Sensitivity analysis in using of artificial neural network models to determine infill well locations in a mature oil field

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Abstract. This paper describes a method to rank potential infill well locations using Artificial Neural Networks (ANN) from existing well data. Sensitivity test was conducted for training and testing data used with comparison 2:8, 4:6, 5:5, 6:4 and 8:2 for each data. Root Mean Square Error difference between training and test data show that the best results obtained from the ratio of training data and testing data 8: 2. Two ANN models were built. The first model predicted top sand depth, resistivity, gamma-ray and density-neutron from infill well location (chosen from structural position and good oil rates from offset wells). The second model predicted initial oil rate from outputs from the first model. Predicted initial oil rates from the ANN model were compared with those from the 3D reservoir simulation model. They shows similar prediction of oil rates which gave high confidence in the predicted oil rate. Very different oil rate prediction between the two models can be used as consideration to improve the simulation model.

Keywords: Mature Oil Field, Artificial Neural Network, Infill Well, Prediction

1. Introduction

Mature fields make a significant contribution to global oil production. A 2011 report from IHS Cambridge Energy Research Associates stated that approximately two-thirds of global oil production comes from mature fields and this percentage is increasing over time [1]. High contribution from mature field was followed by high challenge from its field such as high water cut produced and limited drilling-site availability due to population encroachment. Facing this problem we have limited alternatives to increase the oil production through secondary recovery or tertiary recovery technology but unfortunately this technology will spend high expenditure and longer time caused by detail study that needed to have a good reservoir characterization. Therefore one of the best solutions to keep production decline in a mature field is by drill new infill well. In this study we will share a method to predict infill well location optimally with limited time.

Predicting the well performance need a sufficient data in terms of number and quality of data. For example, when an engineer wants to predict the wells performance by using decline curve analysis, they need to have flow rate of oil production data for a minimum 6 months period since the well has produced. This data will be used to produce the trend line before it forecasted. The quality of the data is very critical to the cumulative oil recovery because if the flow rate measured is smaller than the actual, the result will become pessimistic. On the other hand, when you want to use other methods such as material balanced, it would require additional data beside the production data such asfluid properties consist of gas, oil and water. The most advanced method that is currently widely used to predict the performance of a well is by using 3D reservoir simulation model. To build a 3D reservoir simulation models require large number of data, such as geophysical data, geological data, and production data. Also when building this model,it will take a long time, so hopefully by using Artificial Neural Network (ANN) method for predicting a well, it can be an alternative since the ANN models do not require as much data as the used to construct the 3D reservoir simulation model.

The neural network model was introduced by McCulloch and Pitts [2]. The model is an information processing model that is inspired by the way biological nervous systems. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. The neural network model has been successfully applied to several fields of petroleum engineering such as reservoir engineering such as permeability estimation [3], reservoir heterogeneity characterization [4] and designing improved oil recovery methods [5]; production engineering such as multiphase flow measurements in pipes [6,7], pump identification [8], and production prediction [9]; and drilling engineeringsuch as drill bit diagnostics [10], rate of penetration [11], and bit selection [12-14].

The purpose and objectives of this research are: to identify potential infill well location in a mature oil field, to know the sensitivity of the amount of data between the training data and testing, to reduce uncertainty level in initial oil rate for the upcoming infill well, to increase the level of confidence inpredicting the performance of infill wells and to obtain potential infill welllocations with short time period.

2. Field Background

Melibur Field is located in Malacca Strait Block, east coast of Riau Province, Sumatra, Indonesia, as illustrated in Figure 1. Reservoir structure of the Melibur Field is anticline structure that is broken on a layer of sand rock formations Sihapas. This field was discovered in 1984 and still as an undersaturated reservoir. Following the appraisal and development drilling, this field finally started production in late 1986. Over time, the production of the reservoir Sihapas can no longer rely on the natural driving force due to the pressure reservoir has been declining from a reduced ability of the aquifer to maintain reservoir pressure. So at the beginning of 1988, the reservoir pressure has been reduced to below saturated pressure, which resulted dissolved gas has produced to the surface. Of course this causes problems for the production of oil in the well because of the tendency of gas that more easily to produce than oil.

In mid-1988, the reservoir simulation study has conducted in Melibur Field to optimize the oil recovery from this field. Recorded from the mid 1990s until now infill well drilling program inMelibur Field still continues to maximize oil recovery.

Since the reservoir is controlled by some faults, the reservoir is then divided into four areas/regions based on oil compartment analysis. The oil compartment system has been determined based on some considerations: oil properties, production performance and fluid contacts. The areas and the existing wells of Melibur Field are shown in Figure 2. Hydrocarbon in the Melibur Field trap on four separate areas, namely North West, Main, South and South East. Each area is characterized to have different contacts which are defined by geology as well as the facts and analysis of the technical side.

Until 2009, there are 74 wells in Melibur field, 55 of them still producing. Melibur Field producing oil about 2600 BOPD from Lower Sihapas formation and current cumulative oil production about 40.6 MMSTB based on production data in 2009. Main compartment is the biggest contributor; it is almost 90% of total cumulative production of Melibur field.

Melibur Field consists of four areas: Northwest, Main, South and Southeast. The main priority areas is called Main area that has produced a total oil cumulative per September 2008 is 35 MMSTB or equal to 90% of the total cumulative production in Melibur Field. The peak oil production was 14,700 BOPD and the decline rate in reservoir Sihapas is equal to 7 x 10^{-4} / day as shown in Figure 3.

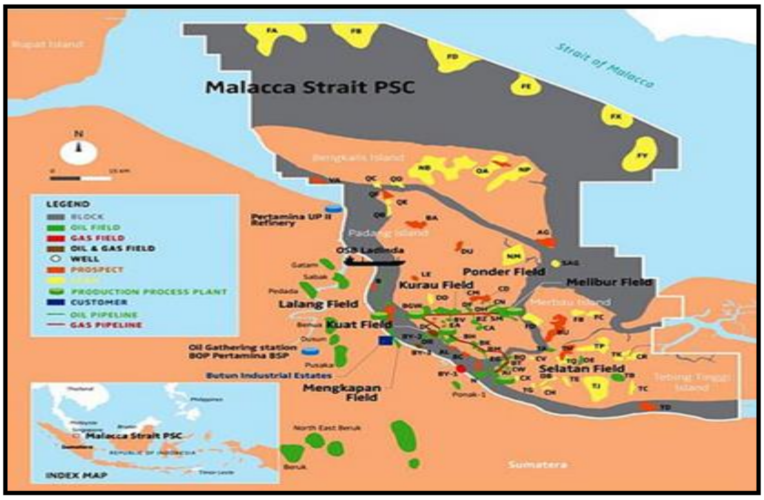

Figure 1. Malacca Strait Block [15].

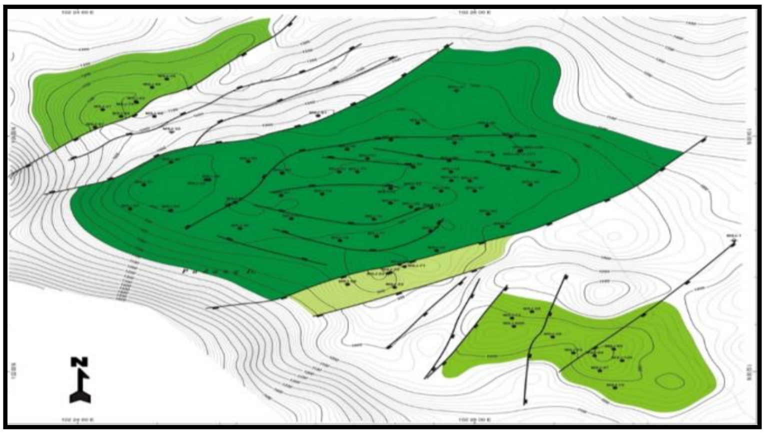

Figure 2. Melibur Field [15].

3. Artificial Neural Network Model

Figure 4 depicts a flow chart used to build the model Artificial Neural Network (ANN) so that the log parameters and initial oil flow rate from certain coordinate can be predicted. Artificial neural network is a computation model that uses analogy from the brain properties. This network consists of a few simple parameters that work in parallel without any major control. The learning process becomes the main processes that occur to minimize the differences in outcomes between the training data and testing. Developed a neural network is a relationship between a set of input data and output data. The general configuration of the neural network with one layer feedforward method consists of two parameters: input neurons and output neurons.

Activation function used during this training is sigmoid function. At the initial condition that the connection weight value entered is the default value. When the network is considered good enough by the parameters entered, then the next general model is made to determine the relationship between input and output. One can determine the effect of a series of parameters in the input to the output by performing sensitivity. In this case the default parameters used due to the sensitivity of the tests are those that can deliver the highest matched value. The default parameters used are as follows:

- Initial Weight: 0.3
- Learning Rate: 0.3
- Momentum: 0.6
- Epochs: 50000

By using the default parameters in the above test, the sensitivity of the amount of training data and testing were examined. Two neural network models were built. The first model was used to predict the log parameters and the second model was used to predict the initial oil flow rate obtained from the output of the first model. In building this neural network model of the comparison between the training data were as follows 2: 8, 4: 6, 5: 5, 6: 4 and 8: 2.

To determine the quality of a model built is good or not, we determined by calculate Root Mean Square Error (RMSE) between the estimated output of neural network models and measured output of the test data-sets. The maximum limit that can be tolerated RMSE authors determined from the difference in the range of data that is multiplied by 30%. Table 1 shows the maximum RMSE values for each parameter.

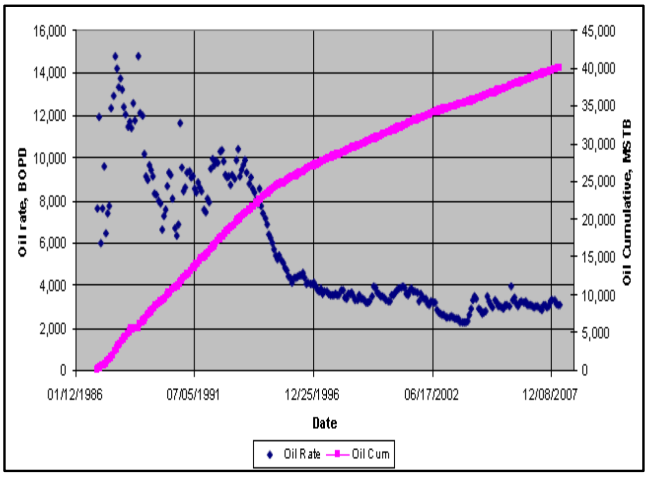

Figure 3. Production History in Melibur Field [15].

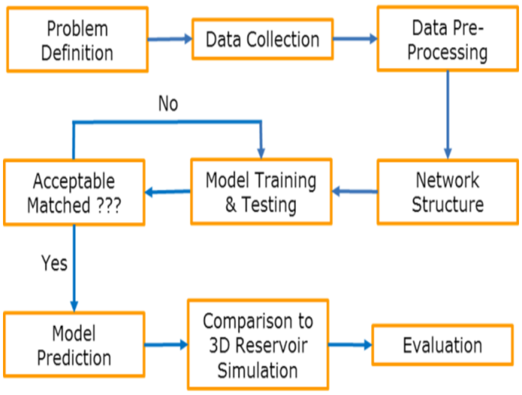

Figure 4. Workflow.

3.1. Training and Testing Data – Log Parameter

The first model has two inputs in form of well coordinates, X coordinates and Y coordinates with 5 output parameters, Top Sand Depth, Gamma Ray Log, Resistivity Log, Neutron Log and Density Logs. Training and testing output data obtained from wireline logging measurement and average value of gross sand was used to input to the model. Detail input and output data can be seen in Appendix Table A.8.

Result of the sensitivity test for ratio data can be seen in Appendix Tables A.1 to A.6. The Table 2 shows the best results of the sensitivity test with a ratio of training data and testing data 8: 2. The sensitivity of the test RMSE values obtained as follows

Table 1. RMSE Max Value.

No	Log Parameter	Min	Max	RMSE Max
1	Top Sand Depth	885	1010	38
2	Gamma RayLog	71	127	17
3	Resistivity Log	6	58	16
4	Neutron Log	33	45	4
5	Density Log	1.96	2.17	0.06
6	Initial Oil Rate	22	534	154

Table 2. RMS Error for Model 1.

No	Log Parameter	RMS Error	
		Training Data	Testing Data
1	Top Sand Depth	15	11
2	Gamma RayLog	11	18
3	Resistivity Log	8	7
4	Neutron Log	2	2
5	Density Log	0.04	0.06

Figures 5 to 9 show the suitability of the results between prediction training data and actual training data for each parameter.

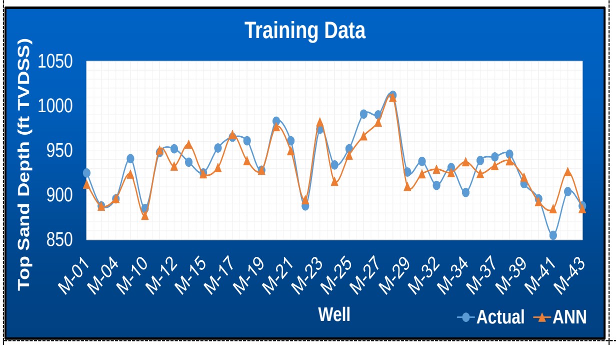

Figure 5. Top Sand Depth Training Data.

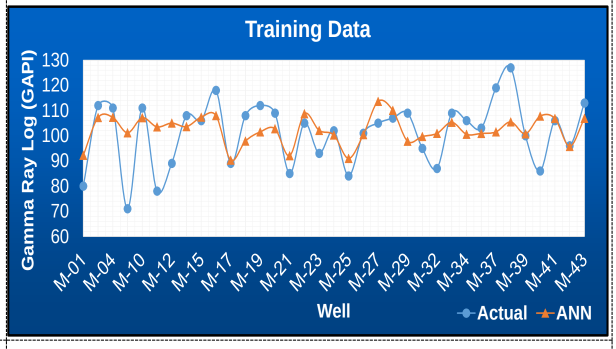

Figure 6. Gamma Ray Log Training Data.

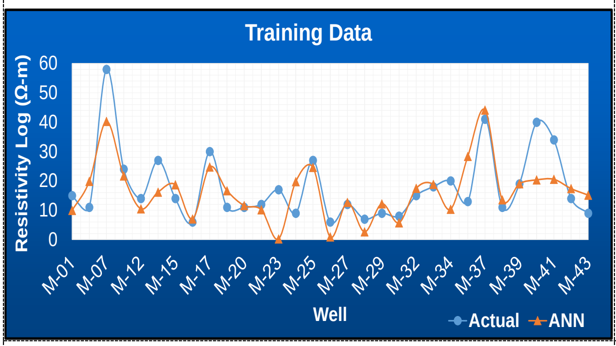

Figure 7. Resistivity Log Training Data.

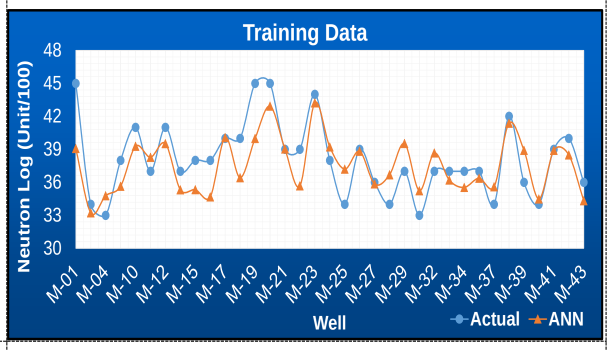

Figure 8. Neutron Log Training Data.

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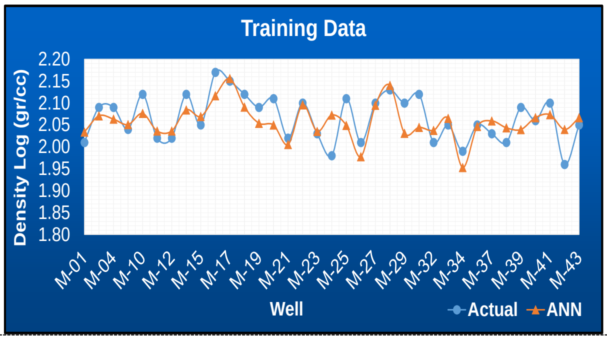

Figure 9. Density Log Training Data.

In addition, Figures10 to 14 below show the suitability of the results between prediction testing data and actual testing data for each parameter.

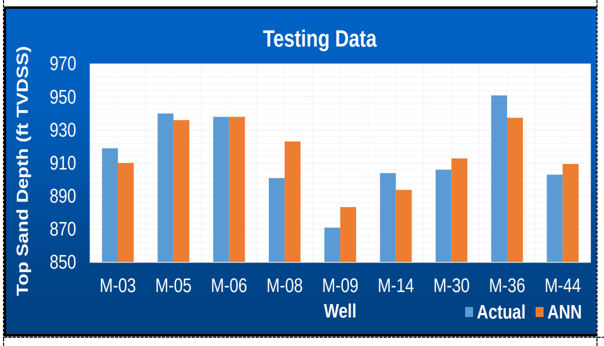

Figure 10. Top Sand Depth Testing Data.

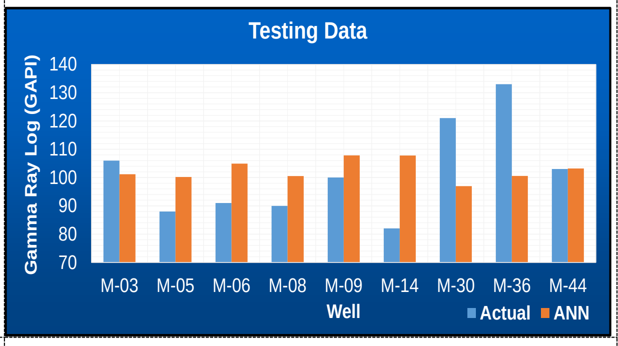

Figure 11. Gamma Ray Log Testing Data.

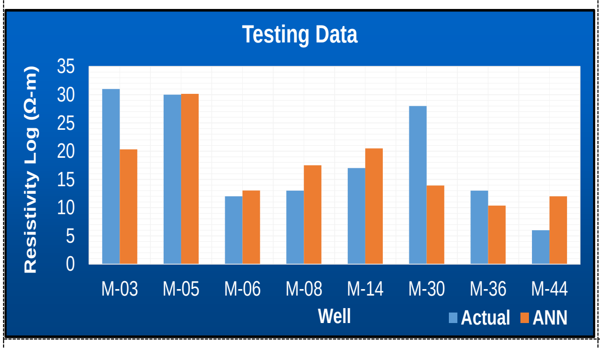

Figure 12. Resistivity Log Testing Data.

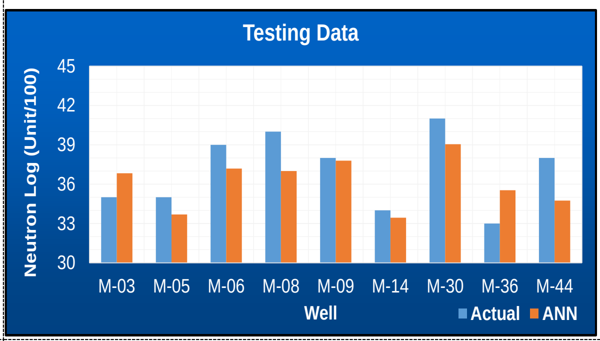

Figure 13. Neutron Log Training Data.

3.2. Training and Testing Data – Initial Oil Rate

The second model is built by using 6 input data which is 5 input was obtained from the first model, top sand depth, gamma ray log, resistivity logs, neutron and density logs while an additional input is production months. Production months is the months that the well start producing. It determined from production months for the first wells in January 1987. These input data will be used to generate an output parameter initial oil rate. There are a total of 35 parameters of logs data and 35 initial oil rate data as output to be used as a training and testing the model.

Based on the sensitivity test conducted for the second model, the best results are obtained by comparison of the training and testing data 8: 2. The RMSE values obtained for the training data is 1, this shows an almost perfect matchedwhile the RMSE values for the test results is 79, which is this value still below the maximum limit of RMSE. Figure 15 shows the suitability of the results between prediction training data and actual training data for initial oil rate. Figure 16 shows the suitability of the results between prediction testing data and actual testing data for initial oil rate.

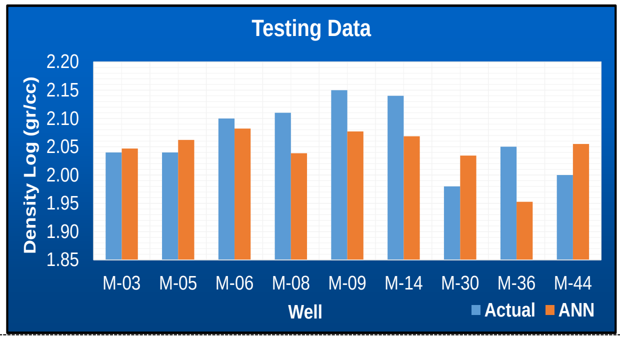

Figure 14. Density Log Testing Data.

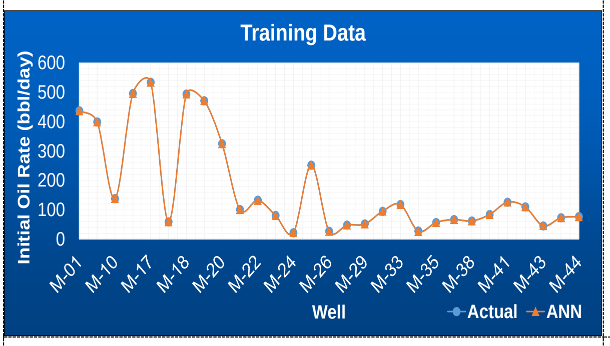

Figure 15. Initial Oil Rate Training Data.

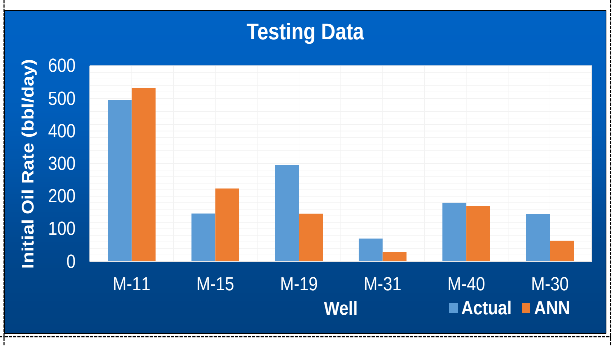

Figure 16. Initial Oil Rate Testing Data.

4. Prediction Result

In order to validate the Artificial Neural Network model, the prediction results from the model are compared with those from reservoir simulation as follows:

4.1. Prediction Result from Artificial Neural Network (ANN)

Based on sensitivity tests performed between the amount of training data and testing of the previous, we conclude that for test results that produce the smallest RMSE value is a model that uses comparison between training data and testing data 8: 2. Therefore the prediction only performed by using the best models 8: 2 that has been saved. Prediction will be conducted to the well locations that will be drilled in the near future. There are 5 wells coordinates which would be predicted .The wells location can be seen in Figure 17.

The selection of these wells coordinates are based on the depth structure (updip structure) and good production profile from the surrounding wells. Thesewells are assumed to be drilled in January 2014. Table 3 indicates the coordinates for each wells that are used as input for the first model to predict the top sand depth, gamma ray log, resistivity logs, neutron log and density logs.

Table A.7. in the appendix is the output obtained from the first models of Artificial Neural Network (ANN). From the outputs obtained from the first model, then the outputs are used as input for the second model which added one more input parameters such as production month for 307 months assuming these wells drilled in January 2014. Table 4 shows the results of the prediction rate Initial oil flow using Artificial Neural network model (ANN).

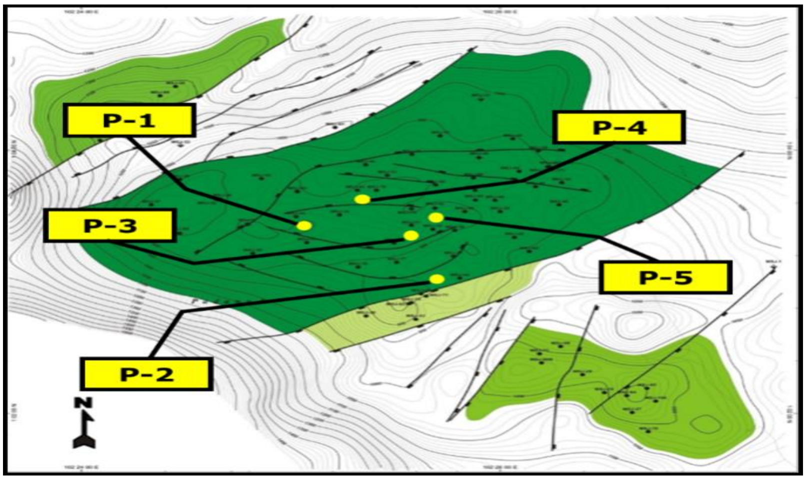

Figure 17. Coordinate location of predicted wells.

Table 3. Well Coordinates for Prediction.

No	Well	X Coordinate (mE)	Y Coordinate (mN)
1	P-01	212653	116936
2	P-02	213839	116240
3	P-03	213534	116818
4	P-04	213278	117214
5	P-05	213896	117025

Table 4. Prediction Result from Artificial Neural Network (ANN).

No	Well	Production Months	Initial Oil Rate (bbl/day)
1	P-01	307	150
2	P-02		67
3	P-03		62
4	P-04		99
5	P-05		105

4.2. Prediction Result from 3D Reservoir Simulation

For convincing the prediction result obtained from the Artificial Neural Network (ANN) model, the initial oil flow rate also determined by using another method which is 3D reservoir simulation. Melibur Field simulation model has high degree of accuracy. It can be seen from the production comparison between reservoir model and actual are identical from the latest infill wells.

Table 5 shows the results of the initial oil flow rate prediction using the 3D reservoir simulation which is the prediction was used liquid constraint 150 BFPD then obtained the following results.

4.3. Prediction Result Comparison

Prediction results from the reservoir simulation results above then compared with the results of the model Artificial Neural Network (ANN), which has been determined previously. Table 6 and Figure 18 present the results of a comparison between the initial oil rate predictions of the Artificial Neural Network (ANN) models and 3D reservoir simulation model.

The calculation result of the RMS error between these two values is 27 BOPD. There is a well P-03 that has a very similar predictive value was within 1 BOPD. Then three wells obtained initial oil rate higher than models of Artificial Neural Network (ANN) and the rest of the wells, P-02 well obtain lower value than reservoir simulation. Overall, predicted initial oil rate from the ANN model were in the same ball park as the 3D reservoir simulation model.

Table 5. Prediction Result from 3D Reservoir Simulation.

No	Well	Initial Oil Rate (bbl/day)
1	P-01	111
2	P-02	85
3	P-03	63
4	P-04	66
5	P-05	84

Table 6. Oil rate prediction comparison between ANN model and 3D reservoir simulation.

No	Well	Initial Oil Rate (bbl/day)	
		Artificial Neural Network (ANN)	3D Reservoir Simulation
1	P-01	150	111
2	P-02	67	85
3	P-03	62	63
4	P-04	99	66
5	P-05	105	84

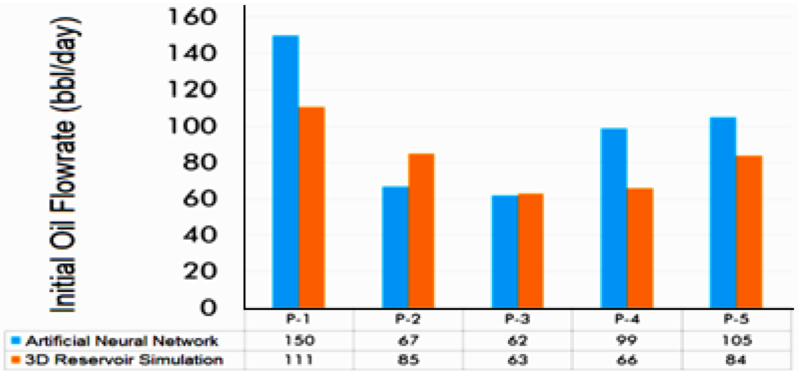

Figure 18. Initial Oil Rate Histogram of Artificial Neural Network (ANN) and 3D Reservoir Simulation.

5. Conclusions

1. Sensitivity analysis for the comparison between training and testing data has been successfully carried out which resulting 8 : 2 comparison give the lowest RMSE value for all parameters and it enter into the matched criteria with maximum RMSE value 30 percent of the difference from the range.
2. The sensitivity tests conducted on the comparison between training and testing datashows that the more training data used, the smaller RMSE values obtained. Otherwise, if the training data usedjust a few data this will lead to higher RMSE values obtained indicate that the model is not accurate enough.
3. Artificial Neural Network (ANN) can be used to estimate initial oil rate (and other economic inputs such as oil decline rate) for reservoirs where we do not have a reservoir simulation model.
4. The calculation result of the RMSE for predicted initial oil ratebetween ANN and 3D reservoir simulation obtain good RMSE value 27 BOPD and overall it were in the same ball park.
5. The process of training and testing data during building Artificial Neural Network (ANN) model is an ongoing and continuous-improvement process to further reduce RMS error which is nearly zero.

Acknowledgments

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Appendices

Table A1. RMSE for Top Sand Depth.

Comparison Training Data : Testing Data	RMSE	
	Training Data	Testing Data
2 : 8	0	34
4 : 6	13	26
5 : 5	16	25
6 : 4	15	25
8 : 2	15	11

Table A2. RMSE for Gamma Ray Log.

Comparison Training Data : Testing Data	RMSE	
	Training Data	Training Data
2 : 8	0	26
4 : 6	8	23
5 : 5	10	20
6 : 4	10	19
8 : 2	11	17

Table A3. RMSE for Resistivity Log.

Comparison Training Data : Testing Data	RMSE	
	Training Data	Testing Data
2 : 8	0	24
4 : 6	4	24
5 : 5	5	24
6 : 4	5	19
8 : 2	8	7

Table A4. RMSE for Neutron Log.

Comparison Training Data : Testing Data	RMSE	
	Training Data	Training Data
2 : 8	0	5
4 : 6	3	5
5 : 5	3	3
6 : 4	2	3
8 : 2	2	2

Table A5. RMSE for Density Log.

Comparison Training Data : Testing Data	RMSE	
	Training Data	Testing Data
2 : 8	0	0.07
4 : 6	0.03	0.07
5 : 5	0.02	0.07
6 : 4	0.03	0.06
8 : 2	0.04	0.06

Table A6. RMSE for Initial Oil Rate.

Comparison Training Data : Testing Data	RMSE	
	Training Data	Training Data
2 : 8	0	161
4 : 6	3	213
5 : 5	0	143
6 : 4	3	113
8 : 2	1	79

Table A7. Artificial Neural Network (ANN) Prediction Result for the First Model.

No	Well	Top Sand Depth (ft TVDSS)	Gamma Ray Log (GAPI)	Resistivity Log (Ω-m)	Neutron Log (%)	Density Log (gr/cc)
1	P-01	886	107	19	34	0.207
2	P-02	923	106	8	39	0.203
3	P-03	918	101	15	36	0.204
4	P-04	905	104	21	36	0.206
5	P-05	923	101	19	38	0.204

Table A8. Data Set ofArtificial Neural Network (ANN) Input and Output Data.

No	Well	X Coordi nate (mE)	Y Coordi nate (mN)	Top Sand Depth (ft TVDSS)	Gamma Ray Log (GAPI)	Resistivit y Log (Ω-m)	Neutron Log (%)	Densit y Log (gr/cc)	Initial Oil Rate (bbl/day)
1	M-01	213683	116010	925	80	15	45	2.01	437
2	M-02	212145	116975	888	112	11	34	2.09	837
3	M-03	213599	117189	919	106	31	35	2.04	1439
4	M-04	212960	117105	896	111	70	33	2.09	2960
5	M-05	214385	117150	940	88	30	35	2.04	884
6	M-06	213385	117660	938	91	12	39	2.10	399
7	M-07	214164	117449	941	71	58	38	2.04	1151
8	M-08	213789	116901	901	90	13	40	2.11	1412
9	M-09	211901	117326	871	100	5	38	2.15	1457
10	M-10	211289	117247	885	111	6	41	2.12	138
11	M-11	213602	117950	948	78	24	37	2.02	495
12	M-12	213972	116526	952	89	14	41	2.02	496
13	M-13	214514	116791	937	108	27	37	2.12	688
14	M-14	212575	117080	904	82	17	34	2.14	471
15	M-15	213120	117450	925	106	14	38	2.05	147
16	M-16	213192	117807	953	118	6	38	2.17	59
17	M-17	214908	117244	965	89	30	40	2.15	534
18	M-18	214700	117500	961	108	11	40	2.12	494
19	M-19	213815	117525	928	112	74	45	2.09	296
20	M-20	213852	118212	983	109	11	45	2.11	325
21	M-21	214935	117555	961	85	105	39	2.02	133
22	M-22	212267	117614	888	105	12	39	2.10	101
23	M-23	214500	118171	974	93	17	44	2.03	81
24	M-24	211162	116870	934	102	9	38	1.98	22
25	M-25	213195	115689	952	84	27	34	2.11	252
26	M-26	214725	118000	991	101	6	39	2.01	27
27	M-27	214645	116591	990	105	12	36	2.10	48
28	M-28	212921	118329	1012	107	7	34	2.13	6
29	M-29	213731	115967	926	109	9	37	2.10	52
30	M-30	213598	115875	906	121	28	41	1.98	146
31	M-31	213470	116440	938	95	8	33	2.12	70
32	M-32	213985	116890	911	87	15	37	2.01	95
33	M-33	213289	117450	931	109	18	37	2.05	118
34	M-34	214557	117715	903	106	20	37	1.99	28
35	M-35	214166	117313	939	103	13	37	2.05	57
36	M-36	214557	117715	951	133	13	33	2.05	73
37	M-37	214151	117622	943	119	41	34	2.03	67
38	M-38	214153	116613	946	127	11	42	2.01	62
39	M-39	213920	117160	913	100	19	36	2.09	84
40	M-40	212725	117068	896	86	40	34	2.06	180
41	M-41	211541	117072	855	106	34	39	2.10	126
42	M-42	213448	115789	904	96	14	40	1.96	110
43	M-43	212590	116780	888	113	9	36	2.05	45
44	M-44	213192	116715	903	103	6	38	2.00	77