Static Model Building Using Artificial Intelligence and Machine Learning Techniques

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Abstract

Conventional Static models are built by integrating Seismic, Geological, Petrophysical and Reservoir data using a geotechnical software. This case study, from a mature field in India, demonstrates building of an artificial intelligence driven static model. Machine learning and data automation techniques were used in analysing and processing of well log data, depth surfaces, well tops, and convert them into properties such as facies, porosity, saturation, and NTG. These properties were distributed in a 3D grid and in place resources were estimated in deterministic and probabilistic approach complete with sensitivity analysis. Machine learning techniques such as random forest classifier and regressor are used to populate the properties beyond the well level. Iso-proportionate layering along with geo-spatial co-ordinates (X, Y) rotated from 0-360, are used in the model as input variables as guiding factors to populate the properties beyond wells. The resultant static model honours geological aspects such as layering structure, faults and directional heterogeneity both in horizontal and vertical directions. Input and model output parameters such as facies, porosity, and saturation showed similar statistical distribution besides a very good match at the well level with accuracy of >90%. The resource estimations compared within 5% variation to the estimates of the benchmark conventional static model. Study results demonstrate that static model workflow can be automated entirely using artificial Intelligence and machine learning techniques. This machine learning based approach also enable a near real time model update. This methodology has automated the model building process from data preparation, data analysis, rock typing, property prediction and distribution, to resource estimation.

Introduction

Static reservoir modelling is the primary step to be done while building a reservoir simulation model, which is used for estimating the reserves, helps in finding out potential location for drilling new wells, and forecasting the production. Geoscientists, Petrophysicists and Reservoir Engineers spend significant amount of time for building a conventional Static and Dynamic model with the help of geotechnical software's. This approach is highly time consuming and involves large human bias, and has potential of developing manual errors (Sridharan, Rahul, and Satyam, 2019). To build a conventional static model, a large number of realizations are required, and it is computationally intense as well. Static modelling is often challenging due to nonlinear and heterogeneous nature of the reservoir (Chaki, Routray, Mohanty 2015). These models carry a uncertainty due to limited data availability, data acquisition biases and limitations in conventional software's capabilities.

To minimize these uncertainties and risks, a unique and novel approach has been performed using machine learning techniques and deployed in a cloud-based infrastructure. This methodology facilitates to input, seismic horizons to create a 3D grid and the well logs to create facies, and further populate in the grid. In this study we experiment a static model building using random forest machine learning approach for property population within the grid. The resultant resource estimation is very much comparable with the conventional static modelling. The whole process is executed in less than 5 hours, and the model ensures that the quality checks are satisfactory. All workflows are automated using machine learning techniques, not only reduces the time required for the processes, but also ensures that the errors are minimized due to human interventions.

Methods

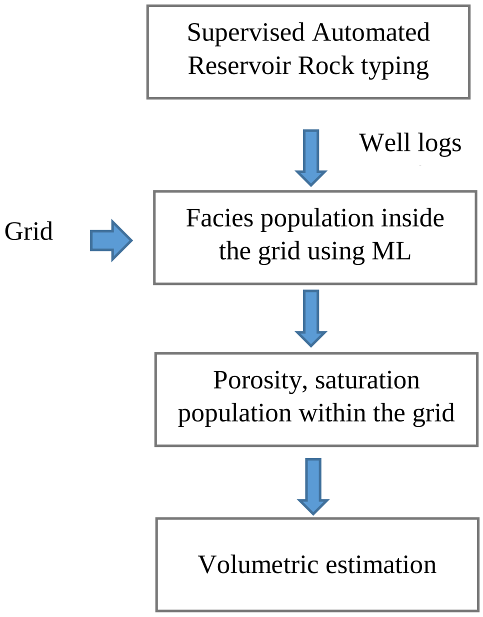


Figure 1: Overall workflow

Input data

A 3D structural grid was created in python, using inputs such as well tops, fault sticks and depth horizons, with iso-proportionate layering of 50 X 50 X 0.5 cell dimensions. K-Nearest Neighbour (KNN), a supervised machine learning algorithm, was used to create reservoir rock typing on well data to generate facies at well level used as input as logs.

Sample input well logs are shown figure 2.

Model prediction

The facies labelled well data is used to train the model, The geo-spatial co-ordinates (X, Y) rotated from 0-360 degree, TVDSS (Z co-ordinate), iso-proportionate layering within the reservoir zone at well locations are used as independent

feature variables to predict and populate facies in the entire reservoir zone using a Random Forest classifier algorithm.

Porosity is also trained with facies, as both of them having good correlation at well level as shown in correlation matrix in figure 2. Porosity, is populated in the entire grid using Random Forest (RF) Regressor using derived facies, geo-spatial co-ordinates (X, Y) rotated from 0-360 degree, TVDSS

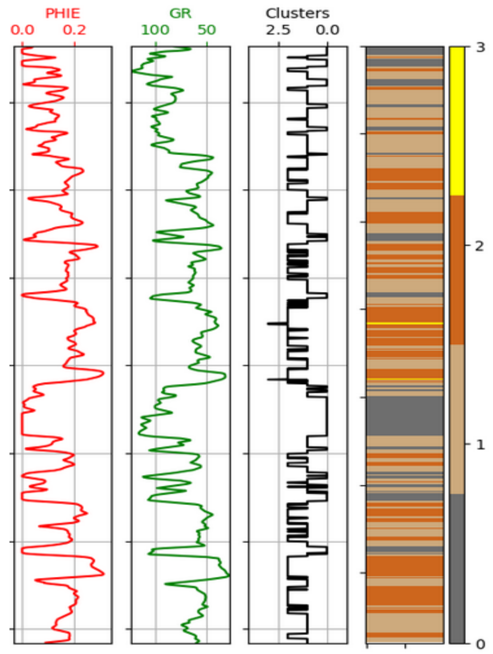


Figure 2: Input logs

(Z co-ordinate), iso-proportionate layering within the reservoir zone, as independent variables.

Saturation is also trained with facies and porosity is populated in the entire grid using Random Forest (RF) Regressor using derived facies, porosity, geo-spatial co-ordinates (X, Y) rotated from 0-360 degree, TVDSS (Z co-ordinate), iso-proportionate layering within the reservoir zone, as independent variables.

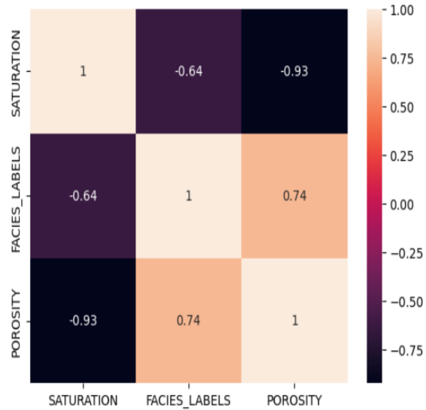
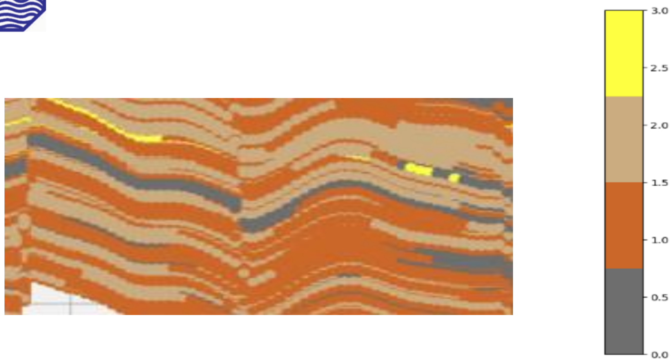
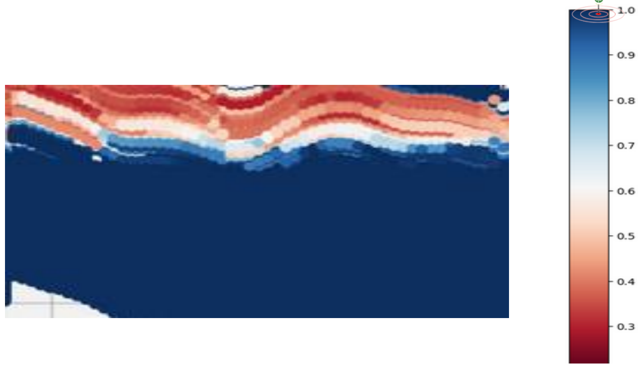


Figure 2) correlation matrix shows relationship between facies, porosity and saturation at well level (-1 to 1 as a whole range where >0.5 and <0.5 considered to be good)





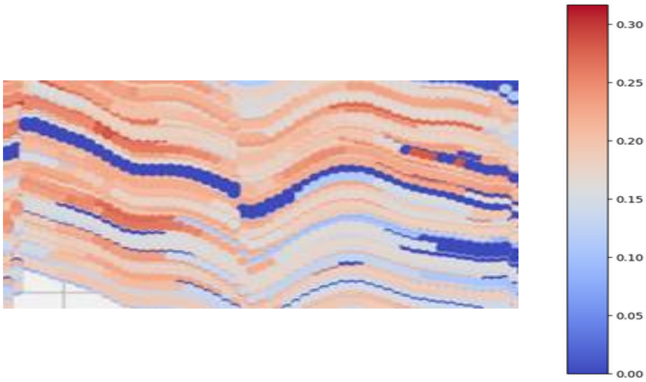


Figure 3: a) Facies 2D section from 3D volume of property data

b) Porosity section

c) Saturation section

Volumetric estimation

In place resources were estimated based on the 3D properties populated in the grid. Each cell is having 50 X 50 X 0.5 cell dimensions, and respective properties are associated with each cell. Estimations were calculated for each individual cells and summed up for all grid cells to reach to the total volumetric of the grid. The entire volumetric calculation is done using building python-based algorithms.

Results

In this case study, the resultant 3D static model (A sample section is shown, Figure 3) honours geological aspects such as layering structure, faults and directional heterogeneity both in horizontal and vertical directions.

The facies population between two wells are shown in Figure 4, indicates that there a good continuity of facies between the wells keeping the well level match intact.

Figure 5 a) and b) is well level data of porosity/saturation and facies for a sample well, these plots indicates that the well level with accuracy of the model >90% between input data and the model.

Input and model output parameters such as facies, porosity, and saturation showed similar statistical distribution besides a very good match.

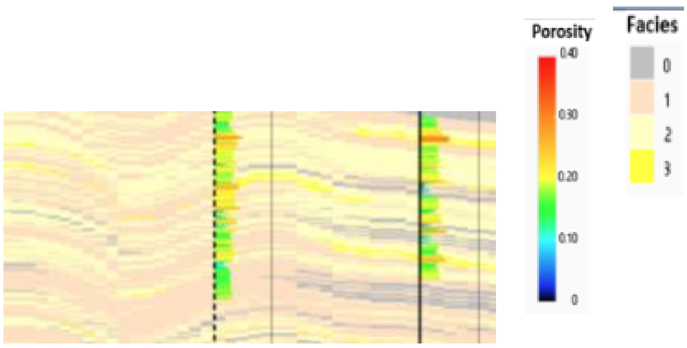


Figure 4: Well level cross section, shows the continuity of facies population between wells.

In place resources were estimated segment wise, reservoir wise, and for the entire model using volumetric equations coded in python. Deterministic and probabilistic (P10-P50-P90) resource estimation and sensitivity analysis were done.

Study results demonstrate that static model workflow can be automated entirely using artificial Intelligence and machine learning techniques.

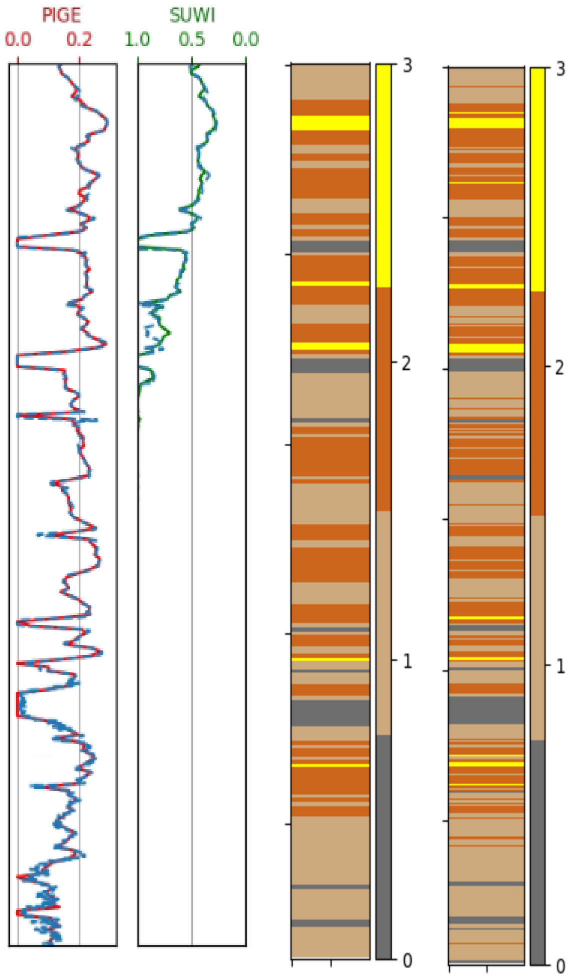


Figure 5 :

a) Input vs model level porosity and saturation, dotted line in both case shows the input data at well level, continues lines indicates model level

b) Input vs model level facies, at well level and model level.

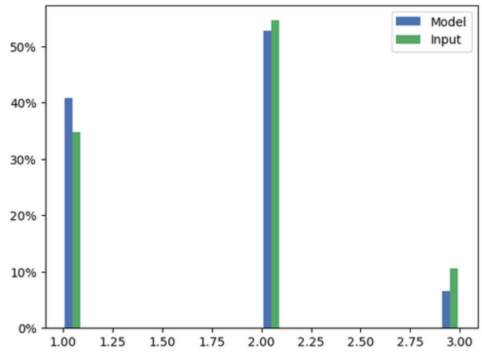
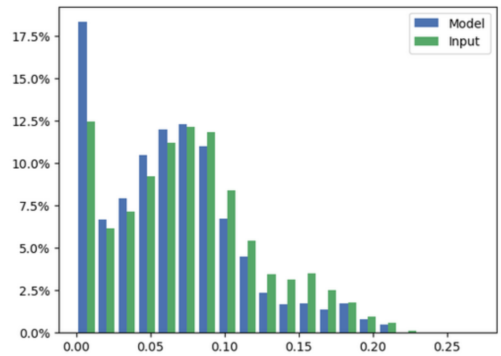
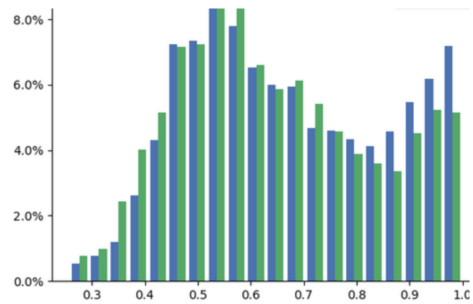


Figure 6: a)



b)



c)

a) Facies distribution Input (well level data) and Model (clusters 1, 2 and 3)

b) Porosity distribution

c) Saturation distribution

Figure 6 a) represent the facies distribution match between the input (well level data) and the model. Similarly Figure 6 b) represents the porosity distribution match, and 6 c) represents distribution match of Saturation. All properties show a very good distribution match in the model to the input well level data.

Conclusion

Using this approach data driven static models can be built in a relatively short time with minimal effort. This machine learning based approach also enable a near real time model update. This methodology has automated the model building process from data preparation, data analysis, rock typing, property prediction and distribution, to resource estimation. This process minimizes the human bias in model building and build a reliable static model. More importantly, this approach can analyse and integrates various datasets in the modelling process, which is not possible in the current geotechnical software.

QC of the model performance is carried out in three different steps such as well level match, overall distribution match and by visualizing the geological aspects of the model. From the QC processes it is evident that ML model is able to generate results that is very much comparable to conventional way of static modelling using geotechnical software.

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