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Characterizing Complex Reservoirs by Virtual Pressure Testing Using Time Delay Neural Networks

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Abstract

Due to the drying up of old oil fields throughout the globe, the age of easy oil is over and the newly discovered fields have reservoirs with complex heterogeneous media. The reservoir parameters are identified indirectly by correctly interpreting well test model which is recognized by the feature of pressure derivative curves. Lost production, equipment and personnel costs turn well testing into a highly cost intensive job making it difficult to cover all the important wells in a particular field.

With the advent of artificial neural networks (ANN) it is now possible to generate synthetic pressure transient data. This technique provides a basis to leach out detailed information from the available pressure transient data and it doesn't eradicate the need for actual well tests. Virtual well testing involves training of a neural network from pressure transient data obtained from designated wells in the field, which has the potential to generate pressure transient responses at other well sites where no well test has been conducted.

In this paper a 3 layer multi-layer perceptron (MLP) Time Delay Neural Network - NARX model has been designed working on resilient backpopagation algorithm for training. Cubic Spline Interpolation has been used for enriching the data before feeding it to NARX model. A simulated example for a heterogeneous field which highlights the efficiency of NARX model using well testing analyses backed inputs in attaining accurate synthetic pressure transient data has been discussed.

Introduction

Due to the complex structures and heterogeneous media, of oil and gas reservoirs, characterizing reservoirs precisely is a herculean task. Petroleum Engineers solve this challenge by acquiring and analysing detailed reservoir information, which is crucial for the study of the reservoir performance (Vaferi et al., 2011). Well Testing or Pressure Transient Testing has proved to be a powerful reservoir characterization tool to study such complex media (Muskat, 1937). Pressure testing is conducted by recording the well bore bottom hole pressure responses which are created as a result of induced flow disturbances. The most general test methods are 1) By creating a pressure drawdown in the wellbore by producing the well at a constant rate, after keeping it in shut-in condition for a set period; 2) By developing a pressure build-up in the wellbore by shutting-in at the bottom hole, due to which formation fluids cannot flow into the wellbore. Thus, measured flow rates and pressures during these tests can provide sufficient information for the characterization of the tested well (Matthews et al., 1967; Earlougher et al., 1977).

However, huge production time losses, manpower and equipment costs turn it into a cost intensive affair (Dakshindas, 1999). Since its introduction to the petroleum engineering industry around 1937 by ground water hydrology scientists (Gringarten, 2008), plethora of novel technologies have been introduced both for data acquisition and analysis. The introduction of electronic pressure gauges was a great step ahead in data acquisition technology, and continuously upgraded versions of these are being developed to meet current challenges. Moreover, for expeditious data acquisition and interpretation to gain in-depth insight of the reservoir, industry anticipates close integration of advanced microprocessors and innovative computational techniques.

Cubic Spline Interpolation

The cubic spline curve is a continuous piecewise third order polynomial, satisfying all the input values. The main purpose of using CSCF technique is to increase data points between minimum and maximum, as with higher amount of input data points better results through ANN can be obtained. Moreover its high accuracy of estimation and capacity to produce seamless curves makes it a popular interpolation technique.

Time Delay Neural Networks (TDNN)

The designing of neural networks can be understood by classifying them into two categories dynamic and static. Static networks are comparatively simple with neither feedback elements nor delays. On the other hand, in case of dynamic networks, the output generated is governed by current inputs, previous inputs, outputs and network states. However, dynamic networks can be trained by the same algorithms used by static networks but due to complex nature of error surfaces computing gradients is more intensive. Moreover in this study NARX model has been implemented which is a type of dynamic network or more specifically Time Delay Neural Network (TDNN).

NARX Neural Network Model

Instead of conventional dynamic networks that are either feedforward networks or focused networks, with only input layer dynamics, here fully connected feedback connections are enclosed in numerous layers of a recurrent dynamic network which is Nonlinear Autoregressive with eXogenous inputs (NARX recurrent models). Contrary to other recurrent networks, feedback comes only from output neuron instead from hidden states, it is modelled with a tapped delay line (embedded memory) which is clubbed to a delayed feeding line from the output, second tapped delay line. This type of limited viewed part of the input series is referred to as *time window* (Diaconnescu, 2008). A NARX model is formulated by the following equation

$$y(t) = f(y(t-1), y(t-2),\ldots.., y(t-n_y), u(t-1), u(t-2),\ldots.., u(t-n_u))$$

where, $y(t)$ and $u(t)$ denotes input and output signal of the network at time t, n_y and n_u signifies input and output order, while f represent the mapping performed by Multilayer Perceptron (Siegelmann et al., 1997). The value of dependent output $y(t)$ is reverted to earlier output values and values of eXogenous input. This real-time feeding of output to the network is called as parallel architecture, which results in more accurate training and due its purely feedforward architecture, static backpropagation can be used.

Proposed Application Methodology

The steps incurred throughout this process are explained below:

1. Candidate Identification: A set of wells are chosen, which are producing from a particular formation (zone). Segregate the wells where prediction is to be done.
2. Information Gathering: Pressure Testing is performed on the selected zone at all picked well locations and PTD is recorded. Other vital information about the reservoir is also acquired and pressure transient analyses is performed on the data to generate useful facts about the reservoir.
3. Data Enrichment: NARX works best when highly dense data sets are fed to it. Thus according to the type of cures produced by the specific pressure testing procedure followed, data interpolation technique is chosen and applied.
4. Normalization: The input data for the NARX is scaled down to the range of 0 to 1.
5. Network Training: The network is configured with appropriate parameters and then input data is fed to the network for training it.
6. Network Testing: Performance of the network is validated against known data sets, if the results are unsatisfactory then the network parameters are tweaked and the NARX is retrained.
7. Prediction: Utilize the trained NARX to simulate data for unknown outputs.

To minimize error and produce the best pressure transient predictions, the whole process was tested numerous times with varied network models and interpolation techniques. Due to the monotonically increasing nature of pressure curve generated using PTD the best suited technologies are identified was Cubic Spline Curve Fitting (CSCF) and NARX neural model.

Case Study

This case deals with simulator generated pressure build-up test data consisting of five active producing wells for a large heterogeneous field **(Figure 1)**. The data was generated using analytical simulator, which is based on principle of superposition and infinite acting line source solution. All the five wells considered had identical shut-in and production time, and different flow rates. The wells are shut-in at 215 hours and the data is recorded for 67 hours.

The ANN is trained from pressure responses of four wells and the data for well 5 is predicted. Complete data set for each well is prepared for training the NARX network. Each well's pressure data, Horner's time [$(tp+\Delta t)/\ \Delta t$], dimensionless pressure [$P_D= (0.00708*k*h(P_i - P_w))/\ (Q*B*\mu)$], dimensionless time [$t_D= (0.000254*k*t)/\ (\phi*\mu*c_t*r_w^2)$], modified inter-well distances, mid time slope [$m= (162.6*Q*B*\mu)/\ (k*h)$] and flow rates along with their functional links are used as inputs for the network **(Figure 2)**. The output from the network is pressure which is generated by also taking into account the interference effects from the proximate wells. Modified distance is formulated to be:

$$\text{Dist.(1-2)} = (Q_{w1} *k_{w2} *h_{w2})* \text{Dist}_{(w1-w2)} / (Q_{w2} *k_{w1} *h_{w1})$$

After taking into account modified distance, dimensionless quantities and functional links better prediction results were observed but with increased CPU usage and network training time. Similarly, initially 60 data values were available, which by using Cubic Spline Interpolation were increased to 89.

Resilient backpropagation algorithm was used to update bias values and connection weights during training because it enables the optimization of weight change magnitude by reducing it in cases where weights are oscillating and increasing it when for several iterations weights change continuously in the same direction. Sigmoid or 'squashing' functions were used as transfer functions for all the neurons at every layer, as the derivative of sigmoid function can be swiftly calculated which is needed to be backpropagated to calculate error. It is defined by:

$$F(i) = (1+e^{-i})^{-1}$$

Where, $F(i)$ is the function output and *'i'* is the input. The performance of the network was judged on the basis of mean square error (MSE). The input set was divided using interleaved indices. The applied NARX model is a three layer network with 18 input layer neurons, 25 neurons in hidden layer and 1 output layer neuron. The time delay configured for this particular problem is 1:4, thus producing 85 outputs for 89 inputs.

A good match is observed between the network and the simulator output **(Figure 3-6)**, confirming that NARX has the potential to predict well test pressure responses accurately. The prediction performed by the network for well 5 is also remarkable considering the complexity of the problem **(Figure 7)**. With increased available data from more number of wells the network will deliver more precise predictions but the wells must be chosen meticulously to ensure inclusion of interference effects, flow rate effects, shut-in and production effects, boundaries and heterogeneity effects. But the risk that network might get over-trained also escalates with increased number of training wells.

Conclusions

In this paper a unique synthetic pressure transient data generation has been introduced. The discussed simulated field case study has justified the approach and delivered recommendations on how to increase the accuracy of the prediction. The precision of the network remarkably improves when neural network is exposed to variety of data from more number of strategically selected wells. Incorporation of more data, better well test analysis theory backed co-relations, statistical functional links, multiple inputs from the field after rigorous iterative testing can increase reliability of the network. Moreover, for cases where due to some downhole equipment failure test couldn't be completed or some data is lost, by using this we can complete the data.

This doesn't eradicate the need for actual well tests, but it remarkably curbs the frequency of actual tests when clubbed with tactical well test pattern planning. Using upcoming efficient ANN engines more informed well tests can be designed by extracting more information from the available data, thus reflecting enormous potential to revamp the petroleum industry by delivering expeditious and reliable solutions.

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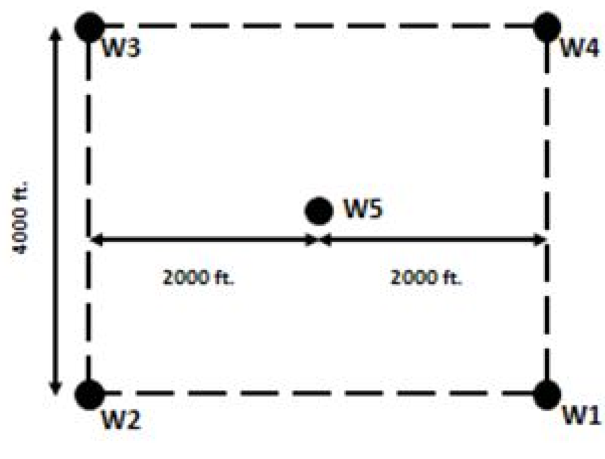

Figure 1: Simulated heterogeneous field with 5 active wells

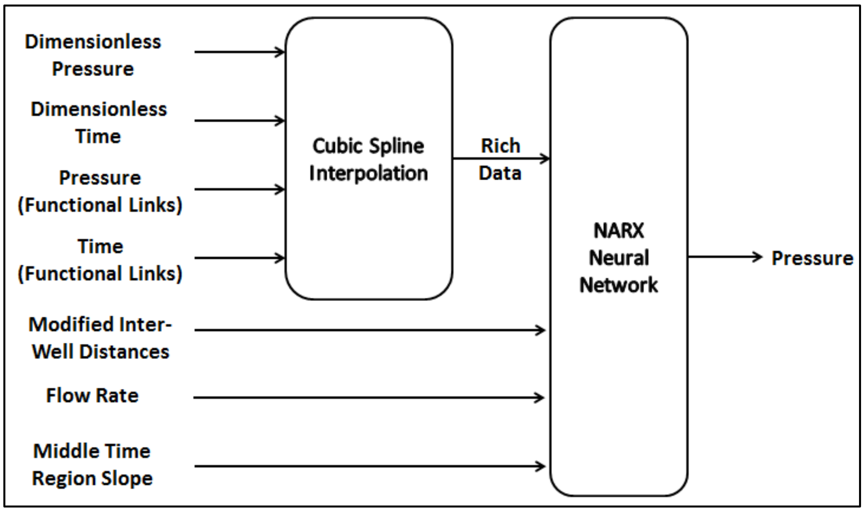

Figure 2: Comprehensive process flowchart for the case study

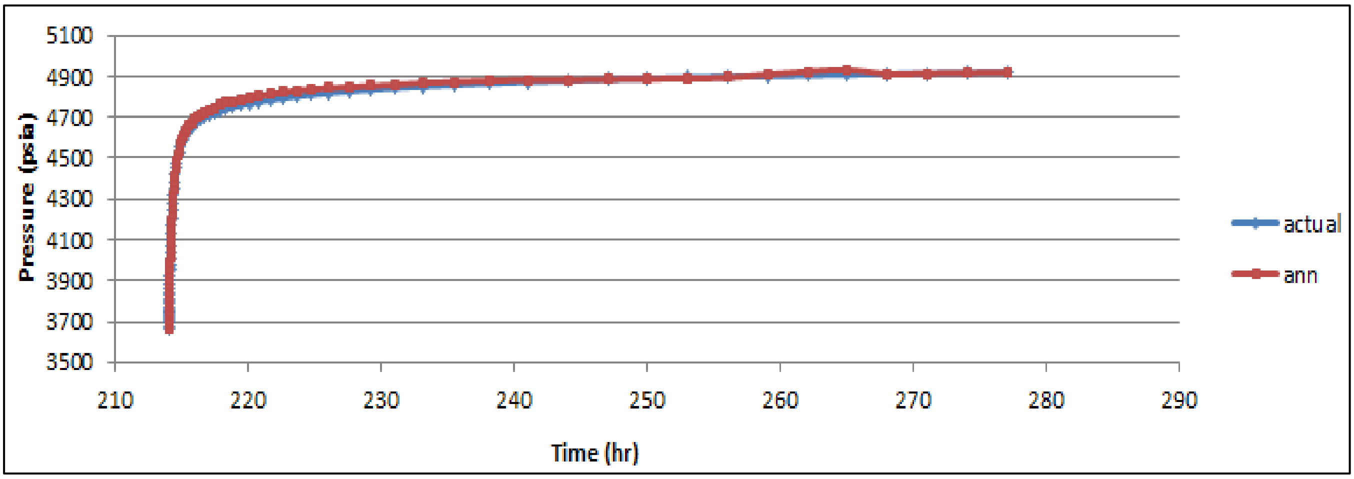

Figure 3: Comparison of simulator and ANN data for Training Well 1

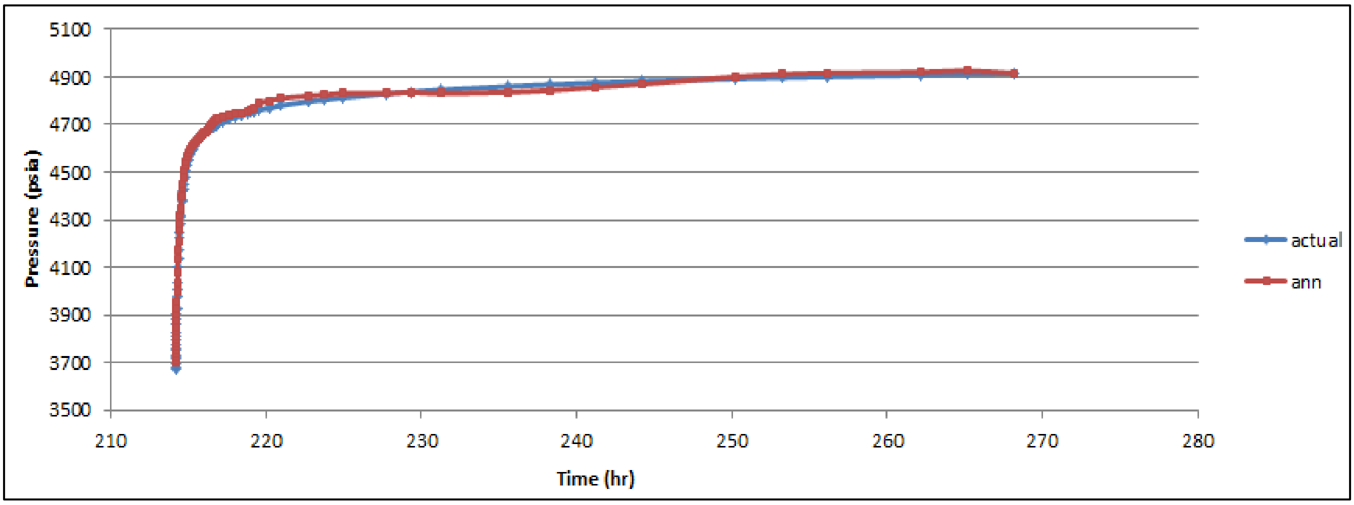

Figure 4: Comparison of simulator and ANN data for Training Well 2

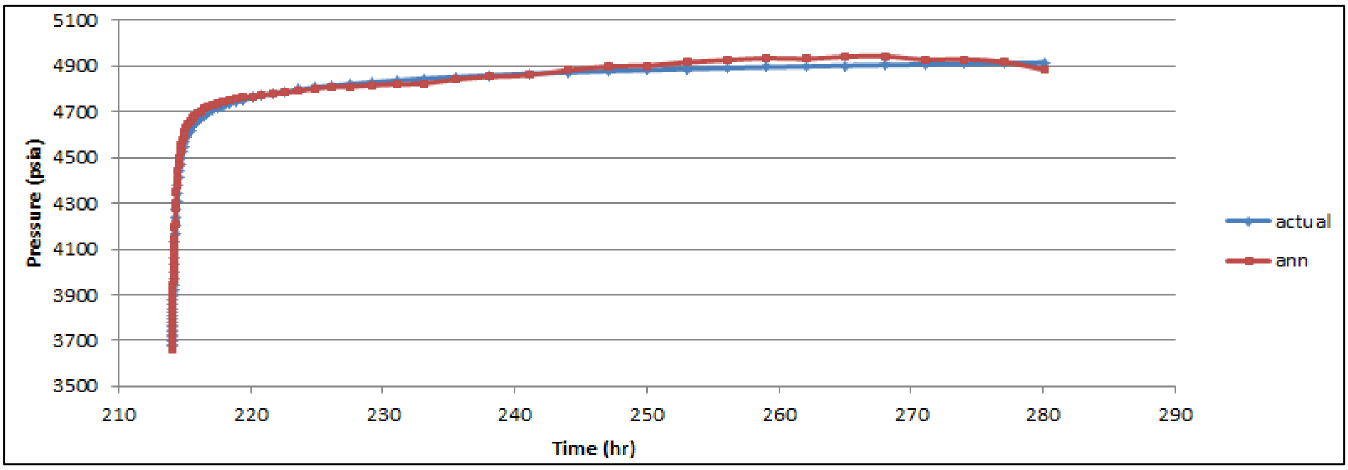

Figure 5: Comparison of simulator and ANN data for Training Well 3

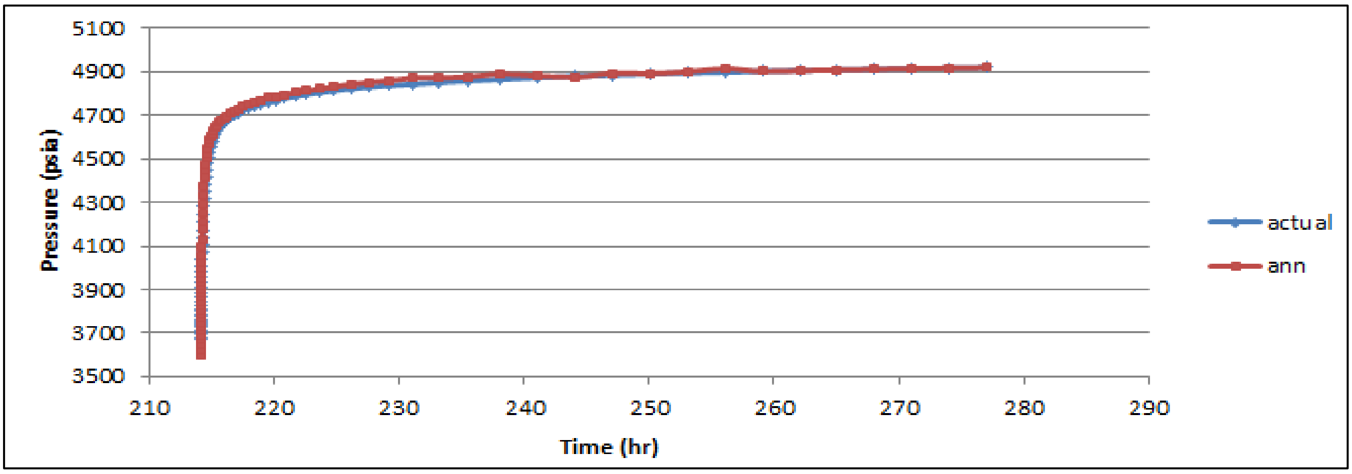

Figure 6: Comparison of simulator and ANN data for Training Well 4

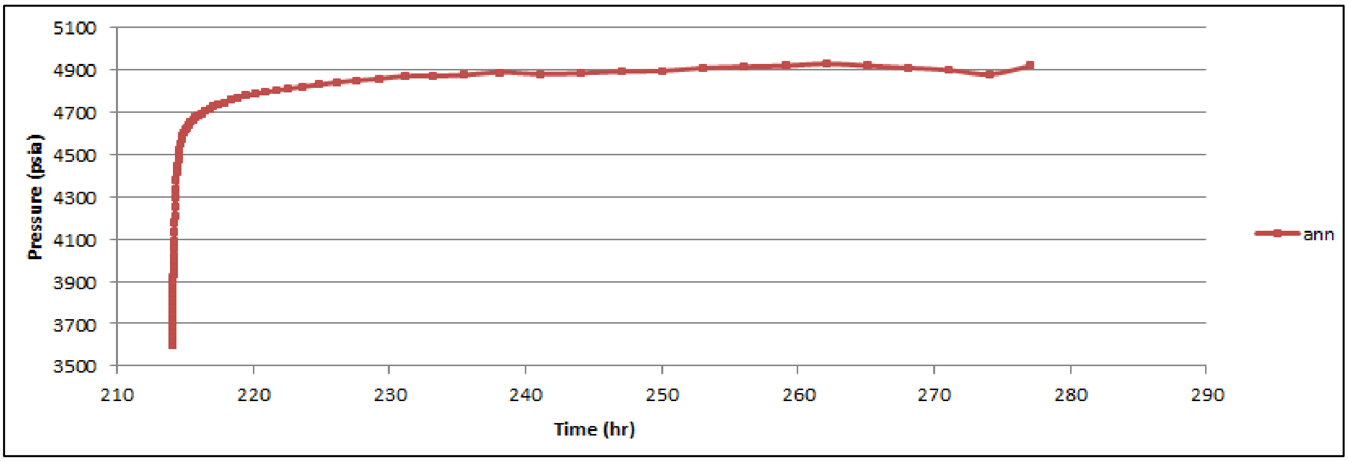

Figure 7: NARX model prediction result for Well 5