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Pattern Recognition and Data-Driven Analytics for Fast and Accurate Replication of Complex Numerical Reservoir Models at the Grid Block Level

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Abstract

Reservoir simulation models are used extensively to model complex physics associated with fluid flow in porous media. Such models are usually large with high computational cost. The size and computational footprint of these models make it impractical to perform comprehensive studies which involve thousands of simulation runs. Uncertainty analysis associated with the geological model and field development planning are good examples of such studies.
In order to address this problem, efforts have been made to develop proxy models which can be used as a substitute for a complex reservoir simulation model in order to reproduce the outputs of the reservoir models in short periods of time (seconds).

In this study, by using artificial intelligence techniques a Grid-Based Surrogate Reservoir Model (SRM_G) is developed. Grid-based SRM is a replica of the complex reservoir simulation models that is trained, calibrated and validated to accurately reproduce grid block level results. This technology is applied to a CO_2 sequestration project in Australia.

This paper presents the development of the reservoir simulation model and the Grid-based SRM. The SRM is able to generate pressure and gas saturation at the grid block level. The results demonstrate that this technique is capable of generating the reservoir simulation output very accurately within seconds.

Introduction

Application of Proxy Models

Reservoir simulation models are the major tools for studying fluid flow behavior in hydrocarbon reservoirs. These models comprise a geological model which is developed by integrating data from geology, geophysics and petro-physics. These data are collected from field observations, measurements and interpretations.
Integration of maximum data from geology, geophysics and petro-physics, contributes to building geologically complex and therefore more realistic models. As the complexity of a reservoir simulation model increases, so does the computation time. Hence, to perform any comprehensive study which involves thousands of simulation runs (such as uncertainty analysis, optimization study or history matching) massive amount of time is needed to complete all the required simulation runs. In many occasions, the sheer number of required simulation run for a complex reservoir model makes accomplishment of project objectives impractical.
In order to address this problem, several efforts have been made to develop proxy models which can be used as a substitute for a complex reservoir simulation model. These proxy models aim to reproduce the outputs of reservoir models in a very short time with a reasonable accuracy.
It should be noted that none of the proxy models are able to generate the results which can mimic the results of a complex reservoir simulation model with 100% accuracy, however their efficiency in generating the results within an acceptable range of error in significantly shorter amount of time that can be seconds compared to several hours or even days, makes them

significantly beneficial and attractive.

During the last decades in petroleum industry many proxy models or reduced order models have been developed with the purpose of replicating the functionality of a numerical simulation models with different objectives such as risk analysis.

These models have been mostly developed to generate the results at the well level. In other words, they reproduce pressure or production profiles at the injection or production wells.

One of the most widely used methods to develop reduced order models is generating a Response Surface for the problem. Response Surface Methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving, and optimizing different processes. It develops an appropriate approximating relationship between the output and the process inputs (Myers Raymond H. et al 2002 and Carley, M. et al, 2004).

Polynomial Chaos Expansion (PCE) is other method that has been recently used as to develop a proxy model for uncertainty quantification of a CO2 storage project. In this technique the output of a numerical simulation model (at the grid block level) is approximated as polynomial function of uncertain parameters of the model. This technique still needs hundreds of simulation runs to provide sufficient samples which can result in an acceptable approximation of the desired output. In order to get the approximation results at the grid block, a single PCE model must be constructed for each grid block at a specific time which will increase the computational effort if the number of grid blocks and the desired time interval increase dramatically (Zhang, Y. et al, 2012).

Artificial Intelligent Approach

Artificial neural networks have proven to be powerful data processing tools and can be applied to a wide variety of problems in different areas such as medical, science, financial, business and etc. It has been about three decades that neural networks became a point of interest in petroleum engineering and geoscience.

Artificial Intelligent (AI) has been applied in petroleum engineering area as an alternative method to develop proxy models to mimic the reservoir simulation outputs. However as mentioned before, this approach has been mostly used to predict the well dynamic parameters such as oil, water and gas production/injection (Y. Bansal1 et al, 2013 and S. D. Mohaghegh, et al, 2006).

The results of some studies in this area (S. Amini and S. D. Mohaghegh, et al, 2012) have demonstrated that the artificial intelligent techniques can be utilized to generate the output of a reservoir simulation model at the grid block level with a reasonable accuracy. In these studies a set of neural networks are developed, trained and verified which are consequently used as a surrogate for a complex reservoir simulation model.

Another recent study similar to this approach (Hector Klie, 2013) shows the successful application of Radial Basis Function (RBF) networks to predict the oil and gas production as well as pressure and gas saturation field.

It is significantly important to notice that in developing a surrogate reservoir model through this method, the physics of the process is not ignored. We are not trying to substitute an absolutely black box to the complex reservoir simulation model, we are rather teaching the network the impact of the physical process of fluid flow in porous media which is simulated in a reservoir simulation model by providing all data which carry corresponding information of the physics of the system.

This work focuses on development of a Surrogate Reservoir Model (SRM) at the grid block level for a CO2 sequestration project. SRM is constructed based on the data which are extracted from handfuls of reservoir simulation runs for this CO2 sequestration project.

Methodology

Reservoir simulation Model Development

The filed under study is located in Otway Basin in Australia. In this field CO2 is injected into a depleted gas reservoir located at about 6561 ft underground. The reservoir was producing natural gas for 18 Months through a single production well (Naylor-1) and after depletion, an injection well (CRC-1) has been drilled in this reservoir to injection and store CO2 in the reservoir as a pilot project (Dancea T. et al. 2008)

Based on the available filed data a reservoir simulation model was developed with 100x100x10 grid blocks. The simulated structure of the reservoir is depicted in Figure (1).

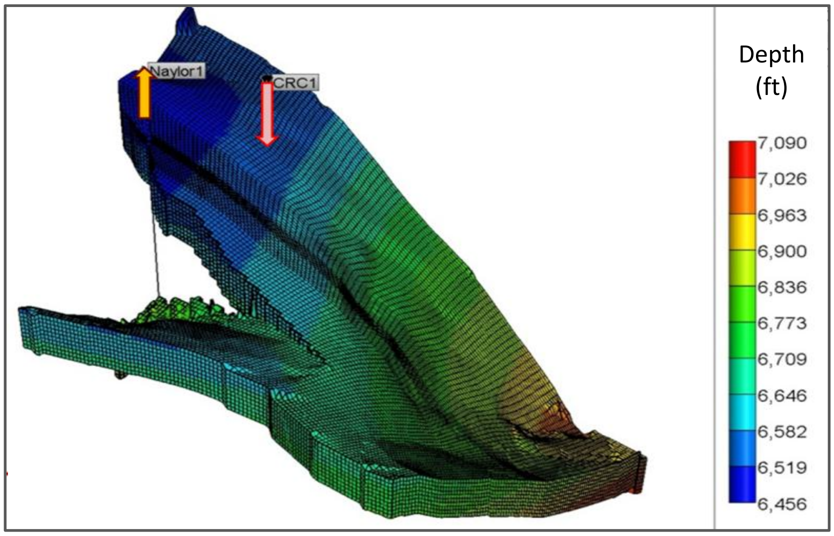

Figure1. Structure of the simulated reservoir

This model was history matched based on the available field data both in natural gas production phase and CO2 injection phase (for more details on model development and history matching process refer to SPE-153843).
It should be noted that based on the objective of this study only the injection period is further used for SRM development.

Surrogate Reservoir Model Development

SRM is a customized model that mimics reservoir simulation results by using Artificial Intelligent & Data Mining techniques with a very low computational cost. The following steps were taken towards SRM development for the mentioned CO2 Storage project.

Simulation Run Design

In order to develop a surrogate reservoir model, a handful of reservoir simulation runs are needed to provide the required data for neural network training. Certainly, design of the simulation runs must be performed based on the objective of the study. In this study the objective is to predict the dynamic parameters of the reservoir (i.e. pressure and saturation) at each grid block when the operational constraints are changing. Therefore, the simulation runs are designed based on 2 parameters of total amount of CO2 injected (G) and the injection duration (L).

We consider the real filed injection (based on available data) as the base case scenario in which 0.593 BCF of CO2 (1G) was injected into the reservoir during 8 months (1L). Assuming that the maximum CO2 injection that can be performed in this reservoir reaches to 3 times the real case and the maximum injection interval can be extended up to 5 times the real case, 10 different injection scenarios are designed based on these two parameters using Latin Hypercube Sampling method (LHS).

To ensure that the SRM is able to generate the results between the minimum and maximum boundaries of the involved parameters, the four combinations of G and L are manually selected to be included in the simulation runs (shown in red stars with circle in Figure (2)). The other six remaining combinations are selected by using LHS method. The following figure shows all combinations of G and L which are used to design the simulation scenarios.

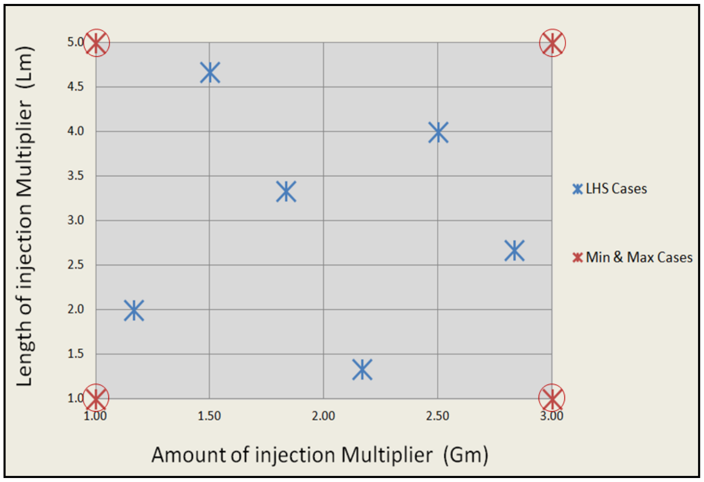

Figure 2. Final G-L multiplier combination using the LHS-Correlation Method (Blue) and the min-max value of G and L multipliers (Red)

Therefore based on the above combinations of G and L, 10 CO2 injection schedule were designed and the corresponding simulation scenarios were developed and run.

Dataset Generation

Since we are using a Data-Driven approach to develop a surrogate reservoir model, a comprehensive spatio-temporal data set is required to effectively teach the model how changes are taking place in the system. Therefore several types of data such as reservoir structure and properties, initial distribution of dynamic parameters and well data must be extracted from the simulation scenarios for each single grid block and integrated into a data set.

Due to the large dimensionality of the data set a computer code was generated to arrange the extracted data into the desired dataset format and perform the required calculations for some parameters such as distance of each grid block to the boundaries, average value of the parameters in the adjacent grid blocks and etc.

Data Sampling

Integrating data from 100,000 grid blocks of each simulation scenario will result in a huge data set matrix of 1,000,000 rows and some tens of columns. This amount of data is far more than the limit which can be utilized to make an SRM through this method. Therefore in order to be able to properly use the available data, a portion of data should be selected. The sampled data must carry the most important information regarding the changes that are taking place in the system.

In this study two different approaches of data sampling were tested. In the first approach data was sampled based on the output parameter spatial distribution. The SRM which was developed using the selected data through this method generally showed a very poor prediction of parameters.

Since in the reservoir simulation models we are dealing with the changes in dynamic parameters at each time step, the second approach for data sampling was perfumed based on the changes in dynamic parameters (pressure and gas saturation) at each time step with respect to the time 0. During this step 10% of the data was selected to be used for neural network training.

Neural Network Development and Training

In order to develop the SRM for this study, data from different simulation cases are integrated which have different injection duration. Therefore, the SRM is decided to be developed for three time steps during the injection interval which are at the end of the first month of injection, middle of the injection interval and at the end of injection.

In the SRM development, the input data are arranged so that besides the static data and well data, the value of the dynamic parameters at time-0 (before injection takes place) is considered as the input and the output is the value of dynamic parameters (pressure, gas saturation) at each time step of interest. Therefore at each time step a single network was developed and trained for each parameter.

In this work, Back Propagation algorithm is used as training method in which the error is feed backed to the network by the end of each training epoch. All the networks contain one hidden layer and one output.

Results

Applying Neural Networks

In order to generate the pressure and gas saturation distribution in the entire grid blocks of reservoir, the developed neural networks were applied to one of the scenarios (scenario#4, in which a total of 0.687 BCF of CO_2 is injected into the reservoir within 16 months).
As an example, the 2D distribution maps of these two parameters at the first layer of the reservoir at three time steps (the first month after injection, in the middle of injection and at the end of injection) are presented below. In each of them, SRM result is compared to its corresponding CMG output.

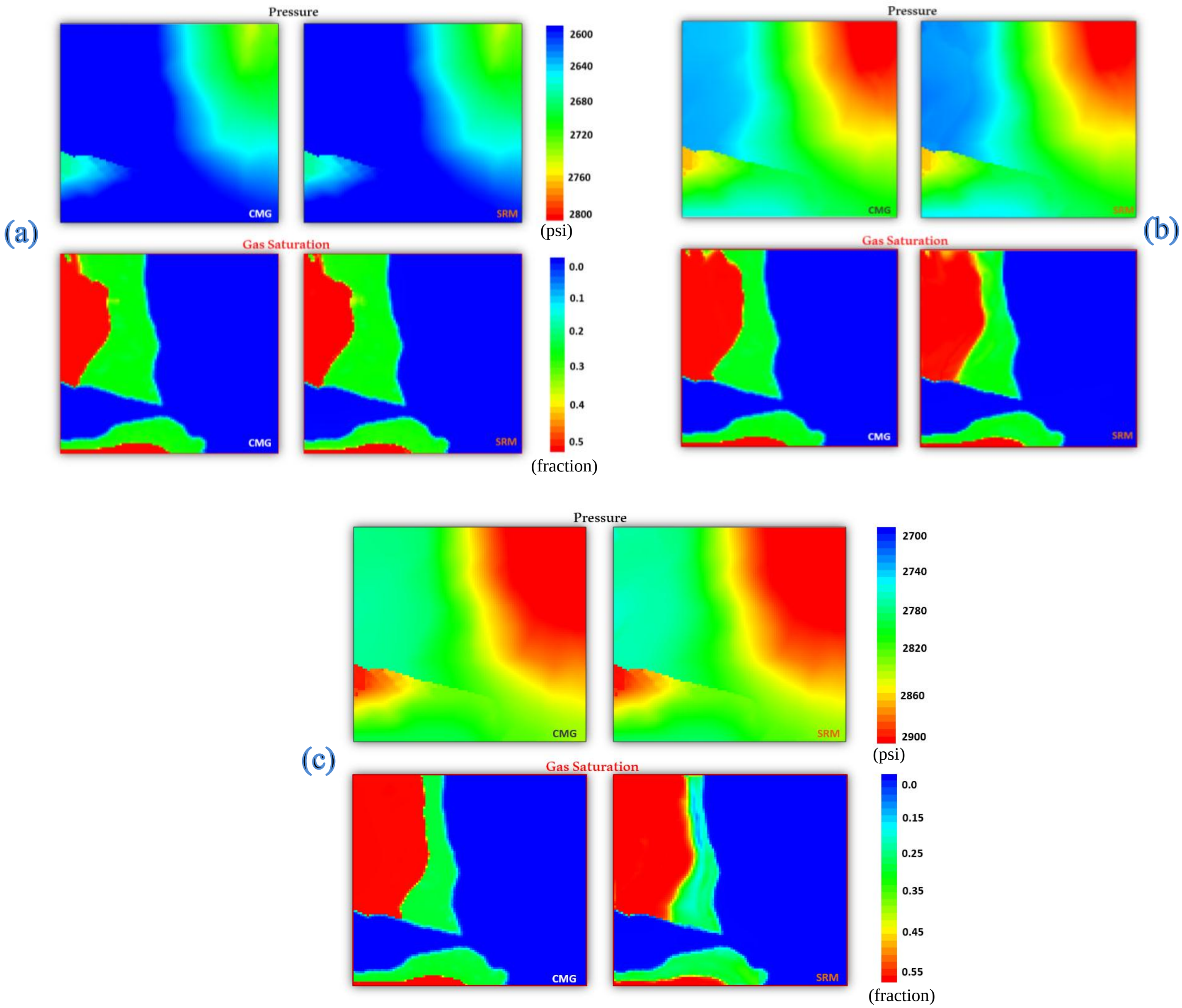

Figure 3. Pressure and Gas Saturation Distribution in the first layer of the reservoir (a) after 1 month of injection, (b) after 8 months of injection and (c) after 16 months of injection

Validation with Blind Scenario

In order to verify the capability of the developed SRM in predicting pressure and saturation under different operational constraint it should be applied to a completely blind injection scenario which was not included in the training set.
Therefore, a blind injection scenario was defined in which 1.778 BCF of CO_2 is injected during 25 months of injection. The required data was extracted and a data set was generated for this new scenario. The developed SRM was applied to this blind scenario and the pressure and gas saturation of the reservoir was predicted under the new condition.
The distribution maps of pressure and gas saturation in the first layer of the reservoir at three time steps are presented below.

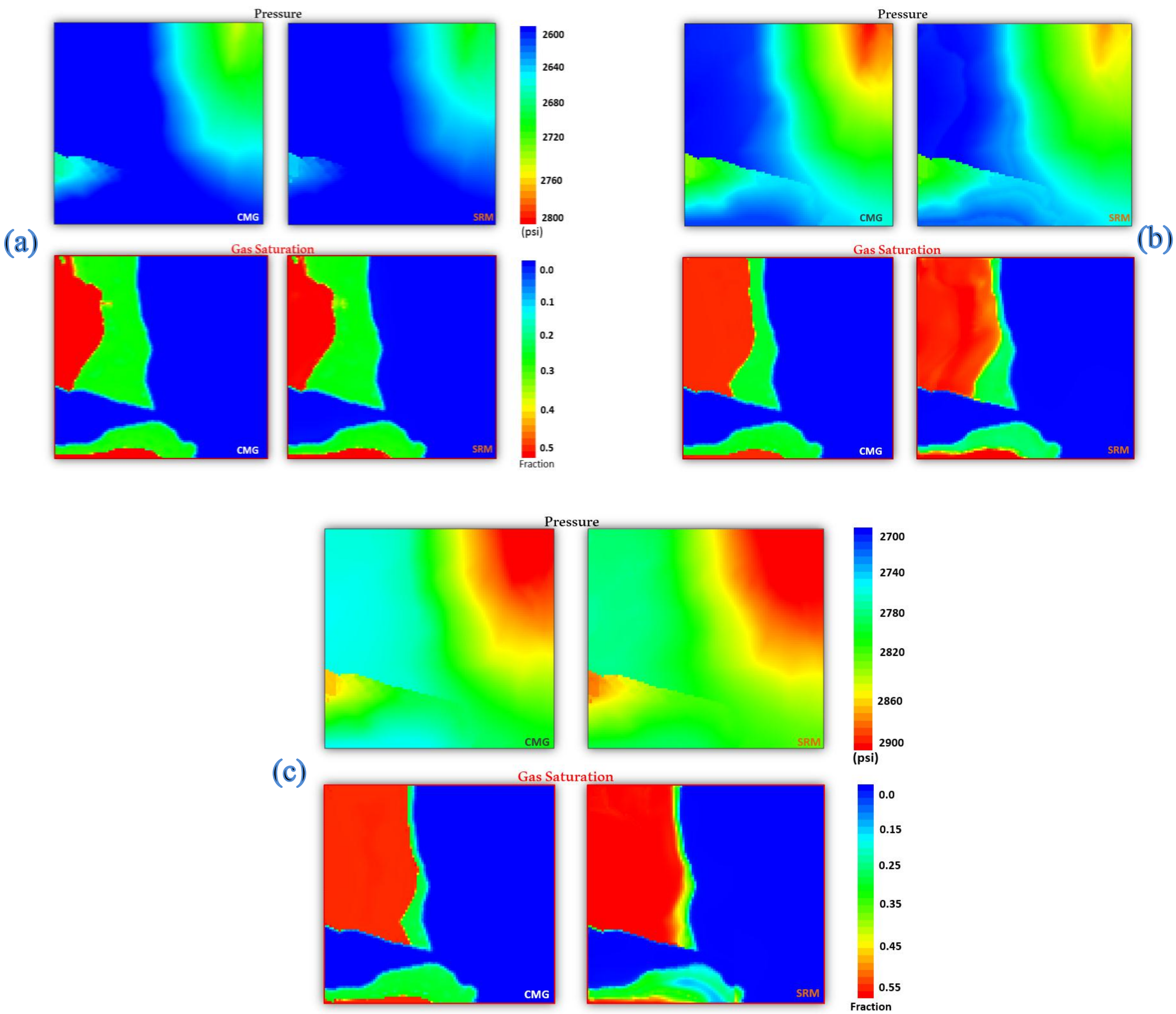

Figure 4. Pressure and Gas Saturation Distribution in the first layer of the reservoir (a) after 1 month of injection, (b) after 12 months of injection and (c) after 25 months of injection-Blind Scenario

The results show that the error of using this method to predict pressure always remains less than 5% and the predictions for gas saturation in 99% of the grid blocks the error falls below 10%.

Conclusion

Based on this study the following items can be concluded:

- Using Artificial Intelligent (AI) technique is a very effective way of developing a proxy model for a complex reservoir simulation model. The characteristic of this method allows us to make use of several types of data in order to teach the model the physics of the fluid flow in porous media and therefore the constructed model can generate the outputs of the reservoir simulation model when the inputs are changes within a range.
- In developing a grid based SRM due to the huge amount of data an adequate sampling method should be used to reduce the number of data. In order to construct an accurate model the sampled data must be a proper representative of the reservoir and further mode they have to carry the information related to the changes which are taking place in the outputs of the model.
- This study shows that the developed SRM is capable of generating the output of a complex reservoir simulation model with high accuracy within seconds.

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