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Candidate Selection for Stimulation of Gas Storage Wells Using Available Data With Neural Networks and Genetic Algorithms

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Abstract

The methodology developed in this study uses several artificial neural networks and genetic algorithm routines to help engineers select restimulation candidates based on available data. The neural networks provide realistic models of the hydraulic frac jobs and chemical treatments in this field. The genetic algorithms provide design optimization and economic analysis (capital investment allocation).

Historically wells in this storage field have been stimulated/restimulated by hydraulic fracturing or by being chemically treated using one, two or sometimes three different chemicals. Several neural network models were developed for different stimulation processes. The first series of genetic algorithm routines are used with each of the neural network models to provide optimum treatment design for each of the stimulation processes. A separate genetic algorithm uses several economic parameters and provides the engineer with an optimum stimulation combination of the candidate wells.

A software tool based on this methodology has been developed for a gas storage field in Ohio. Upon the completion of the analysis, the software tool provides a list of the maximum number of candidate wells. This maximum number is based on the provided stimulation budget for a particular year. The list specifies the type of stimulation for each candidate well - whether it should be refraced or chemically stimulated - and recommends a list of possible parameters to be used during the implementation.

Background

This paper presents the continuation of the efforts that were published in two previous SPE publications. In the first paper authors showed the feasibility of using artificial neural networks to accurately model hydraulic fracturing process in a gas storage field[1]. In a second paper as a continuation of that project, genetic algorithm routines were used in an attempt to optimize the design parameters of hydraulic fracturing process[2]. The study being presented in this paper takes into account new realities that the operators are facing in the field. These realities include fundamentally different stimulation jobs such as refracs versus chemical treatments. Each of these restimulation jobs must be treated differently during the model building process. Economic considerations play an important role in restimulation projects. A new economic optimization tool has been added to the process in this study. Therefore, many challenging complexities that were not included in the previous studies have been addressed here.

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 refraced or chemically treated? What would be the maximum potential post-treatment deliverability if the well were refraced 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, 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 refraced 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 authors use 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[3-5] and other researchers in this area, further discussion on the nature of these sciences will not be included here.

Methodology

Figure 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 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 three for chemical treatments - are trained to work as fitness functions for the optimization 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. Figure 2 provides a schematic diagram of the module two.

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 Equation 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:

$$P = \$g \times [\sum_{1}^{n_F} \Delta Q_F + \sum_{1}^{n_T} \Delta Q_T] - [n_F \times \$F + n_T \times \$T] \quad (1)$$

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

$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. Equation 2 provides the constrain:

$$[n_F \times \$F + n_T \times \$T] \leq \$Total \quad (2)$$

Where:

$Total = annual stimulation program budget

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

$$\$Total - [n_F \times \$F + n_T \times \$T] = \min \qquad (3)$$

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

Results and Discussion

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 1 shows the chemicals used in each category.

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.

Figures 4 and 5 show the accuracy of the module one neural networks. Figure 4 shows the result for the frac and refrac network while Figure 5 shows the network accuracy for the chemical treatments. Figures 6 though 9 are the plots of the actual post-treatment deliverabilities versus neural network predictions for the second module. Four different networks were trained for this module. Figure 6 shows the accuracy of the network trained for frac and refrac jobs. Figure 7, 8 and 9 are graphs of network predictions versus actual post- treatment deliverabilities for one, two and three components chemical treatments. These graphs show how well these networks have been trained.

To clearly demonstrate their generalization capabilities correlation coefficients for all the neural networks are provided in Table 2. In this table two separate correlation coefficients are provided for each network. One for the training data set and one for verification data set. The verification data set includes data that have not been used during the model construction and therefore the networks had not seen them before.

Figure 10 shows an example of module two's outcome. In this figure five different candidate wells are shown. For each candidate well three different post-treatment deliverabilities are shown. The first value - going from back to front - is the actual post-treatment deliverability while the second value is the predictor - module two - neural network's prediction. Please note the accuracy of this network's prediction. The exact same neural model that provided the second value has also predicted the third value. The difference between the second and third post-treatment deliverabilities is in the input to the model.

While the input data related to the well's general information and production history is the same in both cases, the stimulation parameters are different. In the case of the second post-treatment deliverability - the value shown by the bar in the middle - the actual stimulation parameters from the database have been used. But the stimulation parameters to the neural model for the third post-treatment deliverability have been generated by the module two's genetic algorithm. This figure shows the candidate wells potential after an optimum restimulation job.

Figures 11 through 15 show screen shots from the software application that was developed for this study.

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.

Module two includes four neural network models as well as four genetic algorithm routines that provide detail stimulation optimization for all the wells that have passed the module one's rapid screening process. Module two results in a ranked list of candidate wells and their corresponding recommended detail restimulation parameters.

Module three uses module two's ranked list accompanied by a set of provided economic parameters to perform an economic optimization. The outcome of the module three is the final list of candidate wells and their corresponding recommended detail restimulation parameters.

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 can not be used.

References

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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

Table 1: Chemical Treatment Classification.

Neural Networks	Modules in the Software Application		Training set		Verification set	
			Corr. Coeff.	No. of Records	Corr. Coeff.	No. of Records
Hydraulic Fractures	Rapid screening		94%	477	92%	118
	Optimization		96%	454	91%	112
Chemical Treatments	Rapid screening		96%	1830	92%	783
	Optimization	1 comp	97%	370	91%	157
		2 comp	95%	1492	91%	637
		3 comp	97%	63	94%	25

Table 2: Quality of the neural networks that were trained for this study.

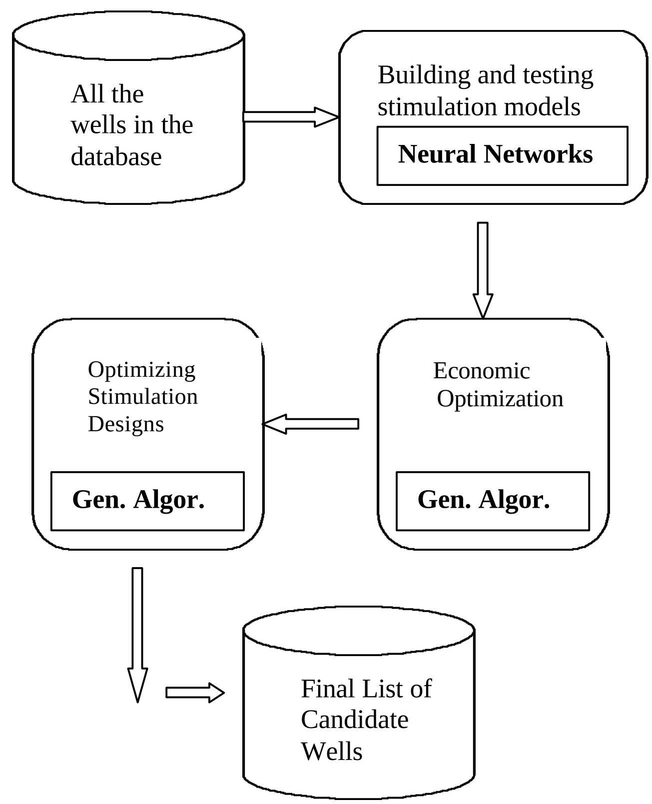

Figure 1. Flow chart of the software application.

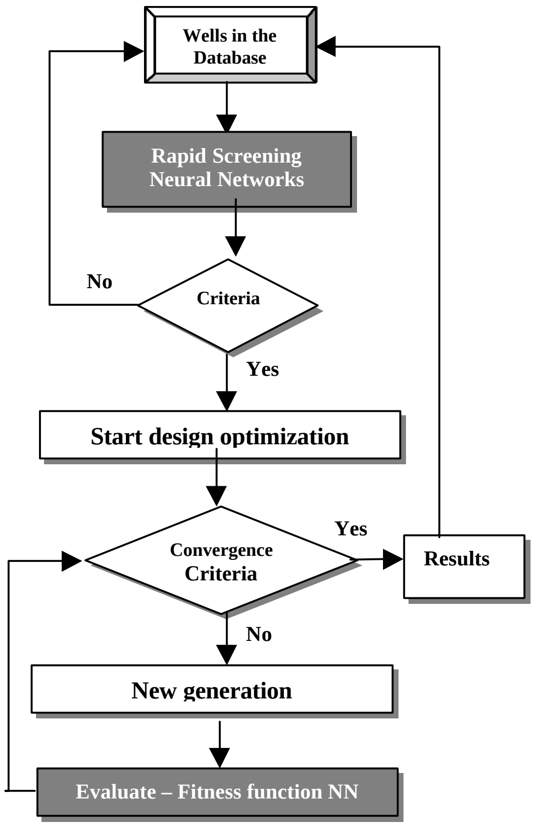

Figure 2. The schematic diagram for the module two process.

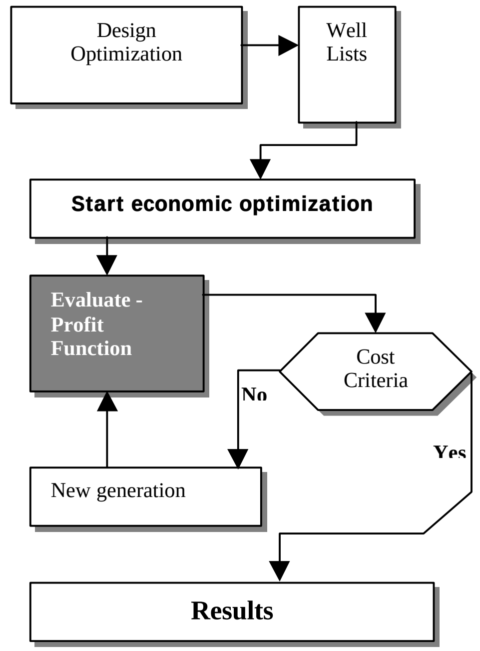

Figure 3: The schematic diagram for the module three process.

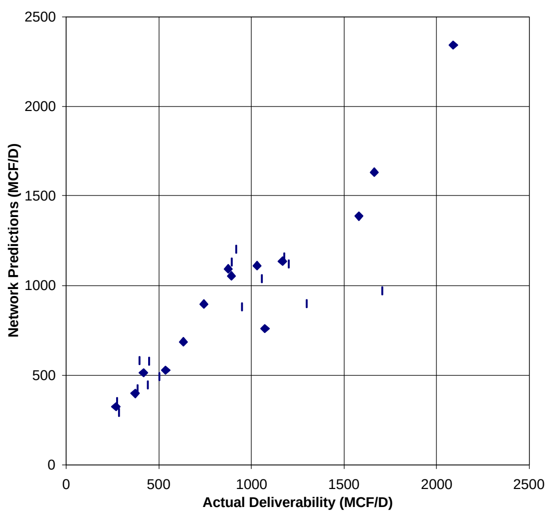

Figure 4: Module one neural net for hydraulic fracs - rapid Screening.

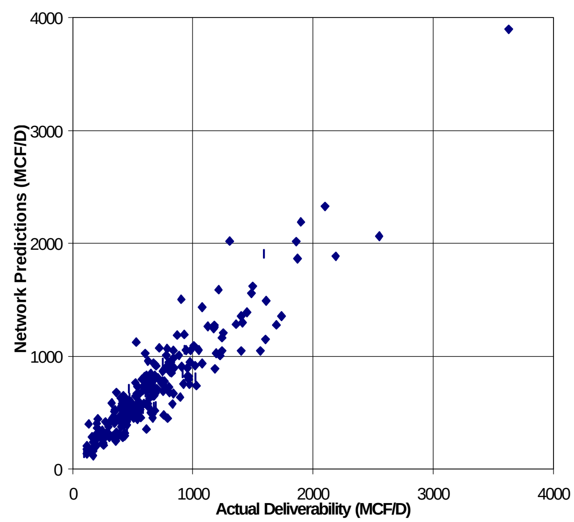

Figure 5: Module one neural net for chemical treatments - rapid Screening.

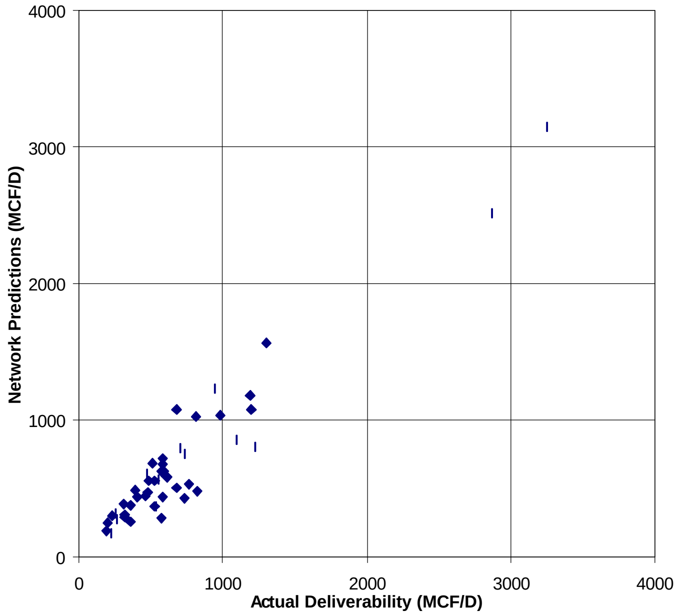

Figure 6: Module two neural net for hydraulic fracs - optimization.

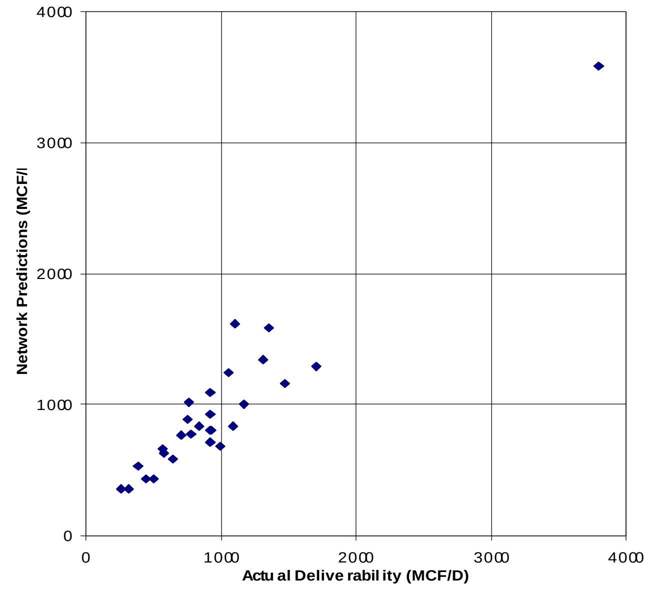

Figure 7: Module two neural net for one component chemical treatments - optimization.

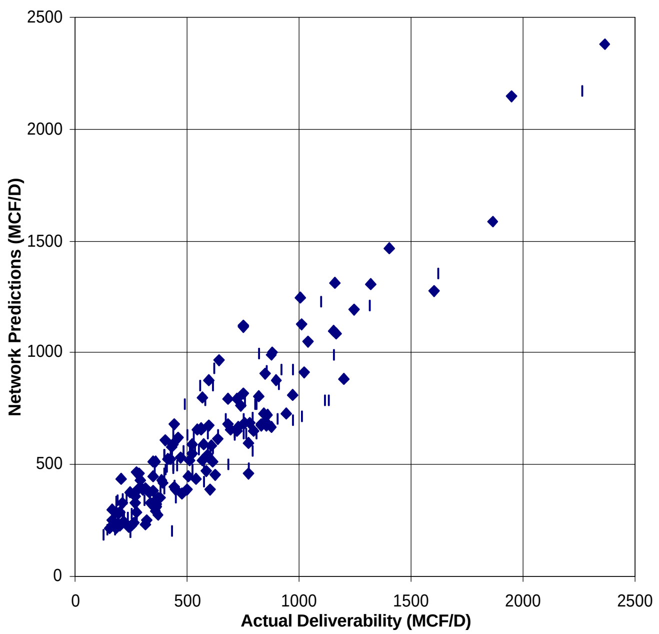

Figure 8: Module two neural net for two component chemical treatments - optimization.

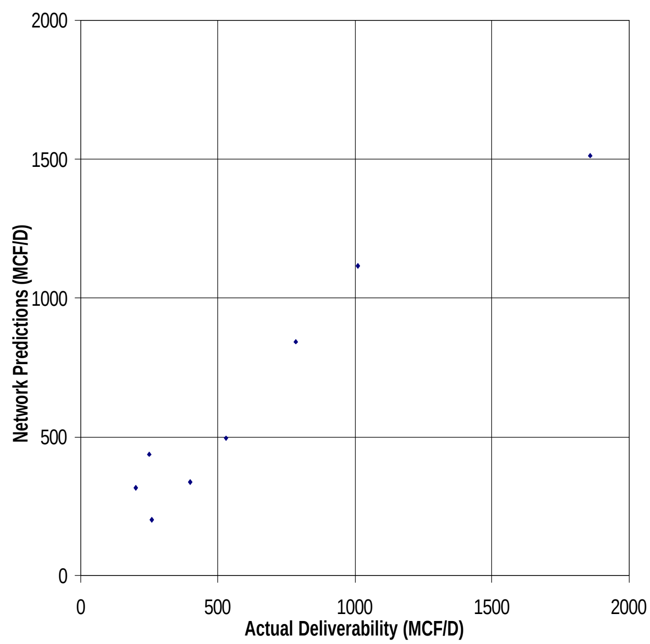

Figure 9: Module two neural net for three component chemical treatments - optimization.

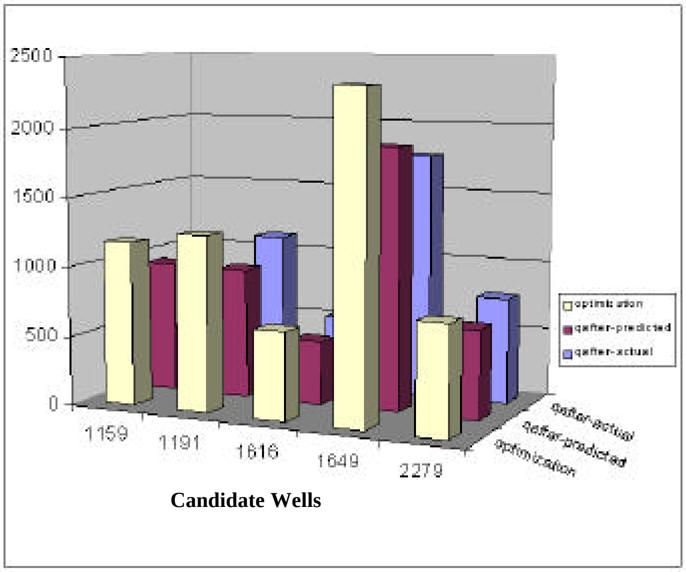

Figure 10: Stimulation optimization of five different candidate wells.

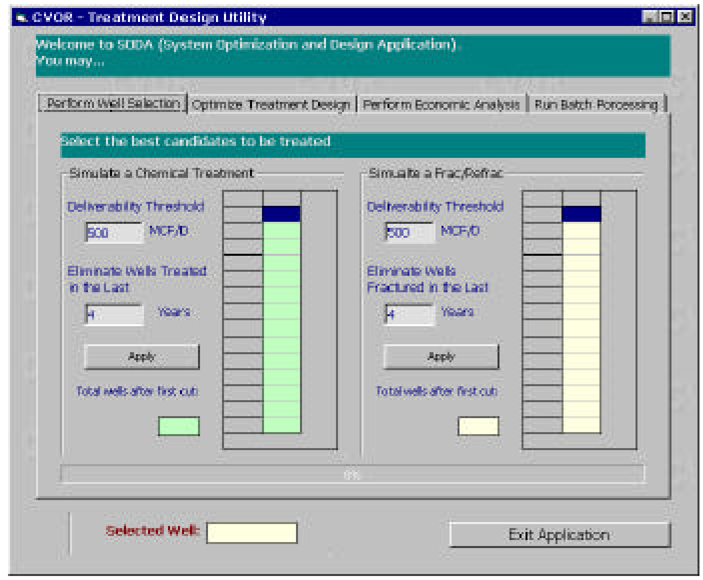

Figure 11: Software application interface for module one.

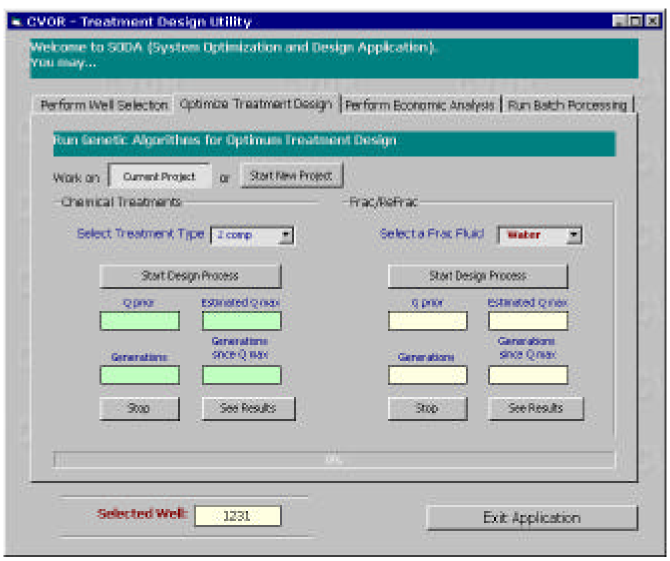

Figure 12: Software application interface for module two.

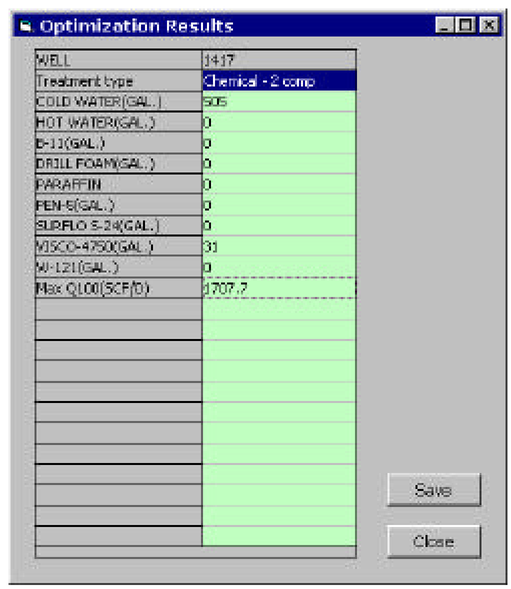

Figure 13: Software application interface.