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Surveillance for oil production enhancement and reduced water production in niger delta using artificial neural network

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Abstract From the inception of the oil and gas industry, water production has always been an aching problem for various operators. Throughout the productive life of a field, oil production is often accompanied with some amount of water production, which in most cases, is so significant and unwanted. Because of the great operating, environmental and economic challenges associated with excess water production, operators are in search for different methods and tools that could be used to identify the sources of water and prevent or mitigate early water breakthrough in producing oil wells. In this study, an Artificial Neural Network (ANN) model named CASNNET1 was developed for accurate prediction of producing well water cut in order to optimize oil production. CASNNET1 was developed and validated with data from one producing well and generalized with data from four other producers in the same reservoir. Water cut values predicted using the developed CASNNET1 model were compared to the actual water cut values from the wells, the R-squared (R^2) and the mean square error values were estimated. The generalization of the network showed that the network has an average predictive accuracy of approximately 84%. The neural network model results were used jointly with reservoir simulation results to suggest possible ways of mitigating excess water production. The developed ANN model can be used as reservoir management tool to proffer solution to excess water production problems.

Keywords production enhancement, water production prediction, artificial neural network, reservoir simulation, XY model

Introduction

The cost of unwanted water production has been estimated by several survey sponsored by oil and gas industries globally and it is within the region of 50 billion US dollars. These outrageous expenses are incurred for many purposes like water flow via fractures; safe water disposal is also added in the costs now. One of the major problems lingering in the oil and gas industry is allocating and shriveling timely well to well production. This is because, it more challenging to validate and relate the data to the wells production rates in a more consistent, coherent and timely way, and taking urgent action beyond collecting real time data from wells and facilities. In order to solve the problem of integrating surveillance in subsea oil and gas production, Sensor Dynamics Ltd designed a sensor system. This designed sensory system was designed to solve many problems regarding subsea oil and gas production and also in deep sea in combination with fiber optic temperature, pressure, acoustic and seismic sensors. Some of the challenges associated with water production include; multiphase flow, valve and choke failure, hydrate and wax dropout. Excessive water production is associated with economic and environmental issues. Operators are in search for different methods and tools that could be employed in the identification of the water sources during oil production. Among available methods for predicting water production include the artificial neural network and reservoir simulation. In this study, both techniques were employed to quantify and possibly suggest ways to minimize excess water production.

During the production of oil and gas from petroleum reservoirs, water production could arise from an adjoining aquifer or from water injection wells in a process of water flooding. When production of water is in excess, the associated costs regarding operating both subsurface and surface production facilities will go up, and also result in scale and corrosion problems. Besides, recovery factor is decreased due to the bypass of oil by the displacement water front. These factors are critical environmental and financial challenges for the oil and gas production industry.

The fundamental objective of this study was to develop an Artificial Neural Network (ANN) model that could accurately forecast well and field water production over the useful life of the field, identify the mechanisms (sources) of water production and recommend ways to reduce water production. Therefore, it is pertinent to state here that the neural network models developed in this study will only do well when fed with data from wells of the XY model. However, since the same process is used in building artificial neural network, neural network models can be developed for any reservoir to solve a well-defined problem. In this study, well water cut is the problem under investigation. Also, the neural network model built in this study is to predict water values which are time dependent variables.

In real cases, controlling excessive water production is really complex, difficult, and always a function of many mechanisms evolving throughout the useful life of the production wells and entire field [1]. He presented a method that could be employed in quick diagnosis, evaluation and determination of the production mechanisms. These usually employ the diagnostic plots derived through history of the producing well data. However, the applications of the diagnostic plot to field data and results from numerical simulations have indicated their limitations, especially the use of derivative plots with noisy production data makes good decision making very difficult. Water production diagnostic model for oil wells on the bases of Spectral Analysis/Fourier Transformation was presented in [2]. The aim of their research was to use mathematical medium to transfer production rate of surface Water oil Ratio (WOR) from time dependent domain/region into periodic dependent domain/region so as to better comprehend the mechanism behind production of water. According to Egbe and Appah in [2], spectral analysis is a mathematical physics tool used in analyzing systems that changes or fluctuates with time. Gasbarri *et al in [3]* proposed an interesting method for diagnosing of water production with the aid of transient test having multiphase flow meter. In their study, they showed how the multiphase flow meter (MPFM) could be used as a tool for better investigation of problems of produced water for wells through imposition of conditions of a transient flow and evaluating its parameters like flow rates, water cut, and gas / oil ratio. Rabiei *et al* in [4] carried out a research to investigate the importance of WOR. They employed data mining techniques to facilitate the extraction of latent information for prediction of oil and water production data. In their study, they explored the graphs of WOR verses oil recovery factor and used WOR behavior to create data for prediction from those graphs to be employed in classification with other parameters of the reservoir. Basically, their methodology adopted a technique of mita learning classification known as Logistic Model Trees (LMT) for diagnosis of mechanism of water production on the bases of the well's WOR data and parameters of static reservoir. Their results indicated that monitoring the WOR is very important for effective prediction of water production mechanism type before the well develops the actual problem. Reyes *et al* in [5] introduced a production of water analysis diagnosis model on the bases of reliability systematic method. They adopted a method that integrated knowledge of petroleum engineering reliability and 6 sigma reservoir production system model tools to represent the entire potential cause effect relations and failure modes for easy identification of the water production origin including their classification. Polymer gels have been successfully used for water production control in many oil producing regions of the world, especially in Poza Rica, Northern Mexico [6]. PQ silicates are highly stable compounds with little or zero bad effect to the environment which is the major problem of most chemical used in controlling water production. During the preparation of the solution used for making polymer gels employed in water plug off processes, it is opined that, polyacryl must be hydrolyzed into amide (HPAM) polymer at complete hydrolysis prior to use for cross linker [7]. The final gel will have lower than optimum mechanical strength, presumably because polymer chains need to be fully unfolded before proper cross linking can occur. In their research, they evaluated the gel strength of “flowing” gels for water shutoff in natural fractures and other non-matrix features as a function of time of addition of cross linker relative to time of hydration of polymer. Gels were prepared from moderately high molecular weight

HPAM cross linked with chromium(III)acetate (CrAc) or polyethyleneimine (PEI).Cross linker was added after either initial wetting of solid polymer particles or complete dissolution of the polymer [7]. There are both mechanical and chemical means of decreasing excess water production. The most common widely used chemical means are “rigid gels” for total shutoff of flow in the near wellbore area (usually applied to hydraulically-isolated matrix or very near well non-matrix water shutoff problems) and “flowing gels” used to extrude into non-matrix flow features, potentially to many tens or even hundreds of feet from the wellbore through which it is injected [8]. Polymers have been very effective in permeability reduction treatment of excess water production from matrix (rigid gels), as well as from fractures, faults and similar non-matrix flow features (flowing gels). The most common polymer gels are derived from a solid-free solution of a water soluble polymer plus a crosslinker [7]. Several methods are available to estimate the water saturation in shaly formations but the most commonly used in the industry are those based on petrophysical models, such as Waxman-Smits and Simandoux. These models have limitations and their input parameters are often not readily available [9]. This consequently leads to either underestimated or overestimated fluid saturations [9]. In their study, a method based on Artificial Neural Network (ANN) models was developed and tested for water saturation prediction with the aid of wire-line logs and core Dean-Stark data. The model utilized in their study was on the basis of three-layered neural network with a Resilient Back-propagation (PROP) learning algorithm. The model was successfully tested on the Hara sandstone formation (in Oman) producing a water saturation prediction with (RMSE) error of around 2.5 saturation units (saturation) correlation factor of 0.91 on the testing data [9].

Methods

The method utilized in this study began with the development of a dynamic reservoir model using SENSOR simulator which paved way for the development an optimized neural network model. The reservoir model is of 24 x 15 x 15 gridblock dimension and it’s a black oil model. Tables 1 to 4 describe the equilibration data of the model and the Rock and fluid properties of both the reservoir and aquifer. The total number of active blocks in the XY model is 9000, which implies that all blocks in the model are affected by the flow dynamics in the reservoir. In the model, there are 26 wells; one injector (WI) and twenty five producers (P2 – P26).

Table 1: Reservoir model description

Reservoir Model Description		
Fluid Model	Black Oil	
Grid:	NX	24
	NY	15
	NZ	15
	Total Grid Blocks	9000
	No. of Active Blocks	9000
Simulation Time:	Start	1/1/1970
	End	1/1/1985
	Days	5479
	Years	15
	Time Steps	115
Avg. Transmissibility:	TX	2.3342
(RB-CP/D-PSI)	TY	0.84991
	TZ	2.1855
Wells:	No. of Injector	1
	No. of Producer	25
WATER	Bwi , RB/STB	1.0034

PROPERTIES:		
	ɣw, (Water = 1.0)	1.0095
	Cw, 1/Psi	0.000001
	µw, cp	0.96
Stock Tank Oil:	ɣo,	0.7206
	ρo, lb/Cuft	44.986
	DEG. API	64.864
GAS:	ɣg, (AIR = 1.0)	0.92
	ρg, lb/SCF	0.07025

Table 2: Reservoir rock properties of model

Rock Compressibility,	Cf, 1/Psi (Field)	0.000001
Reservoir Net Pay	FT	359
Reservoir Gross Th.	FT	359
Avg. Reservoir Porosity	Fraction	0.1262
Avg. Reservoir Kx	Md	108.1
Avg. Reservoir Ky	Md	108.1
Avg. Reservoir Kz	Md	1.081

Table 3: Equilibration parameters

Equilibration (Initialization) Region 1	
Initial Hydrocarbon - Water Contact, FT	9950
Depth to Center of Shallowest Block, FT	9009.85
Depth to Center of Deepest Block, FT	10502.48
Reference Depth, FT	9035

Table 4: Reservoir model's initial fluid in place

Initial Fluids in Place								
	Water	**OIL**	**GAS**	**GOR**	**Bo**	**Bg**	**HC PAVG**	**PAVG**
	MRB	**MRB**	**MMCF**	**SCF/STB**	**RB/STB**	**BB/MCF**	**PSI**	**PSI**
Region 1	211,332	241,712	0	1385	1.1092	0	3,820.10	3,896.30
Region 2	210,696	217,912	301,880	1385	1.1092	0	3,820.10	3,896.30

SENSOR is a black oil and compositional reservoir simulation software used to optimize oil and gas recovery from underground reservoirs. It is a trademark of Coats Engineering and was used extensively in this research to study fluid withdrawal capacity of the reservoir XY model. The simulation was run for 15 years (5479 Days), as shown in Table 1. After 15 years of field depletion (01/01/1970 – 01/01/1985), the simulation run was terminated and an output file which contained the simulation results was automatically created by the simulator. The SENSOR maps which graphically show the IJK slice of the XY reservoir model were generated. With the aid of the SENSOR Plot tool, each well and field summary production data for the depletion period were plotted.

Development of Neural Networks

In this study, several processes were taken to build optimized neural network models which could be used to predict water cut values at well and field scales respectively. The ANN development workflow is shown in Figure 1

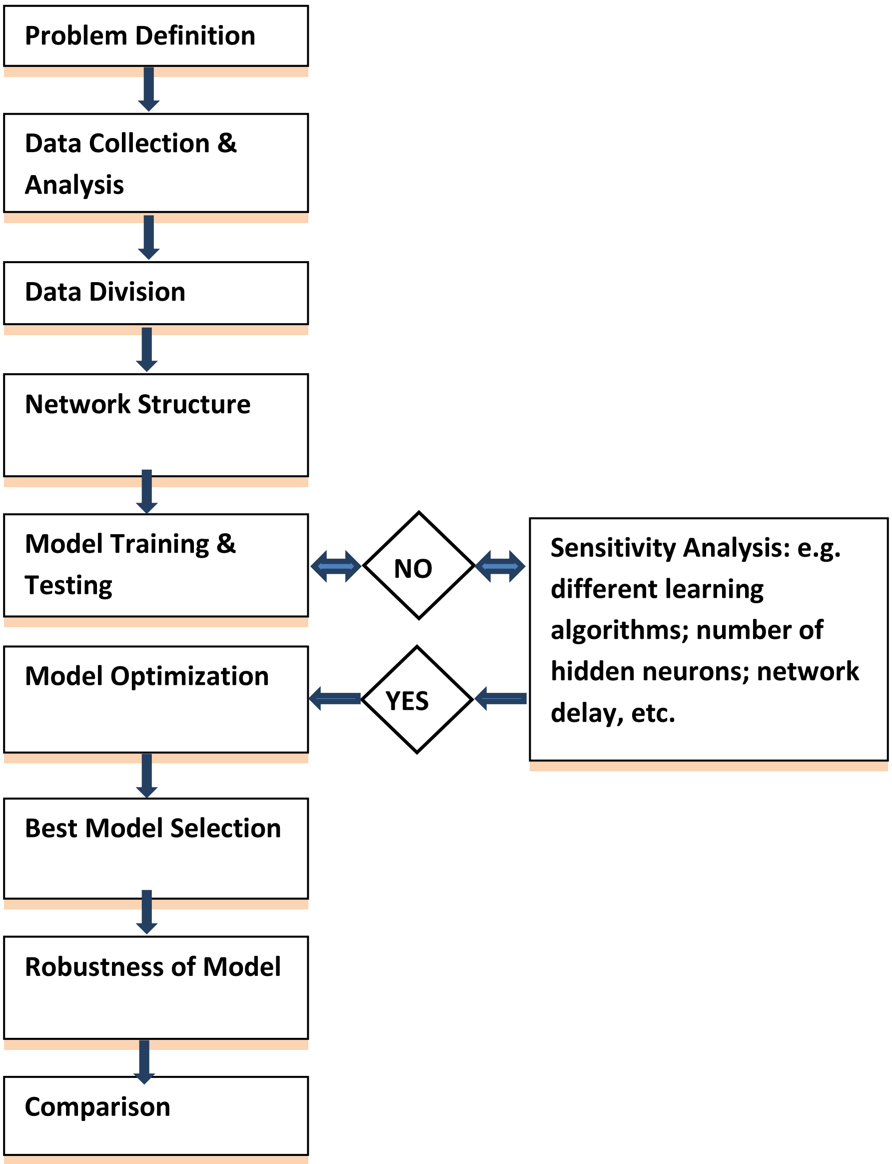

Figure 1: ANN workflow

The workflow defines all the processes involved in developing the neural network models in this study. The different processes include; problem definition, data collection, data preprocessing and division, determination of the network architecture, training and optimizing the network, etc.

CASSNET1, a non-linear auto regressive time series network with exogenous input (NARX) was developed using producer P26's data.

$$\mathbf{y(t)=f[y(t-1),y(t-2),\ldots,y(t-n),x(t-1),x(t-2),\ldots,x(t-n)]} \qquad \mathbf{1}$$

The following value of the output signal was regressed on next values of the output signal and previous values of an independent input signal. In the equation, n is the maximum number of delay, x is a time dependent input variable, while t, t-1, t-2, etc., are time steps. The NARX model can be implemented by using a feedforward neural network to approximate the function f.

In building the CASNNET1, fourteen (14) input parameters and one desired parameter were used. The desired parameter is the water cut values of the producer P26. These parameters are depicted in Tables 5.

Table 5: Input – Output Parameters of CASNNET 1

CASE ONE		
CASNNET 1- Input & Output Parameters		
S/N	**Input Parameters**	**Output Parameters**
1	Well oil production rate (QOIL), STB/D	
2	Well gas production rate (QGAS), MCF/D	
3	Well water production rate (QWAT), STB/D	
4	Well gas - oil ratio (GOR), SCF/STB	
5	Well bottomhole pressure (PBH), Psi	
6	Average grid cell pressure (PGRID), Psi	Well water cut (WCUT), %
7	Gas - oil contact, GOC (Datum Depth), Feet	
8	Initial Oil - water contact, OWC, Feet	
9	Average layer porosity, Fraction	
10	Average layer Kz, md	
11	Average layer Kh, md	
12	Well depth, Feet	
13	Aquifer total (rock + water) compressibility, 1/Psi	
14	Net pay thickness of reservoir, Feet	

The accuracy of the CASNNET1 was tested on data never seen by the network. The well P26 data used in training and validating the CASNNET1 had eighty-five (85) time steps. To further ascertain the predictive capability of the network, the CASNNET1 was used for multistep ahead prediction. Thirty (30) time steps ahead input parameters were fed into the trained network to predict 30 steps ahead water cut values. This was done to check the capability of the built CASNNET1 on P26 data. Similarly, the CASNNET1 was tested on data from wells P16, P17, P22 and P23 and it gave an appreciable result. The accuracy of the network was emphasized on the mean squared error (mse) and R-Squared values of each of the well data.

Results and Discussion

As earlier discussed, reservoir simulation runs were made and results were generated. Maps and plots of the results were generated to properly visualize and adequately analyze the results.

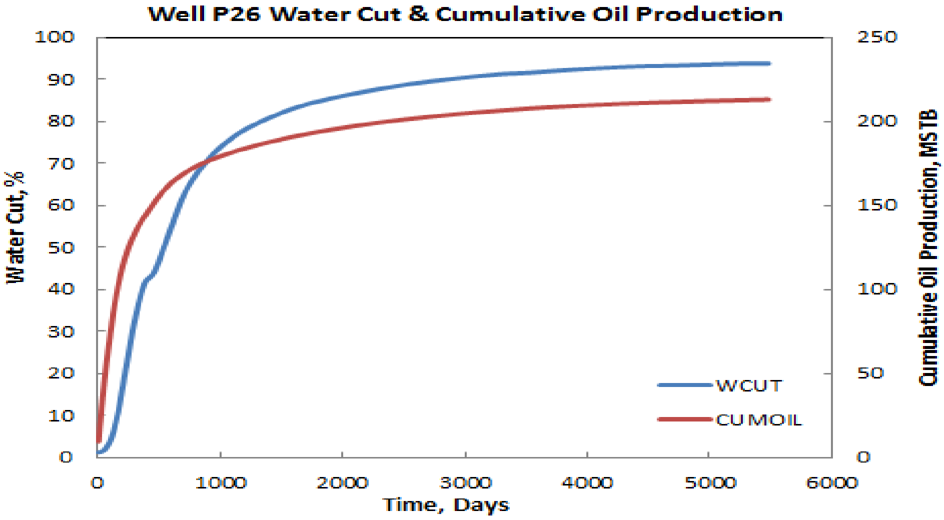

Figure 2: Producer P26's water cut and cumulative production vs. time plot

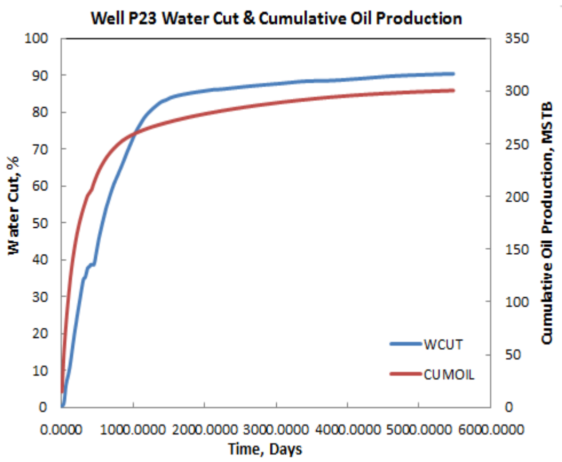

Figure 3: Producer P23's water cut and cumulative production vs. time plot

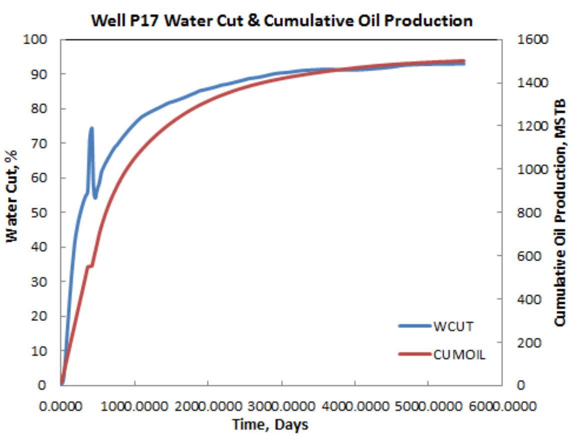

Figure 4: Producer P17's water cut and cumulative production vs. time plot

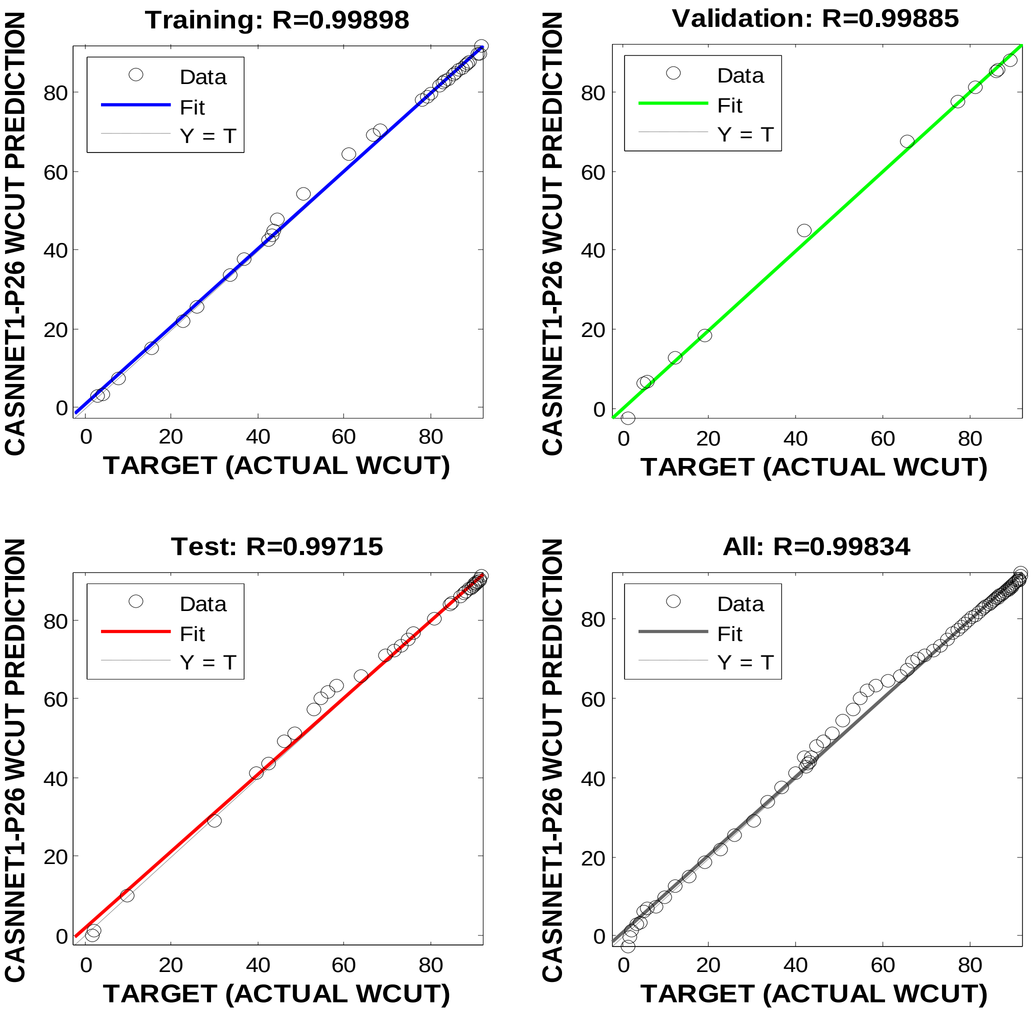

Figure 5: Correlation coefficient values of the CASNNET1 – P26

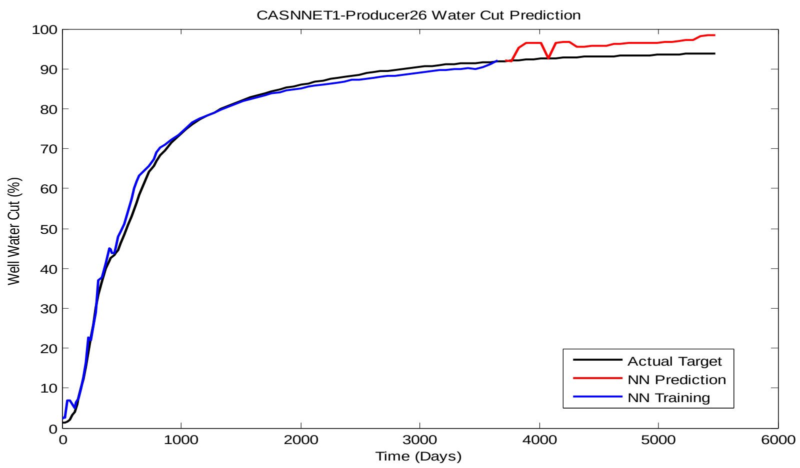

Figure 6: CASNNET1 – P26 water cut prediction and target plot

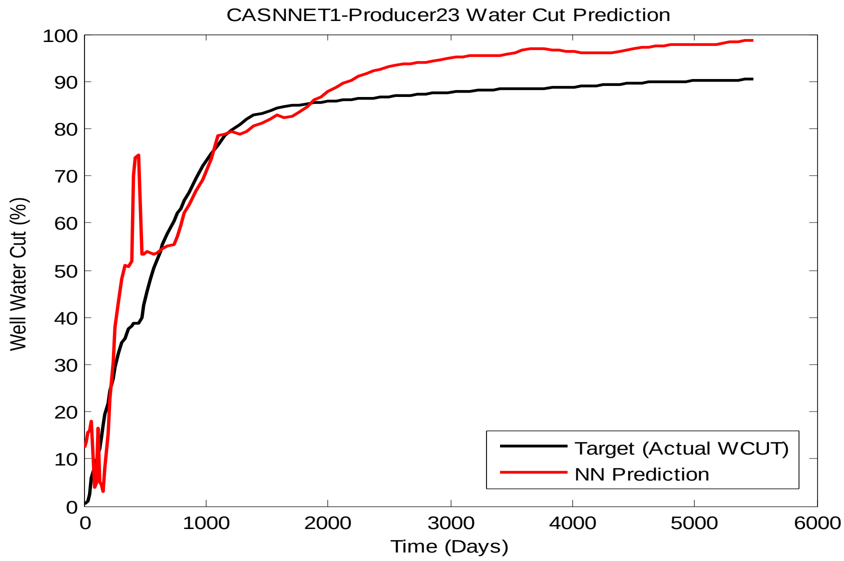

Figure 7: CASNNET1 – P23 water cut prediction and target plot

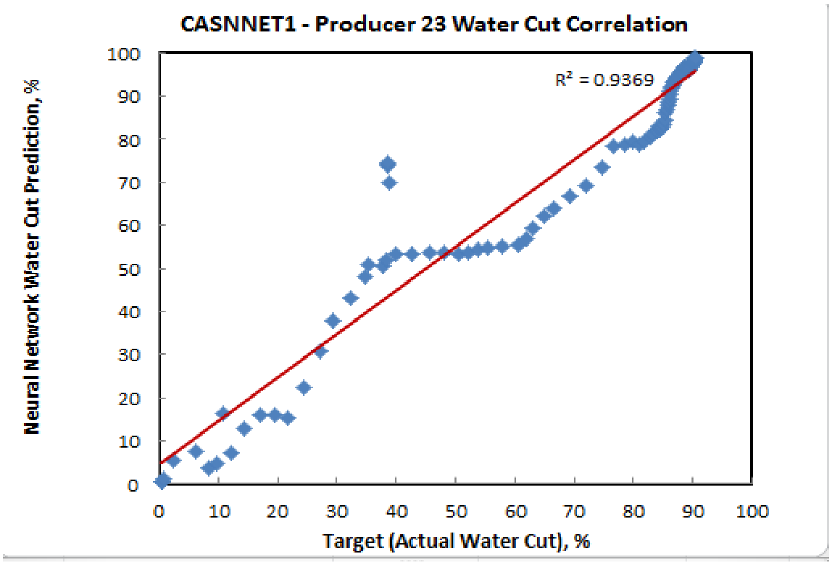

Figure 8: CASNNET1 – P23 water cut correlation plot

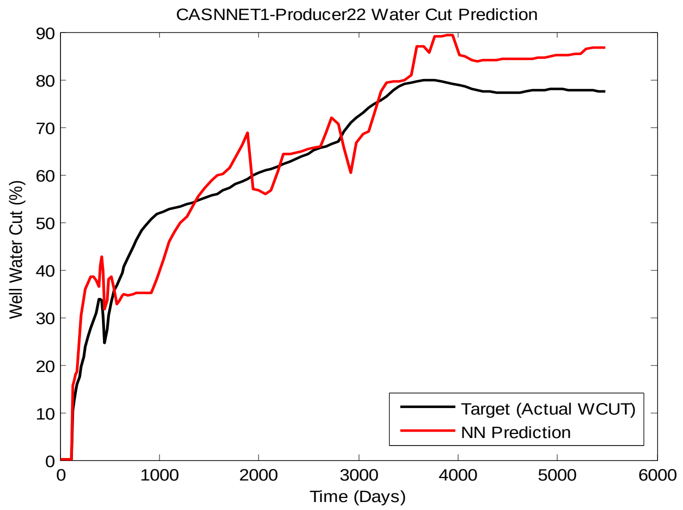

Figure 9: CASNNET1 – P22 water cut prediction and target plot

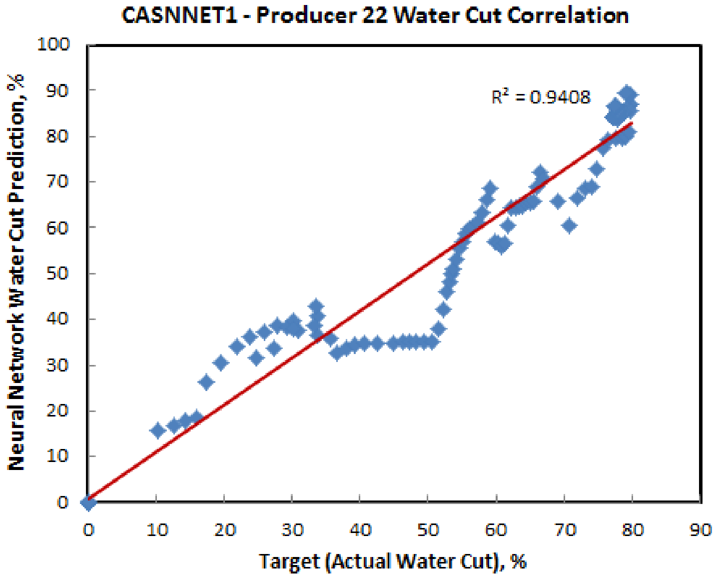

Figure 10: CASNNET1 – P22 water cut correlation plot

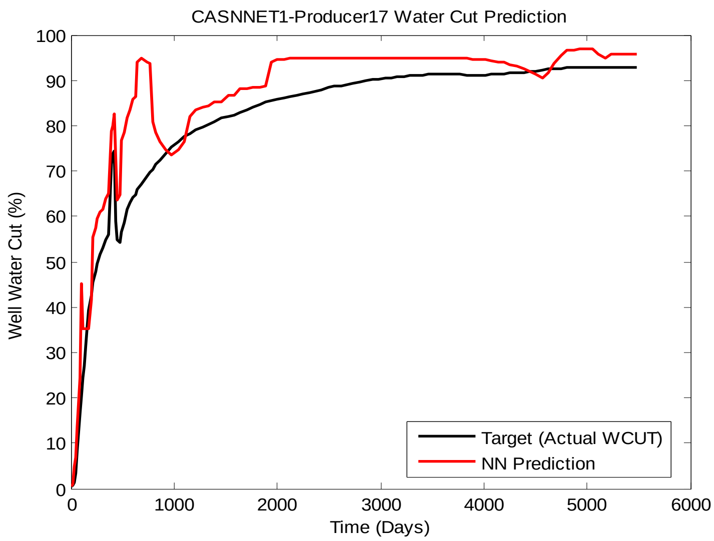

Figure 11: CASNNET1 – P17 water cut prediction and target plot

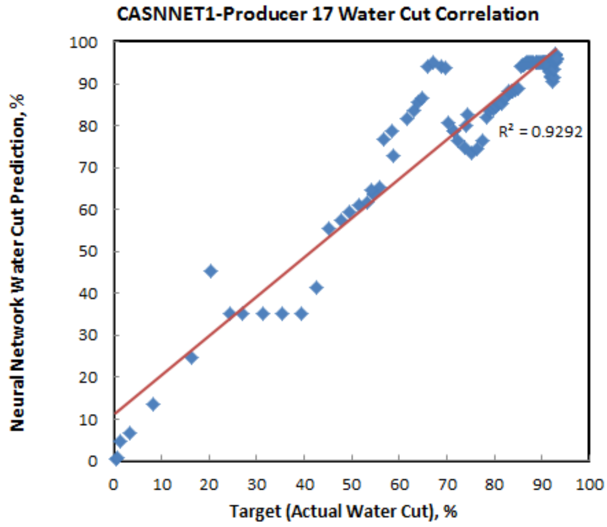

Figure 12: CASNNET1 – P17 water cut correlation plot

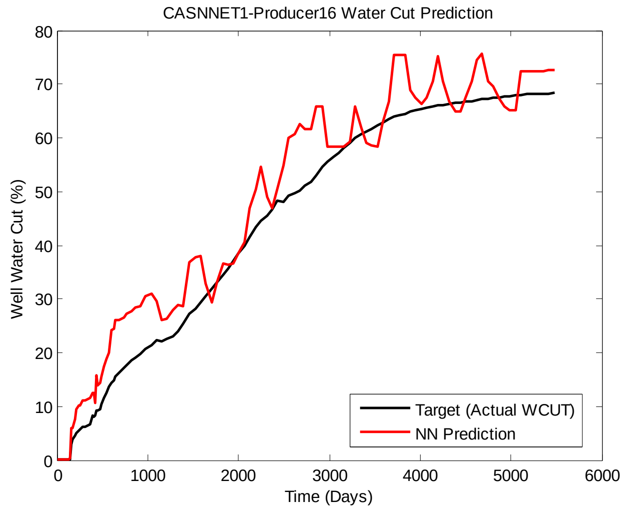

Figure 13: CASNNET1 – P16 water cut prediction and target plot

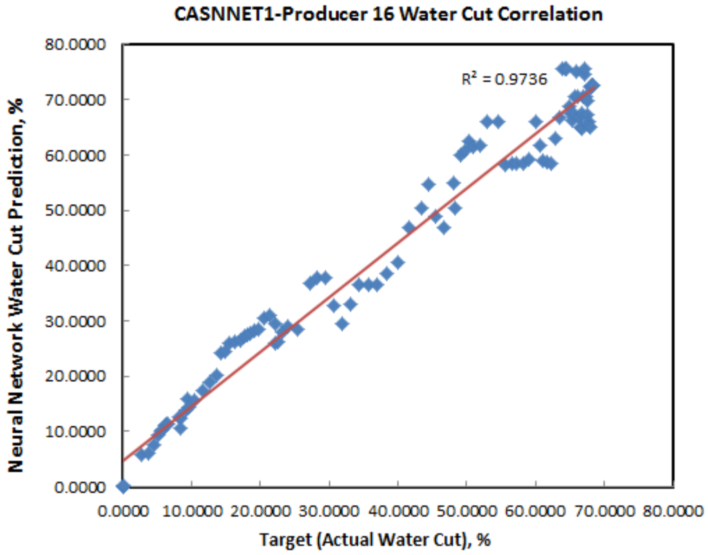

Figure 14: CASNNET1 – P16 water cut correlation plot

Table 6: Summary of CASNNET1 results

CASNNET1 Summary for the Prediction of Well Water Cut				
Well No.	**Correlation Coefficient (R^2)**	**Mean Squared Error (MSE)**	**Average Error Fraction**	**Accuracy of Network (%)**
P26	0.9983	7.3125	0.0966	90.34
P23	0.9369	81.4932	0.1458	85.42
P22	0.9408	45.9222	0.1373	86.27
P17	0.9293	79.8335	0.1421	85.79
P16	0.9736	35.0157	0.2883	71.17
Average		**49.92**		**83.80**

With the aid of the SENSOR Map tool, maps which show the distribution of the XY model fluid and rock properties were created. Since all the producers were completed in layers K2, K3 and K4 and the injector in layers K11, K12, K13, K14 and K15, only the maps for these layers were generated. There was an indication of gas in the reservoir at this state, which implies that it was depleted below its bubble point pressure after 15 years of continuous production.

One of the aims of this study was to evaluate water cut trends in producing wells. In the XY reservoir model under investigation, there are 25 producers (P2 – P26) and 1injector (WI). From the reservoir simulation results, only fifteen of the producers produced water during the depletion period. However, only seven had significant water cut (above 50%) after 15 years of depletion. The production plots of the wells that had water cut values above 90% are shown in Figures 2 – 4. Figures 2 – 4 shows that all three producers had early water breakthrough after 10 days of production (Well P26 = 1.3%, Well P23 = 0.5%, Well P17 = 0.5%). At the end of 5479 days (15 years) of production, the water cut values were: Well P26 = 93.77%, Well P23 = 90.4%, Well P17 = 92.96%.

As earlier discussed, a neural network model named CASNNET1 was developed. The CASNNET1 time series non-linear autoregressive network with exogenous inputs (NARX) was developed to predict water cut values at well scale. The CASNNET1 was built using data from well P26. This network was trained, validated and tested to predict well P26's water cut values. For well P26, there were 115 simulation time steps. The data for the first 85 time steps (10 years) were used for training and validating the network, while the data for time steps 86 – 115 (5 years) were used to make multistep ahead prediction. The well data were divided as: Training data = 40%; Validation data = 15%; and Testing data = 45%. The training algorithm used was the Levenberg-Marquardt back propagation (trainlm). Other training parameters are: Number of delay = 2; number of hidden neurons = 10; number of input neurons = 14; number of output neurons (water cut) = 1. The results generated by the CASNNET1 on well P26 are shown in Figures 5 - 6.

In Figure 5, the network's overall correlation coefficient, R^2 value of 0.99834 is an indication of a good prediction ability of CASNNET1 on well P26's data. This is reflected in the accuracy value of approximately 90% and mean squared error (mse) value of 7.3 as shown in Table 6. In Figure 6, the black line is the observed or desired P26 water cut values for 115 time steps. The blue line is CASNNET1 water cut match during training for 85 time steps, while the red line is the 30 time steps ahead (86 -115) prediction of water cut by the network.

CASNNET1 was originally developed using well P26's data. To test for network generalization, unseen data were fed into the network. Wells P23, P22, P17 and P16 data were used to for this generalization. Table 6 shows the summary results of CASNNET1 on Wells P23, P22, P17 and P16, while Figures 7 – 14 shows the water cut and correlation plots of all four wells.

As shown in the summary result of Table 6, CASNNET1 shows a higher degree of accuracy of 90.34% in predicting well's P26 water cut values. This is because the network was trained and optimized using well P26's data. The accuracy of the network in predicting new data from wells P23, P22, P17 and P16 are 85.42%, 86.27%, 85.79% and 71.17% respectively. Therefore, by generalization, the CASNNET1 neural network model has an average accuracy of approximately 84% on the five wells.

Conclusion

Artificial neural network applications are gaining more grounds in the oil and gas industry. The process of developing the network is cheaper and faster than the reservoir simulation process.

In this study, CASNNET1 was built to accurately predict well water cut values. The CASNNET1 was tested on wells P26, P23, P22, P17 and P16 to evaluate its predictive capacity. The prediction of this neural network on the well showed that CASNNET1 has a predictive ability of approximately 84% accuracy and therefore could be used for predicting water cut in producing wells. This developed neural network model can be used as a reservoir management tool to make forecast of water cut value for any of the wells in the XY Reservoir Model.

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Appendix

Table 7: Casnnet1 Water Cut Prediction and Accuracy on Well p26

TIME	ACTUAL WCUT	NEURAL NETWORK PREDICTION	ABSOLUTE ERROR (AE)	ERROR FRACTION	(AE)^2	MSE	NETWORK ACCURACY
DAYS	%	%	%	Fraction			%
10.00	1.30	1.30	0.00	0.00	0.00		
22.04	1.31	1.31	0.00	0.00	0.00		
31.00	1.38	2.65	1.27	0.92	1.62		
44.43	1.58	6.89	5.31	3.35	28.17		
64.59	2.11	6.97	4.86	2.30	23.59		
90.67	3.17	5.91	2.74	0.86	7.49		
104.72	4.06	4.90	0.84	0.21	0.71		

117.44	5.03	6.36	1.33	0.26	1.76		
128.01	5.97	6.87	0.90	0.15	0.81		
143.85	7.67	7.41	0.26	0.03	0.07		
162.08	9.95	9.86	0.09	0.01	0.01	7.31	90.34
178.58	12.22	12.78	0.56	0.05	0.32		
197.86	15.38	16.37	0.98	0.06	0.97		
219.20	18.99	22.65	3.66	0.19	13.41		
240.85	22.59	22.02	0.57	0.03	0.32		
260.76	25.92	25.53	0.39	0.02	0.16		
285.46	30.16	28.96	1.20	0.04	1.44		
309.96	33.48	36.98	3.51	0.10	12.29		
335.96	36.73	37.72	0.99	0.03	0.98		
365.00	39.83	41.21	1.38	0.03	1.91		
394.37	41.97	45.03	3.06	0.07	9.36		
411.84	42.51	44.79	2.28	0.05	5.20		
424.00	42.74	43.76	1.02	0.02	1.03		
442.23	43.24	43.92	0.68	0.02	0.46		
454.95	43.74	45.13	1.39	0.03	1.92		
470.33	44.60	47.91	3.31	0.07	10.94		
493.40	46.20	49.07	2.86	0.06	8.20		
522.12	48.41	51.16	2.75	0.06	7.55		
551.98	50.77	54.29	3.52	0.07	12.39		
580.63	53.06	57.41	4.35	0.08	18.97		
602.26	54.75	59.96	5.21	0.10	27.16		
622.78	56.40	61.88	5.48	0.10	30.04		
647.62	58.42	63.15	4.73	0.08	22.38		
684.89	61.23	64.38	3.15	0.05	9.95		
732.93	64.09	65.75	1.66	0.03	2.75		
766.85	65.66	67.45	1.79	0.03	3.20		
791.56	66.78	69.11	2.34	0.04	5.46		
828.64	68.27	70.30	2.03	0.03	4.14		
865.69	69.61	71.09	1.48	0.02	2.19		
921.28	71.53	72.23	0.70	0.01	0.49		
981.28	73.25	73.43	0.18	0.00	0.03		
1041.28	74.76	75.07	0.31	0.00	0.10		
1096.00	76.01	76.50	0.49	0.01	0.24		
1156.00	77.19	77.46	0.27	0.00	0.07		
1216.00	78.25	78.26	0.00	0.00	0.00		
1276.00	79.11	79.03	0.07	0.00	0.01		
1336.00	79.95	79.79	0.16	0.00	0.03		
1396.00	80.74	80.49	0.26	0.00	0.07		
1461.00	81.54	81.16	0.38	0.00	0.14		

1521.00	82.22	81.81	0.42	0.01	0.17		
1581.00	82.87	82.41	0.46	0.01	0.22		
1641.00	83.46	82.94	0.53	0.01	0.28		
1701.00	83.97	83.44	0.53	0.01	0.28		
1761.00	84.46	83.87	0.58	0.01	0.34		
1826.00	84.88	84.22	0.66	0.01	0.44		
1884.33	85.28	84.55	0.73	0.01	0.53		
1944.33	85.67	84.88	0.79	0.01	0.62		
2004.33	86.04	85.18	0.86	0.01	0.74		
2064.33	86.40	85.48	0.92	0.01	0.85		
2124.33	86.75	85.78	0.97	0.01	0.94		
2191.00	87.11	86.06	1.06	0.01	1.11		
2251.00	87.43	86.35	1.08	0.01	1.17		
2311.00	87.74	86.64	1.10	0.01	1.21		
2371.00	88.04	86.88	1.16	0.01	1.34		
2431.00	88.32	87.14	1.18	0.01	1.40		
2491.00	88.59	87.37	1.22	0.01	1.50		
2557.00	88.89	87.58	1.31	0.01	1.71		
2613.06	89.11	87.78	1.33	0.01	1.76		
2673.06	89.33	87.99	1.34	0.02	1.81		
2733.06	89.55	88.15	1.39	0.02	1.94		
2793.06	89.75	88.34	1.41	0.02	1.99		
2853.06	89.96	88.57	1.39	0.02	1.93		
2922.00	90.18	88.81	1.37	0.02	1.87		
2982.00	90.37	89.06	1.31	0.01	1.71		
3042.00	90.55	89.30	1.26	0.01	1.58		
3102.00	90.73	89.47	1.25	0.01	1.57		
3162.00	90.90	89.62	1.28	0.01	1.64		
3222.00	91.06	89.75	1.31	0.01	1.71		
3287.00	91.23	89.84	1.38	0.02	1.92		
3347.00	91.33	89.90	1.43	0.02	2.05		
3407.00	91.40	90.07	1.34	0.01	1.79		
3467.00	91.48	89.92	1.56	0.02	2.44		
3527.00	91.58	90.31	1.27	0.01	1.62		
3587.00	91.69	91.19	0.49	0.01	0.24		
3652.00	91.82	92.02	0.19	0.00	0.04		
3712.00	91.95	92.21	0.26	0.00	0.07		
3772.00	92.07	91.90	0.17	0.00	0.03		
3832.00	92.19	95.30	3.11	0.03	9.70		
3892.00	92.31	96.45	4.15	0.04	17.19		
3952.00	92.42	96.49	4.07	0.04	16.56		
4018.00	92.53	96.56	4.03	0.04	16.24		
4078.00	92.62	92.57	0.05	0.00	0.00		

4138.00	92.71	96.57	3.85	0.04	14.86		
4198.00	92.80	96.77	3.98	0.04	15.82		
4258.00	92.87	96.79	3.91	0.04	15.32		
4318.00	92.95	95.49	2.54	0.03	6.44		
4383.00	93.03	95.57	2.54	0.03	6.47		
4443.00	93.08	95.66	2.58	0.03	6.65		
4503.00	93.13	95.70	2.57	0.03	6.61		
4563.00	93.16	95.77	2.61	0.03	6.82		
4623.00	93.20	96.29	3.09	0.03	9.56		
4683.00	93.24	96.30	3.06	0.03	9.38		
4748.00	93.29	96.37	3.08	0.03	9.51		
4808.00	93.34	96.40	3.07	0.03	9.39		
4868.00	93.39	96.46	3.07	0.03	9.43		
4928.00	93.45	96.54	3.10	0.03	9.59		
4988.00	93.50	96.59	3.08	0.03	9.50		
5048.00	93.56	96.67	3.11	0.03	9.66		
5113.00	93.62	96.79	3.17	0.03	10.04		
5173.00	93.67	96.88	3.21	0.03	10.29		
5233.00	93.71	97.20	3.49	0.04	12.21		
5293.00	93.73	97.24	3.51	0.04	12.33		
5353.00	93.74	98.26	4.53	0.05	20.48		
5413.00	93.75	98.35	4.60	0.05	21.15		
5479.00	93.77	98.54	4.77	0.05	22.77		

The same computation carried out on well P26 shown in Table 7 above was also done for the other four wells (P23, P22, P17 and P16)