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# An Intelligent Portfolio Management Approach to Gas Storage Field Deliverability Maintenance and Enhancement; Part One Database Development & Model Building

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## Abstract

The main goal of this paper is to modify and apply the state-of-the-art intelligent, optimum portfolio management to the gas storage field in order to optimize the return on investment associated with well remedial operations. It continues the development of a methodology for candidate selection and stimulation design and optimization using Artificial Intelligence techniques.

The data of an actual gas storage field was used to test the results. The project data include Well-bore, Completion, Perforation, Stimulation, Well-test and Reservoir Data. To make candidate selection for gas storage fields operators predict the effectiveness of the stimulation commonly using three parameters. One in Peak Day rate second is Absolute open flow and third is change in skin provided permeability values in the field don't vary much. The software developed in parallel with this selection methodology includes an easy to use interface that allows the user to edit the data for a gas storage field, perform well-test analysis and use neural networks in association with Genetic optimization tool. The software ranks the well according to maximum change in skin value and recommends the best stimulation slurry based on the weitage given to the skin and cost of stimulation. A decision to select the ranked wells for re-stimulate can be made accordingly.

## Background

Each year gas storage operators spend hundreds of thousands of dollars on workovers, completions and re-stimulation of storage wells in order to battle the inevitable decline in deliverability due to well damage with time. A typical storage field has tens if not hundreds of production wells. Each well will respond to a remedial operation in its own unique way that is a function of a set of uncontrollable parameters such as porosity and permeability and a set of controllable parameters such as completion and stimulation practices which can be controlled by the operator and the service company performing the remedial job and hence identified by the methodology presented in this paper. The software application then allows the user to analyze the remedial operation performed in the storage field and identify the most appropriate candidates for such operations taking into account certain economical parameters. This methodology is modification of previous efforts made to make intelligent decisions for re-stimulation candidate selection of gas storage wells. In all the previous attempts decisions were based on well deliverability parameters (either the Peak day rate or Absolute open flow). The study in this paper takes into account the new reality faced by intelligent systems prediction of candidate wells i.e sometimes artificial neural nets cannot predict with reasonable accuracy from well deliverabilty parameter data. This new methodoly uses change in skin as optimization tool and the software tool made in line with this methodology uses different trained neural networks and is very flexible to design Genetic Algorithm based on different parameters. This flexability gives the engineers an advantage to use the same software to select candidate wells for different storage fields, this tool was not available so far. Figure 1 shows the screen shot of this software which has been named 'Intelligent Storage'.

Economics play a pivotal role in the restimulation candidate selction. The engineers each year have fixed amount of budget to re-stimulate few wells out of hundereds. The new economic optimization tool uses Genetic Algorithm based on both skin and cost of stimulation to optimize the stimulation receipe.

## Methodology

To make an intelligent decision about the candidate well selection we need to have a judgment whether the stimulation was good or bad. To make that decision we collected all the relevant data and put it in a database so that we can manipulate it the way we like to look at it. Permeability analysis was done for all the wells in the storage field and frequency graph was plotted to check the variability of permeability values in the field, which is shown in Figure 2.

Almost more than than 94% wells that had permeability values, the range of permeability was from 5md to 100 md and the well deliverability data was difficult to train the neural networks. Thus this type of data was ideal to work on to make an intelligent candidate selection decision based on change in skin.

The well-test data found was very less so tools to analyze the well-tests by simplified (Figiure 3) and LIT (Laminar Intertial Turbulent flow)) analysis were developed in the software. Another tool to find permeability from an extended build-up test was added later. Now after the analysis neural network was trained to predict the non-linear relationship of skin after the stimulation. Now when we can predict skin from any stimulation we made a Genetic Optimization tool that uses genetic algorithm to find the optimum stimulation parameters. After this as we have got the best stimulation parameters for each well and its corresponding predicted skin we can now rank the wells and select candidate wells. The methodology is shown in Figure 4.

Flow diagram in Figure 5 illustrate the well test analysis procedure and the type of values that we got from the data

**Characteristics of the reservoir:** The data used in this study was taken from a gas storage reservoir field in Ohio and its properties are shown in Table 1.

## Software implimentation

**Neural Network as Skin Predictor:** Neural nets are very powerful in predicting non-linear relationships. As the relationship between skin and stimulation parameters is non-linear and very complicated thus neural nets are used which are very good at it. With skin values before and after the stimulation calculated and stimulation parameters known we can now use these valid stimulations to train the Neural Network to use it as a prediction tool. Intelligent Data Evaluation and Artificial Network IDEA® software by Intelligent Solutions Inc. was used to design the neural network. This software is very versatile in making different nets with different training algorithms. Generalized Regression Neural Net (GRNN) was used to train the neural net. The net had 11 inputs and 1 output as skin. The source of data for the neural net is given in Figure 6.

Out of the 78 valid stimulations available, the Neural Net was trained on 60 data items while 14 were used as calibration data while 4 as verification data. The Neural network showed very good results for all three types of data. The screen shot taken from the IDEA software for training and verification of the neural net is shown in Figure 7 and Figure 8.

**Genetic Algorithm:** Genetic Algorithm code was written to optimize the controllable stimulation parameters used in the neural net. Out of the 11 input parameters 7 can be varied to obtain optimum skin. The GA characteristics that were used are shown in Table 2. These were found to be one of the best for the available data but can be changed if the data is changed or more data is appended in the future.

**Optimization:** Two optimization methods are made available in the software. One is optimization just based on skin and other based on both skin and cost. The optimization objective function is calculated using the following formula and GA minimizes this optimization objective function.

$$Optimization\ Objective\ Function = \frac{Skin - Skin_{min}}{Skin_{max} - Skin_{min}} \times Skin\ weight + \frac{Cost - Cost_{min}}{Cost_{max} - Cost_{min}} \times Cost\ weight$$

**Software compatibility and variability:** In the software user has been given many options to accommodate the particular situation that he has and data availability if different from the data that we have used to verify the results from this software. Figure 9 shows such options.

One of such variability introduced is that the software can use any other neural net if it is required. The option menu of the optimization screen has the option to import any other neural network. Plus there is an option to select the available controllable parameters for the GA. For example if the user does not want to use or does not have foam and nitrogen then he can unselect them from the option form shown in Figure The length of GA will change according to the selection.

As the Neural Net has 'Well-Test Type' as its input so the 'Select Well-Test Type' menu option gives the user an option to choose the test the user wants the skin to be interpreted from with single-point, Open –flow and Multi-point as its option. With changing price of hydrocarbons the petroleum industry is going through fluctuating material cost. The stimulation material prices change frequently and are a factor of demand and supply in that region. The software has the option to change the price of the stimulation material before applying the GA to the available data

## Results and Discussion

The software was tested on the available data and due to the variability of parameters that can be changed for optimization we did analysis on two runs. One in which skin was given 100% weight age in the optimization meaning that we did not cared about the cost but only the skin. Even if several thousand dollars have to be spent to have a slight increase in skin and the other in which skin was given 50% weight age and rest 50% to cost in the optimization. Figure 10 and Figure 11, show the comparison between the actual and two predicted optimized stimulations runs.

The skin - after optimization (GA Skin) in run #1 for skin 100 – cost 0, is always less than the skin prior stimulation (prior Skin). Only in one case for well # 61 it came very close to the actual skin, indicating that the stimulation already done on the well # 61 was excellent resulting in maximum improvement in skin otherwise all stimulations to some degree have chance of improvement. The stimulation slurry predicted in run # 2 for skin 50 - cost 50 was very similar to the one actually used except that the optimization in order to reduce cost compromised the skin from –5.91 to –5.723 instead as shown in Figure 12.

Figure 10 show that the GA optimized the skin and shows that there is potential in the wells to be stimulated again. Figure 11 show that the GA has optimized the stimulation cost and the user can stimulate the wells economically. Figure 13 show the ranking of wells for skin weight age of 100 %. The wells can be ranked for any weight age factor using the software, thus candidate selection can be made based on their rank.

## Conclusions

The main aim of the study was to find the re-stimulation candidate wells with the given data without trying to spend thousands of dollars on well test and gas reservoir simulators. Detailed analysis of well-tests performed on the storage field was done and intelligent tools like Neural networks to predict the Skin and Genetic Algorithms to optimize the stimulation were used to select the best stimulations for a well. The following conclusions can be drawn from this research:

1. The Artificial Intelligence Tool can predict Skin with high confidence.
2. The Portfolio Management for re-stimulation candidate well selection with the software made during this research study can be very cost effective.
3. This software is the first successful attempt to combine Data editing, Well-Test analysis and Artificial Intelligence in one software package.

Please note that due to the unique nature of this methodology many of the topics cannot be discussed in much detail in this paper and some need to be verified further through other techniques. It is our intention to introduce and modify these topics in much more detail in series of upcoming technical papers.

## References

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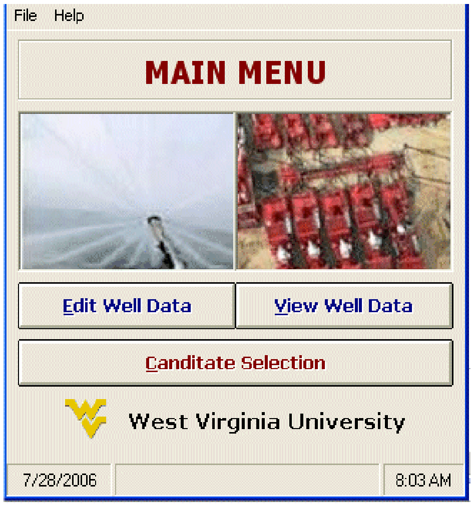


**Figure 1 Snap shot of the software developed in parralell to this research**

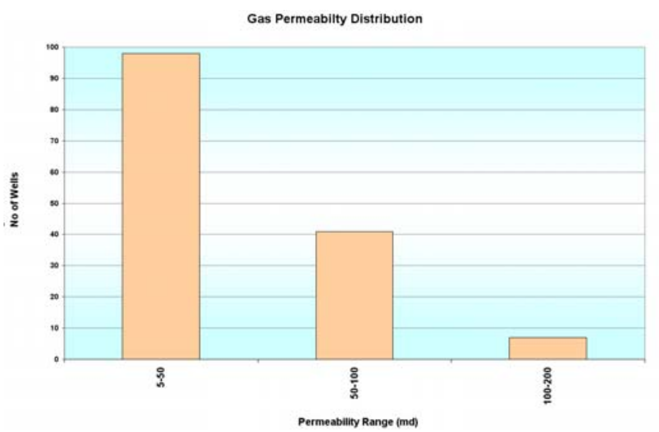


**Figure 2 Permeability Analysis done on the storage wells**

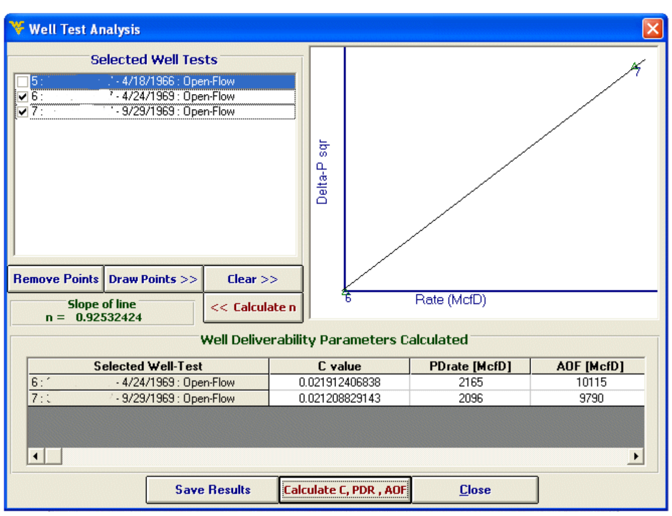


**Figure 3 Snapshot of simplified analysis being done through the software**

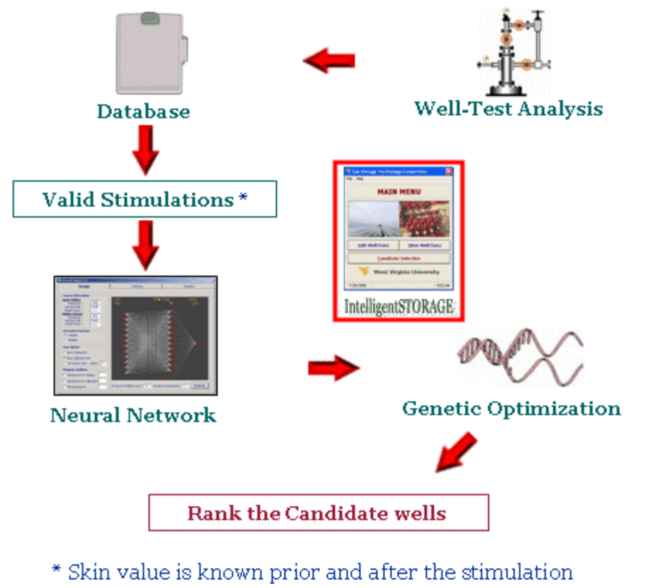


**Figure 4 Flow chart of our problem solving approach**

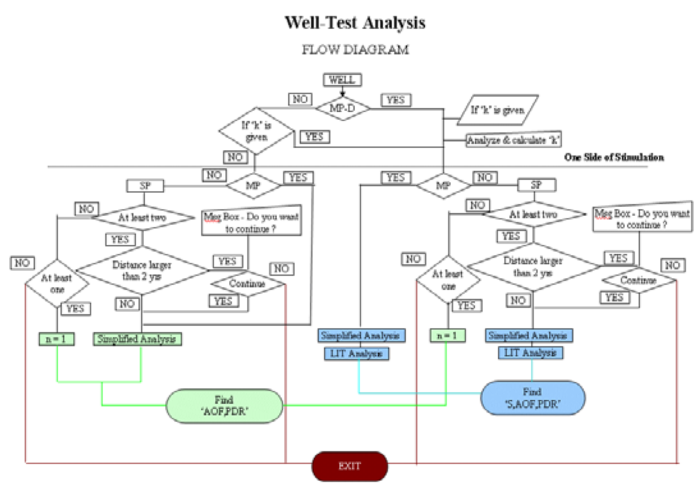


**Figure 5 Flow Diagram of Well Test Analysis procedure**

| | Inputs | Source |
|---|---|---|
| 1 | Lat | Database |
| 2 | Long | Database |
| 3 | Sum Fluids | Sum of item 5,6,7,8 |
| 4 | Prior-kh | Database |
| 5 | Water (bbls) | GA |
| 6 | Acid (bbls) | GA |
| 7 | Gel (bbls) | GA |
| 8 | Foam (bbls) | GA |
| 9 | N2 (Mcf) | GA |
| 10 | Sand Quantity (lbs) | GA |
| 11 | After-Test Type 3- Multi-Point 2- Single-Point 1- Open-Flow | GA |

**Figure 6 Neural Network Inputs and their source**

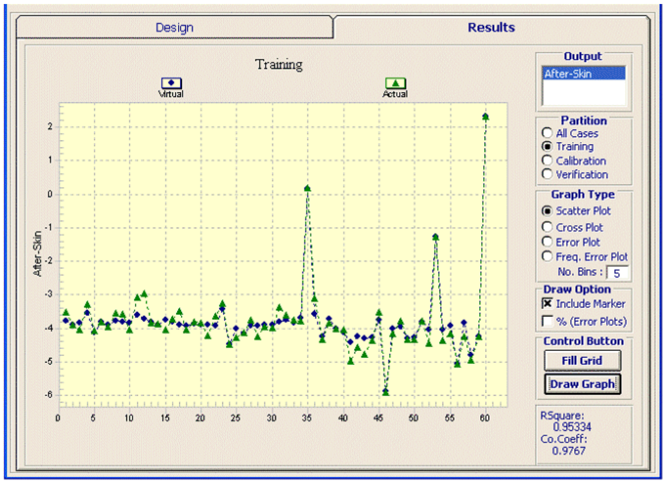


Figure 7 Accuracy of training data for the Neural Net

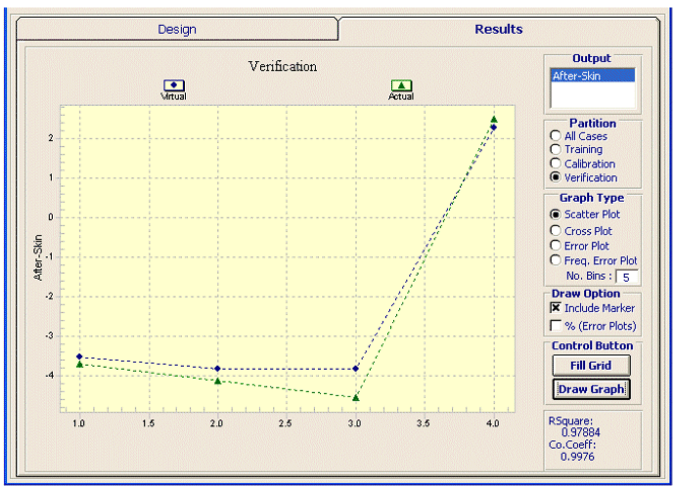


Figure 8 Accuracy of verification data for the Neural Net

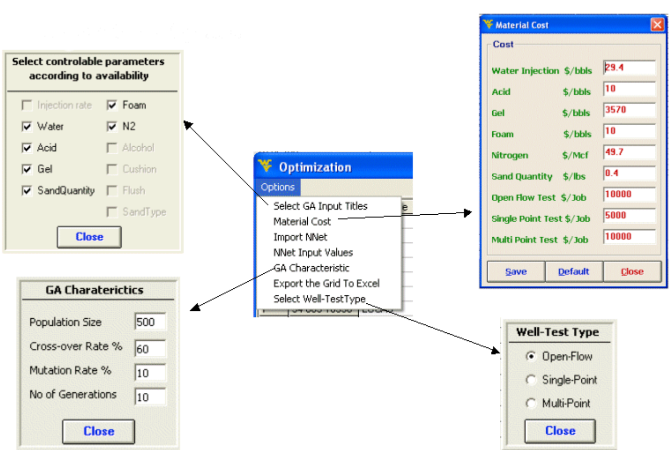


Figure 9 Different options in the software that make it versatile

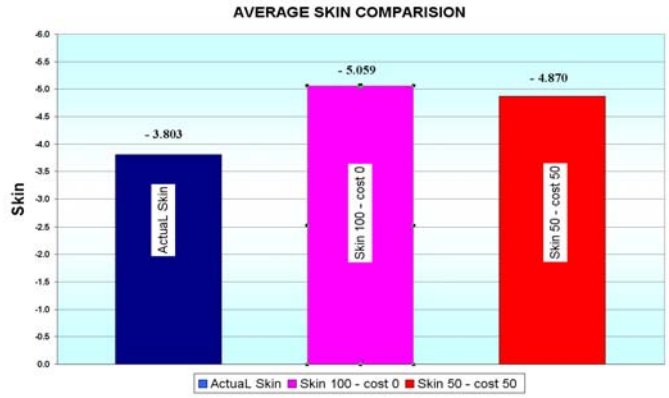


Figure 10 Comparison of Average skin after the stimulations

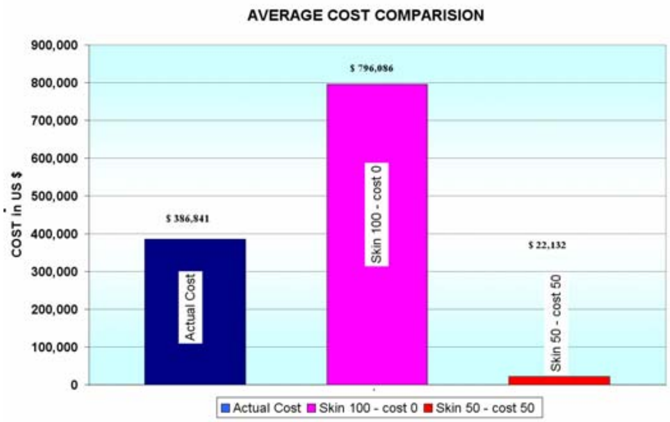


Figure 11 Comparison of Average skin after the stimulations

| | Water | Acid | Gel | Foam | N2 | SumFluids | SandQuantity | After-TestType | GA After-Skin |
|---|---|---|---|---|---|---|---|---|---|
| Actual | 146.51 | 11.69 | 533.43 | 0.02 | 366.56 | 691.65 | 28884.54 | 1 | -5.910 |
| Skin 50 - cost 50 | 298.41 | 11.12 | 0.52 | 0.52 | 218.21 | 310.57 | 9041.1 | 1 | -5.723 |

Figure 12 Comparison of actual & predicted skin of Well # 61

| Skin 100 -cost 0 | | | | |
|---|---|---|---|---|
| Rank | Well No. | GA After-Skin | Prior-Skin | Del Skin |
| 1 | 63 | -5.476 | 1.410 | -6.886 |
| 2 | 34 | -5.046 | -2.179 | -2.867 |
| 3 | 15 | -5.636 | -3.062 | -2.574 |
| 4 | 42 | -5.049 | -2.828 | -2.221 |
| 5 | 64 | -5.883 | -3.776 | -2.107 |
| 6 | 1 | -5.033 | -2.980 | -2.053 |
| 7 | 60 | -5.898 | -3.852 | -2.046 |
| 8 | 68 | -5.048 | -3.038 | -2.010 |
| 9 | 78 | -5.047 | -3.117 | -1.930 |
| 10 | 66 | -5.529 | -3.605 | -1.924 |
| 11 | 23 | -5.037 | -3.197 | -1.840 |
| 12 | 65 | -5.804 | -3.974 | -1.830 |
| 13 | 18 | -5.880 | -4.064 | -1.816 |
| 14 | 4 | -4.461 | -2.661 | -1.801 |
| 15 | 58 | -5.001 | -3.290 | -1.711 |
| 16 | 19 | -5.019 | -3.338 | -1.681 |
| 17 | 13 | -5.049 | -3.395 | -1.654 |
| 18 | 36 | -5.045 | -3.419 | -1.626 |
| 19 | 40 | -5.012 | -3.399 | -1.613 |
| 20 | 63 | -5.049 | -3.449 | -1.600 |

Figure 13 Top twenty wells according to 100% skin

| GAS STORAGE FIELD CHARACTERISTICS | VALUE |
|---|---|
| Specific gravity of gas | 0.585 |
| Porosity | 14 % |
| Average formation depth | 2000 ft |
| Max Allowable Pressure | 1150 psi |
| Delta pressure squared for Peak Day rate | 250,000 |
| Average thickness of storage formation | 10 ft |

**Table 1 Gas Storage Field Characteristics**

| GA CHARACTERISTICS | VALUE |
|---|---|
| Crossover rate | 60 % |
| Mutation rate | 10 % |
| Population size | 500 |
| No of Generations | 10 |
| Next Generation criteria | Top 30 % ranked from previous generation<br>60% from crossover<br>10% from mutation |
| Crossover criteria | Top 25 % has 75 % chance of Crossover |

**Table 2 GA Characteristics**