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Development of an Intelligent Systems Approach for Restimulation Candidate Selection

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Abstract

This paper summarizes the development of a methodology for the restimulation candidate selection in tight gas sands. The methodology incorporates virtual intelligence techniques (artificial neural networks, genetic algorithms and fuzzy logic) to achieve this objective. Artificial neural networks are used to develop a representative model of the completion and hydraulic fracturing process in a specific field. Genetic algorithms are used as a search and optimization tool to identify the missed incremental production based on the neural network model. Finally fuzzy logic is used to capture the unique field experiences of the engineers as well as detrimental parameters (if such parameters are indeed present) and incorporate them in the decision making process. Approximate reasoning approach is used at the decision making level to identify the restimulation candidates. Once the methodology is introduced, it is applied to an actual tight sand field in the Rocky Mountain region and the results are presented.

Statement of the Problem

In 1996, the Gas Research Institute (GRI) performed a scoping study to investigate the potential for natural gas production enhancement via restimulation in the United States (lower 48 onshore). The results indicated that the potential was substantial (over a Tcf in five years). Particularly in tight sand formations of the Rocky Mountains, Mid-Continent and South Texas regions. However, it was also determined that industry's current experience with restimulation is mixed, and that considerable effort is required in candidate selection, problem diagnosis, and treatment selection/design/ implementation for a restimulation program to be successful. Given a lack of both specialized (restimulation) technology and "spare" engineering manpower to focus on restimulation, GRI initiated a subsequent R&D project in 1998 with several objectives. Those objectives are to 1) develop efficient, cost-effective, reliable methodologies to identify wells with high restimulation potential, 2) identify and investigate various mechanisms leading to well underperformance, and 3) develop and test restimulation techniques tailored to each cause of to well underperformance[1].

Addressing the first of the project objectives, an integrated methodology has been developed to select high-potential restimulation candidates in a reliable, cost-effective manner. The technique involves several steps. First, sophisticated statistical approaches are utilized to identify both obvious and subtle differences in well performances, and provide initial insights into potential candidate wells. Secondly, virtual intelligence techniques (a hybrid of artificial neural networks, genetic algorithms, and fuzzy logic) are used to recognize patterns in well performances as they relate to both geologic/reservoir conditions and completion/stimulation operations. With this information, controllable well performance "drivers" can be identified, and this information can in turn be used to select candidate wells, identify possible causes of well underperformance, and begin the treatment selection process. Third, engineering methods such as type-curves are used to high-grade potential restimulation candidates by providing a (relative) indication of reservoir quality and completion efficiency, and hence restimulation potential. Finally, high-potential candidates are individually screened for mechanical integrity, reservoir pressure and other important historical information that may not be uncovered in the previous steps. Lastly, low-cost candidate verification tests are performed to ensure candidate selection potential.

This paper is a review of the second technique used in this study, namely the use of virtual intelligence for identifying restimulation candidates. A brief introduction on the tools used in this study will be presented followed by a description of how techniques were implemented in achieving the project objectives. Application of the methodology to a field in Rock Mountains concludes the paper.

Introduction to Virtual intelligence

Virtual intelligence may be defined as a collection of new analytic tools that attempts to imitate life[2]. Virtual intelligence techniques exhibit an ability to learn and deal with new situations. Artificial neural networks, evolutionary computing and fuzzy logic are among the paradigms that are classified as virtual intelligence. These techniques possess one or more attributes of "reason", such as generalization, discovery, association and abstraction[3]. In the last decade virtual intelligence has matured to a set of analytic tools that facilitate solving problems that were previously difficult or impossible to solve. The trend now seems to be the integration of these tools together, as well as with conventional tools such as statistical analysis, to build sophisticated systems that can solve challenging problems. These tools are now used in many different disciplines and have found their way into commercial products. Virtual intelligence is used in areas such as medical diagnosis, credit card fraud detection, bank loan approval, smart household appliances, subway systems, automatic transmissions, financial portfolio management, robot navigation systems, and many more. In the oil and gas industry these tools have been used to solve problems related to pressure transient analysis, well log interpretation, and reservoir characterization, among other areas.

Artificial Neural Network

Artificial neural networks are probably the best known of the techniques that have been used in this study. Neural networks, a biologically inspired computing scheme, are an analog, adaptive, distributive, and highly parallel system that has been used in many disciplines and has proven to have potential in solving problems that require pattern recognition. The main interest in neural network has its roots in the recognition that the brain processes information in a different manner than conventional digital computers. Computers are extremely fast and precise at executing sequences of instructions that have been formulated for them (algorithms). A human information processing system is composed of neurons switching at speeds about a million times slower than computer gates[4]. Yet, humans are more efficient than computers at computationally complex tasks such as speech understanding and other pattern recognition problems. Artificial neural systems, or neural networks, are physical cellular systems, which can acquire, store, and utilize experiential knowledge. The knowledge is in the form of stable states or mapping embedded in networks that can be recalled in response to the presentation of cues.

Unlike a digital, sequential computer with a central processor that can address an array of memory locations, neural networks store knowledge in the overall state of the network after it has reached some equilibrium condition (stable state). In other words, knowledge in a neural network is not stored in a particular location. Knowledge is stored both in the way processing elements are connected, and in the importance of each input to the processing element (embedded mapping).

Pattern recognition has proven to be one of neural nets' strong points. The essence of pattern recognition is the concurrent processing of a body of information, all of which are available at the same time. The parallel-distributed information processing characteristics of neural networks accommodate this necessity. The science of pattern recognition is concerned with three major issues; 1) The appropriate description of objects, physical or conceptual, in terms of representation space, 2) The specification of an interpretation space, and 3) The mapping from representation space into interpretation space[5].

Another important characteristic of neural networks is their adaptability. Neural networks do not use algorithmic processes. They respond (like humans) to things learned by experience. Therefore, it is necessary to expose the network to sufficient examples, so it can learn and adjust its links and connections between different neurons. Neural networks can be programmed to train, store, recognize, and associatively retrieve patterns or database entries; to solve combinatorial optimization problems; to filter noise from measurement data; and to control ill defined problems; in summary, they estimate sampled functions when we do not know the form of the functions[6]. As such, they are well suited for modeling a complex problem, like the accurate prediction of gas production from tight sand wells, where the factors that influence production are many an varied (e.g., reservoir properties, completion/stimulation procedures, etc.)

Genetic Algorithms

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, or the best stocks to pick. The most common way we solve simple problems is the "trial and error" method. The size of the search space grows exponentially as the number of involved parameters (variables) increase. This makes finding the best combination of parameters too costly and sometimes impossible. In the past, people would solve such problems by making intelligent guesses about the values of the parameters, and with whatever trial and error they could afford.

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 well it can adapt to the environment. In biological evolution, only the winners survive to continue the evolutionary process. Note that one do 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, transportation problems, database query optimization, and gas pipeline operation.

To implement a genetic algorithm a number of chromosomes (a population) are created using random values for each parameter. 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 chromosomes undergo different genetic operation such as selection, crossover, mutation and inversion[7]. 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 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.

Fuzzy Logic

Human thoughts, reasoning and decision-making process is not crisp. We use vague and imprecise words to explain our thoughts or communicate with one another. There is a contradiction between the imprecise and vague process of human reasoning, thinking and decision-making and the crisp scientific reasoning and black and white computer algorithms and approaches. This contradiction has given rise to an impractical approach of using computers to assist humans in decision-making process, which has been the main reason behind the lack of success for traditional artificial intelligence or conventional rule-based systems also known as expert systems. A technology that started in early 1950s and remained in the research laboratories and never broke through to consumer market.

In essence, fuzzy logic provides the means to compute with words. Using fuzzy logic experts no longer are forced to summarize their knowledge to a language that machines or computers can understand. What traditional expert systems failed to achieve finally became reality (as mentioned above) with the use of fuzzy expert systems. Fuzzy logic comprises fuzzy sets, which are a way of representing non-statistical uncertainty, and approximate reasoning, which includes the operations used to make inferences in fuzzy logic[8].

Fuzzy set theory provides a means for representing uncertainty. Uncertainty is usually either due to random nature of events or due to imprecision and ambiguity of information we have about the problem we are trying to solve. In a random process the outcome of an event from among several possibilities is strictly the result of chance. When the uncertainty is a product of randomness of events, probability theory is the proper tool to use. Observations and measurements can be used to resolve statistical or random uncertainty. For example once a coin is tossed no more random or statistical uncertainty remains.

Most uncertainties especially when dealing with complex systems are result of lack of information. The kind of uncertainty that is the outcome of complexity of a systems is the type of uncertainty that rises from imprecision, from our inability to perform adequate measurements, from lack of knowledge, or from vagueness, like the fuzziness inherent in natural language. Fuzzy set theory is a marvelous tool for modeling the kind of uncertainty associated with vagueness, with imprecision, and/or with a lack of information regarding a particular element of the problem at hand[9].

Fuzzy logic achieves this important task through fuzzy sets. In crisp sets an object either belongs to a set or it does not. In fuzzy sets everything is a matter of degrees. Therefore any object belongs to a set to a degree. For example the price of oil today is $24.30 per barrel. Given the price of oil past few years this price seems to be high. But what is high price for oil? Few months ago the price of oil was about $10.00. Now that was low. Give how much it cost to produce a barrel of oil in the United State one can say that the cut off between low and high for oil price is $15.00. If we use crisp sets then $14.99 is low while $15.01 is high. But imagine if this was the criterion that was used by the oil company executives to make decision. The fact is while $15.01 is a good price that many people will be happy with $16.00 is better and $20.00 is even better. Categorizing all these prices as high can be quite misleading. Fuzzy logic proposes the following fuzzy sets for the price of oil.

In this figure the price of oil is $20.00 that is represented with two fuzzy sets good and high. This price has a membership of 0.15 in the good price and a membership of 0.85 in the high price.

Restimulation Candidate Selection Methodology

In this section the methodology of using virtual intelligence techniques for restimulation candidate selection will be presented. The methodology is then applied to a formation in the Rocky Mountains to demonstrate the applicability of this process to an actual field. Figure 1 is a flowchart that represents the process developed for this methodology. We use this figure as a road map to explain the intelligent systems methodology.

Three steps are involved for selecting restimulation candidates using virtual intelligence techniques. Before that, however, a data set that includes all the relevant available data for a particular field should be compiled. The data should include four major categories. First the general information about each well. This can include the location coordinates of the wells, an indication of the depth, and the date the well was put into production. Second category addresses reservoir quality. Information in this category may include net pay, porosity, saturation, permeability (if available) and any kind of pressure indicator. If the reservoir is consists of several layers, it helps to have the above information on a per layer (zone) basis. The third category is the stimulation-related data. This data may include information on the type and amount of proppant that has been used, type and amount of fracturing fluid, perforation density and information on the number of zones and layers involved in each frac job in the event of a layered reservoir. The last category includes mainly production data. This data is used to calculate five-year cumulative production or EUR for each well. The production indicator to which the above parameters are correlated.

The data that needs to be compiled can usually be found in well files and publicly available databases. Once the data set has been compiled, the next step is to apply the virtual intelligence approached. The first step of this process calls for the use of neural networks. Neural networks are used to build a representative model of well performance in the particular reservoir being studied. The data is used as input-output pair to train the neural network. The first three categories – well information, reservoir quality and stimulation related data - are used as input and are coupled with the fourth category – production data – as output.

Since it is impractical to model such a complex process using the conventional modeling techniques – mathematical modeling – neural networks can provide a valuable insight into the intricacies of interaction of the formation with the hydraulic fracturing designs and implementations. Once a reasonably accurate and representative neuro-model of the stimulation processes has been completed for the formation under study, more analysis can be performed. These analyses may include the use of the model in order to answer many “what if” questions that may rise. Furthermore, the model can be used to identify the best and worst completion/stimulation practices in the field.

This brings us to the second step of the methodology. Now that we have a representative model of the stimulation process for the formation being studied, how can we use it to identify in which wells restimulation potential exist? Once the neural model has identified the best practices, each hydraulic fracture treatment can be tested to see that if it was the best design for that particular well at the time it was implemented. The degree of departure from the optimum design is translated to the missed production opportunity, which in turn can be used as a proxy for restimulation potential. Genetic algorithms are used to perform this section of the analysis. The neural networks developed in the first step are used as the “fitness function” for the genetic algorithm routines.

The process of identifying the missed production opportunities - because of less than optimum hydraulic fracturing treatments - is as follows. The neuro-model developed in the first section of the methodology is able to provide an output (e.g., five-year cum.) based on the input to the network, namely, stimulation design, well information and reservoir quality for each particular well. Among these input categories only stimulation design parameters are controllable. Well information and reservoir quality is obviously beyond the engineer’s control. Therefore, the genetic algorithm is set to search among all the possible combinations of the stimulation parameters and identify the most optimum combination. The most optimum combination of stimulation parameters are defined as the combination that for any particular well (based on the well information and reservoir quality) provides the highest output (five-year cumulative production - 5YCum). The difference between the 5YCum from the optimum stimulation treatment and the actual 5YCum produced by the well is interpreted as the production potential that may be recovered by restimulation of that well. This analysis concludes the second part of the methodology. Furthermore, the candidate selection process is not entirely based on the outcome of the genetic algorithms.

The third and final step of the restimulation candidate selection methodology incorporates a fuzzy decision support system. This fuzzy expert system uses the information provided by the neural networks and genetic algorithms. The expert system then augments those findings with information that can be gathered from the expert engineers who have worked on that particular field for many years in order to select the best restimulation candidates. Keep in mind that the information provided to the fuzzy expert system may be different from formation to formation and from company to company. This part of the methodology provides the means to capture, maintain and use some valuable expertise that will remain in the company even if engineers are transferred to other sections of the company where their expertise is no longer readily available. The fuzzy expert system is capable of incorporating natural language to process information. This capability provides maximum efficiency in using the imprecise information in less certain situations. A typical rule in the fuzzy expert system that will help engineers in ranking the restimulation candidates can be expressed as follows:

If the well shows a *high* potential for an increase in 5YCum, **And** has a *moderate* pressure, **And** has a *low* proppant volume for the net pay completed, **Then** this well is a *good candidate* for restimulation.

A truth-value is associated with every rule in the fuzzy expert system developed for this methodology. The process of making decisions using fuzzy subsets using the parameters and relative functional truth-values as rules provides the means of using approximate reasoning in making decisions. This process is known to be one the most robust methods in developing high-end expert systems in many industries.

Application to Frontier Formation, Green River Basin

In this section the above methodology is applied to the Frontier formation in the Green River Basin. As the first step of the methodology, neural networks are used to build a representative model of the well performance in the Frontier formation. Table 1 is a list of input parameters used in the neural network model building process. As can be seen from this table the input data is categorized into four different categories instead of the three categories mentioned in the methodology. Once again, any part of the above methodology may be modified to fit the needs and data availability of any particular field.

Figures 2 and 3 show the results of the neural network trained for this section of the methodology. Figure 2 shows the training data set that has a correlation coefficient of 0.96 and Figure 3 shows the verification data set that has a correlation coefficient of 0.72. Another analysis conducted on the data from the Frontier formation based on a backward elimination methodology explained in a previous paper[10,11]. This analysis has the capability of identifying the most influential parameters in a data set. The results of neural network backward elimination analysis are demonstrated in Figure 4. In this figure all four categories of the input data are shown. The most influential category has the lowest R squared. This figure shows that reservoir quality is the most important category followed by completion and stimulation categories that seem to be equally important. The location related input parameters seem to be the least important parameters when compared to others. Note that among all the parameters involved in this analysis only the last three stimulation related parameters (see Table 1) are considered as being controllable.

This brings us to the second step of the analysis that involves the genetic optimization of the stimulation parameters. In this step the last three input parameters shown in Table 1 namely fluid type, total fluid volume, and total proppant amount, are used in the optimization process. Using the neural network model developed in the first step of the analysis as the "fitness" function of the evolution process, the algorithm searches through all possible combinations of the aforementioned three stimulation parameters and tries to find the combination that results in the highest five year cumulative production (5YCum). This process is repeated for every well individually. The difference between the optimized 5YCum and the actual 5YCum is considered to be the potentially missed production that may be recovered by restimulation. The outcome of this process is called the potential 5YCum and is used as one of the three inputs into step three which is the fuzzy decision support system using approximate reasoning.

Step three is a three-input one-output fuzzy system. The inputs include the above mentioned potential 5YCum., a calculated parameter called Fracs per Zone (FPZ), and pressure. The engineers in the field brought this parameter to our attention. They mentioned that there are wells that have been completed in all zones (there can be as many as 7 zones present) but only one hydraulic fracture has been performed. In other words the ratio of number of treatments performed to the total number zones completed is an important factor. We also found that long-term pressure surveys had been performed in 1995 on many wells. The issue with the pressure surveys is that the shut-in time and the depth where the pressure readings were taken were not consistent throughout the field. This introduces serious imprecision in the pressure values. Therefore, all the three input parameters were subjected to fuzzy subsets using low, moderate and high fuzzy subsets. The output of the fuzzy system is the degree of which a well is a candidate for restimulation. The output fuzzy subsets include 1) the well is a candidate, 2) the well may be a candidate, and 3) the well is not a candidate. The system includes 27 fuzzy rules that are qualified using a set of three truth functions. Figure 5 shows the 27 rules with truth qualification for the fuzzy systems. Figure 6 shows the truth qualification functions used for the approximate reasoning implementation in the fuzzy system. As demonstrated in this figure, each rule can be true, fairly true or very true.

Using this three-step process all the wells (belonging to a particular operator) in the Frontier formation was processed. A list of restimulation candidates was identified.

Results

It should be noted that the intelligent systems approach has gone through some modification as a result of a its application to three formations, two in the Rocky Mountains and one in East Texas. By the time the research team completed its study and candidate selection of the last formation, the intelligent systems approach had been modified from its original application in the Frontier formation. The new and improved intelligent systems approach, which now employs all three virtual intelligence techniques, has been presented in this paper. Based on the original approach (which was a combination of an older version of this approach in combination with two other candidate selection techniques, namely a statistical approach and a type curve approach) three wells were selected and restimulated.

These wells were GRB 45-12, GRB 27-14 and NLB 57-33. Figures 7, 8 and 9 show the preliminary results of the restimulation on these wells. It can be seen that well GRB 45-12 shows an improvement while the other two wells are yet to show any improvements as the result of the restimulation. Table 2 demonstrates the ranking of these wells when the new intelligent systems approach is applied to the Frontier formation.

It should be noted that many high-ranking candidates must be disregarded as a result of mechanical issues with the well that makes restimulation impractical. A detailed explanation on how the original candidates were selected has been presented in a recent article[11].

Conclusions

A new approach for using virtual intelligence techniques to select restimulation candidates for tight gas sands has been presented. This methodology was modified from its original implementation to better capture complexity in the candidate selection process. It was shown that this methodology is now capable of selecting candidate wells that show improvement after restimulation. The methodology is not suited (at its current status) to estimate the potential incremental production. This methodology is improved when used by other techniques used in the GRI project namely the statistical analysis and type curves. Addition of these techniques provides an estimated incremental production.

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Category	Input Parameter	Comments
Location	**X**	X coordinates of the well (east-west)
	Y	Y coordinates of the well (north-south)
	KB Elevation	Kelly Bushing Elevation
Reservoir	**Permeability**	From Type Curve matching analysis
	Drainage Area	From Type Curve matching analysis
	Total Gas-Ft	Sum(Porosity * gas saturation * net pay) (all zones)
Completion	**Total H Completed**	Total completed thickness (all zones)
	Total No. of Holes	Total number of perforation holes
	Completion Date	Date of well completion
	Number of Zones	Total number of zones completed
Frac	**Frac Number**	A well may have up to 7 frac jobs
	Fluid type	Gelled oil, ungelled oil, linear gel, cross-linked gel
	Fluid Volume	Total amount of fluid pumped in all fracs
	Proppant Amount	Total amount of proppant pumped in all fracs

Table 1. Input parameters for the neural network analysis.

Candidate Well	Ranking using the new approach
GRB 45-12	20
GRB 27-14	112
NLB 57-33	No Pressure Data
Wells in the analysis	123

Table 2. Candidates ranking using the new approach.

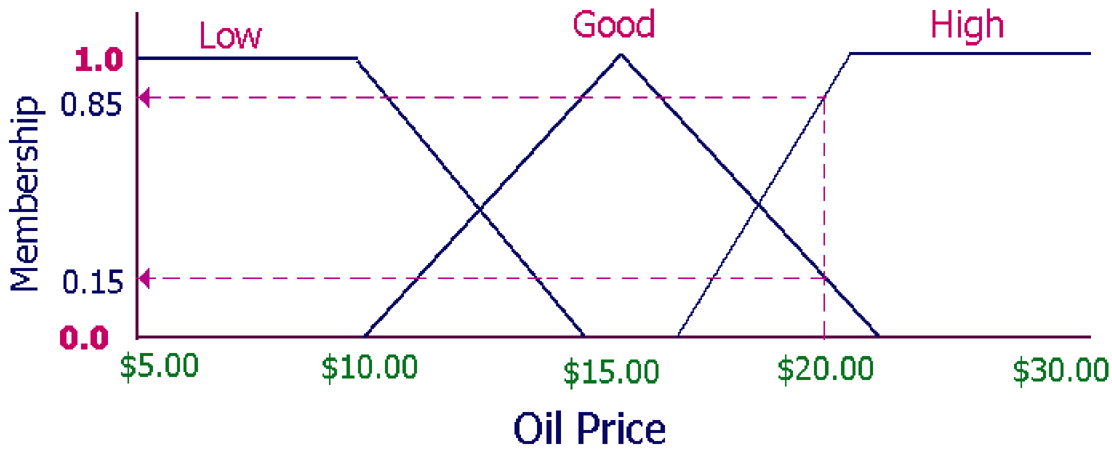

Figure 1. Fuzzy sets representing the oil price.

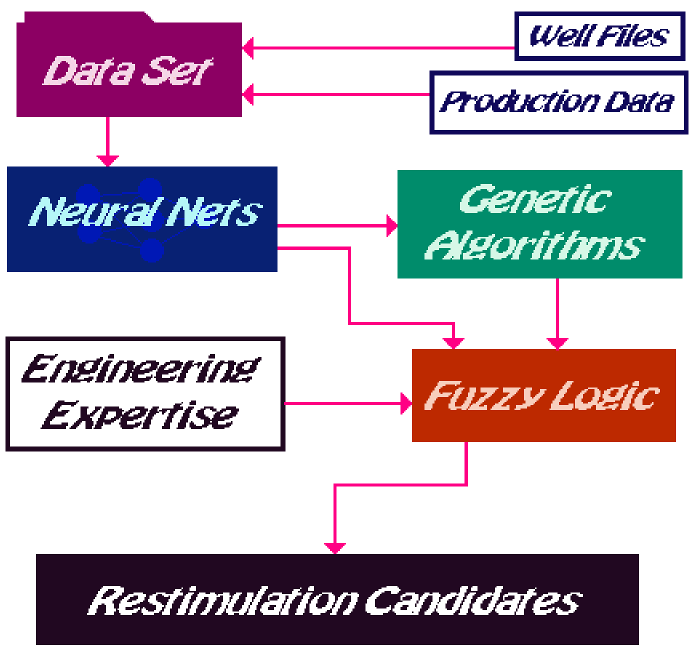

Figure 2. Virtual intelligence approach to restimulation candidate selection.

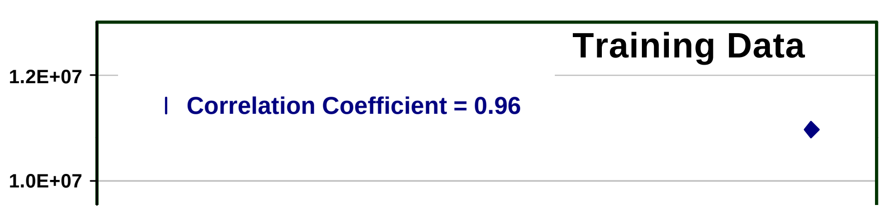

Figure 3. Training data set for the neural network.

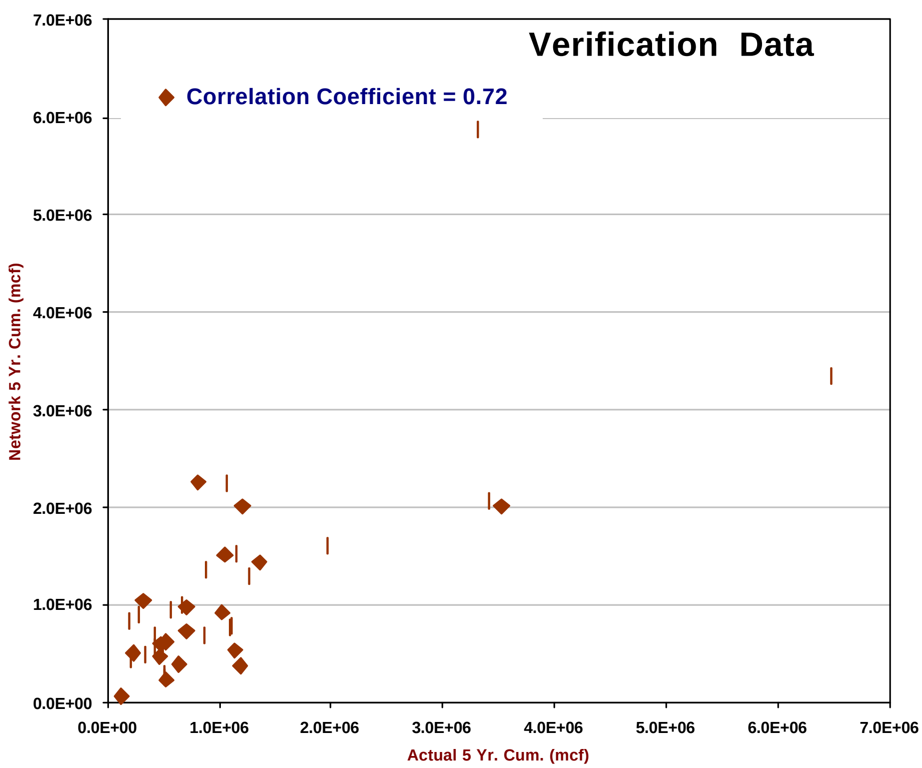

Figure 4. Verification data set for the neural network.

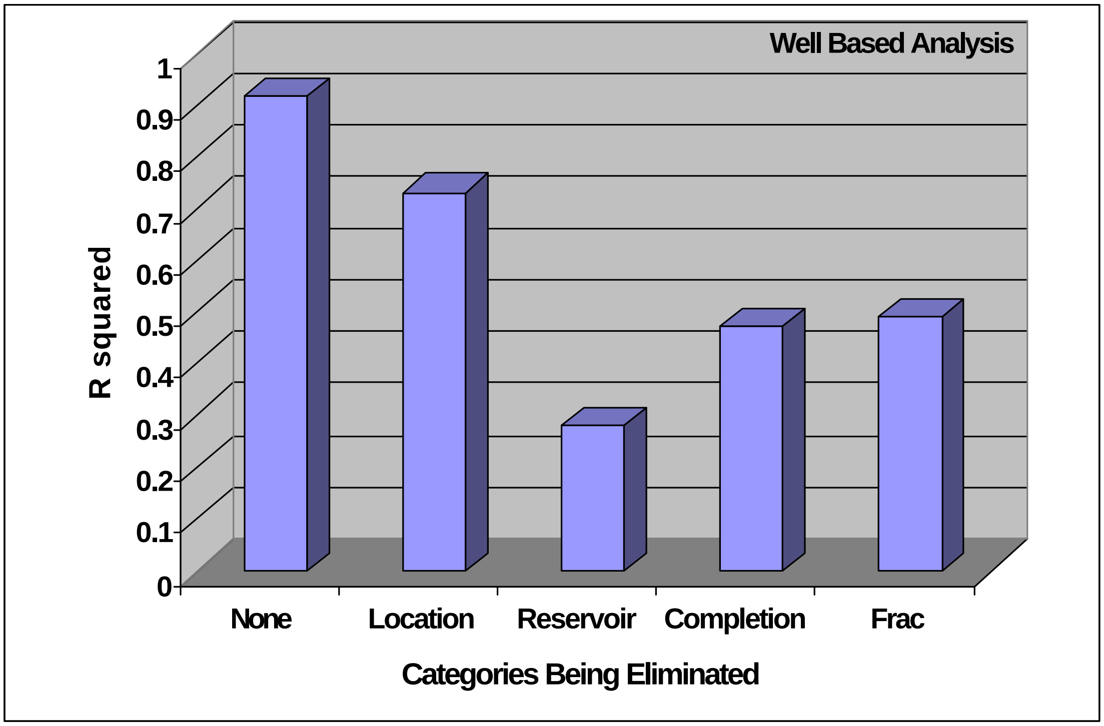

Figure 5. Relative importance of data categories in Frontier Formation.

Pressure	Fracs/Zone	Potential Five Year Cum. Low	Potential Five Year Cum. Med.	Potential Five Year Cum. High
LOW	Low	No (T)	MayBe (fT)	MayBe (fT)
LOW	Med.	No (VT)	No (T)	MayBe (fT)
LOW	High	No (VT)	No (VT)	No (T)
Medium	Low	MayBe (T)	Yes (fT)	Yes (fT)
Medium	Med.	No (fT)	MayBe (T)	Yes (fT)
Medium	High	MayBe (fT)	No (fT)	MayBe (T)
High	Low	Yes (T)	Yes (VT)	Yes (VT)
High	Med.	MayBe (VT)	Yes (T)	Yes (VT)
High	High	MayBe (VT)	MayBe (VT)	Yes (T)

Figure 6. Fuzzy rules with truth qualifications used in the fuzzy system.

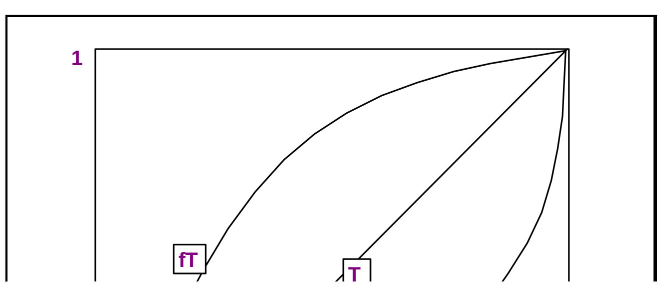

Figure 7. Truth qualification functions used for approximate reasoning.

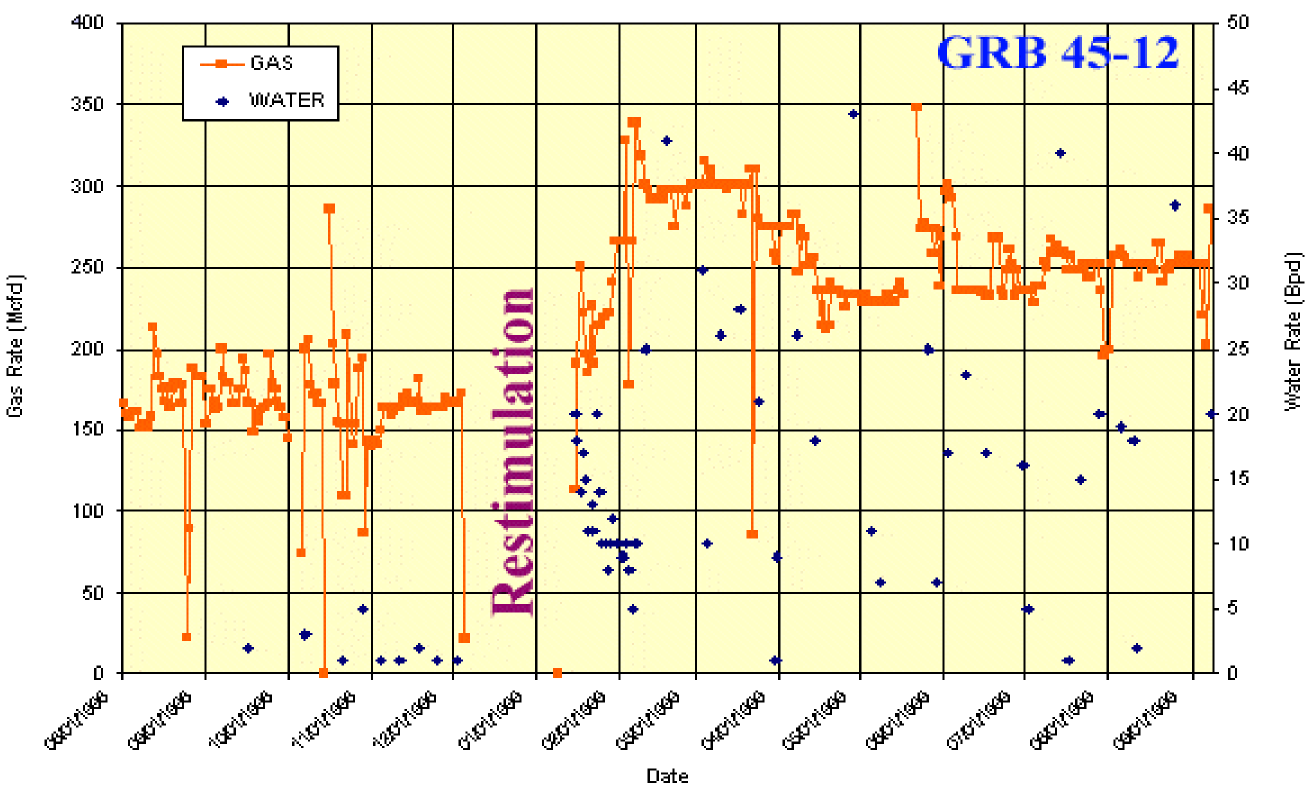

Figure 8. Gas and water production before and after restimulation for well GRB 45-12.

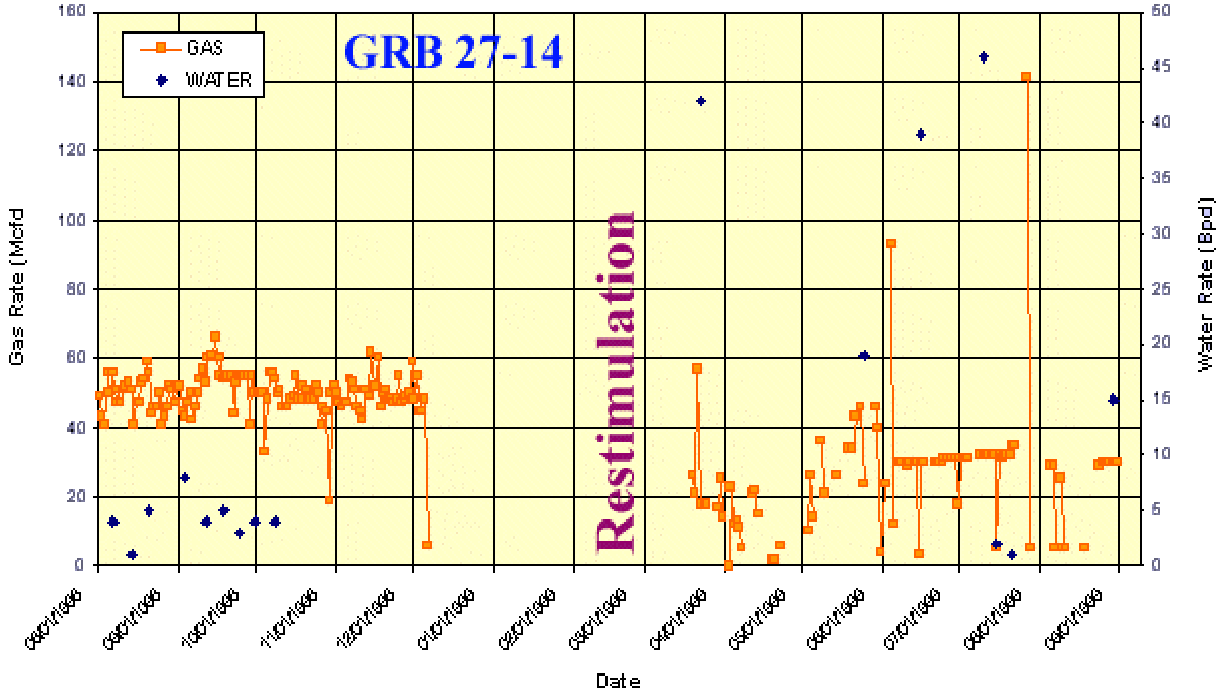

Figure 9. Gas and water production before and after restimulation for well GRB 27-14.

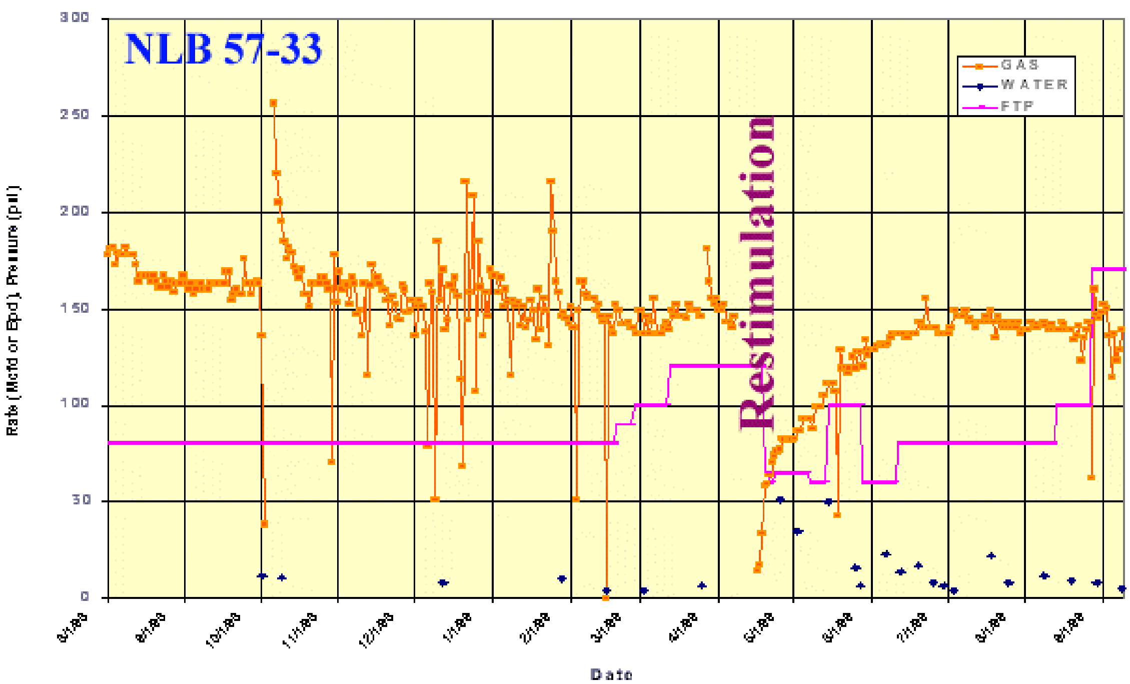

Figure 10. Gas and water production before and after restimulation for well NLB 57-33.