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Identification of Parameters Influencing the Response of Gas Storage Wells to Hydraulic Fracturing with the Aid of a Neural Network

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Abstract

Performing hydraulic fractures on gas storage wells to improve their deliverability is a common practice in the eastern part of the United States. Most of the fields in this part of the country being used for storage are old. Reservoir characteristic data necessary for most reservoir studies and hydraulic fracture design and evaluation are scarce for these old fields. This paper introduces a new methodology by which parameters that influence the response of gas storage wells to hydraulic fracturing may be identified in the absence of sufficient reservoir data. Control and manipulation of these parameters, once identified correctly, could enhance the outcome of frac jobs in gas storage fields. The study was conducted on a gas storage field in the Clinton formation of Northeastern Ohio. It was found that well performance indicators prior to a hydraulic fracture play an important role in how good the well will respond to a new frac job. Several other important factors were also identified.

The identification of controlling parameters serves as a foundation for improved frac job design in the fields where adequate engineering data is not available. Another application of this type of study could be the enhancement of selection criteria among the candidate wells for hydraulic fracturing. To achieve the objective of this study, an artificial neural network was designed, trained and applied. The paper will discuss the results of the incorporation of this new technology in hydraulic fracture design and evaluation.

Introduction

This study was conducted on a large natural gas storage field located in Northeastern Ohio. The formation is a tight gas sandstone called the Clinton Sand. All of the storage wells were initially stimulated by hydraulic fracturing. Refracturing is considered a last resort method of deliverability enhancement in this storage field. However, some wells are elected to be refractured each year based on maintenance history, past fracture response, years since previous fracture and overall deliverability potential. Since 1970, an average of twenty-five wells have been refractured each year for a total of around 600 treatments. Since most wells in the field have been refractured, some up to three times, the need for post fracture well performance estimates and optimal fracture design is very important to maximize deliverability gains.

Several well testing methods are available for predicting hydraulically fractured well performance including type curve matching and computer simulation[1-5]. In addition, two and three dimensional computer simulators are frequently used for fracture design. Use of these tools, however, requires detailed information about rock mechanics and reservoir characteristics. Obtaining accurate reservoir data by electric logs, well testing or coring may be operationally difficult or cost prohibitive.

The objective of this study was to find a method to identify fracturing parameters which influence storage well performance after refracture with only existing data. Identifying these parameters would provide guidelines for fracture design. The following describes how a neural network was trained with existing data to identify influential parameters in hydraulic fracturing of the Clinton Sand. The trained network is then used to make some conclusions about hydraulic fracture design.

Reservoir Characteristics

The Clinton reservoir is a tight gas sandstone. Natural fracturing is thought to account for production in economic quantities. Sand occurs in lenses and is largely discontinuous from one well to another. Therefore, generalization of field or well reservoir properties from core data is very difficult. Pressure testing is often inconclusive because of insufficient data, reservoir heterogeneities, wellbore storage, interference and duration to achieve steady state.

Hydraulic Fracture Design

Many operators in Ohio believe hydraulic fractures of the Clinton Sandstone grow vertically out of zone regardless of rate and fluid viscosity. Therefore, it appears critical to run high proppant concentrations in a viscous fluid to create a conductive fracture in the pay interval. Treatment design for this storage field currently includes a 25 to 30 pound linear gel with maximum sand concentrations from 3 to 4 ppg.

However, many other designs have been tried over the past twenty years with a wide variety of resulting deliverability increases. Therefore, identifying which parameters influence well performance is difficult to determine because of the vast number of variables associated with hydraulic fracturing and the operating characteristics of each well.

Many opinions exist regarding optimum hydraulic fracture design. Two and three dimensional computer simulators are frequently used for fracture design and monitoring. Use of these models, however, require detailed information about rock mechanics and reservoir characteristics. Obtaining accurate information is both difficult and costly. Basic well information such as geographic location, depth, tubular design, completion type, flow tests, past fracture designs and performance history is readily available without additional cost. Most of this data, however, is not considered useful engineering data for hydraulic fracture design. Although many of these variables may contribute to the overall success or failure of a hydraulic fracture treatment in some indirect or complex way.

Using a Neural Network

Artificial neural networks are computing systems based on learning by the interaction between large numbers of simple processing units or neurons. These systems mimic biological systems such as the human brain. The brain is believed to learn by strengthening or weakening connections between billions of neurons. Similarly, artificial neural networks can learn complex patterns by adjusting the connection weights between artificial neurons. An artificial neural network may have a number of layers of artificial neurons. The first layer is designated the input layer, middle layer(s) are hidden, and the final layer is the output layer.

Neural networks have been successfully applied to everything from the stock market to automatic transmissions. This technology has been applied to different petroleum engineering problems to predict formation permeability[6-10], intepret logs[11], and predict pressure and flow patterns in multi-phase flow in pipes[12-13] (many of these papers are available on the World Wide Web site http://www.pe.wvu.edu) . This paper represents the first successful attempt on application of artificial neural networks to hydraulic fracturing. With the vast amount of historical fracturing data available, it was proposed that a neural network would be a viable tool to identify important fracturing parameters and improve fracture design for storage field wells. Although many different types of neural networks exist (Kohonen, Probabilistic, Recurrent, etc.) a three layer feed forward backpropagation network was used in this study[14,15,16].

Training the Network

Training is the most important computational task for a neural network. It is the process of finding a set of connection weights that produce an expected output when presented with an input. Data available for training the network included actual refracture treatment design, basic well information and well performance data. The data was input in a spreadsheet format and totaled 540 entries or patterns. The data was normalized as much as possible to accommodate use of a neural network. A list of the input and output data variables used for training, along with a short description, is summarized as follows:

Well Number - A four digit identification number. The numbers provide a means of identification during data preprocessing and give some indication of relative age and completion type for the well.

Year - The year in which the well was fractured. The year of the fracture also provides a means of identification for preprocessing and gives an indication of fracture technology and chronology.

Date Fractured - Actual reservoir pressures before each fracture were not available. A relative pressure function was created using fracturing date.

Frac Number - The number of times the well has been refractured.

Three distinct fluid systems were used historically: water, gelled water and foam.

Viscosity - The sand laden fluid viscosity.

Total Volume - The total amount of water used.

Nitrogen - The total amount of nitrogen used per barrel of water.

Total Sand - The total amount of sand used.

Sand Concentration - Maximum sand concentration pumped.

Sand Type - The sand mesh size used.

Acid Volume and Type - Acid is used as a prepad.

Chemicals - Iron control, bacteria control, paraffin dispersant, clay stabilizers and surfactant

Average Rate - The average treatment injection rate.

Screen Out - Occurrence of screenout.

Contractor - Three different contractors were used.

Hole Size - Production string outside diameter.
Completion Type - Open hole or perforated style completion.

Well Type - An indicator of how the well is used operationally during the storage output season.

Date Completed - Year the well was drilled and completed.

Date Converted - Year the well was converted to storage.

Group Number - The geographical and functional area the well is used.

Sand Thickness - The overall thickness of clean sand.

Qmin - The minimum twenty year flow test value.

Qmax - The maximum twenty year flow test value.

Qavg - The twenty year average flow test value.

Qprior - The flow test value before refracture.

Qafter - The single output variable. The maximum flow test value after refracture.

Flow Performance Variable Contributions

After training was complete, an attempt was made to identify which parameters had the most influence on post fracture well deliverability. Flow performance variables were found to have roughly four times more influence than other variables (Figure 1). Figure 2 is a closer look at the four major contributing parameters. They have so much influence, a network was trained with only the flow performance data as input to determine if they were the only significant variables. The network trained using only flow performance data performed satisfactorily, but did not correlate as strongly as the original network. Therefore, although post-fracture well performance is strongly dependent on flow performance history, other variables are significant because their contributions create a stronger, more reliable network.

Fracture Design Variable Contributions

The trained network was then used to determine the effect of changing fracture design and well information parameters by applying it to a synthetic pattern file. Synthetic patterns were constructed using four different average well performance values ranginf from a low average rate (prior to fracturing) of 124Mcfd to a high average rate of 2066Mcfd. Individual fracture designs and well information was changed one variable at a time to determine what effect the network would predict on flow performance after fracture. Variables having a significant impact are summarized and briefly explained as follows:

Sand Volume - Sand volumes and concentrations were varied for resulting sand volumes of 100, 200, 300, 400 and 500 sacks. Performance increased with sand concentration in all cases (Figure 3).

Fluid Type - Fluid type was varied between water, gel and foam. The wells responded better to high viscosity gelled and foamed treatment fluid (Figure 4).
Injection Rate - Treatment injection rate was varied between 15, 20, 25 and 30 BPM. Higher treating rates increased performance after fracture for each well type (Figure 5).

Acid Volume - The volume of acid prepad was varied between 500 and 1000 gallons. The results show a gradual increase in well performance with increased acid volumes (Figure 6).

Contractor - The contractor was alternated between A, B and C. Contractor type A performed better in all cases (Figure 7).

Fracture Number - The number of fracture treatments was varied between one (1) and three (3). The results show a gradual decline in after fracture performance with increasing fracture number (Figure 8).

Conclusions

From input variable contribution analysis, previous flow performance appears to be the most important factor governing well response to fracturing. In other words, a low deliverability well may always have relatively low deliverability, no matter what the fracture design. However, fracture design variables do contribute to overall well performance.

Proppant volume and concentration appear to have the most impact on well response. The network predicted increasing proppant volume and concentration would improve well performance. Increasing fluid volumes does not improve performance if proppant volumes and concentrations remain the same. In addition, using higher viscosity fluid at high injection rates to suspend the proppant also increases well performance. This can translate into cost savings, since low volumes of high viscosity fluid can be used without sacrificing well performance.

Acid prepads are used to remove perforation and near wellbore damage. The network shows increasing the prepad volume does increase well perforrnance. Quality control also appears important because of the performance variations between contractors. It is interesting to note that contractor "A" in this case is the more expensive and was thought to have better quality control. Finally, results do gradually degrade with each successive refracture, assuming identical designs.

The preceding described a new application for neural networks to a petroleum engineering problem. The network was able to process subtle data patterns and identify factors contributing to well performance after hydraulic fracturing, in the absence of reservoir data. Adding input variables such as reservoir thickness, porosity, permeability and skin factor may improve network prediction accuracy. Also, it is interesting to note that although no direct information of the physics or engineering aspects of the problem was made available to the network, all of the analysis and predictions made perfect engineering sense. This adds credibility to the use of a neural network for this application.

Finally, this work is currently being continued to improve fracture design based on the network response to some synthetic data. A hybrid system is being developed for fracture design optimization which would take all variables into consideration. Such a system could not only recommend an optimum fracture design, but predict the expected post-fracture well performance.

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SI Metric Converion Factors

bbl X 1.589873	E-01=m3
ft X 3.048*	E-01=m
gal X 3.785412	E-03=m3
lbm X 4.535924	E-01=kg

*Conversion factor is exact