Application of Fast Reservoir Simulation Capacitance-Resistance Method to Predict the Hot Water Flooding Performance

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ORIGINALITY STATEMENT

I, Moldir Almatkyzy, hereby declare that this submission is my work and to the best of my knowledge it contains no materials previously published or written by another person, or substantial proportions of material that have been accepted for the award of any other degree or diploma at Nazarbayev University or any other educational institution, except where due acknowledgment is made in the thesis.

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ABSTRACT

A range of methods is available to assess a reservoir performance. Development and application of fast methods to evaluate the performance of a recovery method and provide a general picture of injectors/producers connectivity is critical to manage a reservoir. Capacitance Resistance Model (CRM) is a useful tool for improving real-time flood management, as it allows rapid modeling and simulation of gas and water flood recovery processes. The CRM approach is based on signal processing methods in which injection rates are accepted as input signals and production flow rates are considered as reservoir response or output signals. The model offers key advantages, including simplicity, immediate results, and optimal performance even with minimal initial data. Over recent years, enhancements in CRM have established it as a reservoir management tool, enabling essential tasks like history matching of production data, forecasting production rates, scheduling injection rates, detecting injection leakage, and estimating fracture distribution (Sayarpour, 2008).

In this study, we expanded the application of CRM to predict the behavior of hot water injection processes. Systems identification is applied for history matching using only injection/production data from commercial simulator to characterize the reservoir models where injection of hot water was applied, evaluating interwell connectivities and time constants. Four case studies were developed with two different injection fluid types. These included a homogeneous model with a five-spot well pattern (Case 1), models featuring high-permeability streaks (Case 2 and 3), and a heterogeneous reservoir model (Case 4). In these cases, bottomhole pressures and production rates remained constant, while injection rates fluctuated over the simulation period. The first three cases were analyzed to predict reservoir performance analytically under specific conditions for homogeneous scenarios. The highest calculated average error was observed during Case 2 for both total liquid production and oil production rates (10.84% and 11.79%, respectively), while the minimum average error values were found in Case 4, with values of 6.50% for liquid rates and 5.76% for oil production rates. In all cases, the results of the developed models exhibited satisfactory agreement with those of a grid-based commercial simulator. We considered these hypothetical cases where modifications were applied to generate a more reliable evaluation of interwell connectivity and time constants, and used the R-squared value of the model as a fitting parameter for history matching processes. This approach, applied across multiple cases, yielded excellent evaluations of both reservoir performance and well connectivity.

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1. INTRODUCTION

The assessment of production conditions at existing oil and gas fields, as well as forecasting the level of their future productivity is one of the most important and challenging tasks not only for reservoir engineers but also for the entire field of oil and gas production. Along with this, there are several other tasks as forecasting the development and exploration of new oil and gas reservoirs, considering various features such data availability.

Currently, there are various methods to assist in these assessment activities, and the most effective method is using reservoir simulation tools. In simple words, reservoir simulation can be achieved by applying mathematical calculations to predict and forecast reservoir performance under different conditions. The process of simulation of the reservoir is not new for the petroleum engineering industry. Although the idea of reservoir simulation is very old, with the rapid development of computer technology it has become possible to use new aspects that describe oil and gas reservoirs using more details, hence more accurate use of reservoir simulation is achieved. However, several issues can arise while running reservoir simulations, for instance understanding and using more detailed input data affects the accuracy of the reservoir simulation.

The first steps of using reservoir simulation were in the 1960s when calculations consisted of large equations, material balances, and one-dimensional (1D) Buckley-Leverett approach (Coats, 1982). The field of reservoir modeling has developed by the rapid evolution of high-speed digital computers. These models could help to solve large sets of finite difference equations that describe two- and three-dimensional (2D and 3D), multi-phase, dynamic flows in heterogeneous media (Coats, 1982). In the 1960s, all modeling work was devoted to the problems of two-phase systems such as gas-water and three-phase gas-water-oil. The simulation models used were limited to reservoir depletion and pressure maintenance only. In the 1970s, the picture began to change due to the sharp rise in oil and gas prices, which led to the development of various methods of enhanced oil recovery (EOR). This has led to the emergence of new simulation systems such as mixed flooding, chemical flooding, CO_2 injection, steam and/or hot water injection, etc. These models help to solve complex oil recovery processes, as well as reduce costs by improving the stability of the formations and their application efficiency. This has led to the fact that the relatively simple understanding of the two-phase (gas and oil) behavior of hydrocarbons in an immiscible flow has been changed to the use of the concept as the displacement of oil under the influence of certain conditions such as temperature and chemical agents. In addition, using conventional multiphase flow in porous medium simulation could respond to changes such as chemical absorption and degradation, reduction in interfacial tension, various reaction kinetics, etc.

As it was mentioned above, these models can be used considering various features of oil and gas production. The purpose of such modeling is to understand the behavior of fluid flow in multi-phase systems such as gas-water, and gas-water-black oil in reservoirs, and on this basis apply the most efficient methods of oil field exploration that will improve the oil recovery performance.

Many types of reservoir modeling can be classified from using simple reservoir analogs to models that are applicable only with an understanding of the physics of all mechanisms of oil production. Thus, given the purpose of modeling and the availability of all basic data, it is possible to predict which type of reservoir modeling can be applied in certain cases. The benefits of using complex types of reservoir simulations, such as the reliability and credibility of the outcomes, come along with numerous requirements and limitations, such as using high-quality input data, which in turn increases the time and using resources, and as a result, requires more computational effort. The same limitations and advantages exist in the application of the simple models, for example, using less initial data and fewer computational resources can lead to the less accurate interpretation of the results, namely their unreliability in real mode. Thus, one can come to some conclusion that even if there a several types of reservoir modeling, each is applicable with some assumptions regarding specific conditions.

To estimate the future behavior and production of the reservoir, various methods are used, such as numerical simulations, predictive models, etc. These methods help in determining the next steps in EOR methods such as water flooding, polymer flooding, CO_2 injection, etc. They are used after the reservoir reaches its peak economic productivity to increase its efficiency namely after primary recovery. When determining which of the methods for predicting an increase in reservoir productivity can be applied in different cases, one of the important economic parameters is using fewer initial data, as well as a small amount of time for the simulation process. Among these methods, which help to determine and predict the future of the reservoir, predictive models are the most cost-effective, as they require only a small amount of data and a small involvement of computing and engineering time.

Crossflow, heterogeneity, injectivity, and areal sweep efficiency are parameters that can affect fluid behavior in a reservoir, and using predictive models as a main one in forecasting reservoir production can obtain all these parameters.

Thereby, new reservoir simulation approaches have been developed that allow rapid reservoir simulation using less input reliable data to quickly evaluate reservoir performance. And one of these models is using CRM. In reservoirs, the fluid flow is caused by a pressure difference. Due to the lack of computational equations and resources before, it was impossible to model this fluid flow behavior. However, the term reservoir simulation implies using similar models behaving like fluid flow in a reservoir; a capacitance resistance model has been developed. Several experiments were carried out in this regard, in which the fluid flow was simulated by a system with an electron flow. The reason for using this method was that the electron flow system has several similarities with the fluid flow system: both of them have some resistance to flow, as well as the ability to store the energy, the first, fluid flow due to its compressibility, the second, flow of electrons due to the storing them in capacitors (De Holanda et al., 2018). This model is based on a quantitative technique, namely the use of a material balance in which only the injection and production rates and well coordinates are used to determine modeling parameters, such as interwell connection and time values. In this model the injection rate is used as an input signal, the production rate as an output signal (Saidi et al., 2015). The parameter for evaluating the efficiency of this model can be considered the proportion of the injected fluid in each of the production wells and the time to process the simulation. The advantages of this model are easy to use, short running time, and a small amount of initial data.

As mentioned before, interwell connectivity is one of the main constitute parameters of CRM, thus understanding of history matching of injection and production wells connectivity in a multiwall system is necessary. CRM are models that are based on using a material balance of the system. For this type of modeling the required data only consists of interference between wells and injection/production rates to be capable of history matching, and knowing the bottomhole pressure (BHP), if it is available.

As CRMs can be described as fast simulation models, there are some cases when using this fast simulation model can be applied:

- to identify the presence of high permeability zones and sealing faults;
- quantification of interference between adjacent wells;
- determination of sweep efficiency;

— fluid distribution identification through secondary recovery and EOR processes.

In this part of the chapter basic concepts of CRM, specifically its physical meaning, controlling parameters, history matching as well as application can be introduced in more detail.

1.1 Problem Definition

The ultimate objective of reservoir modeling and simulation is to develop a model that can accurately forecast reservoir behavior and be applied to quickly arrive at the appropriate management approach. Typically, it requires the fusion of various disciplines, which makes it a challenging assignment to finish on time. The procedure is made more difficult by the fact that petroleum reservoirs are data-poor settings in addition to the porous medium flow phenomenon's inherent physical complexity. Since many reservoir characteristics must be inferred rather than physically measured, complicated models are usually created that are highly unpredictable. In the oil industry, data acquisition can sometimes be highly expensive. So, it is crucial to make sure that the data collected significantly contributes to the decision-making process improvement. Another issue is that data analysis takes time because information must be evaluated and interpreted to be incorporated into a reservoir model, and the industry is frequently under pressure to make choices daily with few resources. To address the aforementioned issues, simplified reservoir models are developed. Using just the producers' BHP and production/injection rates for history matching, the CRM defines a flooded reservoir by calculating interwell connectivities, time constants, and productivity indices (PI). This leads to quick and affordable reservoir modeling and simulation that can be used for real-time optimization.

The experiment was primarily justified in 1942 when the first capacitor resistor circuit was employed to simulate reservoir behavior during floods due to a lack of processing capability to handle the complex reservoir modeling problem (De Holanda et al., 2018). The oil industry is currently working with a different paradigm, called real-time recovery and optimization. Although it is possible to run large reservoir grid-based models and support decision-making, optimization approaches frequently involve performing a huge number of simulations, which is not always practicable.

Furthermore, because of the high level of uncertainty surrounding some crucial parameters (such as porosity and permeability), managerial decisions based on robust mathematical solutions can still be very uncertain, necessitating numerous realizations of the geologic model and estimates of the worst and best-case scenarios. Reduced complexity models are the best option in this situation for optimization purposes because they are quicker to execute, give a good physical understanding of the reservoir, and typically present an objective function with a smoother surface, preventing the optimization algorithm from becoming stuck in local minima. CRM has been used as a tool for managing flooding in many different industries because of these factors.

CRM's central idea is that the reservoir may be conceptualized as a straightforward data-driven input-output model controlled by differential equations for the linear material balance. To regulate the outputs, which are production rates, which are the variables with economic value, the inputs—injection rates and BHPs — can be manipulated.

This chapter will focus on extending the applicability of the capacitance resistance modeling method to thermal recovery processes. Hot water flooding (HWF) in particular is considered in this work. The focus on HWF is for two reasons:

- First of all, an expansion of the CRM method to hot waterfloods is a logical and natural step given how straightforward the HWF process is and how similar it is to cold water flooding (compared to other processes in the thermal stimulation family). If the CRM technology could be successfully applied to hot water flooding, it would provide a solid foundation for tackling more complicated thermal stimulation processes like steam flooding, SAGD, and in-situ combustion;
- The second reason is that CRM is a desirable contender for simulating HWF processes due to its speed and low computing cost. A thermal CRM could offer a less expensive and quicker alternative to or complement numerical thermal simulators since characterizing HWF, like many other thermal processes, is frequently costly and time-consuming.

1.2 Objectives of the Thesis

1.2.1 Main Objectives

With the help of production/injection and BHP variations, the CRMs offer a reduced-order, input-output modeling approach that describes reservoirs. The models have been successfully applied to primary recovery and other EOR processes since they were initially designed for water flooding (secondary recovery) activities. This study focused on expanding CRM technology to thermal stimulation projects and enhancing CRM capabilities for characterization in water-flooded reservoirs.

The 2 key objectives of this research work are as follows:

- Application of CRM technology to thermal recovery projects. Due to its relative speed, lack of reliance on geological data, and applicability to reservoirs with a large number of wells, CRM is particularly appealing for the characterization of thermal projects. The creation of a CRM variation appropriate for heat operations will be the main topic of this research project. For modeling and managing reservoirs undergoing thermal stimulation, a model of this kind will offer quick and simple replacements or complements;
- Effect of HWF on CRM parameters.

1.3 Outline

This thesis contains of 5 chapters such as:

- Chapter 1 is an introduction that describes the relevance of the work and consists of problem statement and objectives of the work;
- Chapter 2 introduces the literature review of CRM and hot water flooding;
- Chapter 3 is a methodology which was used to design CRM;
- Chapter 4 is for results and discussions obtained from CRM for 4 cases based on synthetic fields;
- Chapter 5 is a conclusion and recommendations for future research.

2. LITERATURE REVIEW

To determine the pressure and oil saturation of each grid block in the reservoir various conventional reservoir simulators like Eclipse and the IMEX are used to numerically solve the differential material balance equations (MBE). However, these quantities (pressure and oil saturation) must be updated as the simulation goes on because they change over time in addition to varying spatially from one grid block to another. When a huge reservoir needs to be modeled, this could be an extremely time-consuming operation because large simulations require millions of grid blocks. It takes time and money to gather core samples to determine the rock and fluid parameters that reservoir simulators need as input.

Using just data from the wells, the CRM analyzes the characteristics of an oil reservoir (Weber, 2009). Because this model resembles an RC (Resistor-Capacitor) circuit, the term CRM was chosen for it (Kim et al., 2012). A capacitor's voltage measurement in a parallel RC circuit, where the battery potential is comparable to the injection signal, is akin to a production rate reaction to a step change in injection rate (Sayarpour, 2008). The CRM uses multivariate nonlinear regression to estimate two different types of model parameters: connectivities (or gains), which represent the degree of communication between injector-producer well pairs, and time constants, which represent the degree of fluid storage (compressibility) or pressure dissipation between well pairs.

An ICRM was created by Nguyen et al. (2011) that substitutes cumulative water injection and cumulative total production for water injection rate and total production rate. To get the model estimates, the ICRM (Integrated Capacitance-Resistance Method) uses linear multivariate regression (LMR). In comparison to conventional reservoir simulators, the CM (Capacitance Model), CRM, and ICRM offer a quick assessment of reservoir behavior between injectors and producers because these three models only need producer bottom-hole pressures (BHPs), which are frequently already measured and collected, and water injection rates (or cumulative water injection) and total liquid production rates (or cumulative total liquid production).

2.1 Capacitance Resistance Models

Interwell connectivities (or gains) and time constants are two types of model parameters that must be estimated. In process control, straightforward linear models with gains and time constants are typically employed. The connectivities represent the connection between wells and calculate the effects of fluid characteristics as well as reservoir permeability and porosity.

The time constant reflects the effects of reservoir compressibility, pore volume, and the PI of a producing well and allows for attenuation of the injection signal.

Multivariate nonlinear regression is used to derive the model's parameters using historical data on injection and production rates. Physical reservoir qualities do not need to be estimated a priori. However, the model's history matching historical data yields useful information about the reservoir. For various reservoir control volumes, the CRM provides a variety of alternatives.

Production and reservoir engineers have used a straightforward but effective approach by combining the material balance and inflow equations. This framework makes it easier to evaluate the viability of anticipated flow rates and gives material balance computations a deadline. Such coupling is also the core of CRMs, as stated in Equations from 1-4 (Sayarpour, 2008). The following equation is the material balance in a flooded reservoir:

$$c_t V_p \frac{d\bar{p}}{dt} = \omega(t) - q(t) \qquad \text{Eq. 1}$$

where c_t is total compressibility, V_p is pore volume, $\bar{p}$ is volume averaged pressure, w(t) is injection rate and q(t) is total production rate (oil and water).The formula for the deliverability equation is:

$$q(t) = J(\bar{p}(t) - p_{wf}(t)) \qquad \text{Eq. 2}$$

where p_w f is the producer's BHP and J is the productivity index. From both equations above $\bar{p}$ can be found by using q, p_{wf} and J and replaced in equation 1 to get the following equation for:

$$\tau \frac{dq}{dt} + q(t) = \omega(t) - \tau \frac{dp_{wf}}{dt} \qquad \text{Eq. 3}$$

where τ is time constant and the equation to express it:

$$\tau = \frac{c_t V_p}{J} \qquad \text{Eq. 4}$$

Physically, the time constant τ represents the amount of fluid storage (compressibility) or pressure dissipation between pairs of injector/producer wells. According to the following presumptions, Equation 3 was created by considering some following assumptions:

- No additional drilled wells in the field during the analysis;
- Properties of rock (permeability, porosity, etc.) and fluid (compressibility, viscosity, density, etc.) are considered to be constant;
- The temperature of the reservoir is constant or barely varies;

- The coexistence of two immiscible phases;
- The disregard of the effects of capillary pressure and gravity;
- Application of Darcy's law, and the constancy of the PI.

Opportunities to improve hydrocarbon recovery and field management can be found by analyzing the many scales of the porous media flow phenomenon in reservoirs. The CRM has several forms that depend on the reservoir control volumes (Fig.1).

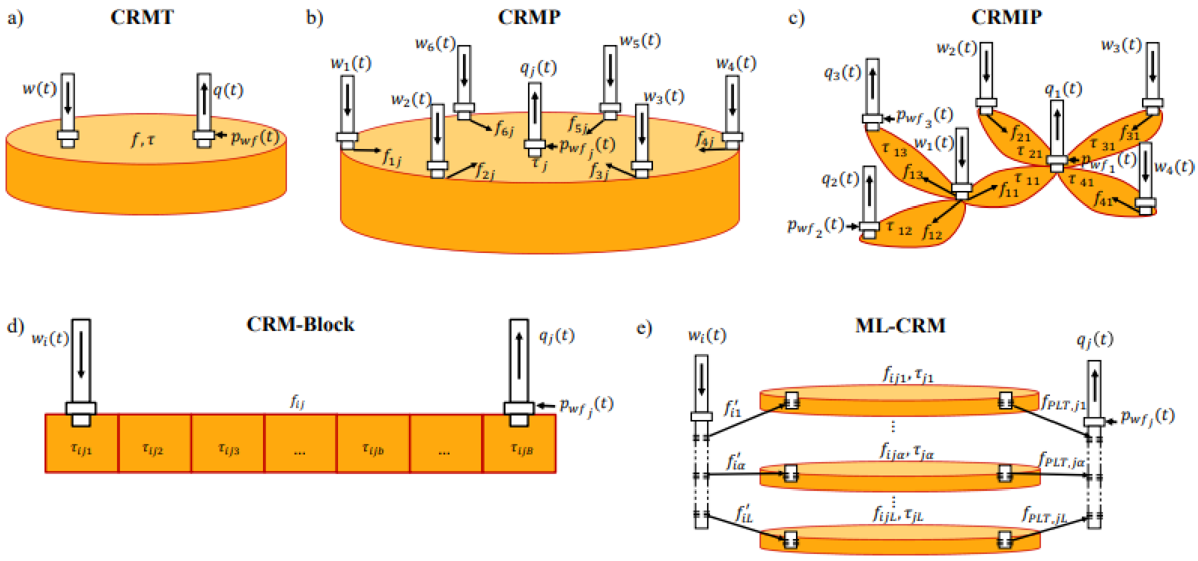


Figure 1. Illustration of CRM based on different reservoir control volume types: (a) single tank (CRMT); (b) producer based (CRMP); (c) injector–producer pair based (CRMIP); (d) blocks in series (CRM-block); (e) multi-layer or blocks in parallel (ML-CRM) (De Holanda et al., 2018).

2.2 CRMT – The Single Tank

The drainage volume of the entire reservoir serves as the control volume in the CRMT formulation for the governing continuity equations. The reservoir can be represented as a single tank with a single injection rate and one production rate by adding the rates of all the production wells into a single pseudo-producer and the rates of all the injection wells into a single pseudo-injector. Figure 3 (a) shows this construction in schematic form.

A model with three parameters — an interwell connectivity f, a time constant τ, and the productivity index J — is produced when the CRM is built as a single tank.

$$q(t) = fI(t) - \tau\frac{dq(t)}{dt} - J\tau\frac{dp_{wf}\,(t)}{dt} \qquad \text{Eq. 5}$$

Equation 5 (Sayarpour, 2008) can satisfy the condition as superposition in time, i.e. that it is possible to substitute the value of the previous period’s production with the equation for that period to arrive at an equation that is only dependent on the initial production rate and the injection rates for each period. Nonlinear regression is used to determine the connectivity and time constant model parameters. To do this, a nonlinear program (NLP) with the following objective function must be created:

$$\min z = \sum_{k=1}^{n_t} (\sum_{j=1}^{n_p} q_{jk}^{abs} - q_k)^2 \qquad \text{Eq. 6}$$

To quickly and easily describe the behavior of the reservoir as a whole, the CRMT (Capacitance-Resistance Model-Tank) is used. There are only two parameters, and by resolving the NLP above, the values obtained can be used as starting points for future more complex CRMs. While it has been demonstrated that this straightforward reservoir description is relatively accurate, typical hydrocarbon reservoirs benefit from a more involved approach (Sayarpour, 2008).

2.3 CRMP – The Producer-Based

The drainage volume of each producer, including all of the injectors that affect their production rates, is defined as producer-based representation (CRMP), as shown in Figure 3 (b).

$$q_j(t) = \sum_{i=1}^{n_i} f_{ij} I_j(t) - \tau \frac{dq_j(t)}{dt} - J_j \tau_j \frac{dp_{wf}^{(j)}(t)}{dt} \qquad \text{Eq. 7}$$

The steady-state proportion of water injected in injector I that contributes to the production of both oil and water in producer J is physically represented by the gain f_{ij}.

Multivariable nonlinear regression is again used to estimate model parameters (the connectivity and time constant). The necessary objective function differs somewhat from the CRMT's as

$$\min z = \sum_{k=1}^{n_t} \sum_{j=1}^{n_p} (q_{jk}^{abs} - q_{jk})^2 \qquad \text{Eq. 8}$$

This Equation 8 has its following limitations:

$$\sum_{j=1}^{n_p} f_{ij} \leq 1 \text{ for all i} \qquad \text{Eq. 9}$$

$$f_{ij},\ \tau_j \geq 0 \text{ for all i and j} \qquad \text{Eq. 10}$$

2.4 CRMIP – The Injector-Producer Pair-Based

The CRMIP's control volume is represented using one τ_{ij} and f_{ij} for each injector-producer pair, shown in Figure 3 (c) above. The total fluid production for this control volume's governing continuity equation is given by:

$$q_{ij}(t) = f_{ij}I_i(t) - \tau_{ij}\frac{dq_{ij}(t)}{dt} - J_{ij}\tau_{ij}\frac{dp_{wf}^{(j)}(t)}{dt} \qquad \text{Eq. 11}$$

J_{ij} - the PI associated with the partial production $q_{ij}(t)$ using the following Equation 12 (Sayarpour, 2008):

$$q_{ij} = J_{ij}(\overline{p_{ij}} - p_{wf}^{(j)}) \qquad \text{Eq. 12}$$

2.5 CRM-Block

The first-order tank formulation presupposes an instantaneous reaction to changes in injection rates. To implement tanks in a series paradigm, the injector-producer control volume was divided into numerous blocks (Fig. 3 (d)). For situations with high dissipation, such as low permeability, high-frequency injection signal, and/or far-off injector-producer pairs, the CRM-block model was developed.

$$q(t) = q_B(t_0)e^{-\frac{(t-t_0)}{\tau_B}} + \sum_{b=1}^{B-1}(q_B(t_0)e^{-\frac{(t-t_0)}{\tau_B}}\prod_{a=1}^{B-b}1 - e^{-\frac{(t-t_0)}{\tau_a}} + \omega(t)\prod_{b=1}^{B}(1 - e^{-\frac{(t-t_0)}{\tau_B}}) \qquad \text{Eq. 13}$$

where B is the total number of blocks between the pseudo-injector and pseudo-producer. The model of CPM-Block is not an attractive solution if the simplicity of the reservoir modeling is a goal that is pursued. As the number of parameters significantly increases, to diminish this issue Sayarpour presented to consider an equal τ_b for all blocks and control the number B in history matching. Moreover, because these control volumes are not spatially specified, the pressures and rates of the blocks cannot be linked to specific reservoir locations. In other words, the primary goal of the CRM-block concept is to simulate the delay in the production response.

2.6 Multilayer CRM: Blocks in Parallel

Since it is typical for impermeable layers to be interspersed within the reservoir rock, compartmentalizing the fluid flow to the wells is more realistic than assuming a single layer, as in the earlier approximations.

The previously described ML-CRMs extended the CRMP material balance Equation 7 to each layer (α), allowing for the following summation of these models:

$$q_{p,j\alpha}(t) = \sum_{i=1}^{N_{inj}} f'_{i\alpha} f_{ij\alpha} w_i(t) - \tau_{j\alpha} \frac{dq_{p,j\alpha}}{dt} - J_{j\alpha}\tau_{j\alpha} \frac{dp_{wf}(t)}{dt} \quad \text{Eq. 14}$$

where $q_{p,j\alpha}$ is the total production rate contributed from layer α disregarding the crossflow ($Q_{p,j\alpha}$ contribution from other layers). Given the cases of cross-flow between layers, care must be taken when increasing the complexity of the model (Mamghaderi et al., 2012). As the number of parameters increases, there will be more combinations that should match the historical data satisfactorily. There is also a risk that many of these models will give poor predictions. In addition, while using this model, the change in cross-flow conditions over time may not be correctly captured.

2.7 CRM Parameters Estimation

The CRM method requires only three types of estimation parameters, two of which were mentioned earlier, these are interwell connectivity (f_{ij}) and time constant (τ_{ij}), also the third parameter is the PI (J_{ij}), while the grid-based model, in comparison with even the most complex CRM type, requires a several rock and fluid properties to model the behavior of a given reservoir, as well as its fluid flow behavior (Holanda, 2015).

Instead of conducting complete physics models straight away, it is feasible to employ CRM simulation based exclusively on production data. In this section of the chapter, the parameters that have the most impact on the simulation outcome will be briefly explained as well as their physical meaning on the process. Therefore, it is assumed that the quantity of parameters required to describe the system is a function of the number of injection and production wells, as well as the chosen formulation of CRM (Holanda, 2015).

2.7.1 Physical Meaning of Parameters

One of the accepted assumptions to most accurately describe the flow behavior of the reservoir is the availability of physical models, for the evaluation of which a large amount of data of various properties is used. As it will be further discussed, some of the reasons why the reservoir modeling process has become a very expensive process will be mentioned.

In practice, processes such as data collection and analysis that need to be handled during the simulation process are very time-consuming and financially demanding due to the varying infrastructure and the requirement for specialized knowledge and manpower. In real cases, the reservoir is a heterogeneous system with different areas with different permeability and porosity; this in turn leads to the use of a large amount of geostatic data. The parameters that are used in this type of simulation are very accessible and easy to use and evaluate, which makes it much faster and most importantly cheaper to provide a workflow for practical implementation.

2.7.2 Interwell Connectivity

The volume fraction of injected fluid from a particular injector that flows to a particular production well is referred to as interwell connectivity or simply gains (De Holanda et al., 2018). In general, these gains are related to the steady state response of the outlet signal caused by changes in the input signal. The general trend of this parameter is related to the interval of variation between injection rates of injection wells. Thus, the more connections, the greater the variation in the output signals. This parameter has great practical importance since it helps determine, with an increase in the injection rate from a certain injection well, how much to expect the increase in the productivity rate of a certain production well.

2.7.3 Time Constant

One of the parameters, which has also a significant effect on an output signal, is the time, takes for a pressure wave due to the change in the rate of injection, to reach and distribute in the porous media. High compressibility, low permeability, as well as large pore volume - all of these are significant assumptions for the slow response of the system to the changes, which is estimated by the high performance of the τ_{ij}. Also, vice versa, high permeability, small pore volume, and small compressibility lead to the fast response signal, and the τ_{ij} is small.

2.7.4 Productivity Index

To obtain the required flow rate of a production well the required pressure drawdown is required to be known, this parameter is called the productivity index. The assumptions applied for the constant PI are that the properties of the rock and liquid in the reservoir are constant over time, due to the total volume of the reservoir as well as its pressure. This is called a steady-state system. However, if the system is not in a steady state, then J_{ij} is not constant.

The CRM assumes that J_{ij} is not constant, while the water injection into the reservoir holds its pressure in approximately the same values; the J_{ij} varies in the range of the same values, as the injection rate values and the BHP of producer values are changing (Holanda, 2015).

2.8 Application of CRM

Different researches have been conducted to analyze injector-producer pairs to determine reservoir properties, and many methods are used to do this, such as tracer testing and/or observing the response of producers to an injection signal. Some researchers used statistical methods in combination with injection and production data to determine the interwell connection. To determine the interaction between pairs of injectors and producers as a potential indicator of flow directionality, a study by Heffer et al. (2007) estimated the Spearman rank correlation coefficient between them. Their study showed that some components of the injection signal received by producers were related to geomechanics. In some respects, the CRM can be thought of as being similar to a streamline approach. An injector's relative number of streamlines supporting a producer is equal to the connection between each pair of injectors and producers. Streamline simulations have become increasingly popular due to their quick processing speed (Cheng et al., 2007).

Panda et al., (1996) used artificial neural networks to predict oil production and evaluate the interaction between pairs of wells. They used simulated case studies to apply this strategy and concluded that artificial neural networks have some limitations when applied to such complex systems. In addition, it is generally recognized that these models are difficult to understand physically. Albertoni and Lake (2003) used multivariate linear regression analysis to quantify interwell communications. Parra et al. (2023) investigated the suitability and significance of using the CRMP-producer-centric approach to characterize both single and multiwell undersaturated oil reservoirs during primary recovery.

Yousef et al. (2006) determined the response of total fluid production to injection signals and changes in bottomhole pressure and created a mathematical model based on this. The differential mass balance equation for a closed control volume with several injection and production wells was essentially solved using this approach. The production response to the effective drainage volume of production wells, fluid compressibility, PI, and the coupling coefficient between pairs of injection and production wells are related by some unknown coefficients in the model. The ability of a system to create fluid can be adequately described by these factors. This model and the equation describing the flow of electric currents in a system of capacitors and resistors have a special similarity.

Several studies have demonstrated the effectiveness of using these data to characterize and manage oil reserves that are undergoing primary or secondary recovery. One of the simplest cases for using this model is a waterflooding process. During a water flooding project, information on injection and production rates is typically abundant. The groundbreaking concept of merely considering production and injection rates to infer connectivity between wells was introduced by Albertoni and Lake (2003). To assess interwell communication, they used multivariate linear regression (MVLR). To take into consideration pressure loss and the lag time between wells, a diffusivity filter was used. Yousef (2006) provided CRM that measured interwell communication without the use of diffusivity filters.

In recent years, improvements in the CRM method have positioned the model as a reservoir management tool capable of assisting in performing key tasks such as history matching of production data, forecasting of production rates, scheduling of injection rates, detection of injection leakage, and estimation of fracture distribution. Salehian et al., (2018) studied a typical realistic reservoir simulation model of a waterflooding process. In this model, the intelligent completion valves (ICVs) of smart wells were regulated using conditional statements known as procedures within a fully commercial, comprehensive numerical reservoir simulator. The simulation data is then used to construct the CRM model, aiming to capture interwell connectivities at the zone level. This goes beyond solely relying on interwell connectivity data, as smart wells offer control and insight into the injection volume into each layer or zone.

The CRM has been used in EOR procedures even though the models that have been provided so far were primarily designed for water flooding. While in some studies, additional developments were made to account for the unique aspects of the EOR process under consideration, in some papers, the models previously provided are employed the same way as in water flooding. Before more intricate and time-consuming simulation models were created, the CRM was a useful tool in many EOR processes by offering insights into the primary forces behind pressure support, reservoir heterogeneity, and the advancement of the flood front.

As an example, to show the applicability of CRM to model an EOR operation, results of a simulation by Nguyen (2012) is presented here. CRM was used to model simultaneous injection of water and CO_2 in a synthetic field. The field had four producers and two injectors. The location of wells is presented on Figure 2. Created two high permeability streaks were from injection I1 to producer P1 and from injector I2 to producer P3. The field was operated underwater injection from year 2000 to 2030, then the water injection rates were kept constant and CO_2 injection was added. The initial reservoir pressure was 5000 psi and all wells are bottom-hole pressure constrained at 3500 psi. From 2000 to 2030, the field production was driven by water injection. The production rates during the period from 2000 to 2005 had fluctuation that was suitable for fitting CRMP. The CRMP results are given in Table 1. It is seen that well pairs I1-P1 and I2-P3 have higher gains and P1 and P3 also have smaller time constants.

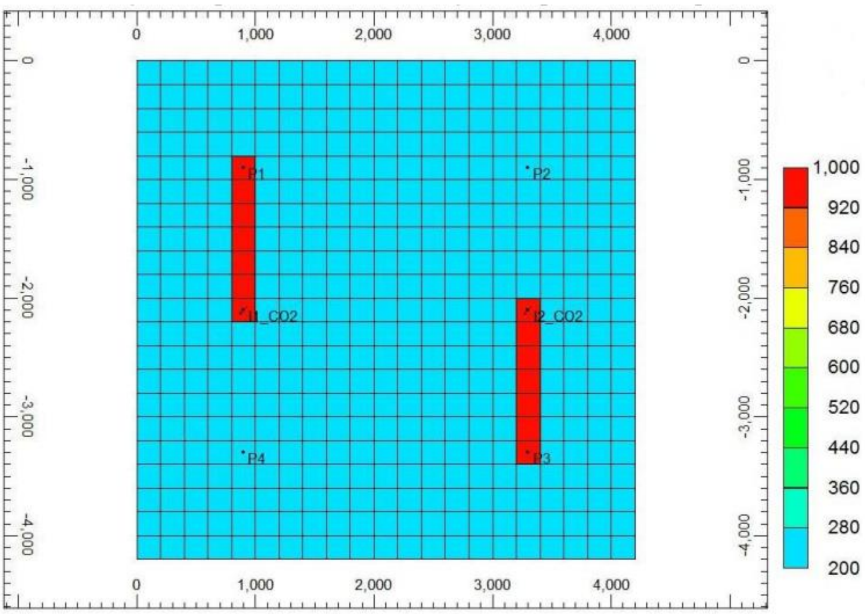


Figure 2. Generated CO_2 flooded field permeability map in mD (Nguyen, 2012).

Table 1. CRMP parameter estimates for the water injection period (Nguyen, 2012)

Gain	**P1**	**P2**	**P3**	**P4**
I1	0.44	0.14	0.18	0.24
I2	0.2	0.24	0.47	0.09
Time constant (days)	5.03	8.18	5.54	7.51

For the purpose of evaluation CRM performance on later CO_2 injection, the fitting window was selected from May 2038 to November 2050. The CRMP corresponded for the producers are shown in Figure 3; the graphical illustration of corresponded matching shown only for one producer. CRMP was able to give a good fluid production rate that fits all producers.

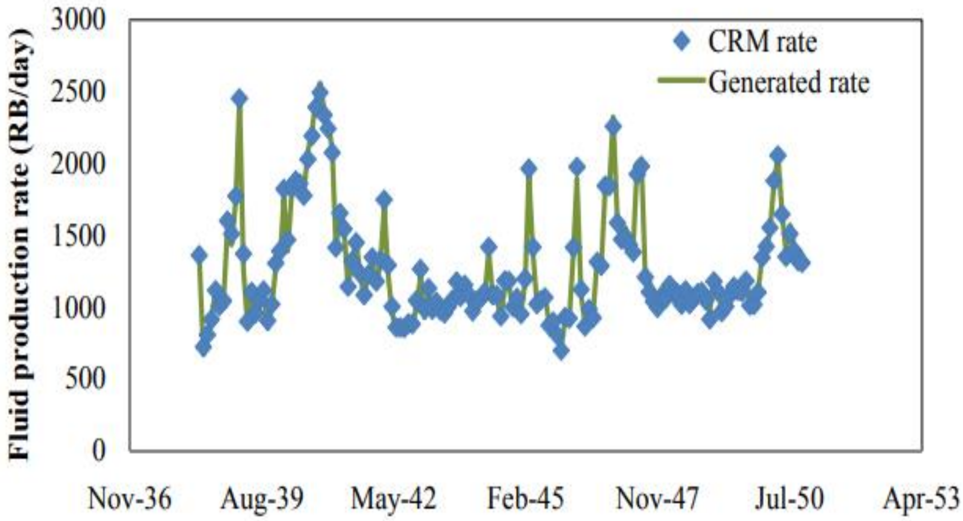


Figure 3. CRMP fit of P1 fluid production rate (Nguyen, 2012).

The f and τ values estimated by CRMP are shown in Table 2. I1-P1 and I2-P3 had the largest interwell connectivity as expected because of the high permeability channels between those well pairs. The results of both parameters were slightly different from the Table 1.

Table 2. CRMP parameter estimation (Nguyen, 2012)

Gain	**P1**	**P2**	**P3**	**P4**
I1	0.62	0.06	0.16	0.15
I2	0.18	0.16	0.58	0.08
Time constant (days)	20.90	21.21	22.60	19.12

As can be seen from Table 1, for the water injection period, the time constants of production wells P1 and P3 should be less than those of production wells P2 and P4. However, a significant amount of CO_2 flowing into the high permeability channels during this simultaneous water and CO_2 flood generated a significant amount of total compressibility (c_t). As a result, the time constants P1 and P3 were almost equivalent to the time constants P2 and P4. It can be seen that because CO_2 is highly compressible, the time constant for CO_2 injection is greater than for water injection, compared to the time constants in Table 1.

Finally, CRMP was used to inject CO_2 after introducing water into the synthetic field. The data obtained show that CRMP can satisfactorily match production data during CO_2 injection, and the predicted gain and time constants differ from those obtained when CRMP was matched to data during waterflooding.

Considering the given example, every EOR technique involves a complex interaction of fluids and rock, a straightforward CRM strategy can be used to match historical data and anticipate such a process. The investigations that were done in this area are summarized in Table 3. The research projects listed in Table 3 demonstrate the advancements made in the analysis of various EOR techniques employing CRM for the process of water flooding.

Table 3. CRM developments and applications to several EOR processes

Reference (s)	**EOR processes**	**Highlights**
Sayarpour, 2008	WAG	A pilot WAG injection in the McElroy field using the CRMT and CRMP and a semi-empirical power-law fractional flow model (Permian Basin, West Texas).
Salazar et al., 2012	Hydrocarbon gas and nitrogen injection	A deep naturally fractured reservoir in the South of Mexico was used to predict production rates of oil, water, hydrocarbon gas, and nitrogen gas using a three-phase, four-component fractional flow model.
Akin, 2014	Geothermal reservoirs	In West Anatolia, Turkey, a geothermal reservoir, the technique for reinjecting produced water has been improved by the history matching of the CRMIP to infer interwell connectivities.
Eshraghi et al., 2016	CO_2 flooding	Application of the CRMP with the semi-empirical power-law fractional flow model and heuristic optimization algorithms for miscible CO_2 flooding cases with data from a grid-based compositional reservoir model.
Duribe, 2016	Hot waterflooding	Used CRM in conjunction with energy balance and saturation equations to account for a time-varying $J_j(t)$ and, subsequently, $j(t)$, mostly caused by an increase in water saturation and a decrease in oil viscosity. A grid-based thermal reservoir simulator was used to compare the outcomes.

Reference (s)	EOR processes	Highlights
Zivar et al., 2022	Low salinity waterflooding	The goal of the study was to see how changes in the time constant can describe physical processes in a porous medium, such as a change in wettability. This work showed the results of various experimental and simulation studies that the time constant of the model increased when the wettability was changed to the water-wet state, with the oil-wet medium showing the smallest time constant and the water-wet showing the highest value.

2.9 Modeling of Thermal Oil Recovery Processes

CRM approach is a promising rapid evaluator of reservoir performance, which has been recently used for reservoir simulation (Mamghaderi & Pourafshary, 2013). As previously mentioned, CRM has traditionally been used for water flooding, however, this work has focused on describing and defining the use of CRM as a reservoir modeling technique for Thermal EOR processes, namely Hot Water Flooding. Thermal oil recovery can be defined as the recovery mechanism in which oil is produced from a reservoir by the supplemental addition of the necessary expulsive energy in the form of heat. This recovery mechanism includes methods like SAGD, steam flooding, hot water flooding, CSS (huff and puff), and in-situ combustion. Generally, recovery, via these methods, is facilitated by the in-situ reduction in oil viscosity due to the addition of heat. However, viscosity reduction (and thus oil recovery) may be enhanced in these methods due to other physical and chemical changes that become possible as heat energy is added.

To maintain profitable operations during the thermal recovery process, reservoir characterization and management are crucial. Reservoir simulators can be used for this, just like in other recovery procedures, to infer energy and fluid flow inside the reservoir by fusing geological information, fluid characteristics, and first-principles equations. Simulations can be expensive financially and computationally because of the vast volume of input data needed to set up these simulators and the unpredictability of the geological data they require. To complement simulators and lessen their high computational intensity, many analytical approaches to reservoir modeling have been created and put into use. Essentially speaking, thermal processes are extremely complicated, making it challenging to effectively simulate them. This is because the viscosity and chemical changes produced by reservoir heating further complicate the interfacial and hydrodynamic phenomena that are typically present in displacement processes.

The literature has a variety of modeling approaches with various focuses, such as Gottfried's work (Gottfried, 1965) on modeling thermal recovery in general, Spillette's model for HWF (Spillette & Nielsen, 1968), and Youngren's model for in-situ combustion (Youngren, 1980). Yet, to adequately represent the complexity of thermal recovery processes, these models rely on geological data. Moreover, the various assumptions required to develop tractable analytical models may result in a loss of generality, rigidity, and frequently erroneous results.

Reduced order models, such as those in the CRM family, are appealing as supplements or even substitutes for numerical simulators when modeling thermal stimulation processes due to their advantageous aspects. With the help of production/injection and BHP variations, the CRMs offer a reduced-order, input-output modeling approach that describes reservoirs. The models have been successfully applied to primary recovery and other EOR processes since they were initially created for water flooding (secondary recovery) operations. This study focused on expanding CRM technology to thermal stimulation projects and enhancing CRM capabilities for characterization in water-flooded reservoirs.

Probabilistic history matching allows obtaining multiple CRM realizations to analyze the uncertainty in the parameter estimates and production forecast. For this purpose, Kaviani et al. (2014) used the bootstrap, which is a sampling with replacement method. Sayarpour et al. (2008) history matched multiple realizations of CRM with a Buckley–Leverett-based fractional flow model starting from different initial guesses. Their main objective was to assess the uncertainty in reservoir parameters such as porosity, irreducible water, and residual oil saturations. Holanda et al. (2015) used a Bayesian framework with the Markov chain Monte Carlo algorithm for production data analysis in unconventional reservoirs.

As has been studied by Tafti et al. (2013) the identification of the CRM parameters and their underlying uncertainty is connected to the following:

- The most important dynamic aspects of the system must be observed in the output signals, which are the production rates.

- The amount of data available for history matching, such as sampling frequency (eg, whether production data is reported daily or monthly) and length of the history matching window;
- Reservoir system properties such as permeability distribution, fluid saturation and overall compressibility (De Holanda et al., 2018).

Originally, the CRM was developed as a dynamic reservoir model with interwell connectivity estimated from variations in the production and injection data that commonly occur in field operations. Thus, ideally, it would not be necessary to change injection rates or producers' BHP merely for the identification of the CRM parameters. However, if in any circumstances it is desired to improve the information content of the input/output signals, the studies of Tafti et al. (2013) and Moreno and Lake (2014) provide guidelines based on systems identification theory.

Moreno and Lake derived an analytical equation to quantify the uncertainty in connectivity estimates for the unconstrained history matching problem, and such an equation accounts for the information content of the injection signal and levels of measurement noise in the liquid production rates. As previously discussed, the reliability of CRM history-matched models is highly dependent on the quality and amount of data available. Several factors might contribute to problematic data, e.g., measurement noise, sudden variations in operational conditions, partially unrecorded production data, completely missing BHP data, and commingled production. Cao (2014) implemented an iterative process for production data quality control based on successive CRM fits to the observed production. The periods of erroneous or missing data are selected. Then, it is replaced by the CRM prediction. This process is repeated until the difference of successive estimated parameters is below a tolerance. One relevant application of this workflow is as a preprocessing step in the history matching of grid-based reservoir models. However, before applying this procedure, one should be cautious and ensure that the CRM is a reliable representation of the reservoir dynamics, i.e., the deviations in the production data are mainly due to problems in the data rather than caused by a physical phenomenon that goes beyond CRM modeling capabilities.

CRM has only been used for modeling isothermal processes, despite being successful in simulating water flooding and other oil recovery methods. To estimate and optimize future output, engineers can quickly and accurately match historical production data using a thermal CRM.

2.10 Review of Hot Water Flooding

To profitably produce heavy oil from a reservoir, thermal stimulation is often necessary as enhanced oil recovery process. This usually means heating the oil in the reservoir to improve its characteristics. Heat is delivered to the reservoir through a fluid (usually steam or hot water), combustion of oil in the reservoir, or electrical (resistance) heating. Reservoir heating by HWF is still possible and cost-effective option. HWF is actually the most desirable thermal stimulation EOR method for viscous oils from an operational aspect.

HWF has long been used as an agent for viscous oils because it is easy to use, the equipment needed to produce and manage hot water is inexpensive, and the approach is comparable to the commonly used conventional water flooding (CWF) method.

Although the use of hot water to extract oil is believed to have begun in the 1930s, the analytical model of the process became popular in the 1950s and later. The temperature profile in a homogeneous, linear, one-dimensional reservoir subject to HWF was first calculated in 1955 (Lauwerier, 1955); Van Heyningen J. and Schwartz N. investigated the effect of reservoir heating on production characteristics in 1955 (primarily oil viscosity) using the temperature model of Lauwerier (1955) (Van Heiningen & Schwarz, 1955). The main processes (chemical, thermodynamic and temperature) that could occur during thermal exposure of linear reservoirs were described by the generalized mathematical model of Gottfried B.S. in 1965 (Gottfried, 1965) and three approximations by Thomas G.W. for analytical calculation of temperature distribution during the injection of hot liquid in 1967 (Thomas, 1967).

The thermal streamline approach is a recent breakthrough in hot water flood modeling. Pasarai and Arihara (2005) developed this method to benefit from the accuracy and speed of the first simplified method developed for conventional water flooding (Pasarai & Arihara, 2005). Over the years, improvements in computing power and thermal flooding modeling techniques have led to faster models. Unfortunately, most of the models used today still require reservoir geological data. This continues to cost for engineer’s time to determine parameters, especially in situations where speed is more important than accuracy. Hence, the CRM is fast, inexpensive, and does not require geological data, it is well suited to provide this important characterization option.

3. METHODOLOGY

This chapter describes the procedure for obtaining CRM simulation results using the actual history data from generated reservoir models with different features in the commercial simulator CMG. For this purpose, four types of reservoir models were considered. The procedure for obtaining adequate CRM results is based on core steps such as choosing the appropriate CRM model, applying the constraints for each case, and using the appropriate Solver type. Detailed methodology is presented in Figure 4.

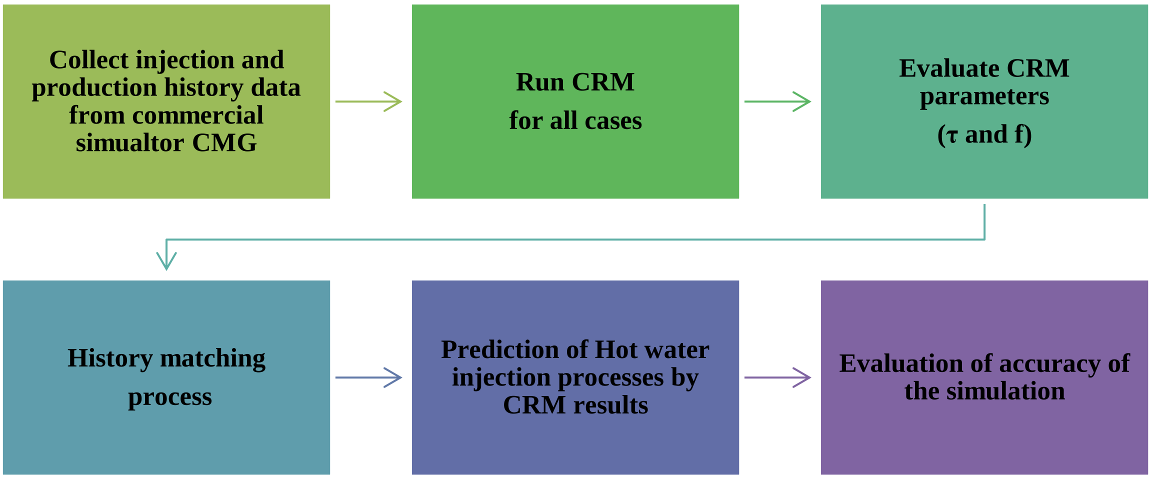


Figure 4. Workflow for the CRM application in history matching for Hot water injection processes.

3.1 Methodology Description

In this section a detailed description of how to apply CRM for the history matching process between the actual production data and modeled data, and obtaining the parameters for cases under evaluation that are used to predict the flow of hot water injection processes is explained.

3.1.1 Collecting injection and production history data from commercial simulator CMG

Since one of the objectives of this project is to evaluate the application of the CRM during hot water injection; it was decided to estimate the theoretical concepts first to ascertain its application using synthetic field data. As before was mentioned that CRM couples only injection/production data as an input data, process of getting the initial data was simplified, since the synthetic reservoir models can have an idealistic parameter. Each case has similar injection/production rates, injection temperatures and oil viscosity values. Injection data consists of injection rate versus time data as shown in Figure 5.

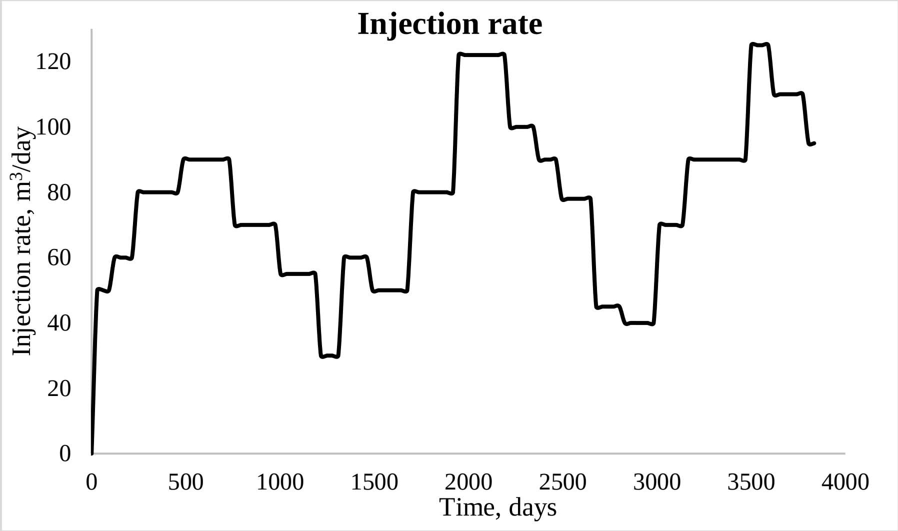


Figure 5. Injection rate of well I1

3.1.2 Application of CRM to Model Homegeneous/Heterogenous cases

This step includes several components including selecting the most suitable model of CRM, defining model constrains, evaluating time constant and well connectivity parameter values, and estimating the error between the actual and modeled production values. For this project CRMP - Capacitance-Resistance Model-Producer Based was selected. This CRM representation is characterized by its ability to account for the influence all injector wells on the drainage volume of each producer well in the reservoir, and CRMP has one τ and f values for each injector-producer well pairs.

To determine the appropriate parameters (τ and f), MS Excel Solver tool was used. It adjusted the τ and f values within specified limits and applied constraints to ensure satisfactory outcomes. From a CRM perspective, well connectivity, f, is defined as the rate fraction of injected fluid from an injection well that contributes to the production of production wells. CRMP based model imposes f as constraints shown in Equation 14 (Eshraghi et al., 2015), sum of the well connectivity values should not be less than 0 and/or equal to 1, and should be only positive values; if reservoir is homogeneous the fraction of injected fluid should be distributed equally to all production wells.

$$f_{ij} \geq 0, \sum_{i=1}^{N_{inj}} f_{ij} \leq 1 \qquad \text{Eq. 14}$$

Generalized Reduced Gradient (GRG) Nonlinear type was chosen for MS Excel Solver tool. GRG Nonlinear solver is an optimization algorithm used mostly for solving the nonlinear optimization problems. This type of solver searches an optimal solution by maximizing or minimizing the objective function while satisfying the applied constrains.

The application of CRM methodology is demonstrated through four case studies, focusing on the history-matching process of production rates from reservoir models subjected to conventional water and hot water injection. Two evaluation parameters (τ and f) will be analyzed using the CRMP on the history data from the CMG-STARS simulator. These case studies are: five spot pattern homogeneous reservoir; streak cases, heterogeneous model case.

1. Case 1 addresses the application of CRM in models featuring hot water injection, compared to normal water injection results. The homogeneous model, with evenly distributed porosity and permeability values throughout the reservoir, is thoroughly described in the next chapter.

Cases 2 and 3 involve reservoir models with conductive paths (streaks) created between different production-injection well pairs. The purpose of creating these models is to see to what extent two evaluation parameters will change under different circumstances.

2. Case 2. The reservoir models with a high permeability streak of 500 mD between P1-I1 well pair under normal water and hot water injection;
3. Case 3. The reservoir models with high permeability streak of 1000 mD between P2-I1 well and 1500 mD between P3-I1 well pairs under normal water and hot water injection;
4. Case 4. The model was created to evaluate the application of CRM in a heterogeneous reservoir with randomly distributed porosity and permeability values to see to what extent the values of the evaluation parameters will change considering changes in input parameters (porosity and permeability).

Case 1. Homogeneous reservoir

To validate the concepts developed in the previous chapters, the method was applied to the simple reservoir with a predictable flow behavior. The reservoir properties are listed in Table 4. The model consists of 1 injector and 4 producers wells; all vertical wells. The injector well is located in the middle of the reservoir and 4 producer wells are located in each corner of the model. The values of injection rates were generated randomly with the fluctuations of values starting from a minimum of 30 m^3/day and a maximum of 122 m^3/day. The surface oil rate values were constant for all 4 producer wells and were equal to 200 m^3/day. Due to the similarity of the model and input parameters varying uniformly in the same range, it is easy to realize a similar production behavior for all 4 producer wells. Figure 6 shows the location of the wells.

The time window used for the history-matching is 3835 days (10 years), for the water breakthrough already happened in all producers to mitigate the nonlinearity in the CRM parameters. Additionally, to visualize the changes in the viscosity of oil in the future running of the model with the case of hot water flooding.

Table 4. Reservoir properties for Case 1.

Parameter	Value
Number of grid blocks	100*100*1
Grid block sizes	10*10*1
Initial Reservoir Pressure, kPa	5000
Porosity	0.2
Viscosity of oil, cp	45
Horizontal permeability, mD	200
Vertical permeability, mD	20
Injection temperature, °C	100

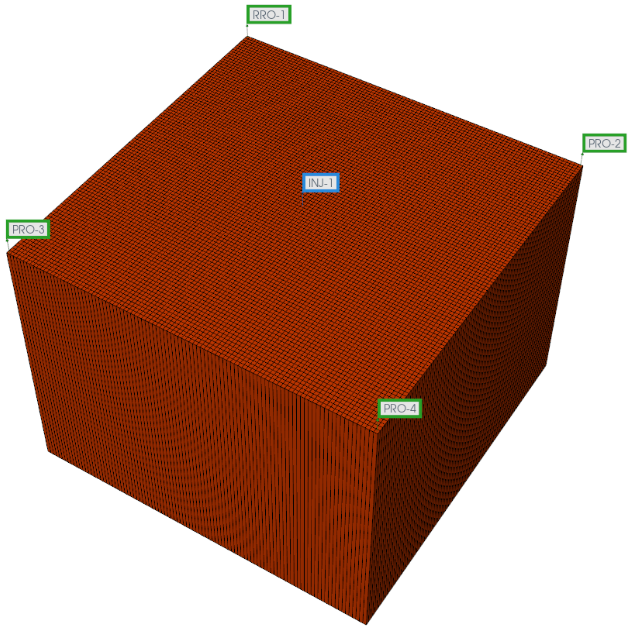


Figure 6. Well location for Case 1. Model with 1 injection (in the middle) well and 4 producer wells (in each corner). Permeability is equal to 200 mD.

Once a flooded reservoir has been created and is suitable for optimization, the necessary data related to reservoir history and reservoir modeling are collected for CRM application.

Case 2. Reservoir models with high permeability streak of 500 mD between P1-I1 well pair

The case study presents the application of CRM on different cases of heterogeneity of reservoir models considering two models with conventional water injection and hot water injection. The streak case models have the same input parameters as the previous models with normal hot water injection. Figure 7 displays the high permeability streak location; the permeability of the reservoir is equal to 200 mD, except for the pathway between producer P1-injection well I1 pair, where the permeability is equal to 500 mD.

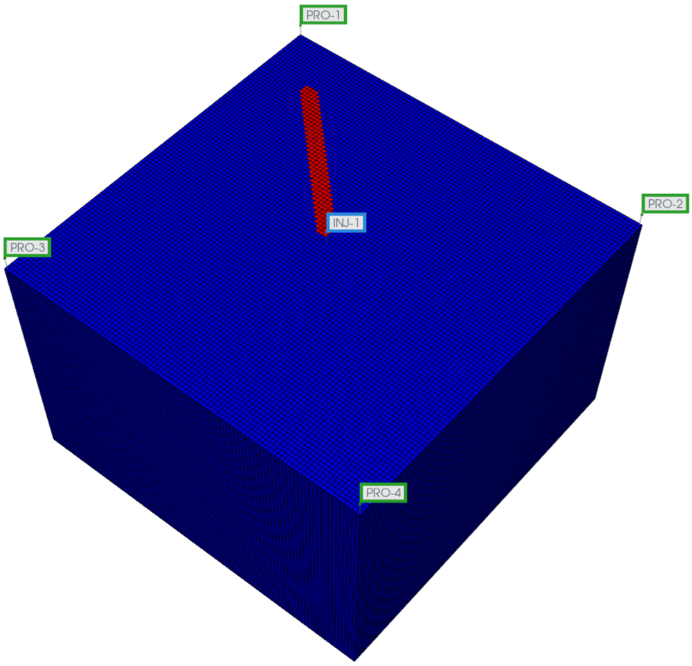


Figure 7. Well location for Case 2. Model with 1 injection (in the middle) well and 4 producer wells (in each corner). Red line corresponds to the location of high permeable conductive path between producer well P1 - injection well I1 pair equal to 500 mD.

Case 3. Reservoir models with high permeability streak of 1000 mD between P2-I1, and 1500 mD between P3-I1 wells pairs

The case study presents the application of CRM using reservoir models with streak case heterogeneity between P2-I1 and P3-I1 wells under conventional cold injection and hot water injection. As in the previous case, the reservoir properties remained the same, except the permeability between producer P2-I1 well, equal to 1000 mD, and P3-I1 with a permeability value of 1500 mD, for both models. Figure 8 shows the location of these streaks between the wells. The study case was created to evaluate the changes in the CRM parameters (τ, f_{ij}), to validate their impact on CRM performance.

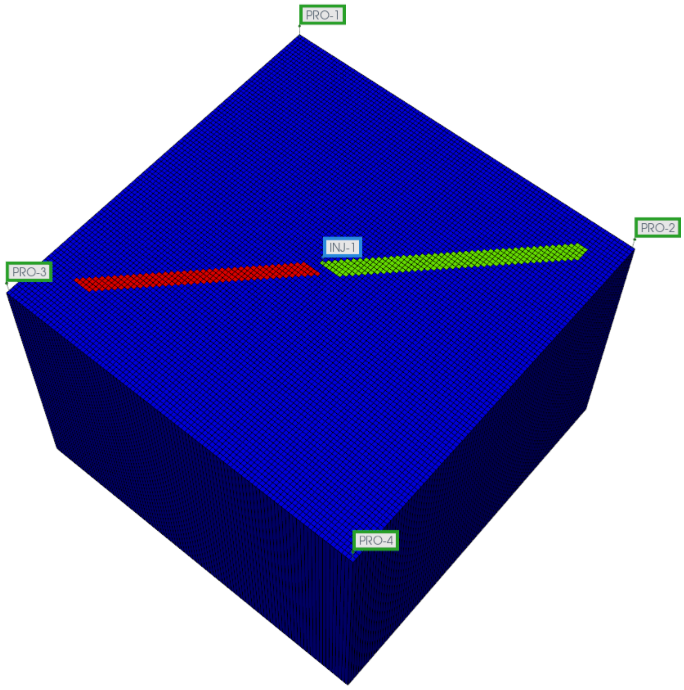


Figure 8. Well location for Case 3. Model with 1 injection (in the middle) well and 4 producer wells (in each corner). Red line corresponds to the conductive path with permeability 1500 mD between producer P3-injection I1 well pair; green line corresponds to the conductive path with permeability 1000 mD between producer P2-injection I1 well pair.

Case 4. Heterogeneous reservoir model

To estimate the effect of hot water flooding on time constant and connectivity in a more realistic case, a heterogeneous reservoir model was created with randomly distributed porosity and permeability values through the whole reservoir. Reservoir model with dimensions 50 (i)*50 (j)*2 (k) was developed by CMG simulator in STARS model (Figure 9). 8 production and 5 injection wells were added to the model, with the minimum porosity value equal to 10 % (0.1) and maximum 50% (0.5), and the minimum permeability value equal to 50 mD and the maximum value equal to 2000 mD. Initial pressure of the reservoir is 5000 kP; injection temperature is 80 °C.

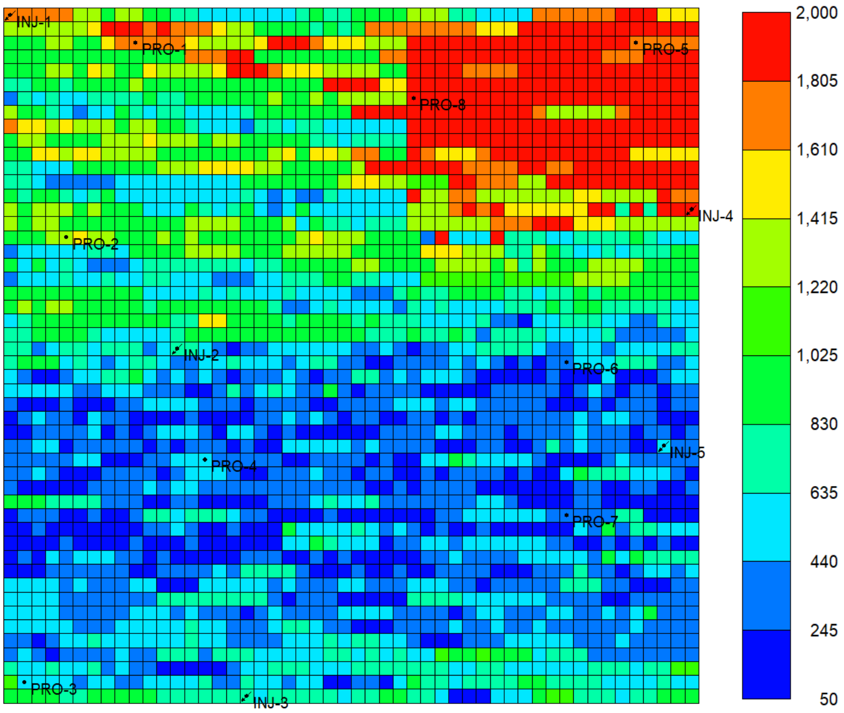


Figure 9. Location of wells in synthetic field within the range of permeability values. Model with randomly located 8 production and 5 injection wells.

All created models have two types of injected water, namely CWF and HWF. All input parameters were kept the same for both cases.

3.1.3 Evaluation of CRM parameters (τ and f)

Next steps of methodology as history-matching process, prediction of hot water injection behavior, and evaluation of modeling error will be explained in the next chapter. To do the history-matching process, the actual production history data and modeled data were taken. Graphical representation of these both data helps to evaluate whether or not the process went well. To measure the accuracy of the process Mean Absolute Error (MAE) in percentages was calculated using previously mentioned data by calculating the average differences between the actual and predicted values, and by finding the average of these absolute differences, and dividing the MAE by the actual values and multiplying the outcome to 100. As a fitting parameter for both curves R^2 values were calculated. It is the proportion of variation of one variable (objective variable or response) explained by other variables (explanatory variables) in regression. This is a widely-used measure of the strength of the relationship in regression. This coefficient is defined as it is shown in Equation 15 (Kasuya, 2018):

$$1-\frac{\sum_{i=1}^{n}(y_i-\widehat{y_i})^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \qquad \text{Eq. 15}$$

where $\widehat{y_i}$ denotes the value of the objective variable (y) predicted by regression for the ith data point. The second term of this expression is the residual sum of squares divided by the sum of squares of y.

4. RESULTS AND DISCUSSIONS

Case 1. Homogeneous reservoir

CWF. Case 1 represents two similar models with different injected fluid types. One model with CWF and the second one with an injection of hot water at 100°C. Figure 10-11 show the graphs of the CRM modeling of the total liquid production and oil production of each well for Case 1 with CWF and HWF. Table 5 represents the values of time constant and well connectivity for the results shown above.

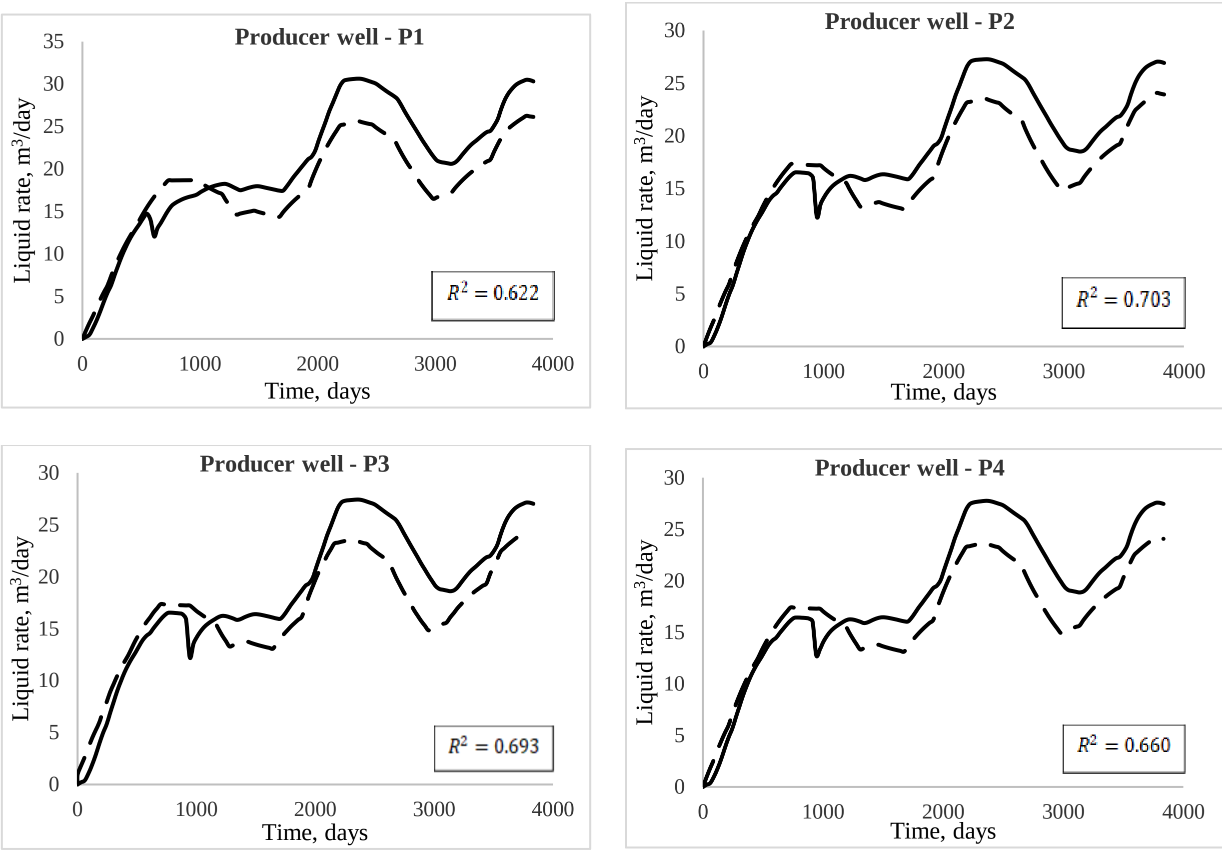


Figure 10. Total production rate vs estimated production rate for all producer wells of Case 1 under CWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual total production rate

Table 5. CRM coefficients of the reservoir model under conventional WF of Case 1

Number of wells	τ	f	MAE, %
P1	394.58	0.26	20.92
P2	375.06	0.24	20.58
P3	375.44	0.24	20.81
P4	376.06	0.24	22.05

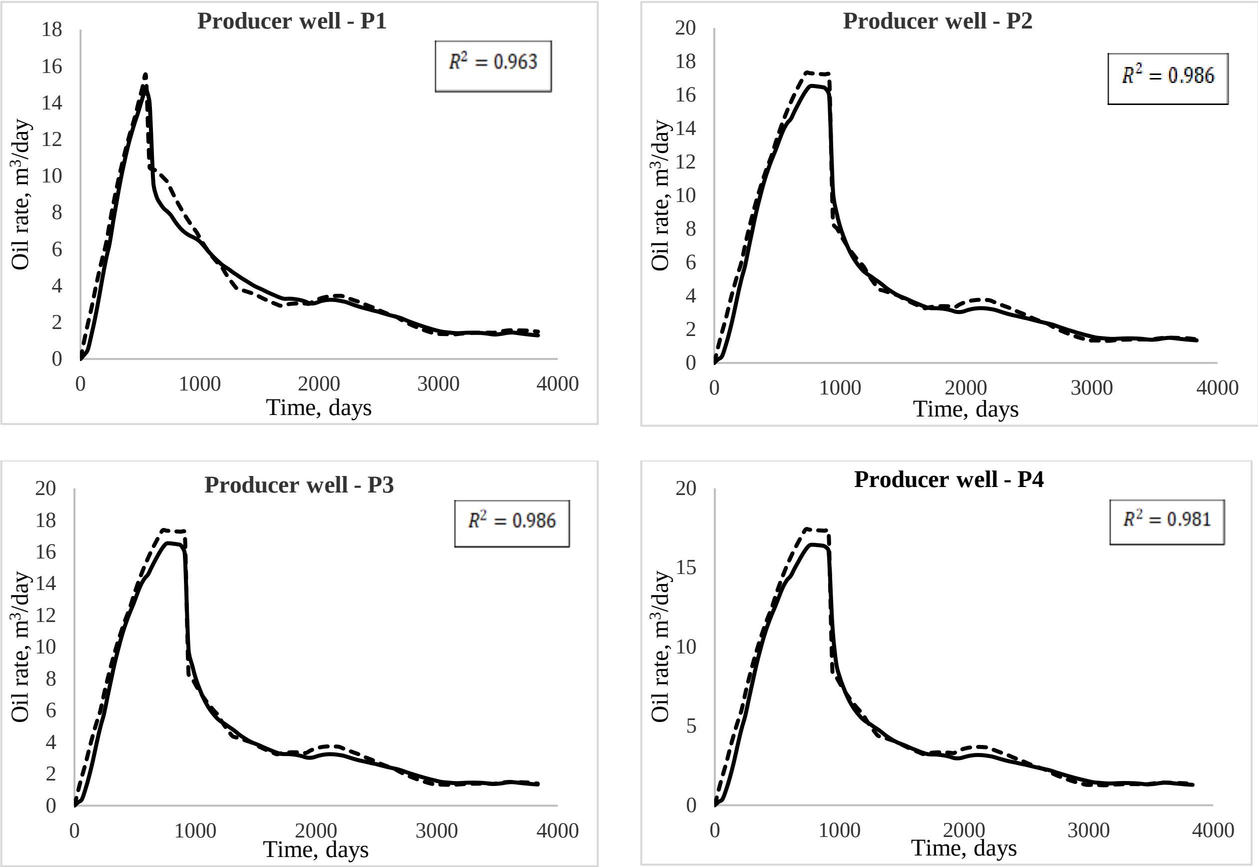


Figure 11. Oil production rate vs estimated production rate for all producer wells of Case 1 under CWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual oil production rate

Table 6. CRM coefficients for modeling oil fractional flow and MAE of history matching process for CWF of Case 1

Number of wells	α	β	MAE, %
P1	6.80E-06	1.318	14.638
P2	5.61E-07	1.55	14.75
P3	5.72E-07	1.55	14.82
P4	3.83E-07	1.59	15.819

According to the results obtained from Table 5, and the Figures 10-11, it can be concluded that CRM is successful to model the injection-production history within the whole time window of the process since a good agreement is attained between two curves of production rate data. Since the Case 1 is considering an ideal case of homogeneous reservoir, as it was expected the values of time constant are more or less close to each other.

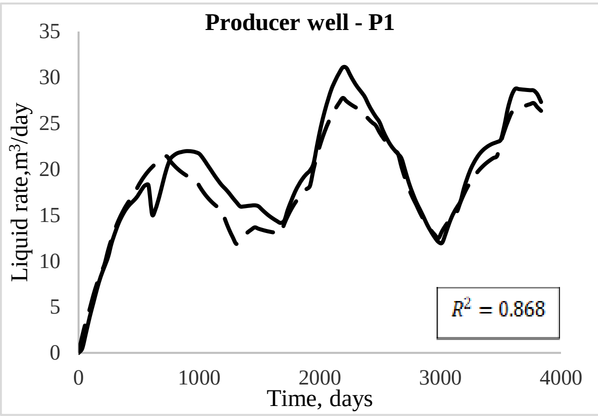
Reservoir heating in a homogeneous reservoir typically doesn't affect steady-state flow patterns, thus maintaining the consistent interpretation of gains, even during a hot waterflooding. Unless significant alterations occur that affect the overall reservoir characteristics, the fundamental understanding of gains remains unchanged.

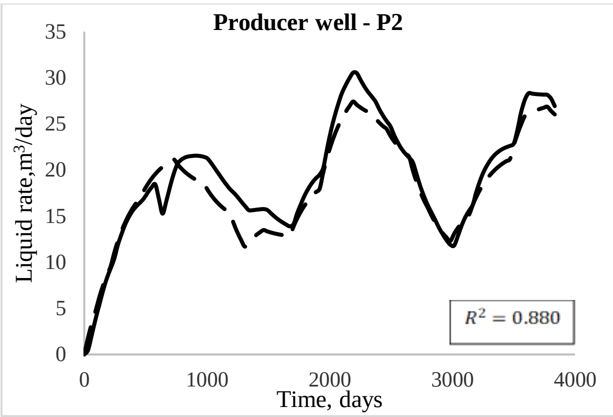
From the Figure 5 it is obvious that I1 injector well will have strong and equally distributed connectivities with all 4 producer wells. To predict fractional oil flow the empirical power-law fractional flow model (EPLFFM) was used with timing included into the calculation of cumulative water injected, W_i and instantaneous water-oil ratio, F_{wo}, using two fitting parameters α and β for flow model shown in in Equation 16.

$$f_o(t) = \frac{1}{1 + F_{wo}} = \frac{1}{1 + \alpha * W_i^{\beta}} \qquad \text{Eq. 16}$$

These two coefficients are often determined through the production history-matching or calibration using available data from the reservoir. The values of the coefficients presented in Table 6.

HWF. Figure 12 shows the results of history matching process for Case 1 for the reservoir model under hot water injection.





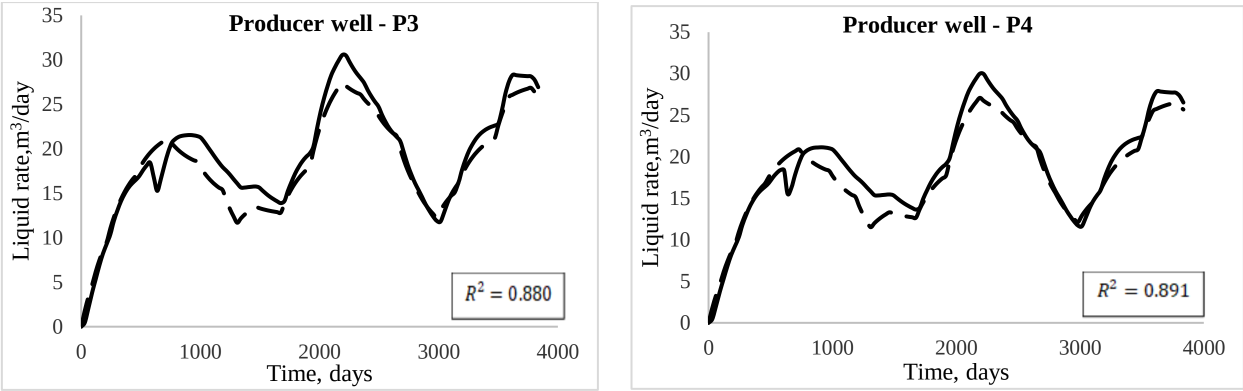


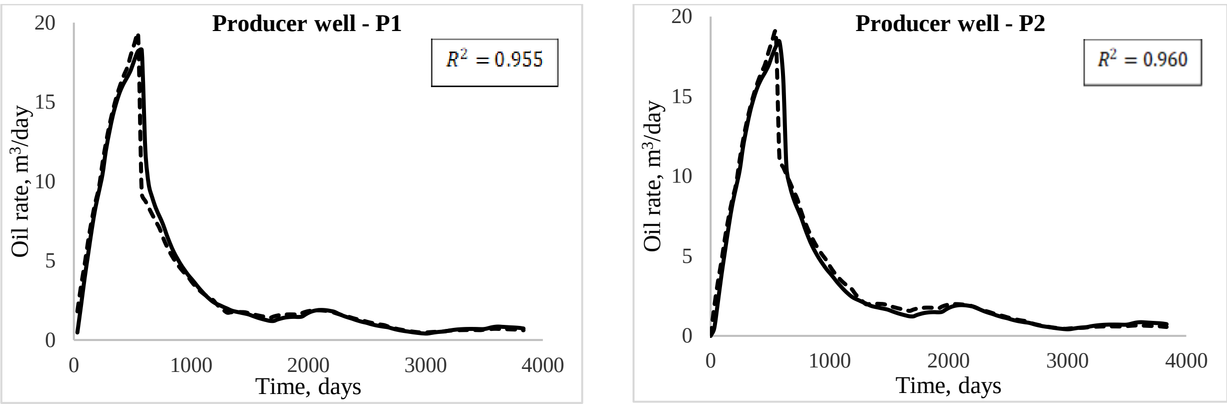
Figure 12. Total production rate vs estimated production rate for all producer wells of Case 1 under HWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual total production rate

τ, f and calculated MAE values are shown in Table 7 for Case 1 for the model with hot water injection.

Table 7. CRM coefficients of the reservoir model under HWF of Case 1

Number of wells	$\boldsymbol{\tau}$	$\boldsymbol{f}$	**MAE %**
P1	195.10	0.25	11.01
P2	194.22	0.25	10.66
P3	194.22	0.25	10.66
P4	193.15	0.24	10.32

Figure 13 represents history matching for oil production rates for HWF of Case 1.



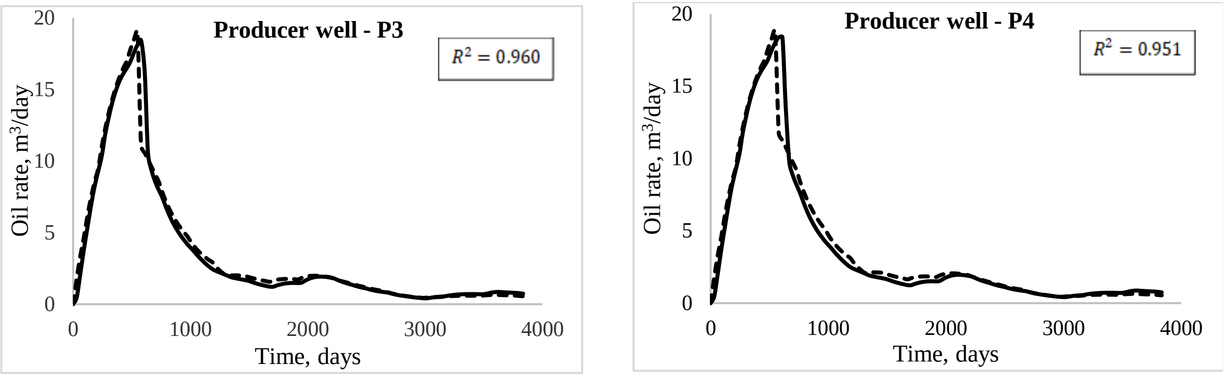


Figure 13. Oil production rate vs estimated production rate for all producer wells of Case 1 under HWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual oil production rate

Table 8. CRM coefficients for modeling oil fractional flow and MAE of history matching process for HWF of Case 1

Number of wells	α	β	MAE, %
P1	9.97E-07	1.57	10.97
P2	1.00E-07	1.78	13.76
P3	1.00E-07	1.78	13.76
P4	4.10E-08	1.87	15.83

Considering Case 1, which refers to homogeneous models, it was anticipated that results of the CRM parameters from model under hot water injection would align with those of CWF. The impact of temperature, which is under examination, was only noted in the results concerning time constants. Unlike the gains, the time constants has been shown to vary significantly even for a cold water flood when saturation changes are significant. In an early-stage cold waterflooding, the shift in time constant values occurs due to changes over time in the PI, which is a function of fluid saturation. Changes in reservoir temperature, leading to variations in viscosity, also imply that the productivity index is influenced by temperature fluctuations. The capacitance model considers the effects of compressibility, pore volume, and PI in nonlinear multivariate regression by introducing a time constant to characterize the time delay of the injection signal at the producers. This parameter is based on reservoir characteristics.

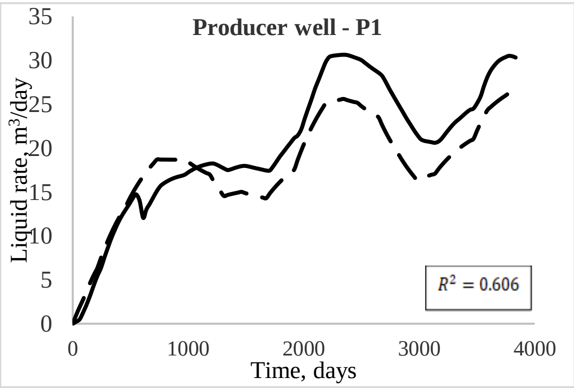
A smaller τ implies a smaller pore volume and compressibility within the system, or higher PI values. Conversely, a larger τ may signify a larger reservoir with lower total compressibility or a smaller reservoir with higher compressibility, or extremely low permeability values. Compressible fluid provides a larger compressibility in comparison to incompressible one (Eshraghi et al., 2016). PI is also directly related to the permeability, thereby causing variations in the time constant (Nguyen, 2012).

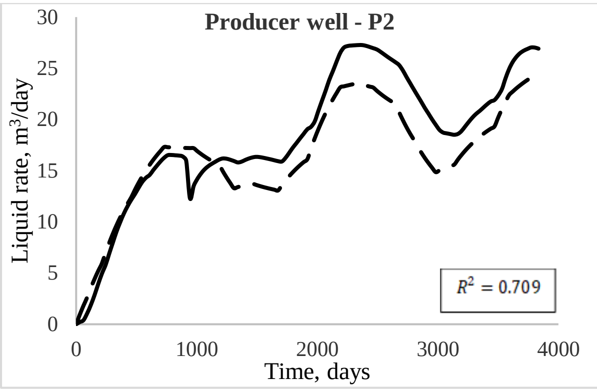
As the primary objective of the project is to assess CRM's applicability in predicting hot water injection processes, an adequate approach is to compare CRM coefficient results between CWF and HWF. Tables 5 and 7 illustrate the coefficients for both models using the same injected fluid at different temperatures. The data clearly indicates that CRM couples much faster during hot water injection compared to CWF. This phenomenon can be attributed to the aforementioned parameters.

Fluid compressibility, although subject to change over time, has minimal impact on modeling results. Throughout the simulation process, BHP remains constant. PI values were computed for both scenarios, with higher values observed in the case of hot water injection compared to normal water injection, due to the easier flow of the injected hot fluid. Since the Equation 4 contributes the PI in the calculation of τ, as it is expected from PI values, τ during hot water injection will have the lower values, as it was observed from the results.

Case 2

CWF. The model description of Case 2 is given in a previous Chapter 3. Figure 14 presents results for Case 2 for model with normal WF.





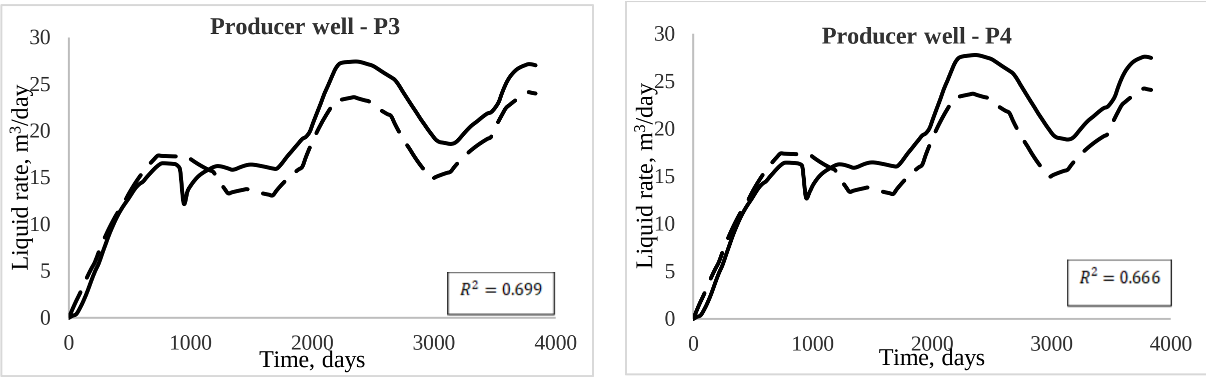
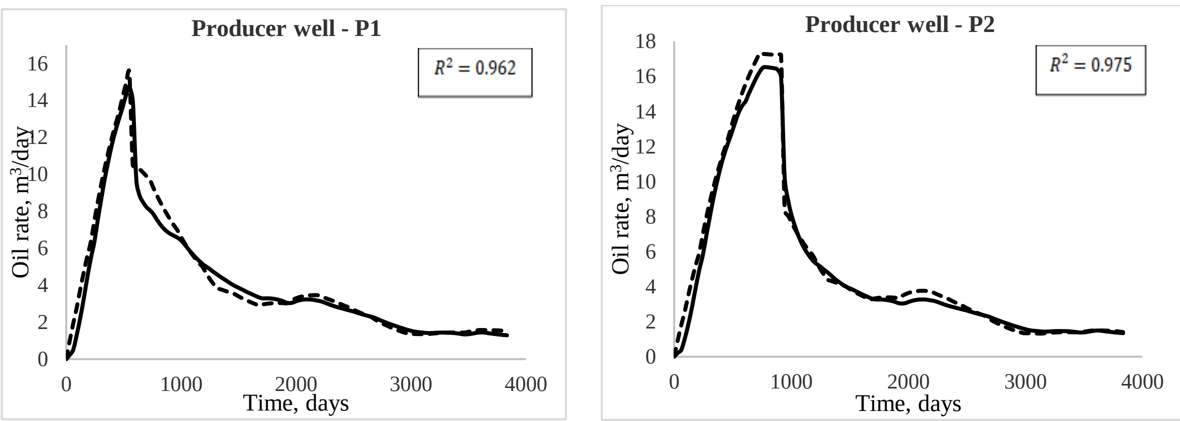


Figure 14. Total production rate vs estimated production rate for all producer wells of Case 2 under CWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual total production rate

Table 9. CRM coefficients of the reservoir model under CWF of Case 2.

Number of wells	***τ***	***f***	**MAE, %**
P1	387.88	0.26	21.20
P2	377.44	0.24	20.25
P3	377.52	0.24	20.50
P4	378.34	0.24	21.72

Comparing results of the coefficients from CWF of Cases 1 and 2, it is seen that there is no considerable changes within applied features in the permeability between P1 producer – I1 injection well pair. Figure 15 displays the oil production rates of both modeled and actual data.



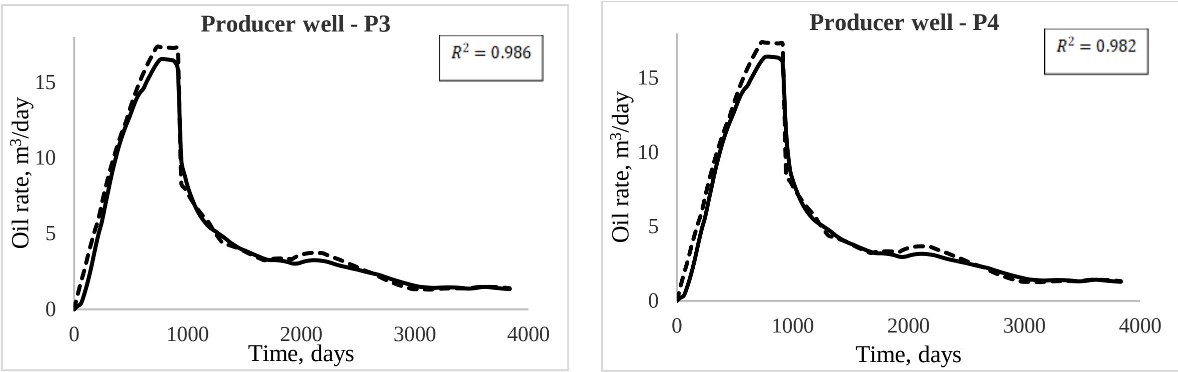
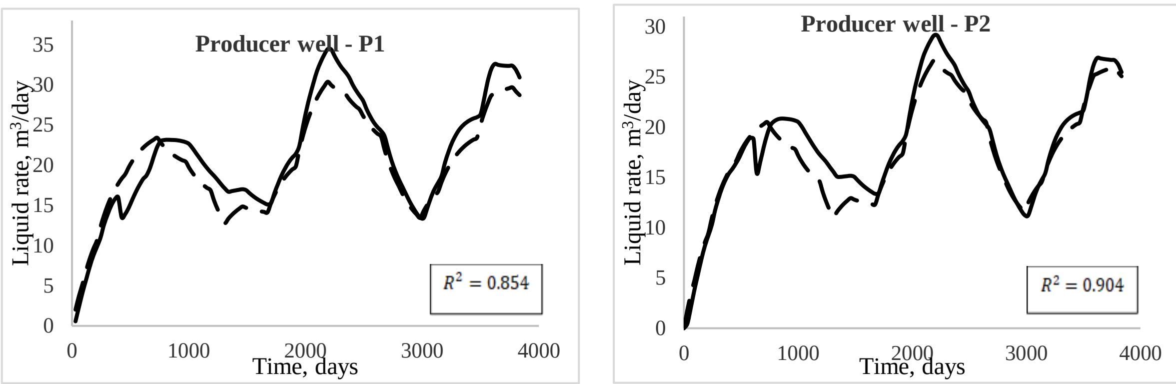


Figure 15. Oil production rate vs estimated production rate for all producer wells of Case 2 under CWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual oil production rate

Table 10. CRM coefficients for modeling oil fractional flow and MAE of history matching process for CWF of Case 2

Number of wells	α	β	MAE, %
P1	6.71E-06	1.31	14.98
P2	5.74E-07	1.55	14.63
P3	5.83E-07	1.54	14.71
P4	3.92E-07	1.58	15.69

HWF. Figure 16 display the graphical results of the history matching of hot water injection processes for Case 2.



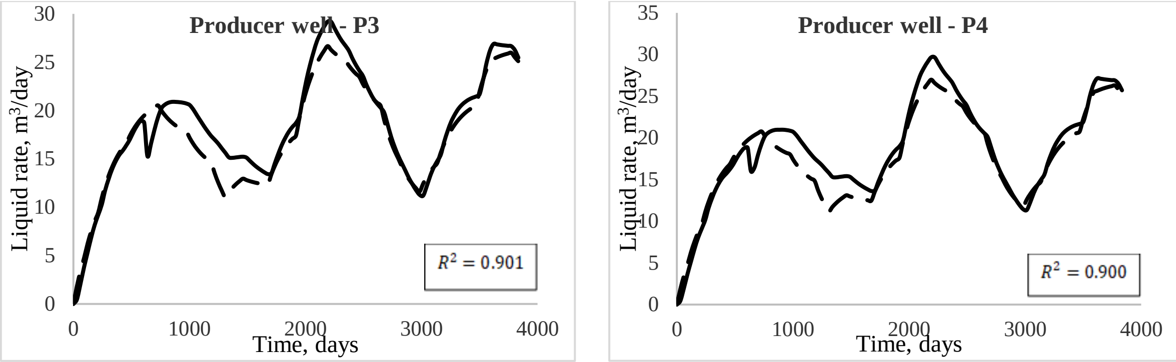
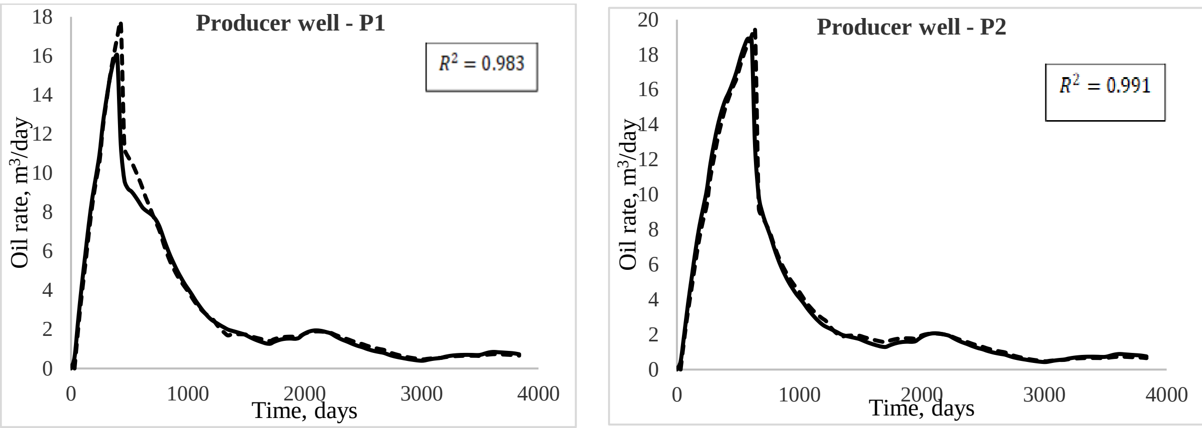


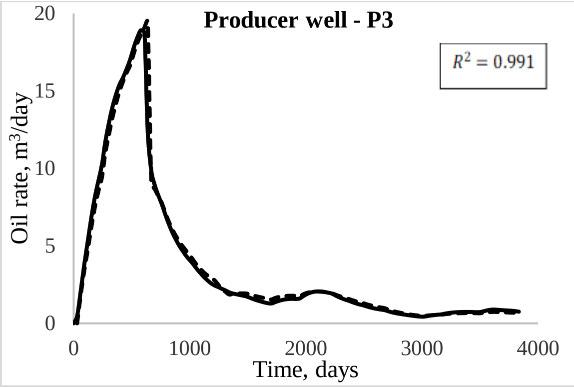
Figure 16. Total production rate vs estimated production rate for all producer wells of Case 2 under HWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual total production rate

Table 11. CRM coefficients of the reservoir model under HWF of Case 2.

Number of wells	τ	f	MAE, %
P1	189.04	0.27	12.46
P2	182.99	0.24	9.98
P3	182.84	0.24	10.13
P4	182.95	0.24	10.80

Graphical representation of history matching of oil production rates for all producer wells are presented in Figures 17.





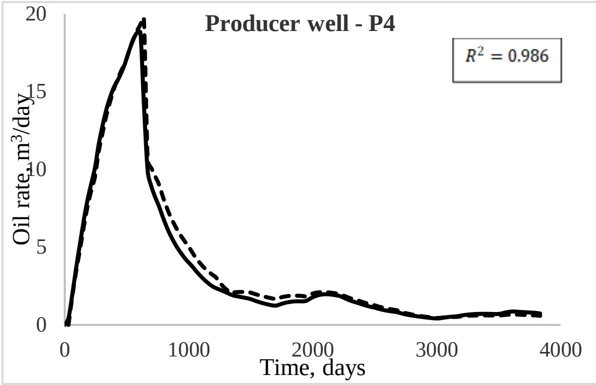


Figure 17. Oil production rate vs estimated production rate for all producer wells of Case 2 under HWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual oil production rate

Table 12. CRM coefficients for modeling oil fractional flow and MAE of history matching process for HWF of Case 2

Number of wells	α	β	MAE, %
P1	1.43E-06	1.53	11.07
P2	3.55E-07	1.66	10.24
P3	3.87E-07	1.65	10.32
P4	5.15E-08	1.84	15.52

As mentioned earlier, Case 2 includes reservoir models with additional heterogeneity, specifically a high permeability streak between wells P1 and I1. This 500 mD permeability b region introduces noise-like variability into the input parameters derived from the CMG. The simulation progresses gradually, just as changes in the injection rate cause a performance response, similar to measuring voltage or current in an electrical circuit.

The results obtained for Case 2 indicate minimal changes in both evaluation parameters. This can be explained by the fact that the modified high-permeability channel does not differ significantly from the overall permeability of the reservoir. Even though there is a region with different parameter, other regions properties are homogeneous and symmetric for sides of P2 and P3 wells. Thus it is reasonable to expect that τ and f values to be about the same. When comparing the results of these two parameters, a natural trend is observed: during HWF, the constant values tend to decrease, which indicates an acceleration of processes - a phenomenon closely related to the viscosity of oil. During the HWF process, the viscosity of the oil gradually decreases over time. This pattern is similarly reflected in the parameter f. However, due to the presence of a conductive streak between wells P1 and I1, the f values in both scenarios are slightly overestimated compared to other pairs of production-injection wells. This suggests that these paths increase the volume fraction of fluid coming from the injection well.

Case 3

CWF. Figure 18 show the history matching of actual and modeled values of total liquid production rate data for CWF for Case 3, where the regions of high permeable streaks exist between the well pairs P2-I1 and P3-I1.

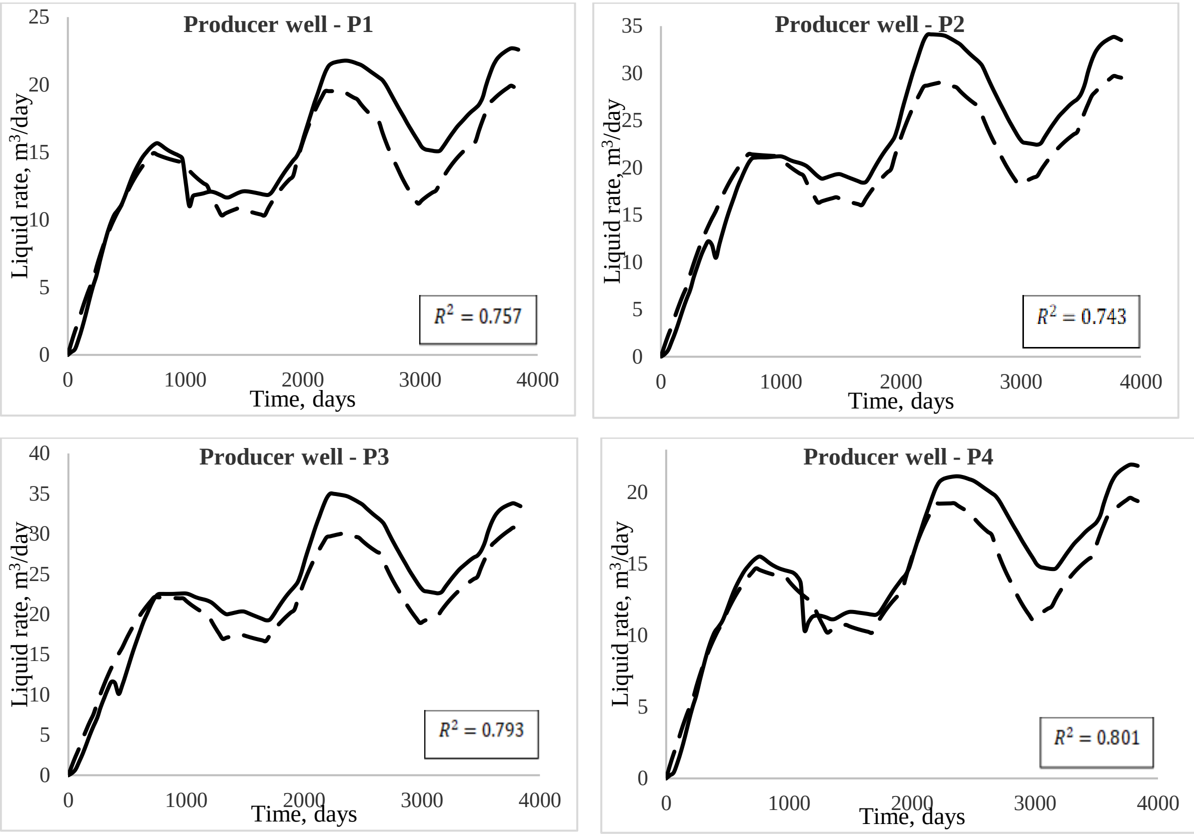


Figure 18. Total production rate vs estimated production rate for all producer wells of Case 3 under CWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual total production rate

Table 13. CRM coefficients of the reservoir model under CWF of Case 3.

Number of wells	τ	f	**MAE, %**
P1	306.12	0.19	17.06
P2	370.24	0.30	18.72
P3	375.13	0.31	18.53
P4	309.02	0.19	16.22

History matching for oil production data for all 4 producer wells of CWF for Case 3 is shown in Figure 19.

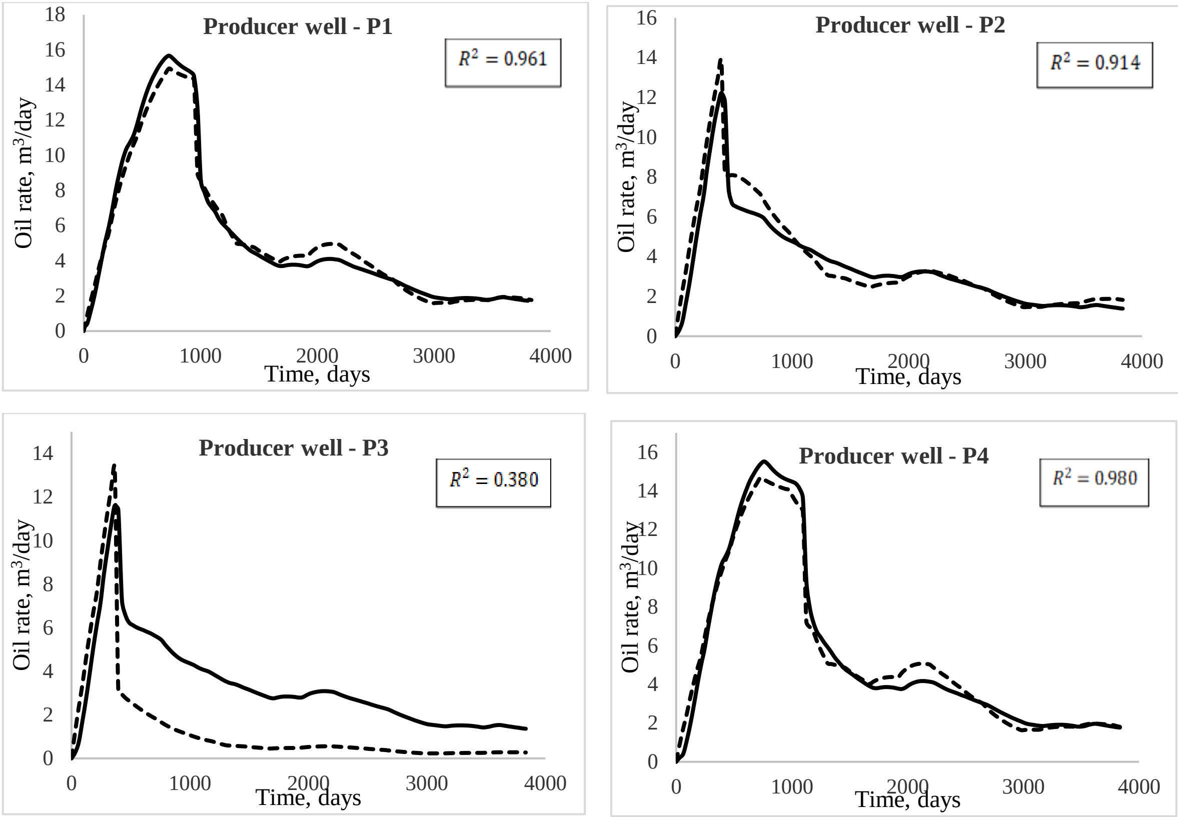


Figure 19. Oil production rate vs estimated production rate for all producer wells of Case 3 under CWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual oil production rate

Table 14. CRM coefficients for modeling oil fractional flow and MAE of history matching process for CWF of Case 3

Number of wells	α	β	MAE, %
P1	6.91E-08	1.73	14.93
P2	3.78E-04	9.40E-01	17.18
P3	7.49E-04	1.05	79.11
P4	5.85E-08	1.74	15.27

HWF. Figure 20 shows the graphs of the results for the reservoir under hot water injection for Case 3.

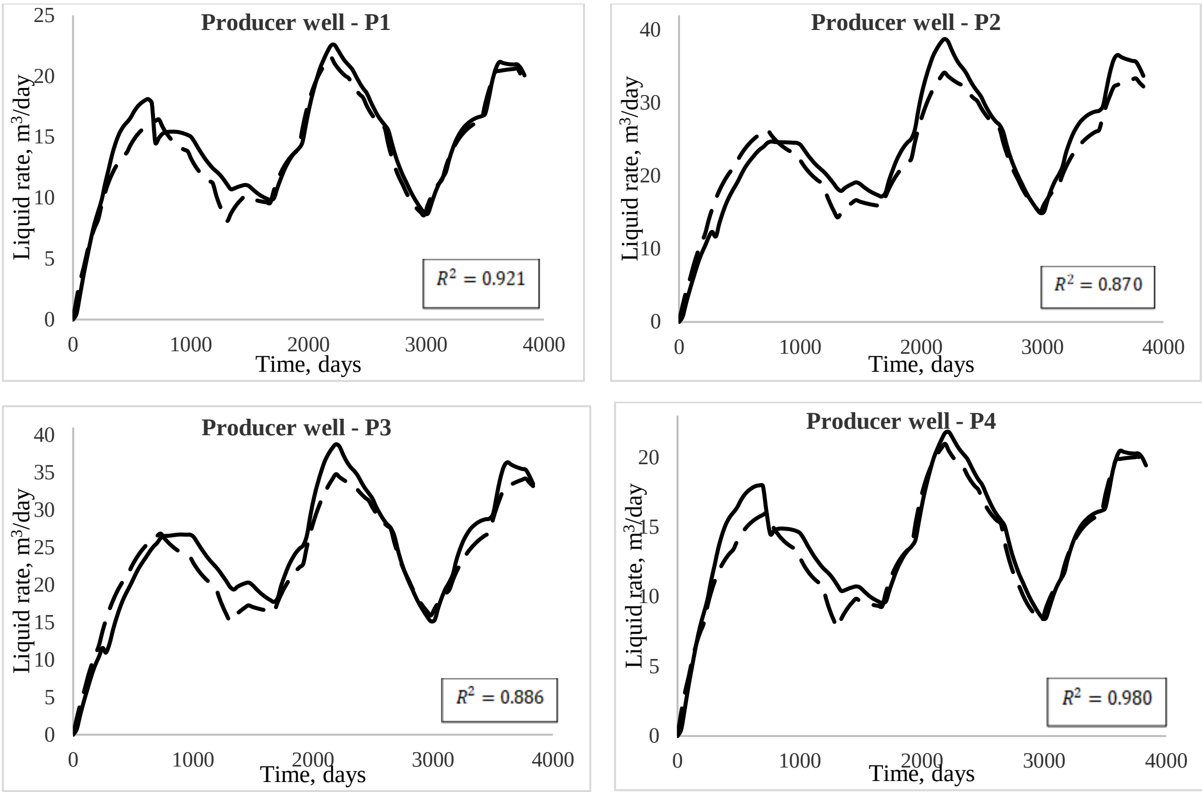
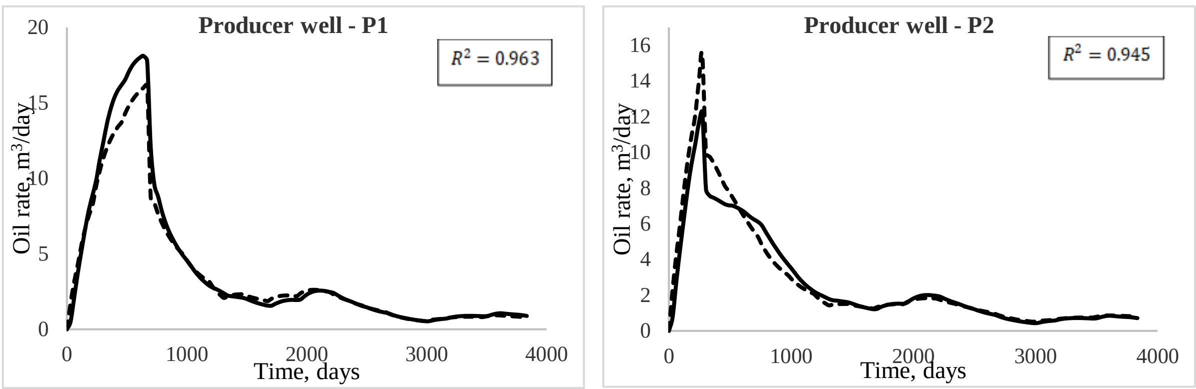


Figure 20. Total production rate vs estimated production rate for all producer wells of Case 3 under HWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual total production rate

Table 15. CRM coefficients of the reservoir model under HWF of Case 3

Number of wells	τ	f	**MAE, %**
P1	148.84	0.18	8.80
P2	187.75	0.30	11.68
P3	202.37	0.31	10.92
P4	145.32	0.18	9.16



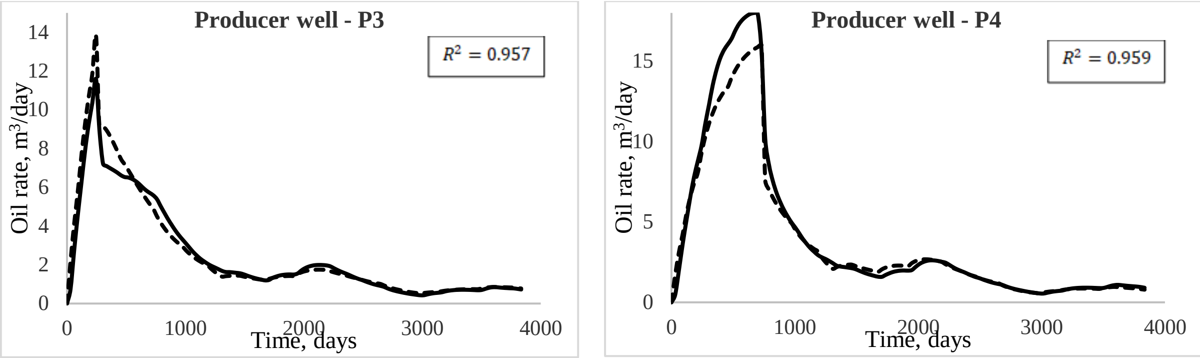


Figure 21. Oil production rate vs estimated production rate for all producer wells of Case 3 under HWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual oil production rate

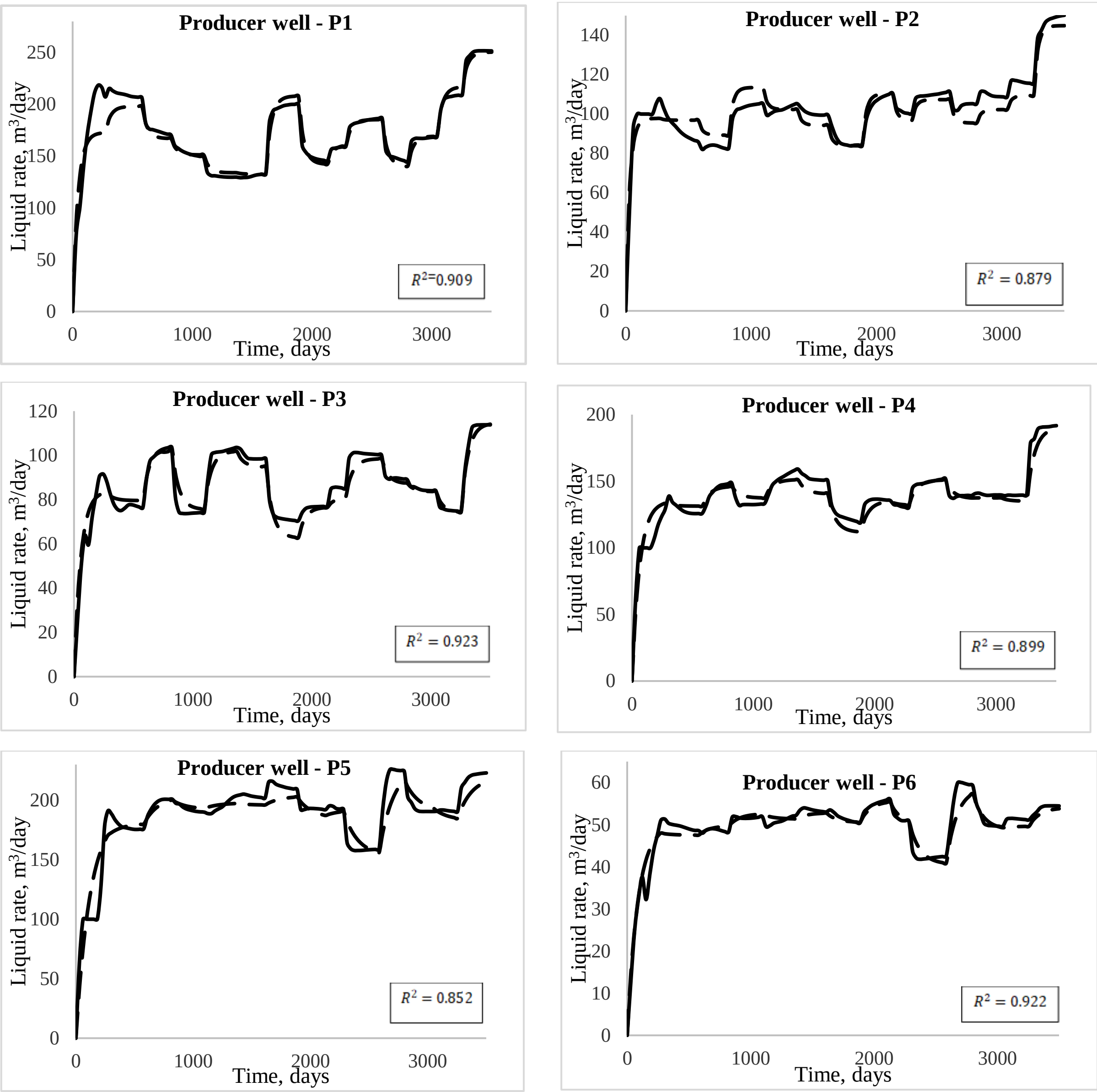
Table 16. CRM coefficients for modeling oil fractional flow and MAE of history matching process for HWF of Case 3

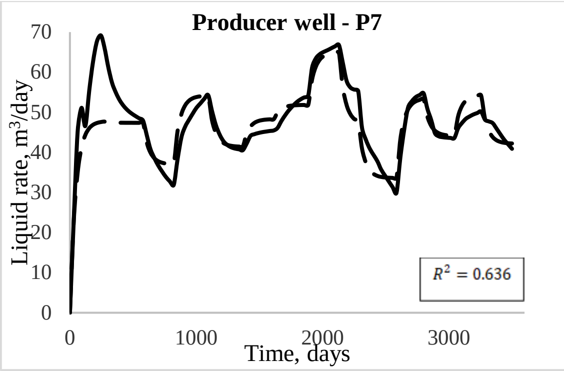
Number of wells	α	β	MAE, %
P1	1.41E-07	1.74	9.98
P2	4.24E-05	1.21	11.52
P3	8.44E-05	1.15	11.21
P4	1.53E-07	1.73	10.38

According to the description given in Chapter 3, Case 3 is a streak case, is a homogeneous reservoir with the permeability equal to 200 mD except where the high-permeability streaks exist. The results of well connectivity between well pairs are in Table 13 and 15, for both CWF and HWF, respectively. On the each side of this high permeable barriers the reservoirs are homogeneous, thus, connectivity is a strong function of well pair distance. The effect of injected fluids temperature and changed permeability values effect on time constant parameter more than in case of well connectivity. The time constant of P2 and P3 has higher values in both cases of the third scenario. When the water cut is very high or very small, reservoir fluid flow is close to a single phase flow (Cao et al., 2014). In this case the total mobility of the system is large, thus it takes less time for fluid to move from injector well to producer wells, consequently take less time constant values,. However, when water and oil saturations compete, it takes more time, thus large τ values. In this scenario, from obtained results of water cut from CMG software, the water cut of these two wells (P2 and P3) increases at early time of the simulation which was caused by altered permeability between the well pairs.

Case 4. Heterogeneous reservoir model

Figure 22 presents the total production match for each of the CRMs with the simulated results of the numerical model for Case 4. After obtaining the weights and time constants for the CRMs, EPLFFMs are used to model oil-production. The parameters αj and βj for each producer for CRMP are in Table 18. History matching of oil production rates are in Figure 23. According to the description of Case 4 in a previous Chapter 3, it is a reservoir with distributed porosity and permeability values. Table 17 represents the CRM evaluation parameters for all 8 producer wells. There are 8 parameters of time constant, and 40 parameters of injected water fraction from an injector wells to producer wells. The effect of each injector on the surrounding producer wells can be obtained from CRM parameters results.





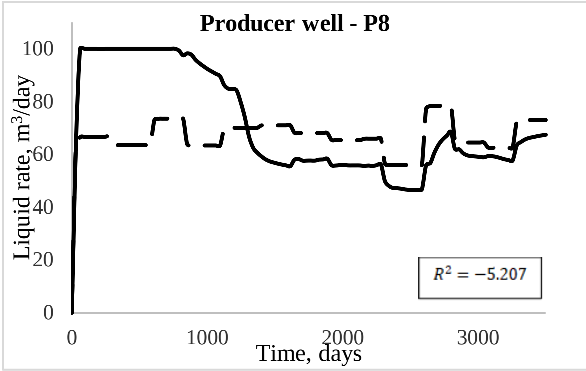
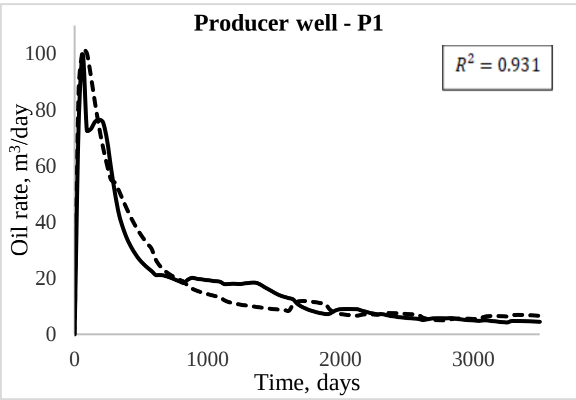
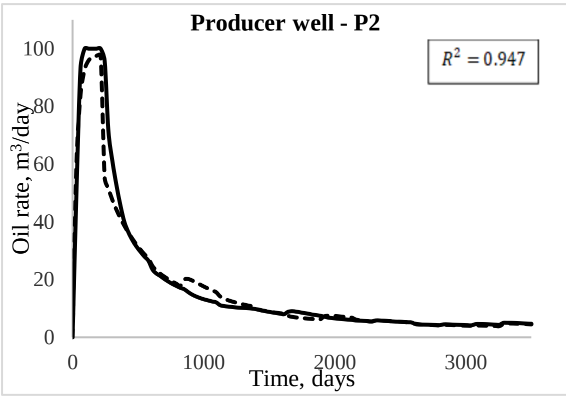


Figure 22. Total production rate vs estimated production rate for all producer wells of Case 4 under HWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual total production rate

Table 17. CRM coefficients of the reservoir model under HWF of Case 4

Number of wells	τ	f_{1j}	f_{2j}	f_{3j}	f_{4j}	f_{5j}	MAE, %
P1	43.33	0.78	0.08	0.06	0.00	0.08	3.56
P2	30.91	0.05	0.35	0.04	0.11	0.002	5.04
P3	56.01	0.00	0.10	0.31	0.02	0.05	4.04
P4	62.66	0.05	0.29	0.27	0.11	0.05	3.87
P5	120.00	0.004	0.12	0.13	0.56	0.29	4.96
P6	85.92	0.008	0.03	0.04	0.08	0.13	2.83
P7	46.592	0.054	0.001	0.000	0.000052	0.233	6.845
P8	11.726	0.032	0.000285	0.109	0.106	0.149	20.862





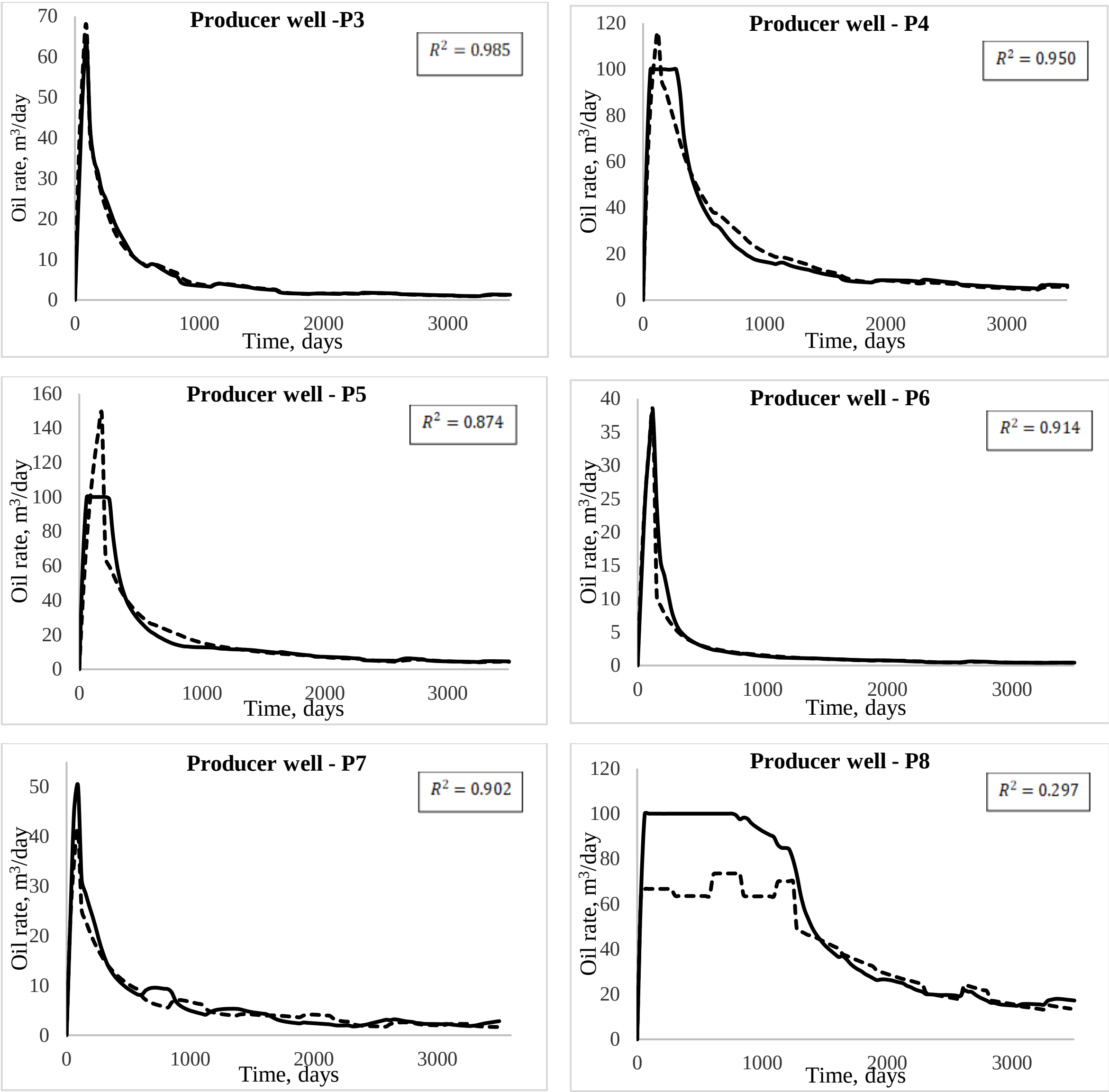


Figure 23. Oil production rate vs estimated production rate for all producer wells of Case 4 under HWF: the dashed black line shows the production profile generated from CRM and the solid line shows the actual oil production rate

Table 18. CRM coefficients for modeling oil fractional flow and MAE of history matching process for HWF of Case 4

Number of wells	α	β	MAE, %
P1	2.33E-05	1.07	24.71
P2	1.18E-06	1.33	9.46
P3	1.48E-05	1.24	6.10
P4	7.27E-07	1.34	12.86
P5	3.04E-05	1.06	11.68
P6	4.45E-04	1.04	5.76

Number of wells	α	β	MAE, %
P7	2.40E-04	9.604E-01	24.24
P8	1.12E-12	2.34	17.42

The methodology proposed in the previous section was implemented to analyze production and injection data using an Excel spreadsheet. A data set was created for the period from 01/06/2000 to 01/01/2010, covering the history of 8 production and 5 injection wells. The Generalized Reduced Gradient algorithm, a nonlinear optimization function available in Excel, was employed for the analysis. An excellent total production matching results can give meaningful model parameters. Good agreement between the calculated with history production data was observed. Average error in total liquid production is 6.504 %, and in oil production rates 14.03 %. With most R-squared (R^2) values being positive, except for P8 well where R^2 is -5.207 for total production rate and 0.297 for oil production rate, indicating a poorer fit between the independent and dependent values for this particular well. CRM demonstrates better performance in instances of production located in a high-permeability area with consistent production rates at the beginning of the period, there is a notably higher Mean Absolute Error (MAE) value compared to other producer wells. The results of the connectivity between well pairs are in Figure 24, where lines indicate connection and color differentiates the intensity of the connectivity.

Figure 24 provides a broad overview of the connectivities obtained from CRM. By examining the well location map shown in Figure 27 alongside the results presented in Table 17, and analyzing the outcomes for each well individually, it becomes feasible to categorize these wells into groups based on the parameters influencing on both τ and f values. Well pairs such as P1-I1, P2-I2, P2-I4, P3-I3, P5-I4, P6-I5, P7-I5, P8-I4 have connectivity due to their close proximity to each other, primarily determined by their geological locations. Conversely, well pairs P3-I2, P4-I3, P5-I3, P5-I5, P8-I3, and P8-I5, while not placed in close proximity, demonstrate strong connections. For instance, wells P5 and P8, positioned in a high-permeability zone (1800-2000 mD), display robust connectivity even with wells located in different areas of the model.

When considering both proximity and the number of supporting injection wells, wells such as P1, P2, and P7 exhibit similar τ values (43.336, 30.919, and 46.592, respectively) due to their proximity to their injection wells, and with no other injection wells affecting their performance in the case of P1 and P7. Additionally, as an example, wells P3 and P4, with slightly higher τ values, are likely located in zones with comparatively lower permeability, despite being supported by multiple injection wells.

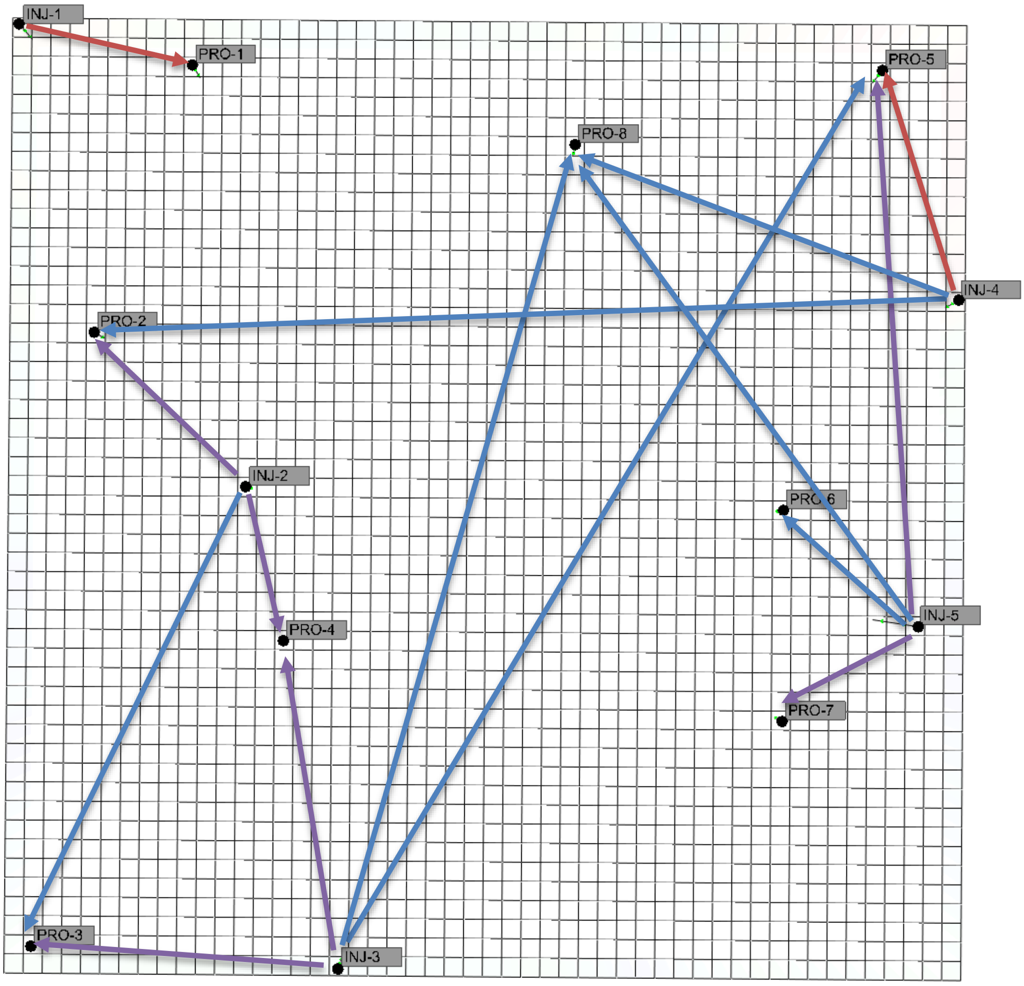


Figure 24. Connectivity map of a heterogeneous hot water injection reservoir model case. Connectitvities presented in figure are interpreted as it is presented below (***f*** below 0.1 are not highlighted in figure)

$f = 0.5 - 0.8$

$f = 0.2 - 0.4$

$f = 0.1 - 0.15$

Results show that the CRM is capable of capturing the heterogeneity of the reservoir through the parameter estimates, particularly when the contrast in heterogeneity is high. Figures 25-27 illustrate the error distribution in the first three cases for both CWF and HWF. Upon analysis of the first and second cases, it's evident that HWF yields error values approximately half those observed during CWF. This reduction can be attributed to the dominant role of viscosity reduction, where the mobility of heated oil relative to water and the reservoir's relative permeability significantly influence production outcomes. CRM performs more effectively when the behaviors of water and oil are similar. Nonetheless, given that the initial viscosity of oil remains at 45 cp during CWF, there are no alterations in the viscosity of oil. Comparing error values in case three, wells with high-conductive pathways exhibit higher error rates compared to those where permeability remains unchanged. Since CRM operates as a signal capturing model and performs optimally in undisturbed systems, such changes are considered as noises in the input signal, altering output results. As previously noted, connectivities dictate the extent to which production rates vary in response to changes in injection rates. Thus, modifying connectivities, equivalent to adjusting the system's permeability, can cause shifts in response, leading to significant errors in history matching. Calculated Mean Absolute Error (MAE) values across all cases for HWF indicate a moderate degree of inaccuracy, with total liquid production rates ranging from a maximum of 20.8% to a minimum of 2.84%, and oil production rates from a maximum of 15.83% to a minimum of 5.76%.

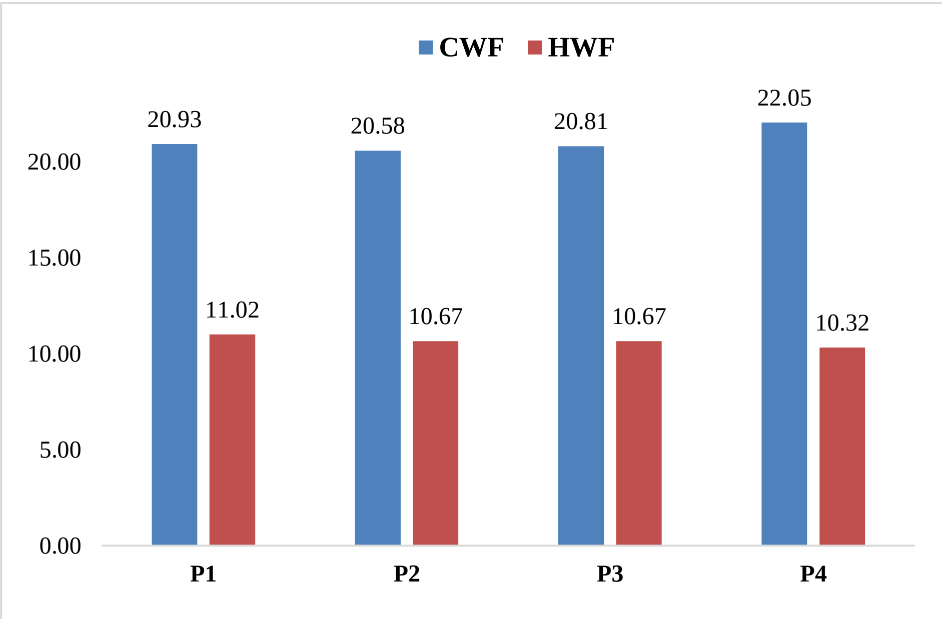


Figure 25. The error distribution of Case 1

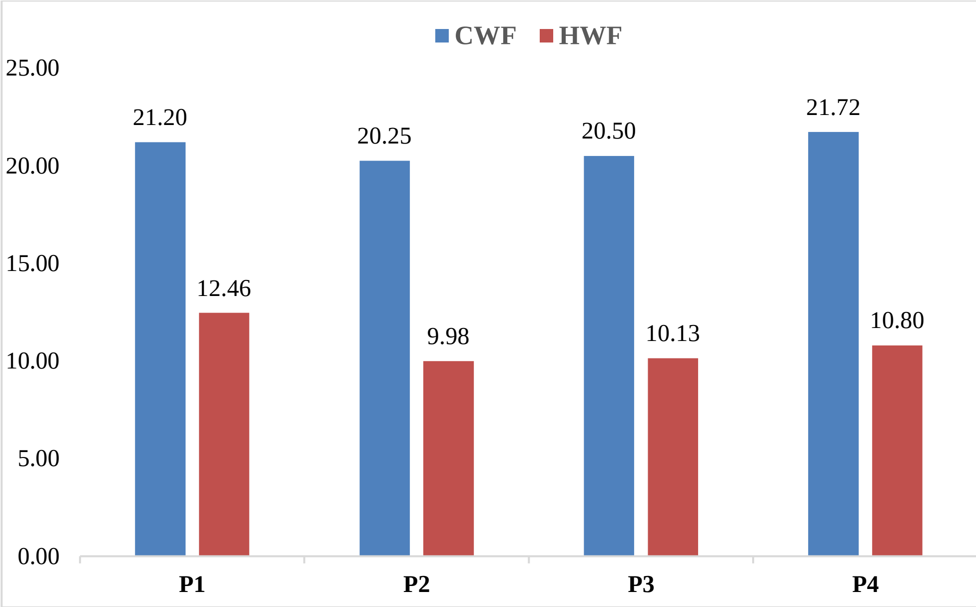


Figure 26. The error distribution of Case 2.

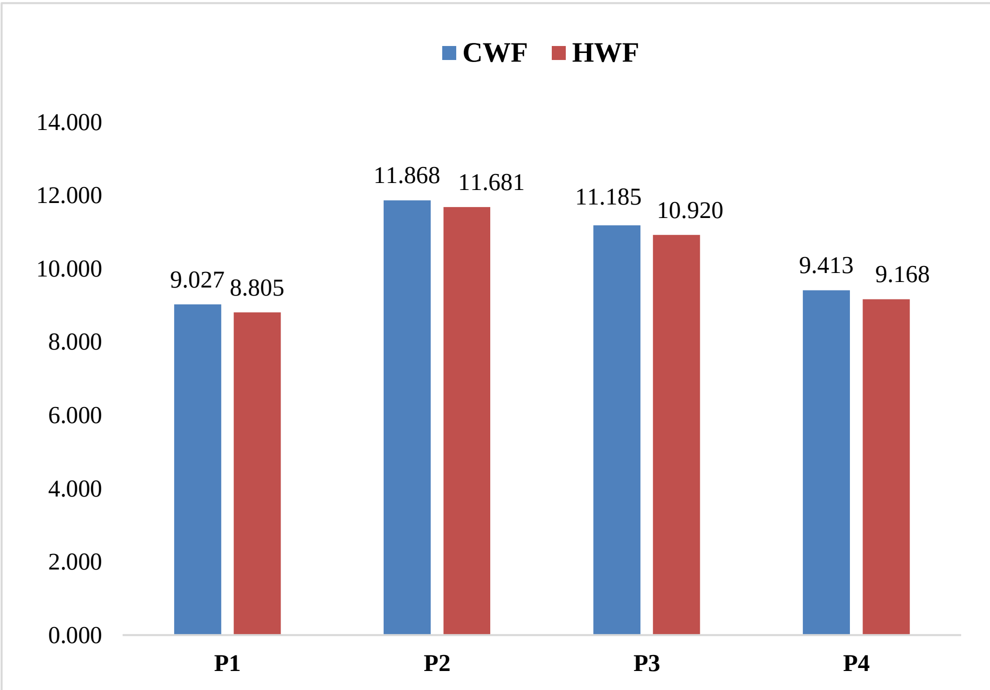


Figure 27. The error distribution for Case 3.

5. CONCLUSIONS AND RECOMMENDATION

The existing approach of applying CRM to model water flooded reservoirs has been expanded to simulate reservoirs undergoing hot water injection. In order to validate this developed model, synthetic reservoir models generated by a commercial simulator were utilized across four case studies during this project. The adapted CRM equations were applied to these reservoirs, using CRMP. Various scenarios were explored to assess the CRM's performance in hot water injection processes, and additional features were developed to comprehend the underlying significance of the CRM's evaluation parameters under specific assumptions. The outcomes of these experiments were analyzed to identify the predominant factors influencing the overall modeling performance. During the modeling of these cases, factors such as well placements, average permeability of the reservoirs, productivity index, and fluid compressibility were taken into account.

In summary, the following conclusions can be made:

1. The application of CRM to several synthetic case studies demonstrated its reliability and effectiveness in history-matching of reservoir performance. The CRM proved capable of modeling hot water injection processes, as corroborated by the results from an ideal homogeneous reservoir model.
2. CRM offers an economical and efficient solution, allowing for preliminary assessment of reservoir characteristics and prediction of future production with minimal reservoir data, particularly injection and production data, requiring minimal computational resources and time.
3. Both nearly-homogeneous and heterogeneous reservoir models were developed to evaluate the CRM parameters and assess the general performance of CRM under different scenarios.
4. Valuable insights into the timing of water flooding can be obtained by estimating the distribution of injected water from the injection well to various production wells, as well as identifying the duration for which the injection signal reaches the producer wells.
5. Both parameters, τ and f, are influenced by several factors including permeability levels, measurement inaccuracies, and well placements.
6. τ is particularly sensitive to changes in the obtained productivity index values compared to fluid compressibility.

7. It was observed that f yields better results in models characterized by high permeability or close proximity between wells.

In modeling, simulation is the process of simulating a real-world system or process to comprehend its behavior under various circumstances. The purpose of simulation is to generate data that mimics the behavior of the real system, allowing analysts to study its dynamics, make predictions, and test various scenarios without directly intervening in the real system. Common approach in simulation where uncertain parameters are modeled using probability distributions it means that instead of assuming fixed values for these parameters, they are represented as random variables following certain probability distributions. Each time the simulation runs, it samples values for these parameters from their respective distributions, generating different outcomes. Relying solely on a single realization of these probability distributions may not adequately capture the full range of possible outcomes or fluctuations in the system. In scenarios like reservoir management, where uncertainties play a significant role, it's crucial to assess a wide range of potential outcomes, including best and worst-case scenarios. To address this limitation, one can employ techniques like Monte Carlo simulation, which involves running the simulation multiple times with different sets of randomly sampled parameter values. By aggregating the results from these multiple simulations, analysts can gain a more comprehensive understanding of the system's behavior under uncertainty, including the likelihood of various outcomes and the range of possible fluctuations.

As a suggestion for future research, it would be beneficial to explore the optimization of CRM processes on wells with hot water injection. Through CRM optimization, various objective functions can be defined to enhance future reservoir performance. These could include maximizing cumulative field oil production within a set of time period, such as a year, by adjusting field injection wells allocation while keeping the total injection rate constant; or minimizing cumulative field water production over a defined time period by reallocating field injection while maintaining the same total injection rate in the field.

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