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Original article

Toward connectionist model for predicting bubble point pressure of crude oils: Application of artificial intelligence

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ABSTRACT

Knowledge about reservoir fluid properties such as bubble point pressure (P_b) plays a vital role in improving reliability of oil reservoir simulation. In this work, hybrid of swarm intelligence and artificial neural network (ANN) as a robust and effective method was executed to determine the P_b of crude oil samples. In addition, the exactly precise P_b data samples reported in the literatures were employed to create and validate the PSO-ANN model. To prove and depict the reliability of the smart model developed in this study for estimating P_b of crude oils, the conventional approaches were applied on the same data set. Based on the results generated by PSO-ANN model and other conventional methods and equation of states (EOS), the PSO-ANN model is a reliable and accurate approach for estimating P_b of crude oils. This is certified by high value of correlation coefficient (R^2) and insignificant value of average absolute relative deviation (AARD%) which are obtained from PSO-ANN outputs. Outcomes of this study could help reservoir engineers to have better understanding of reservoir fluid behavior in absence of reliable and experimental data samples.

1. Introduction

Generally, simulating numerically the hydrocarbon reservoirs, designing efficiently surface facilities, calculating precisely the inflow performance, estimating suitably reserves, analyzing logically the well testing generated data and gaining usefully from the material balance are strong functions of fluid PVT properties, specially the bubble point pressure (P_b) which plays the leading role in all reservoirs' relevant calculations and developing plans [1–12].

Bubble point pressure in term is defined as the maximum pressure in which the first gas bubbles start forming and evolving [13].

In spite of reliable results generated normally with some experimental procedures about P_b, their time-consuming and expensive steps [14] besides their noticeable dependency towards the quality and quantity of gathered samples particularly when the pressure of the reservoir vicinity of the wellbore has fallen below the P_b have always been addressed as main concerns [15–18]. Having lack of ability to predict the target reservoir fluid properties under all the probable thermo dynamical conditions and requiring widespread and detailed knowledge about all compositions forming the oil sample which is a difficult determination in terms of money and time have all in all caused not also to consider Equation of States (EOS) as suitable P_b predicting methods whose accuracies are highly dependent to types of fluids, chosen equations, etc. [19–25].

Therefore, numerous numbers of researches including a variety of EOSs, a diversity of empirical correlations and cutting-edge artificial intelligence based methods have been proposed, derived and developed to overcome the referred hurdle and propose an appropriate solution to predict the P_b, even though

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using some local data to suggest these models is a disadvantage which leads them not to become as much as useful and popular methods to be referenced in all geological areas of the world [13]. In more details, gas solubility, gas gravity, oil gravity and reservoir temperature was firstly taken by Standing to propose a model to predict P_b [26]. Based on oil samples without any non-hydrocarbon impurities and the Henry's law, Lasater performed a model to predict the supposed bubble point pressure [27]. Also, a graphical model which assumes corrections for the presence of gaseous impurities such as H_2, N_2 and H_2S gained from North Sea data was built by Glasoto predict series of parameters including P_b, B_o, total oil formation volume factor (B_t) and μ_o [28]. After running very detailed numerical analysis on a very large and extensive data center, Velarde et al. tuned the already aroused correlations up by introducing a new coefficient [29]. Moreover, Gharbi and Elsharkawy initially implemented an Artificial Neural Network (ANN) to predict PVT properties consist of P_b for crude oil samples gathered from Middle East [30]. Once again Gharbi et al. designed another multilayer perceptron ANN to predict P_b through forming a massive data center gathered from all parts of the world [31]. Next, El-Sebakhy et al. generated a formula to predict the P_b and $B_o$by using support vector regressions and gaining from 3 different PVT databases [32]. Regardless of triumphs represented by applying ANN models to predict PVT properties, its inherent limitations and constrains have caused researcher to look for more analytical, precise and robust methods capable of defeating obstacles resulted from vagueness, complexities, ambiguities and nonlinear behavior natures of reservoirs parameters [33,34]. All in all, made efforts gave rise to put forward applications of up-to-the-minute soft computing schemes such as using Adaptive Neuro-Fuzzy Inference System (ANFIS) normally in predictions of the reservoir characterizations and operations [35] or conducting approach of Support Vector Machine (SVM) to predict the P_b factor, the study that took a set of compositional, handy PVT properties and reservoir thermo dynamical parameter as input [13].

Furthermore, the aim of this research is summarized to introduce and develop a user friend, effective and sharp model to estimate bubble point pressure (P_b) of crude oil samples. To gain this end, hybrid of swarm intelligence and neural network as robust type of artificial intelligent methods was executed to tackle the aforementioned target of this study. Massive P_b data banks extracted from previous works [36–55] were employed to test and validate the PSO-ANN model. To certify the efficiency and integrity of the PSO-ANN model, conventional methods and EOSs were employed to predict the P_b of crude oils. The results gained from both PSO-ANN and EOS models are demonstrated in details in further sections.

2. Data gathering

To start carrying the introduced correlation out, it is necessary to from a database. Farasat et al. [13] published full set data center which includes 123 records in four main divisions to predict the predict P_b [13]. Those are Temperature (°F), bubble point pressure (P_b) and reservoir fluid composition such as nitrogen, methane, ethane, propane, etc. mole fractions. The overview of the published data summarized through Table 1.

Table 1
Statistical parameters of the implemented bubble point pressure data set [13].

Variables	Min	Max	Average
Bubble point pressure, psia	313	6880	2283.2
Temperature, °F	128	324	177.3
Hydrogen sulfide, mol fraction	0	3.68	0.14
Carbon dioxide, mol fraction	0	9.11	1.09
Nitrogen, mol fraction	0	1.67	0.36
Methane, mol fraction	5.63	74.18	33.10
Ethane, mol fraction	0.84	12.45	7.35
Propane, mol fraction	0.43	11.87	6.33
Butanes, mol fraction	0.95	8.40	4.58
Pentanes, mol fraction	0.40	6.65	3.27
Hexanes, mol fraction	0	6.65	3.20
Heptanes-plus, mol fraction	10.72	83.20	40.63
Molecular weight C_{7+}	134	324	230.9
Specific gravity C_{7+}	0.743	0.942	0.861

3. Methodology

3.1. Artificial neural network (ANN)

ANN, a bio-inspired approach which their initial pattern has been recognized from studying the everyday procedures of human brain, is succinctly capable of correlating numerically and inversely the relationships between inputs and outputs of each supposed system by thanks to their distinctive mathematical structures. The gathered laboratorial data are technically implemented to train the network then; the prepared network is gained to estimate the imprecise and blurred data [56–71]. The depicted scheme is conductible through relying on synchronous processing units, known as neurons and nods, located in layers. The input layer, a certain number of hidden layers and an output layer are the basic components of each ANN which the number of their neurons are specified by the available data, designers and target of the discussed problem, respectively. Indisputably, the back-propagation feed forward network and specifically the multilayer perceptron (MLP) networks, those evaluate through considering the classical techniques in relation to their much reduced development time and their potential to make usage of related info, are the most promising and popular kinds of ANN in petroleum engineering [56–66,69–76].

Before tackling by details to the main issue of this study which is carrying an up-to-the-minute optimizing method out to set precisely the ANN related variables. The referred theme has been followed by dividing the database into two main parts apparently named training and testing sets. Regarding this division is due to determine the most appropriate network structure by applying the larger group, training ones, while the testing set which has not earlier been faced to the network in the training step is piloted to examine the reliability of the proposed network in the case of correlating the bubble point pressure. Running the optimization of interconnected weights and node biases is continued up till the performance of the proposed ANN is based on some statistical criteria like Mean Squared Error (MSE) permissible and it is when the values of outputs at the neurons of output layer are very nearly close to the corresponding experimental data [56–60]. The MSE is expressed as follow

$$MSE^{Approach} = \frac{1}{2}\sum_{k=1}^{G}\sum_{j=1}^{m}\left[Y_j(k) - T_j(k)\right]^2 \quad (1)$$

In which m stands for the number of output nodes, G denotes the number of training samples, $Y_j(k)$ stands for the expected target, and $T_j(k)$ denotes the real target. When the MSE closes gradually to the zero, the error of our developed network model starts declining [56–66,69–71] (see Fig. 1).

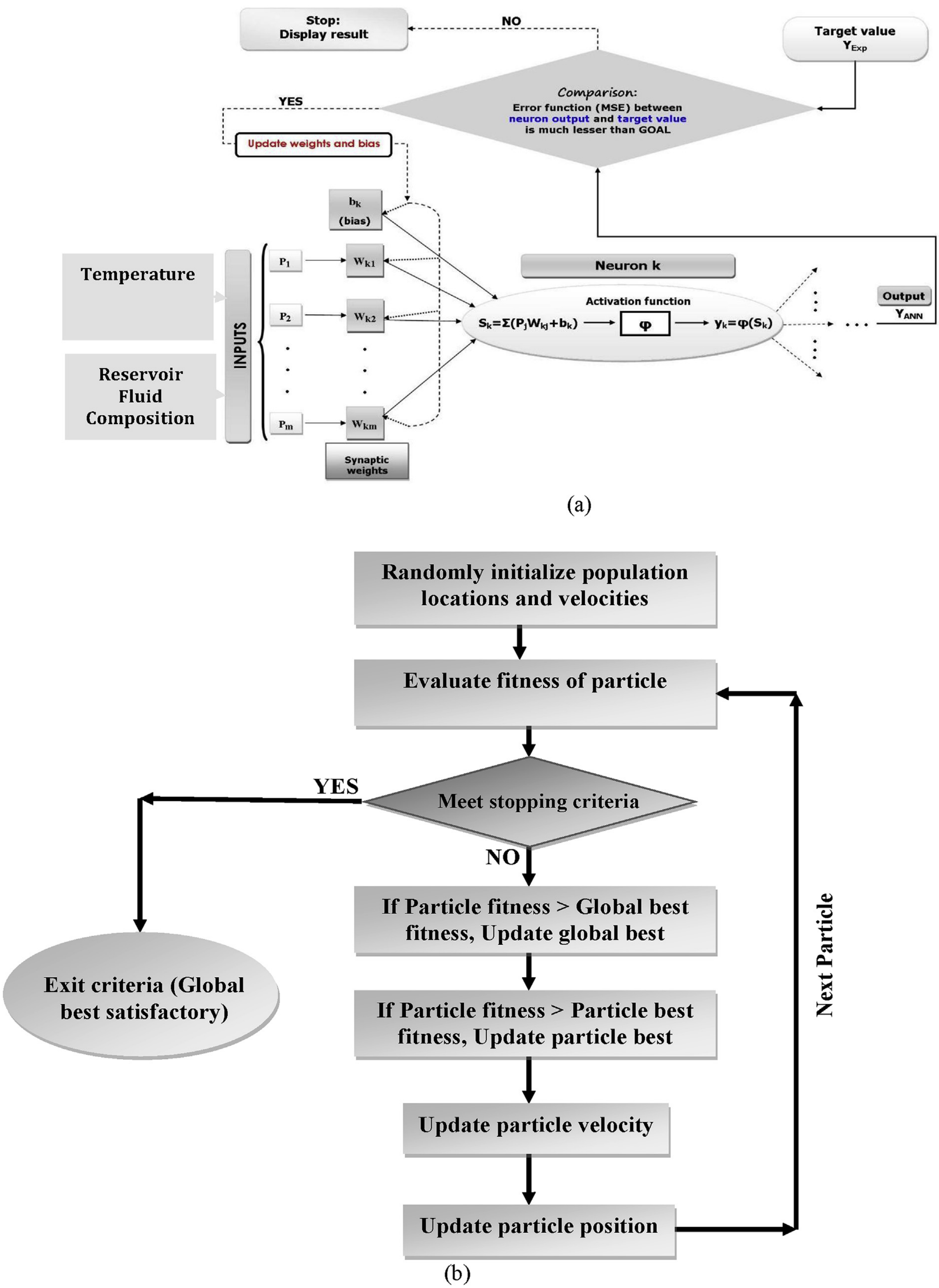

Fig. 1. Flow chart of a) feed-forward neural network b) particle swarm optimization process [56–60,62,69–71].

3.2. Particle swarm optimization (PSO)

Particle Swarm Optimization (PSO) is an optimization which has mathematically been inspired from studying and modeling the behavior of social organisms like a flock of birds. Similarly to the genetic algorithm (GA), particle swarm optimization (PSO) is initiated with a population of random routs, called particles. These particles are supposed to stir within the defined search space with an adaptable velocity to save the best position. Also, in order to keep an eye on the target, each particle has the ability to update its velocity vector as well. This is possible thanks to their own flying experience and the flying experience of the other particles in the search space as illustrated in Fig. 2 [56–63,65,69–71].

4. Results and discussion

Fig. 2 represents the regression plot of the PSO-ANN outcomes versus relevant actual bubble point pressure data. As demonstrated in Fig. 2, the output of the PSO-ANN model for both training and validating phases follow the diagonal line (Y = X). The outputs of the PSO-ANN approach are closet to corresponding real bubble point pressure values. Fig. 3 depicts the outputs of PSO-ANN model and real P_b versus

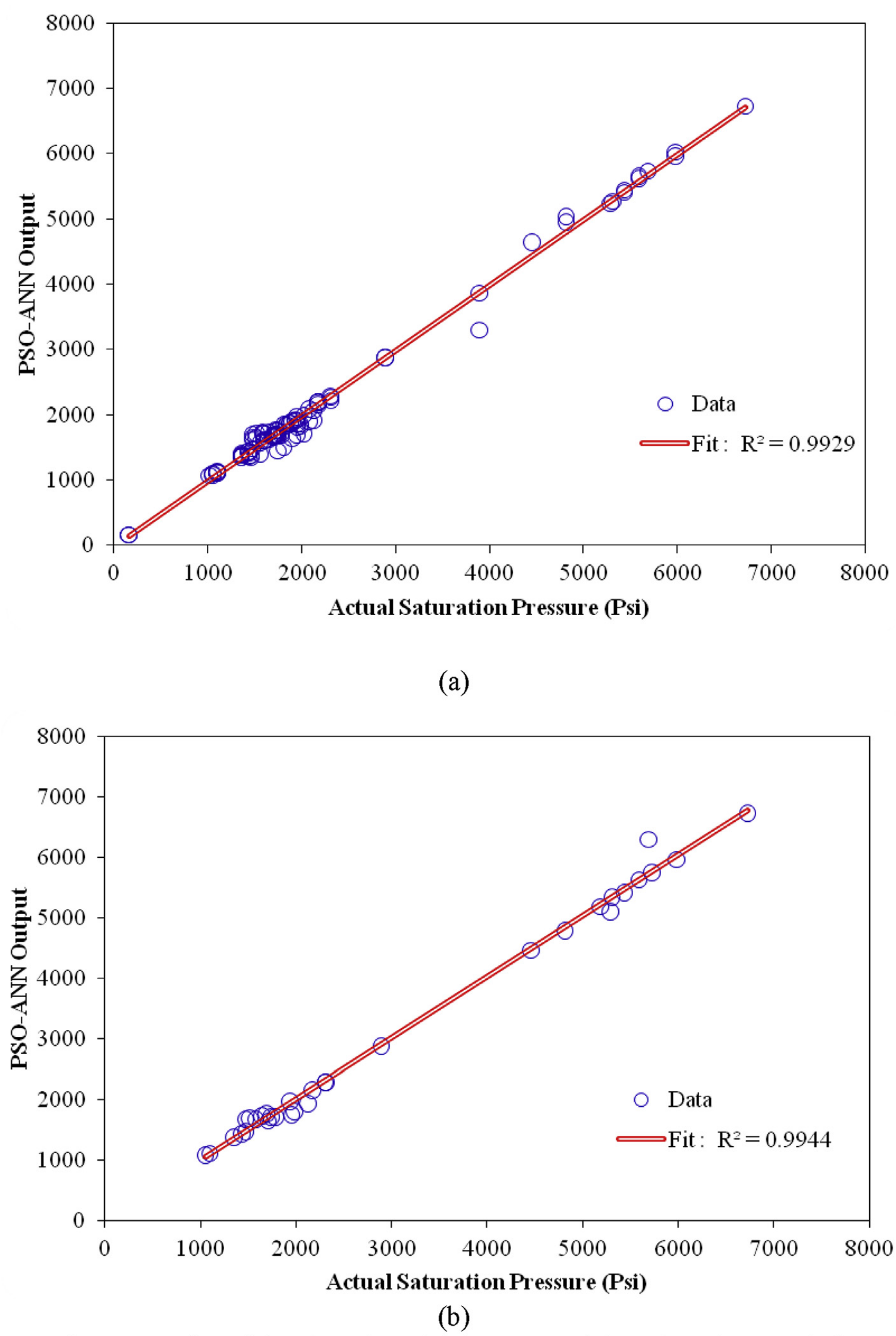

Fig. 2. Performance plot of developed model (PSO-ANN) based on the correlation coefficient (R^2).

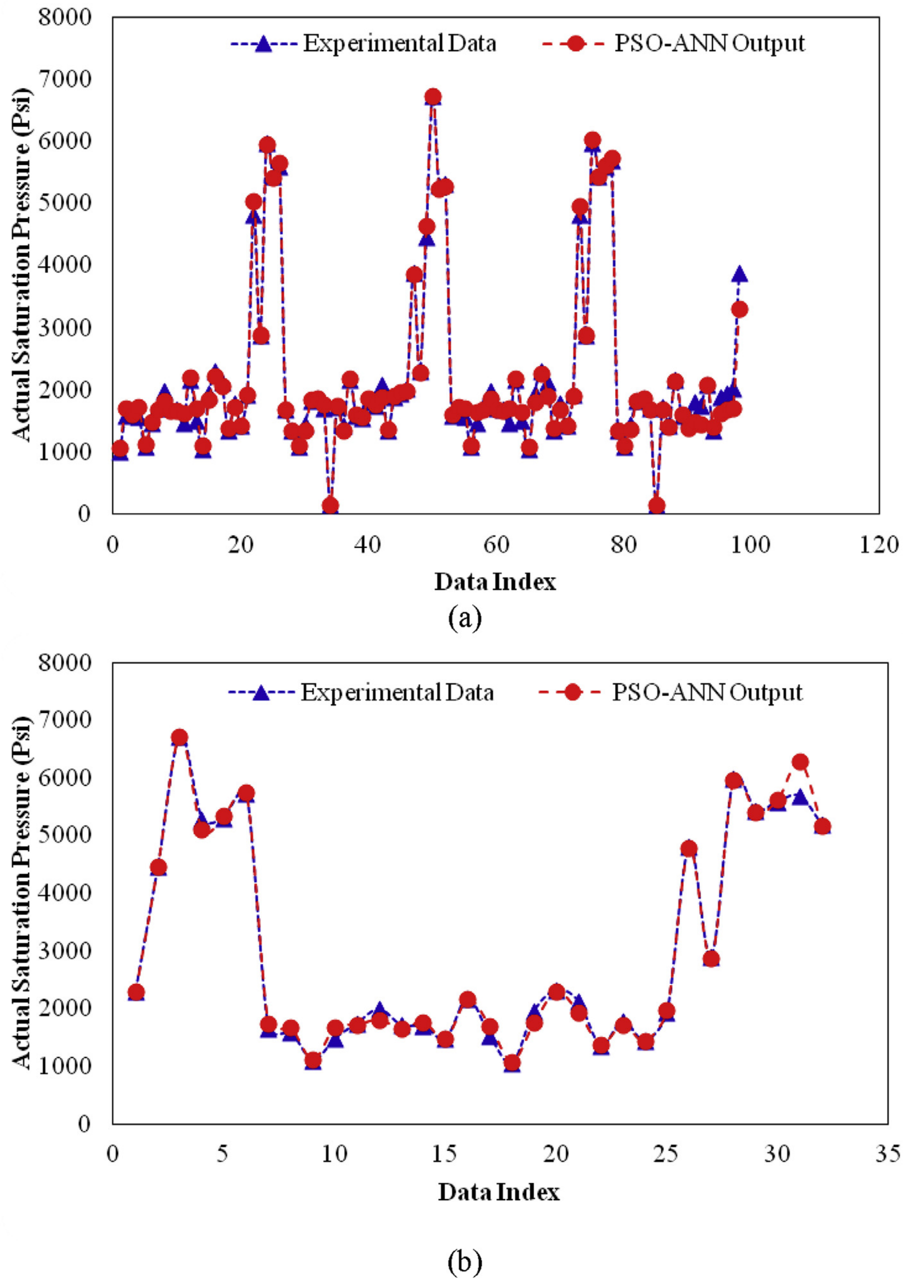

Fig. 3. Comparison between developed model (PSO-ANN) outputs and relevant actual bubble point pressure versus data index a) Training phase b) Testing phase.

corresponding data index. As depicted in Fig. 3, swarm model outputs follow exactly the actual behavior of the real P_b data. Finally, Fig. 4 depicts the relative error distribution of the outputs of the PSO-ANN model versus corresponding bubble point pressure data samples. Furthermore, relative error distribution of the outputs of the PSO-ANN model versus most important parameters such as temperature, molecular weight of C_{7+}, specific gravity of C_{7+} and mole percent of C_{7+} is depicted in Fig. 4. As demonstrated in Fig. 4, the maximum deviation of the PSO-ANN model refers to bubble point pressures in ranges of 1000–2000 Psi, which is around 15%. Moreover, maximum deviations refer to the lower boundary of temperature; however, greater deviations are referred to the higher values of C_{7+} mole percent. Based on the statistical criteria calculated for the used approaches, the PSO-ANN model is superior than the other thermodynamic and/or conventional approaches in estimation bubble point pressure of the crude oil samples.

Fig. 5 demonstrates the comparison between the average absolute relative deviation (AARD%) obtained by different models in prediction bubble point pressure of crude oil samples. As clear be seen from Fig. 5, the PSO-ANN model has lowest AARD% value in comparison with other methods including SRK-EOS, PR-EOS and so on. In other words, the average deviation of PSO-ANN results from the experimental ones are much lower than other methods and this means that results generated by PSO-ANN model are closer to actual ones compared to other approaches. Moreover, the second rank of

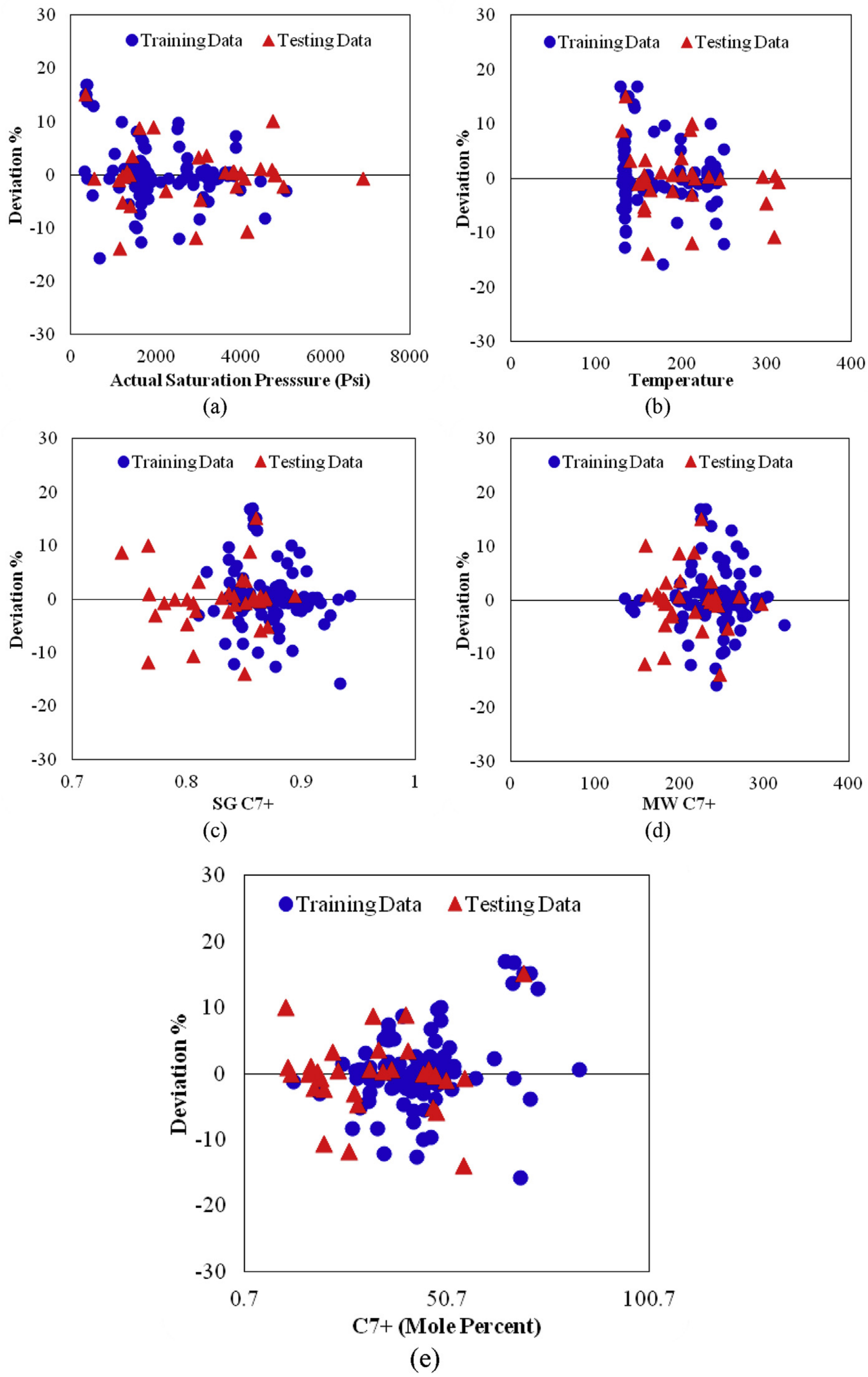

Fig. 4. Relative deviation of developed model (PSO-ANN) outputs against corresponding a) actual bubble point pressure data b) Temperature c) Specific gravity of C_{7+} d) Molecular weight of C_{7+} e) Mole percent of C_{7+}.

efficiency refers to the [77] correlations. The aforementioned correlation has lower AARD% compared to other conventional methods; however, the AARD% of Ahmadi et al., correlation is greater than PSO-ANN model.

Fig. 6 depicts the comparison between the correlation coefficient obtained by different models in prediction bubble point pressure of crude oil samples. As shown in Fig. 6, the PSO-ANN model has a maximum value of correlation coefficient compared to the other methods used in this study.

Fig. 7 illustrates the comparison between the maximum relative deviations obtained by different models in prediction bubble point pressure of crude oil samples. As clear be seen from Fig. 7, the PSO-ANN model has the lowest value of maximum relative deviations compared to the other approaches and EOSs. This means that, the PSO-ANN model has an acceptable reliability margin in comparison with other conventional methods.

Fig. 8 shows the comparison between the predicted bubble point pressure via different models and experimental ones

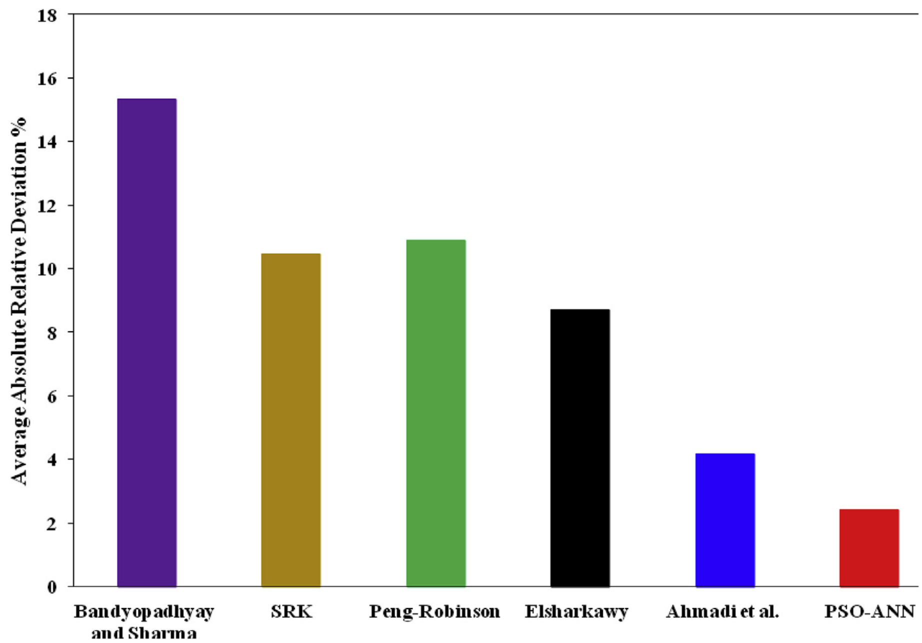

Fig. 5. Comparison between the average absolute relative deviation (AARD%) obtained by different models in prediction bubble point pressure of crude oil samples.

versus corresponding molecular weight of C_{7+}. As depicted in Fig. 8, the PSO-ANN outputs are closer to experimental ones in comparison with outputs generated by conventional methods such as PR-EOS and SRK-EOS.

Fig. 9 depicts comparison between the predicted bubble point pressure via different models and experimental ones versus corresponding specific gravity of C_{7+}. As shown in Fig. 9, the PSO-ANN model has reasonable reliability at different values of specific gravity of C_{7+} in comparison with conventional EOS and other approaches.

Fig. 10 demonstrates the comparison between the predicted bubble point pressures via different models and experimental ones versus corresponding ratio of volatile to intermediate components (Vol/Inter.). As shown in Fig. 10, the PSO-ANN model has reasonable reliability at different values of the ratio of volatile to intermediate components (Vol/Inter.) in comparison with conventional EOS and other models.

The Williams plot of PSO-ANN outcomes are demonstrated in Fig. 11. As shown in Fig. 11, both testing and training data points are falls in the ranges H = [0, 0.323] and R = [−3, +3] and this

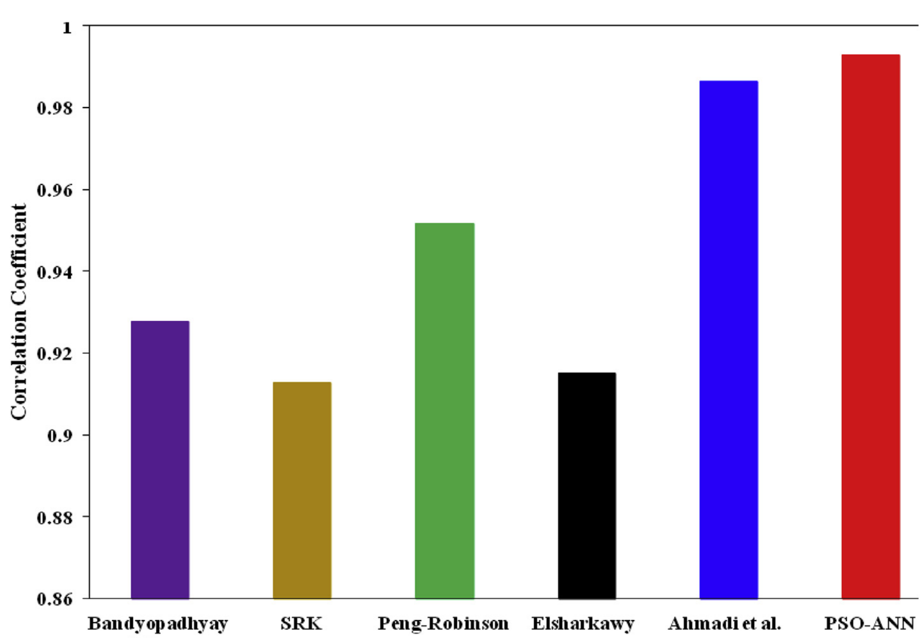

Fig. 6. Comparison between the correlation coefficient obtained by different models in prediction bubble point pressure of crude oil samples.

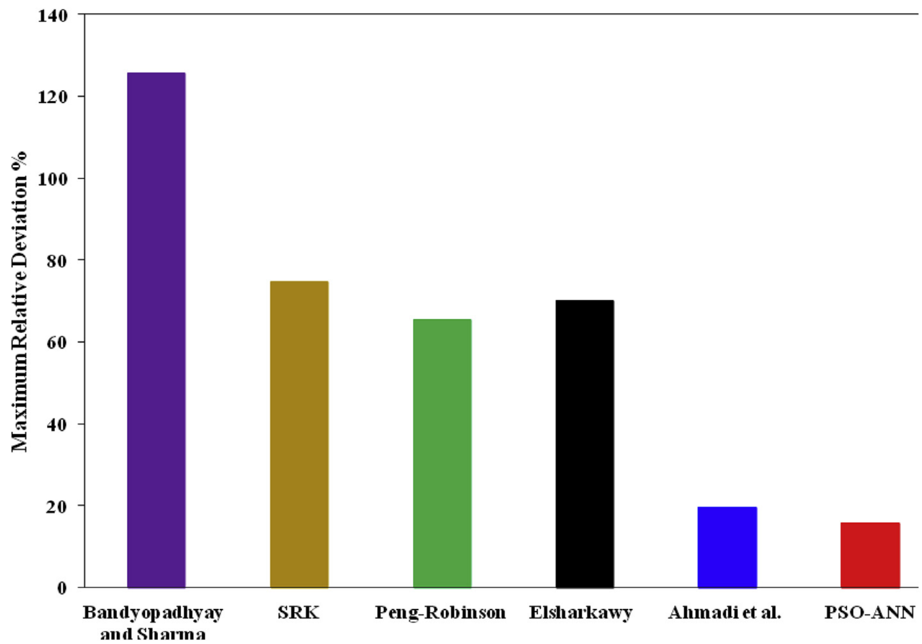

Fig. 7. Comparison between the maximum relative deviations obtained by different models in prediction bubble point pressure of crude oil samples.

means that the PSO-ANN approach is statistically correct and valid.

5. Conclusions

Precise estimation of the P_b of the crude oils has vital impact on the simulation of fluid flow through porous media. This study made attempt to facilitate estimating P_b of crude oils with high degree of precision. To gain this main goal, a couple of swarm intelligence and neural network was used to develop the efficient model to estimate P_b with adequate precision and accuracy. Moreover, the accurate experimental P_b data samples which reported in previous works were employing to tune and validate PSO-ANN model. Based on the outcomes obtained from this research study following conclusions can be drawn:

(1) Adequate agreement between the estimated P_b by swarm intelligence approach versus corresponding experimental ones was observed. However, the correlations between the outputs of the routine methods (such as SRK, Peng-Robinson,

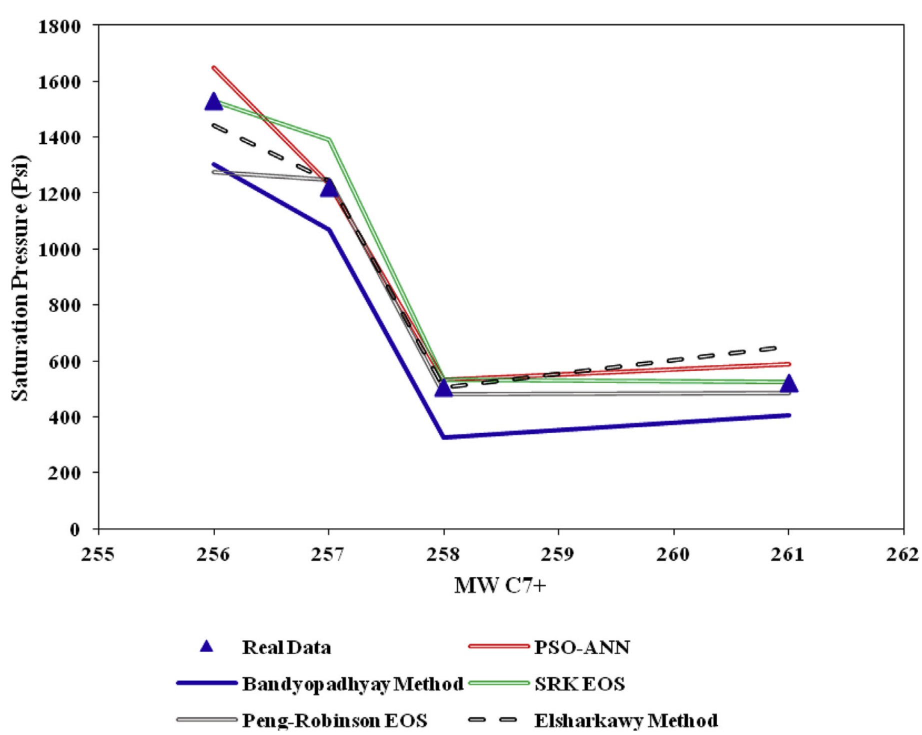

Fig. 8. Comparison between the predicted bubble point pressure via different models and experimental ones versus corresponding molecular weight of C_{7+}.

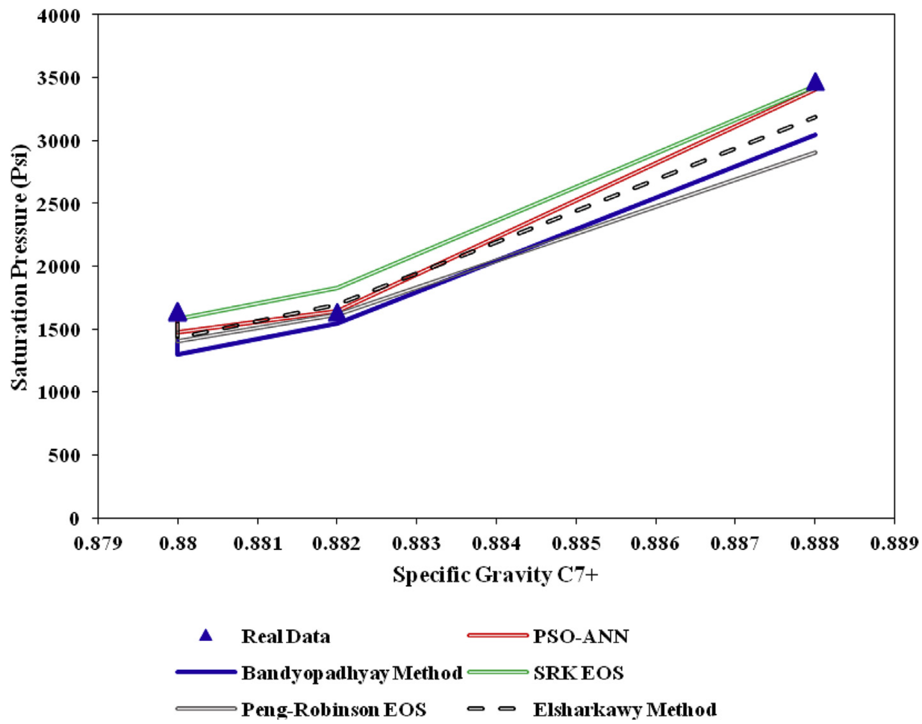

Fig. 9. Comparison between the predicted bubble point pressure via different models and experimental ones versus corresponding specific gravity of C_{7+}.

Elsharkawy and etc.) and corresponding P_b data were unacceptable. In other words, the conventional models fail to predict P_b owing to unacceptable statistical indexes for each of aforementioned methods.

(2) The suggested intelligent model (PSO-ANN) for estimating P_b in petroleum reservoirs is user friend, lucrative and effective for execution. Furthermore, it is very useful for improving the integrity and performance of the commercial reservoir

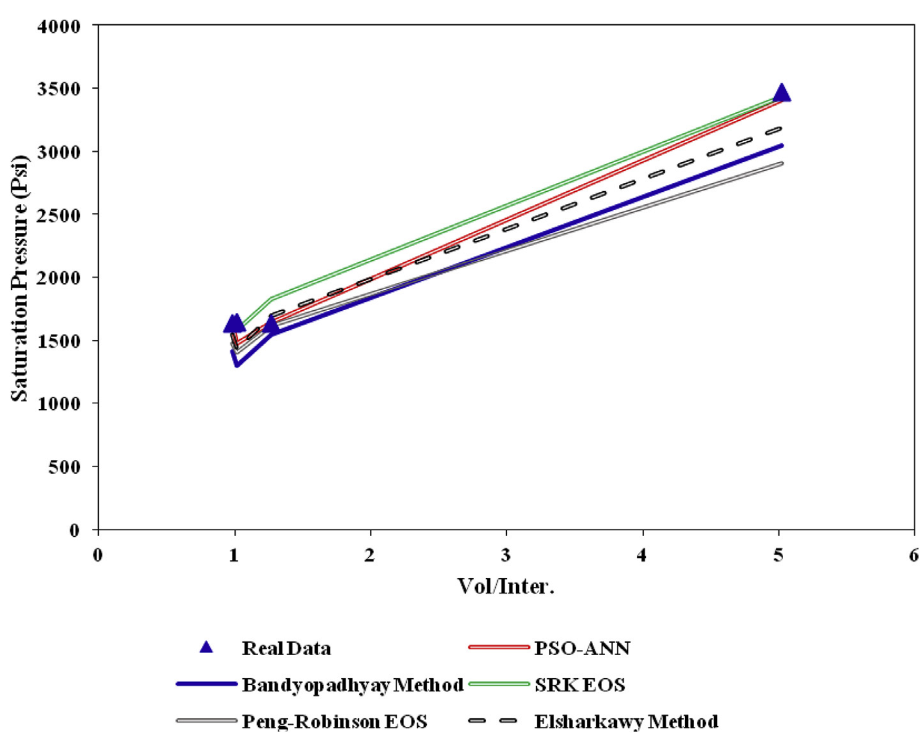

Fig. 10. Comparison between the predicted bubble point pressures via different models and experimental ones versus corresponding ratio of volatile to intermediate components (Vol/Inter.).

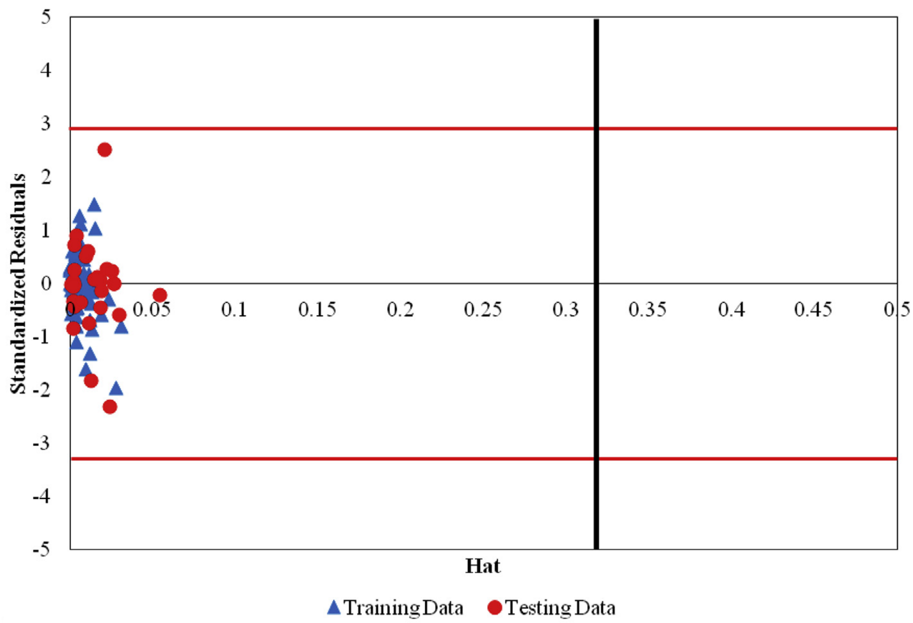

Fig. 11. Detection of the probable doubtful measured bubble point pressure data and the applicability domain of the suggested approach for the bubble point pressure. The H* value is 0.323.

simulators such as PVTi in ECLIPSE package for matching and regression of reservoir fluid properties. In addition, the PSO-ANN model can be implemented as an alternative when the required P_b data are unavailable.

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