Introduction of an Integrated Workflow for Optimal Well Placement Using Machine Learning Methods

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Abstract

Petroleum reservoir modeling procedure for production optimization is a complex problem and requires significant computational costs -rooted in reservoir simulation and post-processing. The advent of Artificial Intelligence -particularly supervised machine learning algorithms- in the petroleum industry is gained much popularity because of efficient functionality in terms of high dimensional data, computational cost and time. Several algorithms and methods were used to built models in order to assess the well placement problem in heterogeneous reservoir models [1,2]. The Extreme Gradient Boosting (xGBoost) and Light Gradient Boosting Machine (LightGBM) algorithms are then used to build intelligent models [3,5]. Three scenarios were defined to evaluate these two algorithms:

Table 1: Description of optimization Scenarios.

Scenario	Description	Optimazation Parameters
1	a homogeneous reservoir with just one production well	Production well Location
2	a heterogeneous channelized reservoir with just one production well	Production well Location
3	a heterogeneous channelized reservoir waterflood flooding	Production and Injection Well Locations

Objectives

- Evaluate the LightGBM and xGBoost algorithms in field optimization using Net Present Value (NPV) Function
- Compare the performance of LightGBM and xGBoost

Reservoir Model

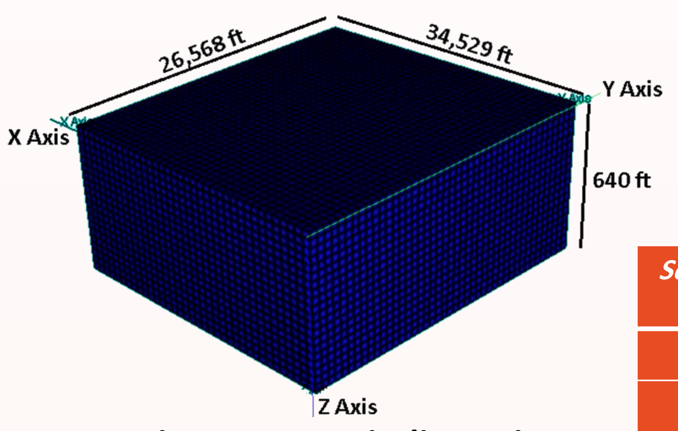


Fig. 1: Reservoir dimensions. It has 30,960 (43×36×20) grids.

Table 2: Reservoir Characterization and operational conditions in each scenarios.

Scenario	Permeability (mD)	Porosity (%)	OOIP ($\times 10^9$ STB)	Production Rate (STB/Day)	Injection Rate (STB/Day)
1	2500	20	1.65	12000	-
2	0 - 14205	0-32	8.14	11000	-
3	0 - 14205	0-32	8.14	10000	10000

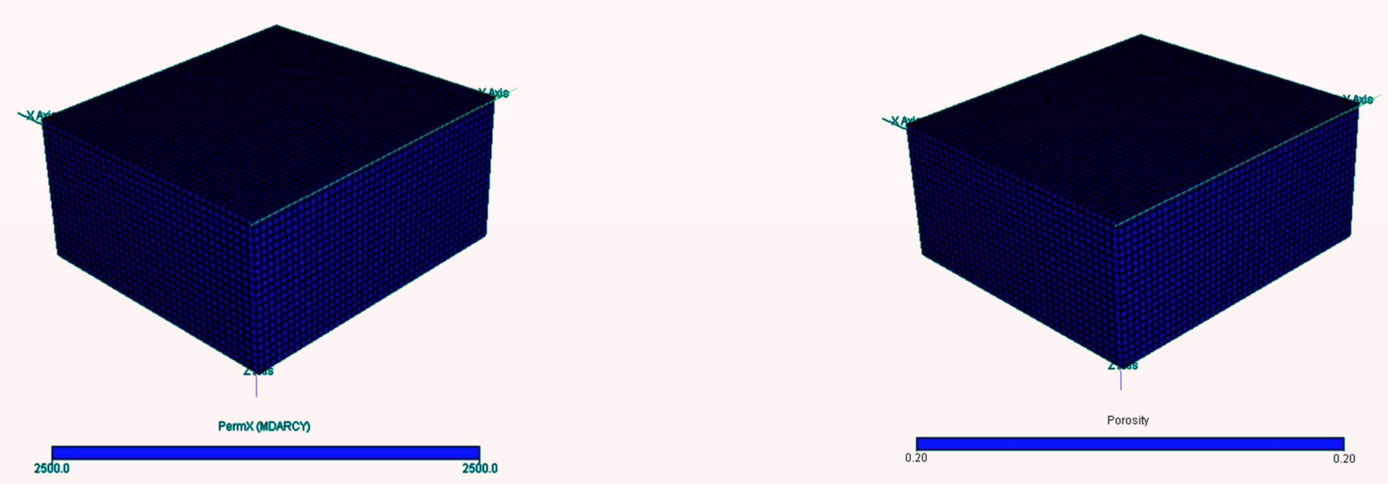


Fig. 2 – permeability (Left), and porosity (Right) distribution in the homogeneous non-channelized scenario

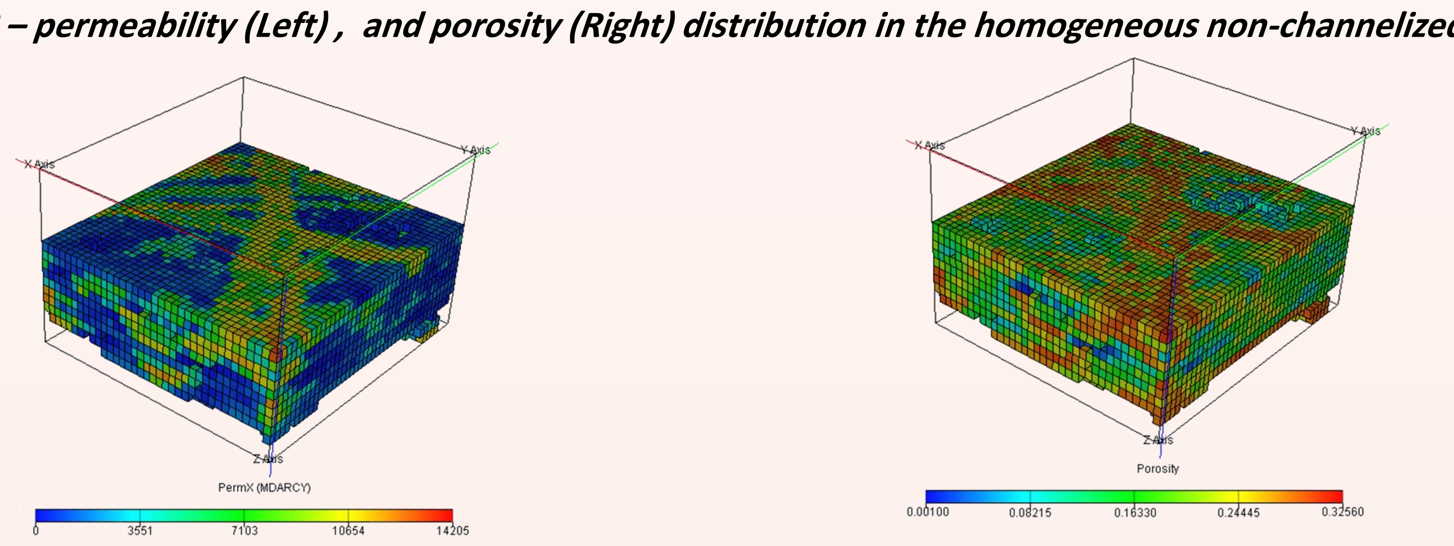


Fig. 3 – permeability (Left), and porosity (Right) distribution in the channelized scenarios (Sliced layers 9-20)

Methodology

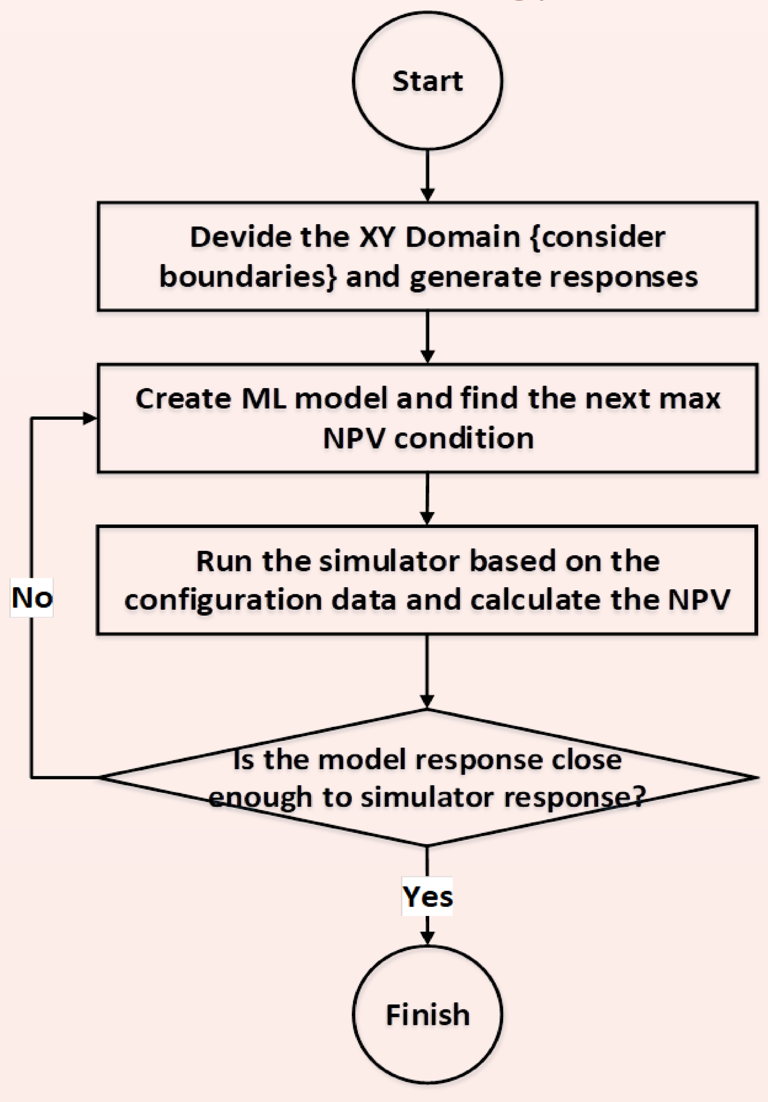
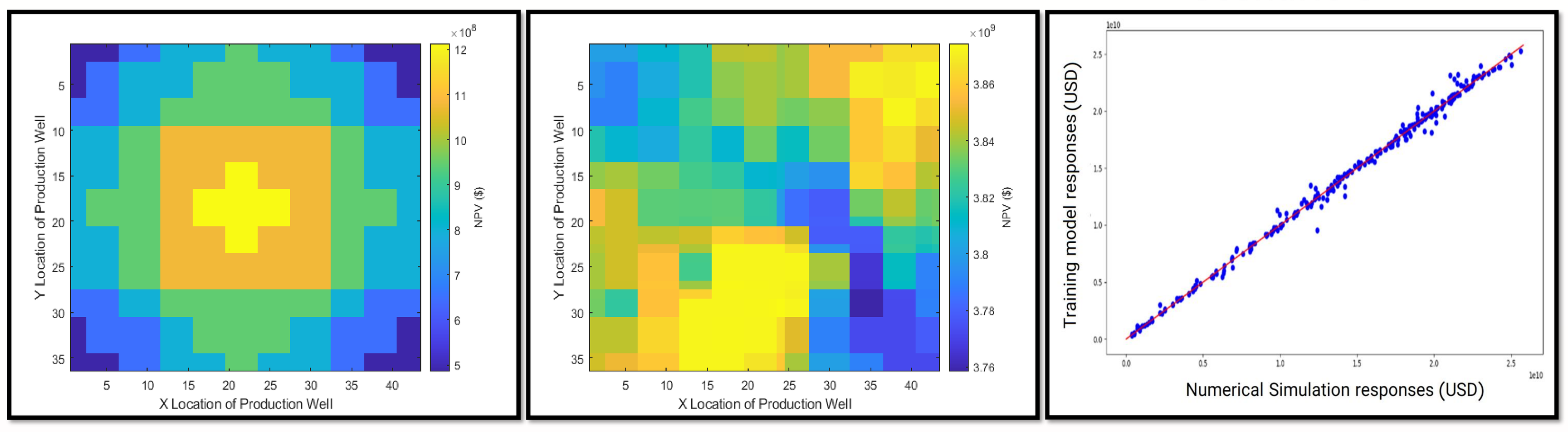


Fig. 4: Methodology and Workflow.

Results

xGBoost Results

Scenario 1 | Scenario 2 | Scenario 3



LightGBM Results

Scenario 1 | Scenario 2 | Scenario 3

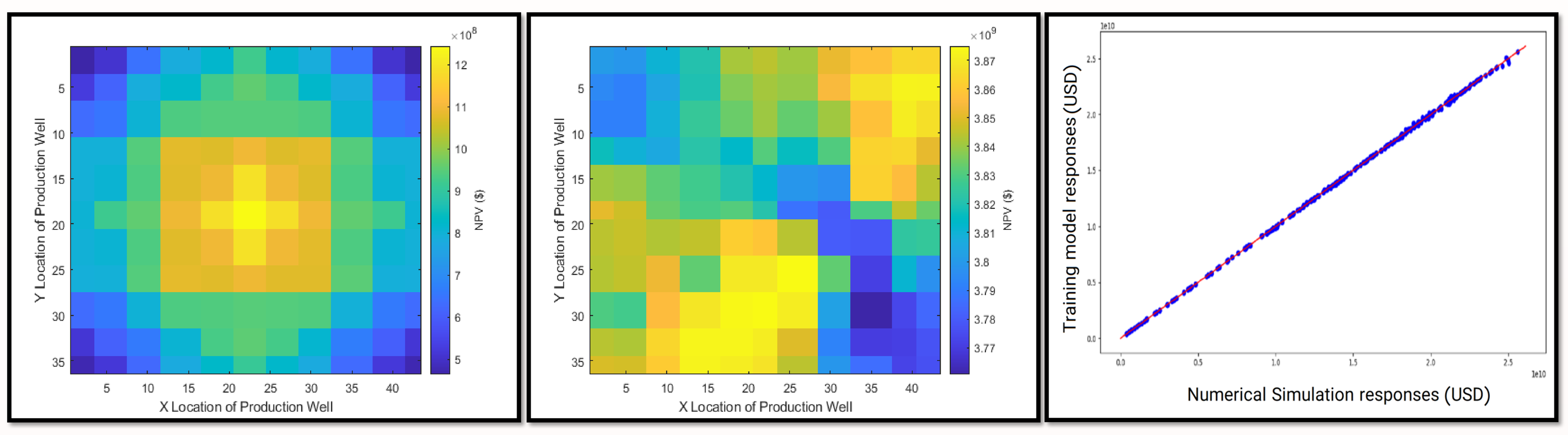


Fig. 5: Result of two xGBoost and LightGBM algorithms in three different scenarios.
Scenario 1: The predicted NPVs of possible locations for production well in homogeneous reservoir.
Scenario 2: The predicted NPVs of possible locations for production well in heterogeneous reservoir.
Scenario 3: The predicted vs calculated NPVs of possible locations for production and injection wells.

Table 3: Results of two different optimization algorithms.
Notice: The total number of possible locations for well placement is 43×36=1548.

Scenario	R-squared (%)		Number of simulation runs
	xGBoost	LightGBM	
1	72.2	90.5	121
2	75.4	88.6	121
3	99.5	99.9	276

Conclusion

Light Gradient Boosting Machine and Extreme Gradient Boosting were the two machine learning approaches, which were used to predict the profit responses as a function of several variables. Three different scenarios were defined to facilitate this comparison.

- Both algorithms show satisfying predictions.
- the LGBM algorithm produces much more complex trees by following leaf wise split approach rather than a level-wise approach which is the main factor in achieving higher accuracy. However, it can sometimes lead to overfitting, which can be avoided by setting the controlling parameters.
- In equal condition and number of simulation runs, LightGBM algorithms has shows more realistic distribution of responses.

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