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Applications of data analysis techniques for oil production prediction

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Abstract

This paper describes two data analysis techniques adopted in a Decision Support System (DSS) that aids users in predicting oil production of an infill well. The system generates predictions in the form of a possible range of cumulative production and length of production life of an infill well. The system also shows the worst and best case scenarios based on different production curves so that the expert can examine the plots of predicted production rates for each existing well and decide which model gives the best fit. The production curve of each individual well was mathematically modeled so that production values beyond the historical data can be produced. Decline curve estimation and neural network approaches were adopted for data analysis in the system. The system was tested with data from two groups of wells from two different fields in Saskatchewan, Canada. Observations on the suitable duration that the historical data set should cover and a comparison among different curve estimation and neural network models are presented.

Keywords: Oil production prediction; Neural networks; Decline curve estimation

1. Introduction

Petroleum engineers have searched for a simple but reliable way to predict oil production for a long time. Prediction of future production of petroleum wells is important for cost-effective operations of the petroleum industry. Production predictions can assist petroleum engineers in economic forecasts, and the approach often adopted by reservoir engineers is numerical simulation based on log and core analysis results. However, this process can be technically difficult, time consuming and expensive in terms of both labor and computational resources. At the same time, there is a vast amount of production data that is collected and stored, but hardly used. This set of production data can be utilized to build a model to predict production. Simple curve estimation could be adopted for this task but its accuracy is often suspect. Hence, the Artificial Neural Network (ANN) technique has been adopted as an alternative approach. The advantages of neural networks include its computational efficiency, non-linear characteristics, generation properties, and ease of working with high-dimensional data. This paper describes a Decision Support System (DSS) that incorporates both curve fitting and ANN approaches, and presents users with a range of possible solutions in the range of cumulative production and length of production of an infill well. By reviewing the range of possible solutions, the user can determine the best production forecast.

The objective of this study is to present this DSS for petroleum production. The basis of the prediction is the well's initial production and its economic cut-off. The assumption adopted in the investigation is that the production of an infill well is similar to existing wells in the same reservoir, therefore production curves of existing wells can provide useful information for future production of an infill well. However, it is also assumed that an expert user is best able to judge how relevant the information is from the existing wells. Hence, the system provides the best and worst case scenarios based on production curves from the existing wells, and the expert

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user selects among the plots of predicted production rates from each existing well to decide which model has the best fit. The system also generates a model based on the average production of the existing wells, which is provided to the user as reference.

In addition to generating the best and worst case scenarios of predicted production curves, the system also mathematically models the production curve of each individual well so that production values beyond the historical data can be produced. Both curve estimation and neural network approaches are adopted for mathematical modeling. In the curve estimation approach, the five types of linear, logarithmic, exponential, harmonic and general hyperbolic curve fitting methods were used. In addition, the system can also conduct neural network modeling and generate a model that associates the amount of oil produced per day in a certain month with the month index.

The paper is organized as follows. Section 2 reviews some background literature on traditional methods for predicting petroleum production, and these are primarily curve estimation and neural network approaches. Section 3 describes the methods and tools used to develop the DSS presented in this study. Section 4 describes the DSS. Section 5 provides some experiment results. Section 6 presents some observations and discussion, and Section 7 concludes the paper with summary and future work.

2. Background literature

2.1. Petroleum production prediction

The five traditional methods of estimating, both physically and economically, remaining reserves of petroleum in an oil well include: (1) by analogy, (2) volumetrics, (3) material balance, (4) decline curve fitting, and (5) reservoir simulation (Thompson and Wright, 1985). Each of these methods can be applied independently and has its strengths and weaknesses. While all five methods can be used for predicting recoverable reserves of a reservoir, the methods have different data requirements. But since the methods can be independently applied, each of them can be used for crosschecking the prediction results generated from the other methods. Features of the five methods are described briefly as follows.

1. *By Analogy*: The prediction is based on a well which is expected to perform similarly to the target well. This method is fast, cheap, and can be used before drilling. However, this method often suffers from lack of accuracy.
2. *Volumetrics*: This estimation of oil-in-place is performed by combining net reservoir volume with other parameters such as porosity, hydrocarbon saturation and recovery factor. This method is relatively fast, requires minimal information, and can be applied early in the well's life. However, this method also makes assumptions on, for example, area of the well or recovery factor. The assumptions may not be true hence the results can suffer from gross errors.
3. *Material balance*: The material balance technique of determining original oil-in-place is based on the law of conservation of mass. This method requires information on pressures, production history, fluid properties and rock properties, and can be used for calculating many parameters such as recovery factor, water influx and gas cap size. The disadvantages of this method include its sensitivity to relative permeabilities and the fact that more information is required than the other methods.
4. *Decline curve fitting*: This method requires information on only production history. It makes no assumptions about size, type or other properties of reservoir. The procedure of generating decline curves is fast and inexpensive. The method can generate production versus time predictions and is very accurate under certain circumstances. Its weakness is that the target well must be producing under constant conditions when this method is applied. Moreover, the method involves curve fitting with at least 6 months of historical data; its performance improves if data of between 2 and 10 years are available. However, the results generated are ambiguous in the sense that the method does not necessarily give a unique answer.
5. *Reservoir simulation*: Reservoir simulation is essentially an extension of the material balance technique. This method requires much more information than the other methods. The strength of the method is that it can handle different rock and fluid properties in different areas of the reservoir; its weaknesses however, include the cost and time required to do the study and the amount of input needed. In the process of applying the method, the parameters are adjusted to better fit pressure-production history of the well of interest. However, since often a unique fit cannot be obtained, it is necessary to exercise judgement so that only reasonable values are used. Moreover, even when a good fit is obtained, assumptions made to obtain the fit may not be true in prediction runs.

2.2. Curve estimation

Research on petroleum reserve estimation and petroleum production has mostly adopted the decline curve analysis approach. Most of the existing decline curve analysis techniques are based on the empirical Arps equations including exponential, hyperbolic, and harmonic equations (Li and Horne, 2003). A problem with the decline curve analysis technique is that it is difficult to foresee which equation can adequately described production of a reservoir. Moreover, each of these curve analysis techniques has some weaknesses. For example, the exponential decline curve tends to underestimate reserves and production rates while the harmonic decline curve tends to overpredict reservoir performance. Moreover, a single curve is often inadequate for describing production data generated during the entire life of the reservoir. Therefore, fitting production data to a decline curve is a difficult process and can result in unreliable predictions (El-Banbi and Wattenbarger, 1996). As well, fitting the data is often difficult if the amount of historical production data is insufficient or if transient data prevail.

Some sample applications of decline curve analysis include (Baker et al., 1998; Fetkovich, 1980; Li and Horne, 2003). Li and Horne (2003) proposed a decline analysis model derived from fluid flow mechanisms and analyzed oil production data from naturally fractured reservoirs developed by water flooding. Relative permeability and capillary pressure were also included in the analysis model. The model showed a linear relationship between the oil production rate and the reciprocal of the oil recovery or the accumulated oil production, especially during the latter period of production. Fetkovich (1980) combined some analytical solutions for transient flow with Arps empirical equations on a log–log graph and developed a typecurve matching technique for production data. Baker et al. (1998) characterized naturally fractured reservoirs using an analytical decline model that combined decline rate data and imbibition data.

2.3. Estimation using neural networks

There is substantial research conducted on estimating oil production using the ANN approach, some sample applications of ANN are presented as follows. Aminzadeh et al. (1999) adopted the ANN technique in estimating oil field reservoir parameters from remote seismic data. Huang and William (1997) developed a model for predicting porosity and permeability from well logs using ANN techniques. Although the core measurements were not used for constructing training examples, the predicted curves and the actual measurements agree except for a few data points. Wong and Taggart (1995) described a model similar to that of Huang and William, but which includes information on lithofacies as input. The results showed that the standard neural network method gave lower root mean square error (RMSE) compared to the simulated method, but the simulated method produces better statistics of the actual data including mean, standard deviation, coefficient of variation, maximum and minimum values. Wong and Taggart believed data pre-processing to be the most important steps in applying the ANN approach to geological problems. Gharbi et al. (1999) presented a universal neural-network-based model as an alternative method for predicting pressure–volume–temperature (PVT) properties. The ANN model showed higher accuracy when compared to any other correlation method; it also produced the lowest errors, the lowest standard deviation, and the highest correlation coefficient for both outputs.

While applicability of the neural network technique for tackling the petroleum prediction problem has been demonstrated, it has also been shown in these studies that prediction accuracy of an ANN was affected when some important predictors were either not included in the analysis or the measurements of some data points were local and not representative of a larger area. Hence, it can be concluded that both the curve estimation and neural network approaches have played a role in estimating petroleum production. Next, we present the DSS that incorporates both modeling techniques.

3. Methods and tools

The DSS adopts two basic modeling approaches: (1) estimation curve, and (2) neural network methods. They are presented as follows.

3.1. Curve estimation models

The prediction models in the DSS can model the production data given using either neural networks or the equations of approximating curves. A given set of data can usually fit more than one type of curves, and the modeling objective is to find a curve with minimal deviation from all the data points. The best fitting curves can be selected based on the method of least squares, which assumes that the best fitting curve of a given type is the curve that has the minimal sum of the squared deviations from a given set of data.

The linear least squares fitting technique is the simplest and most commonly applied form of linear regression and provides a solution to the problem of finding the best fitting straight line through a set of points. In this study, most equations used to fit the data are linear or linearizable. They include the linear, logarithmic, exponential and harmonic equations, which are listed as follows:

- Linear: $p = \beta_0 + \beta_1 t$;
- Logarithmic: $p = \beta_0 + \beta_1 \ln(t)$;

- Exponential: $p = \beta_0 e^{\beta_1 t}$ (Linearized form: $\ln(p) = \ln(\beta_0) + \beta_1 t$);
- Harmonic: $p = (\beta_0/1 + \beta_1 t)$ (Linearized form: $1/p = 1/\beta_0 + \beta_1/\beta_0(t)$).

The coefficients β_0, β_1 of these equations were calculated with the Statistical Package for the Social Sciences (SPSS) Base software (trademark of SPSS Inc.). SPSS is comercial software for solving business and research problems using statistics; it has a broad range of capabilities that support the entire analytical process.

The hyperbolic curve, on the other hand, is not linearizable. In the special case when $\beta_1 = 0$, the well is experiencing exponential decline, and when $\beta_1 = 1$, the decline is harmonic. The hyperbolic equation is stated as follows:

$$\text{Hyperbolic}: p = \beta_0(1 + \beta_1\beta_2 t)^{-1/\beta_1}.$$

Since using SPSS to fit data to a complex curve is complicated, the Excel Solver was used to model hyperbolic curves. The Excel Solver (trademark of Microsoft Corporation) is an add-in facility for Excel 5 and above; it is an optimization procedure which can be used to generate solutions for a wide spectrum of linear, non-linear and integer problems (John, 1998). The Solver finds the optimum value for a given target cell by changing the values of other cells which have been designated as change cells in the problem specification. The target and/or change cells can also be defined within specified constraints.

3.2. Neural network model

The DSS also includes neural network models for modeling the data. Neural networks use more advanced non-linear curve fitting algorithms than the curve fitting equations presented in the previous section. Instead of solving a set of equations to obtain the best coefficients, the neural network model updates weights in the neural networks to reduce the error at each step. Specifically in this study, the back-propagation algorithm implemented in NeurOnline (NOL) Studio (trademark of Gensym Corp.) was adopted to train the neural networks. Details on back-propagation algorithm can be found in Rumelhart et al. (1986). NOL Studio is an environment for developing off-line neural network applications. The tool automates the process of finding the appropriate model architecture, and guides the user step-by-step through the detailed processes of data preprocessing, model configuration, training, validation, and deployment for process analysis, modeling, and optimization (News, 1999).

4. Components of the oil production predictor system

The DSS contains three main components: a user interface, history-matching models, and an analogue predictor. They will be discussed in detail as follows.

4.1. User interface

The user interface receives two input parameters from the user: (1) initial production of target well and (2) expected economic cut-off of the well. The system then outputs the best and worst case scenarios as illustrated by the production curves. Based on his/her experience, an expert can examine the plots of predicted production rates for each existing well to decide which model is most likely predictor of the new well. The system also generates a model based on the averaged production of the existing wells. The set of average production is obtained by averaging month-by-month productions of all the wells, and serves as a reference model for the user. Its advantage is that its plot of data often displays a smooth trend while the production of individual wells may vary greatly over time.

The user interface and the analogue predictor described in Section 4.3 were implemented on Visusal Basic.

4.2. History-matching models

The history-matching models adopt the curve estimation and neural networks techniques described in Section 3. Each model takes the month index as input and outputs a predicted monthly production. The matching involves a process of minimizing RMSE between predicted and observed output values. Neural networks were trained to find the optimal architectures and weights. For the curve estimation methods, a set of curve coefficients were derived.

NOL Studio was used to model the production data for each well. The trained model did not consist of a single neural network; instead it is an ensemble of neural networks with different architectures and weights. Five best neural networks were included in the final ensemble, which ensured that when an individual model made a poor prediction for a particular piece of input data, the effect was reduced by other models. The output of the ensemble was the median of the individual model predictions.

To reduce the chance of the neural network models over-fitting the data, cross-validation was implemented. During training, the data was divided in different ways into two portions for training and validation; and the validation portion was used to measure the performance of the model trained to that point.

The automatic stopping option in NOL Studio was used so that models were continuously created and trained until no further improvements could be made. For most wells in our data sets, convergence was reached in less than 5 min of training.

The average RMSEs of the neural networks for the Oakly group of data were 4.28 bbls for training and 2.48 bbls for testing. These are relatively insignificant with respect to the average initial production of 272 bbls. The average correlation coefficents were 0.996 and 0.982 for training and testing, respectively, which indicates that the models accounted for most of the training and testing data. For the Midale group of data, the average RMSEs were 1.58 and 1.51 bbls while the average initial production was 34 bbls. The average correlation coefficients were 0.93 and 0.9.

The objective of the history-matching models is not only to memorize production curves, but to predict future values beyond the historical data set. A new well with higher initial production values will likely have a longer production life than an existing well with lower initial production values. Hence, the ability to calculate future values is even more necessary to make analogue predictions in the case of higher initial production. If the production life of the new well is shorter than that of the existing well, the observed values from the existing well can be used directly to make analogue predictions and no future value needs to be generated. However, if the life of the new well is longer than that of the existing well, only the observed values are not sufficient, and future predictions are needed.

The history-matching models are imported to the Visual Basic program via a text file so it is easy to add or delete models from the system. The text file includes coefficients of the curves and file paths to the neural network models. The coefficients of the curves are direct results generated from the SPSS or Excel Solver. The results of neural network training were COM-compliant ActiveX object files that can be easily embedded to the Visual Basic system.

4.3. Analogue predictor

The study adopted the analogue method to speculate about the production of a new well-based on decline curves of existing wells. Implicit in this adoption of the analogue method is the asumption that the production decline curve is similar to those of the existing wells in the same area. Another heuristic adopted was developed based on examination of the historical data on a well. It was observed that while the shape of two production curves can be different, the total production volumes of two wells are similar when their initial production volumes are at the same level. That is, when initial production volumes differ, total production volumes are likely to also differ. Hence, to make analogue prediction, the production curve of an existing well is adjusted to match the new level of initial production.

There are several ways to shift the production curve to a new level, these are presented as follows:

1. *Additive*: A constant is added to the monthly production of an existing well;
2. *Multiplicative*: A constant is multiplied to the monthly production of an existing well, and production rate is assumed to be proportional to the initial production;
3. *Linear*: The relationship between monthly production and initial production is expressed as a linear function;
4. *Non-linear*: The relationship between monthly production and initial production is expressed as a non-linear function.

Although the last two approaches are more likely to describe the relationship more accurately, there are often insufficient data for identifying these realationships. Therefore, only the first two methods are considered feasible and adopted. A comparison of the additive versus multiplicative curves shows that the additive curve more closely approximates the original data. This can be seen from the example shown in Fig. 1. Since the multiplicative curve favors or punishes production peaks more heavily, the shape of the additive curve (indicated with square markers) more closely approximates the original curve (indicated with diamond-shape markers) than the multiplicative curve (indicated with triangle markers). However, a disadvantage of the additive method is that it may generate negative production.

The analogue predictor model was used for predicting total production because accuracy of total production is

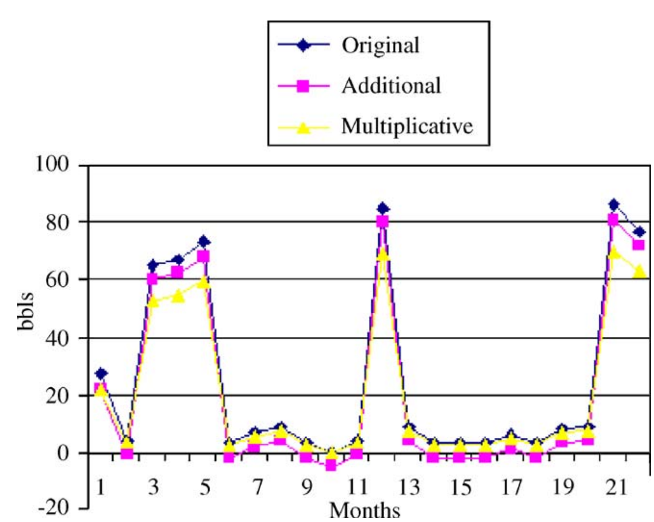

Fig. 1. Additive and multiplicative shifting methods.

Table 1
Additive method on data of Midale group of wells

		Prediction of				
		Well A	Well B	Well C	Well D	Well E
Based on	Well A	**2736.9**	−5000.71	−268359	3050	2919.5
	Well B	11575.8	**3838.19**	4570.4	11888.9	11758.4
	Well C	11058.3	3320.69	**4052.9**	11371.4	11240.9
	Well D	853.2	−6884.41	−6152.2	**1166.3**	1035.8
	Well E	873.9	648.8	−6131.5	1187	**1056.5**

Table 2
Multiplicative method on data of Midale group of wells

		Prediction of				
		Well A	Well B	Well C	Well D	Well E
Based on	Well A	**2736.9**	1257.234	1381.972	2073.422	1862.305
	Well B	8355.44	**3838.19**	4219.002	6329.919	5685.403
	Well C	8026.486	3687.08	**4052.9**	6080.709	5461.568
	Well D	1539.506	707.1941	777.3595	**1166.3**	1047.547
	Well E	1552.664	713.2385	784.0036	1176.268	**1056.5**

more important than that of monthly production. In this model, the primary concern is the relation between total production and initial production. However, some of the wells in the studied group of wells have not completed production. Hence, only data until the end of the shortest well are considered. For the Midale group of wells, two prediction methods were adopted. Tables 1 and 2 indicate the result with the actual production volumes in bold and predicted volumes based on other wells in regular font.

From the tables, it can be seen that the multiplicative method generates more accurate results than the additive method since the predicted values are closer to the range of the observed values, and there are no negative values in the prediction. Hence, we adopted the multiplicative approach in this study.

5. Experimental results

The Oil Production Predictor System was used for analyzing two groups of wells. Group 1 contains 14 short-life wells from the Oakly field and group 2 contains five long-life wells from the Midale field in Saskatchewan, Canada. Short-life wells last for less than 90 months while long-life wells last for 200 or more months.

5.1. System outputs

The system uses the different curve estimation analysis and neural network methods to generate predicted values of the production rates in barrels (bbls) and production life in months. The generated values are displayed in the table on the upper portion of the main output screen of the DSS shown in Fig. 2. The table displays a comparison of predicted values based on data from different wells and analyzed with different methods. The graph displayed at the bottom of Fig. 2 shows the best and worse case scenarios for each method for all the existing wells in the group. The gap between these two curves represents the range of possible production. A comparison of the different predicted curves generated by the different models for a single well is shown in the graphs in Fig. 3. Different models estimate the various possible production lives of the well and the results are displayed as graphs. According to the expert, the results given by the neural network and harmonic models in Fig. 3 provide the best estimates. On comparing the neural network and the harmonic curves, it was observed that the former gives better prediction than the latter in the early production stages. A possible reason is that the harmonic curve estimation process tries to fit the majority of the data points while the neural network tries to memorize every point in the training data set.

5.2. Testing

The performance of the DSS was evaluated by the domain expert, who was satisfied with the system's performance. In addition, accuracy of the system was tested using the available data. However, since some wells in the data set have not reached the end of their production lives, a complete observed data set was not available. A feasible experiment is to test prediction of each well against the others in the same group up to the end of the available data. However, it will not be feasible to extrapolate from the result of this test to the total production up until the point at which production is no longer economically viable.

To illustrate how this constrains the experiment, let us consider an example where the length of available data for well A is 30 months and its initial production is 50 bbls, then the prediction curves from other wells and the averaged data series will be scaled to the level of 50 bbls and well A's actual total production up to 30 months will be compared with the range of predicted volumes from the other wells. Table 3 shows some sample prediction results for three different wells in the two groups. The unit of values in rows is bbls and each column shows the upper or lower prediction values produced by a different method, where LN = linear, LG = logarithmic, EX = exponential, HM = harmonic, and HP = hyperbolic.

As can be seen in Table 3, the DSS generated wide ranges of values. This can be due to the fact that even though the wells are from the same area, their

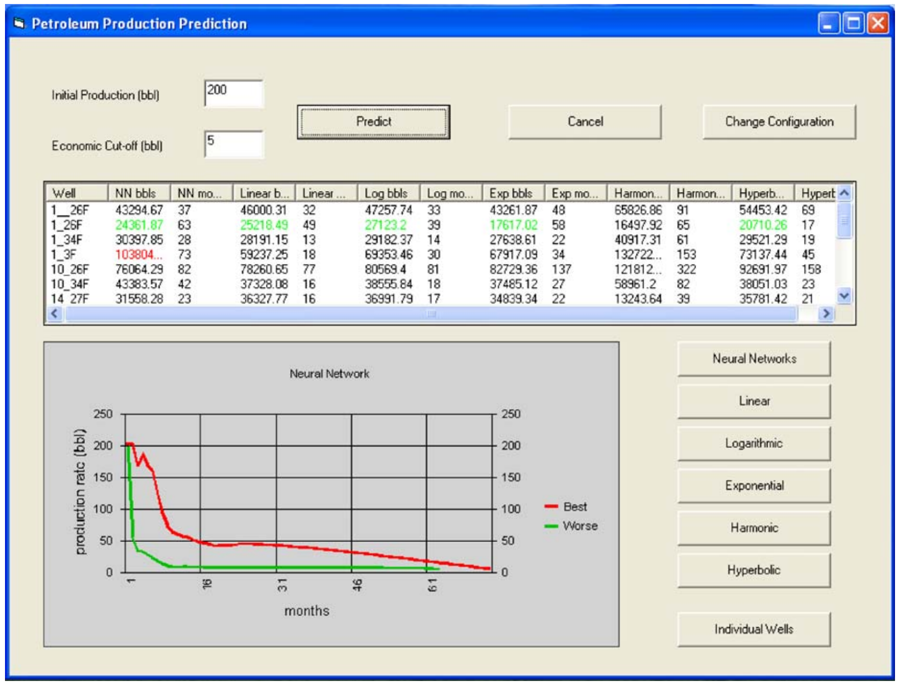

Fig. 2. DSS output on best and worse case scenarios.

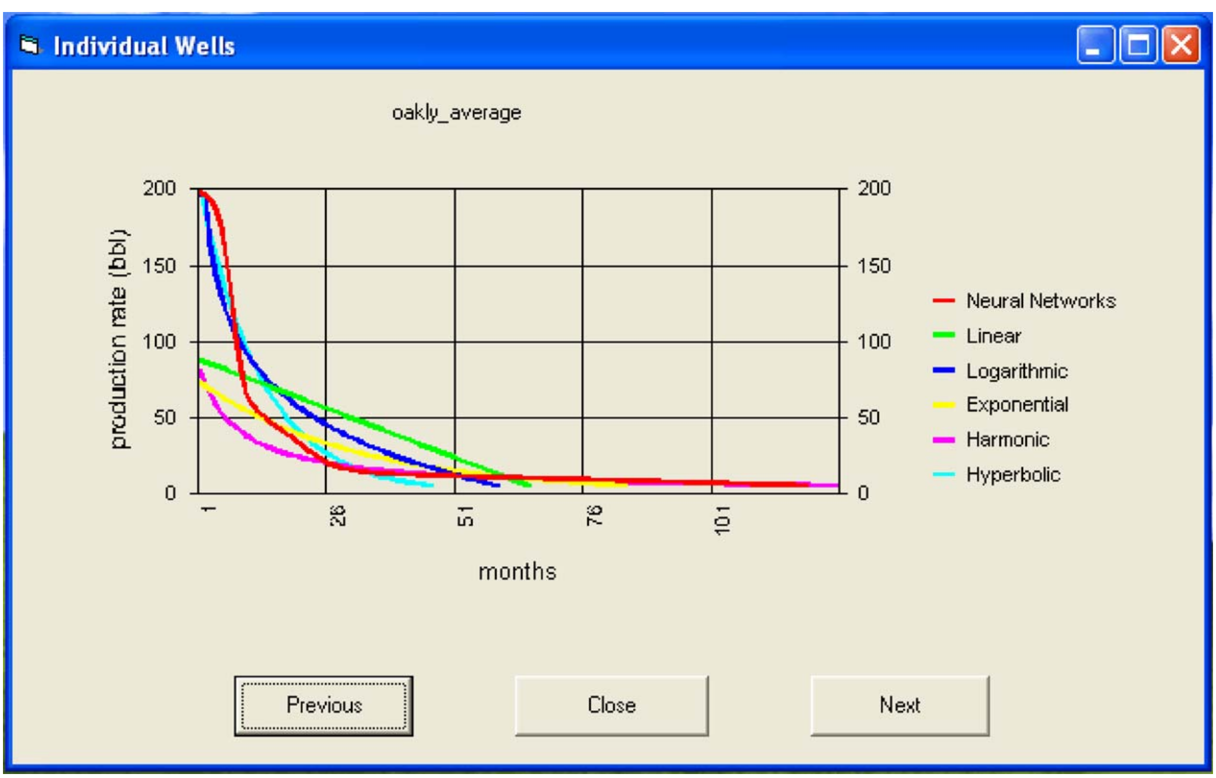

Fig. 3. Prediction graphs generated by different models based on the average of all the wells in Oakly field.

characteristics are significantly different. Some wells are also under or over estimated since the training data sets do not include a variety of characteristics. It can be seen that the harmonic results in the third case are unrealistic, so prediction curves should be applied with caution.

Table 3
Sample prediction results

Actual	NN lower	NN upper	LN lower	LN upper	LG lower	LG upper	EX lower	EX upper	HM lower	HM upper	HP lower	HP upper
4301	724	3642	1165	3677	979	3889	820	3687	599	3721	1152	2874
1057	387	1558	602	1530	511	1419	410	1543	305	1889	630	1713
1170	1155	4825	1328	4327	1368	5683	1317	4873	194	11719	483	5786

6. Observations and discussions

6.1. Fitness of models

To investigate performance of the different methods on the training data, a comparison of the predicted values from all the methods versus actual production rate of one well at Midale was made. Among the curve estimation methods, hyperbolic and logarithmic curves display better fitting abilities. However, as can be observed in Fig. 4, the neural network model fits the training data better than the curve fitting methods.

However, as discussed in the previous section, a good fit to training data does not guarantee high prediction accuracy. As can be seen from Table 3, neural network, hyperbolic and logarithmic approaches do not always give better prediction results. Based on our experimental results, no one model emerges to give consistently reliable predictions and expert judgement is needed in selecting the right method.

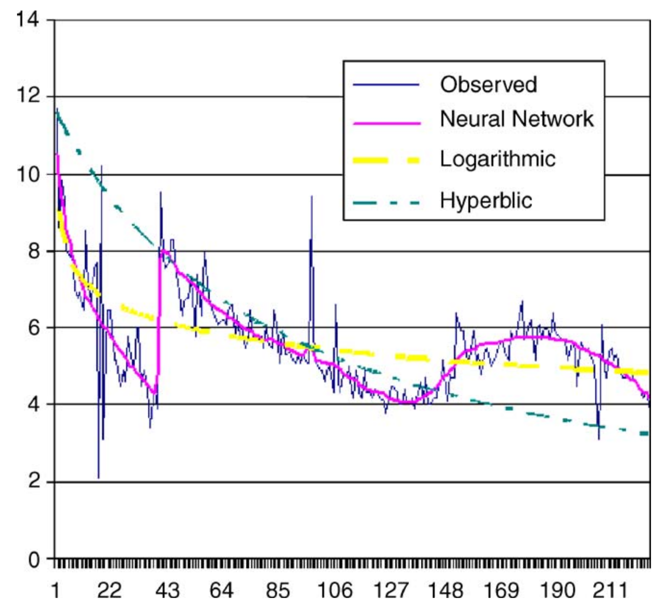

Fig. 4. Fitness of models.

6.2. Problem with neural network models

For some wells, e.g. the one illustrated in Fig. 5, the neural network curve shows an unusual downward trend at the end of the production life. It can be seen from Fig. 4 that the last section of the observed data set shows a sharp downward trend. This has possibly caused the sharp decline of the neural network curve in Fig. 5. Since it is known that oil production does not usually decrease suddenly, this sharp decline may not be representative of data from the population. One solution for this problem of misrepresentation is to retrain the neural networks until the quick decline at the end of a well life is reduced. It was also observed that long-life wells provided better results than short-life wells in terms of smoothness of trend. Insufficient training data can cause overfitting when the neural network is unneccessarily complex. Our experiments showed that sample wells for training should have a production life of 30 months or longer.

6.3. Problem with Excel solver

It was observed that the Excel solver is only semi-automatic. Since it only attempts to solve a problem in a limited time span with limited memory, the solutions obtained may not be the optimal solutions. The Solver could give different results with different initial values for the "change cells", which are key variables to be manipulated for generating the optimal solution. Moreover, its memory capacity is not large enough to handle complex problems with many constraints and large data sets. Therefore, in order to obtain a good fit, considerable trial and error is necessary.

6.4. Narrowing the gap

It is desirable to narrow the gap between the best and worse case scenarios without losing much accuracy. However, this is usually not possible due to considerable variances in characteristics of wells. If heuristic knowledge on similarity of wells can be assumed, then the gap could be narrowed by selecting only the wells that have similar characteristics to the well for which a production estimate has to be made. Unfortunately, this kind of knowledge is often not available. Hence, it is recommended that as much available data as possible on existing wells in the surrounding area be used for modeling, even though this means the gap between the best and worst case senarios will be large.

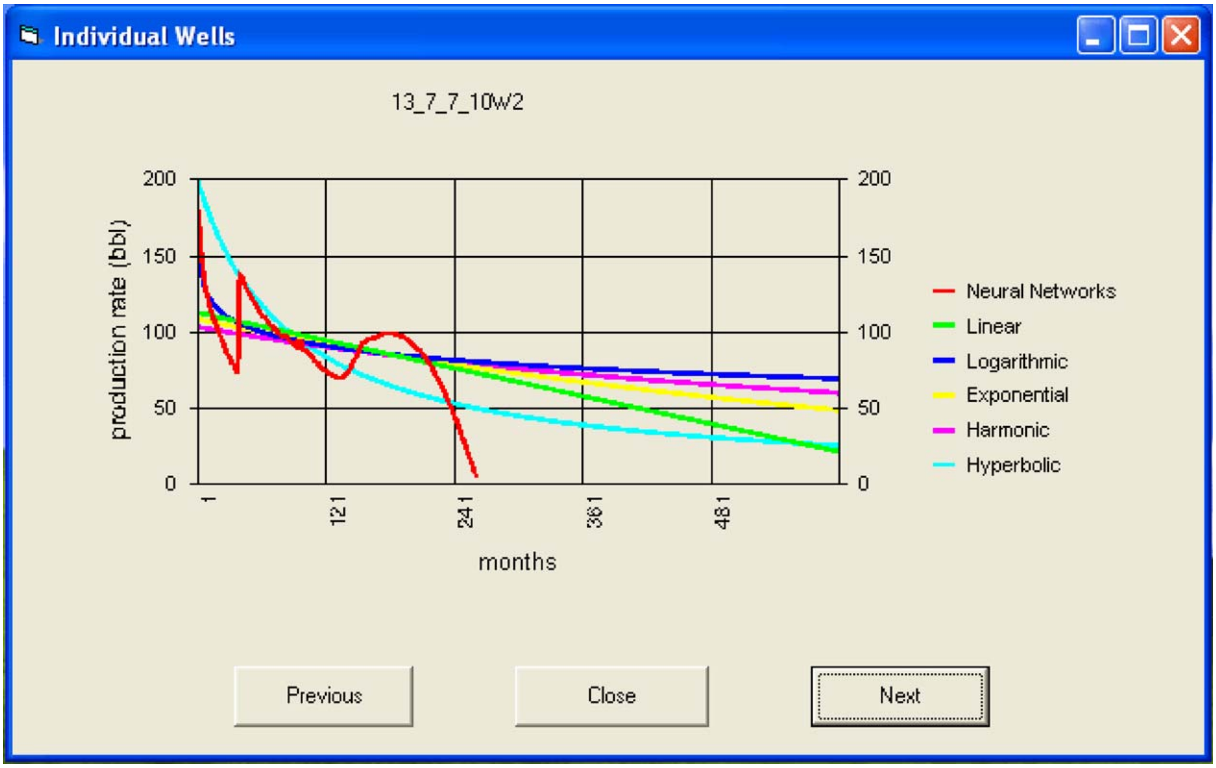

Fig. 5. Output graphs from different models based on a sample well.

7. Conclusion and future work

In recent years, considerable progress has been made in the development of methods for estimating future production of oil wells. However, these methods are usually either difficult to use or inaccurate. The DSS presented in this paper does not attempt to invent a novel prediction method. Instead, it is based on several simple available methods and gives users numerical and visual illustrations of the results so that experienced users can exercise their judgement and decide which scenario is the more likely. Since the models can be developed offline and then imported into the system, it is easy to update the system to include new wells.

One weakness of the DSS is that the input are consecutive integer time indices, so it is easy for the neural networks to over-fit or memorize the training set. In this case, the neural networks do not perform well when extrapolated to the future. A major weakness of the system is the assumption that the production rate is proportional to the initial production. This assumption was made based on the expert's opinion, but it remained untested. The exact relationship between production rate and initial production deserves further study.

Individual wells are recommended for providing best and worse case scenarios. The advantage of using individual wells is that the data are homogenous. However, interpreting the results from the individual well approach requires expert opinions. The averaging approaches on the other hand provide useful information on an average production of a well in the area.

For future work, we will study the relationship between initial production and monthly production. Next, we will attempt to match the new well to the closest existing wells in terms of location and other geoscience characteristics such as permeability and porosity. The added information may give more support to less experienced users in identifying which existing wells are likely to be similar to the new well. The component models can also be improved. To improve upon the averaging approach, it is possible to truncate the last section of the averaged time series. This should be done when the last section contains data from only a few long-life wells.

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