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MODELLING STUDIES BY APPLICATION OF ARTIFICIAL NEURAL NETWORK USING MATLAB

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Abstract

Four ANN models to estimate Bubble point pressure (P_b), Oil Formation Volume Factor (B_{ob}), Bubble point solution Gas Oil Ratio **(**R_{sob}) and Stock Tank Vent GOR (R_{ST}) in the absence of Pressure, Volume and Temperature (PVT) analysis, were proposed as a function of readily available field data. The estimated R_{sob} and R_{ST} values from the proposed models can be used as a basic input variable in many PVT correlations in order to estimate other fluid properties such as the P_b and B_{ob}. Another proposed ANN model has the ability to predict and interpolate average reservoir pressure accurately by employing oil, water and gas production rates and number of producers are used as four inputs for the proposed model without the wells having to be closed. Another ANN model proposed is to predict the performance of oil production within water injection reservoirs, which can be utilized to find the most economical scenario of water injection to maximize ultimate oil recovery. It has reasonable accuracy, requires little data and can forecast quickly. ANN approach to solving the identified pipeline damage problem gives satisfactory results as the error between the ANN output and the target is very tolerable. The results conclusively proved with error 0.0027 that it has the ability to accurately predict the pipeline damage probability by employing the model data obtained in this study.

Keywords: Artificial neural network, PVT models, Reservoir pressure; Oil production; Pipeline damage.

1. Introduction

The PVT properties of crude-oil such as the bubble point pressure (P_b), oil formation volume factor (B_{ob}), dissolved GOR (R_{sob}) and stock tank vent GOR (R_{ST}) play a key role in calculating reserves as well as for identification of reservoir characteristics. The properties are traditionally determined from the laboratory

Nomenclatures

B_{ob}	Oil formation volume factor
d_p	Buried depth
f_t	Fault throw
P_{avg}	Average pressure
P_b	Bubble point pressure
p	Damage probability of buried pipeline
p_s	Pipe-soil friction
Q_g	Gas production
Q_o	Oil production
Q_w	Water production
R_{sob}	Bubble point solution gas oil ratio
R_{ST}	Stock tank vent GOR
W_{10}	Weight
W_{20}	Weight
W_{21}	Weight

Abbreviations

ANN	Artificial Neural Network
ARE	Average Relative Error
BP	Back Propagation
PVT	Pressure, Volume and Temperature
WHO	World Health Organization

analyses of reservoir oil samples. In the absence of experimental analysis, empirical correlations or models can be used to estimate reservoir fluid properties and insight into the average reservoir pressure (P_{avg}), and its change over time, plays a critical role in reservoir development. However, in order to determine the P_{avg}, the well is shut-in for a buildup test, resulting in loss of production. BP-ANN (Back Propagation-Artificial Neural Network) model can be obtained to predict and interpolate P_{avg} without closing the producing wells.

The prediction of oil reservoir production performance has been an on-going challenge for engineers. It is an essential component of petroleum reservoir management. Traditionally, numerical simulations and decline curve analysis have been used to predict a reservoir's future performance based on its current and past performance. Reservoir simulation is very time consuming and offers a non-unique solution with a high degree of uncertainty. In this study, ANN is presented to predict the performance of oil production within water injection reservoirs.

The damages in oil pipeline with its unforeseeable results in pollution, loss of lives, and reduction in production output, spurred the burning desire to proffer a novel solution with the use of (ANN) as a tool to detect pipeline damage and provide useful communication link with the supervisory control and data acquisition as shown by Sheng et al. [1]. Since complicated calculation is necessary, almost all recent theoretical and experimental researches cannot predict the mechanism of pipeline damage instantly based on major factors. The main predictive model is based on statistics, which cannot represent the progress in mechanism analysis and predictive model of ANN is developed in which the damage of pipeline becomes a nonlinear function of influence factors as demonstrated in Pie et al. [2].

2. Materials and Methods

According to 489 groups sample data, MATLAB®2013a 64-bit, is applied to analyze the design of seven predictive models, influences of model structure, concealed layer number, neuron number of concealed layer and training function, to get predictive results. All the data obtained from a single field of Middle East was randomly picked and divided into training, validation and testing data as contained in the neural network training algorithm. Model parameters and preferences are optimized, and four predictive PVT models, average reservoir pressure model, oil production model and pipeline damage model are determined based on results of numerical simulation. Optimum model structures are constructed and advice for modeling and cost effectiveness are proposed according to double parallel feed-forward neural networks. The model structures are analyzed and final optimum network structures are worked out. The predictive models are selected and deployment tests conducted and analyzed statistically for their applications in reservoir engineering as well as pipeline network supervisory control and data acquisition and discussed with respect to similar studies.

The proposed PVT ANN models were developed based on 288 reservoir fluid studies collected from various Middle East oil fields. The reservoir contained a set of 60 oil wells and three water injecting wells. There are just 72 measurements of average reservoir pressure from the period of March 1970 to July 2010 (more than 40 years of production) and 71 datasets for oil production. The overall data used to model were split into four sets - 34 points (47.22%) to the training set, 11.11% (8 points) to the validation set, 11.11% (8 points) to the testing set and 22 points (30.56%) to the deployment set. The training dataset was used to train the ANN models. The damage of pipeline is affected by three main factors, which can be treated as a nonlinear function, they are buried depth, fault throw, and pipe-soil friction and the target vector is damage probability of pipeline. The Neural Network Training Regression and Error analyses of Training and Deployment tests were conducted to evaluate the proposed model performance using 58 groups sample data.

The inputs are selected to be incorporated into the input layer. In order to find an efficient network model and analyze the performance, the data must be pre-processed in order to have a small variation of the output data. It is well known that, in theory, the output data can have a large domain of variation. However, if the domain of variation of the output data is large, the ANN model tends to be less stable. The dimensionless output data ranges from 0 to 1, while the input data ranges from -1 to 1. To specify the number of hidden layers and the number of units in each layer, a trial and error approach was carried out, beginning with one hidden layer and one hidden unit. Hidden units were then gradually added. A total of 70 architectures were compared with the following network parameters: Error function = Sum-of-squares, Fitness criteria = Inverse test error.

The selected architecture was trained using different algorithms. In each case, the architecture was retrained five times with different initial weight randomization. The training algorithm with the lowest average error and highest

r^2 was selected as a best training algorithm. As a final step in the modelling process, the ANN model is deployed to a new dataset. Sensitivity analysis is done and values are reported and discussed by searching for errors in the model by MATLAB itself. The quantitative statistical error analysis for the deployment test is performed that shows a small error obtained on the deployment datasets indicating excellent agreement between the actual and model predicted values. It shows the superiority of the ANN model in performing good generalization. If the validation error increases while the training error steadily decreases, then a situation of over fitting may occur. When the performance of the validation test ceases to improve, the algorithm halts.

3. Results and Discussion

The bubble point pressure BP-ANN model has four inputs, one hidden layer, with 25 nodes in the first, ten nodes in the second and five in the third layer. The model was trained with the Bayesian Regularization training algorithm as given by Kaur and Salaria [3]. The input, hidden and output layers were activated by tansig, logistic and tansig activation functions with an error value of 0.0028. The bubble point oil formation volume factor BP-ANN model was trained with the Levenberg Marquardt training algorithm as given by Levenberg [4] and activated by the logistic activation function with an error value of 0.00069. It has four inputs and one hidden layer with 25 nodes in the input, ten nodes in the second and five in the third layer. The bubble point solution gas/oil ratio BP-ANN model was trained with the Sequential order weight/bias training algorithm and the input, hidden and output layers were activated by tansig, logistic and logistic activation functions with an error value of 0.02426. It has three inputs and one hidden layer. Thirty nodes in the first layer, fifteen nodes are in the hidden layer while ten nodes are in the output layer. The stock-tank vent gas/oil ratio BP-ANN model was trained with the Bayesian Regularization training algorithm as shown by Kaur and Salaria [3] and activated by the tansig and logistic activation functions with an error value of 0.0499. It has three inputs, seven nodes in the first layer and three nodes in the second layer.

The average reservoir pressure BP-ANN model was trained with the Levenberg Marquardt training algorithm as demonstrated by Levenberg [4]. The network consisted of two hidden layers with twenty and ten neurons. The input layer had 35 and output layer had five neurons and all layers activated by logistic activation function with an error value of 0.0275. The input layer received four parameters consisting of oil, gas and water production rates and number of producers. The network was trained using feed forward back propagation, employing the Bayesian Regularization training algorithm as demonstrated by Kaur and Salaria [3]. The average reservoir oil production rate BP-ANN model was trained with the Quasi-Newton training algorithm activated with a logistic function as shown by Press et al. [5] and with the lowest sum-squared-error of 0.1. The chosen network has five inputs viz., the average reservoir oil production rate at time t, the average reservoir gas production rate at time t, the water injection rate at time t+1, the number of oil wells in production at time t +1 and the number of injection wells at time t+1. The Network model consisted of 2 hidden layers, 13 nodes in the first layer and 8 in the second layer.

The error values reported by earlier workers showed a similar trend and the present study depicted a better accuracy with respect to all the six ANN models viz., 0.0589 for P_b of Al-Marhoun and Osman [6]; 0.00511 for B_{ob} of Al-Marhoun and Osman [6]; 0.07 for R_{sob} of Dutta and Gupta [7]; 0.2142 for R_{ST} of Alimadadi and Fakhri [8]; 0.0279 for P_{avg} of Elmabrouk et al. [9] and 0.12 for Q_o of Elmabrouk et al. [10].

Four ANN models to estimate P_b, B_{ob}, R_{sob} and R_{ST} in the absence of PVT analysis, were proposed as a function of readily available field data (Table A-1, *Appendix A*). All the proposed PVT models can be applied straightforwardly in the absence of PVT analysis. No further correlations or experimental measurements are required. The estimated R_{sob} and R_{ST} values from the proposed models can be used as a basic input variable in many PVT imperial correlations in order to estimate other fluid properties such as the P_b and B_{ob}. Since the average reservoir pressure is measured during a pressure build up test while the well is shut-in, a significant economic effect occurs in producing wells during the entire build up test. Moreover, average reservoir pressure is measured periodically, resulting in a loss of production. This study shows the ANN approximation technique provides a new alternative method with which to predict oil reservoir production based on historical production data (Table A-2).

A case study involving a small oil field under water injection located in the Middle East demonstrates the proposed approach can be used to predict oil reservoir performance, and can serve as a practical and robust tool with regard to reservoir management. This approach is suitably employable to find the most economical injection rates by applying various water injection scenarios. Meanwhile, it could be a new window for fast simulators. It has reasonable accuracy, requires little data (Table A-2) and is able to forecast quickly. In general, ANN approximation technique can serve as a practical, cost effective and robust tool for oilfield production management.

Table 1 summarizes the quantitative statistical error analysis for the deployment tests. The analysis shows a very small error obtained on the deployment datasets. It shows the superiority of all the six ANN models in performing a good generalization. The prediction performance of the proposed models provides output values with average absolute relative errors of 0.04 per cent to 9.29 per cent. It has reasonable accuracy, requires little data and is able to forecast quickly. The results show the proposed PVT models and average reservoir pressure model provided high accuracy on testing dataset. This dataset was not viewed by the models during the building process.

Table 1. Statistical error analysis for deployment test (Average).

Factors	Actual Output	ANN Output	ARE
P_b	1604.00336	1604.02318	0.001236
B_{ob}	1.22365	1.22366	0.0004585
R_{sob}	396.99873	396.92636	0.01823
R_{ST}	50.16206	50.18227	0.04028
P_{avg}	1043.54697	1043.77273	0.02162
Q_o	47271.21823	47315.18182	0.09291
P	0.4084	0.4073	0.0027

According to the sample data (Table A-3), optimum network structure is worked out through above analysis. Optimum network structure is with 7 neurons and one concealed layer. Training function was trainlm and Transfer function logsig with an error of 0.0027.

According to double parallel feed-forward neutral network, the final predictive model is constructed. If symbols (dp, ft, ps) represent buried depth, fault throw, and pipe-soil friction, the damage probability of buried pipeline can be expressed as,

$$p_j = (W_{20} + W_{21} \times W_{10}) \begin{Bmatrix} dp_j \\ ft_j \\ ps_j \end{Bmatrix}$$

in which, $W_{20} =$ [0.7612 1.8536 6.5805],

$W_{21} =$ [-51.4881 0.1489 1.7049 -2.020 87.0115 0.6011 76.9068] and

$$W_{10} = \begin{bmatrix} 53.5585 & 35.2558 & 56.8053 \\ 14.6718 & -17.8203 & -30.3219 \\ -30.6276 & -18.6645 & 25.1057 \\ -30.1994 & -16.0786 & 29.7647 \\ 0.2392 & -5.3067 & 29.7978 \\ 22.2621 & 8.2393 & 20.1111 \\ -16.6239 & -18.1158 & 14.5846 \end{bmatrix}$$

The regression value of 0.977 in the neural network training regression shows that there is accurate match between the original data and ANN training output (Fig. 1). Eight data points, which were not used in the process of model derivation, were used in the deployment test to evaluate the proposed model performance. The results conclusively proved with error 0.0027 (Table A-3) that it has the ability to accurately predict the pipeline damage probability by employing the model data obtained in this study.

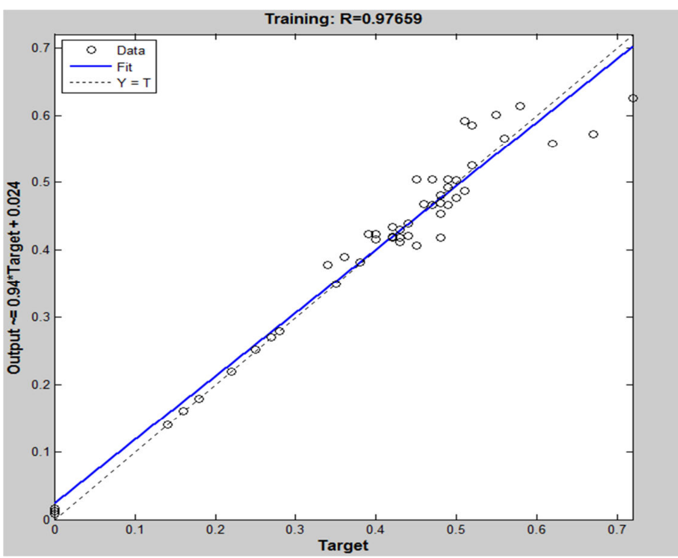

Fig. 1. Neural network training regression for pipeline damage.

4. Conclusions

An investigation has been made of the modelling of Bubble point pressure, Oil Formation Volume Factor, Bubble point solution Gas Oil Ratio, Stock Tank Vent GOR, Average Reservoir Pressure, Oil Production and Pipeline Damage with respect to their predictions based on a series of individual factors. This is done by application of Artificial Neural Network using MATLAB. Some concluding observations from the investigation are given below.

- The results showed that all the seven proposed models provided high accuracy on deployment testing dataset.
- Mean Square Error used for overall, training and validation tests and Relative Error for deployment tests and all tests were showed with acceptable magnitude of errors. No further correlations or experimental measurements are required.
- ANN approximation technique can serve as a convenient, rapid, cost effective and robust tool for oilfield production management and to predict the damage of buried pipeline with high precision, which can deal with fuzzy, nonlinear and noise-bearing data.

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Appendix A

Tables of Field Data

Table A-1. Field data for PVT models.

Sl. No.	Separator Pressure (P_{SP})	Separator GOR (R_{SP})	Stock-Tank Oil Gravity (roST)	Reservoir Temperature (T_R)	Separator Temperature (T_{SP})	Bubble point pressure (P_b)	Oil formation volume factor (B_{ob})	Bubble point solution GOR (Rsob)	Stock tank vent GOR (R_{ST})
1	119.58	352.2	0.84052	201.66	182	1734.4	1.3513	417	62
2	14.7	10	0.7999	100	98	121	1.064	46	0
3	735	1256	0.921	277	285	4244	1.795	1417	247.5
4	72.17	425	0.83286	202.44	138	1695	1.3202	202	115
5	14.7	21	0.7999	100	99	189	1.0640	54	1
6	228	1009.8	0.8927	275	192	4244	1.674	616	144
7	109.92	347.5	0.84027	200.48	110	1698.9	1.2835	392	62.5
8	14.7	10	0.7999	100	98	121	1.047	17	2
9	517	1175	0.921	277	202	4244	1.795	1168	212
10	14.7	10	0.8	12	100	121	1.047	17	0
11	111	365	0.84	108	202	1762	1.293	418	53
12	517	1256	0.92	194	282	4720	1.781	1256	248
13	14.7	31	0.803	73	100	152	1.064	45	0
14	116	342	0.84	107	201	1707	1.286	400	58
15	514	1009	0.92	194	277	4244	1.673	1105	223
16	14.7	21	0.8	64	100	189	1.064	56	0
17	116	363	0.839	106	200	1783	1.290	422	59
18	514	1175	0.918	194	282	4720	1.795	1175	230
19	29.7	10	0.8	100	12	121	1.047	26	6.3
20	132	354	0.84	203.6	110	1831	1.291	419	65.2
21	517	1097	0.92	282	194	4720	1.73	1135	248
22	29.7	31	0.803	100	73	189	1.074	53	7
23	124.3	357	0.842	209.3	109.8	1842	1.298	420	63.25
24	514	1009	0.92	277	194	4244	1.673	1105	223
25	29.7	21	0.8	100	74	189	1.064	56	4
26	144	317	0.838	198.4	109.7	1801	1.27	392	74.58
27	514	850	0.917	282	194	4720	1.65	925	230
28	114.10	339.9	0.84014	200.47	179	1689.7	1.29	404	59
29	14.7	10	0.7999	100	99	121	1.063	44	0
30	517	1175	0.921	277	270	4244	1.792	1098	235
31	90.69	374.6	0.84028	200.64	148	1731	1.32	373	43
32	14.7	13	0.8003	100	98	152	1.048	48	3
33	514	1038	0.92	271.4	268	4244	1.781	1254	232
34	111.1	353.1	0.84078	200.34	165	1707	1.291	398	58
35	14.7	15	0.7999	100	99	121	1.065	55	2
36	447	1097	0.919	275	196	3582	1.652	963	158
37	47.41	450.2	0.83457	209.7	75	1810	1.242	67	12
38	14.7	21	0.8008	134	98	189	1.058	15	1
39	228	109.8	0.8927	275	185	4244	1.653	602	142
40	127.12	250.1	0.84035	206.3	182	1836	1.321	409.3	62.4
41	14.7	10	0.7999	105	99	142	1.046	17	3
42	735	1250	0.921	294	282	4220	1.793	1256	248
43	141.17	316	0.84079	198.2	111.19	1800	1.419	415	68.8
44	29.7	22	0.7999	99.8	73	189	1.045	27	6.3
45	735	1248	0.92	282	194	4244	1.79	1392	288.8
46	92.87	421.6	0.83324	200.32	103.83	1732	1.392	473.2	51.58
47	34.7	21	0.7999	106	73	161	1.178	56	9.8
48	228	1009.8	0.8927	275	158	4244	1.659	1105.9	155
49	111	352.9	0.8407	200.4	176	1707	1.292	420	60.2
50	109.9	346.8	0.8402	199.8	171	1699	1.352	415	61

Table A-2. Field data for average pressure and oil production.

Sl. No.	Average Pressure (P_{avg})	Oil Production (Q_0)	Water Production (Q_w)	Gas Production (Q_g)	Production Well
1	1188	111455	139456	18390	55
2	1138	132741	109078	21902	51
3	1134	132700	109070	21900	51
4	1081	109740	129456	17902	60
5	1072	108020	114499	17823	53
6	1053	107920	114260	17760	45
7	1040	107900	*114200*	17710	47
8	1006	80060	93040	13210	47
9	996	79050	92860	13150	45
10	1004	80060	92939	13198	47
11	986	79040	92810	13130	45
12	994	79072	92930	13126	45
13	1072	108000	114538	17820	53
14	1013	80085	92960	13210	47
15	949	52100	71380	8572	40
16	927	44012	70039	7239	37
17	898	43798	69900	7200	30
18	907	44000	69930	7215	37
19	894	43918	69872	7180	35
20	841	11900	31453	1866	37
21	833	10770	3572	1739	15
22	854	11920	31502	1870	37
23	861	18560	42560	3015	35
24	874	19350	430010	3028	37
25	844	12910	37450	1870	35
26	904	40018	42040	5239	37
27	880	19400	430000	3010	37
28	874	19386	429090	3008	35
29	881	19458	430065	3078	37
30	876	25310	56710	3260	35
31	866	18162	28998	2647	15
32	863	16955	20994	2243	15
33	882	27460	59845	3475	35
34	894	30480	63120	3680	35
35	930	46783	81407	7687	43
36	908	42516	76515	4920	37
37	902	36816	69780	4018	35
38	876	25408	56210	3255	37
39	934	48538	72962	7983	40
40	865	17700	23810	2340	17
41	853	13140	17980	1730	15
42	866	18150	29010	2645	17
43	852	12940	15960	1830	15
44	852	13145	17880	1720	15
45	859	14950	18990	2045	17
46	853	13146	17880	1698	15
47	847	10938	13961	1732	12
48	842	10920	12900	1685	15
49	820	10770	3572	1732	12
50	832	10900	12882	1680	15

Table A-3. Field data for pipeline damage probability.

Sl. No.	Buried depth (d_p)	Fault throw (f_t)	Pipe-soil friction (p_s)	Damage probability (P)
1	0.48	0.64	0.89	0.50
2	0.56	0.20	0.89	0.42
2	0.56	0.20	0.89	0.42
3	0.50	0.65	0.89	0.46
4	0.19	0.04	0.87	0.16
5	0.47	0.64	0.95	0.44
6	0.44	0.36	0.81	0.35
7	0.53	0.20	0.92	0.43
8	0.56	0.16	0.93	0.39
9	0.87	0.47	0.88	0.51
10	0.44	0.36	0.87	0.34
11	0.93	0.49	0.91	0.55
12	0.53	0.65	0.88	0.48
13	0.51	0.60	0.88	0.50
14	0.50	0.18	0.87	0.43
15	0.28	1.00	0.87	0.00
16	0.52	0.18	0.89	0.40
17	0.81	0.56	0.91	0.56
18	0.88	0.47	0.92	0.58
19	0.53	0.18	0.87	0.42
20	0.56	0.65	0.89	0.48
21	0.87	0.47	0.87	0.52
22	0.44	0.36	0.91	0.36
23	0.47	0.65	0.90	0.48
24	0.88	0.55	0.91	0.67
25	0.19	1.00	0.88	0.00
26	0.19	0.07	0.81	0.27
27	0.56	0.19	0.95	0.40
28	0.53	0.20	0.87	0.43
29	0.48	0.65	0.89	0.49
30	0.47	0.65	0.89	0.47
31	0.53	0.18	0.91	0.42
32	0.47	0.65	0.92	0.47
33	0.53	0.18	0.93	0.44
34	0.19	0.00	0.89	0.14
35	0.50	0.60	0.90	0.52
36	0.19	0.04	0.89	0.25
37	0.35	0.36	0.89	0.38
38	0.19	0.06	0.91	0.22
39	0.20	0.14	0.87	0.28
40	0.50	0.28	0.88	0.45
41	0.88	0.52	0.87	0.62
42	0.53	0.15	0.88	0.48
43	0.53	0.18	0.91	0.42
44	0.41	0.58	0.87	0.49
45	0.46	0.65	0.91	0.49
46	0.18	0.04	0.87	0.18
47	0.56	0.60	0.88	0.45
48	0.53	0.36	0.87	0.72
49	0.25	1.00	0.88	0.00
50	0.51	0.67	0.92	0.51