Balancing Static and Dynamic Match and Uncertainty Quantification in Stochastic History Matching

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Abstract

The inherent uncertainties in reservoir models pose a major concern for decision making in the development and management of hydrocarbon reservoirs. Uncertainties in reservoir models result from sparse and indirect data measurements that can compromise the production forecasting reliability. History matching is usually used to reduce uncertainties in reservoir modelling related to observed dynamic data but often neglects the geological consistency of the model. Therefore, although being able of reproducing the dynamic response of the reservoir, the models may be characterized by unrealistic geological features. The present work proposes a geologically consistent methodology for reservoir history matching implemented in a standard industry benchmark case. The history matching process encompasses the use of a multi-objective optimisation approach with adaptive stochastic sampling, the Multi-Objective Particle Swarm Optimisation. Geological parameters are optimised and the match to petrophysical properties and production variables is obtained. The uncertainty of predictions is quantified and characterized by Bayesian inference techniques such as Neighbourhood Algorithm-Bayes and Bayesian Model Averaging. The proposed methodology proved that under different model parameterisations, the quality of the dynamic matches is still good and the static data are reproduced better. A good balance between static and dynamic objectives can be identified leading to model distributions more realistic. When inferring predictions, the different model parameterisations not only showed reliable forecasting at individual wells but also regarding cumulative oil and water production with the truth being encapsulated in the credible interval P10-P50-P90.

KEYWORDS: History Matching, Multi-Objective Particle Swarm Optimisation, Bayesian inference; good balance; static and dynamic.
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Resumo

As incertezas intrínsecas em modelos de reservatórios constituem a principal preocupação na tomada de decisões para o desenvolvimento e gestão de reservatórios de hidrocarbonetos. A incerteza nos modelos de reservatórios resulta da escassa informação e de medições indirectas de dados que podem comprometer a reliabilidade na previsão da produção. O ajuste de histórico é um processo habitualmente usado em modelação de reservatórios com a finalidade de reduzir as incertezas relacionadas aos dados dinâmicos observados, mas geralmente negligencia a consistência geológica do modelo. Assim sendo, apesar de reproduzir a resposta dinâmica do reservatório, o modelo pode evidenciar características geológicas irrealistas. O presente trabalho propõe uma metodologia para ajuste de histórico de reservatórios aplicada num caso de estudo padrão de referência na indústria. O processo de ajuste de histórico passa pela aplicação de uma abordagem de optimização multi-objectivo com amostragem estocástica adaptativa, Multi-Objective Particle Swarm Optimisation. Após optimização de parâmetros geológicos, é obtido o ajuste das propriedades petrofísicas e das variáveis de produção. A incerteza nas previsões é quantificada e caracterizada através de técnicas de inferência Bayesiana tais como Neighbourhood Algorithm-Bayes e Bayesian Model Averaging. A metodologia proposta provou que em modelos com diferentes parametrizações, o ajuste dinâmico continua bom e as propriedades estáticas são melhor reproduzidas. É identificado um bom balanço entre os objectivos estático e dinâmico, o que leva a distribuições mais realistas do modelo. Na dedução das previsões, os modelos com diferentes parametrizações demonstraram previsões fidedignas tanto a nível de poços como de produção cumulativa de óleo e água, estando o valor real englobado no intervalo credível P10-P50-P90.

Palavras-Chave: Ajuste de Histórico, Multi-Objective Particle Swarm Optimisation, inferência Bayesiana, bom balanço, estático e dinâmico.
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<th>Acronym</th>
<th>Meaning</th>
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<tr>
<td>AHM</td>
<td>Assisted History Matching</td>
</tr>
<tr>
<td>B Dyn</td>
<td>Dynamic match of model B</td>
</tr>
<tr>
<td>BHP</td>
<td>Borehole Pressure</td>
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<td>B Sta&amp;Dyn</td>
<td>Static and dynamic match of model B</td>
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<tr>
<td>BMA</td>
<td>Bayesian Model Averaging</td>
</tr>
<tr>
<td>CDF</td>
<td>Cumulative Distribution Function</td>
</tr>
<tr>
<td>C Dyn</td>
<td>Dynamic match of model C</td>
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<tr>
<td>CI</td>
<td>Credible Interval</td>
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<td>C Sta&amp;Dyn</td>
<td>Static and dynamic match of model C</td>
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<tr>
<td>EnKF</td>
<td>Ensemble Kalman Filter</td>
</tr>
<tr>
<td>FOPT</td>
<td>Field Oil Production Total</td>
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<td>FWPT</td>
<td>Field Water Production Total</td>
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<tr>
<td>GOR</td>
<td>Gas-Oil Ratio</td>
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<tr>
<td>HM</td>
<td>History Matching</td>
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<tr>
<td>MO</td>
<td>Multi-Objective</td>
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<tr>
<td>MOO</td>
<td>Multi-Objective Optimisation</td>
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<tr>
<td>MOPSO</td>
<td>Multi-Objective Particle Swarm Optimisation</td>
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<tr>
<td>NAB</td>
<td>Neighbourhood-Algorithm Bayes</td>
</tr>
<tr>
<td>PDF</td>
<td>Probability Distribution Function</td>
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<tr>
<td>PPD</td>
<td>Posterior Probability Distribution</td>
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<td>PSO</td>
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<td>SO</td>
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1. Introduction

1.1. Motivation

Reservoir simulation is a valuable tool for the decision-making process involved in the development and management of hydrocarbon reservoirs. A reservoir simulation model combines rock and fluid properties with a mathematical formulation to describe the fluid flow in porous media (i.e., the reservoir static model). This model is then used to predict the performance of the reservoir under various operating conditions (Gilman & Ozgen, 2013). However, in order to improve the predictive capability of a reservoir model, it is necessary to incorporate all relevant information available about the field. The process of incorporating dynamic data in reservoir models is known in the petroleum literature as history matching.

History matching is an ill-posed problem because the amount of independent data available is much less than the number of variables (Gilman & Ozgen, 2013). Hence, there exists an infinite number of combinations of the unknown reservoir properties that results in reservoir models able to match the observations (i.e., the production data). Furthermore, the information available about the reservoir is always inaccurate and sometimes inconsistent. As a result, reservoir models are constructed with uncertain parameters and consequently, their predictions are also uncertain (Tavassoli, 2004).

Over the last years, increased importance has been attributed to the quantification of uncertainty in reservoir performance predictions and reservoir description so that the risk associated with a given decision can be managed (Mohamed et al., 2009). Because of this interest in the characterization of uncertainty, it is now more frequent to generate multiple history matched models. However, generating multiple history matched models that can reproduce the real reservoir observed historical data, does not inevitably lead to a correct assessment of uncertainty (Tavassoli, 2004). Nevertheless, the fact that good quality matches for the production data are obtained in the ensemble of history matched models does not necessarily mean that the corresponding geology of the reservoir is being realistically reproduced.

This thesis started by history matching a standard industry benchmark case (PUNQ-S3) using 8 years of production history data. Very good quality matched models were obtained but the analysis and comparison between the values of their petrophysical properties (porosity, horizontal permeability and vertical permeability) at the wells and the truth case, appeared to be unsatisfactory. Large differences were identified, namely for horizontal and vertical permeability. Consequently, although the model presents a good ability to reproduce the dynamic response of the system, corresponding geology is being reproduced in an unrealistic way. Geostatistical methods could be used to mitigate this problem but because of grid resolution, a difference
between the values of the petrophysical properties at the wells of the model and the truth case would persist.

History matching has been tackled using stochastic population-based algorithms which can be approached by single objective (SO) or multi-objective (MO). When compared to the SO, the MO approach not only increases the speed in the matching but also the diversity in the models found that produce the same low misfits as in the single objective matching (Christie et al., 2013). Furthermore, under different model parameterisations the multi-objective matching still results in a more diverse set of models leading to a more robust and reliable forecast (Hutahaean et al., 2015). According to the literature, the MO approach has only been applied to obtain the match to production variables which leads to a gap in knowledge regarding the matching results to petrophysical properties.

In this context, this study aims the development of a methodology for history matching using a multi-objective optimisation (MOO) approach in order to obtain a simultaneous match to static and production data. The methodology was implemented in the PUNQ-S3 reservoir.

1.2. Objectives

The main goal of this project is to evaluate the ability of the proposed multi-objective optimisation approach methodology for history matching a reservoir to generate an ensemble of models capable of reproducing both the historical production and geological features of the truth case. This technique balances between the tradeoffs among a multi-objective simultaneous sensitive to the difference in static and difference in production data.

The uncertainty assessment is accomplished by applying the Neighbourhood-Algorithm Bayes to forecast and characterize the uncertainty associated with the models.

The Bayesian Model Averaging is applied to combine the forecast for the different model parameterisations and obtain a single forecast model.

1.3. Thesis outline

This thesis is structured with six chapters:

- Chapter 1 introduces the topic of this work by identifying the problem and the proposed solution with a brief description of the adopted methodology;
- Chapter 2 presents the theoretical background related to the development of this work, explains concepts related to reservoir modelling and inherent uncertainties, history
matching processes and different optimisation approaches, uncertainty characterization of predictions.

• Chapter 3 shows the proposed methodology used in the development of this work.
• Chapter 4 introduces the study case and the different model parameterisations tested with the proposed methodology for history matching and uncertainty characterization.
• Chapter 5 presents and discusses the results obtained in the history matching and uncertainty characterization of predictions with the proposed methodology, for the different model parameterisations.
• Chapter 6 states the conclusions of the application of the proposed methodology in this work.
2. Theoretical background

2.1. Reservoir modelling

In petroleum reservoir development, the description and performance of a reservoir can be obtained by using a model. The main objective of the reservoir model is to supply a reliable representation of the reservoir heterogeneity and its process consists of two main stages. Firstly, reservoir models are built with all available static information, for example, geology, cores, well-logs, seismic, but these information is scarce, resulting in high uncertainties. Therefore, a second stage is needed where the models are modified until they match the production data (Hoffman & Caers, 2007). The integration of these different types of data with different sources into a consistent model is important to understand the reservoir behaviour and improve the predictive performance of the models.

2.1.1. Geological model

In a typical reservoir study one of the most important stages is the definition of the geological model, as the static description of the reservoir is one of the main controlling factors in determining the field production performance (Cosentino, 2001). In most operational studies, the geological study is often performed making use of static information alone while the dynamic information is used only to check the consistency of the model and its ability to reproduce the observed reservoir performance. In a truly integrated geological model, all the available data including both static and dynamic should be included as an intrinsic part of the geo-modelling workflow (Cosentino, 2001). Such model will have a large degree of consistency and it has a better chance of being able to reproduce the observed field performance. According to Cosentino (2001) some of the integration aspects of a typical geological modelling work are the structural model, stratigraphic model, lithological model, reservoir heterogeneity.

The structural model concerns about the definition of the structural top map of the reservoir, associate fault pattern and other structural elements. The definition of these structures is done by seismic interpretation, well data and geological evidence.

The stratigraphic model is described by the definition of the reservoir main flow units. It is done by correlating all the wells, in order to define the surfaces that bound the main reservoir units. These flow units are defined using seismic data, sedimentology, sequence stratigraphy, well logs.
The lithological model consists in populating the reservoir geometry with data that describe the lithological characteristics of the reservoir rock and their spatial variability. It is important to have a detailed lithological model as there is a relation between lithological facies and the petrophysical characteristics. These types of models are built integrating the sedimentological model, the facies definition and a probabilistic approach of the lithological distribution.

The reservoir heterogeneity study tries to analyse the presence, extension and importance of internal heterogeneities within the hydrocarbon reservoir as it can affect the dynamic behaviour of a field. Reservoir heterogeneities are small to large scale geological features that may be insignificant for the static reservoir characterization but do have significant impact on fluid flow.

2.1.2. Dynamic model

Reservoir fluid flow simulation is a mathematical model which parameterises the reservoir into grid-cells, each cell has different reservoir properties (facies, porosity, permeability, water saturation, pressure, etc.) that condition the fluid flow. Reservoir properties of each cell, like porosity and permeability are obtained from the geological model. The reservoir model is used then to estimate a mathematical approximation of the field fluid flow, by calculating flows between adjacent cells of the model.

One of the first steps in reservoir simulations is to identify the number of cells necessary to generate the grid. Since the reservoir property distribution comes from the geological model it is necessary to preserve the geological heterogeneity in the reservoir model, but it is computationally expensive to use the same number of cells in the flow simulation model as that in the geological model. A balance between the grid resolution (number of cells) and the time consumed by the flow simulation is necessary. The resolution of the grid will be dictated by the objectives of the fluid flow simulation.

In general, for reservoir fluid flow simulation it is necessary to provide a grid with cell-dimension that retain the geological heterogeneity of the reservoir and not being computational expensive. It is possible to use a detailed geological grid in a reservoir simulation if the number of cells is not too large (Christie, 1996) or to average the petrophysical properties of the grid to capture the fine scale effects in a coarse grid through a process of upscaling. After upscaling, the static properties from the geological grid to the simulation grid it is necessary to use a mathematical technique able to simulate the fluid movements inside the reservoir (grid cells). The mathematical methods must consider the physical properties of the fluids (viscosity, gravity and capillary).

Peaceman (1977) defines a mathematical model of a reservoir as a model of a physical system composed by a set of differential equations, with a set of boundary equations, which describe the significant physical processes taking place in that system. The processes occurring in a reservoir are basically fluid flow and mass transfer. Since reservoirs contain oil, gas and water the flow
equations must consider necessary to include the interaction of these three phases within the reservoir simulation. The interaction between water and oil is described by relative permeability curves, which reduce the permeability of a fluid in the presence of another. Peaceman (1977) states that the differential equations are obtained by combining Darcy’s law for each facies with a simple differential material balance for each phase.

Schilthuis (1936) presented the material balance equation derived as a volume balance which equates the cumulative observed production, expressed as an underground withdrawal, to the expansions of the fluids in the reservoir resulting from a finite pressure drop. The Volume balance can be evaluated in reservoir barrels (rb) as:

\[ UW(rb) = \text{Oil exp}(rb) + \text{ODG}(rb) + \text{GC exp} + \text{HCPV red} \quad (1) \]

Where:

- \( UW \) is the underground withdrawal;
- \( \text{Oil exp} \) is the expansion of oil;
- \( \text{ODG} \) is the originally dissolved gas;
- \( \text{GC exp} \) is the Gascap gas expansion;
- \( \text{HCPV red} \) is the reduction in HCPV due to connate water expansion.

The one dimension description of a single-phase fluid flow through a porous medium in a horizontal system is described by the Darcy equation which uses the permeability value to calculate volumetric flow rate by the Equation 2:

\[ q = -\frac{k \Delta P}{\mu L} \quad (2) \]

where:

- \( q \) is the volumetric flow rate;
- \( k \) is a homogeneous permeability;
- \( \Delta P \) is the pressure differential over distance \( L \);
- \( \mu \) is the fluid viscosity;
- \( A \) is the cross-sectional area through which the flow is passing.

For flow according to axes \( x, y \) and \( z \), the Darcy equation can be written as:

\[ u_x = -k \left( \frac{\partial P}{\partial x} - \rho g \frac{\partial D}{\partial x} \right) \quad (3) \]
\[ u_y = -k \left( \frac{\partial P}{\partial y} - \rho g \frac{\partial D}{\partial y} \right) \quad (4) \]
\[ u_z = -k \left( \frac{\partial P}{\partial z} - \rho g \frac{\partial D}{\partial z} \right) \quad (5) \]

where:

- \( D \) is depth;
- \( \rho \) is the density of the fluid;
- \( g \) is the acceleration due to gravity.
2.2. Sources of uncertainty

For all data that are used in reservoir modelling there exists a certain degree of uncertainty associated with each data. Uncertainties arising from geological data include errors in geological structure exact locations, reservoir and aquifer sizes, reservoir continuity, fault position, facies determination, and insufficient knowledge of the depositional environment. There are also other types of uncertainty related to upscaling, simplifications of the mathematical model used to simulate the fluid dynamics, and external factors, which all add up resulting in uncertainty associated with the reservoir prediction performance (Cosentino, 2001).

Cosentino (2001) defined four major sources of uncertainty in a typical geological model, such as uncertainties related to data quality and interpretation, structural and stratigraphic models, stochastic models and its parameters and uncertainty related to equiprobable realisations.

The uncertainties related to data quality interpretation are mainly associated with the incorrect calibration and inherent errors present in the instrumentations. Usually, under reservoir modelling these kinds of data are assumed as error free.

Regarding the uncertainty related to the structural and stratigraphic models, as these models are built considering seismic interpretation, well data, sequence stratigraphy and well logs, they are carried out through a deterministic approach which does not allow for any uncertainty estimation. Besides, each geoscientist has his own judgement in the interpretation of these data which also contribute to an increase in the uncertainty.

Different stochastic models can represent the same geological model allowing the exploration of different part of the uncertainty space. Since no specific rules exist to choose one model or another, the choice of the model depends on the geoscientist performing the study. The chosen parameters of the stochastic model also contribute as a major source of uncertainty.

Stochastic modelling studies originate different equiprobable realisations, under the same a priori assumptions, and therefore the comparison between them will allow a better estimation of the uncertainties associated with the reservoir.

Management decision on field development is taken only when the associated uncertainties with both the individual reservoir model parameter and the simulation production forecast is well understood and quantified. If not a decision to obtain additional reservoir data measurement is taken so as to better understand the reservoir.
2.3. History matching

History matching is a calibration process in which the uncertain parameters of a numerical reservoir model are iteratively adjusted in order to obtain an acceptable match between simulated and historical measured production data. According to Gilman and Ozgen (2013), depending whether these uncertain parameters affect material balance or fluid flow, they can be grouped into volumetric and flow parameters, respectively. Volumetric parameters include compartmentalization, fluid contacts, pore volume, drainage capillary pressure curve and endpoints, aquifer properties, fluid influx, PVT properties. In turn, flow parameters include porosity and permeability distribution, fracture properties, matrix-fracture exchange, flow barriers, relative permeability curves, high permeability streaks and conductive faults.

Although History Matching represents a fundamental step in view of a reservoir production forecasting and uncertainty quantification, the calibration of a reservoir model suffers from non-uniqueness. Due to the insufficient constraints and data (Schaaf et al. 2008) history matching is an ill-posed inverse problem which means several combinations of parameters might exist capable to satisfactorily match the past dynamic behaviour of the system. Moreover, a model characterized by a good fit for the production data does not necessarily give a good estimation of the parameters of the reservoir and consequently, this might lead to errors in the prediction of the performance of the reservoir model (Travassoli 2004).

2.3.1. Manual History Matching

Manual history matching aims at matching the global or field engineering parameters and follows with the adjustment of individual flow units or layers, to finally match the well and near-wellbore data. Briefly, based on sensitivity studies carried out to pre-determine which parameters affect production the most, manual history matching entails perturbing the parameters manually in order to find a model that fits the real static and dynamic data (Oliver & Chen, 2011).

This manual approach has been widely used in the last decades and proved to be very flexible because the reservoir engineer can vary the values of the reservoir parameters based on his own experience and good judgement. On the other hand, the reservoir performance can be complex and it may be difficult to understand the behaviour of the reservoir models and the interdependencies among parameters. This makes the calibration of a large number of parameters at the same time an extremely difficult task. Other limitations are related with getting a single history matched reservoir model as it is based on a trial and error procedure, it is time-consuming and expensive. Consequently, there has been considerable research on “automatic” or “assisted” history matching techniques (Cosentino, 2001). Figure 1 illustrates a general workflow used in manual history matching approach.
2.3.2. Assisted History Matching

In assisted history matching (AHM), optimisation algorithms are used to automatically compare the simulated dynamic data with the historical data through the application of a misfit function. The algorithms try to minimize the misfit function by modifying the uncertain parameters reducing the difference between the simulated production data (simulated data) and the production history (observed data) and thus to obtain the model that best approximates the fluid rates and pressure data recorded during the reservoir life. The least square norm (Arnold, 2013) is the most commonly mathematical expression used in history matching to measure this difference and it is called objective function (Equation 6).

\[
M = \sum_{n=1}^{N} \frac{[\text{obs}(t_i) - \text{sim}(t_i)]^2}{2\sigma_i^2}
\]  

(6)

Where:

- \(M\) is the misfit score between the observed and simulated (also called misfit);
- \(\text{obs}\) is the observed data at time \(t_i\);
- \(\text{sim}\) is the simulated data at time \(t_i\);
- \(N\) is the number of data points;
- \(\sigma_i^2\) is a representation of the observed data errors (assuming these data errors are independent and have a normal distribution).

This procedure can be translated into an optimisation problem in which the misfit function is an objective function and the optimisation problem is bounded by the model constraints. Given a set of reservoir parameters to be calibrated, the combination of all the possible solutions is known as search space, whereas the set of all the possible values of the misfit function is known as solution space.
Several of the AHM techniques are used today in the industry. The methods based on heuristic optimisers or direct search, have the advantage of leading to multiple calibrated models that partially address the problem of the non-uniqueness of the solutions (Ferraro and Verga, 2009). A general workflow used in assisted history matching is illustrated in Figure 2.

![General workflow in assisted history matching.](image)

**2.4. Optimisation algorithms**

In assisted history matching, the model output parameters are modified in order to minimize the difference between the model result and the actual field data. The minimization process is referred to as optimisation process and a number of optimisation techniques have been proposed. The most common approaches use gradient methods, data assimilation methods and stochastic search algorithms.

Gradient optimisation has been widely used to optimise objective functions. The gradient optimisation techniques include the Steepest descent, Conjugate gradient, Gauss-Newton, and Dog-leg techniques. The gradient method involves calculation of the objective function gradient with respect to model input parameter. Although it is a fast and easy method for implementation, it has some limitations as there is the possibility of getting trapped in local minima far from the global one and it is a non-linear optimisation algorithm that relies on a single model for perturbation (Christie et al, 2005).

The data-assimilation optimisation can be separated into an analysis (or update) step and a forecast step. At the analysis step, an improved estimate of model variables is obtained by applying Bayes’ theorem to compute the posterior probability density function (PDF) for the model variables given the observations. At the forecast step, the dynamical model is advanced in time and its result becomes the forecast (or prior) in the next analysis cycle (Christie et al, 2005). Ensemble Kalman Filter (EnKF) is a data assimilation technique that has gained increasing interest in the application of petroleum history matching in recent years. The basic methodology
of the EnKF consists of the forecast step and the update step. This data assimilation method utilises a collection of state vectors, known as an ensemble, which are simulated forward in time (Christie et al., 2005). In other words, each ensemble member represents a reservoir model. Subsequently, during the update step, the sample covariance is computed from the ensemble, while the collection of state vectors is updated using the formulations which involve this updated sample covariance.

The Stochastic Optimisation is considered in a subsection as it is used under the scope of this thesis.

2.4.1. Stochastic Optimisation

Adaptive Stochastic Sampling algorithms are population-based optimisation algorithms inspired by process occurring in biological evolution and the most commonly used are Genetic algorithms (Erbas & Christie, 2007), Simulated Annealing (Ingber, 1993), Evolutionary algorithms (Schulze-Riegert et al., 2001) and Swarm algorithms (Mohamed et al., 2010).

Population-based systems are composed of multiple intelligent individuals that improve the quality of solutions by interpreting the interactions among members. While searching for optimal solutions, these kinds of methods also provide the opportunity to balance exploration and exploitation. Exploration is defined as the search for different areas in the parameter space while exploitation refers to the refinement of the previously visited regions to find better answers. The most recent stochastic algorithms are the evolutionary and swarm algorithms which have the ability not to get trapped in local minima so often and therefore achieve better results when quantifying uncertainty (Hajizadeh et al., 2011).

Particle Swarm Optimisation

The Particle Swarm Optimisation (PSO) was developed by Kennedy and Eberhart (1995). It was initially designed to measure the social behaviour of a group of birds but its application has been extended to various fields including petroleum engineering (Hajizadeh et al., 2010). The basic principle behind the algorithm is that birds belonging to a particular flock would generally tend to fly towards regions perceived to exhibit certain habitat characteristics at a particular point in time. Each member of the flock thus has a memory of its best historical location and the flock is often characterized by a global best position. The Particle Swarm Optimisation process involves initiating a swarm of particles which randomly search the sample space in an attempt to obtain a sufficient solution to a particular objective function. This algorithm can be applied both in a single and multi-objective optimisation. When compared to the single objective, the multi-objective
approach of the PSO algorithm presents an improvement in model diversity and is characterized by more efficiency in estimating the uncertainty due to a faster convergence speed (Mohamed et al., 2011).

The basic workflow for the PSO may be summarised:

1) Initialise the particle swarm (i.e. distribute specified number of particles randomly in sample space);
2) Evaluate the objective function for each particle in the swarm;
3) Compare each particle’s fitness value with that corresponding to its best position (pbest). Replace pbest with the current position if the current value of the fitness function is less than that corresponding to pbest;
4) Update the global best position and fitness value of the swarm;
5) Update the velocities and positions of each particle.

This process is repeated until a stopping criteria is reached.

2.4.2. Single Objective vs Multi-Objective Optimisation

The principle of a single objective optimisation is different from that in a multi-criteria optimisation. In single objective optimisation, the goal is to find the best solution, which corresponds to the minimum or maximum value of the objective function (Ferraro & Verga, 2009). This means that the algorithm uses a single match quality number in searching for better solutions. The single objective approach sums up all the misfit components using equation 6, presented in section 2.3.2.

On the contrary, in a multi-criteria optimisation more than one objective is defined, there is no single optimal solution and at least one criteria is verified. The presence of more than one objective (conflicting objectives) makes these objectives to trade-off between each other and so, the improvement in one objective may cause deterioration in another (Ferraro & Verga, 2009). Therefore, it is essential to find solutions that balance these trade-offs, the so called non-dominated solutions, which means solutions that cannot improve any objective without degrading one or more of the other objectives (Mohamed et al, 2011).

As in a multi-objective optimisation the misfit function is split into several components which are optimised simultaneously, the objective function takes the vector form (Mohamed et al, 2011):

\[ F(x) = [f_1(x), ..., f_M(x)] \]  

(7)

Where:

- \( f_i, i=1, ..., M \) are the objective functions.
The formulation of a multi-objective optimisation process is to minimize \( F(x) \) subject to:

\[
\begin{align*}
    h_k^l &\leq x_k \leq h_k^u \\
    x &= \{x_1, x_2, \ldots, x_k, \ldots, x_N\}
\end{align*}
\]

Where:

- \( F(x) : \mathbb{R}^N \rightarrow \mathbb{R}^M \), \( x = \{x_1, x_2, \ldots, x_k, \ldots, x_N\} \) is the vector of the \( N \) variables in the parameterisation;
- \( h_k^l \) and \( h_k^u \) represent the lower and upper boundary for each unknown, respectively.

Since different objectives are not comparable in a multi-objective optimisation, there is the need to use the concepts of Dominance and Pareto Optimality among the objectives. The Dominance concept infers that a solution dominates the other if it is better in all objectives and it is strictly better in at least one objective than in the other (Hutahaean et al., 2015). Therefore, all solutions that satisfy both these conditions are called Pareto optimal solutions set while Pareto front refers to the image of these Pareto optimal set in the objective space. An example of the concepts of Dominance and Pareto optimality in a two-dimensional objective space can be seen in the Figure below adapted from Hutahaean et al. (2015).

![Figure 3 - Illustrative example of Dominance and Pareto optimality in a two-dimensional objective space](adapted from Hutahaean et al., 2015).

In a multi-objective optimisation, as there is no single optimal solution it is essential to find as many Pareto-optimal solutions as possible, i.e. finding a set of solutions which optimally balance the trade-offs among the different objectives. The multi-criteria optimisation entails minimizing the difference between solutions and the Pareto front. This is done by maximising the diversity and
spread of the non-dominated solutions to represent as much as possible of the Pareto front while maximizing the number of elements of the Pareto optimal set found maintaining the ones which were already found (Mohamed et al, 2011).

The MOO was already used in history matching and some of these approaches implemented in different optimisation algorithms have been reported in the literature.

The first application of MOO in HM was implemented by Schulze-Riegert et al. (2007) where they address the problem of multi-objective criteria in a history match study and present analysis techniques identifying competing match criteria by discussing a Pareto-Optimiser.

Ferraro and Verga (2009) employed a genetic algorithm and evolutionary strategies with different parameter combinations in both single and multi-objective optimisation techniques. Their study demonstrated that the application of a multi-objective approach improves the history matching regarding the convergence rate and the distance from the real solution. Additionally, since it is possible to find multiple conflicting objective functions, a range of equally likely scenarios can also be obtained.

Hajidazeh et al. (2011) used a multi-objective stochastic population-based optimisation for history matching and uncertainty quantification of a synthetic case. Multi-objective differential evolution as shown faster convergence, better final misfit value during history matching and obtained stable Bayesian credible intervals in fewer simulations when compared with the objective sum approach using the standard DE.

Mohamed et al. (2011) compared the results between a single objective methodology and the multi-objective particle swarm optimisation scheme on history matching a synthetic reservoir simulation model. They concluded that the multi-objective particle swarm approach is highly competitive in obtaining a well distributed set of good fitting reservoir models. This approach obtained the models faster and with similar quality, providing a more accurate estimation of uncertainty in predictions in comparison to the single objective approach.

Christie et al. (2013) compared the performance of both single and multi-objective versions of the Particle Swarm Optimisation algorithm for history matching a real field. Multi-objective matching proved to increase not only the speed in matching but also a diversity in the models found that produce the same low misfits as in the single objective matching.

Hutahaean et al. (2015) explore the impact of different geological model parameterisations on AHM by comparing the performance of SO and MO AHM approaches. They concluded that under different model parameterisations the MO AHM approach results in a more diverse set of models leading to a more robust and more reliable forecast than the one from SO approach.
2.5. Uncertainty Assessment

The current trend for history match workflows is to find multiple matched models instead of a single set of model parameters that match the data. The importance of achieving multiple solutions is that they can be used for uncertainty quantification of the production forecast.

It is important to produce a set of models that match the production data consistent with the known prior information allowing the quantification of the uncertainty. Through the generation of multiple history matched models it is possible not only to quantify the probability of future production but also to identify what scenario is the most likely and what are the respective confidence intervals.

2.5.1. Bayesian Framework and Uncertainty Quantification

Bayesian inference is based on the Bayes’ theorem and used to perform inferences about the value of some parameters based on prior and newly observed information. Bayes’ Theorem is represented by Equation 10.

\[
P(m|O) = \frac{P(O|m)P(m)}{\int_M P(O|m)P(m)dm}
\]

Where:

- \( P(m|O) \) is the posterior probability of the model;
- \( P(O|m) \) is the data likelihood;
- \( p(m) \) is the initial prior probability distribution;
- \( M \) is the space of the model.

Likelihood of a reservoir model can be defined as the probability that reservoir observation data is equal to simulation responses based on a specific reservoir model. The likelihood is represented by Equation 11.

\[
p(O|m) = e^{-M}
\]

Where:

- \( M \) is the misfit as calculated following for example equation 6.

The Posterior Probability Distribution (PPD) or \( p(m|O) \) represents the updated knowledge about the model \( m \) based on the observations \( O \) and the prior knowledge of the model. It can be calculated using the Neighbourhood Algorithm-Bayes (NAB; Sambridge, 1999) which is based on Markov Chain Monte Carlo. NAB uses Voronoi cells to interpolate values of misfit away from the
known sampled points (models in the parameter space), for which the likelihood is computed exactly, and a Gibbs sampler to estimate the PPD (Christie, 2006). The resulting ensemble of the model with their posterior probabilities can be used to estimate the P10 – P50 – P90 confidence interval to describe the uncertainty envelopes for reservoir performance.

2.5.2. Bayesian Model Averaging

Bayesian Model Averaging (BMA) was first applied in weather forecasting and its success made it to be applied in other study areas such as oil production forecasting (Raftery et al., 2005).

It is a technique applied with the purpose of combining the probability distribution functions (PDF) from different models into a single PDF (Figure 4). The combination of the different PDF encompasses a weighted average of the individual forecast based on the uncertainty forecast and variance between models.

![Figure 4 - BMA PDF (thick curve) based on 5 models (thin curves) (adapted from Raftery et al. 2005).](image)

BMA PDF of a quantity \( y \) based on \( K \) models is given by:

\[
p(y|f_1, ..., f_K) = \sum_{K=1}^{K} w_k g_k(y|f_K)
\]

Where:

- \( f_k \) is the forecasting of model \( k \)
- \( w_k \) is the posterior weight of model \( k \)
- \( g_k(y|f_k) \) is the PDF of \( y \) given the forecast \( f_k \)
Assuming a normal distribution (Raftery et al., 2005), the BMA mean ($E$) is represent by:

$$E(y|f_1, ..., f_K) = \sum_{k=1}^{K} w_k f_k$$  \hspace{1cm} (13)

The posterior weights, $w_k$, are calculated using:

$$w_k = \frac{B_{kj}}{\sum_{i=1}^{k} B_{ij}}$$  \hspace{1cm} (14)

where $B_{kj}$ is the Bayes Factor of model $k$ regarding the assumed best model $j$ (maximum likelihood).

Bayes Factor assumes independent conditional distributions and allows to compare the validity of the different models according to their data. Bayes Factor of model $k$ ($m_k$) regarding model $j$ ($m_j$), $B_{kj}$, can be calculated recurring to Laplace’s Method (Kass and Raftery, 1995):

$$B_{kj} = \frac{p(O|m_k)}{p(O|m_j)}$$  \hspace{1cm} (15)

where $p(O|m_x)$ is the posterior probability of model $x$ around the maximum likelihood model.

BMA is used in this thesis to estimate the cumulative oil and water uncertainty envelopes by combining the uncertainty envelopes associated with the different model parameterisations.
3. Methodology

This project entails the development of a multi-objective optimisation (MOO) stochastic history matching technique able to match simultaneously static and dynamic data. This procedure was implemented in the PUNQ-S3 benchmark reservoir.

In this reservoir, matching exclusively the production data (Gas-Oil Ratio, Borehole Pressure and Water Cut) allows retrieving an ensemble of history matched models able to reproduce the historical production data for these three production variables. Despite the results, when comparing the optimised static models of porosity, horizontal permeability and vertical permeability against the truth case at the well locations, large differences between the values are identified.

The solution proposed to overcome this drawback is to pose history match as a multi-objective problem minimizing simultaneously an objective composed by the differences between real and optimised static data and another with the difference between observed and simulated production data. A Multi-Objective Optimisation approach is applied and the models belonging to the Pareto fronts are studied to make a balance of the trade-offs between the objective with the difference in the static data and the objective with the difference in the production data. The workflow for the proposed methodology is illustrated in Figure 5.

![Figure 5 - Workflow for the methodology applied in this thesis.](image-url)
The proposed multi-objective history matching methodology may be summarized in the following sequence of steps:

1 – Definition of the parameterisation of the geological model;

2 – Optimisation of the geological parameters of the model using the MOPSO algorithm (section 2.4.1);

3 – Introduction of the optimised petrophysical properties in the static objective for minimization;

4 – Run a flow simulator to obtain the dynamic response of the optimised model;

5 – Introduction of the simulated dynamic response in the dynamic objective for minimization;

6 – Minimization of both objectives and identification of the models (Pareto Models) that best approximate both petrophysical properties and dynamic response to the truth case (sections 2.3.2 and 2.4.2);

This process is repeated until a stopping criteria is reached which in this case is the maximum number of iterations.

7 – Characterization and quantification of the uncertainty of predictions of the ensemble of history matched models recurring to the Neighbourhood Algorithm-Bayes algorithm (section 2.5.1).

The Bayesian Model Averaging was then applied to combine the forecast for the different model parameterisations and obtain a single forecast model (section 2.5.2).

In order to evaluate the performance and ability of the proposed MOO technique in both history matching and uncertainty characterization of predictions, a multi-objective optimisation approach for history matching was applied to the different model parameterisations considering two objective functions as described by the match between observed and simulated production data for the dynamic properties under study. The scheme of objective grouping used in this approach was adopted from previous study (Hutahaean et al., 2015) in which the wells are grouped based on geo-engineering judgement in the reservoir model studied.

The workflow for history matching exclusively the model to dynamic data can be seen in Figure 6.

After optimising the geological parameters (section 2.4.1) and obtaining the dynamic response of the model from a flow simulator, the algorithm minimizes the misfit function (section 2.4.2) and consequently identifies the reservoir model that best approximates its dynamic response to the historical production behaviour of the field (section 2.3.2). The uncertainty of predictions of the ensemble of history matched models is then characterized and quantified using the Neighbourhood Algorithm-Bayes algorithm (Section 2.5.1).

The history matching procedure is done by Epistemy’s Raven, which is an assisted history matching software using a multi-objective optimisation approach powered by the Particle Swarm
Optimisation algorithm. This software is integrated with the fluid flow simulator Eclipse® (Schlumberger) to simulate the fluid flow in each model.

Figure 6 - Workflow used for history matching the model to dynamic data.

Five runs of history matching, each with 500 iterations were used to infer about the consistency of the results based on the average misfit convergence and its standard deviation. The geological consistency of the models is evaluated by comparing the values of the petrophysical properties of the Pareto Models at the wells with the respective ones from the truth case. The overall distribution of these properties from the Pareto Models and the truth case is also used in the geological consistency assessment.

The Forecasting and Uncertainty Characterization process is assessed through the study of the uncertainty envelopes obtained for each model parameterisation.
4. Application example

This chapter comprises the description of the benchmark synthetic dataset after which are presented the results of the methodologies applied under the scope of this thesis and its discussion.

4.1. PUNQ-S3 Field description

The PUNQ-S3 (Production forecasting with Uncertainty Quantification variant 3) is a synthetic reservoir model developed for various petroleum engineering studies. It consists of five layers with the reservoir top at 2430m at a dip angle of about 1.5 degrees (Figure 7). The model contains 19 x 28 x 5 grid blocks (i.e., a total of 2660 grid blocks), each one with equal side in the x and y directions of 180 meters, of which 1761 blocks are active (Floris et al., 2001). It has a dome-shaped structure where a small gas cap is located and is bounded to the east and south by a fault, and to the north and west by a strong aquifer.

In order to have more control over the underlying geological and geostatistical model the porosity and permeability fields have been regenerated under a consistent geological description (Floris et al., 2001). The porosity and permeability fields were generated using a geostatistical model based on Gaussian Random Fields and the geostatistical parameters, such as means and variograms have been chosen to be as much as possible consistent with an analogue geological model (Floris et al., 2001). Both porosity and permeability fields have been correlated statistically through the use of collocated co-simulation.

The field has six production wells located around the gas-oil contact and there are no injection wells due to the effect of the strong aquifer. Producers 1 (PRO1), 4 (PRO4) and 12 (PRO12) are completed in layer 4 and 5. Producers 5 (PRO5) and 12 (PRO12) are completed in layer 3 and 4, while producer 15 (PRO15) is completed only in layer 4 (Floris et al., 2001).

![Figure 7 - PUNQ-S3 reservoir model and location of wells in top structure map.](image-url)
The production history of the six wells is characterized by an extended well testing period (build up test) during the first year, a shut-in period for the next three years and a production period for the next 12 years with fixed oil production rate at 150 std m³/d and a 2 week periodic shut-in at the beginning of each year. For history matching the model, eight years of production history data which includes gas-oil ratio (WGOR), water cut (WWCT) and borehole pressure (WBHP), are used (Floris et al., 2001). As the available production of the field lasts for 16.5 years, the following 8.5 years were used exclusively to evaluate the predictive ability of the history matched models in terms of production forecasting (Floris et al., 2001).

4.2. Geological description

The original description of PUNQ-S3 (Floris et al. 2001) does not provide an exhaustive description of the geological background used to generate the dataset. Therefore, under the scope of this work, the background geology was modelled by relying in analogue fields. According to Floris et al. (2001), the sediments in this reservoir model were deposited in a deltaic coastal plain environment.

The following subsections describe this type of environment as well as its typical deposits and facies.

4.2.1. Delta Systems

A delta forms where a river transporting significant quantities of sediment enters a receiving sedimentary basin. It is formed by the interaction of subaerial fluvial processes and subaqueous processes of marine or lake basins that produces a contiguous sediment mass with distinctive facies assemblages (Galloway & Hobday, 1983).

Deltas are fed by a river and there is a transition between the area that is considered part of the fluvial environment and a region considered the delta top or delta plain (Figure 8). Delta channels can be as variable in form as a river and may be meandering or braided, single or divided channels. Branching of the river channel into multiple courses is common, to create a distributary pattern of channels across the delta top (Nichols, 2009). The coarsest delta-top facies are found in the channels, where the flow is strong enough to transport and deposit bedload material (Nichols, 2009). Adjacent to the channels are subaerial overbank areas, which are sites of sedimentation of suspended load when the channels flood (Nichols, 2009).
At the mouth of the channels the flow velocity is abruptly reduced as the water enters the standing water of the lake or sea within the depositary sedimentary basin (Nichols, 2009). The delta front immediately forward of the channel mouth is the site of deposition of bedload material as a subaqueous mouthbar (Figure 8). The coarsest sediment is deposited first, in shallow water close to the river mouth where it may be extensively reworked by wave and tide action (Nichols, 2009). The current from the river is dissipated away from the channel mouth and wave energy decreases with depth, leading to a pattern of progressively finer material being deposited further away from the river mouth. River suspended load enters the relatively still water of sea to form a sediment plume in front of the delta (Nichols, 2009). Fresh river water with a suspended load may have a lower density than saline seawater and the plume of suspended fine particles will be buoyant, spreading out away from the river mouth. As mixing occurs deposition out of suspension occurs, with the finest, more buoyant particles travelling furthest away from the delta front before being deposited in the prodelta region (Galloway & Hobday, 1983).

4.2.2. Deltaic Deposits and Facies

The term facies is often used in the description of sedimentary rocks in terms of depositional environments. A rock facies is a body of rock with specified characteristics that reflect the conditions under which it was formed (Reading & Levell 1996). Describing the facies of a body of sediment involves documenting all the characteristics of its lithology, texture, sedimentary structures and fossil content that can aid in determining the processes of formation. By recognising associations of facies it is possible to establish the combinations of processes that were dominant. The characteristics of a depositional environment are determined by the processes that are present, and hence there is a link between facies associations and environments of deposition (Reading & Levell 1996).
A key feature of many deltas is the close association of marine and continental depositional environments. In delta deposits this association is seen in the vertical arrangement of facies. A single delta cycle may show a continuous vertical transition from fully marine conditions at the base to a subaerial setting at the top (Nichols, 2009). This transition is typically within a coarsening upwards succession from lower energy, finer grained deposits of the prodelta to the higher energy conditions of the delta mouth bar where coarser sediment accumulates (Nichols, 2009).

The delta top contains both relatively coarse sediment of the distributary channel as well as finer grained material in overbank areas and interdistributary bays (Galloway & Hobday, 1983). The channel may be recognised by its scoured base, a fining-up pattern and evidence of flow. Fluvial channel fills (Figure 9(a)) is the typical facies found in channels and consists of interbedded fine sand, silt, and some mud, in which resultant units are lenticular and nearly symmetrical (Galloway & Hobday, 1983).

![Figure 9 - Example of fluvial channel fills (a) and floodplain mudstone (b) facies types (Grundvag et al., 2014).](image)

Deposits in the sheltered interdistributary bays may show thin bedding resulting from influxes of sediment from the delta top. According to Galloway & Hobday (1983) the facies type formed usually consist of natural levee deposits of massive to interbedded silt and mud, marsh and swamp peat, organic-rich clay and mud, and lacustrine mud and clay, resembling comparable to floodplain settings (Figure 9(b)).

The shallower water deposits of the delta front may be extensively reworked by wave and/or tidal action resulting in cross-stratified mouth-bar facies (Figure 10(a)). Mouthbar is characterized by sands and associated silts and muds containing abundant macerated plant debris as well as large chunks of woody material (Galloway & Hobday, 1983). Thin, discontinuous mud drapes and pockets of reworked mud clasts reflect the variability of fluvial scour and deposition. Laterally, mouthbar deposits grade into interdistributary sand, silt, mud and clay, and may be overlain by crevasse-splay sequences (Figure 10(b)).
The geometry and extent of the mouthbar sand bodies is determined by the relative importance of river, tidal and wave processes. Deeper, lower delta slope deposits and prodelta facies are finer grained, deposited from plumes of suspended material disgorged by the river resulting in distal mouthbar facies type. Distal mouthbar (Figure 10(c)) sequences consist of laminated mud, silt, and silty sand and display slump units, compaction and dewatering structures (Galloway & Hobday, 1983). Basinward, this sequences grade into interdeltaic embayment muds and silts deposited in a shoal-water delta platform setting (Figure 10(d)). Embayments represent environments temporarily bypassed by active distributaries in which their deposits form a veneer of burrowed, sporadically fossiliferous muds, silts, and some fine sands (Galloway & Hobday, 1983). Longlived embayments can become isolated from the marine environment, evolving into fresh or slightly brackish lakes.

Deltaic deposits are almost exclusively composed of terrigenous clastic material supplied by rivers. The analysis of thick deltaic sequences usually reveals thin shale, impure limestone, calcareous muddy sand, or coal beds that exhibit unusual continuity, and provide useful markers within the otherwise heterogeneous deltaic stratigraphy (Galloway & Hobday, 1983). In addition, although volumetrically minor, sand bars are isolated sand bodies encased within impermeable muds. Thin shelf and bay mud blankets are effective seals for fluids trapped within constructional sand facies.

According to Floris et al. (2001), in the PUNQ-S3 reservoir model layers 1, 3 and 5 consist of fluvial channel fills encased in floodplain mudstone; layer 2 represents marine or lagoonal clay with some distal mouthbar deposits; layer 4 is featured by a mouthbar or lagoonal delta encased
in lagoonal clays. A summary of the expected sedimentary facies with estimates for width and spacing for major flow units for each layer is given in Table 1 (Floris et al., 2001).

Table 1 - Expected sedimentary facies with estimates for width and spacing for major flow units for each layer.

<table>
<thead>
<tr>
<th>Layer</th>
<th>Facies</th>
<th>Width (m)</th>
<th>Spacing (Km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Channel fill encased in floodplain mudstones</td>
<td>800</td>
<td>2 - 5</td>
</tr>
<tr>
<td>2</td>
<td>Lagoonal shales with distal mouthbar</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>Channel fill encased in floodplain mudstones</td>
<td>1000</td>
<td>2 - 5</td>
</tr>
<tr>
<td>4</td>
<td>Mouthbar within lagoonal clays</td>
<td>500 - 5000</td>
<td>10</td>
</tr>
<tr>
<td>5</td>
<td>Channel fill encased in floodplain mudstones</td>
<td>2000</td>
<td>4 - 10</td>
</tr>
</tbody>
</table>

4.3. Different model parameterisations

In order to assess the performance of the proposed history matching approach, different model parameterisations were tested. The original dataset from the benchmark study is used and one model set with 24 parameters has been considered.

This model set is described as a deltaic coastal plain reservoir with three good quality channel sands of uniform thickness and spacing in each layer 1, 3 and 5, encased in a background floodplain. Layers 2 and 4 are classified in a single zone as poor-quality shale and sand, respectively. This gives a total of 12 zones (Figure 11), with 3 channels in each layer 1, 3 and 5, 1 floodplain, 1 homogeneous layer 2 and 1 homogeneous layer 4 (Floris et al., 2001).
Each zone has a corresponding parameter for porosity and another for horizontal permeability multiplier, resulting in a total of 24 parameters, 12 for porosity and 12 for horizontal permeability multipliers (Table 2; Floris et al., 2001).

Table 2 - Parameter corresponding to each zone of the model.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Porosity Parameter</th>
<th>Horizontal Permeability Multiplier Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Layer 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Channel a</td>
<td>$pa1</td>
<td>$Multipa1</td>
</tr>
<tr>
<td>Channel b</td>
<td>$pb1</td>
<td>$Multipb1</td>
</tr>
<tr>
<td>Channel c</td>
<td>$pb3</td>
<td>$Multipc1</td>
</tr>
<tr>
<td>Background floodplain</td>
<td>$pbackground</td>
<td>$Multipbackground</td>
</tr>
<tr>
<td>Homogeneous layer 2</td>
<td>$p2</td>
<td>$Multip2</td>
</tr>
<tr>
<td>Layer 3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Channel a</td>
<td>$pa3</td>
<td>$Multipa3</td>
</tr>
<tr>
<td>Channel b</td>
<td>$pb3</td>
<td>$Multipb3</td>
</tr>
<tr>
<td>Channel c</td>
<td>$pc3</td>
<td>$Multipc3</td>
</tr>
<tr>
<td>Homogeneous layer 4</td>
<td>$p4</td>
<td>$Multip4</td>
</tr>
<tr>
<td>Layer 5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Channel a</td>
<td>$pa5</td>
<td>$Multipa5</td>
</tr>
<tr>
<td>Channel b</td>
<td>$pb5</td>
<td>$Multipb5</td>
</tr>
<tr>
<td>Channel c</td>
<td>$pc5</td>
<td>$Multipc5</td>
</tr>
</tbody>
</table>

This model set is characterized by some geological inconsistencies namely in layers 2, 4 and 5. While in the truth case layers 2 and 4 are featured by two different facies types, in the model the same layers are described has homogeneous regions and so, have no ability to encompass the uncertainty associated with the different geological facies. The analysis of deltaic depositional sequences from analogue reservoirs also allows to infer that mouthbar facies type is usually found near the upper parts of the vertical sequence of facies rather than being deposited in the fourth layer. Regarding layer 5, although it is featured with three channels, they are placed next to each other which is neither geologically consistent or coherent with the truth case.

Three different model parameterisations were used for comparison and are described in the following subsections.

### 4.3.1. Parameterisation A

The results obtained in history matching model parameterisation A were the basis for stimulating the implementation of the proposed MOO methodology for reservoir history matching. The
problem in history matching the PUNQ-S3 reservoir only to production variables was identified through the analysis of the results from this model parameterisation.

Model Parameterisation A is based on the geological facies description of PUNQ-S3 to define the porosity range for each zone (Table 3). Although based on the geological facies description, the prior ranges for the different petrophysical properties were not set considering the prior distributions from the truth case (TC).

In this model parameterisation, horizontal and vertical permeabilities are correlated from porosity values obtained based on least square fitting of well data crossplots, using Equations 16 and 17.

### Table 3 - Porosity ranges of different facies used in model parameterisation A.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Porosity range (fraction)</th>
<th>Horizontal permeability range (mD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channels (layer 1, 3, 5)</td>
<td>0.15 – 0.30</td>
<td>13 - 30000</td>
</tr>
<tr>
<td>Background floodplain</td>
<td>0.05 – 0.15</td>
<td>1.5 – 1330</td>
</tr>
<tr>
<td>Homogeneous layer (2 and 4)</td>
<td>0.05 – 0.15</td>
<td>1.5 - 1330</td>
</tr>
</tbody>
</table>

\[
\ln(K_h) = \ln(\text{Mult}) + (0.77 + 9.03\phi) \\
K_v = 3.124 + 0.306K_h
\]

(16) \hspace{5cm} (17)

The calculation of \(K_h\) from \(\phi\) leads to errors which are compensated using multipliers as variable parameters and then the vertical permeability is calculated from horizontal permeability.

This model parameterisation was only used to history match to the production data using the workflow described in section 3 for history matching the model to dynamic data.

### 4.2.2. Parameterisation B

Model parameterisation B was history matched using the proposed methodology to obtain the match for both static and dynamic data.

With the purpose of improving the geological consistency of the model, the prior distributions of the parameters were modified based not only in the distributions of the TC but also in the range in which porosity and permeability vary between wells within the same zones of the model. The ranges in which porosity and horizontal permeability vary are in Table 4. The correlation between porosity and both permeabilities is the same used in model Parameterisation A (Equations 16 and 17).
Uncertainty in porous media

As this model was not only matched to production but also to static data (porosity, horizontal permeability and vertical permeability), sigmas for the three petrophysical properties had to be assigned so that the uncertainty related to the porous media could be characterized. The sigmas are the ranges in which the petrophysical properties that belong to the same facies type vary. They represent acceptance limit values that allow to evaluate and infer about the quality of the matches. Therefore, if the value of the optimised parameter is within the sigma range, the match is considered of good quality. On the other hand, the match is of poor quality if the optimised parameter is outside the sigma interval.

### Table 4 - Porosity and horizontal permeability ranges for the different zones used in model parameterisation B.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Porosity range (fraction)</th>
<th>Horizontal Permeability range (mD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channels (layers 1, 3, 5)</td>
<td>0.05 – 0.30</td>
<td>8 – 1065</td>
</tr>
<tr>
<td>Floodplain (layers 1, 3, 5)</td>
<td>0.08 – 0.30</td>
<td>3 – 903</td>
</tr>
<tr>
<td>Homogeneous layer 2</td>
<td>0.03 – 0.12</td>
<td>1 – 107</td>
</tr>
<tr>
<td>Homogeneous layer 4</td>
<td>0.11 – 0.22</td>
<td>40 – 630</td>
</tr>
</tbody>
</table>

Before defining the sigmas, a geological analysis of the reservoir was done so that the different facies types could be identified. To do that, firstly, the ranges in which the petrophysical properties...
vary in each layer were identified and then these properties at all wells were plotted. The regions where the wells are placed in the TC were also taken into account. Considering these values and the description of analogue depositional environments and facies (Galloway & Hobday, 1983; Barwis et al., 1990; Reading & Levell 1996; Nichols, 2009; Grundvag et al., 2014), the facies types were defined. This analysis led to the identification of 6 different facies and the wells belonging to the same facies type were grouped (Figure 12).

After grouping the wells by facies type, the variation between their petrophysical properties was studied. Considering this variation as well as the geological characteristics of each facies, the sigmas were assigned to make a distinction between the facies with good capacity for the fluids to flow, storage hydrocarbons and the ones which have an impermeable behaviour. Therefore, larger sigmas were assigned to the petrophysical properties from fluvial channel fills and mouthbar facies types than the ones from floodplain mudstones, lagoonal shales, distal mouthbar and lagoonal clays facies types. The sigmas assigned to each petrophysical property from the different facies types in model B are shown in Table 5.

Table 5 - Sigmas assigned to the petrophysical properties (porosity, horizontal permeability and vertical permeability) for the different facies types.

<table>
<thead>
<tr>
<th>Petrophysical Property</th>
<th>Facies Type</th>
<th>Fluvial Channel</th>
<th>Floodplain Mudstones</th>
<th>Lagoonal Shales</th>
<th>Distal Mouthbar</th>
<th>Mouthbar</th>
<th>Lagoonal Clays</th>
</tr>
</thead>
<tbody>
<tr>
<td>Porosity (fraction)</td>
<td></td>
<td>0.1</td>
<td>0.03</td>
<td>0.01</td>
<td>0.02</td>
<td>0.05</td>
<td>0.02</td>
</tr>
<tr>
<td>Horizontal Permeability (mD)</td>
<td></td>
<td>200</td>
<td>20</td>
<td>10</td>
<td>20</td>
<td>160</td>
<td>60</td>
</tr>
<tr>
<td>Vertical Permeability (mD)</td>
<td></td>
<td>100</td>
<td>10</td>
<td>4</td>
<td>10</td>
<td>40</td>
<td>20</td>
</tr>
</tbody>
</table>

For terms of comparison, model B was used for history matching to static and dynamic data (B Sta&Dyn) as well as only to dynamic data (B Dyn).

4.2.3. Parameterisation C

In model parameterisation C not only the facies, prior distributions and sigmas were adjusted but also a new zone orientation was tested. There was the need to test a different zone orientation as the zonation of the original model is not geologically coherent with the truth case. This lack of
coherency can be observed when comparing the facies type of some wells from the TC and the zones where they are located in the original zone orientation model, namely in layers 1, 3 and 5. Figure 13 illustrates this proposition where it is possible to see that in layer 1, for wells PRO1, PRO11 and PRO12, while in the truth case they are characterized by a floodplain facies type, in the original zone orientation model they are located in channels; in the same layer, wells PRO4 and PRO15 are placed in a channel while in the model they are in a floodplain zone. In layer 3, while in the TC wells PRO1, PRO4 and PRO12 are characterized by floodplain mudstones in the model they are placed in channels; the same happens with well PRO15 which is situated in a channel and in the original model correspond to a floodplain zone. In layer 5, well PRO12 is the only one in the model which is not coherent with the truth case. Besides this fact, layer 5 also presents the channels in the grid placed side by side which does not happen in the TC neither is geologically coherent.

Figure 13 - Differences between the facies types of the wells in the Truth Case and the original zone orientation model.
After identifying these geological differences between the TC and the original model, a new zone orientation model was created. The purpose of the new model was to improve the geological consistency to the truth case. The new zone orientation model can be seen in Figure 14, where the azimuth of the channels in each layer (1, 3 and 5) of the TC was also taken in account.

In model parameterisation C, the facies types of the wells were also revisited and the facies of well PRO11 in layer 4 was adjusted. Figure 15, adapted from Barwis et al. (1990), presents the porosity and horizontal permeability correlation for the Mouthbar facies type from a river dominated deltaic reservoir.
Figure 15 - Porosity/horizontal permeability correlation for the mouthbar facies type (adapted from Barwis et al., 1990).

When plotting the porosity versus horizontal permeability correlation of well PRO11 in layer 4 in the same plot, which in model Parameterisation B was considered to belong to Lagoonal Clays facies type, it suggests that this well corresponds to Mouthbar facies type rather than belonging to Lagoonal Clays. Consequently, in model C well PRO11 in layer 4 is considered as Mouthbar facies type and the horizontal permeability sigma for this type of facies was also adjusted. The sigmas used for the different facies types of the wells for history matching the model are shown in Table 6.

Table 6 - Sigmas assigned to the petrophysical properties (porosity, horizontal permeability and vertical permeability) for the different facies types.

<table>
<thead>
<tr>
<th>Petrophysical Property</th>
<th>Facies type</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fluvial Channel</td>
</tr>
<tr>
<td>Porosity</td>
<td>0.1</td>
</tr>
<tr>
<td>Horizontal Permeability</td>
<td>200</td>
</tr>
<tr>
<td>Vertical Permeability</td>
<td>100</td>
</tr>
</tbody>
</table>

In this parameterisation the ranges in which the parameters vary are similar to the TC and presented in the following Table.
Table 7 - Porosity and horizontal permeability ranges for the different zones used in model parameterisation C.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Porosity Range (fraction)</th>
<th>Horizontal Permeability (mD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channels (layers 1, 3, 5)</td>
<td>0.12 – 0.30</td>
<td>14 – 1170</td>
</tr>
<tr>
<td>Floodplain (layers 1, 3, 5)</td>
<td>0.01 – 0.12</td>
<td>0.7 – 178</td>
</tr>
<tr>
<td>Homogeneous layer 2</td>
<td>0.01 – 0.17</td>
<td>0.7 – 201</td>
</tr>
<tr>
<td>Homogeneous layer 4</td>
<td>0.01 – 0.22</td>
<td>0.7 – 514</td>
</tr>
</tbody>
</table>

For the floodplain zone and homogeneous layers 2 and 4, the porosity and both permeabilities are correlated using the same equations as in model Parameterisation A and B. Regarding the channels from layers 1, 3 and 5, the corresponding correlation from the truth case per individual layer was used.

For terms of comparison, model C was used for history matching to static and dynamic data (C Sta&Dyn) and also to the dynamic data only (C Dyn).
5. Results and Discussion

This chapter introduces the results of the methodologies applied in the scope of this thesis and its discussion. The presented results refer to the Pareto Models generated under the different model parameterisations from the applied methodologies, as they correspond to the solutions that have the best balance between the static and dynamic objectives.

5.1. Match Quality in History Matching

In the History Matching procedure, the uncertainty parameters used to calibrate the different model parameterisations are geological parameters. The different models are featured with 12 regions and each region has a parameter for porosity and another for horizontal permeability multiplier. Five runs with 500 iterations of history matching are used to infer about the consistency of the results based on the average misfit convergence and its standard deviation. For a clear and better comparison between the different model parameterisations and methodologies used, the quality of the dynamic and static matches are considered in different sections, using the Pareto models obtained in each model parameterisation.

5.1.1. Dynamic Misfit

Figure 16 represents a zoomed-in plot of the dynamic misfit convergence for the different model parameterisations. The dynamic match of model Parameterisation A achieves the lowest misfit dispersion of the dynamic misfit towards the end of the runs when comparing with the other model parameterisations. Although more disperse than A, the dynamic match of model parameterisations B (B Dyn) and C (C Dyn) also show a good convergence. The misfit convergence is more pronounced in these runs as these models are only matching to dynamic data. On the other hand, as the B Sta&Dyn and C Sta&Dyn model parameterisations are both matching to the static and dynamic data, the misfit dispersion is higher. Nevertheless, the static and dynamic match of model parameterisation C shows a lower misfit dispersion than B Sta&Dyn model description.

The dynamic match of model A is the one characterized by the lowest average dynamic misfit value (4.31 at iteration 512), followed by the dynamic match of model B (4.96 at iteration 426) and model C (5.24 at iteration 280). Models C Sta&Dyn and B Sta&Dyn parameterisations have the
highest average dynamic misfit value when compared with the others, showing an average misfit of 6.44 at iteration 436 and 10.83 at iteration 460, respectively.

![Figure 16](image1.png)

Figure 16 - Zoom-in on average dynamic misfit for the different model parameterisations.

Figure 17 represents the standard deviation of the multiple runs for the different model parameterisations. The models matched only to dynamic data (A, B Dyn and C Dyn) produce more consistent runs with lower standard deviation than the models matched to static and dynamic data (B Sta&Dyn and C Sta&Dyn). The lowest standard deviation is observed in the runs for model A.

![Figure 17](image2.png)

Figure 17 - Zoom-in on Standard Deviation for the different model parameterisations.

The convergence speed of each model parameterisation can be inferred by the interpretation of the plot of the average minimum misfit per iteration for the five runs (Figure 18). As it happens
with the standard deviation, the models matched only to the dynamic data are the ones characterized by the highest convergence speed. In this case, model B Dyn parameterisation shows the highest convergence speed in the first few iterations and achieves values very close to the global lowest average misfit at iteration 179. Although model A starts with the lowest values of average minimum misfit, it has a low convergence speed reaching values of global lowest average misfit at iteration 362. Model C Dyn parameterisation presents a high rate of convergence in the first iterations but only achieves values of lowest average misfit at iteration 280.

![Figure 18 - Dynamic Average Minimum Misfit for the different model parameterisations.](image)

Models B Sta&Dyn and C Sta&Dyn parameterisations are characterized by the lowest convergence rate when compared with the others. Although B Sta&Dyn model description starts with a higher value of lowest average misfit than model C Sta&Dyn parameterisation, it has a higher convergence speed in the first few iterations but never achieves values close to the global lowest average misfit. On the other hand, model C Sta&Dyn parameterisation reaches the global lowest misfit at iteration 436. The fact that model A has the lowest misfit dispersion, standard deviation and average dynamic misfit value makes it the best history matched model to the dynamic data.

It is important to emphasize the impact that each methodology used for history matching the different models have in the convergence speed, standard deviation and minimum misfit value of the different model parameterisations. The models which are used to match only to the production data present higher convergence speeds, lower standard deviation and minimum misfit values than the models matching to static and dynamic data. The different zone orientation used in model C also seems to have impact in the misfit convergence has model C Sta&Dyn parameterisation reaches values encompassed in the global lowest dynamic misfit while model B Sta&Dyn parameterisation is not.
5.1.2. Matching the Production Variables

This subsection presents the analysis of the dynamic matches at well scale obtained in the history matching process of the different model parameterisations. The production response of the Pareto Models is used to assess the quality of the dynamic matches. Full plots can be consulted in Appendix A. The match is considered of very good quality if the Pareto Models include all the historical data. If the Pareto Models do not include one historical data point or less than 50% of the Pareto Models do not show deviation between the error assumed for the historical data, the match is considered of good quality. If more than 50% of the Pareto Models show deviation between the error assumed for the historical data, the match is considered of poor quality. The results presented in this section correspond to the results obtained for the first run of each methodology applied to the different model parameterisations.

When comparing the summary figures of the quality of the dynamic matches of the Pareto Models obtained among the different model parameterisations, it is possible to infer better quality matches in the models history matched only to dynamic data. The Pareto Models of model parameterisation A are characterized by very good quality matches for the different production variables, namely for BHP, GOR and WCT (Figure 19). Only one well regarding GOR shows good quality matches.

<table>
<thead>
<tr>
<th>Model/Match Type</th>
<th>Production Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WBHP</td>
</tr>
<tr>
<td>Dynamic A</td>
<td></td>
</tr>
<tr>
<td></td>
<td>WGOR</td>
</tr>
<tr>
<td></td>
<td>WWCT</td>
</tr>
</tbody>
</table>

Figure 19 - Analysis of the matches to the different production variables (WBHP, WGOR and WWCT) at well scale for the dynamic match of model A.

Like in model A, the dynamic match of model parameterisation B also presents very good quality matches. Figure 20 evidences that when matching to production data, the Pareto Models obtained in model B are capable of reproducing the dynamic response of the system for the different production variables at the different wells.
The same does not happen with the static and dynamic match of model parameterisation B. Regarding Borehole Pressure there is no well showing very good quality matches. For this production variable three wells achieved good matches while the others present poor matches. The Gas-Oil Ratio was the variable better matched in this model as it demonstrates five wells with very good quality matches and one with good responses. Like Gas-Oil Ratio, the matches to Water Cut are also of very good quality as only two wells show good matches and other presents matches of poor quality.

<table>
<thead>
<tr>
<th>Model/Match Type</th>
<th>Production Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WBHP</td>
</tr>
<tr>
<td>Static &amp; Dynamic</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td></td>
</tr>
<tr>
<td>Dynamic</td>
<td></td>
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Figure 20 - Analysis of the matches to the different production variables (WBHP, WGOR and WWCT) at well scale for the dynamic and the static and dynamic matches of model B.

The overall quality of the matches in C Dyn model description for the production data is very good (Figure 21). All wells have the ability to reproduce the historical dynamic response regarding the different production variables matched.

Looking to the static and dynamic match of model parameterisation C, it is also possible to infer overall good quality matches (Figure 21). Borehole Pressure appears with very good quality matches at one well, good matches at four wells and only one well is characterized by poor quality matches. Gas-Oil Ratio shows three wells with good matches having the rest three wells very good quality matches. Water Cut is presented with a similar response to the truth regarding the six wells.
When compared with the static and dynamic match of model B, the Pareto Models from C Sta&Dyn parameterisation present an improvement in the quality of the dynamic matches, namely for WBHP and WWCT, which must be due to the zone orientation that is coherent with the sentence case.

<table>
<thead>
<tr>
<th>Model/Match Type</th>
<th>Production Variables</th>
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<th>WWCT</th>
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Figure 21 - Analysis of the matches to the different production variables (WBHP, WGOR and WWCT) at well scale for the dynamic and the static and dynamic matches of model C.

The different model parameterisations have impact in the convergence rate and minimum dynamic misfit value but it seems that when history matching the models only to dynamic data, they do not have a great effect on the quality of the dynamic matches. The methodology used for history matching the models to dynamic data (A, B Dyn and C Dyn) proved the ability of generating Pareto Models capable of reproducing the historical production at well scale with very good quality, even under different parameterisations.

Using the history matching methodology to match static and dynamic data, although the Pareto Models also show very good quality matches, it is possible to see a decrease in the quality of the dynamic matches at some wells. In these models, the quality of the matches at well scale decreased when compared to the models matching only to dynamic data, as they are not only trying to respect the historical production but also the geology of the TC.
5.1.3. Static Misfit

The average static misfit convergence for model parameterisations B and C is illustrated in Figure 22. When comparing the average static misfit of both model parameterisations, it is possible to see that although model B (Sta&Dyn) is the one achieving the lowest average misfit dispersion along the run, model C (Sta&Dyn) also shows a good misfit convergence towards the end.

![Figure 22 - Average static misfit for model parameterisations B and C.](image)

Model C is also characterized by the lowest value of average static misfit (14.09 at iteration 370) contrasting with the static match of model Parameterisation B (31.78 at iteration 482).

The standard deviation of the multiple runs for the different model parameterisations is presented in Figure 23. Although being featured by a more disperse static misfit standard deviation than model B, model C presents the lowest standard deviation towards the end of the run.

The interpretation of the plot of the minimum average static misfit per iteration (Figure 24), evidences that model C not only shows the highest convergence speed but also finishes with a lower value of static misfit when compared to model B.

While in model B the convergence speed starts reaching its plateau at iteration 142, in model C the same happens at iteration 370. The fact that model C has the lowest standard deviation and average static misfit value makes it the best history matched model to the static data.

The zone orientation and prior distributions similar to the TC seem to play a key role in the results. While model B is parameterised with the original zonation in which some of the zones where the
wells are placed are not geologically coherent with the reservoir, the zone orientation of model C is consistent with the geology of the TC.

Figure 23 - Zoom-in on Standard Deviation for model parameterisations B and C.

The geological consistency of the new zone orientation as well as the application of the truth case distributions have impact in the increase of the speed convergence, lower average standard deviation towards the end and lowest average misfit value.

Figure 24 - Static Average Minimum Misfit for model parameterisations B and C.
5.1.4. Pareto Front

Through the analysis of the Pareto Front models of both B Sta&Dyn and C Sta&Dyn parameterisations (Figure 25) it is possible to observe that C Sta&Dyn parameterisation produce the most consistent Pareto Front models across runs. This means that this model description produces less spread of models that can be a solution to the history matching process. Although C Sta&Dyn parameterisation produces a narrower Pareto Front, and therefore a less diverse set of possible solutions, it minimizes the misfit associated with the static and dynamic matches in a more efficient way than model B Sta&Dyn parameterisation.

![Figure 25 - Pareto Front Models for the static and dynamic match of model parameterisations B and C.](image)

The uncertainty related with the parameters describing porosity (Figure 26) resulting from the Pareto Front models show a visible trend, namely in model parameterisation C. This means that independently on the Pareto Front models and their runs, the porosity parameters tend to converge and concentrate in the same area and range of values. Regarding model parameterisation B, the majority of the parameters also show a similar trend as in model C, with the exception of some porosity parameters from different channels ($pa1$, $pc1$, $pc3$ and $pa5$) and from the background floodplain ($pbackground$). These parameters change depending on the Pareto Front models from the different runs and do not show a clear convergence. Therefore, model B originate a more diverse set of porosity parameters on each run than model C.

The analysis of the horizontal permeability parameters (Figure 27) resulting from the Pareto Front models for both model parameterisations show no visible trend with the exception being the parameters for the background floodplain ($Multipbackground$) and for layer 2 ($Multip2$). Model
B also presents some horizontal permeability parameters from different channels ($Multipa1$, $Multipb1$) characterized by convergence as they concentrate on the lower half of the range.

![Figure 26 - Porosity of the Pareto Models obtained in the static and dynamic match of model parameterisations B and C vs Static Misfit.](image)

Regarding the uncertain porosity parameters plotted versus the dynamic misfit (Figure 28) for both model parameterisations, there is no visible trend as the parameters change depending on the Pareto Front models and their runs. A clear parameter convergence does not occur with the exceptions being two channel parameters from layer 5 ($pb5$ and $pc5$), layer 2 ($p2$) and layer
4 ($p4$) as they concentrate in a specific range of values. Channel parameter $pb1$ from model parameterisation B also shows some convergence on the lower half of the range.

Figure 27 - Horizontal permeability of the Pareto Models obtained in the static and dynamic match of model parameterisations B and C vs Static Misfit.

Figure 29 also shows no trend for the horizontal permeability multipliers when plotted with the dynamic misfit of the Pareto Models. It is possible to see that for the Pareto Models with similar dynamic misfits in both model parameterisations some parameters are dispersed within the range.
they can vary. Moreover, there are also parameters concentrated in the same range of values corresponding to different misfits of Pareto Models, especially for model B parameterisation.

Figure 28 - Porosity of the Pareto Models obtained in the static and dynamic match of model parameterisations B and C vs Dynamic Misfit.

Under the different model parameterisations, it seems that the different parameters dispersed within several range of values can reproduce the dynamic response of the truth case, leading to a low value of dynamic misfit in the Pareto Models. On the other hand, the value of the static misfit only decreases when the parameters of the Pareto Models converge to a specific range of values.
When comparing both model parameterisations, the results show that model C is the one that achieves best history match results, not only because the Pareto models minimize both static and dynamic misfit but also produce the most consistent results across runs.

Figure 29 - Horizontal permeability of the Pareto Models obtained in the static and dynamic match of model parameterisations B and C vs Dynamic Misfit.
5.2. Geological Consistency

The geological consistency of the different model parameterisations is inferred by evaluating the quality of the static matches (porosity, horizontal permeability and vertical permeability) at well scale by facies type from the Pareto Models. As models A, B dyn and C dyn parameterisations were only history matched to dynamic data, for terms of comparison their static matches were computed after running the history matching procedure.

The porosity versus horizontal permeability (Phi/PermX) and horizontal permeability versus vertical permeability (PermX/PermZ) joint distributions of the Pareto Models from the different model parameterisations are plotted. These joint distributions are plotted together with the same joint distributions from the TC in order to evaluate the overall model distributions and validate the geological consistency. The results presented in this section correspond to the results obtained for the first run of each methodology applied to the different model parameterisations.

5.2.1. Static Matches

Through the analysis of the Figures below it is possible to interpret that there are some differences in the quality of the static matches at well scale by facies type among the different model parameterisations.

- **Fluvial Channel Fills**

Model parameterisation A is the one characterized by the poorest quality matches for the three petrophysical properties (Figure 30).

![Model A](image)

Wells:
1 - PRO1 Layer 5; 2 – PRO4 Layer 1; 3 – PRO4 Layer 5; 4 – PRO5 Layer 1; 5 – PRO5 Layer 3; 6 – PRO11 Layer 3; 7 – PRO11 Layer 5; 8 – PRO12 Layer 5; 9 – PRO15 Layer 1; 10 – PRO15 Layer 3; 11 – PRO15 Layer 5.

Figure 30 - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of model A for fluvial channel fills facies type.
For this model parameterisation, the generated Pareto Models are able to reproduce the porosity seen in this facies type for the majority of the wells but the same does not happen regarding horizontal and vertical permeabilities. For horizontal permeability, some wells reach horizontal permeability values of about 4/5 Darcies which is geologically unrealistic. On the contrary, for vertical permeability the Pareto Models present underestimated values for most of the wells. Using the methodology to obtain exclusively the dynamic match, model parameterisation A generates Pareto Models that are not featured by the petrophysical properties that characterize fluvial channel fills facies type.

In parameterisation B Sta&Dyn (Figure 31) the overall quality of the matches is slightly better when compared with A Dyn model description, but they are not yet satisfactory. For porosity all wells evidence good quality matches but for both permeabilities the Pareto Models show underestimated values, hardly found in this facies type. Similar quality matches for the three
petrophysical properties can be observed when history matching model B only to the production data (Figure 31).

The static and dynamic match of model parameterisation C (Figure 32) shows a clear improvement in the quality of the matches for the three petrophysical properties when compared with the previous model parameterisations. The Pareto Models present good quality matches for both porosity and horizontal permeability with realistic values allowing to infer a good Phi/PermX correlation. For vertical permeability, although some wells are matched, others present both underestimated and overestimated values which is traduced in a poor PermX/PermZ correlation. In Figure 32 similar quality matches can also be seen for the dynamic match of the same model parameterisation.

**Figure 32** - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of the dynamic and static and dynamic match of model C for fluvial channel fills facies type.
• Floodplain Mudstones

**Model A**

Wells:
1 - PRO1 Layer 1; 2 – PRO1 Layer 3; 3 – PRO4 Layer 3; 4 – PRO5 Layer 5; 5 – PRO11 Layer 1;
6 – PRO12 Layer 1; 7 – PRO12 Layer 3.

Figure 33 - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of model A for floodplain mudstones facies type.

For this facies type, model A is the one characterized by the poorest quality matches (Figure 33) when compared to the other parameterisations (Figures 34 and 35).

**Model B Static & Dynamic**

Wells:
1 - PRO1 Layer 1; 2 – PRO1 Layer 3; 3 – PRO4 Layer 3; 4 – PRO5 Layer 5; 5 – PRO11 Layer 1; 6 – PRO12 Layer 1; 7 – PRO12 Layer 3.

Figure 34 - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of the dynamic and static and dynamic match of model B for floodplain mudstones facies type.
In this model parameterisation, the Pareto Models are characterized by overestimated values regarding the different petrophysical properties for most of the wells. This values per petrophysical property are neither characteristic or geologically coherent with floodplain facies type.

In parameterisation B Sta&Dyn, although some Pareto Models demonstrate good quality matches regarding porosity and both permeabilities at all wells, there are also Pareto Models presenting overestimated values that are not geologically consistent with floodplain facies type (Figure 34). This model evidences improvement in the quality of the matches when compared with model A as it is not only used to match dynamic data but also to static data. Regarding the dynamic match of model B, the quality of the static matches decreased when compared to its static and dynamic match. Figure 34 shows that for the three petrophysical properties there are wells that are not obtaining matches being the values constantly overestimated.

Figure 35 - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of the dynamic and static and dynamic match of model C for floodplain mudstones facies type.

Wells:
1 - PRO1 Layer 1; 2 – PRO1 Layer 3; 3 – PRO4 Layer 3; 4 – PRO5 Layer 5; 5 – PRO11 Layer 1; 6 – PRO12 Layer 1; 7 – PRO12 Layer 3.
Parameterisation C Sta&Dyn is characterized by very good quality matches for the different petrophysical properties as all wells are being matched (Figure 35). The Pareto Models generated with the proposed methodology are capable of reproducing the porosity, horizontal and vertical permeability fields of floodplain facies type. Similar results were obtained in C Dyn model description being the exception one well that is not matching both permeabilities (Figure 35). C Sta&Dyn and C Dyn have the same parameterisation but as C Sta&Dyn is matching the static and dynamic data, the quality of the matches to porosity, horizontal permeability and vertical permeability is slightly better.

- **Lagoonal Shales**

Model A is the one presenting the poorest quality matches for this facies type. For porosity, the Pareto Models are characterized by good quality matches for most of the wells but regarding both horizontal and vertical permeabilities all values are overestimated (Figure 36). In this model the porosity and permeability fields of lagoonal shales facies type are unrealistically reproduced.

The B Sta&Dyn model parameterisation for this facies type presents good quality matches at almost all wells for the different petrophysical properties (Figure 37). The Pareto Models are characterized by realistic values of porosity and both horizontal and vertical permeabilities. Therefore, they are capable of reproducing the corresponding fields of the petrophysical properties from this facies type. With regards to the dynamic match of the same model (Figure
37), besides the decrease in the quality of the matches at some wells for vertical permeability, similar results can be seen to those obtained with the proposed methodology.

In C Sta&Dyn and C Dyn model descriptions (Figure 38) the quality of the matches is quite similar for the three properties and improved when compared to the other model parameterisations. For both methodologies, the obtained Pareto Models are characterized by realistic values of porosity, horizontal and vertical permeabilities, being geologically consistent with lagoonal shales facies type.
Where:
1 - PRO1 Layer 2; 2 – PRO4 Layer 2; 3 – PRO5 Layer 2; 4 – PRO11 Layer 2

Figure 38 - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of the dynamic and static and dynamic match of model C for lagoonal shales facies type.

• Distal Mouthbar

Figure 39 - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of model A for distal mouthbar facies type.
Apart from model A, all parameterisation models show similar quality matches for this facies type (Figure 39, 40 and 41). In model A (Figure 39) the matches to the different petrophysical properties is of poor quality and so, the geological characteristics of this facies type are unrealistically reproduced by the Pareto Models.

**Model B Static&Dynamic**

**Model B Dynamic**

Figure 40 - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of the dynamic and static and dynamic match of model B for distal mouthbar facies type.

Figure 40 shows that for both match types of model B, the quality of the matches to static data is quite similar. Although for horizontal permeability there is one well not being matched, the porosity, horizontal permeability and vertical permeability fields of the Pareto Models are coherent with the corresponding fields of distal mouthbar facies type.

C Sta&Dyn and C Dyn model descriptions present identical quality matches (Figure 41). Although the Pareto Models obtained from both methodologies do not present good quality matches for horizontal permeability, their values still coherent with the ones from distal mouthbar facies type. Therefore, this facies type was reproduced with good quality in the Pareto Models generated when history matching model parameterisation C using both methodologies.
Figure 41 - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of the dynamic and static and dynamic match of model C for distal mouthbar facies type.

- **Mouthbar**

Figure 42 - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of model A for mouthbar facies type.
In this facies type (Figure 42) the overall matches of model A are of poor quality. Although for porosity most of the wells present good quality matches the same does not happen regarding horizontal and vertical permeabilities. While for horizontal permeability the Pareto Models are characterized by overestimated values, for vertical permeability the values are being underestimated. These results show that the Pareto Models obtained from model parameterisation A are not geologically consistent with mouthbar facies type.

Model B Static&Dynamic

Model B Dynamic

Wells:
1 - PRO1 Layer 4; 2 – PRO4 Layer 4; 3 – PRO5 Layer 4; 4 – PRO12 Layer 4; 5 – PRO15 Layer 4.

Figure 43 - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of the dynamic and static and dynamic match of model B for mouthbar facies type.

The B Sta&Dyn model description is the one characterized by the best quality matches in this facies type when compared to the other model parameterisations. Through the analysis of Figure 43 it is possible to see that for the three petrophysical properties all wells are featured by very good quality matches. This model parameterisation when history matched with the proposed methodology generates Pareto Models with coherent porosity, horizontal permeability and vertical permeability fields when compared with the corresponding fields of this facies type. The same does not happen when it comes to B Dyn parameterisation (Figure 43), where for the three
petrophysical properties there are some wells that are not being matched. Consequently, the mouthbar facies type is not being realistically reproduced by the obtained Pareto Models.

In model description C Sta&Dyn the overall quality of the matches is good (Figure 44). For the different petrophysical properties most of the wells are being matched and the correlations between the petrophysical properties are geologically coherent with this facies type. The Pareto Models generated are characterized by similar porosity, horizontal permeability and vertical permeability fields as in mouthbar facies type. Model parameterisation C Dyn appears in this facies type with the poorest quality matches among the different model parameterisations (Figure 44). The Pareto Models present overestimated values for most of the wells regarding the different petrophysical properties. Therefore, there is an evident lack in geological consistency when comparing their petrophysical property fields with the corresponding fields of mouthbar facies type.

Figure 44 - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of the dynamic and static and dynamic match of model C for mouthbar facies type.
- **Lagoonal Clays**

For a matter of geological coherency, this facies type is not considered in model parameterisation C (subsection 4.2.3.).

![Figure 45 - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of model A for lagoonal clays facies type.](image)

Through the analysis of Figure 45 it is possible to see that although the Pareto Models obtained from model parameterisation A present good quality matches for porosity and vertical permeability, for horizontal permeability the values are being overestimated. The fact that the horizontal permeability reaches values around 600 mD, makes the Pareto Models geologically inconsistent with lagoonal clays facies type.

Although some of the Pareto Models obtained from B Sta&Dyn model description (Figure 46) exhibit very good quality matches for the three petrophysical properties, there are also others presenting overestimated values. The Pareto Models with overestimated values for the different properties are not reproducing realistically the geological characteristics of lagoonal clays facies type. For model parameterisation B Dyn (Figure 46), all the Pareto Models generated show overestimated values for the three petrophysical properties which is not consistent with the corresponding fields of lagoonal clays facies type.

This section showed that the proposed methodology for history matching improved the quality of the matches to the petrophysical properties at well scale. While in the methodology used to match dynamic data the Pareto Models are not featured by good quality static matches at the different wells, the new approach was able to generate Pareto Models capable of reproducing the geological characteristics of the truth case.

The static and dynamic match of model C presents the best results when compared to the others as it is parameterised with similar prior distributions to the truth case and the new zone orientation model has also impact in the quality of the static matches, especially in layers 1, 3 and 5.
Figure 46 - Static (porosity, horizontal permeability and vertical permeability) matches at well scale of the dynamic and static and dynamic match of model B for lagoonal clays facies type.

5.2.2. Overall Distributions of the Pareto Models

The previous subsections encompassed the evaluation of the quality of the static matches at well scale for the different model parameterisations regarding the three petrophysical properties. To assess the geological consistency of the models, in this subsection the Phi/PermX and PermX/PermZ bi-plots of the Pareto Models from each model parameterisation are plotted by facies type, with the correspondent correlations from the TC. These correlations can be seen in Figures 47 and 48.

Figure 47 illustrates the Phi/PermX and PermX/PermZ joint distributions of the Pareto Models for Fluvial Channel Fills and Floodplain Mudstones facies type. For Fluvial Channel Fills it is possible to observe that only model C for both methodologies (dynamic and static and dynamic matches) respects the Phi/PermX joint distribution of the truth case. The parameters of the Pareto Models from model C parameterisation with respect to this facies type, not only follow the same trend but
also have a similar dispersion as the TC. For both parameterisations B Dyn and B Sta&Dyn, although there are some parameters that reproduce the joint distribution seen in the TC, others are not following the same trend. Model A seems to be the one characterized by a completely different joint distribution from the sentence case as there are parameters from the Pareto Models not only underestimating but also overestimating this correlation. Regarding the PermX/PermZ joint distribution of the Pareto Models for Fluvial Channel Fills, the same happens for the different model parameterisations as with the Phi/PermX joint distribution.

For Floodplain Mudstones facies type, the Pareto Models of model A do not show the same Phi/PermX joint distribution of the TC, as most of the parameters of the Pareto Models are overestimating it. The majority of the Pareto Models of model parameterisations B Dyn and B Sta&Dyn are also characterized by a different Phi/PermX joint distribution when compared to the truth. Again, only model C in both methodologies is characterized by the same joint distribution of the study case. When looking at the PermX/PermZ joint distribution for this facies type, only model A is not featured by a similar joint distribution as in the TC.

![Fluvial Channel Fills](image1)
![Floodplain Mudstones](image2)

Figure 47 - Comparison between the Phi/PermX and PermX/PermZ correlations of the Pareto Models of the different model parameterisations and the Truth Case for Fluvial Channel Fills and Floodplain facies types.

Figure 48 shows the Phi/PermX and PermX/PermZ joint distributions of the Pareto Models plotted with the same distributions of the sentence case for layers 2 and 4. Although both layers are featured by different facies types, they are plotted as single layers as there are only one parameter for porosity and another for horizontal permeability multiplier matching each layer.
In layer 2, all the Pareto Models from the different model parameterisations present a similar Phi/PermX joint distribution as in the TC. Model B and C, for both match types, also show an identical distribution characteristic of the truth. With respect to the PermX/PermZ joint distribution, all model parameterisations present a similar dispersion as in the sentence case.

In layer 4, only the Pareto Models of model A do not show the same Phi/PermX and PermX/PermZ joint distributions of the truth. Although being inside of the TC distribution for this layer, the Pareto Models of B Dyn and C Dyn parameterisations tend to concentrate their values in the top parts of both joint distributions (Phi/PermX and PermX/PermZ). On the contrary, the static and dynamic match of both models (B and C) are characterized with the same joint distributions and trend of the study case.

These results allow inferring that the best dynamic matches at well scale were obtained for the dynamic match of the different model parameterisations. The fact that using this methodology all models can reproduce the production history of the reservoir does not necessarily mean that these models are geologically consistent. Subsections 5.2.1 and the current one, where the geological consistency of the different model parameterisations is assessed, demonstrates that these models are not geologically coherent with the truth case. They were only history matched to the production data and although obtaining very good dynamic matches, there is an evident lack in geological consistency and consequently, the overall distributions of these models are unrealistic. On the other hand, when applying the proposed methodology, which encompasses
history matching the models to static and dynamic data, it was proved that the models are able to reproduce both the dynamic response of the system and the geological properties of the TC. Therefore, when history matching a model to static and dynamic data, the balance obtained between these two objectives is responsible for making the model capable of reproducing the dynamic response of the system and the geological features of the truth case. The overall model distributions are then more realistic.

5.3. **Forecast and Uncertainty Characterization**

The production of PUNQ-S3 reservoir lasts a total of 16.5 years and the first 8 years were used to history match the different model parameterisations. In this project, the forecast was performed based on the ensemble of history matched models using the NAB algorithm for the following 8.5 years. Table 8 represents the values of the NAB parameters used in this procedure.

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<tr>
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**5.3.1. Forecasting at Well Scale**

The qualitative analysis of the forecasts of production variables used in the assisted history matching (WBHP, WGOR and WWCT) at the individual wells for the different model parameterisations can be seen in Figures 49, 50 and 51. Full plots are compiled in Appendix B. The results presented in this section correspond to the results obtained for the first run of each methodology applied to the different model parameterisations.

Figure 49 shows that the forecasting for model parameterisation A did not result in reliable Bayesian interval for the different production variables for all the individual wells. It is possible to interpret that the forecast for WBHP does not encapsulate the truth production for any individual well. Instead, it only produced a tight interval encapsulating the truth at wells PRO11 and PRO12, while at the other wells the truth case is outside the P10-P90 interval. The forecast for WGOR obtained a reliable interval at well PRO1 in all the historic but at the remaining wells, the truth case is encapsulated in a tight credible interval (wells PRO5 and PRO12) and outside the interval (wells PRO4, PRO11 and PRO15). Regarding WWCT, three wells produced reliable forecasting
(wells PRO4, PRO5 and PRO11) while for the others (wells PRO1, PRO12 and PRO15) the P10-P90 interval is not encapsulating the period of production time.

<table>
<thead>
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<th>Model/Match Type</th>
<th>Production Variables</th>
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<td>WGOR</td>
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<td></td>
<td>WWCT</td>
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![Figure 49 - Forecasting of production variables (WBHP, WGOR and WWCT) at well scale for model parameterisation A.](image)

Figure 50 shows the comparison between the forecasts at individual wells for model parameterisation B regarding the dynamic match and static and dynamic match. In the dynamic match of model B, the forecast for the production variable WBHP did not produce any P10-P90 interval encapsulating the historic at any well. For WGOR, only one well (PRO1) obtained good quality forecast with the truth case inside the P10-P90 interval while in the remaining wells the historic is outside the interval. Regarding WWCT, the forecast produced a reliable interval at wells PRO11 and PRO12 but at the other wells, the period of production is not encapsulated in the P10-P90 credible interval. When comparing the forecast of the dynamic match of model B with the static and dynamic match, some improvements in the reliability of the forecasting can be observed, namely for WBHP and WGOR. For WBHP, there is now one well (PRO11) which produced a reliable P10-P90 interval encapsulating the truth case and wells PRO11, PRO12 and PRO15 have their historic inside a tight credible interval. With regards to WGOR, one well (PRO15) obtained a poor quality of forecast, four wells (PRO4, PRO5, PRO11 and PRO12) produced a tight credible interval encapsulating the truth while for well PRO1 all the production history is inside the P10-P90 interval. For WWCT in wells (PRO5, PRO11, PRO12 and PRO15) the truth case is outside the interval while wells PRO1 and PRO4 present a reliable P10-P90 credible interval encapsulating the historic.

When comparing the forecast of production variables between the dynamic match of model C with the static and dynamic match of the same model parameterisation, it is possible to see similar quality forecasts at individual wells (Figure 51). Regarding WBHP, the ensemble of matched models from the static and dynamic match of model C have more reliable Bayesian credible intervals than from the dynamic match at the well scale. While in the static and dynamic match all
wells produce P10-P90 intervals encapsulating the truth case, in the dynamic match there is one well (PRO1) with the truth outside the credible interval. For WGOR, in both dynamic and static and dynamic matches there is only one well (PRO15) obtaining an unreliable P10-P90 interval with the production history outside the interval. The remaining wells, for both match types, produce credible intervals encapsulating the truth case. For WWCT, both match types produce the same quality of forecast at the individual wells. Wells PRO1, PRO11 and PRO12 produce reliable forecasts while in the remaining wells the truth case is outside the P10-P90 credible intervals.

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Figure 50 - Forecasting of production variables (WBHP, WGOR and WWCT) at well scale for the dynamic and static and dynamic matches of model parameterisation B.

The results presented in section 5.1.2 showed that for the different model parameterisations, the best quality of dynamic matches is obtained when history matching the models only to the production variables. Despite this fact, this section proved that the ensemble of history matched models with better fitness does not necessarily result in a better capability in future predictions. The static and dynamic match of model parameterisations B and C is characterized by a lower dynamic fitness when compared to the respective models matched only to dynamic data (section 5.1.2). However, this section shows that for the different model parameterisations there is an improvement in the ability of future predictions with the ensemble of history matched models obtained with the proposed methodology than the one produced with the methodology matching only to dynamic data.
<table>
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<tr>
<td></td>
<td>WBHP</td>
</tr>
<tr>
<td>Static&amp;Dynamic</td>
<td></td>
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<tr>
<td>C</td>
<td></td>
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<tr>
<td>Dynamic</td>
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**Figure 51** - Forecasting of production variables (WBHP, WGOR and WWCT) at well scale for the dynamic and static and dynamic matches of model parameterisation C.

History matching a model to static and dynamic data, not only produces an ensemble of history matched models with the ability of reproducing the historical production and characterized by overall distributions more realistic but also improves the capability and reliability when forecasting the response of the system.

### 5.3.2. Forecasting at Field Scale

This subsection presents the results obtained in forecasting the field oil production total (FOPT) and field water production total (FWPT) for the different model parameterisations (Figures 52, 53 and 54).

Figure 52 shows the uncertainty quantification in forecasting total oil and water recovery of the entire life of the field for model A. It is possible to see that for both FOPT and FWPT the truth case is encapsulated in the reliable Bayesian credible interval. Furthermore, the P50 value in this run for both oil and water recovery is also close to the truth case value at the end of production.
Looking at the forecasting of FOPT and FWPT obtained for the dynamic match of model B, Figure 53 shows that although this model reproduces the water recovery of the field, the same does not happen with regards to the oil recovery. In the last years of production, the model is not able of obtaining the same response of the field and produces an overestimated oil recovery. Therefore, the P10-P90 credible interval does not encapsulate the truth case.

Comparing this results with the ones obtained for the static and dynamic match of the same model, the latter presents some improvements in the quality of the forecasting. With this
methodology, model B is now able to reproduce a reliable forecasting for FOPT with the ensemble of matched models resulting in a credible interval of forecasting encapsulating the truth. It also appears to be more robust in forecasting the FWPT as it produces a wider P10-P90 credible interval when compared to the same interval obtained in the dynamic match.

Similar results are obtained for the different match types of model C as for model B. Figure 54 shows that for the dynamic match of model C, the ensemble of matched models results in a P10-P90 credible interval of forecasting encapsulating the truth for FWPT, but for FOPT the truth is outside this interval in the last years of production history. When history matching model C to static and dynamic data, the ensemble of matched models not only produces a reliable P10-P90 credible interval encapsulating the truth for FOPT but also a wider P10-P90 interval for FWPT forecasting.

The ensemble of history matched models from the dynamic match of both models B and C, is able to give reliable predictions for FWPT but is not capable of predicting the FOPT. On the other hand, the static and dynamic match of both models B and C, originate an ensemble of history matched models able to retrieve reliable predictions simultaneously for forecasting FOPT and FWPT with more robustness than the same models history matched only to the dynamic data.

Figure 54 - Forecasting of oil and water recovery from the field for the dynamic and static and dynamic matches of model parameterisation C.
These results suggest that history matching a model to static and dynamic data originate an ensemble of matched models that give predictions with more reliability and robustness than the ensemble of history matched models generated in the dynamic match.

The different model parameterisations originated different predictions for cumulative oil and water production. Bayesian Model Averaging (section 2.5.2) was then used to combine these predictions from model parameterisations A, B Sta&Dyn and C Sta&Dyn into a global prediction, based in the dynamic likelihood and the static and dynamic likelihood. The results presented correspond to the results obtained for the first run applied to these different model parameterisations.

Model parameterisation C Sta&Dyn presents the maximum dynamic likelihood achieved by iteration 192 and so is considered the reference model for calculating Normalised Bayes Factor (BF) shown in Figure 55. The BF results show that model descriptions A and B Sta&Dyn, 0.0269 and 0.1448 respectively, have only a small part of the reference model which is due to the differences between their maximum dynamic likelihoods (0.004469 for model A, 0.018474 for model B and 0.095741 for model C).

![Figure 55 - Normalised Bayes Factors of model parameterisations A, B Sta&Dyn and C Sta&Dyn based in the dynamic likelihood.](image)

The PDF of the different models in a moment in time can be averaged to obtain a new probability curve, using the corresponding BF. The average Cumulative Distribution Function (CDF) for the last timestep of the forecasting period of FOPT and FWPT with the new P10, P50 and P90 values are presented in Figure 56. From Figure 56 it is possible to see that the new CDF for both FOPT and FWPT follows almost exactly the CDF of model C. These results can also be seen in Figure 57 where the uncertainty envelope for the BMA is plotted together with the original uncertainty envelopes of the different model descriptions. The averaged uncertainty envelope of FOPT (362522.09 sm$^3$) encompasses part of the envelope of model A (260961.19), all envelope of model B (198620.23 sm$^3$) and almost all of model C (367892.92 sm$^3$). Regarding the averaged uncertainty envelope for FWPT (259784.67 sm$^3$), it overlaps all envelope of model C (229856.36 sm$^3$) disregarding most of the envelopes of models A and B (512701.13 sm$^3$ and 490906.61 sm$^3$, respectively).
Similar results can be seen in the static and dynamic match as model parameterisation C Sta&Dyn also dominates over the others, being the reference model with the maximum static and dynamic likelihood achieved by iteration 428.
The Normalised Bayes Factors are shown in Figure 58. While model A does not have any part of the reference model (BF = 0), model B has only a small part (BF = 1.46x10^{-9}). This is due to their maximum static and dynamic likelihoods (0 for model A, 3.81x10^{-18} for model B, 2.36x10^{-9} for model C).

![Figure 58 - Normalised Bayes Factors of model parameterisations A, B Sta&Dyn and C Sta&Dyn based in the static and dynamic likelihood.](image)

Figure 58 presents the average CDF for the last timestep of the forecasting period of FOPT and FWPT with the new P10, P50 and P90 values. It is possible to see that the new CDF for both production variables follow exactly model C’s CDFs. Figure 60 shows the averaged uncertainty envelope plotted together with the uncertainty envelopes from the different models.

![Figure 59 - CDF based in the static and dynamic likelihood of the different model parameterisations for the end of the forecasting period for FOPT and FWPT.](image)

The averaged uncertainty envelope for FOPT (369361.27 sm^3) encompasses part of the envelope of model A (260961.19), all envelope of model B (198620.23 sm^3) and almost all model C (367892.92 sm^3). Regarding the averaged uncertainty envelope for FWPT (176797.44 sm^3), it overlaps most of model C’s envelope (229856.36 sm^3) and only few parts of the envelopes of both models A and B (512701.13 sm^3 and 490906.61 sm^3, respectively).
Figure 61 shows the average of credible interval (P10-P50-P90) in forecasting of total oil recovery at the end of production of the field over 5 runs from the different types of matches of the different model parameterisations. For terms of comparison, the uncertainty envelope obtained in the BMA based on both likelihoods (dynamic and static and dynamic) as well as the uncertainty envelope of the True geostatistical model related to the random seed are also presented in the Figure.

![Combined uncertainty envelope](image)

From the Figure 61 it is possible to infer that except for B Dyn model parameterisation, the forecasts from both type of matches of the different model parameterisations are reliable as the credible interval encapsulates the truth value. The credible interval obtained for the history matched models to static and dynamic data is more reliable and robust than the intervals obtained from the same models only matched to dynamic data. Moreover, under different parameterisations the mean value of each credible interval in forecasting from the ensemble of history matched models obtained with the proposed methodology is comparable, while from the ensemble produced in the dynamic match is collapsed to different range of credible interval.

The uncertainty envelopes obtained in the BMA based in both dynamic and static and dynamic likelihoods are also reliable and robust. The truth is encapsulated in the P10-P90 intervals and their mean P50 is similar to the truth history. The different BMA envelopes are resemblant and...
comparable to the credible interval from the static and dynamic match of model C as this model is characterized by both maximum dynamic and static and dynamic likelihoods.

![Figure 61](image_url)

**Figure 61** - Average of credible interval (P10-P50-P90) in forecasting of oil recovery at the end of production from the field of the different model parameterisations, BMA based in dynamic and static and dynamic likelihoods and True geostatistical model related to the random seed.

Among the different P10-P90 intervals obtained from the different model parameterisations, the one obtained from model description C Sta&Dyn not only produces a mean P50 closer to the truth history value but also has a range of uncertainty comparable with the stochastic uncertainty associated with the True geostatistical model related to the random seed.

### 5.3.3. Comparing overall forecasting at individual well

Figure 62 presents the comparison between model parameterisations A, B Sta&Dyn and C Sta&Dyn of the truth case falling into the credible interval (CI) regarding the different production variables for each individual well. The results obtained for both BMA based in dynamic and static and dynamic likelihoods are also presented in the Figure.

In Figure 62, the wells are considered to have the truth case within the credible interval (green) if the P10-P90 interval encapsulates the truth historic for the different production variables during all forecasting period. The wells are considered to have the TC mostly within the CI (yellow) if the truth historic regarding GOR, BHP and WCT is encapsulated in the credible interval during most of the forecasting period. If the P10-P90 interval for the different production variables only encapsulates parts of the truth history during all timesteps of forecasting, the wells are considered...
to have the truth case mostly outside the credible interval (red). Full plots can be consulted in Appendix B.

Among the different model parameterisations, Model C was the one that produced better quality forecast at well scale considering the three production variables. While model description A presents three wells with the TC mostly within the CI and the others with the TC mostly outside the CI, model parameterisation B shows improvements at some individual wells but on the other hand, a decrease in the forecasting quality at others (Figure 62). When compared to model parameterisation A, model description B is characterized by improvements namely at well PRO1 (TC within CI) and well PRO4 (TC mostly inside CI).

![Models/BMA Reservoir](image)

Figure 62 - Comparison of the truth case falling into the credible interval regarding the different production variables between model parameterisations A, B Sta&Dyn and C Sta&Dyn and BMA based in dynamic and static and dynamic likelihoods.
In model description A, regarding BHP at well PRO1 the truth historic is encapsulated in the P10-P90 interval only at the end of the forecasting period and for GOR the credible interval encapsulates the truth historic at all period of the forecasting (Appendix B – Figure B.1). In model parameterisation B not only the history of the same production variables at the same well is within the credible interval as the same happens regarding WCT (Appendix B – Figure B.3). Well PRO4 in model A only for WCT has the history inside the Bayesian interval (Appendix B – Figure B.1) while in model description B it has also parts of the truth history of BHP and GOR inside the CI (Appendix B – Figure B.3), namely for the last timesteps of the forecasting period. When it comes to wells PRO5 and PRO12 (Appendix B – Figure B.1), in model parameterisation A all the production variables have the truth history inside the CI at some timesteps of the forecasting period. For model description B the same does not happen, namely for BHP at well PRO5 and WCT at well PRO12 (Appendix B – Figure B.3). Regarding wells PRO11 and PRO15, the truth history is mainly outside the P10-P90 interval for both model parameterisations A and B regarding the three production variables (Appendix B – Figures B.1 and B.3).

Model description C, when compared to the other model parameterisations, presents improvements in the quality of forecasting at each well, being the exception well PRO1. For wells PRO1, PRO4, PRO5 and PRO12, the historical production during almost all forecasting period is enclosed in the P10-P90 interval regarding the different production variables (Appendix B – Figures B.5). Well PRO11 is characterized by the best quality of forecasting with the TC within the CI for the three production variables at all timesteps (Appendix B – Figure B.5). The poorest quality of forecasting can be found at well PRO15, where GOR has the truth history enclosed in the P10-P90 interval only at the beginning of the forecasting period and the WCT production history is outside the credible interval for the entire period of forecasting (Appendix B – Figure B.5).

For both BMA based in dynamic and static and dynamic likelihoods the truth case falling into the credible interval at each individual well outcomes similar to model C as this model is characterized by the highest likelihoods when compared with the others. For the BMA based in static and dynamic likelihood the forecasting of the different production variables at individual well is almost exactly similar to model C (Appendix B – Figure B.7). For the BMA based in dynamic likelihood, although it is similar and follows the same trend as in model C, there are some differences at particular wells and variables. When compared to model C, well PRO1 in the BMA based on dynamic likelihood presents a wider credible interval during all forecasting period regarding BHP (Appendix B – Figure B.6). For GOR and WCT it is also wider but specially at the last timesteps of forecasting (Appendix B – Figure B.6). Well PRO4 also shows a larger CI for GOR during the entire period of forecasting and for WCT, it is wider but only until the first half of forecasting (Appendix B – Figure B.6). Regarding well PRO5, for both BHP and WCT the P10-P90 interval is larger during all timesteps of forecasting (Appendix B – Figure B.6). WCT at well PRO11 is the only production variable presenting a wider CI (Appendix B – Figure B.6).
6. Conclusions

Over the last years the history matching has been approached by multi-objective optimisation powered by stochastic population-based algorithms. This approach provides a more diverse set of matched models leading to a better production forecast and uncertainty quantification. These techniques have been applied exclusively by matching multiple production variables from the historical production data of the reservoir. However, due to the nature of history matching problems, the fact that a reservoir model reproduces the dynamic response of the system does not necessarily mean it is respecting the geological characteristics from the field.

The methodology proposed under the scope of this thesis entails history matching the reservoir model through the application of a multi-objective optimisation approach, not only by matching the production data but also the petrophysical properties at the well locations. Different model parameterisations, which represent different geological uncertainty in the reservoir, were studied. For terms of comparison, the different model parameterisations were also history matched using a multi-objective optimisation approach to obtain exclusively the match to production data.

Under different model parameterisations (A, B and C) both methodologies showed good ability to generate Pareto Models able to reproduce the dynamic response of the truth case. Using the methodology to obtain only the dynamic match, the different model parameterisations presented very good quality matches to the different production variables at well scale. Although the quality of the dynamic matches decreased when using the proposed approach, the obtained Pareto Models are also characterized by overall good quality matches at individual well and therefore, able of reproducing the historical production of the reservoir.

Regarding the quality of the matches to the petrophysical properties at well scale, it was possible to see some improvements in the quality of the results when comparing the Pareto Models obtained from the proposed methodology with the ones generated from the methodology to obtain exclusively the dynamic match. The Pareto Models generated from the different model parameterisations history matched with the methodology to obtain the dynamic match are featured by poor quality static matches at the different wells. On the other hand, history matching model parameterisations B and C with the proposed methodology generated Pareto Models capable of reproducing the geological characteristics of the different facies types. The static and dynamic match of model C presents the best results when compared to the others. This model is parameterised with similar prior distributions to the truth case and the new zone orientation model has also impact in the quality of the static matches, especially in layers 1, 3 and 5 (fluvial channel fills and floodplain mudstones facies types). Only the Pareto Models obtained from the static and dynamic match of model C are characterized by Phi/PermX and PermX/PermZ joint distributions concordant with the correlations of the truth case allowing to infer realistic overall model distributions. The Pareto Models of the different model parameterisations obtained from the
methodology for the dynamic match do not show the same joint distribution as the truth case and therefore are geologically inconsistent.

The ensemble of history matched models obtained when history matching model parameterisations B and C with the proposed methodology is capable of giving reliable production predictions at both well and field scale. When compared to the ensemble of history matched models from the methodology to obtain the dynamic match, the ensemble from the proposed methodology is characterized by more wells located within the Bayesian plausible interval for the different production variables. Both FOPT and FWPT are also predicted with a P10-P90 interval more reliable and robust. It was proved that adding static data to the history matching has impact in predicting the cumulative oil production rather than cumulative water production. It was also proved that forecasting the production uncertainty range with a simple multiplier model with basic geology produces a P10-P50-P90 credible interval comparable to the uncertainty associated with the True geostatistical model related to the random seed.

Using the Bayesian Model Averaging to combine the uncertainty envelopes of FOPT and FWPT of model parameterisations A, B Sta&Dyn and C Sta&Dyn based in both dynamic and static and dynamic likelihoods showed that model C dominates over the others. The combined uncertainty envelope of cumulative oil and water productions based in both likelihoods, encompasses and follows almost exactly the uncertainty envelopes of model C disregarding the ones from the other models.

The best quality of overall forecasting at well scale is found in the static and dynamic match of model parameterisation C. When compared with the other model descriptions, model C evidences more wells with the ability to give reliable predictions regarding the different production variables. As model parameterisation C is characterized by the maximum dynamic and static and dynamic likelihoods, the BMAs based in both likelihoods are resemblant. BMA based in static and dynamic likelihood presents similar credible intervals for the three production variables at the different wells. BMA based in dynamic likelihood is also similar and follows the same trend but has larger P10-P90 intervals for some variables at particular wells.
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Appendix A – Matching the Production Variables

- **Model A**

![Figure A.1 - Dynamic matches of the different production variables (BHP, GOR and WCT) at wells PRO1, PRO4, PRO5, PRO11, PRO12 and PRO15 for model A parameterisation.](image-url)
- Model B Dyn

Figure A.2 - Dynamic matches of the different production variables (BHP, GOR and WCT) at wells PRO1, PRO4, PRO5, PRO11, PRO12 and PRO15 for B Dyn model parameterisation.
• Model B Sta&Dyn

Figure A.3 - Dynamic matches of the different production variables (BHP, GOR and WCT) at wells PRO1, PRO4, PRO5, PRO11, PRO12 and PRO15 for B Sta&Dyn model parameterisation.
Model C Dyn

Figure A.4 - Dynamic matches of the different production variables (BHP, GOR and WCT) at wells PRO1, PRO4, PRO5, PRO11, PRO12 and PRO15 for model C Dyn parameterisation.
Figure A.5 - Dynamic matches of the different production variables (BHP, GOR and WCT) at wells PRO1, PRO4, PRO5, PRO11, PRO12 and PRO15 for model C Sta&Dyn parameterisation.
Appendix B – Forecasting and Uncertainty Characterization

- Model A

Figure B.1 - Forecasting of the different production variables (BHP, GOR and WCT) at wells PRO1, PRO4, PRO5, PRO11, PRO12 and PRO15 for model A parameterisation.
• **Model B Dyn**

Figure B.2 - Forecasting of the different production variables (BHP, GOR and WCT) at wells PRO1, PRO4, PRO5, PRO11, PRO12 and PRO15 for model B Dyn parameterisation.
Model B Sta&Dyn

Figure B.3 - Forecasting of the different production variables (BHP, GOR and WCT) at wells PRO1, PRO4, PRO5, PRO11, PRO12 and PRO15 for model B Sta&Dyn parameterisation.
Figure B.4 - Forecasting of the different production variables (BHP, GOR and WCT) at wells PRO1, PRO4, PRO5, PRO11, PRO12 and PRO15 for model C Dyn parameterisation.
- Model C Sta&Dyn

Figure B.5 - Forecasting of the different production variables (BHP, GOR and WCT) at wells PRO1, PRO4, PRO5, PRO11, PRO12 and PRO15 for model C Sta&Dyn parameterisation.
- BMA based in Dynamic Likelihood

Figure B.6 - Forecasting of the different production variables (BHP, GOR and WCT) at wells PRO1, PRO4, PRO5, PRO11, PRO12 and PRO15 for the BMA based in dynamic likelihood.
• BMA based in Static and Dynamic Likelihood

Figure B.7 - Forecasting of the different production variables (BHP, GOR and WCT) at wells PRO1, PRO4, PRO5, PRO11, PRO12 and PRO15 for the BMA based in static and dynamic likelihood.