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Uncertainty Assessment of Reservoir Modeling for Oilfield in the South of Iraq

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Abstract

A reservoir is formed due to geologic deposition processes and is not created randomly. However, because of subsurface complexity and limited data, there are many uncertainties in reservoir characterization. Uncertainties can be reduced by gathering more data and/or employing improved technology and scientific methods. Under uncertainty and risk, uncertainty analysis should be performed for investigational analyses as well as decision-making. The main focus of uncertainty analysis in reservoir characterization and management should be to understand what needs to be known and what can be known. Therefore, there are several reservoir parameters' uncertainties and their quantitative influence on cumulative oil production and water cut were studied.

In this paper, sensitivity analysis and uncertainty quantification were conducted for several parameters to study their effect on cumulative oil production. The Monte Carlo method was used to carry out the uncertainty quantification. In this study, we examined two methods which are the Monte Carlo simulation using a Reservoir simulator (MCRS) and the Monte Carlo simulation using a Proxy (MCP) to overcome the issue of the high number of simulation runs requirement and to reduce time consumption.

The results showed that The MCP method is a very useful and powerful tool to conduct the uncertainty quantification than the MCRS because the MCP performs the objective function with extremely less time-consuming and very accurate and identical results compared to the results of the MCRS method. The results of uncertainty quantification for production forecast show there is a low risk due to the small gap difference between the P50 and P90. While the sensitivity analysis results showed that the oil-water-contact depth is the dominant parameter that affects cumulative oil production while porosity is the less influential parameter.

Keywords: Sensitivity analysis, Uncertainty quantification, Monte Carlo method, Reservoir simulator, Proxy, Cumulative oil production.

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1. Introduction:

To mimic the reservoir very well, the model parameters must be accurate because some parameters are biased from true values (geological, petrophysical, human errors in measurements). Therefore, there are several reservoir parameters' uncertainties and their quantitative influence on cumulative oil production and water cut were studied. Therefore, uncertainty quantification is considered an essential requirement to assess the impact of risk to help us in decision-making. To optimize reserve portfolios and better formulate exploration and exploitation strategies for oil and gas fields, more creative and efficient handling of uncertainty is required.

The structural and petrophysical parameters are mainly focused by uncertainty analysis. Uncertainty analysis uses various optimization algorithms to study the influence of each uncertain parameter and their interplay influence between parameters themselves to assess the uncertainties and their impact on reservoir characterization. Each uncertainty parameters have a special probability distribution which is considered more realistic to describe uncertainty in variables of a risk analysis. Also, the probability density function (PDF) is used to limit variation of the objective prediction to maintain the P10/P90 ratios within the appropriate ranges [1]. A new Bayesian approach was used for history matching and uncertainty assessment. The posterior PDF is explored with Markov chain Monte Carlo to sample an ensemble of reservoir models that assess the uncertainty. The converged proxy functions make a powerful tool with which we can sample as many statistics as we wish, without the need for more flow simulations. The possibilities for post-processing, such as identifying trends, correlations, etc., are tremendous [2]. Mohaghegh (2006) [3] used the surrogate reservoir model to represent the reservoir to perform the Monte Carlo Simulation for uncertainty analysis of the reservoir because performing Monte Carlo Simulation by using a traditional simulator is impractical because of its requirement for a huge number of runs (reach to hundreds or thousands of simulation runs) to acquire on meaningful results.

Novel computationally efficient method for uncertainty quantification with the Metropolis-Hastings Markov chain Monte Carlo (MH-MCMC) algorithm in which the reservoir simulator is replaced by a reliable proxy model. The constructed proxy is the least squares support vector regression (LS-SVR) model, a machine learning regression algorithm that uses kernel functions and has been found to have a good performance when applied to nonlinear functions [4]. Artificial neural network (ANN) is used in the uncertainty quantification and selection of models representative because of its ability to quantify the geological uncertainties with high accuracy in

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a much shorter time when compared its results with two commonly used methods, namely the distance-based clustering techniques and traditional ranking [5]. Camacho et al. analyze the uncertainty propagation (that exists in the input parameters) through the model to its output by using Polynomial chaos expansions (PCE). This technique illustrates the result of the model as a polynomial.

For convergence consideration, PCE is a fast convergence method than Monte Carlo simulation (low-pace convergence which leads to high computational cost). The base of PCE is made up of multidimensional orthogonal polynomials, so the approximation of the model response Y is fast. Its precision is directly influenced by how efficient the method by which the coefficients are estimated. [6].

From the above-mentioned studies and other studies that didn't include in this thesis, we notice the importance and power of using artificial intelligence in the reservoir development field. Artificial intelligence enters different fields in petroleum

2. Uncertainty:

Uncertainty and error aren't synonyms. There is indeed a close relationship between them, but they are intrinsically different. Uncertainty describes a state of unknown and the lack of acknowledgments of reservoir information due to sparsity and errors. The errors arise from the uncertainty in reservoir representation, but the uncertainty does not necessarily carry any error [7]. The uncertainties of any reservoir may be categorized due to data sparsity, data measurement errors, and simulation errors. Data sparsity is a result of the limited data measurement points by logging, coring, and well-testing compared with the huge scale of the field. For that, the petrophysical properties away from the locations of measurement data are estimated by some inferring methods which are represented by analog outcrops and knowledge of how the reservoir was formed. While errors in data measurement are related to:

a. Errors caused by humans or devices when obtaining results from direct measurements (e.g. Data obtained during laboratory work from the core plugs).
b. Errors of indirect measurements called inherent errors (data from wells' logs).
c. The dynamic data's error (e.g. production data) due to the reading blunders [8].

While the errors in the simulation runs are (1) errors in input, which relates to errors in data collection (e.g. porosity and permeability); (2) physics error is attributed to inappropriate physical

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system representation (grid system to capture the heterogeneity); and (3) solution errors, which are represented by cutting off part of the reservoir as a sector, and suppositions and facilitation of fluid flow's mathematical equations. These errors belong to numerical solution errors [9]. These sources of uncertainties may exist in any stage of reservoir modeling construction (e.g. petrophysical distribution modeling, history matching, and up-scaling) and may behave as deterministic, discrete, and stochastic uncertainties [10] [11].

When geological and reservoir modeling is prepared and history matching has been achieved, the objective function of this study is ready to be conducted. The uncertainty assessment comprises three major stages which are reservoir modeling, sensitivity analysis for parameters screening, and Monte Carlo simulation [12].

3. Monte Carlo Simulation:

The geostatistical reservoir modeling provides a framework for assessing uncertainty by using Monte Carlo sampling. Monte Carlo sampling proceeds by [13].

1- Create a model of the domain.
2- Drawing N realizations from a probabilistic model.
3- Processing the N realizations through some performance calculations, and
4- Assembling a histogram of the N responses to rep-count for the various sources of uncertainty.

Probability statistics usually are used to study the uncertainty quantification in the model optimization methods. There are three international criteria which are P10 (pessimistic probability), P50 (most probable probability), and P90 (optimistic probability). P10 indicates that 10% of the probability of calculated estimates will be equal to or exceed the P10 estimate while P90 is indicating that the 90 % of the probability of calculated estimates is greater than or equal to the P90 estimate for that the P 10 and P 90 represent the lowest probability of occurrence for simulations results. P 50 is considered the median and highest probability of occurrence because the likelihood of being greater than or less than the corresponding reserve is 50% [14] [15].

4. Defining the objective function:

To select the parameters and their probability range that may affect the objective function. In this study, the objective function is to study the uncertainty quantification of parameters and its effect on the estimation of STOIIP and cumulative oil production. The parameters that were used are:

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- Oil-waterer contact (OWC)
- water saturation (SeedSw) as Seed variable
- porosity (SeedPHI) as Seed variable
- net to gross (SeedN/G) as Seed variable
- permeability (Seedperm) as Seed variable

5. Sensitivity analysis:

This step aims to illustrate the most influential parameters on the STOIIP for the static model and cumulative oil production in the dynamic model. The most influential parameters will be transferred to uncertainty quantification while the parameters with negligible effect will be ignored. Figure (1) shows the Sensitivity analysis of parameters on STOIIP for the geological model. The results illustrate that the oil-water contact's depth is the most predominant parameter influence on the STOIIP then comes net to gross (NTGseed), water saturation (SwSeed), and porosity (PHIseed) respectively. As obvious from the figure, all parameters affect STOIIP and these parameters will be taken into account in uncertainty analysis.

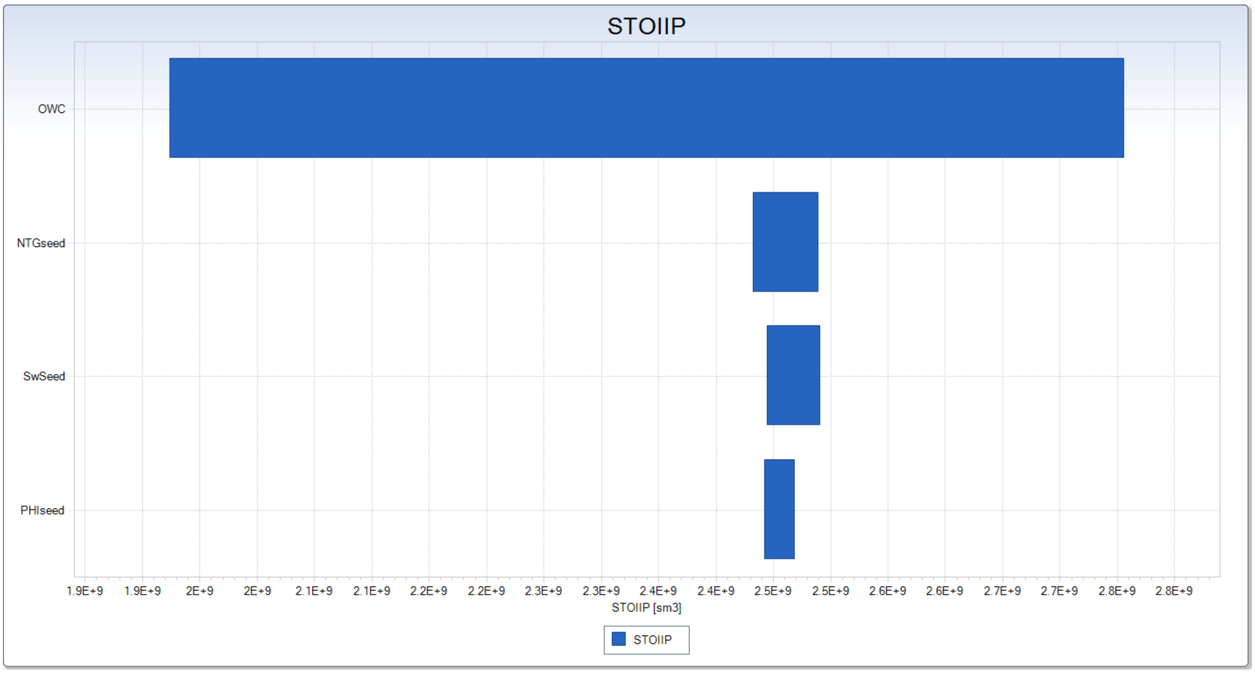

Fig. (1): Sensitivity analysis of parameters on STOIIP for geological model

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6. Geological Model Uncertainty Analysis:

In this step, the probability distribution is used to study the uncertainty quantification of the volumetric properties of a reservoir which are represented by pore volume, bulk volume, hydrocarbon pore volume (HCPV), and STOIIP. This work created 250 geological models (Realization) to capture geological uncertainties. Table (1) and Figure (2) show the uncertainty analysis for stank original oil in place for the geological model and estimates the probability of P10, P50, and P90.

Table (1) Uncertainty analysis for STOIIP calculation

Probability	STOIIP MMsm^3
P 10	1987.19
P 50	2360.53
P 90	2734.97
Case	2516.99

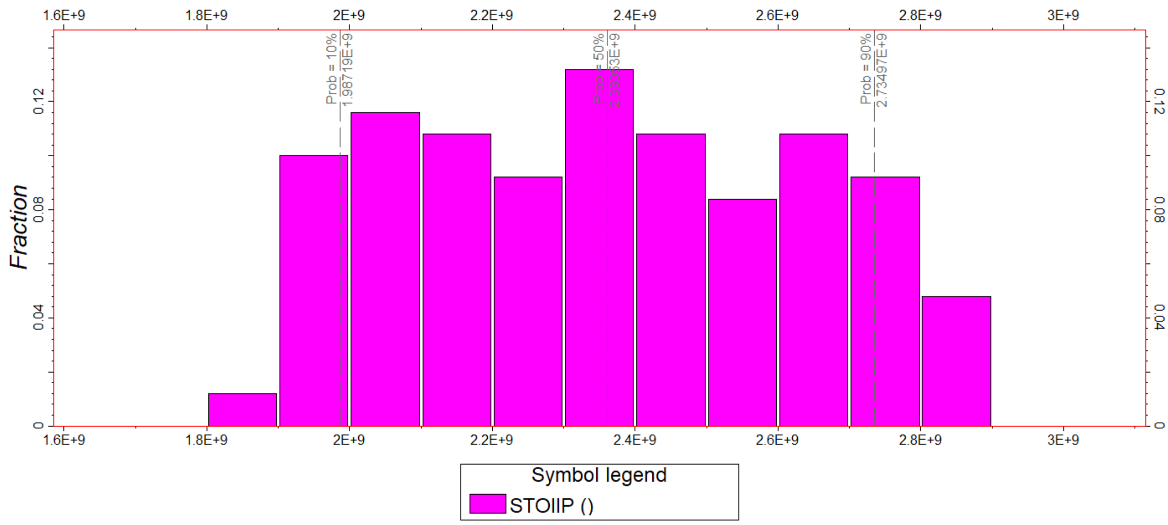

Fig. (2): Uncertainty analysis for stank original oil in place for the geological model.

7. Dynamic Model Sensitivity and Uncertainty Analysis:

In this step, the geological uncertainties' parameters in a reservoir model are transferred to reservoir performance forecasting [16]. The importance of reservoir forecasting is represented by its impact on business decisions. In common, the business decision is governed by uncertainty, and these two components (uncertainty and business decision) form the risk analysis.

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In dynamic model uncertainty analysis, new parameters are added to this analysis compared to geological model analysis such as permeability, permeability ratio, and rock compressibility. Figure (3) illustrates the sensitivity analysis of the reservoir's parameters on oil production cumulative. The figure shows that the OWC depth is also the dominant parameter that affects oil production rate and oil cumulative production while the other parameters come after. Porosity will be ignored in the uncertainty analysis because of its low efficiency in the cumulative production of oil.

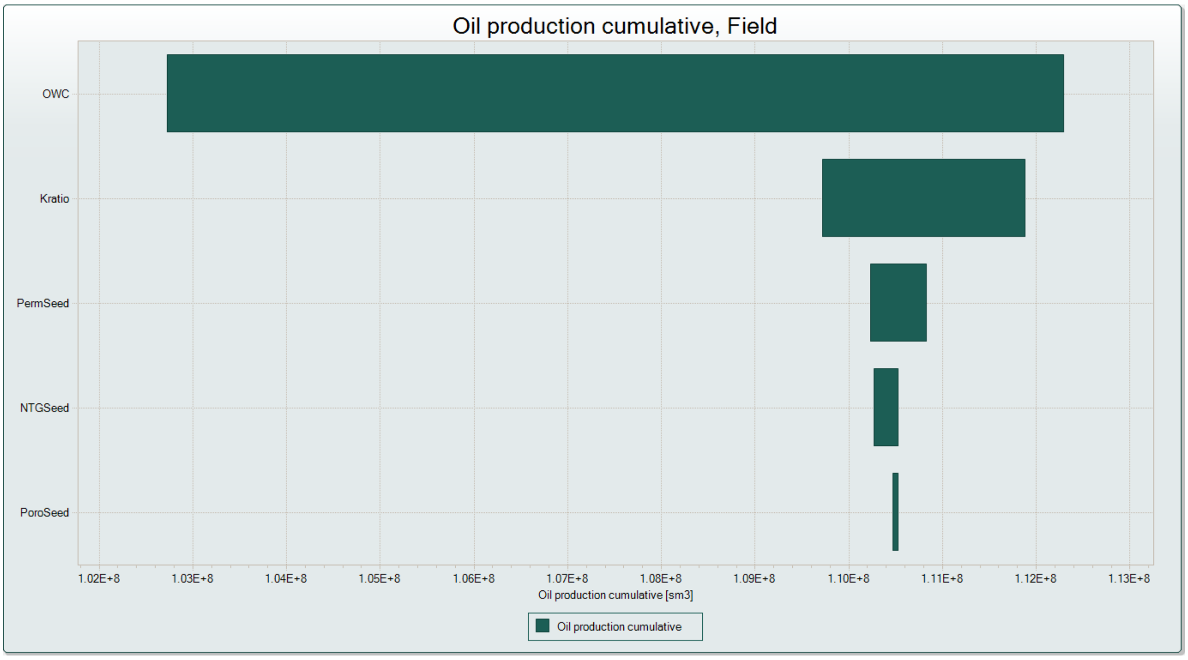

Fig. (3): The sensitivity analysis of reservoirs' parameters on oil production rate and oil production cumulative.

To achieve the uncertainty analysis, 150 simulation runs were conducted. The uncertainty was achieved along with the duration from 2014 to 2020 which is the same as the real-time of the field in the production then the results were compared with the actual cumulative oil production. Figure (4) illustrates the histogram of oil cumulative production and cumulative density function.

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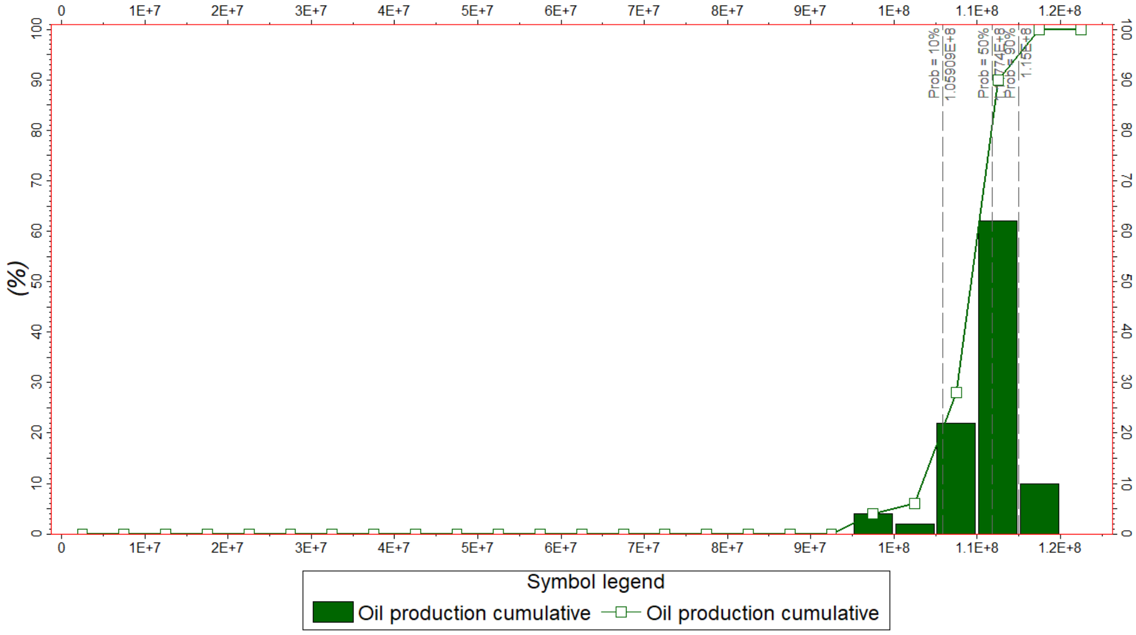

Fig. (4): The histogram of oil cumulative production and cumulative density function for dynamic model uncertainty analysis.

Table (2) and Figure (5) show the cumulative oil production for P10, P50, and P90 compared with the actual cumulative function for the field. The results show that the real case is closer to P50 and that indicates the model's uncertainty is moderate and not biased for optimistic or pessimistic results. The uncertainty was compared with the production history because the production history represents the actual reservoir representative to know our reservoir model biases for any probability.

Table (2): Comparison of cumulative oil production of the statistical probability of dynamic model uncertainty with actual observed data of field.

Probability	Cumulative oil production MMsm^3
P 10	105.9
P 50	111.7
P 90	115
Case study	110.5

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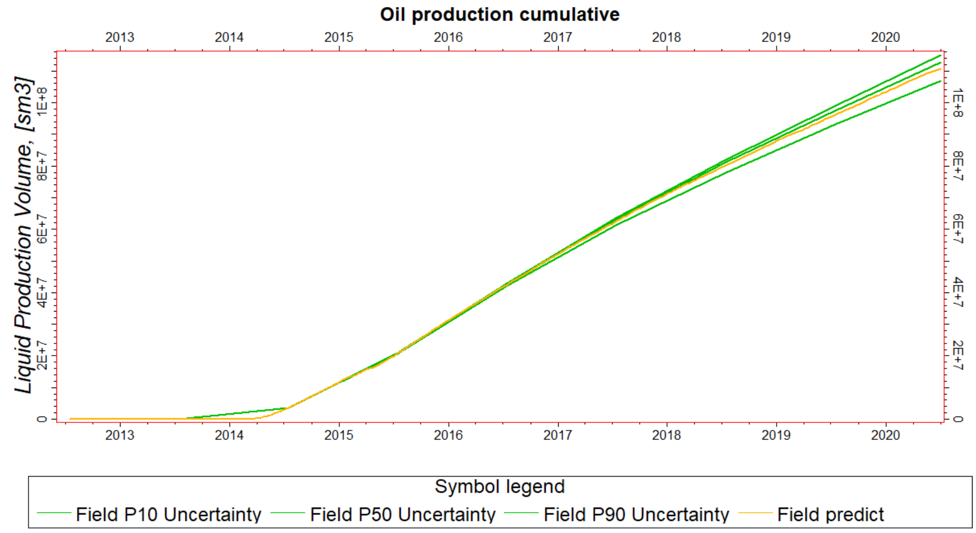

Fig. (5): The cumulative oil production for P10, P50, and P90 comparison with the actual cumulative function of the field.

8. Forecast uncertainty and methods comparison:

This section will conduct uncertainty quantification for the cumulative oil production for the reservoir model. Two parameters are included in this study which are the permeability ratio and the oil-water-contact depth due to their high influence on the oil cumulative oil production. The uncertainty assessment extended from 2020 to 2030.

The uncertainty quantification faces the major task of conducting a huge number of simulation runs reaches to hundreds to thousands of runs and this sometimes is impractical, especially for huge reservoirs due to the extremely time-consuming.

In this study, we are applying the Monte Carlo simulation on two engines to compare their capability and performance. The engines that were used in this dissertation are:

1- **Monte Carlo Simulation Using Reservoir Simulator (MCRS):** In this case, the inputs selected from the Monte Carlo simulation are run through the simulator to determine the uncertainty in the reservoir model.
2- **Monte Carlo Simulation Using Proxy (MCP)**: Using Monte Carlo simulation, inputs are randomly generated from probability distributions to simulate the process of sampling from an actual population. These inputs are then fed into the response surface model, which is

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used to determine the uncertainty in the reservoir model. The proxy model type that is used in this goal is the radial basis network.

The goal of this section is to carry out a comparison between these two methods to overcome the issues of high numbers of simulation runs and the time-consuming taking into account the quality of performance. The results of the comparison could be illustrated as follows:

1. The results of the two methods (MCRS and MCP) were identical in Monte Carlo simulation for cumulative probability and probability density as shown in the Figures (6 and 7) and this is important evidence of the capability of the proxy model to replica the actual reservoir model behaviors. Table (3) illustrates the comparison between the two methods in the probability of estimation. The error percentages between the two methods don't exceed 0.1% and that is very accurate from the proxy model to perform the uncertainty quantification.
2. From Figures (6 and 7), we notice that the P50 is more closer to P90 than to the P10 and that means the risk is low due to the small gap between the P50 and P90.

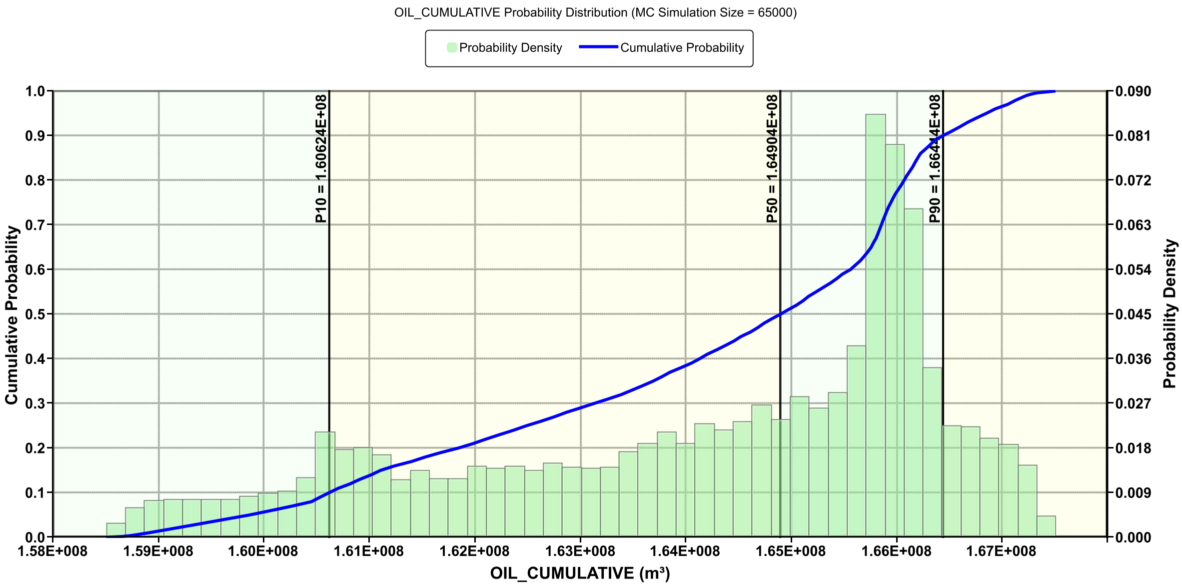

Fig. (6): Monte Carlo simulation for cumulative probability and probability density by MCRS method.

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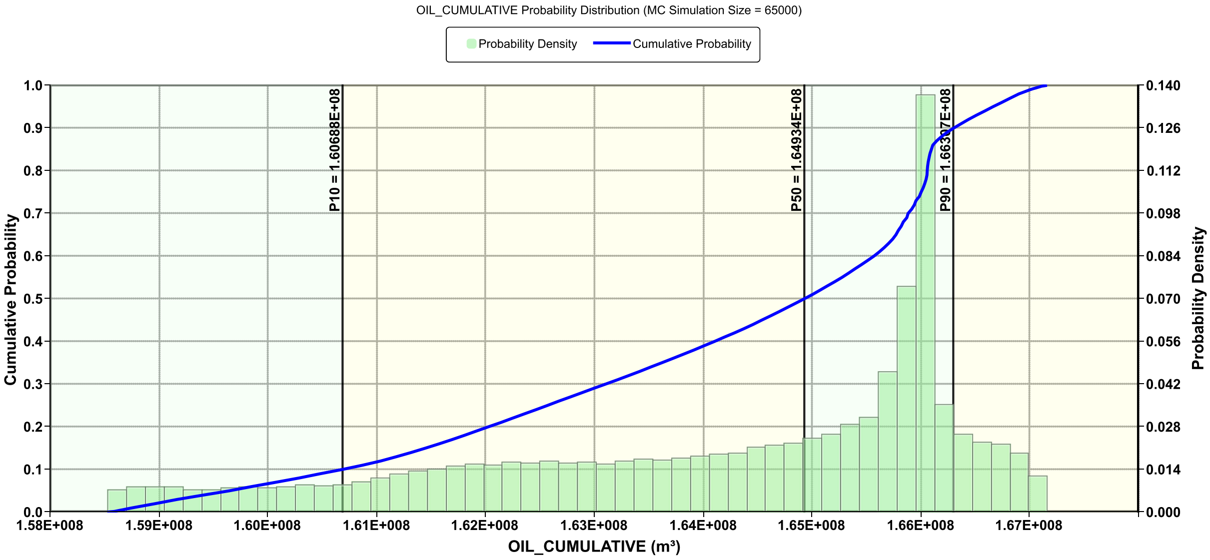

Fig. (7): Monte Carlo simulation for cumulative probability and probability density by MCP method.

Table (3): Probability comparison between MCRS and MCP.

Probability	MCRS method *10^8 m^3	MCP method *10^8 m^3	Error
P 10	1.60624	1.60688	0.04 %
P 50	1.64904	1.64934	0.02 %
P 90	1.66444	1.66307	0.08 %

3. The number of simulation runs is considered an extremely essential point in any objective function perform, especially in uncertainty assessment due to the high number of run requirements. In the MCRS method, 500 simulation runs are conducted to perform the uncertainty quantification while the MCP method requires 15 simulation runs to perform the objective function (the number of runs in the MCP depends on the number of uncertain parameters). Therefore, the process of uncertainty assessment in the MCP conducted the objective function for 2 hours while the MCRS method required 4 days to perform the objective function with the same results. Figures (**Error! Reference source not found.** and 9) illustrate the number of simulation runs and time-consuming for each method.
4. The proxy validation is a very high degree where the coefficients of determination of training and validation were 100 % and 95 % respectively. This proxy model could be used to perform more experiments with accurate and reliable results in any artificial intelligence as shown in Figure (10).

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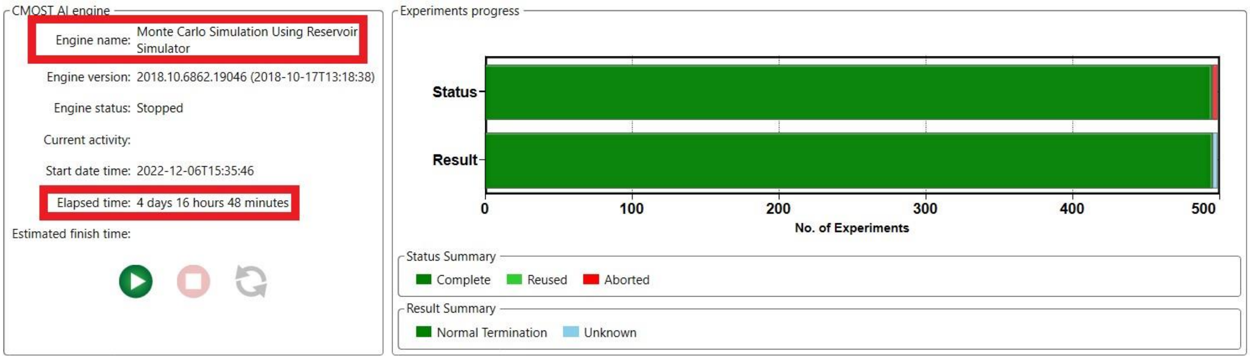

Fig. (8): The number of simulation runs and time-consuming for the MCRS method.

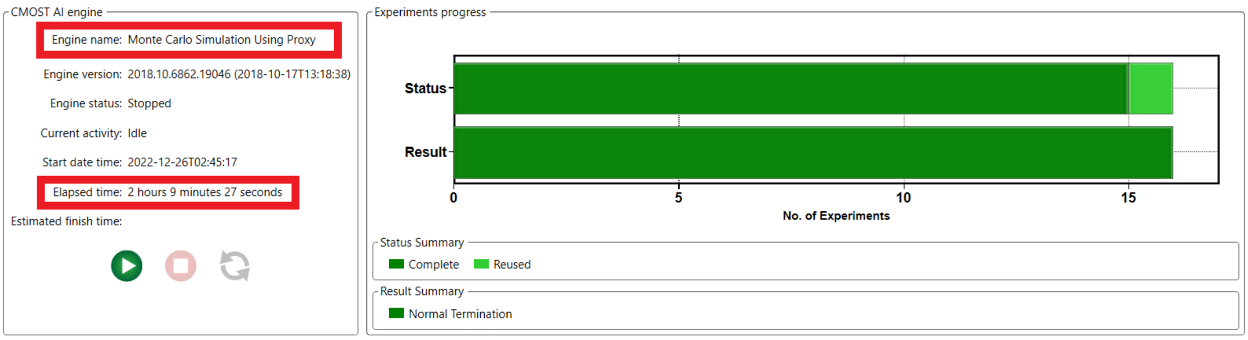

Fig. (9): The number of simulation runs and time-consuming for the MCP method.

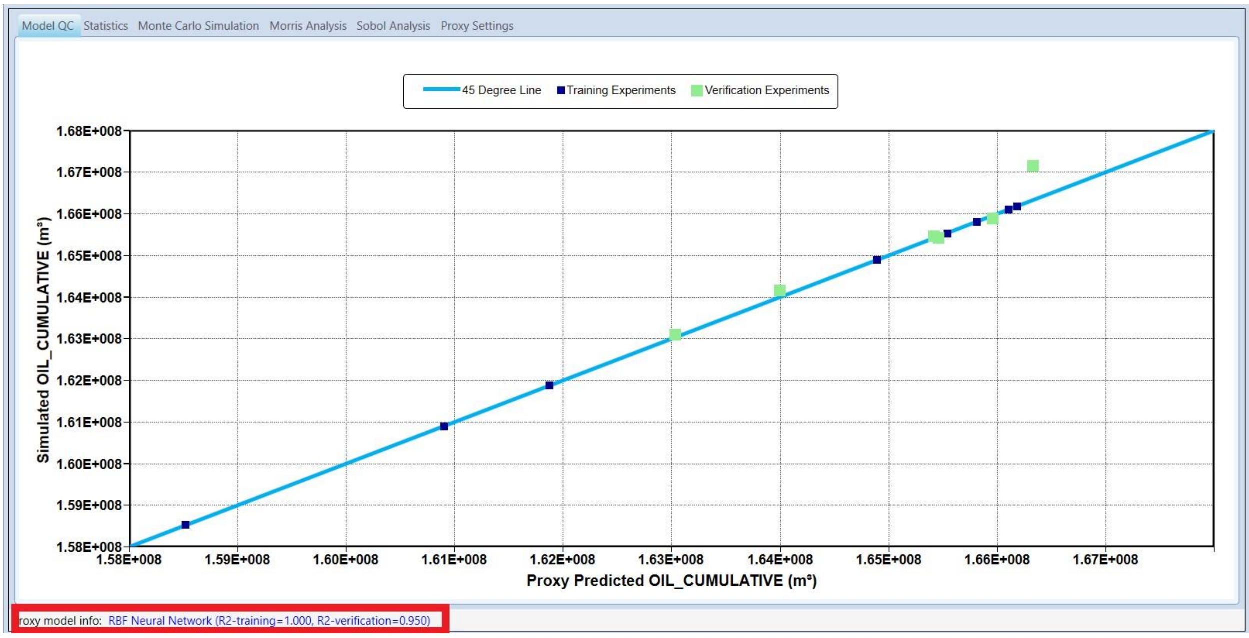

Fig. (10): Proxy model validation by cross plot between proxy model vs. simulation model.

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Figures (**Error! Reference source not found.** and 12) illustrate the identical between the MCRS and MCP methods in performing the uncertainty assessment through the behavior of the cumulative oil production.

The summarization of the comparison between these two methods is that the MCP is a very useful and powerful tool to conduct the uncertainty quantification than the MCRS method because the MCP performs the objective function with extremely less time-consuming than the MCRS method at the same time the results are very accurate and identical with the results of the MCRS method.

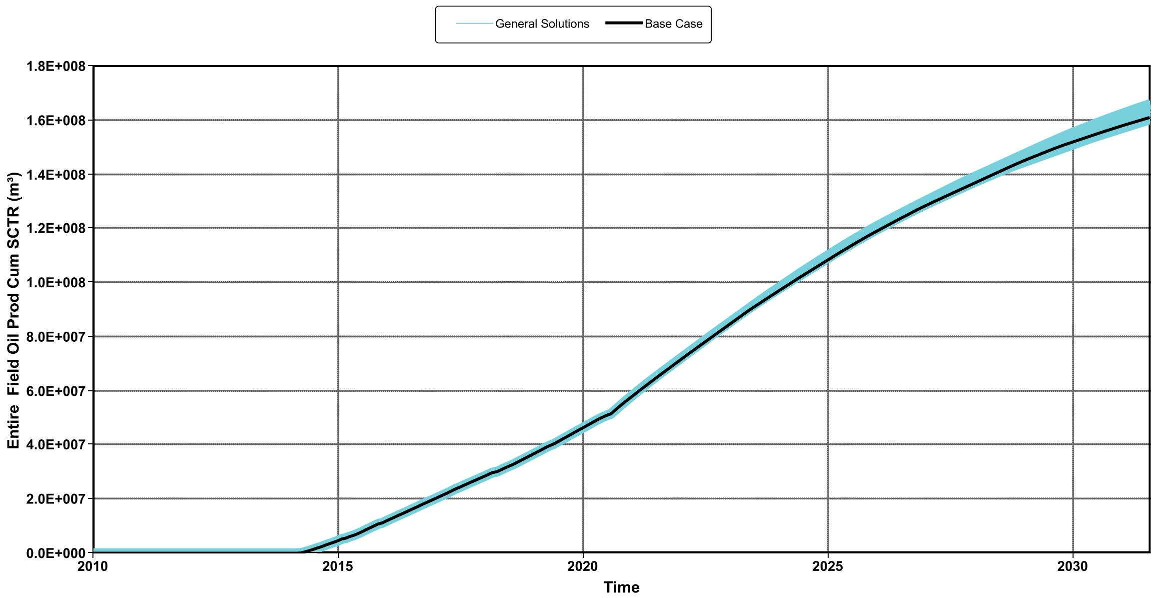

Fig. (11): Effect of Geological Uncertainty on Field Cumulative Oil Production by Monte Carlo simulation using reservoir simulator.

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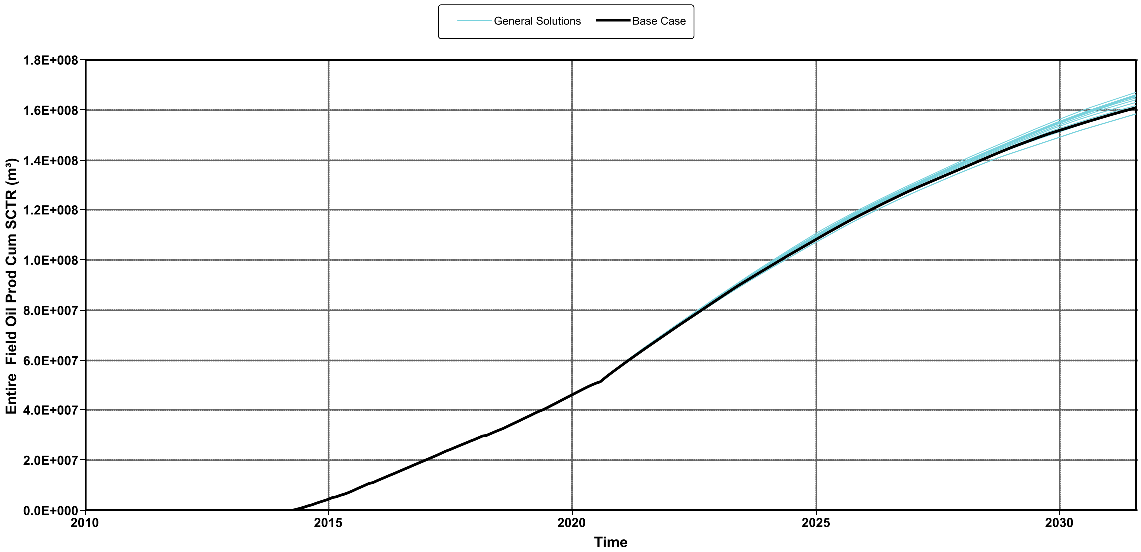

Fig. (12): Effect of Geological Uncertainty on Field Cumulative Oil Production by Monte Carlo simulation using Proxy.

5. Conclusions:

1- The oil-water-contact depth is the dominant parameter that affects cumulative oil production while porosity is the less influential parameter.

2- The results of uncertainty of dynamic model and compared it with the observed data for real production time show that the real case is closer to P50 and that indicates the model's uncertainty is moderate and not biased for optimistic or pessimistic results.

3- The Monte Carlo using Proxy method (MCP) is very useful and powerful tool to conduct the uncertainty quantification than the Monte Carlo using Reservoir Simulator method (MCRS) because the MCP performs the objective function with extremely less time-consuming and a very accurate and identical results compared to the results of the MCRS method.

4- The results of uncertainty quantification for production forecast shows there is a low risk due to the small gap difference between the P50 and P90.

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