

Monitoring, analyzing, and optimizing Waterflood Responses

Leon Fedenczuk, Gambit Consulting Ltd. Calgary, Alberta*

ABSTRACT

During a waterflood, large amounts of injected water are used to maintain and/or increase oil production from a petroleum reservoir. This paper shows how comparing the changes in oil, gas, and water production (relative to the water injection changes) helps assess fluid communication through a reservoir. The results are presented with special diagrams and contour maps, which show up to six communication parameters.

The communication parameters are integrated with other geological parameters and used to develop predictive models. These predictive models help estimate the production capacity or production probability in waterflooded reservoirs.

This paper also shows how decision tree models support a two to four times more accurate selection of high production wells than historically implemented selections.

Finally, this paper shows the implementation of a profit matrix in a decision process for outcome optimization.

INTRODUCTION

This paper is based on our developments for analyzing injection responses in vertical and horizontal patterns for waterflood optimization. The injection responses are estimated from non-parametric correlations between changes in the injection rates and the corresponding changes in the production rates (oil, water, gas, and total fluid). In addition, we estimate the time lag of the above responses. Our analytical principles were developed based on our experiences from studies of a variety of fields (e.g. Golden Lake, Swan Hills, Midale, Valhalla, Goose River, Cactus Lake, Mirage, and Pekisko B.) and recently published in the JCPT Journal (June 2001)¹ and CIM Technical Meeting (at CIPC2002)². Furthermore, the same technique was successfully applied to detect communication between producers and helped in designing new waterfloods.

WATERFLOOD RESPONSES

A waterflood response is estimated as a rank correlation between two series of rate changes for all of *injector-producer* pairs. Specifically, the non-parametric Spearman rank correlation coefficient is calculated based on ranks of the injection and production rate changes³.

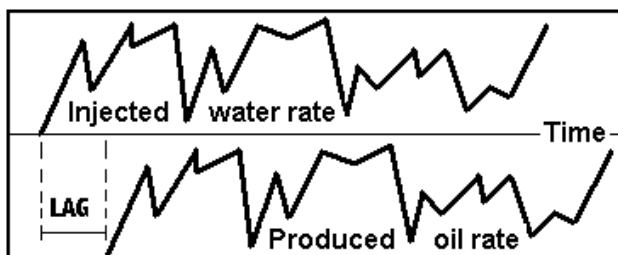


Figure 1. Perfect lagged waterflood response.

Figure 1 shows a perfect correspondence or correlation between two time series (the injection rate and the oil production rate). However, the oil rate is shifted in time, which characterizes the waterflood response time lag. In this case the waterflood response (based on the oil rate) would have a correlation equal to one. In practice, we calculate a set of lagged correlations at time lags from zero to 12 or more months. Then, we find the highest correlation and the corresponding time lag. Water, gas, and total

fluid responses are calculated in the same fashion³.

The correlation and the time lag between the injection and the associated production rate changes, allow us to compress a series of rates into a pair of simple parameters: the correlation (response strength) and the time lag for every produced fluid.

RESPONSE INTEGRATION

Injection-production correlations and the corresponding time lags for oil, gas, water, and the total fluid, can be integrated with geological parameters at local and global scales. There are two main approaches to the integration process. In the first, a more traditional approach is used where each parameter or a combination of parameters is presented in the form of a special graph or map. These graphical forms are interpreted on their own or together with other geological parameters by performing a visual comparison and analysis. Overlaying graphs and maps on a light table further enhances such analyses. In the second approach integration processes involve numerical and statistical techniques, which are based on regression, neural network, and decision tree modeling.

Both the waterflood response parameters and geological data sets are noisy and account for a relatively small portion of the total variance in the target variables (e.g. production). Predictive modeling helps summarize these multivariate data sets and relates them to geological and production events. In addition, it helps identify the most important factors, which are then used to develop the predictive models. These models can be quantified, and used to select the development efforts in areas with the highest possible potential.

SPECIAL VISUALIZATION TOOLS

In analysis and predictive modeling, special visualization tools improve the interpretation process of the waterflood responses and results. In regular patterns with vertical wells, the correlations (oil, gas, and total fluid responses) and associated time lags can be presented in the form of a single or a *composite spine diagram*.

The correlations for non-symmetrical patterns or patterns with horizontal wells can be presented on *spider graphs*, which show both the short and the long distance communication.

Figure 2a is an example of a composite spine diagram for oil responses. Individual spine diagrams for every pattern are presented on an xy crossplot with injector and producer locations (red circles, green squares, green and red spine lines).

Wells that could not be analyzed (no data or too few points) are marked with green diamonds. The injector's location is at the centre of each spine diagram. Figure 2b shows a composite spine diagram for total fluid responses, which are represented by blue and red spines.

These diagrams show normalized absolute responses on a scale of 0-1.0 between the center and the outside of the circle. A light line in the middle marks the half mark on the scale. Green and red spines in Figure 2a represent the positive and negative oil-based responses (correlations). The blue and red spines represent the total fluid responses in Figure 2b.

Furthermore, normalized volumes at each injector and producer govern the size (radius) of the specific spine diagram. The projection volumes are normalized or ranked relative to the field's total.

Figure 3a and Figure 3b show composite spider diagrams, which are based on an xy-crossplot as well. Each injector well is the source of a spider net. These diagrams are made of radiating

lines that connect to wells that responded to the specific injector above the assigned correlation level. A correlation cut-off equal to 1/2 presents the strongest responses, while a lowered cut-off identifies wells with a wider range of responses. As with the spine diagrams, green or blue and red lines represent positive and negative correlations respectively. In addition, two line types increase the dimensionality of the system. Solid and dashed lines represent responses with a time lag below and above six months respectively. The two examples in Figure 3a and Figure 3b incorporate the normalized injection and production volumes at each well.

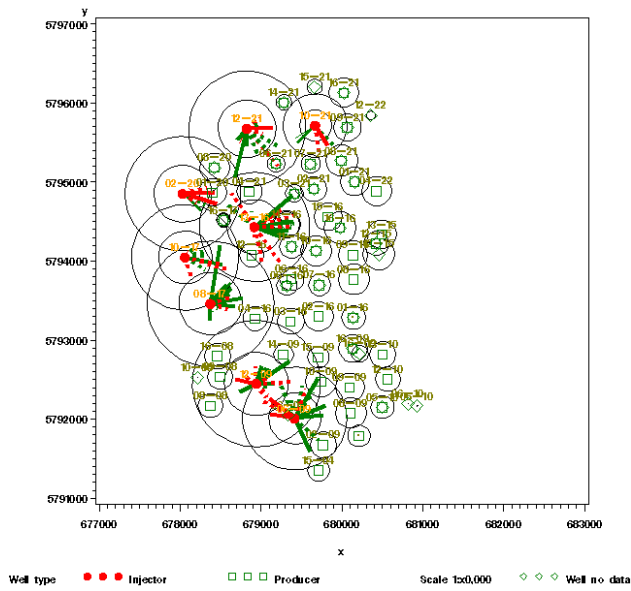


Figure 2a. Composite spine diagram for oil responses.

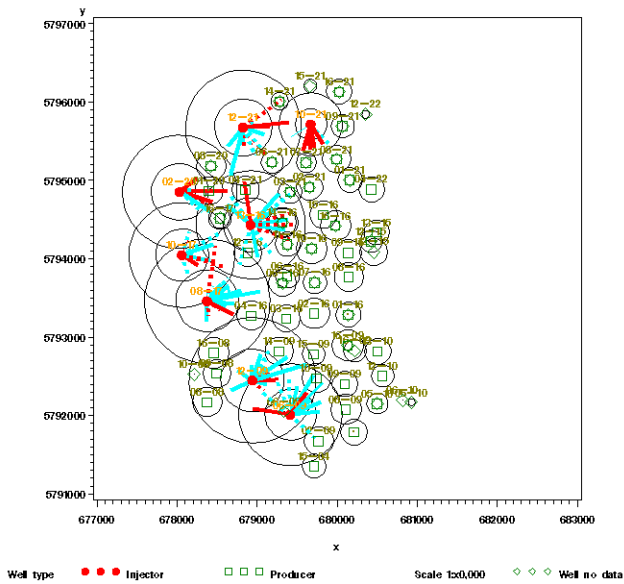


Figure 2b. Composite spine diagram for total fluid responses.

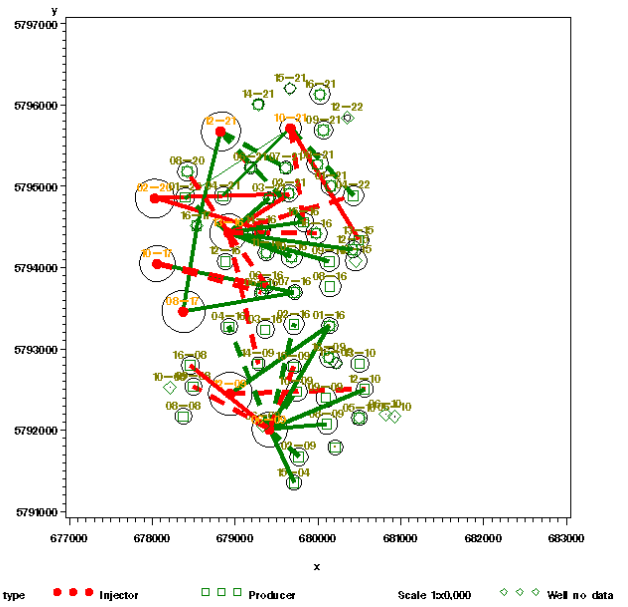


Figure 3a. Composite spider diagram for oil responses.

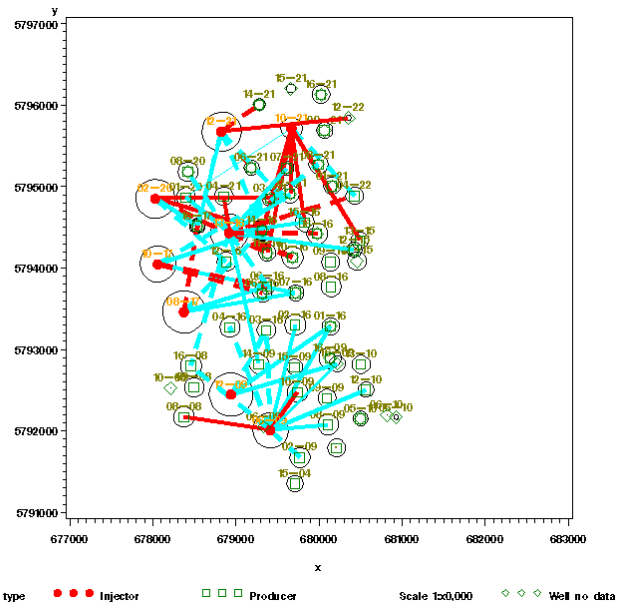


Figure 3b. Composite spider diagram for oil responses.

RESPONSE TYPE

The same visualization diagrams can be utilized to present a new parameter that links two responses based on two different fluids. The new parameter is based on one of the following response (correlation) pairs:

- oil and total fluid
- oil and water
- oil and gas.

In general, we call these response combinations “*type of waterflood response*”. These response types can be compared with parameters that represent geological, geophysical, and petrophysical properties. Details on the waterflood response definition can be found in our earlier publications^{4,5}.

Figure 4 presents a contour map (image on the right) of flow units that were based on the waterflood response type. This response type was derived from the oil and total fluid responses. The left

image shows definitions of nine classes for the response types based on two responses and a cut-off, above which the individual responses are defined as strong.

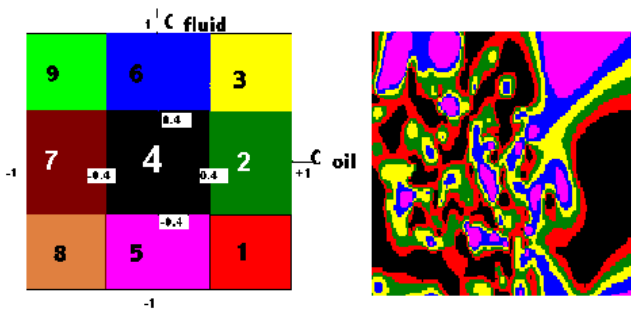


Figure 4. Response type definition and contour map of flow units based on the oil and total fluid response types.

Composite diagrams and maps of the injection responses and their combinations (classes or response types) are utilized to evaluate:

- sweep efficiency
- selection of areas for the infill programs
- identification of ineffective injectors
- identification of producers without support
- better estimates of the production allocation
- areas with fluid losses
- communication / correction maps for reservoir simulation.

PREDICTIVE MODELING

A numerical integration of geological, completion, treatment, and waterflood response parameters is the ultimate technique for predicting oil production during enhanced recovery processes^{6,7}. Predictive models can be developed for a continuous target variable (production) or for a binary target variable (poor or good well). In each case, different model types have to be built and compared. These models can be based on regression, neural networks, and decision trees. A model that has the best predictive powers and stability can be implemented to predict well performance in a specific area or the whole field. Figure 5 shows a decision tree, which classifies wells into two groups of good and poor performers². The target variable was predicted based on the netpay (P_Net_Oil), non-lagged gas response (C_Oil_0), and the top's subsee (P_SUB_Top). The indicator variable (Y/N for Good/Poor well) was derived from the normalized oil production and identified the best 25% of all wells in the whole field. The normalized oil production was characterized by a well's production relative to the whole field's production.

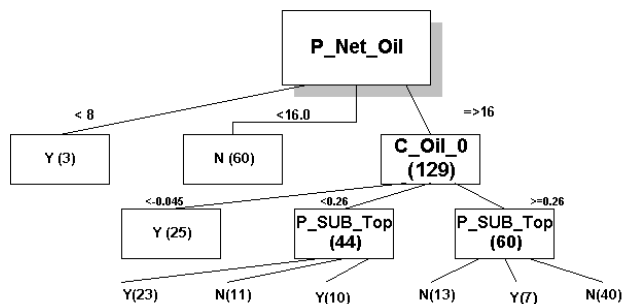


Figure 5. Decision tree model, based on the geological and waterflood injection parameters (Y/N=Good/Poor well).

An advantage of the decision tree model over other types of

models is that it utilizes interpretable English rules. For example, "If netpay is greater than 6 m and the lag zero gas response is negative, then oil production will be in the top 25% of the best production with a probability of 80%". In the above case, the model based well selection resulted in a success rate of two to four times better than by traditional methods and historically observed in the field².

An example of a pseudo code that corresponds to some portions of this decision tree is presented below:

```
IF      16.1 <= P_NET_OIL < 17.9
      AND -1250.35 <= P_SUB_TOP < -1244.95
      AND 0.26 <= C_OIL_0
THEN
P1      = 100.0%
P0      = 0.0%
```

```
IF      P_SUB_TOP < -1252.21
      AND -0.045 <= C_OIL_0 < 0.26
      AND 16.1 <= P_NET_OIL
THEN
P1      = 65.2%
P0      = 34.8%
```

```
IF      C_OIL_0 < -0.045
      AND 16.1 <= P_NET_OIL
THEN
P1      = 20.0%
P0      = 80.0%
```

where

- P1 is probability of good well
- and
- P0 is probability of poor well.

The actual decision model can be implemented with any available software package (e.g. C, C++, Excel).

OPTIMIZING AVERAGE RETURN

Many modeling decisions as well as the model selection, depended on the misclassification rates. Figure 6 shows a confusion (classification) chart with agreements between the actual and the predicted counts for a tree model at the 50% threshold value. This diagram helps verify the agreement between the actual and the predicted classes at different threshold levels. The threshold level is the cutoff that was applied in classifying observations based on the evaluated posterior probabilities. If a predicted score was below the threshold value, then the predicted production class was assigned to zero (production below the desired level), otherwise the class was assigned to one (good production).

A threshold-based interactive profit chart represents a higher degree in decision making. This chart enables observing the relationship between the return/profit and the threshold value for a specified profit matrix. Well identification efforts and drilling programs have associated costs and returns on investment for each case of all possible outcomes. Figure 7 presents a profit matrix for four cases of relationships between the predicted and the actual outcomes for a binary outcome. A simple (0/1 or N/Y) decision schema had two cases of misclassification and two cases of correct classification. The assigned profit was based on a simple principle that a successful prediction (identified as a good prospect) would generate 10 units (in millions of \$, see 1/1

cell with return=10). A non-successful well pick, which was classified as a good producer, had a negative return related to the corresponding loss (-0.5). The predicted non-events were classified in a similar way, where 0 was assigned for the 1/0 case (no revenue or missed opportunity), and 0 for the 0/0 case (the correct prediction of the non-event). This was one of many scenarios that were used to test the model performance, stability, and sensitivity. The presented values do not reflect actual values in this particular field.

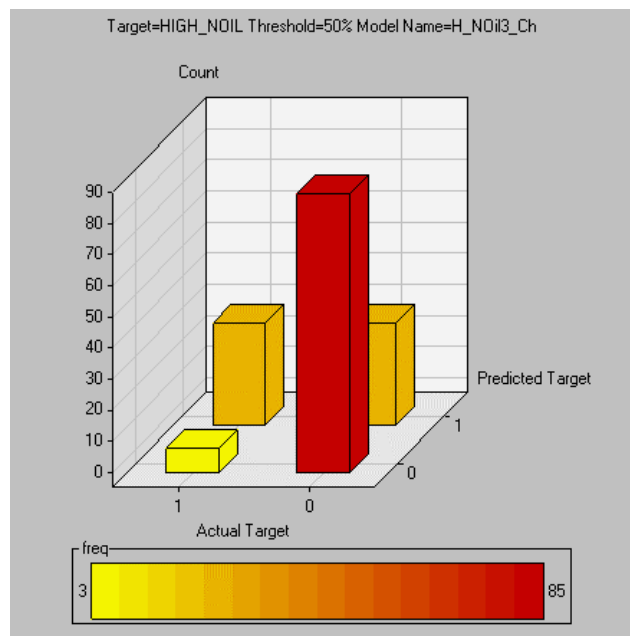


Figure 6. 3D confusion (classification) chart for a tree model at a threshold of 50%.

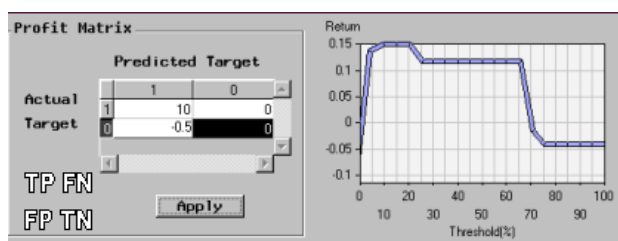


Figure 7. Profit matrix and profit (return) chart.

The corresponding profit (return) chart in the above shows a relationship of the estimated average return versus the classification threshold value (if posterior probability \geq threshold, then class=1). The diagram shows that thresholds in a range of 5-50% should generate the highest average return per well. It shows that the best average return and the highest total production volumes could be achieved at the 5% threshold value (If posterior probability \geq 5% then GOOD).

The above example characterized a relatively successful waterflood implementation, where a large amount of laboratory studies was undertaken before decisions were made. The fine-tuning of a threshold value, which is used in a final model, is especially important in projects where specific misclassifications affect the economical outcomes (e.g. missing good wells – false negative).

CONCLUSIONS

A new exploitation set of tools for analyzing production data during waterfloods has been designed and tested with the use of the SAS® system. The SAS BASE, SAS/GRAPH, SAS/STAT, SAS Enterprise Miner, PROC G3D, PROC G3GRID, PROC GCONTOUR, annotate, and macro facilities have been chosen to build the system. The above system produces special plots and predictive models. This paper demonstrates how these special plots (diagrams) can be incorporated in multidimensional data analysis. Furthermore, these diagrams improve interpretation of production changes, lead to better understanding of field behavior, and help in verifying results of statistical models, which is difficult or impossible with other graphical tools.

In a typical study we generate a few dozen composite diagrams and contour maps that show oil, gas, water, total fluid responses, their corresponding time lags, and a variety of response types.

In an integration process, sets of composite star diagrams are overlaid with contour maps of facies or maps of the netpay. These presentations help find the significant relationships between the producer's responses and the underlying geology.

Predictive models help estimate the production capacity or production probability, and are based on available geological, completion, and engineering data in waterflooded reservoirs. We built models that derive solutions with decision trees that are equivalent to sets of English based rules.

These models support a two to four times more accurate selection of wells with high oil production during EOR than historically implemented selections.

Our special visualization tools and predictive modeling lead to a better understanding of field behavior. They also help to evaluate sweep efficiency, selection of areas for the infill programs, identification of ineffective injectors, identification of producers without support, better estimates of the production allocation, finding areas with fluid losses, and developing communication/correction maps for reservoir simulation.

The advantage of our analysis and the prediction of waterflood responses is the method's capability for an unbiased and quick analysis and interpretation of large fields during enhanced oil recovery (waterflood).

The analysis is based only on the available injection and production history (publicly available data). Furthermore, the same methodology can be used to predict waterflood communication paths based on the primary production from interaction between producers.

REFERENCES

1. Leon Fedenczuk, Paul Pedersen, Marc Marshall, Analyzing Waterflood Responses for Pekisko B., *Journal of Canadian Petroleum Technology*, vol. 40, No. 6, June 2001, pp. 29-35.
2. L. Fedenczuk, K. Hoffmann, and T. Fedenczuk, Predicting Waterflood Responses with Decision Trees, Canadian International Petroleum Conference 2002(The 53rd Annual Technical Meeting of the Petroleum Society), June 11 – 13, 2002, Calgary, Alberta, paper 2002-028.
3. Mark L. Berenson and David M. Levine, "Basic Business Statistics Concepts and Applications", *Prentice-Hall, Inc., Englewood Cliffs, New Jersey 07632, 1983, ISBN 0-13-057620-4*.
4. L. Fedenczuk, K. Hoffmann, Surveying and Analyzing Injection Responses for Patterns with Horizontal Wells, *International Conference on Horizontal Well Technology, November 1-4, 1998, paper No. SPE 50430*.

5. Leon Fedenczuk, Paul Pedersen, Marc Marshall, The Petroleum Society of CIM – 50th, *Paper 99-46, Annual Technical Meeting, June 14-18, 1999*
6. L. Fedenczuk, K. Hoffmann, “Data Integration and Analysis for Optimal Field Development”, *The Petroleum Society of CIM - 48 th Annual Technical Meeting, June 8-11, 1997, paper 97-45.*
7. John C. Davis, “Statistics and Data Analysis in Geology”, *John Wiley & Sons, 2nd Edition, 1986, ISBN 0-471-08079-9.*

CONTACT INFORMATION

Your comments and questions are valued and encouraged.

Contact the author at:

Leon L. Fedenczuk or Kristina Hoffmann
Gambit Consulting Ltd.
268 Silvercrest Dr. N.W.
Calgary, Alberta, T3B 3A4 Canada
Tel: (403) 288-6754
Email: leon@gambitconsulting.com

*Currently with Kemper Insurance, Long Grove, IL.