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Sand-Selective Optimization Methodology reduces Water Cut and Improves Production in Mature Fields: San Francisco, Colombia

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Abstract

A new methodology, in order to optimize production on a per-sand basis, was developed for the San Francisco field, Colombia. In the year 2009, a breakthrough methodology was been implemented in the San Francisco field, Colombia, to yield an additional 12% in remaining reserves by optimizing production and injection based on key principles of the ´learning theory´. However, the need for a more thorough optimization was evident.

The San Francisco Upper Caballos formation produces from 8 different sand bodies, KCUA-KCUF. These sands differ petrophysically and in saturations. With over 15 years of water injection, recent ILTs were proof that several sands had not experienced good waterflooding, mainly due to their less favorable petrophysical properties. A methodology to identify remaining saturations per sand, as well as design injection patterns that would remedy this will be presented.

Historical decline of the San Francisco field was between 14-17%. For the years 2009-2011 decline has remained steady at 8.5%, a value previously unseen. Additional reserves are already evaluated at 0.6 MMbo as of 2011, from adjustments to injectors and producers. This paper will present this methodology and its viability in mature waterflooded fields.

Introduction

The San Francisco field was discovered in 1985. It is located 20 km northwest of the city of Neiva in the Upper Madgalena basin (Colombia), and produces at a depth of 3,000 ft. This north-to-south trending structure is controlled by a basement-rooted ramp-style thrust fault.

San Francisco mainly produces from the Cretaceous Upper Caballos formation. There is also commercial production from the Lower Caballos formation and from overlying Villeta formation limestones.

San Francisco field total cumulative oil production was of 162.8 MMbbl and average production was 7,556 bopd in August of 2010.

The field has a history of water injection with good success (ref. 1 & 2). Any tertiary recovery technique or alternative technology could not practically be applied, as this would have taken a long time to test and validate, which would defer financial return.

Therefore, the best strategy for HOCOL was to amplify the effectiveness of the water injection project, using any possible leverage. This included horizontal and vertical injection-pattern fine-tuning. Additional investment has been considered: conversion of producers into injectors, surface treatment and/or improved injection facilities. But also, a reshuffling of the whole existing water-injection hardware had to be envisaged.

After a first optimization project in the KCU formation, where the right balance between producers and injectors and appropriate injection rates was identified (2008, ref 3.), a further waterflood improvement was contemplated in selectively readjusting and amplifying the injection and production per layer. Because of the complexity of the geology and the past unstable production trends, a huge combination of possible development plans needed to be contemplated.

Therefore, only a massive optimization process could properly tackle this challenge. This requires, first, a relevant understanding of the field mechanisms, and second, the use of an Optimization Engine.

Global Methodology

A selective, optimized injection and production program (in limiting/stopping injection/production at certain depths) has been developed by:

(i) Using log tests available and by carrying out a five-month field test, in order to collect specific production data coming from selective injection and production, and improved oil-cut and/or liquid production;

(ii) Reducing constraints related to surface equipment (water injection), in order to further boost oil production, through a massive optimization of the injection pattern.

Deliverables of this project were:

- A well-selective intervention pilot which allowed learning of reservoir behavior from well response to production/injection parameter changes at individual layers of the Upper Caballos (KCU) formation;

- Recommendation for further layer-selective injection and production jobs;
- A learning process derived from past behavior of the whole field and from the pilot results, leading to a customized Production Simulator for field-wide optimizations.
- As a result of a massive optimization process, quantified and precise recommendations (injection/production rates) in order to optimize the injection scheme over the full field, with available facility capacity/limitations taken into account.

Geological Layer Model

Layer allocation is mainly based on log interpretation – wherever available.
The layer allocation firstly used was based on 1994 data. In 1997 the layer allocation was reworked partially. Since this 1997 work was not completed, the set of data is not fully consistent. The reallocation job was resumed in 2010 to complete and build a full set of data.

The new allocation relies on a fluvial deposition model. The top marker for the E layer (KCUE) is found in every well. It corresponds to a Paleolithic fluvial topography (after tectonic) after which latter layers accumulated. The top marker for the A1 layer (KCUA1) is found in every well as well. The main job consisted of indentifying thicknesses and tops for layers A2 through C3 (KCUA2-KCUC3).

The topographic depositional map is presented below (Fig 1). Blue areas represent fluvial channels. After deposition was completed, tectonics created the anticline and fractures present today.

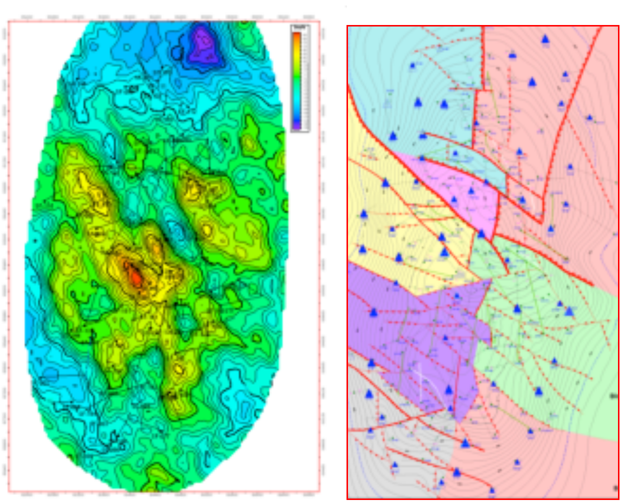

Figure 1. Topographic despositional map (left) and the current structural map (faults/ blocks) (right).

Layer tops were identified from well logs for most wells, with thicknesses being determined from these. In remaining wells, layer thicknesses were interpolated from surrounding wells and populated starting from the top. If the available space in thickness was not sufficient, the lower layers were discarded.
Allocation of layers is also linked to vertical connectivity. Some wells do not present an inter layer marker. Interlayer bounding must be checked individually per well. A GR log – when available – is the main indicator of vertical connectivity. When a selective layer job is proposed, the GR log data is used to check for behind-casing feasibility of selective layer stimulation and production. This guarantees the efficiency of such selective treatment in the given well.

Identifying favorable layers

The pilot phase aimed at identifying and stimulating layers having the best oil-increment potential. A statistical approach, based on uneven perforations of producers, was used to choose layers with the best oil cut at present.
Production data was used as input. Monthly average flow is considered and calculated as the average daily fluid flow over the full production period. Targeted outputs are allocation of flow per layer for the given set of wells. Even with a limited set of wells in one given block, the quality of the result is supported by the number of equations – wells –, which is sufficiently greater than the number of unknowns – layers –. The variety of perforated layers per well is illustrated by the table below (Figure 2):

BLOCK B-1	SF-002	SF-007	SF-009	SF-011	SF-026	SF-029	SF-030	SF-032	SF-033	SF-034	SF-035	SF-036	SF-037	SF-038	SF-042	SF-045	SF-067	SF-073	SF-074	SF-075	SF-084	SF-085	SF-086	SF-090	SF-091	SF-111	SF-112	SF-123	SF-124	SF-170	SF-179	SF-184	SF-186
CABALLOS - KCUA1			■																		■		■			■		■					■
CABALLOS - KCUA2			■	■													■				■		■			■	■	■		■			■
CABALLOS - KCUB	■	■	■	■	■			■	■	■	■	■	■	■		■	■	■	■		■	■	■	■		■	■	■		■	■		■
CABALLOS – KCUC1	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■		■	■			■		■	■	■	■	■	■	■	■	■	
CABALLOS - KCUC2	■	■	■	■	■	■	■	■	■	■	■	■	■		■	■		■	■	■		■		■	■	■	■	■	■	■	■	■	
CABALLOS - KCUC3		■		■	■	■	■	■	■		■	■	■	■	■			■	■	■		■						■		■			
CABALLOS - KCUD		■				■	■	■			■	■			■			■	■	■		■								■			
CABALLOS – KCUE	■		■		■	■	■	■	■	■						■		■	■	■	■	■		■	■	■	■	■			■		
CABALLOS - KCUF			■		■				■	■			■	■		■		■	■	■	■				■	■	■	■			■	■	

Figure 2. Variability of perforated layers in KCU depending on the well.

Flow distribution among the layers in a given well is dictated by the flow mechanism, and can be described by equations. In the first order, fluid allocation per layer is driven by perforation height and permeability.
Local distortions of the driving parameters are averaged out over the set of wells.
The main assumptions and limitations considered were:

- Differential flowing pressure between reservoir and well. Differential pressure varies for each layer pressure and for each flowing well.
- Permeability: Each layer has different rock properties and permeability to fluids; for a given layer, permeability varies over the field.
- Local Skin effect (damage) varies from well to well and varies from layer to layer for the same

well.

The purpose of this method is to identify properties that describe each layer. Local distortion effects are aimed to be averaged out.

Pressures of the different layers are considered equal and constant in the first order for a given block. This assumption is supported by the Production Simulator results from a 2008 study (ref. 3) that was based on the same principle.

In each well, the aim was to have the lowest bottom-hole flowing pressure possible – according to the activation method. In the first order the differential pressure is then considered constant over the full set of wells for a given block.
Permeability is considered constant in each layer for a given block. Average permeability of each layer can be considered equal in the first order. Allocating different permeability values for each layer with values ranging from 1 to 4 gives same conclusion.
Skin effect is not considered between layers in the same well. Major skin contrasts are present in wells with two different reservoirs having completion, i.e. perforated casing and open hole in the same well. The number of such wells is limited over the field and their influence on field-scale results was proven to have no impact.

The tables below summarize the average value of oil cut per layer and per block in the year 2009. This information allows choosing selective stimulation jobs that will limit water recycling and yield the best increase in oil production. Stimulation must be avoided in low oil-cut layers. High oil-cut layers must be stimulated selectively and water injection adjusted to support and increase the overall oil production.

Oil Cut year 2009								
Block	B-1	B-2	B-3	B-4	B-5	B-6	B-7	B-8
A1	2%	1%	5%		5%	4%	4%	2%
A2	3%	2%	3%	6%	5%	5%	4%	3%
B	2%	2%	3%	8%	6%	5%	5%	2%
C1	1%	1%	3%	8%	0%	4%	3%	4%
C2	2%	2%	3%	6%	4%	5%	4%	3%
C3	2%	2%	3%	6%	5%	6%	3%	3%
D	2%	1%	3%		5%	10%	3%	3%
E	1%	3%	3%	6%	3%	10%	2%	2%
F	2%	2%	4%	5%	5%	6%	4%	15%

Figure 3. **Estimated oil-cut per layer and per block prior to the 2010 geology review.**

Oil Cut year 2009								
Block	B-1	B-2	B-3	B-4	B-5	B-6	B-7	B-8
A1	9%	2%	5%	15%	4%	4%	7%	6%
A2	4%	2%	3%	13%	5%	10%	4%	2%
B	3%	2%	4%	8%	5%	5%	4%	3%
C1	2%	2%	4%	9%	5%	5%	3%	3%
C2	2%	2%	4%	7%	5%	4%	3%	3%
C3	2%	1%	3%	8%	6%	5%	3%	3%
D	1%	1%			5%		5%	
E	2%	3%	5%	7%	3%	8%	3%	6%
F	2%	2%	4%	15%	4%	5%	5%	9%

Figure 4. **Estimated oil-cut per layer and per block after the 2010 geology review.**

Layer-selective production pilot plan

The pilot will provide a first estimate of layer contribution and possible improvement in terms of oil production. Data is gathered by stimulating specific layers in some wells – producers and injectors – and monitoring effects in production. In order to optimize production gains during the pilot phase, highest-potential layers are first identified to conduct the pilot. The goal is to identify and stimulate these layers.
The different actions are linked to responses, in order to refine the Production Simulator. Individual actions are changes in flow rate of individually selected layers in producers and injectors. This is achieved through acid stimulation and flow control in selective injection wells. Responses are identified as change in fluid flow – interaction between wells – and oil vs. water distribution (Oil Cut).

For high-selectivity jobs, targeted layers are those layers with the best oil incremental production potential. They are chosen according to the remaining oil-cut estimation. Only the targeted layers are stimulated. Each targeted layer is stimulated individually wherever possible. When the perforation intervals overlap with a non-targeted layer, the set of perforations is discarded if other intervals have been selected and feasible. In any case, an RPM (Relative Permeability Modifier) can be used to chemically target and block intervals with the least oil saturation.

For low-selectivity jobs, wells are chosen based on an overall need for stimulation. All layers are targeted. However, the job will aim at being as selective as possible. Each set of perforations is separated using a packer in the stimulation string. For each stimulation interval, an acid job is performed, followed by an RPM to block water zones.
Overall stimulation campaign results are pictured in Figure 5.

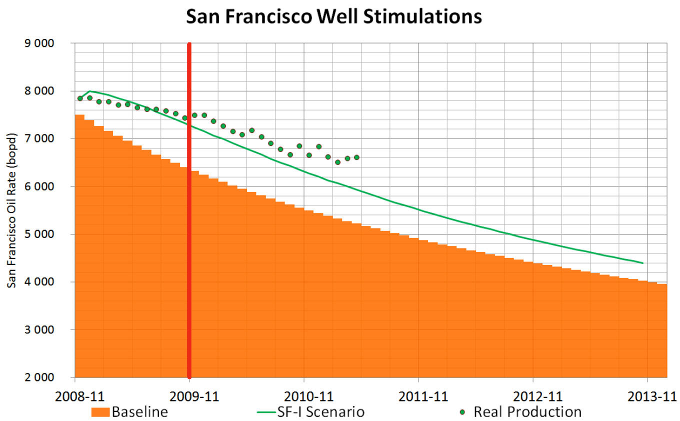

Figure 5. San Francisco field: Effect of well stimulation campaigns (started in November 2009)

More specifically, the following results were observed for non-selective jobs performed in previous years (1990-2007):

- Liquid production increase (expected result of any stimulation);
- Increase of oil production (in many cases marginal);
- Increase of water-cut (undesirable result).

The pilot aim, on the other hand, was to increase production without increasing the water-cut. The idea was rather to identify a methodology to favor production with affecting the WOR, possibly even decrease the water-cut, something completely different when compared to previous stimulation campaigns. Figure 5 shows the effect of our stimulation campaign on oil production rate. The increase in production versus the optimized forecast (green line) seen in November of 2009 and in May of 2010 correspond to the first two stimulation campaigns. The increase in production in October 2010 corresponds to the pilot selective stimulation campaign.

For each job the type or results that are expected can be summarized as:

- Increase of liquid production (expected result of any stimulation);
- Increase in oil production;
- Stable or decreasing water cut.

The first part of the study was beneficial in both oil production increase and data collection. The cumulative oil production increase after performing jobs was above 200 bopd. There was no reduction in oil production and no drastic increase of water cut observed even when liquid production increased.

Demonstrating the reliability of the San Francisco Production Simulator

After this successful pilot phase, the next phase was to refine the Production Simulator, as described in a previous SPE paper for the San Francisco field (ref. 2). This breakthrough field simulator relies on recent results of the statistical learning theory (ref. 4). Such new approach requires both (i) adjusting the model complexity (as defined by its Vapnik-Chervonenkis (*VC*) dimension h) to the number of available past production and field data, and (ii) constraining the choice of the model by the laws of the reservoir and well physics. This leads to an impressive forecasting accuracy, which could be demonstrated by two severe “blind tests”, as described below.

A two year data set has been available to compare actual production with forecasted production.
The first year data (first blind test) shows a very good match between the forecast and the real data (more than 99% average accuracy). The figure below presents a graphical comparison between real and forecasted oil production.

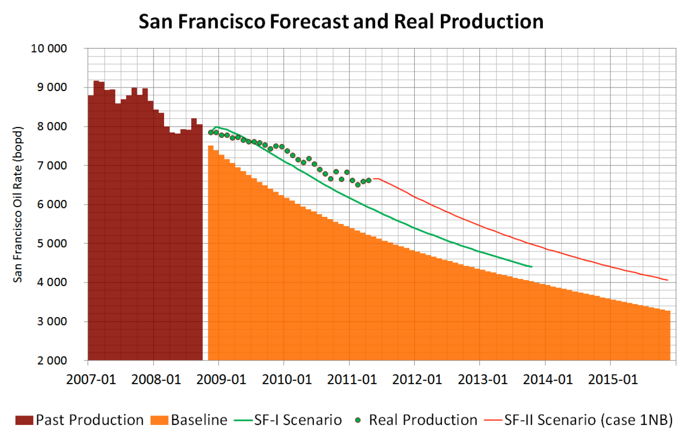

Figure 6. San Francisco FOROIL model forecast compared with 2-year real production (past production in dark red; base line in orange; forecast in green after first optimization and red after sand-selective optimization; real production in green dots)

In order to better understand and fine tune the Production Simulator and to take into account selective jobs, a second blind test has been carried out for the latest 10-month production data, period during which these jobs have been carried out. Model forecasts have been run from November 2009 to August 2010 without any input from real production data. Real water injection rates of injectors and measured bottom hole flowing pressures of producers have been taken as input data.
This model was then established with only production data prior to November 2009. The learning period for this last run did not cover any 2010 stimulation job or pilot result.

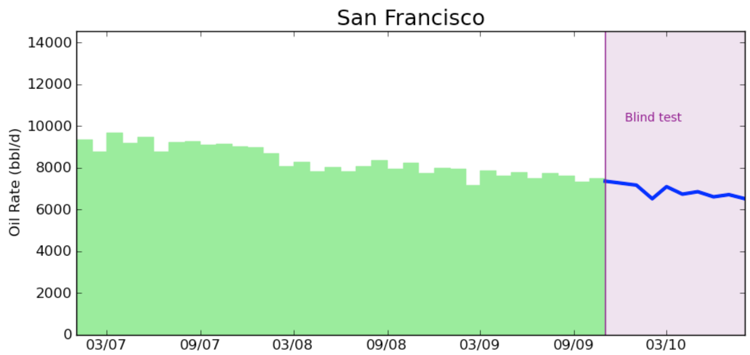

Figure 7. **San Francisco blind test monthly oil production rates (green area: real past production data; blue line: forecast data)**

The model forecast has been compared with the field measured data. The 10-month cumulative oil production forecast is 97% accurate for real monthly production, in average.

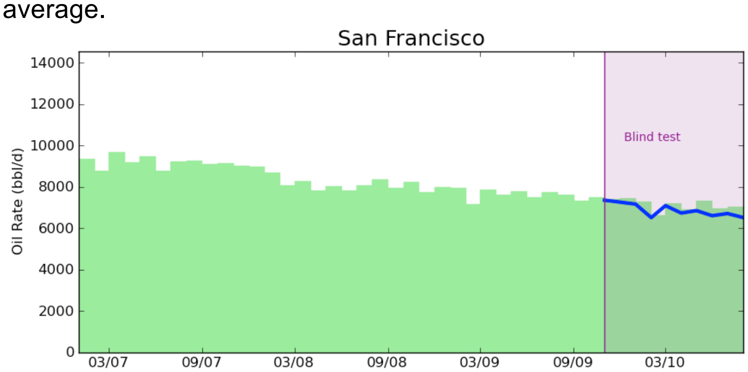

Figure 8. **San Francisco blind test monthly oil production rates comparison with real production (green area: real production data; blue line: forecasted data)**

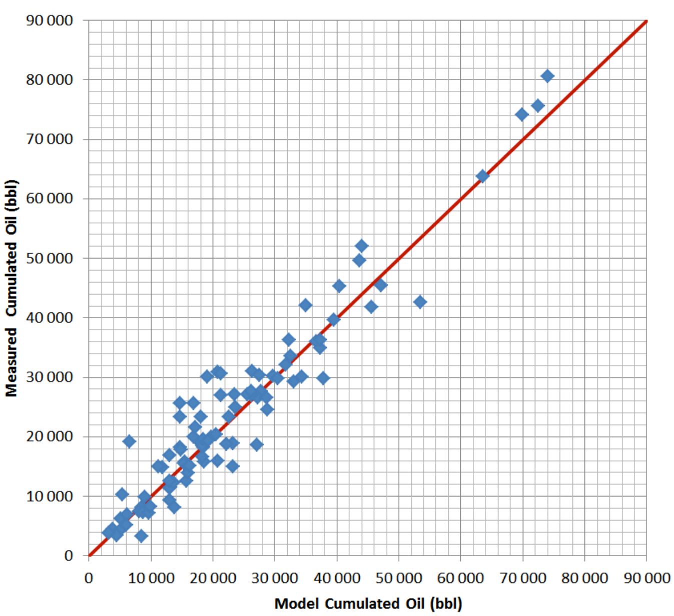

Figure 9. **San Francisco blind test well by well real oil production compared to oil production forecast (red line is the 100% match between forecast and real production)**

Figure 9 (above) plots each San Francisco producing well according to its effective cumulative oil production (horizontal axis) over the November 2009 - August 2010 period vs. its forecasted cumulative oil production (vertical axis). When the production forecast exactly matches real production, the well is located along the red line (y=x). The main information this figure displays is:

- The well diamond cloud is spread along the 100% match red line,
- Well diamonds located at either side of the line represent a difference in oil rate and cumulative volume to the modeled.

Figure 10 is the same plot as Figure 9 with the addition of two lines representing plus and minus 15% in the oil production forecast. Wells located with red diamonds are those that have benefited from production stimulation jobs that were not embarked in the field model. The main information this figure displays is:

- Oil production forecast does not deteriorates with higher oil production wells,
- The location of the red diamonds indicates that the overall effect of the stimulation campaign was beneficial in terms of oil production versus de modeled.
- Location of the remaining blue diamonds shows better accuracy of the model for the wells with no unexpected job.

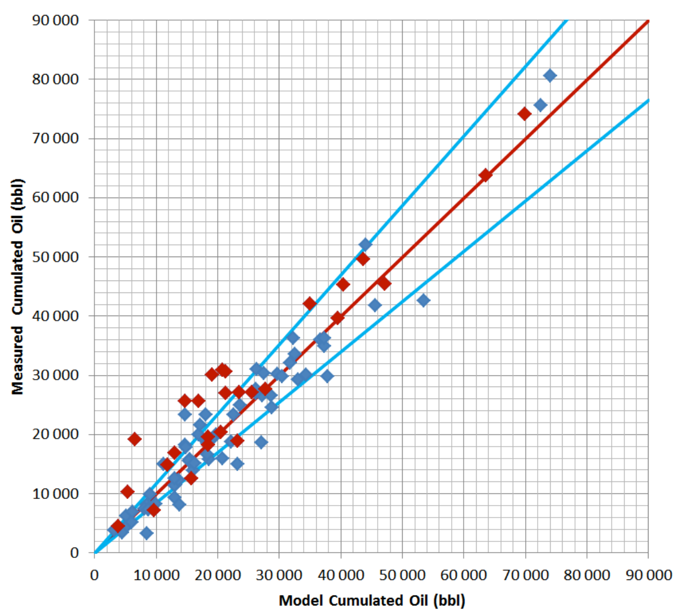

Figure 10. **San Francisco blind test well by well real oil production compared to oil production forecast (red line is the 100% match between forecast and real productions; bleu lines are + and – 15% match; red diamonds locate wells that have been stimulated during the blind test period)**

Massive Optimization Process for boosting overall injection

As the reliability of the Production Simulator is fully demonstrated and the running time for a single five-year forecast is very small (less than one second), an Optimization Engine that selects and play 100,000s scenarios will show a very good capacity to converge to an optimum scenario.

As an example, Figure 11 shows the maximization history of the Cumulative oil production as the number of iterations increased. The computation is wisely parallelized so that several scenarios are tested per iteration. In the run displayed in Figure 11, 20 scenarios are tested per iteration of the main loop, so that over 1,700,000 scenarios have been defined, forecast and compared to each other in this optimization run. Of course, good alternative scenarios could exist, but they could not outperform the optimum scenario achieved.

Fundamentally, the Optimization Engine is designed to extensively explore the space of production scenarios, under operator technical and financial constraints. Of course, there is some granularity in the process of selecting the scenarios to be played, but a very good scenario could not be missed, as it cannot escape the screening mechanism (heuristic, deterministic and non-deterministic) of the Optimization Engine.

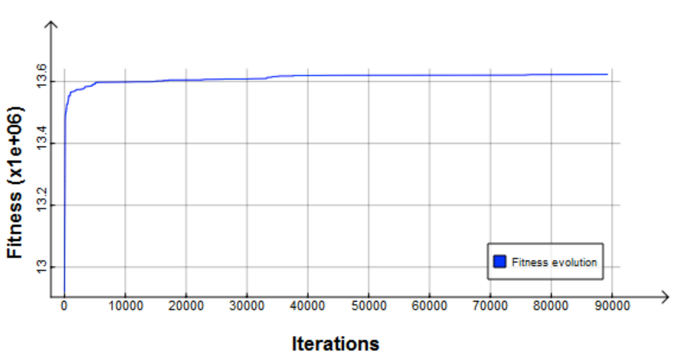

Figure 11. Convergence of the *Optimization Engine*™ as a function of the iteration number.

Impressive forecasted increases in production have been identified through this massive optimization method. This will be presented in a further paper, together with actual production results.

Conclusion

With over 15 years of water injection, recent ILTs were proof that several sands had not experienced good waterflooding, mainly due to their less favorable petrophysical properties. A methodology to identify remaining saturations per sand, as well as a massively optimized design for injection patterns, has shown reliability and actual production increase field-wide.
Historical decline of the San Francisco field was between 14-17%. For the years 2009-2011, decline has remained steady at 8.5%, a value previously unseen. Additional reserves are already evaluated at 0.6 MMbo as of 2011, only from adjustments to injectors and producers.

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References

1. Gaviria, W; Borja, H., Hocol S.A.; Groff F. and Gamble S., Schlumberger. “Optimización de Producción mediante una Metodología Estructurada de Análisis de Información en el Campo San Francisco”. ACIPET Colombian Petroleum Congress. October 2001.
2. Andrés Felipe Suárez, SPE, Hocol S.A.; William Gaviria, Schlumberger; Jaime Pavas, Hocol S. A.; Mikael Frorup, SPE, Schlumberger “Beating The Marginal Well Performance in a Mature Field: San Francisco Field in Colombia”. SPE Latin and Caribbean Petroleum Engineering Conference, Rio de Janeiro, Brazil, 20 – 23 June 2005.
3. Andrés Felipe Suárez, David Soto, & Hubert Borja, SPE, Hocol S. A.; Remi Daudin, FOROIL “Massive Optimization Technique Improves Production of Mature Fields: San Francisco, Colombia”. SPE-138979-PP
4. Vladimir N. Vapnik “The Nature of Statistical Learning Theory” – Second Edition (314 pp.). Springer, 1999.