Novel Applications Of Artificial Intelligence Neural Network In Hydraulic Fracturing

Karim M. Magdy, Ahmed A. Gawish, Adel M. Salem

Abstract: Increasing productivity is a critical target for petroleum industry especially upon increased demand on petroleum products. The primary goal of a hydraulic fracturing treatment is to create a highly conductive flow path to the wellbore that economically increases well production, so Hydraulic frac is one of the major methods used to increase productivity if not the most efficient one. Field containing many wells makes it difficult to choose the most efficient one suitable for high productive frac .There are different screening criteria used, but still there are not sharp efficient, so I try in this research using artificial intelligence neutral networks to create a platform model for selecting the best well candidate for maximum overall productivity of an oil field, study the different affecting parameters on reservoir stimulation and predict the performance and future optimum designs . Artificial intelligence neural network is an information processing system simulating the natural neural system in the human brain. Using it, you can solve many complex petroleum problems that are difficult for traditional models and computing systems. It has shown great potential for generating accurate analysis and results from large amount of historical data that otherwise would seem not to be useful in the analysis. It also can make the best selection for any output relevant to several inputs and calculate the optimum value of it for different cases.

Index Terms: Hydraulic Fracturing, Machine Learning, Neural Networks, Productivity Index, Design Optimization

1. INTRODUCTION

Understanding well performance potential and variability is critical for optimization of reservoir development and well completion methods. The various faults in Gulf of Suez presents an especially challenging environment for analysis because of the commingled productivity of greater than 50 fluvial sand packages in a single wellbore distributed over greater than 5000 feet of gross vertical section. Single variable parametric analysis has been used to identify correlations or trends of completion parameters that impact hydraulic fracture stimulation stage performance. Examples of single variable analysis have been presented previously for proppant type evaluation and selection.1, 2, 3 Challenges of analysis in a reservoir system with a highly variable permeability distribution have been discussed previously.2 Reducing uncertainty in the analysis requires a large sample data set. Single variable analysis (SVA) techniques require isolated parametric variation to enable quantification of the impact of each parameter. Unfortunately, most data sets, including the one discussed in this paper, have coincident variation in multiple parameters. A summary of the SVA is presented to demonstrate the limitations of SVA for our data set. To evaluate the relative impact of system variables we make not control (such as permeability and subsurface geology), and operational variables we can control (such as proppant volume and flowback methods), we analyzed the data set using a multivariable analysis (MVA) technique.

- *Karim M. Magdy: Reservoir Engineering, Gulf Of Suez Petroleum Company, Egypt*
- *Ahmed A. Gawish: Petroleum Engineering, Faculty of Petroleum and Mining Engineering, Suez University, Egypt*
- *Adel M. Salem: Petroleum Engineering, Faculty of Petroleum and Mining Engineering, Suez University, Egypt*

A neural network (NN) modeling method was chosen because of the large data set available for training, calibration, and verification of the NN. Categorical flow rate output parameters were defined and a probabilistic method developed to identify sensitivities to input parameters. The neural network training and analysis process is discussed and application of the calibrated neural network model is then demonstrated for completion optimization decisions. Results of the completion optimization process are quantified, including an economic value evaluation.

2. DATABASE INTEGRATION FOR WELL PERFORMANCE AND COMPLETION ANALYSIS

To identify potential issues or trends related to poor or exceptional well production performance and enable optimization of development opportunities and completion methods, it is essential to create, maintain, and integrate a relational database that includes all of the important evaluation parameters.

The database includes: General well information, Well Completion and Stimulation data, Production inflow distribution data as measured by production logging tools (PLT), Formation Physical Property data, Flowback data, and Well Production data. A brief description of the data in each of these systems is described below:

GENERAL WELL INFORMATION

- Location, section, wellbore diagram, etc.
- Total of 100 wells
- 1000 Stage

WELL STIMULATION DATABASE

- Stimulation treatment data
- Total of 100 wells

PLT DATA

- Total of 50 wells
- Total of 90 PLTs
- Multiple PLT production analysis results1, 2

FORMATION PHYSICAL PROPERTY DATA

- Sums and average of Petrophysical data for sands and formations
- 200 wells

FLOWBACK DATA

- 100 wells

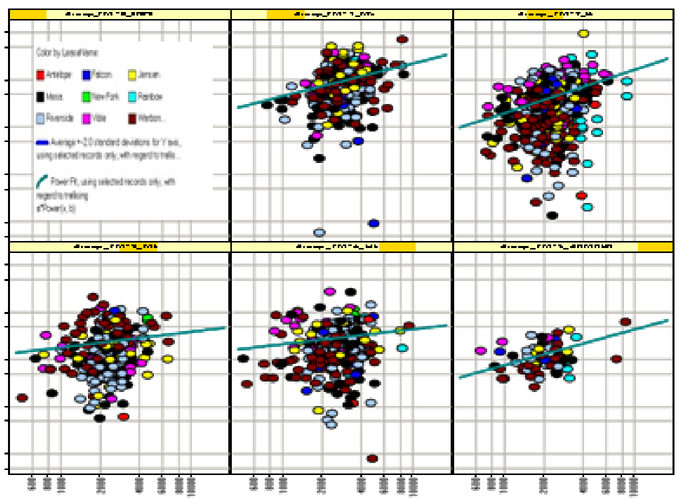
WELL PRODUCTION DATA

- Link to the network server production database

This data was initially compiled in separate data systems. To enable data mining for evaluation we integrated each of these data systems into a relational database. Zangl and Hannerer 4 present expectations for the data mining process and define the three main components as: 1) data preparation; 2) surveying the data; and 3) modeling the data. The time duration distribution to complete each task is estimated as 75%, 18%, and 7% respectively. We would add a fourth component, which is field trial validation of the model, and estimate our actual time duration distribution for the scope of this paper was 55%, 15%, 10%, and 20%.For best results and value, this entire process is iterative and continually updated as additional data is compiled. Time spent on each component is proportional to many variables including: resources allocated to each task; skills and competencies of the people executing each task; and drilling and completion schedules for the acquisition of the initial database and field trial validation testing. Quality of results is highly dependent on the skills and competencies of the people executing each task.

SINGLE VARIABLE ANALYSIS

Initial efforts to evaluate variation in well performance were performed using single variable analyses (SVA) of common parameters known to have potential impact on flow rate. Parameters considered were geologic location, proppant volume, proppant type, flowback method, and calculated petrophysical properties: net feet of pay (NFP or h, H), and permeability thickness (kh). At Gulf of Suez, there is large variability in well characteristics due to: 1) vertical and areal sand distribution in the fluvial depositional system; 2) pore pressure gradients ranging from 0.44 psi/ft to 0.83 psi/ft; and 3) closure stresses on proppant ranging from 4000 psi to 11000 psi. As a result of this high variability, total well production is not an appropriate discriminator for evaluation metrics. Also, due to the long gross interval and variable vertical distribution of sand intervals at Gulf of Suez, effective stimulation distribution requires partitioning the wellbore into frac stages with one or more sand intervals treated per stage. When more than one sand interval is completed in a stage, a limited-entry perforating design is employedAt Gulf of Suez, there is large variability in well characteristics due to: 1) vertical and areal sand distribution in the fluvial depositional system; 2) pore pressure gradients ranging from 0.44 psi/ft to 0.83 psi/ft; and 3) closure stresses on proppant ranging from 4000 psi to 11000 psi. As a result of this high variability, total well production is not an appropriate discriminator for evaluation metrics. Also, due to the long gross interval and variable vertical distribution of sand intervals at Gulf of Suez, effective stimulation distribution requires partitioning the wellbore into frac stages with one or more sand intervals treated per stage. When more than one sand interval is completed in a stage, a limited-entry perforating design is employed. The parameter chosen for comparative evaluation is the stage rate at a fixed time following production initiation. Production logging tools (PLTs) are run on each well to measure the vertical distribution of inflow from the multiple producing intervals. When single variable analysis efforts began, the average time for running the initial PLT was approximately 100 days. 1, 2, 3 We have chosen to continue to use the stage gas rate at 100 days as our comparison metric and use the term Qg100 to denote this normalized gas rate. Figure 1 is a cross-plot of normalized Qg100 per net feet of pay vs. total proppant per net feet of pay for each of the major geologic sub-intervals. Although there is significant variability in the data, there is a trend of increasing rate with increasing proppant in all of the geologic sub-intervals.



Total Pro p p er Net H

***Figure 1**. Amount of Proppant Used on Stage Productivity by Geologic Interval*

Figure 2 is a chart of average Qg100 for three different proppant types in the Mesa Verde (MV) interval. The numbers on each bar is the number of samples for each proppant type. The yellow bar is an economy lightweight ceramic proppant (EWLC), the black bar is an intermediate strength ceramic proppant (ISP), and the green bar is a high- strength ceramic proppant (HSP. HSP has only been applied in four stages in a Warbonnent well, but indicate excellent results. The ISP has outperformed the EWLC in a significant number of stages in the MV interval. Figure 3 is a chart of average Qg100 for three different proppant types in the Lower Lance (LL) interval. The numbers on each bar is the number of samples for each proppant type. The red bar represents results from 190 stages using a 20/40 white sand. The yellow bar is an economy lightweight ceramic proppant (EWLC) and the black bar is an intermediate strength ceramic proppant (ISP). Again, the ISP has outperformed the EWLC in a significant number of stages, and ISP and EWLC has outperformed the sand in the LL.
Flowback methomakelogy changed over time at Gulf of Suez to capture cost reduction opportunities through cycle time reduction and greater completion operations efficiencies. Evaluation of stage performance indicates that frac stages with extended shut-in for greater than 1 day (ESIT) have demonstrated lower flow rates compared with

frac stages with limited shut-ins of less than or equal to 1 day (LSIT). Figure 4 shows the cumulative distribution of 100 day normalized stage rate data. This data indicates comparable production performance for LSIT stages and a significant difference in well performance for the ESIT stages.

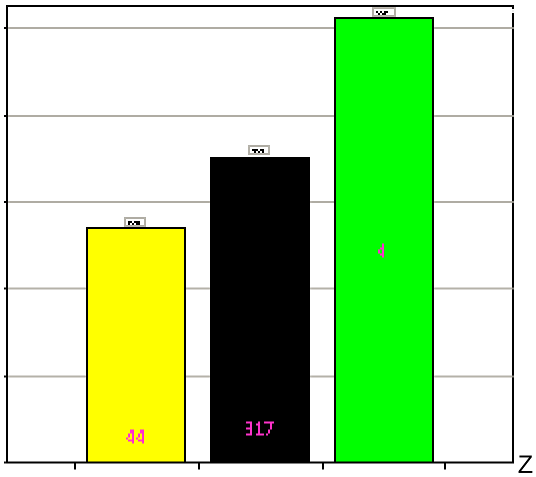


Figure 2. *Performance Comparison of*

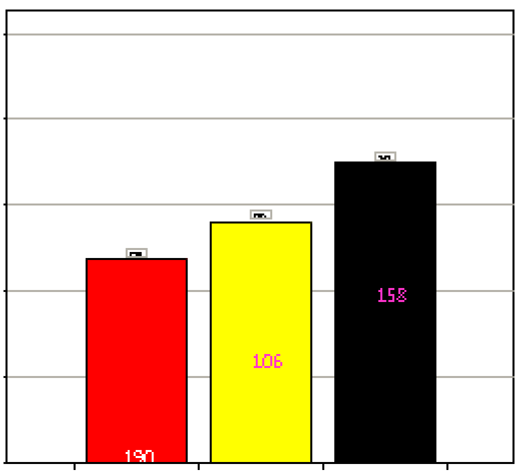


Figure 3. *Performance Comparison*

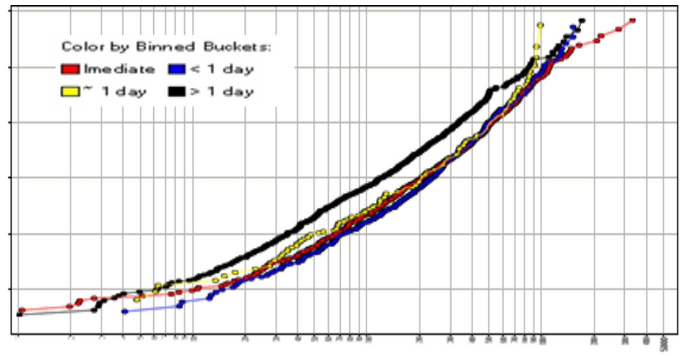


Figure 4. *Cumulative Distributions of Flowback Initiation Times.*

An additional layer of complexity in our data set is introduced by the distribution of well locations over time. Table 1 shows the ratio of wells that were completed in more crestal areas , as compared to wells that were completed in more flank areas , during the yearly time intervals of 2002 – 2004 and 2005 - 2006.

TABLE 1: RATIOS OF WELLS COMPLETED IN NR CREST VS. NR FLANK.

	NR Crest		NR Flank	
2002-04	17	53.1%	15	46.9%
2005-06	15	39.5%	23	60.5%

Figure 5 is a summary of expected ultimate recovery (EUR) vs. gas in place (GIP) results for crestal areas relative to flank areas north of the New Fork River. The crestal area clearly performs better than the flank areas for equivalent calculated GIP. Figure 6 is a summary of the crestal area EUR vs. GIP for wells completed in 2002-2004 as compared to wells completed in 2005-2006. Low-end GIP wells have equivalent EUR for each time period, but high-end GIP areas are experiencing lower EUR in the 2005-2006 time period. We expect we are experiencing more significant depletion in the higher GIP areas

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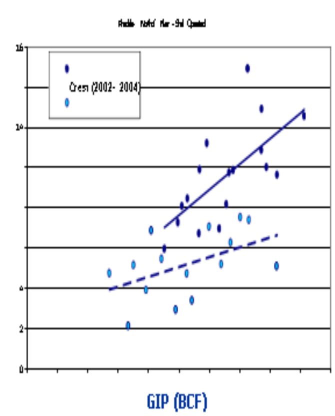

Figure 5. *Performance of Crest vs. Flank Figure 6. Performance of Crest vs. Time*

Neural Network Model Development

Applications of Neural Networks (NN) for well performance evaluation and completion optimization have been presented previously. 6-18 The objectives of the Gulf of Suez NN model development were frac design optimization and identification and characterization of geologic “sweet” spots for well performance. A FeedForward Neural Network process was used in a supervised learning mode with backpropagation to perform sensitivity analysis to determine how each input parameter affects the output (well performance). The dataset described above for single variable analysis was used and consisted of 1194 stages. Seventy percent (70%) of the data was used to iteratively “train” the NN until the level of error in predicted outputs were acceptable. Backpropagation with multi-layer perceptrons in the hidden layer, was used to determine the correlation and weighting factors between input and output variables, calibrate the “weighting functions” for each input variable, and reduce prediction error. Thirty percent (30%) of the data set was used to check the performance of the trained NN model against the “unseen” validation dataset.

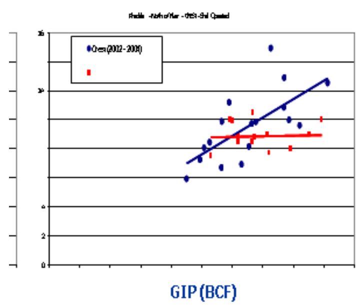

Figure 6. *Performance of Crest vs. Time*

Input variables found to have significant impact on the output variables were lumped into non-operational geologic and petrophysical input variables (such as: structural location, petrophysical H, porosity, and gas saturation) and operational completion input variables (such as: proppant volume and flowback timing). As discussed previously, the parameter chosen for comparative evaluation is the stage gas rate at a normalized 100 days (Qg100), as determined from PLT measurements. The FeedForward Neural Network with geologic, petrophysical, and operational parameter input variables, multi-layer perceptrons in the hidden layer, and categorical Qg100 output variables is illustrated in Figure

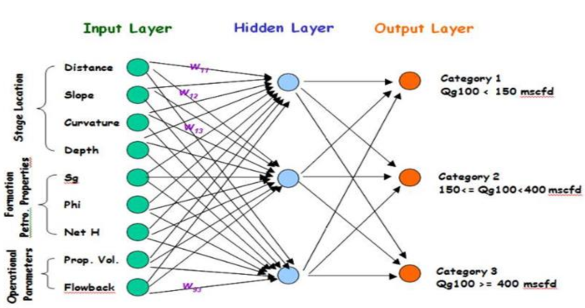

Figure 7. *FeedForward Neural Network with Geologic, Petrophysical, and Operational Parameter Input Variables and Categorical Qg100 Output Variables*

The geological parameters used to characterize stage location include:

- Distance = Distance away from global maximum location at the peak of the anticline structure.
- Slope = Slope of Structure Gradient (first derivative).
- Curvature = Laplacian (second derivative), Concave or Convex Curvature.
- Depth (or DeltH) = True vertical depth from the top surface of the structure, gamma ray marker (GRMRKR).

The formation petrophysical properties that have the greatest impact on stage productivity performance are:

- Sg = Gas Saturation
- Phi = Porosity
- Net H = Net feet of petrophysical pay

The operational parameters having the greatest impact on stage productivity performance are:

- Proppant Volume = Total volume of proppant placed in formation per stage
- Flowback = Flowback initiation timing after stimulation treatment

Proppant type varies as a function of depth as illustrated in Figure 8. Data clustering was required to create different models to assess the impact of different operational parameters. Only shallow stages with sand as the proppant, and deep stages with intermediate strength proppant (ISP), have sufficient sample size for effective data mining. Initially two NN models were developed to evaluate the two separate sand and ISP data sets.

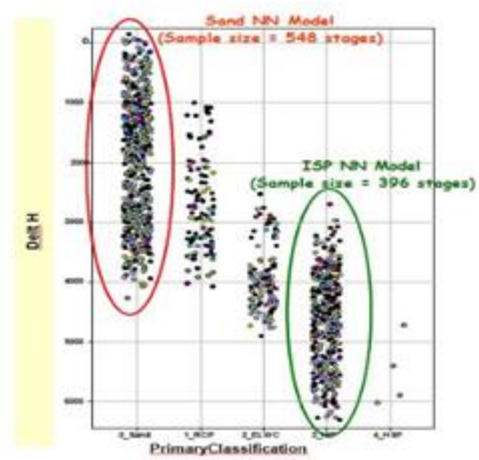

Figure 8. *Proppant Type as Function of Depth Below Top of Productive Interval (DeltH)*

The remainder of this paper will focus on the ISP NN model, as this model has extensive field trials to demonstrate the application process. The accuracy matrix of the training data set for the ISP NN model is shown in Figure 9. Note that the accuracy along the matched predicted/actual diagonal is 60 – 67%. Note also, the error for predicted Category 1 resulting in actual Category 3 is only 5% and the error for predicted Category 3 resulting in actual Category 1 is only 6%. This matrix demonstrates the confidence that can be expected in the prediction model.

Predicted

	1	2	3
3	5%	21%	67%
2	28%	60%	27%
1	67%	20%	6%

	1	2	3
3	5%	21%	67%
2	28%	60%	27%
1	67%	20%	6%

***FIGURE 9**. ACCURACY MATRIX OF THE ISP TRAINING DATA SET FOR THE NN MODEL.*

The relative impact of the most significant variables on stage production performance is summarized in the Figure 10. This data suggests that on average, over 80% of the stage production performance is controlled by subsurface geological and petrophysical characteristics. Less than 20% of the stage production performance is impacted by completion design parameters. Note that 10% of the stage performance is impacted by total proppant volume, and 9% of the stage production performance is impacted by shut-in time prior to flowback operations (FB2G1 = Flowback beginning at greater than 1 day).

TotalProppant 10%

Sg 12%

Net 15%

FB2G1 9%
DeltH
9%

Gradient 9%

Phi 6%
Distance 5%

Laplacian 25%

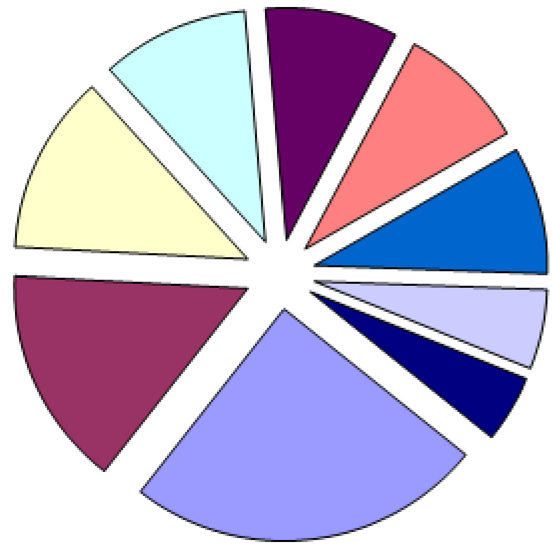

***Figure 10**. Average Contribution of Each Input Parameter to Neural Network for ISP Model.*

The implementation value of the NN process we developed is that probability distributions are calculated for potential Category 1, 2, and 3 outcomes as a function of input variables. These probability distributions provide the basis for

completion optimization opportunities and “sweet spot” identification.

An example of application of the ISP NN for completion optimization associated with proppant volume is further developed in the next section

.

Application for Completion Optimization

The completion application process described in this paper is limited to proppant volume optimization. A similar process could be applied to flowback methods, proppant type selection, or other operational variable opportunities as identified in a NN development phase. After drilling the well, acquiring evaluation logs, and calculating petrophysical properties for the gross interval to be completed, a multidisciplinary team gathers for a “stage-out” meeting to select intervals to be completed. Following the “stage-out” meeting, the completion engineer designs a limited entry fracture stimulation treatment to optimally combine multiple sand intervals into completion “stages”. These stage characteristics are then input to the trained NN model and probability distributions are calculated for each stage to identify sensitivities to proppant volume. Figure 11 illustrates the probability distributions for Category 3 Qg100 outcome vs. total proppant placed for stages 1 – 7 of a 2009 NR Crest well. The shape of the data points on the curves identifies the stage number. The color of the data points indicates whether the likely outcome will be a Category 1, 2, or 3 Qg100 as indicated in the legend.

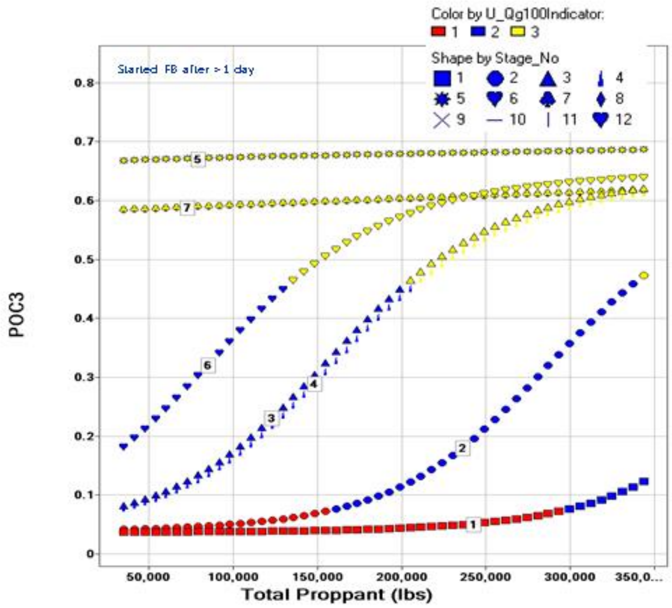

Figure 11. *Probability Distributions for Category 3 Outcome vs. Total Proppant Placed for stages 1 – 7 for 2009 NR Crest well.*

Note that stages 5 and 7 have very little sensitivity to proppant volume and are likely to be Category 3 stages independent of proppant pumped. Stage 1 also has very little sensitivity to proppant volume and is likely to be category 1 stage independent of proppant pumped. Stages 3, 4, and 6 are very sensitive to proppant volume and the outcome may fall in a Category 2 or 3 stage dependent on the proppant volume pumped. Stage 2 has some sensitivity to proppant volume and the outcome may fall in a Category 1 or 2 Qg100 dependent on the proppant volume pumped.
Note that a minimum areal proppant concentration (APC) of 1.0 pounds per square foot is pumped in each stage for a calculated 400 foot fracture half length, even for stages with little sensitivity to proppant volume from the NN model. A total number of 195 stages with PLT results were evaluated for 2009 ISP NN trials. Of these 195 stages, 49 stages were identified for proppant volume increases. One thing to note is the cumulative distribution of Qg100 for these 2009 trial stages is significantly less than the NN model Qg100 distribution as illustrated in Figure 12. The reduction of Qg100 in the 2009 stages is primarily due to the pressure depletion we are experiencing from infill makewnspacing compared to the 2002 – 2006 training data used for the NN model calibration.

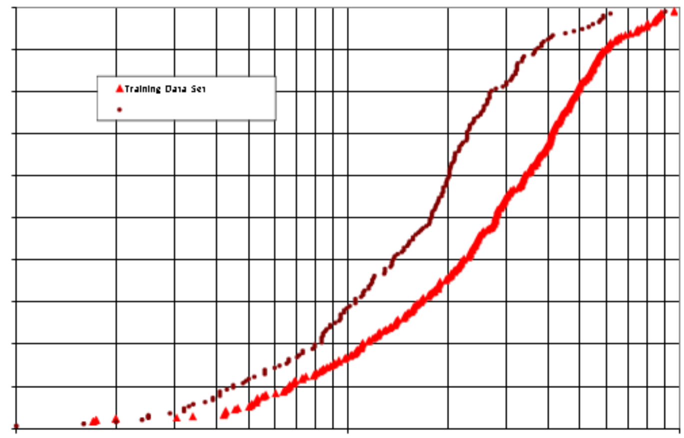

Figure 12. *Cumulative distribution of Qg100 for 2009 trial stages compared with the NN model Qg100 distribution.*

Even with the uncertainty introduced from the impacts of pressure depletion from makewnspacing, we have experienced excellent results from the 2009 trials..

SUMMARY AND CONCLUSIONS

The value of developing, maintaining, and analyzing a comprehensive database has been demonstrated in this paper. Limitations of single variable analysis (SVA) in a complex geologic environment have been highlighted. The complexity of sub-surface variability, the distribution of development well locations over time, and non-sequential coincidentcompletion variable modifications makes SVA very challenging and results in large uncertainty in the well performance interpretations. To better understand the significance of this complexity, variability, and uncertainty, we developed a multi-variable analysis (MVA) method to calibrate a Neural Network (NN) model and process to perform sensitivity analysis to determine how each input parameter affects the well performance. Operational variables that were important for well performance were determined to be proppant volume and flowback timing. An optimization process was developed that enables identification of stages with high or low sensitivity to proppant volume and/or flowback timing, and the probability of realizing high, average, or low stage productivity. Application of the ISP NN model for proppant volume optimization was demonstrated with 195 stages during the 2009 development program at Gulf of Suez. Forty-nine stages were selected for increasing the proppant volume and resulted in an incremental 1,962 Mscf/d production at a cost of $2.23 million. Economic return on investment was very favorable for gas price $3.00 per Mscf/d, with breakeven economics at a $2.60 gas price.

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