Statistical Analysis Methods for Well Placement

Introduction

Driven by the oil and gas marketplace, reservoir engineering practices are challenged to maximize the return on investment and improve hydrocarbon recovery. One of those practices is optimal well placement. There has been abundant work done on sweetspots identification; however, well trajectory design in sweetspots still remains an outstanding challenge. The challenge is due to a number of factors including the size and complexity of the reservoir as well as the availability of computing resources. Field development plans that include placing large number of wells require a significant amount of time and effort to explore and analyze all possible scenarios before selecting the optimum one.

Several studies in literature used metaheuristic optimization (Al-Ismael et al., 2018) with an objective function to maximize the net present value (NPV). This requires running numerical simulation to evaluate and rank each scenario during the optimization. Such methods reported very good results on small models and few number of wells. For large models, numerical simulation in such optimization will consume excessive amount of hardware resources and will have long turnaround time. For that reason, some studies used proxy models to overcome numerical simulation challenges. Although proxy modelling is becoming widely used in many applications, developing a reliable proxy model as replica to the numerical simulation model is yet another challenge. To avoid dependency on numerical simulation and proxy models, a number of studies (AlQahtani et al., 2014) defined the objective function as the amount of contact with sweetspots instead of using NPV. This approach reduced the turnaround time of the optimization significantly since it does not run simulation during optimization. The runtime of this approach depends highly on the size of the search space and number of wells. In addition, running this approach in large models would require running it in high-performance clusters (HPC).

This work presents a new approach that uses statistical data analysis (SDA) to enable quick and seamless placement and design of hundreds of wells in high potential locations within the reservoir. The approach uses clustering algorithms to identify the location of wells in a sweetspots map and then applies 3D orthogonal distance regression (ODR) to design and place well trajectories.

Sweetspots and Locations of Wells

The sweetspot map used in this work is a 3D property that describes the quality of each grid cell in a reservoir model. Each grid cell is assigned one value, which is calculated using different reservoir features. There are many methods for generating the sweetspot maps and, hence, each method will give slightly different outcomes. Depending on the nature of the reservoir, data availability and the objective of the study, a suitable sweetspot identification method is selected. This work focuses more on the well placement and design process with the assumption that a sweetspot map is given. The sweetspot map used in this study is generated using Reservoir Opportunity Index (ROI), which is common and widely used method in literature (Faqehy et al., 2017). The index ROI is a combination of reservoir variables which include pressure, mobile oil volume and the Rock Quality Index (RQI).

$$ROI = \sqrt[3]{P \times D_x \times D_y \times D_z \times \Phi \times S_o \times RQI}$$

where,

$$RQI = \sqrt{\frac{K}{\Phi}}$$

where, P is pressure in psi. D_x, D_y, and D_z are the grid cell dimensions in x, y and z directions, respectively. Φ is porosity, S_o is oil saturation and K is permeability. The index ROI in this work is normalized between 0 and 1, where 1 indicates rich location and good quality rock. To identify the locations for placing the new wells, the 3D sweetspot map is filtered to highlight the high potential regions. Filtering the sweetspot map will result in scattered grid cells in the 3D space. **Figure 1** shows 2D top view of the filtered sweetspot map.

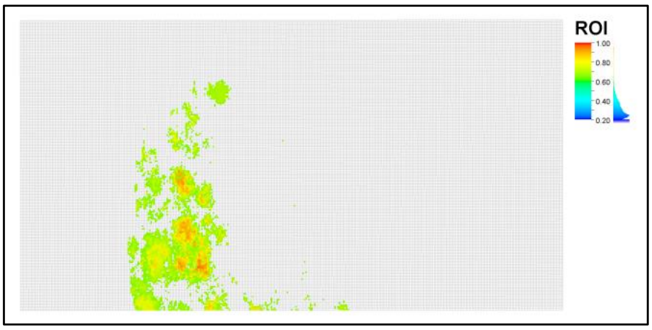

Figure 1: *2D top view of the sweetspot map*

Clustering algorithms were applied on the sweetspot map to group the filtered grid cells into different regions based on proximity. Each region is then used to place a single well. Since each clustering algorithm has different approach, each algorithm produces different result of clusters. In this work, two clustering algorithms were used to assess their viability for well placement application. **Figure 2** shows ten (10) clusters generated using the K-Means algorithm which is a partitioning clustering technique that classifies data into multiple groups based on similarity of selected features. The main feature used in this work is the distance between the grid cells. K-Means algorithm requires the number of clusters, K, as input. Since each cluster is used to place a single well, K will represent the number of the new wells in the context of this study. In contrary, other clustering algorithms can identify the appropriate number of clusters such as the Density-Based Spatial Clustering of Applications with Noise (DBSCAN). DBSCAN is a density-based algorithm that identifies distinctive and contiguous clusters of high point density. Two main parameters are required for this algorithm, which are epsilon (ε) and the minimum number of points required to form a dense region (minPts). The parameter ε defines the radius of the circle to be created around each data point to check the density threshold. **Figure 3** shows the clustering result using DBSCAN algorithm with $\varepsilon = 1$ and minPts = 5 which found to be the best values (in this example) that give the same number of clusters generated using the K-Means algorithm.

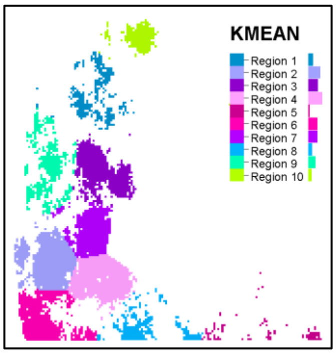

Figure 2: *Clusters generated using K-Means*

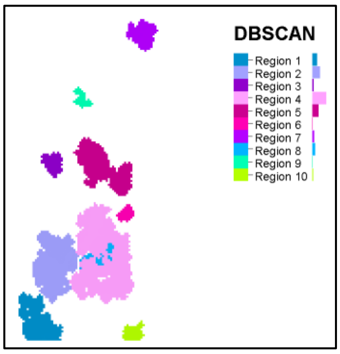

Figure 3: *Clusters generated using DBSCAN*

The resulted clusters from both algorithms are different as depicted by **Figure 2** and **Figure 3**. K-Means algorithm generates random center points in the spatial dataset and starts grouping the points based on proximity. It does not take into consideration the points' connectivity and, hence it results in many outliers within each cluster. **Figure 2** shows scattered grid cells that are grouped into discontinuous clusters using K-Means. DBSCAN is rigorous when dealing with outliers, which resulted in more connected clusters. The result of DBSCAN in **Figure 3** shows dense clusters with no outliers.

Well Design

Well placement and design in this work is accomplished by using principal component analysis (PCA) to fit a linear regression. The well is generated by best fitting a 3D orthogonal distance regression (ODR) line to the sweetspots grid cells. The process is done across all the identified clusters where the perpendicular distances between the well and the grid cells within each cluster is minimized. **Figure 4** shows an example in 3D view of one well designed and placed using 3D ODR line fitting in one of the clusters generated using DBSCAN algorithm.

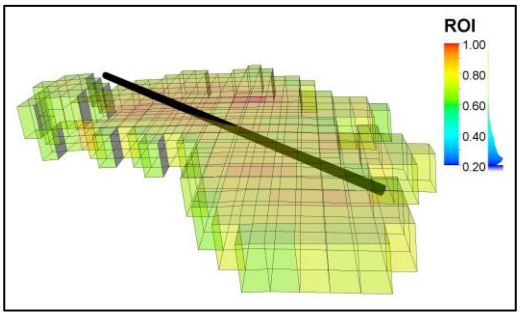

Figure 4: *A well designed using 3D Orthogonal Distance Regression*

Figure 5 and **Figure 6** show 2D view of ten (10) wells that are designed and placed using 3D ODR line fitting in the sweetspot clusters that were generated using K-Means and DBSCAN algorithms, respectively. The wells are plotted on the sweetspots map where each cluster of grid cells is highlighted using a colored polygon. Notice that the two wells that appear to be in the same location in **Figure 6** are actually in different layers, hence, they do not cross each other. The wells generated by the statistical data analysis (SDA) methods, which use clustering algorithms and 3D ODR line fitting, are compared against ten wells generated using mathematical optimization, MO (Al-Ismael et al., 2019), **Figure 7**.

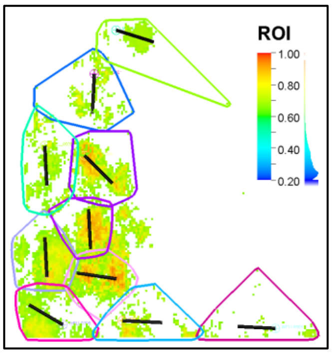

Figure 5: *New wells generated on the K-Means clusters*

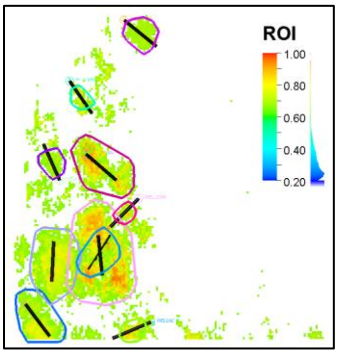

Figure 6: *New wells generated on the DBSCAN clusters*

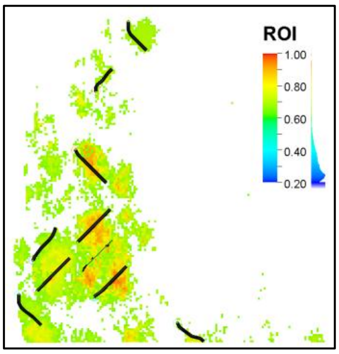

Figure 7: *New wells generated using mathematical optimization*

It is worth mentioning that the lengths of the placed wells slightly vary due to the 3D discretization of the grid cells, which have different values of D_x, D_y, and D_z. In addition, MO method generates wells that vary in their lengths depending on the availability of the sweetspot grid cells and the constraints such as the minimum distance between wells. Therefore, the wells used in comparison in this work have a slight variation in their lengths. The total and average lengths of all wells are almost the same.

Results

The wells generated using SDA methods resulted in more total oil production than the wells generated using MO as depicted by **Figure 8**. Although MO guarantees the maximum contact with the sweetspots, it does not have the concept of clustering and volume analysis. MO searches for the best grid cells regardless of the quality of their neighboring grid cells. SDA methods place and design the wells in volumes of grid cells, which can give better results than MO as the case in this example. It is also noted that different clustering algorithms resulted in different total oil production. ODR-K-Means gave better results than ODR-DBSCAN in this case. One of the reasons is that the clusters generated using K-Means in this case are larger than the clusters generated using DBSCAN. Therefore, K-Means gives the wells exposure to a wider range of grid cells. Wells placed and designed using ODR-K-Means also produced less total water production among the other methods (**Figure 9**). On the contrary, due to the lack of clustering and volume analysis in MO method, it resulted in more total water production. It is also noticed that wells placed and designed using SDM-DBSCAN produced more water. This is due to the small size of its clusters and wells are long in which they extend beyond the edges of their clusters and might cause contacting some grid cells with water.

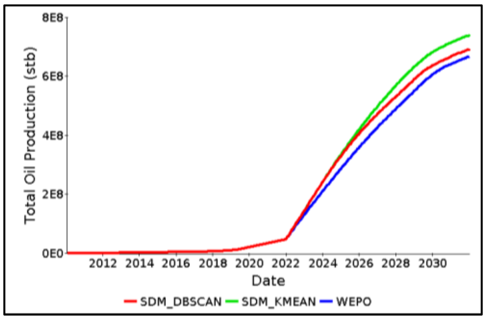

Figure 8: *Total oil production*

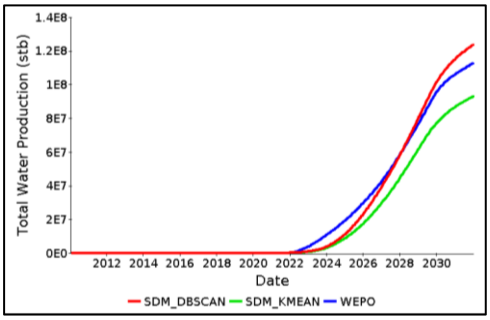

Figure 9: *Total water production*

In addition to the good well performance, SDA methods have much less turnaround time. SDA methods are statistical based and can run very fast on workstations. However, MO requires to run on high-performance clusters (HPC) and might consume a considerable amount of time. The runtime (in seconds) of ODR-K-Means, ODR-DBSCAN and MO was 7, 2 and 160, respectively.

Conclusions

In this work, SDA methods showed better well placement results. Well placement in less heterogeneous reservoirs will reduce the dispersion of the sweetspots grid cells, which will improve the results of MO. The main advantage of SDA over MO is the significant reduction in runtime. SDA is capable to place large number of wells in large models in a very short time. This enables rapid evaluation of field development plans and help in maximizing recovery, maximizing return on investment, and maintaining economical production plateaus. SDA approach avoids excessive use of HPC resources during field development planning and management. It also demonstrates how machine-learning solutions can be employed for developing large and complex oil and gas fields.

References

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