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A NEW INTEGRATED STATIC-DYNAMIC ASSISTED HISTORY MATCHING AND PROBABILISTIC FORECASTING WITH NPV ANALYSIS FOR "L" FIELD

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Abstract

This paper performed a workflow in history matching process and obtain the geological realism in L Field, that started from static-dynamic history matching until economy analysis for forecast. The method that will be use has been implemented in several field around the world, proving able to reduce time of history matching process and lead into better production strategy. The method begins with obtain multiple static model using sensitivity of porosity and rock characteristic analyzation using Hydraulic Flow Unit. For the matching process, begins with build an integrated assisted history matching workflow. Then perform assisted history matching that starts from sensitivity analysis using the Latin Hypercube Algorithm and uncertainty analysis in the static-dynamic model. The process continues with the optimization process using the Particle Swarm Optimization Algorithm to minimize the different values between historical data and calculation. This method also allows the use multi objective function. After providing history matching, a forecast is conducted including the economic analysis. The integrated static-dynamic assisted history matching is conducted and matched with the historical data. There are 11 uncertainty variables that was obtained for the matching process. The most sensitive uncertainty variables are permeability by region, depth of fluid contact, relative permeability, and aquifer strength. Proposed probabilistic forecast on several parameters will give estimated of Net Present Value (NPV) for each scenario. As the use of integrated static-dynamic history matching workflow, the model result still fulfills the realism of geology and reservoir characteristic. The importance of involving static property in history matching to minimize geological realism, reducing cost & time using Artificial Intelligence (AI) for history matching and performing probabilistic study based on document Pedoman Tata Kerja (PTK) from SKK-Migas related on plan of development of oil and gas in Indonesia.

Keyword: Integrated Static-Dynamic, Assisted History Matching, Probabilistic Forecast, Net Present Value.

1 Introduction

1.1 Background

An oil and gas field development require information from geology and reservoir engineering. The importance of understanding theories related to both of geological and reservoir interpretation can facilitate the making of optimal and realistic model of reservoir. One of the important processes that are needed for making a model is history matching. The calibration process in which needed to modified the uncertainty parameters to obtain an acceptable match between simulated and historical measured production data. The process includes identifying and adjusting uncertainties in geological and/or reservoir parameter (Syrtlanov et al., 2019), for example porosity, relative permeability, and aquifer strength that have an impact to production performance of the reservoir.

Traditionally, history matching process is carried out on a dynamic model without considering the static model. That process can eliminate actual geological and petro physical factors that can be affected for future field development (Chong et al.,2015). Therefore, this study proposes a new methodology that combines uncertainty analysis in a static and dynamic approach to obtain matched reservoir model.

Commonly history matching is still done using deterministic methods. The method only gives one result due to the technological limitations and if still want to produce multiple scenarios it takes a lot of time, that expensive and very complicated. Therefore, Assisted History Matching (AHM) techniques is preferred (Mattax and Dalton 1990; Cosentino 2001; Cancelliere et al., 2011), because it provided several sets of parameters to be calibrated at the same time using mechain learning, which may have resulted a set of result that more realistic in shorter time, also determine as probabilistic methods. Based on PTK-037/SKKMA0000/2018/50, that field development can provide probabilistic scenarios that reduce the risk of errors in development and make better and more economical decisions.

1.2 Objectives

The purpose of this paper is to modify a workflow in history matching process to generate cases that match the historical data, obtain the geological realism in L Field, and further be used for future performance prediction of 20 years with include economy analysis. The purpose is described for goals that can be set as follows:

a) To perform integrated static-dynamic workflow in history matching process
b) To define uncertainty variable as an input in the history matching process, running experimental design and optimization simulation cases
c) To generate model that has the least difference to the historical data and geological realism
d) To generate probabilistic forecast scenario with sensitivity of several parameters.
e) To calculate economy parameter for forecast result

1.3 Basic Theory

1.3.1 Integrated Static-Dynamic Workflow

Generally, history matching in reservoir model is performed with “Small Loop” workflow. This workflow is done in dynamic model, without direct update to the geological or static model. The integration of both static and dynamic models is proposed to be a pragmatic and ideal workflow to fully investigate and understand both static and dynamic subsurface uncertainties (Chong et al.,2015). This integration named as “Big Loop” workflow. This workflow allows parameterization of uncertainty variables from structural uncertainty, static property modelling until PVT, relative permeability, and even development scenarios. This workflow is not widely applied, because it is time-consuming, and expensive. Both workflow can be seen on **Figure 1**.

1.3.2 Assisted History matching & Probabilistic Forecasting

History matching consists of calibrating reservoir simulation models to the observed production history data. It is a critical and necessary step in optimizing reservoir management decision (Al-Akhdar, et al., 2012). The aim of history matching is to have reservoir model with the least difference between simulation and history data. It also can give a better prediction performance for field production. In built the model, there are several adjusting process in reservoir parameter, such as: aquifer strength, transmissibility, rock region, relative permeability, static properties, etc. Generally, this process is done with manually that needed a long time process. To overcome that problem, there is an assisted history matching process with automatic strategies for history matching. Over the parameterization, sensitivity study is applied in order to detect the most influential reservoir parameter (Al-Akhdar, et al. 2012).

Assisted History matching is one of the methods to done the matching process. It is composed of three big topics, experimental design, proxy modeling, and optimization theory (Shams, M., 2016). Starting from analyze uncertainty parameters that possible to be modified for the matching process. Apply the parameters for the variables of experimental design. Experimental design is process that contain of several test which have different in design factors according to a predefined rule for the maximum and minimum samples value (Shams, M., 2016). This process is used to guide the choice of experiment to be conducted in an efficient way. The experimental design generally followed by proxy modelling. Monte Carlo and Latin Hypercube are one of technique.

Latin Hypercube

Latin Hypercube is used because it allows to cover a search space for a small number of variants specified by user. It is also one of the most efficient experimental design. The key to this method is stratification of the input probability distribution. The stratification divides the cumulative curve into equal intervals. A sample is then randomly taken from each stratification. Compare to Monte Carlo, Latin Hypercube is more memorable sampling which means there is only one sample in each row and each column. The difference can be seen on **Figure 2.**

Objective Function (OF) is a mathematical expression that represent the difference between observation and simulated data (Shams, M., 2016). It helps to choose the best model's variants for given parameter. OF is minimized using appropriate optimization algorithm. It can be expressed as a single or multi objective function. The multi objective functions have advantage of simultaneously minimizing several and different kinds of data using the Pareto Criteria (Cancelliere, et al., 2011). Below is the expression of OF:

$$\sum_{objects} w_{object} = \sum_{P} W_P O(obj, P)$$

Optimization algorithms is used to minimize the OF in an attempt to minimize the misfit between observed and simulated data (Shams, M., 2016). There are several type of optimization algorithms, such as Particle Swarm Algorithm and Differential Evolution.

Particle Swarm Algorithm

Particle Swarm Algorithm (PSO) was developed by Kennedy and Eberhart (2015). It operates with a set of particles, called swarm. Each particle is described by position in search space, velocity vector, and local best position (tNavigator AHM User Manual, 2018). First is calculate the OF at particle position, then the global and local position is updated. Due to the updated data, the particle's velocity vector will update. The formula for velocity update is given in **Equation 1** below:

$$v' = v + r1.(P_{best} - X) + r2\,(G_{best} - X) \quad (1)$$

The particle moves along the calculated vector and for optimize the OF, swarm will explore search space. Each particle will remember its local best position, while the swarm will remember its global best position. If the swarm size is bigger, then better search space will be explored. PSO algorithm has an ability to contain multiple objective function.

In forecasting, generally done using deterministic method that determine best scenario based on creaming curve result. Probabilistic forecast is a method of forecasting process that including the sensitivity of uncertainties that influence hydrocarbon production. These uncertainties can be classified into two categories: (a) Non controllable uncertainties of reservoir characterization parameters, and (b) controllable uncertainties in the reservoir exploitation schemes (Palenzuela, Julio C.M.B., et al. 2012).

1.3.3 Project Economy

During project development, economy is one of important factors to determine the future best development scenario. In oil and gas industry, there are several calculation of economy parameters that can be done using Production Sharing Contract (PSC) mechanism. Indicator of economy calculation are Pay Out Time (POT), Net Present Value (NPV), Internal Rate of Return (IRR), etc. POT is the time it takes for the amount order revenue equals the amount of investment / cost. POT shows how long it is investment capital can return. NPV is difference between the present value of cash inflows and the present value of cash outflows over a period of time. The formula shown on **Equation 2** below:

$$NPV = IC + \sum_{t=1}^{n} \frac{(CF)}{(1+i)^t} \quad (2)$$

Internal rate of return is interest rates that cause NPV = 0 or CF sum of cash flow series is zero.

2 Methodology

The methodology for this study shown on **Figure 3**. Studying history matching process from tNavigator user guide, that give the introduction of several approaches of history matching, such as Assisted History Matching and History Matching using Discrete Cosine Transform. Data gathering consist of collecting SCAL & RCAL data, production history data, static and dynamic data for model derivation. As defining the integrated static-dynamic assisted history matching, the process begins with reservoir study. The reservoir study is needed to integration a large number of data (geological, geophysical, petro-physical, and engineering information) into a model and to define the uncertainty variables that has effect to calculation result. Adjusting the most uncertainty geological and/or reservoir parameter such as porosity, aquifer strength, fluid contact, transmissibility, and relative permeability. After define uncertainty variables, set value of base, minimum and maximum in each variable as a predefined rule for experimental design in assisted history matching process.

The static model that given by geologist have several variant volume reservoirs based on P10, P50, and P90. As the change of volume reservoir, the porosity distribution and value also change. The variant of porosity values is defining to be porosity of P10, P50, and P90. It also represents that others static property have several variant too. SCAL and RCAL data is used for rock characteristic analysis to define the rock type of reservoir. There are several approaches of rock typing, such as Hydraulic Flow Unit, Winland, and Leverett's J-Function. As the rock type is defined, the process continues to analyze the relative permeability and capillary pressure in each rock type.

Assisted History Matching process begin with creating an integrated static-dynamic workflow. The workflow is used to simplified and faster the process of matching. The workflow contains of uncertainty parameter and the variant of static properties. Simulation of assisted history matching started with running several cases experimental design using Latin Hypercube Algorithm. This process is used to evaluate the effect of uncertainty variable and their varying ranges (min, base, max) before running optimization process. Define multi objective function and analyze the most effected variables from Pareto Chart. Adjust several variables that will be used for optimization. The optimization process begins by chosen 3 best cases from experimental design to be optimize. Simulate several cases using Particle Swarm Optimization Algorithm to get the minimum misfit.

After having best optimization result, which has the least liquid and oil total difference, forecast is then performed to get the best development scenario for L Field. In this process, forecast is approached through several experiments including sensitivity parameter in each scenario using assisted history matching. The parameter that will be used are interval of perforation, bottom hole pressure, and liquid control. As the best forecasting result founded, several economy parameters will calculate using cost recovery and gross split schematic based on PTK-037/SKKMA0000/2018/50 with assumption of oil price \$45 USD/bbl, exploration well \$20 MMUSD, and surface facilities cost 7% from well cost.

3 Case Study

The "L" Field used in this study is located in South Sumatera Basin, Indonesia. It is divided into 8 blocks. Block "LT" and "LB" have total 130 wells. The biggest oil producing is located in "LT" block with only 5 producing key wells as shown on **Figure 4**. The reservoir contained in "L" Field is sandstone reservoir with water drive and solution drive as driving mechanism. of Reservoir characterization can be seen in **Table 1**. The reservoir contains of three fluid phase system (oil, water, and gas), one PVT regions, twenty-one equilibration region, eight saturation regions, and one rock compressibility region. There are 4 rock types in the reservoir with mix-wet reservoir nature.

In the tNavigator Model Designer, the static model has 80108 active blocks. Reservoir initialization obtained using several sensitivity of static properties and the result shown on **Table 2**. Map of porosity distribution, permeability, and water saturation shown on **Figure 5 to Figure 7**. In this study, the process is implementation to match the liquid, oil, and water total. For the pressure data, it is assumed to be matched as there is no specific data given. Uncertainty analysis is done to reservoir and the best result of AHM will be selected to perform the forecast. The forecast experiment is set until 2039 years, under liquid rate control 600-2000 bbl/day. There are also several development strategies will be applied, such as workover, implementation of artificial lift, and infill drilling. For this process, the project assume that PVT variant is valid, the process already validates with MBAL, and gas production not analyze because less data.

4 Result and Discussion

The purpose of reservoir simulation is modelling reservoir condition by integrating geological, geophysical, petro-physical, and reservoir data to obtain reservoir performance and production scenario for various wells to gain best development strategies. For starting simulation process, the static property has to obtain based on geological interpretation and data analysis. There are several static properties that shows probabilistic value for simulation, such as porosity, permeability, and water saturation. As reservoir volume changes are classified into P10, P50, and P90, the realization of porosity changes with similar trend shows on **Figure 8**. The static properties then adjust into three variants value that shows on **Figure 5 to Figure 7**.

As the properties adjusted, determination of rock type is needed to determine the flow of fluid in the cell and directly related to reservoir characteristic, which classified a good or bad property. The method that used for rock typing in this study is Hydraulic Flow Unit (HFU). This was chosen because this method considers the porosity and permeability value. Based on SCAL data and HFU analysis, the region is divided into 4 rock type as shown on **Figure 9**. Each rock type will have one relative permeability curve and capillary pressure curve based on SCAL analysis and J-Function method. **Figure 10** is shown the relative permeability curve and **Figure 11** capillary pressure curve for 4 rock type. For the fluid model, there are 3 variants of PVT data. The two PVT models were created using laboratory measurements of two wells from same layer and one was created by blending the composition. **Figure 12** shown the PVT model result using tNavigator PVT designer.

After determining and analyzing the static and dynamic properties, workflow is needed to run the experiment. **Figure 13** shown the integrated static and dynamic workflow for AHM process. One of the purposes of this study is matching the simulation and historical data by considering the change of geological realism (static properties). The parameters analyzed are liquid, oil, and water production rate as well as cumulative production. L Field has 130 wells, with 5 key wells that can represent performance of the entire field. From historical production data in L Field and the simulation, **Figure 14** shown the unmatched result when the base static and dynamic properties is applied. Based on that result, the model reservoir must be analyzing and readjusting in several uncertainty parameters.

Quantifying uncertainty parameter in the reservoir simulation requires a comprehensive reservoir understanding. As mention before, the aim of this study is matching the oil and production data. For achieving that aim, there are several readjusting process of uncertainty variables, such as aquifer strength, global permeability multiplier, relative permeability, fluid contact, etc.

The simulation running with oil rate control to reach best match result in oil production at all key wells. Initial simulation result of oil, water and liquid production is lower than historical as shown on the **Figure 14**. Water total production has a significant difference than history data. It can be indication of early water breakthrough. To overcome this issue, the aquifer strength should be adjusted. In this model, the aquifer calculation is using Fetkovich method. Sensitivity analysis is performed to aquifer, that will be determine which aquifer properties have the most significant impact to the reservoir. The result and analysis presents that initial volume of aquifer and aquifer productivity index as the most impactful parameter. Besides aquifer strength, the difference of water production between simulation and historical data can be caused by the possibility of uncertainty in determining fluid contact and analysis of relative permeability curve in each rock type. In general, fluid contact is adjusted by analyze the logging data and relative permeability is analyze using SCAL data. To minimize the difference, depth of water oil contact and value of end of water relative permeability (krw) are adjusted to be one of the uncertainty parameter in assisted history matching process.

Oil total production has closer result with history data. After reviewing the result, there are 2 wells that have lower production of oil than the historical. To reach the best matching oil total production, permeability multiplier is applied in specific location. On the other hand, to increase the liquid production and fluid flow in the reservoir, the permeability multiplier is adjusted in the model. The multiplier is applied to all grids. The greater the permeability value, the easier the fluid will flow.

Starting the process by lists the AHM variables and value of the range that distributed uniformly. The variables and ranges is shown in **Table 3**. Sixty-experiments of Latin Hypercube algorithm are done by trial-and-error method to modify the range values. Three best result for rate and total production is shown on **Figure 15 -16**. Objective function is determined to maximize or minimize several parameters, such as maximize water production. In this case, parameters defined are liquid, water, oil total in field scale. Before moving to second experiment, variables should be analyze using Pareto Chart to determine values that must be adjusted to get best matched result in optimization. As shows on **Figure 16** from three best experiments result, the oil total production is matched but the liquid total production must be reducing. **Figure 17** shows the Pareto Chart analysis using Pearson Correlation. To reduce the total liquid and water production, uncertainty parameter value that has negative correlation (blue color) with percentage more than 50% should be increasing or uncertainty parameter value that has positive correlation (green color) with percentage more than 50% should be decreasing. The second experiment is calculated using Particle Swarm Optimization algorithm. Optimization result are shown in **Figure 18 - 19**. There are several value change from initial properties, such as relative permeability curve as shown on **Figure 20**. Using cross-plot, the result of first and second experiment are compared. As shown on **Figure 21**, second experiment from optimization process has lower result than the first experiment and it shows that the optimization result is closer to historical data with difference value shown on **Table 4**. Using plot of history data vs calculation result on **Figure 22** to **Figure 24**, best case after applying AHM studied show almost all key wells are located in matched zone and the difference between fluid production history and simulation is shown on **Table 5**. Therefore, it can be concluded that result from optimization process is representative to be used for forecasting.

Forecasting is done using AHM. Forecasting is performed twenty-year prediction of oil production started from 2019. In AHM process for forecasting, bottom hole pressure, top perforation, bottom perforation and liquid rate control will be used as sensitivity variables. It also provided several scenario of development such as implementation of workover, artificial lift and infill drilling. For workover, the interval perforation depth is determined by analyze good value of permeability, porosity, and oil saturation. While for the location of infill drilling is analyze by Hydrocarbon Pore Volume value that shown on **Figure 25** and infill well will apply every 4 months. Result of forecasting process is divided into two scenario of probabilistic prediction. First, scenario is using each model of P10, P50, and P90. Forecast is done with nine result of total oil production describe as P10, P50, and P90 scenario from each model. The value of P10, P50, P90 is determined using cdf plot that shown on **Figure 26**. The probabilistic forecast result shown on **Figure 27**.

In the other scenario, all result of forecasting from P10, P50, and P90 model will generally analyze to determine result of total oil production based on P10, P50, and P90 value. Result from second scenario shown on **Figure 28.** As the shown on result, there is a different value between first scenario and second scenario that can be seen on **Table 5**. First scenario gives more realistic prediction that contains nine result from several uncertainty parameters included static properties for each model. However, second scenario only give prediction based on one model value for P10, P50 and P90 result.

Economy analysis the applied for first probabilistic scenario that more representative as forecast with several sensitivity parameter and present result from probabilistic model. The process is calculated to get highest Net Present Value and Internal Rate of Return based on PTK-037/SKKMA0000/2018/50. Calculation process is done using cost recovery and gross split schematic that shown on **Figure 29** The economy calculation result of both schematic shown on **Table 6 to Table 14**. The range of Net Present Value (NPV) and Internal Rate of Return (IRR) project calculation from probabilistic scenario result shown on **Table 15**.

5 Conclusion

1. This study presents the most suitable integrated static-dynamic workflow that is used for L Field, which uses the assisted workflow from static and dynamic properties. Started from sensitivity of static properties (porosity, permeability, etc.) and dynamic properties, such as fluid data. Continues with matching process (experimental and optimization) until forecasting with several sensitivities, that end with NPV calculation.
2. There are eleven uncertainty variables from static and dynamic properties for history matching and four variables of uncertainty variables for forecasting. Successfully running experimental design using Latin Hypercube Algorithm and optimization using Particle Swarm Optimization Algorithm for AHM process.

3. Successfully generate model with difference less than 5% of the history data and cover geological realism.

4. There are two scenario of probabilistic forecast for twenty-years prediction of field production with sensitivity in interval perforation depth, liquid control, implementation artificial lift, and infill well.

5. Economy calculations for the result of probabilistic scenario using cost recovery and gross split rules provide several NPV and IRR values.

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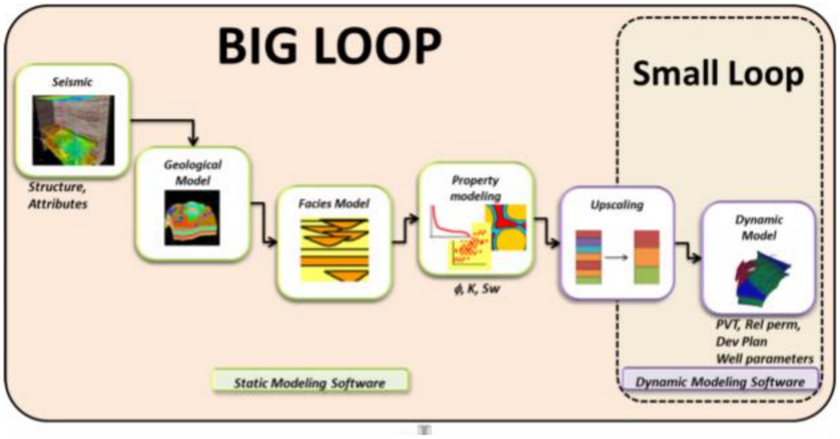
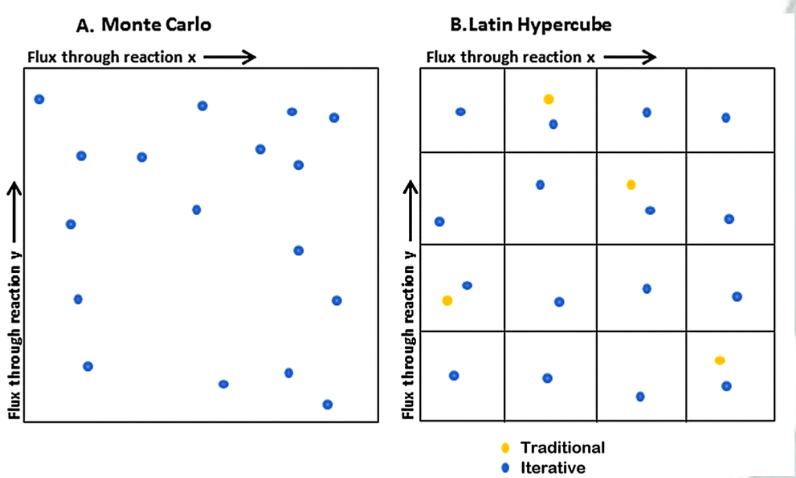


Figure 1. Comparison “Small Loop” and “Big Loop” Workflow from (Chong, et.al., 2015).



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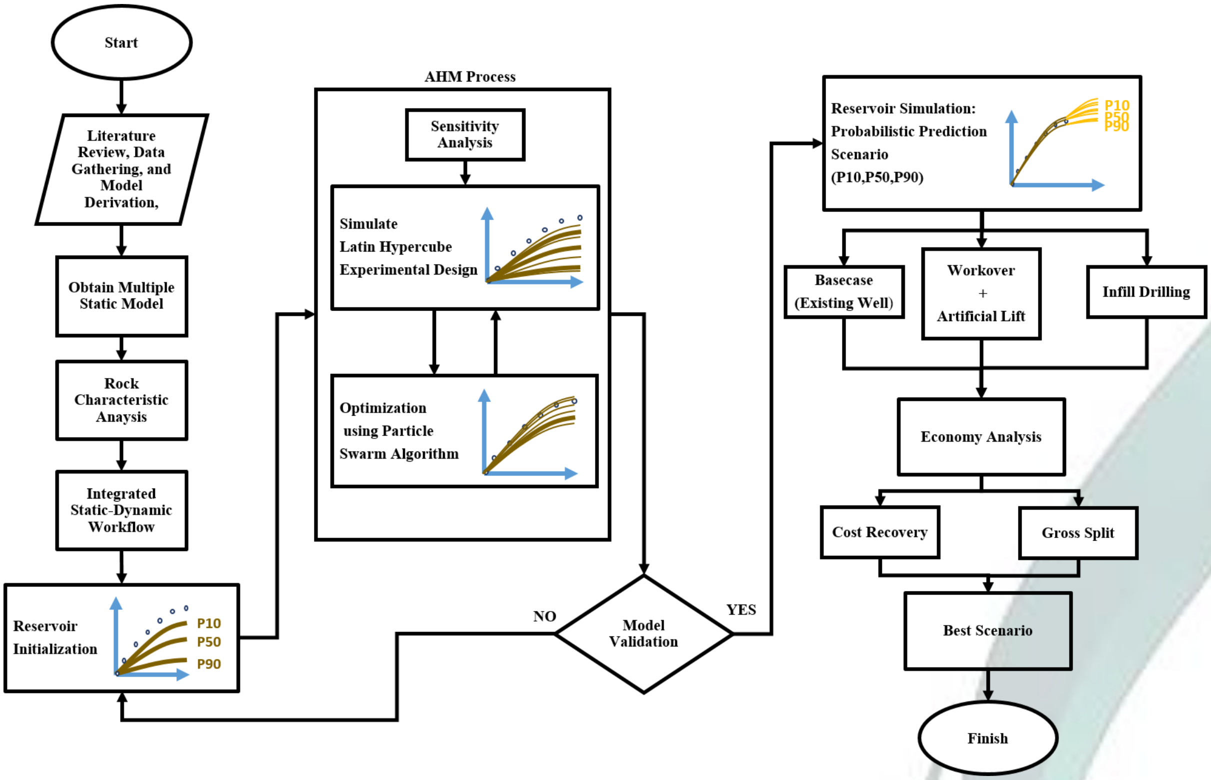


Figure 3. Methodology Workflow

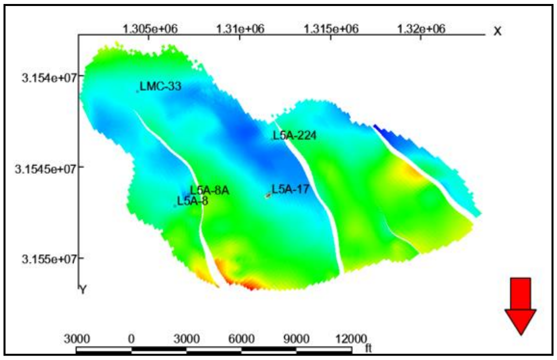


Figure 4. Location of 5 Key Wells in “L” Field

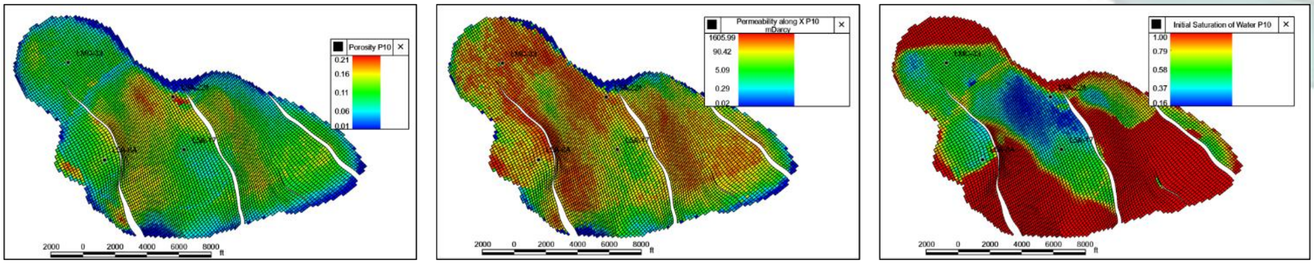


Figure 5. Static Properties of P10 Model

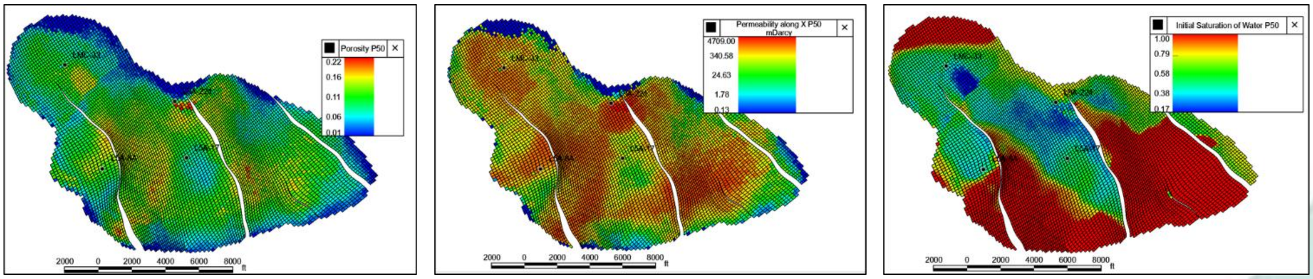
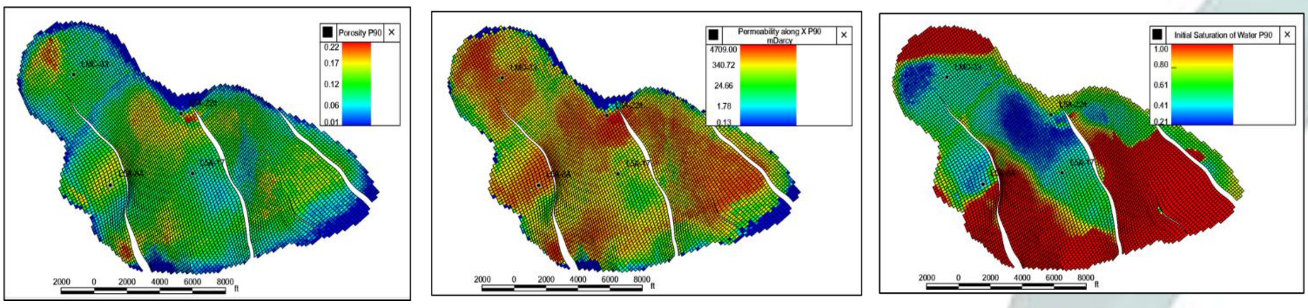


Figure 6. Static Properties of P50 Model



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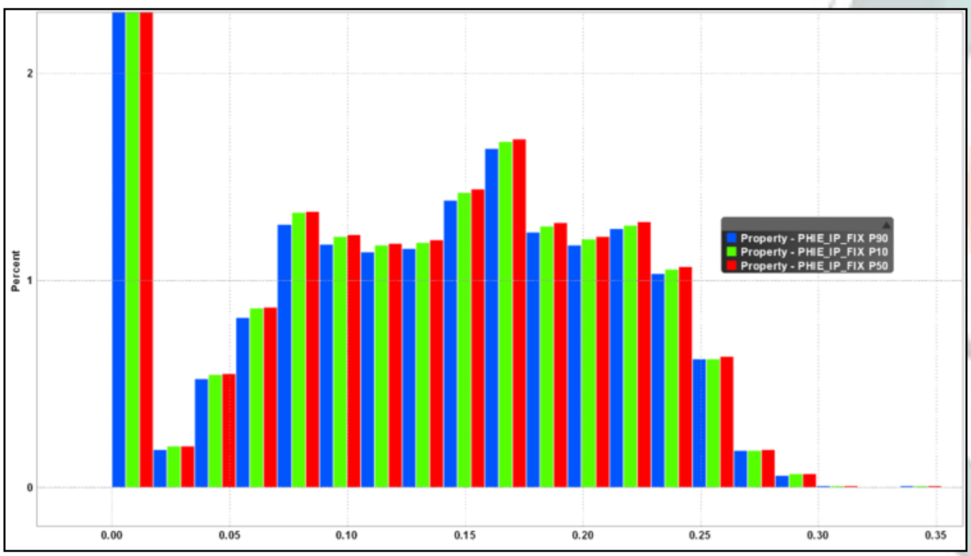

Figure 8. Porosity Distribution of Probabilistic Value

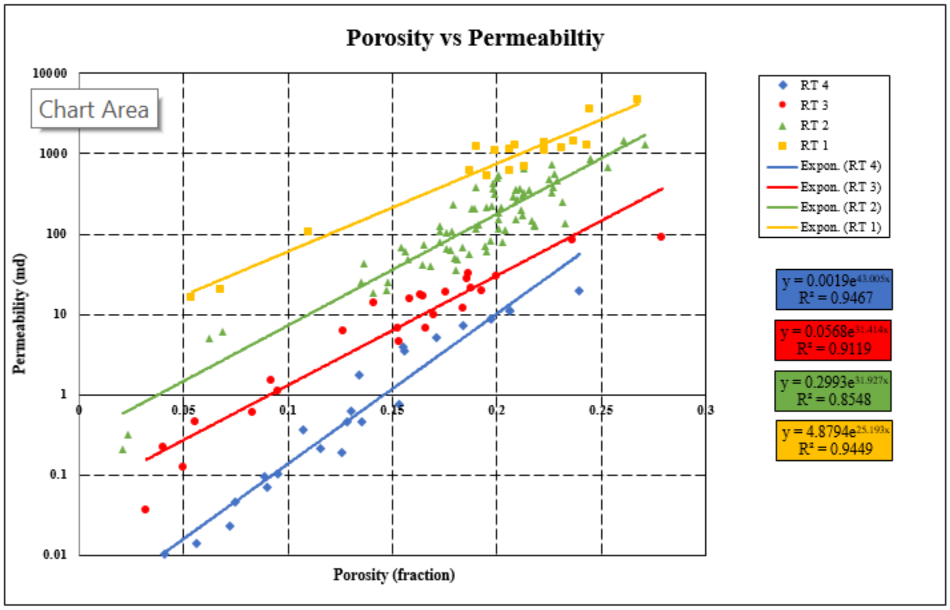

Figure 9. Rock Type Distribution based on Porosity vs Permeability

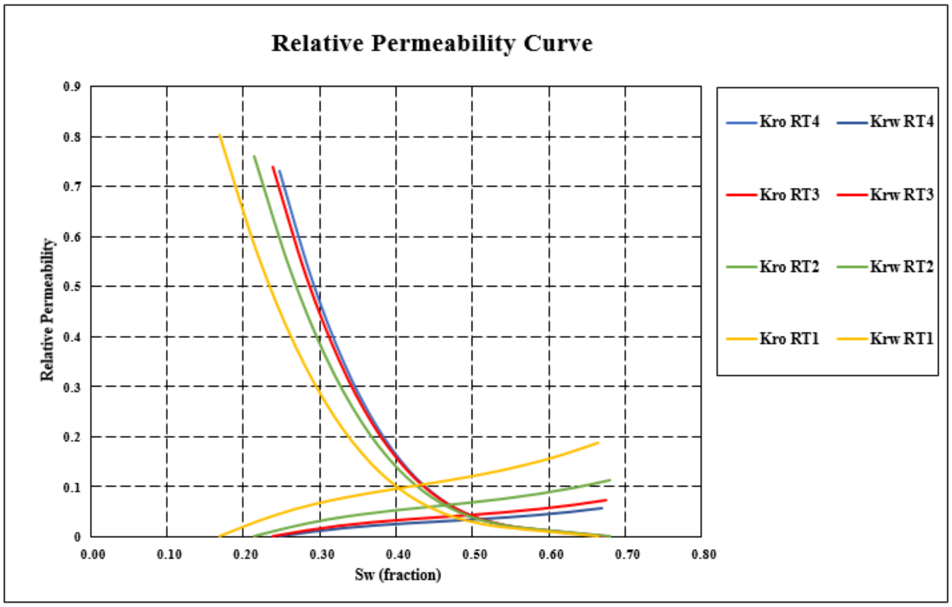

Figure 10. Relative Permeability Curve

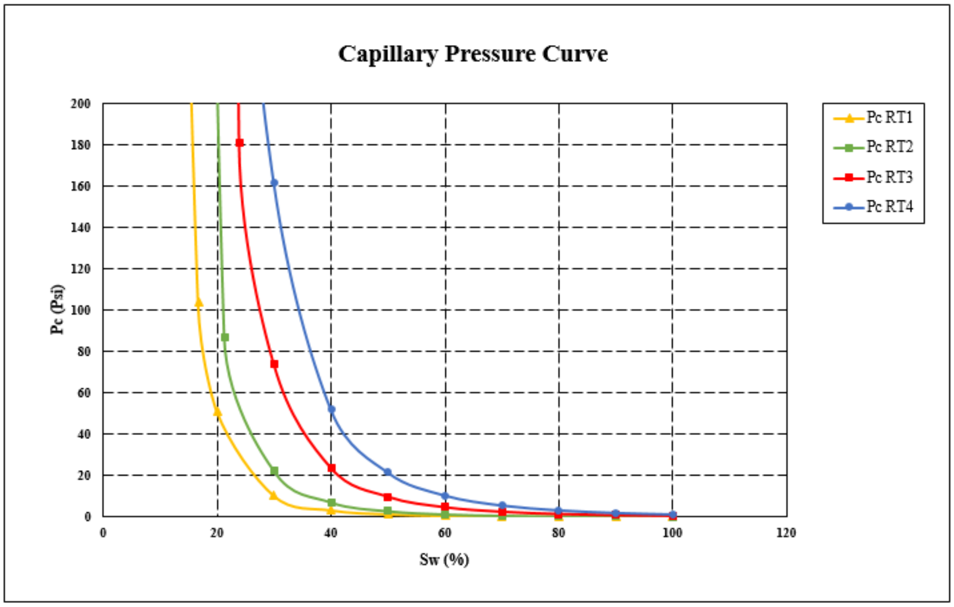

Figure 11. Capillary Pressure Curve

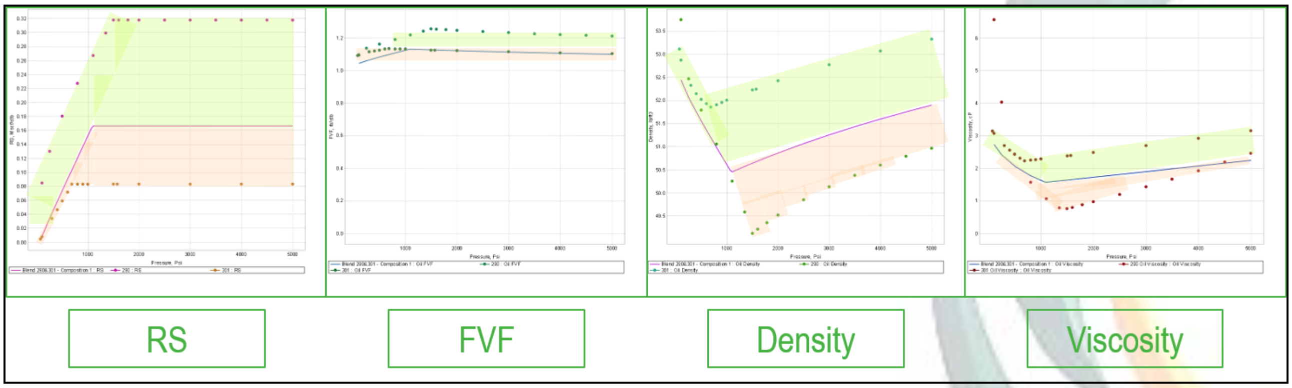

Figure 12. PVT Model Result

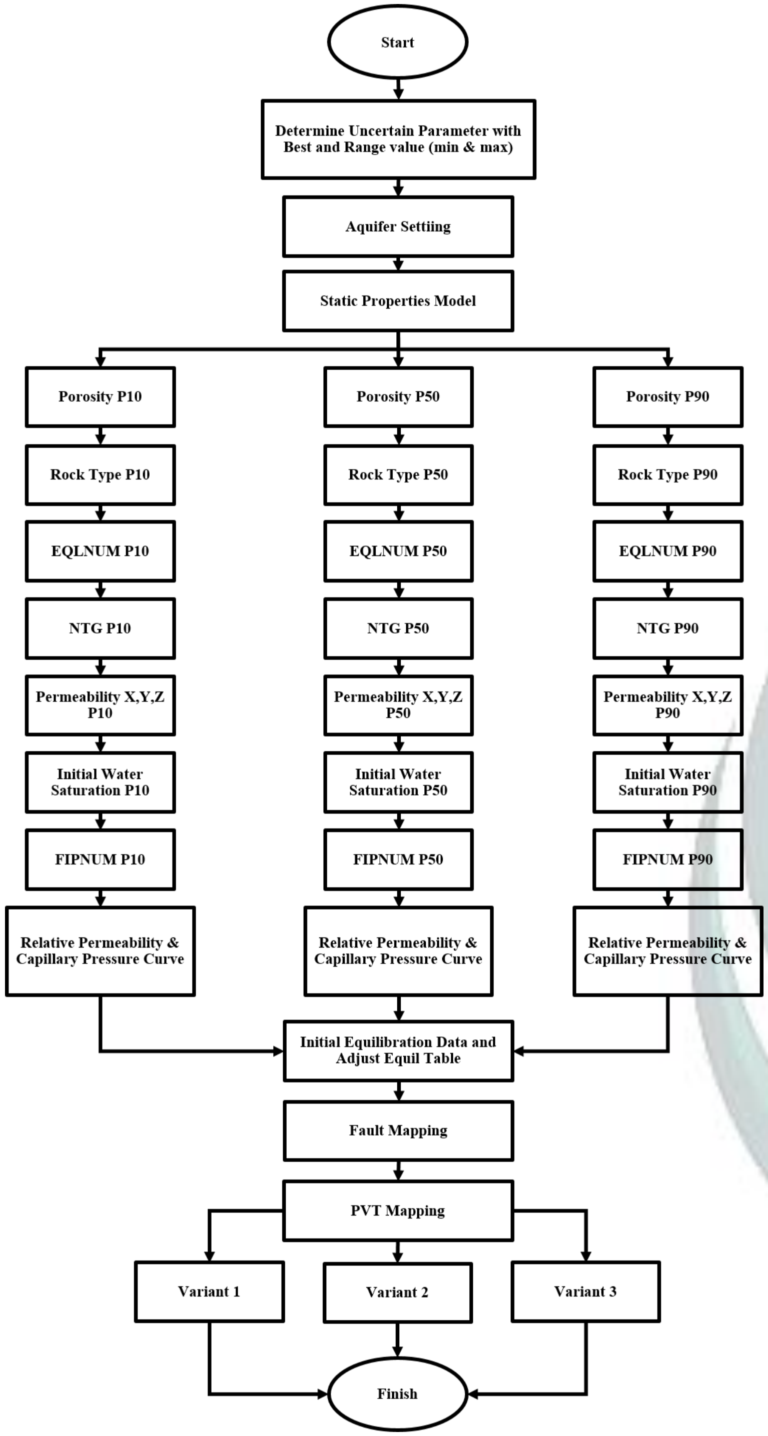

Figure 13. Integrated Static-Dynamic Workflow for AHM process

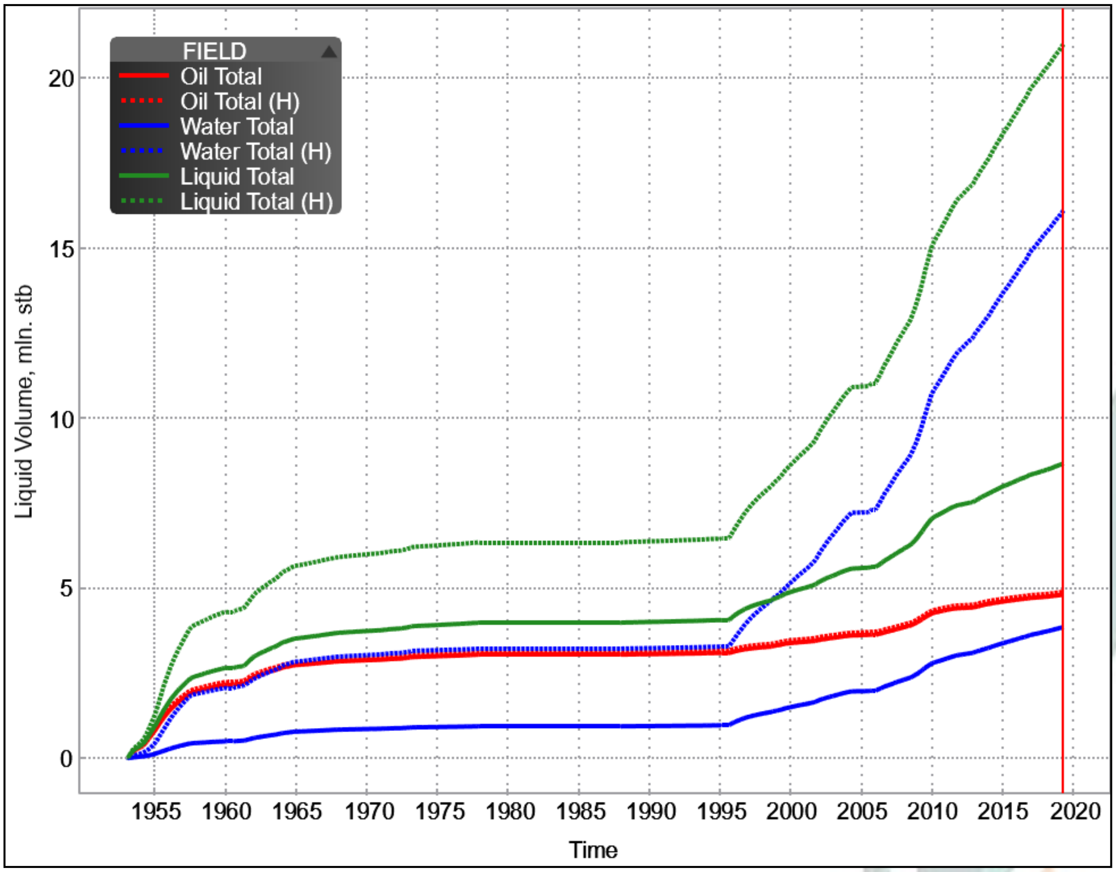

Figure 14. Unmatched Fluid Production in Initial Model

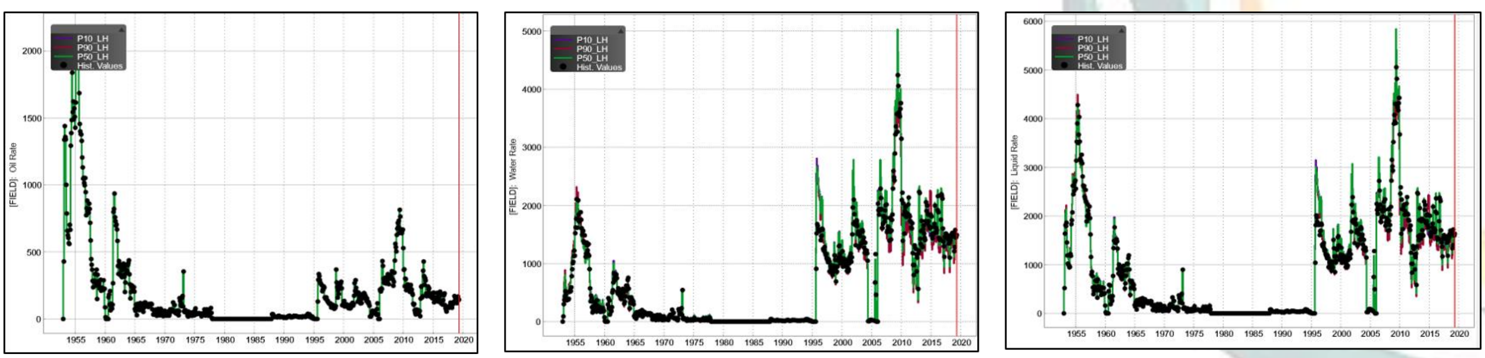

Figure 15. Oil, Water, and Liquid Rate Matching (3 Best Result of Latin Hypercube Experimental)

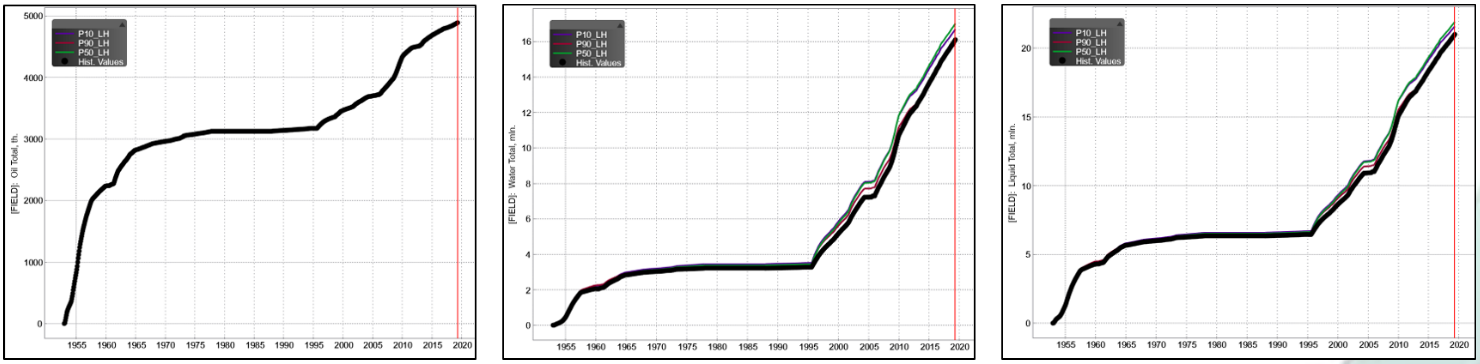

Figure 16. Oil, Water, and Liquid Total Production Matching (3 Best Result of Latin Hypercube Experimental)

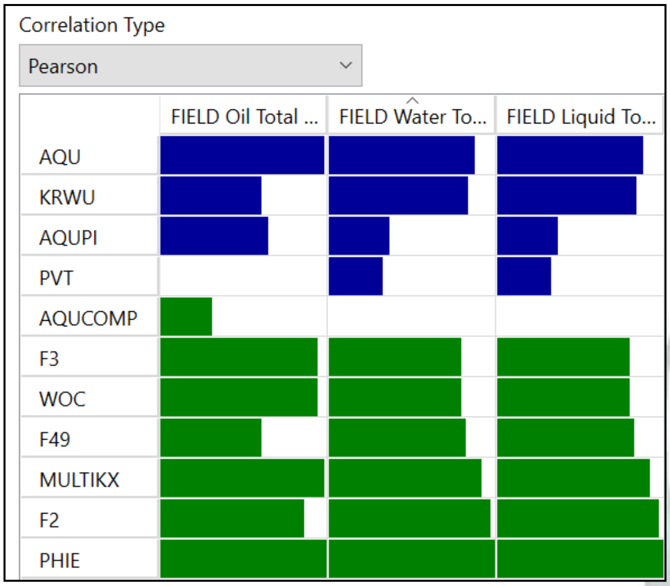

Figure 17. Pareto Chart Analysis

Figure 18. Oil, Water, and Liquid Rate Matching (Optimization Result)

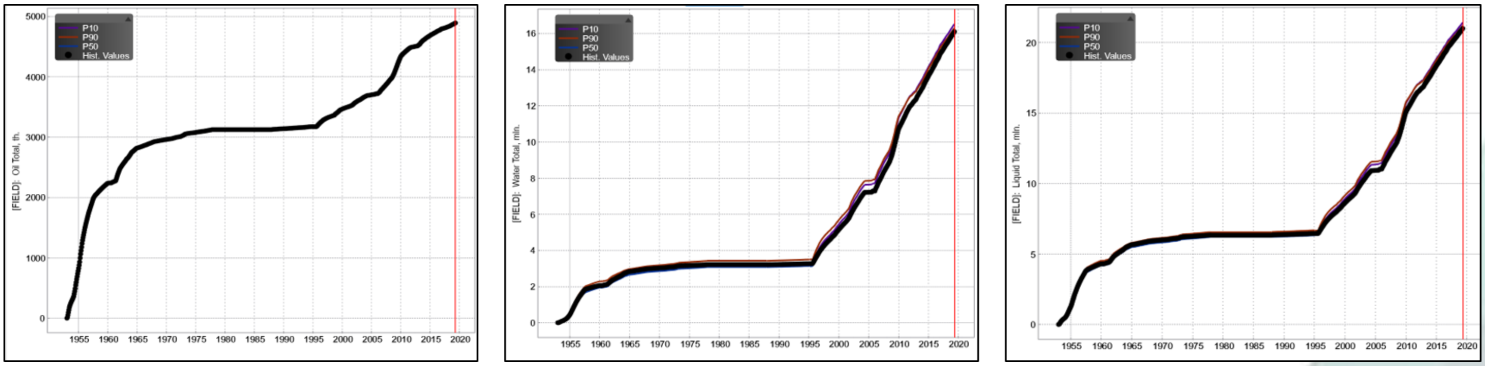

Figure 19. Oil, Water, and Liquid Total Matching (Optimization Result)

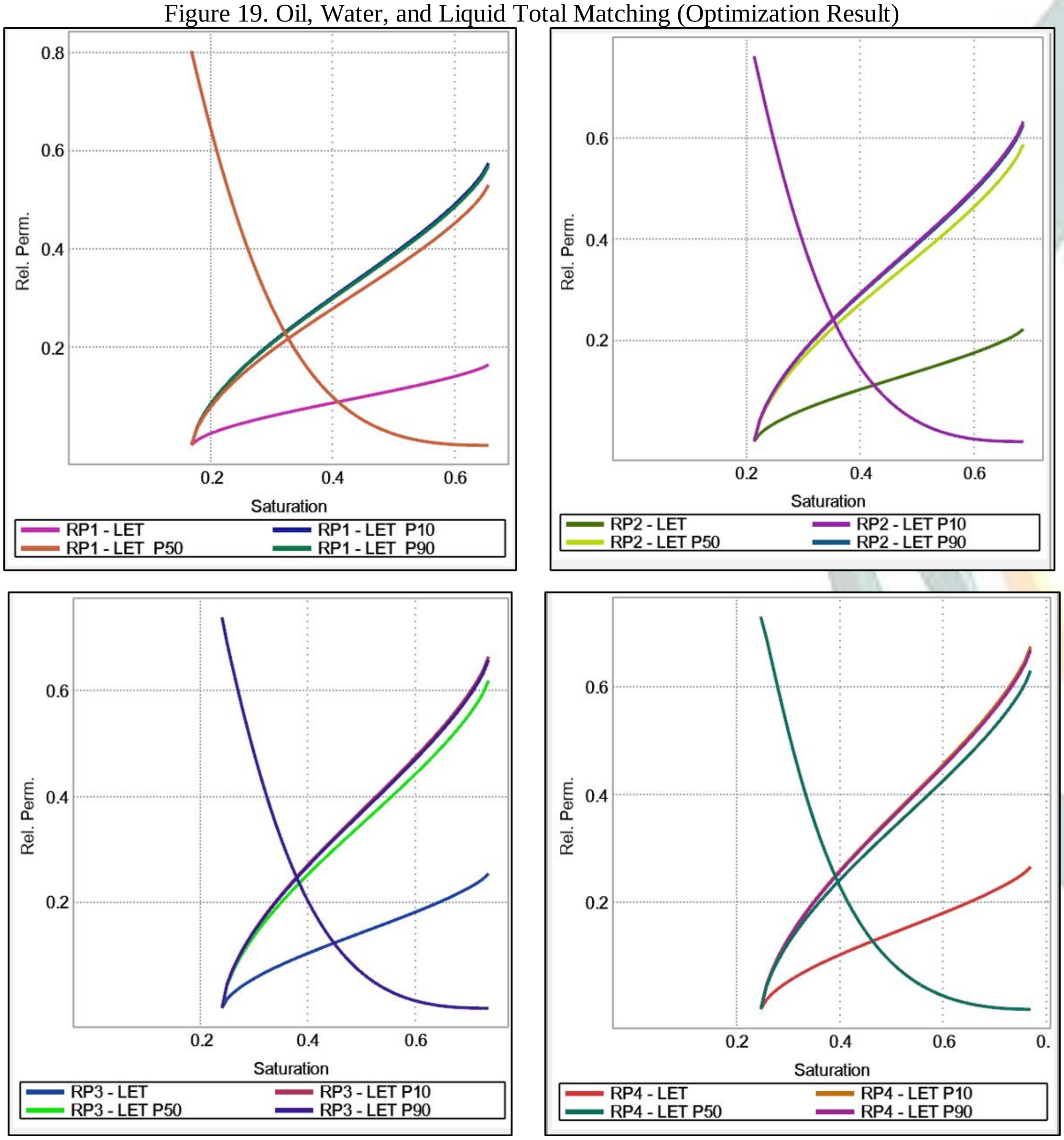

Figure 20. Relative Permeability Shifting

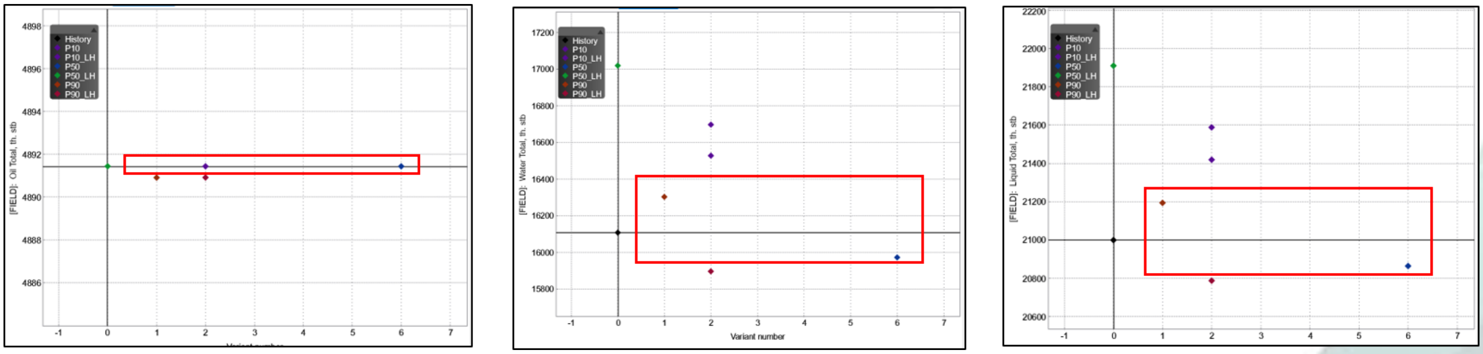

Figure 21. Crossplot Oil, Water, and Liquid Total

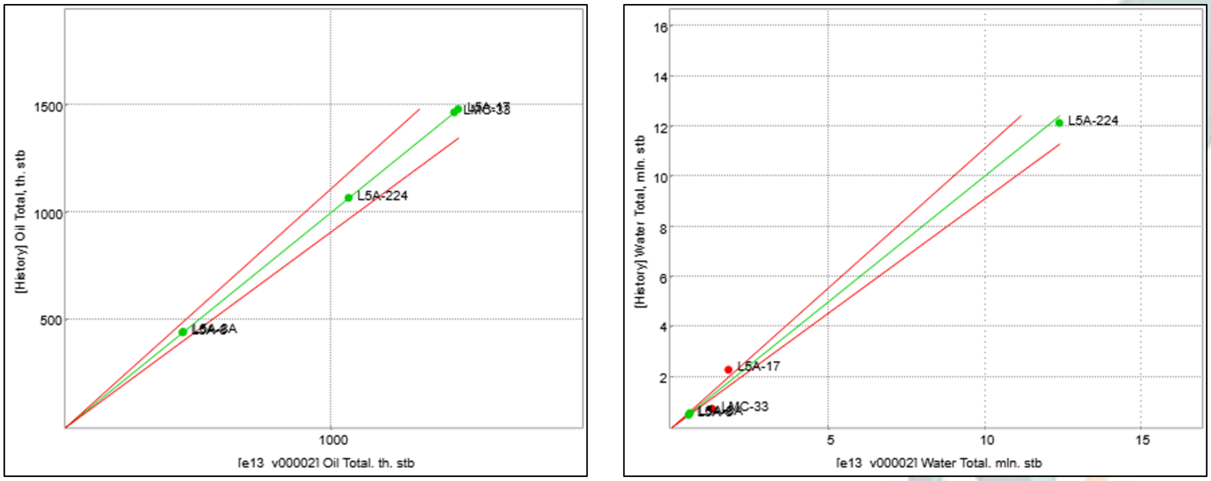

Figure 22. Historical vs Calculation Oil and Water Total of P10 Model

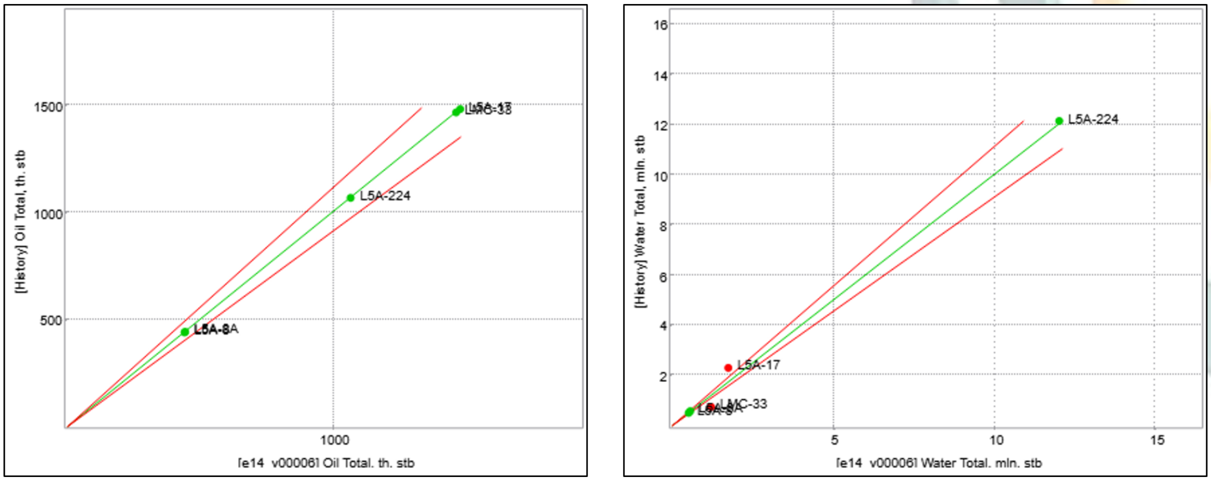

Figure 23. Historical vs Calculation Oil and Water Total of P50 Model

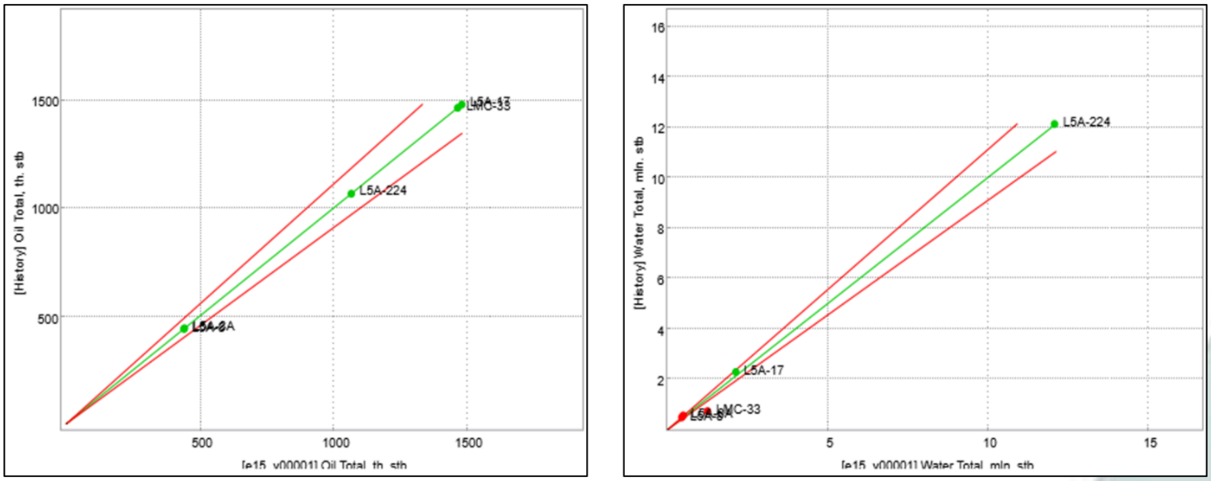

Figure 24. Historical vs Calculation Oil and Water Total of P90 Model

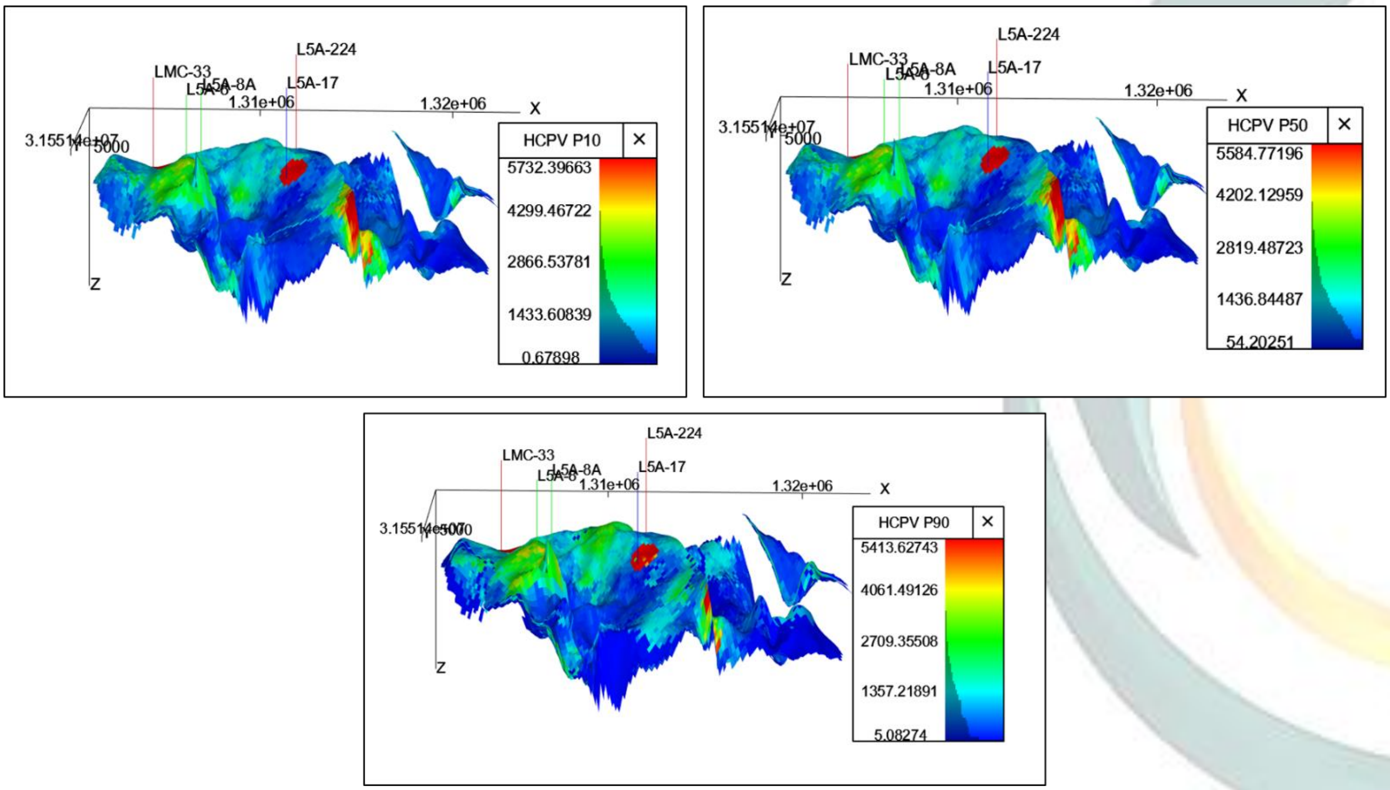

Figure 25. Hydrocarbon Pore Volume Map

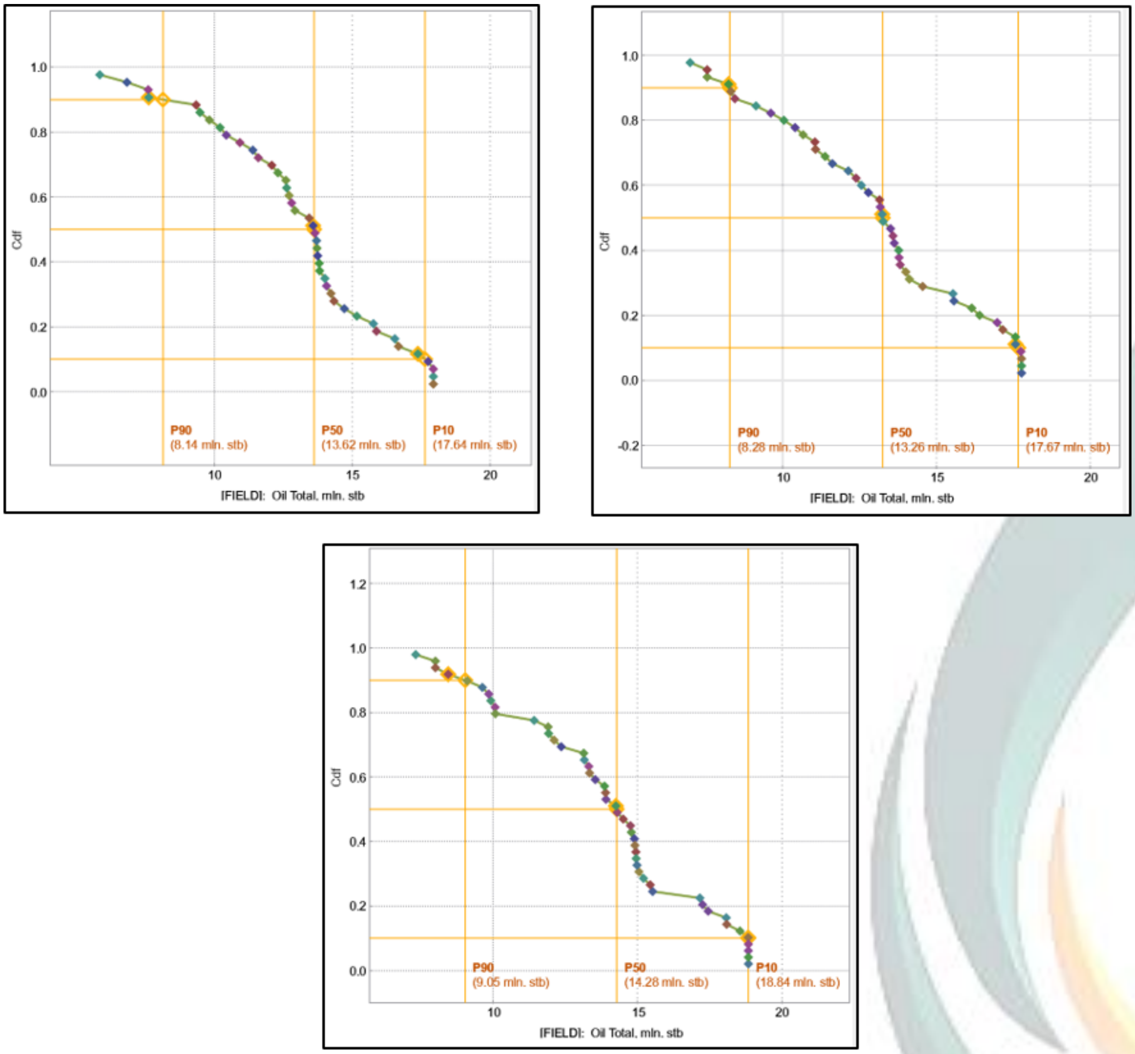

Figure 26. Distribution of P10, P50, and P90 in each model for Oil Total Production

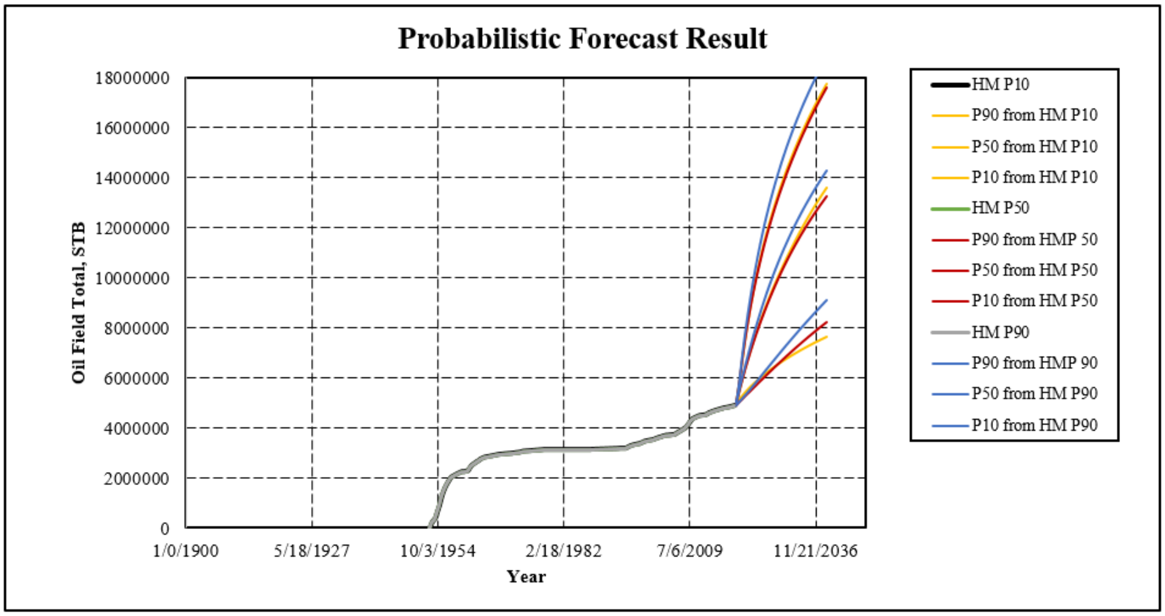

Figure 27. Probabilistic Forecast Scenario 1 Result

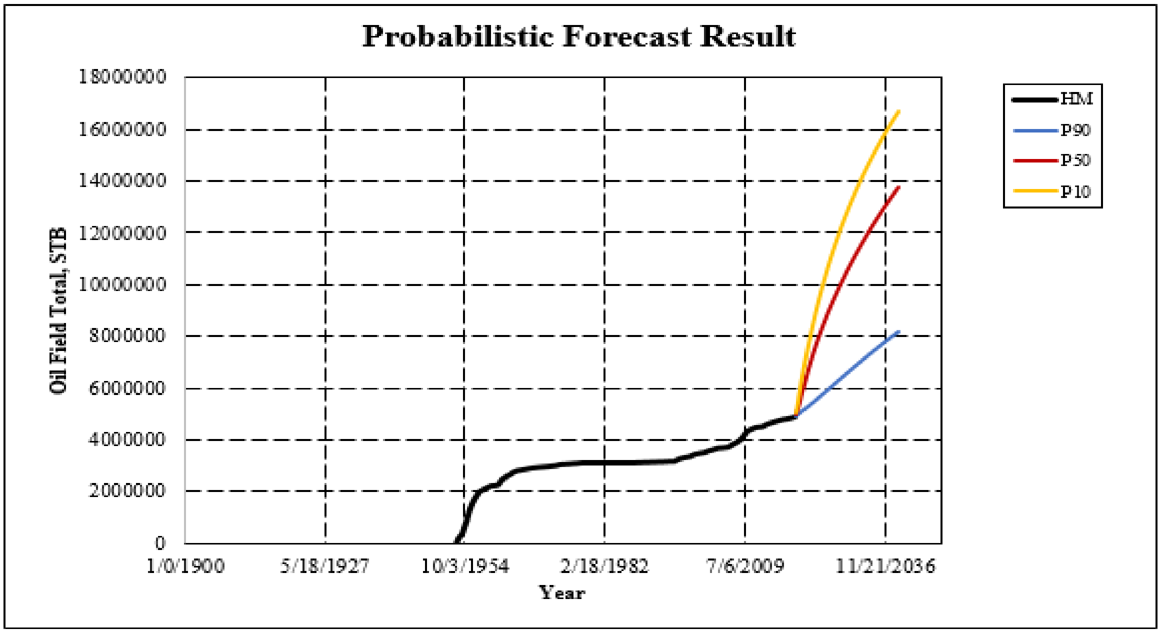

Figure 28. Probabilistic Scenario 2 Result

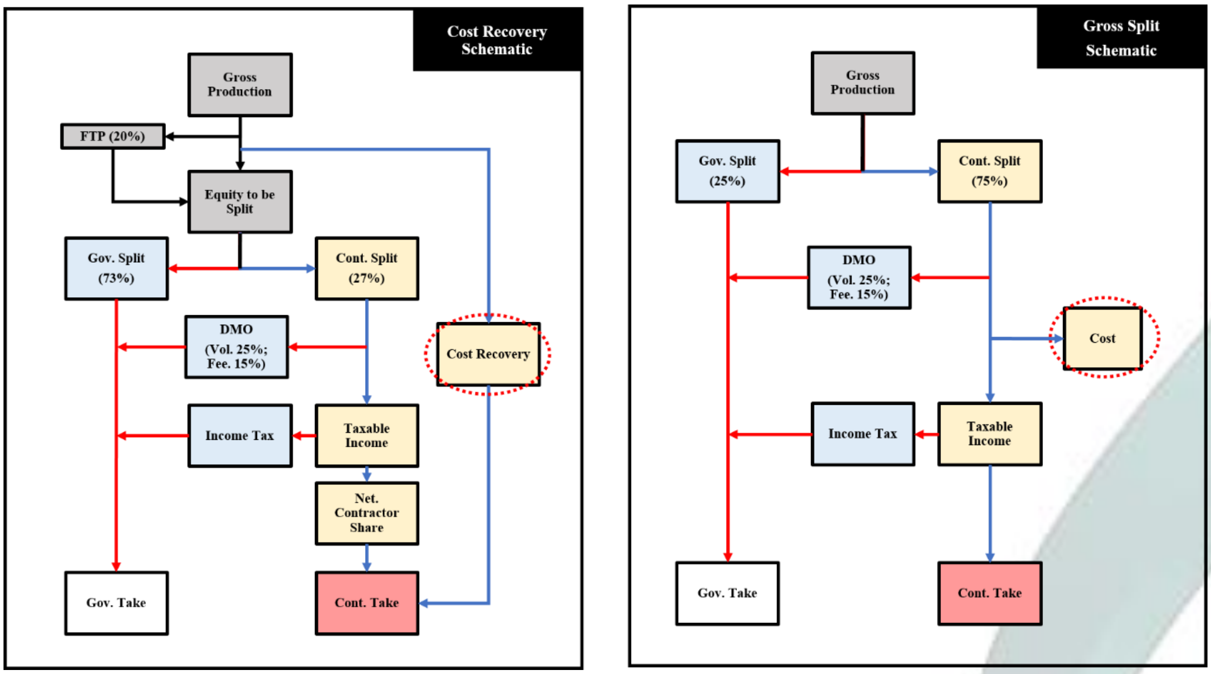

Figure 29. Cost Recovery and Gross Split Schematic for Economy Analysis

List of Tables

Table 1. Reservoir Characterization

Properties	Value	Units
Area	800	acre
Res. Temperature	210	°
Res. Pressure	2,020	psi
Porosity	0.205	fraction
Typical Permeability	670	mD
OOIP	106.67	MMSTB

Table 2 Initial Oil In Place Calculation

Properties		Units	P10	P50	P90
Original Oil In Place	**Static**	MMSTB	114.09	106.67	102.37
	Dynamic		118.06	111.59	106.56
Difference		%	3.36	4.4	3.94

Table 3. Uncertainty Variable and Range

Variable	Base	Min	Max	Distribution	Value
MULTIKX	1	1	12	Uniform	
AQU	5	1	10	Uniform	
F3	1	0	1	Uniform	
F2	1	0	1	Uniform	
F49	1	0	1	Uniform	
WOC	0	0	5	Uniform	
AQUPI	10	10	20	Uniform	
KRWU	0	0	0.2	Uniform	
PHIE	PHIE_P50			Uniform	PHIE_10, PHIE_50, PHIE_90
PVT	Variant 1			Uniform	Variant 1, Variant 2, Variant 3
AQUCOMP	1	0	10	Uniform	

Table 4. Field Total Production Difference between historical and simulation

Model	Oil Total Difference, %	Water Total Difference, %	Liquid Total Difference, %
P10	0.00	2.61	2.00
P50	0.00	3.36	2.59
P90	0.01	2.07	1.58

Table 5. Result Forecasting

Model	Oil Total Production, MMSTB			Recovery Factor, %		
	P90	P50	P10	P90	P50	P10
			Probabilistic Scenario 1			
Model P10	7.63	13.58	17.75	6.46	11.50	15.04
Model P50	8.24	13.24	17.58	7.39	11.86	15.75
Model P90	9.11	14.26	18.84	8.55	13.38	17.68
			Probabilistic Scenario 2			
All Model	8.02	13.79	16.68	6.79	12.36	14.17

Table 6. Description of Economy Analysis for Model 10

Model P10				
	P90	**P50**	**P10**	**Units**
Jumlah WO	0	5	5	
Jumlah Infill	0	2	3	
Total Investment	23.70	27.50	31.30	MMUSD
Oil Cum. Produced	7.63	13.58	17.75	MMSTB
Oil Recovery Factor	6.46	11.50	15.04	%
Number of Wells	5	7	8	

Table 7. Cost Recovery Result Calculation for Model P10

Cost Recovery				
	Case			Units
	P90	P50	P10	
Govt. NPV @10%	16.70	77.67	132.02	MMUSD
Cont. NPV @10%	(7.18)	(1.94)	0.96	
Project NPV @10%	9.52	179.37	132.98	
Cont. IRR, %	1.47	7.43	11.27	%
Project IRR, %	16.77	50.17	80.66	
Cont. Payout Time	6.69	2.73	1.61	Years

Table 8. Gross Split Result Calculation for Model P10

Gross Split				
	Case			Units
	P90	P50	P10	
Govt. NPV @10%	24.48	79.62	129.12	MMUSD
Cont. NPV @10%	(14.96)	(3.89)	3.86	
Project NPV @10%	35.61	169.15	263.93	
Cont. IRR, %	0.00	7.12	12.87	%
Project IRR, %	16.77	50.16	80.66	
Cont. Payout Time	-	7.71	4.70	Years

Table 9. Description of Economy Analysis for Model 50

Model P50				
	P90	**P50**	**P10**	**Units**
Jumlah WO	5	5	5	
Jumlah Infill	0	2	6	
Total Investment	21.80	27.50	33.20	MMUSD
Oil Cum. Produced	8.24	13.24	17.58	MMSTB
Oil Recovery Factor	7.39	11.86	15.75	%
Number of Wells	5	7	11	

Table 10. Cost Recovery Result Calculation for Model P50

Cost Recovery				
	Case			Units
	P90	P50	P10	
Govt. NPV @10%	20.67	76.44	128.32	MMUSD
Cont. NPV @10%	(6.58)	(1.64)	0.74	
Project NPV @10%	14.09	74.79	129.05	
Cont. IRR, %	2.16	7.66	10.97	%
Project IRR, %	18.61	52.38	78.96	
Cont. Payout Time	5.89	2.65	1.74	Years

Table 11. Gross Split Result Calculation for Model P50

Gross Split				
	Case			Units
	P90	P50	P10	
Govt. NPV @10%	26.47	77.76	126.59	MMUSD
Cont. NPV @10%	(12.38)	(2.97)	2.46	
Project NPV @10%	49.81	163.64	257.89	
Cont. IRR, %	0.09	7.63	11.78	%
Project IRR, %	18.61	52.39	78.97	
Cont. Payout Time	20.37	7.13	4.98	Years

Table 12. Description of Economy Analysis for Model 90

Model P90				
	P90	**P50**	**P10**	**Units**
Jumlah WO	5	5	5	
Jumlah Infill	0	2	9	
Total Investment	21.80	27.50	38.78	MMUSD
Oil Cum. Produced	9.11	14.26	18.84	MMSTB
Oil Recovery Factor	8.55	13.38	17.68	%
Number of Wells	5	7	14	

Table 13. Cost Recovery Result Calculation for Model P90

Cost Recovery				
	Case			Units
	P90	P50	P10	
Govt. NPV @10%	27.77	88.26	141.29	MMUSD
Cont. NPV @10%	(5.70)	(0.90)	1.07	
Project NPV @10%	22.07	87.36	142.36	
Cont. IRR, %	3.04	8.71	11.37	%
Project IRR, %	22.31	58.81	82.78	
Cont. Payout Time	4.88	2.43	1.93	Years

Table 14. Gross Split Result Calculation for Model P90

Gross Split				
	Case			Units
	P90	P50	P10	
Govt. NPV @10%	32.79	88.22	140.07	MMUSD
Cont. NPV @10%	(10.72)	(0.86)	2.29	
Project NPV @10%	70.12	187.51	282.12	
Cont. IRR, %	1.51	9.31	11.55	%
Project IRR, %	22.31	58.81	82.78	
Cont. Payout Time	15.86	6.24	5.34	Years

Table 15. Difference Result between Cost Recovery & Gross Split Calculation

		Cost Recovery			Gross Split		
		Project NPV, MMUSD	Project IRR, %	Payout Time, years	Project NPV, MMUSD	Project IRR, %	Payout Time, years
Model P10	P90	9.53	16.77	6.69	35.61	16.77	-
	P50	179.38	50.16	2.73	169.15	50.16	7.71
	P10	132.98	80.66	1.61	263.93	80.66	4.70
Model P50	P90	14.08	18.61	5.89	49.81	18.61	20.37
	P50	74.79	52.39	2.65	163.64	52.39	7.13
	P10	129.05	78.97	1.74	257.88	78.97	4.98
Model P90	P90	22.07	22.32	4.88	70.15	22.31	15.86
	P50	87.36	58.82	2.43	187.52	58.81	6.24
	P10	142.36	82.78	1.93	282.12	82.78	5.34