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The Use of Optimization Procedures to Estimate Minimum Miscibility Pressure

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An important factor in the design of gas injection projects is the minimum miscibility pressure (MMP). A new genetic algorithm (GA)–based correlation and two neural network models (one of them is trained by back propagation [BP] algorithm and another is trained by particle swarm optimization algorithm) have been developed to estimate the CO_2–oil MMP. The correlation and models use the following key input parameters: reservoir temperature, molecular weight of C_5^+, and mole percentage of the volatiles and intermediate components (for the first time, the mole percentages are used as independent variables). Then results are validated against experimental data and finally compared with commonly used correlations reported in the literature. The results show that the neural network model trained by BP algorithm and the correlation that has been developed by GA can be applied effectively and afford high accuracy and dependability for MMP forecasting.

Keywords: genetic algorithm, minimum miscibility pressure, neural network, optimization

1. INTRODUCTION

Minimum miscibility pressure (MMP) is the lowest pressure where the gas is miscible with reservoir fluid (Wang and Orr, 2000). Slim tube displacement experiments, rising bubble apparatus, and mixing cells are a number of methods that use for measurement of the MMP. But these methods are very costly and time consuming. Therefore, a method for rapid estimation of MMP with acceptable precision is needed. Limited number of correlations has been proposed. Examples of commonly used CO_2–oil MMP correlations are in section 3.

2. REVIEW OF ARTIFICIAL INTELLIGENCE THEORY

2.1 Genetic Algorithms

Based on the Darwinian theory of evolution, the genetic algorithm (GA) is a computer-based search procedure that can be used in a wide range of optimization and search procedures, including those that are very difficult to handle by more conventional techniques (Jefferys, 1993). It involves a

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random generation of potential design solutions accompanied by an evaluation and refinement of the solution until stopping criteria are met (Goldberg, 1989).

2.2 Neural Networks

The neural network is able to learn basic relationships from a collection of training samples. Two training algorithms are used in this study: in 1986, error back propagation (BP) algorithm was presented by Rumelhart et al. (1986). In this algorithm, Rumelhart et al. first assumed that network weights are randomly selected. Network output in each step is calculated and according to difference between this output and the desired output, weights are adjusted until finally this error be minimized.

Particle swarm optimization (PSO) is a multiagent global optimization algorithm originally attributed to Kennedy and Eberhart (1995). In the PSO algorithm a population of particles (termed a *swarm*) are initially placed at random positions in the search space, moving in randomly defined directions. The directions of particles are influenced by their own previous success and the success of their neighbors, searching in regions that have been proven relatively successful and potentially discovering even better regions with lower objective function. PSO is fast, simple, and effective with a superior global optimization ability compared to other stochastic algorithms. Figure 1A illustrates the velocity update mechanism in PSO.

2.3 Commonly Used CO_2–oil MMP Correlations and Models

In 1974, Holm and Josendal presented a graph that it showed the MMP as a function of temperature and molecular weight of $C_5{}^+$ in the oil that are shown as solid lines on Figure 1B.

In 1978, Cronquist presented a Formula to predict the MMP in light oil reservoirs. In this formula the oil composition is specified by two parameters: molecular weight of $C_5{}^+$ and mole percents of methane and nitrogen. This equation is as follows:

$$\mathrm{PMISC} = 15.988\mathrm{T}^{(0.744206+0.0011038(\mathrm{MWC5P})+0.0015279(\mathrm{MPC1}))} \tag{1}$$

In 1981, Mungan developed Holm and Josendal's graph for a wider range of molecular weight of $C_5{}^+$ that are shown as dash lines on Figure 1B.

In 1980, Yellig and Metcalfe presented a simple equation that MMP is the only function of temperature:

$$\mathrm{MMP} = 1833.717 + 2.2518055\mathrm{T} + 0.01800674\mathrm{T}^2 - 103949.93/\mathrm{T} \tag{2}$$

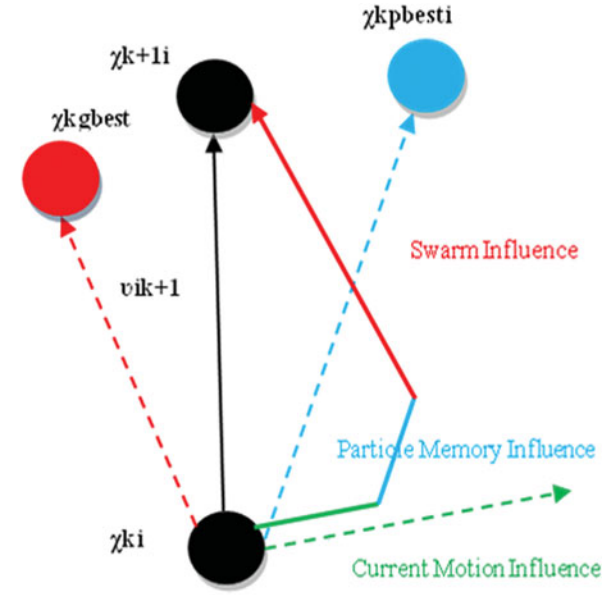
Five years later, Glaso (1985) presented the following equation:

$$\text{For } \mathrm{C_2{-}C_6} > 18\%: \mathrm{MMP} = 810 - 3.404\mathrm{M}_{\mathrm{C7}}^{+} + 1.7 \times 10^{-9}\mathrm{M}_{\mathrm{C7}} + \hat{(}3.730)[\mathrm{e}\hat{(}786.8\mathrm{M}_{\mathrm{C7+}}^{-1.058)} \times \mathrm{T} \tag{3}$$

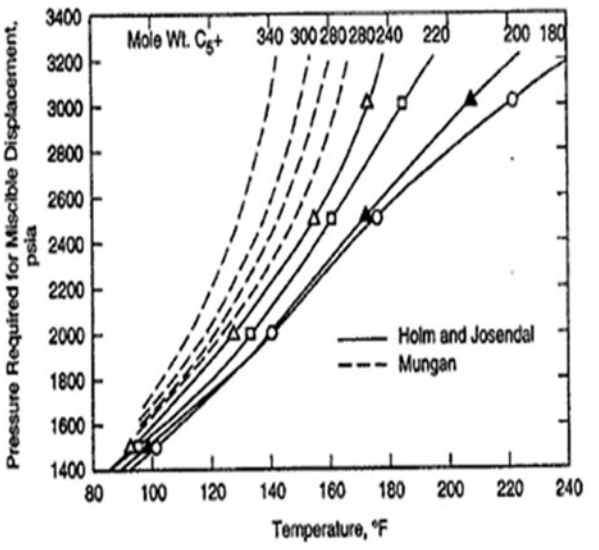
$$\text{For } \mathrm{C_2{-}C_6} < 18\%: \mathrm{MMP} = 2947.9 - 3.404\mathrm{M}_{\mathrm{C7}}^{+} + 1.7 \times 10^{-9}\mathrm{M}_{\mathrm{C7+}}\hat{(}3.730)[\mathrm{e}\hat{(}786.8\mathrm{M}_{\mathrm{C7+}}^{-1.058)} \times \mathrm{T} - 121.2\mathrm{C}_{2-6}. \tag{4}$$

In the same time, Alston et al. (1985) using a large number of experimental data presented the following empirical formula:

$$\mathrm{MMP} = 6.05 \times 10^{-6}(1.8\mathrm{T} - 460)^{1.06}\mathrm{M}_{\mathrm{c5+}}^{1.78}[\mathrm{X_v}/\mathrm{X_l}]^{0.136} \tag{5}$$



(A)



(B)

FIGURE 1 (A) Velocity component construction. (B) Determination of MMP by Holm and Josendal and Mungan.

In 2003, Huang et al. developed an artificial neural network model that trained by BP. In this model because of structure of neural network, the average relative errors of output results of ANN model prediction is nearly 6% more than the average error of training results that this is a weakness in their structure.

In 2004, Emera et al. presented a formula by using GA that in their theory two of the input parameters (the mole percentages) were dependent variables. So it could not investigate the effect of each parameter individually and the type of code (real number), selection technique (roulette wheel) and rest of the controlling parameters are different rather than our study. The generated equation is as follows:

$$\mathrm{MMP} = 5.0093 \times 10^{-5}(1.8\mathrm{T_R} + 32)^{1.06}\,\mathrm{M}_{\mathrm{c5+}}^{1.2785}\,[\mathrm{X_v}/\mathrm{X_l}]^{0.1073} \tag{6}$$

4. FACTORS AFFECTING CO_2–OIL MMP

It has been widely recognized that major factors that affect the CO_2–oil MMP are oil composition and reservoir temperature (Alston et al., 1985). Elsharkawy et al. (1992) reported three trends of MMP for different oils as a function of temperature. Depending on the oil used they observed concave downward, concave upward, or linear trends with temperature. In some of the correlation, the methane content of the oil is assumed not to significantly affect the MMP (Orr et al., 1993). Therefore, for more accuracy, we assume the effect of volatile components. In addition, Alston et al. stated that $C_5{}^+$ molecular weight is better for the correlation purpose than oil API gravity. In this study four input parameters were selected for the estimation of MMP: reservoir temperature, $C_5{}^+$ molecular weight, volatiles component percent (C_1 and N_2), and intermediate component percent (C_2–C_4, H_2S, CO_2).

5. DEVELOPING CO_2–OIL MMP CORRELATION AND MODELS

5.1 GA-based CO_2–oil MMP Correlation

To develop GA-based correlation we used an initial random population with a population size of 100 chromosomes. Double vector chromosomes are used to encode the correlation coefficients values. Each chromosome (solution) in the population is evaluated according to a fitness function value that depends on the objective function. This fitness value is calculated as follows:

$$\mathrm{Fit} = (\mathrm{MMP_{cal.}} - \mathrm{MMP_{mea}})^2 \tag{7}$$

A tournament parent selection is carried out to select two parents (chromosomes) from the population to produce two children (new chromosomes) by the reproduction operators. In each reproduction, elite proportion is 10, mutation proportion is 20, and, finally, crossover proportion is 70 chromosomes. A one-point crossover has been used. Many correlation models were tested. However, the following correlation model appears to better express the relationship among the key parameters:

$$\mathrm{MMP} = 0.00092 \times \mathrm{T}^{1.17071} \times \mathrm{M}_{\mathrm{c5+}}^{1.67943} \times \mathrm{X}_{\mathrm{vol}}^{0.11088} \times \mathrm{X}_{\mathrm{int}}^{-0.13688} \tag{8}$$

Where T is temperature in °F, M_{c5+} is C_5^+ molecular weight, X_{vol} is volatiles component percent (C_1 and N_2), X_{int} is intermediate component percent (C_2–C_4, H_2S, CO_2), and MMP is in Psi.

The correlation results are compared to available experimental data in Table 1 and shown in Figure 2A.

TABLE 1
Results of the GA-based Correlation Prediction and Comparison Between Its Prediction and Slim Tube Data

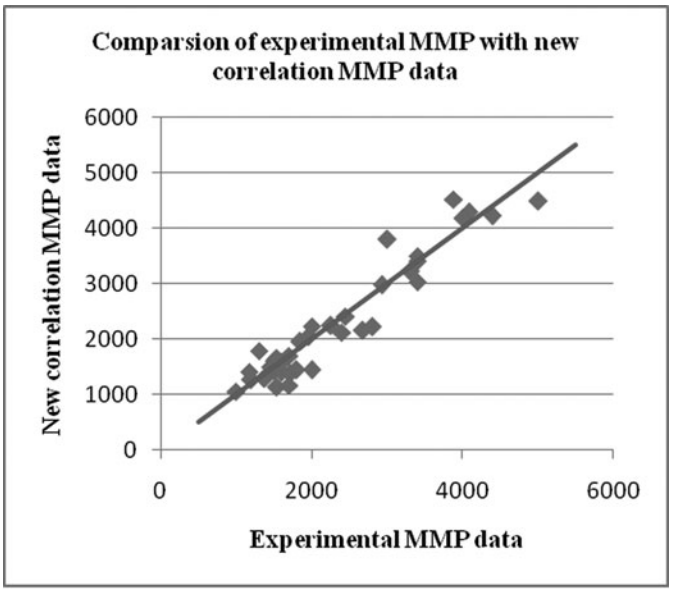
							GA	
References	*T*	*Mc5+*	*Mc7+*	*VOL*	*Inter*	*STMMP*	*Calcd. MMP*	*PE, %*
Alston et al., 1985	130	185.83	192	5.4	38.4	1375	1299.48	5.49
Alston et al., 1985	142	185.83	192	5.4	38.4	1500	1440.98	3.93
Alston et al., 1985	130	185.83	192	5	7.5	1500	1611.19	7.41
Alston et al., 1985	130	185.83	192	22.9	38.4	1500	1525.24	1.68
Alston et al., 1985	130	235.56	245	5.4	35.5	1850	1956.11	5.74
Alston et al., 1985	100	235.56	245	4.9	1.9	2400	2125	11.46
Alston et al., 1985	154	203.81	210	31	22.9	2450	2410.74	1.6
Cardenas et al., 1984	160	207.9	218	4.4	13.9	2250	2247.7	0.1
Graue and Zana, 1981	130	171.2	191	29.5	31.8	1594	1402.61	12.01
Dicharry et al., 1973	109	171	197.4	19.3	23.6	1540	1131.89	26.5
Gardner et al., 1981	243	185	205	36.34	30.72	3400	3416.76	0.49
Frimodig et al., 1983	90	187.8	208.9	10.5	14.28	1000	1060.04	6
Frimodig et al., 1983	105	187.8	208.9	10.5	14.28	1200	1269.69	5.81
Frimodig et al., 1983	135	187.8	208.9	10.5	14.28	1700	1704.02	0.24
Frimodig et al., 1983	120	187.27	208.9	34.34	22.82	1600	1580.23	1.24
Frimodig et al., 1983	150	187.27	208.9	34.34	22.82	1950	2051.99	5.23
Alston et al., 1985	210	190.7	195	40.14	2.95	4390	4222.97	3.8
Alston et al., 1985	230	180.6	185	32.51	35.64	2930	2977.89	1.63
Holm&Josendal, 1974	135	183	196	31.88	3.48	2000	2238.71	11.94
Rathmell et al., 1971	109	204.1	222	17.07	20.95	1500	1527.67	1.84
Rathmell et al., 1971	103	199.7	223	27.84	21.81	2000	1447.14	27.64
Rathmell et al., 1971	186	248	268	44.53	18.34	5000	4486.54	10.27
Alston et al., 1985	160	221	227	41.27	6.99	3400	3507.24	3.15
Alston et al., 1985	216	205	210	51.28	9.84	4085	4294.01	5.12
Alston et al., 1985	176	240.7	245	53.36	8.6	3880	4526.41	16.66
Clark et al., 2008	285	131.46	155	31.53	46.39	2680	2158.46	19.46
Moudi et al., 2009	198	209.98	253	27.37	30.85	3315	3220.83	2.84
Moudi et al., 2009	195	232.13	256	40.08	18.76	4015	4181.06	4.14
Thakur et al. 1984	245	171.1	192	34.2	28.6	3401	3034.88	10.77
Shelton and Yarborough, 1977	94	212.56	227	16.78	10.76	1450	1503.7	3.7
Henry and Metcalfe, 1983	120	205.1	227	12.5	22.62	1536	1647.83	7.28
Harmon and Grigg, 1988	170	217.67		39.63	5.17	3000	3807.96	26.93
Harmon and Grigg, 1988	130	168.39		29.73	29.43	1708	1379.89	19.21
Spence and Waskins, 1980	104	202.2	221	24.25	23.85	1800	1453.9	19.23
Spence and Waskins, 1980	109	221	235	17.04	17.24	1300	1792.89	37.91
Bon et al., 2005	279	136.18		24.68	39.37	2810	2223.37	20.88
Metcalfe et al., 1979	160	134	134	25	30	1700	1173.04	31
Sebastian et al., 1985	88	223		16.48	17.01	1175	1414.18	20.36
							E (%)	**10.54**

In this paper, the type of error used for comparison with the measured data is relative percent error, that is calculated as follows:

$$\text{Percent Error} = \text{PE} = |(\text{MMP}_{\text{cal}} - \text{MMP}_{\text{mea}})| / \text{MMP}_{\text{mea}} \tag{9}$$

And average percent error:

$$\text{E} = 1/\text{n}(\Sigma\, \text{PE}_{\text{i}}) \tag{10}$$



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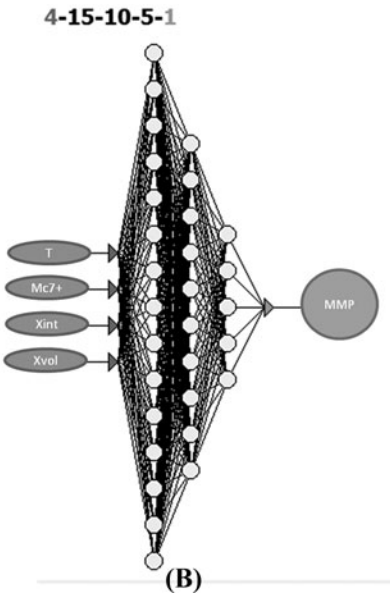
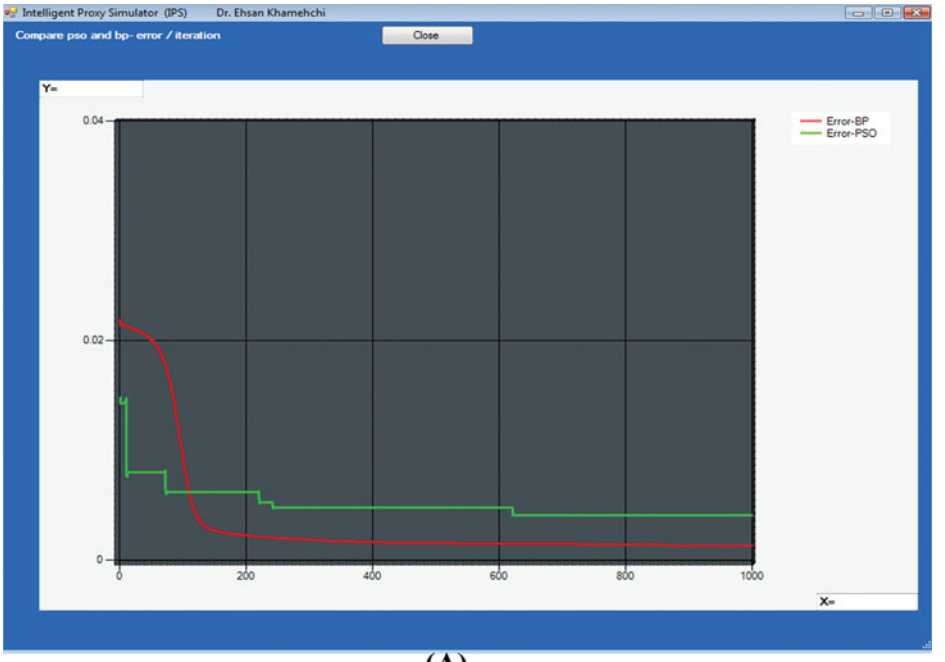


(B)

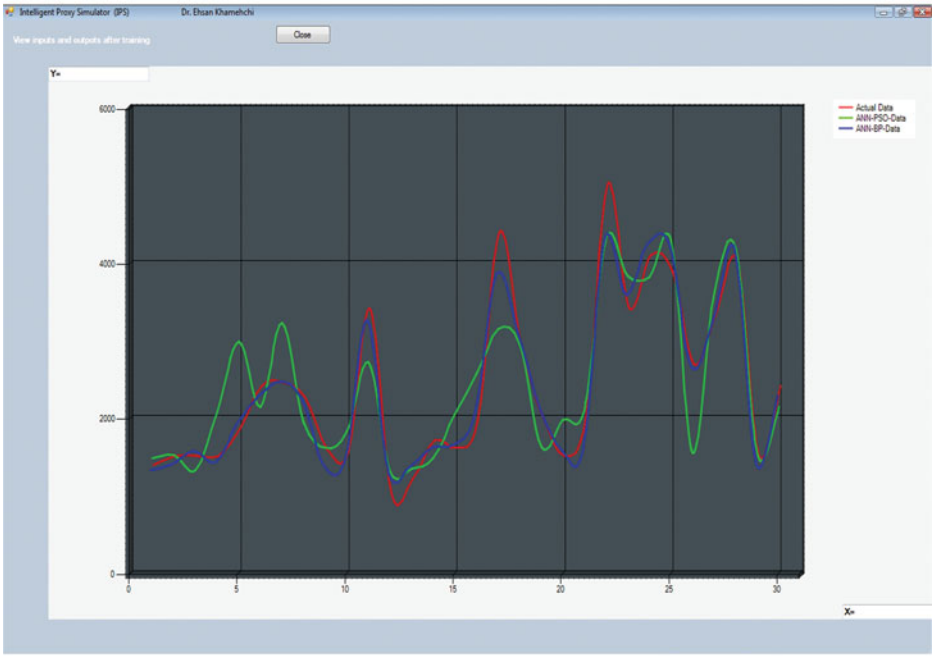
FIGURE 2 (A) Comparison between CO_2–oil MMP prediction by the GA-based correlation and experimental data. (B) The structure of the neural network.

5.2 Developing Gas–oil MMP Model by Neural Network

In this section IPS software (Intelligent Proxy Simulator) programmed, which applies BP and PSO algorithms to train the network. In order to obtain the best result, the parameters of the network,

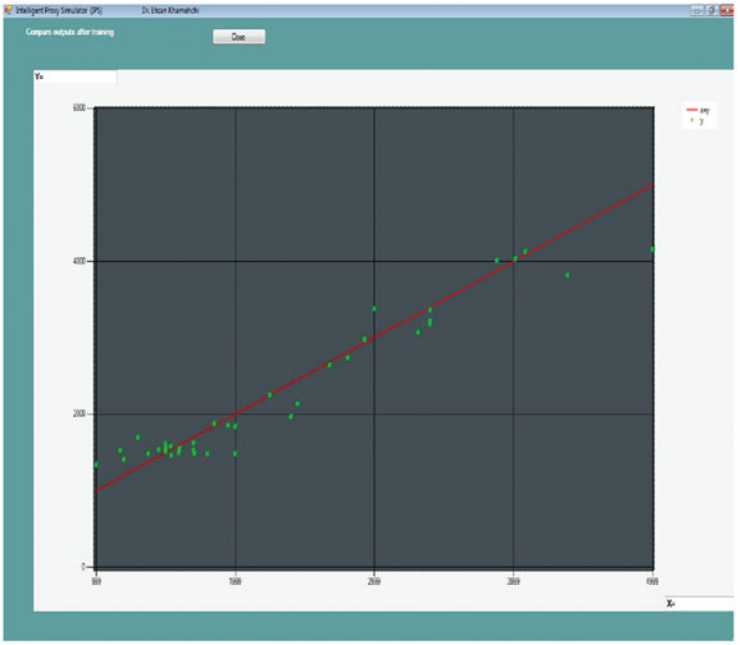


(A)

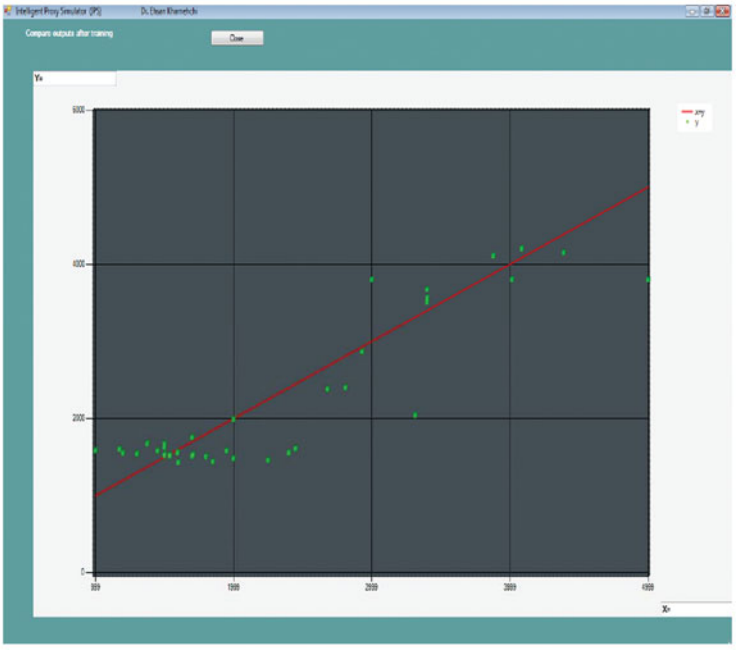


(B)

FIGURE 3 (A) Error while training. (B) Output trained by BP and PSO algorithm in comparison with actual data.



(A)



(B)

FIGURE 4 (A) Comparison between CO_2–oil MMP prediction by model trained by BP and experimental data. (B) Comparison between CO_2–oil MMP prediction model trained by PSO and experimental data.

TABLE 2
Comparison of Predicted MMP With Other Correlations

References	STMMP	GA		BP		PSO		Yelling et. al.		Cronquist		Glaso		Alston	
		Calc.	PE(%)	Calc.	PE(%)	Calc.	PE(%)	Calc.	PE(%)	Calc.	PE (%)	Calc.	PE (%)	Calc.	PE (%)
Alston,1985	1375	1299	5.49	1445	5.06	1497	8.9	1631	18.63	1691	22.96	1616	17.52	1269	7.71
Alston,1985	1500	1441	3.93	1515	0.97	1504	0.28	1785	18.97	1840	22.65	1751	16.71	1394	7.1
Alston,1985	1500	1611	7.41	1611	7.38	1362	9.19	1631	8.74	1686	12.38	1616	7.73	1568	4.54
Alston,1985	1500	1525	1.68	1512	0.8	1788	19.2	1631	8.74	1926	28.38	1616	7.73	1545	2.97
Alston,1985	1850	1956	5.74	1862	0.62	1588	14.2	1631	11.83	2208	19.38	1808	2.29	1956	5.74
Alston,1985	2400	2125	11.5	1989	17.1	1315	45.2	1199	50.02	1687	29.69	1385	42.29	2177	9.3
Alston,1985	2450	2411	1.6	2138	12.7	2420	1.22	1933	21.12	2676	9.23	1936	20.97	2436	0.59
Cardenas et al., 1984	2250	2248	0.1	2269	0.82	1355	39.8	2005	10.88	2316	2.93	2046	9.06	2156	4.16
Graue & Zana,1981	1594	1403	12	1498	5.99	2061	29.3	1631	2.33	1870	17.29	1615	1.33	1417	11.1
Dicharry,1973	1540	1132	26.5	1458	5.34	1755	14	1339	13.02	1461	5.12	1382	10.24	1154	25.1
Gardner,1981	3400	3417	0.49	3202	5.82	3462	1.81	3016	11.28	3970	16.76	2961	12.9	3264	4
Frimodig,1983	1000	1060	6	1334	33.4	1512	51.2	1027	2.72	1243	24.34	1170	17.01	1097	9.66
Frimodig,1983	1200	1270	5.81	1400	16.7	1513	26.1	1279	6.56	1443	20.28	1349	12.39	1291	7.6
Frimodig,1983	1700	1704	0.24	1620	4.72	1506	11.4	1696	0.24	1841	8.28	1706	0.34	1685	0.86
Frimodig,1983	1600	1580	1.24	1595	0.28	2498	56.1	1497	6.44	1950	21.87	1527	4.55	1631	1.97
Frimodig,1983	1950	2052	5.23	1874	3.9	2749	41	1884	3.4	2439	25.09	1884	3.37	2067	5.99
Alston,1985	4390	4223	3.8	3804	13.4	3136	28.6	2606	40.64	3658	16.67	2525	42.48	4114	6.28
Alston,1985	2930	2978	1.63	2952	0.74	3629	23.9	2852	2.65	3544	20.96	2716	7.32	2848	2.81
Holm& Josendal,1974	2000	2239	11.9	1910	4.51	2298	14.9	1696	15.21	2105	5.26	1677	16.15	2268	13.4
Rathmell,1971	1500	1528	1.84	1507	0.48	1664	10.9	1339	10.7	1707	13.79	1426	4.92	1580	5.32
Rathmell,1971	2000	1447	27.6	1511	24.5	2066	3.3	1247	37.63	1702	14.88	1353	32.34	1521	23.9
Rathmell,1971	5000	4487	10.3	4221	15.6	3576	28.5	2317	53.67	4661	6.79	2867	42.67	4568	8.64
Alston,1985	3400	3507	3.15	3148	7.4	3392	0.25	2005	41.02	3317	2.44	2098	38.29	3579	5.27
Alston,1985	4085	4294	5.12	4068	0.42	3809	6.76	2679	34.42	4490	9.92	2677	34.46	4231	3.58
Alston,1985	3880	4526	16.7	3956	1.96	3877	0.07	2197	43.37	4514	16.35	2456	36.71	4641	19.6
Peter Clark,2008	2680	2158	19.5	2645	1.31	3064	14.3	3573	33.33	3200	19.41	3369	25.73	1951	27.2
Moudi,2009	3315	3221	2.84	3067	7.48	3335	0.59	2461	25.78	3478	4.92	2859	13.75	3165	4.52
Moudi,2009	4015	4181	4.14	4069	1.35	3523	12.3	2424	39.62	4316	7.49	2852	28.97	4196	4.5
Thakur et al. 1984	3401	3035	10.8	3357	1.3	3438	1.08	3042	10.56	3613	6.24	2907	14.53	2869	15.6
Shelton et al. 1977	1450	1504	3.7	1546	6.62	1656	14.2	1099	24.23	1534	5.77	1248	13.92	1586	9.35
Henry et al., 1983	1536	1648	7.28	1561	1.63	1553	1.13	1497	2.54	1826	18.89	1583	3.06	1674	8.98
Harmon et al., 1988	3000	3808	26.9	3366	12.2	3357	11.9	2125	29.15	3425	14.17			3849	28.3
Harmon et al., 1988	1708	1380	19.2	1495	12.5	2168	27	1631	4.5	1845	8.01			1392	18.5
Spence,1980	1800	1454	19.2	1494	17	1880	4.42	1263	29.83	1697	5.7	1361	24.4	1524	15.4
Spence,1980	1300	1793	37.9	1695	30.4	1613	24.1	1339	3.03	1863	43.28	1470	13.04	1869	43.7
Bon et al.,2005	2810	2223	20.9	2750	2.13	2442	13.1	3491	24.24	3046	8.38			2009	28.5
Metcalfe et al., 1979	1700	1173	31	1512	11.1	1973	16.1	2005	17.96	1796	5.65	2238	31.66	1126	33.8
Sebastian et al.,1985	1175	1414	20.4	1525	29.8	1589	35.2	990	15.74	1508	28.36			1509	28.5
		E (%)	10.5	E (%)	8.56	E (%)	17.4	E (%)	19.34	E (%)	15	E (%)	17.96	E (%)	12.21

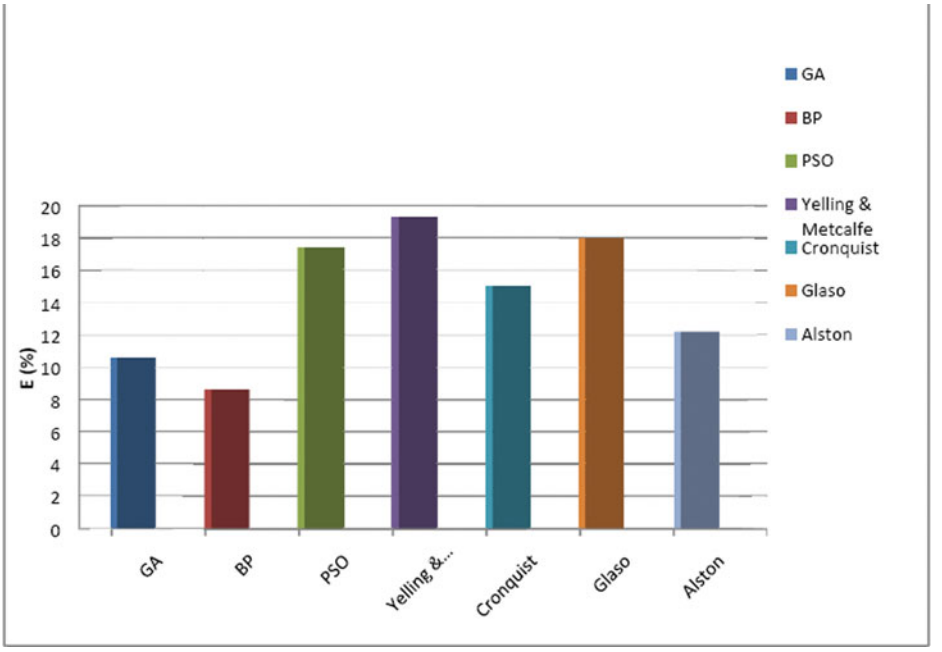


FIGURE 5 Comparison between accuracy of correlations.

such as number of hidden layers, number of neurons in the hidden layers, momentum, and learning coefficients are treated as variables that the user defined. The structure is shown in Figure 2B. The fitness is evaluated after training the network for specific iterations, which is kept as the mean square error (MSE) of the network and the final values are chosen. The final network is then trained by BP and PSO up to the desired level of MSE. Error for two algorithms is obtained while generation and final output trained by the two algorithms are shown in Figure 3. The models results are compared to available experimental data in Figure 4.

6. CONCLUSIONS

GA-based correlation and neural network model trained by BP gives a more accurate prediction among all other tested correlations when predicting CO_2–oil MMP. Table 2 shows that the average relative error for these correlation and models are lower than other frequently used CO_2–oil MMP correlations. The average percent error of correlation and two models presented in this paper are compared to each other and other correlations and results are shown in Figure 5. In this study a point is noticeable that training by BP algorithm about the functions that are specified with mathematical equations (such as sinusoidal functions) or be continuous well acted and BP methods in such cases have better results than PSO (Kashefi Kaviani, 2004).

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