CAPACITANCE RESISTANCE MODEL (CRM) APPLICATION TO RAPID EVALUATE AND OPTIMIZE PRODUCTION IN PERIPHERAL WATERFLOOD FIELD, PANDHAWA FIELD

CASE STUDY

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ABSTRACT

Waterflooding is one of the most effective methods to improve oil recovery in mature fields because of its high success ratio, easy in application and cost efficiency. Development until now has shown that Capacitance Resistance Model (CRM) can be used as alternative from reservoir model and simulation studies. CRM can be used as model to predict reservoir characterization and reservoir performance quickly and accurately with only require historical production and injection data. CRM characterizes the reservoir by calculating the connectivity value and the response delay between the injections well and the production well as unknown parameters. Pandhawa Field is a heterogeneous carbonate reservoir with an average permeability of 65 mD with peripheral waterflood since 20 years ago. By knowing the injection efficiency, the optimization process can be carried out by increasing the water injection rate in injection wells that have high efficiency and vice versa. In this study, the performance of waterflood is analyzed using the Capacitance-Resistance Injection-Production Model (CRM-IP) to determine the connectivity of each injection and production well. This study also discusses CRM-IP implementation on MATLAB programming language and optimization of injection rate allocation for the most optimum cumulative oil production. Result of this study indicate total additional oil 505 MBO will be obtained during 120 months period by conduct redistribution water injecti on management for each injector. By using CRMIP methodology, waterflood management in this field can be done much faster, therefore decision taken for this field will be more effective.

Keywords: Capacitance Resistance Model (CRM), waterflood, optimization, interwell connectivity.

ABSTRAK

Injeksi air adalah metode yang tepat guna untuk meningkatkan perolehan minyak di lapangan yang sudah tua karena tingkat kesuksesan yang tinggi, kemudahan dalam implementasi dan biaya yang efisien. Perkembangan sampai dengan saat ini menunjukkan bahwa Capacitance Resistance Model (CRM) bisa dipergunakan sebagai alternatif dari model reservoir dan studi simulasi. CRM bisa digunakan sebagai model untuk memprediksi karakteristik dan performa reservoir secara cepat dan akurat dengan hanya membutuhkan data historis produksi dan injeksi. CRM melakukan karakterisasi reservoir dengan menghitung nilai konektifitas dan respon jeda antara pasangan sumur injeksi dengan sumur produksi sebagai parameter yang tidak diketahui. Lapangan Pandhawa adalah reservoir karbonat yang heterogen dengan permeabilitas rata-rata sebesar 65 mD dengan injeksi air secara peripheral sudah dilakukan sejak 20 tahun yang lalu. Dengan mengetahui efisiensi injeksi maka bisa dilakukan proses optimisasi dengan menaikkan laju injeksi air pada sumur injeksi yang memiliki efisiensi tinggi dan sebaliknya. Dalam studi ini performa injeksi air dianalisis menggunakan Capacitance-Resistance Model Injection-Production (CRM-IP) untuk menentukan konektifitas setiap sumur injeksi dan produksi. Dalam studi ini juga mendiskusikan implementasi CRM-IP dengan menggunakan bahasa pemrograman MATLAB dan
optimisasi alokasi laju injeksi untuk mendapatkan jumlah perolehan produksi kumulatif minyak yang paling optimal. Hasil studi ini menunjukkan bahwa perolehan minyak lapangan Pandhawa bisa dioptimisasi dengan cara melakukan distribusi rate injeksi masing-masing sumur injeksi. Total didapatkan tambahan minyak sebesar 505 MBO dalam kurun waktu 120 bulan. Dengan menggunakan CRMIP, manajemen waterflood di lapangan ini bisa dilakukan jauh lebih cepat sehingga keputusan yang diambil akan lebih efektif.

Kata kunci: Capacitance Resistance Model (CRM), waterflood, optimisasi, konektifitas antar sumur

INTRODUCTION
One of proven strategy to increase oil recovery in mature field is waterflooding. Water is the most injected fluid to maintain reservoir pressure and push oil from injectors to producers because of it is availability, low cost compared to other techniques and easier to inject. Reservoir characterization and simulation are the important activities in order to evaluate reservoir performance. Evaluation reservoir performance can be conducted by many methods such as material balance, streamline simulation, numerical simulation, etc. Currently reservoir simulation is one on the methods that is commonly used by petroleum engineers. Reservoir simulation has limitation such as require long time consuming and processing, data uncertainty (geological, petrophysical, reservoir engineering), furthermore to long term response of reservoir management. Effective reservoir management in waterflooding field needs quick action regarding injected fluid distribution to improve areal and vertical sweep efficiency during secondary process. Therefore, simpler method that deliver rapid results to counterpart reservoir simulation are important for reservoir management. Capacitance Resistance Model (CRM) is one of verified method to solve the above challenges. Nowadays CRM arrest various attention because of its ability of rapid evaluation in reservoir performance. Common benefits of CRM application are the low execution time, high level of accuracy adapted to available input data quality, can determine inter-well connectivity, needs no geologic information and fluid flow modelling and can be adapted for an excel spreadsheet (Kansao, 2017). Changes in the sweep area will happen along with the injection process. Therefore, it is necessary to re-optimize and even re-modify it to get the optimum oil recovery. Capacitance Resistance Model Injector-Producer (CRM-IP) was selected because it provides a better insight into the well-to-well connectivity (Yousef, Gentil, Jensen, & Lake, 2006) and depending on the heterogeneity of the reservoir, different injectors can impact the production rates of a certain producer with different velocities (Holanda, Gildin, & Jensen, 2015). The CRMs use only production/injection history data to predict performance, which provides simplicity and speed of calculation (Sayarpour, Zuluaga, Kabir, & Lake, 2009). The capacitance–resistance model (CRM) offers the promise of rapid evaluation of waterflood performance. Noticeably, it will take long time if done manually. In this study, a computer program based on MATLAB was created with only the most recent input of production and injection history data to solve this problem. The program will semi-automatically provide a recommendation output for the optimization of the injection rate at certain wells.

I. Basic Theory
II.1 Waterflooding
The objective of water injection is to give energy support into reservoir, as well as to increase recovery factor. The water injection is expected to sweep oil that cannot be produced naturally (primary recovery). Furthermore, the water injection can be used to maintain the reservoir pressure.

II.2 Capacitance Resistance Model (CRM)
Capacitance Resistance Model (CRM) is a predictive method that relies upon signal processing, in which water injection rates are treated as input signals and production rates as
output signals. The name CRM is derived from its analogy to resistor-capacitor (RC) circuit (Thompson, 2006). Production rates response to a step-change in injection rate is analogous to the voltage change of capacitor in a parallel RC where battery potential is equivalent to the injection rate. CRM may also be viewed as a nonlinear multivariate regression analysis tool, which accounts for compressibility and fluid flow in the reservoir (Yousef, Gentil, Jensen, & Lake, 2006). There are unknown parameters in CRM, which are inter-well connectivity as well as time response delay. These parameters reflect connectivity between injector and producer well based on historical injection and production data.

II. Methodology

Capacitance resistance model (CRM) characterizes a flooded reservoir by estimating inter well connectivity, time constants and productivity index using production/injection rates for history matching. Figure 1 shows the flow of modeling using Capacitance resistance model (CRM). For this case using the CRIMP model and the figure 2 show the illustration of CRIMP. CRIMP was chosen because it provides a better insight into well to well connectivity (Yousef, A. A., Gentil, P.H., Jensen, J.L., Lake, L.W., 2006) and depending on the heterogeneity of the reservoir, different injectors can impact the production rate of a certain producer with different velocities (Holanda, R.W., Gildin, E, Jensen, J.L, 2015).

Modeling using CRM begins with collecting field data such as injection and production rate history, and then predicting total production and oil production using the CRIMP model equation as follows (Sayarpour, 2008)

\[ q_{ij}(t_k) = q_{ij}(t_{k-1})e^{-\frac{\Delta t}{\tau_{ij}}} + \left(1 - e^{-\frac{\Delta t}{\tau_{ij}}}ight) \left[ j_i f_{ij}^{(k)} - J_i \frac{\Delta P_{wf}^{(k)}}{\Delta t_k} \right] \]  

Oil production can be calculated using the empirical oil-cut model. This model is presented by Liang et al. (2007). This model considering relationship between water oil ratio over time and cumulative injected water. Therefore, the fractional flow of oil can be written as below. Calculation of oil production rate is require evaluation of the value \( \alpha \) and \( \beta \) from oil production history each producers.

\[ f_o(t_k) = \frac{1}{1 + aW_i^{-\beta}} \]  

Estimation of oil production rate each injector could be calculated using this equation

\[ qo_{ij}(t_k) = q_{ij}(t_k) f_o(t_k) \]  

In CRIMP, for each injector/producer pair, four model parameters exist: \( q_{ij(to)} \), \( \tau_{ij} \), \( f_{ij} \), and \( J_{ij} \). Make initial estimates for these parameters then this parameter will be optimized to produce the smallest error. The procedure for determining the initial guess of \( f_{ij} \) by looking at the distance of the injector to the producer, where the closer distance will have a greater \( f_{ij} \) value than those who have farther distance, the number of connectivity \( (f_{ij}) \) of one injector to each well must not exceed one or more, can be written as:

\[ \sum_{i=1}^{N_i} f_{ij} \leq 1 \]  

For this model we use some assumptions such as:
1. Constant Pwf, \( \Delta P_{wf} = 0 \)
2. Fluid density are constant and capillary pressure are neglected
3. Immiscible fluid water and oil only

After calculating the total liquid production and oil production, the calibration is carried out between the observed data and the predicted results by minimizing the error by optimizing time constant \( (\tau_{ij}) \), connectivity \( (f_{ij}) \), alpha \( (\alpha) \) and beta \( (\beta) \). fmincon function with interior-point algorithm, which already provided in MATLAB optimization toolbox is used to minimize the error. History Match Error can be written as

\[ MSE = \frac{\sum_{n=1}^{n_{data}} (q_{act} - q_{est})^2}{n_{data}} \]  

A suitable CRM model is obtained after the smallest error is obtained and it is also seen on the chart that the data observe with the estimation results are suitable, then this model will be used to predict oil production for the future. However, it is also important to note that history matching in CRM is an ill-posed problem which can lead to uncertainty of CRM model parameter. The uniqueness of CRM model parameter in history match will depend on the amount of historical rate
data available, measurement noise, diffusivity constant, and number of producers per area (Kaviani et. al., 2014).

IV. RESULT AND DISCUSSION

IV.1 Field Case Study

Pandhawa Field is an oilfield located in South Sumatra, Indonesia. Main oil production came from BRF reefal carbonates with minor contribution from TAF and TSF sandstone. Oil gravity produced in Pandhawa Field is considered as light oil with API gravity at 36° API. The reservoir is described as a single continuous zone with minor faults occurrence. The BRF carbonates have good reservoir quality except at several local areas where tight facies occurs and which provides a permeability barrier and stratigraphic entrapment exceeding the simple four-way structural closures. In contrast, the TAF and TSF reservoirs are rather tight.

The Pandhawa Field OOIP is estimated at 230 MMSTB and currently have implemented peripheral waterflood to improve its recovery. There are a total of 238 production wells in Pandhawa field which are divided into 61 clusters. However, for this study we will only consider well that produce from BRF that consist of 58 production wells and 36 injection wells. Production and injection rate history along with voidage replacement ratio (VRR) used in study are given in figure 3(a) and 3(b) respectively. The VRR plot indicates a good balance of injection and production as the values ranging between 1 – 1.2.

IV.2 CRM Result

History matching of liquid rates was successfully performed in this analysis. This is conducted to observe whether the liquid produced matches the simulation results. In figure 4 and figure 5, it can be seen that the total liquid rate field and each well generated from calibration of CRM is quite similar trend, however the quality is not yet satisfactory to the actual data. CPU time for history match took only 91.7 seconds on processor 4 core 2.1 GHz.

From the connectivity map in figure 6, it can be seen that due to the scattered distribution of injector the connectivity of injector to producer is quite disordered. However, as injector is intended to be peripheral, general connectivity trend showed that injection is directed to nearest producer. On the other hand, several injection wells show connectivity for producer that are located very far (> 10 km interwell distance) which could make the result unphysical.

Calculated allocation factor ($f_{ij}$) consistency check can also be done by comparing the values between allocation factor and distance. Generally, further well pairs will have weaker interwell connectivity. Scatter plot of $f_{ij}$ versus interwell distance given on figure 7 confirmed this description.

In determining the oil rate match, empirical parameter in fractional flow model is calibrated by minimizing the mean square error between predicted oil rates and actual oil rates. Gentil (2005) fractional flow model is used to predict oil rates as it avoid implicit calculation of the fractional flow in each time step. It can be seen in figure 8 and figure 9 that the oil rate data field and each producers is sufficiently matched to the fractional oil flow model used. Calibrated fractional flow model is then used for oil rate forecast and injection allocation optimization.

Base case forecast scenario in which no change in allocation rate for injector is carried out to provide base estimate of future reservoir performance. Optimized scenario is then run by the same total injection capacity as in basecase, however allocated injection rate will be optimized by interior-point algorithm to obtain maximum cumulative oil produced at the end of forecast period. Maximum injection rate constraint based on history injection rate per well is also imposed to observe achievable value of injection rate and avoid induced fracturing.

Field oil production profile and injection rate allocation for base and optimized scenario are given on figure 10 and figure 11 respectively. By optimizing injection rate allocation, additional 505 Mbbl oil is expected to be recovered, which is equivalent to 0.22% incremental oil recovery factor.

From interwell connectivity standpoint, optimal allocation rate calculated by CRM can be interpreted as increasing injection support for production wells with the highest oil rate. Producers with the highest oil rate at the start of forecast, hence by CRM logic, the injectors with highest connectivity to these wells will be given priority to increase liquid throughput. Well by
well comparison of base and optimized case scenario is provided in figure 12. Some workaround has been attempted such as by limiting connectivity only in “influence radius”, that is the maximum distance of possible interwell connectivity. The history match result by implementing influence radius of 2 km is shown on figure 14. Note that influence radius cannot be too small such that a producer is left without injection support as shown in figure 13. The history match result from implementing influence radius did not improve significantly. However, sensitivity analysis of influence radius magnitude can be exercised to infer whether optimal influence radius exists that minimize history match error. Such exercise is planned for future phase.

V. CONCLUSION

Based on current study, we conclude that

• A computer program for CRM-IP implementation based on MATLAB has been successfully constructed and validated using Pandhawa field data.
• CRM-IP has been shown to generate interwell connectivity estimation. Computational cost of CRM-IP is also much lower than reservoir simulation.
• CRM-IP model calibration quality are sensitive to data quantity and measurement error, diffusivity parameter an number of producers per area.
• Interwell connectivity estimate for full field peripheral waterflood data proven to be challenging as more connected well pair does not mean better CRM calibration.

VI. FUTURE WORKS

Several works are planned to be exercised to further the research progress, such as

• Sensitivity analysis of radius influence for field case.
• Optimization algorithm performance comparison for CRM Implementation in Matlab.
• Implementing clustering algorithm to reduce well production data dimensionality while still providing accurate CRM calibration.
• Extension of CRM to include aquifer model such as Carter-Tracy analytical model to aid in uncertainty analysis.
• Test of another objective function for waterflood optimization such as NPV or maximum produced liquid capacity.
• GUI implementation for current Matlab Source Code

Nomenclature

\( f_o \) : fractional flow of oil
\( f_{ij} \) : interwell connectivity
\( I_i \) : injection rate ,bbl/day
\( J_{ij} \) : productivity index,bbl/(day,psi)
\( p_{wf} \) : producer bottomhole pressure,psi
\( q_o \) : oil production rate,bbl/day
\( q_{ij} \) : liquid production rate,bbl/day
\( t_k \) : time at \( k \) timestep,day
\( W \) : cumulative water injected,bbl
\( \alpha \) : power–law coefficient for semi–empirical fractional flow model
\( \beta \) : power–law exponent for semi–empirical fractional flow model
\( \tau_{ij} \) : time constant,day
\( MSE \) : Mean Square Error
\( N_{data} \) : number of data points
\( k \) : average reservoir permeability,md
\( A \) : reservoir area,acre
\( \phi \) : average porosity
\( \mu \) : average fluid viscosity,cp
\( ct \) : total compressibility, psi−1
\( \Delta t \) : average time interval between each data points,day
\( q_{act} \) : fluid rate actual
\( q_{est} \) : fluid rate estimation

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Figure 5. Well Liquid Rate History Matching Result
Figure 12. Injection rate allocation comparison between base and optimized case
