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New Artificial Intelligent Approach for Bubble Point Pressure

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ABSTRACT: Bubble point pressure is the most crucial Pressure-Volume-Temperature property of reservoir fluid, which plays a critical role in almost all tasks related to reservoir and production engineering. There are numerous approaches for predicting various Bubble point pressure properties, namely, empirical correlations and few computational intelligence schemes. The achievements of Neural Networks (NN), Fuzzy Logic (FL) Genetic Algorithm (GA), and Expert System (ES) alone open the door to the Hybrid Systems; a genetically optimized neural network (GA-ANN) and Neuro-Fuzzy (NF) modeling techniques to play a major role in petroleum industry.

In this paper, a novel comprehensive approach to the prediction of the bubble point pressure (Pb) using two hybrid systems (GA-ANN and NF) and Expert System is introduced. A total of about 160 data points from Middle East oil samples were used. Twenty three correlations of Pb are integrated to develop Expert System. The performance of the proposed techniques is compared against performance of the most accurate general correlations for Pb calculation. Statistical error analysis was also used to check the validation of the proposed techniques. From the results of this study, it can be pointed out that these methods are more accurate and reliable.

KEYWORDS: Neural Network, fuzzy logic, Neuro-Fuzzy, Expert Systems.

1 INTRODUCTION

Bubble point pressure is one of the most critical quantities for characterizing an oil reservoir. So, accurate determination of this property has been the main challenge in reservoir development and management.

1.1 EMPIRICAL CORRELATIONS

Since the 1940s engineers have realized the importance of developing empirical correlation for bubble point pressure. Studies carried out in this field resulted in the development of new correlations. **Table1** shows the most published correlations for estimation the bubble point pressure from 1947 till now.

Table 1. Bubble Point Pressure Correlations, Moradi [1] and Al-Shammasi [2].

Authors	Samples Origin	No. of Data Points	No. of Reservoir	Authors	Samples Origin	No. of Data Points	No. of Reservoir
Standing (1947)	California	105	22	Farshad, Leblance, Garber & Osorio [Single Stage] (1996)	Colombia	98	-
Lasater (1958)	Canada	158	137	Almehaideb (1997)	UAE	62	15
Vazquez &Beggs (1980)	World Wide	5008	600	Hanafy, Macary, ElNadi, Baiomi& El Batanony (February 1997)	Egypt	324	123
Glaso (1980)	North Sea	41	45	Hanafy, Macary, ElNadi, Baiomi& El Batanony (1997)	Egypt	324	123
Al-Marhoun (1988)	Middle East	160	69	Khairy and El-Tayeb (1998)	Egypt	43	-
McCain (1991)	World Wide	100	-	Boukadi, Al-Alawi, Al-Bemani& Al-Bemani (1999)	Oman	45	-
Kartoatmodjo and Schmidt (1991)	World Wide	5392	740	Velarde, Blasingame& McCain (1999)	World Wide	2097	world
Dokla& Osman (1992)	U.A.E	51	-	Al-Shammasi (1999)	World Wide	1709	world
Macary and El-Batanoney (1992)	Gulf of Suez	90	30	Dindoruk&Christman (2001)	Gulf of Mexico	99	100
Petrosky&Farshad (1993)	Gulf of Mexico Texas	81	-	Bolondarzadeh, Hashemi&Soltani (2006)	Iran	166	-
Omar &Todd (1993)	Malaysia	93	38	Mehran, Movagharnejad and Didanloo (2006)	Iran	387	-
-	-	-	-	Hemmati&Kharrat (2007)	Iran	287	30

1.2 Hybrid Artificial Intelligent

The achievements of Neural Networks, Fuzzy Logic and Genetic Algorithm alone open the door to the Hybrid modeling techniques to play a major role in the oil and gas industry. Unfortunately, the used NN, GA, and FL modeling schemes alone have many drawbacks and limitations (**Table 2**).

Table 2. Advantages and disadvantages of the NNs, FL and GAs.

Technology	Advantage	Disadvantage
NN	Adaptation, learning, approximation	Slow convergence speed, 'black box' data processing structure
FL	Approximate reasoning	Difficult to tune, lacks effective learning capability
GA	Systematic random search, derivative-free optimization	Difficult to tune, no convergence criterion

1.2.1 ANN Optimization by GA

The non-linearity and non-continuity of oil field optimization problem makes GA a more preferable option over traditional method of back propagation (BP). A hybrid genetic algorithm–neural network strategy (GA-ANN) were used by (Rumelhart et al. [3]; Miller et al. [4]; Marshall and Harrison [5]; Bornholdt and Graudenz [6]; Huanga et al. [7]; Chena and Lina [8]; Saemi et al. [9]; Rasoul and Reza [10]; and Hossein K. et al. [11] for permeability prediction modeling.

In additional, several hybrids of genetic algorithm with ANNs were proposed by Balan et al. [12] for hydraulic fracture treatment design and optimization. Mohsen et al. [13] proposed a new method for the auto-design of ANN based on Genetic

Algorithm. In Oloso et al. [14] a differential evolutionary artificial neural network was introduced for predicting viscosity and gas/oil ratio curves.

1.2.2 Neuro-Fuzzy

Adaptive neuro-fuzzy inference systems have been proposed as a new intelligence frame work for both prediction and classification based on fuzzy clustering optimization criterion and ranking (Jang et al. [15]). In 2000, Ouenes [16] used fuzzy neural networks to fractured reservoir characterization. In 2012, Khoukhi [17] also used GA to optimize ANN model to estimate the two PVT properties of crude oil systems; namely bubblepoint and oil formation volume factor (Bob). Fatai A. et al [18] used different versions of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) to predict the porosity and permeability. Abbas M. Al-Khudafi and et al. [19] used ANFIS for estimating K-values for heptanes plus fractions.

1.2.3 Expert System (ES)

Expert system technology has recently gained an increasing importance in the petroleum industry. Application areas include diagnosis, planning, design, prediction, interpretation, monitoring, debugging, repair, and control of different processes in oil and gas engineering.

An expert system developer can choose three different approaches in developing an ES, which are: using programming language (example Matlab); using an Expert System shell; and using the tools in an artificial environment. Sayyouh, M.H et al [20]; Khaled A. Fattah et al. [21]; and Elradi and Cheng [22] applied of an Artificial Intelligence (AI) technique to assist in the selection of an Enhanced Oil Recovery method (EOR). Ahmed Al-Zahaby et al. [23] developed an expert system that checks the input parameters (e.g. reservoir parameters) against the valid ranges of input data for different correlations, and then recommends which correlations to use for specific input parameters. Senan A. Ghallab and et al. [24] designed an expert system to predict temperature, pressure, crude oil density, gravity and gas density factors.

2 Data Acquisition and Processing

A total of about 160 data points were available from Middle East oil samples. The overall range of experimental data points used for this study was summarized in Table 3. Data is normalized between (0 1), in order to data rate reduction, noise suppression and avoiding ill conditioning.

$$V_{norm} = (V - X_{min}) / (X_{max} - X_{min}) \quad \text{.................................} \quad (1)$$

Where: V is a current value of the variable X, Xmin, is the minimum value for this variable, and Xmax, is the maximum value for that variable X in the data set. Then data renormalized between (0.2-0.8) to alleviate saturation problem by an equation such as:

$$Y = V_{norm} \times (0.8 - 0.2) + 0.2 \quad \text{..............................} \quad (2)$$

Table 3. Range of data used in this study.

Parameter	Maximum	Minimum
P_b	3573	130
Gas Oil Ratio (R_S)	1602	26
Gas Specific Gravity (γ_g)	1.367	0.752
API	44.6	19.4
Temperature (T ^oF)	240	74
Formation Volume Factor (FVF)	1.997	1.032

3 Building the Models

3.1 Design of the hybrid GA-ANN Model

In this work we investigate how the reliability and predictability of artificial neural network (ANN) are improved when it genetically optimized by genetic algorithm (GA).

The ANN learning process consists of two stages: Firstly GA is employed to search for optimal or approximate optimal connection weights and thresholds for the network, then the back-propagation learning rule and training algorithm is used to adjust the final weights (Figure1).

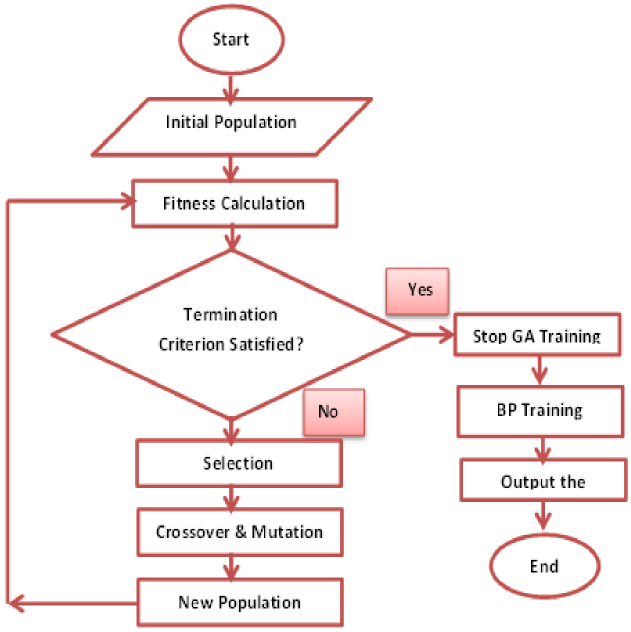

Fig. 1. Genetic Algorithm-Backpropagation Flow Chart.

The operations are as follows: The ANN weights and thresholds are initialized as genes of chromosomes, and then the global optimum is searched through selection, crossover and mutation operators of genetic algorithm. This procedure is completed by applying a BP algorithm on the GA established initial connection weights and thresholds. Therefore in this study, hybrid genetic algorithm-back propagation neural network would be applied to estimate Bubble Point Pressure.

3.2 Design of the Neuro-Fuzzy Modeling

The fuzzy logic Pb modeling system used in this study is a multi-input single output (MISO) Takagi-Sugeno system. Neuro-fuzzy inference systems are hybrid forecasting frameworks, which learn the rules and membership functions from data. It is a network of nodes and directional links. Associated with the network is a learning rule, for instance, back-propagation. These networks are learned a relationship between inputs and outputs. This type of network covers a number of different approaches, namely Mamdani type and Takagi–Sugeno–Kang (TSK) type (see Jang et al. [25]) for more detail. The TSK fuzzy objective modeling method is a framework for generating fuzzy if-then rules from input/output numerical data. A way to construct a TSK fuzzy model from numerical data proceeds in three steps: fuzzy clustering, setting of the membership functions, and parameter estimation (Jang and Gulley [26]). Figure2 shows an ANFIS System with a two-inputs two-rules one-output arrangement.

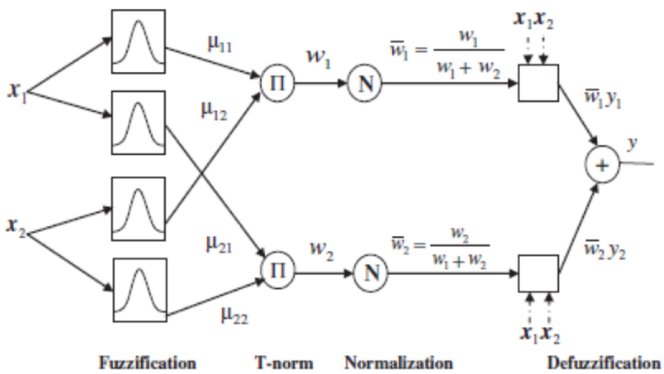

Fig. 2. ANFIS system with two inputs two-rule one-output, [15].

The implemented ANFIS in the study at hand is made up of six layers. The first layer is the input layer, characterizing the crisp inputs. The second layer performs the fuzzification of the crisp inputs into linguistic variables, through transfer functions. The thirds rule layer, which applies the product T-norm to produce the firing strengths of each rule. This is followed by a normalization layer, at which each node calculates the ratio of a rule's firing strength to the sum of the firing strengths of all rules. The fifth layer performs the defuzzification. The last layer conducts the aggregation, where an output is obtained as the summation of all incoming signals. The training rule option used is the Levenberg-Marquard version of the gradient back-propagation algorithm.

3.3 DESIGN OF THE EXPERT SYSTEM

As it shown from Table1,some bubble point pressure correlations was developed using data from particular region with different reservoir conditions whereas the others can be developed using data from different region and reservoir conditions. The most correlation can be predicted either by recalculating the coefficients of pervious correlation or by evaluating the exist correlations without respect of region and reservoir types. Thus, the problem will arise in which correlation is better to use. Therefore, the Expert System was developed to solve this problem by getting the nearest value of Pb that agrees with region and reservoir conditions. The Expert System integrated all correlations with respect to their limitations.

The development of the Expert System of PVT properties involves the following three phases Knowledge Acquisition, System Formulation, and System Verification and validation.

3.3.1 Knowledge Acquisition

Understanding the main input parameters and the range of each published correlations (limitations) are the first step as well as the identification of the expert systems. The developed Expert System for the bubble point pressure correlations considers the Table5 as a knowledge data base.

3.3.2 System Formulation

The system formulation formulates the acquired knowledge from the first phase through rules. The rules are conditional statements in the form of IF-THEN statements. The system was developed by using Matlab Program that flexible to allow the system to perform its task easily. Figure3 shows bubble point pressure Expert System utilization.

3.3.3 Expert System Utilization and Validation

The developed Expert System could be utilized to determine bubble point pressure by integrated 23 correlations. The developed Expert System can check the different input reservoir parameters and run each correlation regarding into their limitation. Each correlation can utilize in some input data and exclude in others which don't achieve the criteria of the limitation of the input parameters.

The reservoir parameters are processed through developed software to determine the most accurate bubble point pressure regarding to the minimum absolute error.

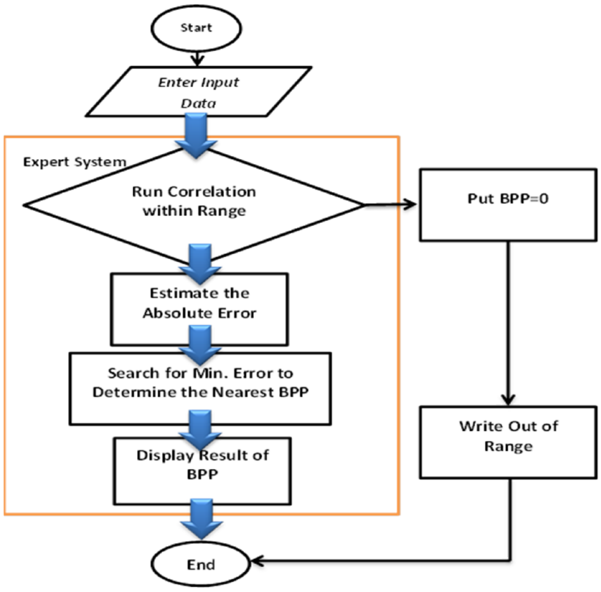

Fig. 3. Bubble Point Pressure Expert System Utilization.

4 RESULTS AND DISCUSSION

4.1 THE HYBRID GA-ANN MODEL

The total number of chromosomes was (300chromosomes×50 generation×2 layers), although there was no difference between chromosomes in one generation with one in another generation of each case. BP network has two layers including input layer, one hidden layer, and output layer. There have 5 input neurons in the code and the output layer neuron is 1.

In our model we set the hidden layer number is 14 deliver neuron functions is tansig in the hidden layer, and the output layer's deliver neuron function is purelin. The simulation performance of the GA-ANN model (Figure4) was evaluated on the basis of mean square error (MSE= 9.96*10-4) and correlation coefficient (R2 = 0.99988).

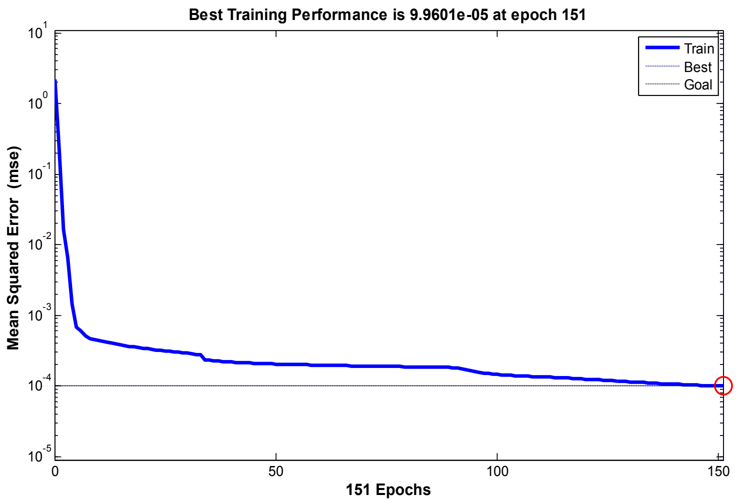

Fig. 4. RMSE training performance by GA-ANN optimization.

4.2 THE NEURO-FUZZY MODELLING

In this stage of study, an adaptive neuro-fuzzy inference system (ANFIS) was used to optimize the fuzzy model. The schematic structure of ANFIS model, formulating PVT data to bubble point pressure, is illustrated inFigure5.

Two versions based on the training algorithm, of the ANFIS hybrid model were used in this study: Grid Partitioning, and Subtractive Clustering. The ANFIS with Grid Partitioning (ANFIS-GP) was used to generate a single-output Sugeno-type fuzzy inference system (FIS) using a grid partition on the data. The Neuro-Fuzzy model always needs to select the suitable input-output data. All options of this model were applied and the optimal option was chosen.

The ANFIS with Subtractive Clustering (ANFIS-SC) was also used to generate a FIS by first applying subtractive clustering on the data. This is accomplished by extracting a set of rules that models the data behavior by first using the genfis2 function to determine the number of rules and antecedent membership functions and then using linear least squares estimation to determine each rule's consequent equations.

In order to find the optimum radii, firstly different radii were proposed to estimate the bubble point pressure. The RMSE and the correlation coefficients (R2) were calculated. From Figures 6&7, the optimal clustering radius was specified (0.42) whereas the optimal output function with RMSE equal to 35 and 90.4 and R2 equal to 0.9994 and 0.996 for training and testing data respectively.

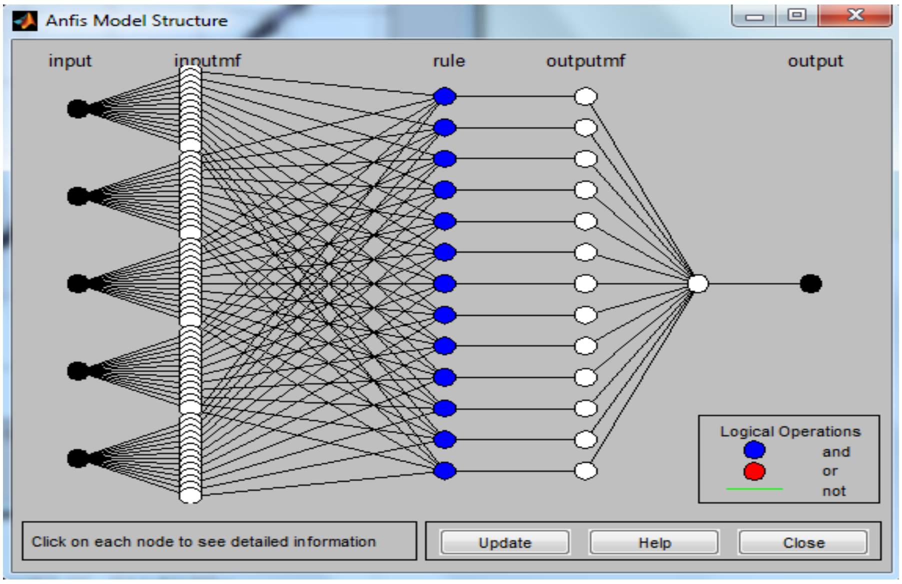

Fig. 5. ANFIS model structure of Pb prediction.

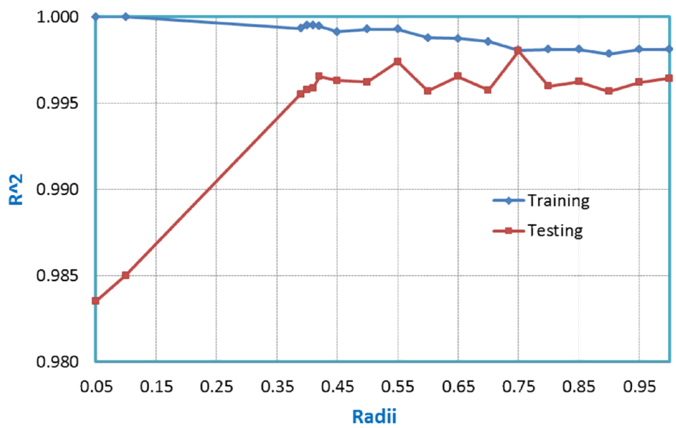

Fig. 6. Optimal Radii for ANFIS-SC with Dataset.

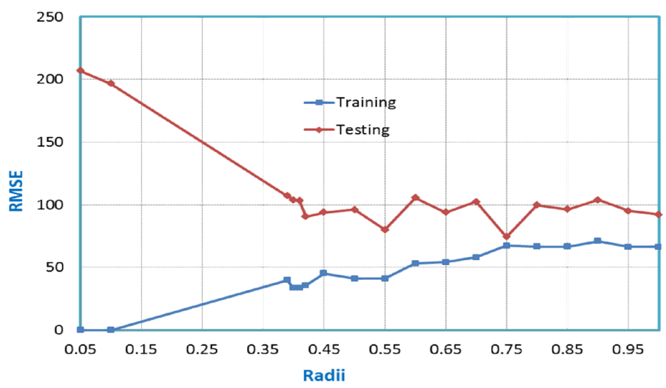

Fig. 7. Optimal Radii for ANFIS-SC with Dataset.

A hybrid optimization method which combines least squares estimations with back-propagation was used to adjust the membership functions' (MFs) parameters. Several input MFs types with different number function (2, 3) were tried with linear and constant output MFs. The grid partition method first uses the genfis1 function to determine the optimal number and type of membership functions from input-output bubble point pressure datasets. This is summarized and shown in Figures8 & 9. However, Gaussian MFs with linear output MF were found to be highly competitive in performance. A further comparative investigation showed that the Gaussian MF is optimal for this problem. This agrees with literature of Quintana [26] who presents the Gaussian MF as the best for most applications.

$$\mu_{Ai}(x) = exp\left(\frac{-(x-c)^2}{2\sigma^2}\right) \dots\dots\dots\dots\dots\dots\dots (3)$$

Where C and σ^2 are the centre and width of the fuzzy set Ai respectively.

Two Gaussian MFs were found as the optimal input function whereas the linear function as the optimal output function with RMSE equal to 13.8 and 10.7 and R2 equal to 0.99992 and 0.999952 for training and testing data respectively.

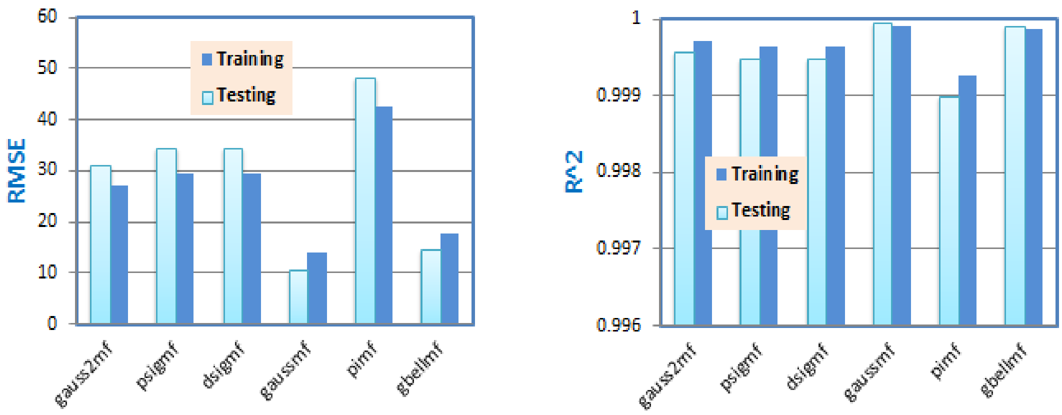

Fig. 8. Performance of Three Input MFs for Linear Output MF.

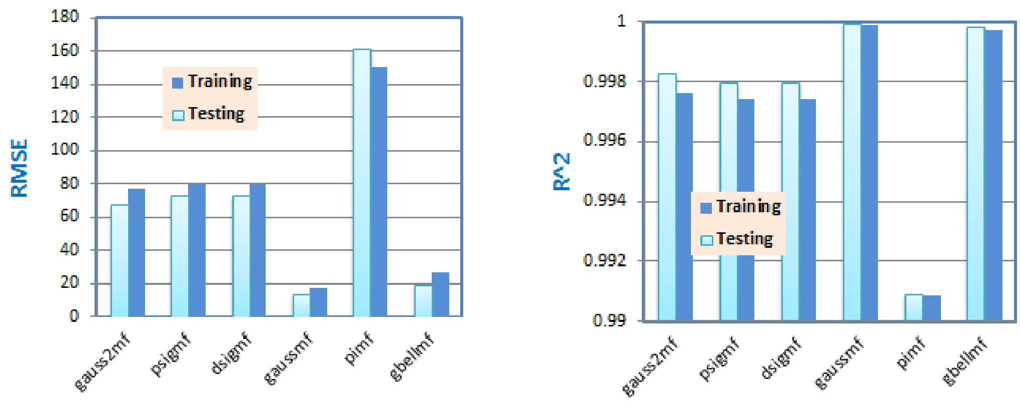

Fig. 9. Performance of Three Input MFs for Constant Output MF.

4.3 The Expert System Modelling

Figure11 illustrates the AAPRE and RMS of twenty three correlations with expert system. The results show the improvement in Pb accuracy by using ES with AAPRE equal to 1.94 and RMS=36.7 (red column).Figure 10 Shows the participation rate of each correlation in Expert System correlation.

Expert system is able to determine the best empirical correlations. To check the validation of ES program, the different data from different region was chosen. The results (Figure12) show that the ES correlation gives better accuracy in estimating bubble point pressure of Malaysian crudes (93 data points) than other known correlations available in the literature. The ES correlations give low values of AAPRE=2.16 and RMS=78 with correlation coefficient values close to an ideal value of 1.0.Table 4 shows a wide range of parameters that can be used in this Expert System.Figure 11&12 illustrates the user-friendly interface and result of Expert System.

Table 4. The limitations of developed Expert System.

Parameter	Maximum	Minimum
P_b	12230	15
R_S	4569	0
γ_g	1.872	0.335
API	124	6
T °F	327	59
FVF	4.35	1.007

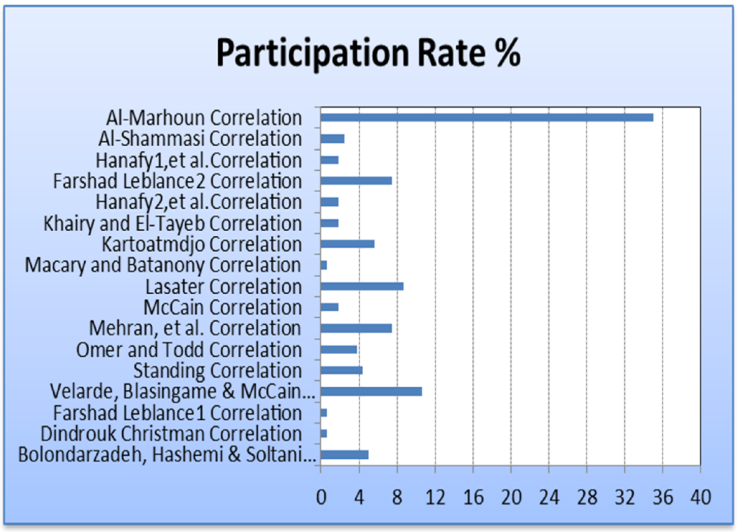

Fig. 10. Participation Rate of Correlations.

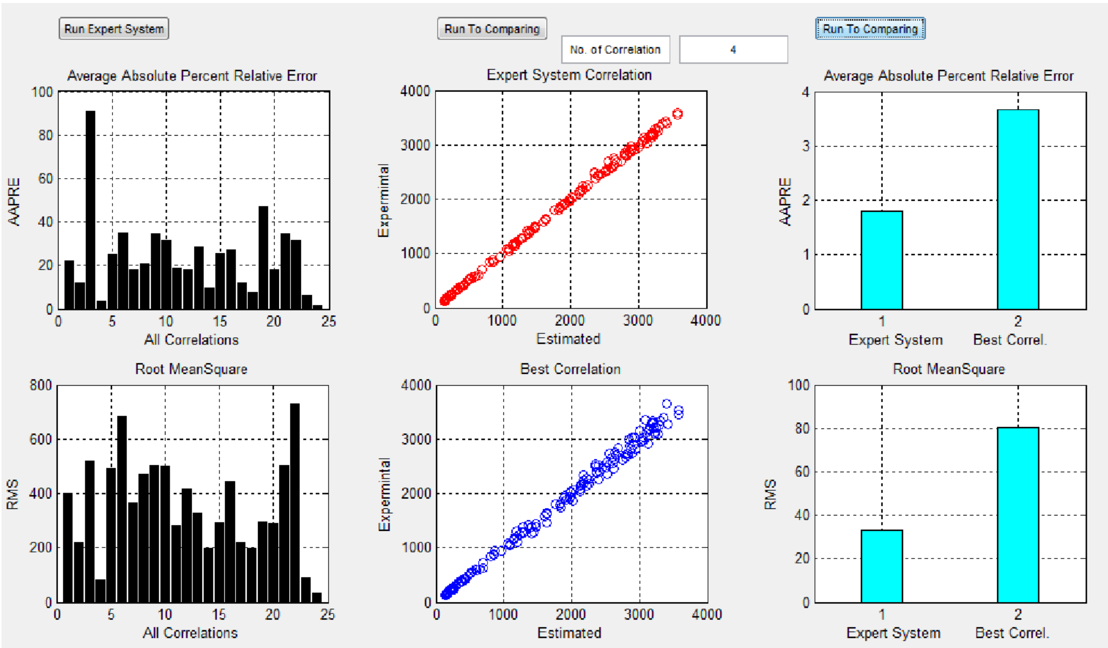

Fig. 11. AAPRE and RMS for 23 Correlations with ES result from Middle East Data.

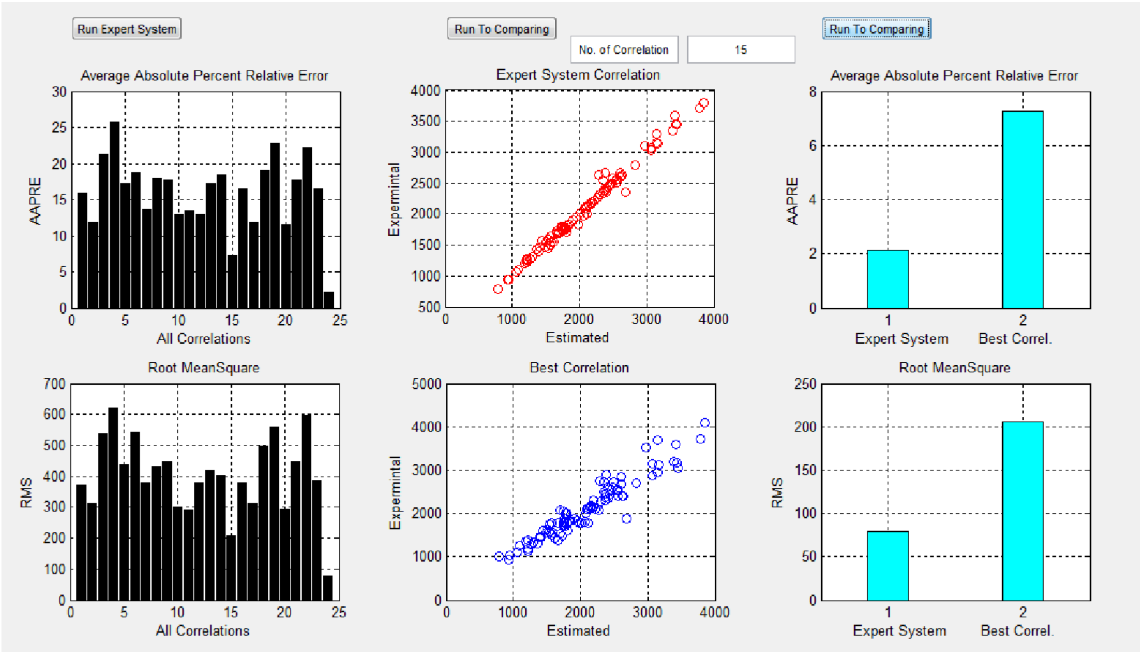

Fig. 12. AAPRE and RMS for 23 Correlations with ES form Malaysian Crudes.

4.4 Comparison

The comparison was done between Artificial Intelligent methods and the most accurate empirical correlations (Al-Marhoun, Fig.11). The results show that the performance of Artificial Intelligent models is more accurate than the empirical correlation. The results also showed that, in terms of R2 and RMS, the GA-ANN hybrid model outperformed all the other hybrid models with the highest accuracy as shown in (Figs. 13-16). Expert System and ANFIS models might perform equally well as GA-ANN models (Figs.14-16). Based on the result of this study, Al-Marhoun did not perform well as Artificial Intelligent.

5 Conclusions

The following conclusions have been drawn from this study:

- A novel methodology for predicting bubble point pressure was introduced.
- Intelligent techniques are powerful tools which overcome incompleteness, imprecise and uncertainty existent in reservoir parameters.
- The hybrid models showed superior performance with the highest correlation coefficients, and lowest root mean square errors.
- Hybrid optimization method is faster and more accurate than any artificial intelligent algorithm alone.
- A detailed comparative study of 23 Bubble Point Pressure correlations, GA-ANN, Expert System, and 2 versions of Adaptive Neuro-Fuzzy Inference System are presented in this paper.
- The two versions of ANFIS used in this study are equally good and demonstrate competitive capabilities due to the excellent performance of the grid partitioning (ANFIS-GP), and subtractive clustering (ANFIS-SC) algorithms.
- A comparison was based on the prediction of bubble point pressure of oil reservoirs obtained from diverse fields with different lithological and geological formations.
- Neuro-fuzzy systems are data driven fundamentally. Thus, more data for training the system, better performance and more generalization will be achieved.

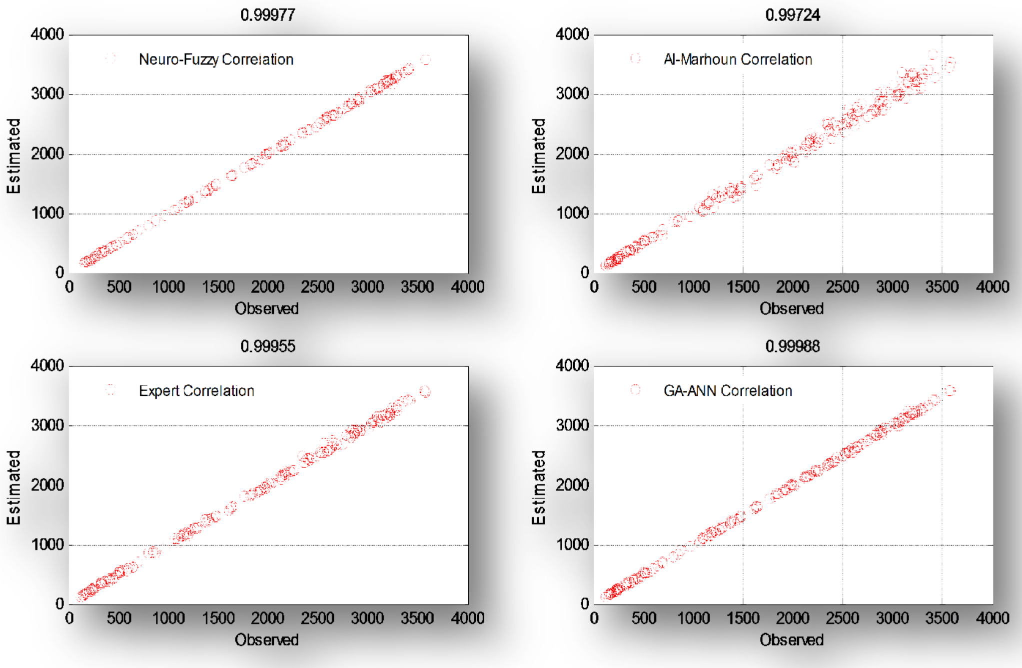

Fig. 13. Cross Plot of Neuro-Fuzzy, Al-Marhoun, Expert System, and GA-ANN Correlations.

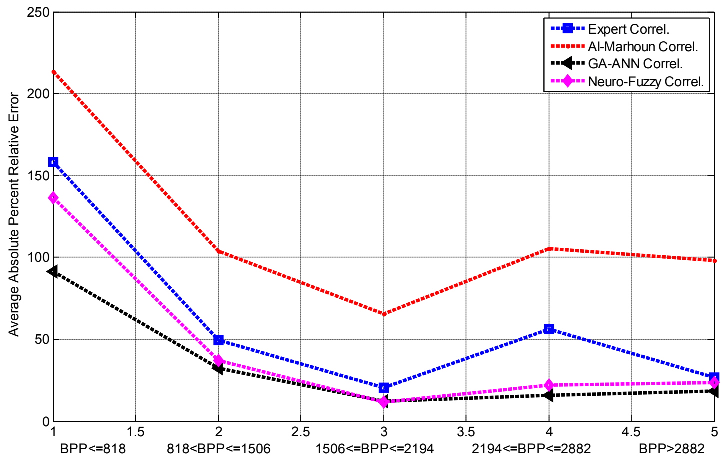

Fig. 14. Statistical accuracy of total grouped of Pb.

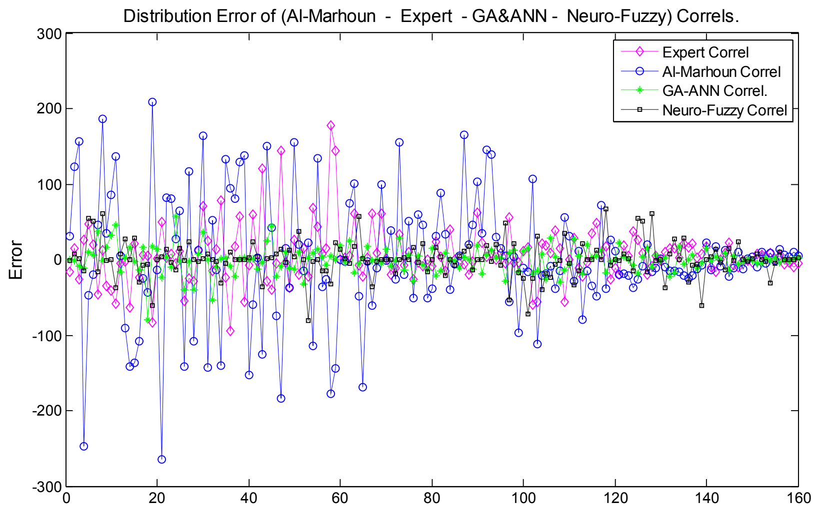

Fig. 15. Error distribution of the Four Models.

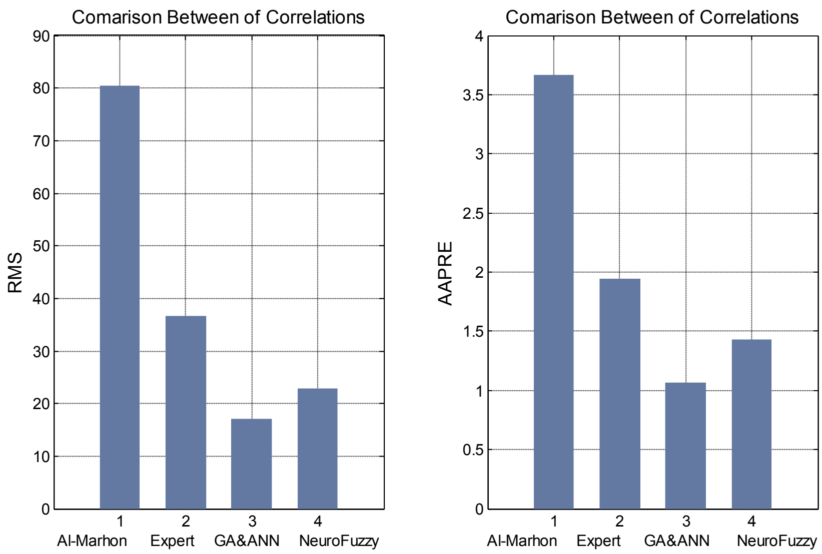

Fig. 16. Comparison of R2 and AAPRE for different Pb models.

Table 5. Input Parameters Ranges for Bubble Point Pressure Correlation

Authors	Pb	API	γ_g	T	GOR	FVF
Standing (1947)	7000-130	63.8 -16.5	0.95-0.59	258-100	1425-20	2.15-1.024
Lasater (1958)	5780-48	51.1-17.9	1.2-0.57	272-82	2905-3	
Vazquez &Beggs	6055-15	59.3-15.3	1.35-0.51	294-75	2199-0	2.226-1.028
Glaso (1980)	7142-165	48.1-22.3	1.276-0.65	280-80	2637-90	2.588-1.032
Al-Marhoun (1988)	3573-130	44.6-19.4	1.367-0.752	240-74	1602-26	1.997-1.032
Kartoatmodjo and Schmidt	6055-15	58.9-14.4	1.71-0.38	320-75	2890-0	2.747-1.007
Dokla& Osman (1992	4640-590	40.3-28.2	1.29-0.80	275-190	2266-181	2.493-1.216
Macary and El-Batanoney (1992)	4600-1200	40-25	1.0-0.7	290-130	1200-200	2-1.2
Petrosky&Farshad (1993)	6523-1574	45-16.3	0.8519-0.5781	288-114	1406-217	1.623-1.118
Omar &Todd (1993)	3851-790	53.2-26.6	1.32-0.612	280-125	1440-142	1.954-1.085
Farshad, Leblance, Garber & Osorio [Single Stage] (1996)	4138-32	44.9-18	1.73-0.66	260-95	1645-6	2.747-1.007
Farshad, Leblance, Garber & Osorio [Single Stage] (1996)	4138-32	44.9-18	1.73-0.66	260-95	1645-6	2.747-1.007
Almehaideb (1997)	4822-501	48.6-30.9	1.12-0.75	306-190	3871-128	3.562-1.142
Hanafy, Macary, ElNadi, Baiomi& El Batanony (February 1997)	5003-36	48.8-17.8	1.627-0.623	327-107	4272-7	4.35-1.032
Hanafy, Macary, ElNadi, Baiomi& El Batanony (March 1997)	5003-36	48.8-17.8	1.627-0.623	327-107	4272-7	4.35-1.032
Khairy and El-Tayeb (1998)	4930-236	54.3-30.7	1.417-0.675	282-120	4569-15.8	-
Khamechi, Rashidi, RasouliEbrahimian 2009	-	124-33.4	0.858-0.554	306-100	1708-83	-
Velarde, Blasingame& McCain (1999)	6700-70	55-12	1.367-0.556	327-74	1870-10	-
Al-Shammasi (1999)	7127-31.7	63.7-6	3.44-0.51	341.6-74	3298.6-6	2.916-1.02
Dindoruk&Christman (2001)	12230-926	40-14.7	1.027-0.6017	276-117	3050-133	2.8984-1.0844
Bolondarzadeh, Hashemi&Soltani (2006)	5300-100	-	-	-	1527-334	1.8492-1.1851
Mehran, Movagharnejad and Didanloo (2006)	4930-236	-	1.872-0.335	306-77.5	3539-83	3.23-1.09

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