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Predicting Well Stimulation Results in a Gas Storage Field in the Absence of Reservoir Data, Using Neural Networks

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ABSTRACT

Selection of candidate wells for stimulation treatment to increase their productivity is a challenging task. A systematic approach using a three-layer back propagation neural network, introduced in this paper, assists engineers in predicting post-stimulation well performance to select candidate wells for stimulation treatment. This approach can also be used to optimize the stimulation design parameters. Unlike conventional simulators that are based on mathematical modeling of the fracturing process, the process introduced in this paper uses no specific mathematical model. As a result, access to explicit reservoir data such as porosity, permeability-thickness and stress profile is not essential. This is a major advantage over conventional hydraulic fracturing simulators, which can translate to considerable savings since it eliminates the need for expensive data collection. The application of this methodology to a gas storage field is presented in this paper. The developed neural network can predict the post-fracture well deliverability with approximately 95% accuracy. These results were achieved in the absence of reservoir data (permeability, porosity, thickness and stress profiles) that makes conventional fracture simulation impossible. This process is currently being used to select candidate wells for future stimulation treatment in the aforementioned field.

INTRODUCTION

Gas storage fields have numerous wells that are used for both injection during low demand periods and withdrawal during high demand periods. As these wells age, their deliverability declines due to several factors. Stimulation treatments (hydraulic fracturing of the formation) are routinely used in gas

industry to improve gas well productivity. Due to the finite financial resources available, engineers must select the candidate wells with the highest potential of improvement after stimulation. This process is best done using two or three dimensional hydraulic fracturing simulators that are available in the industry. In order to use these simulators, however, access to several types of reservoir data is essential. Reservoir data necessary for hydraulic fracture simulation include porosity, permeability, thickness and stress profiles of the formation. Experience has shown that given the aforementioned data and assuming availability of a good geologic and structural definition of the reservoir, hydraulic fracturing simulators can predict the outcome of the hydraulic fracturing process with reasonable accuracy.

When dealing with storage fields that are old (this is true for most of the storage fields since they are usually old, depleted gas fields that have been converted to storage fields), the aforementioned information is not available. Acquiring these types of information on an old reservoir is usually very expensive. It involves massive coring of the reservoir, where pieces of the rock from the target formation are brought to the surface and tested in the laboratory under simulated field conditions to measure the reservoir's porosity and permeability. It also involves elaborate well testing procedures and subsequent analysis of well test data. This paper introduces a new and novel method for predicting the outcome of hydraulic fracture treatments in gas storage fields, with minimal cost.

BACKGROUND

This study was conducted on a large natural gas storage field located in Northeastern Ohio. The formation is a tight gas sandstone known as the Clinton Sand. The Clinton is a tight gas-bearing 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 the required duration to achieve steady state.

All of the wells in the storage field were initially stimulated by hydraulic fracturing. Since 1970, an average of twenty-five wells have been refractured each year for a total of around 600 treatments. Most wells in the field have been refractured, some up to three times. The experience with the Clinton Sandstone indicates that hydraulic fractures grow vertically out of the zone, regardless of rate and fluid viscosity. Therefore, it appears critical to use high proppant concentrations in a viscous fluid to create a conductive fracture in the pay interval. Treatment design for the storage field currently include a 25 to 30 pound linear gel with maximum sand concentrations from 3 to 4 pounds per gallon (ppg)⁶.

Presently, the wells are selected to be refractured each year based on maintenance history, past fracture response, years since previous fracture, and overall deliverability potential with mixed results. Post-fracture well performance estimates and optimal fracture treatment design are critical in maximizing deliverability enhancements. An accurate estimate of post-fracture well deliverability is necessary for engineers to select the candidate wells that would respond with acceptable post-fracture deliverability and to avoid investing in the wells with unsatisfactory post-fracture deliverability. The use of type curve matching and computer simulation¹⁻⁵ for predicting hydraulically fractured well performance are not practical in this field since obtaining detailed information about rock mechanics and reservoir characteristics by electric logs, well testing, or coring is operationally difficult or cost prohibitive.

METHODOLOGY

The challenge was to develop a methodology that would not require expensive well testing, coring and other operations for data collection, and yet provide post-fracture well deliverability on all wells. Basic well information, such as geographic location, depth, tubular design, completion type, flow tests, past fracture designs and performance history, is readily available. Most of this data, however, are not considered to be useful engineering data for hydraulic fracturing treatment design. However, many of these variables may contribute to the overall success or failure of a hydraulic fracture treatment in some indirect or complex way.

It should be noted that it is necessary to provide the network with 'some' information on the reservoir being considered. In this study, the historical data on the previous fracture treatments were available and were used for the training. Data available on this field can be divided into three categories. Well data, Flow data, and Hydraulic Fracturing data. Well data mainly provide information about the type of the well (injection or withdrawal), its location and when it was drilled. Flow data are a series of data collected routinely by the field operator using simple two-point flow tests. The company operating this field uses a "yard stick" called Q100, which is the flow rate at $\Delta p^2=100,000 \text{ psi}^2$. Hydraulic fracturing data are the parameters used in design and implementation of the hydraulic fracture.

A three layer feed forward backpropagation network was used in this study^{7,9}. The network consisted of 59 input neurons with linear normalization between 0 and 1. The single hidden layer had 51 neurons using logistic function as the activation function. The sole output of the network was the peak post-fracture gas storage well deliverability. The neural network developed for this study was trained using the information provided in Table 1. A complete definition of each of the entries is available in Reference 6.

RESULTS AND DISCUSSIONS

The available data covers 1968-91 period. As a first attempt, 13% of the entire data were randomly selected and put aside as the test set and the network was trained on the remaining 87% of the data. Once the network reached convergence, network's predictions were compared against actual field results. This comparison provided a coefficient of correlation of 0.97 for training data and 0.98 for the test set. Figure 1 shows the result of this part of the study for the entire data.

In order to simulate a practical situation, the data from 1968 to the end of 1988 were used to train the network. The input-output pairs were presented to the network for training. Once the network reached a stable state, the network's prediction on the training data was compared to the output that was provided to the network. It produced a coefficient of correlation of above 0.96. To test the generalization capabilities of the developed network, the input data from the years 1989, 1990, and 1991 were given to the network to forecast the post-fracture well deliverability. This would be the results upon which candidate wells for fracturing would be selected. Figures 2, 3, and 4 show the comparison between network's predictions with actual flow test data. The result is quite satisfactory. Using flow test indicator of 500 as the cut off point, the figures show that a total of 9 wells (five wells from 1988, 1 well from 1990, and 3 wells from 1991) would not have been chosen for refracturing if this tool was available at that time. Using this tool, the cost involved in fracturing these 9 wells would have been saved and also 9 other wells with acceptable post-fracture deliverability would have been fractured, which means even more economic benefits. The time for a well to reach its peak deliverability after a hydraulic fracture (the indicator that is the target of this study) is between two to three years. At the time this study was being completed, results from 1991 were the most recent peak post-fracture deliverabilities that were available. Recently, authors used the developed network to predict the peak post-fracture deliverabilities for the wells stimulated in 1992. During 1992, nineteen wells were stimulated. By the time this manuscript was being completed, results from 11 wells had become available. Figure 5 shows the comparison between network's prediction and actual field results for the year 1992. As can be seen, network made quite accurate predictions for all but one well, which is the first well in Figure 5. For this well, neural network predicted a post-fracture deliverability of 1400, while the actual deliverability peaked at about 900. Since 500

was used as the cut-off point, neural network's prediction (1400) would have suggested that hydraulic fracturing be performed on this well. In retrospect, this would have been a good suggestion since the actual deliverability was above 500.

In a separate attempt to demonstrate the power and robustness of this new methodology, the network was trained with data from 1968 to 1974. The coefficient of correlation at this point was almost 0.98. In 1975, a new fracturing fluid was used for the first time (foam). When data from 1975 was introduced to network, the performance of the network degraded and its prediction accuracy dropped to 0.88. This performance bounced back up by the year 1980, when network observed and learned the new behavior that was displayed by the new fracturing fluid. This process was repeated two more times, when new fluids were introduced in 1981 and 1989. Figure 6 shows the neural network's prediction capabilities as new information is added to the network. This further proves the notion that systems developed, based on neural network, do not break down when new situations are encountered, rather, they degrade gracefully.

It is also important to note that the so called "conventional engineering wisdom" (whatever it may mean) about the available data may not be quite applicable here. In other words, a piece of data that might look very unimportant in terms of information it provides about the reservoir, well or the fracturing process, may actually contain valuable *implicit* information useful for the neural network. An example on our experience may clarify this point. During our analysis, it was noted that the well ID number played a role in the overall pattern that has been established between inputs and the post-fracture deliverability. It prompted us to look further into the conventions that might had been used in numbering these wells. It was later determined that these wells were numbered according to *a*) their date of completion, and *b*) their relative geographic location in the field. Although this information was not explicit and was unknown to us at the beginning, the network was able to deduce it from the data. It was also interesting to note that, although no information regarding the physics of the problem was provided to the network during the training, once the network was trained, it provided us with information that made perfect engineering sense⁶.

CONCLUSIONS

Methodology presented in this paper is capable of forecasting post-fracture deliverability based on historical data in Clinton Sandstone gas storage field without detailed reservoir data. This methodology provides considerable cost savings by eliminating the need for costly reservoir data collection in old gas storage fields. Using this methodology, post-fracture well deliverability was predicted with approximately 95% accuracy. The neural network developed in this study is currently being used to select candidate wells for hydraulic fracturing in the Clinton Sandstone. This procedure can be applied to other

fields provided some historical data for training of neural network is available. This methodology not only predicts post-fracture well deliverability, but can also assist the practicing engineer in designing the optimal fracture treatment. Development of a hydraulic fracture design tool based on the neural network presented in this paper is near completion.

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Data Type	Parameters
INPUT	Well number, Year well was fractured, Date well was fractured (A relative pressure function), Number of times well was fractured, Type of fracture (water, gelled water, foam), Fluid viscosity, Total water used, Nitrogen used per barrel of water, Total sand used, Sand Concentration, Sand type, Acid volume and type, Chemicals (Iron control, bacterial control,...), Treatment injection rate, Occurrence of screen out, Contractor, Hole size, Completion type, Well type (Injection, Production), Date of completion, Date converted to storage, Well group number, Sand thickness, Minimum 20 year flow test value, Maximum 20 year flow test value, Average 20 year flow test value, and Flow test before refracture.
OUTPUT	Maximum Flow Test After Fracture

Table 1. Data used in this study

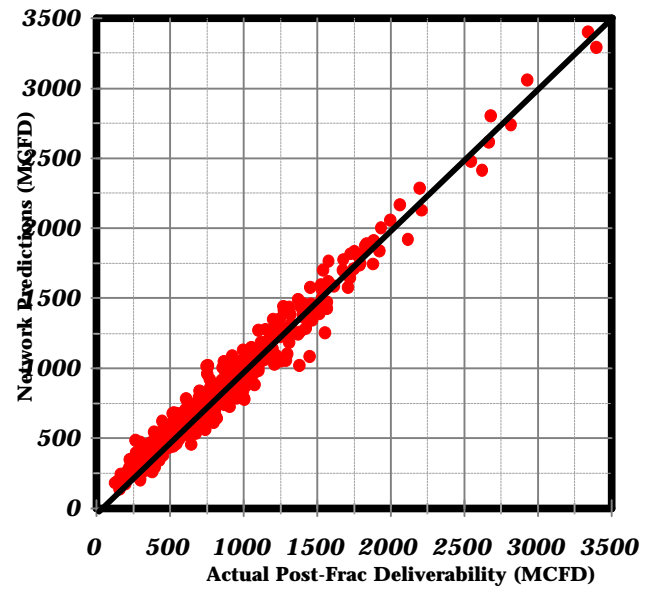


Figure 1. Neural Network's Prediction for all the available data

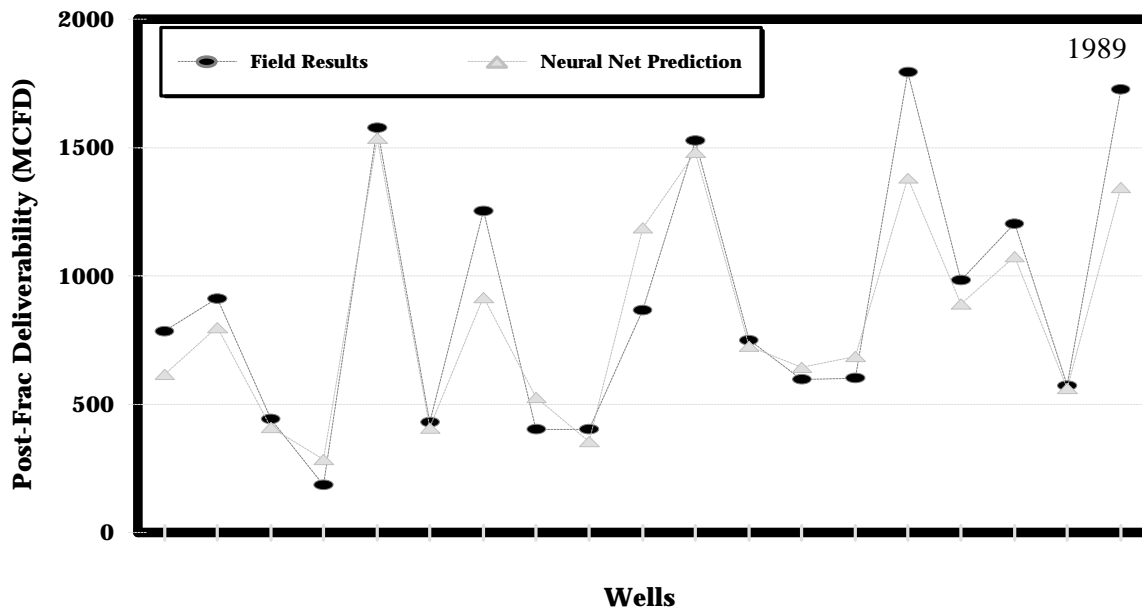


Figure 2. Comparison between network's prediction vs. Field results. Network was trained using data from 1968 to 1988.

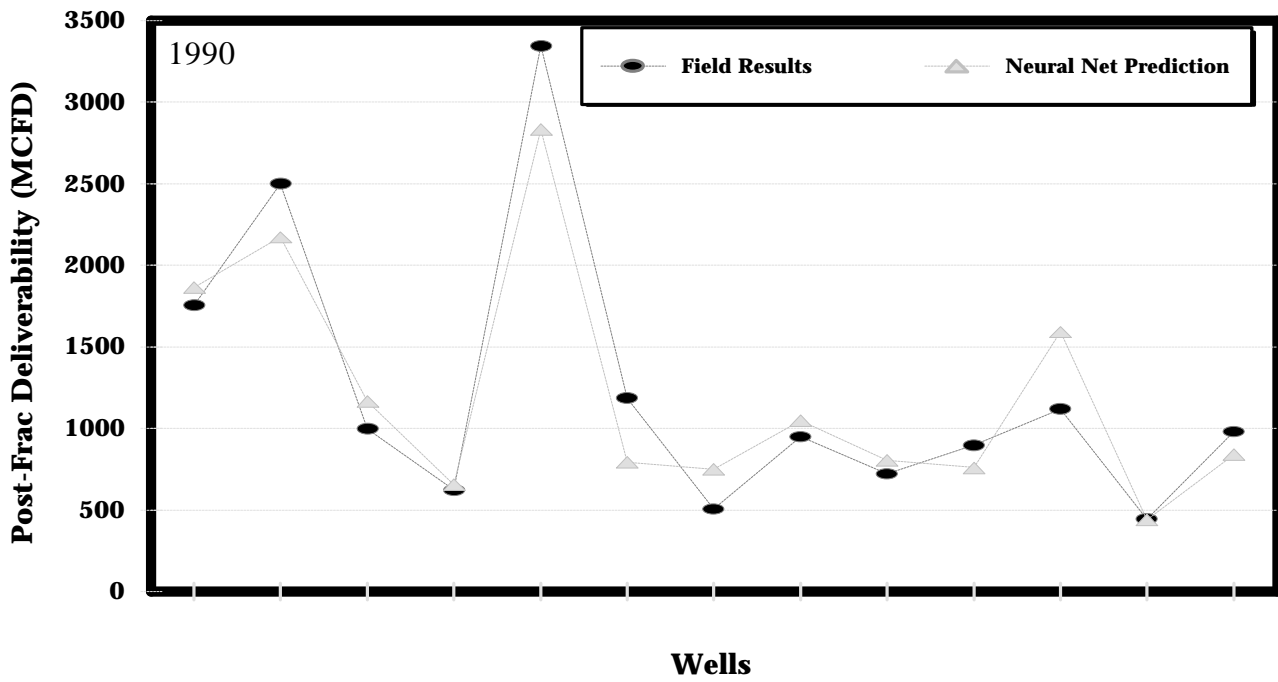


Figure 3. Comparison between network's prediction vs. Field results. Network was trained using data from 1968 to 1989.

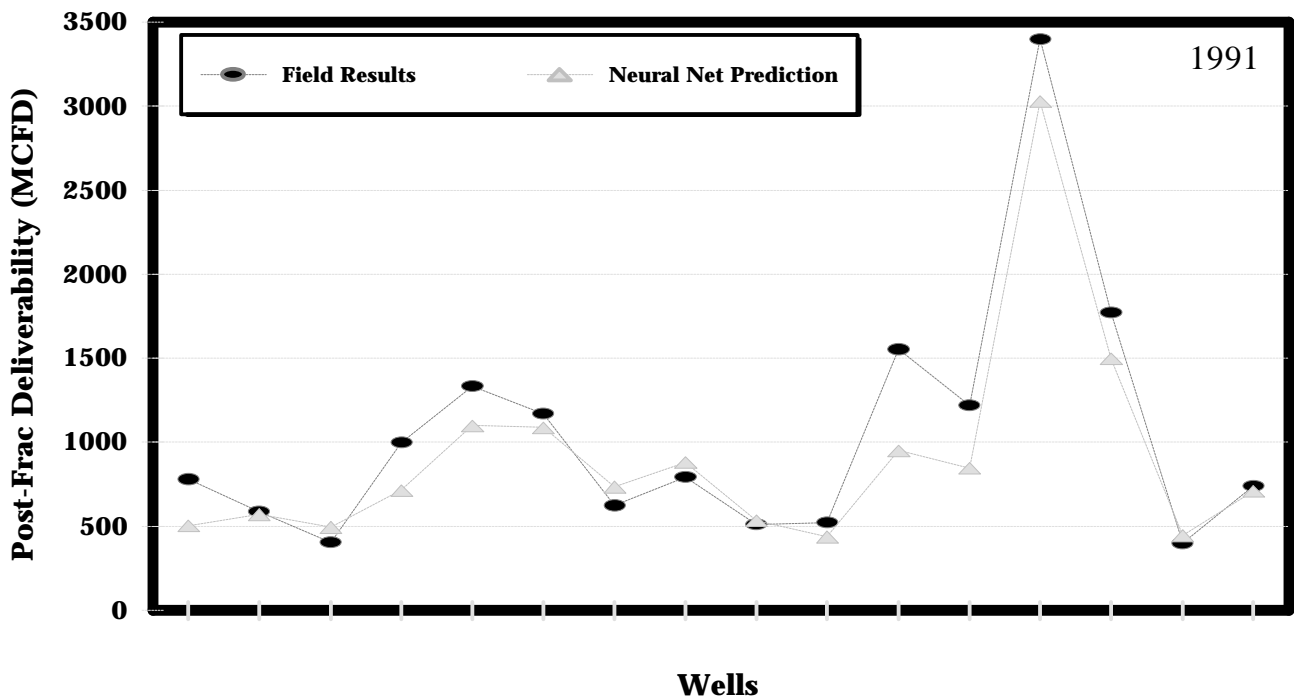


Figure 4. Comparison between network's prediction vs. Field results. Network was trained using data from 1968 to 1990.

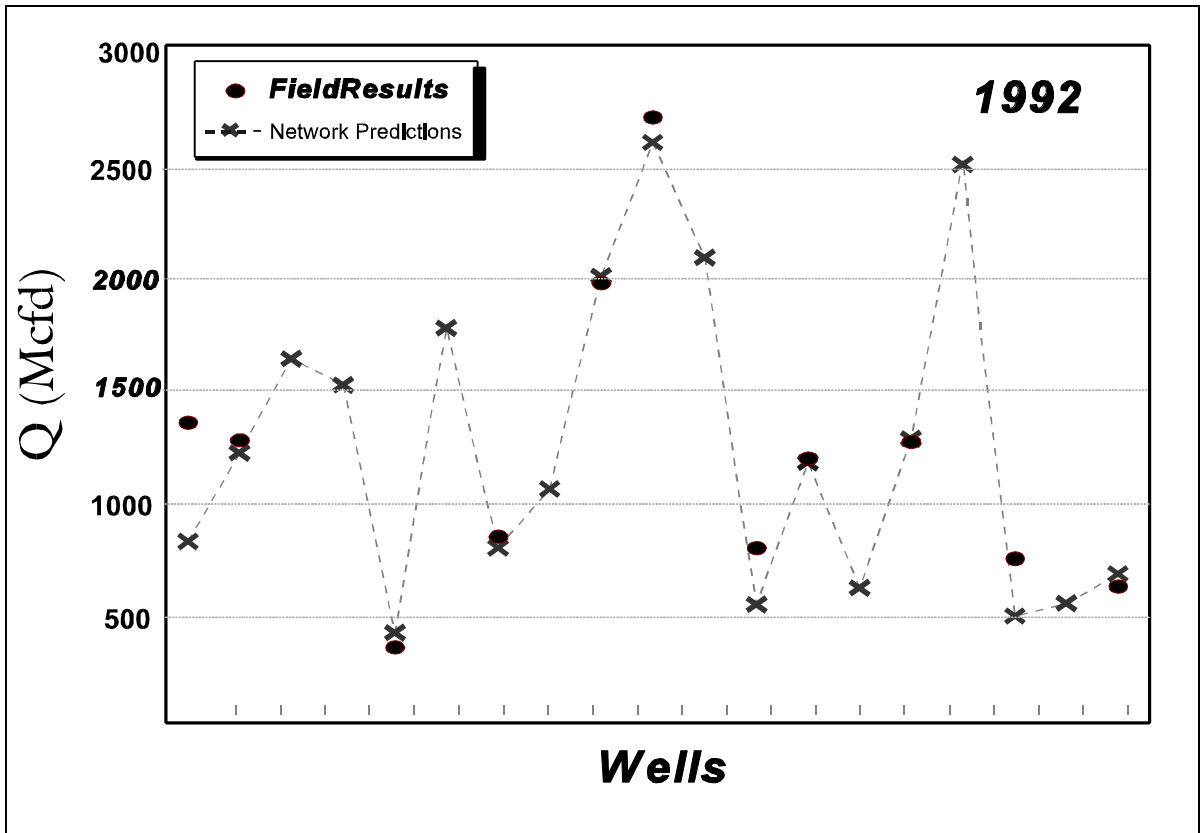


Figure 5. Comparison between network's prediction vs. Field results for 1992.

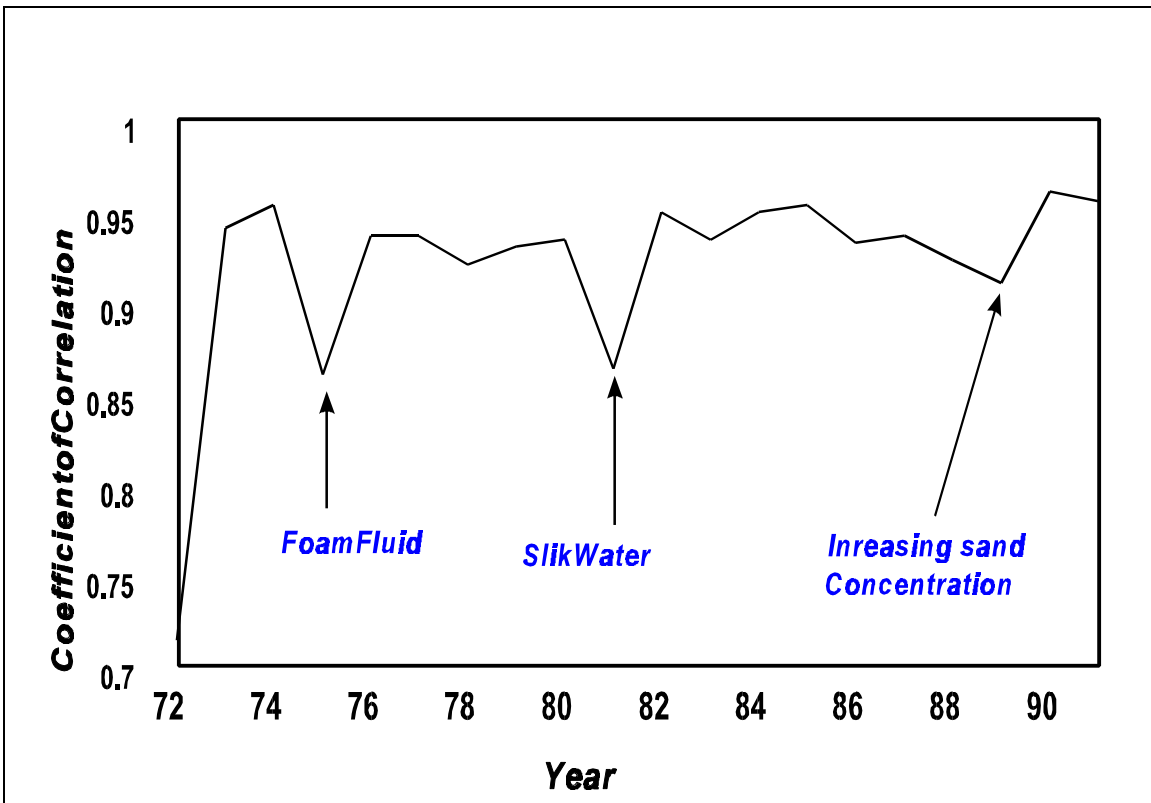


Figure 6. Robustness of the neural network as new information is added to the database.