Capacitance Resistance Model (CRM) as a Scikit-Learn Estimator

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Abstract

Often the only data available during reservoir simulation are the production and injection rates. This limiting factor is what CRM deals with. CRM has been used to simulate the production rate of producers in a reservoir given an injection rate and the production rate at various times. CRM does not require a diversity of data and most of the data it needs can be readily obtained. CRM is implemented as a Scikit-Learn estimator in this paper in order to make it convenient to use in data pipelines and easy to compare to other models. Implementing CRM as a Scikit-Learn estimator takes advantage of a common API standard, which Scikit-Learn has developed. This makes the code more readable and shareable. We are evaluating the ability of CRM to predict the production rate a 7 producer and 4 injector reservoir using real production data. The results show that CRM is a good predictor of production rate. This is most likely due to CRM being a physics based model with few parameters. This is promising for CRM as it could be used in a variety of applications beyond production rate estimation. For example, CRM could be used as a good starting point to predict the oil production or to optimize injection rate in order to maximize oil production or expected return on investment.

1 Introduction

CRM models the reservoir along with its injectors and producers as a series of capacitors and resistors. This was first proposed in the 1940's, [1].

CRM has a long history starting in 1943. This first paper did not describe the methodology as digital, but it did use a similar concept that was physically analogous, which later would become modern CRM. The reservoir was modeled using a series of capacitors and resistors with a current passed through the electrical device. This was used to characterize a reservoir with production and injection wells. This was accomplished by dividing the reservoir into grid blocks, which were represented by capacitors and resistors, [1].

In Figure 1, it shows an electrical device designed to model the flow of fluid from one grid block to another. The grid block's storage capacity is modeled as a capacitor, and the transmissibility from one grid block to another is modeled using resistors. Transmissibility is the inverse of resistance.

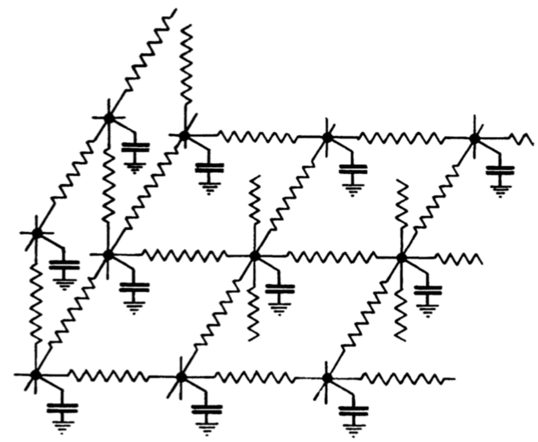

Figure 1: Schema of Electrical Device by [1]

This was later expanded upon by others into equations, which allowed us to implement it numerically. This confers benefits of scale and speed. The physical device would have many constraints, such as slow iteration, experiments could not be run in parallel, and cost.

CRM has two hyperparameters that must be fit prior to testing the model. The first is the time constant, τ, in days, and the second are the gains, f_{ij}. In this case, the i, represents the injector, and the j represents the producer. So f_{ij} refers to how fluid injected at injector i interacts with producer j. Though, the equations do not need to be in the form of days. They could be in any arbitrary time unit, as long as the units are consistent, [2].

τ equation uses values for total comprehensibility, c_t, psi^{-1} , pore volume ,V_p, in bbls, and productivity index, J, $\frac{bbl}{day*psi}$. The equation for τ is shown below [2].

$$\tau = \frac{c_t V_p}{J}$$

The gains are the normalized transmissibility from one injector to a particular well, hence dimensionless. Transmissibility has units of $\frac{bbl}{day*psi}$. The sum of all the gains for a particular well is equal to or less than one.

$$f_{ij} = \frac{T_{ij}}{\sum_{j=1}^{N_{prod}} T_{ij}}$$

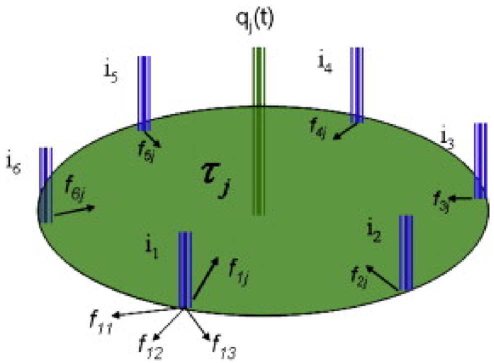

Figure 2: Capacitance Resistance Model Producer Volume, [2]

In Figure 2, we see a visual representation of the how the fluid traveling from an injector to producer is modeled in Capacitance Resistance Model Producer Volume (CRMP), which is what we implement in this paper.

$$q_j^k = q_j^{k-1} exp(\frac{-\Delta t^k}{\tau}) + (1 + exp(\frac{-\Delta t^k}{\tau})) \sum_{i=1}^{N} I_i f_{ij}$$

These equations can be solved numerically, and they can be generalized to an arbitrary number of injectors and producers. This is valuable as the model can expand to include the true complexity of scenario [2].

The assumptions made by CRM are the reservoir is held at a constant temperature, slightly compressible fluids, no formation gas is produced, negligible capillary pressure effects, constant volume, constant productivity index, and constant transmissibilities. One of the main implications of these assumptions, is that the time constant doesn't change with time, and the gains remain constant over time [2].

2 Description of Work

First, synthetic data was used to create a sample reservoir for model validation. The data generated was for a field of four production wells and two injection wells using CRMP. This relatively small field was used for a proof of concept in order to validate the correctness of the CRMP by ensuring that it fit the parameters used to generate the data, [3].

In order to evaluate the model, the data is split up into training and testing sets. The training set is the first 50% of the known data. The testing set is last 50% of the known data. The reason for the splits to be separated chronologically is because in a time series data set not doing so would case look ahead. That would bias the data by providing future information that would not be available in production, causing "lookahead".

The training step will involve taking the training data and having the models tune their parameters to the training data. The hyperparameters for CRM would be the gains and time constant.

While tuning the parameters of a model, the initial guesses for those parameters can cause the model to either fail to converge or to not converge to the true solution. In order to prevent this, we tried a large set of initial guesses to ensure the model converges to the true solution. We should expect this to occur across the parameter space since CRMP is defined by a linear and convex equation.

As can been seen in Figure 3, the model goes to the true solution across the parameter space. This ensure that the model was implemented correctly. This well's data was created using $f_{11} = 0.2$, $f_{21} = 0.8$, and $\tau = 1.5$ as parameters.

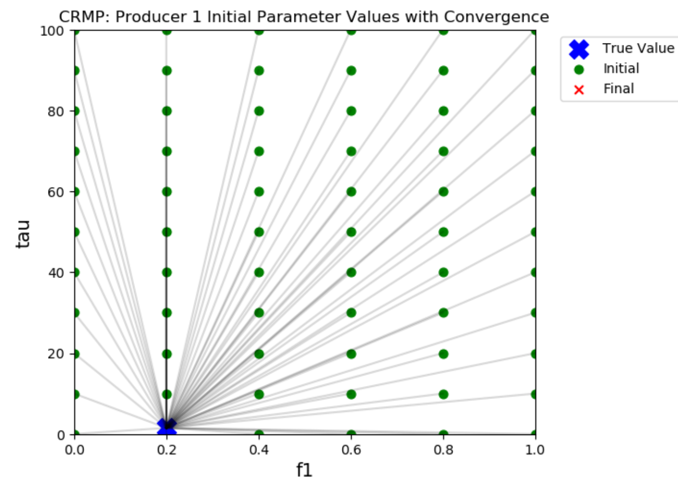

Figure 3: Initial Parameter Values with Convergence

In Figure 4, we can see that the model perfectly fits and predicts the data. In fact, the black line containing the actual data is not visible since it has been overlaid by the red and green lines.

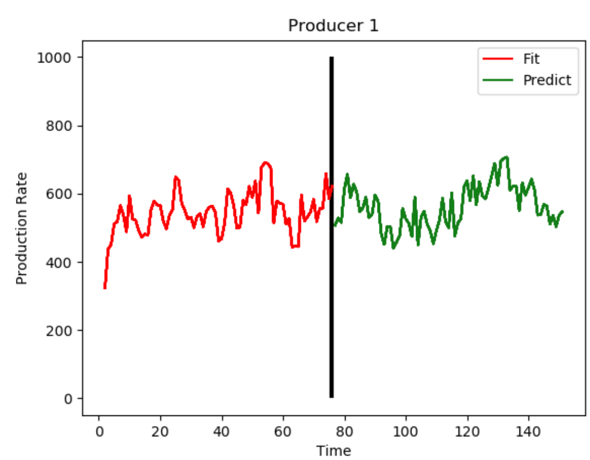

Figure 4: Producer 1 (Synthetic Data): Production Rate vs Time for All Initial Guesses

3 Results

We then used CRMP to both fit and predict the production rate of real wells, like we did with the synthetic data.

Figures 5 - 11, show that CRMP is a fairly good estimator of production rate. This can be seen by the fact that the red and green lines follow the black line, which represents, the true production values. However, it must be noted that during certain period, especially those of shut-ins CRMP is not a good estimator.

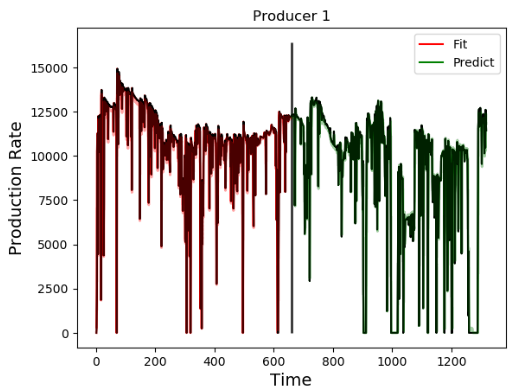

Figure 5: Producer 1 (Real Data): Production Rate vs Time for All Initial Guesses

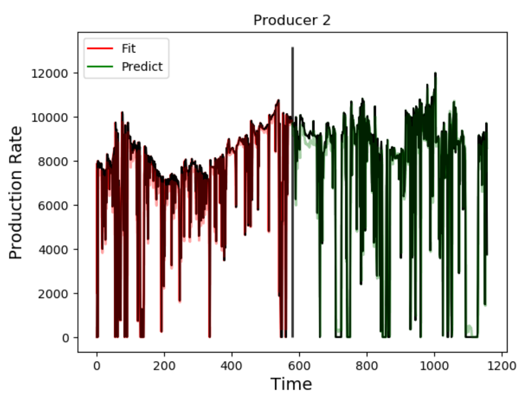

Figure 6: Producer 2 (Real Data): Production Rate vs Time for All Initial Guesses

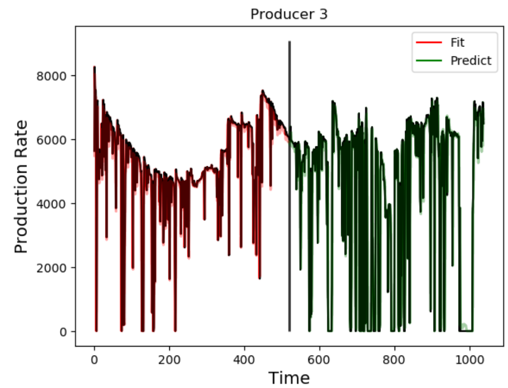

Figure 7: Producer 3 (Real Data): Production Rate vs Time for All Initial Guesses

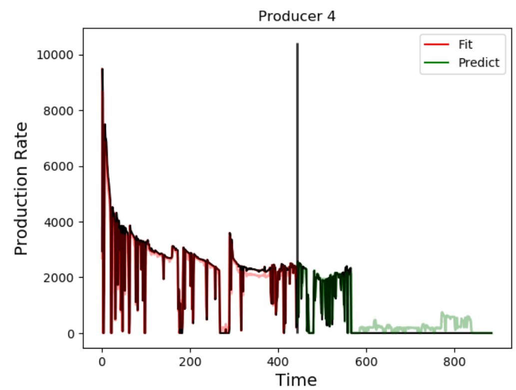

Figure 8: Producer 4 (Real Data): Production Rate vs Time for All Initial Guesses

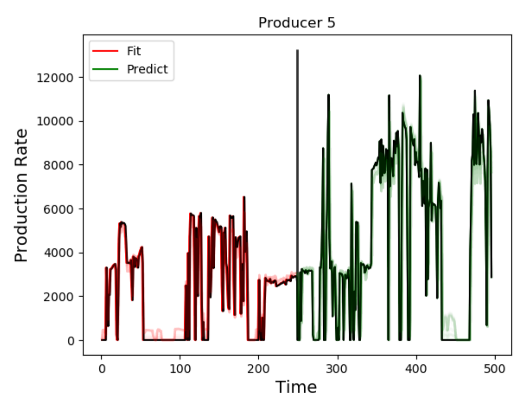

Figure 9: Producer 5 (Real Data): Production Rate vs Time for All Initial Guesses

4 Future Plans

In the future, we hope to further validate CRM's efficacy by using data from real wells to compare the estimator to. This will allow us to see how CRM performs with the complexity of real data and scenarios. In addition, the Scikit-Learn estimators used could be evaluated again [2].

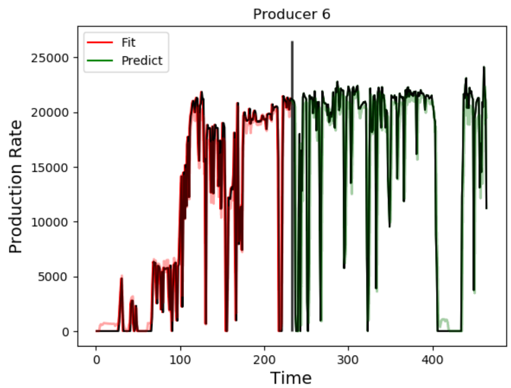

Figure 10: Producer 6 (Real Data): Production Rate vs Time for All Initial Guesses

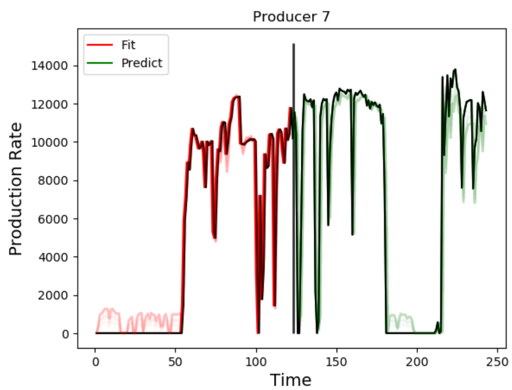

Figure 11: Producer 7 (Real Data): Production Rate vs Time for All Initial Guesses

CRM has a wide range of potential applications beyond just estimating the production rate in the future. CRM could be used for injection scheduling. This would allow us to use CRM in order to optimize the injection so we can maximize net production [2].

Analyzing net oil production would be another goal. Since the current CRM model works on total net production. We would not want a case where the oil cut is too low for the continued production of the well to no longer be financially viable. An accurate net production analysis is needed to be thought of in terms net oil production. So combining CRM with a Koval factor or another method to estimate the oil cut would be a valuable line of work. This also brings up a chance to evaluate CRM again with the various machine learning estimators in order to accurately compare CRM's optimization potential with other algorithms [2].

5 References

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