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Abstract

Use of smart well technologies to improve the recovery has caught significant attention in the oil industry in the last decade. Capacitance-Resistance (CRM) methodology is a robust data-driven technique for reservoir surveillance. Reservoir sweep is a crucial part of efficient recovery, especially where significant investment is done by means of installation of smart wells that feature inflow control valves (ICVs) that are remotely controllable. However, as it is a relatively newer concept, effective use of this new technology has been a challenge. In this study, the objective is to present the efficient use of ICVs in intelligent fields through the integrated use of capacitance-resistance modeling and smart wells with ICVs. A standard realistic SPE reservoir simulation model of a waterflooding process is used in this study where the smart well ICVs are controlled with conditional statements called procedures in a fully commercial full-physics numerical reservoir simulator. The simulation data is utilized to build the CRM model to obtain the inter-well connectivities at the zonal level beyond only the inter-well connectivity data as smart wells provide control and information on the amount of injection into each layer or zone. Thus, after analyzing the CRM model to detect the inter-well connectivities at the zone/layer-level in an iterative way, the optimum injection not only at the well level but also at the perf/zone level is found. The workflow is outlined as well as the improvements in the results.

The smart well technology has been challenged with the associated cost component thus, it is important to present the benefits of this technology with applications in more diverse cases with different workflows. It has been observed that a robust reservoir characterization in an intelligent field can provide an insight into the physics of reservoir including smart wells with ICVs. The results are presented in a comparative way against the base case to illustrate the incremental value of the use of ICVs along with key performance indicators. Most importantly, it has been shown that smart well use without a robust reservoir management strategy does not always lead to successful results.

In reservoir management, it is not only important to catch the well level details but also see the big picture at the field level to improve the performance of the reservoirs beyond individual well performances taking into account the interference between wells. This method takes the reservoir surveillance to the next level where reservoir characterization is improved using smart field technologies and capacitance-resistance modeling as a robust cost-effective data-driven method.

Introduction

Smart completion technology has been initiated for particularly horizontal and multilateral offshore wells to optimize hydrocarbon production and to reduce water production. In fact, these methods are quite powerful in terms of delaying water breakthrough and justifying water coning. Since premature water breakthrough bypasses oil and causes a reduction in ultimate recovery. All motivation in smart completion is to obtain uniform production profile in, particularly highly heterogeneous reservoir by creating an extra pressure drop across high permeable section [1]. It is needless to mention that good knowledge of reservoir geology, as well as properties such as saturation, pressure, permeability, and skin distribution, are key to get the maximum benefit from smart completion. Using smart completion techniques is also quite useful for multi-layer commingled reservoirs in both producer and injector wells when water injection process is executed.

One of the biggest issues in waterflooding is unfavorable sweep due to the areal variation of layering and individual rock properties such as permeability, porosity, saturation in a specific layer. Identifying high permeable zones (also called thief zone) is not an easy task since they are sometimes quite thin. Although it is quite costly, the integration of some sophisticated logging and testing tools with advanced interpretation techniques are quite helpful to recognize vertical heterogeneity by locating thief zones [2]. However, areal heterogeneity is quite complex and may bring surprising sweep efficiencies even if costly high-quality data is acquired. When the waterflooding project started, the injection profile is generally obtained running basic production logging services. Mostly uneven injection profile is observed when vertical and areal heterogeneity exist if conventional completion is used. In order to prevent early water breakthrough through thief zones, smart completion provides a dynamic solution. When injection started, thief zones can easily be obtained by running production log, and these zones may be closed to water injection to prevent early water breakthrough. Thanks to smart completion, better sweep efficiency is achieved by adjusting the inflow control devices periodically.

Rahman, Allen [3] introduced the new generation of interval control valves and discussed the importance of using smart wells in future reservoir environments. Sefat, Elsheikh [4] then explained that smart well's downhole control apparatuses can be categorized as follows:

1) Inflow Control Devices (ICDs), which are single-positioned and provide a fixed level of flow control,
2) Autonomous Inflow Control Devices (AICDs), which are self-adjusted and provide a pre-designed, fluid-dependent flow control, and
3) Interval Control Valves (ICVs), which have multiple positions to provide a flexible flow control.

According to Sefat, Elsheikh [4], as ICVs can be utilized for implementation of different production scenarios to maximize the economic profit, they are frequently preferred and studied in the literature. Moreover, since using smart wells provides the layer-by-layer injection and production control, this flexibility allows the engineers and operators to achieve the optimum production/injection scenario. Thus, a comprehensive investigation into the use of characterization methods in smart environments would create a deep insight into the reservoir management and production optimization problem.

Reservoir Characterization Using Capacitance-Resistance Model

In CRM, a liquid (oil + water) production rate is construed as a response resulted in a change (shock) in the water-injected rate. For each pair of injection-production well, two parameters should be determined. These parameters correspond to the degree of connectivity and the fluid storage degree between producers and injectors. Using injection and production rates, respectively, as a shock (input) and response (output), the capacitance-resistance model can be derived based upon the total fluid mass balance in the control volume [5, 6]. It should be noted that using mass balance entails integrating the effect of compressibility in the model. The main advantage of the CRM is its speed and simplicity which allows reservoir engineers to match production history of the reservoir and forecast the future performance based on available data (injection and production rates and, if available, bottomhole pressure). After finding the CRM parameters (connectivities and time constants), prediction of future performance can be obtained with the fitted model parameters. From a mathematical point of view, the CRM can be regarded as a nonlinear multivariate regression analysis tool that simulates compressibility and fluid flow for a reservoir based upon the time constant [7, 8]. The simulation method in CRM, however, works with the interactions between producer-injector pairs. These interwell connectivities explain the magnitude of permeability in the reservoir. From another perspective, the CRM can be considered as a streamlined approach in which the interwell interactions are identical to the relative number of streamlines of an injector that supports a producer [9]. Taking all-aforementioned into account, the CRM utilizes a nonlinear multivariate regression analysis in which the effect of compressibility, pore volume and productivity index are all considered in a parameter called time constant. The time constant is in a direct relationship with the time delay of the injection signal at the producers. Hence, the interwell connectivities and time constants are able to describe the reservoir. The literature reports various limitations of CRM. Most of the limitations are due to the inability of the model to include day-to-day operations (workovers), variation in fluid compressibility and strong aquifer support. From these, accounting for well intervention during the lifetime of the reservoir presents a major challenge [10]. Shut-ins especially results in re-allocation of streamlines between the injector and producer, which leads to a difficulty in determining the injection weights for CRM [11]. Recently, Salehian and Soleimani [12] developed a comprehensive mathematical formula for CRM to predict waterflood performance and match the history of either vertical or horizontal wells including shut-in periods.

There are several versions of CRM in the literature. Yousef, Lake [8] introduced a nonlinear data-driven model to accurately estimate the interwell connectivity between production and injection wells under various conditions. They also validated that approach by applying it to real reservoirs. Sayarpour [5] categorized CRMs based on the attribution of the model parameters to different control volumes; CRMT: Tank representation of entire field (control volume is the whole field), CRMP: Producer based representation (each producer has a drainage volume), CRMIP: Producer-injection based representation (a control volume for each injector-producer pair). Kim [13] presented a linear multivariate regression analysis (ICRM) which fits the cumulative total production with cumulative water injections. Salehian and Soleimani [12] improved the accuracy of ICRM by utilizing two consecutive objective functions. Salehian [11] developed a dynamic CRM (D-CRMP) to address the issue of CRMs with shut-in periods in historical data. Recently, there are some efforts to characterize layered reservoirs with different versions of CRMs [14-16]. In this study, as we do not have shut-in periods in our historical data, we use the CRMP which was first introduced by Sayarpour [5]. The governing equation of CRMP is as follows:

$$q_j(t_k) = q_j(t_{k-1})e^{\frac{-\Delta t_k}{\tau_j}} + \left(1 - e^{\frac{-\Delta t_k}{\tau_j}}\right)\left(\sum_{i=1}^{N_I} f_{ij} i_i(t_k) - J_j \tau_j \frac{P_{wf,j}^{k} - P_{wf,j}^{k-1}}{\Delta t}\right) \qquad [1]$$

where $\Delta t = t_k - t_{k-1}$ and $q_j(t_k)$ is the liquid production of producer j at time step t_k. The f_{ij} is the connectivity between injector i and producer j, and τ_j represents the time constant of producer j. Having only production and injection data, one can use the CRMP to infer the interwell connectivity between producer-injector pairs. Furthermore, one can utilize the CRM to rapidly predict the future production performance of each producer at any injection rate and producer's BHPs after determining the model parameters. If BHP does not change (constant BHP), Equation [1] can be simplified as follows:

$$q_j(t_k) = q_j(t_{k-1})e^{\frac{-\Delta t}{\tau_j}} + \left(1 - e^{\frac{-\Delta t}{\tau_j}}\right)\left(\sum_{i=1}^{N_I} f_{ij} i_i(t_k)\right) \qquad [2]$$

According to the mass conservation, the sum of interwell connectivities for each injection well should be less than or equal to one. Moreover, all f_{ij}s are bigger than zero. Mathematically, we have the following constrains:

$$f_{ij}, \tau_j \geq 0 \text{ (for all } i \text{ and } j) \text{ and } \sum_{j=1}^{N_P} f_{ij} \leq 1 \text{ (for all } i) \qquad [3]$$

The model parameters of CRMP can be estimated via different mathematical approaches. In this regard, an objective function should be defined and minimized to obtain the gains and time constants. In this work, we set the sum of squared errors between the observed total injection rate, denoted as $q_{j_{obs}}(t_k)$, and the calculated total injection rate by the model, denoted as $q_{j_{CRM}}(t_k)$.

$$Objective\ Function = min\left\{\sum_{k=1}^{N_T}\sum_{j=1}^{N_P}\left(q_{j_{obs}}(t_k) - q_{j_{CRM}}(t_k)\right)^2\right\} \qquad [4]$$

where,
N_P =Total number of producers
N_T =Number of time steps selected to fit the model
Using CRMP results in the following parameters to be determined:

τ_j for $j = 1, 2, \dots, N_P$ (N_P unknowns)
f_{ij} for $i = 1, 2, \dots, N_I$ and $j = 1, 2, \dots, N_P$ ($N_P \times N_I$ unknowns)
J_j for $j = 1, 2, \dots, N_P$ (N_P unknowns)

This results in total number of $N_P \times (N_I + 2)$ model parameters. If BHP is assumed to be constant, the number of model parameters reduces to $N_P \times (N_I + 1)$.

Case 1:

The synthetic SPE9 model [17] is modified and used in this study. Although the completion in the standard SPE9 model was limited to top three layers for producers and bottom 3-4 layers for injectors, the model has been modified so that the injector and producers could be completed in all 15 layers. As we aim to investigate the magnitude of connectivity in our examples, we complete all layers in general, which facilitates the characterization by CRM and ICV mimicking process. The modification of SPE9 model was extended to change the permeability in all layers (**Figure 1**), which allows us to observe the impact of heterogeneity in CRM connectivity values. The reservoir consists of four sections with equal volumes but different permeability, where each section is dedicated to a producer. The remaining fluid and rock properties are identical to SPE9 model and can be found at Killough [17]. In layer 7, a high permeability (100x10 = 1000md) thief zone is introduced between injector and producer 4 (**Figure 2**). In layer 11, another high permeability (100x20 = 2000md) thief zone has been introduced between injector and producer 1 (**Figure 3**). The simulation starts in 1980 and ends in 1990. **Figure 4** depicts the injection scenario during the simulation.

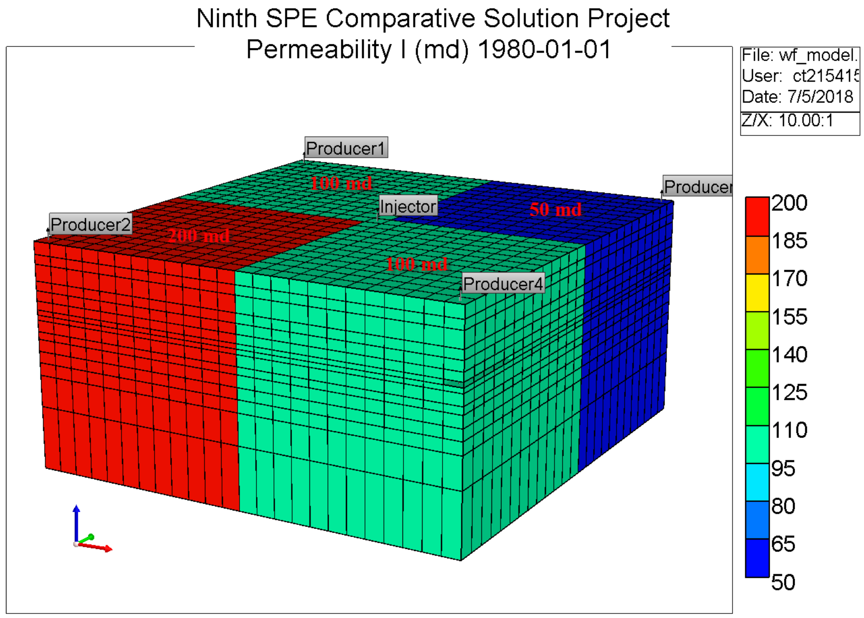

Figure 1. SPE9 modified model.

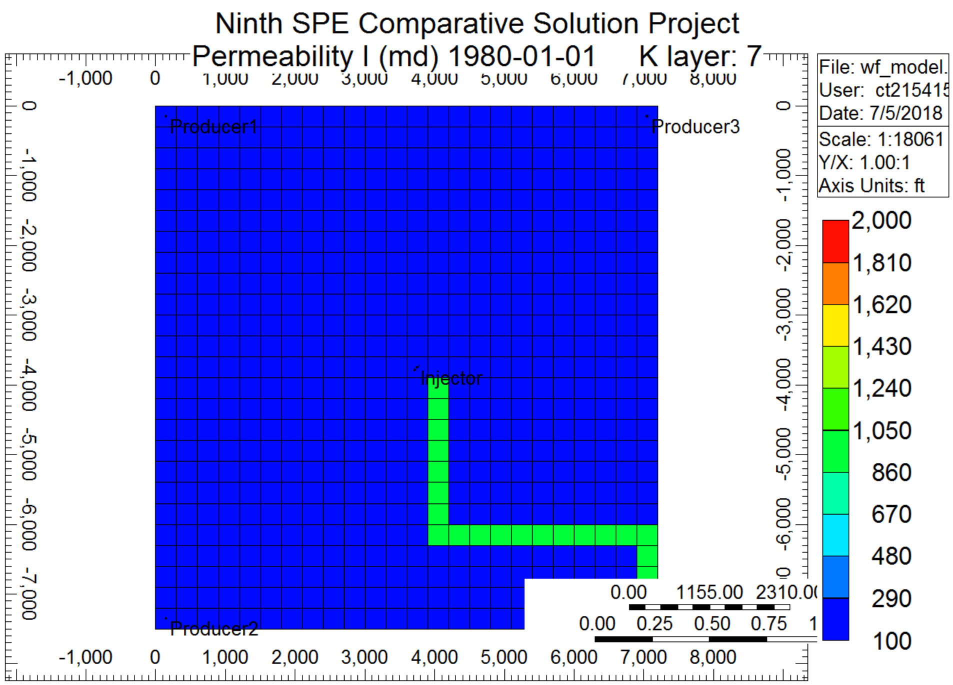

Figure 2. The high permeability thief zone in layer 7 of SPE9 modified model.

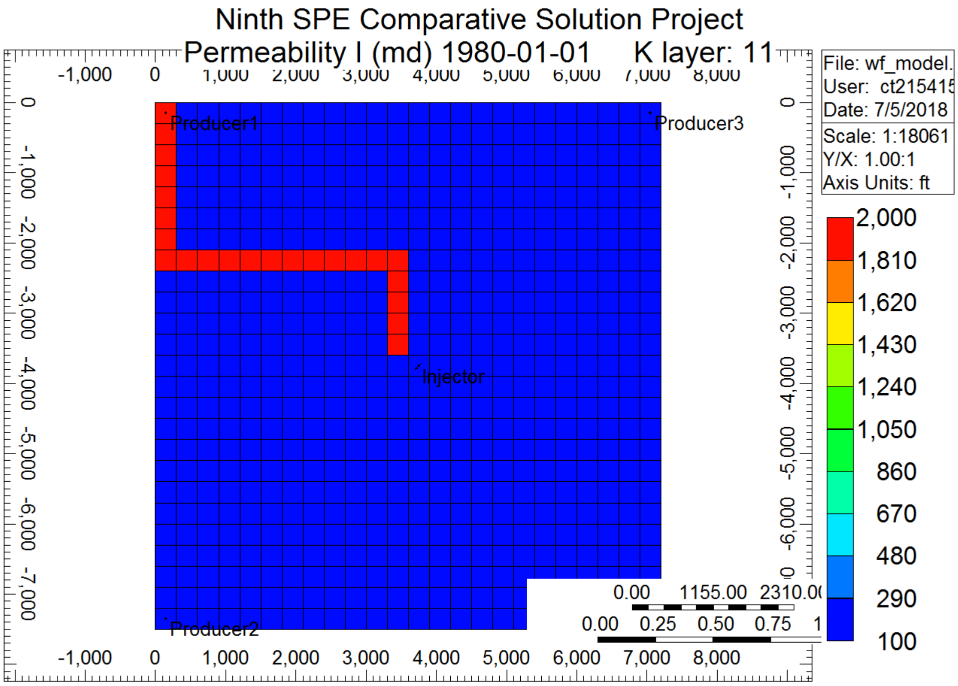

Figure 3. The high permeability thief zone in layer 11 of SPE9 modified model.

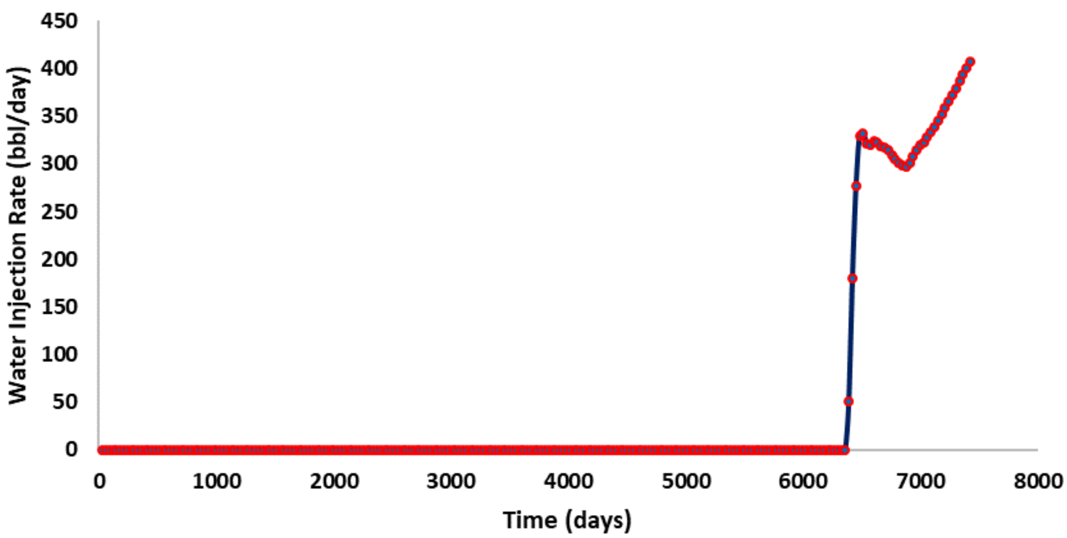

Figure 4. The water injection rate history of the SPE9 modified model.

In the SPE9 modified model, BHP of producers is assumed to be constant. Since there is one injector ($N_i = 1$) and four producers ($N_P = 4$), we need to find eight CRM parameters. In this work, we investigate five cases that are different in the perforation of injector and producers. In case 1, the central injector and all producers are fully perforated in all 15 layers of the reservoir. In case 2, the injector's perforation is closed in the layer 7. In case 3, the perforation of the injector is closed in layer 7 and 11. In case 4, the producer P4's perforation is closed in layer 7. In case 5, the perforation of P1 and P4 are closed in the layer 11 and layer 7, respectively. After running the simulation and minimizing the objective function through the CRMP equation, the model parameters of case 1 are obtained and listed in Table1.

Table 1. Estimated CRMP parameters in SPE9 modified model (Case 1).

	P1	P2	P3	P4
f_{ij}	0.2679	0.2516	0.1641	0.3164
τ_j	900.0	871.21	876.16	899.99

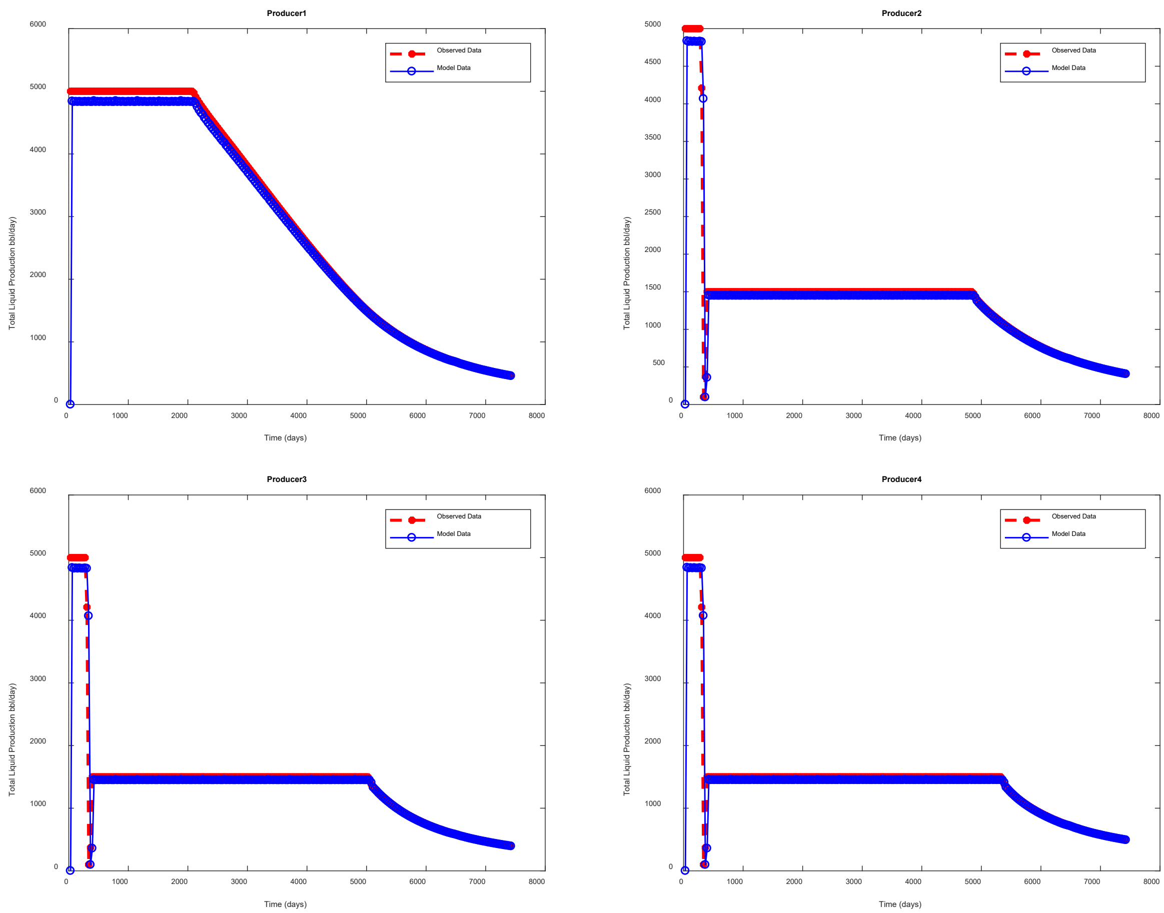

Figure 5. Liquid production match by CRMP in SPE9 modified model (Case 1).

Figure 5 shows the total liquid production match for all producers in the field. The perfect production match indicates that the CRMP successfully catches the production behavior of the SPE9 modified field. As it is shown in Table 1, the P4 has received the largest connectivity, which accounts for the presences of extremely high permeability thief zone between injector and P4. The high value of connectivity between the injector and P1, which are connected with another high permeability thief zone, confirms the fact that both thief zones had intensely impacted the connectivity between wells. The high permeability region around P2 positively impacted on the connectivity with the central injection, however, it could not overcome the extremely high permeable thief zones around P1 and P4. Hence, an extremely high permeable thief zone, even in a thin layer, can change the connectivity between producers and injectors and overcome the general heterogeneity of the reservoir. Despite the connectivity, which is highly dependent on heterogeneity and thief zones, the time constant is less sensitive to the permeability of the reservoir. That is, no remarkable differences can be observed in the time constant values of producers. Nevertheless, P1 and P4 have received the largest values of time constant as they are connected with two thief zones with the central injector. In addition, the time constant in P2 is slightly lower than P3, which is due to the high permeability region that P2 is located in. It should be pointed out that the unusual large values of time constants for all producers are due to the fact that the majority of the reservoir is low permeable.

Case 2:

In this case, the perforation of the central injector is closed in layer 7, which interrupts the flow in the thief zone toward the producer P4. The obtained interwell connectivities show that liquid flow toward the producer P4 has been improved, as the perforation has been closed in a thief zone that is not high permeability channel for all producers. Hence, the closure of injector's perforation in layer 7 results in sacrificing the displacement of liquid towards other producers and, consequently, strong communication (usually associated with high water cut) with the producer P4. In other words, although the injector's perforation in layers 7, a channel of fluid transform toward producer P4, has been closed, the crossflow of injected water and fluid front from upper and lower layers toward the layer 7, which is now an empty channel, supports the production of P4, thereby increasing the interwell connectivity value of P4. The time constants of P2 and P3 has slightly decreased, which can be considered as unchanged, similar to the time constant values of P1 and P4. **Figure 6** exhibits the liquid production match by CRMP in Case 2.

Table 2. Estimated CRMP parameters in SPE9 modified model (Case 2).

	P1	P2	P3	P4
f_{ij}	0.240	0.212	0.172	0.376
τ_j	900.0	870.96	875.27	899.99

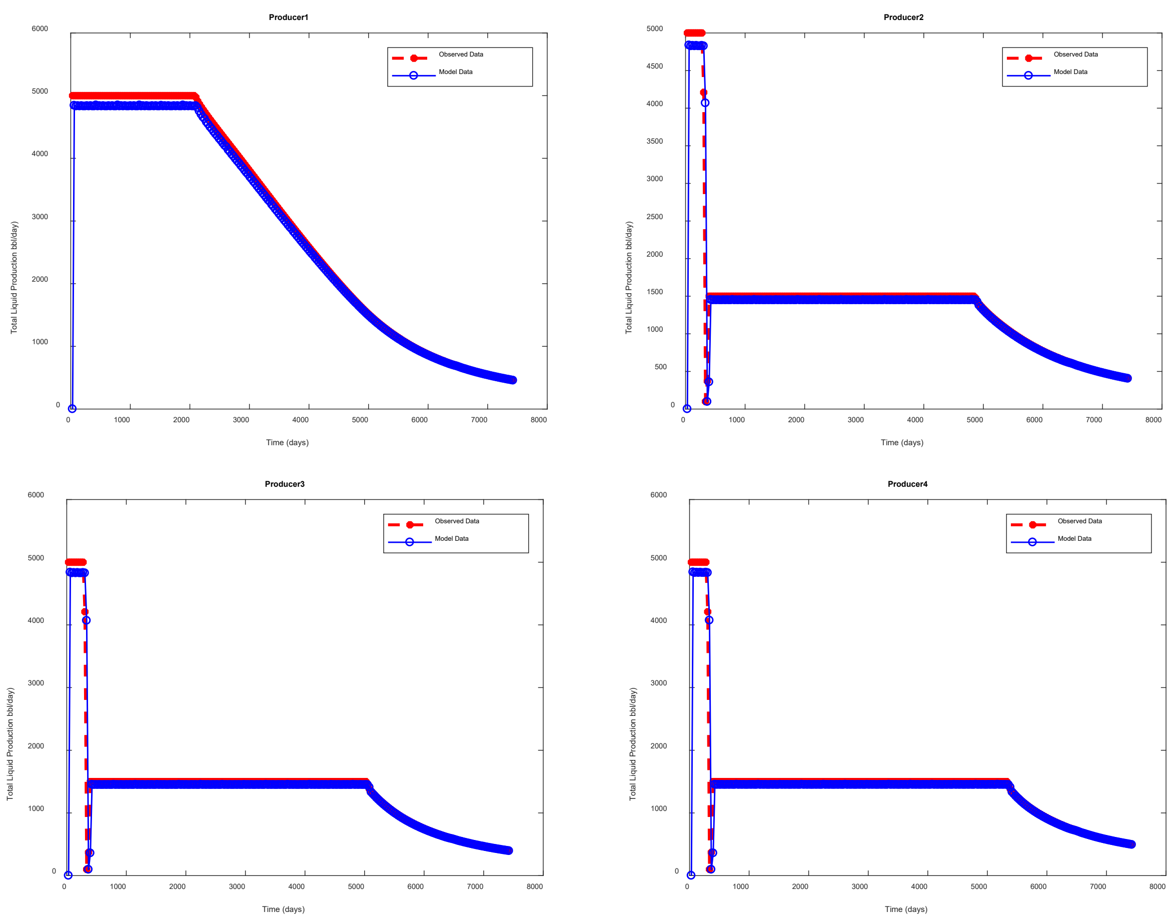

Figure 6. Liquid production match by CRMP in SPE9 modified model (Case 2).

Case 3:

In this example, the perforation of the central injector has been closed in layers 7 and 11, in which two thief zones belong to producers P4 and P1, respectively. Similar to the previous case, as the injector's perforation is closed in two thief zones connected to two producers, the interwell connectivity between the injector and those two producers (P1 and P4) increases. This can be observed in Table 3. As it was mentioned before, the time constant does not change remarkably. **Figure 7** depicts the high-quality liquid production match by CRMP in Case 3.

Table 3. Estimated CRMP parameters in SPE9 modified model (Case 3).

	P1	P2	P3	P4
f_{ij}	0.2805	0.1801	0.1541	0.3854
τ_j	900.0	870.68	875.53	899.99

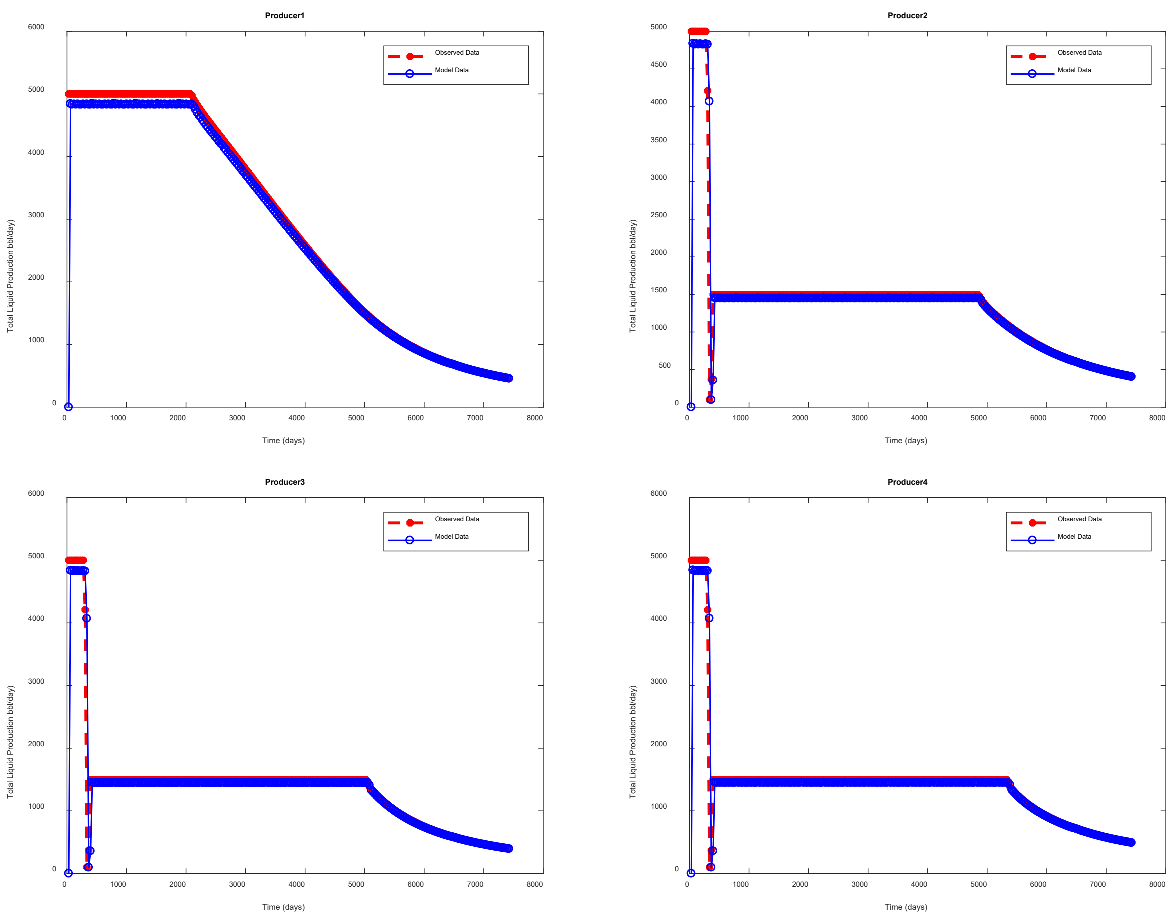

Figure 7. Liquid production match by CRMP in SPE9 modified model (Case 3).

Case 4:

In this case, we close the perforation of producer P4 in layer 7, which is a thief zone towards the central injector. It can be seen from the connectivities (Table 4) that the communication of injector with producer P4 has been improved in comparison with the base Case 1. The closure of P4's perforation in layer 7 creates a high permeability no-flow stream toward the injector. This high permeable empty channel, which is only connected to producer P4, allows the liquid in layers nearby to flow toward the P4 and increase the connectivity. The increase in the connectivity of P4 can be investigated along with the decrease in connectivities of P1 and P2, which confirms the displacement of liquid toward P4 after closing the perforation in layer 7. **Figure 8** shows the liquid production match by the CRMP.

Table 4. Estimated CRMP parameters in SPE9 modified model (Case 4).

	P1	P2	P3	P4
f_{ij}	0.2462	0.1928	0.2008	0.3602
τ_j	900.0	871.695	876.3231	899.99

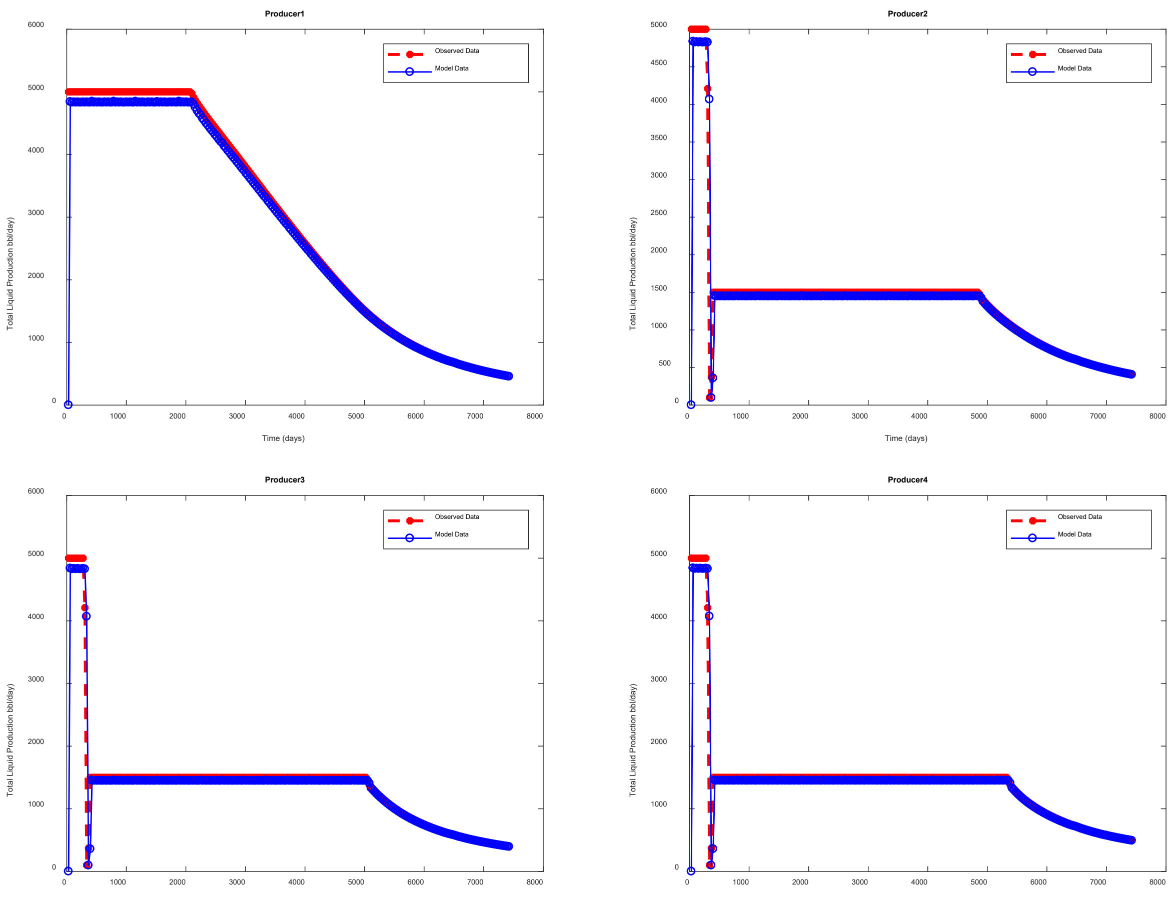

Figure 8. Liquid production match by CRMP in SPE9 modified model (Case 4).

Case 5:

In the fifth example, the perforation of P4 in layer 7 and the perforation of P1 and layer 11 are closed at the same time. The closure of P1's perforation in the layer 11 (P1's thief zone) has clearly enhanced the connectivity of P1 and, consequently, reduced the communication between P4 and the injector. The comparison between Case 4 and Case 5 indicates that the closure of perforations in two producer acts against each other. In other words, the large liquid displacement towards P4 in Case 4 has been decreased after another perforation was closed in P1. Hence, each perforation closure leads to stronger communication with the injector, if the thief zone connects injection well to one producer. Table 5 summarizes the model parameters obtained by CRMP. The liquid production match by CRMP has been represented in **Figure 9**.

Table 5. Estimated CRMP parameters in SPE9 modified model (Case 5).

	P1	P2	P3	P4
f_{ij}	0.2776	0.2248	0.1676	0.3299
τ_j	900.0	870.103	874.779	899.99

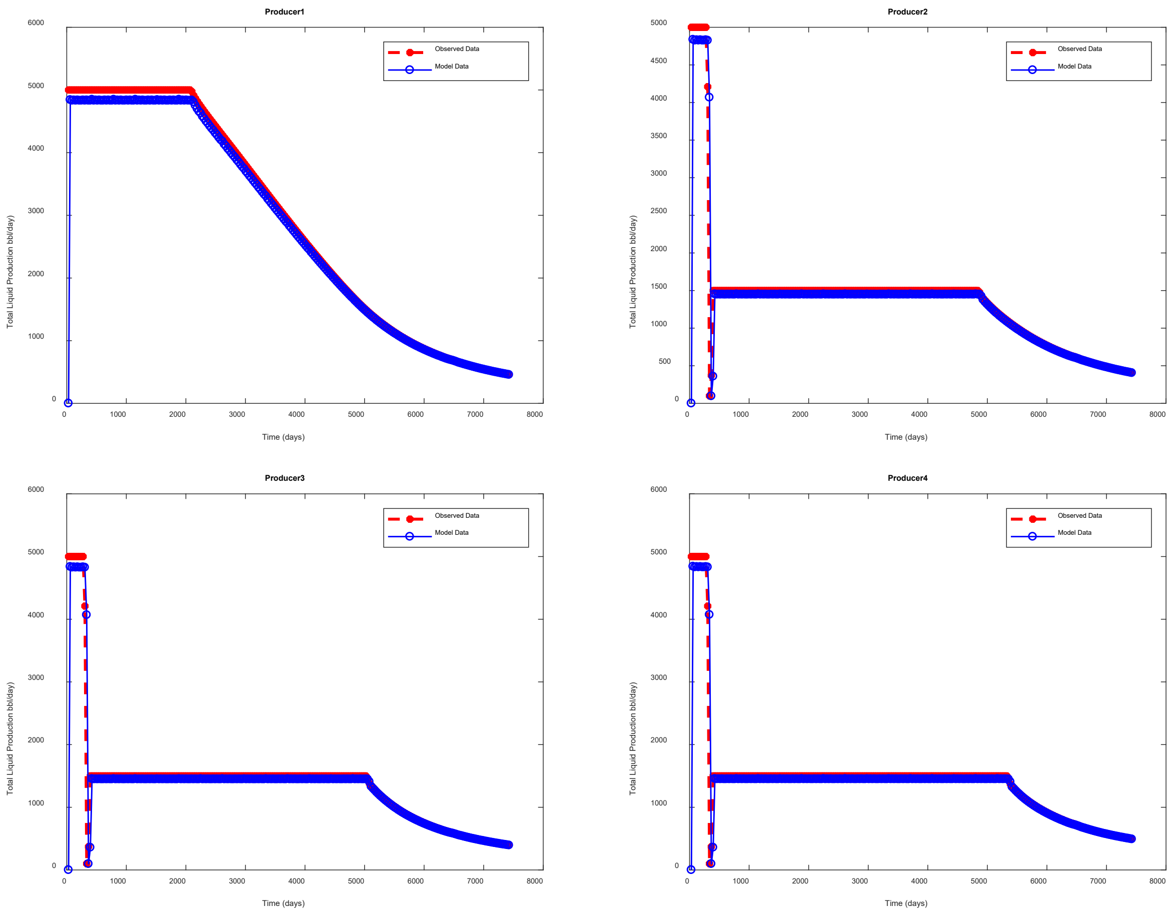

Figure 9. Liquid production match by CRMP in SPE9 modified model (Case 5).

Conclusions:

This study implements the capacitance-resistance method as an effective data-driven model to characterize the smart reservoir environments including intelligent wells. Results show the capability of CRM to provide a high-quality history matching and reliable model parameters. The comparison between five cases and their corresponding model parameters obtained by CRM reveals the impact of well perforation on the interwell connectivities (interwell communication) in heterogeneous reservoirs including thief zones. A high permeable thief zone, even in a thin layer, significantly changes the connectivity between producers and injectors to overcome the general heterogeneity of the reservoir. Despite the connectivity, which was highly depended on heterogeneity and thief zones, the time constant was less sensitive to the permeability of the reservoir. That is, no remarkable differences were observed in the time constant values of producers after implementing thief zones in the reservoir.

As the perforation of the central injector was closed in thief layer, interwell connectivities showed that liquid flow toward the producer P4 has been improved. This was due to fact that the perforation has been closed in a thief zone that is not high permeability channel for all producers. Hence, the closure of injector's perforation in the thief layer results in sacrificing the displacement of liquid towards other producers and, consequently, creating a strong communication (usually associated with high water cut) with the producer P4. The closure of P4's perforation in layer 7 created a high permeability no-flow stream toward the injector. This high permeable empty channel, which was only connected to producer P4, allowed the liquid to flow in layers nearby toward the P4 and increase the connectivity. The increase in the connectivity of P4 was investigated along with the decrease in connectivities of P1 and P2, which confirmed the displacement of liquid toward P4 after closing the perforation in layer 7. The closure of P1's perforation in the layer 11 (P1's thief zone) boosted the connectivity of P1 and, consequently, reduced the communication between P4 and the injector. In other words, the large liquid displacement towards P4 in Case 4 has been decreased after another perforation was closed in P1 in Case 5. Thus, each perforation closure leads to stronger communication with the injector, if the thief zone connects injection well to one producer. Further investigations in future are recommended to evaluate the capability of multi-layer CRM approaches as a proxy model for production optimization in uncertain models by considering several economic objectives.

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