Uncertainity Analysis in The Sawan Static Reservoir Model and Optimization of Facies Using Neural Network Technology*

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ABSTRACT

Sawan Gas Filed (approx. 2 Tcf) has been in the phase of production and therefore to have a sustainable exploitation and management, an efficient reservoir model (static and dynamic) is required which normally is a risky and uncertain business. For the Sawan model several attempts have been made to minimize the range of uncertainties which is an integral part of all the multidisciplinary G&G data starting from acquisition to interpretation. Each data from each discipline carries its own range of uncertainty and eventually biased the GIIP. During the recent attempt it has been focused upon the most critical factor which is largely influencing the GIIP. While computing GIIP calculation in the model, sensitivity analysis was performed and therefore it is observed that the geological reservoir classes using three parameters (rock facies, porosity and permeability) found to be a major source of uncertainty. For the total cored sediments of Sawan "C" sand, 22 reservoir classes were generated which were having a wide range of overlapping properties and no discrete relationship was observed. Further uncertainty was added by lumping of these classes into 6 classes to use them in the geocelluler model as flow units. Such flow units actually require a discrete porosity-permeability relationship which was not possible using geological reservoir classes. Therefore it was decided to apply Neural network method to generate reservoir classes which bears a discrete relationship with respect to porosity-permeability and which can further help in defining flow units to be used in future static model.

INTRODUCTION

The geostatistical method is one of popular methods for integration of all geological, geophysical and reservoir engineering data to build a realistic model and is in use for last two decades. A geostatistical static model is comprises spatially distributed parameters like facies porosity, permeability and water saturation on a "by Layer" and "by-facies basis" [1] within structural configuration

Stochastic models provide a measure of uncertainty by running multiple realizations of facies and petrophysical properties. In all these realizations each model is equally probable with given set of parameters. The space of uncertainty created by multiple realizations is realistic when the conceptual geological framework and statistical variables and size of distributions, are well known. These variables are not usually well known during the early stage of lifecycle of reservoir which is the only reason that there is more uncertainty than measured by a set of geostatistical realizations using the same set of variables. In this study we will deal with all these parameters to get closer to certainty.

Geological Setting

Sawan D&P Lease lies in the Thar Desert which geologically forms a platform slope area of the Middle Indus Basin. A large number of wells have been drilled in and around this area (Figure. 1) and many of those penetrated within L.Goru. The Lower Goru Member is divisible into 4 distinct

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intervals, A, B, C and D [3]. The subsurface data shows that Sawan area lies on the southeastern limb of the Jacobabad paleohigh (identifiable on the regional seismic sections) initiated closer to the K-T boundary.

Seismic data shows that area is dissected by a number of strike-slip faults. Majority of the deep basement related and shallower wrench-tectonics related faults terminate against the K/T unconformity. Generally, the NW-SE oriented wrench faults cut the entire Cretaceous section, changing character from strongly linear and single fault at the top Chiltan to multiple en echelon left-lateral segments at the Lower and Upper Goru levels. This tectonic event was a result of trans-tensional tectonics related to the first docking of the India-Eurasia plates and counter-clockwise rotation of the Indian plate. During the last inversion phase the paleohighs probably underwent recurrent phases of upheaval (as peripheral bulge or fore-bulge) in response to the successive phases of thrust loading in the west and northwest. The final modification of the shapes of the traps and potentially the secondary hydrocarbon migration and reservoir charge took place during this period [3].

Based on core sedimentology, Sawan C-Sands are interpreted as “mixed-influenced lowstand shelf-edge delta system” [5]. Prograding clinoforms are visible on seismic data. The main reservoir facies of “C” sands were deposited as a proximal deltaic topsets / channelized mouth bar. A synsedimentary fault passing between Sawan-4 and Sawan-1 defines two informal compartments Sawan south and Sawan north.

In 2004 ROXAR has made the Sawan static model using chronostratigraphic approach including 7 wells in that model from Sawan and Gambat-1 from the Gambat Block. In 2006 OMV in-house built another model using the using Petrel software using same chronostratigraphic approach but this time 14 wells were from Sawan, Kadanwari and Gambat area.In 2007- 08 it was realized to revisit the core thoroughly again and apply the lithostratigraphic approach in the static model using 16 wells in the model. This paper deals with the latest model which is based on lithostratigraphy.

Main Challenge

Based on core facies, porosity and permeability in Sawan Field, 22 reservoir classes (facies) were generated through sedimentlogy work which subsequently lumped together to make 6 reservoir classes so that these can be easily used in the static model as flow units. It has been observed that these 22 reservoir classes have a wide range of porosity and permeability which are substantially overlapping with each other (Figure. 2). For an effective reservoir model, a discrete relationship in porosity and permeability and geological facies is required for defining flow units. To overcome this problem a different approach is applied that is “Neural network” which is based on two parameters (porosity and permeability) as input. Using this technique a discrete relationship was achieved for defining flow units.

STATIC MODELLING

Database

Following are the input data used in this project.
- Top C depth surface
- Isopachs

- Faults Polygons
- Sparse spike inversion cube in depth.
- Facies (Core Facies)
- Petrophysical logs

Workflow for the Static Model

Following standard workflow of modeling, the initial earth model was built using one "Top C" seismic horizon calibrated with well markers and the AI cutoff based isopachs surfaces derived from the sparse spike inversion data (Figure. 3).

Since a syndepositional fault zone passes through the Sawan Filed (between S1 and S4); and considered as one of the reason for having different sediments thickness across it and likewise different reservoir properties, therefore static model is also divided into two regions i.e. North and South. In the model different isopachs and reservoir properties were used for the two regions. Fault polygons were used in building the structural model. Pillar gridding method were used in the fault modeling. The cell geometries have been kept orthogonal to avoid any anticipated simulation problems during dynamic modeling. The cell size was kept 200 by 200 meter and same models were used in the dynamic step without doing any upscaling from fine to coarse grid. The objective of this idea of keeping the cell size same at static and dynamic modeling was to quickly move back and forthward between the two models. "Follow top" Stratigraphic layering scheme was adopted and vertical cell thickness was kept 1 meter in the main reservoir zones and 2 meter in all other zones. Before stepping forward, QC (Quality Check) of the structural and stratigraphic modeling was done and subsequently facies and petrophysical data was brought into the model for further population. Petrophysical data was conditioned to facies during scaling up well logs process. Facies logs were brought into the model using Most of method whereas "arithmetic" method was used for porosity and permeability logs. Population of facies and petrophysical properties was done separately in the two regions. The objective of separate population was achieved by special structural modeling and some arithmetical and logical operations. SIS (Sequential Indicator Simulation) method [1] was used for populating Facies (Figure. 4). Acoustic impdence data in depth domain was brought into the model by geometrical resampling method. Crossplots between AI and porosity were developed. SGS (Sequential Gaussian Simulation) method [1] was used for populating porosity and AI\ cube was used as secondary variable (Figure. 5).

Variogram maps have been generated using acoustic Inversion cube. Since most of the wells in the area are along the depositional strike therefore conceptual understanding was used in defining horizontal variograms. For permeability modeling cloud transform was made between porosity and log10 of permeability at wells location and was used in permeability modeling Leverett J function was used for modeling water saturation. SCAL data of all Sawan wells were taken into account for defining the J-function.

Uncertainty Analysis in GIIP Calculation

The quantitative measure of uncertainty indicates the level of reliability of the model. After populating facies and pertophysical properties, GIIP (Gas initially in Place) was calculated and this first GIIP run was taken as base case for sensitivity analysis. Care was taken while running sensitivity analysis. Latin Hypercube sampling method was selected during these runs for its smart sampling in these realizations. Computing 200 realizations and compiling the results to make sensitivity plot (Figure. 6) and Tornedo plot (Figure. 7) helped in identifying the main problem

Analysis of these plots showed that Classes variable carried most uncertainity range and should be handeled with care. Displaying all these realizations show the behavior of CDF curve and P90, P50 and P10 scenarios (Figure. 8). Seed points responsible for all these scenarios are fed again in the system to regenerate these models.

Latin Hypercube Sampling

The number of realizations to achieve confidence for uncertainty computations in the model depends on the input parameters. For each variable, the bigger the range the more realizations required to assess all the outcomes from all outlying statistics. Latin Hypercube is a sampling method that requires fewer model iterations to approximate the desired variable distribution than random pick. It achieves this by dividing the probability distribution into areas of equal probability density. The process works by dividing the range of the chosen variable(s) into equal bins. The number of bins will be equal to the number of runs. One sample is selected randomly from each bin during each workflow loop in order to achieve equal sampling through each variable (Figure. 9). Outcome of the same input variable using Latin Hypercube sampling is shown in Figure. 10.

The figure represents normal distribution function with seven samples from Monte Carlo simulation

A STEP TOWARDS SOLUTION

Neural Network

Artificial Neural network is information processing technology inspired by the study of human brain and nervous system. It consists of multiple independent inputs variables but one dependent variable output [4].

After it has been figured out that the facies variable is contributing more in uncertainty, the next step was to make facies in such a way that could behave as flow unit in the model. For this purpose Neural network was considered as a main approach. Neural network is an algorithm that takes multiple inputs and returns one or several outputs. Since in our case we did not have any input which could be used as guidance so it was decided to use the unsupervised method for classification. This method makes a decision as to what output is best for a given input and reorganizes accordingly, and the parameters are determined as a result of a self-organizing process. In initial iterations of these runs, it was observed that many inputs like wireline and Petrophysical logs which gives the same kind of geological information should not be included as input for classifications. For this different crossplot between different input were made to decide the final input parameters for facies generation.

In the final iterations, porosity and permeability logs calibrated with core data were used for final classifications. Six classes were created which bears discrete relationship with respect to porosity and permeability (Figure. 11). Now these faceis can be used in the model as flow units.

CONCLUSION

Arithmetic and logical operation has made it possible to populate facies and Petrophysical properties into two regions of Sawan Model. Tornedo plot and sensitivity plots tools helped in identifying the critical parameter of "classes" which carries the maximum uncertainty. Unsupervised Neural Network method produced reservoir classes which bear discrete relationship with porosity and permeability and behave as flow units.

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