INVESTIGATION OF CONSISTENCY BETWEEN DETERMINISTIC AND PROBABILISTIC RESERVES ESTIMATES USING RESERVOIR SIMULATION

A Thesis

by

MOHAMED IBRAHIM OMAR SULIMAN

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Chair of Committee,	Duane A. McVay
Committee Members,	W. John Lee
	Yuefeng Sun
Head of Department,	A. Daniel Hill

August 2016

Major Subject: Petroleum Engineering

ABSTRACT

Over time, oil and gas producing companies have used various techniques and approaches to estimate their hydrocarbon reserves. Their approaches are set according to their own internal business needs and/or according to their interpretation of the regulatory requirements.

Reservoir simulation has been used more commonly as an optimization, production forecasting, and reservoir management tool than as a reserves and resources estimation tool, particularly for reserves estimates provided to regulatory agencies. Deterministic and probabilistic reservoir simulation approaches for reserves estimation are currently in practice with different procedures. The problem is that there is usually inconsistency in estimates from the different methods.

The objective of this work was to determine how to estimate reserves using reservoir simulation with both deterministic and probabilistic approaches such that the resulting reserves estimates from the two approaches are consistent with one another in some way. Since all the simulation runs were terminated at a fixed simulation time instead of an economic limit, the production calculated is technically not reserves. The recovery from the end of history to the end of prediction, i.e., the quantity that was recovered for the 8.5 years of prediction, was termed ROP and was used as an approximation for reserves in this study.

In this study, a distribution of the ROP estimate was generated using multiple simulation models with the probabilistic approach. A deterministic ROP estimate was derived using the simulation model that has the best history match out of the simulation models that were generated using the probabilistic approach.

It is concluded that the consistency between the deterministic and probabilistic reserves cannot be guaranteed and it is hard to say where exactly the deterministic reserves will fall on the probabilistic reserves distribution. The consistency between the deterministic and probabilistic reserves is controlled by the relationship between reserves and the uncertain parameter, the relationship between the uncertain parameter and mismatch objective function (OF), and the acceptance threshold of the models to be included in generating the reserves distribution.

Therefore, deterministic reserves estimates should be used with caution, as it is uncertain which reserves categories the deterministic estimate represents for any situation.

DEDICATION

To my beloved parents for all their unlimited love, sacrifices, and support

ACKNOWLEDGEMENTS

I would like to express my gratitude to my advisor, Dr. Duane McVay, for his patience, technical support, and encouragement throughout my graduate studies at Texas A&M University.

Also I would like to thank my committee members, Dr. John Lee, and Dr. Yuefeng Sun for their guidance and support throughout the course of this research.

Thanks also go to my friends and colleagues and the department faculty and staff for making my time at Texas A&M University a great experience.

Finally, thanks to my family for their encouragement, patience and love.

NOMENCLATURE

2D	=Two dimensional
3D	=Three dimensional
BHP	=Bottom hole pressure
d	=Day
m	=Meter
md	=Millidarcy
NPV	=Net present value
OF	=Objective function
OIIP	=Oil initial in place
phi	=Porosity
PVT	=Pressure, volume and temperature relationship
SE	=South east
STB	=Stock tank barrel

TABLE OF CONTENTS

Page

LIST OF FIGURES

Page

LIST OF TABLES

1. INTRODUCTION AND LITERATURE REVIEW

1.1 Introduction

Over time, oil and gas producing companies have used various techniques and approaches to estimate their hydrocarbon reserves. Their approaches are set according to their own internal business needs and/or according to their interpretation of the regulatory requirements.

Reservoir simulation has been used more commonly as an optimization, production forecasting, and reservoir management tool than as a reserves and resources estimation tool, particularly for reserves estimates provided to regulatory agencies. There are no published standards regarding the best practices for evaluation of reserves and resources using reservoir simulation as noted in the Guidelines for Application of the Petroleum Resources Management System (PRMS 2011).

The United States Securities and Exchange Commission (SEC) published the new rules "Modernization of Oil and Gas Reporting" in January 2009 (SEC 2009). The new rules in paragraph (a) (25) of rule 4-10 on page 2192 require that a "Reliable Technology," including computational methods, must be demonstrated in practice on a repeatable and consistent basis to provide the claimed level of certainty for reporting reserves of any category; however, it does not specify the reliable technology that can be used (SEC 2009). Moreover, the new rules in paragraph (a) (24) of rule 4-10 on page 2192 allow using both deterministic and probabilistic approaches in reserves estimation (SEC 2009).

Estimators who prefer deterministic methods find it straightforward, easy to explain, and needing less effort. According to Capen (1996), many competent engineers feel that a qualified engineer ought to be able to find the answer without significant error and, thus, applying probabilities to reserves makes no sense. On the other hand, reserves are always uncertain and the ultimate goal is to quantify the uncertainty. To achieve that ultimate goal, the systematic probabilistic approach is the best auditable and justifiable method (Wolff 2010b). Deterministic and probabilistic approaches are currently in practice with different procedures (Patricelli and McMichael 1995, Purvis et al. 1997, Dehghani et al. 2008, Sajjadian et al. 2010). The problem is that there is usually inconsistency in estimates from the different methods (Rietz and Usmani 2009, Dehghani et al. 2008, Purvis et al. 1997).

Reliable reserves estimates are important for governments, companies, regulators, analysts, investors, and the public. For instance, an analyst who assesses companies' worth is usually influenced by short-term earnings and stock prices that are strongly reserves related. An investor is interested in development costs and reserves replacement ratios because of the fact that the ability to generate revenue in the future will shrink if no new reserves replaced the produced volumes. Producing companies compete between each other for capital with reserves-based borrowing. According to Dharan (2004), 70% of a producer's total market value is based on its proved reserves, and the value of the total proved reserves of over 150 publicly owned US oil and gas companies has exceeded $3 trillion. Finally, government and regulatory bodies, such as the SEC, require US-based oil and gas companies to report and disclose their proved reserves annually.

1.2 Background

1.2.1 History of Reserves Definitions

The development of reserves definitions started in 1936 by the American Petroleum Institute (API), which was involved in the annual studies of oil reserves in the U.S., while the American Gas Association (AGA) joined the API and set definitions for natural gas reserves in the annual studies of oil and gas reserves in 1946 (Harrell and Gardner 2005). In 1964, the Society of Petroleum Engineers (SPE) issued similar definitions. After that, the SEC in 1975 was required to take necessary steps to guarantee that persons involved in the production of crude oil or natural gas in the United States are following the accounting practices by the Energy Policy and Conservation Act of 1975 (US-Code 2012). In 1978, the SEC established definitions for proved oil and gas reserves. In 1987, both the SPE and the World Petroleum Council (WPC) published similar reserves definitions independently. Later, the SPE and the WPC jointly published the first standardized reserves definitions that could be used internationally in 1997. In 2000, the "Petroleum Resources Classification System and Definitions" was approved by the SPE, the WPC, and the American Association of Petroleum Geologists (AAPG). After that, the Society of Petroleum Evaluation Engineers (SPEE) with the SPE, the WPC, and the AAPG updated and approved the previous definitions as the "Petroleum Resources Management System" (PRMS) in 2007. On December 31, 2008, the SEC updated their rules as the "Modernization of Oil and Gas Reporting" using PRMS as a guide (PRMS 2007). On January 14, 2009, the new rules were published in the Federal Register (SEC 2009).

According to PRMS (2007), reserves are classified into three categories based on the range of uncertainty: proved (1P), proved-plus-probable (2P), and proved-plus-probable-plus-possible (3P). When a probabilistic approach is used to represent the range of uncertainty, the three classes shall be presented such that:

- There should be at least 90 % probability (P90) that the recovered quantities will be equal or exceed the proved reserves estimate.
- There should be at least 50 % probability (P50) that the recovered quantities will be equal or exceed the proved-plus-probable estimate.
- There should be at least 10 % probability (P10) that the recovered quantities will be equal or exceed the proved-plus-probable-plus-possible estimate.

1.2.2 The Role of the SEC

There is large consistency between the revised reserves definitions of the SEC and PRMS definitions (Lee 2009). However, the SEC is a law enforcement organization, whose job is to assure responsible reporting of oil and gas reserves by operators that will "protect investors, maintain fair, orderly, and efficient markets, and facilitate capital formation" (SEC 2013). According to the West's Encyclopedia of American Law (2008), the SEC writes rules, establishes laws and enforces its rules by prosecuting violators, in addition to holding adjudicative hearings and acting as judge and jury to settle conflicts and prescribe sanctions. Such authority was given when the Congress passed the Administrative Procedures Act (APA) in 1946. Therefore, US-based oil and gas companies have to disclose their oil and gas proved reserves to the SEC annually.

Reserves definitions are the criteria that qualify forecasted recoveries as reserves regardless of the method used. The SEC has established several definitions that US-based oil and gas companies have to compute their reserves in accordance with. In January 2009, the SEC published the new rules known as "Modernization of Oil and Gas Reporting; Final Rule" in the Federal Register on pages 2190 to 2192 (SEC 2009).

1.2.3 Reserves Estimation Methods

Reserves are estimated using different methods such as analogs, volumetrics, decline curve analysis, and material balance. Reservoir simulation has been used more commonly as an optimization, production forecasting, and reservoir management tool than as a reserves and resources estimation tool, particularly for reserves estimates provided to regulatory agencies.

Reservoir simulation is a sophisticated methodology that applies computer programs (simulators) to model static geological characteristics and dynamic flow characteristics. One of the benefits of reservoir simulation is that it integrates rigorously and simultaneously almost all geoscience and engineering data that influence the production behavior of the reservoir (Mattax and Dalton 1990).

Lee et al. (2011) concluded that simulation is a potential reliable technology once it satisfies the criteria of consistency and repeatability. The authors applied the steps of the scientific method described by Sidle and Lee (2010) to demonstrate the required consistency and repeatability. A hind-cast test, which matches a portion of the history data and predicts the remaining portion of history data, is used by the authors as strong evidence of reliability of simulation predictions. Accurately honoring the match period and hind-cast period gives confidence to the standard of consistency according to the authors. The standard of repeatability is judged by the authors by showing that sensitivity runs of key assumed input data have either little/no impact on predictions after the end of actual history, or significant impact on both the match period and the hind-cast period.

Over time, oil and gas producing companies have used various techniques and approaches to estimate their recoverable hydrocarbons deterministically and probabilistically. Their approaches are set according to their own internal business needs and/or according to their interpretation of the regulatory requirements.

1.2.4 Deterministic vs Probabilistic

Deterministic and probabilistic reservoir simulation approaches for reserves estimation are currently in practice with different procedures. The deterministic approach is used to report a single representative estimate, which is usually considered as proved-plus-probable, i.e., the median, or P50. The approach is typically conducted by using a single value of each of the input parameters to derive a single outcome of the recoverable volume. In general, estimators consider the model that shows the best history match as the best estimate of the truth or the most-likely scenario to exist. The purpose of history matching is to compare the simulation results with the observed data and adjust the uncertain parameters in the simulation model to reduce the mismatch between the simulation results and observed data. The resulting simulation model should capture the level of details necessary for production forecasts with high predictive confidence.

In the probabilistic approach, probability distributions of all possible values of each input parameter are used to derive a probability distribution of all possible outcomes of recoverable volumes. It is called uniform search because the sampling from the uncertain parameters distributions was just random and it was not controlled by optimization process for minimizing the mismatch objective function as in computer-assisted history matching process. To eliminate the effect of the prior distribution on the consistency between the deterministic and the probabilistic reserves, uniform distributions of the uncertain parameters were used.

Estimators who prefer deterministic methods find it straightforward, physically easy to explain, and needing less effort. According to Capen (1996), many competent engineers feel that a qualified engineer ought to be able to find the answer without significant error and, thus, applying probabilities to reserves makes no sense. On the other hand, assessment of subsurface petroleum resources is complex and always subject to many uncertainties. Therefore, reserves are always uncertain and the systematic probabilistic approach is the best auditable and justifiable method to quantify the uncertainty (Wolff 2010b).

McVay and Dossary (2014) quantified the value of assessing uncertainty and the consequences of overconfidence. The authors demonstrated that expected disappointment (the difference between estimated portfolio NPV and realized portfolio NPV) was 30-35% of estimated NPV in cases of moderate overconfidence and optimism and up to 100% of the estimated NPV with greater degrees of overconfidence and optimism. They noted that elimination of overconfidence and optimism will eliminate expected disappointment, which will improve the performance of the organization over all.

1.2.5 Reserves Estimation Using Reservoir Simulation

According to the Guidelines for Application of the Petroleum Resources Management System (PRMS 2011), there are no published standards regarding best practices for evaluation of reserves and resources using reservoir simulation. The SEC previous rules do not specify criteria for the use of reservoir simulation models in the reserves estimation process, other than the model must have a “good history match” to derive the proved reserves (Rietz and Usmani 2005).

The SEC new rules in paragraph (a) (25) of rule 4-10 on page 2192 require that a “Reliable Technology,” including computational methods, must be demonstrated in practice on a repeatable and consistent basis to provide the claimed level of certainty for reporting reserves of any category; however, it does not specify the reliable technology that can be used (SEC 2009). Moreover, the new rules in paragraph (a) (24) of rule 4-10 on page 2192 allow using both deterministic and probabilistic approaches in reserves estimation (SEC 2009).

Patricelli and McMichael (1995) discussed the method used by Mobile Oil E&P Corp. for reserves and resources evaluation. In the deterministic analysis, a geological model was developed with calculated values of rock volume and recovery factor parameters that were claimed to be appropriate, based on a conclusive formation evaluation, to estimate proved reserves. Similarly, calculated values of rock volume and recovery factor parameters were used to estimate proved-plus-probable reserves. In the probabilistic analysis, the minimum values of rock volume and recovery factor parameters were set equal to the values used to calculate the deterministic proved reserves. Similarly, the values used to calculate the deterministic proved-plus-probable reserves were set as the most-likely values in the probabilistic analysis. Moreover, upside values of the parameters were used as maximum values in the probabilistic analysis. After that, Monte Carlo simulation was run to derive the cumulative probability distribution of the reserves and the proved-plus-probable-plus-possible reserves were derived. The authors used the deterministic and probabilistic methods as a combined approach and did not discuss any comparison between the deterministic and probabilistic estimates of the reserves categories. However, they demonstrated that a company could uses a single deterministic simulation model to estimate proved reserves, and similarly to estimate proved-plus-probable reserves, according to their own internal business needs and/or according to their interpretation of the regulatory requirements.

Purvis et al. (1997) used Monte Carlo techniques with reservoir simulation to quantify the uncertainty in production forecasts. The authors identified net thickness, gas-water contact, porosity, water saturation and permeability as uncertain parameters. A symmetrical triangular distribution was used for net thickness with a mode equal to the deterministic value. A uniform distribution was used for fluids contacts with equal height below and above the deterministic depth. A normal distribution centered at zero was used for the measurement error of porosity and water saturation so that the mode would be equal to the deterministic value with measurement error of zero. A skewed triangular distribution was used for permeability multiplier so that it is centered at one, with fifty percent of cases to be high by up to a factor of three and fifty percent of cases to be low by down to a factor of one-third. The results showed that there is agreement between the deterministic estimate and the P50 probabilistic estimate in the early years of the production rate forecast, with mismatch in the later years. The authors noted that the deterministic and P50 estimates may not be the same since they are different types of forecasts. That is, the P50 is a median value that is greater than half of the forecasted rates and less than the other half of the forecasted rates. On the other hand, the deterministic forecast is the most likely outcome, not the median outcome. The study was to be used for internal company decision-making and not to report reserves. Also, a 2D cross sectional simulation model was used in this study and the uncertainty in porosity, permeability and water saturation was addressed only in the vertical direction.

Dehghani et al. (2008) conducted an integrated probabilistic reservoir simulation study to address uncertainties and better manage the Tangiz field. Static and dynamic uncertainties were investigated and a “base model” was constructed by setting each of the uncertain parameters to a reasonable “most likely” value based on the geological and engineering judgment of the authors. To handle the geostatistical uncertainty, random seed values and variogram lengths were used with geostatistical techniques such as sequential Gaussian simulation to provide a set of non-unique realizations of reservoir properties. The simulation model was history matched and uncertainty analysis on the prediction runs were conducted for different combinations of the dynamic parameters. The results of the uncertainty analysis were used to generate a response surface. After that, Monte Carlo simulation is conducted to generate the cumulative distribution of recoveries using the response surface and distribution of the parameters. For the desired probability, the combination of parameters is selected for a final deterministic simulation run. As the objective of their study was to understand the uncertainties in the recoveries, the authors did not discuss any comparisons between reserves estimates from the deterministic base model and P50 from the generated cumulative distribution. However, they stated that the base model may not have the same original oil volume as the P50 model from the probabilistic study because of the uncertainty in the locations of the boundaries between regions away from wells.

Sajjadian et al. (2010) conducted a risk analysis to quantify the uncertainty in the oil initially in place (OIIP) and reserves using reservoir simulation. No distributions of the uncertain parameters were used. However, collection of different realizations that represent discrete sets of the uncertain parameters is defined. The addressed uncertainties are structure, net-to-gross ratio (NTG), porosity, initial water saturation, absolute permeability, relative permeability shape and endpoints, skin factor, and minimum well-head pressure. After that, Monte Carlo simulation was run to generate 200 simulation models with different combinations of the uncertain parameters. Subsequently P10, P50, and P90 percentiles were derived from the oil initial in place (OIIP) and reserves distributions. The authors concluded that, for the addressed reservoir, the top structure uncertainty has the most impact on the OIIP calculations and NTG with permeability uncertainty have the most impact on reserves. The authors did not use the deterministic approach and therefore did not compare probabilistic and deterministic estimates. However, they demonstrated using probabilistic reservoir simulation according to their own internal business needs to quantify the uncertainty in the OIIP and reserves.

The Guidelines for Application of the Petroleum Resources Management System noted that a multidisciplinary team with appropriate skills and experience is required to develop a meaningful reservoir simulation model that can generate reliable results with reasonable certainty once it showed reasonably good history match (PRMS 2011). The guidelines mentioned two cases of using reservoir simulation to evaluate and categorize reserves. In the first case, three different reservoir simulation models based on three different geological realizations, representing low, best, and high estimates are used directly to estimate hydrocarbons in place and reserves. The realizations are selected depending on the estimator's choice of the uncertain parameters values that are the most appropriate for the corresponding reserves category. In the second case, a single simulation model that represents the most-likely or best estimate is used to derive the best estimate of reserves and then sensitivity runs are used to derive the range of uncertainty and assign the low and high reserves estimates accordingly. The reserves are categorized based on the degree of uncertainty the estimator determined to exist in the reserves estimates. There are no published standards regarding the best practices for evaluation of reserves and resources using reservoir simulation as noted in the Guidelines for Application of the Petroleum Resources Management System (PRMS 2011).

1.2.6 Categorizing Reserves from Reservoir Simulation

Simulation models traditionally have been used as a reservoir management tool for improving the understanding of reservoir performance and making better development decisions. According to Palke and Rietz (2001), optimizing a reservoir development plan based on proved reserves could under-deplete the reservoir and reduce the overall production. Therefore, the most-likely scenario is more commonly considered for optimization purposes. The SEC recognizes that simulations models are usually built to estimate most-likely or proved-plus-probable cases and therefore the models need to be adapted before being used for estimating proved reserves (Harrell and Gardner 2005).

Rietz and Usmani (2009) provided a case study illustrating the adjustment of reservoir simulation models and using their results to assist in quantifying reserves. In this study, an initial base-case simulation model was constructed using the most-likely input parameters and considered as the proved-plus-probable estimate. After that, a probabilistic Monte Carlo study was performed to assess the likely distribution of ultimate recovery. The authors found that the Monte Carlo probabilistic P50 showed ultimate recovery less than the 2P estimate from the deterministic base-case model. They explained that the parameters chosen to build the base case were more optimistic than the parameters used to derive the probabilistic P50. However, they did not provide any insights on how to ensure consistency between deterministic and probabilistic reserves estimates.

Lee et al. (2011) suggest that if the sensitivity runs showed good history matches while giving different predictions then 1P, 2P, and 3P reserves estimates can be extracted according to the appropriate level of certainty. Two examples were demonstrated by the authors: the first is a single model that was used for both 1P and 2P scenarios by changing just the operational conditions, and the second example consists of multiple models that have good history matches and represent a range of internally consistent scenarios from 2P, with higher estimate of reserves, to 1P, the most conservative case. The full probabilistic approach considering the full range of outcomes was beyond the scope of their work.

1.3 Summary of the Literature and Research Objectives

To sum up the literature, different estimators use different approaches based on their own internal business needs and/or according to their interpretation of the regulatory requirements (Patricelli and McMichael 1995, Purvis et al. 1997, Dehghani et al. 2008, Sajjadian et al. 2010). The base deterministic case is traditionally built using the most-likely values of the input parameters (Patricelli and McMichael 1995, Purvis et al. 1997, Palke and Rietz 2001, Harrell and Gardner 2005, Dehghani et al. 2008, Rietz and Usmani 2009, PRMS 2011).

There were some attempts to compare deterministic estimates with probabilistic estimates using reservoir simulation. Purvis et al. (1997) showed that there is agreement between the deterministic estimate and the P50 probabilistic estimate in the early years of the production rate forecast, with mismatch in the later years. Dehghani et al. (2008) stated that the base model may not have the same original oil volume as the P50 model from the probabilistic study because of the uncertainty in the locations of the boundaries between regions away from wells. Rietz and Usmani (2009) found that the Monte Carlo probabilistic P50 showed ultimate recovery was less than the 2P estimate from the deterministic base-case model.

To my knowledge there has been no thorough investigation of the consistency between the two approaches and how the estimates can be reconciled. The objective of this study is to determine how to estimate reserves using reservoir simulation with both deterministic and probabilistic approaches such that the resulting reserves estimates from the two approaches are consistent with one another in some way.

2. METHODOLOGY AND MODEL DESCRIPTION

2.1 Available Data

A set of available data including a simulation model and a rough geological description, well porosities and well permeabilities and a production strategy were acquired from the literature. The data set is publically available under PUNQ-S3 model on the internet page of the petroleum engineering & rock mechanics research group at the department of earth science and engineering at Imperial College (Elf 1997). These data were used to build the truth-case simulation model and generate the synthetic history.

2.1.1 PUNQ-S3 Simulation Model

A project of production forecasting with uncertainty quantification was carried out to compare different techniques of quantifying uncertainty in the oil production forecast. The project involved oil companies, research institutes, and 10 European universities. A synthetic reservoir simulation model known as PUNQ-S3 was created by one of the involved organizations (Floris et al. 2001). The model is a small-size industrial reservoir engineering model containing 19x28x5 grid blocks with 1761 active blocks of 180 meters length and width each. PVT data and relative permeability functions were also defined in the simulation model. Zero capillary pressure was assumed. A strong aquifer surrounds the reservoir from the north and west, whereas a fault delimits the reservoir from the south and east. A small gas cap is centered in the dome-shaped reservoir. **Fig. 1** shows the top structure map of the reservoir.

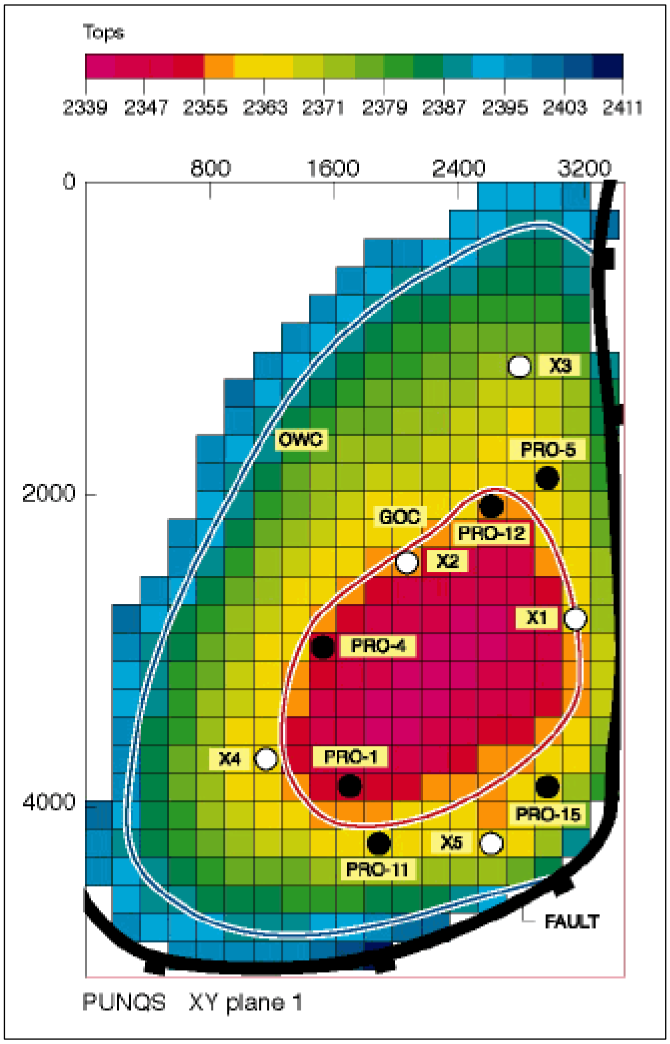

Fig. 1—Top structure map of PUNQ-S3 (adapted from Floris et al., 2001)

2.1.2 Geological Description

Based on the knowledge of the regional geology, the reservoir was geologically described as good quality layer in Layers 1, Layer 3, Layer 4, and Layer 5. These layers represent fluvial channel fills and lagoonal delta. In Layers 1, Layer 3, and Layer 5 there are linear streaks of high-porosity sands (phi > 20 %) with an azimuth somewhere between 110 and 170 degrees SE. The streaks are embedded in low quality matrix (phi < 5 %) and their width and spacing vary between layers. In contrast, Layer 2 represents poor quality lagoonal shales with low-porosity (phi < 5%) shaly sediments and some irregular patches of somewhat higher porosity (phi > 5%). An intermediate-porosity region (phi ~ 15%) with an approximate lobate shape embedded in a low-porosity matrix (phi < 5%) forms Layer 4. The longest axis of the lobate shape is perpendicular to the paleocurrent (which is between 110 and 170 degrees SE).

2.1.3 Production Strategy

There are six production wells located around the gas-oil contact and no injection wells are present due to the strong aquifer. The provided production strategy starts with one year of extended well testing that consists of four three-month production periods, each having its own production rate, followed by a three-years shut-in period, followed by 12.5 years of field production. In every year of the 12.5 years, each well is shut in for 2 weeks for testing to collect shut-in pressure data. The wells are operating under oil production rate control with upper limit of 150 m^3/day/well, and BHP lower limit of 120 bars, below which the wells will switch to BHP control. Also, well cut-back limits were set to reduce the oil flow rate with a factor of 0.75 whenever the gas-liquid ratio exceeds 200 sm^3/sm^3 and/or the well block pressure drops below 120 bars. The total simulation period is 16.5 years. **Fig. 2** shows the field oil production rate according to the provided production scheme of PUNQ-S3 model.

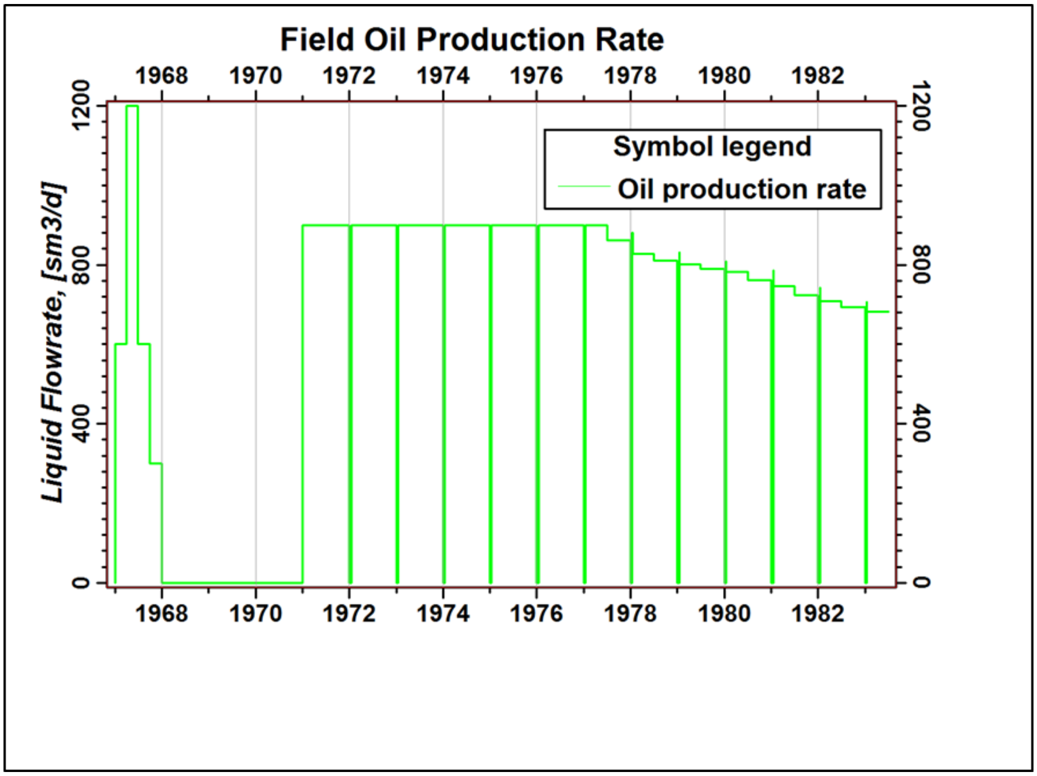

Fig. 2—Field oil production strategy for PUNQ-S3 model

2.2 Truth-Case

A truth-case simulation model is needed to generate the synthetic history to be used in the history matching process. Geological and dynamic modeling workflows are applied to generate the truth-case model using Petrel & Eclipse softwares.

2.2.1 Truth-Case Generation

To model the available geological description, using Petrel software, a property modeling process is performed by filling the grid blocks with continuous properties such as porosity and permeability. The objective of the property modeling process is to distribute properties between the available wells so it realistically preserves the reservoir heterogeneity and matches the well data. Porosity and permeability values at the well blocks were provided and will be used in the property modeling process.

As the property modeling processes are used to describe the natural random variation in a property, the variogram should describe this natural variation. Based on the concept that two points close together are more likely to have similar values than points far away from each other, the variogram is described by some parameters like major range (MJR), minor range (MNR), and azimuth. The range is the maximum distance in meters where sample values are dependent on each other. The range is given in a major horizontal distance that is called a major range and a minor distance that is normal to the major range and it is called a minor range. The azimuth is the orientation of the major range.

Gaussian Random Function is the geostatistical estimation technique that was used to map the porosity field in the truth-case model honoring well data, input distributions, and variograms. This geostatistical estimation technique uses a random seed in addition to the variogram parameters, so while consecutive runs will give similar equal probability realizations with the same variogram parameters, the details of the realizations will be different. The 3D grid is organized in numbered cells. The value of the property is calculated at the cells according to a random path that is decided by the seed number. The seed number is the integer value that represents the start point of the random path and it is used to preserve the random nature throughout the model. For every seed number, a kriging algorithm is run to estimate the value of the property at the starting point using the neighboring data points. After that, the value of the property is calculated using the neighboring data points and the recent estimated point at a new point on the random path that is decided by the seed number. The same process is repeated until all points on the random path have their values of the property estimated. The result will be a unique realization for each unique seed number. The values of the geostatistical parameters were defined to be as consistent as possible with the geological description. Porosity and Permeability fields were truncated with minimum and maximum limits to avoid any non-physical values. A global seed number of 100 was used for the five layers. **Table 1** shows the values of the geostatistical parameters and truncation limits that were used to model the geological description. **Fig. 3** shows the porosity maps of the five layers in the truth-case model.

Table 1—Truth-case geostatistical parameters

Layer	MJR m	MNR m	Azimuth	Porosity		Horizontal Permeability md		Vertical Permeability md		Seed
				Min	Max	Min	Max	Min	Max	
1	7000	1000	-40	0.01	0.3	0.8	998	0.3	498	
2	2500	2200	-60	0.01	0.17	0.5	198	0.2	50	
3	5000	1000	-40	0.01	0.3	5.9	999	6.0	469	100
4	3500	650	50	0.01	0.22	0.5	499	0.4	100	
5	5000	800	-40	0.01	0.3	0.9	999	0.8	498	

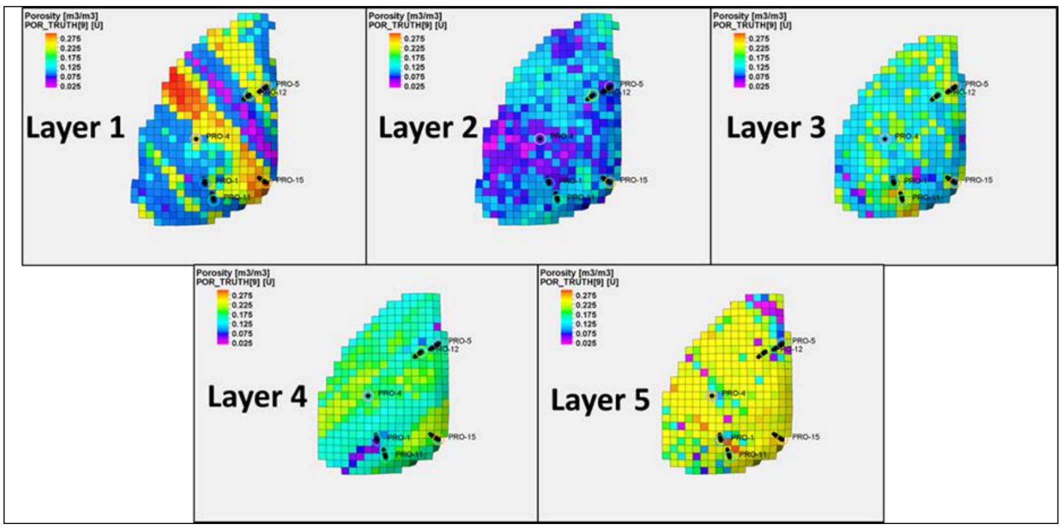

Fig. 3—Porosity maps of the truth-case model

In many cases, the properties being modeled are likely to be related to one another; permeability is often high in areas of high porosity. In the PUNQ-S3 project and in this study, a correlation coefficient between porosity and horizontal permeability of 0.8 and a correlation coefficient between horizontal permeability and vertical permeability of 0.8 were used. Reliable permeability data is usually much less available than porosity data. Therefore, there is often a relationship between these two properties and it is common practice to base the permeability model directly upon the porosity model. Collocated Co-simulation calculates the horizontal permeability in the area of each cell using the porosity as secondary variable, together with the correlation coefficient of 0.8, to keep consistent correlation between porosity and horizontal permeability. **Fig. 4** shows the horizontal permeability maps of the five layers in the truth-case model. The porosity vs permeability cross plot from the generated porosity and horizontal permeability maps of the truth-case model in this study, shows that the correlation coefficient is 0.8 as was used in PUNQ-S3 project (**Fig. 5**).

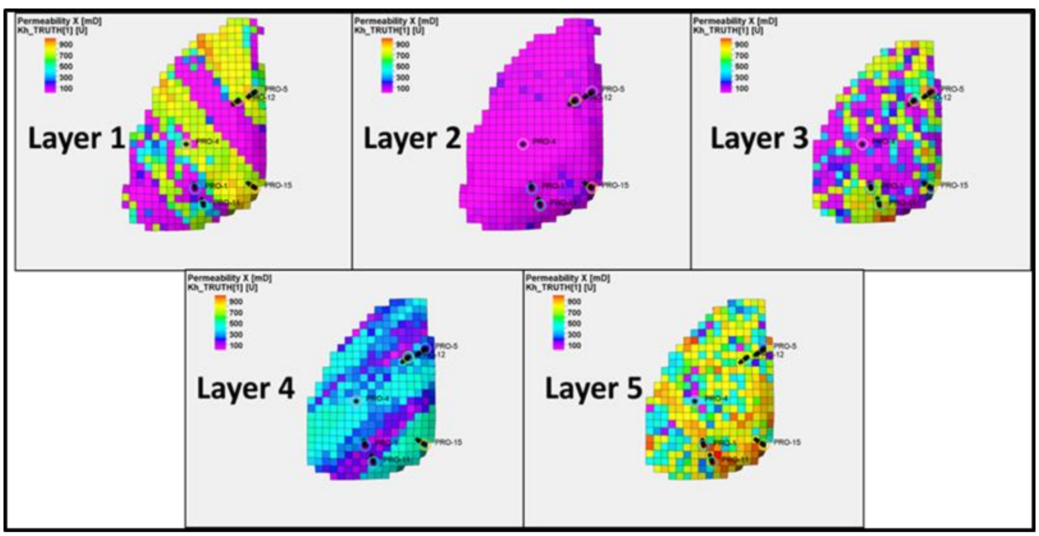

Fig. 4—Horizontal permeability maps of the truth-case model

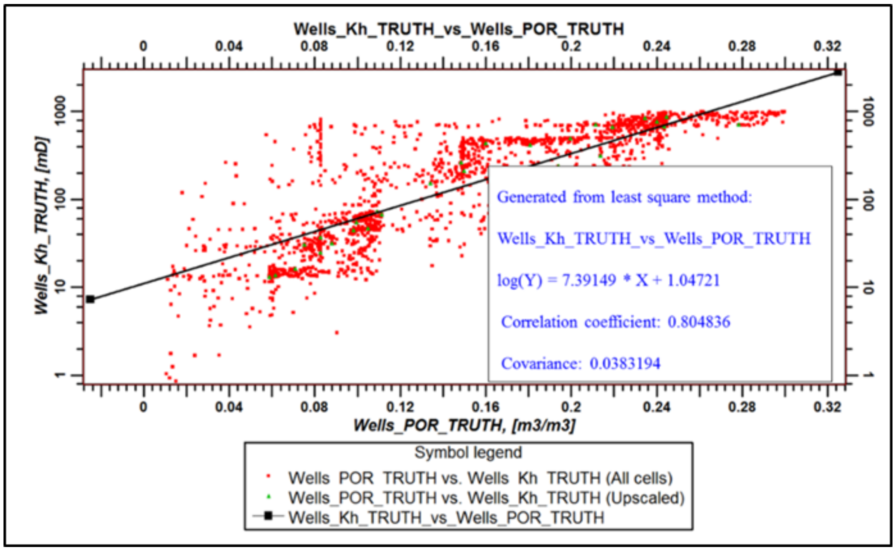

Fig. 5—Porosity vs permeability cross plot from the generated porosity and permeability maps

Similarly, Collocated Co-simulation calculates the vertical permeability in the area of each cell using the horizontal permeability as secondary variable, together with the correlation coefficient of 0.8, to keep consistent correlation between horizontal permeability and vertical permeability. **Fig. 6** shows the horizontal permeability maps of the five layers in the truth-case model.

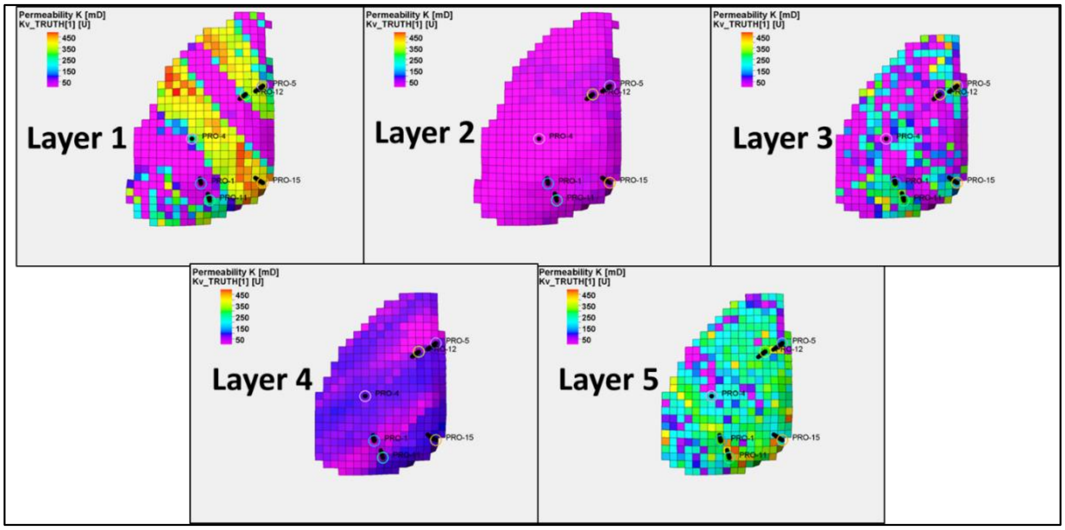

Fig. 6—Vertical permeability maps of the truth-case model

A Carter-Tracy aquifer model is used to simulate amounts of water connected to the reservoir and how it affects the reservoir behavior. The aquifer model is defined to have the initial pressure in hydrostatic equilibrium with the reservoir. The datum depth is 2355 m at the gas-oil contact and the oil-water contact depth is 2395 m. The aquifer permeability is 137.5 md and the aquifer porosity is 0.2125. After that, the truth case was created, and the truth-case simulation model was ready to run.

2.2.2 Observed Data Generation

After the truth-case model was built, the next step was to run the generated simulation model and create a synthetic history that was used in the history matching process. The generated synthetic history includes oil rates, gas-oil ratio (GOR), water cut (WCT), static bottom-hole pressure (SBHP) and flowing bottom-hole pressure (FBHP) for every single well. The synthetic history was reported at a frequency of monthly in the first year, annually in three-years shut-in period, and semiannually in the years of production. In every year of the production years, each well was shut in for 2 weeks for testing to collect shut-in pressure data. The wells were operating under oil production rate control with upper limit of 150 m^3/day/well, and BHP lower limit of 120 bars, below which the wells switches to BHP control. Also, well cut-back limits were set to reduce the oil flow rate with a factor of 0.75 whenever the gas-liquid ratio exceeds 200 sm^3/sm^3 and/or the well block pressure drops below 120 bars.

To mimic the systematic nature of errors in production data, a Gaussian noise with standard deviation (Std) of measurement error was added to the production ratios and pressures considering the shut-in/flow periods and the breakthrough times. The measurement error for pressures during the flowing period was 3 bars and during the shut-in period was 1 bar, as a shut-in pressure is more accurate. The measurement errors of WCT was defined as 2% before water breakthrough and 5% after water breakthrough. Similarly, GOR measurement error was set to 10% before gas breakthrough and 25% after gas breakthrough. The limits of the Gaussian noises were truncated to avoid generating extreme noisy measurements. The truncation limits for pressures during the flowing period was 5 bars and during the shut-in period was 3 bar, as a shut-in pressure is more accurate. The truncation limits of WCT was defined as 3% before water breakthrough and 7% after water breakthrough. Similarly, GOR truncation limits was set to 15% before gas breakthrough and 30% after gas breakthrough. **Table 2** shows the noise levels applied to each measurement. Well PRO-5 had water breakthrough during the 6th year, Well PRO-1 had gas breakthrough in the 5th year, and Well PRO-4 had gas breakthrough in the 7th year.

Fig. 7-Fig. 13 show comparisons between the truth-case performance and the generated noisy observed data at the reservoir and well levels. The ECLIPSE data file of the truth-case model is included in Appendix A.

Table 2—Observed data noise levels

Measurement	Error
SBHP	1 bar
FBHP	3 bar
GOR Before Gas Breakthrough	10%
GOR After Gas Breakthrough	15%
WCT Before Water Breakthrough	2%
WCT After Water Breakthrough	5%

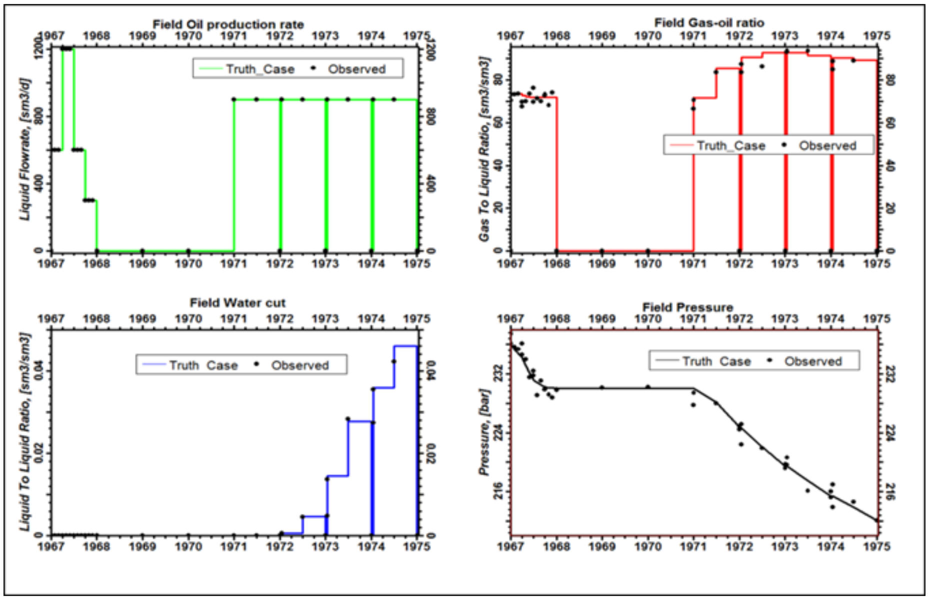

Fig. 7—Comparison of the truth-case and noisy observed field performance

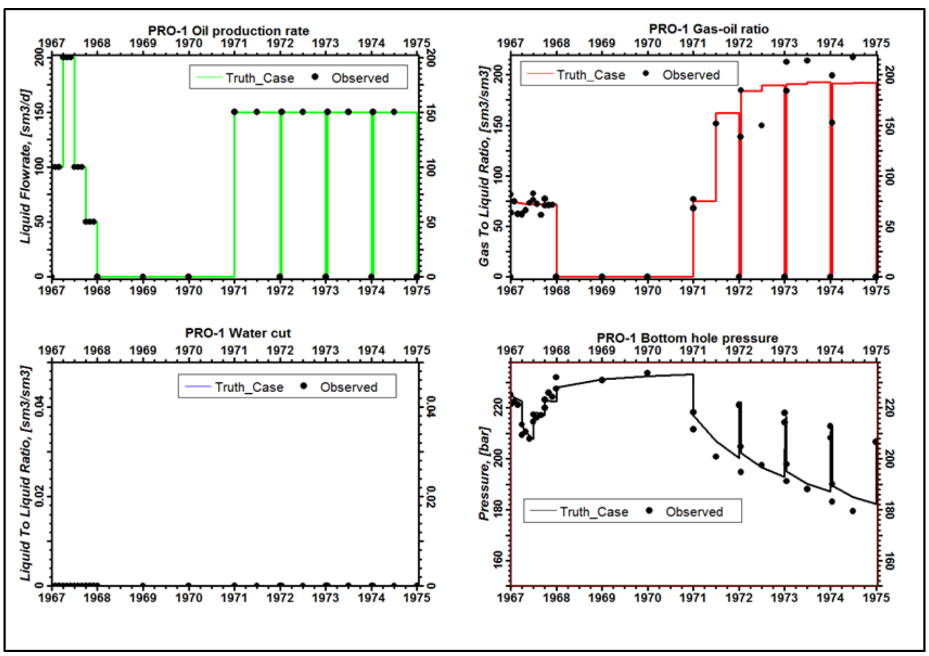

Fig. 8—Comparison of the truth-case and noisy observed PRO-1 performance

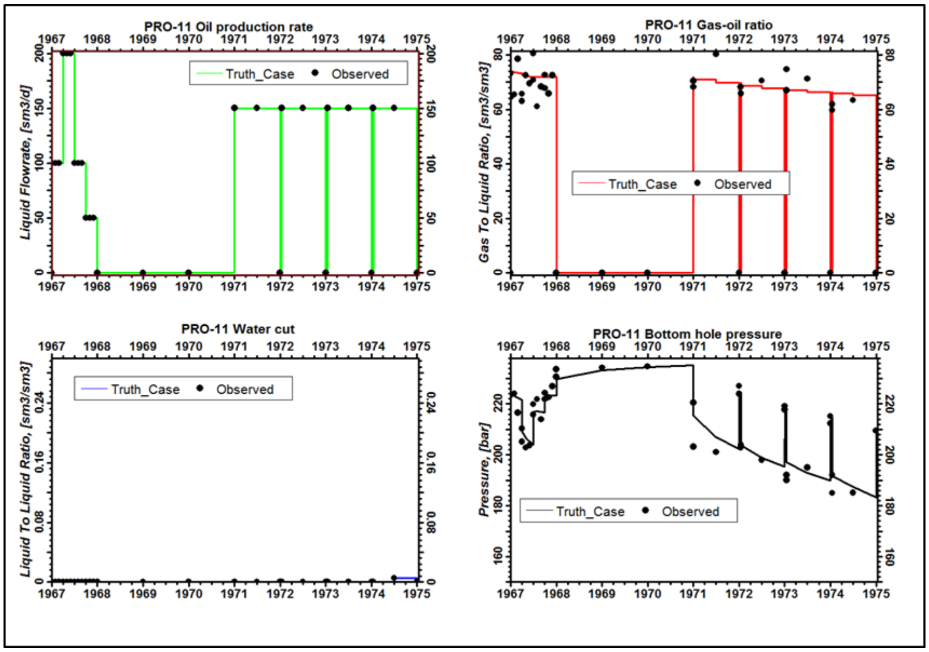

Fig. 9—Comparison of the truth-case and noisy observed PRO-11 performance

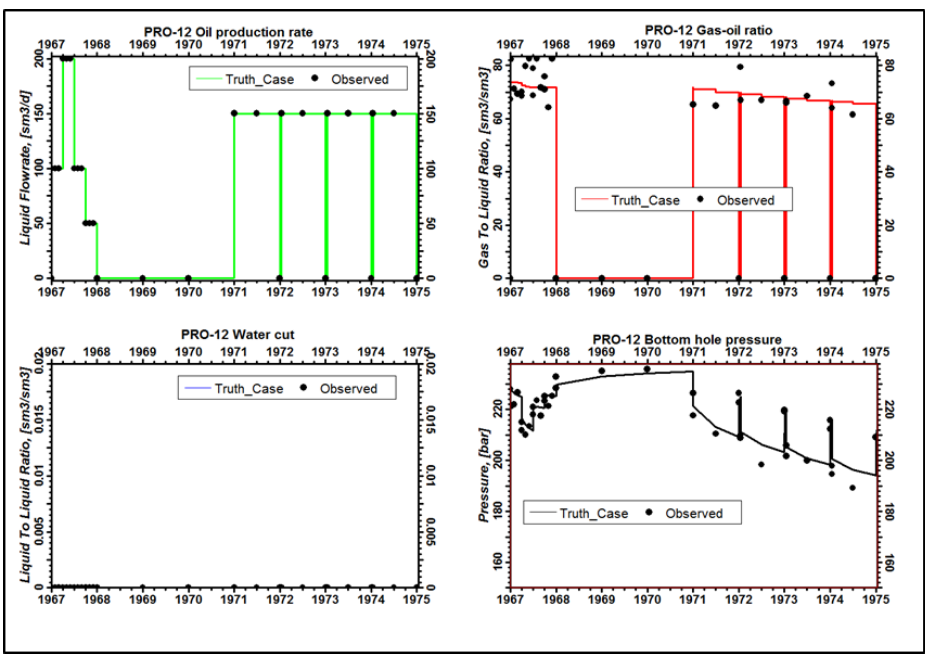

Fig. 10—Comparison of the truth-case and noisy observed PRO-12 performance

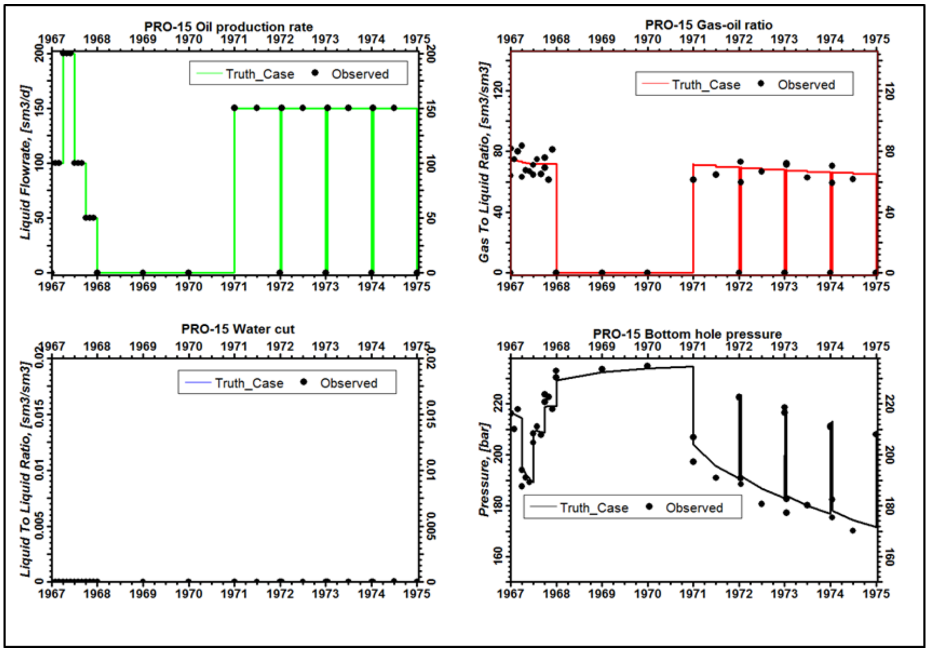

Fig. 11—Comparison of the truth-case and noisy observed PRO-15 performance

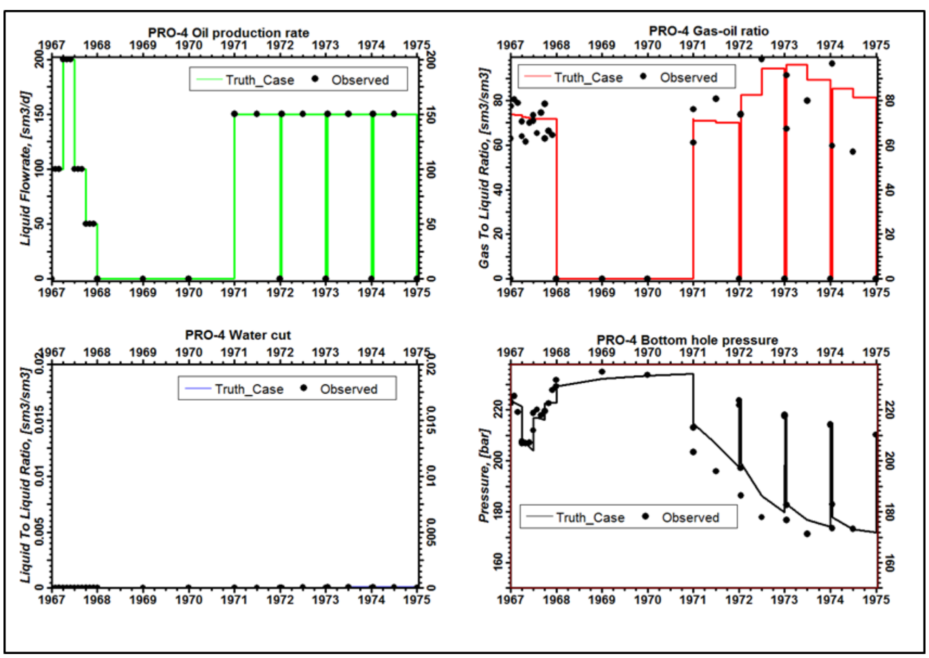

Fig. 12—Comparison of the truth-case and noisy observed PRO-4 performance

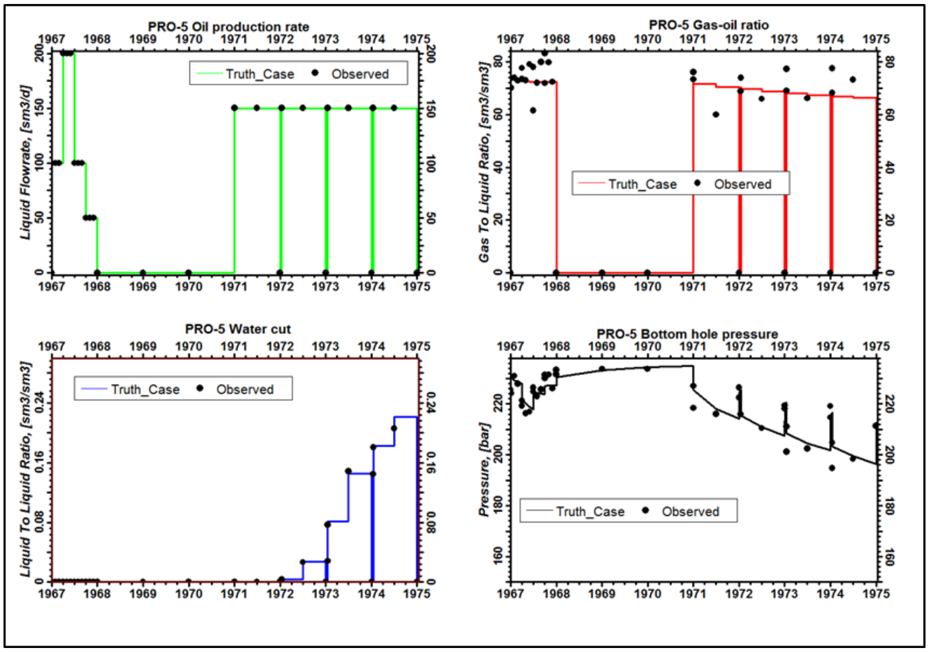

Fig. 13—Comparison of the truth-case and noisy observed PRO-5 performance

2.3 Reserves Estimation Workflow

In the PUNQ-S3 project and in this study, the total simulation time was 16.5 years including 8 years of history plus 8.5 years of prediction and all the simulation runs were ended at the end of the simulation time. Therefore, the total cumulative production for 8 years of history plus 8.5 years of prediction in this study is called the total recovery at the end of history plus prediction (TRHP). The recovery from the end of history to the end of prediction is the quantity that was recovered for the 8.5 years of prediction (ROP). Therefore, ROP was determined by subtracting the cumulative production for 8 years of history from the total recovery for 16.5 years. Since all the simulation runs were ended at the end of simulation time instead of an economic limit, ROP was used as an approximation for reserves in this study.

After the noisy synthetic observed data were generated, the deterministic and probabilistic approaches were carried out to estimate ROP using reservoir simulation. In real life, the truth case is unknown and the generated simulation models forecast different recovery values based on the values of the uncertain parameters.

2.3.1 Identification of Uncertain Parameters

Including as many uncertain parameters as possible is theoretically preferred; however, in practice a compromise is often needed. In this study, the uncertainties addressed were petrophysical properties, aquifer properties, oil relative permeability curves, and geostatistical parameters. Traditionally, an integrated multi-disciplinary team conducts a comprehensive study to determine the distributions of the uncertainties. In most cases, the range of the uncertain parameter distribution (minimum to maximum), has a stronger impact on forecasts than distribution shape (Wolff 2010a). To eliminate the effect of the prior distribution on the consistency between the deterministic and the probabilistic forecasts, uniform distributions of the uncertain parameters were used in this study.

Petrophysical uncertainties included porosity and permeability at the well locations to mimic the uncertainties associated with wireline data quality and processing. Therefore, a well porosity and permeability multiplier (PHIKMULT) was used as an uncertain parameter.

To address the uncertainty in the porosity and permeability in between wells and in portions of the reservoir that were not sampled by logs, I used a Gaussian random function—a geostatistical estimation technique—to provide a set of unique realizations of porosity and permeability maps. This geostatistical estimation technique uses a random seed in addition to the variogram parameters, so while consecutive runs will give similar equal probability realizations with the same variogram parameters, the details of the realizations will be different. For every seed number, a kriging algorithm is run to estimate the value of the property at the starting point using the neighboring data points. The result will be a unique realization of porosity and permeability map for each unique seed number. Therefore, the seed variable was selected as uncertain parameter to consider the uncertainty of porosity and permeability between wells and in portion of reservoirs that are not sampled. In addition, the azimuth in Layer 1, Layer 3, and Layer 5 was selected as an uncertain parameter with a range of uncertainty from -70° to -10°. The azimuth value was the same for the three layers. Also the variogram major range in Layer 3 and Layer 5 was selected as uncertain parameter with an uncertainty range from 1500 m to 9000 m. The major range value was the same for the two layers.

There is a strong aquifer in the model and the analytical Carter-Tracy aquifer permeability was selected as an uncertain parameter. Also, the oil relative permeability curves were picked as an uncertain parameter in this study.

2.3.2 Mismatch Objective Function

A mismatch objective function was defined to quantify the mismatch between the simulation model results and the observed data. The mismatch computations are based on the reservoir production data: oil rates, GOR, WCT, SBHP and FBHP for the 6 wells at all reporting time steps. **Eq. 1** represents the mismatch between the simulation results and observed data at every reporting time step.

$$MM(t) = Sim(t) - Obs(t) \qquad (1)$$

where the simulation results $Sim(t) = Sim_1(t_1), \dots \dots . Sim_N(t_N)$ and the observed data $Obs(t) = Obs_1(t_1), \dots \dots . Obs_N(t_N)$. The mismatch is normalized to the observed data as in **Eq. 2**

$$NMM(t) = MM(t)/Obs(t) \qquad (2)$$

In PUNQ-S3 project and this study, to mimic the systematic nature of errors in production data, the noise level in the shut-in period was smaller than in the flow period to reflect the more accurate shut-in pressures. Therefore, higher time weights $W(t)$ were assigned to shut-in periods and lower time weights for the flow period. Similarly, the noise level in the WCT and GOR was smaller before the breakthrough than after the breakthrough. Therefore, higher time weights $W(t)$ were given to WCT and GOR before breakthrough and lower time weights after the breakthrough. **Eq. 3** represents the global mismatch objective function that combines the mismatch of oil rates, GOR, WCT, SBHP and FBHP which were assigned equal quantity weight $W(q)$ for the 6 wells at all reporting time steps.

$$OF = \sum_q W(q) \sqrt{\frac{\sum_{t=1}^{N} W(t) NMM^2(t)}{\sum_{t=1}^{N} W(t)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

The objective function was used in the deterministic approach to select the model with the minimum mismatch between the simulation model and observed data. Moreover, the objective function was used in the probabilistic approach as a probability weighting factor.

2.3.3 Probabilistic Approach

The approach is conducted by using Monte Carlo simulation to sample randomly "all" possible combinations of the uncertain parameters values and generate a sufficient number of models with different combinations of the uncertain values. It is called uniform search because the sampling from the uncertain parameters distributions was just random and it was not controlled by an optimization process for minimizing the mismatch objective function as in computer-assisted history matching. To eliminate the effect of the prior distribution on the consistency between the deterministic and the probabilistic ROP, uniform distributions of the uncertain parameters were used.

The generated simulation models were run under the control of the specified production strategy to forecast the total recovery at the end of history plus prediction

(TRHP) at 16.5 years. Using the mismatch objective function, the models were assigned different probabilities based on their history match quality. Exponential weighting was used to calculate the probabilities to be assigned to the simulation models as a function of the mismatch objective function (**Eq. 4**). Using the weighted probabilities, the reserves distribution was generated and P10, P50, P90, mean, and mode statistics were derived. Since the prior distribution is uniform, the likelihood distribution and the posterior distribution are the same.

$$P(x) = \frac{e^{-\frac{1}{2}{OF_i}^2}}{\sum_{i=1}^{n} e^{-\frac{1}{2}{OF_i}^2}} \quad (4)$$

2.3.4 Deterministic Approach

As was demonstrated in the literature review, the deterministic approach is performed by using a single value of each of the input parameters to derive a single outcome of the recoverable volume. In general, estimators consider the model that shows the best history match to be the best estimate of the truth or the most-likely scenario to exist. The purpose of history matching is to compare the simulation results with the observed data and adjust the uncertain parameters in the simulation model to minimize the mismatch between the simulation results and observed data. The resulting simulation model should capture the level of detail necessary for production forecasts with high predictive confidence. In this study, a deterministic ROP estimate was derived using the simulation model that has the best history match out of the simulation models that were generated using the probabilistic approach. An example of the quality of the history match for oil rate, GOR, WCT, and pressures on the field and wells levels that can be achieved with mismatch objective function of 1.884 is sown in **Fig. 67** - **Fig. 73** in Appendix A.

3. RESULTS

3.1 Effect of Uncertain Variable Type

To study the effect of the type of uncertain parameter on the ROP distribution, a single uncertain variable was altered at a time. The other uncertain variables were held at constant values. In the first case, the well porosity and permeability multiplier was examined. In the second case, the aquifer permeability was investigated, then the oil relative permeability curve was the uncertain parameter in the 3rd case. After that, Case 4 is combination of the uncertain variables in Case 1, Case 2, and Case 3 that were altered simultaneously. Last, in Case 5 the geostatistical parameters were added to the three uncertainties in Case 4.

3.1.1 Case 1: Well Porosity and Permeability Multiplier (PHIKMULT)

The generated simulation models forecasted different values of ROP as a function of the well porosity and permeability multiplier PHIKMULT values (**Fig. 14)**. These models have different values of history match quality as a function of the uncertain variable and the deterministic model was selected with the minimum mismatch OF on the small scale axis (**Fig. 15)**. The weighting function (**Eq. 4**) assigns high probabilities to ROP values with low mismatch objective function values and low probabilities to ROP values with high mismatch objective function (**Fig. 16)**. Moreover, **Fig. 16** shows that models with mismatch OF less than 3.5 get the main part of probability weights. These models have PHIKMULT values ranging from -0.05 to 0.15 (**Fig. 15)** and ROP values ranging from 2.32 to 2.56 MM Sm3 while deterministic ROP estimate derived from the deterministic model is 2.40 MM Sm3 (**Fig. 14)**. **Fig. 17** shows that models with high probability weight make the main part (more than 80%) of the ROP distribution with P10, P50, P90 equal to 2.51, 2.43, and 2.35 MM Sm3, respectively. **Fig. 18** and **Table 3** show that the deterministic ROP does not correspond to any of the statistical measures of central tendency – mean, median, mode.

In general, estimators consider the model that shows the best history match as the best estimate of the truth or the most-likely scenario and use it to report the P50 proved-plus-probable estimate (PRMS 2011, Rietz and Usmani 2009, Dehghani et al. 2008), but this is not the case. Some might consider it to be the same as the mode, since the deterministic model corresponds to the most-likely history match, but this is also not the case. The results show that the deterministic estimate is pessimistic compared to the P50 and it fell on percentile P64.5 (**Fig. 18, Table 3**).

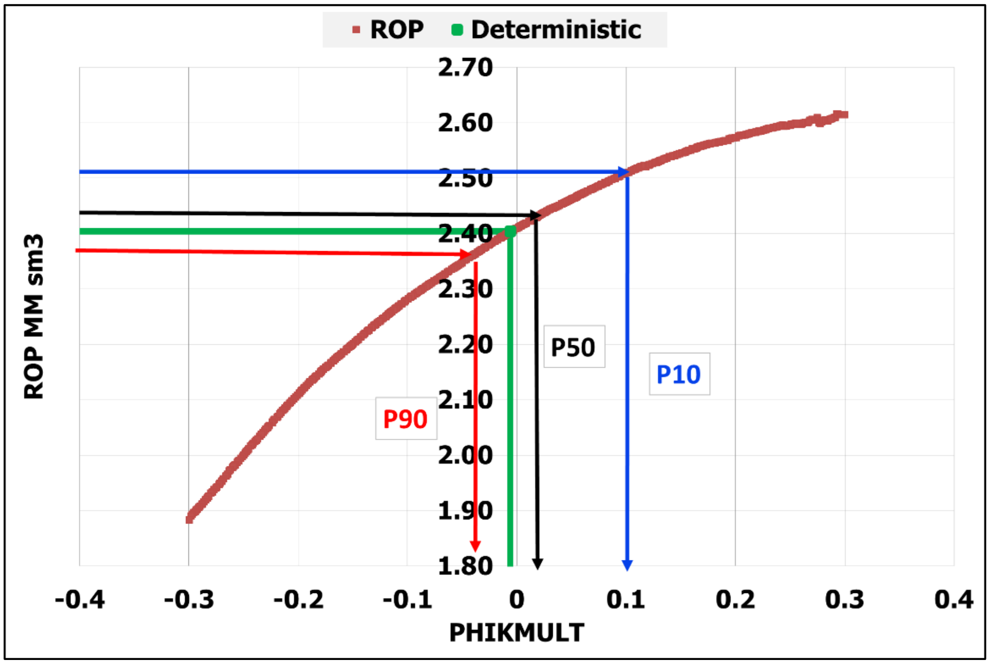

Fig. 14—Case 1 well porosity and permeability multiplier: ROP as a function of well porosity and permeability multiplier

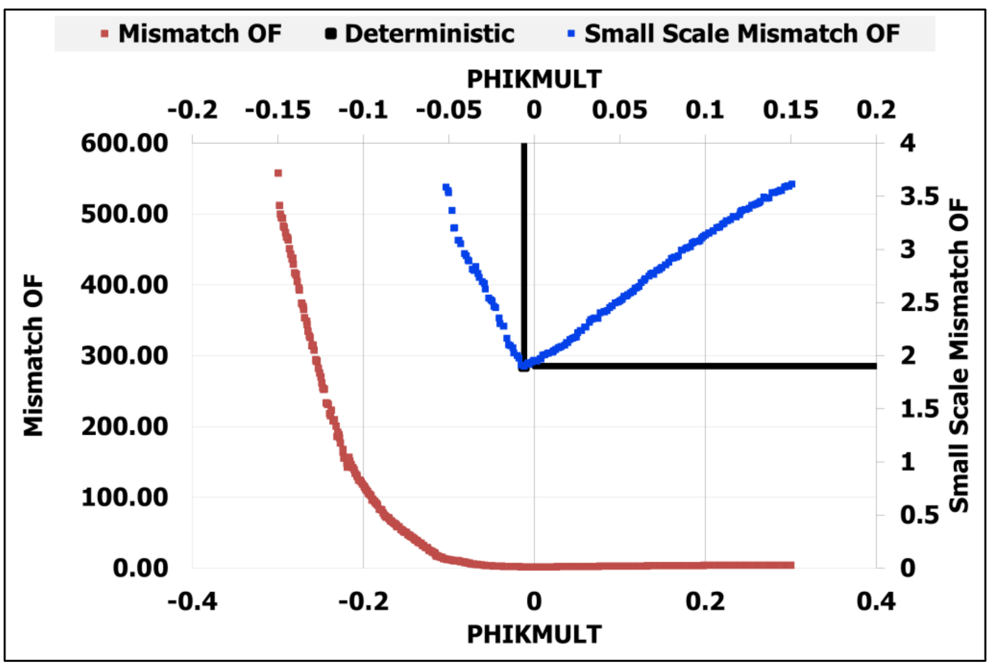

Fig. 15—Case 1 well porosity and permeability multiplier: mismatch objective function of the models based on the uncertain parameter

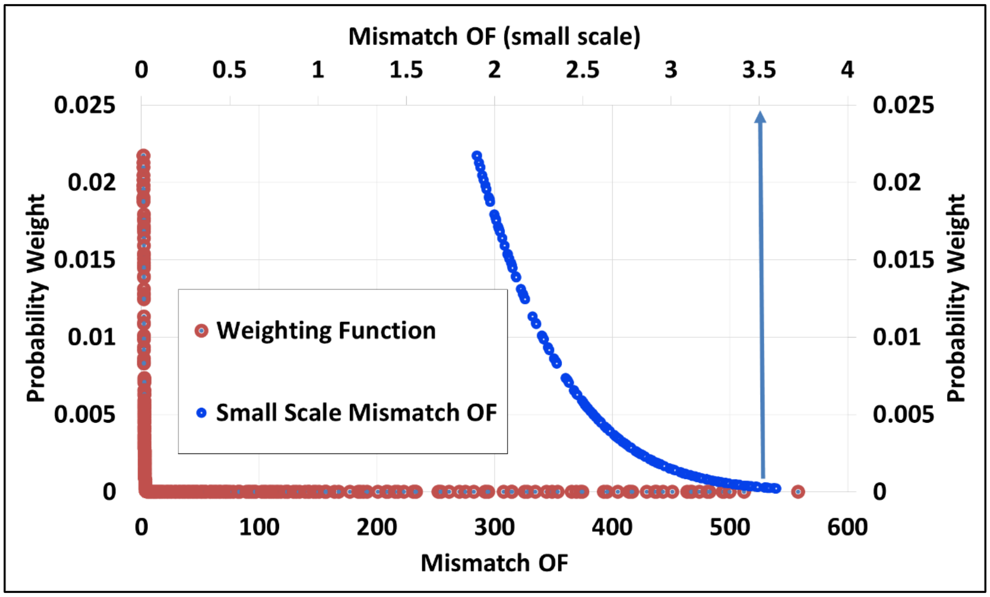

Fig. 16—Case 1 well porosity and permeability multiplier: probability weights based on history match quality

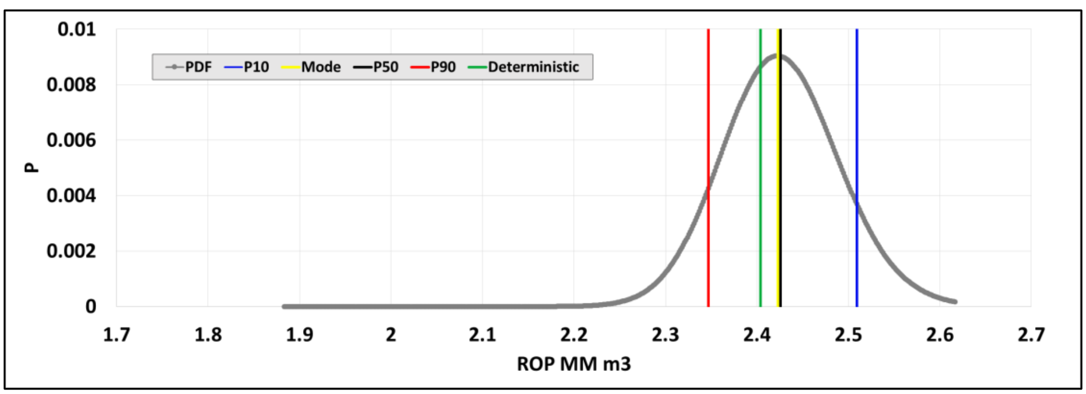

Fig. 17—Case 1 well porosity and permeability multiplie: PDF of ROP distribution

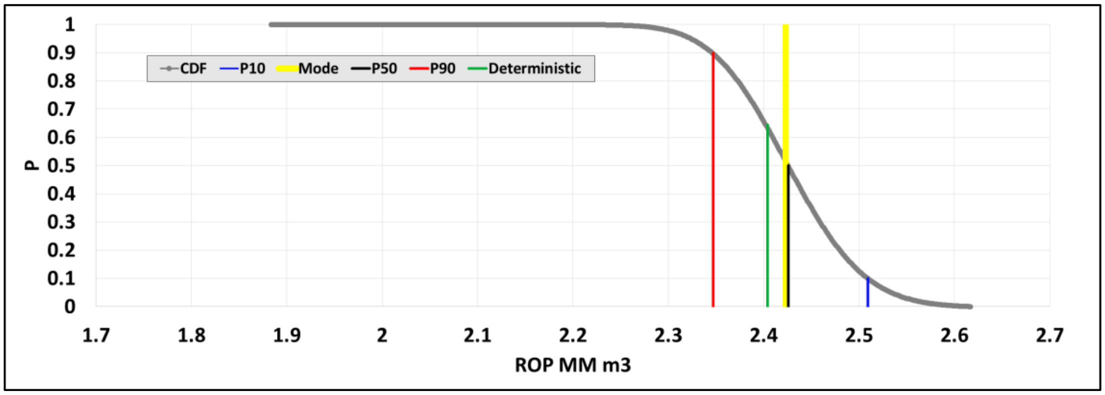

Fig. 18—Case 1 well porosity and permeability multiplie: CDF of ROP distribution

Table 3—Case 1 well porosity and permeability multiplie: statistical parameters of ROP distribution

ROP MM sm3					
P10	P50	P90	Mode	Mean	Deterministic
2.51	2.43	2.35	2.42	2.43	2.40

3.1.2 Case 2: Aquifer Permeability (AQPERM)

The generated simulation models forecasted different values of ROP as a function of the aquifer permeability (AQPERM) values (**Fig. 19)**. These models have different values of history match quality as a function of the uncertain variable (**Fig. 20)**. The weighting function assigns high probabilities to ROP values with low mismatch objective function values and lower probabilities to ROP values with high mismatch objective function (**Fig. 21**). **Fig. 21** also shows that models with mismatch OF less than 4 get most of the probability weights. These models have AQPERM values ranging from 80 to 500 md and the deterministic model was selected with the minimum mismatch objective function with $AQPERM of 146.7 md as (**Fig. 22**). The models with high probability weights showed ROP values ranging from 2.25 to 2.55 MM Sm3 and the deterministic reserves derived from the deterministic model is 2.42 MM Sm3 (**Fig. 19)**. **Fig. 23** shows that high probability weight models make the main part of the ROP distribution with P10, P50, P90 equal to 2.50, 2.42, and 2.33 MM Sm3 respectively. The ROP distribution is near symmetrical and the deterministic ROP and mode lie on the P50 (**Fig. 23**, **Fig. 24**, **Table 4**). **Fig. 24** shows that the deterministic ROP is consistent with P50 as it fell on the percentile P49.8. The statistical parameters of the distribution are shown in **Table 4**.

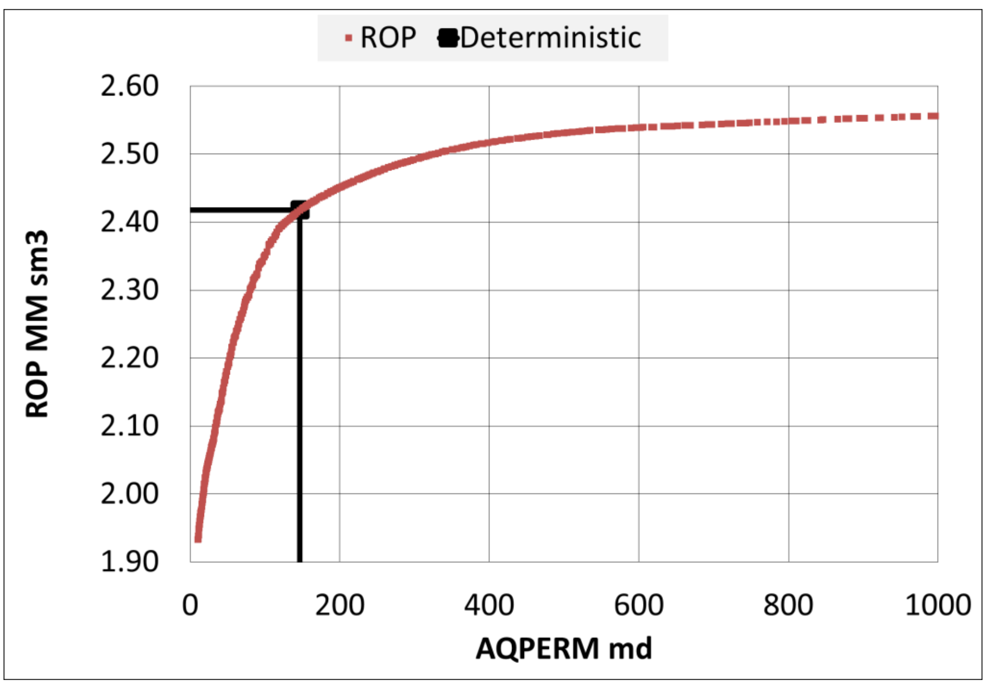

Fig. 19—Case 2 aquifer permeability: ROP as a function of aquifer permeability

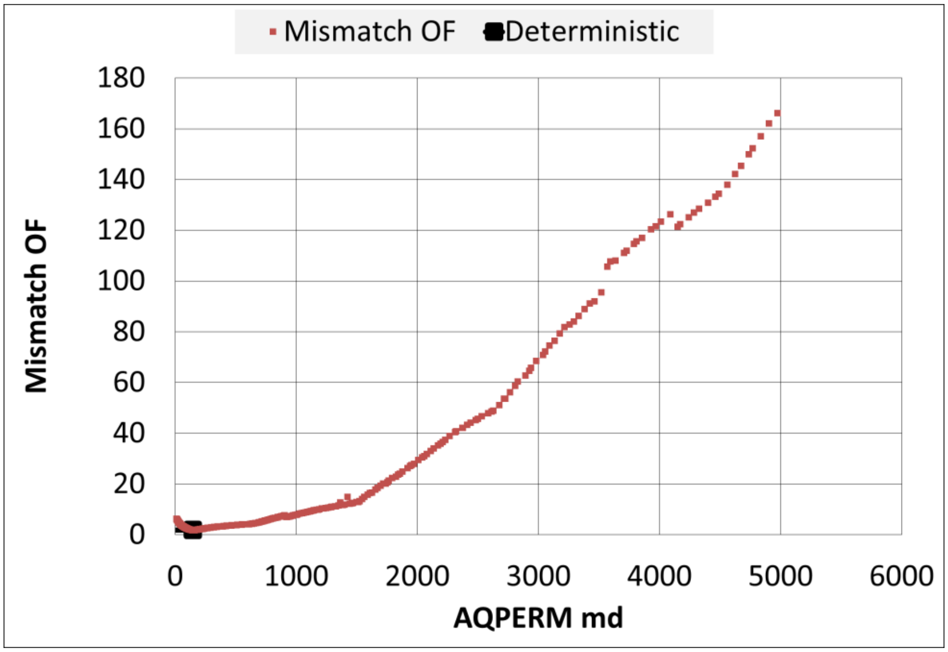

Fig. 20—Case 2 aquifer permeability: mismatch objective function of the models based on the uncertain parameter

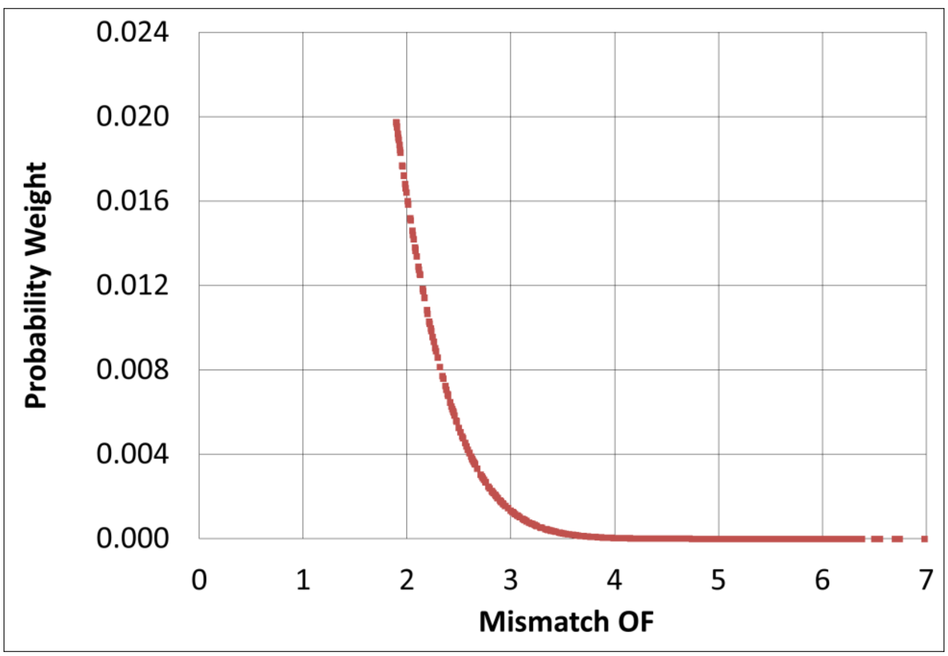

Fig. 21—Case 2 aquifer permeability: probability weights based on history match quality

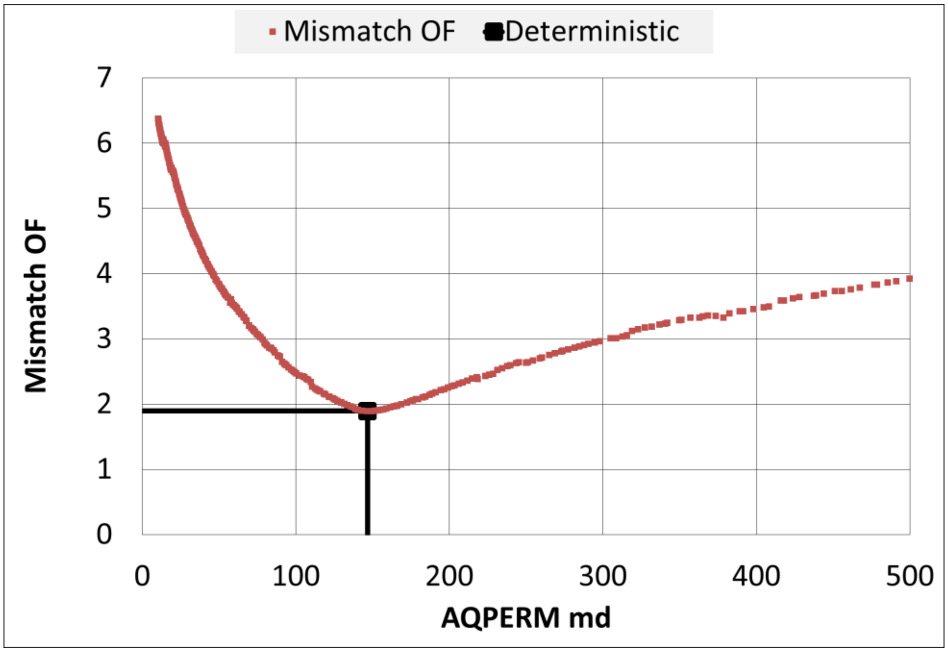

Fig. 22—Case 2 aquifer permeability: selecting the deterministic model

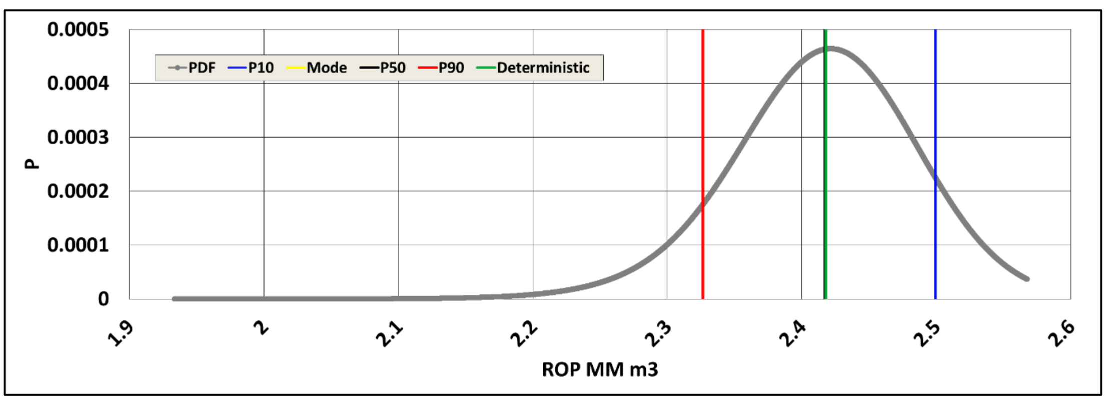

Fig. 23—Case 2 aquifer permeability: PDF of ROP distribution

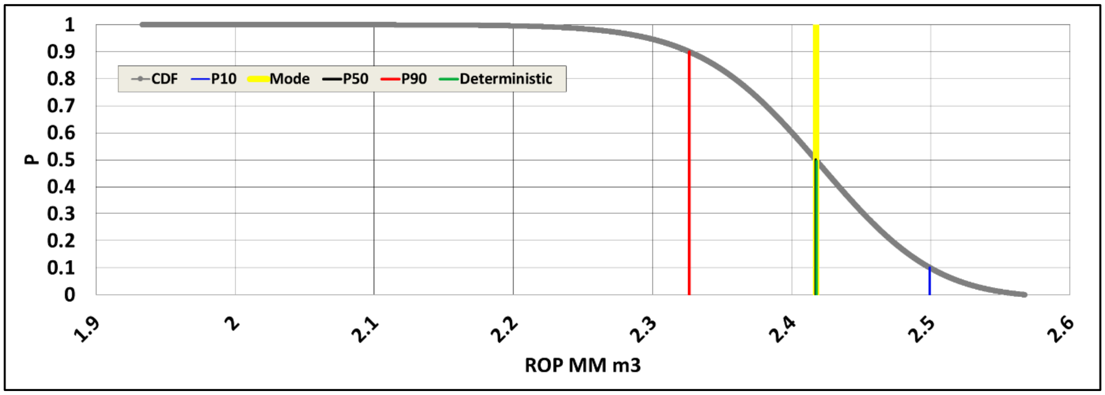

Fig. 24—Case 2 aquifer permeability: CDF of ROP distribution

Table 4—Case 2 aquifer permeability: statistical parameters of ROP distribution

Reserves MM sm3					
P10	P50	P90	Mode	Mean	Deterministic
2.50	2.42	2.33	2.42	2.41	2.42

3.1.3 Case 3: Oil Relative Permeability (Kro)

The generated simulation models forecasted different values of ROP as a function of the aquifer permeability (Kro) values (**Fig. 25**). These models have different values of history match quality as a function of the uncertain variable (**Fig. 26**). The weighting function assigns high probabilities to ROP values with low mismatch objective function values and lower probabilities to ROP values with high mismatch objective function values (**Fig. 27**). **Fig. 27** also shows that models with mismatch OF less than 4 get most of the probability weights. These models have Kro values ranging from 0.82 to 1 and the deterministic model was selected with the minimum mismatch objective function with Kro of 0.90 (**Fig. 28**). The high probability weight models derived ROP values ranging from 2.29 to 2.49 MM Sm3 and the deterministic ROP derived from the deterministic model is 2.41 MM Sm3 (**Fig. 25**). **Fig. 29** shows that high probability weight models make the main part of the ROP distribution with P10, P50, P90 equal to 2.46, 2.40, and 2.33 MM Sm3 respectively. **Fig. 30** shows that the deterministic ROP is optimistic comparing to P50 as it fell on the percentile P42. The statistical parameters of the distribution are shown in **Table 5**.

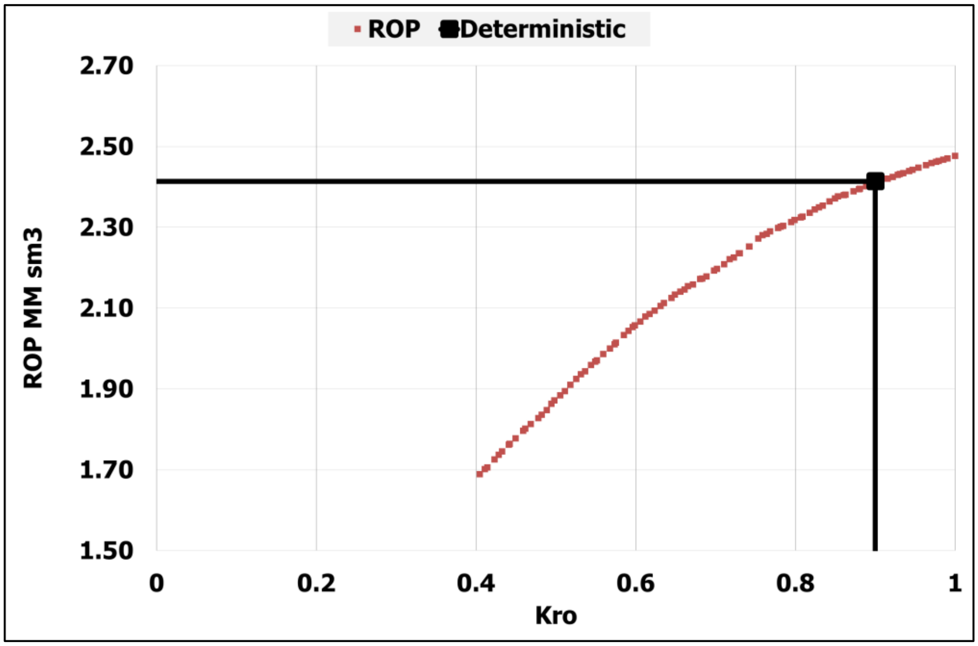

Fig. 25—Case 3 oil relative permeability: reserves as a function of oil relative permeability

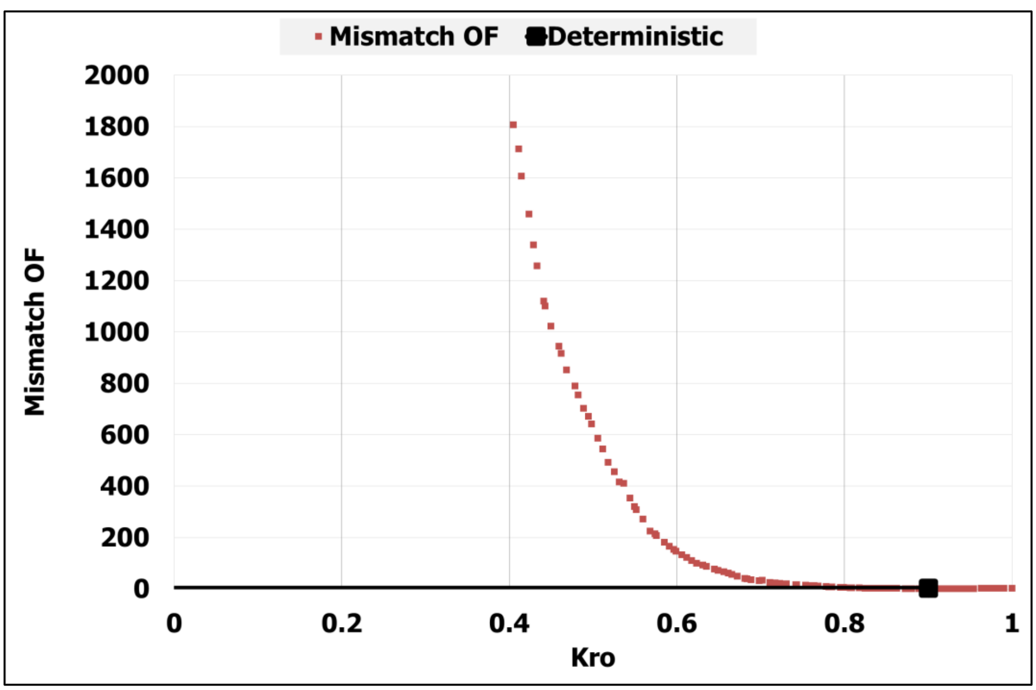

Fig. 26—Case 3 oil relative permeability: mismatch objective function of the models based on the uncertain parameter

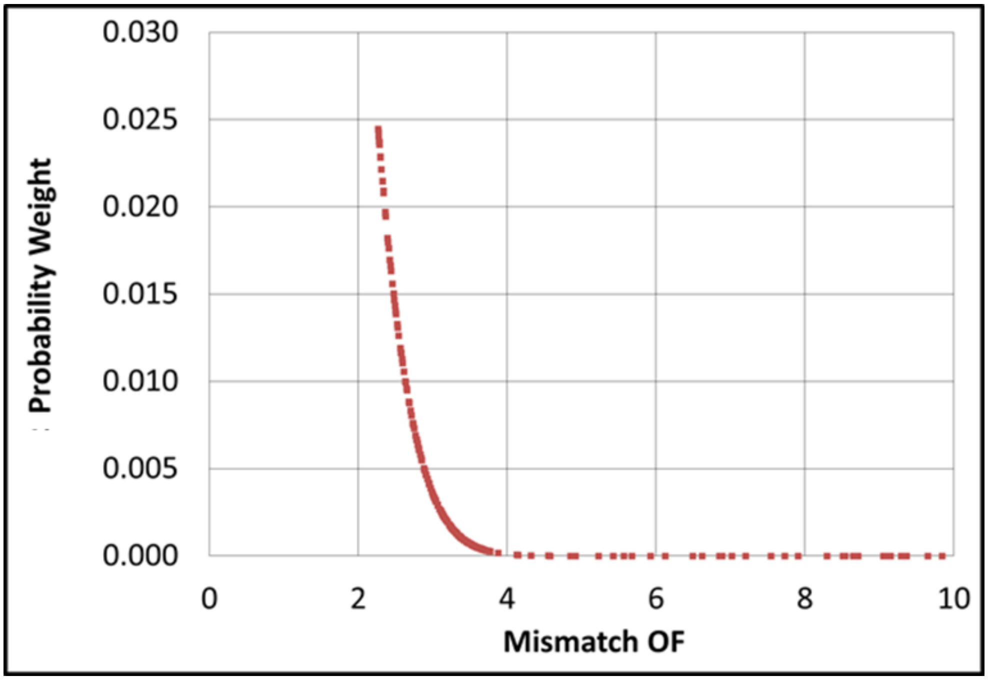

Fig. 27—Case 3 oil relative permeability 3: probability weights based on history match quality

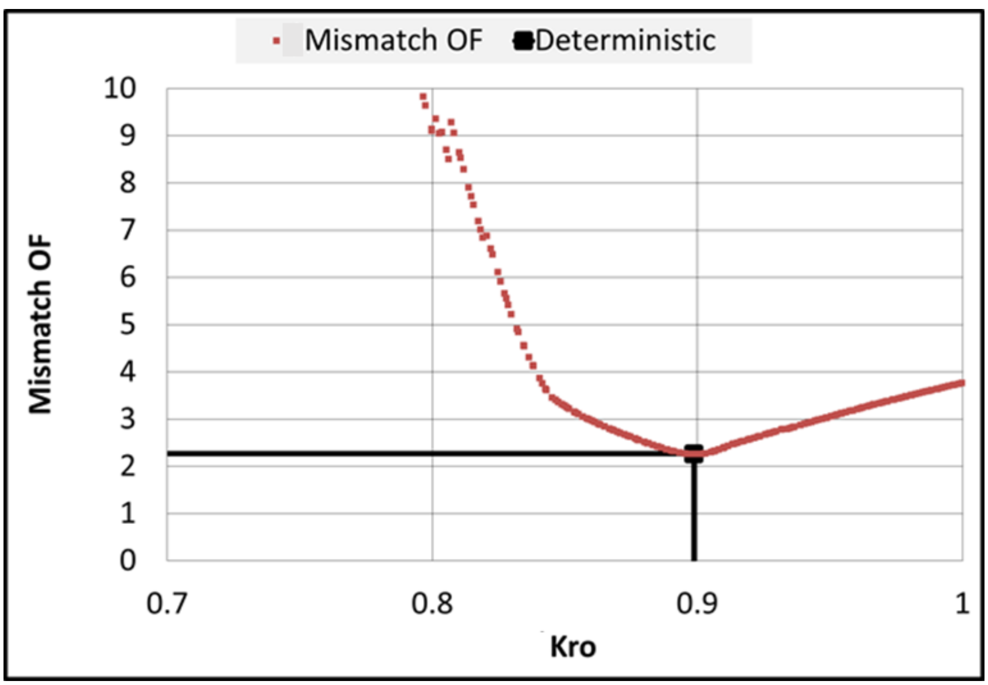

Fig. 28—Case 3 oil relative permeability: selecting the deterministic model

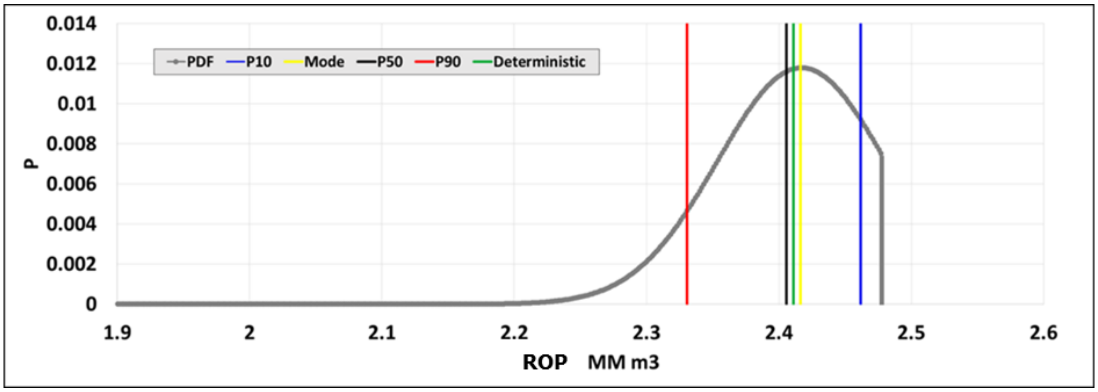

Fig. 29—Case 3 oil relative permeability: PDF of reserves distribution

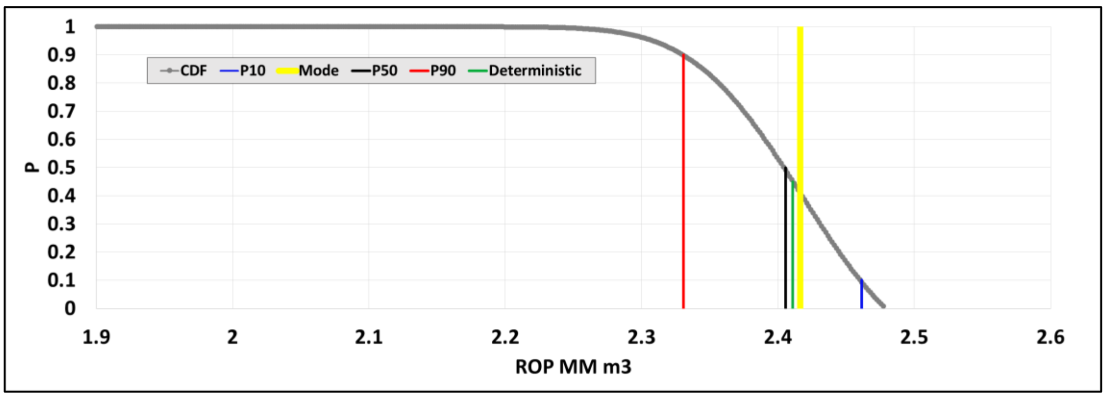

Fig. 30—Case 3 oil relative permeability: CDF of reserves distribution

Table 5—Case 3 oil relative permeability: statistical parameters of reserves distribution

Reserves MM sm3					
P10	P50	P90	Mode	Mean	Deterministic
2.46	2.40	2.33	2.42	2.40	2.41

3.1.4 Case 4: Combinations of Case 1, Case 2, and Case 3

In this case the uncertain variables in Case 1, Case 2, and Case 3 are altered simultaneously to understand the combined impact of the uncertainties on the ROP distribution. The generated simulation models forecasted different values of ROP as a function of combinations of (PHIKMULT), (AQPERM), and (Kro) values. **Fig. 31** shows the ROP plotted versus AQPERM. ROP does not vary systematically with AQPERM because other parameters are varying as well. These models have different values of history match quality as a function of the uncertain variables (plotted versus only AQPERM in **Fig. 32**). The weighting function assigns high probabilities to ROP values with low mismatch objective function values and lower probabilities to reserves values with high mismatch objective function (**Fig. 33**). The figure also shows that models with mismatch OF less than 4 get most of the probability weights. The deterministic model was selected with the minimum mismatch objective function with LOGSMULT, AQPERM, and Kro of -0.007, 128.4 md, and 0.88 respectively (**Fig. 34**). **Fig. 31** shows that the deterministic ROP derived from the deterministic model is 2.43 MM Sm3. **Fig. 35** shows that high probability weight models make the main part of the ROP distribution with P10, P50, P90 equal to 2.59, 2.44, and 2.29 MM Sm3 respectively. **Fig. 36** shows that the deterministic ROP is pessimistic comparing to P50 as it fell on the percentile P54. The statistical parameters of the distribution are shown in **Table 6**.

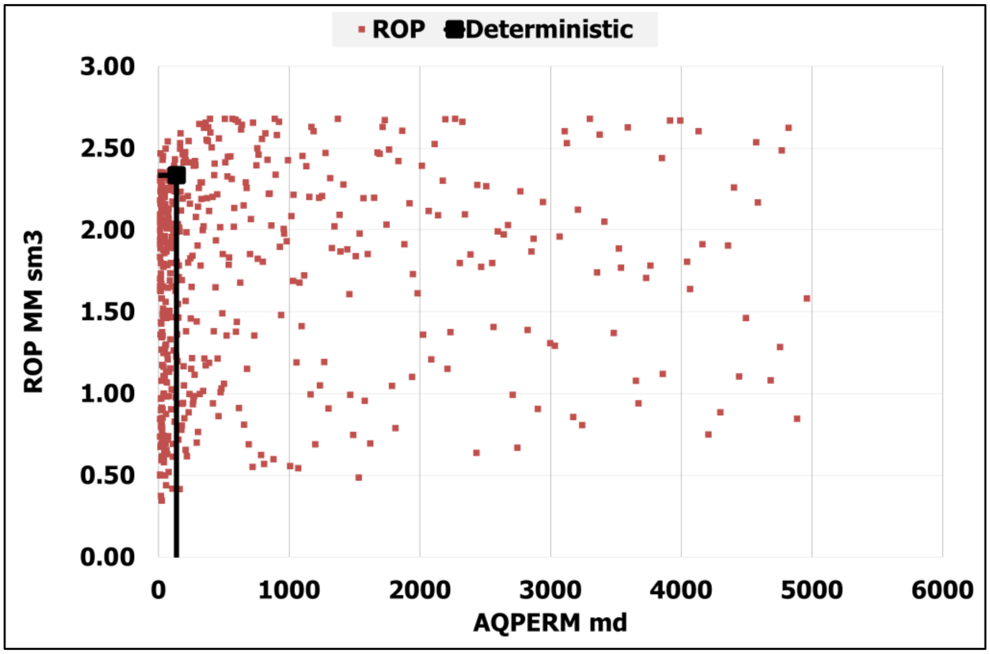

Fig. 31—Case 4 combination of PHIKMULT, AQPERM, and Kro: ROP as a function of aquifer permeability

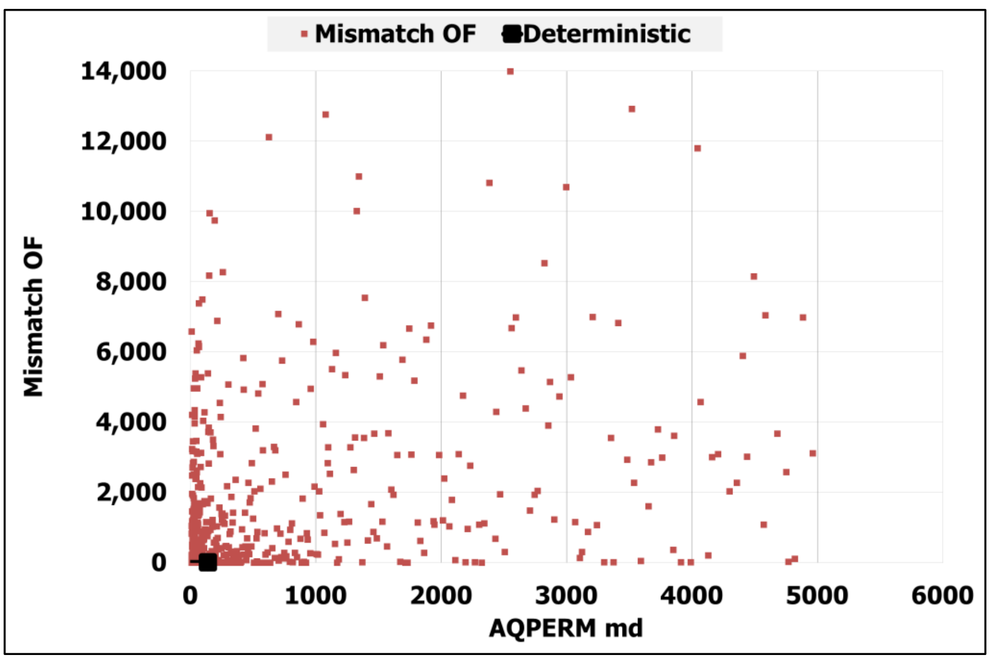

Fig. 32—Case 4 combination of PHIKMULT, AQPERM, and Kro: mismatch objective function of the models based on the uncertain parameter

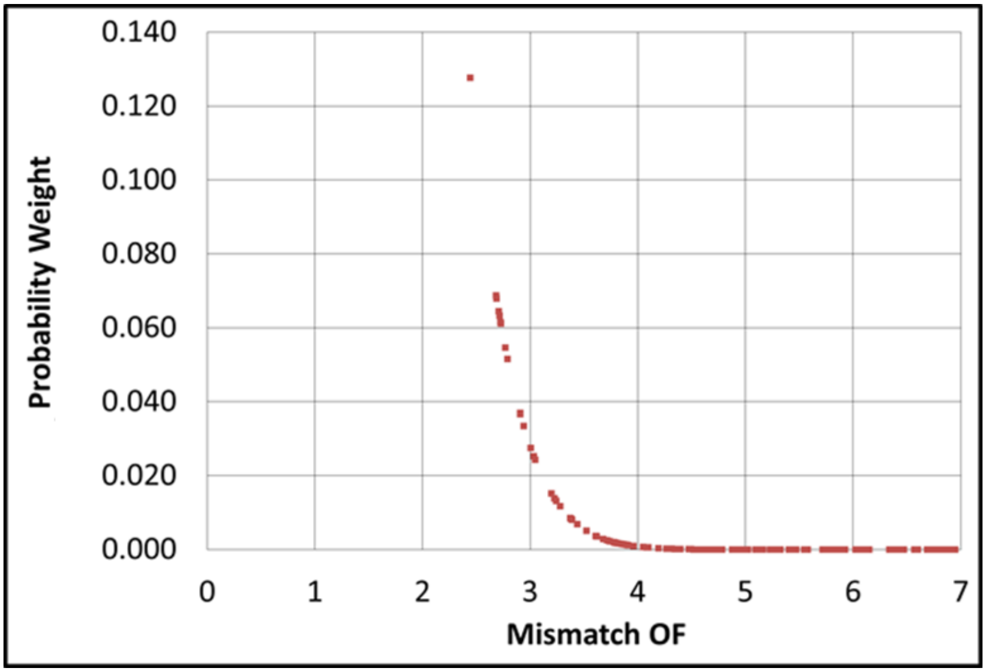

Fig. 33—Case 4 combination of PHIKMULT, AQPERM, and Kro: probability weights based on history match quality

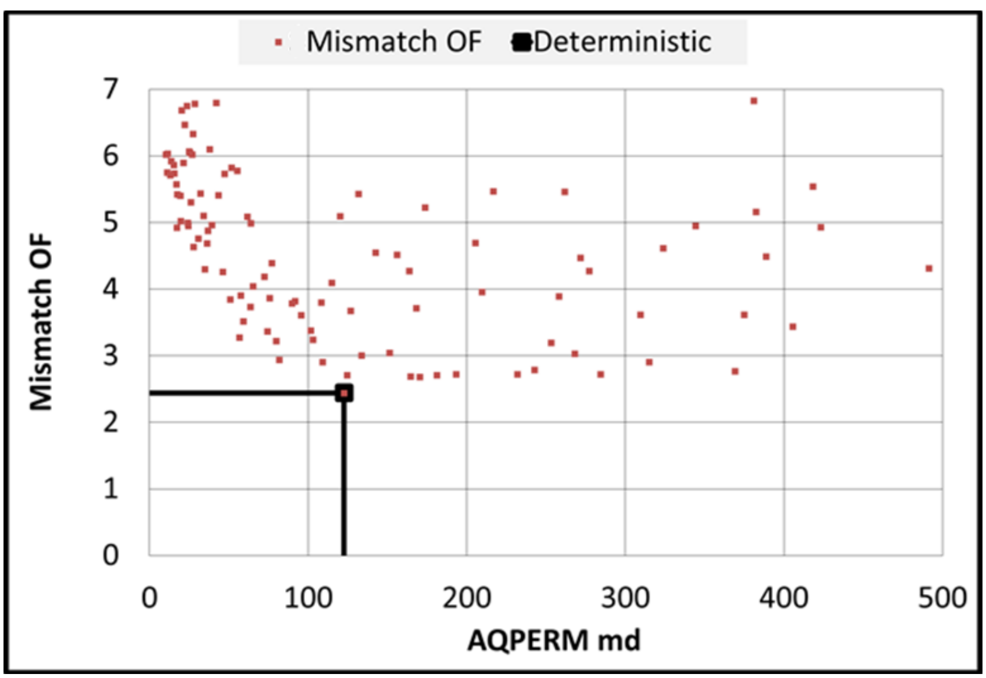

Fig. 34—Case 4 combination of PHIKMULT, AQPERM, and Kro: selecting the deterministic model

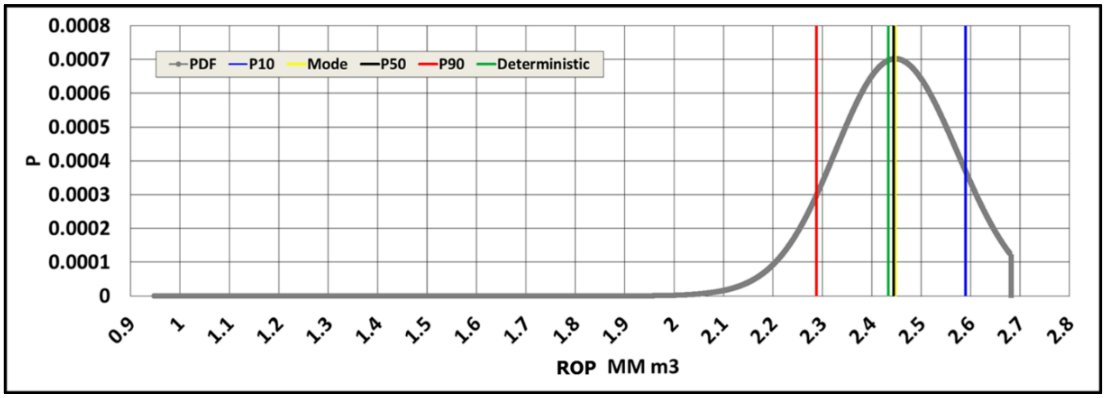

Fig. 35—Case 4 combination of PHIKMULT, AQPERM, and Kro: PDF of ROP distribution

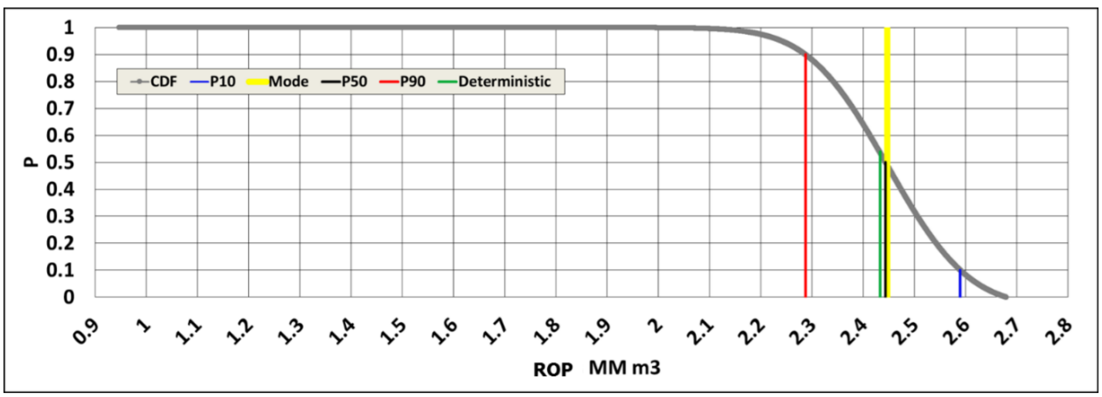

Fig. 36— Case 4 combination of PHIKMULT, AQPERM, and Kro: CDF of reserves distribution

Table 6—Case 4 combination of PHIKMULT, AQPERM, and Kro: statistical parameters of reserves distribution

ROP MM sm3					
P10	P50	P90	Mode	Mean	Deterministic
2.59	2.44	2.29	2.45	2.44	2.43

3.1.5 Case 5: Combinations of Case 4, and Geostatistical Uncertainty

Because the Gaussian random function provides a set of non-unique realizations of reservoir properties, the random seed variable was selected as a global geostatistical uncertain parameter in all layers. In addition, the azimuth (Azimuth135) in Layer 1, Layer 3, and Layer 5 and the variogram major range in Layer 3 and Layer 5 (MJR35) were included in the geostatistical uncertainties.

In this case, the uncertain variables in Case 1, Case 2, and Case 3 and the geostatistical uncertainties are altered simultaneously to understand the combined impact of the uncertainties on the ROP distribution. The generated simulation models forecasted different values of ROP as a function of combinations of PHIKMULT, AQPERM, and Kro and geostatistical parameters. **Fig. 37** shows the ROP plotted versus AQPERM. ROP does not vary systematically with AQPERM because other parameters are varying as well. These models have different values of history match quality as a function of the uncertain variables (plotted versus only AQPERM in **Fig. 38**). The weighting function assigns high probabilities to ROP values with low mismatch objective function values and lower probabilities to ROP values with high mismatch objective function values (**Fig. 39**). **Fig. 39** also shows that models with mismatch OF less than 5 get most of the probability weights. The deterministic model was selected with the minimum mismatch objective function with LOGSMULT, AQPERM, Kro, SEED, MJR35, and Azimuth135 of 0.257, 265.7 md, 0.834, 14207, 2735.7 ft, and -61.9°, respectively (**Fig. 40**). **Fig. 37** shows that the deterministic reserves derived from the deterministic model is 2.49 MM Sm3. **Fig. 41** shows that high probability weight models make the main part of the reserves distribution with P10, P50, P90 equal to 2.59, 2.47, and 2.31 MM Sm3, respectively. **Fig. 42** shows that the deterministic ROP is optimistic compared to the P50 as it fell on the percentile P40. The statistical parameters of the distribution are shown in **Table 7**.

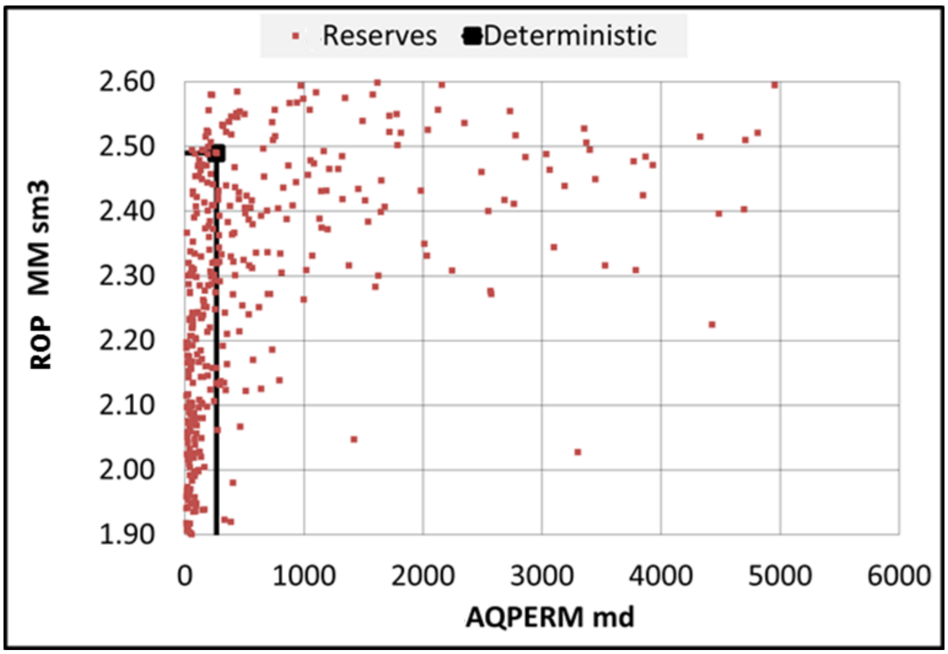

Fig. 37—Case 5 combination of PHIKMULT, AQPERM, Kro, and geostatistical uncertainty: ROP as a function of aquifer permeability

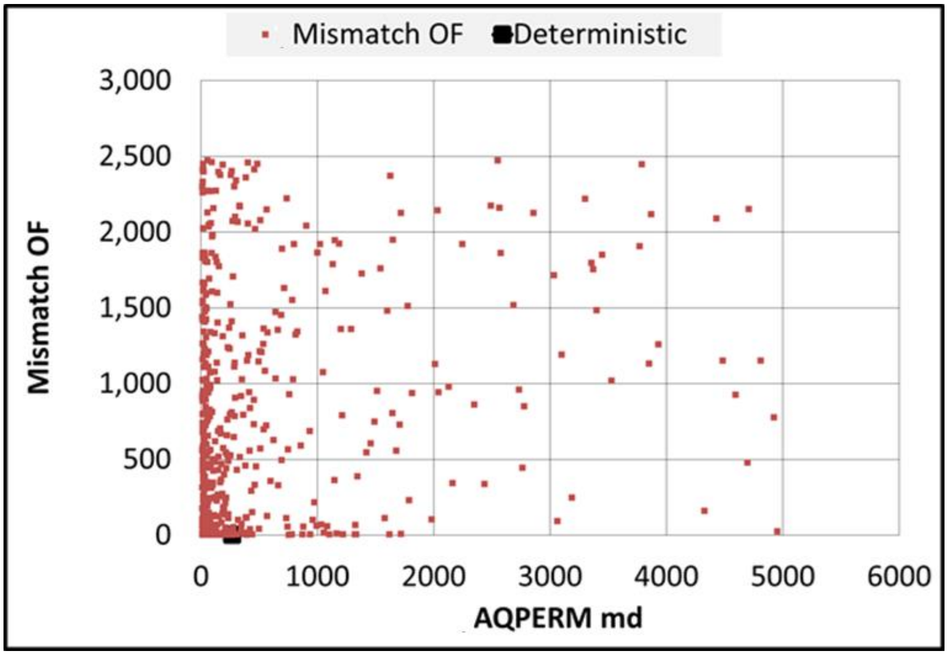

Fig. 38— Case 5 combination of PHIKMULT, AQPERM, Kro, and geostatistical uncertainty: mismatch objective Function of the models based on the uncertain parameter

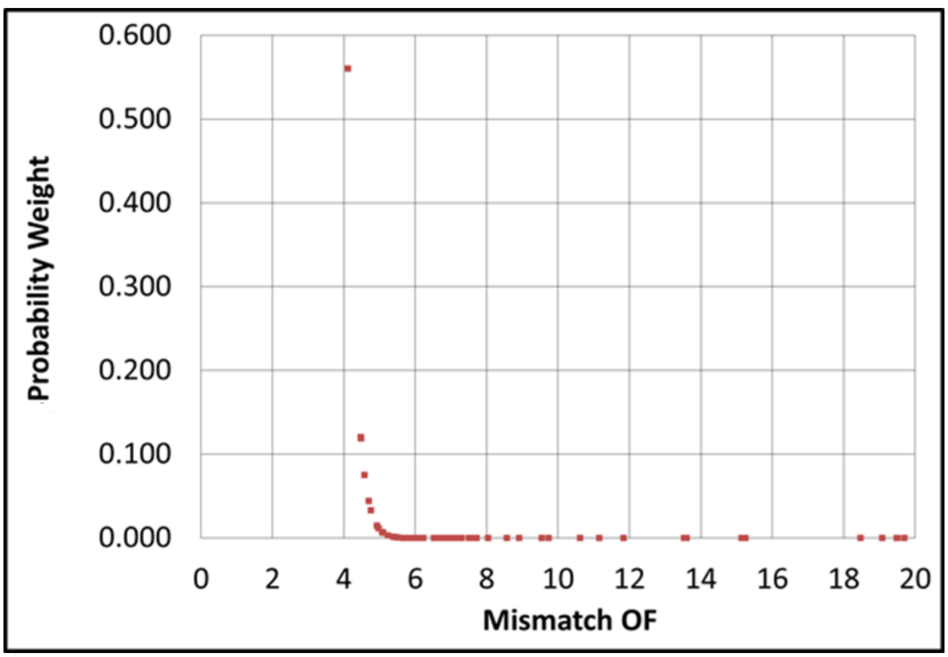

Fig. 39—Case 5 combination of PHIKMULT, AQPERM, Kro, and geostatistical uncertainty: probability weights based on history match quality

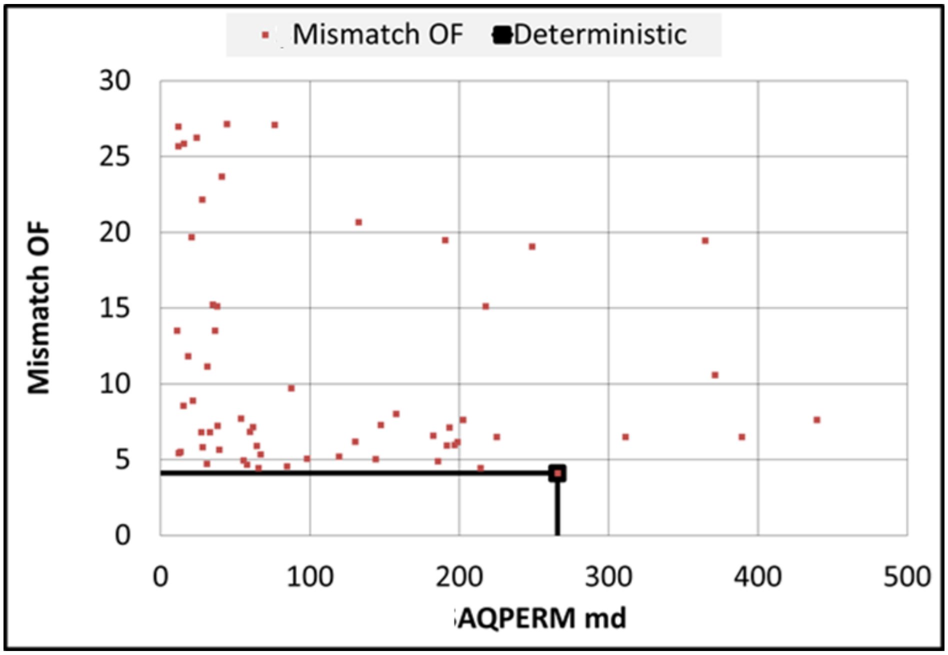

Fig. 40—Case 5 combination of PHIKMULT, AQPERM, Kro, and geostatistical uncertainty: selecting the deterministic model

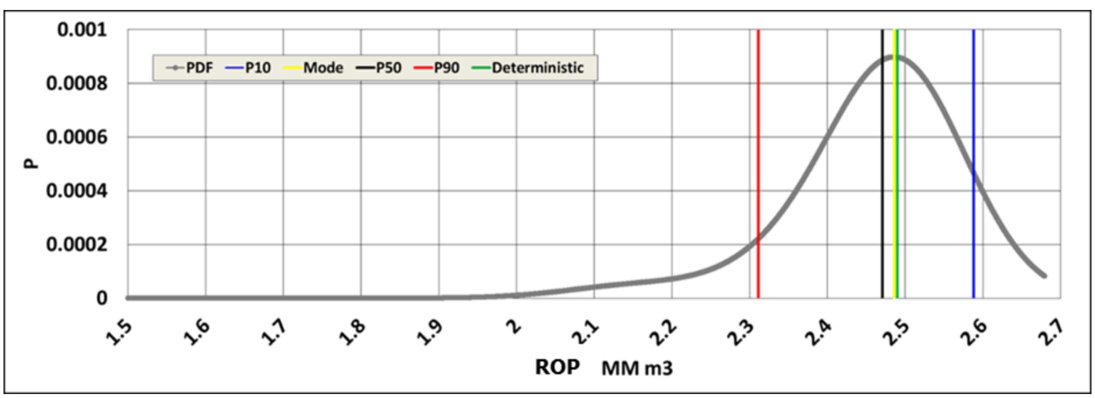

Fig. 41—Case 5 combination of PHIKMULT, AQPERM, Kro, and geostatistical uncertainty 5: PDF of ROP distribution

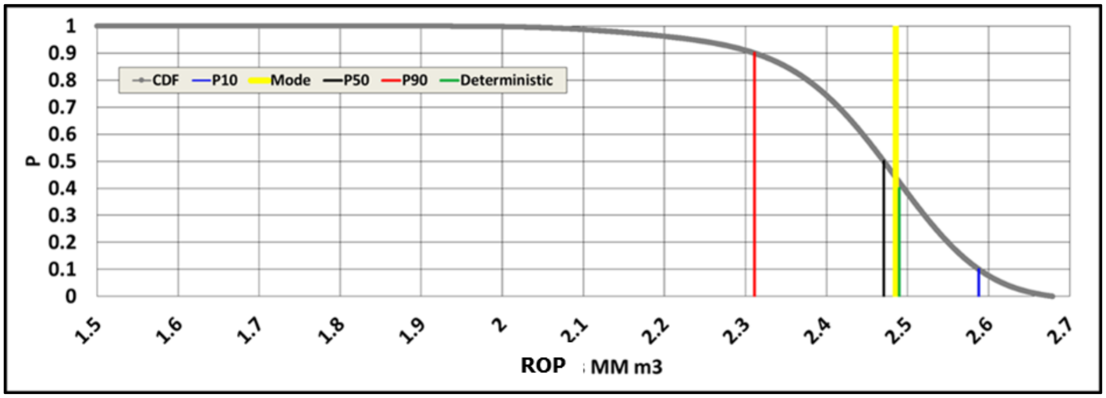

Fig. 42—Case 5 combination of PHIKMULT, AQPERM, Kro, and geostatistical uncertainty: CDF of reserves distribution

Table 7—Case 5 combination of PHIKMULT, AQPERM, Kro, and geostatistical uncertainty: statistical parameters of ROP distribution

ROP MM sm3					
P10	P50	P90	Mode	Mean	Deterministic
2.59	2.47	2.31	2.49	2.46	2.49

3.1.6 Summary

Fig. 43 and **Table 8** show that in comparison with the P50, the deterministic ROP was pessimistic in case of the well porosity and permeability multiplier and fell on percentile P64.5. The deterministic ROP in case of the aquifer permeability was consistent with P50 and fell on percentile P49.8. On the other hand, for oil relative permeability the deterministic ROP was optimistic and fell on percentile P42. When the uncertain variables in Case 1, Case 2, and Case 3 were altered simultaneously to generate multiple combinations, the deterministic ROP fell on percentile P54 and was slightly pessimistic compared to the P50. When the geostatistical uncertainty was added to Case 4, the deterministic ROP was optimistic and fell on percentile P40.

I conclude that the consistency between deterministic and probabilistic reserves estimates cannot be guaranteed. It is difficult to predict exactly where the deterministic reserves will fall on the probabilistic reserves distribution. Thus, one cannot conclude that a deterministic reserves estimate will correspond to either proved reserves (P90) or proved-plus-probable reserves (P50), or that it will correspond to the mean, most-likely, or any other statistic from a probabilistic reserves assessment. Therefore, deterministic reserves estimates should be used with caution, as it is uncertain which reserves categories the deterministic estimate represents for any situation.

The shape of the ROP distribution and the difference between the probabilistic and deterministic ROP is controlled by:

- The relationship between reserves and the uncertain parameter which represents the complexity of the reservoir physics involved in predicting the flow and how the uncertain parameters are interacting with the reservoir physics, and
- The relationship between the uncertain parameter and mismatch objective function (OF).

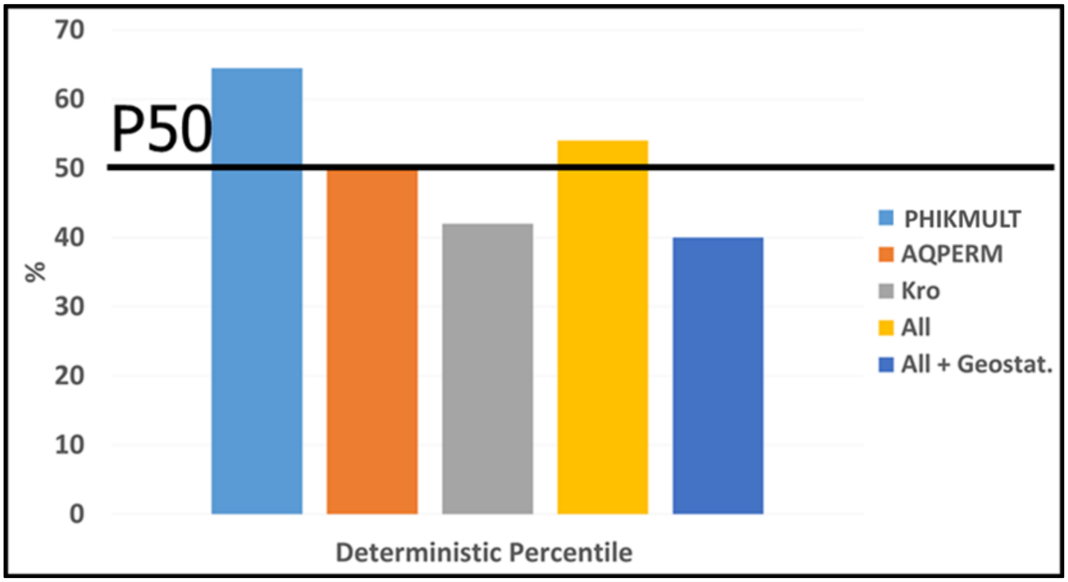

Fig. 43—Deterministic percentiles comparisons of Case 1, Case 2, Case 3, Case 4, and Case 5

Table 8—Deterministic percentiles comparisons of Case 1, Case 2, Case 3, Case 4, and Case 5

Type	Deterministic Percentile
PHIKMULT	64.5
AQPERM	49.8
Kro	42
All	54
All + Geostat.	40

3.2 Effect of Models Acceptance Threshold

To study the effect of the acceptance threshold on the ROP distribution, different OF thresholds were examined. The OF acceptance threshold was used as the criterion to include the models with “good” history matches and exclude the ones with “bad” history matches in generating the ROP distribution. The case of well porosity and permeability multiplier (PHIKMULT) from the Section 3.1.1 was used to examine the effect of excluding models with lower history match quality in the generation of the ROP distribution. In Section 3.1.1, no filtering was applied and all models were included in generating the ROP distribution. The results of this case were discussed in Section 3.1.1. Next, the acceptance threshold was lowered to different levels and more models with “bad” history matches were filtered out.

3.2.1 Mismatch OF Less Than 167

The acceptance threshold for including the simulation models in generating the ROP distribution was set to 167. The models simulation models with mismatch OF higher than 167 were excluded. 438 models were included in generating the ROP distribution (**Fig. 44)**. The generated simulation models forecasted different values of ROP as a function of the well porosity and permeability multiplier (PHIKMULT) values which ranged from -0.21 to 0.3 (**Fig. 45)**. These models have different values of history match quality as a function of the uncertain variable (**Fig. 46**). The resulting ROP distribution showed P10, P50, P90 equal to 2.48, 2.43, and 2.36 MM Sm3 respectively (**Fig. 47**). **Fig. 48** shows that the deterministic ROP is pessimistic compared to the P50 as it fell on the percentile P65. The statistical parameters of the distribution are shown in **Table 9**.

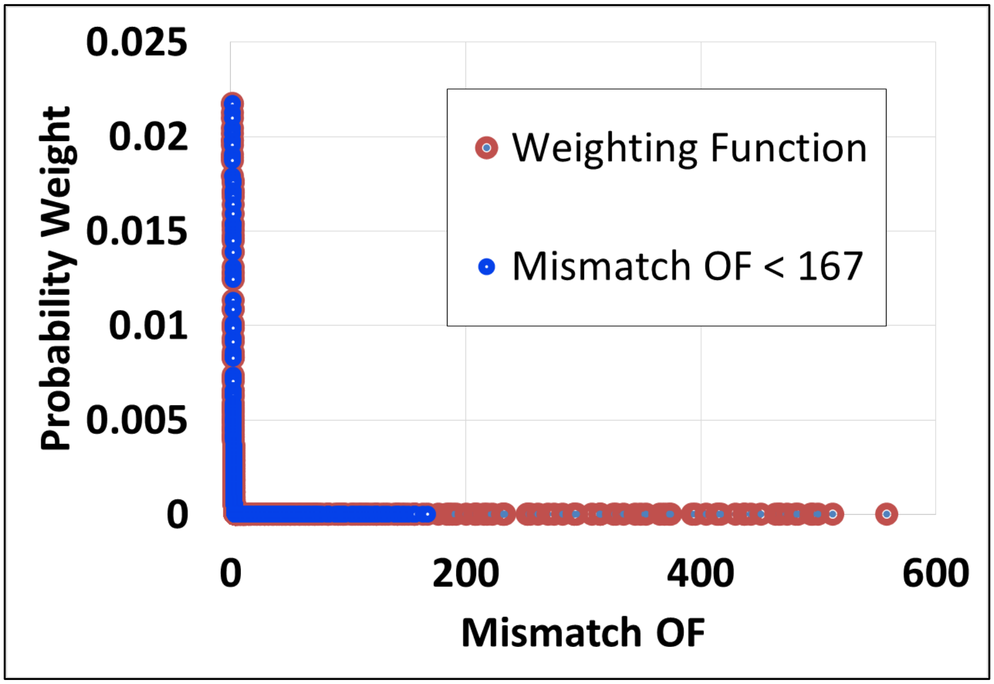

Fig. 44—Mismatch OF <167:438 models included

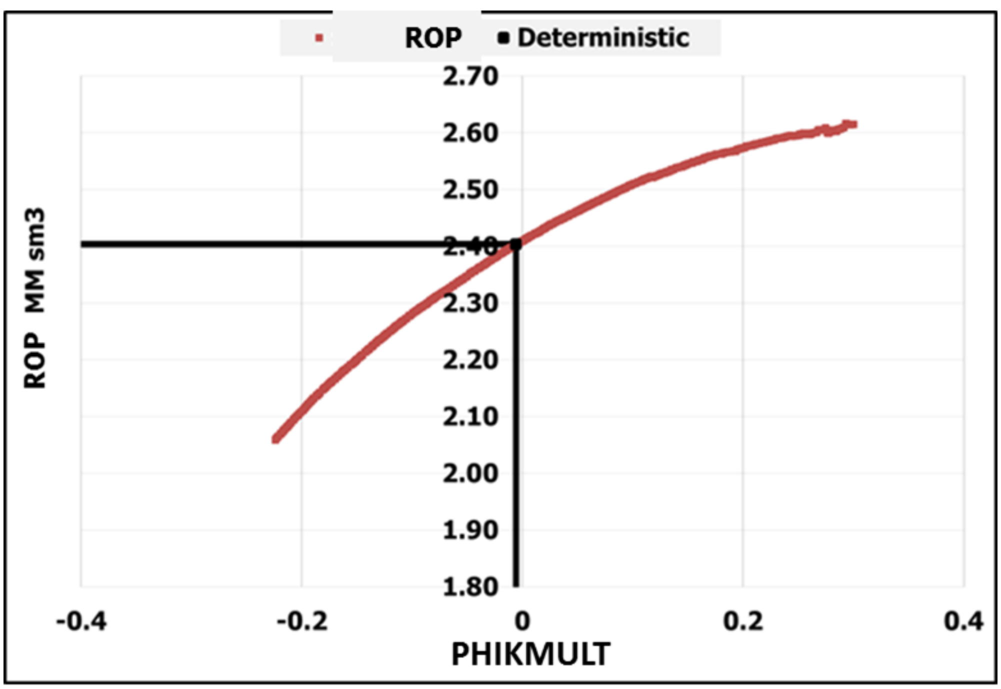

Fig. 45—Mismatch OF <167: ROP as a function of well porosity and permeability multiplier

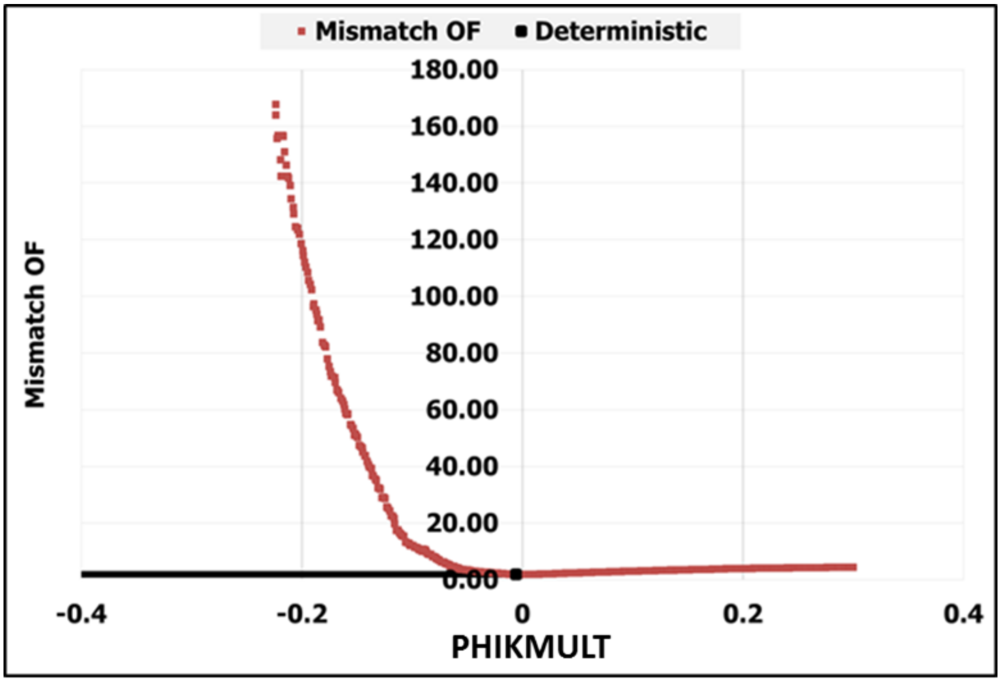

Fig. 46—mismatch OF <167: mismatch objective function of the models based on the uncertain parameter

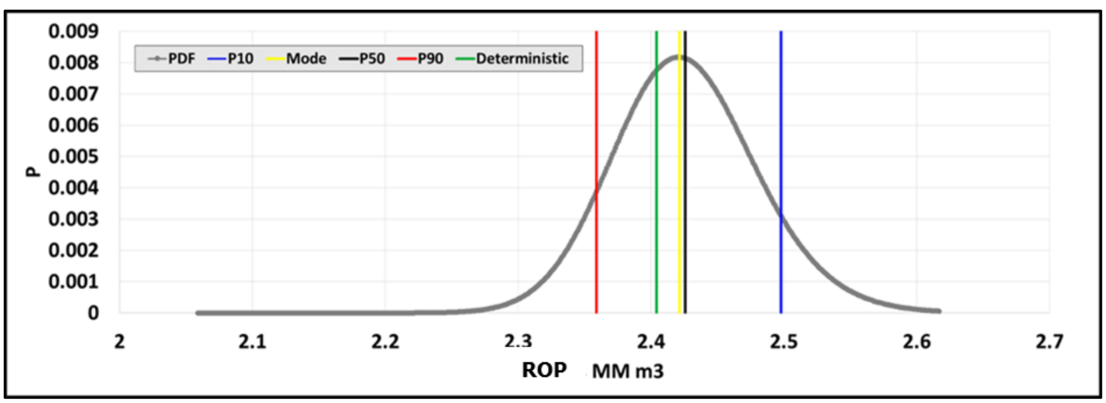

Fig. 47—Mismatch OF <167: PDF of ROP distribution

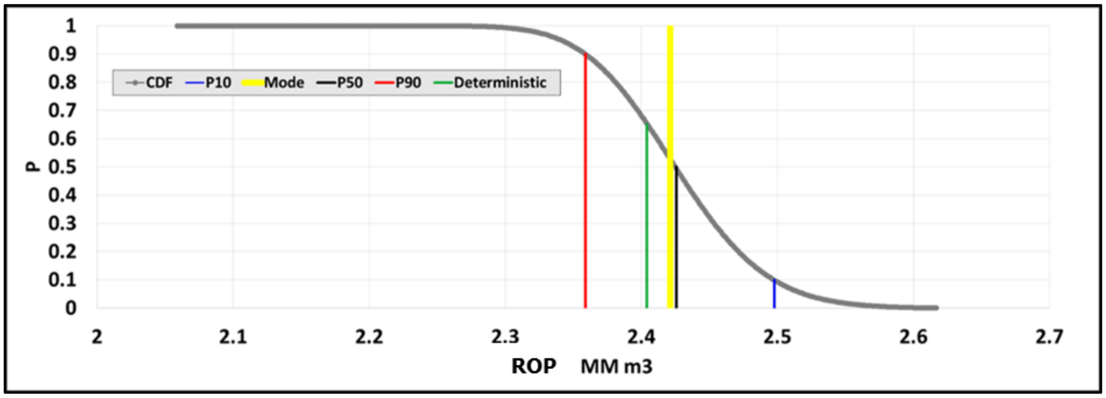

Fig. 48—Mismatch OF <167,:CDF of ROP Distribution

Table 9—Mismatch OF <167:statistical parameters of ROP distribution

ROP MM sm3					
P10	**P50**	**P90**	**Mode**	**Mean**	**Deterministic**
2.50	**2.43**	**2.36**	**2.42**	**2.43**	**2.40**

3.2.2 Mismatch OF Less Than 39

The acceptance threshold was set to 39 and the models with mismatch OF higher than 39 were excluded. 364 models were included in generating the ROP distribution (**Fig. 49**). The generated simulation models forecasted different values of ROP as a function of the well porosity and permeability multiplier (PHIKMULT) values which ranged from -0.12 to 0.3 (**Fig. 50**). These models have different values of history match quality as a function of the uncertain variable (**Fig. 51**). The resulting ROP distribution showed P10, P50, P90 equal to 2.49, 2.42, and 2.37 MM Sm3 respectively (**Fig. 52**). **Fig. 53** shows that the deterministic ROP is pessimistic compared to the P50 as it fell on the percentile P68. The statistical parameters of the distribution are shown in **Table 10**.

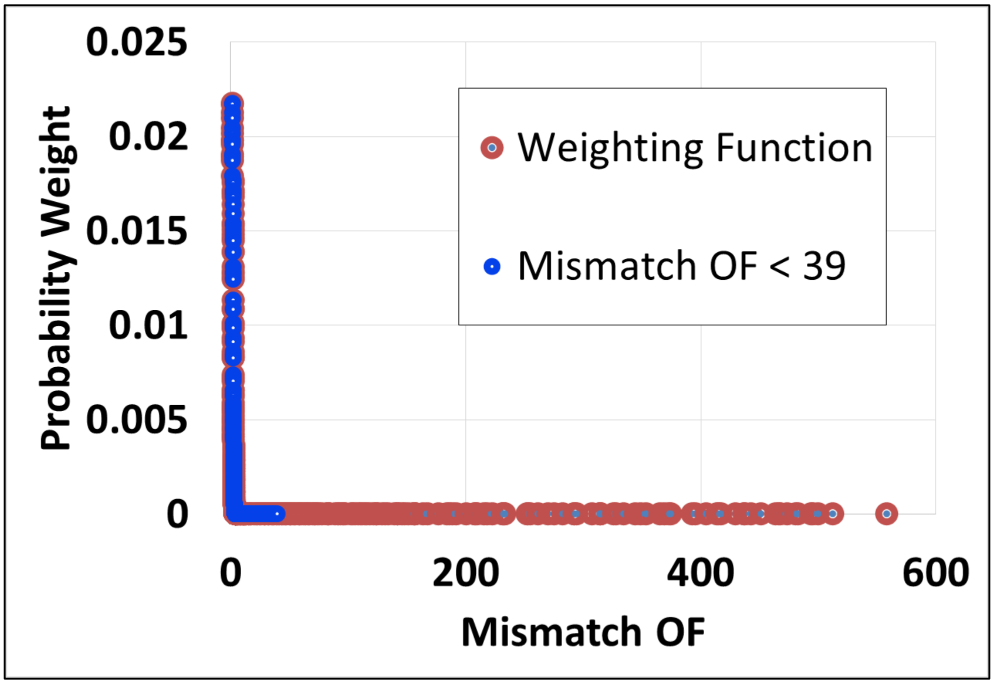

Fig. 49—Mismatch OF <39, 364 models included

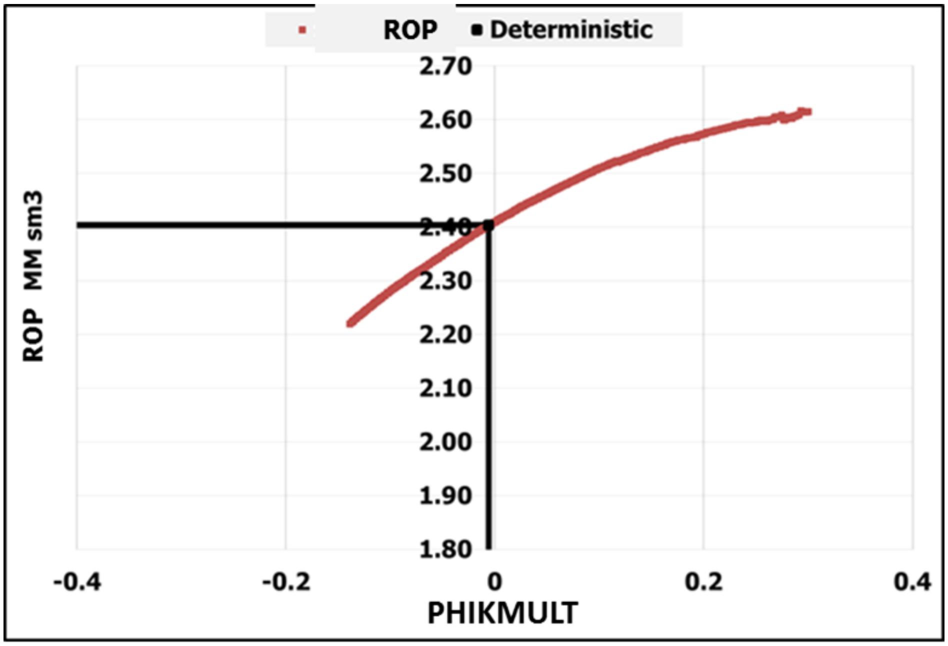

Fig. 50—Mismatch OF <39: ROP as a function of well porosity and permeability multiplier

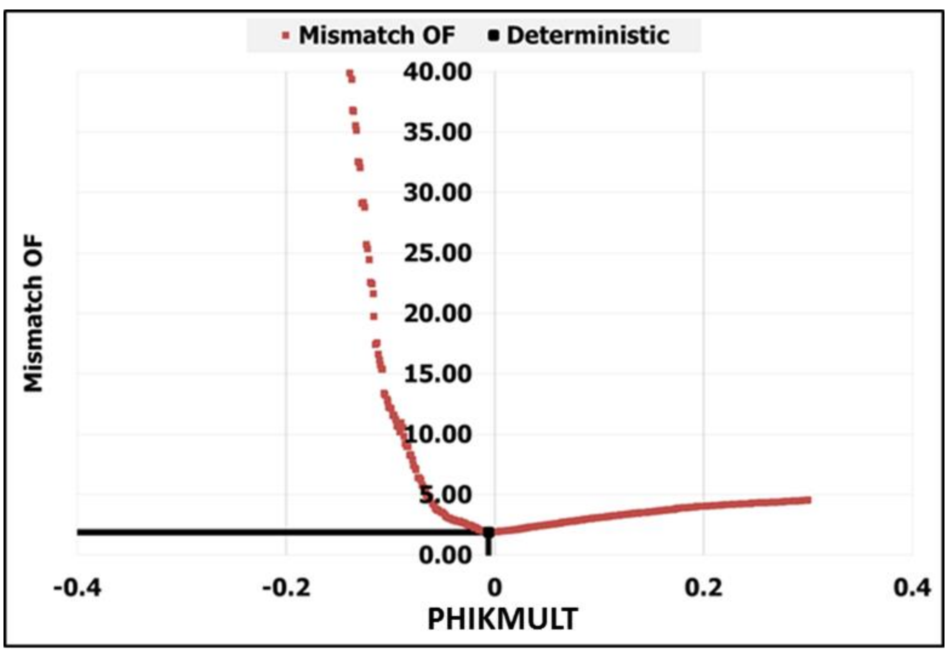

Fig. 51—Mismatch OF <39: mismatch objective function of the models based on the uncertain parameters

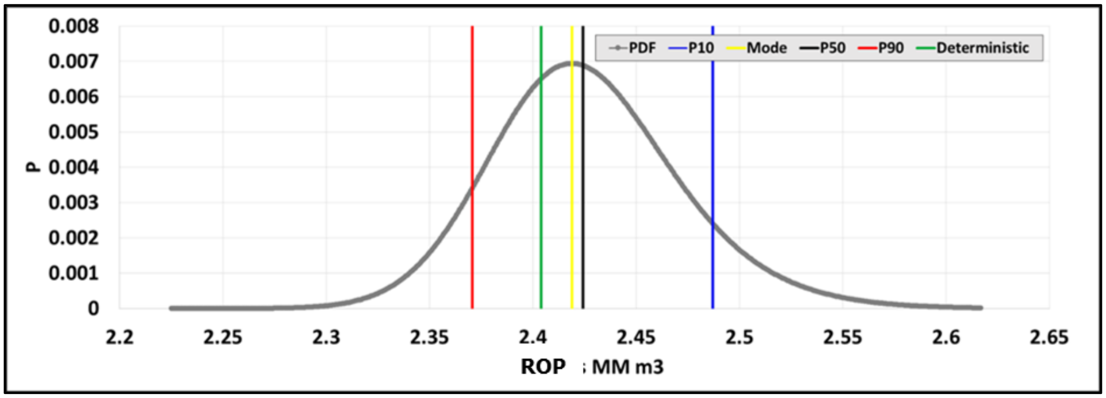

Fig. 52—Mismatch OF <39: PDF of ROP distribution

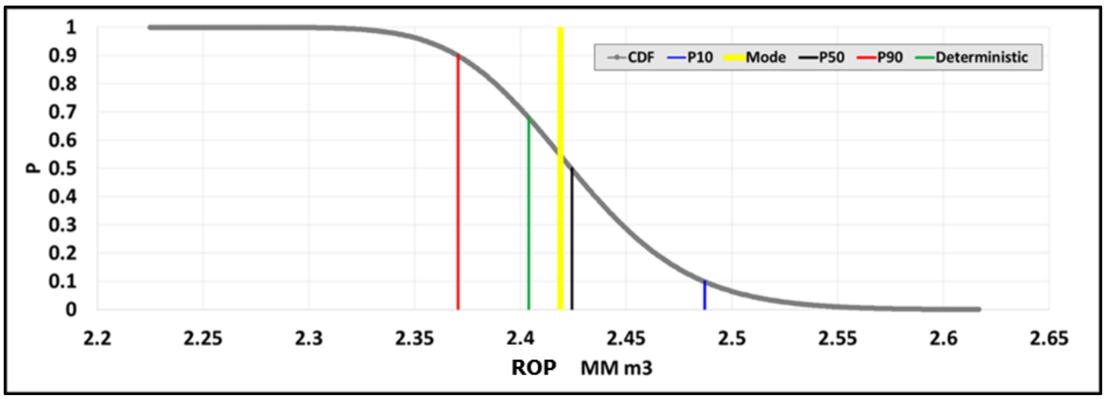

Fig. 53—Mismatch OF <39: CDF of ROP distribution

Table 10—Mismatch OF <39: statistical parameters of ROP distribution

ROP MM sm3					
P10	**P50**	**P90**	**Mode**	**Mean**	**Deterministic**
2.49	2.42	2.37	2.42	2.43	2.40

3.2.3 Mismatch OF Less Than 3.5

The acceptance threshold was set to 3.5 and the models with mismatch OF higher than 3.5 were excluded. 157 models were included in generating the ROP distribution

(**Fig. 54**). The generated simulation models forecasted different values of ROP as a function of the well porosity and permeability multiplier (PHIKMULT) values which ranged from -0.048 to 0.139 (**Fig. 55**). These models have different values of history match quality as a function of the uncertain variable (**Fig. 56**). The resulting ROP distribution is showed P10, P50, P90 equal to 2.47, 2.42, and 2.38 MM Sm3 respectively (**Fig. 57**). **Fig. 58** shows that the deterministic ROP is pessimistic compared to the P50 as it fell on the percentile P72. The statistical parameters of the distribution are shown in **Table 11**.

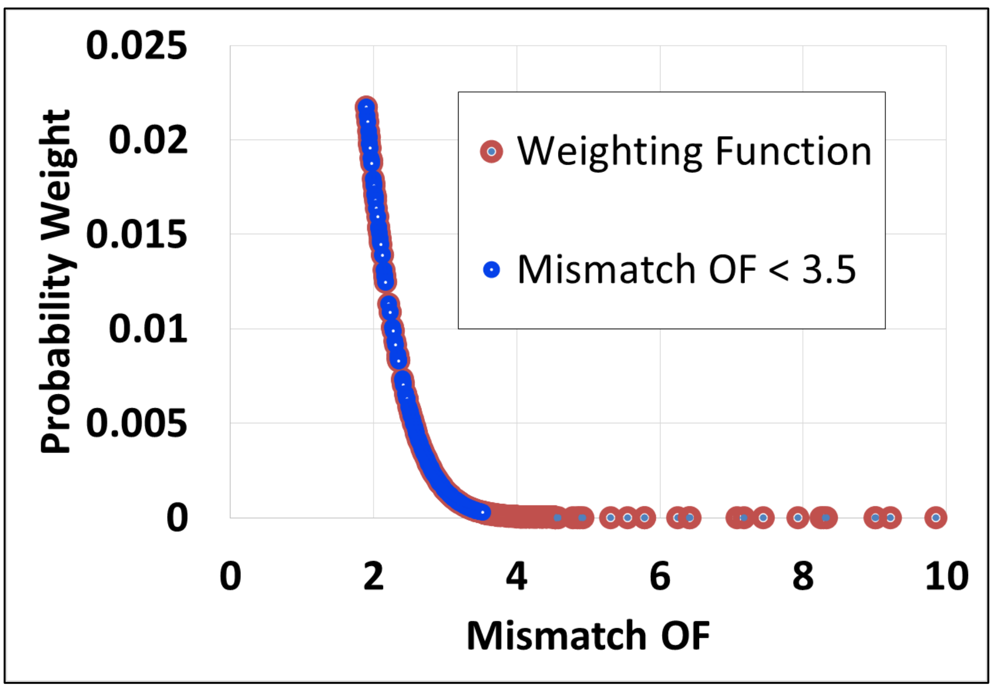

Fig. 54—Mismatch OF <3.5: 157 models included

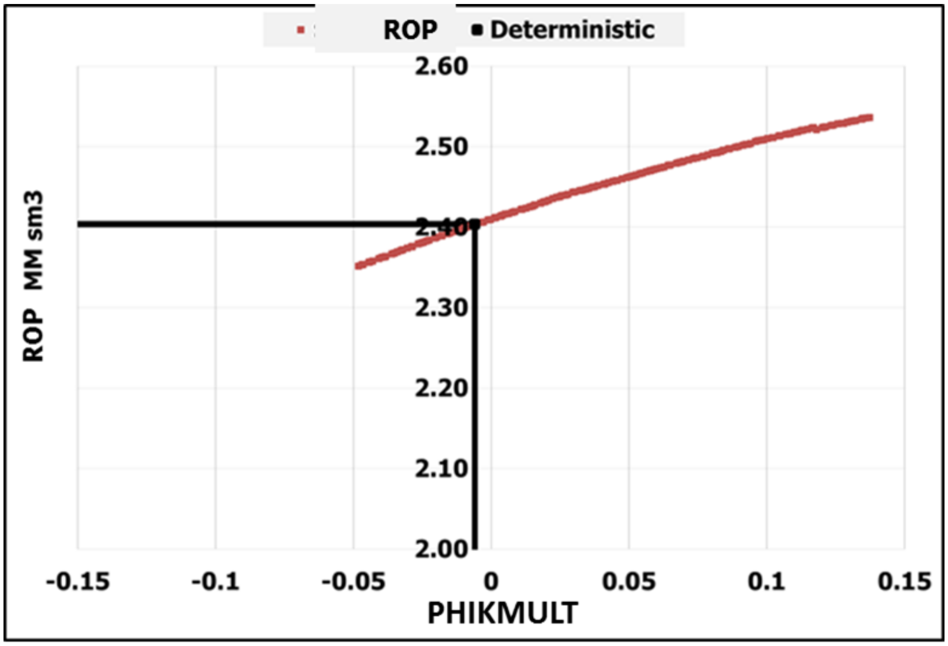

Fig. 55—Mismatch OF <3.5: ROP as a function of well porosity and permeability multiplier

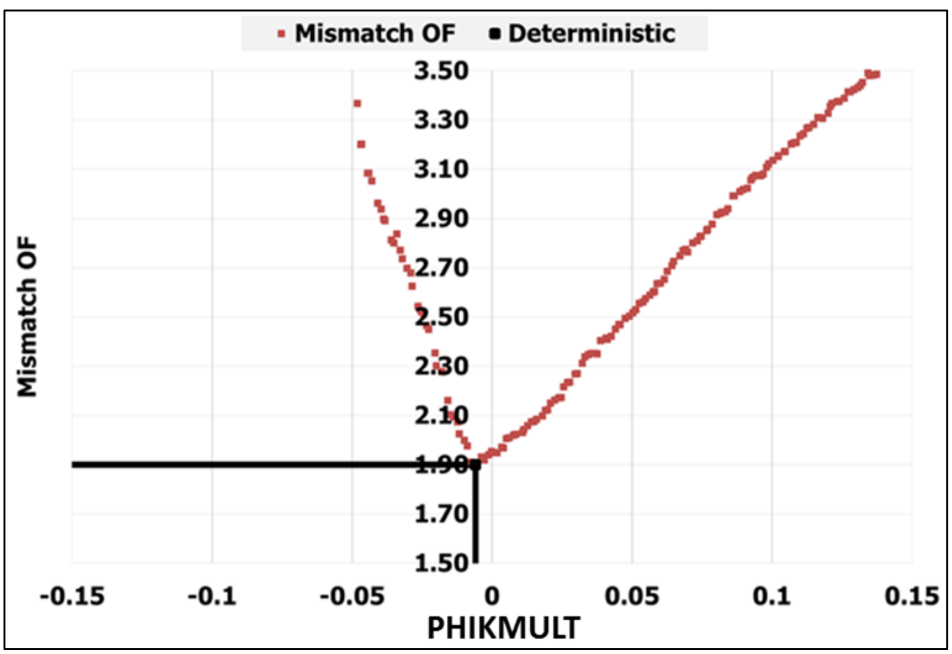

Fig. 56—Mismatch OF <3.5: mismatch objective function of the models based on the uncertain parameter

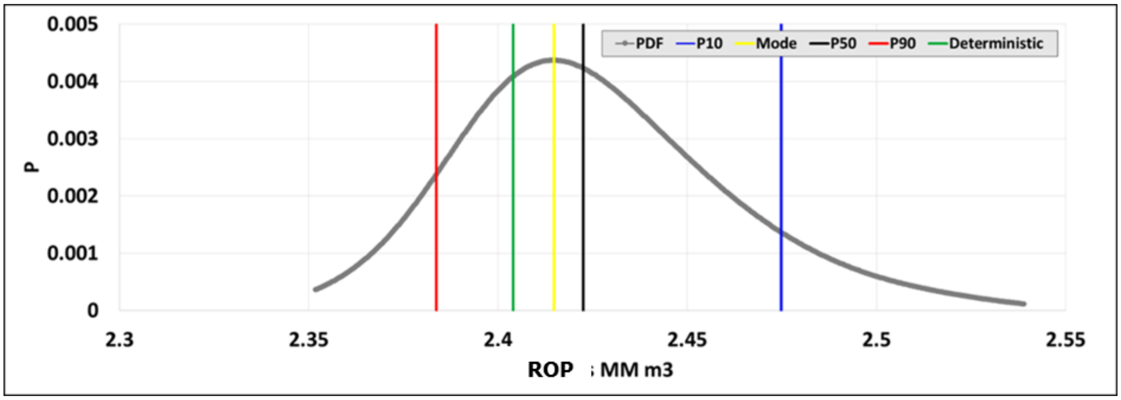

Fig. 57—Mismatch OF <3.5: PDF of ROP distribution

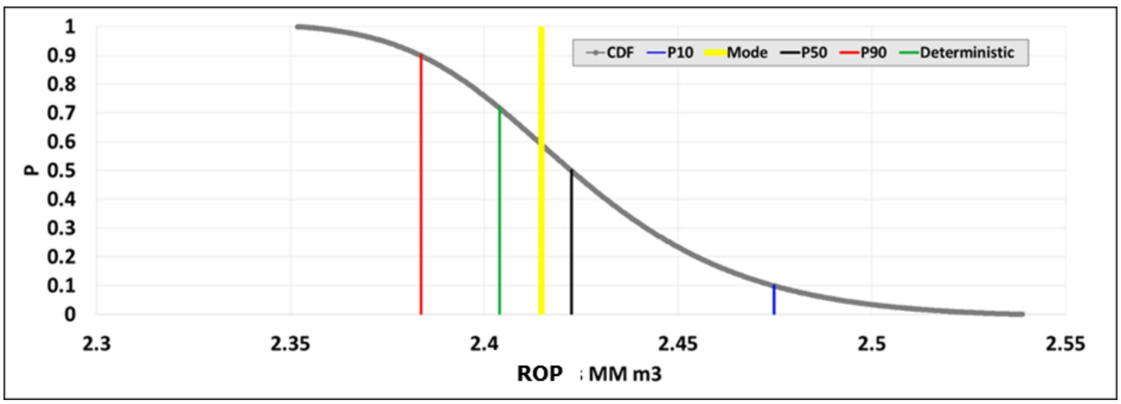

Fig. 58—Mismatch OF <3.5: CDF of ROP distribution

Table 11—Mismatch OF <3.5: statistical parameters of ROP distribution

ROP MM sm3					
P10	P50	P90	Mode	Mean	Deterministic
2.47	2.42	2.38	2.41	2.43	2.40

3.2.4 Mismatch OF Less Than 3.5 with Equal Probability

In this case, the 157 models that were included in generating the ROP distribution, as in Section 3.2.3, were assigned equal probability. The resulting ROP distribution showed P10, P50, P90 equal to 2.52, 2.45, and 2.38 MM Sm3, respectively (**Fig. 59**). **Fig. 60** shows that the deterministic ROP is pessimistic compared to the P50 as it fell on the percentile P78. The statistical parameters of the distribution are shown in **Table 12**.

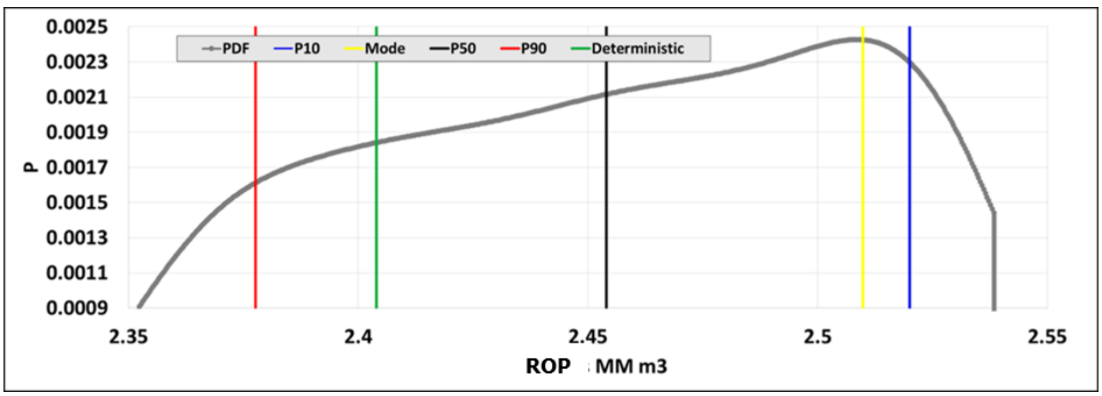

Fig. 59—Mismatch OF <3.5 with equal probabilities: PDF of ROP distribution

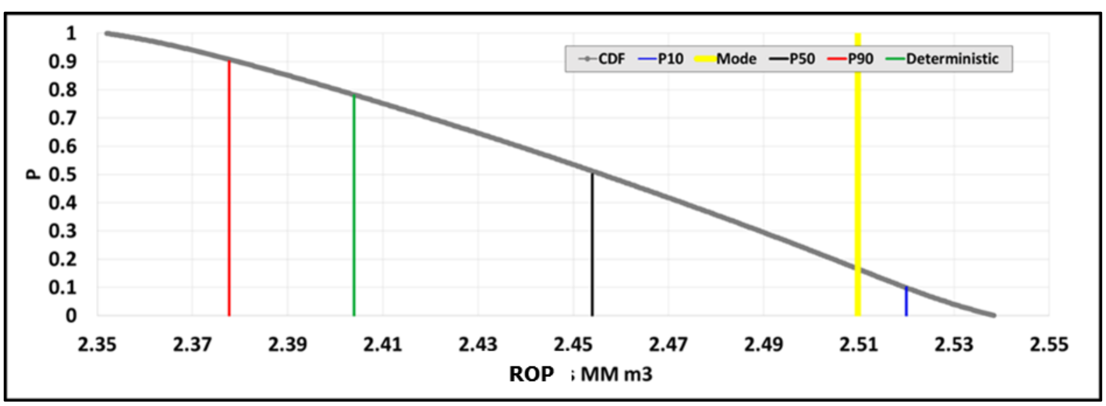

Fig. 60—Mismatch OF <3.5 with equal probabilities: CDF of ROP distribution

Table 12—Mismatch OF <3.5 with equal probabilities: statistical parameters of ROP distribution

Reserves MM sm3					
P10	P50	P90	Mode	Mean	Deterministic
2.52	2.45	2.38	2.51	2.45	2.40

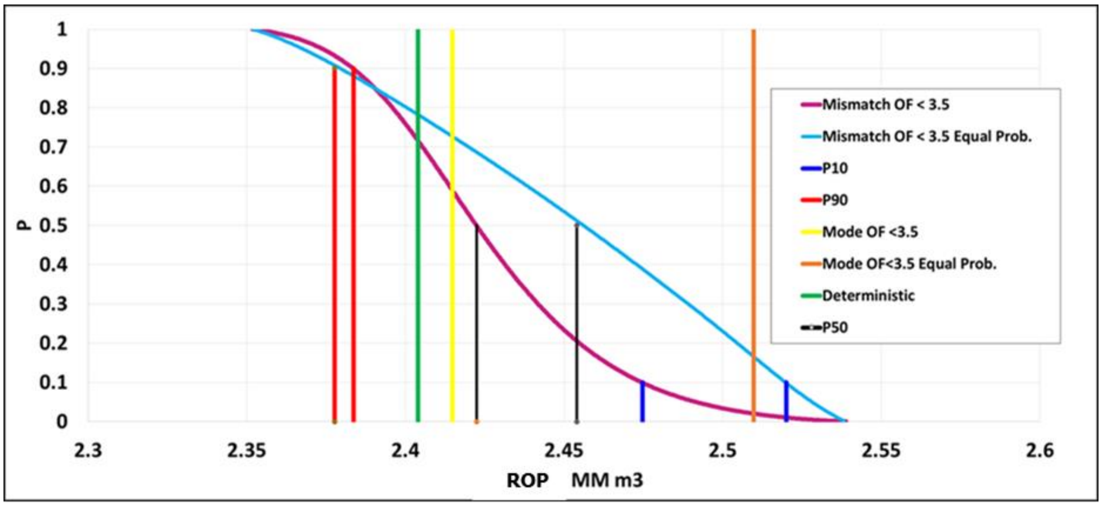

Fig. 61—Mismatch OF <3.5: comparisons of CDF when assigning weighted and non-weighted probability to the models

3.2.5 Summary

Excluding models with "bad" history matches from the full range by using more conservative acceptance thresholds eliminated the models with "bad" history match quality. Such models lie on both sides of the mismatch OF curve (**Fig. 15, Fig. 46**, **Fig. 51**, **Fig. 56).** Therefore, excluding these models truncated the ROP curve from both ends (**Fig. 14, Fig. 45, Fig. 50**, and **Fig. 55)**, which leads to decrease in the P10 and increase in the P90, narrowing the distribution (**Fig. 62** and **Table 13**). As the truncation of the ROP curve is greater from the lower end of the ROP curve (**Fig. 15, Fig. 46**, **Fig. 51**, **Fig. 56),** the percentile of the deterministic ROP increased from P64.5 to P72 when the acceptance threshold was set to 3.5 (**Fig. 63**). There was no noticeable change in the P50, the mode, and the mean (**Fig. 62**, **Fig. 63**, and **Table 13**).

A comparison between assigning the filtered models weighted probability with their history match quality and assigning them equal probability weights was made (**Fig. 61**). When the filtered models were assigned equal probability weights, the effect of the weighting function (**Eq. 4**) was no longer active. The probability of the models with high PHIKMULT values and relatively high mismatch OF values (**Fig. 56**) actually increased because those models were not assigned lower probability weights. These models have high PHIKMULT and thus high ROP values (**Fig. 55**). Therefore, assigning the models equal probability weights changed the ROP distribution skewness from right-skewed (**Fig. 57**) to left-skewed (**Fig. 59**) and increased the P50, the mode and the mean (**Fig. 61**, **Table 12**). Moreover, P10 was increased and P90 decreased and the distribution got wider (**Fig. 61**) because the probability weights of models at both ends of the ROP distribution (**Fig. 57**) increased when the weighting function (**Eq. 4**) was deactivated. That change in the ROP distribution increased the percentile of the deterministic ROP from P72 to P78 (**Fig. 61**).

I conclude that the consistency between the deterministic and probabilistic ROP estimates also depends on how the probabilistic analysis was conducted. For example, assigning the models equal probabilities, instead of a weighted probability based on their mismatch OF values, significantly altered the statistical parameters of the probabilistic ROP distribution and thus changed the relationship between the deterministic ROP and the statistical parameters of the probabilistic ROP distribution. Moreover, excluding models with “bad” history matches from generating the ROP distribution leads to decreasing P10 and increasing P90, narrowing the distribution. Such practices could overestimate P90 and underestimate P10 with the probabilistic analysis. All this suggests that proper care should also be taken in conducting probabilistic analyses as well as deterministic analyses. To reliably quantify the full uncertainty with probabilistic methods, it appears the best practice is use high thresholds to admit as many models as possible and then weight these models appropriately using probabilities derived from OF mismatch values.

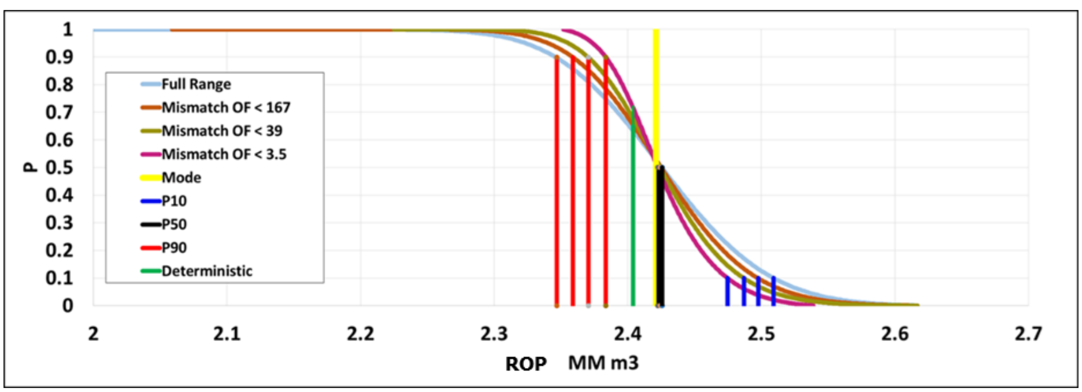

Fig. 62—Comparisons of CDF using different OF acceptance thresholds

Table 13—Comparisons of ROP distribution using different OF acceptance thresholds

Acceptance Threshold	Number of Models	P10	P50	P90	Mode	Mean	Deterministic	Deterministic Percentile
Full Range	500	2.509038	2.42581	2.34688	2.42294	2.42635	2.403951	0.645
Mismatch OF <167	438	2.497681	2.42564	2.35905	2.42127	2.42613	2.403951	0.65
Mismatch OF <39	364	2.487146	2.4243	2.37066	2.41894	2.42627	2.403951	0.68
Mismatch OF <3.5	157	2.474798	2.42247	2.38368	2.41478	2.42597	2.403951	0.72

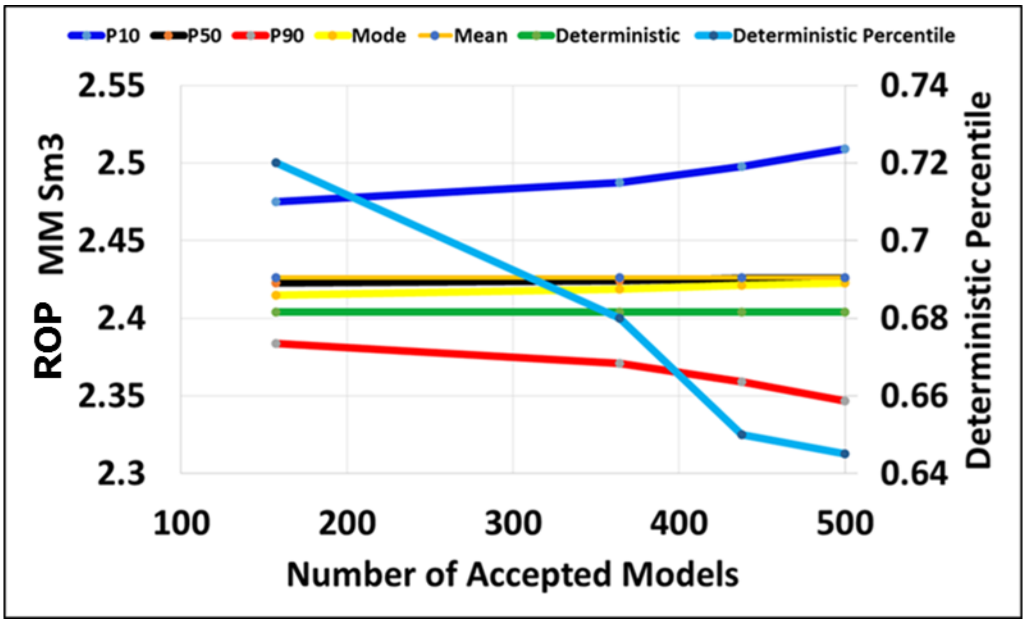

Fig. 63—ROP statistics and deterministic ROP percentiles using different OF acceptance thresholds

3.2.6 Volumetric Method

An experiment was run to compare deterministic reserves with probabilistic reserves using the volumetric method. Distributions for porosity, initial water saturation, formation volume factor, net pay, area, and recovery factor were generated (**Fig. 64)**. The modes (most-likely values) of the input parameters distributions were selected as the deterministic values in the deterministic approach. The volumetric calculations were determined using **Eq. 5**

$$N = \frac{7758\, A\, h\, \emptyset\, (1 - S_w) R_f}{Bo} \quad \text{...} (5)$$

where

N = oil in place, stb

A = drainage area, acres

Boi = initial formation volume factor,rb/stb

h = thickness, ft

$\emptyset$ = porosity, fraction

Swi = water saturation, fraction

R_f = recovery factor

Fig. 65 shows the reserves distribution that was generated by sampling randomly from the distributions of the input parameters using Monte Carlo simulation and plugging them in **Eq. 5.** The P10, the P50, and the P90 of the reserves distribution are equal to 1011.796, 236.922, and 56.943 MM STB, respectively. **Fig. 66** shows that the deterministic reserves is pessimistic compared to the P50 as it fell on percentile P85. The statistical parameters of the reserves distribution are shown in **Table 14**.

Similarly to the simulation method, in the volumetric method the relationship between the deterministic reserves and probabilistic reserves is controlled by two sets of functions. The first set of functions is the distributions of the uncertain parameters. The distributions are prior distributions for the volumetric method, while they are either likelihood or posterior distributions for the simulation method because they are a function of history match quality. The second set of functions is the relationships between the reserves and the uncertain parameters, which are linear for the simple volumetric equation. For the simulation method, these functions are not necessarily linear because they depend on flow physics, heterogeneity and other complexities. Thus, similarly to the simulation method, because of the interaction of the two sets of functions, the consistency between the deterministic reserves and probabilistic reserves distribution cannot be guaranteed for the volumetric method.

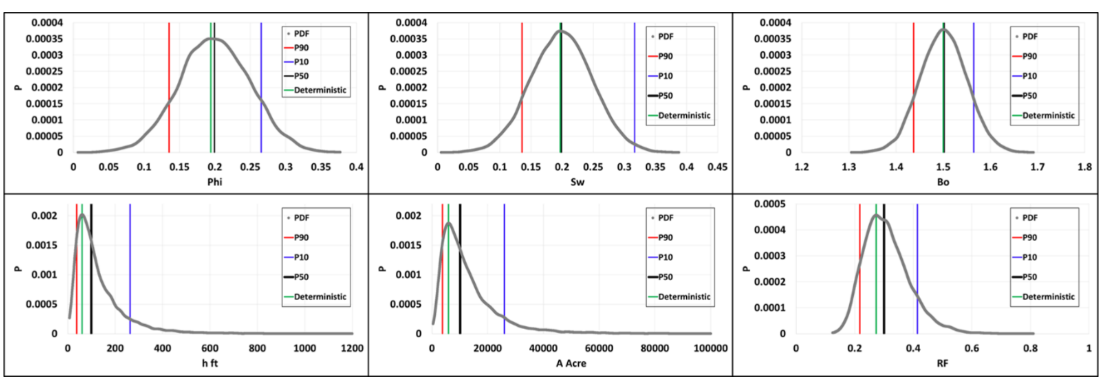

Fig. 64—Volumetric method: distributions of the input parameters

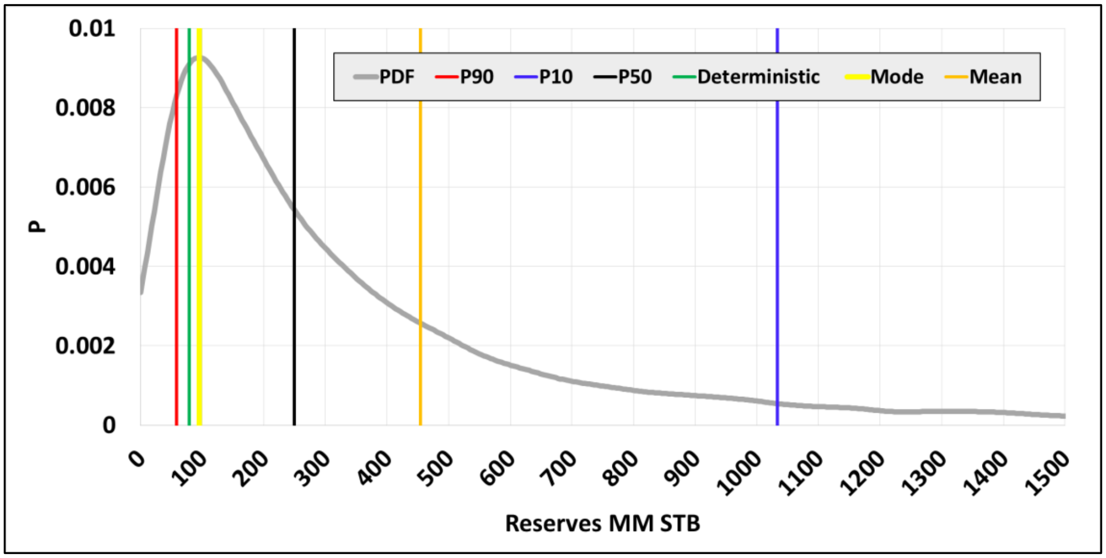

Fig. 65—Volumetric method: PDF of reserves distribution

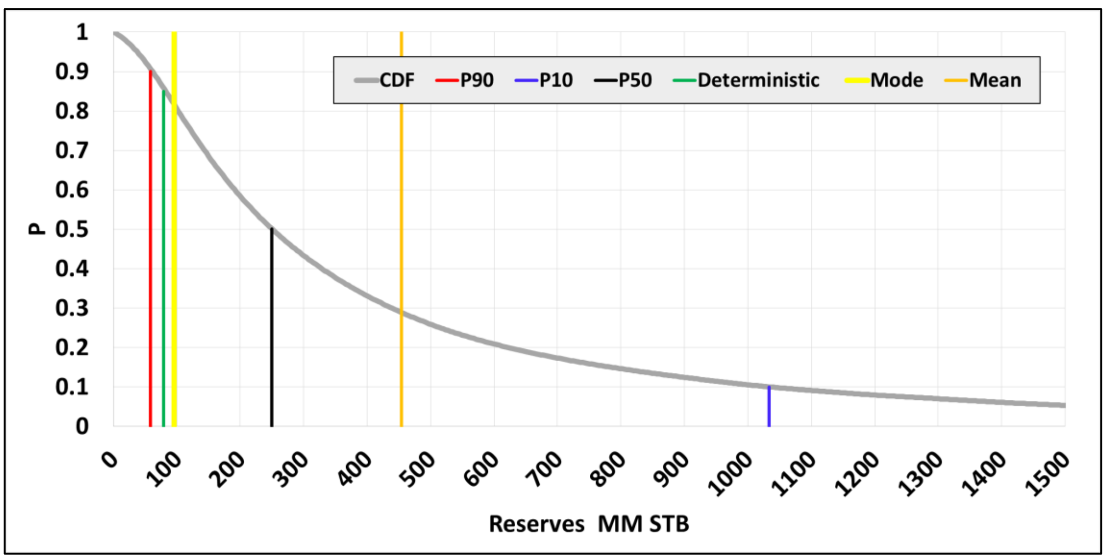

Fig. 66—Volumetric method: CDF of reserves distribution

Table 14—Volumetric method, statistical parameters of reserves distribution

Reserves MM STB					
P10	P50	P90	Mode	Mean	Deterministic
1011.796	236.922	56.943	94.064	453.899	79.499

4. CONCLUSIONS AND RECOMMENDATIONS

4.1 Summary of Conclusions

Based on the results for the PUNQ-S3 reservoir and the volumetric method experiment, the following can be concluded:

- The consistency between deterministic and probabilistic reserves estimates cannot be guaranteed. It is difficult to predict exactly where the deterministic reserves will fall on the probabilistic reserves distribution. Thus, one cannot conclude that a deterministic reserves estimate will correspond to either proved reserves (P90) or proved-plus-probable reserves (P50), or that it will correspond to the mean, most-likely, or any other statistic from a probabilistic reserves assessment. Therefore, deterministic reserves estimates should be used with caution, as it is uncertain which reserves categories the deterministic estimate represents for any situation.
- In the volumetric method, the deterministic reserves fell on the 85^{th} percentile of the probabilistic reserves distribution.
- For the PUNQ-S3 cases, the deterministic reserves estimate was optimistic in two cases, showed good agreement in another case and was pessimistic in two other cases compared to the P50 of probabilistic reserves. The relationship between the deterministic and probabilistic reserves estimates is controlled by:
    - The relationships between reserves and the uncertain parameters, which represents the complexity of the reservoir physics involved in

predicting the flow and how the uncertain parameters are interacting with the reservoir physics,

  - The relationships between the uncertain parameters and mismatch objective function (OF), and
  - The OF acceptance threshold of the models to be included in generating the reserves distribution.

- Excluding models with "bad" history matches from generating the reserves distribution leads to decreasing P10 and increasing P90, narrowing the distribution. Such practices could lead to underestimation of uncertainty with probabilistic methods. Although the threshold did not have noticeable effect on the P50, the mode, and the mean for the cases studied, assigning models equal probability weights had significant effect on the reserves distribution and the resulting statistical parameters like the P50, the mode and the mean.
- The relationship between the deterministic and probabilistic reserves estimates depends also on how the probabilistic analysis was conducted.

4.2 Recommendations for Future Works

- Since all the simulations were run to a common simulation end time of 16.5 years, as was used in the PUNQ-S3 project, the production calculated is technically not reserves. Therefore, it is advised to use an economic limit to terminate the simulation runs in future studies.
- Using the PUNQ-S3 model with the parameters I chose resulted in P10/P90 ratios no greater than 1.13, while P10/P90 ratios in practice normally range between 5 and 10. Therefore, these experiments should be repeated with either modification of the PUNQ-S3 model or use of another simulation model to investigate larger P10/P90 ratios.
- The deterministic reserves were calculated using the modes of the parameters distributions. The deterministic analysis should be conducted using the means from the parameter distributions to see if this results in consistency with the probabilistic result.

REFERENCES

Capen, E. C. 1996. A Consistent Probabilistic Definition of Reserves. *SPE Reservoir Engineering* 11 (1): 23-28. http://dx.doi.org/10.2118/25830-PA

Dehghani, K., D. J. Fischer and M. Skalinski. 2008. Application of Integrated Reservoir Studies and Techniques To Estimate Oil Volumes and Recovery-Tengiz Field, Republic of Kazakhstan. *SPE Reservoir Evaluation & Engineering* 11 (2): 362-378. http://dx.doi.org/10.2118/102197-PA

Dharan, B. G. 2004. Improving the Relevance and Reliability of Oil and Gas Reserves Disclosures. Paper Presented to the US House Committee on Financial Services, July 21, 2004.

Elf Exploration Production. 1997. PUNQ-S3 Model Data Set, https://www.imperial.ac.uk/engineering/departments/earth-science/research/research-groups/perm/standard-models/eclipse-dataset/.

Floris, F., M. Bush, M. Cuypers et al. 2001. Methods for quantifying the uncertainty of production forecasts: a comparative study. *Petroleum Geoscience* 7 (S): 87-96. 10.1144/petgeo.7.S.S87

Harrell, D. R. and T. L. Gardner. 2005. Significant Differences in Proved Reserves Estimates Using SPE/WPC Definitions Compared to United States Securities and Exchange Commission Definitions. *SPE Reservoir Evaluation & Engineering* 8 (6): 520-527. http://dx.doi.org/10.2118/84145-PA

Lee, W. J. 2009. Modernization of the SEC Oil and Gas Reserves Reporting Requirements. *SPE Economics & Management* 1 (1): 4-10. http://dx.doi.org/10.2118/123793-PA

Lee, W. J., R. E. Sidle and D. McVay. 2011. Reservoir Simulation: A Reliable Technology? Paper presented at the SPE Annual Technical Conference and Exhibition, Denver, Colorado, USA, 30 October-2 November 2011. SPE-146524-MS http://dx.doi.org/10.2118/146524-MS.

Mattax, C. C. and R. L. Dalton. 1990. *Reservoir simulation*. Richardson, TX, Henry L. Doherty Memorial Fund of AIME, Society of Petroleum Engineers (Reprint).

McVay, D. A. and M. N. Dossary. 2014. The Value of Assessing Uncertainty. *SPE Economics & Management* 6 (2): 100-110. http://dx.doi.org/10.2118/160189-PA

Palke, M. R. and D. C. Rietz. 2001. The Adaptation of Reservoir Simulation Models for Use in Reserves Certification Under Regulatory Guidelines or Reserves Definitions. Paper presented at the SPE Annual Technical Conference and Exhibition, New Orleans, Louisiana, 30 September-3 October 2001. SPE-71430-MS http://dx.doi.org/10.2118/71430-MS.

Patricelli, J. A. and C. L. McMichael. 1995. An Integrated Deterministic/Probabilistic Approach to Reserves Estimations (includes associated papers 31056 and 35248). *SPE Journal of Petroleum Technology* 47 (1): 49-53. http://dx.doi.org/10.2118/28329-PA

Society of Petroleum Engineers (SPE). 2007. Petroleum Resources Management System, http://www.spe.org/industry/docs/Petroleum_Resources_Management_System_2007.pdf#redirected_from=/industry/reserves/prms.php downloaded 12 January 2013.

Society of Petroleum Engineers (SPE). 2011. Guidelines for Application of the Petroleum Resources Management System, http://www.spe.org/industry/docs/PRMS_Guidelines_Nov2011.pdf downloaded 12 January 2013.

Purvis, D. C., R. F. Strickland, R. A. Alexander et al. 1997. Coupling Probabilistic Methods and Finite Difference Simulation: Three Case Histories. Paper presented at the SPE Annual Technical Conference and Exhibition, San Antonio, Texas, 5-8 October 1997. SPE-38777-MS http://dx.doi.org/10.2118/38777-MS.

Rietz, D. C. and A. H. Usmani. 2005. Reservoir Simulation and Reserves Classifications-Guidelines for Reviewing Model History Matches To Help Bridge the Gap Between Evaluators and Simulation Specialists. Paper presented at the SPE Annual Technical Conference and Exhibition, Dallas, Texas, 9-12 October 2005. SPE-96410-MS http://dx.doi.org/10.2118/96410-MS.

Rietz, D. C. and A. H. Usmani. 2009. Case Studies Illustrating the Use of Reservoir Simulation Results in the Reserves Estimation Process. *SPE Reservoir Evaluation & Engineering* 12 (1): 149-158. http://dx.doi.org/10.2118/110066-PA

Sajjadian, S., A. A. Hossein, M. Roostaeian et al. 2010. Integrated Uncertainty Quantification by Probabilistic Forecasting Approach in the Field Development Project. Paper presented at the Trinidad and Tobago Energy Resources Conference, Port of Spain, Trinidad, 27-30 June 2010. SPE-132948-MS http://dx.doi.org/10.2118/132948-MS.

US Securities and Exchange Commission. 2009. Modernization of Oil and Gas Reporting. Final Rule, 17 CFR Parts 210, 211, 229, and 249,[Release Nos. 33–8995; 34–59192; FR–78; File No. S7–15–08], RIN 3235–AK00, US SEC, Washington, DC (14 January 2009), http://www.sec.gov/rules/final/2009/33-8995fr.pdf downloaded 15 Januarry 2013

US Securities and Exchange Commision. 2013. The Investor's Advocate: How the SEC Protects Investors, Maintains Market Integrity, and Facilitates Capital Formation, http://www.sec.gov/about/whatwedo.shtml# downloaded 18 January 2013.

Sidle, R. E. and W. J. Lee. 2010. The Demonstration of a "Reliable Technology" for Estimating Oil and Gas Reserves. Paper presented at the SPE Hydrocarbon Economics and Evaluation Symposium, Dallas, Texas, USA, 8-9 March 2010. SPE-129689-MS Society of Petroleum Engineers.

Office of the Law Revision Counsel, U.S. House of Representatives. 2012. Title 42-The Public Health and Welfare, Chapter 77-Energy Conservation, Subchapter IV-General Provisions, Part A-Energy Database and Energy Information, § 6383-Accounting Practices http://uscode.house.gov/view.xhtml?req=(title:42%20section:6383%20edition:prelim)%20OR%20(granuleid:USC-prelim-title42-section6383)&f=treesort&edition=prelim&num=0&jumpTo=true.

West's Encyclopedia of American Law. 2008. Administrative Law and Procedure, http://legal-dictionary.thefreedictionary.com/Administrative+Law+and+Procedure downloaded 19 January 2013.

Wolff, M. 2010a. Probabilistic Subsurface Forecasting. Paper SPE-132957-MS, 01 Jan 2010.

Wolff, M. 2010b. Probabilistic Subsurface Forecasting - What Do We Really Know? *Journal of Petroleum Technology* 62 (5): 86-92. http://dx.doi.org/10.2118/118550-JPT

APPENDIX A

A.1 ECLISPE Data File of the Truth Case

```
  RUNSPEC
  PUNQ-S3 MODEL
= NDIVIX NDIVIY NDIVIZ
  19   28     5 /
= OIL WAT GAS DISGAS VAPOIL QAPITR QWATTR QGASTR NOTRAC NWTRAC NGTRAC
  T  T  T    T     F     F     F     F     0     0     0  /
= UNIT CONVENTION
   'METRIC'                          /
=  NRPVT  NPPVT  NTPVT NTROCC QROCKC QRCREV
   30    30     1     1     F     F     /
= NSSFUN NTSFUN QDIRK QREVK QVEOP QHYST QSCAL QSDIR QSREV NSEND NTEND
   35     1     F    T    F    F    F    F    T    1    1  /
= NDRXVD NTEQUL NDPRVD QUIESC QTHPRS QREVTH QMOBIL NTTRVD NSTRVD
   5     1   100     T     F     T     F     1     1       /
=  NTFIP QGRAID QPAIR QTDISP NTFRG QTDSK NRFRG NMFPR NETRC MHISTM NMHISTR
   5  F  F  F  0  F  0  0  0 /
= NWMAXZ NCWMAX NGMAXZ NWGMAX  NLGRMAX  NMAXCL
    20    40     2   20       0     0    /
= QIMCOL NWCOLC NUPCOL
    F     0     3                    /
= MXMFLO MXMTHP MXMWFR MXMGFR MXMALQ NMMVFT
   10     10    10    10    1     1     /
= MXSFLO MXSTHP NMSVFT
   10     10     1                    /
= NANAQU NCAMAX NIFTBL NRIFTB
    2    120    0     0               /
=   DAY   MONTH  YEAR
   01    'JAN'  1967                   /
= QSOLVE NSTACK QFMTOU QFMTIN QUNOUT QUNINP NGDISK IDYNAM
    T    25     F     F   T     T      /

MESSAGES
8* 10000 /

NOECHO
GRID

GRIDFILE                          -- Generated : Petrel
  0 0 /

GRIDUNIT                           -- Generated : Petrel
  METRES /

MAPUNITS                            -- Generated : Petrel
```

```
  METRES /

MAPAXES                          -- Generated : Petrel
  0.00 -999.00 0.00 1.00 1000.00 1.00 /

NOECHO                           -- Generated : Petrel

INCLUDE                          -- Generated : Petrel
'TRUTH_CASE_GRID.GRDECL' /

INCLUDE                          -- Generated : Petrel
'TRUTH_CASE_PROP_PERMX.GRDECL' /

INCLUDE                          -- Generated : Petrel
'TRUTH_CASE_PROP_PERMY.GRDECL' /

INCLUDE                          -- Generated : Petrel
'TRUTH_CASE_PROP_PERMZ.GRDECL' /

INCLUDE                          -- Generated : Petrel
'TRUTH_CASE_PROP_PORO.GRDECL' /

ACTNUM
  0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 0
  0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1
  0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 0
  0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 0
  0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 0
  0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 0
  0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
  1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
  1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
  1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0
  0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0
```

0 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0
0 0 0 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0

0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 0
0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1
0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 0
0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0
0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0
0 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0
0 0 0 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 0
0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0
0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0
0 0 0 0 0 1 1 1 1 1 1 1 1 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 0
0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0
0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0
0 0 0 0 0 1 1 1 1 1 1 1 1 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0

0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 0
0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 0
0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 0

```
0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0
0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 0
0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 0 0 0 0
0 0 0 0 0 1 1 1 1 1 1 1 1 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0

/

NOECHO

ECHO                              -- Generated : Petrel

EDIT

PROPS

SWFN
0.2  0.0      0.0
0.3  0.00024  0.0
0.4  0.0039   0.0
0.5  0.02     0.0
0.6  0.062    0.0
0.7  0.152    0.0
0.8  0.316    0.0
0.9  0.585    0.0
1.0  1.0      0.0
/

SOF3
0.1  0.0   0.0
0.2  0.018 0.0
0.3  0.073 0.025
0.4  0.165 0.1
0.5  0.294 0.225
```

```
0.6  0.459 0.4
0.7  0.661 0.625
0.8  0.9   0.9
/

SGFN
0.0  0.0       0.0
0.1  0.00000077 0.0
0.2  0.000049   0.0
0.3  0.00056    0.0
0.4  0.0032     0.0
0.5  0.012      0.0
0.6  0.036      0.0
0.7  0.091      0.0
0.8  0.2        0.0
/

PVTO
11.460    40.000   1.064   4.338   /
17.890    60.000   1.078   3.878   /
24.320    80.000   1.092   3.467   /
30.760   100.000   1.106   3.100   /
37.190   120.000   1.120   2.771   /
43.620   140.000   1.134   2.478   /
46.840   150.000   1.141   2.343   /
50.050   160.000   1.148   2.215   /
53.270   170.000   1.155   2.095   /
56.490   180.000   1.162   1.981   /
59.700   190.000   1.169   1.873   /
62.920   200.000   1.176   1.771   /
66.130   210.000   1.183   1.674   /
69.350   220.000   1.190   1.583   /
72.570   230.000   1.197   1.497   /
74.000   234.460   1.200   1.460
         250.000   1.198   1.541
         300.000   1.194   1.787   /
80.000   245.000   1.220   1.400
         300.000   1.215   1.700   /
/

PVDG
 40.00   0.02908   0.00880
 60.00   0.01886   0.00920
 80.00   0.01387   0.00960
100.00   0.01093   0.01000
120.00   0.00899   0.01040
140.00   0.00763   0.01090
150.00   0.00709   0.01110
160.00   0.00662   0.01140
```

```
170.00   0.00620   0.01160
180.00   0.00583   0.01190
190.00   0.00551   0.01210
200.00   0.00521   0.01240
210.00   0.00495   0.01260
220.00   0.00471   0.01290
230.00   0.00449   0.01320
234.46   0.00440   0.01330
/

DENSITY
912.0   1000.0   0.8266
/

PVTW
234.46   1.0042   5.43E-05   0.5   1.11E-04   /

ROCK
      235          0.00045   /

STONE1

REGIONS

NOECHO                             -- Generated : Petrel

NOECHO

INCLUDE                            -- Generated : Petrel
'TRUTH_CASE_PROP_SATNUM.GRDECL' /

INCLUDE                            -- Generated : Petrel
'TRUTH_CASE_PROP_PVTNUM.GRDECL' /

INCLUDE                            -- Generated : Petrel
'TRUTH_CASE_PROP_ROCKNUM.GRDECL' /

INCLUDE                            -- Generated : Petrel
'TRUTH_CASE_PROP_EQLNUM.GRDECL' /

ECHO                               -- Generated : Petrel

SOLUTION

AQUANCON
1   14   14   4   4   5   5   'I-'   1180.7   /
1   15   15   4   4   5   5   'J-'   1186.7   /
1   16   16   4   4   5   5   'J-'   1189.7   /
1   17   17   4   4   5   5   'J-'   1197.7   /
```

```
1  18  18   4   4  5  5  'I-'  1204.3  /
1  12  12   5   5  5  5  'I+'  1094.6  /
1  13  13   5   5  5  5  'I-'  1115.7  /
1  11  11   6   6  5  5  'J-'  1031.0  /
1  10  10   7   7  5  5  'I-'   999.6  /
1   9   9   8   8  5  5  'I-'   983.6  /
1   8   8   9   9  5  5  'I-'   987.8  /
1   7   7  10  10  5  5  'I-'  1001.5  /
1   6   6  11  11  5  5  'I-'  1005.3  /
1   6   6  12  12  5  5  'I-'   966.6  /
1   5   5  13  13  5  5  'I-'   911.7  /
1   5   5  14  14  5  5  'I-'   877.4  /
1   4   4  15  15  5  5  'I-'   835.6  /
1   4   4  16  16  5  5  'I-'   819.1  /
1   3   3  17  17  5  5  'I-'   755.5  /
1   3   3  18  18  5  5  'I-'   720.2  /
1   3   3  19  19  5  5  'I-'   673.3  /
1   3   3  20  20  5  5  'I-'   633.9  /
1   3   3  21  21  5  5  'I-'   596.0  /
1   3   3  22  22  5  5  'I-'   607.8  /
1   3   3  23  23  5  5  'I-'   614.3  /
1   3   3  24  24  5  5  'I-'   598.3  /
1   3   3  25  25  5  5  'I-'   460.6  /
1   4   4  26  26  5  5  'I-'   153.2  /
1   5   5  26  26  5  5  'J+'   256.8  /
1   6   6  27  27  5  5  'I-'   251.4  /
1   7   7  27  27  5  5  'J+'   255.2  /
1   8   8  27  27  5  5  'J+'   247.2  /
1   9   9  27  27  5  5  'J+'   232.8  /
1  10  10  27  27  5  5  'J+'   227.4  /
1  11  11  27  27  5  5  'J+'   222.8  /
1  12  12  27  27  5  5  'I+'   223.2  /

1  14  14   4   4  4  4  'I-'  1180.7  /
1  15  15   4   4  4  4  'J-'  1186.7  /
1  16  16   4   4  4  4  'J-'  1189.7  /
1  17  17   4   4  4  4  'J-'  1197.7  /
1  18  18   4   4  4  4  'I-'  1204.3  /
1  12  12   5   5  4  4  'I+'  1094.6  /
1  13  13   5   5  4  4  'I-'  1115.7  /
1  11  11   6   6  4  4  'J-'  1031.0  /
1  10  10   7   7  4  4  'I-'   999.6  /
1   9   9   8   8  4  4  'I-'   983.6  /
1   8   8   9   9  4  4  'I-'   987.8  /
1   7   7  10  10  4  4  'I-'  1001.5  /
1   6   6  11  11  4  4  'I-'  1005.3  /
1   6   6  12  12  4  4  'I-'   966.6  /
1   5   5  13  13  4  4  'I-'   911.7  /
1   5   5  14  14  4  4  'I-'   877.4  /
```

```
1   4   4  15  15  4  4  'I-'   835.6  /
1   4   4  16  16  4  4  'I-'   819.1  /
1   3   3  17  17  4  4  'I-'   755.5  /
1   3   3  18  18  4  4  'I-'   720.2  /
1   3   3  19  19  4  4  'I-'   673.3  /
1   3   3  20  20  4  4  'I-'   633.9  /
1   3   3  21  21  4  4  'I-'   596.0  /
1   3   3  22  22  4  4  'I-'   607.8  /
1   3   3  23  23  4  4  'I-'   614.3  /
1   3   3  24  24  4  4  'I-'   598.3  /
1   3   3  25  25  4  4  'I-'   733.9  /
1   4   4  26  26  4  4  'I-'   303.9  /
1   5   5  26  26  4  4  'J+'   256.8  /
1   6   6  27  27  4  4  'I-'   251.4  /
1   7   7  27  27  4  4  'J+'   255.2  /
1   8   8  27  27  4  4  'J+'   247.2  /
1   9   9  27  27  4  4  'J+'   232.8  /
1  10  10  27  27  4  4  'J+'   227.4  /
1  11  11  27  27  4  4  'J+'   222.8  /
1  12  12  27  27  4  4  'I+'   223.2  /

1  14  14   4   4  3  3  'I-'  1180.7  /
1  15  15   4   4  3  3  'J-'  1186.7  /
1  16  16   4   4  3  3  'J-'  1189.7  /
1  17  17   4   4  3  3  'J-'  1197.7  /
1  18  18   4   4  3  3  'I-'  1204.3  /
1  12  12   5   5  3  3  'I+'  1094.6  /
1  13  13   5   5  3  3  'I-'  1115.7  /
1  11  11   6   6  3  3  'J-'  1031.0  /
1  10  10   7   7  3  3  'I-'   999.6  /
1   9   9   8   8  3  3  'I-'   983.6  /
1   8   8   9   9  3  3  'I-'   987.8  /
1   7   7  10  10  3  3  'I-'  1001.5  /
1   6   6  11  11  3  3  'I-'  1005.3  /
1   6   6  12  12  3  3  'I-'   966.6  /
1   5   5  13  13  3  3  'I-'   911.7  /
1   5   5  14  14  3  3  'I-'   877.4  /
1   4   4  15  15  3  3  'I-'   835.6  /
1   4   4  16  16  3  3  'I-'   819.1  /
1   3   3  17  17  3  3  'I-'   755.5  /
1   3   3  18  18  3  3  'I-'   720.2  /
1   3   3  19  19  3  3  'I-'   673.3  /
1   3   3  20  20  3  3  'I-'   633.9  /
1   3   3  21  21  3  3  'I-'   596.0  /
1   3   3  22  22  3  3  'I-'   607.8  /
1   3   3  23  23  3  3  'I-'   614.3  /
1   3   3  24  24  3  3  'I-'   598.3  /
1   3   3  25  25  3  3  'I-'   733.9  /
1   4   4  26  26  3  3  'I-'   303.9  /
```

```
1   5   5  26  26  3  3  'J+'   256.8  /
1   6   6  27  27  3  3  'I-'   251.4  /
1   7   7  27  27  3  3  'J+'   255.2  /
1   8   8  27  27  3  3  'J+'   247.2  /
1   9   9  27  27  3  3  'J+'   232.8  /
1  10  10  27  27  3  3  'J+'   227.4  /
1  11  11  27  27  3  3  'J+'   222.8  /
1  12  12  27  27  3  3  'I+'   223.2  /

2  15  15   1   1  2  2  'I-'   979.0  /
2  16  16   1   1  2  2  'J-'   963.7  /
2  17  17   1   1  2  2  'J-'   940.0  /
2  18  18   1   1  2  2  'I+'   904.5  /
2  14  14   2   2  2  2  'I-'   860.9  /
2  11  11   3   3  2  2  'I-'   665.4  /
2  12  12   3   3  2  2  'J-'   657.5  /
2  13  13   3   3  2  2  'J-'   652.0  /
2  10  10   4   4  2  2  'I-'   586.0  /
2   9   9   5   5  2  2  'I-'   620.4  /
2   8   8   6   6  2  2  'I-'   743.0  /
2   7   7   7   7  2  2  'I-'   213.5  /
2   6   6   8   8  2  2  'I-'   284.7  /
2   6   6   9   9  2  2  'I-'   366.6  /
2   5   5  10  10  2  2  'I-'   395.4  /
2   5   5  11  11  2  2  'I-'   464.4  /
2   5   5  12  12  2  2  'I-'   504.3  /
2   4   4  13  13  2  2  'I-'   553.3  /
2   4   4  14  14  2  2  'I-'   595.7  /
2   3   3  15  15  2  2  'I-'   716.9  /
2   2   2  16  16  2  2  'I-'   583.6  /
2   2   2  17  17  2  2  'I-'   576.6  /
2   2   2  18  18  2  2  'I-'   518.7  /
2   1   1  23  23  2  2  'I-'   750.1  /
2   1   1  24  24  2  2  'I-'   767.4  /
2   1   1  25  25  2  2  'I-'   698.9  /
2   2   2  26  26  2  2  'I-'   721.1  /
2   3   3  27  27  2  2  'I-'   666.0  /
2   4   4  28  28  2  2  'I-'   644.2  /
2   5   5  28  28  2  2  'J+'   743.7  /

2  15  15   1   1  1  1  'I-'  1958.0  /
2  16  16   1   1  1  1  'J-'  1927.4  /
2  17  17   1   1  1  1  'J-'  1880.5  /
2  18  18   1   1  1  1  'I+'  1809.0  /
2  14  14   2   2  1  1  'I-'  1721.9  /
2  11  11   3   3  1  1  'I-'  1330.8  /
2  12  12   3   3  1  1  'J-'  1315.0  /
2  13  13   3   3  1  1  'J-'  1303.9  /
2  10  10   4   4  1  1  'I-'  1172.1  /
```

```
2   9   9   5   5  1  1  'I-'  1240.8  /
2   8   8   6   6  1  1  'I-'  1486.0  /
2   7   7   7   7  1  1  'I-'  1222.1  /
2   6   6   8   8  1  1  'I-'  1242.7  /
2   6   6   9   9  1  1  'I-'  1171.9  /
2   5   5  10  10  1  1  'I-'   988.7  /
2   5   5  11  11  1  1  'I-'   961.8  /
2   5   5  12  12  1  1  'I-'  1022.0  /
2   4   4  13  13  1  1  'I-'  1110.6  /
2   4   4  14  14  1  1  'I-'  1189.5  /
2   3   3  15  15  1  1  'I-'  1131.3  /
2   2   2  16  16  1  1  'I-'  1350.2  /
2   2   2  17  17  1  1  'I-'  1491.5  /
2   2   2  18  18  1  1  'I-'  1442.2  /
2   1   1  23  23  1  1  'I-'  1167.1  /
2   1   1  24  24  1  1  'I-'  1253.7  /
2   1   1  25  25  1  1  'I-'  1306.9  /
2   2   2  26  26  1  1  'I-'  1183.3  /
2   3   3  27  27  1  1  'I-'  1070.9  /
2   4   4  28  28  1  1  'I-'  1179.4  /
2   5   5  28  28  1  1  'J+'  1260.5  /
/

EQUIL
   2355.00 234.46 2395.0 0.00  2355.0 0.000    1    1*     0  /

RSVD                            -- Generated : Petrel
      2175        74
      2496        74
 /


AQUCT                            -- Generated : Petrel
 1 2355 234 137.5 0.2125 3.5E-5 3000 19.6 95 1 1* 0.0 /
 2 2355 234 137.5 0.2125 3.5E-5 3200 6 95 1 1* 0.0 /
 /

NOECHO

RPTSOL                           -- Generated : Petrel
 /

SUMMARY

WBP9
 /

FPR
```

```
DATE

SEPARATE

RUNSUM

WSTAT                              -- Generated : Petrel
 /

WBHP
 /

WWGR                               -- Generated : Petrel
 /

GWGR                               -- Generated : Petrel
 /

FWGR                               -- Generated : Petrel

WWCT                               -- Generated : Petrel
 /

GWCT                               -- Generated : Petrel
 /

FWCT                               -- Generated : Petrel

TIMESTEP                           -- Generated : Petrel

WVPR                               -- Generated : Petrel
 /

GVPR                               -- Generated : Petrel
 /

FVPR                               -- Generated : Petrel

WVPT                               -- Generated : Petrel
 /

GVPT                               -- Generated : Petrel
 /

FVPT                               -- Generated : Petrel

WVIR                               -- Generated : Petrel
 /
```

```
GVIR                        -- Generated : Petrel
 /

FVIR                        -- Generated : Petrel

WVIT                        -- Generated : Petrel
 /

GVIT                        -- Generated : Petrel
 /

FVIT                        -- Generated : Petrel

WPI                         -- Generated : Petrel
 /

WWPR                        -- Generated : Petrel
 /

GWPR                        -- Generated : Petrel
 /

FWPR                        -- Generated : Petrel

WOPR                        -- Generated : Petrel
 /

GOPR                        -- Generated : Petrel
 /

FOPR                        -- Generated : Petrel

WGPR                        -- Generated : Petrel
 /

GGPR                        -- Generated : Petrel
 /

FGPR                        -- Generated : Petrel

WWPT                        -- Generated : Petrel
 /

GWPT                        -- Generated : Petrel
 /

FWPT                        -- Generated : Petrel

WOPT                        -- Generated : Petrel
```

```
 /

GOPT                        -- Generated : Petrel
 /

FOPT                        -- Generated : Petrel

WGPT                        -- Generated : Petrel
 /

GGPT                        -- Generated : Petrel
 /

FGPT                        -- Generated : Petrel

FWIP                        -- Generated : Petrel

FOIPG                       -- Generated : Petrel

FGIPL                       -- Generated : Petrel

FOIP                        -- Generated : Petrel

FOIPL                       -- Generated : Petrel

FGIP                        -- Generated : Petrel

FGIPG                       -- Generated : Petrel

WWIR                        -- Generated : Petrel
 /

GWIR                        -- Generated : Petrel
 /

FWIR                        -- Generated : Petrel

WOIR                        -- Generated : Petrel
 /

GOIR                        -- Generated : Petrel
 /

FOIR                        -- Generated : Petrel

WGIR                        -- Generated : Petrel
 /

GGIR                        -- Generated : Petrel
```

```
 /

FGIR                          -- Generated : Petrel

WWIT                          -- Generated : Petrel
 /

GWIT                          -- Generated : Petrel
 /

FWIT                          -- Generated : Petrel

WOIT                          -- Generated : Petrel
 /

GOIT                          -- Generated : Petrel
 /

FOIT                          -- Generated : Petrel

WGIT                          -- Generated : Petrel
 /

GGIT                          -- Generated : Petrel
 /

FGIT                          -- Generated : Petrel

WGOR                          -- Generated : Petrel
 /

GGOR                          -- Generated : Petrel
 /

FGOR                          -- Generated : Petrel

FAQR                          -- Generated : Petrel

FAQT                          -- Generated : Petrel

RPTONLY                       -- Generated : Petrel

NOECHO

SCHEDULE

WELSPECS                      -- Generated : Petrel
'PRO-1'   'G1'   10   22   2362.2   'OIL'   1*   'STD'   3*   'SEG'   /
'PRO-4'   'G1'    9   17   2373.0   'OIL'   1*   'STD'   3*   'SEG'   /
```

```
'PRO-5'   'G1'  17  11  2381.7  'OIL'  1*  'STD'  3*  'SEG'  /
'PRO-11'  'G1'  11  24  2386.0  'OIL'  1*  'STD'  3*  'SEG'  /
'PRO-12'  'G1'  15  12  2380.5  'OIL'  1*  'STD'  3*  'SEG'  /
'PRO-15'  'G1'  17  22  2381.0  'OIL'  1*  'STD'  3*  'SEG'  /
--'PRO-23'  'G1'   5  23  2380.7  'OIL'  1*  'STD'  3*  'SEG'  /
--'PRO-24'  'G1'   7  14  2382.5  'OIL'  1*  'STD'  3*  'SEG'  /
--'PRO-29'  'G1'  15   7  2376.7  'OIL'  1*  'STD'  3*  'SEG'  /
--'PRO-50'  'G1'  12  12  2362.2  'OIL'  1*  'STD'  3*  'SEG'  /
/

GRUPTREE                    -- Generated : Petrel
 'GROUP 1' FIELD /
 /

DRSDT                       -- Generated : Petrel
   0  /

------------------- WELL SPECIFICATION DATA --------------------------

------------------- WELL SPECIFICATION DATA --------------------------

------------------- WELL SPECIFICATION DATA --------------------------

COMPDAT                       -- Generated : Petrel
--                          RADIUS   SKIN
'PRO-1'   10  22  5  5  'OPEN'  2*  0.15  1*  5.0 /
'PRO-1'   10  22  4  4  'OPEN'  2*  0.15  1*  5.0 /
'PRO-4'    9  17  5  5  'OPEN'  2*  0.15  1*  5.0 /
'PRO-4'    9  17  4  4  'OPEN'  2*  0.15  1*  5.0 /
'PRO-5'   17  11  4  4  'OPEN'  2*  0.15  1*  5.0 /
'PRO-5'   17  11  3  3  'OPEN'  2*  0.15  1*  5.0 /
'PRO-11'  11  24  4  4  'OPEN'  2*  0.15  1*  5.0 /
'PRO-11'  11  24  3  3  'OPEN'  2*  0.15  1*  5.0 /
'PRO-12'  15  12  5  5  'OPEN'  2*  0.15  1*  5.0 /
'PRO-12'  15  12  4  4  'OPEN'  2*  0.15  1*  5.0 /
'PRO-15'  17  22  4  4  'OPEN'  2*  0.15  1*  5.0 /
--'PRO-23'   5  23  2  2  'OPEN'  2*  0.15  1*  5.0 /
--'PRO-23'   5  23  1  1  'OPEN'  2*  0.15  1*  5.0 /
--'PRO-24'   7  14  2  2  'OPEN'  2*  0.15  1*  5.0 /
--'PRO-24'   7  14  1  1  'OPEN'  2*  0.15  1*  5.0 /
--'PRO-29'  15   7  2  2  'OPEN'  2*  0.15  1*  5.0 /
--'PRO-29'  15   7  1  1  'OPEN'  2*  0.15  1*  5.0 /
--'PRO-50'  12  12  3  3  'OPEN'  2*  0.15  1*  5.0 /
--'PRO-50'  12  12  2  2  'OPEN'  2*  0.15  1*  5.0 /
/

WCONPROD                      -- Generated : Petrel
'PRO*'  'SHUT'  6* 120.0 /
/
```

```
WCUTBACK                          -- Generated : Petrel
'PRO*' 1* 200.0 2* 0.75 'OIL' 120.0 /
/

-------------------- PRODUCTION SCHEDULE ---------------------------

TSTEP                             -- Generated : Petrel
0.01
/

WELOPEN                           -- Generated : Petrel
 'PRO-1'   'OPEN'  /
 'PRO-4'   'OPEN'  /
 'PRO-5'   'OPEN'  /
 'PRO-11'  'OPEN'  /
 'PRO-12'  'OPEN'  /
 'PRO-15'  'OPEN'  /
/

WELTARG                           -- Generated : Petrel
 'PRO-1'   'ORAT'  100.0 /
 'PRO-4'   'ORAT'  100.0 /
 'PRO-5'   'ORAT'  100.0 /
 'PRO-11'  'ORAT'  100.0 /
 'PRO-12'  'ORAT'  100.0 /
 'PRO-15'  'ORAT'  100.0 /
/

TSTEP                             -- Generated : Petrel
 1 /

-------------------- PRODUCTION SCHEDULE ---------------------------

DATES                             -- Generated : Petrel
1  'FEB'  1967  /
/

DATES                             -- Generated : Petrel
1  'MAR'  1967  /
/

DATES                             -- Generated : Petrel
1  'APR'  1967  /
/

WELTARG                           -- Generated : Petrel
 'PRO-1'   'ORAT'  200.0 /
 'PRO-4'   'ORAT'  200.0 /
```

```
 'PRO-5'   'ORAT'  200.0 /
 'PRO-11'  'ORAT'  200.0 /
 'PRO-12'  'ORAT'  200.0 /
 'PRO-15'  'ORAT'  200.0 /
/

TSTEP                          -- Generated : Petrel
 1 /

DATES                          -- Generated : Petrel
1  'MAY'  1967  /
/

DATES                          -- Generated : Petrel
1  'JUN'  1967  /
/

DATES                          -- Generated : Petrel
1  'JUL'  1967  /
/

WELTARG                        -- Generated : Petrel
 'PRO-1'   'ORAT'  100.0 /
 'PRO-4'   'ORAT'  100.0 /
 'PRO-5'   'ORAT'  100.0 /
 'PRO-11'  'ORAT'  100.0 /
 'PRO-12'  'ORAT'  100.0 /
 'PRO-15'  'ORAT'  100.0 /
/


'PRO*' 100 5* Y /
/

TSTEP                          -- Generated : Petrel
 1 /

DATES                          -- Generated : Petrel
1  'AUG'  1967  /
/

DATES                          -- Generated : Petrel
1  'SEP'  1967  /
/

DATES                          -- Generated : Petrel
1  'OCT'  1967  /
/
```

```
WELTARG                          -- Generated : Petrel
 'PRO-1'   'ORAT'  50.0 /
 'PRO-4'   'ORAT'  50.0 /
 'PRO-5'   'ORAT'  50.0 /
 'PRO-11'  'ORAT'  50.0 /
 'PRO-12'  'ORAT'  50.0 /
 'PRO-15'  'ORAT'  50.0 /
/


'PRO*' 50 5* Y /
/

TSTEP                          -- Generated : Petrel
 1 /

DATES                          -- Generated : Petrel
1  'NOV'  1967  /
/

DATES                          -- Generated : Petrel
1  'DEC'  1967  /
/

DATES                          -- Generated : Petrel
1  'JAN'  1968  /
/

-- End for test purposes

WELTARG                          -- Generated : Petrel
 'PRO-1'   'ORAT'   0.0 /
 'PRO-4'   'ORAT'   0.0 /
 'PRO-5'   'ORAT'   0.0 /
 'PRO-11'  'ORAT'   0.0 /
 'PRO-12'  'ORAT'   0.0 /
 'PRO-15'  'ORAT'   0.0 /
/


'PRO*' 0 5* Y /
/

TSTEP                          -- Generated : Petrel
 1 /

-- Just to include shut-in

DATES                          -- Generated : Petrel
```

```
1  'JAN'  1969  /
/

DATES                          -- Generated : Petrel
1  'JAN'  1970  /
/

DATES                          -- Generated : Petrel
1  'JAN'  1971  /
/

-- End for buildup-test purposes

WELTARG                          -- Generated : Petrel
 'PRO-1'   'ORAT'   150.0 /
 'PRO-4'   'ORAT'   150.0 /
 'PRO-5'   'ORAT'   150.0 /
 'PRO-11'  'ORAT'   150.0 /
 'PRO-12'  'ORAT'   150.0 /
 'PRO-15'  'ORAT'   150.0 /
/


'PRO*' 150 5* Y /
/

TSTEP                          -- Generated : Petrel
 1 /

DATES                          -- Generated : Petrel
1  'JUL' 1971  /
/

-- work over --

-- work over --

-- work over --

DATES                          -- Generated : Petrel
1  'JAN'  1972  /
/

WELTARG                          -- Generated : Petrel
 'PRO-1'   'ORAT'   0.0 /
 'PRO-4'   'ORAT'   0.0 /
 'PRO-5'   'ORAT'   0.0 /
 'PRO-11'  'ORAT'   0.0 /
 'PRO-12'  'ORAT'   0.0 /
```

```
  'PRO-15'  'ORAT'   0.0 /
/


'PRO*' 0 5* Y /
/

TSTEP                           -- Generated : Petrel
  1 /

DATES                           -- Generated : Petrel
15  'JAN'  1972  /
/

WELTARG                           -- Generated : Petrel
  'PRO-1'   'ORAT'   150.0 /
  'PRO-4'   'ORAT'   150.0 /
  'PRO-5'   'ORAT'   150.0 /
  'PRO-11'  'ORAT'   150.0 /
  'PRO-12'  'ORAT'   150.0 /
  'PRO-15'  'ORAT'   150.0 /
/


'PRO*' 150 5* Y /
/

TSTEP                           -- Generated : Petrel
  1 /

DATES                           -- Generated : Petrel
1  'JUL'  1972  /
/

DATES                           -- Generated : Petrel
1  'JAN'  1973  /
/

WELTARG                           -- Generated : Petrel
  'PRO-1'   'ORAT'   0.0 /
  'PRO-4'   'ORAT'   0.0 /
  'PRO-5'   'ORAT'   0.0 /
  'PRO-11'  'ORAT'   0.0 /
  'PRO-12'  'ORAT'   0.0 /
  'PRO-15'  'ORAT'   0.0 /
/


'PRO*' 0 5* Y /
```

```
/

TSTEP                          -- Generated : Petrel
  1 /

DATES                          -- Generated : Petrel
15  'JAN'  1973  /
/

WELTARG                           -- Generated : Petrel
  'PRO-1'   'ORAT'   150.0 /
  'PRO-4'   'ORAT'   150.0 /
  'PRO-5'   'ORAT'   150.0 /
  'PRO-11'  'ORAT'   150.0 /
  'PRO-12'  'ORAT'   150.0 /
  'PRO-15'  'ORAT'   150.0 /
/


'PRO*' 150 5* Y /
/

TSTEP                          -- Generated : Petrel
  1 /

DATES                          -- Generated : Petrel
1  'JUL'  1973  /
/

DATES                          -- Generated : Petrel
1  'JAN'  1974  /
/

WELTARG                           -- Generated : Petrel
  'PRO-1'   'ORAT'   0.0 /
  'PRO-4'   'ORAT'   0.0 /
  'PRO-5'   'ORAT'   0.0 /
  'PRO-11'  'ORAT'   0.0 /
  'PRO-12'  'ORAT'   0.0 /
  'PRO-15'  'ORAT'   0.0 /
/


'PRO*' 0 5* Y /
/

TSTEP                          -- Generated : Petrel
  1 /
```

```
DATES                          -- Generated : Petrel
15  'JAN'  1974  /
/

WELTARG                          -- Generated : Petrel
  'PRO-1'   'ORAT'   150.0 /
  'PRO-4'   'ORAT'   150.0 /
  'PRO-5'   'ORAT'   150.0 /
  'PRO-11'  'ORAT'   150.0 /
  'PRO-12'  'ORAT'   150.0 /
  'PRO-15'  'ORAT'   150.0 /
/


'PRO*' 150 5* Y /
/

TSTEP                          -- Generated : Petrel
  1 /

DATES                          -- Generated : Petrel
1  'JUL'  1974  /
/

DATES                          -- Generated : Petrel
1  'JAN'  1975  /
/

WELTARG                          -- Generated : Petrel
  'PRO-1'   'ORAT'   0.0 /
  'PRO-4'   'ORAT'   0.0 /
  'PRO-5'   'ORAT'   0.0 /
  'PRO-11'  'ORAT'   0.0 /
  'PRO-12'  'ORAT'   0.0 /
  'PRO-15'  'ORAT'   0.0 /
/


'PRO*' 0 5* Y /
/

TSTEP                          -- Generated : Petrel
  1 /

DATES                          -- Generated : Petrel
15  'JAN'  1975  /
/

WELTARG                          -- Generated : Petrel
```

```
 'PRO-1'   'ORAT'   150.0 /
 'PRO-4'   'ORAT'   150.0 /
 'PRO-5'   'ORAT'   150.0 /
 'PRO-11'  'ORAT'   150.0 /
 'PRO-12'  'ORAT'   150.0 /
 'PRO-15'  'ORAT'   150.0 /
/

TSTEP                        -- Generated : Petrel
 1 /

DATES                        -- Generated : Petrel
1  'JUL'  1975  /
/

DATES                        -- Generated : Petrel
1  'JAN'  1976  /
/

WELTARG                        -- Generated : Petrel
 'PRO-1'   'ORAT'   0.0 /
 'PRO-4'   'ORAT'   0.0 /
 'PRO-5'   'ORAT'   0.0 /
 'PRO-11'  'ORAT'   0.0 /
 'PRO-12'  'ORAT'   0.0 /
 'PRO-15'  'ORAT'   0.0 /
/

TSTEP                        -- Generated : Petrel
 1 /

DATES                        -- Generated : Petrel
15  'JAN'  1976  /
/

WELTARG                        -- Generated : Petrel
 'PRO-1'   'ORAT'   150.0 /
 'PRO-4'   'ORAT'   150.0 /
 'PRO-5'   'ORAT'   150.0 /
 'PRO-11'  'ORAT'   150.0 /
 'PRO-12'  'ORAT'   150.0 /
 'PRO-15'  'ORAT'   150.0 /
/

TSTEP                        -- Generated : Petrel
 1 /

DATES                        -- Generated : Petrel
1  'JUL'  1976  /
```

```
/

DATES                        -- Generated : Petrel
1  'JAN'  1977  /
/

WELTARG                        -- Generated : Petrel
 'PRO-1'   'ORAT'   0.0 /
 'PRO-4'   'ORAT'   0.0 /
 'PRO-5'   'ORAT'   0.0 /
 'PRO-11'  'ORAT'   0.0 /
 'PRO-12'  'ORAT'   0.0 /
 'PRO-15'  'ORAT'   0.0 /
/

TSTEP                        -- Generated : Petrel
 1 /

DATES                        -- Generated : Petrel
15  'JAN'  1977  /
/

WELTARG                        -- Generated : Petrel
 'PRO-1'   'ORAT'   150.0 /
 'PRO-4'   'ORAT'   150.0 /
 'PRO-5'   'ORAT'   150.0 /
 'PRO-11'  'ORAT'   150.0 /
 'PRO-12'  'ORAT'   150.0 /
 'PRO-15'  'ORAT'   150.0 /
/

TSTEP                        -- Generated : Petrel
 1 /

DATES                        -- Generated : Petrel
1  'JUL'  1977  /
/

DATES                        -- Generated : Petrel
1  'JAN'  1978  /
/

WELTARG                        -- Generated : Petrel
 'PRO-1'   'ORAT'   0.0 /
 'PRO-4'   'ORAT'   0.0 /
 'PRO-5'   'ORAT'   0.0 /
 'PRO-11'  'ORAT'   0.0 /
 'PRO-12'  'ORAT'   0.0 /
 'PRO-15'  'ORAT'   0.0 /
```

```
/

TSTEP                       -- Generated : Petrel
 1 /

DATES                       -- Generated : Petrel
15  'JAN'  1978  /
/

WELTARG                       -- Generated : Petrel
 'PRO-1'   'ORAT'   150.0 /
 'PRO-4'   'ORAT'   150.0 /
 'PRO-5'   'ORAT'   150.0 /
 'PRO-11'  'ORAT'   150.0 /
 'PRO-12'  'ORAT'   150.0 /
 'PRO-15'  'ORAT'   150.0 /
/

TSTEP                       -- Generated : Petrel
 1 /

DATES                       -- Generated : Petrel
1  'JUL'  1978  /
/

DATES                       -- Generated : Petrel
1  'JAN'  1979  /
/

WELTARG                       -- Generated : Petrel
 'PRO-1'   'ORAT'   0.0 /
 'PRO-4'   'ORAT'   0.0 /
 'PRO-5'   'ORAT'   0.0 /
 'PRO-11'  'ORAT'   0.0 /
 'PRO-12'  'ORAT'   0.0 /
 'PRO-15'  'ORAT'   0.0 /
/

TSTEP                       -- Generated : Petrel
 1 /

DATES                       -- Generated : Petrel
15  'JAN'  1979  /
/

WELTARG                       -- Generated : Petrel
 'PRO-1'   'ORAT'   150.0 /
 'PRO-4'   'ORAT'   150.0 /
 'PRO-5'   'ORAT'   150.0 /
```

```
 'PRO-11'  'ORAT'   150.0 /
 'PRO-12'  'ORAT'   150.0 /
 'PRO-15'  'ORAT'   150.0 /
/

TSTEP                          -- Generated : Petrel
 1 /

DATES                          -- Generated : Petrel
1  'JUL'  1979  /
/

DATES                          -- Generated : Petrel
1  'JAN'  1980  /
/

WELTARG                        -- Generated : Petrel
 'PRO-1'   'ORAT'   0.0 /
 'PRO-4'   'ORAT'   0.0 /
 'PRO-5'   'ORAT'   0.0 /
 'PRO-11'  'ORAT'   0.0 /
 'PRO-12'  'ORAT'   0.0 /
 'PRO-15'  'ORAT'   0.0 /
/

TSTEP                          -- Generated : Petrel
 1 /

DATES                          -- Generated : Petrel
15  'JAN'  1980  /
/

WELTARG                        -- Generated : Petrel
 'PRO-1'   'ORAT'   150.0 /
 'PRO-4'   'ORAT'   150.0 /
 'PRO-5'   'ORAT'   150.0 /
 'PRO-11'  'ORAT'   150.0 /
 'PRO-12'  'ORAT'   150.0 /
 'PRO-15'  'ORAT'   150.0 /
/

TSTEP                          -- Generated : Petrel
 1 /

DATES                          -- Generated : Petrel
1  'JUL'  1980  /
/

DATES                          -- Generated : Petrel
```

```
1  'JAN'  1981  /
/

WELTARG                          -- Generated : Petrel
 'PRO-1'   'ORAT'   0.0 /
 'PRO-4'   'ORAT'   0.0 /
 'PRO-5'   'ORAT'   0.0 /
 'PRO-11'  'ORAT'   0.0 /
 'PRO-12'  'ORAT'   0.0 /
 'PRO-15'  'ORAT'   0.0 /
/

TSTEP                         -- Generated : Petrel
 1 /

DATES                         -- Generated : Petrel
15  'JAN'  1981  /
/

WELTARG                          -- Generated : Petrel
 'PRO-1'   'ORAT'   150.0 /
 'PRO-4'   'ORAT'   150.0 /
 'PRO-5'   'ORAT'   150.0 /
 'PRO-11'  'ORAT'   150.0 /
 'PRO-12'  'ORAT'   150.0 /
 'PRO-15'  'ORAT'   150.0 /
/

TSTEP                         -- Generated : Petrel
 1 /

DATES                         -- Generated : Petrel
1  'JUL'  1981  /
/

DATES                         -- Generated : Petrel
1  'JAN'  1982  /
/

WELTARG                          -- Generated : Petrel
 'PRO-1'   'ORAT'   0.0 /
 'PRO-4'   'ORAT'   0.0 /
 'PRO-5'   'ORAT'   0.0 /
 'PRO-11'  'ORAT'   0.0 /
 'PRO-12'  'ORAT'   0.0 /
 'PRO-15'  'ORAT'   0.0 /
/

TSTEP                         -- Generated : Petrel
```

```
 1 /

DATES                          -- Generated : Petrel
15  'JAN'  1982  /
/

WELTARG                        -- Generated : Petrel
 'PRO-1'   'ORAT'   150.0 /
 'PRO-4'   'ORAT'   150.0 /
 'PRO-5'   'ORAT'   150.0 /
 'PRO-11'  'ORAT'   150.0 /
 'PRO-12'  'ORAT'   150.0 /
 'PRO-15'  'ORAT'   150.0 /
/

TSTEP                          -- Generated : Petrel
 1 /

DATES                          -- Generated : Petrel
1  'JUL'  1982  /
/

DATES                          -- Generated : Petrel
1  'JAN'  1983  /
/

WELTARG                        -- Generated : Petrel
 'PRO-1'   'ORAT'   0.0 /
 'PRO-4'   'ORAT'   0.0 /
 'PRO-5'   'ORAT'   0.0 /
 'PRO-11'  'ORAT'   0.0 /
 'PRO-12'  'ORAT'   0.0 /
 'PRO-15'  'ORAT'   0.0 /
/

TSTEP                          -- Generated : Petrel
 1 /

DATES                          -- Generated : Petrel
15  'JAN'  1983  /
/

WELTARG                        -- Generated : Petrel
 'PRO-1'   'ORAT'   150.0 /
 'PRO-4'   'ORAT'   150.0 /
 'PRO-5'   'ORAT'   150.0 /
 'PRO-11'  'ORAT'   150.0 /
 'PRO-12'  'ORAT'   150.0 /
 'PRO-15'  'ORAT'   150.0 /
```

```
/

TSTEP                           -- Generated : Petrel
  1 /

DATES                           -- Generated : Petrel
1  'JUL'  1983  /
/

END                             -- Generated : Petrel

DATES                           -- Generated : Petrel
  1 JUL 1983 /
  /
```

A.2 History Match of Reservoir Performance

In the deterministic approach, the best history match was achieved with mismatch objective function of 1.884. The achieved history match showed good results on the field and wells levels. **Fig. 67** - **Fig. 73** show the quality of history match for oil rate, GOR, WCT, and pressures on the field and wells levels.

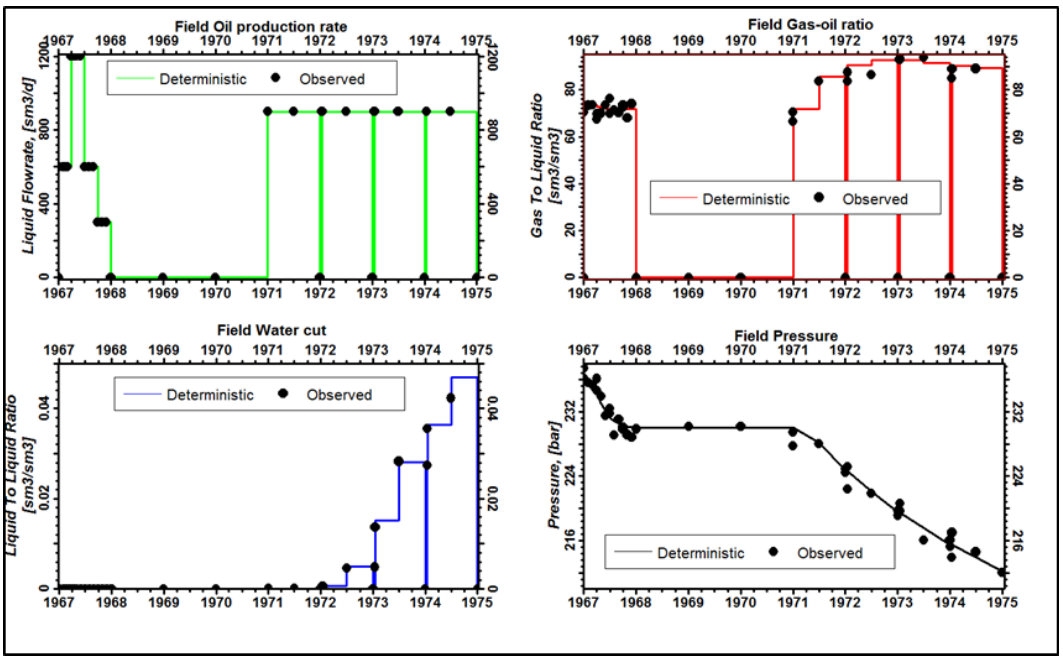

Fig. 67—Field level history match

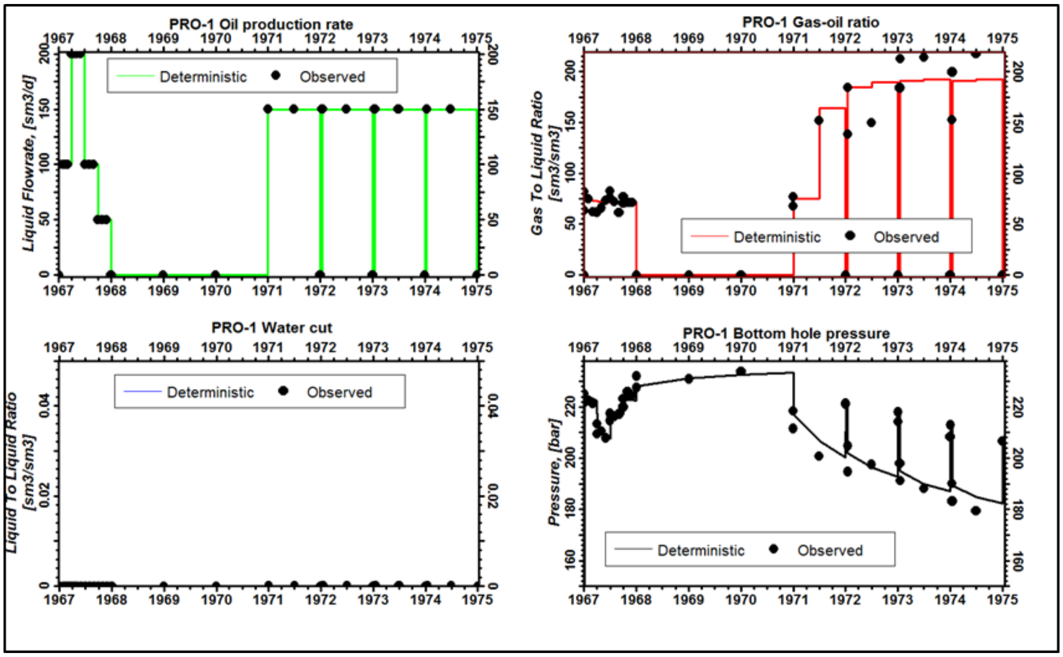

Fig. 68—PRO-1 history match

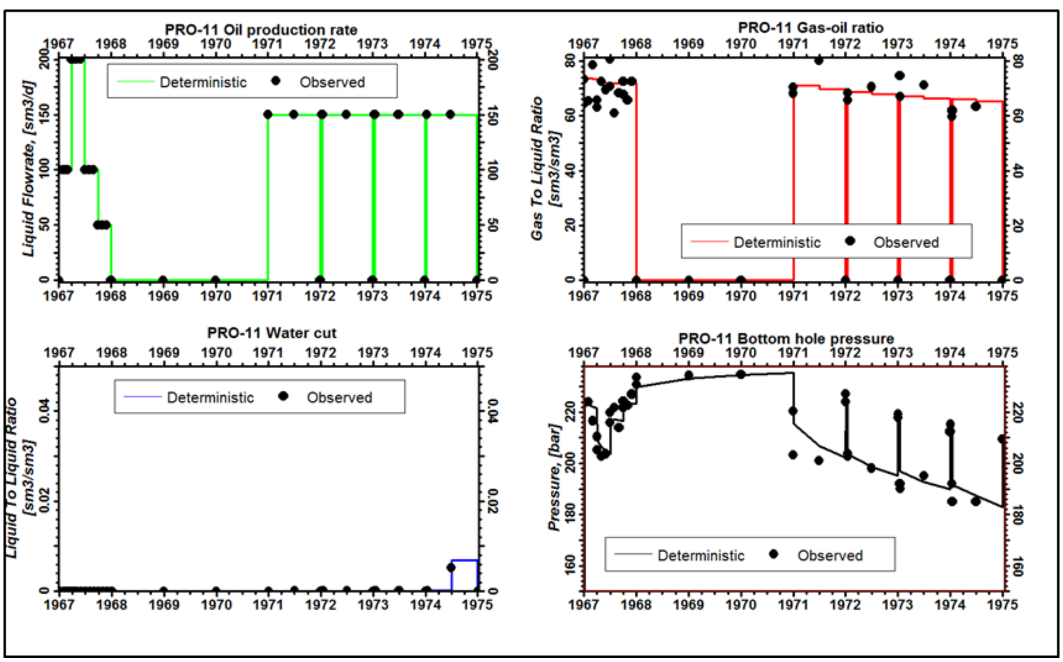

Fig. 69—PRO-11 history match

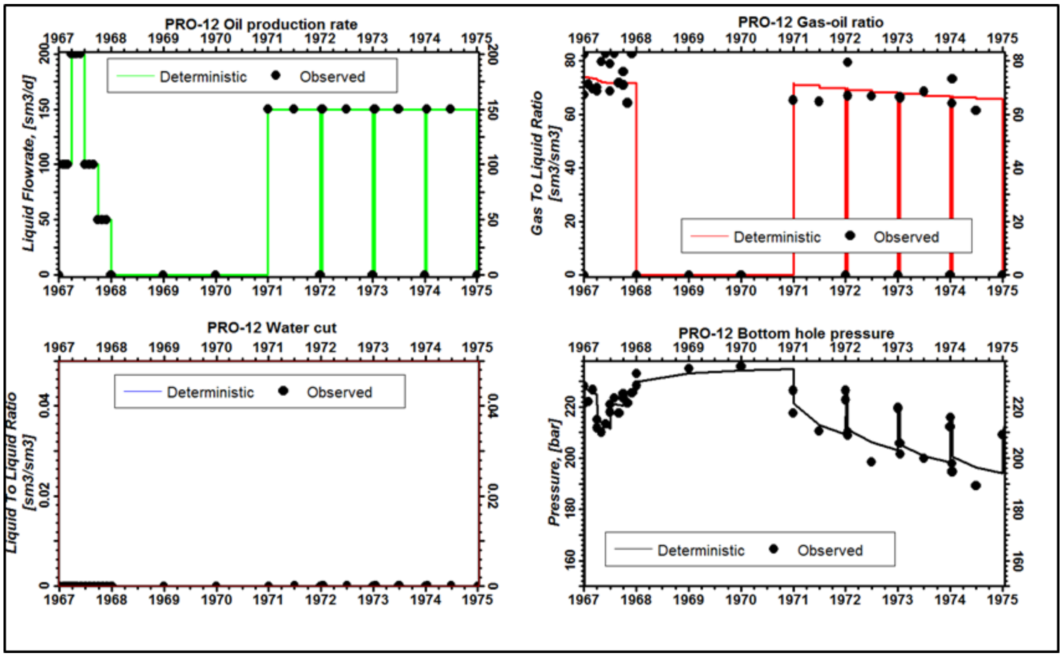

Fig. 70—PRO-12 history match

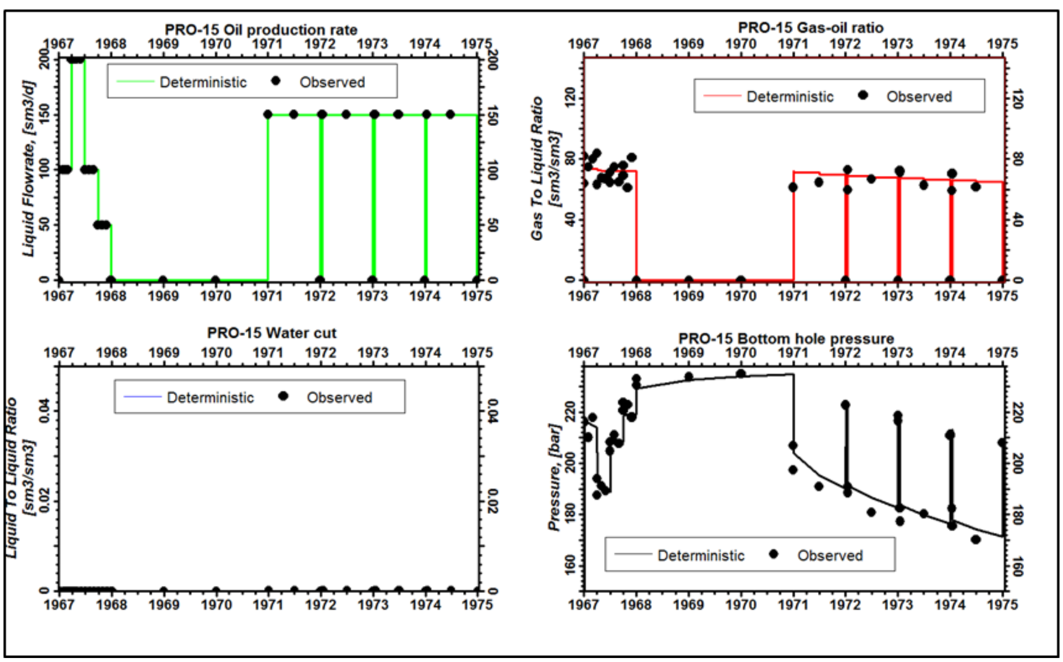

Fig. 71—PRO-15 history match

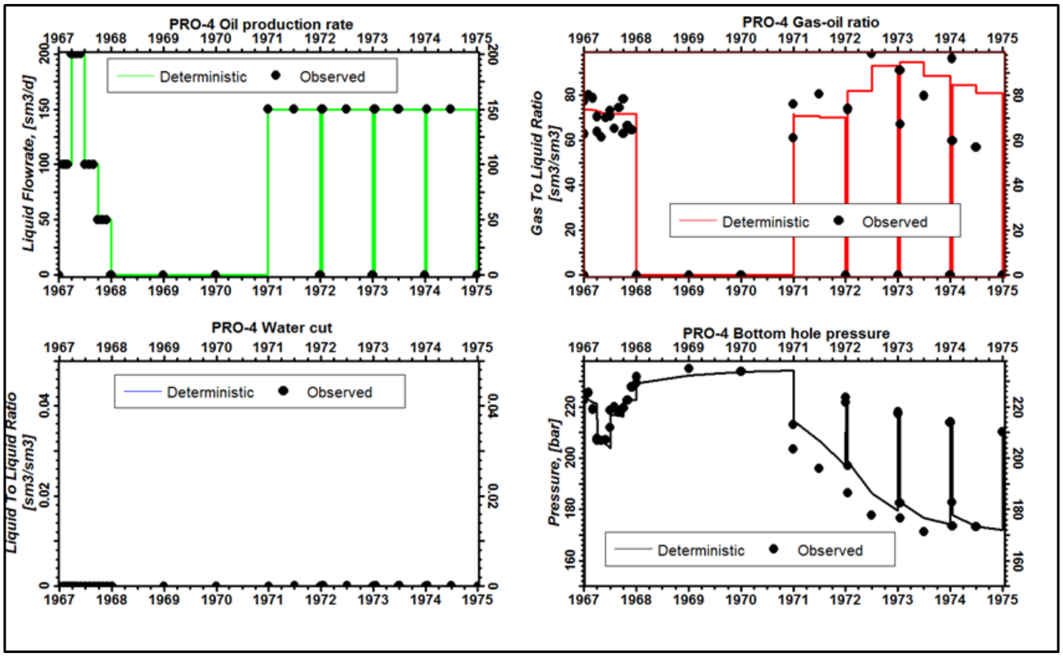

Fig. 72—PRO-4 history match

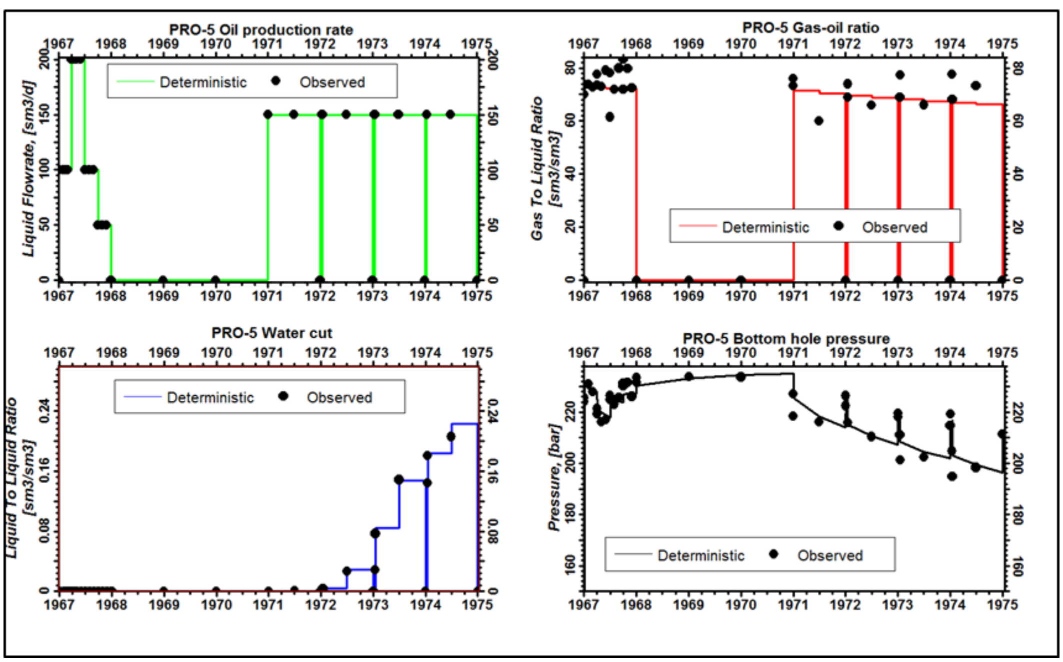

Fig. 73—PRO-5 history match