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Production Forecast in Gas Reservoirs Using Machine Learning

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Abstract

Numerous methods have been employed to estimate gas reserves as well as forecasting the future performance of the reservoirs using different input parameters. Decline curve analysis and its modified form have been in used for decades. Artificial Intelligence (AI) is gaining attention in different fields in which oil and gas industry is not an exception. In our research, Machine Learning (ML) is adopted to make predictions of future production of four different wells in a reservoir based on time series data. The Neural Net Time Series application solves three types of non-linear times series dependent problem adopting a dynamic network. This is accomplished by selecting data set, dividing it for training, validation, and testing sets. The evaluation of the well indicated that wells A and B show good prediction while wells C and D showed a flatten predictions. They might be due to erroneous data source or additional need for big data volume for efficient training, validation and testing for accurate forecast. ML can serve as a very good and efficient tools for reservoir and production engineers that are always interested in future production of a reservoir or wells for proper planning.

Keywords: *Forecast; Machine learning; Artificial intelligence; Time series; Decline curve analysis; Gas rate.*

1. Introduction

Estimating reserves, monitoring of reservoir performance as well as forecasting the future production of oil and gas is a crucial routine in the petroleum and gas industry. Decline Curve Analysis (DCA) is one of the methods that are used in this regard. The method requires extensive production data to forecast future gas and oil production and estimate remaining reserves in the life of a field [1]. Arp's Model is widely and commonly used for the drawdown decline analysis. The key concept behind this model is that future production performance can be modelled with historical data [2]. Numerous researchers have tried to modify or even provide an alternative to the Arp's model of prediction [1, 3-9]. Artificial intelligence (AI) is a highly sophisticated techniques that is applied to solve highly complex problems with a high-speed computing [10]. This technique and its applications have recently gained a great deal of attention in different fields such as Engineering, Economics, Mathematics, Neuroscience and even gaming. Common applications of AI in our day to day activities are data analytics, robotics pattern recognition and machine learning (ML) [10]. AI methods have been reported to be applied in the flowing key areas in oil and gas industry as well: production optimization, recoverable hydrocarbon prediction, PVT properties estimation, pattern recognition application to well placement and even reservoir characterization - an indication that oil and gas industry is not an exception to this great advancement and development [12-13].

In this research, Machine learning as a subset of artificial intelligence is adopted to forecast gas production in wells A, B, C and D using time series data where past data were used to project into the future of the likely production life of each well.

2. Methodology

2.1. Data collection process

About four (4) different wells were considered in this research. Data set were collected from secondary source and they were properly organized into excel format that can be easily imported into MATLAB for analysis. The raw format of the data organization is illustrated in Table 1.

Table 1.Input data example

Time (days)	GP (MMscf)	qg (Mscf/d)	Time (days)	GP (MMscf)	qg (Mscf/d)	Time (days)	GP (MMscf)	qg (Mscf/d)
30	416	416	630	7964	299	1230	14033	261
60	865	449	660	8266	302	1260	14277	244
90	1340	475	690	8560	294	1290	14553	276
120	1836	496	720	8862	302	1320	14773	220
150	2299	463	750	9211	349	1350	15004	231
180	2739	440	780	9539	328	1380	15226	222
210	3062	323	810	10000	461	1410	15537	311
240	3080	18	840	10408	408	1440	15869	332
270	3445	365	870	10758	350	1470	16263	394
300	3857	412	900	11040	282	1500	16444	181
330	4222	365	930	11315	275	1530	16518	74
360	4617	395	960	11587	272	1560	16719	201
390	4988	371	990	11619	32	1590	17005	286
420	5378	390	1020	12018	399	1620	17295	290
450	5780	402	1050	12332	314	1650	17591	296
480	6140	360	1080	12662	330	1680	17880	289
510	6540	400	1110	12964	302	1710	18125	245
540	6941	401	1140	13227	263	1740	18291	166
570	7329	388	1170	13509	282	1770	18513	222
600	7665	336	1200	13772	263	1800	18772	259

2.2. Model procedure

The method of approach to this research was application of ***Neural Network for time series*** *to* train some set of data, validate them and then make future predictions using MATLAB. The Neural Net Time Series application solves three types of non-linear times series dependent problem adopting a dynamic network. This is accomplished by selecting data set, dividing it for training, validation, and testing sets. The network architecture is further defined and trained. Next is performance evaluation using mean squared error and regression analysis, error autocorrelation plot or histogram of the errors. Finally, the performance of the network can be evaluated on a test set. If results are not satisfactory, the network can be retrained with modified settings or on a larger data set.

Deep Marching Learning (DML) forecasts the values of future time steps of a sequence, a sequence-to-sequence regression can be trained. Long short-term- Memory layer (LSTML) learns between time steps in time series and sequence data, where the responses are the training sequences with values shifted by one-time step. That is, at each time step of the input sequence, the LSTM network learns to predict the value of the next time step.

The sequential steps used for this analysis are summarized below:

1. The test data was standardized using the same parameters as the training data- file name changed.
2. Levenberg-Marquardt backpropagation was used as the training models
3. "narnet" MATLAB code was applied by defining feedback delays (1:2) and hidden layer size (10) as illustrated in Figure 1.
4. Data was Prepared for training by using PREPARETS MATLAB function
5. Next was to prepare the data, for, training (70%), validation (15%) and testing (15%).
6. Root mean squared error was calculated
7. Closed loop, the input is joint to the output and used for multi- step prediction
8. Finally, plots were generated for analysis

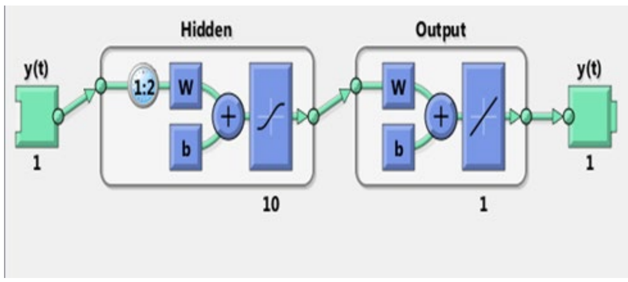
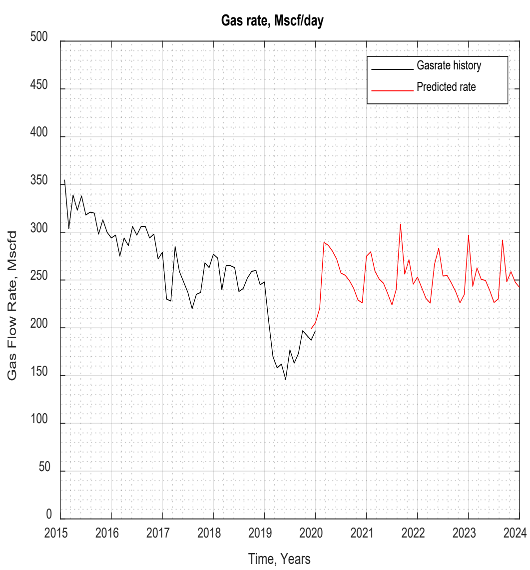


Figure 1. Illustration of computation process

3. Results and discussion

The results output for well A is presented in Figure 2. It is evident from the figure that gas well A has fluctuations in the production rate history and as such same pattern was reported and maintained in the predictions. The well has economic life beyond 2024 projection limit that was set. Figure 4shows the regression plots generated, the training, validation as well as test have good match.



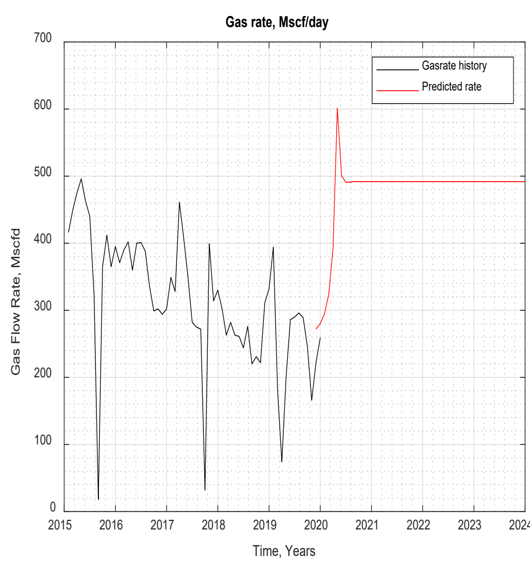


Figure 2. Gas production rate prediction for well A

Figure 3. Gas production rate prediction for well B

Figure 3 shows the prediction plot for well B, the historical data set showed the well's unstable flow rate. It can be observed that there was high gas flow rate beyond 2020 for like 3 months after which the gas production rate drops and flatten, indicating that the well might likely not produce at higher rate beyond the predicted rate irrespective of any stimulation or workover operations carried out. The overall regression plot shows some degree of match between the experimental and test data Figure 5.

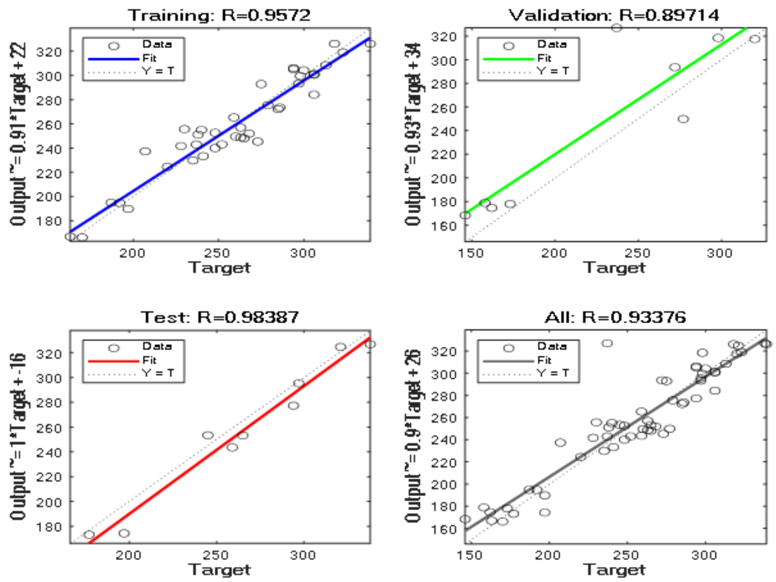


Figure 4. Regression plots for well A

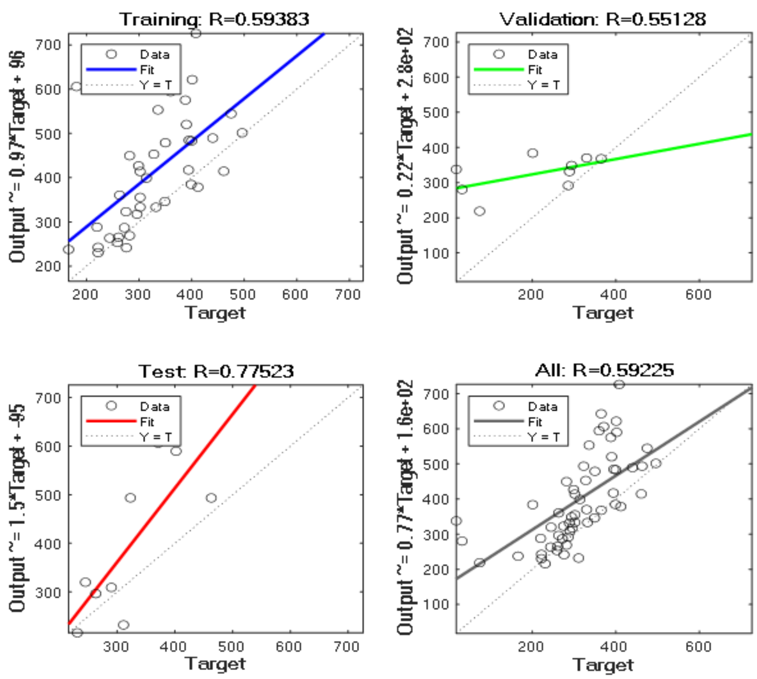


Figure 5. Regression plots for well B

Predictions of gas flow rates per day per well from the other data set showed a flattened trend of prediction. This can be as a result of erroneous data set obtained from the literature that affected the proper predictions (Figures 6-7). For such wells, further data set are required in order to make a reliable and perfect predictions that will guide the operational engineers in taking economic as well as technical decisions concerning the wells. For well C as shown in Figure 6, the economic limit of the well was reached at 400Mscf/day while for well D, the economic limit predicted to be roughly 175 Mscf/day(Figure 7).

Furthermore, comparisons were made for wells A and well B between the predicted and the actual historical data set for a period of 12 months as shown in Figure 8a and 8b. A good match was observed between the experimental and the prediction data. This is an indication of the effectiveness of Neural network time series in making predictions by training data set, validate it and project into the future based on the historical data as a function of time.

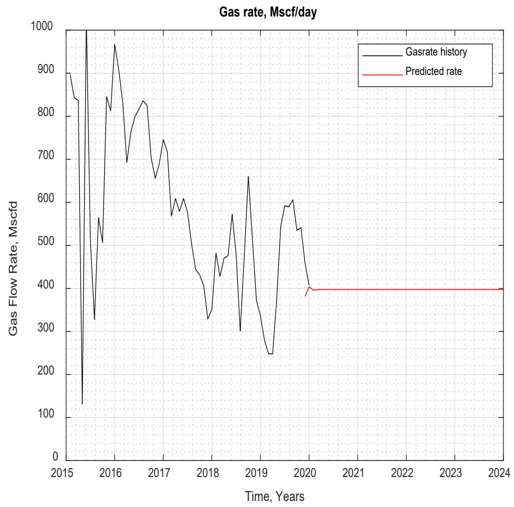


Figure 6. Gas production rate prediction for well C

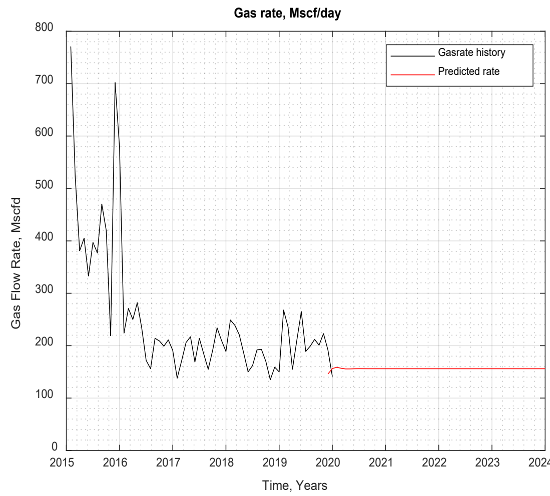


Figure 7. Gas production rate prediction for well D

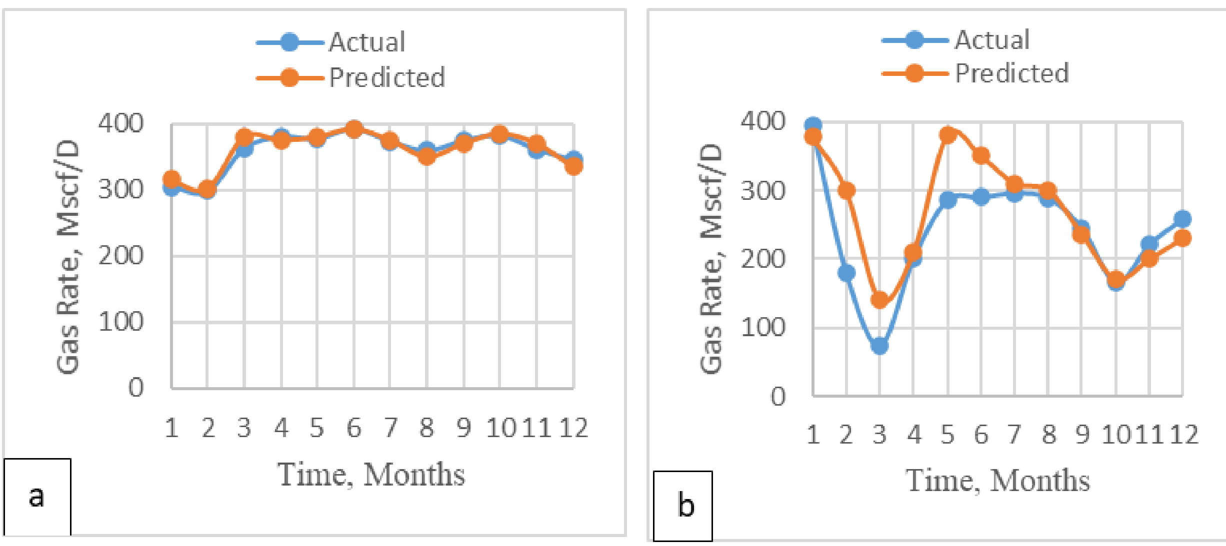


Figure 8. Comparison of observed data with forecast data for a) well A. and b) well B

4. Conclusion

Machine learning model aimed to predict gas production rate from different gas wells in a reservoir can be successfully modelled using large set of production data as a training framework. In this study, ML has been applied to different four wells to forecast the likely production rate of each well for the next five years. Two of the wells produced satisfactory results while wells C and D indicated a flat prediction. This might be due to erroneous input data or larger data are required for accurate and more precision prediction. This will enable the engineers concerned, either production, reservoir, or the petroleum economic team to take decisive technical decisions. This MLM can replace decline curve that requires some mathematical formulations. The model is simple, straight forward and accurate. The larger the data set, the better the training validation and finally the prediction.

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