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A Hybrid, Neuro-Genetic Approach to Hydraulic Fracture Treatment Design and Optimization

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Summary

This paper summarizes the efforts conducted toward the development of a new and novel methodology for optimal design of hydraulic fracture treatments in a gas storage field. What makes this methodology unique is its capability to provide engineers with a near optimum design of a frac job despite very little (almost none) reservoir data availability. Lack of engineering data for hydraulic fracture design and evaluation had made use of 2D or 3D hydraulic fracture simulators impractical. As a result, prior designs of hydraulic frac jobs had been reduced to guess works and in some cases dependent on engineers with many years of experience on this particular field, who had developed an intuition about this formation and its possible response to different treatments. This was the main cause of several frac job failures every year. On the other hand, in case of relocation of engineers with experience on this particular field the risk of even more frac job failures was imminent.

The unique design optimization method presented here is a logical continuation of the study that was covered in two previous papers^{1,2}. To thoroughly understand this methodology, reading of these two references are highly recommended. This method will accept available data on each well, which includes basic well information and production history, and provides engineer with a detail optimum hydraulic fracture design unique to that well, along with the expected post-frac deliverability. Please note that there are no simulated data throughout this study and all data used for development and verification of all methods are done using actual field data.

Background

In two previous papers^{1,2} a systematic approach using a three-layer back propagation neural network was introduced. The approach assisted engineers in predicting post-stimulation well performance and to select candidate wells for stimulation treatment. In those papers it was mentioned that this approach can also be used to optimize the stimulation design parameters. The optimization of frac design is the subject of this paper. Unlike conventional simulators that are based on mathematical modeling of the fracturing process, the process introduced in these papers used no specific mathematical model. As a result, access to explicit reservoir data such as stress profile, porosity, permeability and thickness is not essential. This was the 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 was presented. It was demonstrated that the developed neural network can predict the post-fracture well deliverability with better than 95% accuracy. These results were achieved in the absence of reservoir data (permeability, porosity, thickness and stress profiles) that makes conventional fracture simulation impossible. A complete version of these papers can be downloaded directly from our World Wide Web site at <http://www.pe.wvu.edu>.

Genetic Algorithm

Many problems in life are solved through some kind of searching process. In a world of almost unlimited combinations, we need to find the best time to schedule meetings, the best mix of chemicals, the best way to frac a well, the best stocks to pick, or the best way to stack boxes. The most common way we solve simple problems is the "trial and error" method. The problem is that search spaces are frequently too large for us to examine every possible combination. The model being investigated in this study has seventeen parameters which has been encoded into a 74 bit long chromosome. A chromosome is the binary form of all parameters concatenated to form one member of the genetic population. All the possible combinations of genes within this chromosome makes this problem to have 10^{21} distinct possible solutions. If we could examine 10^6 solutions per

second, it would still take us 10^{15} seconds (about 300 million years) to exhaustively search the model space. In the past, people would solve problems like this by making intelligent guesses about the values of the parameters, and with whatever trial and error as they could afford, time-wise.

In 1975 John Holland proposed an optimization technique that exploited an analogy between function optimization and the biological process of evolutionary adaptation. Genetic algorithms maintain a population of individuals (potential solutions) and act in a way that favors the creation and "survival" of better individuals. This innovative technique solves complex problems by imitating Darwinian theories of evolution on a computer. In nature, organisms evolve as they adapt to dynamic environments. The more "fit" an organism is, the longer it will live, and the more chance it has to reproduce and pass along those "fit" genes to another generation. New organisms are generated through reproduction, and each organism essentially gets "evaluated" by proving how long it can live in a harsh world. In biological evolution, only the winners survive to continue the evolutionary process. Note that one does not need to know what aspect of the organism makes it a winner, nature just assumes that if it lives, it must be doing something right. Genetic algorithm applies the same evolutionary technique to a wide variety of real-world problems like wire routing, scheduling, adaptive control, optimal control, game playing, transportation problems, traveling salesman problem, database query optimization, gas pipeline operation, inverse modeling in geophysics, etc...

To implement a genetic algorithm a number of chromosomes (a population) is created by setting the parameters randomly throughout the search space. From this population of solutions, the worst are discarded and the best solutions are then "bred" with each other by mixing the parameters (genes) from the most successful organisms, thus creating a new population. During reproduction, the chromosome undergoes different genetic operations such as selection, crossover, mutation and inversion³. The selection operator is responsible for choosing two organisms to become parents. Selection routines can be thought of as professional breeders, with a bias towards selecting only the most fit organisms in the population.

As in real life, this type of continuous adaptation creates a very robust organism. The whole process continues through many "generations", with the best genes being handed down to future generations. The result is typically a very good solution to the problem. By continually cycling these operators, we have a surprisingly powerful search engine which inherently preserves the critical balance needed with any search: the balance between exploitation (taking advantage of information already obtained) and exploration (searching new areas). Although simplistic from a biologist's viewpoint, these algorithms are sufficiently complex to provide robust

and powerful search mechanisms.

As mentioned earlier one of the keys to a successful genetic algorithm is having a way of ranking solutions. This is done using a "fitness function." Fitness function in any problem is the model or the function that is being optimized. In this study the neural network that has been developed and successfully tested as the neural model of the hydraulic fracture treatment in this field (neural module #2) is the fitness function.

Methodology

In the past two papers^{1,2} it was shown that we have developed a tool that is able to predict post-frac deliverability of the Clinton Sand with 95% accuracy given:

- a) well basic information,
- b) well production history, and
- c) frac design parameters such as sand concentration, rate of injection, sand mesh size, fluid type, etc.

The developed tool was trained on more than 570 different frac jobs and was thoroughly tested. It was shown that this tool can predict post-frac deliverability even on new frac jobs (i.e. frac jobs it had not been trained on or had never seen before). This was demonstrated on more than 50 frac jobs that were not used to develop the system. Figure 1 shows the neural network's predictions versus field results for three consecutive years, 1989 to 1991. At this point authors felt comfortable with the tool's robustness. It was then decided that it is now safe to conclude that by inputting any combination of frac parameters the developed tool will provide the post frac deliverability with acceptable accuracy.

A two stage process is now developed to achieve the main objective of this study, i.e. optimized frac design in Clinton Sand. A detail, step by step procedure will be covered in the following section. Figure 2 presents a schematic diagram of the procedure. For the first stage a new neural network (neural module #1) is designed and trained. 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 Sand. 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. Figure 3 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.

Procedure

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

(A) Stage One: Screening

In this stage a criteria is set for screening the candidate wells (Figure 4). 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.

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 (Figure 4). He/she will select one well at a time and enters the second stage for optimization.

(B) Stage Two: 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 aforemen-

tioned field in the past. In a previous paper Mohaghegh et al² demonstrated that if a new procedure (which has not been tried before in this field or is an experimental procedure) is used, (a procedure that this software has not been trained on), the software will provide the user with a reasonable answer. This is due to the fact that computational intelligence paradigms do not undergo complete breakdown, once they encounter new and unfamiliar environments and information. They rather “degrade gracefully”.

Actually in the same paper Mohaghegh et al² showed that once the software has been exposed to the new procedure, it will learn it quickly and therefore its performance enhances back to normal. In other words the software bounces back to its original accuracy. (please refer to Figure 6 of reference 2)

Step 2: One hundred random combination 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 field² is used to forecast post-frac deliverability for 100 cases generated in step 1 (Figure 3).

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.

A graphical representation of the design optimization process is provided to the design engineer (Figure 5). One may stop the process at any time he/she decides a better design can not be achieved. Two different convergence criteria is suggested. The software provide the design engineer with information to make this decision. During the optimization process the highest post-frac deliverability ever achieved is displayed along with number of generation that has past without any enhancement in post-frac deliverability. One may decide that if after so many generation no enhancement is taken place then it is time to stop the process. As a second convergence criteria the engineer may look at the cumulative post-frac deliverability curve for each generation that is displayed by

the software on real time. Slope of this curve determines whether every new generation is an improvement over the last generation. A positive slope indicates overall improvement of one generation to next and suggest that the optimization should continue. A zero or negative slope, on the other hand, suggest no improvement and therefore a criteria for stopping the search process.

Results and Discussions

In order to demonstrate the application of this 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) to see how much enhancement would have been made if this software was 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.

Figures 7, 8 and 9 show the results of this demonstration. In these figures actual field results are shown by circles, and software's prediction on the same frac designs are shown by crosses. It is obvious that the software does a fine job predicting frac treatment results from frac design parameters. Frac treatment parameters that have been generated by the software itself using the combined neuro-genetic procedure resulted in the frac treatment results shown by triangles. 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 was being carried out, many of the wells that could not have been optimized to give better result, would have probably been substituted by those with better return.

Table 1 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 accuracy this methodology could have enhanced this well's post-frac deliverability by 55 to 73 percent.

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 fields⁴. 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.

Conclusions

A hybrid system that is consisted of two neural networks and a genetic algorithm routine is developed for design and optimization of hydraulic fracturing procedures in a gas storage field in Ohio. The major difference between this system with conventional two or three dimensional frac simulators is that the developed hybrid system provide a solution for frac treatment design and optimization in the absence of conventional reservoir data that are an absolute necessity when using conventional (2D or 3D) simulators. The main component of the hybrid system has been successfully tested and is currently being used.

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 can 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 higher than 95% accuracy. This system is also capable of helping the practicing engineers to design optimum hydraulic fractures. The developed system is currently being used to select candidate wells and to design frac jobs in the aforementioned field.

References

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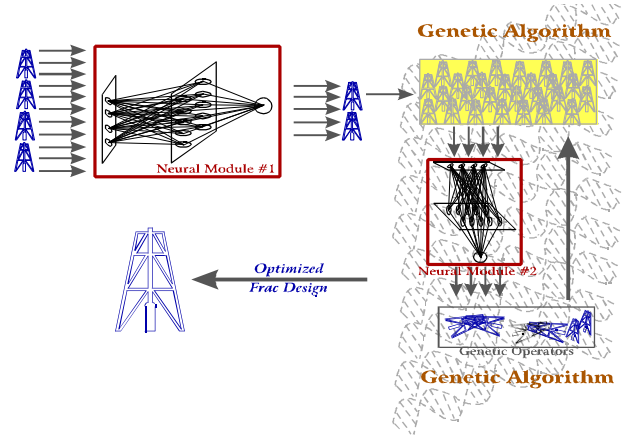


Figure 2. A schematic diagram of the hybrid, neuro-genetic approach.

Table 1. Optimization analysis on a well in Clinton Sand.

Well No.	1166
Actual (MCFD)	918
Software prediction (MCFD)	968.6
Percent difference	5.5
After optimization (MCFD)	1507.5
Within the % Diff. (MCFD)	1590 - 1425
Enhancement (MCFD)	672 - 507

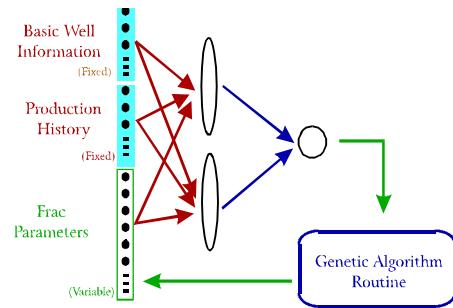


Figure 3. A schematic diagram of neural module #2.

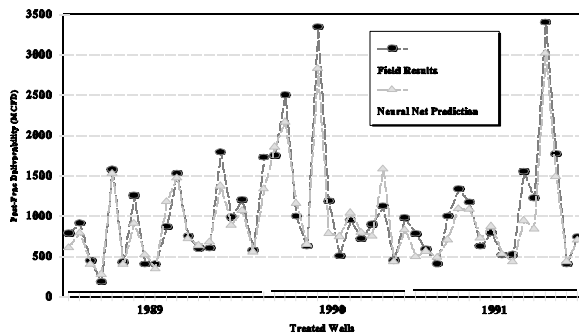


Figure 1. Field results and neural network predictions of 48 different wells in Clinton sand.

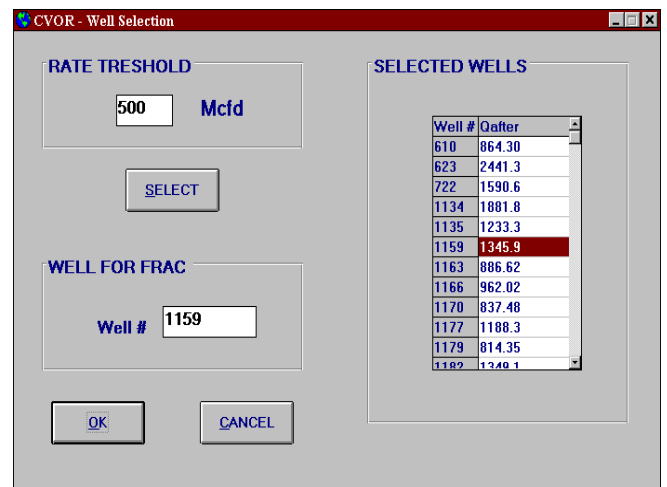


Figure 4. A screen shot of the software for screening the wells to pick the best candidate for optimization process.

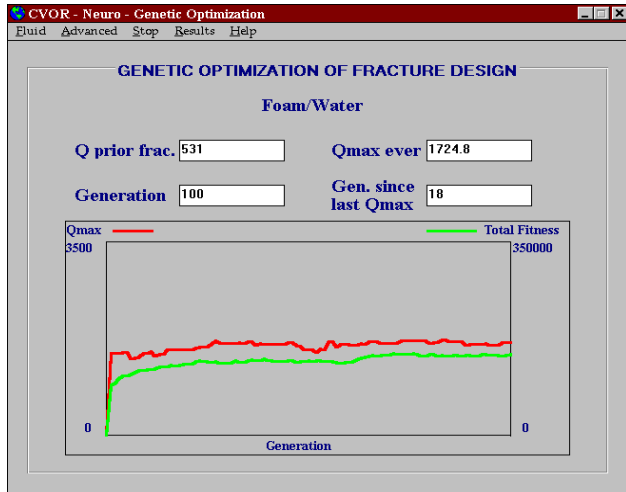


Figure 5. A screen shot of real time operation of the optimization process.

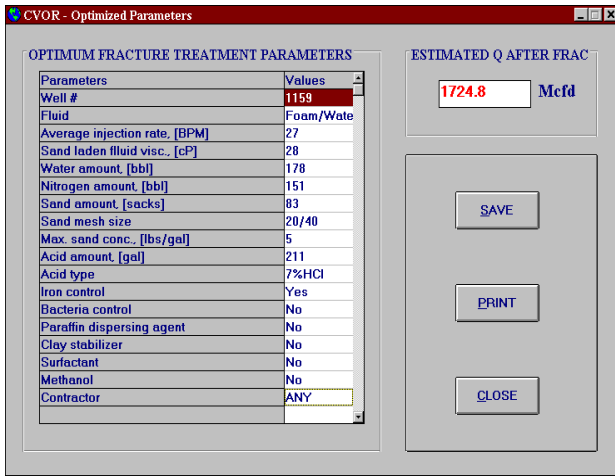


Figure 6. A screen shot of the final phase of the software. Here the optimized frac design is presented to the engineer.

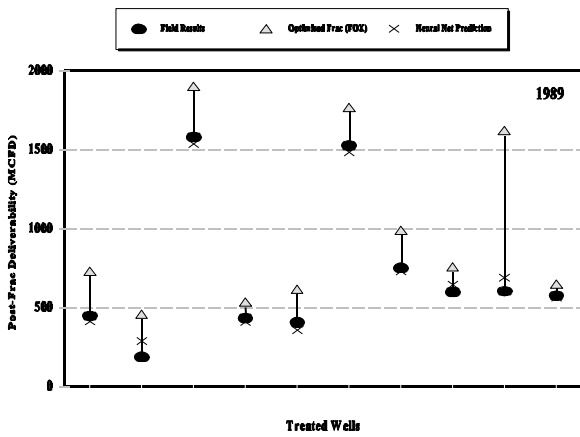


Figure 7. Enhancement that could have been achieved on wells treated in 1989.

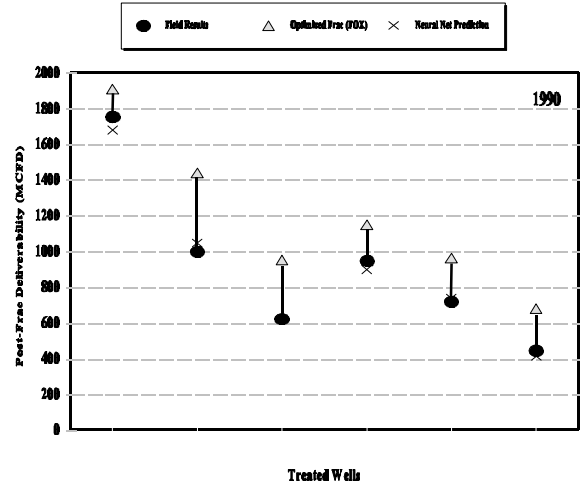


Figure 8. Enhancement that could have been achieved on wells treated in 1990.

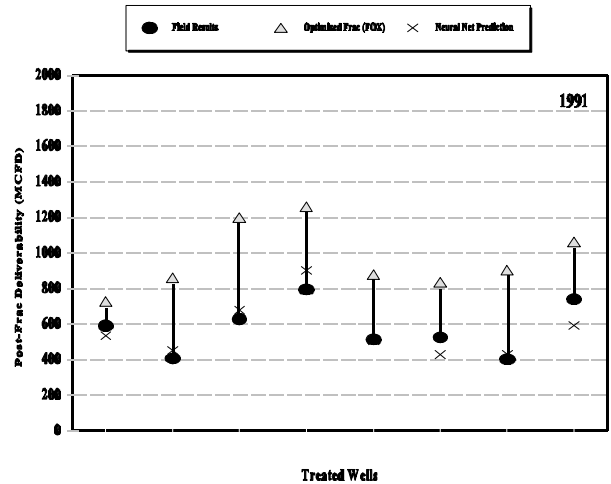


Figure 9. Enhancement that could have been achieved on wells treated in 1991.