized residual) equal to three is regarded to accept the data points within ± 3 range standard deviations from the mean (to cover 99% normally distributed data). If majority of data points exist in the ranges of $0 \leq H \leq H^* \; and \; -3 \leq R \leq 3$, it demonstrates that both model development and its predictions are done in applicability domain and demonstrating that the model is statistically valid.

5. Results and Discussion

5.1. Results with building data (training, testing and validation)

Table 5 shows the results of performed sensitivity analysis for investigation of the number of neurons in the hidden layer for ANN-BP (only topologies, which have been trained several times and show a high degree of accuracy are presented in Table 5). The optimal configuration has been selected by finding the structure that has a high accuracy based on the statistical error analysis. It can be clearly seen that the 12 is the best number of neurons in the hidden layer and the configuration $10 \times 12 \times 1$ (one input layer containing the inputs showed in Table 2, one hidden layer with twelve nodes and one output layer containing one node which is bottom-hole pressure) can be considered as an optimal topology in this study.

In the intelligent session of our study (as it is mentioned before), we investigated the application of optimized ANNs through evolutionary and metaheuristic algorithms discussed above. In order to create an equal competition for our compared models (ANN-BP, ANN-ANN-GA-BP, ANN-PSO-BP and ANN-GWO-BP), we used the same topology as that of ANN-BP, i.e. $10 \times 12 \times 1$. Then, the problem was formulated as an optimization problem to find a set of weights and biases of the ANNs that minimized the difference between the predictions and the target values in the training set of data (a total of 80 wells data are used in this section). It should be noted that the proposed hybridizations could have other possible structures and consequently possibly provides better results, but in this study and since we investigated the optimization of weights and biases of ANNs using these methods, we used the same topology for all applied methods. Different sets of weights and biases were generated randomly and evolved/updated using these algorithms. Matlab® 2016-a [51] was used in this study. As already mentioned, in order to check the accuracy of the developed models, some statistical error analyses have been measured and the results are reported in Table 6. This table demonstrates the statistical parameters of the training process. In addition to statistical error analysis, cross plots of this process are also presented in figures 5 and 6. Fig. 5 shows the results of the BHP ANN-BP which concern the training process. Fig. 6 illustrates the results of the hybridization naturally inspired algorithms with ANNs-BP after the training process as follows: in the subplot (a), measured BHP (the data used) is compared against those of ANN-GA-BP (training); subplots (b) and (c) present measured BHP versus BHP ANN-PSO-BP (Training) and BHP ANN-GWO-BP (Training) respectively.

5.2. Results with predictive data (predictive test)

Once the neural networks were built and trained, they are used to predict BHP with blind data (in our study, a set of 20 wells data are used). The results of this predictive part are presented in Table 7 and Fig. 7. Table 6 illustrates the values of the AARD%, R^2 and SD which are existed between experimental and calculated values by the developed models for the blind data. Subplots of Fig. 7 are cross plots of experimental BHP versus calculated BHP by the developed models for the predictive process.

5.3. Discussion of the obtained results

Tables 6 and 7 highlight that the proposed models predictions (the optimized ANN with the evolutionary and metaheuristic algorithms) are in excellent agreement with experimental data, either in the training or in the predictive sections. The cross plots of the models (Figs. 5-7) show that the most of calculated data lay on the unit slope line, and this proves their perfect accuracy and robustness. In addition, we should note that the proposed ANN techniques (combined with GWO, GA and PSO), achieved minimum mean square error and standard deviation. Thus, these models yield better robustness and stability over the BP artificial neural networks alone.

5.4. Comparison of the ANN models against existing correlations and mechanistic models

To demonstrate the robustness of the developed ANNs models, a performance comparison between these ANNs against existing correlations and mechanistic models is presented in Table 8 through statistical error analyses.

As depicted in Table 8, from existing models (correlations & mechanistic models), and for the whole data used in our study, we see that Gray, Aziz et al. and Ansari et al. correlations are the best outperformed models. Investigation of Table 8 clearly demonstrates the outstanding performance of the established ANNs models. Based on the statistic parameters obtained, the ANN-GWO-BP is the most accurate ANN developed with an AARE value of 4.64% and a standard deviation of 6.90%.

5.5. Outlier detection

To check the range of reliability of the developed models, the H matrix, hat indices and standardized residuals were calculated through the Leverage approach and Williams plots were illustrated. In this study, the number of parameters is ten, and the number of data points is 100. Therefore, $H^*$of the model is set to be 0.33. Fig. 8 shows Williams plot (outlier data detection and applicability domain) of the established models in this work to predict BHP. As can be seen in this figure, Good High Leverage points are accumulated in the domains of $0.33 \leq H^*$ and $-3 \leq R \leq 3$ for the ANNs based naturally inspired algorithms. In addition, nearly all the data points (expect 3 points) are within the applicability domain of the developed ANN-GWO-BP model (in the range of $0 \leq H \leq H^*$ and $-3 \leq R \leq 3$). This is a proof of validity and robustness of this model.

Finally, for utilizing of our best established model (i.e. ANN-GWO-BP) and exact reproducing its results, the detailed information, i.e. its weight and bias matrixes, are reported in Table 9. This model contains one input layer containing the inputs as arranged in Table 10, one hidden layer (it contains twelve nodes) and one output layer (contains one node) which is bottom-hole pressure. The Sigmoid activation function was used as the transfer function from input layer to hidden layer, and the Linear function was taken as the activation function in the last layer. The normalization of dataset followed is expressed in equation (14) with respect to the bounds shown in Table 2.

6. Conclusions

In this study, we developed several intelligent models by adapting methodologies using three naturally inspired algorithms (GA, PSO and GWO) to search optimal feed-forward network weights and biases for predicting BHP in vertical wells from Algerian fields data. A comparison of developed methods to other models, based on the statistical parameters (R^2, AARE and SD) and graphical analyses, showed the superiority of the newly developed methods: the new models provided exceptionally accurate predictions over the best available empirical correlations and mechanistic models. With respect to accuracy ranking, ANN-GWO-BP outperformed the other models, whether intelligent or correlations. Furthermore, Leverage approach reveals that this model is statistically correct and valid with only three probably doubtful data points in the whole experimental data set.

References

[1] A.R. Hagedorn, K.E. Brown, others, Experimental study of pressure gradients occurring during continuous two-phase flow in small-diameter vertical conduits, J. Pet. Technol. 17 (1965) 475–484.

[2] H. Duns Jr, N.C.J. Ros, others, Vertical flow of gas and liquid mixtures in wells, in: 6th World Pet. Congr., 1963.

[3] J. Orkiszewski, others, Predicting two-phase pressure drops in vertical pipe, J. Pet. Technol. 19 (1967) 829–838.

[4] D.H. Beggs, J.P. Brill, others, A study of two-phase flow in inclined pipes, J. Pet. Technol. 25 (1973) 607–617.
[5] K. Aziz, G.W. Govier, others, Pressure drop in wells producing oil and gas, J. Can. Pet. Technol. 11 (1972).
[6] H. Mukherjee, J.P. Brill, Pressure Drop Correlations for Inclined Two-Phase Flow, J. Energy Resour. Technol. 107 (1985) 549. doi:10.1115/1.3231233.
[7] A.M. Ansari, N.D. Sylvester, O. Shoham, J.P. Brill, others, A comprehensive mechanistic model for upward two-phase flow in wellbores, in: SPE Annu. Tech. Conf. Exhib., 1990.
[8] R.N. Chokshi, Z. Schmidt, D.R. Doty, others, Experimental study and the development of a mechanistic model for two-phase flow through vertical tubing, in: SPE West. Reg. Meet., 1996.
[9] L.E. Gomez, O. Shoham, Z. Schmidt, R.N. Chokshi, T. Northug, others, Unified mechanistic model for steady-state two-phase flow: horizontal to vertical upward flow, SPE J. 5 (2000) 339–350.
[10] H.E. Gray, Vertical flow correlation in gas wells, User Man. API14B, Subsurf. Control. Saf. Valve Sizing Comput. Progr. (1974).
[11] R.B.C. Gharbi, G.A. Mansoori, An introduction to artificial intelligence applications in petroleum exploration and production, J. Pet. Sci. Eng. 49 (2005) 93–96. doi:10.1016/j.petrol.2005.09.001.
[12] X. Li, J. Miskimins, B.T. Hoffman, others, A combined bottom-hole pressure calculation procedure using multiphase correlations and artificial neural network models, in: SPE Annu. Tech. Conf. Exhib., 2014.
[13] Z. Li, N. Hovakimyan, G.-O. Kaasa, Bottom hole pressure estimation and □1 adaptive control in managed pressure drilling system, Int. J. Adapt. Control Signal Process. 31 (2017) 545–561.
[14] R. Ashena, J. Moghadasi, Bottom hole pressure estimation using evolved neural networks by real coded ant colony optimization and genetic algorithm, J. Pet. Sci. Eng. 77 (2011) 375–385.
[15] N. Ghaffarian, R. Eslamloueyan, B. Vaferi, Model identification for gas condensate reservoirs by using ANN method based on well test data, J. Pet. Sci. Eng. 123 (2014) 20–29.
[16] B. Vaferi, R. Eslamloueyan, S. Ayatollahi, Automatic recognition of oil reservoir models from well testing data by using multi-layer perceptron networks, J. Pet. Sci. Eng. 77 (2011) 254–262.
[17] Z. Jeirani, A. Mohebbi, Estimating the initial pressure, permeability and skin factor of oil reservoirs using artificial neural networks, J. Pet. Sci. Eng. 50 (2006) 11–20.
[18] B. Vaferi, R. Eslamloueyan, Hydrocarbon reservoirs characterization by co-interpretation of pressure and flow rate data of the multi-rate well testing, J. Pet. Sci. Eng. 135 (2015) 59–72.
[19] B. Vaferi, R. Eslamloueyan, CHARACTERIZATION OF GAS/GAS CONDENSATE RESERVOIRS BY DECONVOLUTION OF MULTIRATE WELL TEST DATA, J. Porous Media. 19 (2016).
[20] B. Vaferi, R. Eslamloueyan, N. Ghaffarian, Hydrocarbon reservoir model detection from pressure transient data using coupled artificial neural network—Wavelet transform approach, Appl. Soft Comput. 47 (2016) 63–75.
[21] E.-S.A. Osman, M.A. Ayoub, M.A. Aggour, others, An Artificial Neural Network Model for Predicting Bottomhole Flowing Pressure in Vertical Multiphase Flow, in: SPE Middle East Oil Gas Show Conf., 2005.
[22] G. Takacs, others, Considerations on the selection of an optimum vertical multiphase pressure drop prediction model for oil wells, in: SPE/ICoTA Coiled Tubing Roundtable, 2001.

[23] A. Witek-Krowiak, K. Chojnacka, D. Podstawczyk, A. Dawiec, K. Pokomeda, Application of response surface methodology and artificial neural network methods in modelling and optimization of biosorption process, Bioresour. Technol. 160 (2014) 150–160.

[24] O. Ronneberger, P. Fischer, T. Brox, U-net: Convolutional networks for biomedical image segmentation, in: Int. Conf. Med. Image Comput. Comput. Interv., 2015: pp. 234–241.

[25] F. Amato, A. López, E.M. Peña-Méndez, P. Va\vnhara, A. Hampl, J. Havel, Artificial neural networks in medical diagnosis, (2013).

[26] W. Huang, K.K. Lai, Y. Nakamori, S. Wang, L. Yu, Neural networks in finance and economics forecasting, Int. J. Inf. Technol. Decis. Mak. 6 (2007) 113–140.

[27] M. Aiken, J. Krosp, M. Vanjani, C. Govindarajulu, A neural network for predicting total industrial production, J. End User Comput. 7 (1995) 19.

[28] Y. Tighilt, F. Bouttout, A. Khellaf, Modeling and design of printed antennas using neural networks, Int. J. RF Microw. Comput. Eng. 21 (2011) 228–233.

[29] A.H. Zaabab, Q.-J. Zhang, M. Nakhla, A neural network modeling approach to circuit optimization and statistical design, IEEE Trans. Microw. Theory Tech. 43 (1995) 1349–1358.

[30] J.E. Rayas-Sánchez, EM-based optimization of microwave circuits using artificial neural networks: The state-of-the-art, IEEE Trans. Microw. Theory Tech. 52 (2004) 420–435.

[31] B. Vaferi, R. Eslamloueyan, S. Ayatollahi, Application of recurrent networks to classification of oil reservoir models in well-testing analysis, Energy Sources, Part A Recover. Util. Environ. Eff. 37 (2015) 174–180.

[32] M. Nait Amar, N. Zeraibi, K. Redouane, Optimization of WAG Process Using Dynamic Proxy, Genetic Algorithm and Ant Colony Optimization, Arab. J. Sci. Eng. (2018) 1–14. doi:10.1007/s13369-018-3173-7.

[33] B. Malakooti, Y. Zhou, Approximating polynomial functions by feedforward artificial neural networks: capacity analysis and design, Appl. Math. Comput. 90 (1998) 27–51.

[34] Y.-W. Huang, Neural Networks for Chemical Engineers Edited by AB Bulsari (Lappeenranta University of Technology, Finland). Elsevier: Amsterdam. 1995. ix+ 680 pp. $285.25. ISBN 0-444-820970-3., (1996).

[35] K. Hornik, M. Stinchcombe, H. White, Multilayer feedforward networks are universal approximators, Neural Networks. 2 (1989) 359–366. doi:10.1016/0893-6080(89)90020-8.

[36] J.-R. Zhang, J. Zhang, T.-M. Lok, M.R. Lyu, A hybrid particle swarm optimization–back-propagation algorithm for feedforward neural network training, Appl. Math. Comput. 185 (2007) 1026–1037.

[37] S. Mirjalili, S.Z. Mohd Hashim, H. Moradian Sardroudi, Training feedforward neural networks using hybrid particle swarm optimization and gravitational search algorithm, Appl. Math. Comput. 218 (2012) 11125–11137.

[38] S.N. Sivanandam, S.N. Deepa, Introduction to genetic algorithms, Springer, 2007.

[39] J. Kennedy, R. Eberhart, PSO optimization, in: Proc. IEEE Int. Conf. Neural Networks, 1995: pp. 1941–1948.

[40] Y. Shi, R.C. Eberhart, Empirical study of particle swarm optimization, in: Evol. Comput. 1999. CEC 99. Proc. 1999 Congr., 1999: pp. 1945–1950.

[41] Y. Shi, R. Eberhart, A modified particle swarm optimizer, in: Evol. Comput. Proceedings, 1998. IEEE World Congr. Comput. Intell. 1998 IEEE Int. Conf., 1998: pp. 69–73.

[42] M. Clerc, The swarm and the queen: towards a deterministic and adaptive particle swarm optimization, in: Evol. Comput. 1999. CEC 99. Proc. 1999 Congr., 1999: pp. 1951–1957.

[43] S. Mirjalili, S.M. Mirjalili, A. Lewis, Grey wolf optimizer, Adv. Eng. Softw. 69 (2014) 46–61.

[44] N. Samani, M. Gohari-Moghadam, A.A. Safavi, A simple neural network model for the

determination of aquifer parameters, J. Hydrol. 340 (2007) 1–11. doi:10.1016/j.jhydrol.2007.03.017.
[45] B. Vaferi, F. Samimi, E. Pakgohar, D. Mowla, Artificial neural network approach for prediction of thermal behavior of nanofluids flowing through circular tubes, Powder Technol. 267 (2014) 1–10.
[46] G. Cybenko, Approximation by superpositions of a sigmoidal function, Math. Control. Signals Syst. 2 (1989) 303–314.
[47] X.-Q. Bian, B. Han, Z.-M. Du, J.-N. Jaubert, M.-J. Li, Integrating support vector regression with genetic algorithm for CO2-oil minimum miscibility pressure (MMP) in pure and impure CO2 streams, Fuel. 182 (2016) 550–557.
[48] P.J. Rousseeuw, A.M. Leroy, Robust regression and outlier detection, John wiley & sons, 2005.
[49] C.R. Goodall, 13 Computation using the QR decomposition, Handb. Stat. 9 (1993) 467–508. doi:10.1016/S0169-7161(05)80137-3.
[50] P. Gramatica, Principles of QSAR models validation: internal and external, Mol. Inform. 26 (2007) 694–701.
[51] MATLAB - MathWorks 2016.

Table 1: examples of the ranges and application intervals of some BHP correlations & mechanistic models

BHP Correlations/ Mechanistic models	year of publication	Conditions/ range of development
Hagedorn and Brown [1]	1965	1500 ft experimental vertical well. 1.0, 1.25, 1.5 in nominal diameter tubes; Liquids with different viscosities: 0.86 cp (water), 30, 35 and 110 (oil); Liquide flow rates: 30-1680 bbl/day; and, Gas-liquid ratios: 0-3270 scf/bbl.
Beggs and Brill [6]	1973	The parameters studied and their range of variation were, . Gas (air) flow rate: 0 to 300 Mscf/day; . Liquid (water) flow rate: 0 to 1029 bbl/day . Pipe diameter: 1.0 to 1.5 in; . Liquid holdup: 0 to 0.870; . Pressure gradient: 0 to 0.80 psi/ft; . Inclination angle: -90° to +90°;
Aziz et al. [5]	1972	Oil flow rates are between 44 and 1850 bbl/day API gravity of 36 to 47.3
Orkiszewski [3]	1967	Oil flow rates are between 175 and 3166 bbl/day Wells depth from 3705ft to 4766 ft

Table 2: the ranges of the used data

	Parameters	Max value	Min value
Inputs	Q_{oil} (bbl/d)	1660	8
	Q_{gas} (Mscf/d)	572	22500
	Q_{water} (bbl/d)	750	0
	Oil gravity	0.931	0.569
	Gas gravity	0.884	0.602
	ID (in)	4.404	1.61
	Depth (ft)	14742	3678
	WHP (Psi)	8472	450
	WHT (°F)	184	46
	GOR (bbl/scf)	1170000	701
Output	BHP (Psia)	11250	653

Table 3: Values of linear relationship between considered variables in BHP estimation

Depth	ID	GOR	Oil gravity	Gas gravity	Q_{oil}	WHP	WHT	Q_{water}	Q_{gas}	BHP	Variables
1.0	-0.29	-0.14	0.40	-0.09	0.31	0.72	0.28	0.19	-0.07	0.77	Depth
-0.29	1.0	0.23	-0.45	0.27	0.21	-0.44	-0.03	-0.17	0.61	-0.42	ID
-0.14	0.23	1.0	-0.08	-0.08	-0.23	-0.15	-0.04	0.00	0.23	-0.17	GOR
0.40	-0.45	-0.08	1.0	-0.24	0.0	0.50	0.17	0.23	-0.21	0.51	Oil gravity
-0.09	0.27	-0.08	-0.24	1.0	0.37	-0.39	-0.03	-0.20	0.12	-0.32	Gas gravity
0.31	0.21	-0.23	0.0	0.37	1.0	0.08	0.08	-0.14	0.42	0.16	Q_{oil}
0.72	-0.44	-0.15	0.50	-0.39	0.08	1.0	0.21	0.26	-0.21	0.97	WHP
0.28	-0.03	-0.04	0.17	-0.03	0.08	0.21	1.0	0.03	0.05	0.24	WHT

0.19	-0.17	0.0	0.23	-0.20	-0.14	0.26	0.03	1.0	-0.16	0.31	Q_{water}
-0.07	0.61	0.23	-0.21	0.12	0.42	-0.21	0.05	-0.16	1.0	-0.18	Q_{gas}
0.77	-0.42	-0.17	0.51	-0.32	0.16	0.97	0.24	0.31	-0.18	1.0	BHP

Table 4: Naturally inspired algorithms setting used in the study

algorithm	Parameters	Value/setting
GA	Population size	50
	Crossover's probability	90 %
	Mutation's probability	0.01%
	Type of selection	Linear ranking
	Max number of generation	250
	Coding	Binary
PSO	Size of the Swarm	50
	Max number of iteration	250
	C1	2.05
	C2	2.05
	χ	0.729
GWO	Number of wolves	50
	Max number of iteration	250
	a	linearly decreased from 5 to 0

Table 5: AARE (%), R^2 and SD (%)values for various ANN topologies

Number of hidden neurons	AARE (%)	R^2	SD (%)
4	8.87	0.9931	13.21
10	6.78	0.9951	8.79
12	**5.18**	**0.9970**	**7.99**
16	9.31	0.9945	13.73
20	6.27	0.9965	8.94
27	7.57	0.9938	11.25

Table 6: Results of the building section

	AARE (%)	**R^2**	**SD (%)**
ANN-BP	5.18	0.9970	7.99
ANN-GA-BP	4.86	0.9983	6.51
ANN-PSO-BP	4.62	0.9984	6.70
ANN-GWO-BP	4.10	0.9980	6.16

Table 7: Results of the prediction section

	AARE (%)	R^2	SD (%)
ANN-BP	7.97	0.9834	11.53
ANN-GA-BP	6.34	0.9893	10.03
ANN-PSO-BP	6.90	0.9890	10.35
ANN-GWO-BP	6.81	0.9921	9.87

Table 8: Comparison of the developed models with the common correlations and mechanistic models to predict BHP

	Model	AARE (%)	R^2	SD (%)
The developed Models (training + prediction)	**ANN-BP**	5.738	0.9943	8.70
	ANN-GA-BP	5.156	0.9965	7.21
	ANN-PSO-BP	5.076	0.9965	7.43
	ANN-GWO-BP	4.642	0.9968	6.90
The existing models	**Ansari et al.**	5.89	0.9937	7.95
	Beggs & Brill	8.06	0.9934	11.72
	Duns et Ros	8.94	0.9921	12.04
	Aziz et al.	5.79	0.9937	7.75
	Hagedorn et Brown	6.40	0.9931	8.23
	Gray	5.33	0.9950	7.28
	Mukherjee et Brill	9.08	0.9906	12.31
	Orkiszewski	18.50	0.9855	22.59

Table 9: Weights and biases of the ANN-GWO-BP

Neurons	Weight values of connections between input and hidden layer									
1	0.5757	-1.1635	-0.8763	1.4949	0.7954	-0.6475	-1.6290	-1.7631	0.5552	1.1967
2	-2.2366	-0.7505	-1.7698	0.5346	1.1133	0.1721	-1.8439	0.3027	0.3900	0.6366
3	1.0230	1.4026	-1.6195	-0.8070	0.0930	0.9736	-0.7396	0.5130	-1.6048	-1.7160
4	1.8853	-1.7139	0.7817	-1.1562	-1.2866	-0.6320	0.8445	1.0901	0.0484	-0.2232
5	-0.9390	0.1201	0.8347	-0.0610	-0.7509	1.8678	1.2313	1.6444	1.0299	-0.9241
6	-1.0118	0.0014	1.0990	1.3180	-1.1244	0.9807	-1.5145	0.6989	-1.5218	-0.8136

7	-1.1619	0.3702	0.7682	-1.6552	-0.6756	0.3022	-1.0408	0.0210	0.0248	-1.5820
8	0.1217	-1.5722	-0.2641	1.2784	0.2881	1.1623	-1.1465	1.7998	0.7862	1.6195
9	0.4207	2.2443	-0.3439	1.5695	1.7279	-0.0864	1.0836	0.8775	-0.3140	-0.8922
10	-0.2855	1.8144	-0.7272	1.9593	0.4484	-1.6312	0.4802	-1.2393	0.6730	0.2976
11	-0.2225	2.0064	-0.6391	1.3521	1.4044	-0.5485	-0.6333	1.2238	0.3653	1.2372
12	0.5439	-0.4550	-1.5728	0.2667	-0.0263	-0.0998	2.8425	-1.3738	-0.8637	-0.4769

Weight values of connections between hidden and output layer

-0.6203	-0.4544	-0.1717	0.0438	0.7390	-0.3602	-0.3600	0.3843	0.4329	0.4798	-0.4288	0.8237

Biases of the hidden layer

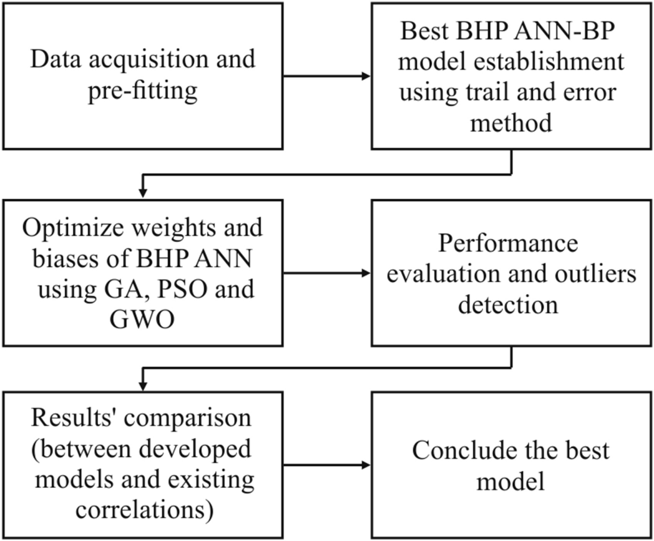
-3.6524	2.5227	-2.157	-1.338	1.1527	0.6006	-0.5242	0.6321	-1.6766	2.6273	-2.9119	-3.1651

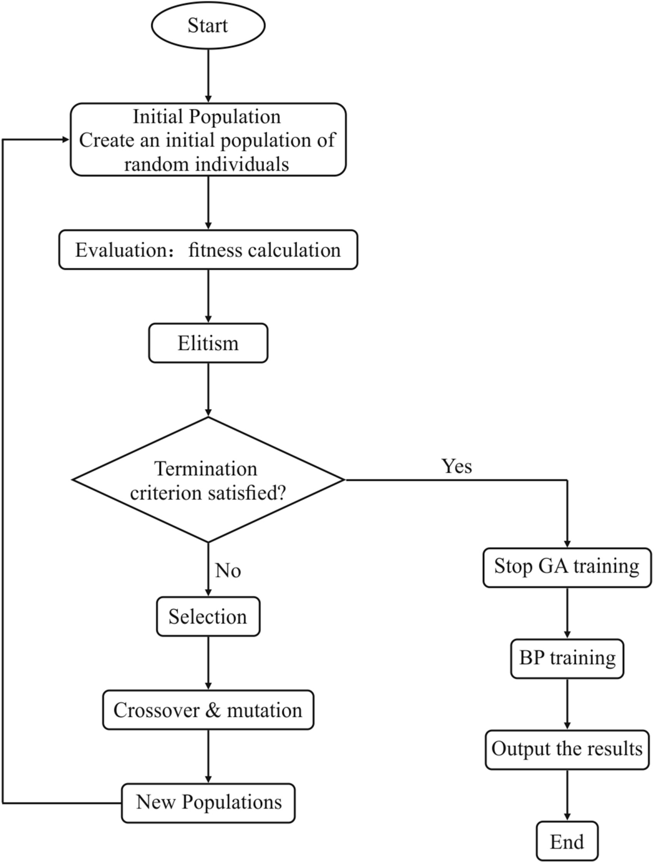
Biases of the output layer

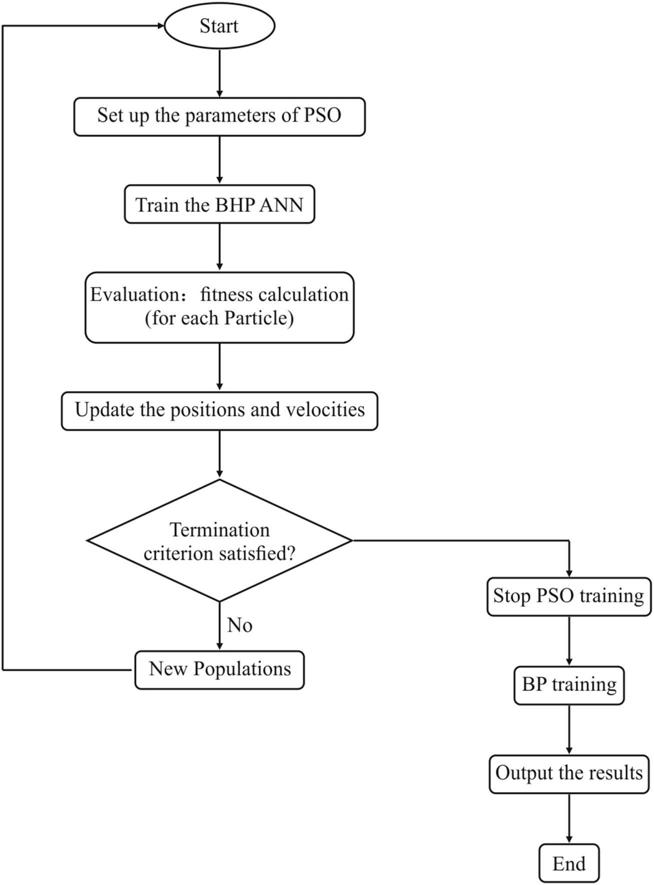
-0.2000

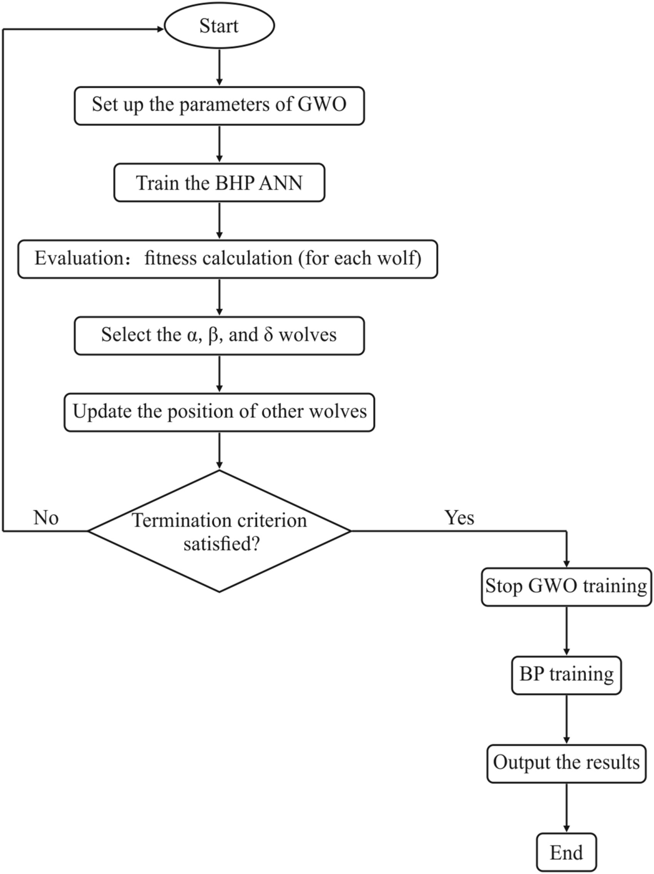
Table 10: order of the inputs in the input layer of the ANN-GWO-BP

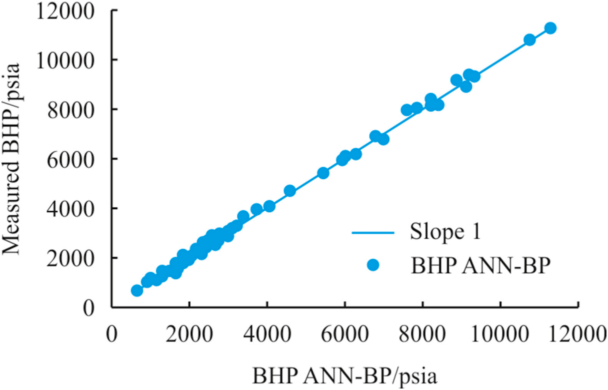
Input layer (order of the inputs)	
	Depth
	ID
	GOR
	Oil gravity
	Gas gravity
	Q_{oil}
	WHP
	WHT
	Q_{water}
	Q_{gas}


Data acquisition and pre-fitting
Best BHP ANN-BP model establishment using trail and error method
Optimize weights and biases of BHP ANN using GA, PSO and GWO
Performance evaluation and outliers detection
Results' comparison (between developed models and existing correlations)
Conclude the best model

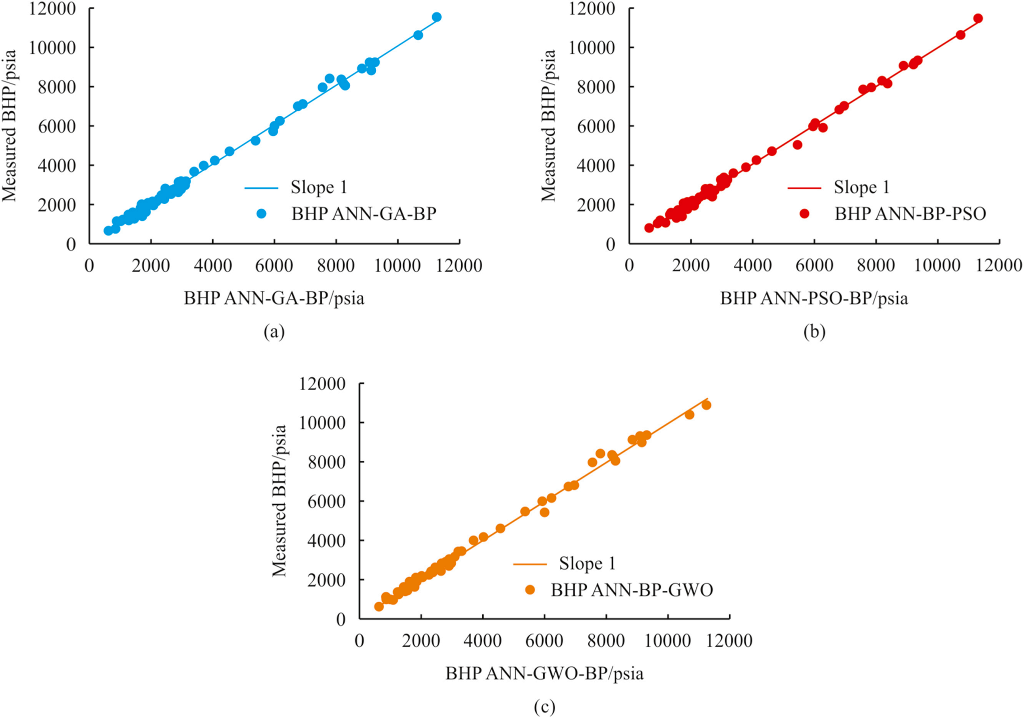

Start
Initial Population
Create an initial population of random individuals
Evaluation： fitness calculation
Elitism
Termination criterion satisfied?
Yes
No
Selection
Crossover & mutation
New Populations
Stop GA training
BP training
Output the results
End

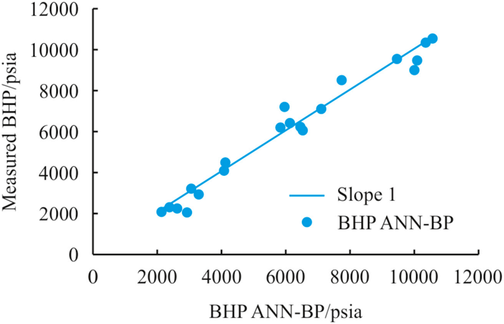

Start
Set up the parameters of PSO
Train the BHP ANN
Evaluation：fitness calculation (for each Particle)
Update the positions and velocities
Termination criterion satisfied?
No
New Populations
Stop PSO training
BP training
Output the results
End


Start
Set up the parameters of GWO
Train the BHP ANN
Evaluation： fitness calculation (for each wolf)
Select the α, β, and δ wolves
Update the position of other wolves
Termination criterion satisfied?
No
Yes
Stop GWO training
BP training
Output the results
End

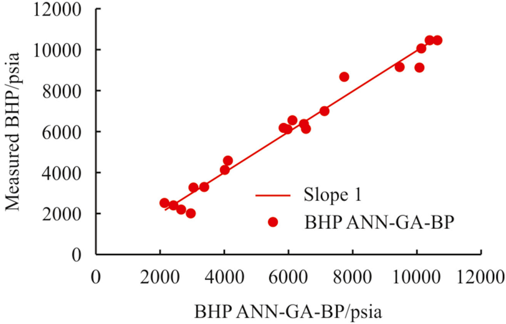


Measured BHP/psia
BHP ANN-BP/psia
Slope 1
BHP ANN-BP
0
2000
4000
6000
8000
10000
12000

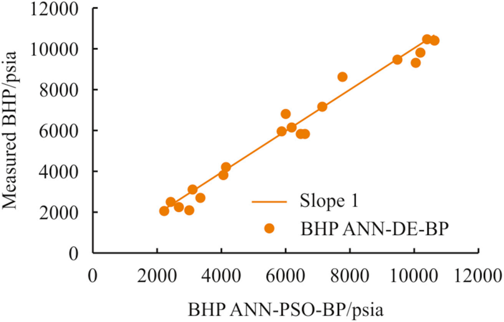

12000
10000
8000
6000
4000
2000
0
Measured BHP/psia
0
2000
4000
6000
8000
10000
12000
BHP ANN-GA-BP/psia
Slope 1
BHP ANN-GA-BP
(a)
Measured BHP/psia
BHP ANN-PSO-BP/psia
Slope 1
BHP ANN-BP-PSO
(b)
Measured BHP/psia
BHP ANN-GWO-BP/psia
Slope 1
BHP ANN-BP-GWO
(c)


12000
10000
8000
6000
4000
2000
0
Measured BHP/psia
0
2000
4000
6000
8000
10000
12000
BHP ANN-BP/psia
Slope 1
BHP ANN-BP

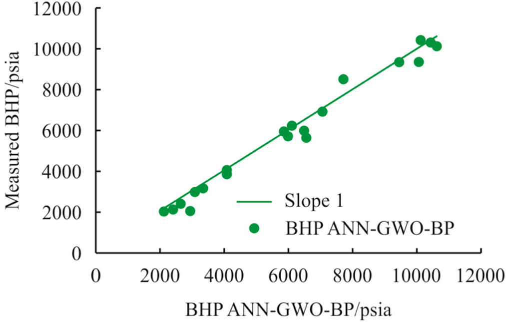
(a)


12000
10000
8000
6000
4000
2000
0
Measured BHP/psia
0
2000
4000
6000
8000
10000
12000
BHP ANN-GA-BP/psia
Slope 1
BHP ANN-GA-BP

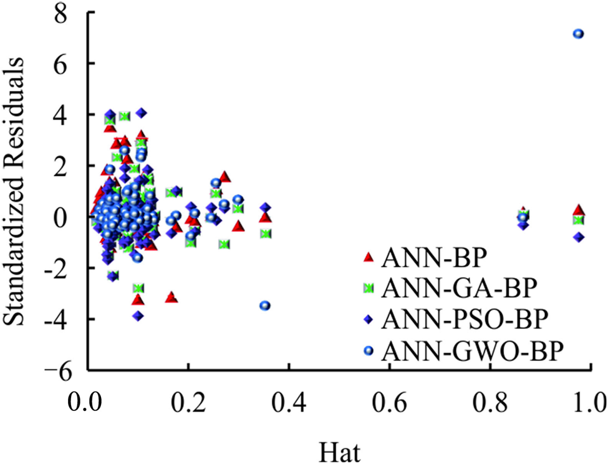
(b)


12000
10000
8000
6000
4000
2000
0
Measured BHP/psia
0
2000
4000
6000
8000
10000
12000
BHP ANN-PSO-BP/psia
Slope 1
BHP ANN-DE-BP

(c)


12000
10000
8000
6000
4000
2000
0
Measured BHP/psia
0
2000
4000
6000
8000
10000
12000
BHP ANN-GWO-BP/psia
Slope 1
BHP ANN-GWO-BP

(d)


Standardized Residuals
Hat
ANN-BP
ANN-GA-BP
ANN-PSO-BP
ANN-GWO-BP
8
6
4
2
0
-2
-4
−6
0.0
0.2
0.4
0.6
0.8
1.0

Highlights

- BHP is a needed parameter for effective well design.
- Several correlations and mechanistic models exist, but they fail to cover the whole range of application's condition.
- A new approach to apply artificial neural network combined with evolutionist and meta heuristic algorithms was established.
- A Hybrid GA-BPANN, PSO-BPANN, and GWO-BPANN models are used to estimate BHP with a significant range of conditions.
- The models have a robust performance compared with the existing methods.
- GWO-BPANN is the most accurate over the developed models.