Estimation of Mature Waterflooding Performance and Optimization by Using Capacitance Resistive Model and Fractional Flow Model by Layer

Francisco Castillo Gamarra, Néstor Ramos, and Ignacio Borsani

Abstract—**Waterflooding is the oldest and most extended method to enhance recovery from oil reservoirs in primary production with low natural energy in the Golfo San Jorge Basin, Argentina. Water injection has proven to be an effective method to enhance recovery from oil reservoirs for project CM-123-A at Cañadón Minerales field, Golfo San Jorge Basin. Defining the optimized injection rates and injection patterns, which depend on the geological structure of the reservoir, is an essential operational and economical decision for reservoir management.**

In this paper, the capacitance resistive model (CRM), which takes into account implicitly the geological and reservoir parameters, is used to find inter-well connectivity by layer (independent reservoir), optimize injection rates with the complement of net sand maps and petro-physical and production test data, and check the consistency of the solutions with all the available data to support the decisions.

The CRM receives the injection rates variations as input signal, from the different reservoirs, whereas the producer responses determine the injector/producer pair connectivity quantitatively. The different runs of the CRM can be used to detect how some abrupt changes in the artificial lift of the producers affect the connectivity and propose some improvements. Also, this model is used to predict gross production for individual reservoir, together with a multilayer FFM (fractional flow model) can be estimated the oil production for each individual reservoir, identify the potential from different reservoirs and improvements in the injection rates to optimize the oil production. The results reveal that the CRM has the capability to match the production history to calibrate the dynamical effective parameters and with this characterization optimize the injection rates of the different wells injectors and reservoirs, during the immiscible flooding, understand water injection movement, and as accessory the joint validation of the net sand maps. The CRM was able to detect inter-well connectivity for producers connected not only at the first line but also at the second line, with a clear response in the field.

Index Terms—**Reservoir engineer, mature waterflooding, multilayer CRM (capacitance resistive model), multilayer fractional flow model, nonlinear optimization, mathematical programming, AML, gams, conopt, octave, R.**

I. Introduction

It is common to evaluate the dynamic behavior from waterflooding project through simple plots of field production data to full-field numerical reservoir simulation models. The latter requires an extensive set of data, such as PVTs (physical properties of the fluids in the function of the pressure and temperature) and petro-physical parameters. These data are often not available for typical waterflooding projects at Golfo San Jorge Basin consisting of multiple sands, many of which are independent hydraulic units during the times of water injection response. Also, history matching and forecasting for these models are complex with large computing time and lack of reliability due to high uncertainty with reservoir parameters, with the hardware, and software that currently is available.

The project CM-123-A is a multiple sand commingled production. Sands water injection is done selectively through mandrels and regulated valves. Due to the limitations described above in evaluating the waterflooding project CM-123-A, an alternative Parametric mathematical programming (PMP) model, i.e., CRM, was tested. This PMP model, i.e., CRM, is used to simplify the problem, but keeping the influence of each sand at each injector over the neighbor producers at the first and second lines (if is necessary). The goal of this model is to calculate the waterflooding production only at the maturity stage or when there is enough information to conclude that the main driven energy for the project is obtained from waterflooding. At the maturity stage, it is assumed that the effect of primary production is low due to project maturity. This simplification is also assumed to have used a multilayer fractional flow model (FFM) [1], [2] to calculate oil production from the layer gross production at the CRM. The workflow starts collecting necessary data to build the multilayer CRM. The available data includes the following:

a) Tank well production tests. Sometimes production test by sand, measured using PLTs [1], is available
b) Injection flow measurement at each sand layer for each injector.
c) History of well intervention for each producer and injector. This data reports for each producers and injectors the open or shut-in sands time evolution.
d) Projected sand coordinates; vertical wells only require one pair of values.

The first step is to process the information and build the multilayer CRM in a framework of an optimization problem. The details of the methodologies can be found at [1], [3]. The problem consists on solving a continuous variables nonlinear optimization problem with a local optimum criterion using the AML GAMS with CONOPT (GAMS) solver. This is done to calibrate the parameters with the history matching of

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the total production.

The next stage is building, for each sand layer, the FFM using the same optimization problem framework as above and then calibrating the parameters of FFM with oil production history.

Qualitative consistencies of the model solutions against structural maps, net sand maps, and production history were checked. The production of each sand and each well from the model is compared with that of the net sand calculated from petro-physical analysis, as well as production test from each sand, if available. It is suggested that no anomalous solutions exist, for example, that most well production is not calculated from a sand layer that has actually zero net sand or very low values of net sand coincident with a dry test of production (if available). Then the model solution is considered to have a good qualitative agreement with all the available data. This is important for decision support.

II. Model Description

There are several CRMs that can be learned at [1], [3], [4], [5], with each having different approaches. The use of a multilayer CRM with dynamical inter-well connections, in a simple way, is extensive and well described in [3]. The option used in this paper to infer inter-well connections and gross production by layer is CRMP (capacitance resistive model with producer-based representation of the reservoir), with dynamical connectivity, and without cross-flow between layers.

In this paper, we use a similar notation and terminology as [3]. Let i, j, α, k be the index for injectors, producers, layers, and time, respectively. If $S_{j\alpha}$ (k) is a binary variable 1 or 0 that indicates if a perforation of producer j and layer α is open or closed at time k; τ_j is the response time of producer j; $f_{ij\alpha}(k)$ is the inter-well connection between injector i ,producer j and layer α at time k ; $X_{j\alpha}(k)$ is the gross production from producer j, layer α at time k and $I_{i\alpha}(k)$ is the water injection from injector i, layer α at time k. Then the set of equations for time evolution of $X_{j\alpha}(k)$is:

If $S_{j\alpha}(k)>0$, $k>1$

$$X_{j\alpha}(k) = X_{j\alpha}(k\text{-}1) * e^{-\frac{1}{\tau_j}} + \left(1 - e^{-\frac{1}{\tau_j}}\right) \times F_{ij\alpha}(k-1) \quad (1)$$

$$F_{ij\alpha}(\text{k-1}) = \sum_{i/neighbor\ j} I_{i\alpha}(\text{k-1}) \times f_{ij\alpha}(k\text{-}1) \quad (2)$$

$$X_{j\alpha}(k) = 0 \text{ in other case} \quad (3)$$

where the index of the sum in (2) is over $i/neighbor\,j$. Subsequently, a Euclidean distance needs to be defined, in this way only consider neighbors injectors i located in a distance minor or equal than R of the producers j. Also, if all neighbors injectors i to producer j at distance minor than R, has $I_{i\alpha}(k)$ =0 then $X_{j\alpha}(k) = 0$ even $S_{j\alpha}(k)$ >0 for this producer j. This means that only the production due to the influence of the waterflooding process needs to be calculated. In this paper, this condition is reliable because the layers that are not selected for water injection have low initial fluid rates, compared with those selected for waterflooding, and almost without vertical connection between layers, considering the time of response of the waterflooding process and the very late implementation of the waterflooding process. So, those sands are considered to have a negligible contribution to the production due the high depletion for the maturity of the project. The distance R is also a possible change for each producer j that requires more distance in order to match the total production coincident with the layers with great areal extension.

For the time evolution of $f_{ij\alpha}(k)$, if $S_{j\alpha}(k)>0$:

$$f_{ij\alpha}(\text{k}) = f_{ij\alpha}(\text{k-1}) \text{ if } S_{j\alpha}(k) = S_{j\alpha}(k\text{-}1) \quad (4)$$
$$\forall\, j\ /neighbor\ to\ i$$

Unless

Open or shutting a layer.

An abrupt leap or drop in the gross production, coincident with a change in the artificial lift system for the producer or the well shut-in.

$$f_{ij\alpha}(\text{k}) = 0\ if\ \ S_{j\alpha}(k) = 0 \quad (5)$$

Finally, the single objective function is minimized as follows:

$$Objective = \sum_{j,\alpha,k} (X_{j\alpha}(\text{k}) - Q_j(k))^2 \quad (6)$$

where $Q_j(k)$ is the historical gross production from producer j at time k. Also the use of (6) and aggregate restrictions is possible if some measures of PLTs (production logging tests) in some producer j_q at time k_r is available.

Solving the optimization problem considering the variables with the defined constraints, can be obtained as $f_{ij\alpha}(k), \tau_j, X_{j\alpha}(k{=}1)$. This optimization problem can be solved using GAMS (General Algebraic Modeling System) and CONOPT3/4 solver, the algebraic language, of which allows writing the problem in a simple and general form. Because enormous amount of equations and restrictions are needed in the model in the language of GAMS, the model was generated using Octave and R. Then GAMS–CONOPT3/4, with reference in this type of optimization problem at [1] and [3], were used in this paper.

The next step was to calculate the total oil production by sand, which is related with the sand gross production calculated using the CRMP multi-sand model with dynamical connectivity and without cross-flow between layers. In this work, it is used a similar empirical power law technique at [1], [2] and [6].

The oil production calculated for the model is given through the power law:

$$Oil_{j\alpha}(k) = X_{j\alpha}(k)/(1 + a_{j\alpha} \times (CumX_{j\alpha}(k) + b_{j\alpha})^{c_{j\alpha}}))$$
$$CumX_{j\alpha}(k) = (\int_1^k X_{j\alpha}(k\text{-}1) \times dx) \quad (7)$$

where $Oil_{j\alpha}(k)$indicates the oil production from producer j and layer α at time k. The $a_{j\alpha} > 0, b_{j\alpha} > 0, c_{j\alpha} > 1$ indicate the empirical exponents for producer j and layer α. Here, it is possible to calculate oil production from sands with the influence of the waterflooding process. The contribution of sands to oil production without water injection is considered negligible. This is a reliable assumption for the majority of the producers j. However, there are a few cases that exists contribution to the total oil production from a sand α, producer j without waterflooding and this contribution may be not negligible compared with the total oil production of the producer j . Again, the use of (7) and aggregate restrictions is possible if some measures of PLTs in some producer j_q at time k_r are available.

The single objective function is minimized as follows:

$$Objective = \sum_{j,\alpha,k}(Oil_{j\alpha}(\mathrm{k}) - (Oil\ Historical_j(\mathrm{k}))^2 \quad (8)$$

where $(Oil\ Historical\ _j(\mathrm{k})$is the historical gross production of oil from producer j at time k.

Solving the optimization problem using the variables with the defined constraints, the parameters $a_{j\alpha}, b_{j\alpha}, c_{j\alpha}$ can be obtained. The optimization problem is again solved using GAMS-CONOPT3/4 solver. Again, due to the enormous amount of equations and restrictions needed in the model, the model was generated using Octave and R.

III. Model Calibration

A. History Match Gross Production

The waterflooding project CM-123-A has 41 producers, 21 injectors, and 18 sands on injection. The project has been under waterflooding for almost 300 months. The complete waterflooding project data was used to adjust the CRMP model.

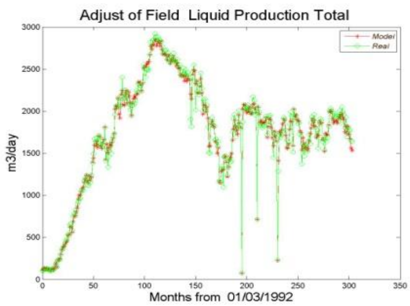

Fig. 1. Adjustment of field total production.

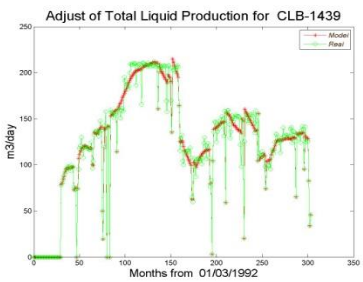

Fig. 2a. Example of producers with good adjustment.

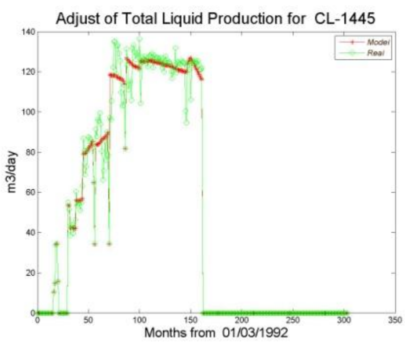

Fig. 2b. Example of producers with acceptable adjustment.

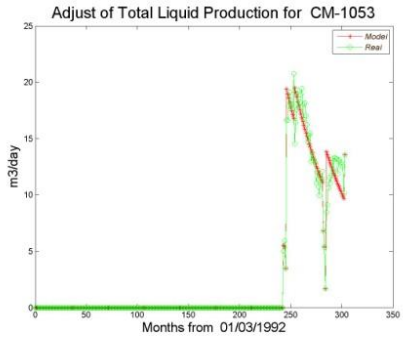

Fig. 3. Example of producers with poor adjustment.

Figure 1 presents a very good matching for total gross production for the whole project. The adjustment for each producer $j$was classified as good, acceptable, or poor. Ninety percent of the producers have a good or acceptable adjustment coincident with a good waterflooding response, and 10% of the producers have a poorer adjustment showing poor response. Figure 2a and 2b show examples of producers with good and acceptable adjustment, whereas Fig. 3 shows examples of producers with poor adjustment.

The results are consistent because the model can only calculate the total production from the predominant energy, in this case, waterflooding. The model is calibrated with the parameters $f_{ij\alpha}(k), \tau_j$that minimize Equation (6).The model solutions are quality control against net sands maps, fault system, and production tests for individual layers (where data are available). It is assumed that characterization of gross production time evolution from producers as function of the water injected at each sand of each injector is possible.

B. History Match Oil Production

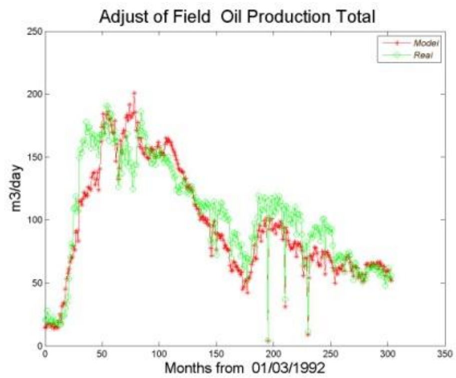

Fig. 4. Adjustment of field oil production.

Figure 4 presents a very good match between total model oil production and total actual oil production. This good match is due to the fact that total model oil production has a strong dependence on total cumulative production, as presented in Equation (7). Typically, the adjusted oil production rate has a lower quality than the gross production. This can be attributed to wells that oil production is from sands α that are not under waterflooding. These sands can have lower water cut, and then, the contribution to the oil production is not negligible. Also, the adjusted oil production depends on the gross production adjustment, and drags some deviation. Also, for gross production, the adjusted oil production for each producer j was classified as good, acceptable, or poor.

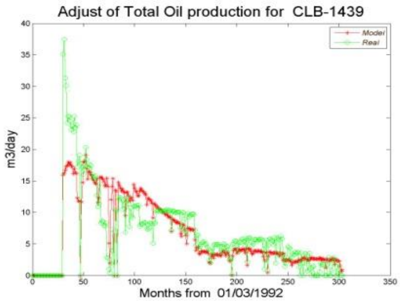

Fig. 5a. Example of producers with good adjustment.

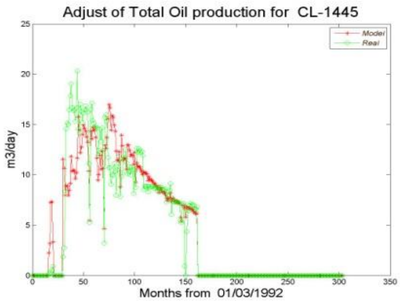

Fig. 5b Example of producers with acceptable adjustment.

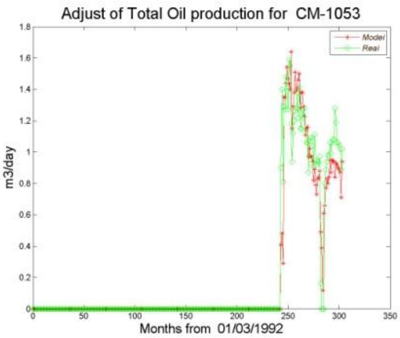

Fig. 6. Example of producers with poor adjustment.

Figures 5a and 5b show examples of producers with good and acceptable adjustment, whereas Fig. 6 shows examples of producers with poor adjustment.

Eighty five percent of producers have a good or acceptable adjustment coincident with a good waterflooding response, and 15% of producers have a poorer adjustment showing poor response.

C. Validation

The validation objective is to analyze the model forecasting capacity, with emphasis on the oil production.

To prove the model capacity to forecast a blind test with historical production was done. Four scenarios were chosen: 12 months, 24 months, 36 months, and 48 months. The maximum time for prediction was limited to 48 months because the historical data for the producer's interventions are noisy, i.e., events, such as injectors cleaning or producer/injector reparations, shut-in of producers, or injectors have uncertainty so model boundary conditions may change strongly. In each period of the forecast, these events are not present. The cumulative of these events are not enough to produce strong deviations. Also is a reasonable time to estimate forecast production oil curve for the economics analysis.

The validation for each scenario is very simple using the historical match with production history for a given period and forecasting for the rest. For each scenario the model calibrates, the relevant parameters for the multilayer CRM and FFM will all the data up to 48 months before present time, for the 48 months case. Then model forecast the production for the last, uncalibrated, 48 months, and compare with actual, i.e., real production. The other scenarios, 36, 24, and 12 months, were performed in a similar way. The 0 month scenario corresponds to matched model with all historical production up to present.

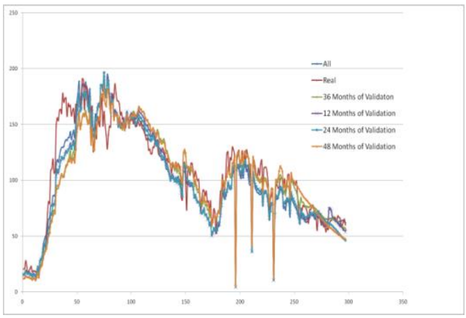

Fig. 7. Comparison between months of validation in the oil production forecast.

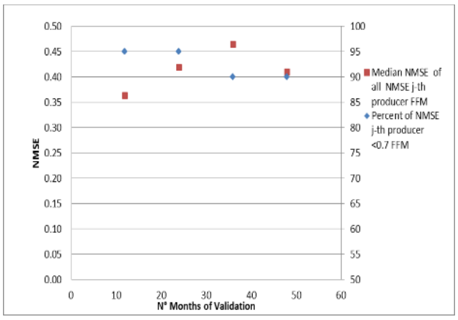

Fig. 8. Quality check of history match FFM.

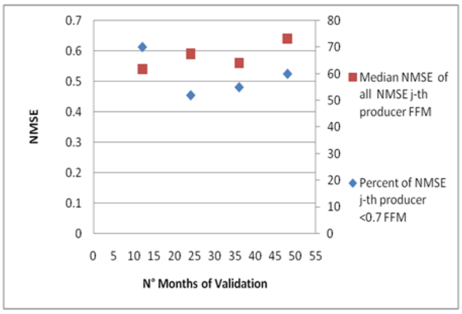

Fig. 9. Check of forecast from FFM.

The results are presented in Figure 7 wherein an acceptable agreement between the model forecasting for the different time ranges (12, 24, 36, and 48 months) can be seen.

The normalized mean square error (NMSE) for each producer is used as a measurement of the goodness of fit between the forecast and actual data and is given as:

$$NMSE_{Model} = \frac{\sum_j (Q_{j,hist} - Q_{j,for})^2}{(Q_{j,hist} - \bar{Q}_{j,hist})^2} \quad (9)$$

where $Q_{j,ac}$is the historical oil production,$Q_{j,for}$ is the model forecast oil production, and $\bar{Q}_{j,ac}$is the historical mean oil production in all cases for the j-th producer. The same criteria adopted at [7] are applied. If the NMSE of each j-th producer is <0.7, then the history matched, and model forecast oil production from FFM are considered valid or acceptable. The median of the NMSE of all j-th producer represent the reported quality of adjustment. The results are presented in Figs. 8 and 9.

Figures 8 and 9 show the ability of the FFM to predict oil production. Clearly, the ability for the Model in History Match is better than forecast. In the forecast, the percentage of j-th producer with the NMSE < 0.7 is always greater than 50%, and these producers have more than 75% of the weight in the total oil production of the field. The best forecast quality agreement is for 12 months, but even 48 months is reasonable. Also, to verify the ability of the model to forecast production, the results are compared with those of traditional decline curve analysis (DCA). DCA is a common method of forecasting waterflooding projects and the most accepted way in the Oil Reserves Certification, which directly impacts the value of a company.

$$NMSE_{DCA} = \sum_j (Q_{j,ac} - Q_{j,DCA})^2 / (Q_{j,ac} - \bar{Q}_{j,ac})^2 \quad (10)$$

To prove that CRM and FFM can forecast production, in the short term, better than traditional DCA method, the DCA NMSE is calculated using Equation (10). The results of the comparison between $NMSE_{Model}$ and $NMSE_{DCA}$ are presented in Fig. 10, for the 12 month, 24 month, 36 month, and 48 month scenarios.

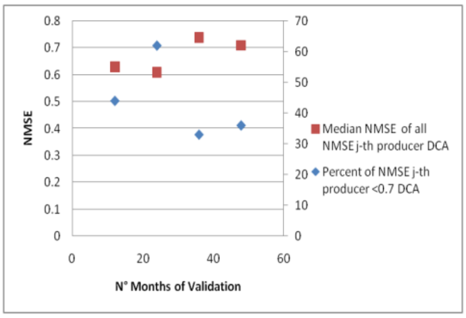

Fig. 10. Quality check of forecast from DCA.

Figure 10 shows the ability of the DCA to predict oil production. The prediction of the DCA is always worse than that of FFM, considering the median of the NMSE of all j-th producers, which represent the reported quality of adjustment.

D. Heuristic Consistency Check of the Solutions: Analysis of the Model Oil Production by Layer and Net Sand Interpreted

The first step is to analyze the relationship between the production by sand for each producer from the FFM, to the well logging calculated h_k (net sand) value.

This relationship implies the use of Darcy's law that relates net sand to oil production among other variables. The other necessary variables, PVT properties, absolute permeability, relative permeability, oil saturation, skin, reservoir pressure, and bottom hole pressure, are not available for the CM-123-A project. Also, to properly understand the relationship (h_k and oil production by layer), the time dynamical events (i.e., shut-in of producers, lost in the injectivity of the injectors due to formation damage) of the waterflooding project evolution and the water injection design and strategy need to be considered. In fact, the detection of strong deviation from the relationship between h_k and oil production by layer (i.e., very low oil production by some layerα with many producers with good values of h_k) could be related to a bad water injection strategy and could define possible optimization of the waterflooding project. This heuristic analysis can be used to compare model calculation of oil production by layer with h_k estimations and to detect anomalies in either one to improve the water injection strategy. Because a reduced physical model instead of a complete numerical simulation is used for this paper, and also because the only reliable data is $h_k$for this paper, we will analyze the average performance in oil production by sand for the producers with respect to its h_k.

To represent the oil production performance by sand for each producer, it is calculated oil cumulative production from the FFM and divides by t, the total active production months that is called $Np_{weighted}$.Also, for each sand from project CM-123-A, considering all the wells that the sand is present and with water injection, the net sand values h_k can be divided into several intervals, from 0 m to maximum, i.e., 0–2, 2–4, and 4–6 m. Then, grouping the wells that are in a given sand layer and range, the average, or median of $Np_{weighted}$ can be calculated, i.e., $[Np_{weighted}]_{average}$.Table I presents the calculations for more productive layers. It can be used to verify that model calculates statistically best cumulative production for sands that have the best net sand h_k.

TABLE I: OIL PRODUCTION STATISTICAL ANALYSIS BY SAND AND h_k(NET SAND)

Layer	Interval of h_k(m)	$[Np_{weighted}]_{average}$ (m^3/month)	N° of well producers in each interval
mbCO-rB100	[0,2]	0	1
mbCO-rB100	(2,4]	26.94	7
mbCO-rB100	(4,6]	21.51	22
mbCO-rB100	[6,8]	65.46	8
mbCO-rB0	[0,2]	9.33	5
mbCO-rB0	(2,4]	18.69	11
mbCO-rB0	(4,6]	97.02	3
mbCO-rB3-1	[0,2]	18.11	3
mbCO-rB3-1	(2,4]	23.03	22
mbCO-rB3-1	(4,6]	36.41	13
mbCO-rB3-1	[6,8]	29.86	2

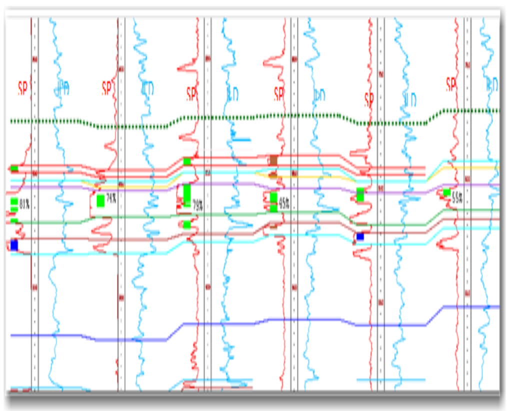
Fig. 11. Example of correlation; layers are amalgamated in some wells, and separated in others.

The static model was created from sand correlation between the wells at the CM-123-A project. The sands in the project are typically presented as sand packages with considerable extent, similar to that presented in Fig. 11. Sometimes, the sands appear as amalgamated and can then be presented separately. Sands presenting as large packages in this area, which is a typical characteristic, has the advantage of easy correlation between wells. However, when individual sands from these packages are correlated with the amalgamation in some wells and separation in others offers an important difficulty. Then, defining each net sand thickness along the area, in which they develop requires a detailed analysis.

Since the wells in the area are mostly from the 60s or 70s and no porosity logs were available, an alternative procedure to determine the net sand thickness was used. The procedure consisted on the direct observation of the spontaneous potential (SP) curve at the 1: 200 scale logs, between sand top and bottom, and select net sand thickness when SP is fully developed Fig. 12.

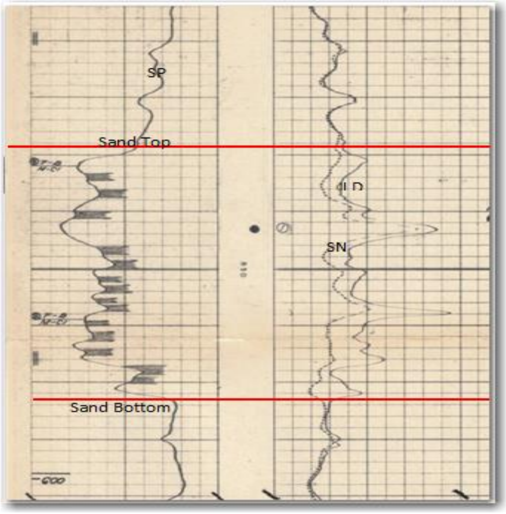

Fig. 12. Example of a layer with clay intercalation; the sand top and bottom are marked. The gray marks are the clay intervals that are discounted from the total sand thickness.

The direct observation method has proven to have very good results when the calculated net sand thicknesses were compared with the well production data, providing consistency with recovery factors related to sand pore volume. The information obtained from the net sand calculations for each layer was used to make the thickness map grid that later was used to heuristically check the CRM and FFM.

E. Heuristic Consistency Check of the Solutions: Well Connectivity

There are other heuristic checks that can be done to verify the model parameter calculations. The model calculates well connectivity, along project evolution. If for a given time net map sand is superposed with vectors that show the connection between an injector and a producer and looking at the wells production and injection history to verify that well connectivity is possible and matches with net sand h_k. That means that if there is a good net sand h_k, the connectivity is possible, and the model parameters are properly connected.

Figure 13 presents the connection between producers and injectors for a given sand. The best connection, dark vectors, are calculated for the best net sand h_k and when injection if from the base of the reservoir to the top. Poor, lighter vector, o no connectivity is calculated by the model for those wells that have poorer net sand h_k or when injection is from the reservoir top to the reservoir bottom. The figure shows the same cases wherein the model calculates connectivity between the injector and the second line producers.

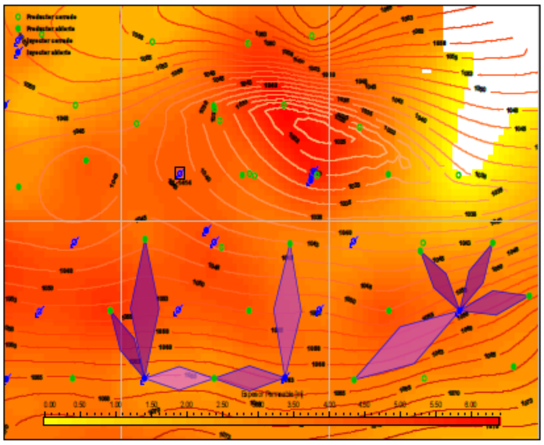

Fig. 13. Connections between injectors and producers for a layer net sand thickness map are shown.

These consistency checks inspect the coherence between the data and the model results, but there are many cases wherein the areal distribution of h_k is not related to the connectivity due to areal barriers or discontinuities. Due to these complexities, this work reports the use of multilayer CRM and multilayer FFM.

IV. Conclusions

The waterflooding project CM-123-A is a real case to applies the methodology descript in this work and has an extensive production history and. Even the complexity, from the waterflooding project history matched has a median of the NMSE of all j-th producers, minor than 0.46, with more than 90% of the j-th producer with the NMSE < 0.7. Also, the model was used to forecast production, based on the history matched, in a simple cross validation. For the four periods of forecast ranging from 12 to 48 months, blind test was conducted forecast oil production. The median of the NMSE of all j-th producers in the forecast is always minor than 0.65. This is a reasonable accuracy considering the limited amount of data and the complexity of the phenomena. The prediction of the FFM shows better performance than that of the DCA methodology. Clearly, the ability of the methodology, presented in this paper, in history matching is always better than forecasting. In each period of the forecast, there are events that could change the connectivity between producers and injectors (i.e., producer/injector reparations or shut-in) by layer, and the cumulative of these events could be enough to produce strong deviations. Due to this, the maximum time for prediction was limited to 48 months.

The times to build and solve the nonlinear optimization problems with GAMS (CONOPT3/4) are in agreement with the times of management of the project. The methodology is effective in guiding different optimization strategies for the waterflooding project.

The model was able to detect producer/injector connectivity up to the second line from injector, with a clear response in the field.

Finally, a heuristic methodology was presented to assess if the quality of the solutions of the models are compatible with the available single production test data and net sand maps. This is important for the reliability of the methodology and for support for future decisions.

AUTHOR CONTRIBUTIONS

Francisco Castillo Gamarra Author is responsible for the programming in the GAMS language of the Multilayer CRMs and Multilayer FFM to solve each optimization problem using the solver CONOPT3/4 available in GAMS. Interpret the results of the models and suggest possible optimization of the waterflooding project.

Néstor Ramos Author is responsible for obtaining the historical interventions of producers and injectors and water injection by layer. These data are the input data to build the Multilayer CRMs and Multilayer FFM. Interpret the results of the models and suggest possible optimization of the waterflooding project.

Ignacion Borsani is responsible for build the geological correlation between layers which is a crucial input data.

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