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Chapter 21

ENHANCING GAS STORAGE WELLS DELIVERABILITY USING INTELLIGENT SYSTEMS

SHAHAB D. MOHAGHEGH [1]

West Virginia University, 345E Mineral Resources Building, Morgantown, WV 26506, USA

1. 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.

This study was conducted on a large natural gas storage field located in Northeastern Ohio. The formation is tight gas sandstone and is called the Clinton Sand. All of the storage wells were initially stimulated by hydraulic fracturing. Restimulation is considered a last resort method of deliverability enhancement in this storage field. However, some wells are selected to be restimulated each year based on maintenance history, past fracture response, years since previous stimulation and overall deliverability potential. Since 1970, an average of twenty-five wells have been refractured (restimulated) each year for a total of around 600 refracturing treatments. Since most wells in the field have been refractured (restimulated), some up to three times, the need for post stimulation well performance estimates and optimal fracture design is very important to maximize deliverability gains. 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 designs 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) (McVay et al., 1994).

Several well testing methods are available for predicting hydraulically fractured well performance including type curve matching and computer simulation (Millheim and Cichowicz, 1968; Gringarten et al., 1975; Cinco-Ley et al., 1978; Agarwal et al., 1979; Hopkins and Gatens, 1991). In addition, two- and three-dimensional computer simulators are frequently used for fracture design. Use of these tools, however, requires access to several types of reservoir data. 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.

[1] Tel.: +1 (304) 293-7682 ext. 3405, fax: (304) 293-5708, E-mail: shahab@wvu.edu

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 article introduces a new and novel method for predicting the outcome of hydraulic fracture treatments in gas storage fields, with minimal cost.

Another important factor that must be considered is that fundamentally different stimulation jobs such as refracturing versus chemical treatments have been historically practiced in the Clinton Sandstone. Each of these restimulation jobs must be treated differently during the model building process. Moreover, economic considerations play an important role in restimulation projects.

During a stimulation/restimulation program the engineers face several challenging questions. The hydraulic fractures cost four to five times as much as a chemical treatment, and yet some wells respond reasonably well to chemical treatments. Given the economic parameters involved, should a well be refractured or chemically treated? What would be the maximum potential post-treatment deliverability if the wells were refractured as oppose to chemically treated? Would the decline behavior be different? Would extra cost of the refrac job justify the extra deliverability gains? These are not simple questions to be answered. Considering the fact that every year the engineers must select a handful of wells for restimulation from a total of more than 700 wells emphasizes the complexity of the problem.

In order to address this problem and expect reasonable result it is obvious that many factors must be taken into account. These factors include the history of the well. How it has responded to different hydraulic fractures and refrac processes in the past? Have chemical treatments been performed on the well? If yes, then how did the well responded to those treatments? If the well has been through several fracs, refracs and chemical treatments, do the sequence of these jobs have any significance on the post-treatment deliverability? Has the decline in post-treatment deliverability been sharper in the case of refracs or chemical treatments? These and many other technical questions may be posed.

In addition to the above technical questions many economical considerations also need to be addresses. It is a fact that refracs cost much more than chemical treatments yet many wells have shown that a well-designed and implemented chemical treatment may provide the same kind of post-treatment deliverability. Economic parameters other than the cost of the treatment may include the price of the gas and the total budget for the year's stimulation/restimulation program.

The objective of this study is to provide a methodology – and build a software tool based on this methodology – to address the above questions. The ultimate output of the software tool is a list of the restimulation candidates for each year. The list will contain the selected candidates and specifies whether that particular candidate should be refractured or chemically treated. In either case the software tool would provide recommendation on the parameters used in the refrac or the number and amount of chemical used for the chemical treatment.

It is not hard to see that the problem that has been described here is one of process modeling and optimization, and a challenging one. The software tool will take into account all the economic as well as technical concerns that were mentioned here through the use of virtual intelligence techniques. In a nut shell, virtual intelligence – also known as computational intelligence and soft computing – is an attempt to mimic life in solving highly complex and non-linear problems that are either impossible or unfeasible to solve using conventional methods.

In this study author uses a series of artificial neural networks and genetic algorithm routines, integrated with an extensive relational database – specifically developed for this study – to achieve the goals of the project. Since introductory discussions about neural networks and genetic algorithms have been published in the many previous SPE papers by the authors (Mohaghegh et al., 1996a,b; 1997) and other researchers in this area, further discussion on the nature of these sciences will not be included here.

2. METHODOLOGY

Fig. 1 is a schematic diagram of the flow of the information through the software application that was developed for this study. As it is shown in this figure the input data that resides in a relational database is fed into the application. The input data includes general well information, such as well ID number, well location, and some wellbore characteristics, some historical deliverability indicators such as pre-treatment

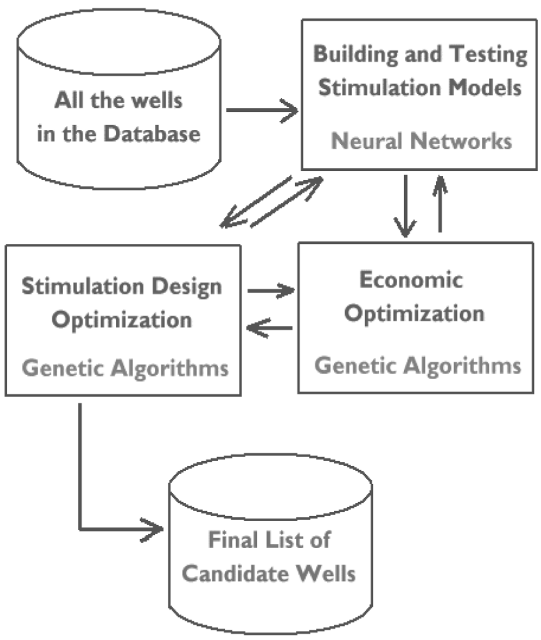

Fig. 1. Flow chart of the process used to build the software application.

deliverability, maximum and minimum deliverability for the life of the well and average deliverability for the past twenty years, as well as stimulation parameters.

It is worthwhile to mention that an extensive relational database was created for this particular gas storage field. This database is used as input data source for the application as well as a valuable source during the training of the several neural networks that are used as the main engines of the application. The database also provides an excellent manual rapid screening tool for the engineers. Several useful queries are built into the database in order to simplify visualization of the extensive amount of data that reside in the database.

The software application includes three separate modules. The first module includes the rapid screening neural networks – one network for the refracs and one for the chemical treatments. These networks use general well information and the historical data as input and attempts to predict the post-treatment deliverability. The rapid screening module works as follows: The user specifies a minimum post-deliverability (threshold). The rapid screening module – using the two neural networks – will identify all the wells that have the potential to meet this minimum. These are the wells that are used into the next modules.

To construct the second module, four neural networks – one for refracs and three for chemical treatments – are trained to work as fitness functions for the optimization process using genetic algorithms. The input data into these neural networks include the same data as rapid screening networks plus detail stimulation data. Second module includes four genetic algorithm routines, one for each neural network. Working in the batch mode this module optimizes all possible stimulation treatments for each well and ranks them. The user at this time has the option to inspect the results one well at a time or he/she may continue with the batch mode. Fig. 2 provides a schematic diagram of the module two.

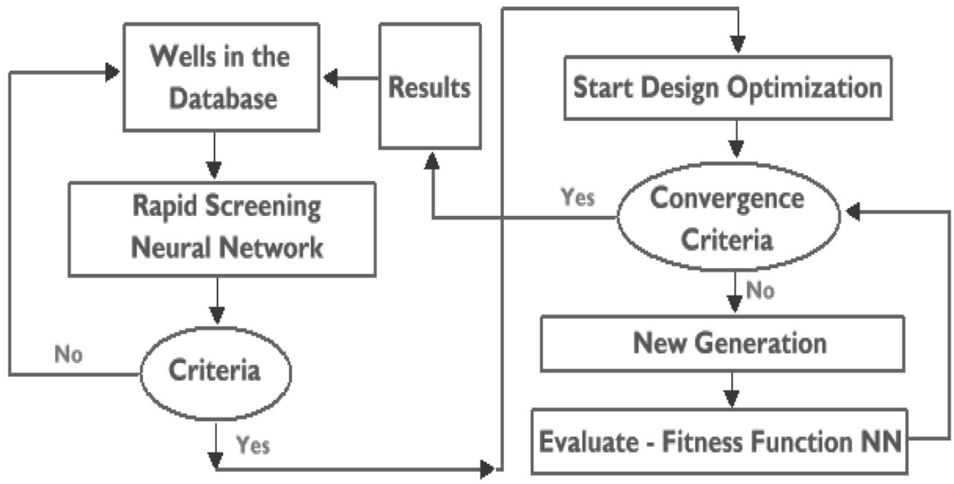

Fig. 2. The schematic diagram for the module two process.

In the batch mode, after completion of the second module the third module takes over. This module is a specialized genetic algorithm routine that uses the provided economic parameters to optimize the return on investment. The outcome of this module is a list of candidate wells and the type of the stimulation job that should be performed on each well.

During the second module design optimization is applied to a number of wells that have passed the rapid screening process. At this point the best candidates are identified. But there still remains one question to be answered. Given the cost of frac jobs and chemical treatments – which are inputs to the third module as economic parameters – what is the optimum combination of frac jobs and chemical treatments to be performed? And which wells are to be fractured or treated, in order to maximize the return on the investment?

Module three is an attempt to answer this question. The economic optimization genetic algorithm in this module is designed to provide the optimum list of candidate wells and the corresponding stimulation jobs that should be performed on each well. The function to be optimized in this module is what we call the profit function. As can be seen from Eq. (1), the profit function at this time is a simplified function. Increasing the complexity of this function will not in any shape or form change the applicability of this module. The profit function to be optimized is given by the following equation:

$$P = \$g \times \left[\sum_{1}^{n_{\mathrm{F}}} \Delta Q_{\mathrm{F}} + \sum_{1}^{n_{\mathrm{T}}} \Delta Q_{\mathrm{T}} \right] - \left[n_{\mathrm{F}} \times \$F + n_{\mathrm{T}} \times \$T \right] \tag{1}$$

where P = profit; $\$g$ = market gas price; ΔQ_{F} = total deliverability increase due to applied frac jobs; ΔQ_{T} = total deliverability increase due to applied chemical treatments; n_{F} = number of frac jobs performed; n_{T} = number of chemical treatments performed; $\$F$ = average cost of a frac job; and $\$T$ = average cost of a chemical treatment

In the above equation the only variables are the numbers of frac jobs and chemical treatments to be performed. The goal is to find the optimum combination of these two values such that it would maximize P. There is, however, a constraint that has to be imposed, namely the capital investment available for each stimulation program, i.e. annual stimulation budget. Eq. (2) provides the constrain:

$$\left[n_{\mathrm{F}} \times \$F + n_{\mathrm{T}} \times \$T \right] \leqslant \$\mathit{Total} \tag{2}$$

where $\$\mathit{Total}$ = annual stimulation program budget.

While the above equation provides assurance that we are not overspending, Eq. (3) is imposed as another constrain so the budget is spent in a fashion that most of it is used:

$$\$\mathit{Total} - \left[n_{\mathrm{F}} \times \$F + n_{\mathrm{T}} \times \$T \right] = \min \tag{3}$$

In module three the genetic algorithm maximizes the profit function – as the fitness function – using the two constrain equations. It should be noted that during this optimization process the genetic algorithm uses the list of the wells that have already gone through the stimulation optimization process in module two.

The total number of candidate wells and their optimum stimulation job are identified at this point. The data is stored in a database and can be viewed. A recommended set

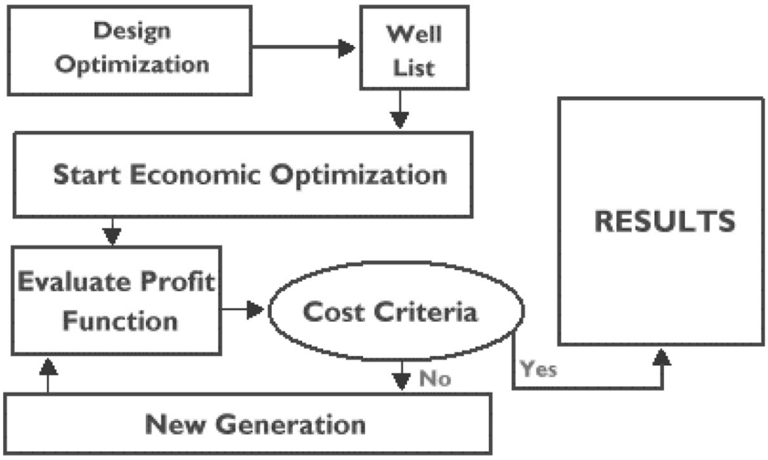

Fig. 3. The schematic diagram for the module three process.

of parameters for the frac jobs or the chemical treatments – whatever the case may be – accompanies the candidate. Fig. 3 shows a schematic diagram of the module three.

3. RESULTS AND DISCUSSION

In this section the results of neural model built for the refracturing process is presented first. The application of the genetic algorithms to optimize the refracturing design will follow the first set of results. The quality of the neural model that has been constructed and trained for the chemical treatment will then be presented.

For the refracturing process, available data covers the 1968–1991 period. Table 1 is the list of parameters that was available for all the hydraulic fracturing jobs. The data has been divided into two parts, input and output. The input, as can be seen from Table 1

TABLE 1

Data used in this study

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 Post-Fracture Deliverability

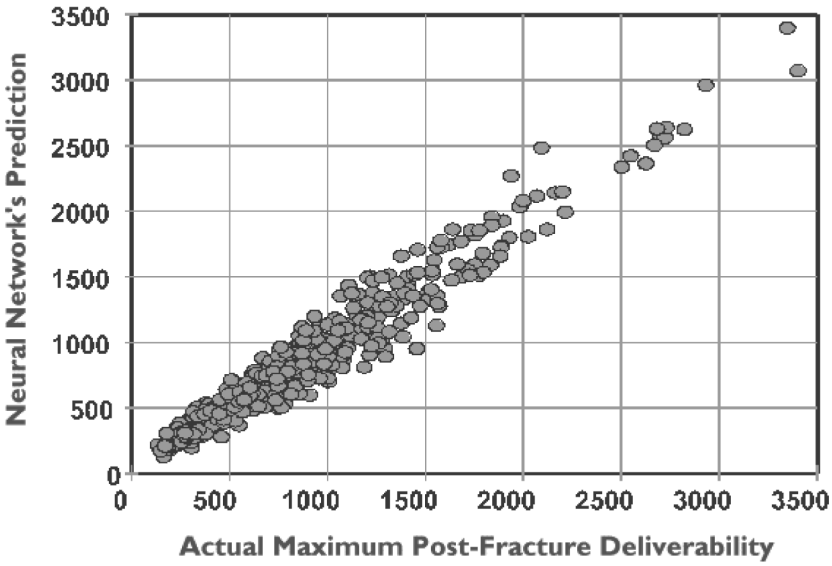

Fig. 4. Neural network's prediction for all the available data.

contains all the parameters but the one parameter that has been designated as the output. 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. Fig. 4 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 result upon which candidate wells for fracturing would be selected. Figs. 5–7 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. At a later time, the

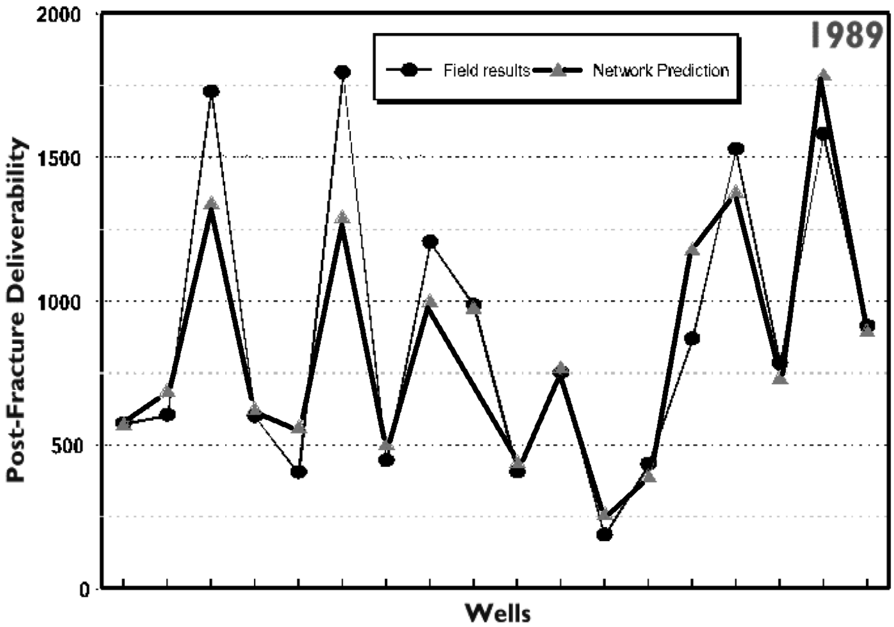

Fig. 5. Comparison of network's prediction and actual field results for the year 1989. Network was trained using data from 1968 to 1988.

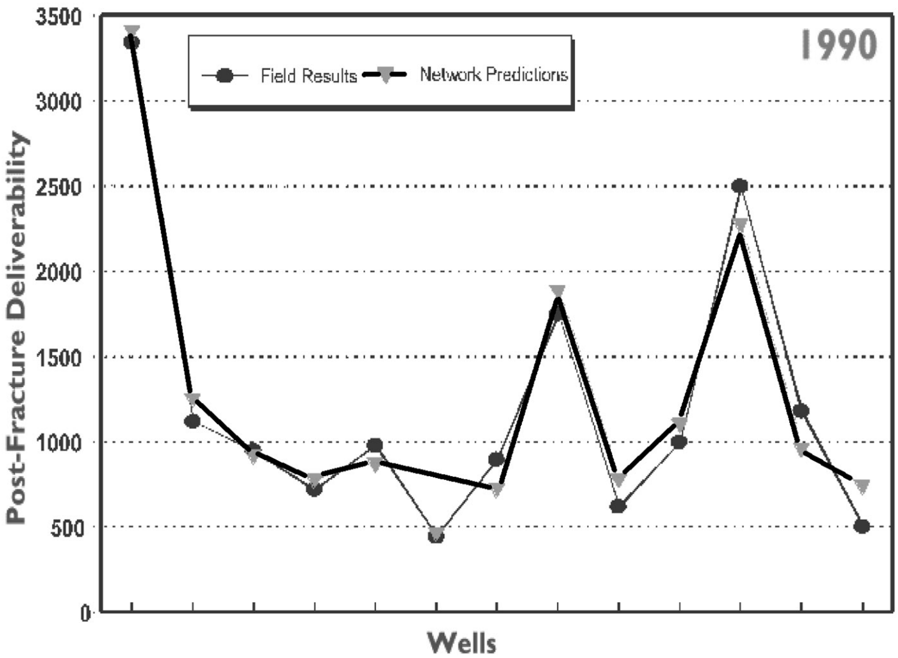

Fig. 6. Comparison of network's prediction and actual field results for the year 1990. Network was trained using data from 1968 to 1988.

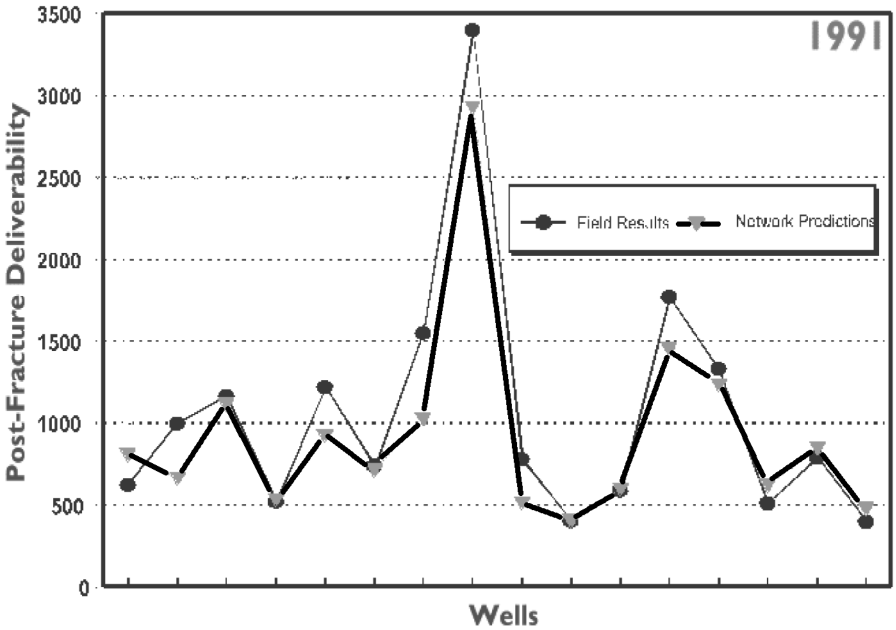

Fig. 7. Comparison of network's prediction and actual field results for the year 1991.Network was trained using data from 1968 to 1988.

developed network was used to predict the peak post-fracture deliverabilities for the wells stimulated in 1992. During 1992, nineteen wells were stimulated. By the study was being completed, results from 11 wells had become available. Fig. 8 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 Fig. 8. For this well, neural network predicted a post-fracture deliverability of 1400 mscfd, while the actual deliverability peaked at about 900 mscfd. Since 500 mscfd was used as the cut-off point, neural network's prediction (1400 mscfd) 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 mscfd.

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 introduces in 1981 and 1989. Fig. 9 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.

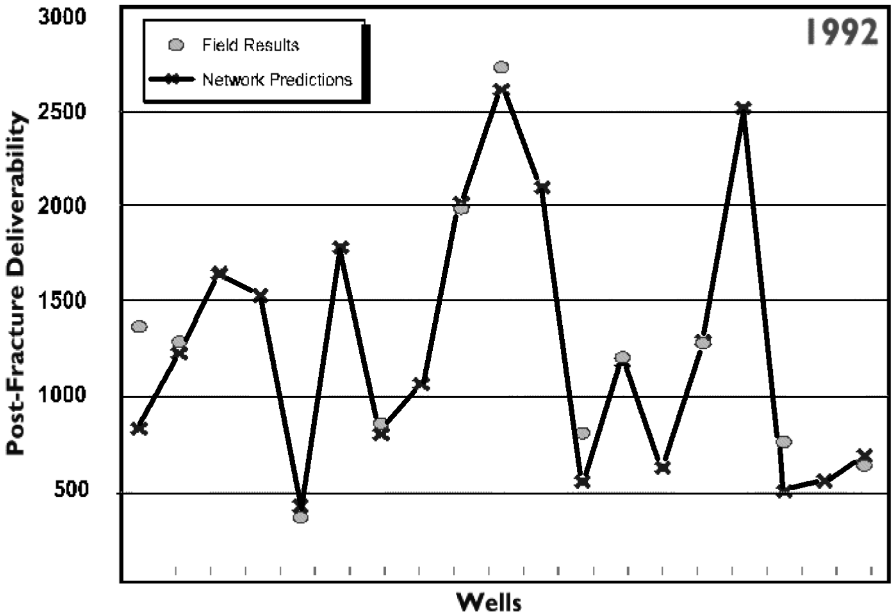

Fig. 8. Comparison of network's prediction and actual field results for the year 1992. Network was trained using data from 1968 to 1988.

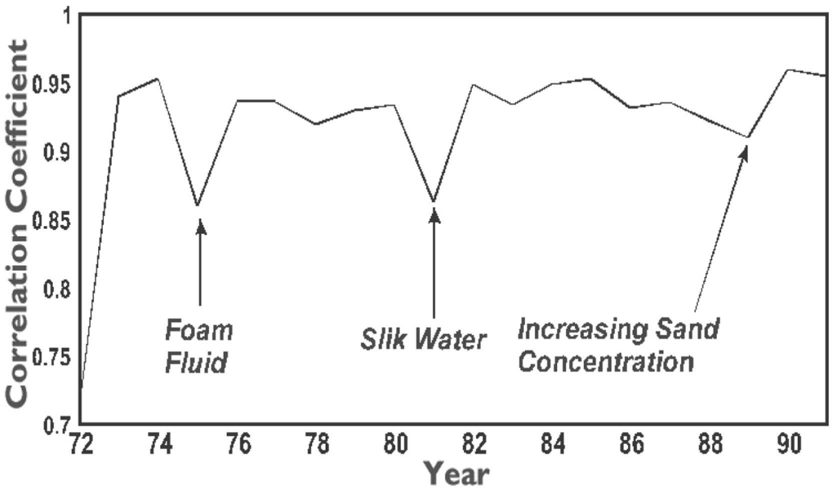

Fig. 9. Neural networks robustness demonstrated by its reaction to addition of new information to the dataset.

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 its information content about the reservoir, the 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 have 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 time of analysis, 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 sense (McVay et al., 1994).

3.1. Genetic optimization

Once the neural model for the hydraulic fracturing was constructed and tested and it was concluded that its performance is satisfactory, the next step was to incorporate this neural model into a genetic optimization routine to identify optimum refracturing design. This neural network (neural module #2) would be the fitness function for the genetic algorithms. A two-stage process is now developed to optimize the frac design in Clinton Sandstone. A detail, step by step procedure will be covered in the following section. Fig. 10 presents a schematic diagram of the procedure. For the first stage a new neural network (neural module #1) is designed and trained. As it was mentioned earlier this neural network is not given any information on the frac design parameters. The only data available to this neural net is basic well information and production history. After all this will be all the information that will be available in each well that is being considered for a frac job. This neural network is trained to accept the aforementioned information as input data and estimate a post-frac deliverability as output. The post-frac deliverability predicted by this neural net is the same as an average (generic) frac job within a certain degree of accuracy.

This neural net is used only as a screening tool. It will identify and put aside the so-called ‘dog wells’ that would not be enhanced considerably even after a frac job. The wells that have passed the screening test will enter the second stage that is the actual frac design stage. A second neural net (neural module #2) has been trained for this stage. This neural net has been trained with more than 570 different frac jobs that have been performed on Clinton Sandstone. This network is capable of providing post-frac deliverability with high accuracy given well information, historical data and frac design parameters. This neural net will play the role of fitness function or the environment in the genetic algorithm part of the methodology. Fig. 11 is an elaboration on how this neural network is being used in conjunction with the genetic algorithm. The output of the genetic algorithm portion of this methodology is the optimized frac design for each well. The tool will also provide the engineer with expected post-frac deliverability once the suggested design is used for a frac treatment. This result may be saved and printed. The design parameters can then be given to any service company for implementation.

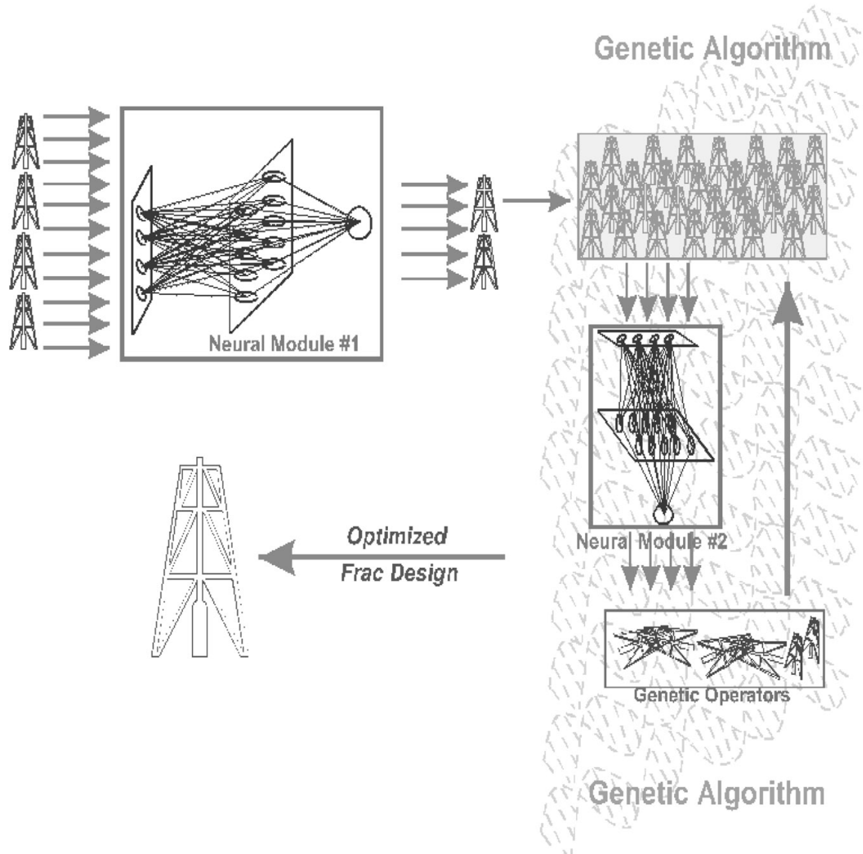

Fig. 10. Schematic diagram of the genetic optimization procedure.

3.2. Procedure

The well selection and hydraulic fracture design take place in two stages:

3.2.1. Stage 1: Screening

In this stage a criteria is set for screening the candidate wells. Neural module #1 that has been trained on well completion and production history is used to screen the candidate wells, and selects those wells that meet a certain post-frac deliverability, set by design engineer as threshold. In other words, well completion and production history for all candidate wells are provided to the software with a threshold value for post-frac deliverability. Those wells that meet or exceed the threshold will be identified and prepared for further analysis and hydraulic fracture design. A preliminary post-frac deliverability for each well will be calculated and displayed. The post-frac deliverability that is presented at this stage is what is expected if a generic frac is designed for this well, i.e. with no optimization.

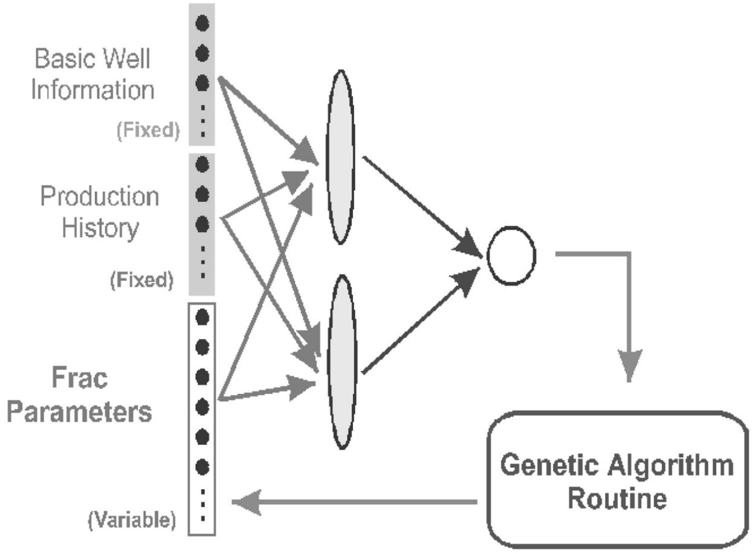

Fig. 11. Schematic diagram of the neural module #2.

It must be noted that if actual threshold is for example 500 mcfd, then 400 mcfd should be used at this point. This is due to the fact that optimization process has an average post-frac deliverability enhancement of 20% in this field.

At this point design engineer is presented with a list of candidate wells that meet and or exceed the post-frac deliverability threshold set previously. He/she will select one well at a time and enters the second stage for optimization.

3.2.2. Stage 2: Optimization

In this stage following steps will be taken:

Step 1: One out of four frac fluids (water, gel, foam, foam and water) is selected. Please note that these four frac procedures were chosen because they have been routinely performed in the aforementioned field in the past.

Step 2: One hundred random combinations of input variables (frac parameters) are generated. This is called the original population.

Step 3: Neural module #2 that has been proven to have higher than 95% accuracy in predicting post-frac deliverability for this particular field is used to forecast post-frac deliverability for 100 cases generated in step 1.

Step 4: The outcome of neural module #2 will be ranked from 1 to 100, 1 being the highest post-frac deliverability.

Step 5: The highest-ranking frac parameters combination (design) is compared with the last highest-ranking design and the better of the two is saved in the memory as optimum design.

Step 6: Top 25 designs of step 4 will be selected for the next step and rest will be discarded.

Step 7: Crossover, mutation, and inversion operators are used on the top 25 designs of step 6 and a new population of 100 designs is generated.
Step 8: Procedure is repeated from step 3.

In order to demonstrate the application of this optimization methodology it was decided to perform design optimization on wells that were treated during 1989, 1990, and 1991. Since the actual results of frac treatments on these wells were available, it would provide a good comparison. We used the software to

(a) Predict the frac treatment results (please be reminded that these results were not seen by the software in advance and they are as new to the software as any other set of input values) and compare it with the actual field results, and
(b) See how much enhancement would have been made if this software were used to design the treatment.

Neural module #2 in the software is responsible for prediction of output (frac treatment results) from new sets of input data (frac designs for particular wells). It would be reasonable to expect that if this module predicts frac treatment results within a certain degree of accuracy for one set of the input values, it should predict the results of another set of input values approximately within the same degree of accuracy.

Figs. 12–14 show the results of this demonstration. In these figures actual field results are shown (Field Results) as well as software's prediction (Predicted). It is obvious that the software does a fine job predicting frac treatment results from frac design parameters, however this had already been established. Frac treatment parameters that have been generated by the software itself using the combined neuro-genetic procedure resulted

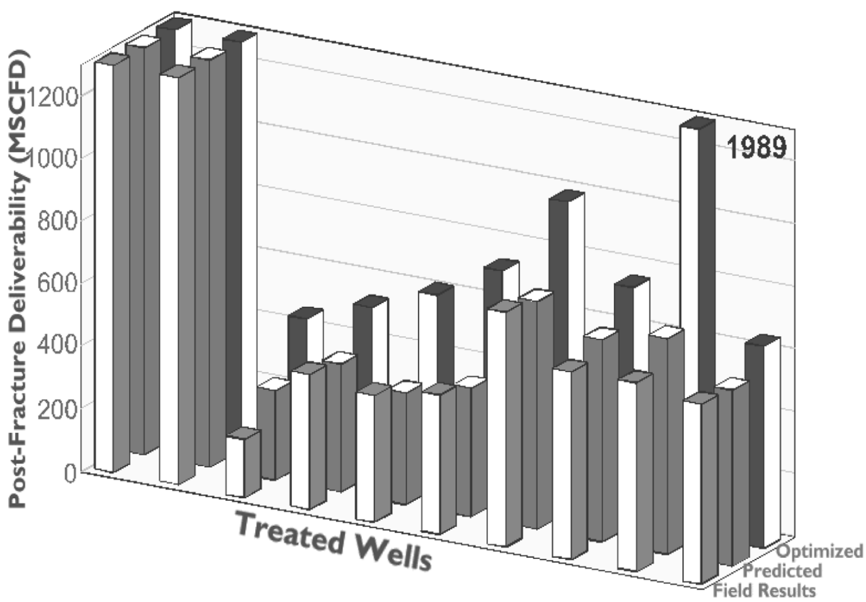

Fig. 12. Enhancement that could have been achieved on wells treated in 1989.

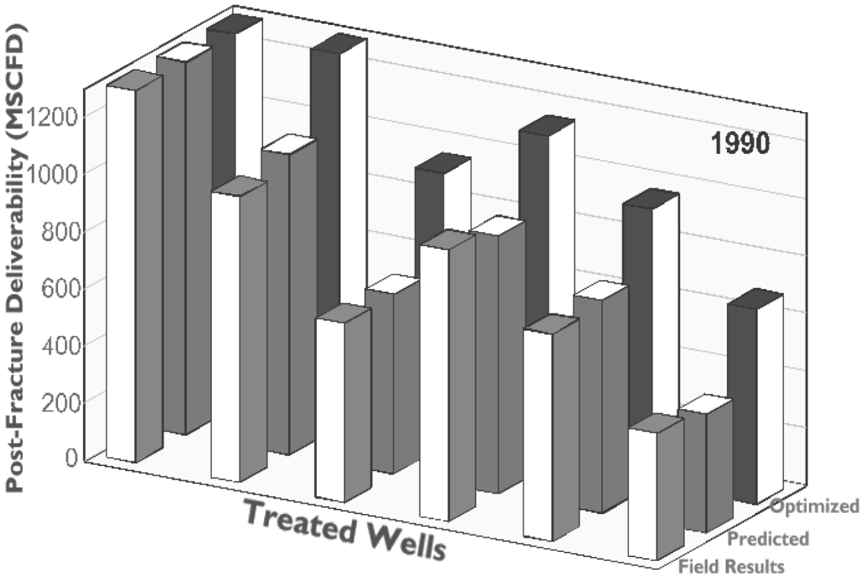

Fig. 13. Enhancement that could have been achieved on wells treated in 1990.

in the frac treatment results shown in the figures as ‘Optimized’. Again, please note that the same module in the software that has produced the triangles has produced the crosses, and in both cases from new set of input data (new to the module).

From these figures it can be seen that by using this software to design a frac treatment for this field, one can enhance treatment results by an average of 20 percent. It should also be noted that these wells were chosen from among 100 candidate wells each year. If this software was available at the time the selection process a different set of wells might have been used as restimulation candidates.

Table 2 shows the result of this process on particular well. Well #1166 was treated and its post-frac deliverability was determined to be 918 mcfd. The software predicted this well’s post-frac deliverability to be 968.6 mcfd, which is within 5.5% of the actual value. Using the neuro-genetic optimization process introduced here the software predicts a post-frac deliverability of 1507.5 mcfd. Using the 5.5% tolerance for the software’s

TABLE 2

Optimization results from well #1166

Well number	1166
Actual, mscfd	918
Prediction, mscfd	968.6
Percent difference, %	5.5
After optimization, mscfd	1507.5
Within the 5.5% difference, mscfd	1590–1425
Enhancement, mscfd	672–507

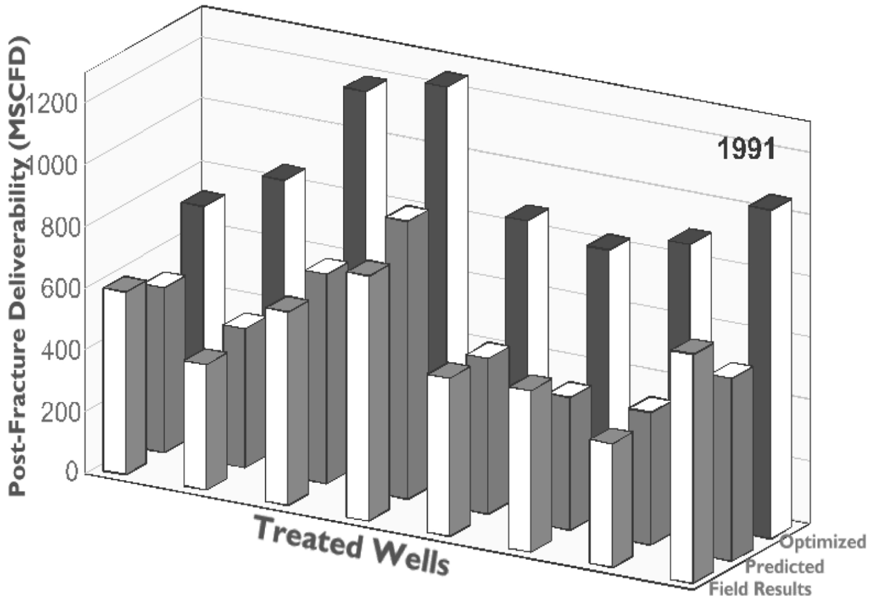

Fig. 14. Enhancement that could have been achieved on wells treated in 1990.

accuracy this methodology could have enhanced this well's post-frac deliverability by 55 to 73%.

3.3. Chemical treatments

As was mentioned before historical data in this field included many frac and refrac jobs as well as a variety of different chemical treatments. Upon a closer inspection of the data it was possible to classify the chemical treatments into three categories. The classification was made based on the number of chemicals used in the treatments. They were divided into one, two and three components chemical treatments. Table 3 shows the chemicals used in each category.

For chemical treatments, similar to the refracturing procedure, module one of the software application includes the rapid screening neural nets. These nets are constructed and trained to look at the general information of the well and the historical data to estimate a post-stimulation deliverability. The only information provided to the network about the stimulation job at this point is the type of the stimulation jobs i.e. refrac or chemical treatment.

A separate set of neural networks were constructed and trained for module two. These networks are trained using all available data that includes detail stimulation parameters. These are the networks that are used as fitness functions in the genetic algorithm routines.

Fig. 15 shows the accuracy of the module one neural networks for the chemical treatments. Figs. 16–18 are the plots of the actual post-treatment deliverabilities versus neural network predictions for the second module of the chemical treatment

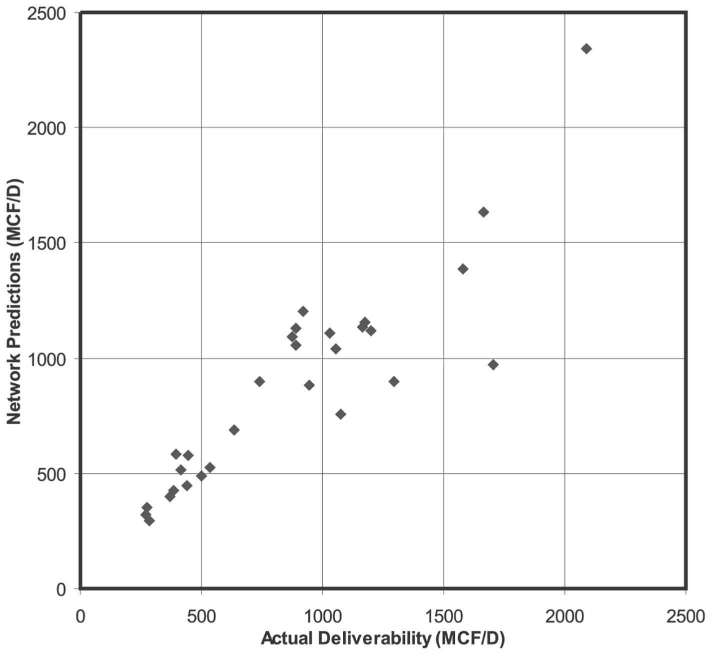

Fig. 15. Module one neural net for chemical treatments; rapid Screening.

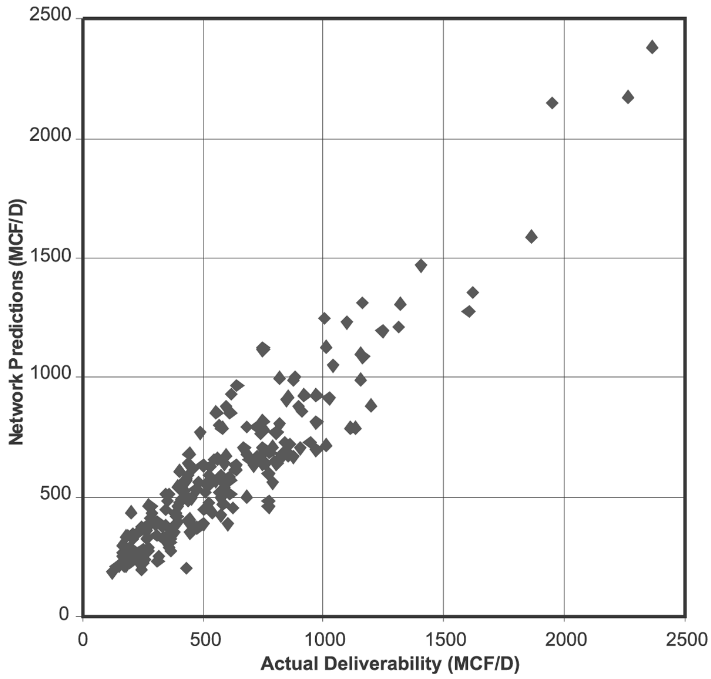

Fig. 16. Module two neural net for one component chemical treatments; optimization.

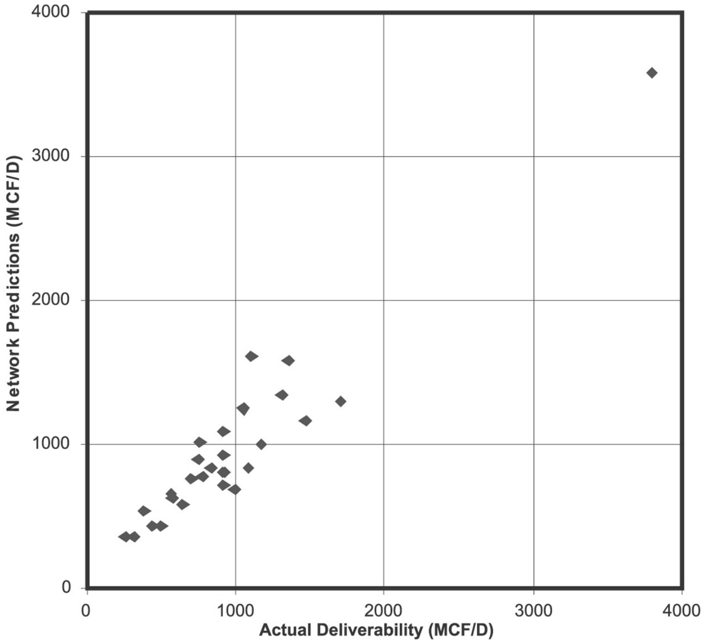

Fig. 17. Module two neural net for two component chemical treatments; optimization.

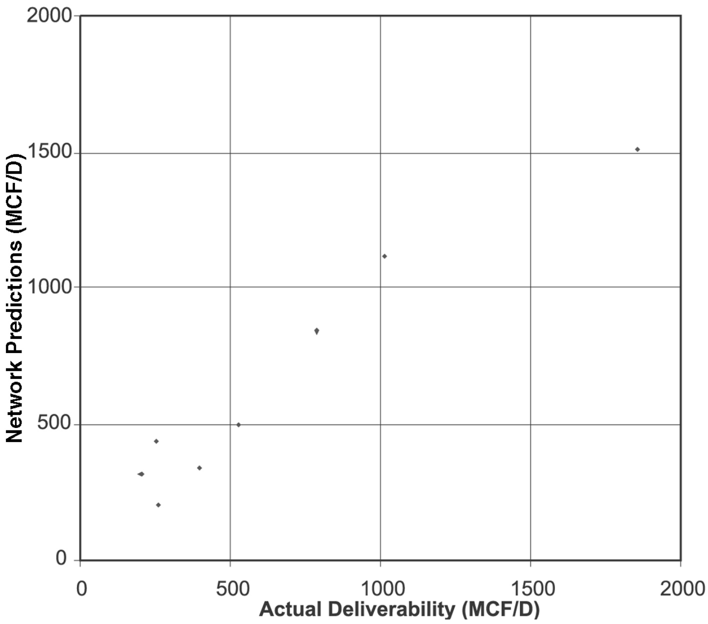

Fig. 18. Module two neural net for three component chemical treatments; optimization.

TABLE 3

Chemical treatment classification

Treatment type	Types of chemicals used	
One component		Kerosene Solvent Surfactant Water
Two components	Cold water-based	Paraffin dispersant PEN-5 VISCO 4750
	Hot water-based	B-11 Drill foam Nalco Paraffin dispersant PEN-5 Surflo S-24 Tretolite VISCO W-121
Three components	Acid-based	Methanol + water
	Water-based	Methanol + B-11 Methanol + SEM-7 Methanol + W-121

portion of the software application. Three different networks were trained for this module. Figs. 16–18 are graphs of network predictions versus actual post-treatment deliverabilities for one-, two- and three-component chemical treatments. These graphs show how well these networks have been trained.

To clearly demonstrate their generalization capabilities correlation coefficients for these neural networks are provided in Table 4. In this table two separate correlation coefficients are provided for each network, one correlation coefficient for the training data set and one for verification data set. The verification data set includes data that have

TABLE 4

Quality of the neural networks that were trained for this study

Neural Networks	Modules in the software application		Training set		Verification set	
			Cor. coef.	Rec.	Cor. coef.	Rec.
Chemical treatments	Rapid screening		96%	1830	92%	783
	Optimization	1 component	97%	370	91%	157
	Optimization	2 components	95%	1492	91%	637
	Optimization	3 components	97%	63	94%	25

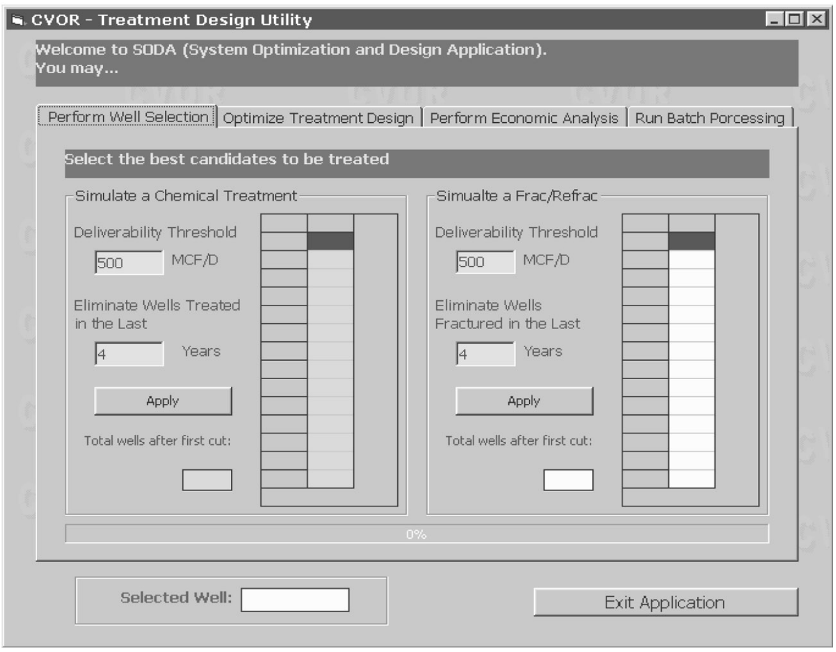

Fig. 19. Software application interface for module one.

not been used during the model construction and therefore the networks had not seen them before.

Figs. 19–21 show screen shots from the software application that was developed for this study.

4. APPLICATION TO OTHER FIELDS

This methodology can be applied not only to gas storage operation but to other types of operations as well. This is true as long as production history for some wells and results of some prior treatment are available. With some modifications this methodology can also be applied to new fields where no hydraulic fractures are performed in the past. It should be noted that in such cases (no prior frac jobs) it is necessary that some reservoir data be available. This data may be in the form of well logs with corresponding core data as well as some stress profiles from several wells in the fields (Cinco-Ley et al., 1978). The reason a specific number of wells are not suggested (for logs, cores and stress profiles) is due to the fact that it is a function of the size of the field under investigation.

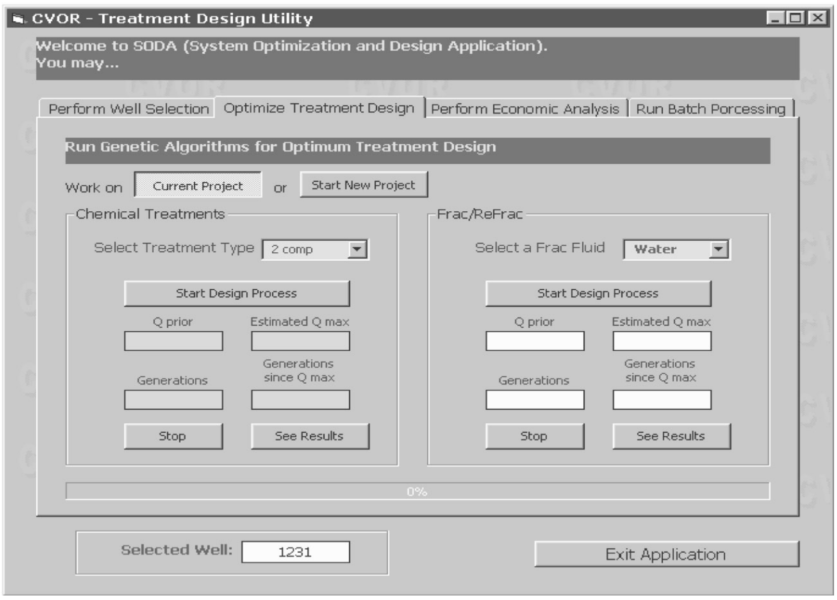

Fig. 20. Software application interface for module two.

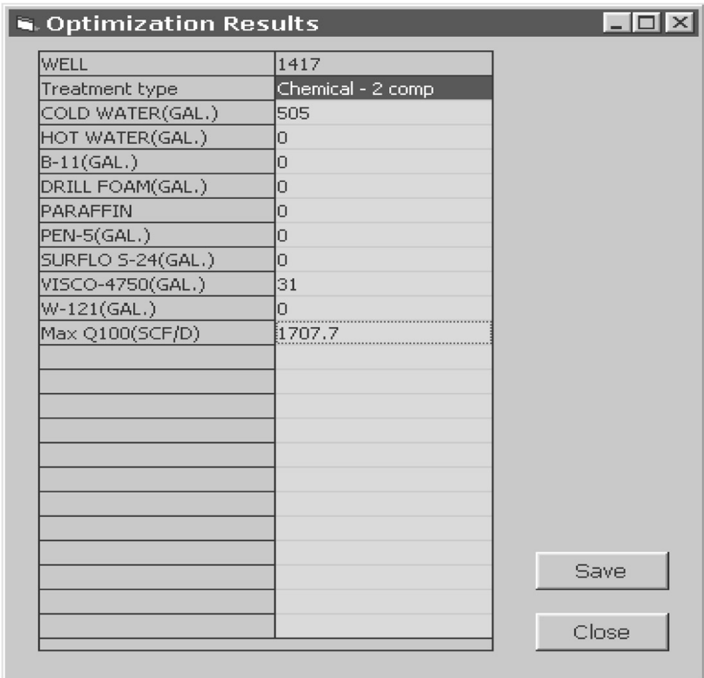

Fig. 21. Software application interface.

5. CONCLUSIONS

A comprehensive software tool has been developed that will assist engineers to select candidate wells for restimulation. The application has been developed using a relational database, six different neural network models and five different genetic algorithm routines. The software application includes three different independent modules that share information. Module one uses two neural models as its main engine and provides a rapid screening tool to identify the wells that need to be studied in more detail.

Reservoir data such as permeability, porosity, thickness and stress profiles are among the essential data that make conventional hydraulic fracture simulation possible. Success of simulation and fracture design process is directly related to the goodness of such data. Acquisition of the above mentioned data could be very expensive especially for older fields. The methodology introduced in this paper, uses available data, without access to reservoir data such as permeability, porosity, thickness and stress profiles. The hybrid system developed in this study is able to forecast gas storage well deliverabilities with high accuracy. This system is also capable of helping the practicing engineers to design optimum stimulation treatments. The developed system is currently being used to select candidate wells and to design frac jobs in the aforementioned field.

This software application has been custom made for a gas storage field in Ohio. The customization of the application is related to the neural network models and the genetic algorithm routines. These models and routines are specific to this storage field since they have been developed using the data from this field. The same methodology may be used to develop similar tools for other fields. This application will make it easier for the engineers to select candidate wells in the situation that other conventional methods cannot be used.

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REFERENCES

Agarwal, R.G. Carter, R.D. and Pollock, C.B., 1979. Evaluation and performance prediction of low permeability gas wells simulated by massive hydraulic fracturing. *J. Pet. Technol.*, March, pp. 362–372.

Cinco-Ley, H., Samaniego-V., F. and Dominguez, N., 1978. Transient pressure behavior for a well with a finite conductivity vertical fracture. *Soc. Pet Eng. J.*, Aug., pp. 253–264.

Gringarten, A.C., Ramey, H.J., Jr. and Raghavan, R., 1975. Applied pressure analysis for fractured wells. *J. Pet. Technol.*, July, pp. 887–892.

Hopkins, C.W. and Gatens, J.M., 1991. Stimulation optimization in a low-permeability, Upper Devonian sandstone reservoir: a case history. *SPE Gas Technology Symposium*, Houston, TX, Jan. 23–25, SPE Paper 21499.

McVay, D., Mohaghegh, S. and Aminian, K., 1994. Identification of parameters influencing the response of gas storage wells to hydraulic fracturing with the aid of a neural network. *Proc. of 1994 SPE Eastern Regional Conference and Exhibition*, Charleston, WV, SPE Paper 29159.

Millheim, K.K. and Cichowicz, L., 1968. Testing and analyzing low-permeability fractured gas wells. *J. Pet. Technol.*, Feb., pp. 193–198.

Mohaghegh, S., Arefi, R. and Ameri, S., 1996a. Petroleum reservoir characterization with the aid of artificial neural networks. *J. Pet. Sci. Eng.*, 16: 263–274.

Mohaghegh, S., Arefi, R. and Ameri, S., 1996b. Virtual measurement of heterogeneous formation permeability using geophysical well log responses. *Log Analyst*, March–April, pp. 32–39.

Mohaghegh, S., Arefi, R. and Ameri, S., 1997. Determination of permeability from well log data. *SPE Formation Eval. J.*, Sept., pp. 263–274.

Mohaghegh, S., Aminian, K., Ameri, S. and McVey, D.S., 19XX. Predicting well stimulation results in a gas storage field in the absence of reservoir data, using neural networks. *Soc. Pet. Eng.*, SPE Paper 31159. ? Year of reference?