Automation of Brownfield Development Workflows

Master Thesis

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Mit montanstudentischem Glück Auf!

(Andreas Al-Kinani)

Acknowledgments

I am very proud about having accomplished this work, but I am very well aware of the fact that there are a lot of people, who have helped me getting to this point.

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Abstract

Brownfields are gaining increased attention by the oil and gas industry as they bear a high potential of being an important energy source, providing a big part of future's hydrocarbon production. Brownfields are very old fields with a long production history. Usually the wells in a Brownfield are approaching the end of their productive lives and very often they are being produced with the technology that has been installed back then when the fields were brought on-stream. In the first part of this work an approach to identify development opportunities in a Brownfield is presented. The available data to evaluate these fields are usually restricted to produced and injected monthly volumes and very few petrophysical data. Based on this sparse set of information a series of workflow steps is performed to suggest an optimal field development plan. The suggested operations in the field development plan are drilling additional infill wells, recomplete wells in another layer, change wells from producer to injector or do a work over operation on a specific well. The second part of this work elaborately deals with the implementation of the workflow steps in a software product. The software product reduces the necessary time for a field study from eight weeks to three or four days by simultaneously improving the overall study accuracy. The user is automatically guided through the workflow and the necessary user intervention is reduced to a minimum. In the given version the software is able to automatically generate a rough geologic model, forecast the well production, find significantly better or worse producing wells (outliers) and suggest the best infill locations.

Das Interesse der Erdöl- und Erdgasindustrie an „reifen“ Öl- bzw. Gasfeldern steigt, da diese Felder oft noch wirtschaftliche Mengen an produzierbaren Kohlenwasserstoffen enthalten. Reife Öl- bzw. Gasfelder sind Felder, aus denen seit einigen Jahrzehnten mit üblicherweise sehr geringen Produktionsraten gefördert wird und in die in den letzten Jahren normalerweise sehr spärlich investiert wurde.
Der erste Teil der vorliegenden Arbeit präsentiert eine Evaluierungsmethode für reife Öl- und Gasfelder. Ziel dieser Prozedur ist es, das noch vorhandene Produktionspotential in einem Feld zu identifizieren und einen Feldentwicklungsplan vorzuschlagen. Die Problematik hierbei liegt in der üblicherweise sehr begrenzten Menge an Produktions- und geologischen Daten. Basierend auf diesen wenigen Informationen liefert die präsentierte Prozedur einen optimierten Feldentwicklungsplan. Der Feldentwicklungsplan schlägt die besten Lokationen für neue Sonden vor, empfiehlt gewisse Sonden von Produzenten in Injektoren umzuwandeln und schlägt vor, welche Sonden gewarten werden sollen.
Der zweite Teil dieser Arbeit befasst sich sehr detailliert mit der Implementierung dieser Prozedur in ein Computerprogramm. Das Programm reduziert den notwendigen Zeitaufwand fuer ein Studie von acht Wochen auf ca. vier Tage. Die notwendigen Eingriffe der Benutzerin bzw. des Benutzers wurde auf ein Minimum reduziert. Die derzeitige Version des Programms ist in der Lage automatisch ein grobes geologisches Modell zu generieren, die zukünftige Produktion aller Sonden vorherzusagen, signifikant besser oder schlechter produzierende Sonden zu identifizieren und die besten Lokationen für neue Sonden vorzuschlagen. Abschliessend wird das Computerprogramm am Beispiel einer Gaslagerstätte präsentiert .

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1. Introduction

1.1. Outline

Brownfields are gaining increased attention by the oil and gas industry as they bear a high potential of being an important energy source, providing a big part of future's hydrocarbon production. Brownfields are old fields (developed 30 years or longer ago) with a long production history. The fields are generally mature with declining production rates. Usually the wells in a Brownfield are approaching the end of their productive lives[28] and very often they are being produced with the technology that was installed back then when the field was brought on-stream. The Recovery Efficiency in a typical Brownfield lies between 35 [%] and 40 [%]. Today Brownfields account for approximately 70 [%] of worldwide oil production.[29] The willingness to invest a lot of money into their development is usually rather low since most of the Brownfields are high cost, low productivity fields[29]. Therefore companies do not want to invest too much money or too much time to find development opportunities. However, especially infill drilling operations and stimulation jobs can extend the decline phase of the field production profile thus leading to an extended cash flow, which subsequently would be beneficial to the whole economic situation of the field. Many publications and a lot of research therefore focus on investigating Brownfields very quickly but as accurately as possible. Since there is neither enough time nor enough data, the integrated field review usually is restricted to monthly production rate data and very few values for some geologic parameters. It is therefore very challenging to give decisive and precise recommendations.

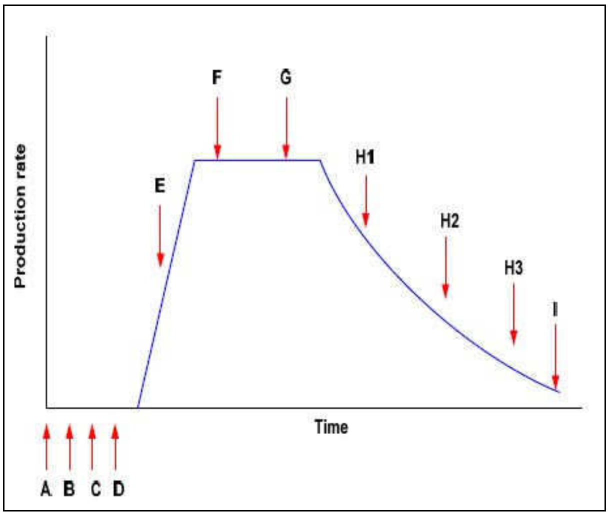


Figure 1: Typical Production Profile[28]

Figure 1 shows a typical production profile of an oilfield or a gas field. At first the exploration phase is initiated and the first exploration wells are drilled (Phase A to D). This phase is very expensive and there is no hydrocarbon production that covers the high exploration costs. Then the development phase (Phase E) starts and the production rate increases up to a plateau (Phase F - G), which – especially depending on the field operation strategy – can be longer or shorter in time. This should also be the time frame, when the capital that has been expended should be earned back by the oil or gas sales (Payback time). From now on the field production will lead to a positive cash flow. Then the peak production rate is encountered and the production rate as well as the cash flow in general starts to decrease leaving a long tail towards the end of the production life time (H1, H2, H3, I).

Brownfields are usually already in Phase H. The production rates are generally declining and the cash flow from the field decreases with every month. However, if the production rate tail in Figure 1 can be extended for a few years, the additional cash flow could be very significant, especially considering the high energy prices as encountered in the year 2006. The main operations to extend the tail period of the production profile are stimulation (i.e. fracturing jobs) or infill drilling operations[29]. Infill drilling operations help to drain the so called ‘sweet spots’ (undrained parts of the reservoir) leaving less oil or gas behind than the original well spacing set up. Stimulation jobs create a high permeability path from the well bore to the reservoir, generally increasing the drainage area of the well and thus producing hydrocarbon volumes that could not be reached by the unstimulated well.

1.2. Scope of work

This document contains a detailed technical description about the so-called RAPID processes implemented in BRIGHT and about the development of BRIGHT. BRIGHT is a software tool that automates the RAPID Brownfield Development workflows that have been developed in the Schlumberger DCS office in Calgary, Canada. In its final version, BRIGHT will perform a field production review and automatically suggest the economically most feasible next projects, for example drilling an infill well, change wells from producer to injector, completing wells in another layer, do a work over operation, etc. BRIGHT’s primary goal is the enhancement of production (extend the Phase H in Figure 1) and subsequently the improvement of the economic performance indicators of a field's production strategy.

This work should cover a detailed documentation about the development of the first version of BRIGHT. It will cover an elaborate view on the underlying RAPID workflow and a first implementation version in BRIGHT. The first BRIGHT version will offer the infill well candidate selection workflow as the only field development option, leaving the other development projects (work over candidate selection, potential injectors candidate selection, recompletion candidate selection) for later versions of BRIGHT.

The workflow steps will be presented in the order as they are performed by the software to increase the readability and understanding of this document. The RAPID processes as underlying theory will be described prior to the BRIGHT implementation efforts.

1.3. RAPID Workflows

RAPID is a Schlumberger internal Workflow definition that should guide the engineer through the necessary tasks to perform a field study for mature fields. The idea behind RAPID is to define a uniform and systematic approach to field studies to streamline the approaches of individual engineers. To achieve that goal a series of MS Excel Spreadsheets, MS Access Database Templates and Macros and Reporting Templates have been set up to assist the engineer in the field review.

RAPID is filling a gap in reservoir evaluation and field production review between a less accurate quick review of available data and a time consuming but accurate evaluation of the field with the help of an integrated 3D dynamic numerical reservoir simulation model.

This requirement is presented schematically in the figure below[1]. The diagram points out the dependency of the accuracy of a solution to the time that a team has to invest. Depending on the preconditions (available data, involved tools, experience of the engineer/the team this curve can be flatter or steeper). What this diagram also shows, though, is that the accuracy most generally will converge to an 'overworked solution'. Any more time invested from a certain time point on will not lead to an increased accuracy and is therefore not beneficial for the project.

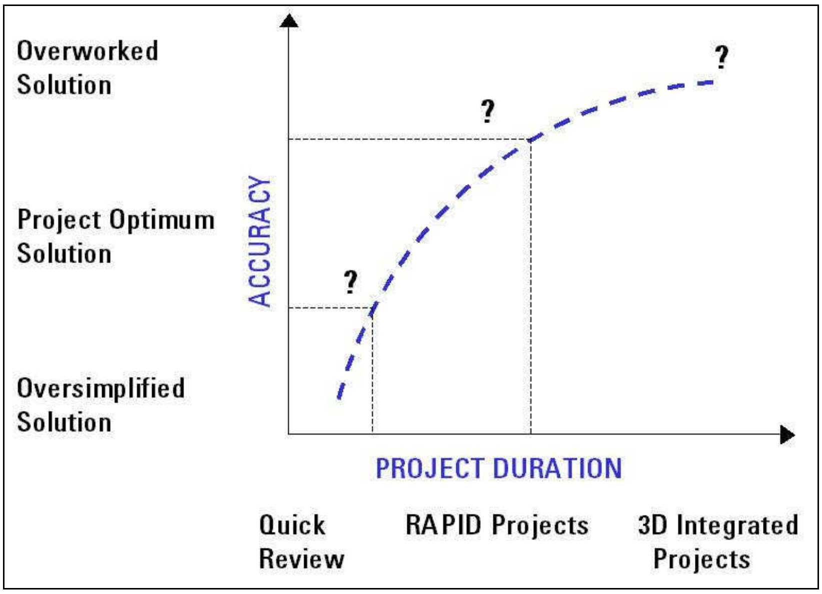


Figure 2: Accuracy vs. Project Duration

The question marks in Figure 2 indicate that the accuracy of the RAPID studies will be in between the two extremes – a "Quick Review" and a "3D Integrated Project". RAPID will enhance the accuracy of a quick review by consuming less time than a fully integrated project.

The cornerstones of RAPID are:

- A fixed timeline: Schlumberger DCS guarantees that the field evaluation will take eight weeks. This timeline is independent of the field size, the number of wells or the complexity of the reservoir.
- Fixed Costs: Since the approach is unified and the amount of work and time can therefore be estimated fairly accurately, Schlumberger DCS guarantees to stay within the proposed budget. The above considerations (independent of field size, independent of number of wells, independent of complexity of reservoir) do apply here too.

RAPID employs a series of statistical tools and interpolation techniques to investigate a field, based on its historical production data and very few petrophysical data. The goal is to "assess, optimize, enhance and manage overall production"[1]. A RAPID study should help define the next field development steps:

- Identify the most promising infill drilling locations ("Infill Drilling Workflow")
- Identify wells, that have been shut in, but might be profitable, when they come back on stream ("Reactivation Workflow")

- Select wells to be recompleted in a different reservoir layer or from a producing well to an injecting well ("Recompletion Workflow")
- Find wells that most probably need a work over ("Work over Workflow").

The ten steps of the RAPID workflow are depicted in Figure 3.

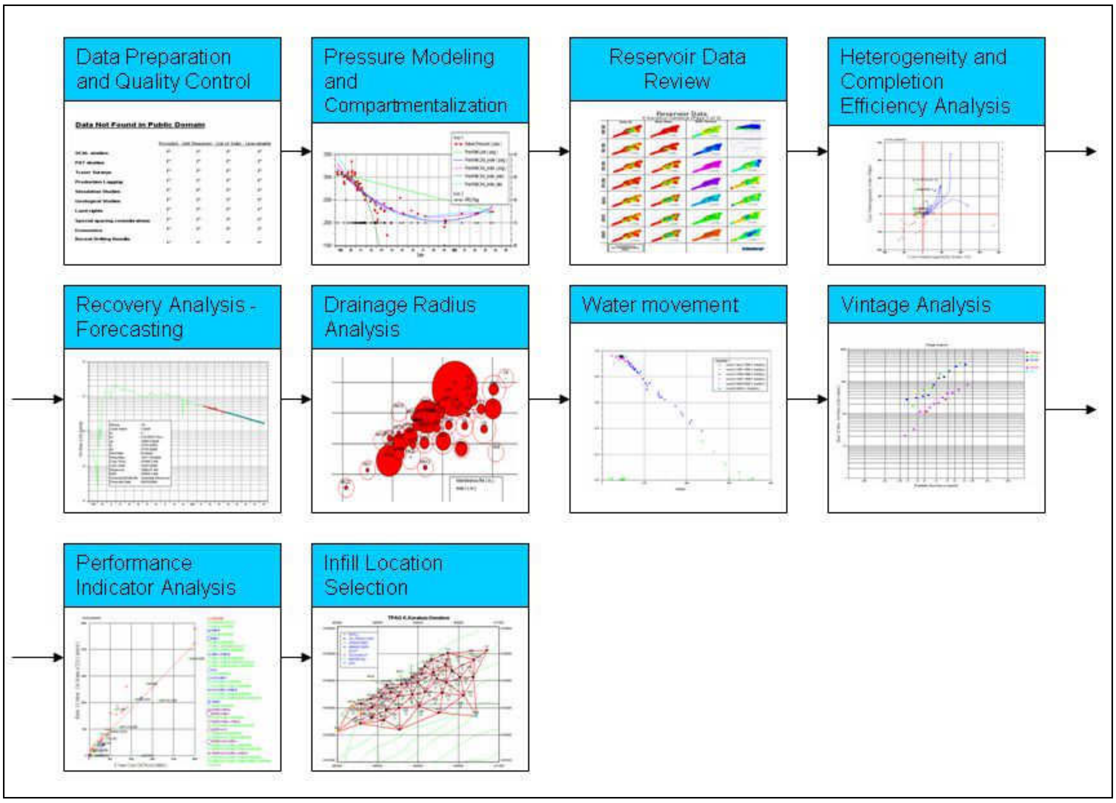


Figure 3: The ten steps of the RAPID Workflow

The techniques that have been employed to fulfill all these tasks are described in Chapter 3. Briefly summarized the main steps are:

1. Data Preparation and Quality control: The client provides the data that have to be organized in a way that they fit in RAPID's Database template. This is due to the fact that the automated macros are synchronized with the template and therefore they only work properly when entered in the given template.

   Another important aspect of that step is that the engineer gets familiar with the data. He or she gains a better knowledge of the field and therefore knows better what to expect. This is very often a tedious step and plays a very important role in the workflow.
2. Pressure Modeling: It is beneficial (but not compulsory) to have continuous pressure information about the field of interest. The pressure curves are created for each well individually and, if the pressure signatures of the wells are similar,

summarized and averaged to obtain a pressure curve on the compartment or field level.

3. Reservoir Review Data Analysis: The main production performance indicators are presented in plots at different time points in the life of the field. That way discrepancies and abnormalities should be detected.
4. Recovery Analysis: Individual well recoveries are investigated by creating production decline curves for each well. This provides the engineers with a rough estimation of well and aerial performance.
5. Vintage Analysis: Vintage Analysis groups the wells according to events. Very often the different development cycles of a field (as presented in Figure 1) are used for determining the vintage cycles. That allows the comparison of the performance of the wells belonging to similar time intervals of the field's life.
6. Heterogeneity Index Analysis and Completion Efficiency Analysis: Different performance indicators are compared to surrounding wells (peer group) to find under or over performing wells. Completion Efficiency additionally takes petrophysical data into account, to find for a given petrophysical setting abnormal production performance.
7. Secondary Phase Movement Analysis: The goal of this step is to identify unswept areas based on transient water cut analysis and aerial traction and investigation of the injected or produced secondary phases.
8. Performance Indicator Analysis: Performance Indicators such as 'Best 12 Month Hydrocarbon production', '5 years cumulative Hydrocarbon production', etc. are compared to find correlations, outliers and trends that have to be regarded when suggesting a new infill location.
9. Production/ Interference Radius Analysis: The Production/ Interference Radius Analysis should guarantee a maximum recovery for the infill wells. For gas wells it should be avoided to place an infill well into an area with severe interference and therefore higher pressure drawdown. For oil fields the investigation should detect swept areas that will most probably not contain any hydrocarbons.
10. Infill Selection and Reporting: All preceding steps are needed to prepare the data, which are needed to come up with a reliable infill location suggestion. By having performed steps 1 to 9 the engineer should be able to suggest infill locations and give information about its most probable initial hydrocarbon production rate, estimated hydrocarbon recovery and hydrocarbon recovery factor. The selection

procedure will be validated before it is used for a forecast. In the validation process the wells of the last infill drilling campaign are considered as nonexistent and it is tested, whether the RAPID workflow comes up with similar estimated values for the initial rate and forecasted recovery as measured or determined for these wells. If this is the case, RAPID is a reliable tool to forecast infill well's production and recovery.

A series of plots are created in the framework of a RAPID study. These plots are referred to as "Wallpaper", because of their size and ability to cover all the walls in an office room – most of the time even of a conference room.

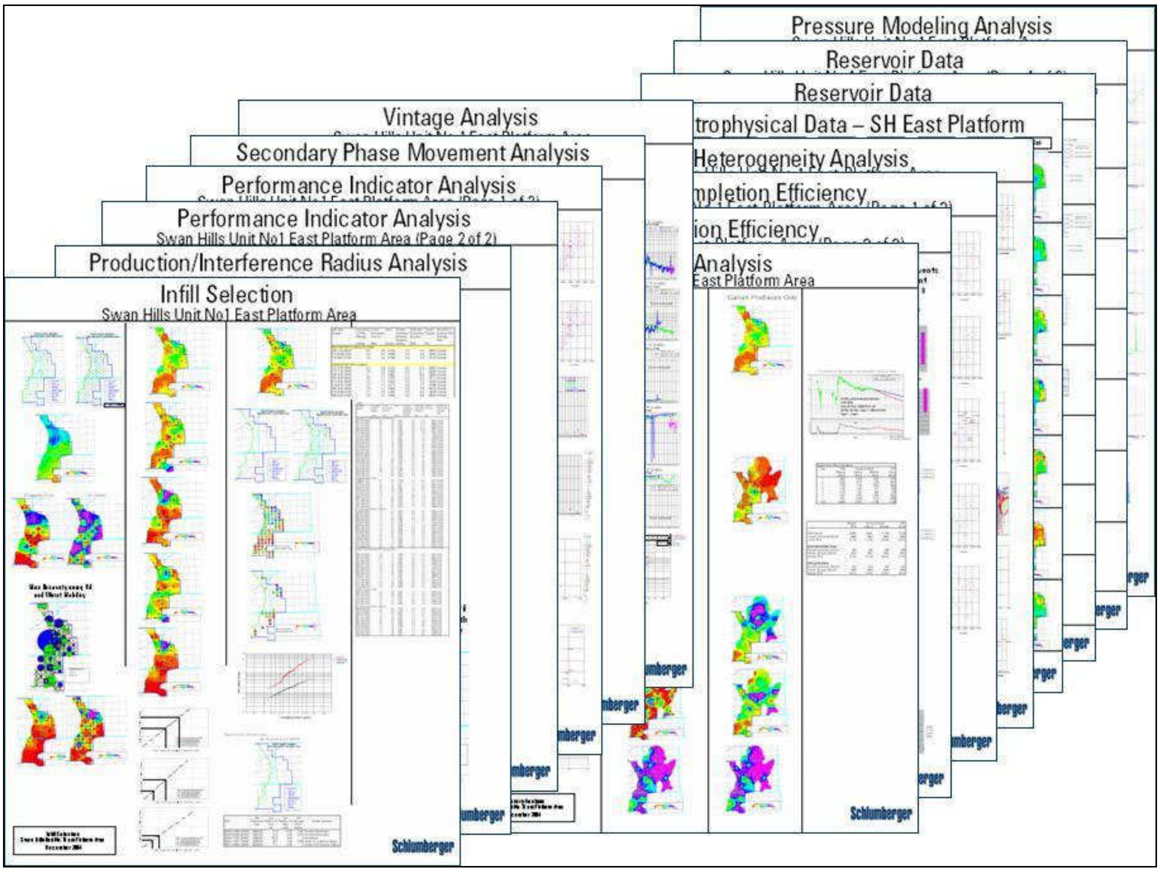


Figure 4: Key Performance Indicator Wallpaper

The plots usually show the development of a transient key performance indicator in time, as production continues. By comparing the plots of the parameters and by looking into the time dependency, engineers tried to find abnormalities, such as high cumulative hydrocarbon production in a geological unfavorable area, possibly unswept areas, pressure communications between producing wells and between injecting and producing wells, etc.

1.4. BRIGHT Advisor

BRIGHT is a software tool that should fulfill the above requirements and simultaneously reduce the required user intervention to a minimum. The basis for the development of BRIGHT is a documentation compiled by the engineers, who performed RAPID studies on a regular basis. The main request to the software is – besides the far lower time requirement – an increase in accuracy, so that in Figure 2 BRIGHT will be located closer to the integrated 3D projects regarding accuracy.

BRIGHT will be able to automatically extract similar information that has been derived out of the RAPID workflow steps described earlier and present them as clearly and accurately as possible. The necessity for all the huge wallpaper plots (Figure 4) etc. should be reduced and subsequently the time required for completing a project should be much shorter. It has been estimated that for any given study an eight week RAPID project should be reduced to a three day BRIGHT study.[2]

The eight steps of a BRIGHT project are depicted in Figure 5.

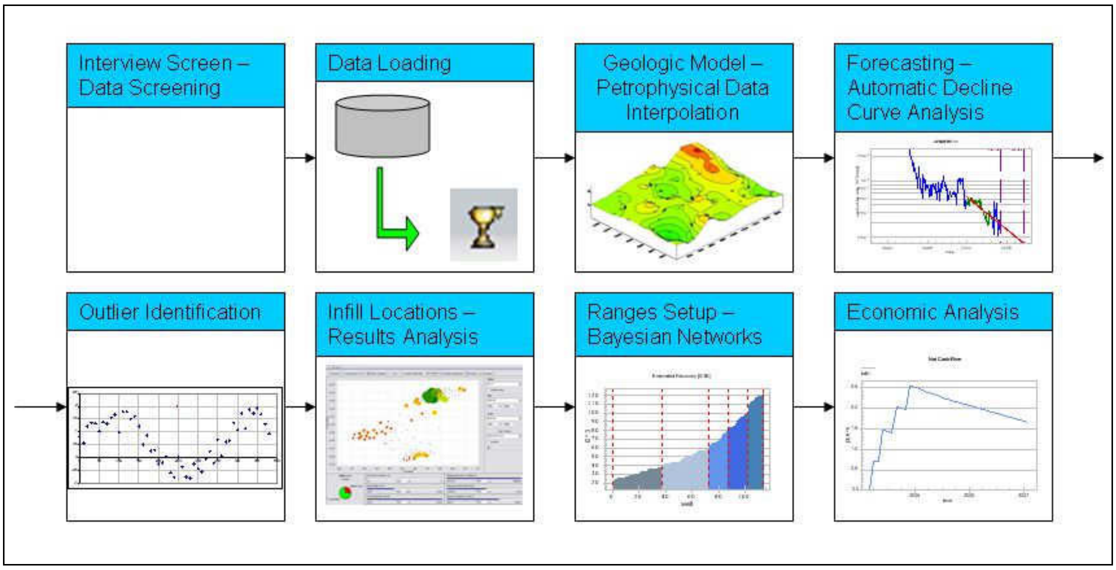


Figure 5: The eight steps of the BRIGHT workflow

As the RAPID workflow, BRIGHT is organized in a sequence of workflow steps that should guide the user through a field study. A summary of the workflow steps is given below. A detailed description of each of these steps will be presented in Chapter 3.

1. Interview Screen: BRIGHT is a software tool that heavily relies on statistics, and more importantly, on interpolation. It is therefore extremely important that the user is aware of the restrictions of the usage of BRIGHT or its risk, when used in very complex reservoirs and/or under highly transient conditions.

   The interview screening makes sure that the given project is suitable to be analyzed with BRIGHT and that the user is familiar with the data. The result of the Interview screening is a score that can be roughly translated as a 'reliability score' and a recommendation on how to proceed (e.g. BRIGHT is the appropriate tool, use BRIGHT with caution or BRIGHT should not be used for the given geologic setting or production environment).
2. Data Loading: One of the main requests in the development of BRIGHT is that BRIGHT should be able to perform a study with very few data. The data that need s to be loaded are therefore usually only the time dependent production volumes per well, and if available, a few petrophysical data. The reliability of the study and of the interpolation increases with the amount of reliable data available.
3. Petrophysics: BRIGHT uses a minimum of petrophysical data for its analysis. However, a certain amount of data is needed to come up with values for HCIP (hydrocarbons in place) and subsequently Sweep Efficiency, Recovery Factor, etc. BRIGHT only needs the petrophysical data for a few wells and based on that information it will interpolate the data for the other wells either by determining the arithmetic mean of the available values or by ordinary Kriging.
4. Basic Locations and Well Selection: BRIGHT presents the available and interpolated data in a bubble plot, where the well locations are presented in the x-y plane and the parameters can be displayed as either the bubble size or the bubble color or both. The plot informs roughly about the potential and history in different areas of the reservoir and helps the engineer to choose an area to focus on.
5. Automatic Decline Curve Analysis: The production forecast for each well is created separately and fully automated. BRIGHT searches for the best exponential curve fit in a predefined interval of data to create a decline curve. The accuracy of the fit is measured with the correlation coefficient and the Root Mean Square Error (RMS Error) (see Chapter 3.7).

$$RMS = \sqrt{\sum \left(q_{measured} - q_{Curvefit}\right)^2}$$

Equation 1

BRIGHT will automatically optimize the best fit decline curve by iterating while changing the decline rate to minimize the RMS Error.

6. Outlier detection: Detecting outliers is a very crucial step in BRIGHT's workflow. Outliers are defined as wells that perform either significantly better or significantly worse than its surrounding neighbors. The procedure to find outliers is called 'Exclusion Mapping' and described in detail in Chapter 2.4.
7. Analysis: The output is presented in a bubble map similar to the Basic Locations and Well selection part. Again the possible locations of the infill wells are presented in the x-y plane and the forecasted and interpolated parameters are presented as either bubble size or bubble color or both. Besides the interpolated values of future performance indicators (e.g. forecasted 3 Year cumulative production, Estimated Recovery, Decline Rate, etc.) a score can be displayed. This score is calculated in a series of conditional probability calculations (Bayesian Networks, see Chapter 2.1.3, Chapter 3.10) and reduced to a single numeric value through marginalization (Chapter 2.1.4). The calculation takes all of these future performance indicators into account and can therefore be used to compare the locations and determine which of these locations is most likely to be successful.
8. Results: In the results section the values are displayed in a grid to allow a numeric evaluation of the result. The wells can be ranked according to their score and color coded to highlight wells with a higher score. The grid shows all parameters that have been used to evaluate the score.
9. Range Setup: The range setup is a way to modify the underlying assessment logic. This is very important since the algorithm is hard coded; the engineer's assessment to a reservoir however is very subjective. The Range Setup influences the severity of a certain parameter in the evaluation of the score. It is in the engineer's responsibility to assign certain weights based on importance to the parameters by changing the range limits. A detailed description is given in the Chapter on Range Setup (Chapter 3.10.3).
10. Economics: BRIGHT performs a basic economic analysis based on information about the economic environment and based on a selection of projects to be executed. BRIGHT will therefore calculate the economics for a base case, where none of the projects will be started and for an infill case, where the selected projects will be executed.

The input will contain economic thresholds and a price. The engineer has to enter the Capital Expenditure that will be invested in that field in the upcoming years. Moreover the input will contain technical constraints such as the number of rigs or the number of wells that can be drilled in a certain season. Based on this input an automated field development plan will be suggested that takes into account all of the capital and technical constraints.

The economics part of this project is not described here since this would go beyond the scope of this technical documentation.

2. Literature Review

2.1. Probabilistic Reasoning under Uncertainty

2.1.1 Uncertainty

Uncertainty is a very important part of BRIGHT. Therefore it is compulsory to come up with a way to describe uncertainty and to provide an integrated, reliable and comprehensive description of the field's properties to the engineer. All engineers involved in BRIGHT development agree that it is more important to address and characterize the uncertainty than to strive for a more and more precise single numeric value forecast.

The concept of uncertainty is presented in the following chapter. The discussion of how uncertainty is applied in BRIGHT is found in Chapter 3.9.

In Reference 6 Korb and Nicholson present the main sources for uncertainty. According to them uncertainty arises through:

- *Ignorance:* Due to the "limits of our knowledge" there will never be absolute certainty about facts and values somebody has to deal with.

  In the field of Brownfield Development, ignorance is a very important and frequent source of uncertainty. Due to the very often highly heterogeneous nature of a field it is basically impossible to fully and accurately describe the whole field. There will generally be some areas of the field with poor measurement frequencies or no measurements at all.
- *Physical randomness or indeterminism:* According to Korb and Nicholson this relates to the fact that even if every possible property about an object can be measured, there will still be some uncertainty due to nature's randomness. The authors presented the imaginary example of the coin toss, where everything can be perfectly measured (e.g. exact measurements of coin properties, exact coin spin measurements, etc.). Yet there will still be the uncertainty about the outcome of a coin toss due to the physical randomness.

  In the reservoir modeling part of BRIGHT's workflow this kind of uncertainty does not play such an important role since geologic parameter usually are not purely randomly distributed but follow a certain spatial distribution. However, when looking at highly heterogeneous reservoirs, the uncertainty due to randomness or indeterminism plays an important role.

- *Vagueness:* Vagueness refers to the difficulty in describing or classifying a certain state. Many expressions used in everyday conversations are not a hundred percent clear. For example certain evidence can be classified as "high" without being totally clear about what "high" stands for. That leads to problems in understanding and even more in reproducing a certain assessment and adds uncertainty to an issue.

  In BRIGHT the uncertainty due to vagueness is approached by implementing the so called "Range setup", which will be explained later. The purpose of the Range Setup is to clarify the ranges for certain expressions ("states") by defining the upper and lower value limit for e.g. "high".

2.1.1.1 Uncertainty in Reservoir Modeling

In the context of reservoir modeling Jeff Caers explains in Reference 10 the reason for uncertainty as the "incomplete knowledge regarding relevant geological, geophysical, and reservoir-engineering parameter of the subsurface formation". Caers further exemplifies uncertainty in reservoir modeling as being subdivided into three groups: (1) the uncertainty about the reservoir structure and petrophysical properties such as e.g. Porosity, Net pay thickness, etc. (2) the uncertainty about fluid properties and their distributions and initial states (e.g. initial Formation Volume Factors, initial water saturations, etc.) and (3) the uncertainty about how fluids and reservoir rocks behave under changing physical conditions.

BRIGHT preferably addresses the uncertainty due to lack of knowledge about the petrophysical parameters and the initial distribution of fluids in the reservoir. In BRIGHT's workflows the information about hydrocarbons in place plays an important role and a good estimate for a well's petrophysical values and the associated uncertainty is therefore of great importance. The introduction of an uncertainty parameter, which will be discussed later, should increase the reliability of forecast and project evaluations. Preferably this parameter will indicate regions in the reservoir where the estimation of petrophysical parameters is not reliable.

Caers warns especially from "Data uncertainty" and "Model uncertainty". Data uncertainty comes from acquisition, processing and interpretation of the measured data. It has to be clear that to consistently compare and interpolate data each measurement of the parameter of interest should be performed under the same condition with the same measurement tool setup. As can be easily understood, in Brownfields with operating histories of some decades it is almost never the case, that a series of accurate and reliably consistent measurements of petrophysical parameters have been performed. BRIGHT's approach to "Data uncertainty" is to use a one-fold cross validation outlier detection. This concept will be explained later in this document.

Regarding Model uncertainty Caers points out that each interpolation for a parameter at a certain location is based on an underlying model. Assuming that the available measurements of a certain parameter in several locations in the reservoir are perfect (no uncertainty) there are still a series of possible spatial models of that parameter that – regarding the constraints due to the locations with exact measurements – are all valid. The underlying model therefore has to "choose" one of the realizations and therefore inevitably introduces randomness and subsequently uncertainty. Since this is especially an issue of spatial density of measurements and lies in the nature of a petroleum reservoir, BRIGHT does not and cannot specifically address this issue.

2.1.1.2 Uncertainty in forecasting of time series

The uncertainty associated with the forecast of a time series as encountered when forecasting the production data of a well is only poorly documented in current research papers. The measurement of the quality of a fit of a forecasted decline curve is identified as a very significant factor in determining the uncertainty of a forecast. BRIGHT uses curve fitting methods to reduce the Root mean square error in the fitted part of the curve. Outliers in the time series of the production data would drag the fitted curve into a wrong direction and therefore falsify the result or lead to a suboptimal fit. Therefore one of the main efforts in the strive for a reduced uncertainty is to eliminate the outliers in the time series and at the same time decrease the Root mean square error of the fit.

Reference 11 discusses the application of wavelets for the detection of outliers in time series. In BRIGHT development the authors' ideas were used to come up with a methodology to identify these outliers. Bilen and Huzurbazar describe the existence of two types of outliers in time series, the 'Additive Outlier (AO)' and the 'Innovational Outlier (IO)'. To illustrate these two types of outliers the authors compare an

observed time series Z_t with a parallel outlier free series X_t, that is fit according to the so called ARIMA model (Auto regressive integrated moving average technique) of order *p*, *d*, and *q*. *p* is a description for the numbers of autoregressive terms, *d* is a count of the seasonal filters and *q* is defined as the number of lagged forecast errors.
The additive outlier per definition only has an influence at the time point of the disturbed measurement. An *AO* has therefore no disturbing effect on surrounding points. The definition of an AO is:

$$Z_t = X_t + \omega_{AO} \cdot I_T(t)$$ **Equation 2**

ω_{AO} describes the magnitude of the disturbance and this is multiplied by $I_T(t)$, which is 1 if the time point of interest lies within the time series. ω_{AO} is randomly distributed and its magnitude can not be correlated with the time series itself.
The innovational outlier (IO) however affects surrounding observations. It is therefore defined as:

$$Z_t = X_t + \omega_{IO} \cdot \Gamma \cdot I_T(t)$$ **Equation 3**

The terminology is basically the same as for the AO in Equation 2. The introduction of Γ accounts for the disturbance effects on surrounding points beyond the time point *T* of the measurement through the memory of the system.
Additive outliers have the biggest influence on a time series, since they influence or falsify the statistics and therefore also lead to a worse curve fit and essentially to a wrong forecast. The authors propose an approach using wavelets to eliminate these additive outliers. To explain the methodology of wavelets in details is beyond the scope of this work. Wavelet transforms can be considered as a form of time-frequency representation that is localized in both time and frequency.[12] The idea of wavelet analysis in outlier detection of time series is to use the discrete wavelet transform (DWT) to decompose the time series Z_t in vectors of wavelet coefficients $D(J-1), D(J-2), ..., D(0), C(0)$. C(0) is the coefficient vector of the wavelet transform after performing all possible decompositions to obtain all D vectors. The D vectors contain the high frequency content and are therefore extremely sensitive on jumps or bumps in the data. It is now possible to analyze $D(J-1), D(J-2), ..., D(0)$ in order to find outliers.

In BRIGHT a very similar but in terms of coding less demanding approach was pursued. The idea is to calculate a series of moving averages of the production rate vs.

time relationship. The calculated moving averages are the 4 months moving average and the 8 months moving average. The production rate itself captures the high frequency part of the time series, the 4 months moving average captures the medium frequency part of it and the 8 months moving average represents the "long term" average of the time series. Comparing these three values leads to different discrepancies (Figure 8), which can easily be identified as outliers in the plot of the actual time series (Figure 7).

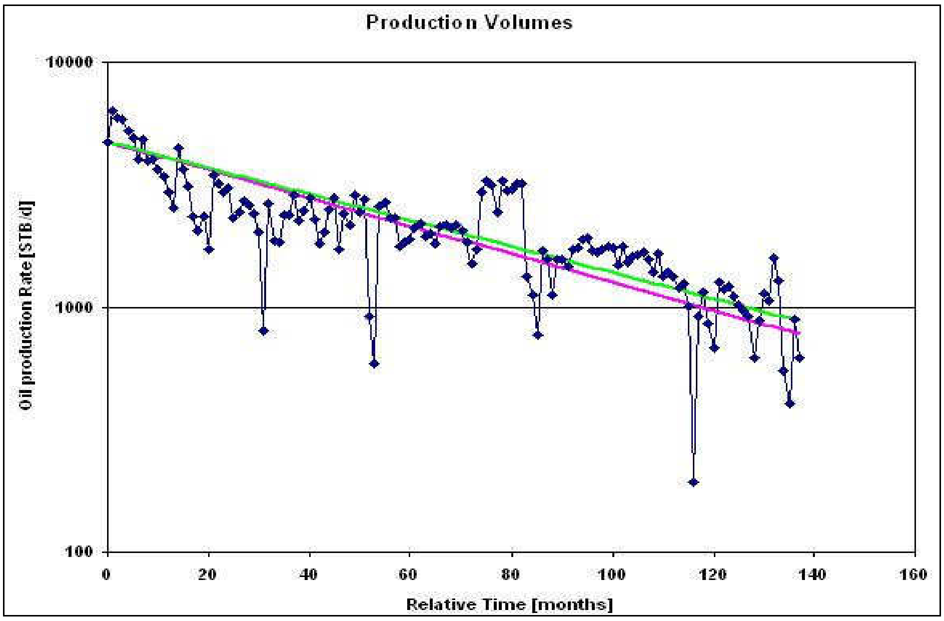


Figure 6: Production Rate vs. relative Time of an oil well, pink line is fitted with all points; green line is not regarding outliers

Figure 6 presents the discrepancy of a curve fit regarding the outliers versus a curve fit without regarding them in a semi logarithmic plot. As can be seen due to the outliers (peaks below 1000 [STB/d]) the decline of the pink (lower) line is significantly steeper than the green (upper) line (not regarding outliers). Thus the production forecast by the pink line will be more conservative leading to a different field development strategy as with the green line, which represents the true behavior of the well better.

In Figure 7 and Figure 8 the 4 month average of the oil production rate was compared to the 8 moth moving average and to the actual value for the oil production rate. For example the 4 months moving average is given as

$$q_{4moavg}^{n} = \frac{\sum_{i=n-2}^{n+2} q^{i}}{5} \qquad \textbf{Equation 4}$$

If a point in the time series were an outlier the absolute difference between the measured value and its moving averages would be higher than for a point that follows the general trend of the time series.

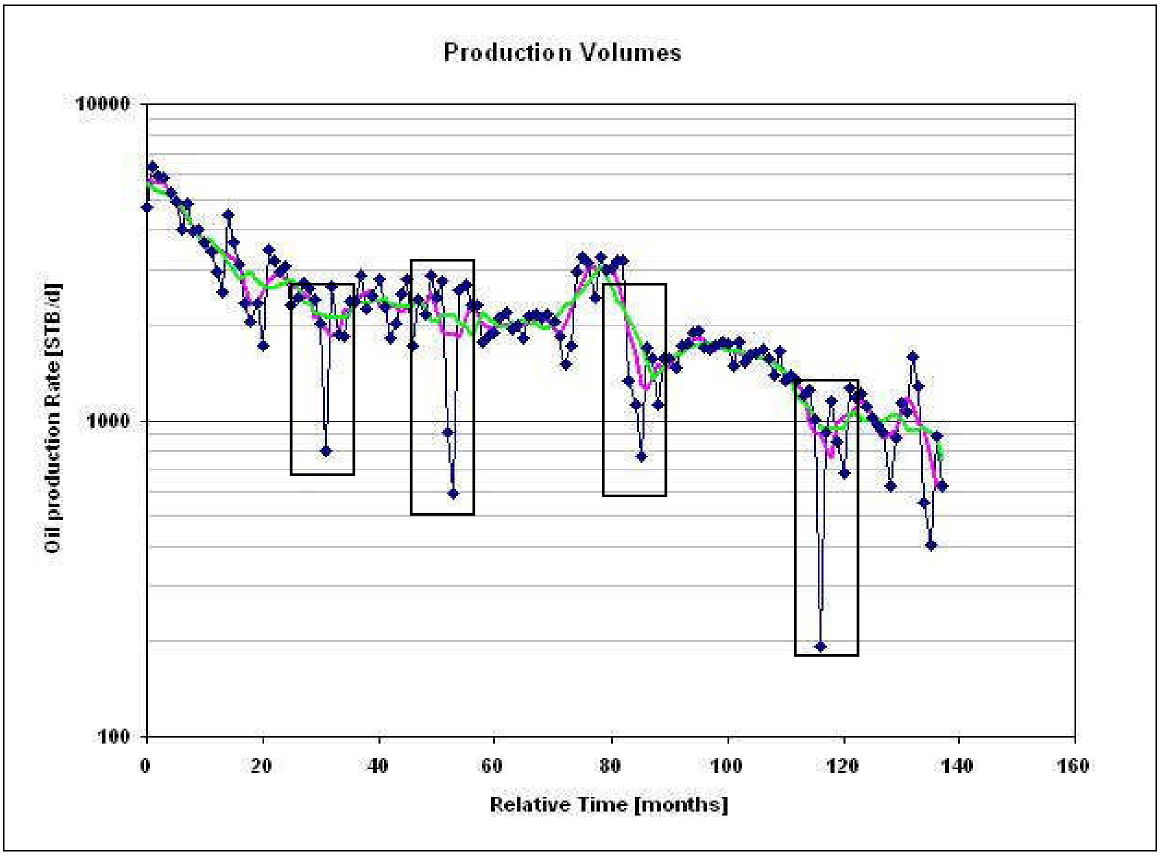


Figure 7: Outlier detection with 4 months moving average (pink) and 8 months moving average (green)

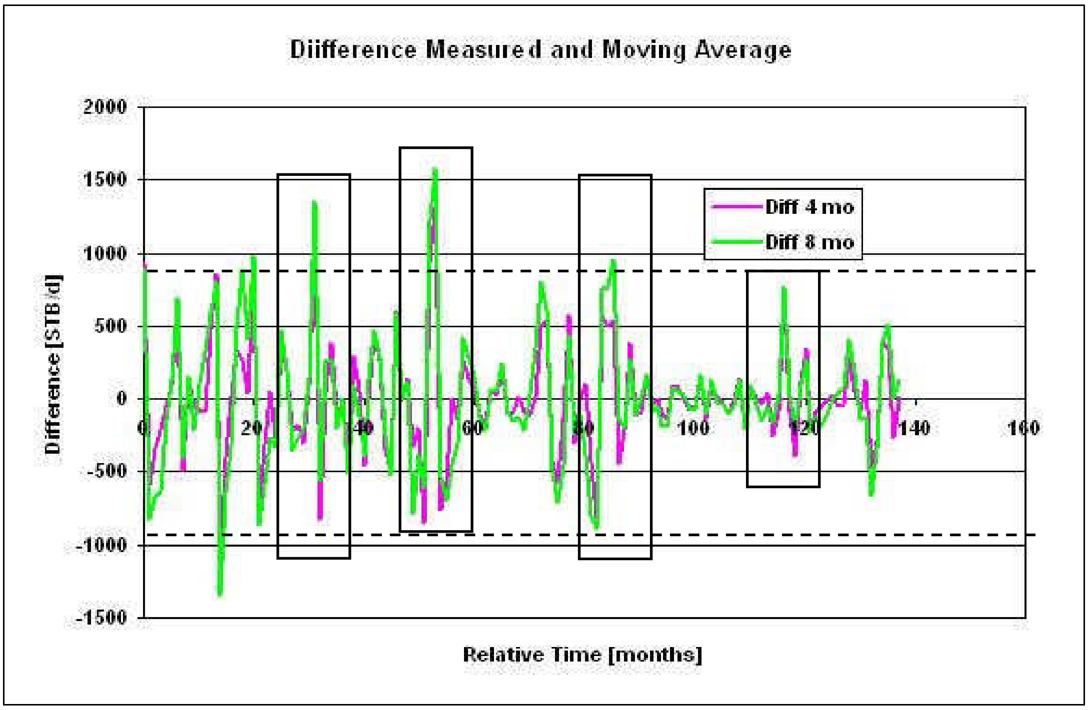


Figure 8: Difference Plot (pink: 4 months average vs. measured; green: 8 months average vs. measured)

The points will be identified as outliers in the time series and will not be regarded when fitting the decline curve. That way the RMS error is significantly decreased, the reliability in the forecast is much higher and the forecast uncertainty is reduced to a minimum.

2.1.2 Conditional Probabilities and Baye's Theorem

Probability Calculus plays a very important role in BRIGHT. BRIGHT's reasoning is based on a series of Conditional Probability equations. Conditional Probabilities express the probability of the occurrence of an *event* (*A*) given an *observation* (*B*), given that *A* and *B* are not *mutually exclusive*. A common question could be: "What is the probability that *A* occurs when *B* is observed?". If *A* and *B* are not mutually exclusive, Baye's theorem (Equation 5 and Equation 6) has to be applied to come up with $p(A|B)$, the so called posterior probability.

$$p(A|B) \times p(B) = p(B|A) \times p(A)$$ **Equation 5**

$$p(A|B) = \frac{p(B|A) \times p(A)}{p(B)}$$ **Equation 6**

Where, as mentioned, *p(A|B)* is the posterior probability, *p(B|A)* is the prior knowledge or the so called *joint probability*, *p(A)* is the probability that an event *A* occurs and *p(B)* is the probability that an event *B* occurs.
An essential factor in Baye's equation is the prior knowledge. As demonstrated in the famous cab example presented below the prior knowledge can alter the result significantly. Therefore the joint probability has to be defined prior to solving the equation. In BRIGHT's case the prior knowledge / joint probability tables has been introduced by experienced engineers and stored in the so called conditional probability tables.

Application of Baye's Rule: The cab problem

A cab was involved in an accident. Two cab companies, the green and the blue, operate in the city. You know that:

- 85% of the cabs in the city are green; 15% are blue.
- A witness says the cab involved was blue.
- When tested, the witness correctly identified the two colours 80% of the time.

The question is: How probable is it that the cab involved in the accident was blue, as the witness reported, rather than green?
The Conditional probability calculation that is performed to come up with a solution is based on Baye's theorem:

$$P(blueC|blueW) = \frac{[P(blueW|blueC) \cdot P(blueC)]}{[P(blueW|blueC) \cdot P(blueC) + P(blueW|greenC) \cdot P(greenC)]}$$

$$P(blueC|blueW) = \frac{(0.80 \times 0.15)}{(0.80 \times 0.15 + 0.20 \times 0.85)} = 0.41$$

The posterior probability – the probability that the cab was blue as stated by the witness is only 41%. Hence the probability that the cab was green, not blue, is 59%.

As presented in that example the prior knowledge can change the outcome significantly. This big advantage can be applied to not entirely rely on probabilistic assumptions but to also take domain or expert knowledge into account; the experience of engineers together with the facts obvious due to the observed data. Another big advantage of using conditional probability equations is the possible introduction of uncertainty. Conditional Probabilities do not necessarily require a single numeric input but can handle probabilistic inputs, which – considering all the uncertainty involved in the determination of the various variables (e.g. all forecast variables, spatial interpolated geologic parameters, etc.) – is a feature that can improve the results significantly. Having stated that, it is clear that the Bayesian way of solving e.g. an inference problem differs significantly from the way the "Classical" Statistics is going by using the relative frequency approach to probabilities. The Bayesian approach uses probability intervals to infer something about the relative frequencies. Moreover by using Baye's Rule unknown probabilities of unknown or unobservable events can be inferred from known probabilities of other events.[16]

In BIGHT the conditional probability equations are used in networks, grouping parameters that are related to each other. These networks are called Bayesian Networks or Bayesian Belief Networks. Bayesian Belief Networks will be described in detail in the next Chapter. For the purpose of this work a software package called Netica[14] was used to model these networks.

2.1.3. Bayesian Belief Networks

2.1.3.1. Introduction to Bayesian Belief Networks

Bayesian Belief Networks are models for reasoning under uncertainty; each parameter is represented by a node and a connection represents a conditional dependency between parameters. The underlying equation in a Bayesian Belief Network is Baye's Theorem that is solved in a network. The advantage of using these equations in a network is that the engineer can look at a variable space containing multiple parameters rather than only on single dimension problems.

As mentioned in Chapter 2.1.2 in contrast to classical inference methods, Bayesian Belief Networks (BBN) allow to introduce prior domain knowledge to the reasoning process in order to draw improved decisions based upon the observed data. This prior domain knowledge is stored in conditional probability tables, which are used in the inference process to come up with probability values for possible outcomes.

BBN use a probabilistic approach to inference. The input parameter as well as the output can be given as a probability distribution rather than as a single numeric value. This enables the engineer to introduce uncertainties. Moreover, unlike many other inference methods, BBN can make decision based on incomplete datasets. If values for a certain parameters are missing the BBN uses the frequency distribution of the values in the remaining field, to determine the probability distribution of that parameter and to make an optimal decision by reasoning about these probabilities together with the observed data.

Bayesian Networks are applied especially when:

- Decisions have to be made based upon uncertain inputs (probabilistic inference)
- Knowledge of experienced experts as well as real cases or measurements have to be incorporated
- Complex Workflows have to be reduced to concise graphical representations
- It is desired, that the reasoning system improves itself by investigating measurements (Bayesian Learning)
- The causal relationship between parameters has to be captured and quantified
- Convincing results have to be produced, even though only very limited or erroneous data are available.

Common fields of applications are e.g. the support (trouble shoot) for software products or computer hardware, bio informatics, medical diagnosis, etc. A graphical depiction of a Bayesian Belief Network as implemented in BRIGHT can be seen in Figure 9. The depiction shows a so called Directed Acyclic Graph (DAG). A DAG is frequently used to set up large Bayesian Belief Networks, because it is easier to explore and identify conditional dependencies and independencies. In a DAG each variable is represented by a 'node' and a casual relationship is denoted by an arrow ('edge'). For each casual relationship a Conditional Probability Table that stores the information about the joint probabilities has to exist. The elements of the DAG are explained in the following chapters.

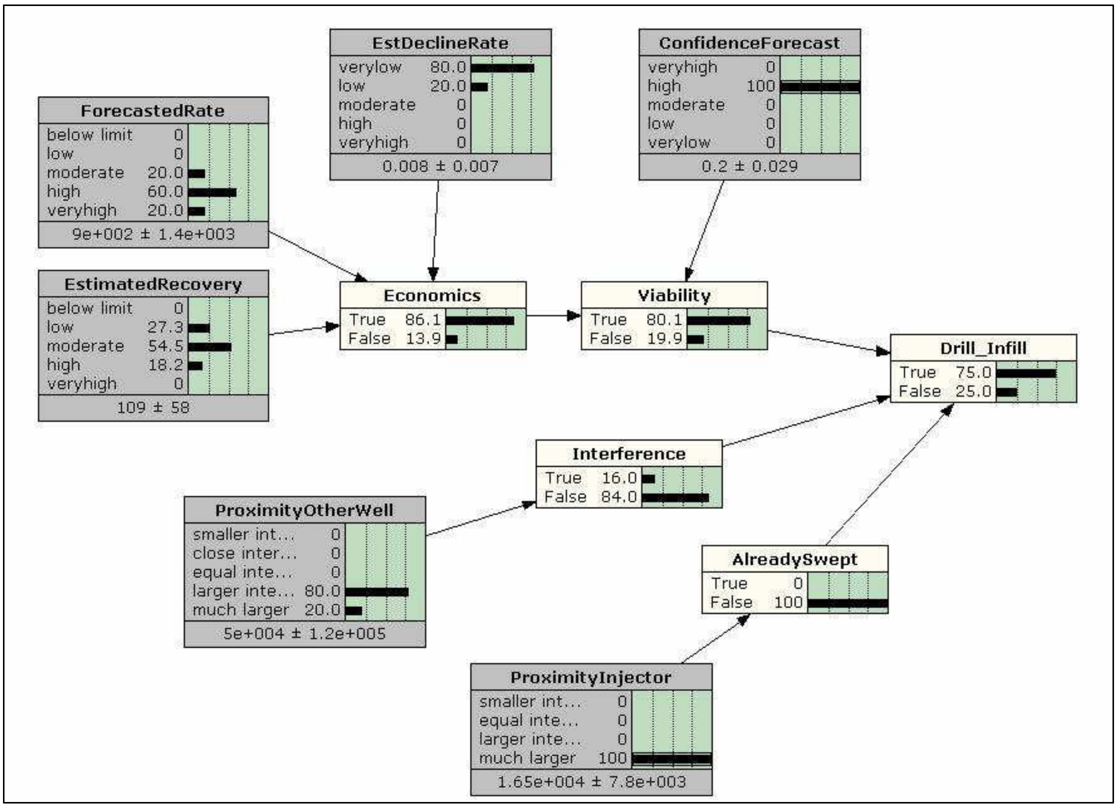


Figure 9: Graphical Representation of a Bayesian Belief Network as implemented in BRIGHT

2.1.3.2. Nodes

Each parameter is represented by a node, which is described by several different states. The input parameters are presented as so called 'Nature Nodes' or 'Parent nodes' (in Figure 9 for example 'EstimatedRecovery', 'Forecasted Rate'). The input probability function or single numeric values for the Nature Nodes are not determined using Baye's Theorem but by observation and statistically describing the respective parameter in a frequency histogram. A lot of these parameters either come from measurement or from computation. The nature nodes contain information about the a priori or prior probabilities of certain evidence. Comparing this chapter with Equation 5, the Nature node would represent *p(A)*.

The dependent nodes are called 'Decision Nodes' or 'Child Nodes' (In Figure 9 for example 'Economics', 'Interference', etc.). They contain information about the joint probabilities and define the output, the posterior probability. In analogy with Equation 5 the posterior probability is given by *p(A|B)*.

In Figure 9 an example for a Nature Node would be 'Estimated Recovery', 'Forecasted Rate', 'Proximity to other well', etc. Decision Nodes would be 'Economics', 'Viability', 'Interference' and finally 'Drill Infill'.

Decision nodes can be input for other Decision Nodes. Once the first Decision Node is calculated its result, the posterior probability, is carried on and passed to the next Decision Node as prior probability.

2.1.3.3. States[13,16]

A Node stands for a certain parameter and is described by several states. A state is a value range that puts the measured value – or a part of the probability density function- into a bin. The states cover the whole value range of a certain parameter and usually subdivide it into discrete classes (they can be continuous too, but in this work only discrete state formulations are used). The resolution of a model increases with the number of states introduced for each parameter. However, it is important to notice that for joint probability reasons in the conditional probability table each state of this node has to be combined with every state of all the other nodes that are not conditionally independent of the given node. Therefore an increase of states in one node would propagate exponentially and would finally lead to huge conditional probability tables.

As mentioned earlier the input is very often given as a distribution rather than a single numeric value. Since the states however, are discrete a discretization procedure has to be performed to determine the aliquot fraction for each state.

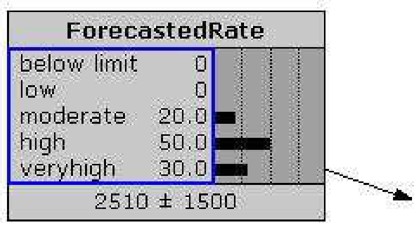


Figure 10: The parameter's value range is subdivided into five different states

Consider the normal distributed density function of an arbitrary parameter as given in Figure 11. As suggested in the depiction of Figure 10 the parameter is subdivided into five states, ‘below limit’, ‘low’, ‘moderate’, ‘high’, ‘very high’. To determine the fraction of that value belonging to a certain state the range limits have to be configured first. In BRIGHT this part of the discretization is used to give the user the possibility to introduce his or her assessment or personal opinion about a field. The density function is then integrated within the given limits. The fraction or probability that a certain state is encountered is given by:

$$p(input \in State_j) = \int_{Lowever\ x}^{Upper\ x} inputfunction(x)dx$$ **Equation 7**

This equation is repeated for each state for any given parameter. If the integral over the whole value range of the input parameter does not exceed one, the sum of all discretizised parts of the function will certainly also not exceed unity.

By choosing the limits of the range e.g. more towards the low end of the value range most of the highest fraction will be in the range 'high' and 'very high', whereas choosing range limits in the higher part of the value range will lead to a more conservative classification with most of the density function binned into the bins such as 'very low' and 'low'.

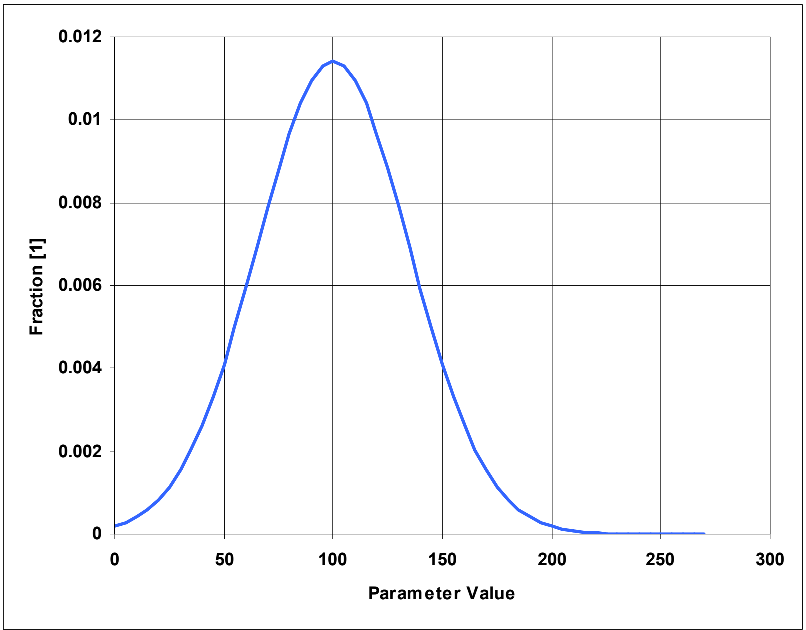


Figure 11: Normal distributed density function for an arbitrary parameter

Case (a): The range limits are set almost evenly distributed in the parameter's value range.

	from	to	Fraction [-]
very low	0	30	0.02
low	30	90	0.36
moderate	90	165	0.58
high	165	235	0.03
very high	235	270	0.00

Table 1: Range Setup

In the diagram in Figure 12 an almost normal distribution can be recognized that somehow resembles a very discretizised density function as in Figure 11.

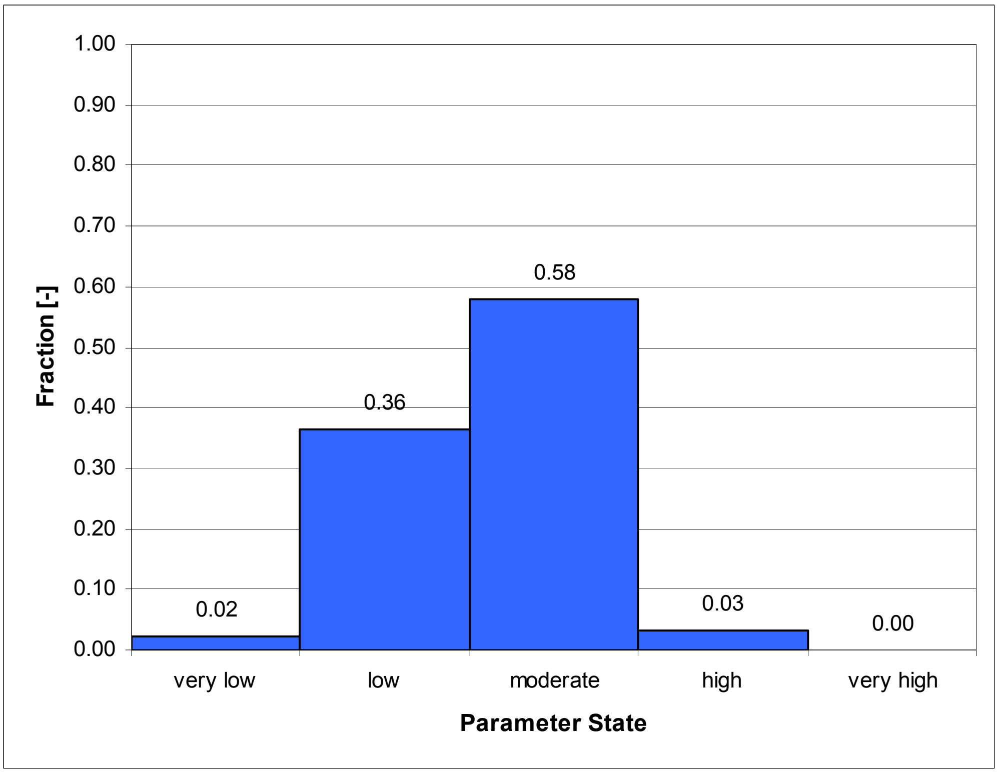


Figure 12: Evenly distributed range limits

Case (b): A more pessimistic approach is chosen to describe the density function in Case b. Therefore the range limits are set towards the upper end of the value range, thus increasing the ranges for ‘very low’ and ‘low’ and therefore increasing the aliquot fractions of the density function in these states.

	from	to	Fraction [-]
very low	0	75	0.24
low	75	185	0.75
moderate	185	220	0.01
high	220	245	0.00
very high	245	270	0.00

Table 2: Pessimistic Range setup

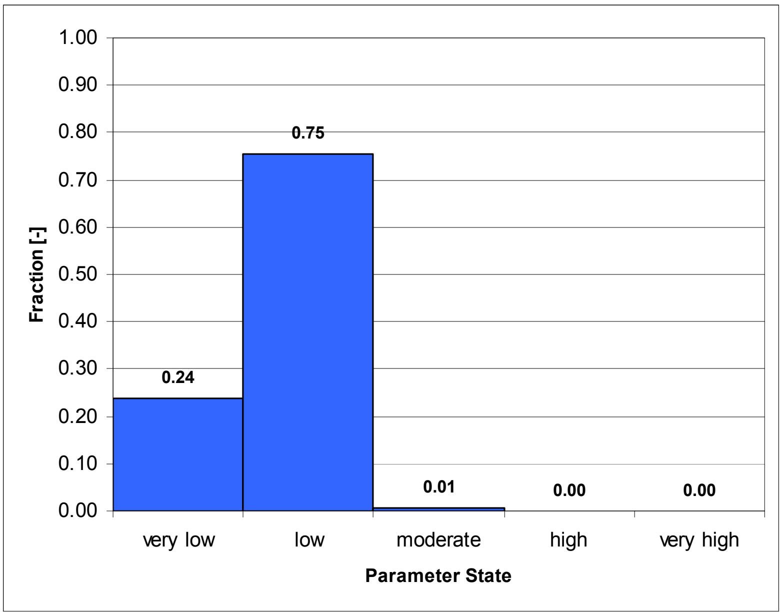


Figure 13: Pessimistic Range setup

As can be seen very clearly in Figure 13 the distribution forces a higher fraction into the lower ranges than into the higher ranges. The effect on the output will be that the posterior probability will be lower, since the biggest part of the distribution is classified as 'very low' and 'low'. To create a more optimistic assessment of the situation it is possible to place the limit boundaries in the lower end of the value range. That way, the ranges for 'high' and 'very high' cover a much larger range and therefore the fraction of values in that range will increase accordingly.

	from	to	Fraction [-]
very low	0	5	0.00
low	5	30	0.02
moderate	30	60	0.10
high	60	130	0.68
very high	130	270	0.20

Table 3: Optimistic Range setup

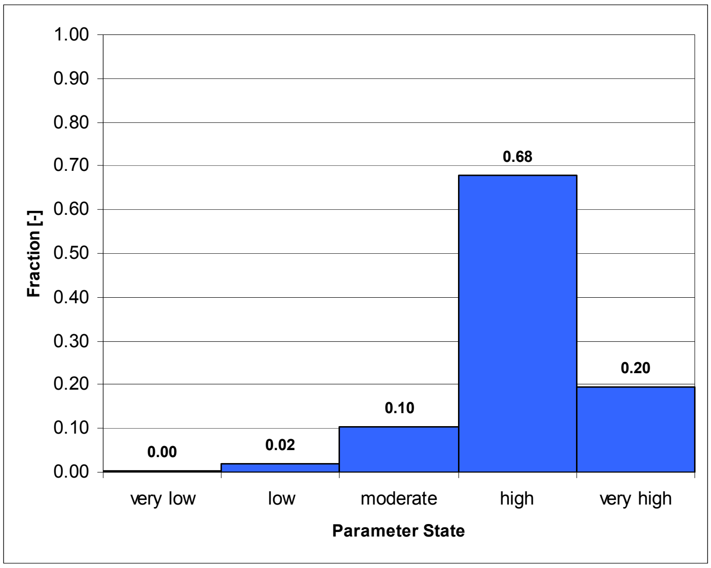


Figure 14: Optimistic Range Setup

Due to the different range setup the fractions in the higher parameter ranges increase and the posterior probability calculated with Baye's theorem increases accordingly.

Therefore, by shifting the ranges, somebody who has not been involved in the setup of the Conditional Probability Tables has an excellent chance to bring in her or his own assessment of the situation. In BRIGHT it was concluded that external persons should not have the chance to change the Conditional Probability Tables. Therefore this mentioned approach has been implemented to allow an alteration of the assessment according to the personal preferences without touching the underlying algorithm.

2.1.3.4. Edges

Edges from one Node to the other indicate that the two connected parameters are not conditionally independent. Vice versa two nodes that are not connected by a node are said to be conditionally independent regarding another set of nodes.

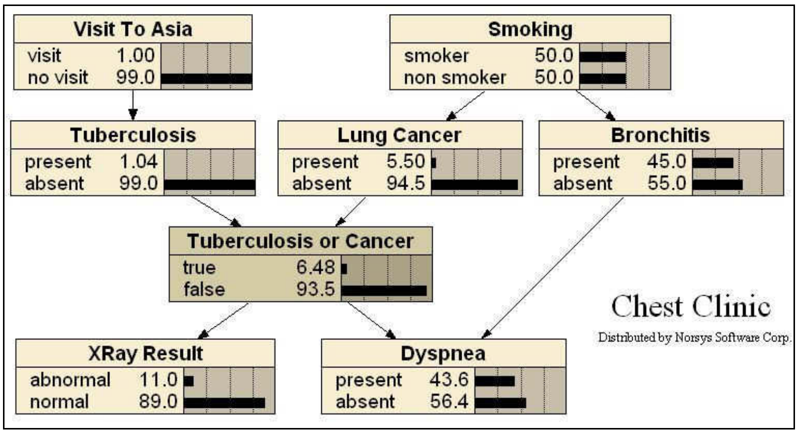


Figure 15: Conditionally independence and dependency[14]

Figure 15 shows a very famous and simple example that should illustrate the concept of conditional independence and conditional dependence. As indicated by the directions of the arrows, the fact whether the patient is smoking or not is not influencing his or her probability of having 'Tuberculosis'. These two parameters are said to be conditionally independent and do not interfere. However, 'Bronchitis' and 'Lung Cancer' are dependent on 'Smoking' and therefore a change in information about whether the patient is a smoker or not will significantly change the probabilities of having these diseases.

Another concept in Bayesian Networks discusses the propagation of information from one node to the descendent and its descendent etc. If e.g. 'Smoking' is set to a value, because it is know whether the patient is a smoker or not 'Tuberculosis or Cancer' will change, because 'Lung Cancer' most probably might have changed. However, if there is an observation for 'Lung Cancer' and so called 'hard evidence' is entered into that node, 'Smoking' and 'Tuberculosis or Cancer' are d-separated regarding 'Lung cancer'. In domain literature this fact is also referred to as 'Markov Condition'.[13]

For each set of conditionally dependent nodes a so called Conditional Probability Table (CPT) has to be set up. The CPT contains information about the joint probabilities of these parameters and can either be set up by looking at measured data or by experts. For BRIGHT these CPTs have been set up by experienced engineers, who are working on RAPID studies for a long time and who know about the parameter that influence their decisions.

Looking closer at one part of the Bayesian Belief Network as in Figure 9 (highlighted with blue rectangle in Figure 16) the CPT that is used to calculate the posterior probability for ‘Drill Infill’ out of the a priori probabilities of ‘Viability’, ‘Inference’ and ‘Already Swept’ will look like depicted below.

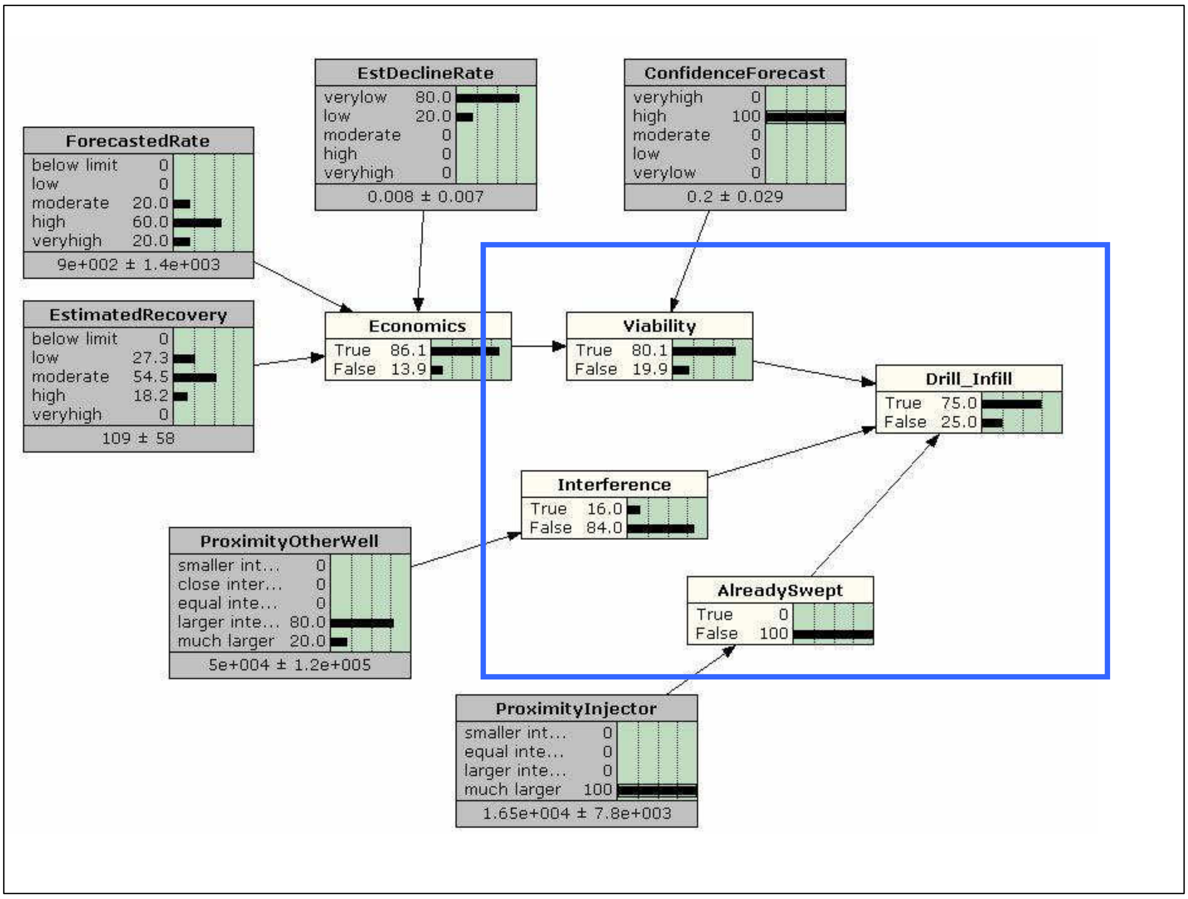


Figure 16: Part of the Bayesian Belief Network described in Figure 9

			Drill Infill	
Viability	**Interference**	**Already swept**	**true**	**false**
high	yes	yes	0	1
high	yes	no	0.6	0.4
high	no	yes	0.2	0.8
high	no	no	1	0
low	yes	yes	0	1
low	yes	no	0	1
low	no	yes	0.1	0.9
low	no	no	0	1

Table 4: CPT 'Drill Infill'

Table 4 shows the CPT for the node ‘Drill Infill’. It is clear that the number of lines in the CPT increases with the number of states. The number of lines can be calculated as:

$$\text{Number of Lines in CPT} = \prod_j NumberOfStates_j \qquad \textbf{Equation 8}$$

Equation 8 shows the main limitation in setting up these CPTs. For example the node 'Economics' is calculated out of three precedent nodes with five states respectively. The CPT that stores the information about the joint probabilities for economics therefore contains of 125 lines that were set up manually. It would be difficult to add another node or another state, because that would lead to a manifold increase in the number of lines and therefore the consistent population of the CPTs becomes more and more questionable.

The Markov Condition[16] facilitates in setting up the CPTs. According to the Markov Condition it is not necessary to define how e.g. 'Forecasted Rate' is influencing 'Viability', since there is another node 'Economics' in between that can be evaluated first. Therefore the number of CPTs and subsequently the number of lines in the CPTs is reduced significantly. This enables the creator of the Bayesian Network to see each conglomerate of a few converging nodes as a self containing entity. Only the posterior probability e.g. calculated in 'Economics' is passed on to 'Viability' and will there be used as input, regardless of the values or density functions used to describe 'Forecasted Rate', 'Estimated Recovery' and 'Decline Rate'.

2.1.4. Marginalization and Evaluation of Posterior Probability

Once the Bayesian Network has been set up the calculation of the final posterior probability can be started. To compute the final probability value all possible state combinations have to be evaluated and its joint probability have to be calculated. Moreover all the precedent nodes before the final node have to be fully evaluated before the final posterior probability can be calculated.

According to the already mentioned Markov Condition, each set of nodes can be evaluated separately and independent of the descendent nodes. The posterior probability – the output – of one set of nodes is then used as an input in the descendent nodes.

Below a simplified scheme of how the solution is obtained is presented:

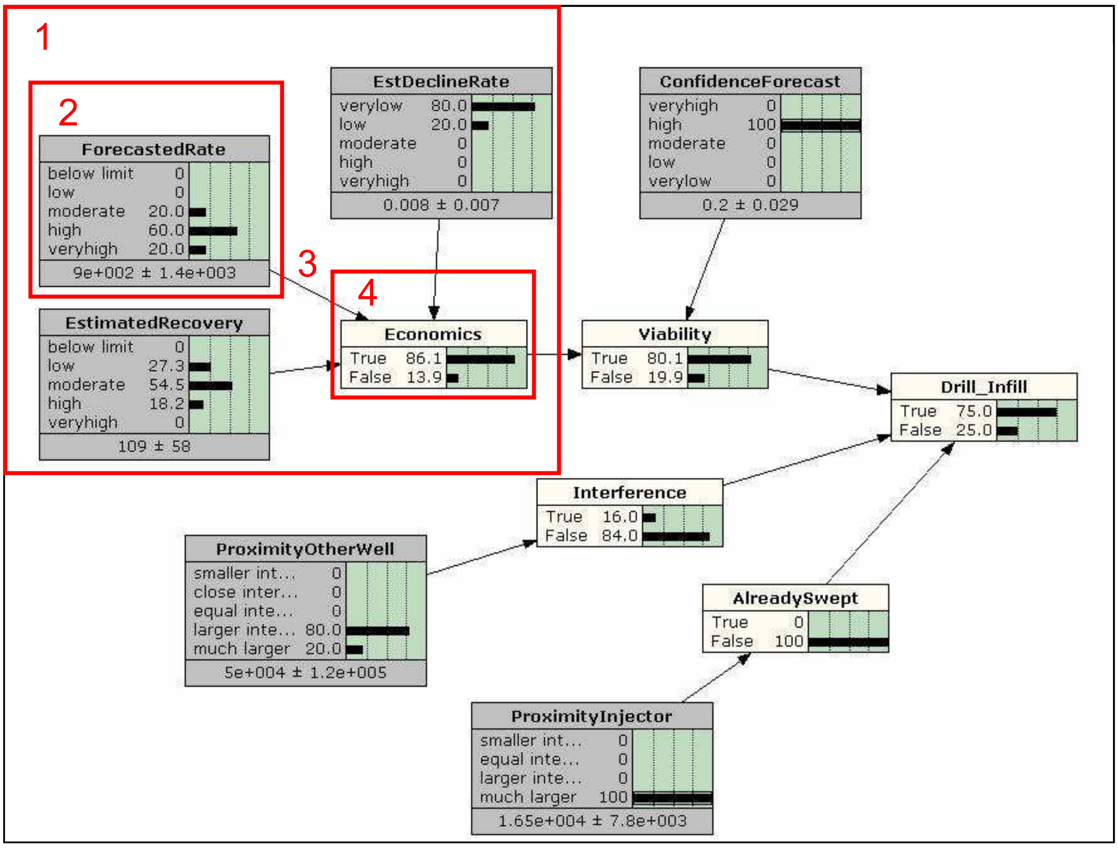


Figure 17: Workflow to determine the posterior probability in a Bayesian Network

<u>*Step 1:*</u> A set of nodes that feed into the same child node has to be selected. The set of nodes chosen has to be complete and all the nodes that feed into that same child node have to be considered.

<u>*Step 2:*</u> For each parent node in that set, the input values or input density functions are entered. If there is neither a value nor a density function known that can be entered, the input can be left blank and the Bayesian Network will use the most probable values in determining the posterior probability in the child node.

The discretization procedure explained earlier in this document (Equation 7) has to be applied in order to come up with the correct values of fraction per state per parameter.

<u>*Step 3:*</u> All parent nodes that feed into the same child node are now defined by some value or density function. They are combined in the child nodes by regarding the Conditional Probability table in the following procedure:

Present states for ‘Forecasted Rate’ are ‘moderate’, ‘high’ and ‘very high’. For ‘Estimated Recovery’ the available states are ‘low’, ‘moderate’ and ‘high’. For the Decline Rate ‘very low’ and ‘low’ are indicated.

All possible state combinations have to be created. In the example case a total of 18 different state combinations are possible. For each of these state combinations the joint probability value for 'Economics' has to be looked up in the Conditional Probability table.

			Economics	
Forecasted Rate	Estimated Recovery	Decline Rate	true	false
very low	very low	very low	0	1
very low	very low	low	0	1
very low	very low	moderate	0	1
very low	very low	high	0	1
very low	very low	very high	0	1
very low	low	very low	0	1
very low	low	low	0	1
very low	low	moderate	0	1
very low	low	high	0	1
very low	low	very high	0	1
very low	moderate	very low	0	1
very low	moderate	low	0	1
very low	moderate	moderate	0	1
very low	moderate	high	0	1
very low	moderate	very high	0	1
very low	high	very low	0	1
very low	high	low	0	1
very low	high	moderate	0	1
very low	high	high	0	1
very low	high	very high	0	1
very low	very high	very low	0	1
very low	very high	low	0	1
very low	very high	moderate	0	1
very low	very high	high	0	1
very low	very high	very high	0	1
low	very low	very low	0	1
low	very low	low	0	1
low	very low	moderate	0	1
low	very low	high	0	1
low	very low	very high	0	1
low	low	very low	0.76	0.24
low	low	low	0.74	0.26
low	low	moderate	0.72	0.28
low	low	high	0.7	0.3
low	low	very high	0.68	0.32
low	moderate	very low	0.81	0.19
low	moderate	low	0.79	0.21
low	moderate	moderate	0.77	0.23
low	moderate	high	0.75	0.25
low	moderate	very high	0.73	0.27
low	high	very low	0.86	0.14
low	high	low	0.84	0.16
low	high	moderate	0.82	0.18
low	high	high	0.8	0.2
low	high	very high	0.78	0.22
low	very high	very low	0.91	0.09
low	very high	low	0.89	0.11
low	very high	moderate	0.87	0.13
low	very high	high	0.85	0.15
low	very high	very high	0.83	0.17
moderate	very low	very low	0	1
moderate	very low	low	0	1
moderate	very low	moderate	0	1
moderate	very low	high	0	1
moderate	very low	very high	0	1
moderate	low	very low	0.79	0.21
moderate	low	low	0.77	0.23
moderate	low	moderate	0.75	0.25
moderate	low	high	0.73	0.27
moderate	low	very high	0.71	0.29
moderate	moderate	very low	0.84	0.16
moderate	moderate	low	0.82	0.18
moderate	moderate	moderate	0.8	0.2
moderate	moderate	high	0.78	0.22
moderate	moderate	very high	0.76	0.24
moderate	high	very low	0.89	0.11
moderate	high	low	0.87	0.13
moderate	high	moderate	0.85	0.15
moderate	high	high	0.83	0.17
moderate	high	very high	0.81	0.19
moderate	very high	very low	0.94	0.06
moderate	very high	low	0.92	0.08
moderate	very high	moderate	0.9	0.1
moderate	very high	high	0.88	0.12
moderate	very high	very high	0.86	0.14
high	very low	very low	0	1
high	very low	low	0	1
high	very low	moderate	0	1
high	very low	high	0	1
high	very low	very high	0	1
high	low	very low	0.82	0.18
high	low	low	0.8	0.2
high	low	moderate	0.78	0.22
high	low	high	0.76	0.24
high	low	very high	0.74	0.26
high	moderate	very low	0.87	0.13
high	moderate	low	0.85	0.15
high	moderate	moderate	0.83	0.17
high	moderate	high	0.81	0.19
high	moderate	very high	0.79	0.21
high	high	very low	0.92	0.08
high	high	low	0.9	0.1
high	high	moderate	0.88	0.12
high	high	high	0.86	0.14
high	high	very high	0.84	0.16
high	very high	very low	0.97	0.03
high	very high	low	0.95	0.05
high	very high	moderate	0.93	0.07
high	very high	high	0.91	0.09
high	very high	very high	0.89	0.11
very high	very low	very low	0	1
very high	very low	low	0	1
very high	very low	moderate	0	1
very high	very low	high	0	1
very high	very low	very high	0	1
very high	low	very low	0.85	0.15
very high	low	low	0.83	0.17
very high	low	moderate	0.81	0.19
very high	low	high	0.79	0.21
very high	low	very high	0.77	0.23
very high	moderate	very low	0.9	0.1
very high	moderate	low	0.88	0.12
very high	moderate	moderate	0.86	0.14
very high	moderate	high	0.84	0.16
very high	moderate	very high	0.82	0.18
very high	high	very low	0.95	0.05
very high	high	low	0.93	0.07
very high	high	moderate	0.91	0.09
very high	high	high	0.89	0.11
very high	high	very high	0.87	0.13
very high	very high	very low	1	0
very high	very high	low	0.98	0.02
very high	very high	moderate	0.96	0.04
very high	very high	high	0.94	0.06
very high	very high	very high	0.92	0.08

Figure 18: Conditional Probability Table – Economics Node in Infill Location Selection Workflow

Comparing the Conditional Probability table to the combinations of possible states the table reduces to:

			Economics	
Forecasted Rate	Estimated Recovery	Decline Rate	true	false
moderate	low	very low	0.79	0.21
moderate	low	low	0.77	0.23
moderate	moderate	very low	0.84	0.16
moderate	moderate	low	0.82	0.18
moderate	high	very low	0.89	0.11
moderate	high	low	0.87	0.13

high	low	very low	0.82	0.18
high	low	low	0.8	0.2
high	moderate	very low	0.87	0.13
high	moderate	low	0.85	0.15
high	high	very low	0.92	0.08
high	high	low	0.9	0.1
very high	low	very low	0.85	0.15
very high	low	low	0.83	0.17
very high	moderate	very low	0.9	0.1
very high	moderate	low	0.88	0.12
very high	high	very low	0.95	0.05
very high	high	low	0.93	0.07

Table 5: Conditional Probability Table for selection

Step 4: The posterior probability for the node 'Economics' has to be calculated. The equation that is applied to compute the posterior probability for the sample set of nodes is given below. The explanation of the terms follows after the equations.

$$p\left(\begin{array}{l} Estimated\,\mathrm{Re}\cos ery, \\ ForecastedRate, \\ DeclineRate \end{array} \middle| Economics = true \right) =$$

$$\sum_{States} p\left(Economics = true \middle| \begin{array}{l} ForecastedRate = State_i, \\ Estimated\,\mathrm{Re}\cos ery = State_j, \\ DeclineRate = State_k \end{array} \right) \times$$
$$\times\, p(ForecastedRate = State_j) \times p(Estimated\,\mathrm{Re}cvoery = State_j) \times$$
$$\times\, p(DeclineRate = State_k) \qquad \textbf{Equation 9}$$

The posterior probability that has to be determined is given by $p\left(\begin{array}{l} Estimated\,\mathrm{Re}\cos ery, \\ ForecastedRate, \\ DeclineRate \end{array} \middle| Economics = true \right)$. The expert knowledge that is stored in the Conditional Probability tables in terms of joint probabilities is looked up from the Conditional Probability table as in Figure 18 or Table 5 and is used in Equation 9 as $\sum_{States} p\left(Economics = true \middle| \begin{array}{l} ForecastedRate = State_i, \\ Estimated\,\mathrm{Re}\cos ery = State_j, \\ DeclineRate = State_k \end{array} \right)$. The values for $p(ForecastedRate = State_j) \times p(Estimated\,\mathrm{Re}\cos ery = State_j) \times p(DeclineRate = State_k)$ have to be computed during the pre-processing and forecasting workflows. Since they are input parameters into that particular Network, they are not dependent on any other node in that particular Bayesian Network.

The resulting value in Equation 9 is subsequently used for the next set of nodes as an input value (it will be used the same way as e.g. *p(ForecastedRate=State$_i$)* in Equation 9). This procedure is repeated for each set of nodes until the final posterior probability is calculated (in analogy to the Bayesian Network in Figure 17 the final posterior probability would be the value in the node 'Drill Infill').

2.2. Production Forecasting Techniques used in BRIGHT

2.2.1 Decline Curve Analysis[8]

The only forecasting technique used in BRIGHT so far is the Decline Curve Analysis. In BRIGHT an automatic decline curve analysis is implemented that generates the decline curve for each well in the field in a very short time (a few seconds). Arps' equation is used as the underlying equation for the Decline Curves:

$$\frac{dq/dt}{q} = -K \cdot q^n \qquad \textbf{Equation 10}$$

dq/dt is the change of production rate regarding time [STB/d^2] or [Mscf/d^2], q is the production rate [STB/d], [Mscf/d]. K and n are the decline constant, where K is referred to as the Decline rate [1/d] and n is the decline exponent [-].

Due to the difficulties in optimizing the other decline curve types, it was decided to only use Exponential Decline curves in BRIGHT. For exponential decline curves, n is set to zero and after rearranging the equation to a more convenient form Equation 10 simplifies to Equation 11. The advantage from a software implementation and automatic curve fit optimization point of view is that Equation 11 has only one parameter that has to be optimized – the Decline Rate K -, whereas hyperbolic decline curves have two parameters to be optimized – the Decline Rate K as well as the Decline Exponent n.

$$q(t) = q_i \cdot \exp(-K \cdot dt) \qquad \textbf{Equation 11}$$

Harmonic Decline curves are a special case of the Decline curves and should only be implemented if there is no apparent straight line in a semi log plot of Production rate vs. Cumulative Production. Therefore it was not regarded in BRIGHT. However, the user of BRIGHT has the possibility to chose a more appropriate Decline curve, generate this decline curves in an external application and copy the values into BRIGHT.

The experience with other cases however has shown that in fields, where BRIGHT is considered to be an applicable software tool, the automatic decline curve analysis gives very satisfying results.

BRIGHT optimizes the decline curve by altering the decline rate until the best fit is achieved. The best fit is the curve with the lowest RMS error in the fit range. RMS stands for 'Root mean square' error and is given by:

$$RMS = \sum_{i=1}^{n} \sqrt{\left(q_{measured,i} - q_{curvefit,i}\right)^2}$$ **Equation 12**

$q_{measured}$ is the rate as measured and given in the data for any given time point [STB/d] or [Mscf/d], $q_{curvefit}$ is the rate as calculated according to the fitted curve at the same time point [STB/d] or [Mscf/d]. This square root of the squared difference between the measured and the fitted rate is summed up to get one RMS value in each iteration. While iterating, BRIGHT is modifying the decline curve coefficient *K* in order to minimize the RMS error. This essentially leads to the lowest deviations from the measured data of the fitted curve and hence to the best fit. .

However, the quality of fit is measured with the easier to compare correlation coefficient r^2. The correlation coefficient is a very frequently used mathematical tool that allows to determine the dependency of two sets of values $X=(x_1, x_2, \ldots, x_n)$ and $Y=(y_1, y_2, \ldots, y_n)$. The range of values for the correlation coefficient is $-1 \leq r^2 \leq 1$, 0 indicating that there is no dependency between *X* and *Y*, 1 indicating that there is a positive linear dependency of 100% (100% directly proportional), -1 indicating that the dependency between *X* and *Y* is 100% negative (100% inversely proportional). Thus the advantage of indicating the quality of curve fit with the correlation coefficient lies in the comparability of the correlation coefficients, since they always stay between zero and one.

The correlation coefficient is calculated as[17]:

$$r_{xy}^{\ 2} = \left(\frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2 \cdot \sum_{i=1}^{n} (y_i - \bar{y})^2}} \right)^2$$ **Equation 13**

Where the numerator stands for the covariance of *X* and *Y*, and the denominator denotes the variances of *X* and *Y* respectively.

The user has then the chance to go through the list of highlighted wells with a too low correlation coefficient and to either improve their decline curve fit manually or to mark the well as an outlier and therefore ban it for the further forecasting workflows.

2.3. Geologic Interpolation[10, 22]

In BRIGHT ordinary Kriging is used in many different workflows in order to interpolate the values for any given parameter at locations, where the value is not known (e.g. Infill locations, locations without measurement). Kriging is an interpolation method especially suitable for spatially dependent variables. That means in contrast to e.g. random dice throws, geologic parameters such as e.g. porosity are not totally random but spatially related to one another. That means that geologic samples are spatially distributed with the constraining assumption that a value for a parameter at one location is similar to values at close locations and less similar to locations far away. Therefore, to estimate a value for a not sampled location Kriging uses a weighting system that - to compute an expected value - weights sampled locations nearby more and regards locations far away less. The underlying basic equation that is applied by Kriging is:

$$E(u) = \sum_{i=1}^{n} w_i \cdot E(u_i)$$ **Equation 14**

E(u) is the expected value for the parameter at the unsampled location, $E(u_i)$ is the expected value at the sampled location (i.e. the measured value), w_i is the weight that is individually determined for each given location. *n* is the number of samples that are used to calculate the interpolated value. w_i is a function of the distance. In contrast to linear weighted interpolation methods ordinary Kriging does not simply take the inverse Euclidian distance between the unsampled and the sampled locations, but it is regarding spatial trends and clusters of sampled locations. Caers demonstrates this advantage of Kriging with an example similar as the one depicted below. Instead of determining the weights solely based on the inverse linear distance to the unsampled location and therefore giving each measured value the same weight, Kriging notes that point 2 and 3 are in a cluster and therefore distributes the weights in a way, that the information about the cluster (e.g. region) is captured rather than the information about each specific well. Therefore in Kriging it is not possible that one region is overrepresented or too much influencing the result of the interpolation just because there are more sample wells in that region. The weights are well distributed within a cluster of wells in the same region and lead to an even weighting of the regions.

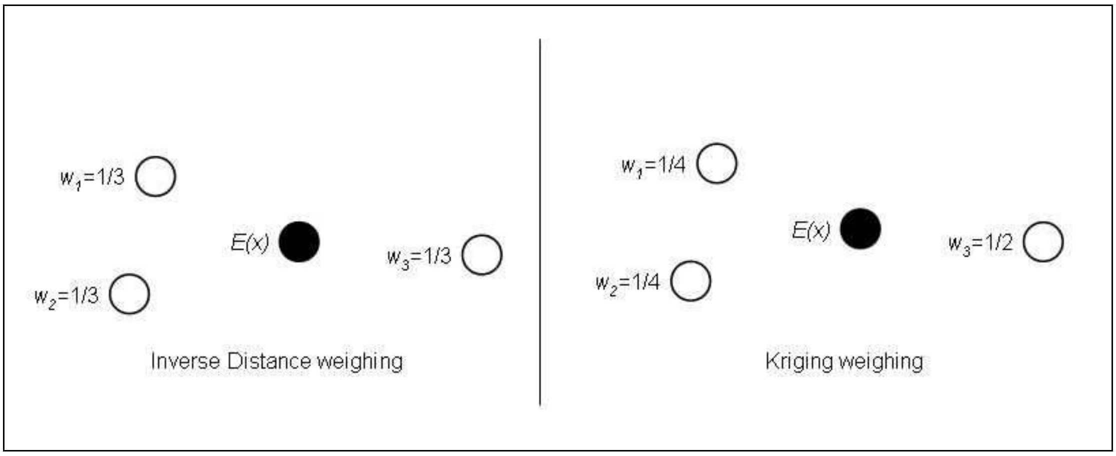


Figure 19: Inverse Distance weighing vs. Kriging weighing[10]

The information about the spatial trends is input through a semivariogram[10], which captures the information about the spatial variability of a trend. Usually ordinary Kriging takes the main indicators of a semivariogram into account (e.g. Sill, Range, lag distance, azimuth, dip, etc.). In the Kriging algorithm the distribution of weights will be regarding the semivariogram input.

As every interpolation algorithm Kriging tends to be very conservative. That means that ordinary Kriging usually overestimates extremely low values and underestimates extremely high values. The reason for that is that the Kriging algorithm tries to minimize the residual error, which essentially is the sum of the squared differences between the measured values and the estimated values at the same locations (RMS error; Equation 1). This is achieved by fitting a surface into the value field that is as smooth as possible; subsequently the kriged surface is not able to follow the extreme values.

2.4. Outlier Detection[5]

BRIGHT relies a lot on interpolation and its accuracy and reliability is therefore highly dependent on the smoothness of the data. This affects not only the outlier in the time series of production rate data, but also the outliers regarding the geologic model (e.g. which well's measured porosity is significant higher than the porosity of all its surrounding wells). Outliers impose a significant change in the trend of the dataset and have therefore to be identified. Outliers will not be used for further interpolations in BRIGHT, since they disturb the data trends and falsify the interpolated response surface.

2.4.1. Definition Outlier

An outlier in BRIGHT is defined as a well that performs significantly worse or significantly better than the surrounding wells. Moreover in BRIGHT it is desired to find wells with significantly different values for Porosity, Net pay, water saturation and Sweep Efficiency, since these parameters play an important role in the decision for a field development plan. A detailed information about the parameters that are used for the outlier search as well as the criteria to define an outlier is given in Chapter 3. In this chapter the procedure how an outlier is detected is explained in more detail.

2.4.2. 'Leave-one-out' Cross validation[12]

The difficulty in finding outlier is to identify abnormal behavior due to a strange value or an erroneous measurement. It was important that BRIGHT can distinguish between a change in trend due to normal heterogeneity and a change due to unreasonably high or unreasonably low values.

In statistics there are several different methods to test a hypothesis that has been created out of measured data, against these measured data. The reason to apply a check of the hypothesis is to determine whether the hypothesis is correct and good enough to be applied to estimate values for new, arbitrary samples. In machine learning this hypothesis evaluation techniques are very important, because they are indicating the quality of the learning algorithm. In BRIGHT these evaluation algorithms where used to detect errors and in contrast to learning algorithms, BRIGHT does not try to change the hypothesis to include erroneous values but first highlights the places where these values appear.

The hypothesis evaluation algorithm used in BRIGHT is a special form of the "*k*-Fold Cross validation". In the *k*-Fold Cross validation the dataset is divided into *k* arbitrary

sub samples. Each one of these *k* groups is once left out of the dataset and not used to create or train the hypothesis. After the hypothesis is defined, these *k* samples are used to evaluate them according to the new hypothesis and test its accuracy. BRIGHT uses a k-Fold Cross validation method, where *k* is equal to the number of available datasets, which is also known as *"Leave-one-out"-Cross validation (LOOCV).*
In LOOCV a single sample is left out while training the hypothesis with all the other data. Then, the created hypothesis is tested or validated against this single sample. This procedure is repeated for each single sample in the set.
The hypothesis in BRIGHT is represented by the kriged surface. As mentioned in the chapter about Kriging, in Kriging the smoothest possible surface is found that satisfies all constraints given be the measurements at the wells by simultaneously minimizing the occurring residuals. In BRIGHT the "Leave-one-out"-Cross Validation equivalent operation is applied to generate several kriged maps of a certain parameter. Each of these maps does not consider one of the wells, but only all the others. For example in a field with 120 sampled wells, 120 maps for the same parameter are generated each one of these lacking one well respectively. As mentioned in the previous chapter the residual is the sum of deviations from a fitted curve or surface. If an outlier is left out, the kriged surface is supposed to be a lot smoother thus reducing the residuals. Whereas when a well is removed, which's value follows the trend of its neighboring wells, the residual will not be significantly different than the residuals for the kriged maps for most of the other runs.
A list is generated with the well name and the according value for the residual, when this well is left out from generating the kriged surface for one parameter. Thus, the wells with significantly lower associated values can be regarded as outliers.
This procedure is demonstrated with two examples. At first a very simple two dimensional problem has been set up with a series of data that generally follow the trend of a sinusoidal curve.
The x-Axis represents the distance to an arbitrary reference point and the y-Axis represents the values. As can be seen very clearly the red point is far off the trend of all the other points and should therefore be identified as an outlier.

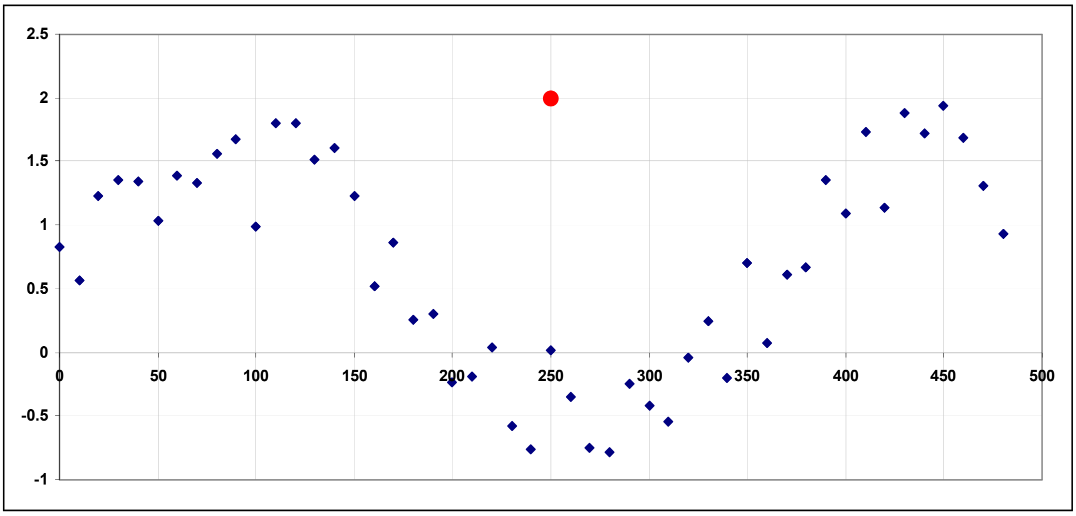


Figure 20: Sinusoidal distribution of values

The best fit curve will be generated in multiple runs; in each of those runs one of the points is left out and not regarded in finding this best curve. When the red point is left out an almost sinusoidal shaped curve will be identified as a trend line, reducing the relative distances of all other points to that curve. The sum of all deviations (the residual) will be the smallest and therefore the red point identified as an outlier.

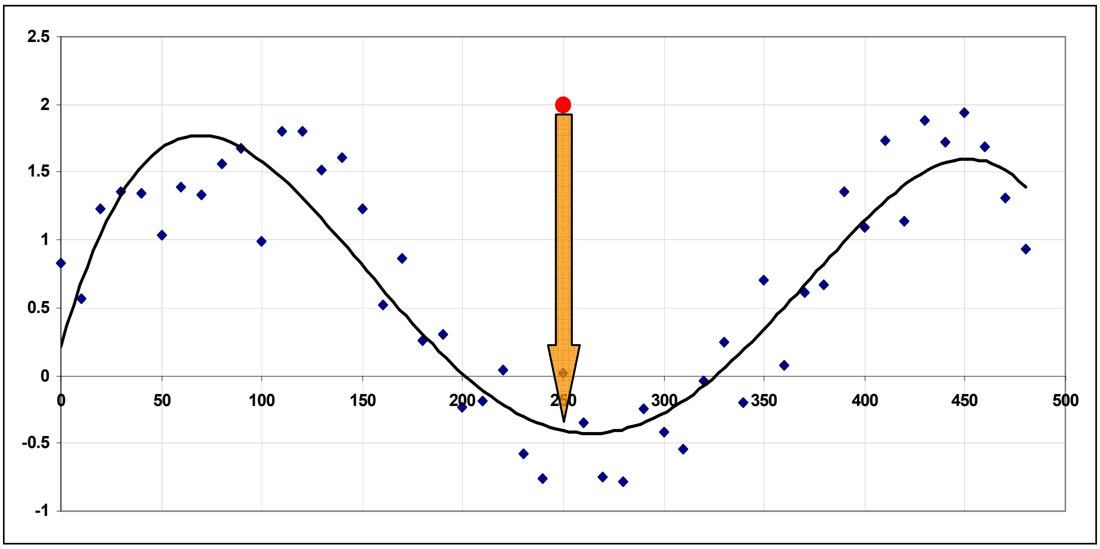


Figure 21: Outlier is identified as having a very large relative distance to the best fit curve

The same approach is now demonstrated in a three dimensional example as it is also applied in BRIGHT. The example problem shows a field with porosity measurements for all wells. The porosity values for all wells in a field are given. The porosity value for one well was increased intentionally. One well therefore has a significantly higher porosity value of about 25 [%] whereas all other wells have porosity values in the range of 12 [%] to 16 [%]. The kriged map of the porosity looks as depicted in Figure 22.

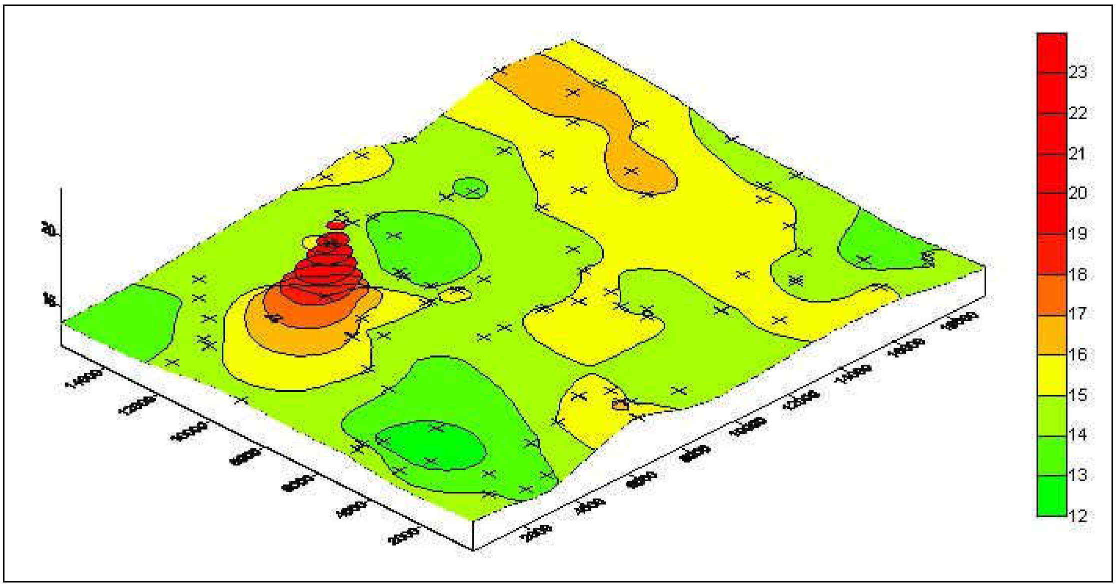


Figure 22: Kriged map of Porosity

It is clearly visible that one well in the lower left corner of this reservoir depiction has a significantly higher value. When removing any other well from the dataset and determining the residual it will be in the range of about 2.1 [-].

However, when the obvious outlier well is removed from that example reservoir, the kriged map will looked as depicted in Figure 23.

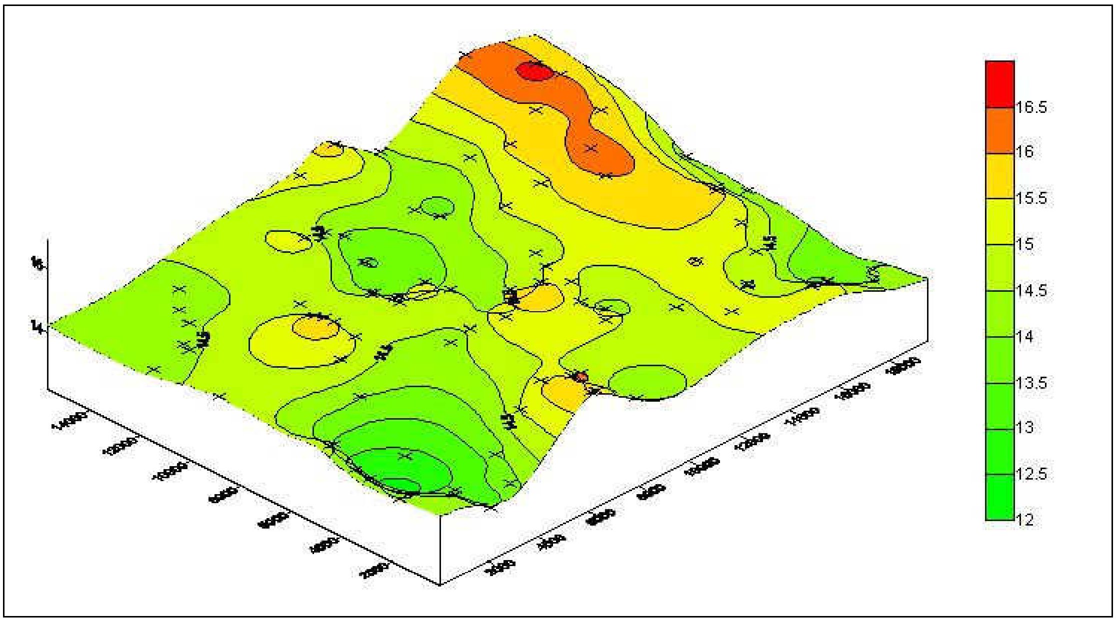


Figure 23: Kriged map of Porosity without outlier

The value for the residual when the outlier well is removed is 0.21 [-], which is significantly higher than the values around 2.1 [-] as seen with the other kriged maps for the porosity in that field. Moreover, 0.21 is a very satisfying value in terms of reservoir modeling and increases the reliability in the forecast and in further spatial interpolations significantly. It is therefore clear that the well that has been removed in Figure 23 is an outlier and should not be used for any further interpolation work.

2.4.3. Severity and Reliability

The described approach is intended to find outliers due to erroneous measurements, yet it should still consider variations in the data due to reservoir heterogeneity as valid as far as possible. It is clear that for highly heterogeneous reservoirs this demand is very hard to fulfill. The problem is that all interpolation algorithms - and certainly also ordinary Kriging - depend on a smoothness or steadiness of the data. In highly heterogeneous reservoirs (e.g. highly fractured reservoirs, high variation in permeability and porosity due to meandering reservoir systems, etc.) it is very questionable whether the presented reservoir model as well as the presented list of outliers matches the real reservoir.

By decreasing the search radius in the Kriging algorithm its interpolation resolution will be much higher and heterogeneities will be captured better. However, the search radius should not be too low, since a few wells should be within the circle to be included in the interpolation computation for the missing value.

It is impossible to find the optimum search radius, since this would imply to know about the optimum and real reservoir representation. It is therefore much more important that the user of BRIGHT knows about the reservoir heterogeneity and decides, whether BRIGHT can be used with a reasonable amount of reliability. The interview screen that will be explained later is intended to make the user aware of whether BRIGHT is the applicable software tool for any given reservoir.

3. Theory

3.1 Rapid Workflow[1, 3, 18]

This chapter is intended to make the reader familiar with the processes and workflow steps that have been performed in RAPID studies. RAPID is a combination of established, industry recognized techniques and Schlumberger internally developed processes that are used to "examine historical data from a reservoir using a series of statistical and analytical techniques to assess, optimize, enhance and manage overall production"[1]. The desired output of a RAPID study is mainly the selection of promising infill well locations, the selection of reactivation candidates (wells that have been shut-in and might be economically successful if being reactivated), recompletion candidates (wells that do not perform too well and should rather be recompleted to injectors or completed in another layer of the reservoir) and work over candidates. RAPID should give a suggestion of which projects to go for and how to proceed in the development of the field.

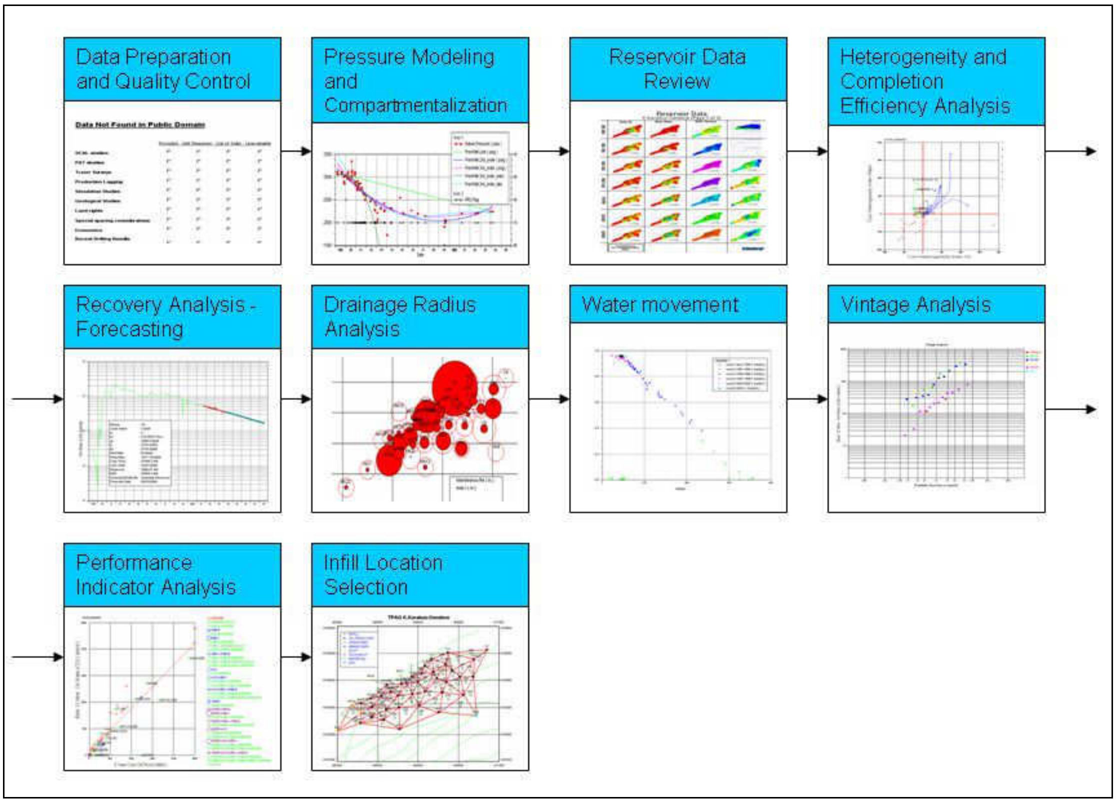


Figure 24: Ten steps of the RAPID workflow

The individual steps of the RAPID workflow as depicted in Figure 24 were defined in the Schlumberger DCS office in Calgary, AB, Canada. As already mentioned the main reason for defining the RAPID workflows is to deliver a guideline for engineers to evaluate a Brownfield and to ensure that a consistent and high quality product is delivered to Schlumberger DCS' customers. Important constraints for a RAPID study are time and money. RAPID studies never took more than 8 weeks; no matter how large the field to be investigated is and the production of how many wells is to be analyzed.

3.1.1 Data Preparation and Quality Control

Data Preparation and Quality Control is the first step in a RAPID study and is probably also the step that takes the longest time. The main objective for this step is to make sure all necessary data have been gathered and are ready to be analyzed. The *minimum data requirement* for a RAPID study is production volumes, injection volumes and some pressure data on a monthly basis for each individual well.

Since RAPID's concept is concentrating on the Canadian working environment, production data usually are easy to obtain since they are publicly available. Data that are available in public domain usually cover:

- Production and Injection volumes
- Pressure data
- Bottom hole locations
- Well status (active or shut-in)
- Operator (company that is operating the well)

Sometimes available, but usually not found in public domain databases are the following parameters.

- KB elevation (Kelly Bushing elevation)
- Formation tops (top depths of reservoir formation), Formation net pay thicknesses, Water saturations, Porosities, Permeabilities, Volume percent of shale
- Completion history (perforations that have been shot, plugs that have been taken, stimulation jobs, etc.)
- Drill stem test summaries

- AOF summaries (Absolute Open Flow Potential determination)
- Deviation surveys

These data are very important for the workflow though. That is why RAPID engineers usually need to obtain some of these parameters from the client companies. Usually MS Access macros have been used to organize the data and keep track of the various data sources.

The purpose of this step is to gather all data and to perform a quick screening to decide whether a RAPID study is possible and how to proceed regarding the data availability and reliability. A location/status map is generated to see whether the given Bottom hole locations are correct and to get a first impression of the field. The status map gives a good overview, which wells are producing, which wells are shut-in and which wells are injecting fluids. Moreover compartments might already be visible. Compartments are certain areas in the reservoir that include wells that have a very similar pressure signature. This similar pressure behavior indicates a pressure and/or fluid communication between the wells in that part of the field and allows to analyze these similar wells together and independently from another compartment, which might have (has) its own pressure system. As can be seen in Figure 25 at least three compartments might be identified in the given field. Of course this assumption has to be checked with the pressure data, which will be described in the next step.

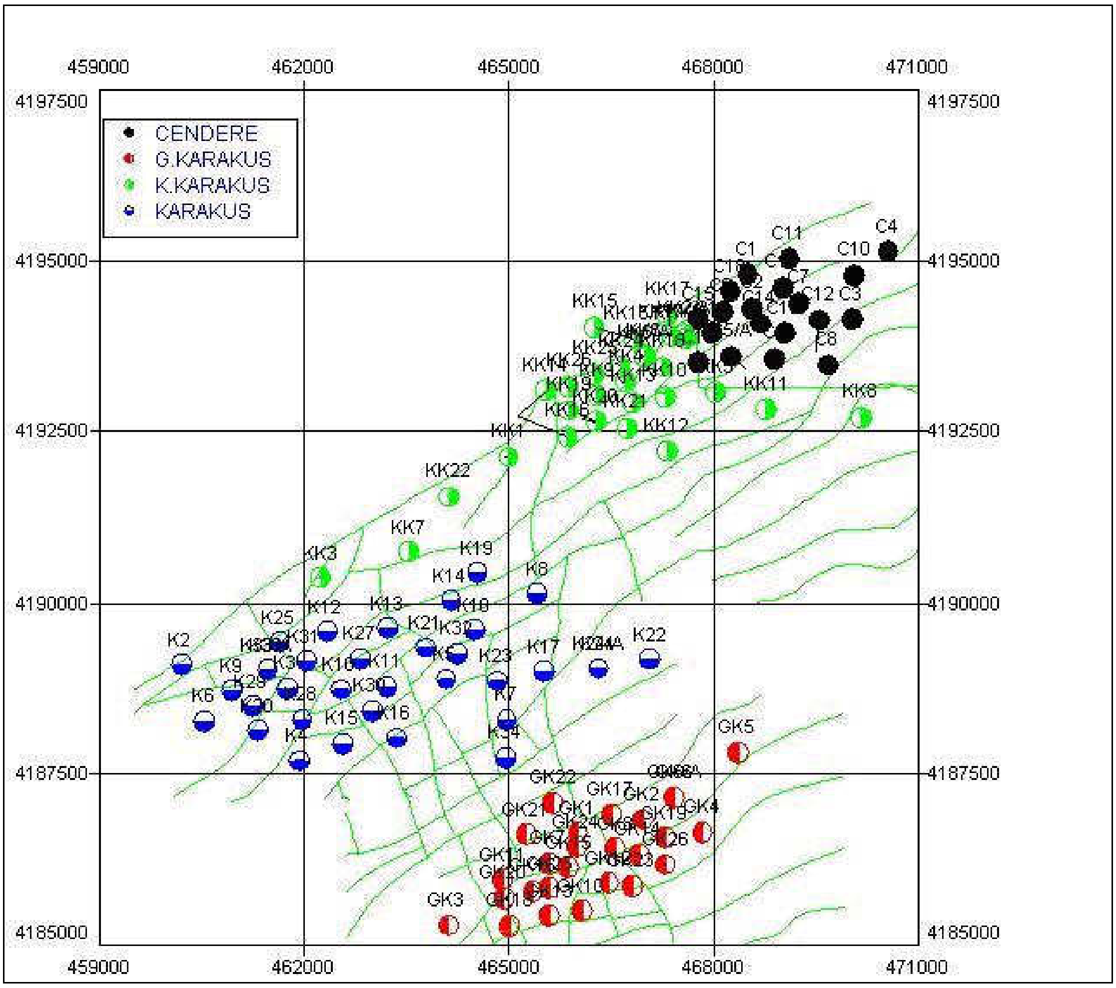


Figure 25: Status map for an oil field[18]

3.1.2 Reservoir Compartmentalization and Analysis

Once the location and the pressure data are available the compartmentalization step can be started. The main reason to compartmentalize the field is to analyze only these parts of a field that behave similarly regarding pressure and production performance. That makes the whole procedure more consistent and comparative.

The first step in compartmentalizing a reservoir is to check the map for very probable compartments. In Figure 25 it is very probable that three compartments will be encountered (the green and black wells in the north, the blue wells in the center part and the red wells in the south).

This geographical compartmentalization has to be checked and validated using pressure data. The problem in this step is that usually only a few pressure measurements per well are available.

At first the pressures have to be corrected to datum depth. The reason for that correction is that the pressure measurements are usually taken at the perforation depth but to make them comparable a reservoir datum depth has to be determined to which all measured pressures are corrected. This datum depth is very simply calculated by:

$$DatumDepth = \frac{1}{n} \cdot \sum_{ActiveWells} (PerforationMidpoint - DepthReference) \qquad \textbf{Equation 15}$$

where *DatumDepth* is the datum depth in [ft], *n* is the number of active wells [-], *Perforation Midpoint* is the depth to the perforation midpoint of the formation of interest in [ft] and *DepthReference* is the Reference Depth in [ft]. Reference Depths are usually Kelly Bushing Elevation or offshore sea level.

The pressure at datum depth is then calculated for each well as:

$$p = p_{perforationMidpoint} + \frac{dp}{dD} \cdot (DatumDepth - PerforationMidpoint) \qquad \textbf{Equation 16}$$

where $p_{perforationMidpoint}$ is the well shut-in pressure at perforation midpoint depth in [psia], *dp/dD* is the well shut-in pressure gradient in [psia/ft], *DatumDepth* is the datum depth that has been determined in Equation 15 in [ft] and *PerforationMidpoint* denotes the depth to the perforation midpoint in [ft].

The pressure correction to datum depth has to be done for each given pressure measurement in the dataset. Afterwards the calculated pressures are plotted versus time for each well.

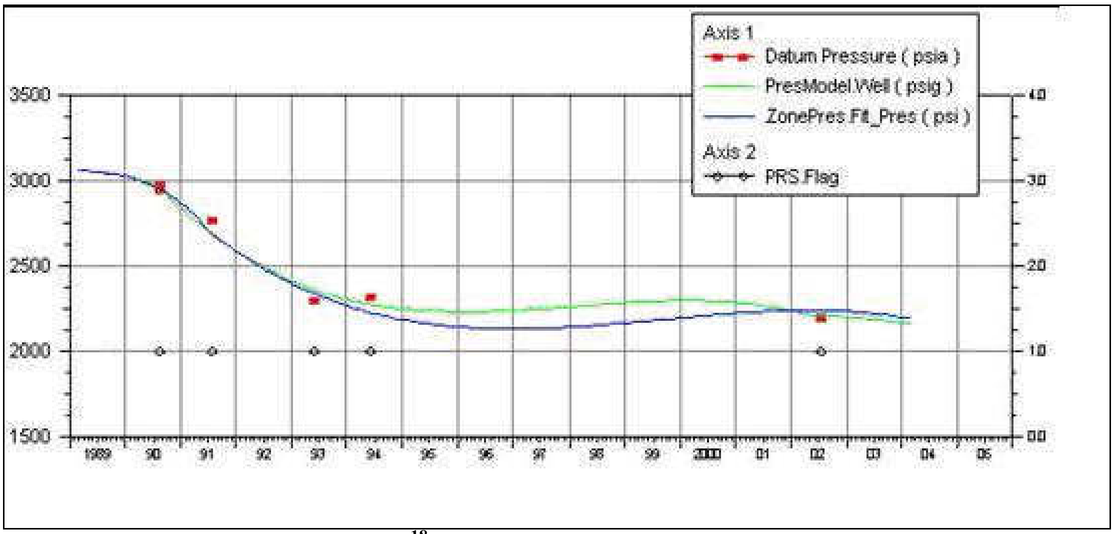


Figure 26: Pressure profile of a well[18]

In Figure 26 the problem of very rare available data is demonstrated. The well in this figure is producing since 1998 and the analysis was done in 2004. During these six years only five pressure measurements were performed as indicated by the red squares in the depiction. Sometimes the situation is even worse as demonstrated in the pressure plot in Figure 27.

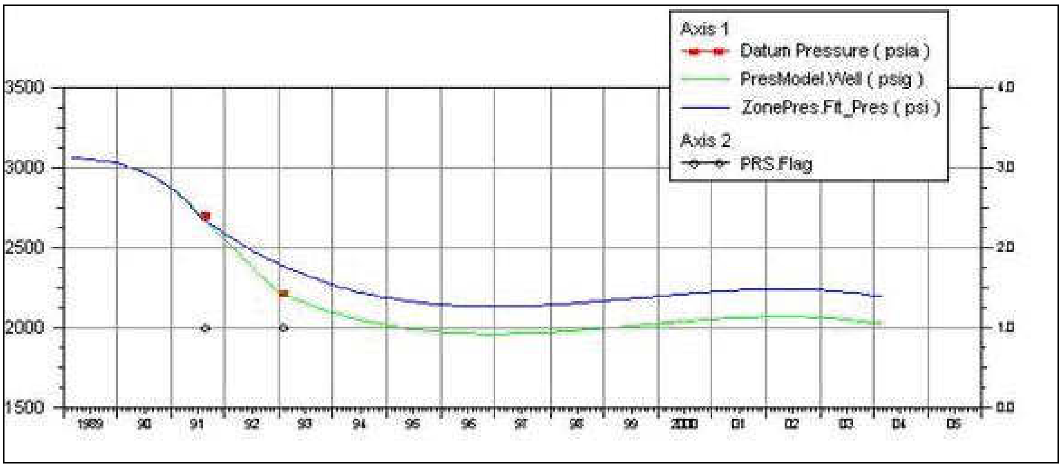


Figure 27: Pressure profile for a well with only two measurements[18]

Only two pressure measurements have been performed in almost 16 years of production.

The way to find a pressure curve during a RAPID study is to use wells with a couple of pressure measurements together in one plot and fit a curve that fits the pressure distribution. This is of course not the most accurate way of determining pressure points for wells. However, considering the constraint due to time and due to lack of adequate measurements, this is probably as accurate as a pressure modeling can get (without applying time consuming Material Balance or numerical flow simulation).

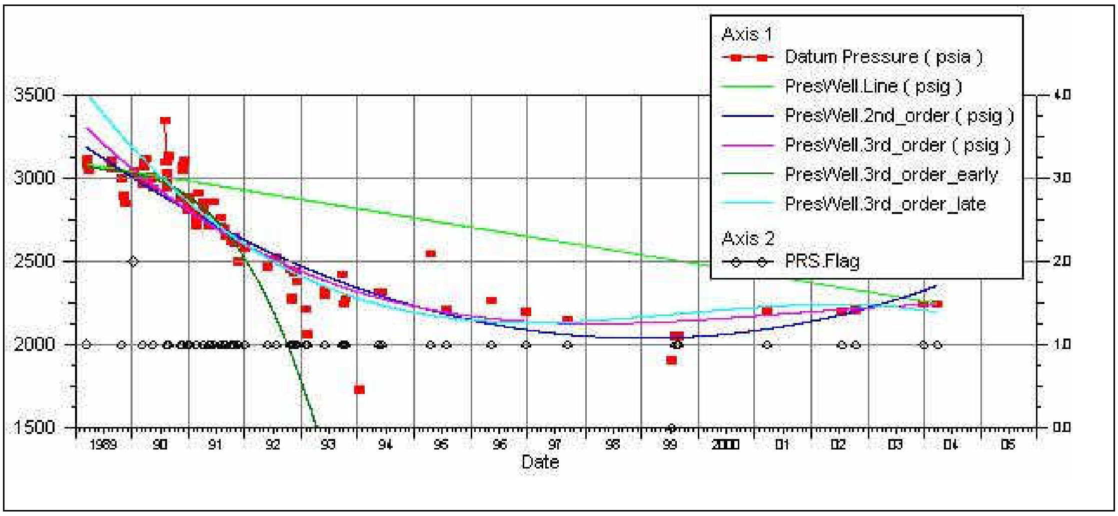


Figure 28: Pressure profile compartment[18]

In the situation presented in Figure 28 the third degree polynomial fit curve was used to describe the pressure in the compartment. In case there are almost no measurements another approach has to be used, since there most probably will not be enough points to match a curve. Usually a rough numerical well inflow simulation model for a few wells is set up to come up with a pressure curve for a compartment. However, considering the already mentioned time constraint the engineers will prefer to first try hard to fit the polynomial curves before they start to set up any numerical flow simulation model.

In the end ordinary Kriging is used to spatially interpolate pressure values within the wells at the same given time points to come up with a pressure map that allocates each point in time a space a certain pressure value.

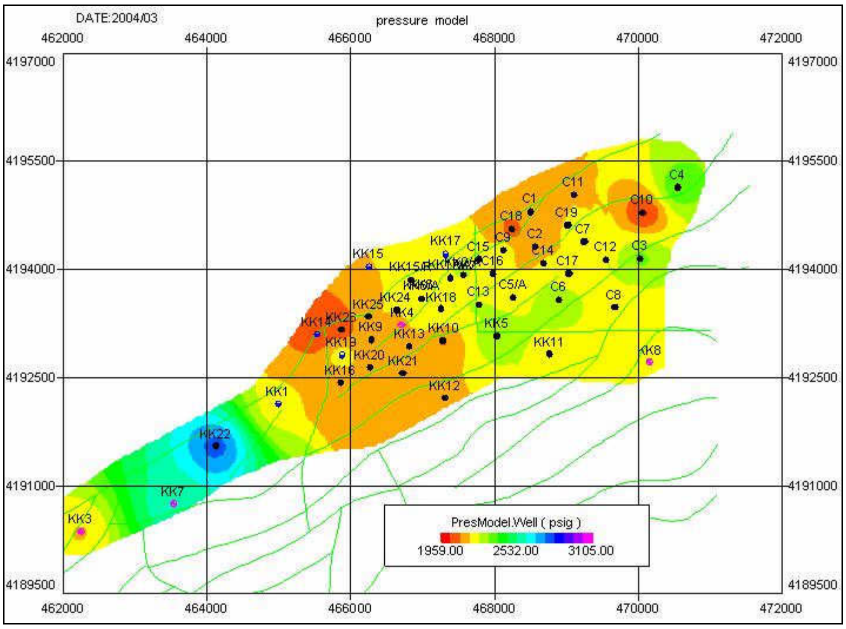


Figure 29: Pressure Map[18]

3.1.3 Reservoir Data Review

The purpose of the Reservoir Data Review is to obtain a deep insight into the performance of the wells in the field. By handling and comparing all of the data and by comparing time dependent data with static data the engineer develops an understanding for the performance of the wells as well as for the geology of the reservoir. The reservoir data review is a graphical analysis where time dependent production performance data as well as static petrophysical data are presented in maps. The objective of this step is to analyze production characteristics of certain areas in the field as well as of specific wells. It is desired to find abnormalities in the field, e.g. areas or wells in the reservoir that are performing well, even though they are in a geologically unfavorable part of the reservoir ('Best Practice Wells') or vice versa.

An example of some of the created diagrams can be seen in Figure 30 and Figure 31.

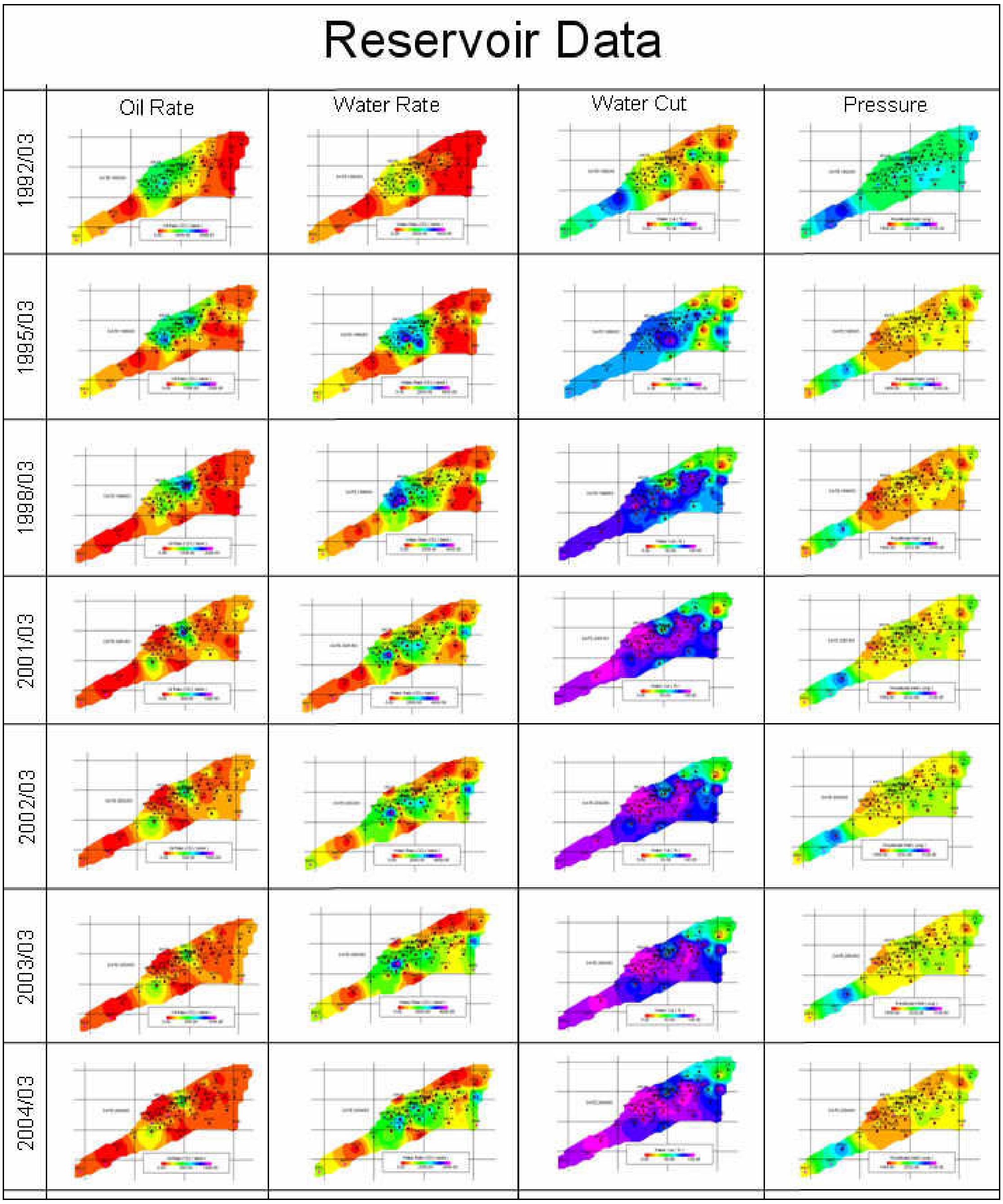


Figure 30: Production Performance Maps[18]

Figure 30 shows the production key performance indicators in a specific time range. Lower values are marked red whereas higher values are blue or violet. The presented key performance indicators are oil rate at the time point defined on the left hand side of the line, water rate, water cut and pressure at the same time point.

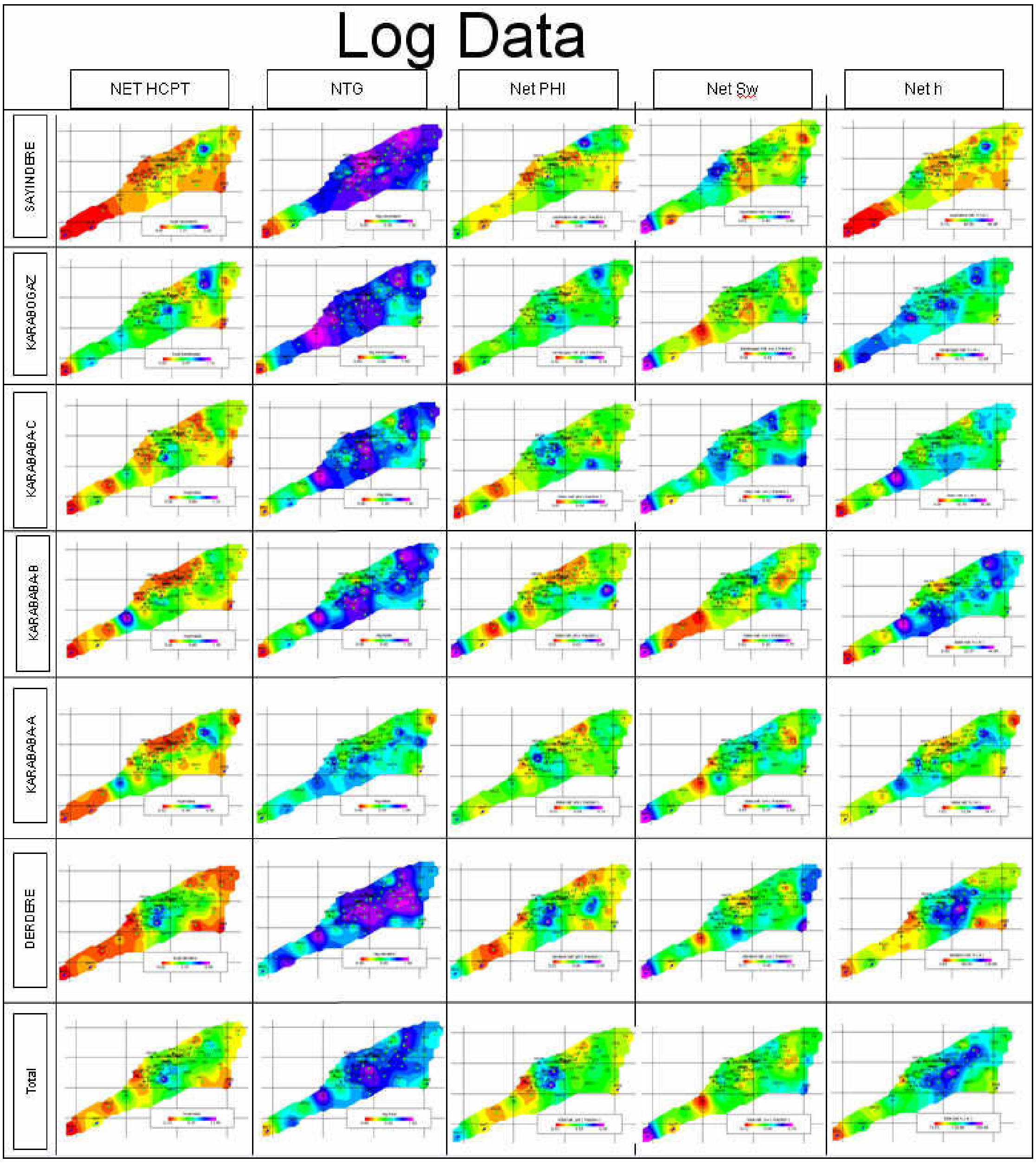


Figure 31: Log Data Maps[18]

Figure 31 shows maps of different log data in different layers of the reservoir. The layer changes from line to line in the given Figure. The parameters presented from left to right are Formation Tops [ft], Net Hydrocarbon pore thickness [ft], net to gross ratio [-], net porosity [-], net water saturation [-] and net pay [ft]. Again low values are highlighted red, whereas high values are marked blue or violet.

These diagrams are usually plotted on very big papers in order to hang them next to each other and to analyze them simultaneously. The objective is to obtain an integrated view on the field, to understand whether good performance is due to good geologic areas or due to better completion, etc.

3.1.4 Heterogeneity Index Analysis[3, 19]

The objective of the Heterogeneity Analysis is to compare the performance of a well with the average performance of a group of surrounding wells. The basic information gain out of this kind of analysis is, which well is producing better or worse than its neighbors.

According to Reference 19 the Heterogeneity Analysis enables the investigator to analyze the well performance based on completion method and efficiency and reservoir quality and 'tank size' (= Hydrocarbons initially in place (HCIIP)). The wells are therefore all normalized regarding their time on production and regarding the reservoir pressure. This allows the comparison of well performances of different wells can be compared without falsifying the results by not considering the impact of different time ranges of historical production.

In RAPID studies a slightly modified equation than given in Reference 19 was used:

$$HI_{Fluid}(t) = \left(\frac{cumulativeFluid\,\mathrm{Pr}\,oduction_{Well}(t)}{cumulativeFluid\,\mathrm{Pr}\,oduction_{\mathrm{Re}\,servoir}(t) \cdot {}^{1}\!/_{n(t)}} \right) - 1 \qquad \textbf{Equation 17}$$

HI_{Fluid} denotes the dimensionless time dependent parameter Heterogeneity Index [-] for any given fluid. This parameter can be calculated for oil, gas, barrel of oil equivalent, condensate, etc. $cumulativeFluidProduction_{Well}(t)$ is the cumulative production of the fluid to be analyzed for a certain well at a time point t ([STB] of [Mscf]). $cumulativeFluidProduction_{Reservoir}(t)$ is the cumulative production volume of the same fluid for the whole field or the whole peer group of wells at a certain time point t, that are used as a reference group ([STB] or [Mscf]). $n(t)$ is the number of active wells at a certain time point t.

The values for the Heterogeneity Index are usually in the range of negative one to one. Sometimes wells behave significantly better thus the value for HI exceeds positive one. A well that performs exactly as the average performance of all the wells in the peer group will have a HI value of zero. The advantage of the slight modification (subtracting 1 from the original HI equation) is that a well that behaves exactly as the average of the surrounding wells has a HI value of zero instead of one as it would be with the original equation.

It is important to notice that this analysis can only be performed if the wells have a somehow similar performance. If there are one or two wells that exceed the well performance of the other wells by far, the average peer group cumulative production volume might be too high to obtain reasonable HI values for the other wells leaving other good wells with too low HI values.

Reese presents a set of type curves in his paper[19]. The basic idea is that a well completion and reservoir performance can be classified according to the features in a plot of HI of the main producing phase (e.g. oil) versus time. For example, a well that starts off with a very low HI (smaller than zero), but later during production shows HI values of larger than zero can be classified as a well with a bad completion but a good performance due to reservoir properties. On the other hand decreasing values of HI indicate that the performance is restricted due to the reservoir size. The completion of a well that starts off with a HI value of much larger than zero can be regarded as exceptionally good.

The following depiction shows the heterogeneity index for oil of a well in the earlier presented field. As apparent in Figure 32 the well is a rather good producer with some slight problems in the beginning. Its completion should be compared to the neighboring wells to see, whether a larger initial HI value would have been possible.

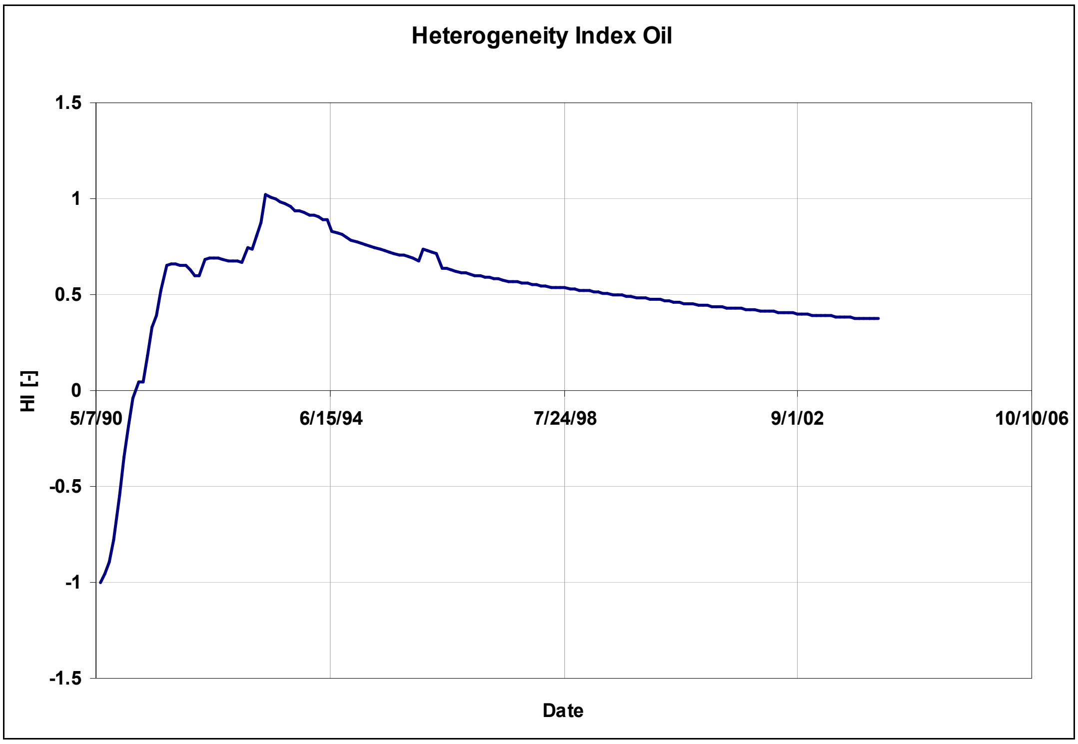


Figure 32: Heterogeneity Index Oil for a well

Figure 33 shows the HI oil versus time plot of a bad performing well. This well starts off with a HI oil value of smaller than one, which indicates a poor completion. The well never recovers and stays below zero all the time. This indicates that not only has the completion been suboptimal also the reservoir performance cannot make up what the mechanics (completion and well installations) have set up badly.

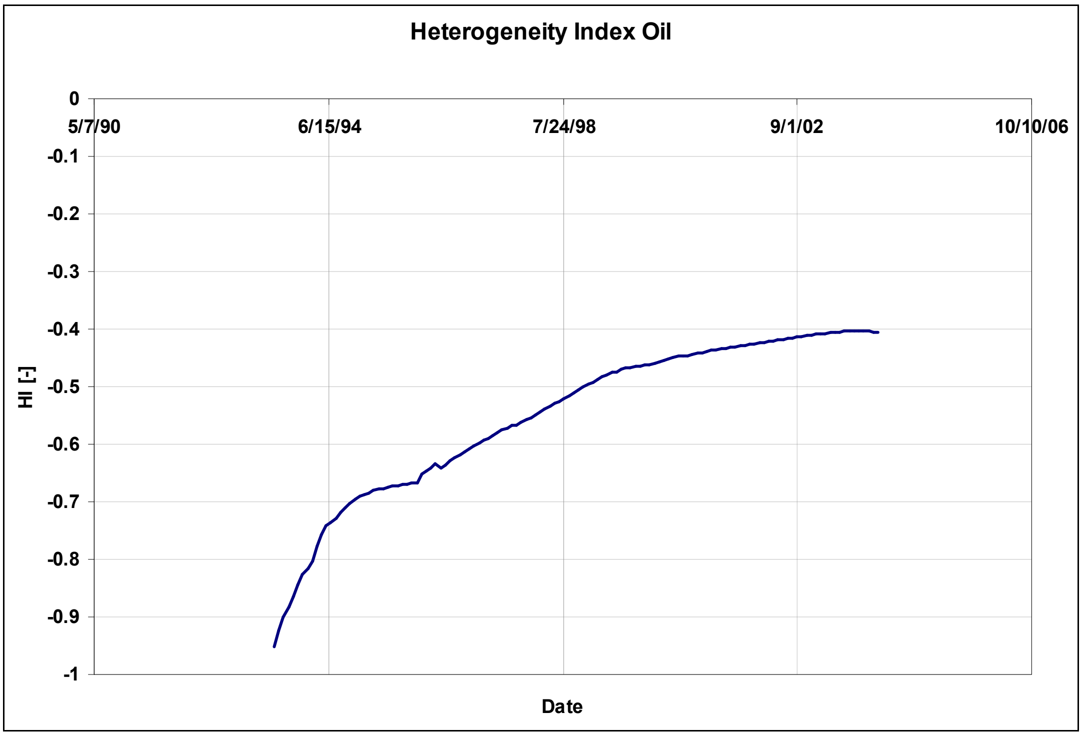


Figure 33: Heterogeneity Index Oil for a well - Bad Performer

In RAPID studies the Heterogeneity Indices of several parameters have been used simultaneously to analyze the performance of a well in an integrated way. The main concern is that a well that is producing more oil than its neighbors should not automatically be identified as a very well completed well, since the water production of the same well can be significantly higher than the average too. A 'best practice' well should therefore have a HI oil of larger than zero and e.g. a HI water value of smaller than zero, which indicates a higher than the average oil production and a lower than the average water production. RAPID engineers plot HI water versus HI oil to analyze the wells.

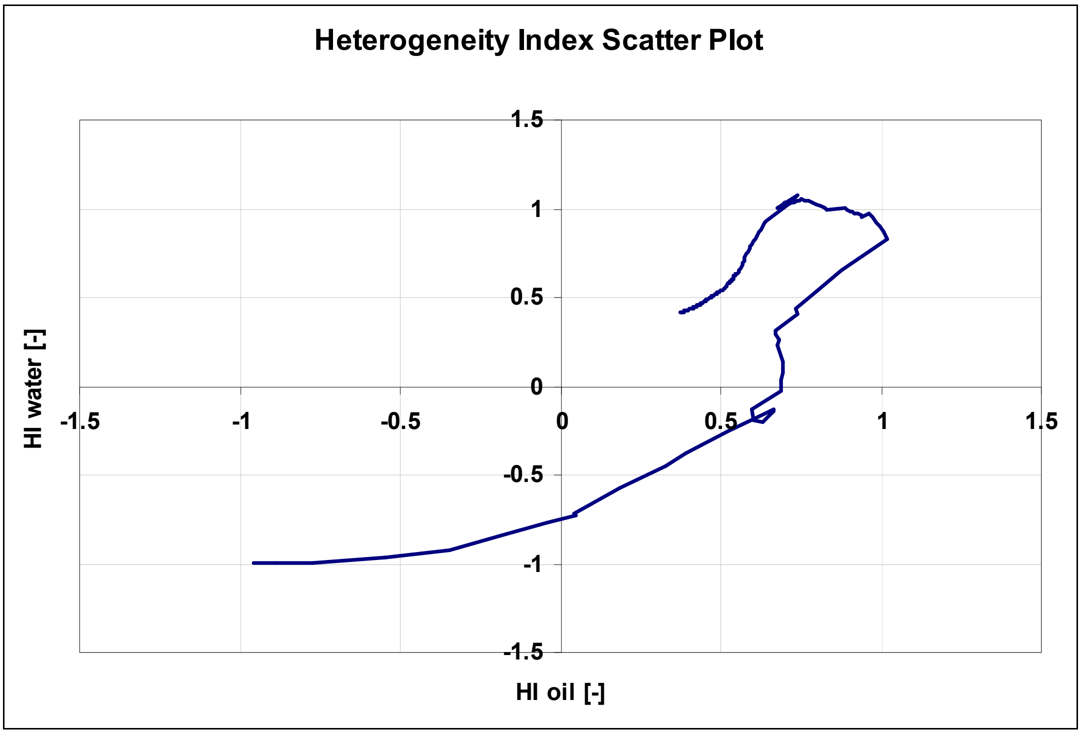


Figure 34: Heterogeneity Index Scatter Plot

The scatter plot assists in analyzing trends in the production performance of a well. The area in the second and third quadrant (top right and bottom left) of the diagram can be regarded as normal areas. If a well's HI water vs. HI oil is located in either one of these quadrants it is performing as expected. That means a well in the second quadrant is producing more oil than the other wells but also more water, whereas a well in the third quadrant is producing less oil than the average well and also less water. HI trends that go into one of these two quadrants are therefore not subject of further investigation.

The situation changes though if a well is in either quadrant one or four. A HI water vs. HI oil value that leads the plot to the upper left quadrant of the plot would mean that the well is producing more water than the surrounding wells yet it is also producing less oil. A well with a HI scatter plot signature like this should be investigated regarding the actions that have been taken (e.g. unsuccessful well interventions such as workovers, stimulation jobs, etc.).

On the other hand a well in the fourth quadrant is performing very well. Basically it can be concluded that it is producing more oil than the other wells and also less water. The well is identified as a 'best practice' well. RAPID engineers would check this well's history to see which actions coincide e.g. with direction changes such as can be seen in Figure 35 highlighted with a red circle.

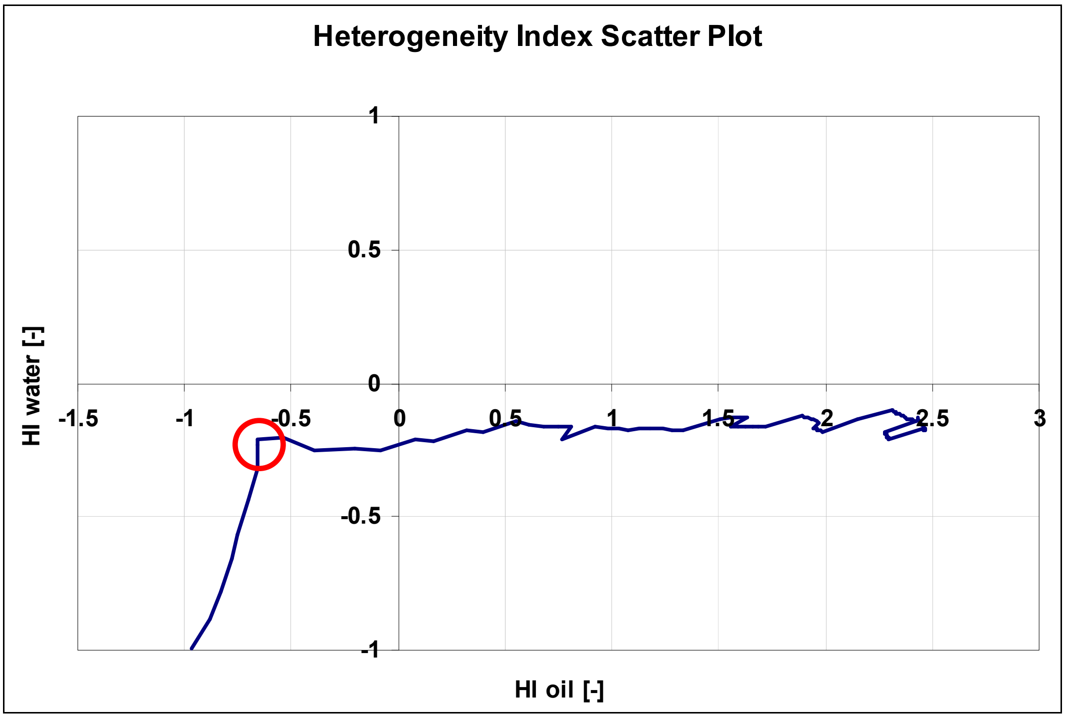


Figure 35: Heterogeneity Index Scatter Plot - well performing well

Finally a comparison on field level will be done to quickly find good and bad performers. To compare the wells on a field level either the whole HI water vs. HI oil plot is used for each individual well, or – as presented in Figure 36 only the last calculated HI oil and HI water values are used.

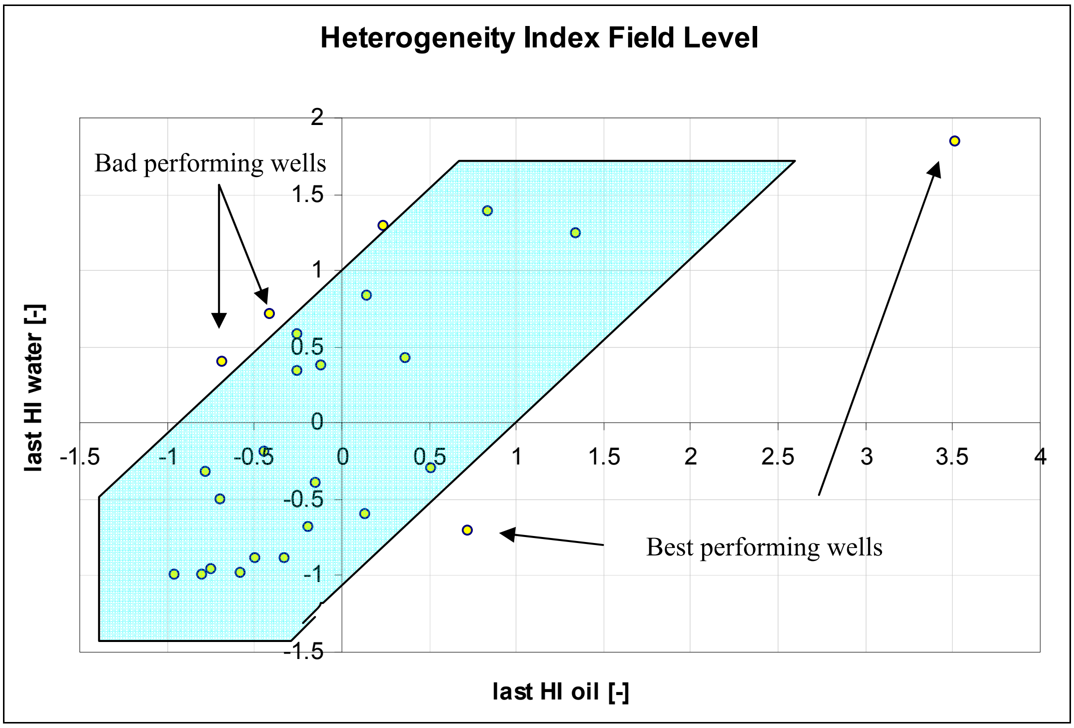


Figure 36: Heterogeneity Index on a field level

3.1.5 Completion Efficiency Analysis

The Completion Efficiency Analysis has a very similar underlying concept as the Heterogeneity Index. However, in that step of the RAPID study a well performance is compared to the petrophysical properties that have been measured at a well's location. The petrophysical properties should lead to conclusions about the quality and potential of a certain part of the formation. While comparing geologic information with the production performance, wells should be identified that perform better than expected.

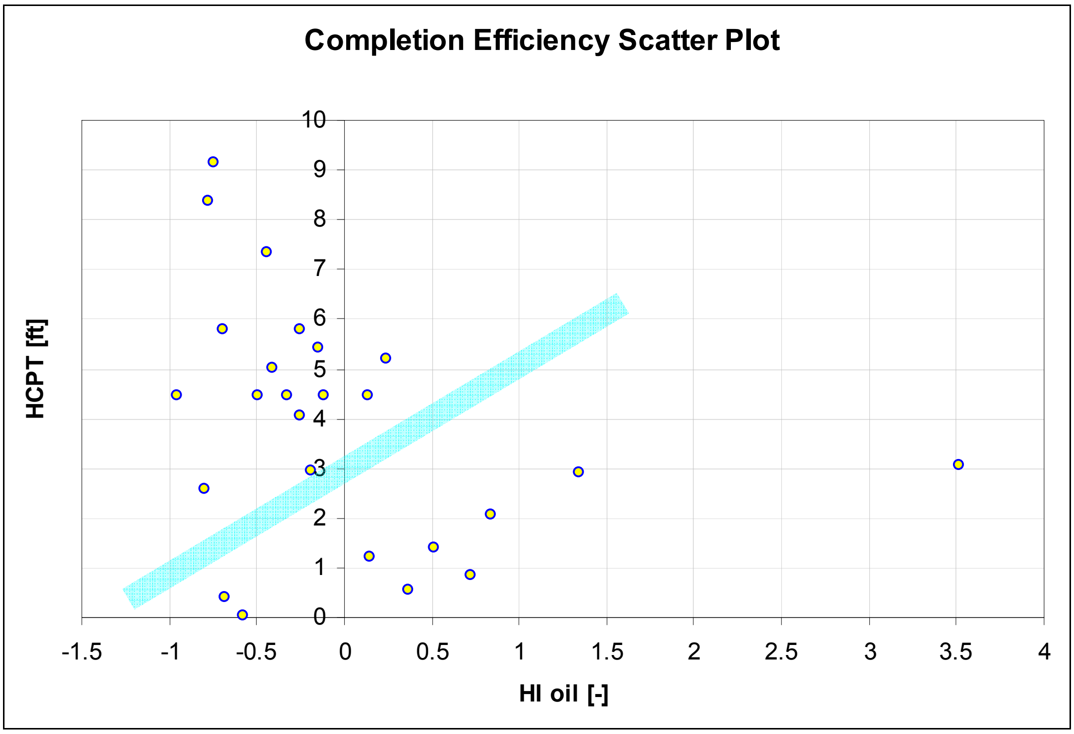


Figure 37: Completion Efficiency Scatter Plot

Figure 37 shows HCPT (Hydrocarbon pore thickness) [ft] vs. HI oil. HI oil is calculated according to Equation 17, HCPT is calculated as:

$$HCPT = h \cdot \phi \cdot (1 - sw)$$ **Equation 18**

Where h denotes the average net pay thickness in [ft], ϕ denotes the average reservoir porosity as a fraction [-] and s_w stands for the average reservoir water saturation [-]. HCPT is an indicator of the hydrocarbon potential of a formation. A high HCPT but low HI oil is encountered for wells that produce worse than the geologic potential would allow.

The blue bar divides the good performers (below the blue bar) from the bad performers (above the blue bar). Wells below the blue bar, especially those towards the right end (high values for HI oil) should be subject to deeper investigation of actions that have been taken in the life time of the well. Since they are performing very well their completion technique should be investigated as well as all well interventions during the life time of the well (e.g. stimulation jobs, workovers, etc.).

Especially the Heterogeneity Index Analysis and the Completion Efficiency Analysis should give a good overview of which wells need intervention. It should furthermore indicate which well interventions have been more successful than others. Therefore a good database of interventions and their impact as well as a good outline of what actions have to be taken in future should be available to the engineer.

3.1.6 Recovery Analysis

To estimate the production potential for each well production decline techniques (Decline Curve Analysis, Water cut prediction, etc.) are employed. With the help of Decline Curve Analysis the engineers determine the following key performance indicators:

- *Estimated Ultimate Recovery (EUR)* ([STB] for oil wells and [Mscf] for gas wells): EUR is the well’s cumulative production to the end of forecast life (e.g. date at which production rate is equal zero)
- *Forecast Life [days] or [months]:* The production rates in the DCA plots are extrapolated until the production rate is equal to zero. The first day at which this condition is true is the last day in the production of a well. The time until this date is calculated and mapped as ‘Forecast Life’.
- *Estimated three/five year recovery in [STB] or [Mscf]:* Even though in many fields the production decline allows production forecasts for another 15 or 20 years it is not very accurate to predict the production for more than three or five years. RAPID engineers usually predict the well’s future performance with a discrepancy of 1% within a year. However, the longer the forecasting time range the less reliable the forecasted volumes are and the higher the expected discrepancy between forecast and actual values.

- *Remaining Reserves in [STB] or [Mscf]:* This value is describing the remaining production potential of a well. It is calculated as:

  $$RR = EUR - Q$$ **Equation 19**

  Where RR denotes the Remaining Reserves in [STB] or [Mscf], EUR denotes the Estimated Ultimate Recovery as described earlier in this chapter and Q is the cumulative hydrocarbon production until the forecast start date.
- *Decline Rate in [1/d]:* The decline rate is an indicator of how fast the production rate is depleting and therefore combined with the available values for 'Estimated three or five year recovery' or 'Remaining Reserves' is a good indication of how much of a production potential is in a certain area.
- *Initial Production Rate [STB/d] or [Mscf/d]:* The initial production rate is the production rate encountered at the forecast start date. E.g. if the last day in the production history of a field is 3/1/2004, then 'Initial Production Rate' would be the forecasted production rate at 4/1/2004. An analysis of 'Initial Production Rate' gives a good overview on how well certain wells are doing in terms of production rates and reservoir pressure.

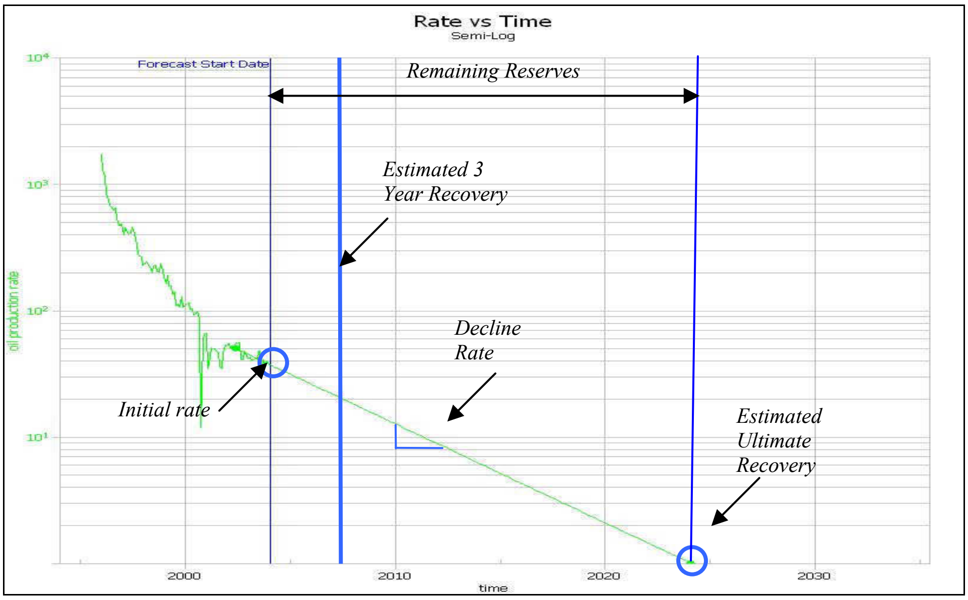
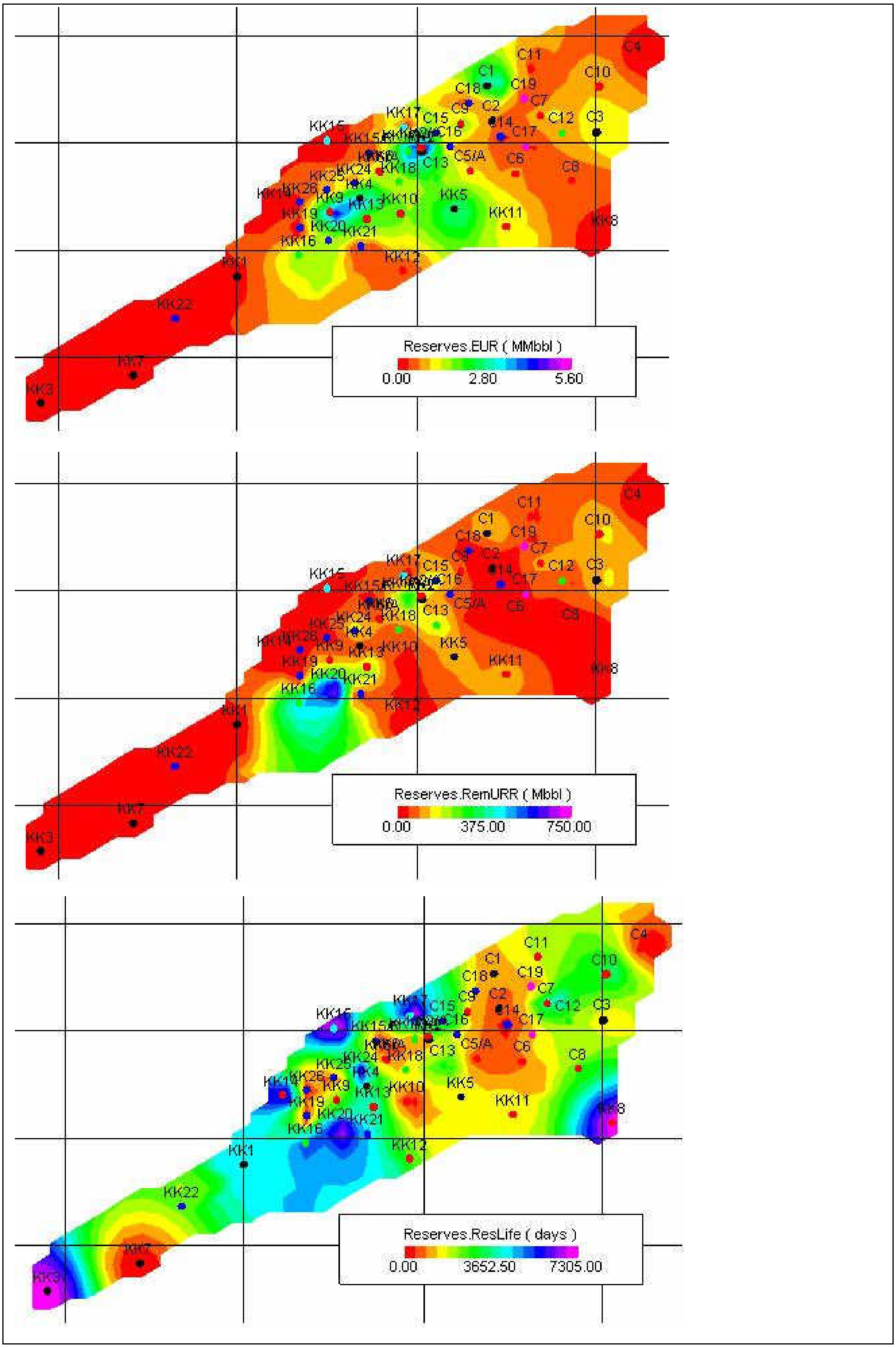


Figure 38: Forecast Key Performance Indicators

During that step of the RAPID analysis the team of engineers wants to get an outlook on field performance in the nearer future. The six mentioned parameters are determined for each well and are spatially interpolated (ordinary Kriging) and mapped to compare them on a field level.


Reserves.EUR (MMbbl)
0.00 2.80 5.60
Reserves.RemURR (Mbbl)
0.00 375.00 750.00
Reserves.ResLife (days)
0.00 3652.50 7305.00

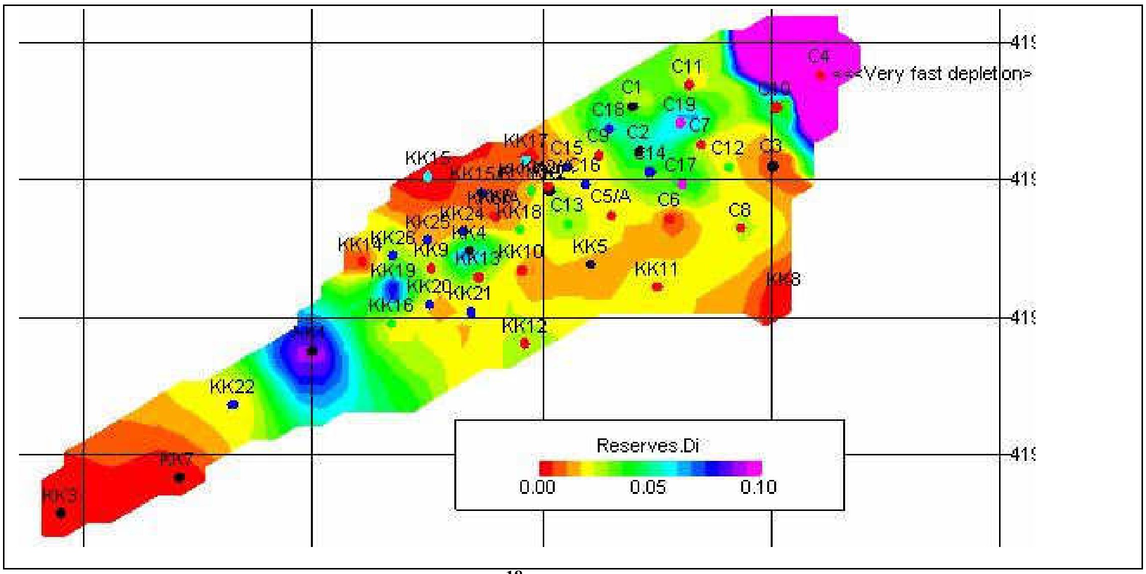


Figure 39: Maps of Forecasted Parameters[18]

Apparent in Figure 39 is a rather promising central area of that field. The EUR as well as the Remaining Reserves show rather good values as well as the Decline Rate as interpolated is expected to stay below 0.05 [1/d]. This information will be used especially for the recommendation of infill candidates and reactivation candidates.

3.1.7 Drainage Radius Analysis[24]

The main purpose of this step in the analysis is to allocate a certain area around the well as the drainage area of that particular well and to plot this drainage area on a bubble plot for each well. Hence it will be very easy to find parts of the field that are not drained yet; this assists in the picking of infill locations.

Precondition in order that this step can be accomplished is the availability of petrophysical information such as average net pay, average reservoir porosity and average reservoir water saturation). It is very important not to confuse the drainage radius calculated here with drainage radius used in transient well testing. The drainage radius here is calculated based on production data and volumetric calculations and will show areas that have been drained and not, as is the case in well testing and simulation, the areas contributing to flow. Depending on the drive depletion mechanism the drainage radius is calculated as presented:

- If the production of hydrocarbons for the reservoir is assumed to be steady state ($\frac{\partial p}{\partial t} = 0$, e.g. due to water influx, water drive, etc.), the drainage radius is defined as:

$$r_e = \sqrt{\frac{43560 \cdot Q \cdot B_o}{7758 \cdot \pi \cdot h \cdot \phi \cdot (1 - s_w - s_{or})}}$$

Equation 20

- If the production is in a semi-steady state ($\frac{\partial p}{\partial t} = const$), the drainage radius can be calculated as:

$$r_e = \sqrt{\frac{43560 \cdot Q}{7758 \cdot \pi \cdot h \cdot \phi \cdot \left(\frac{1 - s_{wi}}{B_{oi}} - \frac{1 - s_w - sg}{B_o} \right)}}$$

Equation 21

In Equation 20 as well as Equation 21 the parameters are: r_e is the drainage radius in [ft], Q is the cumulative hydrocarbon production in [STB], h is the average reservoir net pay thickness in [ft], ϕ is the average reservoir porosity given as a fraction [-], s_w is the average reservoir water saturation at current conditions [-], s_g is the average reservoir gas saturation at current conditions [-], s_{or} is the residual oil saturation [-], B_o is the formation volume factor for oil at current condition [bbl/STB] and B_{oi} is the formation volume factor for oil at initial conditions.

The drainage radii are presented in a bubble map where the bubble size is proportional to the drainage radius size. That way it is easy to find undrained areas in the reservoir.

For gas reservoirs interference radii are calculated rather than drainage radii; the latter are more associated with oil wells since they present swept areas. The interference areas show the area around a well, where the pressure is affected by a certain gas well. It is therefore very possible that interference areas of several wells overlap, which indicates that these wells might have a decreased performance. Areas that are not part of the interference area of any well, are potentially good infill locations.

3.1.8 Secondary Phase Movement Analysis

This analysis step should provide information about swept and unswept areas due to water movement in the reservoir. If secondary phase (e.g. water) production is tracked spatially over time, it is possible to generate maps of e.g. equal water cut, thus getting a good estimation about the sweep in the reservoir. The engineers usually generate a set of maps displaying the movement of water (e.g. last 5 year cumulative water production in a map, cumulative water cut in a map, etc.). The output of this analysis step is identification of swept areas and of permeability trends.

3.1.9 Vintage Analysis

Vintage Analysis is another important step in the RAPID workflow. Its purpose is to group wells by specific events to compare the characteristics of groups of wells in time. Very often the events to classify the wells into time groups are either found in a plot of initial production rate of the wells versus time or number of active wells versus time. The idea of both plots is to reliably define time ranges in the development of the field's life. For example in Figure 40 several development stages in the life of the field can be distinguished.

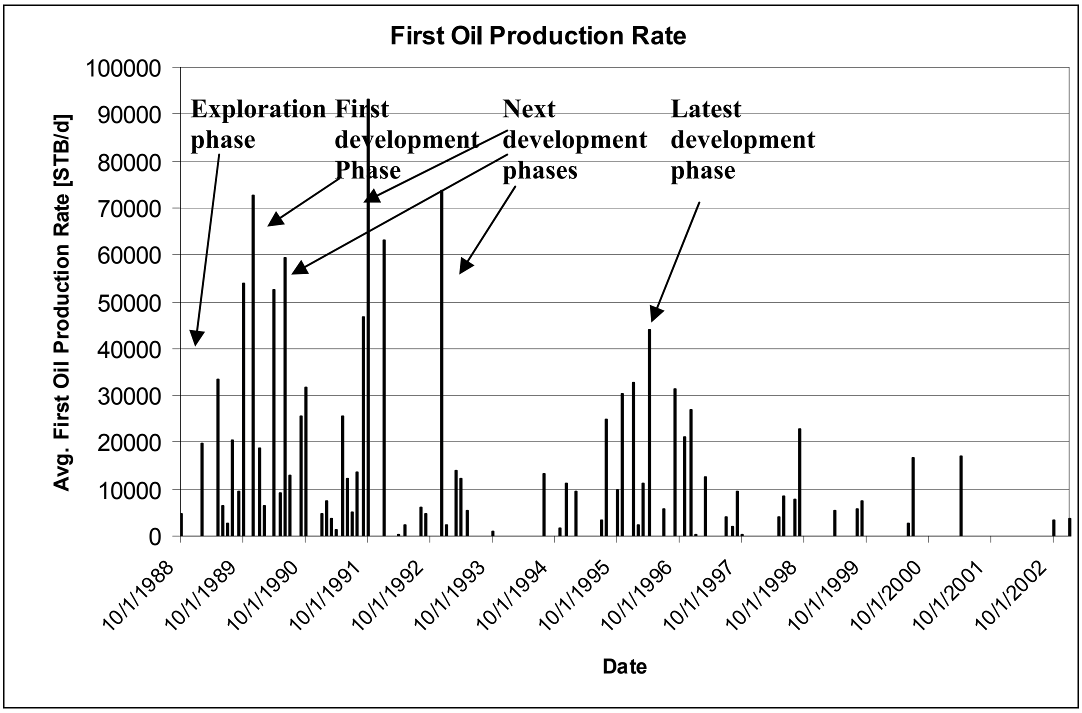


Figure 40: Vintaging - Event Identification

After the vintage groups have been determined the analysis starts. With Vintage Analysis engineers try to see how a new well will be performing and to verify their forecasts. The visual tool to do this is the Cumulative Frequency Plot (CFD Plot). An example of a CFD plot is shown in the next depiction.

The figure shows a plot of a common key performance indicator versus cumulative frequency on a semi logarithmic plot. Best 12 month oil production in [STB] is determined by computing the 12 month moving average of the oil rate and the maximum value is the value used as 'Best 12 month oil production'. The way to calculate the cumulative frequency CFD is presented in the artificial example below:

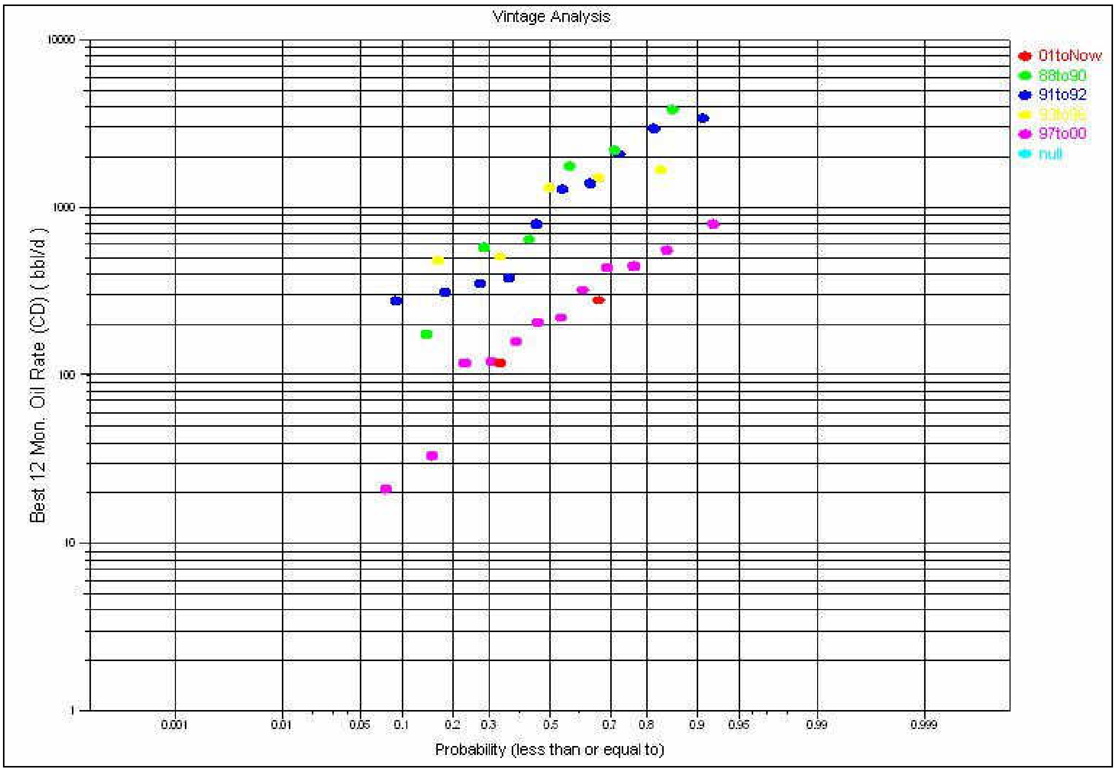


Figure 41: CFD Plot Best 12 Month Oil Rate [STB/d][18]

Step 1: Categorize the wells into the different vintage intervals. Determine the number of wells in a vintage group.

Step 2: Rank the parameter to be analyzed within a vintage group

Step 3: The cumulative frequency is calculated as:

$$CFD = {(RankWell - RankWellout)}\Big/{n+1} \qquad \textbf{Equation 22}$$

CFD is the cumulative frequency value for that well [-], *RankWell* is the rank of the well's parameter, *RankWellout* is the parameter rank of the well with the lowest rank that is not in the same vintage group as the well for which *CFD* is calculated. n is the number of wells in the vintage group.

Step 4: The parameter to be analyzed is plotted against the respective values for CFD.

Well	Vintage Interval	EUR	Rank	**CFD EUR**	Number of Wells in Interval
Well 1	1	5600	1	**0.167**	5
Well 2	1	6200	2	**0.333**	5
Well 3	1	7300	3	**0.500**	5
Well 4	1	8200	4	**0.667**	5
Well 5	1	8900	5	**0.833**	5
Well 6	2	5500	6	**0.250**	3

Well 7	2	5900	7	**0.500**	3
Well 8	2	7900	8	**0.750**	3
Well 9	3	3800	9	**0.100**	9
Well 10	3	3900	10	**0.200**	9
Well 11	3	4200	11	**0.300**	9
Well 12	3	4800	12	**0.400**	9
Well 13	3	4900	13	**0.500**	9
Well 14	3	5300	14	**0.600**	9
Well 15	3	5900	15	**0.700**	9
Well 16	3	6200	16	**0.800**	9
Well 17	3	7000	17	**0.900**	9
Well 18	4	2100	18	**0.111**	8
Well 19	4	2400	19	**0.222**	8
Well 20	4	2600	20	**0.333**	8
Well 21	4	2700	21	**0.444**	8
Well 22	4	2900	22	**0.556**	8
Well 23	4	3200	23	**0.667**	8
Well 24	4	3600	24	**0.778**	8
Well 25	4	4000	25	**0.889**	8
Well 26	5	1800	26	**0.167**	5
Well 27	5	1900	27	**0.333**	5
Well 28	5	2000	28	**0.500**	5
Well 29	5	2100	29	**0.667**	5
Well 30	5	2200	30	**0.833**	5

Table 6: CFD calculation

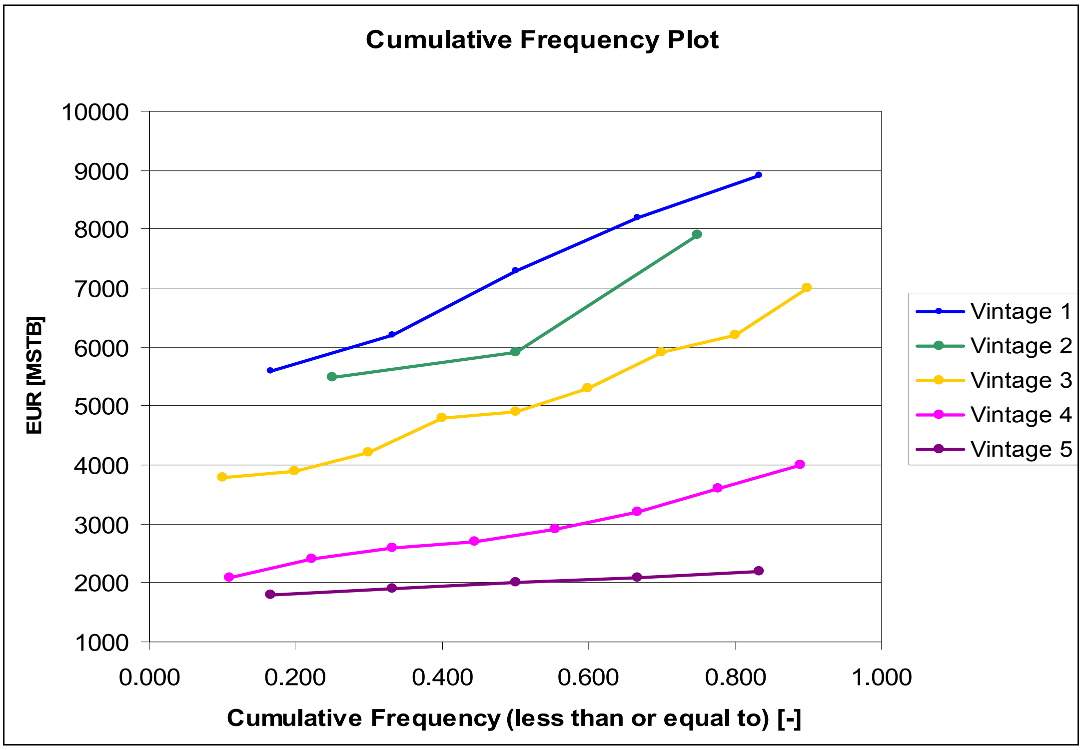


Figure 42: Cumulative Frequency Plot

The forecast for a new well has to fit in into the pattern that can be recognized out of these five curves. If a new forecast for example would end up above the curve for vintage interval three the results of the forecast should be seriously questioned. Usually RAPID engineers are satisfied if the new forecasts can be plotted on or below the curve for the latest Vintage interval (in Figure 42 Vintage Group 5).

3.1.10 Performance Indicator Analysis

This step is purely a statistical analysis of production performance. A set of key performance indicators is calculated and plotted in scatter diagrams to investigate, whether there are correlations. Common indicators are: Best 12, 6, or 3 month production rates [STB/d] or [Mscf/d], 10, 5, or 3 year cumulative production [STB] or [Mscf], initial production rates [STB/d] or [Mscf/d] and average well spacing [ft].

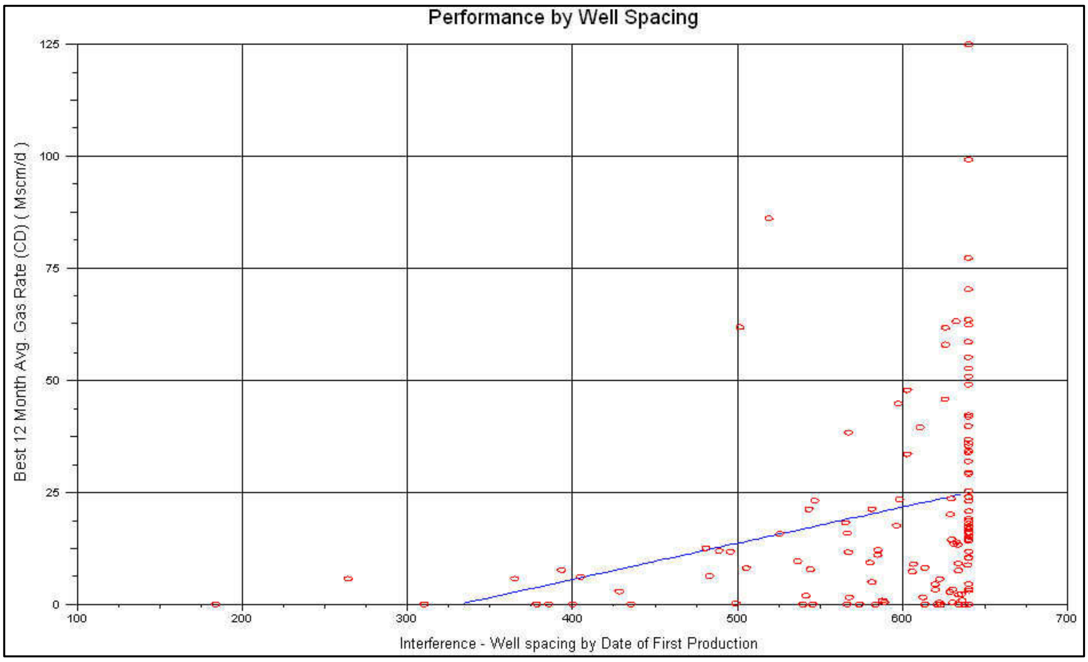


Figure 43: Best 12 month production rate versus Well spacing

Figure 43 shows that wells with a larger well spacing tend to have higher values for ‘Best 12 month average gas rate’, which would lead to the conclusion, that a new infill well should be placed in a location where maximum well spacing can be guaranteed.

3.1.11 Infill selection

The last step in the RAPID process is to identify potentially good infill locations. “Infill location” in this document is a possible well location in the reservoir that is analyzed for its probable hydrocarbon production. A series of key performance indicators is calculated for the existing wells and by using ordinary Kriging these key performance indicators are spatially interpolated for the infill locations. The key performance indicators used are:

- *Initial Production Rate [STB/d] or [Mscf/d]:* As defined in the Chapter about Recovery Analysis, the ‘initial production rate’ is the hydrocarbon production rate at the forecast start date.
- *4 months average oil/gas rate [STB/d] or [Mscf/d]:* This is the four months moving average of the rate. The major idea to use the 4 months moving average in addition to the rate is that the last rate value might not be representative for the recent production history. A four months moving average however rules out the chance of a wrong result due to an outlier as a last value.
- *Productivity Index hydrocarbon phase: [STB/psi d] or [Mscf/psi d]*
- *Productivity Index total liquid [STB/psi d]*

For each location four different values for initial rate are given, two from the above rates and the other two calculated from the Productivity indices. The spread of these four values is proportional to the associated uncertainty; the larger the four values are apart from each other the lower is the reliability of the forecast.

The team of engineers tries to incorporate all of this information to find spots in the map that could be good infill locations. The difficulty is to rank the large amount of wells considering the multidimensional data space. Once the ranking is done, the best wells will be suggested as promising locations for infill wells.

The list of the infill locations will then be presented to the client, together with a list of work over candidates from earlier workflow steps. This is the point, where the RAPID study ends.

3.2. BRIGHT Workflow

3.2.1. Introduction

The workflow in BRIGHT basically follows a very similar structure as just discussed for the RAPID workflow. In this introduction chapter the workflow steps will be introduced. The details about the individual workflow steps can be found in the following chapters.

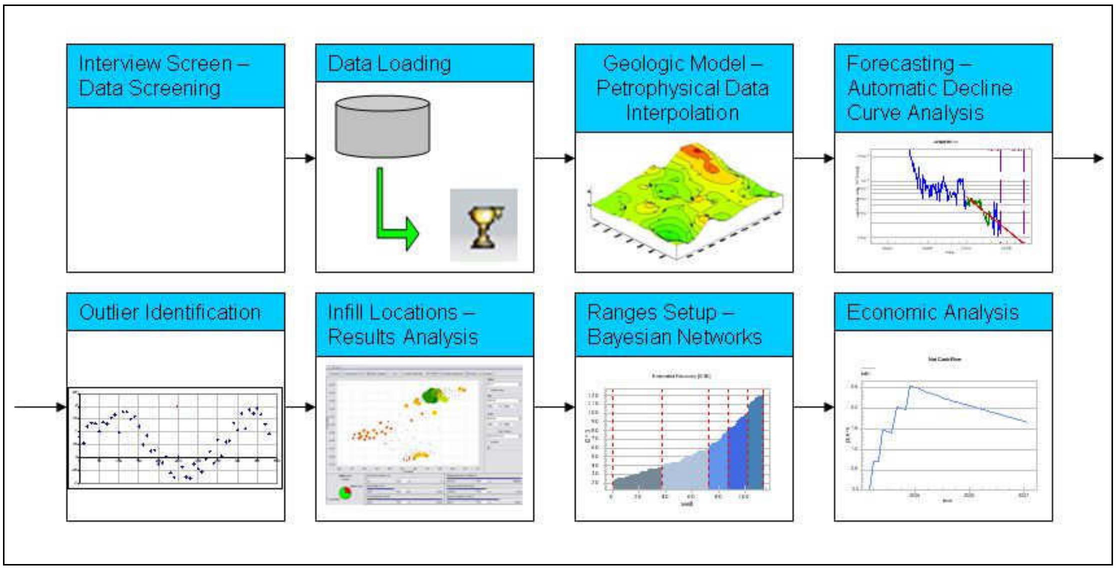


Figure 44: BRIGHT's Workflow

The main objective in BRIGHT's development was to simplify the working steps thus minimizing the necessary user intervention. The software is set up in a way that the user is guided in a correct order through the individual steps.

Due to the highly automated nature of BRIGHT the user is not required to work intensively on data preparation anymore (except for preparing the database to be used in BRIGHT). Associated problems are that the user is not that familiar with the data as she or he would be after a rigorous and long 'Data Analysis and Quality Control' step in RAPID. Therefore an 'Interview Screen' was introduced to make sure that the user is familiar with the given field. The interview asks general questions about the reservoir and automatically determines whether BRIGHT is an applicable software tool for the given problem.

In BRIGHT as well as in RAPID a lot of interpolation work and forecasting is done and so BRIGHT as well as RAPID relies heavily on having very smooth and reliable data. If the interview screen logic concludes that this cannot be guaranteed, BRIGHT is most probable not a suitable software tool for the given problem.

3.3. Interview Screen

The purpose of the interview screen is to check, whether BRIGHT is the applicable software tool for a given situation. The main concern in the development of BRIGHT is that the users, who use BRIGHT do not have to work a lot with the data. This situation is even more severe, if the data are already prepared in a well organized database. The user only has to retrieve the data from that database and is not bound to check the data before the analysis. The interview screen therefore asks questions about the reservoir to make sure whether the person, who is using BRIGHT is familiar with the situation - or motivated by the questions in the interview screen - starts to make himself or herself familiar with the reservoir and the environment of the BRIGHT study.

The questions are divided into several categories, each of which is covering a certain aspect of the study:

- Project Info: The project info contains general information about the project which is very useful to organize the project. It contains information about the field name, the Client Company, contact persons, regions, etc.

  BRIGHT will ask here whether the production and injection rate data are reliable. If ‘No’ is clicked here, BRIGHT will explicitly warn the user to use BRIGHT and in case the user wants go on, she or he is strongly advised to proceed carefully.

  Moreover the Project Info screen is querying very important information about the fluid system. There are question about what is the primary producing phase (e.g. Oil or Gas), what is the most important secondary phase (e.g. Water, Condensate, Sand, etc.), if there is free gas evolvement in the reservoir, etc.

  The Project info tab of the interview screen will result in a basic recommendation about whether BRIGHT is applicable in the given situation. Problems arise if the given data are not reliable, if the gas oil ratio (GOR) is significantly higher than the initial GOR (indication of free gas evolvement and therefore a complicated three phase recovery mechanism) and if an injected phase other than water is selected.
- Reservoir Characterization: The questions in the ‘Reservoir Characterization’ mainly gather information about boundary conditions and about the “degree

of unconventionality”; e.g. BRIGHT is asking about Dual Porosity or Dual Permeability behavior, which is mainly encountered in highly fractured reservoirs or whether the given reservoir is an unconventional gas reservoir (which in general behaves a lot different than a ‘usual’ reservoir in terms of production). Other important questions are whether more than one layer is present in the reservoir and whether commingled production takes place. Commingled production means that a well is completed and producing in several layers simultaneously, sometimes without multiple completions (only one production tubing is installed; therefore it is very difficult to back allocate the total production volumes to the respective layers). BRIGHT (as well as RAPID analysis) is only capable of analyzing a single layer or a multilayer system with communication between the layers. If more than one layer is present and the layers are isolated, an accurate allocation of the production volumes to the respective layers has to be assured and the layers should be analyzed individually. Otherwise the consistency of the analysis is not given and production performances in one layer are compared with production performances in a probably completely differently behaving layer.

- Operating Strategy: As the name says, the ‘Operating Strategy’ tab is focusing on how the reservoir is being produced. It has to be pointed out here, that BRIGHT right now can only be applied in a water flood reservoir. Due to very complex flow physics other EOR projects (e.g. gas injection, Steam injection, polymer injection, etc.) would lead to a too complex flow behavior and therefore the interview screen issues a recommendation to not use BRIGHT.

  BRIGHT checks for the existence of highly deviated or horizontal wells. The problem with highly deviated or horizontal wells is that their drainage area is different than the drainage are of an (almost) vertical well. It is rather elliptical with the larger half-axis along the deviated section of the well[8]. However, in the calculation of many performance indicators (e.g. Hydrocarbons in place, sweep efficiency, etc.) BRIGHT is using a drainage area determined solely based on the geographic location of the completions (see chapter about Voronoi Grid). BRIGHT does not take into account the different drainage shape due to a specific well geometry and therefore the interview screen warns in case highly deviated or horizontal wells are present. Moreover BRIGHT checks whether there was no recent change in the operating strategy. A recent change in operating strategy would be the installation of pumps in several wells, the change of surface installation pressure or generally the change in any production performance relevant parameter. Changes in operating strategy introduce transient behavior of production rates and pressure to the performance of the wells and therefore one of the main constraints for the forecasting engine in BRIGHT is not fulfilled; steady state or pseudo state production.

- Data Availability: The Data Availability check is intended to give the user a feeling of what data are necessary and to give BRIGHT a chance to check, whether enough data for a statistically sound analysis are available. BRIGHT will compute a score according to an internal logic to evaluate the data availability. It is important that there is a statistically reasonable amount of wells and of production volume data history.

  Minimum Data requirement for a BRIGHT study in the current version is:

  Time dependent data:

  - Production data (e.g. monthly oil production volumes [STB] or monthly gas production volumes [Mscf], monthly water production volumes [STB])
  - Injection data (monthly water injection volumes [STB])

  Static data:

  - Average net reservoir thickness [ft]
  - Average net reservoir porosity [-]
  - Average net reservoir water saturation [-]

  However, the user has the chance to acquire much more data for the sake of organization or to use the data in other applications that can access the database.

An internal scoring algorithm will determine a score for the individual steps in the interview and will come up with a final score. According to that score the output will be OK, Warning or Problem. The associated recommendation is, whether to go on with the study, to go on with the study with increased caution or to reconsider the application of BRIGHT for the given situation.

3.4. Petrophysical Data

One of the cornerstones in BRIGHT is to not only look at production rates and mechanical performance indicators but also set them into relation to the geologic environment. To be able to analyze the geologic surrounding of a well or an infill location, a geologic model has to be set up. Of course, the geologic model in BRIGHT will be rather simple, but considering the usually very limited data availability a simple model is generally a very good representation of the project reservoirs; the correctness of a highly sophisticated geologic model cannot be guaranteed given the lack of available data.

3.4.1. Petrophysical Data Requirement

In the current version of BRIGHT several workflow steps need a calculated hydrocarbon in place volume (HCIP). Especially of interest is the initial hydrocarbon in place, since e.g. Recovery Factors are calculated by using the initial HCIP. The equation used for the HCIP is:

$$HCIP = \frac{A \cdot h \cdot \phi \cdot (1 - s_{wi})}{B_i} \qquad \textbf{Equation 23}$$

HCIP is the hydrocarbon in place volume, usually given in [STB] or in [MSTB] or for gas fields [Mscf] or rather [MMscf]. A is the drainage area of the well that is determined from the Voronoi grid [acres]. ϕ is the porosity as a fraction [-], s_{wi} is the average initial reservoir water saturation for the given Voronoi grid block. B_i is the formation volume factor of the phase that is being analyzed in the given BRIGHT study.

An accurate representation of the HCIP is very important, since the calculation of a representative recovery factor value is based on a good HCIP value. The recovery factor will later on be used to determine wells that behave significantly better or worse than the surrounding wells and that should therefore be excluded from further workflows. So, the more accurate the geologic model can be set up, the more reliable all these parameter values can be determined and the more sound the outlier identification and subsequently the analysis will be.

3.4.2. Interpolation Techniques

The problem is that usually (especially old) fields do not have petrophysical measurements (e.g. core analysis, well logs, etc.) for each well. Figure 45 shows in a map, which wells have petrophysical measurements in general (e.g. no information about whether the data (e.g. porosity) were obtained by well logging or out of core measurements). The green squares denote all wells with petrophysical data, whereas the wells represented by the blue dots – the majority - are without any measurement of petrophysical parameters and thus the values for these wells have to be computed.

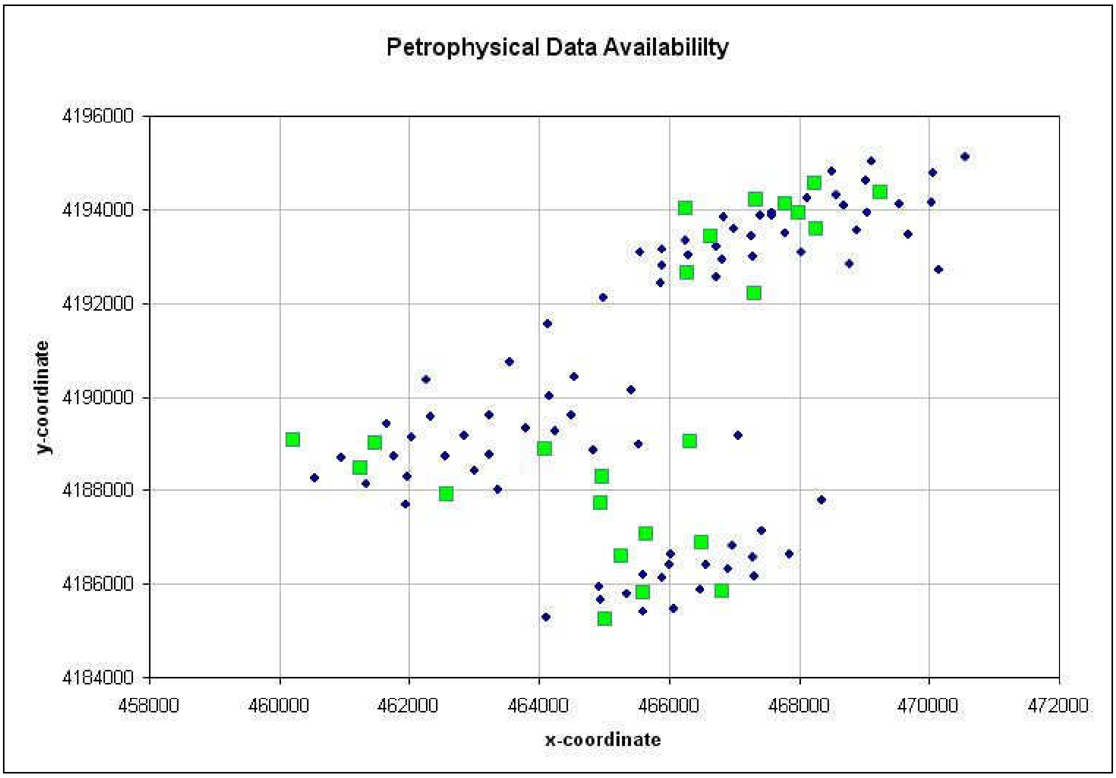


Figure 45: Petrophysical Data Availability

Therefore in the 'Petrophysical Data Interpolation' BRIGHT basically can get the petrophysical data at each location through three different techniques.

- Averaging
- Ordinary Kriging
- User Input

3.4.2.1. Averaging

Averaging is a very simple way of filling the gaps with a single value. Especially in a situation, when only very few measurements are available Averaging would be the technique to use rather than ordinary Kriging, which needs a certain spatial sample density in order to reliably interpolate in arbitrary locations within the field. The assumption behind the Averaging procedure is that the few measurements of the respective petrophysical parameters are independent and randomly taken (*mutually exclusive*) – this is generally not the case but regarding the lack of a for this problem suitable interpolation routine, this is a reasonable assumption. Therefore, according to the Central Limit Theorem[12] their values are approximately normally distributed. Thus, the best estimator for each parameter is the expected value, which for any given Normal distribution is the arithmetic mean of all sample values. Given a number of *n* different measurements the estimated value *E(x)* for any parameter will therefore be given as:

$$E(x) = \frac{1}{n} \cdot \sum_{i=1}^{n} x_i \qquad \textbf{Equation 24}$$

3.4.2.2. Ordinary Kriging

As mentioned in Chapter 2.3. BRIGHT uses ordinary Kriging as its main interpolation technique. Kriging is used for every performance and forest interpolation step, since it is one of the cornerstones of BRIGHT that a statistically sound number of wells and therefore of production data is available. In the 'Petrophysical Data' interpolation step, BRIGHT has to offer 'Averaging' and 'user input' in addition to ordinary Kriging since the petrophysical data are usually not as readily and numerously available as the production data.

The details about Kriging can be found in Reference 10 and Reference 22 and in Chapter 2.3 of this work. In this chapter ordinary Kriging is presented on a real example. The maps in Figure 46 show maps of interpolated average net pay thickness in [ft] for a Turkish oil field. The left depiction in Figure 46 is the map obtained by ordinary Kriging the right map is the map as obtained after filling the gap values with the field average as described in Chapter 3.4.2.1.

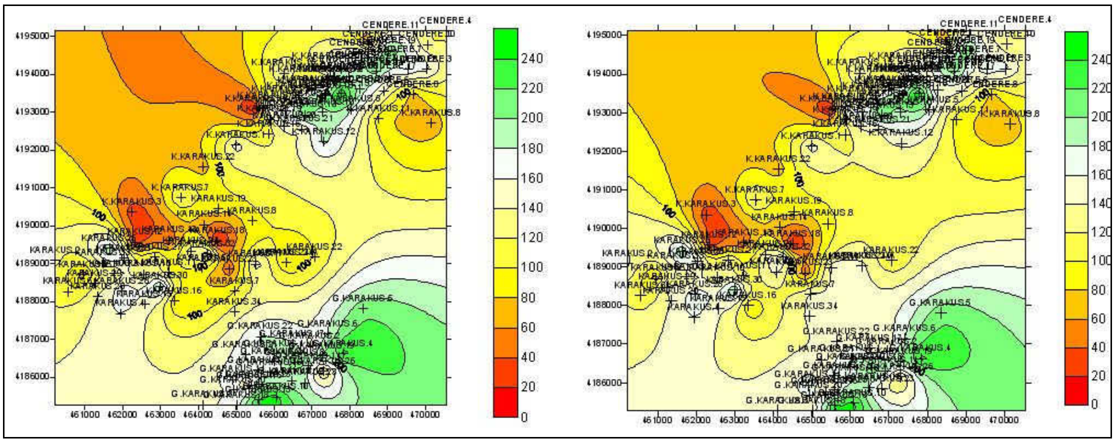


Figure 46: ordinary Kriging for gaps (left) compared to averaging for gaps (right)

Since the data availability was rather high, the two maps do not differ too much from each other, which shows that ordinary Kriging delivers a - considering the given purpose of the study - sound and reliable map.

BRIGHT further on employs Kriging whenever a parameter is to be interpolated within the wells into the infill locations. For example the forecasts of the existing wells are kriged into the infill locations to obtain a forecast at that location.

3.4.2.3 User Input

The user can also input values that she or he assumes to be the best approximation for the given petrophysical parameter. This is especially a good idea if a geologic model for the given reservoir already exists in a different application and the values at the well locations are therefore known. The user would want to import these data and this is possible with the user input function. Moreover, sometimes no petrophysical data exist at all (e.g. there were no measurements or more probable the company performing the study has not yet received any petrophysical parameters). If that is the case the engineer has to go with her or his best guess, which can also be a very good approximation, if the engineer is familiar with the specific region in general.

3.6 Gridding

In BRIGHT two types of grids are used for two different purposes. (1) The Voronoi grid is used to obtain a good estimate for the drainage area of a well and therefore to be able to obtain values for hydrocarbons in place that can be allocated to a certain well and subsequently sweep efficiency. (2) A Delaunay Triangulation grid is then used to (a) come up with infill locations, which are always located in the center of a triangle's block inner circle and (b) to find an infill location's most relevant neighbors (see Chapter 3.9. on calculation of uncertainty).

3.6.1 Voronoi

The Voronoi Grid is a flexible grid that is also known as PEBI grid in flow simulation models. The grid creates flexible polygons around the points, which is given by the well locations. The Voronoi Polygons represent the area surrounding a well that is closer to it than to any other well. This is achieved by drawing an imaginary linear connection between two wells and setting the grid edge perpendicular to the connection line exactly in the center of the line (therefore the name PEBI, which means perpendicular bisection).

The grid is depicted in Figure 47. Since the algorithm itself does not consider reservoir boundaries, the edge wells are given too large areas. Therefore BRIGHT offers the so called bounding radius function.

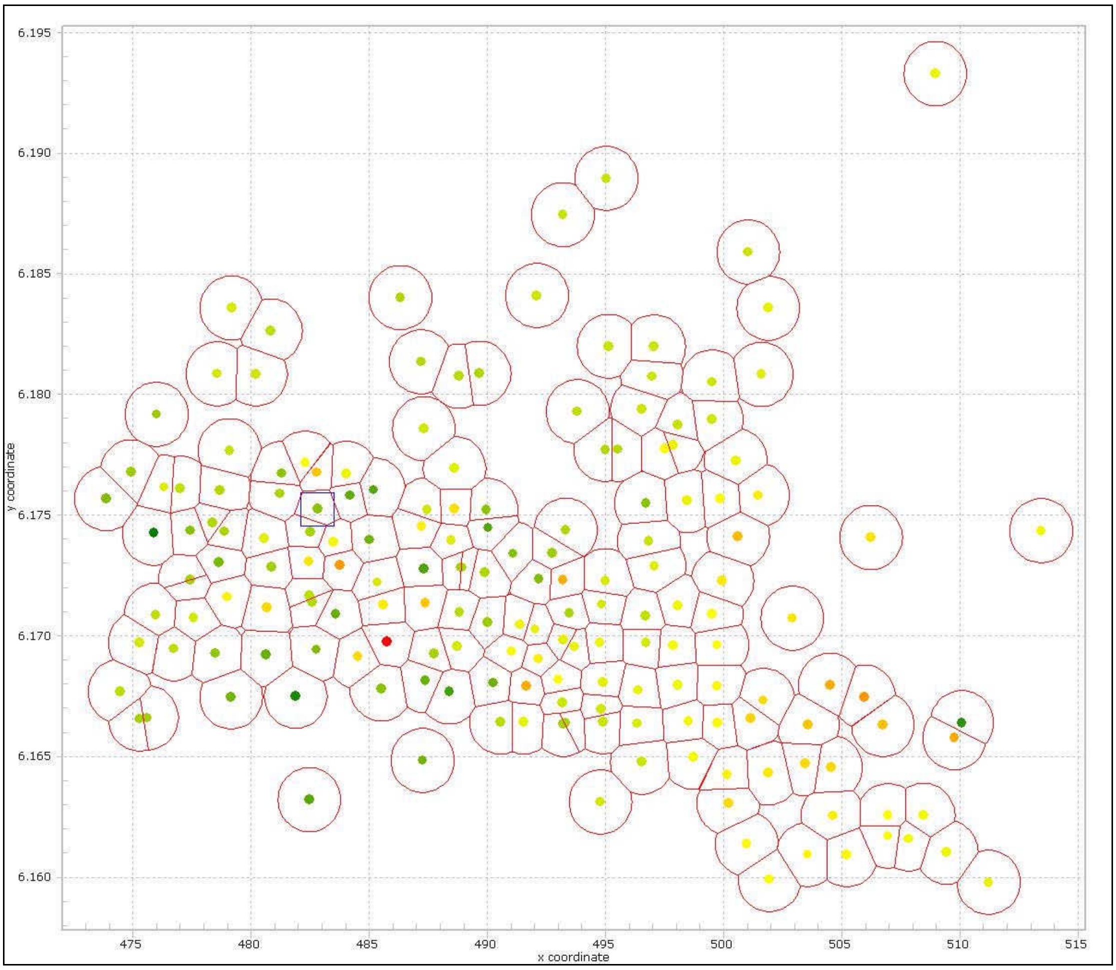


Figure 47: Voronoi Grid Diagram

Bounding Radius basically draws an imaginary circle around each well with the radius that can be input by the user. If the Voronoi area of a well exceeds the boundary of this imaginary circle, the grid area will be cropped and the area that is outside of the circle area will not be regarded as Voronoi area for the specific well.

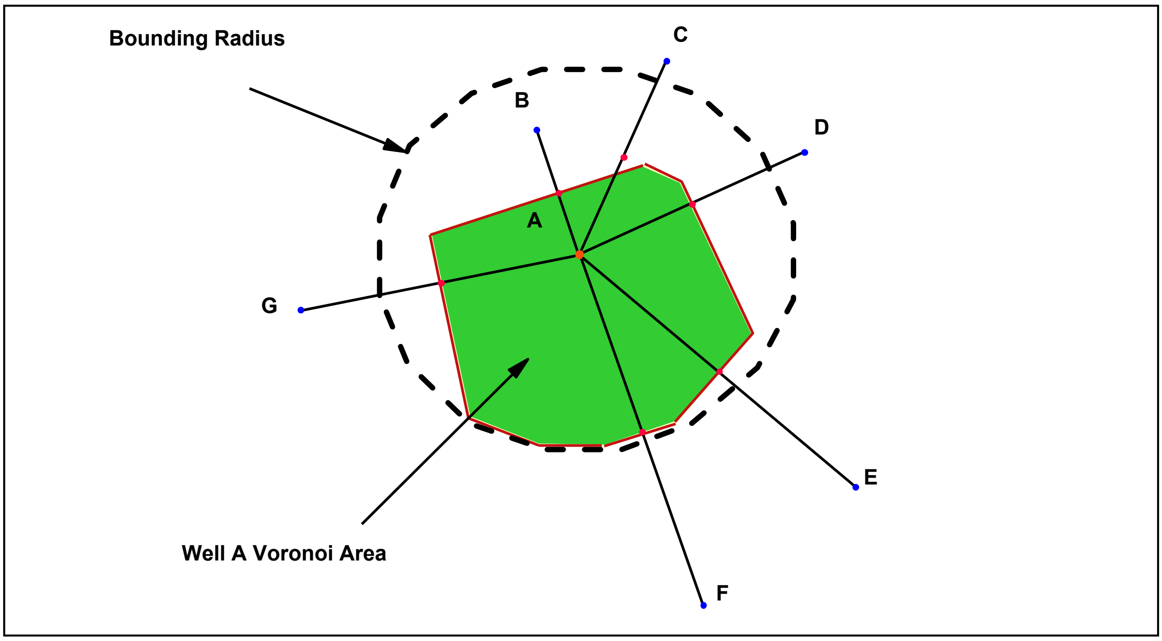


Figure 48: Bounding Radius

The cropping of the much too large Voronoi areas of the reservoir's edge wells is very important since the Voronoi area will be used later in the workflow to determine the area of the reservoir and therefore the hydrocarbons in place allocated to the well. Subsequently this value is used in the denominator in the Equation for the Recovery Factor:

$$\eta = \frac{Q}{A \cdot h \cdot \phi \cdot (1 - s_{wi}) \cdot \frac{1}{B_{o,g}}}$$ **Equation 25**

η is the recovery factor [-], Q is the cumulative production (either oil [STB] or gas [Mscf], A is the drainage area as determined with the Voronoi grid, h is the average reservoir net pay thickness in [ft] in the grid block defined by the Voronoi area, ϕ is the average porosity in the grid block [-], s_w the average reservoir water saturation [-] and *Bo,g* is the formation volume factor of either oil [bbl/STB] or gas [bbl/Mscf].

If the Voronoi area is too large as apparent for the wells at the reservoir edge in Figure 47, the denominator in Equation 25 would be too large, thus underestimating the recovery factors of the edge wells significantly.

3.6.2 Delaunay Triangulation

The triangulation algorithm employed in BRIGHT creates a grid that connects the wells in close proximity into triangles. A triangle is very commonly applied e.g. in finite elements application to break down a very complex shape into easy to handle small triangular surfaces. The triangulation grid is said to be dual[23] to the Voronoi grid. That means that the triangulation grid is the basis for the Voronoi grid, which is created by bisecting the edges of the Delaunay triangles. In BRIGHT the triangulation grid plays a very important role for finding the infill locations. An infill location is positioned in the center of the inner circle of each triangle. It is important to notice that those wells that have been identified as outliers (as described in Chapter 3.8) are not used to create these triangles and to come up with the infill locations.

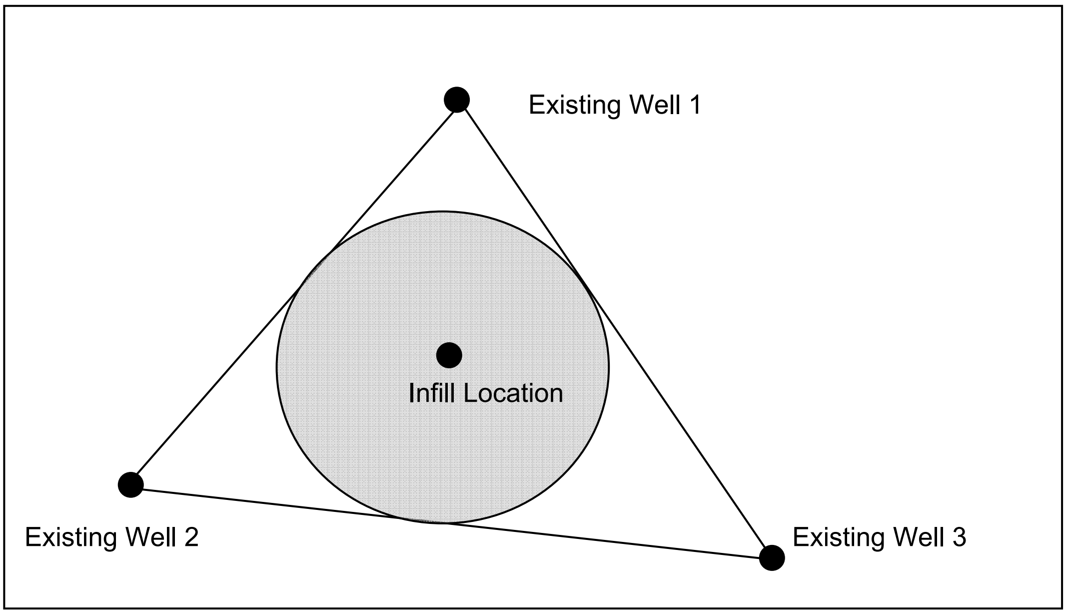


Figure 49: Triangulation and infill location position

The triangles play another important role in the calculation of the uncertainties. BRIGHT determines the triangulation neighbors for each infill location and uses their values for a certain parameter (e.g. Decline rate [STB/psia d] or [Mscf/psia d]) to linearly interpolate this parameter into the infill location. The linearly interpolated value is then compared to the value obtained by ordinary Kriging and if these two values are too far off, the interpolation uncertainty associated with this point is given a high value. This procedure is described in detail in Chapter 3.9.1 of this document.

To avoid that an infill location is positioned on the edge of a field, a triangle filter was implemented in BRIGHT. When constructing a triangle with existing wells that are located on the edge of a field, the triangles usually are very sharp and incorporate a very small angle. This information can be used to filter for triangles with angles e.g. below 10 [degrees], hence eliminating all the infill locations that would be created on the edge or even outside of the area of interest.

Figure 50 shows the triangulated grid and in the center of each triangle the dot representing the infill location.

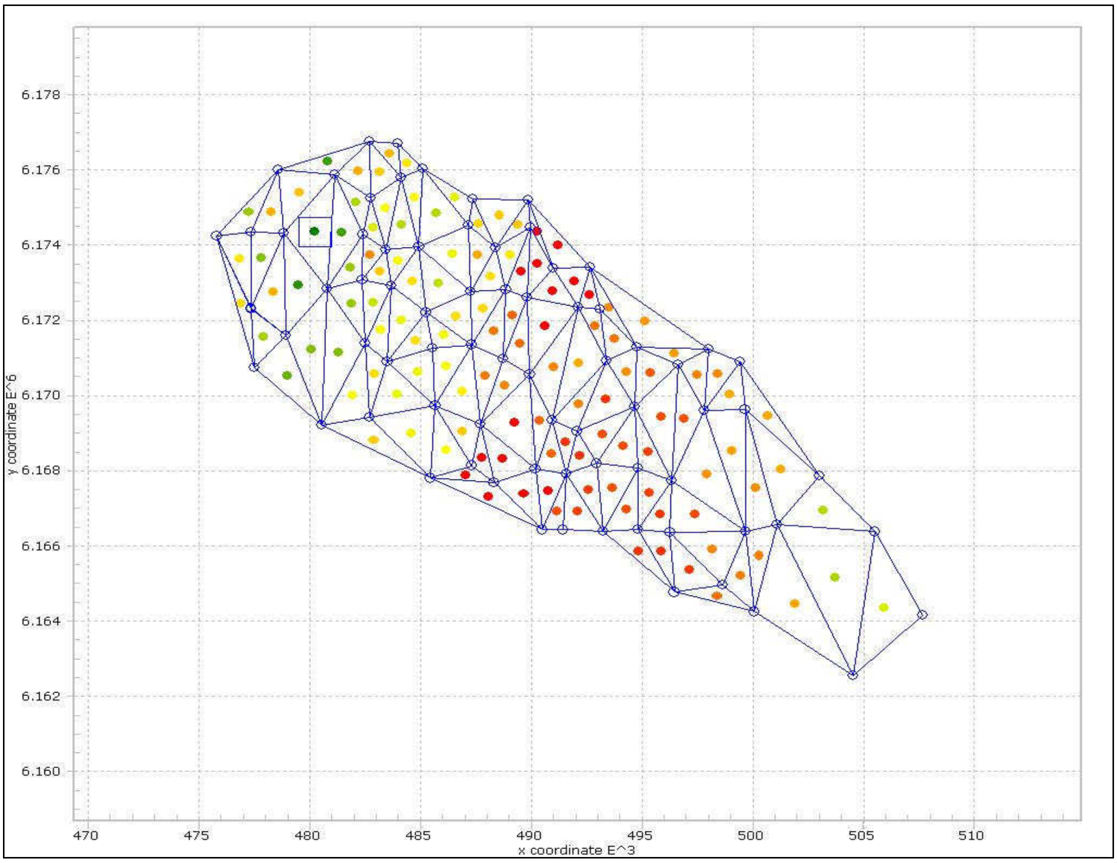


Figure 50: Triangulation Grid with infill locations

3.7 Automatic Decline Curve Analysis

As mentioned in Chapter 2.2.1 BRIGHT uses exponential decline curves to forecast he production rates. As mentioned in Chapter 2.2.1 the DCA module in BRIGHT aims to minimize the RMS error (Equation 12) of the fitted curve regarding the measured data.

The automatic decline curve analysis module uses several different input parameters to make the application more flexible for applications in many different fields no matter whether it is a gas or an oilfield. The two main input parameters are the ‘Fit Range’ and the ‘Max. time back’ parameter.

The main target for the DCA module in BRIGHT is to minimize the RMS error of the fit. 'Fit Range' therefore defines the number of data point BRIGHT should find with the best fit. E.g. if the use enters 10, BRIGHT is iterating to find the best fit (i.e. lowest RMS error) with ten data points. 'Max time back' defines the search space for this best fit. That means that the user can restrict how far the iteration algorithm can go back in production history to find the best fit. E.g. if the user enters 36, BRIGHT has a search space of 36 months (3 years) and iterates to find the best fit with ten data points in the last 36 months. To define the search space for the automatic decline curve analysis is very important. Not only because CPU time is decreased significantly the shorter the search space, but also the assumptions for a reliable decline curve analysis have to be fulfilled. If for example a water injection project was started four years before the last date of production the engineer might want to restrict the search space to a time range where the transients in rates and pressures due to the water flooding project are not that apparent anymore and steady state production or semi-steady state production can be assumed.

The user can also decide, which correlation coefficients should be highlighted red (e.g. 0.50 and below) and she or he can go through each of these decline curves and decide whether it is necessary to manually improve the curve fit.

In the current version of BRIGHT it is possible that the best fit for a decline curve has a positive slope, which would mean an increasing production rate in the future. Of course this is not possible and wells like that are (a) highlighted red, so subject of revision and (b) identified by the outlier search algorithm and therefore not being taken into account for any further performance interpolations in subsequent workflows.

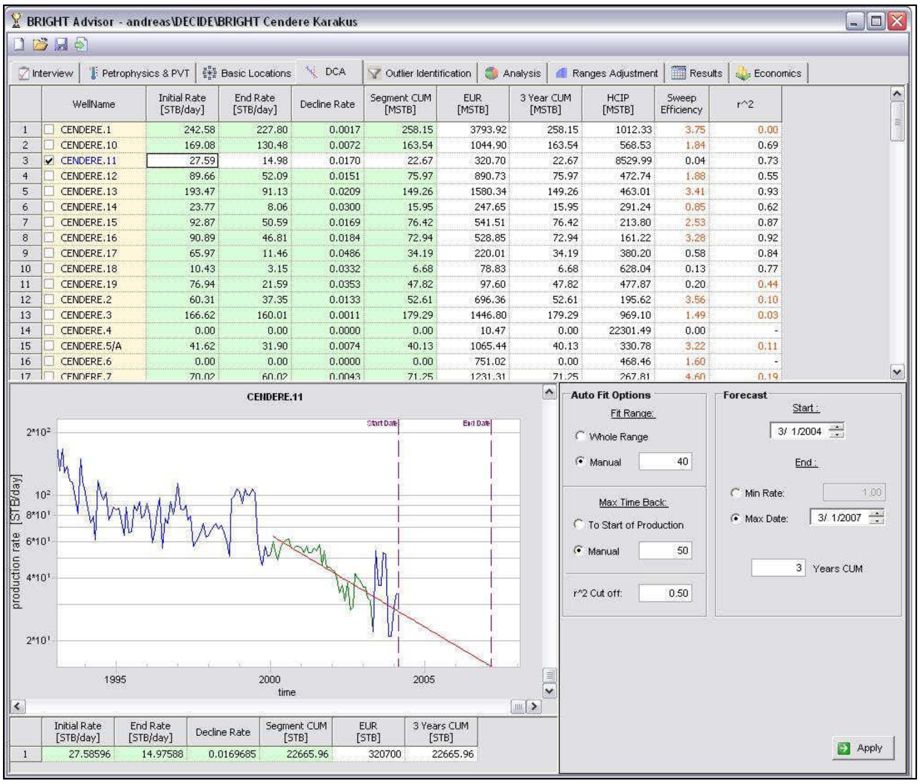


Figure 51: Decline Curve Analysis screen

It is very important to point out that this forecasting technique has to be used very carefully. Arps' equation uses a lot of assumptions that are reasonable yet have to be fulfilled in order to use the decline curve analysis with certain reliability. It is therefore important to notice, that Arps' considers steady state or pseudo steady state well flow under constant flowing pressure. New fields with a lot of wells in a transient flow regime can therefore not be forecasted reliably. Therefore BRIGHT is always promoted as a tool for Brownfields where the transient period is generally assumed to be over and the wells are all producing with a certain steadiness. Also it has to be clear that fields in which the operating strategy has significantly changed only a short time before the BRIGHT study are also subject to increased uncertainty. A new water flood project or new pumps in several wells would falsify the extrapolated decline curves and would not give a reliable forecast.

The stopping criterion for the forecast is either a maximum date that can be entered by the user or a minimum rate, which also can be entered manually according to economic considerations.

3.8 Outlier Detection

The outlier detection is a very important step in BRIGHT's workflow as well as in RAPID's workflow. As described in Chapter 2.4 the outliers are detected by the 'leave-one-out'-cross validation technique. In BRIGHT this analysis step is called exclusion mapping, since in each iteration step a map is generated excluding the well that is being analyzed in the respective iteration step.

There have been a lot of discussions of which parameters should be used to reliably find outliers. The main concern was to not only be focus on performance parameters but also to come up with a technique that takes into account geologic differences. After several attempts the most reliable and stable results were obtained by using the following three parameters in the Exclusion mapping procedure:

- *Forecasted Rate [STB/d] or [Mscf/d]:* BRIGHT uses a new parameter, the 'Forecasted Rate' to investigate the uncertainty of its interpolation and forecasting.

  $$q_{Forecast} = \frac{q_{Initial} + q_{DCA} + q_{4moavg}}{3} \qquad \textbf{Equation 26}$$

  $q_{Forecast}$ is the 'Forecasted Rate' [STB/d or Mscf/d], $q_{Initial}$ is the initial production rate as defined in Chapter 3.1.6., q_{DCA} is the Production Rate at forecast start date determined by the decline curve analysis and q_{4moavg} is the production rate given by the 4 months moving average at the forecast start date. The reason for calculating the average of three rates at the same day is that by using 'forecasted rates' calculated out of various sources, individual outliers in the wells performance do not influence the determination of 'Forecasted Rate' too much. The forecasted rate for infill locations is therefore calculated by interpolating this parameter instead of just e.g. $q_{initial}$. This will lead to a more robust and reliable forecast for all infill locations throughout the field. Figure 52 shows the three components of 'Forecasted Rate'.

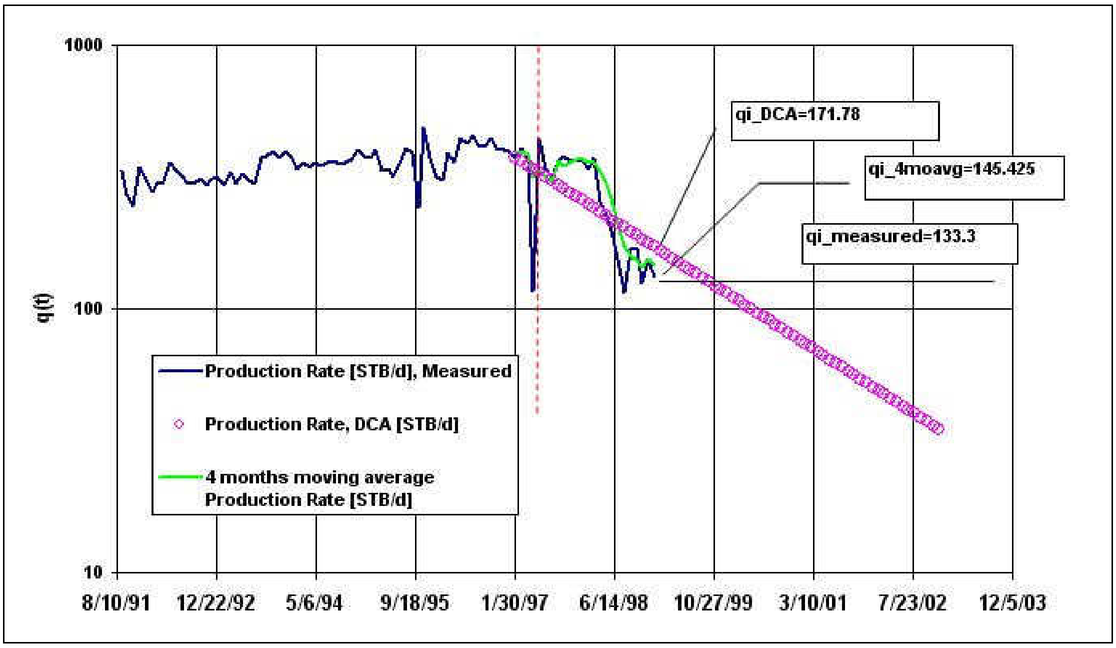


Figure 52: Forecasted Rate and its three components

- *Decline Rate [1/day]:* as determined by the decline curve analysis.
- *Recovery Factor 3Y Cum [-]:* The Recovery Factor 3Y Cum is the recovery factor after the first three forecasted years of hydrocarbon production. This parameter is therefore defined as:

$$\eta_{3Y} = \frac{Q_{3Y}}{A \cdot \phi \cdot h \cdot \left(1 - s_{wi}\right) \cdot \frac{1}{Bi}} \qquad \textbf{Equation 27}$$

i

where η_{3Y} is the three year future recovery factor [-], Q_{3Y} is the forecasted cumulative hydrocarbon production in the upcoming three years. The denominator stands for the initial hydrocarbons in place, A is the area as determined from the Voronoi grid [acre], ϕ is the porosity [-], h is the average reservoir net pay [ft], s_{wi} is the average initial reservoir water saturation in the drainage area defined by the Voronoi grid [-] and Bi is the formation volume factor of the phase that is being analyzed in the given study [RB/STB] or [RB/Mscf].

Equation 27 is therefore introducing the geologic properties, which leads to a more integrated view when looking at the performances of the well and the identification of the outliers.

The main reason for choosing these parameters is obvious when looking at the way BRIGHT is forecasting the well performance of the infill locations. BRIGHT is calculating the Estimated Recovery for an infill location using the Forecasted Rate at the infill location and the decline rate at the infill location. No spatial interpolation for the Estimated Recovery itself is being performed. Therefore special care has to be taken that these parameters have been prepared thoroughly. The Recovery factor is used as the control parameter that is taken into account well performance as well as geology.

BRIGHT calculates the absolute difference between the parameter as computed in the forecasting workflow and the value for the same parameter as obtained by ordinary Kriging in the same point. A cut off value that can be modified by the user is applied to highlight the wells that have an absolute difference to the computed value that is higher in percent (given by the cut off value) as the highest occurring difference.

For example if the highest occurring difference for decline rate is e.g. 0.56 [1/day] given a cut off value of 60% each well that has a difference to the computed decline rate of higher than 0.56 [1/day] x 60% = 0.336 [1/day] and lower than – 0.336 [1/d] is highlighted as an outlier regarding decline rate.

A well is identified as an outlier as soon as the absolute difference in two of those three parameters is larger than the cut-off value. As can be seen in Figure 54 the well is then checked in the table and highlighted red.

Another criterion that defines a well as an outlier is the shut-in time. BRIGHT is determining the last date of production. If this date is longer back than the by the user tolerated shut-in time in [months], the well is automatically identified as an outlier and will not be regarded in any forecasting workflow.

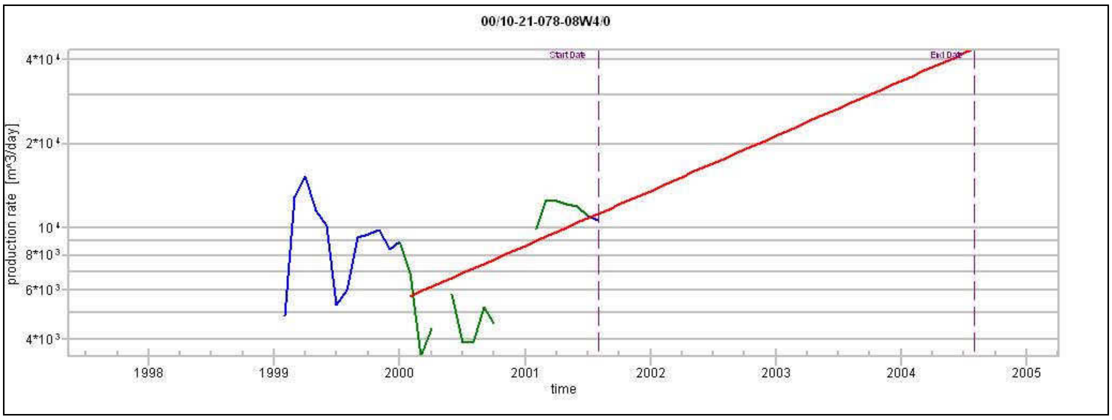
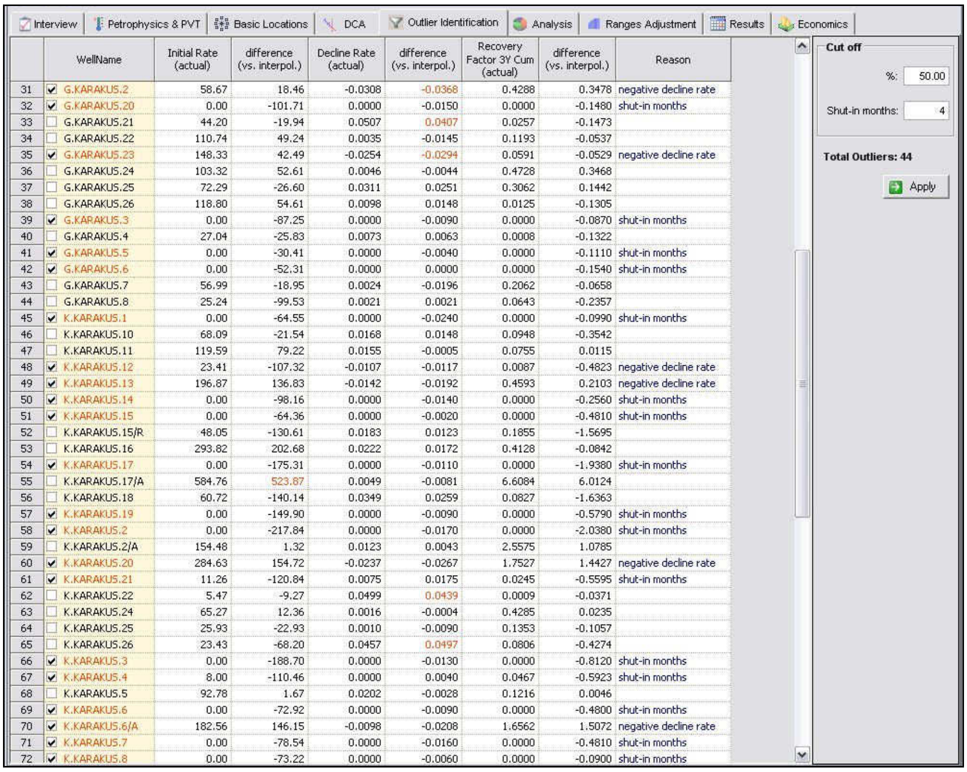


Figure 53: Decline curve with negative slope

The third criterion that identifies a well as an outlier is a negative decline rate (Figure 53). A negative decline rate exists because the automatic decline curve analysis tries to find the best fit (lowest RMS error between fit curve and measured production rate values) even if this would mean an increasing decline curve. Of course this has to be changed in further versions of BRIGHT. However, for the first release the work around is to immediately define a well that has an increasing decline curve slope as an outlier.



		WellName	Initial Rate (actual)	difference (vs. interpol.)	Decline Rate (actual)	difference (vs. interpol.)	Recovery Factor 3Y Cum (actual)	difference (vs. interpol.)	Reason
31	☑	G.KARAKUS.2	58.67	18.46	-0.0308	-0.0368	0.4288	0.3478	negative decline rate
32	☑	G.KARAKUS.20	0.00	-101.71	0.0000	-0.0150	0.0000	-0.1480	shut-in months
33	☐	G.KARAKUS.21	44.20	-19.94	0.0507	0.0407	0.0257	-0.1473	
34	☐	G.KARAKUS.22	110.74	49.24	0.0035	-0.0145	0.1193	-0.0537	
35	☑	G.KARAKUS.23	148.33	42.49	-0.0254	-0.0294	0.0591	-0.0529	negative decline rate
36	☐	G.KARAKUS.24	103.32	52.61	0.0046	-0.0044	0.4728	0.3468	
37	☐	G.KARAKUS.25	72.29	-26.60	0.0311	0.0251	0.3062	0.1442	
38	☐	G.KARAKUS.26	118.80	54.61	0.0098	0.0148	0.0125	-0.1305	
39	☑	G.KARAKUS.3	0.00	-87.25	0.0000	-0.0090	0.0000	-0.0870	shut-in months
40	☐	G.KARAKUS.4	27.04	-25.83	0.0073	0.0063	0.0008	-0.1322	
41	☑	G.KARAKUS.5	0.00	-30.41	0.0000	-0.0040	0.0000	-0.1110	shut-in months
42	☑	G.KARAKUS.6	0.00	-52.31	0.0000	0.0000	0.0000	-0.1540	shut-in months
43	☐	G.KARAKUS.7	56.99	-18.95	0.0024	-0.0196	0.2062	-0.0658	
44	☐	G.KARAKUS.8	25.24	-99.53	0.0021	0.0021	0.0643	-0.2357	
45	☑	K.KARAKUS.1	0.00	-64.55	0.0000	-0.0240	0.0000	-0.0990	shut-in months
46	☐	K.KARAKUS.10	68.09	-21.54	0.0168	0.0148	0.0948	-0.3542	
47	☐	K.KARAKUS.11	119.59	79.22	0.0155	-0.0005	0.0755	0.0115	
48	☑	K.KARAKUS.12	23.41	-107.32	-0.0107	-0.0117	0.0087	-0.4823	negative decline rate
49	☑	K.KARAKUS.13	196.87	136.83	-0.0142	-0.0192	0.4593	0.2103	negative decline rate
50	☑	K.KARAKUS.14	0.00	-98.16	0.0000	-0.0140	0.0000	-0.2560	shut-in months
51	☑	K.KARAKUS.15	0.00	-64.36	0.0000	-0.0020	0.0000	-0.4810	shut-in months
52	☐	K.KARAKUS.15/R	48.05	-130.61	0.0183	0.0123	0.1855	-1.5695	
53	☐	K.KARAKUS.16	293.82	202.68	0.0222	0.0172	0.4128	-0.0842	
54	☑	K.KARAKUS.17	0.00	-175.31	0.0000	-0.0110	0.0000	-1.9380	shut-in months
55	☐	K.KARAKUS.17/A	584.76	523.87	0.0049	-0.0081	6.6084	6.0124	
56	☐	K.KARAKUS.18	60.72	-140.14	0.0349	0.0259	0.0827	-1.6363	
57	☑	K.KARAKUS.19	0.00	-149.90	0.0000	-0.0090	0.0000	-0.5790	shut-in months
58	☑	K.KARAKUS.2	0.00	-217.84	0.0000	-0.0170	0.0000	-2.0380	shut-in months
59	☐	K.KARAKUS.2/A	154.48	1.32	0.0123	0.0043	2.5575	1.0785	
60	☑	K.KARAKUS.20	284.63	154.72	-0.0237	-0.0267	1.7527	1.4427	negative decline rate
61	☑	K.KARAKUS.21	11.26	-120.84	0.0075	0.0175	0.0245	-0.5595	shut-in months
62	☐	K.KARAKUS.22	5.47	-9.27	0.0499	0.0439	0.0009	-0.0371	
63	☐	K.KARAKUS.24	65.27	12.36	0.0016	-0.0004	0.4285	0.0235	
64	☐	K.KARAKUS.25	25.93	-22.93	0.0010	-0.0090	0.1353	-0.1057	
65	☐	K.KARAKUS.26	23.43	-68.20	0.0457	0.0497	0.0806	-0.4274	
66	☑	K.KARAKUS.3	0.00	-188.70	0.0000	-0.0130	0.0000	-0.8120	shut-in months
67	☑	K.KARAKUS.4	8.00	-110.46	0.0000	0.0040	0.0467	-0.5923	shut-in months
68	☐	K.KARAKUS.5	92.78	1.67	0.0202	-0.0028	0.1216	0.0046	
69	☑	K.KARAKUS.6	0.00	-72.92	0.0000	-0.0090	0.0000	-0.4800	shut-in months
70	☑	K.KARAKUS.6/A	182.56	146.15	-0.0098	-0.0208	1.6562	1.5072	negative decline rate
71	☑	K.KARAKUS.7	0.00	-78.54	0.0000	-0.0160	0.0000	-0.4810	shut-in months
72	☑	K.KARAKUS.8	0.00	-73.22	0.0000	-0.0060	0.0000	-0.0900	shut-in months

Figure 54: Outlier Detection Screen

The ‘Outlier Identification’ screen in BRIGHT presents all the information and all the values in a grid. Additionally BRIGHT informs about the reason, why a specific well has been identified as an outlier in the ‘Reason’ column. As mentioned earlier, wells that have been identified as outliers are tossed out and not regarded for forecasting of any parameter.

3.9 Uncertainty

As mentioned several times earlier in this document the characterization of uncertainty is a very important step in BRIGHT's workflow. In BRIGHT's workflow development it was decided to integrate an uncertainty parameter into the evaluation of the locations of the various workflows (e.g. infill drilling location selection, reactivation selection, etc.). The uncertainty would therefore be another parameter to be considered besides only performance indicator as in traditional field development studies.

In Chapter 2.1.2 it was discussed that there are already multiple attempts in today's production/reservoir engineering techniques to involve uncertainties; especially the uncertainty in a geologic model and the uncertainty due to a misfit in the history match. For BRIGHT a different formulation of the uncertainty therefore has to be developed that incorporates on the one hand uncertainties due to spatial interpolations but on the other hand also uncertainties due to the apparent risk in using simple extrapolation techniques to forecast production.

BRIGHT uses three different types of uncertainties and out of these three values a final uncertainty value is calculated.

The uncertainties defined in BRIGHT are:

- *Spatial Interpolation Uncertainty [-]:* This parameter is necessary to describe how reliable a certain value for the 'Forecasted Rate' obtained by ordinary Kriging is.
- *End rate Uncertainty [-]:* In the End rate Uncertainty the production profile of a well at the last measured date is investigated. It should give more information of how stable an extrapolated trend is.
- *DCA fit Uncertainty [-]:* A parameter was incorporated that quantifies the quality of the decline curve analysis fit in order to characterize the misfit.
- *Total Uncertainty [-]:* The final parameter incorporates all three of these uncertainties with respective weights. The user can therefore decide for each situation individually, which uncertainty weight mix is more applicable for a given situation.

3.9.1 Spatial Interpolation Uncertainty

The ‘Spatial Interpolation Uncertainty’ is a description of how reliable a certain value obtained by ordinary Kriging is. It is important to not misunderstand this value as a description of the quality of fit of the kriged surface (as for example the residuals are). The ‘Spatial Interpolation Uncertainty’ should rather warn if discrepancies between the interpolated and the real value are very probable.
The ‘Spatial Interpolation Uncertainty’ is calculated by comparing the value obtained by ordinary Kriging at an infill location with the value obtained by linear interpolation of the kriged parameter of the three surrounding triangle wells.

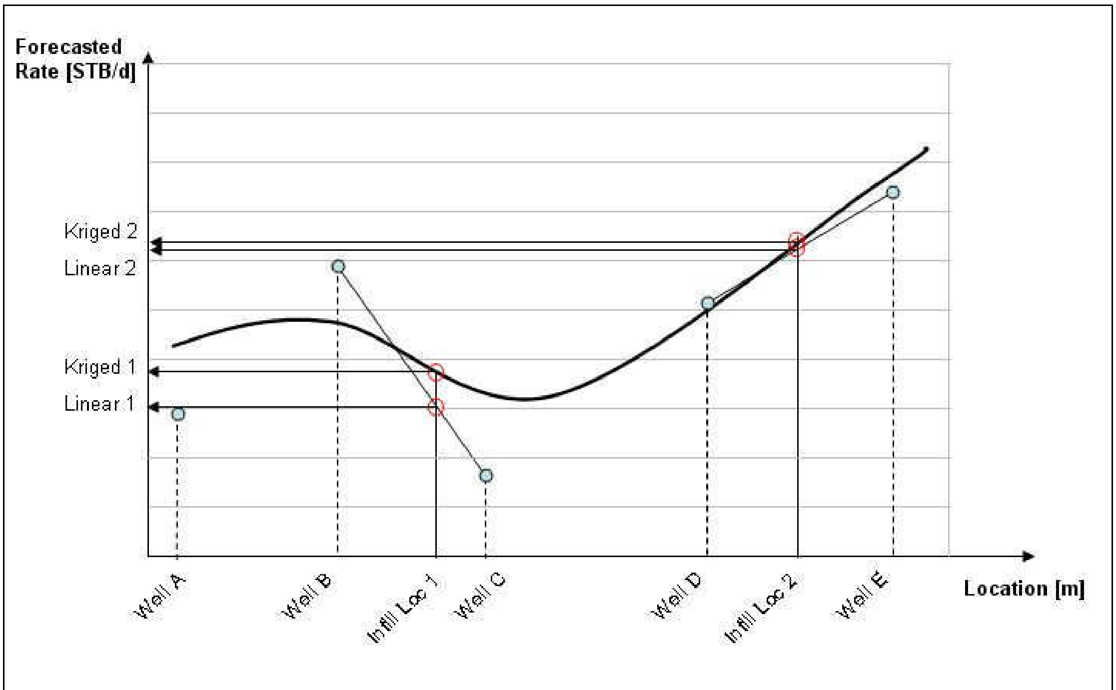


Figure 55: Linear Interpolation vs. ordinary Kriging

Figure 55 is a simplified presentation of this discrepancy. The depiction shows an artificial, highly simplified, one dimensional version of the approach. The values for Forecasted Rate in [STB/d] are given for each well, indicated by the light blue dots in the diagram. The probable kriged response surface is displayed by the thicker, curved line. As apparent in Figure 55 the linear interpolation of the value for Estimated Forecasted Rate for the Infill Location 1 between Well B and Well C computes a fairly different value as the value determined by ordinary Kriging. However, the linear interpolation between Well D and Well E is not significantly different than the kriged surface and therefore the discrepancy between the kriged value and the value obtained by linear interpolation in Infill Location 2 is rather small. This will lead to the conclusion that the spatial interpolation in Infill Location 1 is less reliable then the spatial interpolation in Infill Location 2, which will be quantified as shown in Equation 31.

The linear interpolation of the value in the infill location located in the middle of the triangle of existing wells is always done by applying the equation for a plain surface for each existing well:

$$\begin{aligned} A \cdot x_1 + B \cdot y_1 + C &= P_1 \\ A \cdot x_2 + B \cdot y_2 + C &= P_2 \\ A \cdot x_3 + B \cdot y_3 + C &= P_3 \end{aligned} \qquad \textbf{Equation 28}$$

Where x_1, x_2 and x_3 are the x-coordinates for *Wells 1*, *2* and *3* in the triangle and y_1, y_2 and y_3 are the y-coordinates respectively. P_1, P_2 and P_3 are the values for the parameter that is to be interpolated (in BRIGHT: *'Forecasted Rate'*). A, B and C are coefficients that are equal for each point located on the plain surface defined by these three equations.

Rearranging Equation 28 to solve for the coefficients A, B and C leads to:

$$\begin{aligned} A &= \frac{(P_1 - P_3) - \left(\frac{y_1 - y_3}{y_2 - y_3}\right) \cdot (P_2 - P_3)}{(x_1 - x_3) - (x_2 - x_3) \cdot \left(\frac{y_1 - y_3}{y_2 - y_3}\right)} \\ B &= \frac{(P_2 - P_3 - A \cdot (x_2 - x_3))}{y_2 - y_3} \\ C &= P_3 - A \cdot x_3 - B \cdot y_3 \end{aligned} \qquad \textbf{Equation 29}$$

Once the coefficients A, B and C have been determined, the value for the linearly interpolated parameter at the infill location is given by:

$$P_{Infill} = A \cdot x_{Infill} + B \cdot y_{Infill} + C \qquad \textbf{Equation 30}$$

P_{Infill} is the value for the interpolated parameter ('Forecasted Rate') in the infill location that is given by its x-coordinate x_{Infill} and its y-coordinate y_{Infill}

This interpolation is repeated for each infill location. Once the linearly interpolated value for 'Forecasted Rate' is computed for each infill location it is compared with the value obtained by ordinary Kriging. The spatial interpolation uncertainty (IU) is calculated as:

$$IU = \frac{\left| q_{FRlinear} - q_{FRordKriging} \right|}{q_{FRordKriging}}$$ **Equation 31**

IU is the spatial interpolation uncertainty [-], $q_{FRlinear}$ is the forecasted rate obtained by linear interpolation [STB/d], $q_{FRordKriging}$ is the forecasted rate determined by ordinary Kriging [STB/d].

The depiction below shows the 'Spatial Interpolation Uncertainty' on a map for each infill location. The depiction shows a map (x-coordinate on x-Axis, y-coordinate on y-Axis) and the result value for Spatial Interpolation Uncertainty as bubble size (the larger the bubble the larger the Spatial Interpolation Uncertainty).

The result is very comprehensible since the wells between the northern part of the field and the central part of the field (compare with status map in Figure 25) show a high uncertainty. This is because their neighboring wells are too far away to provide a guidance of what the value in the infill location should be. In the northern part of the field there are also a few infill locations with high uncertainty. A very possible reason is that the variation of the values for 'Forecasted Rate' in this area is very high. This should be investigated in more detail in order to make a good decision whether an infill location is worth of being drilled.

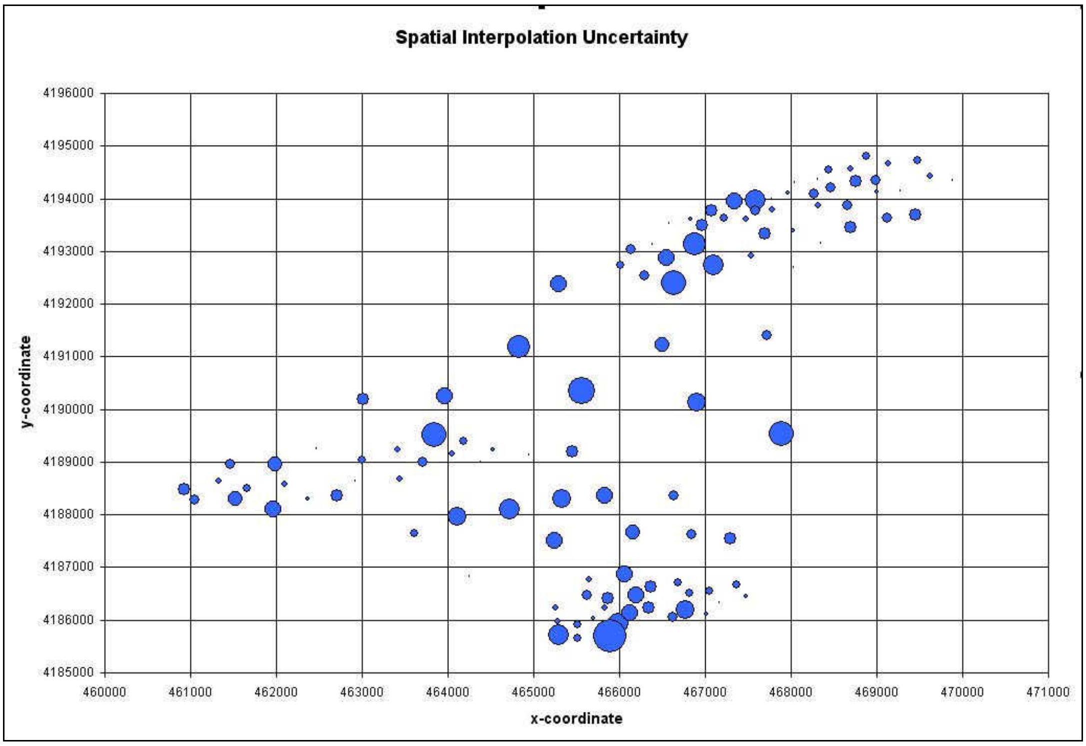


Figure 56: Spatial Interpolation Uncertainty Map

3.9.2 End rate Uncertainty

The dimensionless 'End rate Uncertainty' is a parameter that has been introduced to characterize the stability of the trend that is followed by the decline curve. This is an important investigation since the decline curve fitting procedure tries to minimize the fitting error throughout the whole fit range (see Chapter 3.7) and does not especially concentrate on the later part of the production history or the fit range. In order to make a judgment about how accurately the later part of the trend is modeled and therefore how accurately the short term forecast can be, the latest rate value before the forecast start date has to be compared to the decline curve value at the same date. Additionally BRIGHT compares those two values to the value of the four months moving average, in order to have a more stable and less varying value as a reference value.

The larger the spread of these three values is, the higher is the End rate Uncertainty. A depiction of a real case is given in the two depictions below. It is to be noted that in the two depictions only the production rate [STB/d] and the decline curve fit rate [STB/d] are displayed. However, the four months moving average rate will also be taken into account when calculating the 'End rate Uncertainty', but it will not be displayed in BRIGHT.

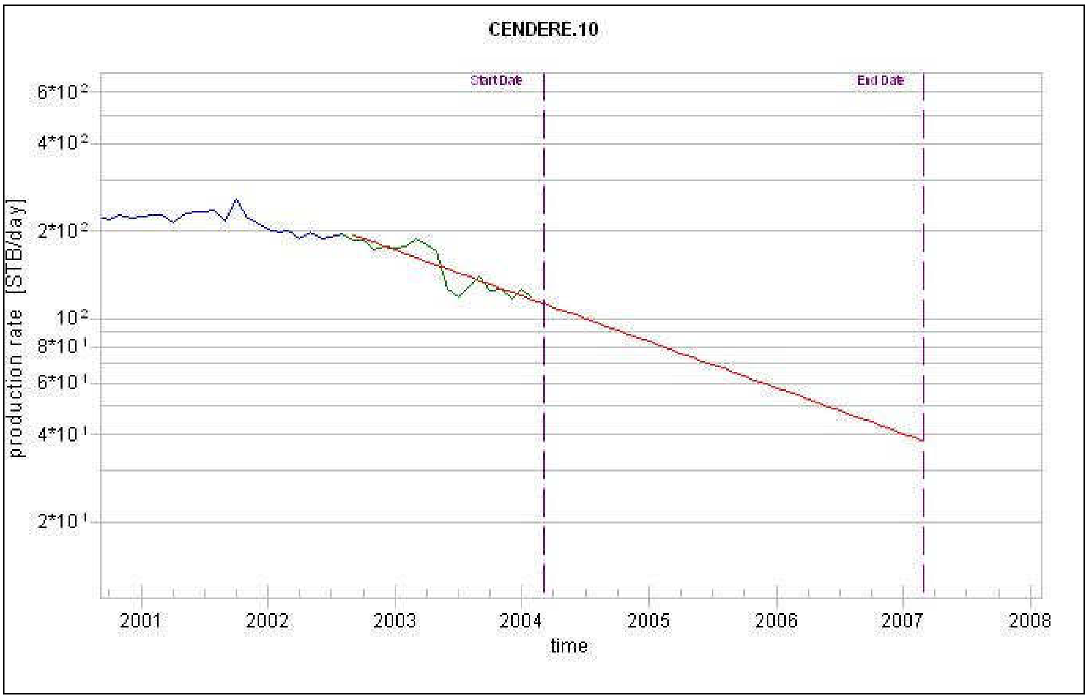


Figure 57: Low End rate Uncertainty

Figure 57 shows an example, where the last measured rate is very much alike the rate that is determined by the decline curve at the last date of the fit. This leads to the conclusion that especially for a short term forecast the decline curve can be given a high reliability thus a low value for the End rate uncertainty.

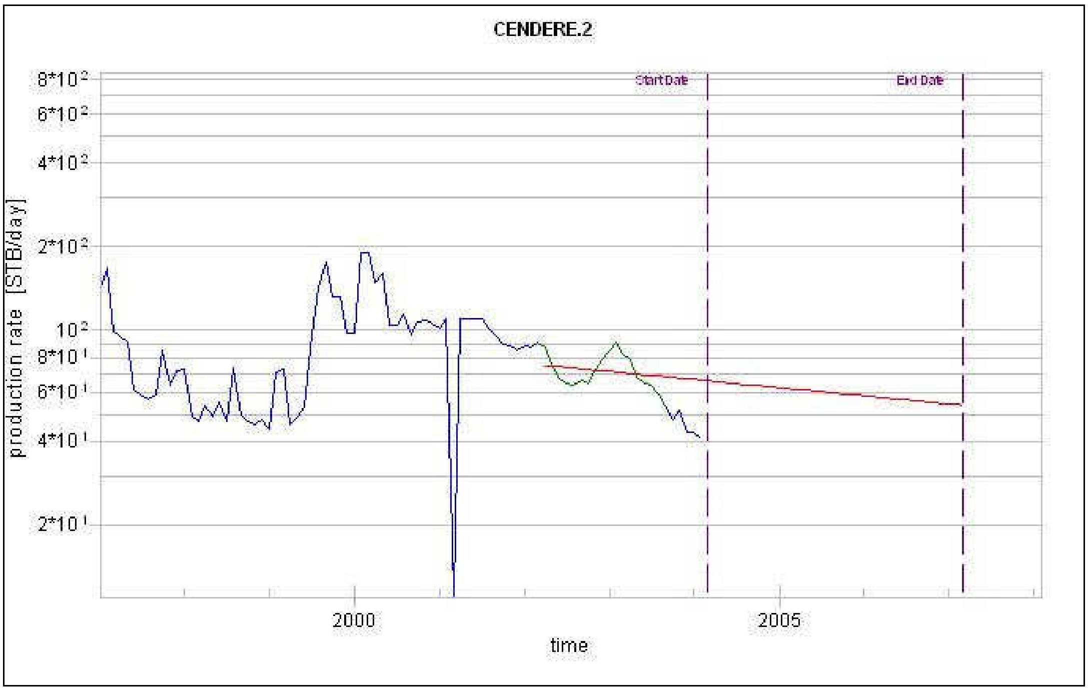


Figure 58: High End rate Uncertainty

Figure 58 shows a different situation. The last measured rate is significantly different than the computed rate by the fitted decline curve. Therefore the reliability of the forecast should be downgraded to account for the discrepancy.

The End rate uncertainty is then calculated as:

$$q_{\max} = \max(q, q_{4moavg}, q_{DCA})$$
$$q_{\min} = \min(q, q_{4moavg}, q_{DCA})$$
$$\bar{q} = \frac{q + q_{4moavg} + q_{DCA}}{3} \qquad \textbf{Equation 32}$$
$$ERU = \frac{q_{\max} - q_{\min}}{\bar{q}}$$

Where q_{max} is the maximum value of the three rates measured at the forecast start date [STB/d] or [Mscf/d], q_{min} is the minimum value of the three rates measured at the forecast start date [STB/d] or [Mscf/d] and $\bar{q}$ is the mean value of the same three rates [STB/d] or [Mscf/d]. The End rate uncertainty (denoted as ERU in Equation 32) is calculating the ratio between the difference of maximum and minimum value and the mean value for the production rate. The idea is to capture the spread of these three values as good as possible.

Earlier versions of BRIGHT calculated the End rate uncertainty as:

$$\sigma = \sqrt{\frac{1}{3}\sum_{i=1}^{3}\left(q_i - \overline{q}\right)^2}$$

$$ERU' = \frac{\sigma}{\overline{q}}$$

Equation 33

Again $\overline{q}$ denotes the mean value calculated out of the three rates measured at the forecast start date. σ is the standard deviation of the three values [STB/d] or [Mscf/d]. In Equation 33 the idea was also to characterize the spread of the three rate values measured at the forecast start date.

However, when looking at the diagram of End rate uncertainty versus Well the advantages of an End rate uncertainty calculation as in Equation 32 is apparent. Especially for higher End rate uncertainties the first equation leads to much more severe values thus penalizing bigger spreads more than Equation 33. Therefore the prior is the better choice, which is not that sensible to larger spreads.

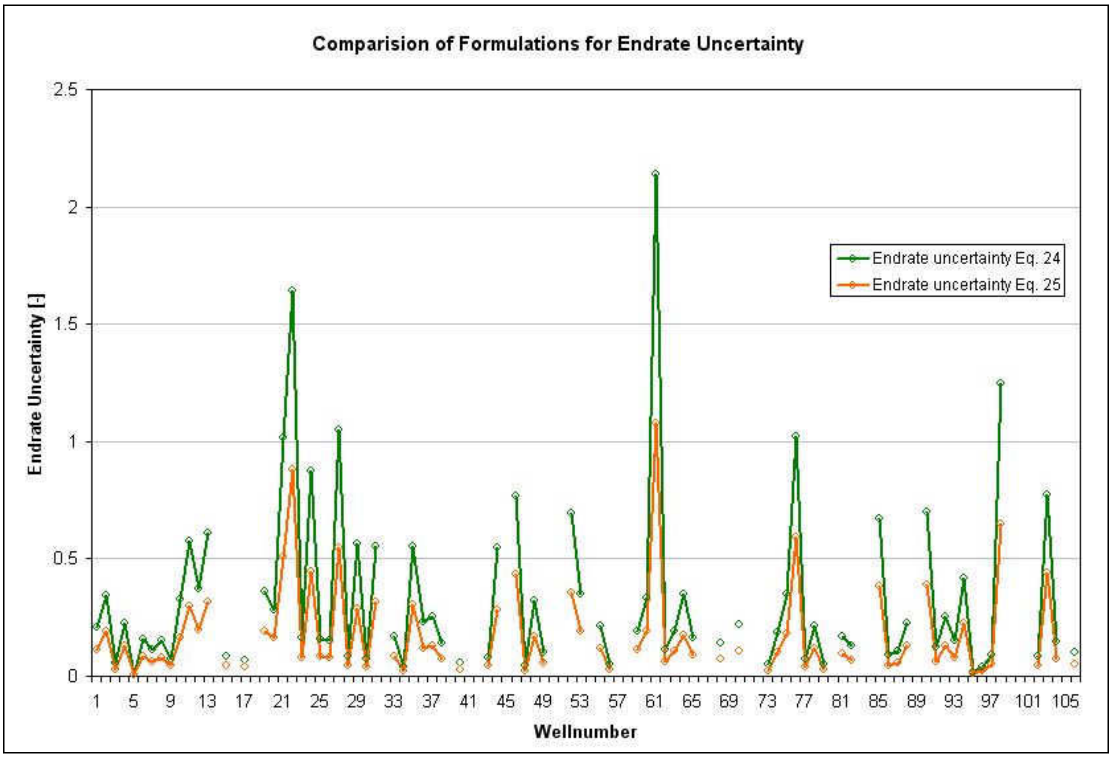


Figure 59: Comparison of Formulations for Endrate Uncertainty

The value for the End rate Uncertainty is calculated for each existing well location. Afterwards the values are kriged into the infill locations to gain information on how stable the forecasts were around the infill locations, which subsequently lead to the information of how reliable the interpolation of the Forecasted Rate in the infill location can be.

Figure 60 shows a bubble map (x-coordinate on x-Axis, y-coordinate on y-Axis) of the End rate Uncertainty (the larger the bubble the higher the End rate Uncertainty). Comparing this map with the map in Figure 56 it is obvious that the Distribution of uncertainties looks significantly different. The reason for that is that the End rate Uncertainty is not dependent on the distance of the neighboring wells but only on the spread between the rates measured at the forecast start date. Therefore the wells in the middle part of the field show a much lower End rate Uncertainty than Spatial Interpolation Uncertainty.

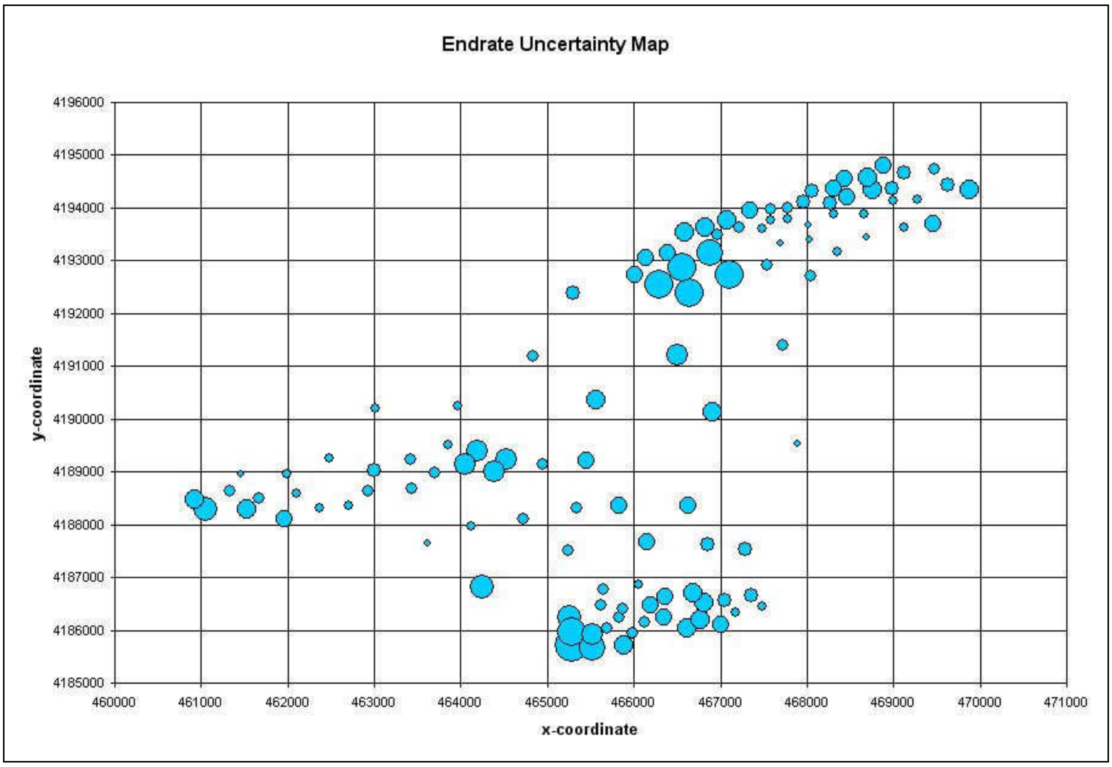


Figure 60: Endrate Uncertainty Map

3.9.3 DCA Uncertainty

The purpose of the DCA uncertainty is to capture the quality of the DCA fit and subsequently the reliability in its extrapolated curve. The main idea behind his parameter is to determine the quality of the DCA fit in the surrounding wells and thus indicating the reliability of the forecast in the infill location. In earlier versions of BRIGHT the Root mean square error (Equation 1) was used to define the quality of the decline curve fit. However, during testing the software it became obvious that the application of the correlation coefficient (Equation 13) is more beneficial for the user. The advantage of the correlation coefficient is, that it is normalized between negative one (strong indirect proportionality; not of importance for BRIGHT), zero (no dependency at all) and positive one (strong direct proportionality). The user can therefore compare several cases easier, since the values are always in the well known range of negative one to positive one.

The values for the correlation coefficients of the decline curve fits of the surrounding wells are linearly interpolated in the infill locations to present a value that informs about the reliability of the forecasts that were used to come up with the probable production of the infill locations to the user. The closer the value is to one, the better. Vice versa, to calculate the uncertainty associated with a decline curve forecast at a certain infill location the following equation is applied:

$$DCU = 1 - r^2 \qquad \textbf{Equation 34}$$

DCU stands for the uncertainty connected to the decline curve forecast; r^2 is the correlation coefficient as determined for the existing wells. A high value for *DCU* at a certain infill location therefore indicates that the reliability in the forecast at this location is rather low and should therefore be investigated before going ahead.

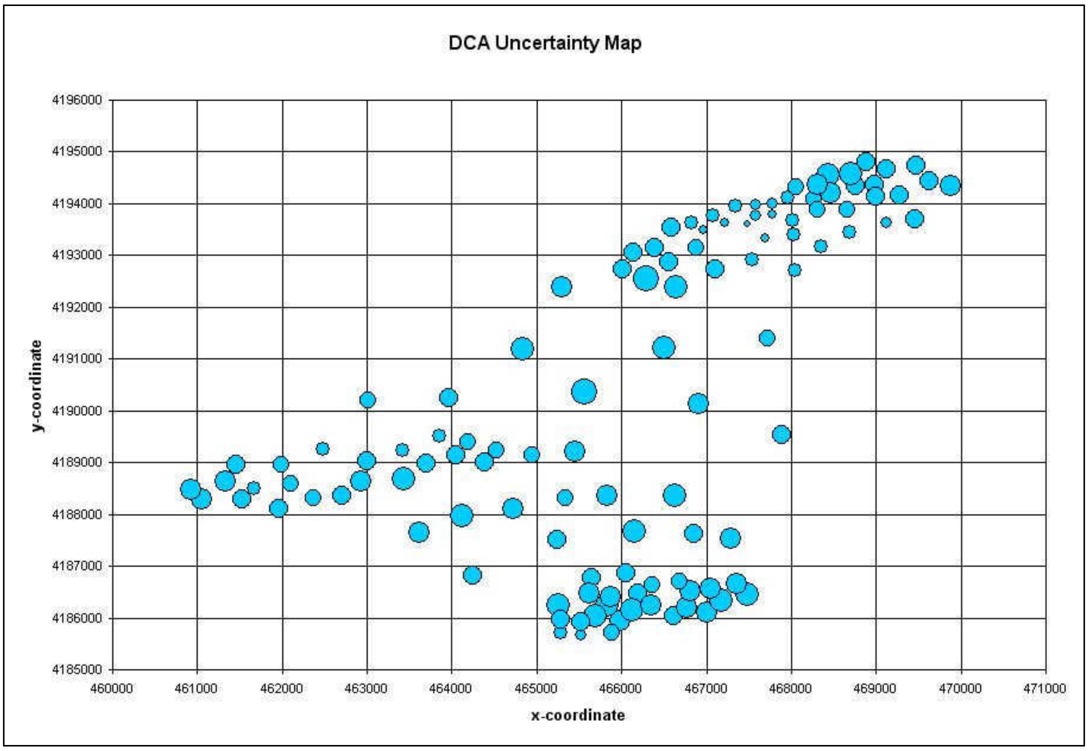


Figure 61: DCA Uncertainty Map

Figure 61 shows that especially the southern part of the field shows high uncertainties associated with the decline curve forecasts. The user should therefore investigate that part of the field (especially their decline curves) in more detail before going on with the study.

3.9.4 Total Uncertainty

The total uncertainty combines the three uncertainty values to come up with a single, final uncertainty value. The user can assign weights to each type of uncertainty in case she or he wants the influence of a certain type of uncertainty to be more severe than the influence of another uncertainty type.

After entering the weights for the Spatial Interpolation uncertainty (w_1), the End rate uncertainty (w_2) and the DCA Uncertainty (w_3), the total uncertainty (*TU*) is calculated as:

$$TU = IU \cdot w_1 + ERU \cdot w_2 + DCU \cdot w_3 \qquad \textbf{Equation 35}$$

IU, *ERU* and *DCU* are the uncertainties as defined in Equation 31, Equation 32 and Equation 34. The condition that has to be applied to use this equation is:

$$\sum_{i=1}^{3} w_i = 1 \qquad \textbf{Equation 36}$$

Since the values for TU can be larger than one, the final step in calculating TU is to normalize TU by dividing each TU value with the maximum occurring TU value. The values will therefore stay between zero and one.

Figure 62 helps to get an overview over the uncertainty values and over the severity of the specific types of uncertainty on certain wells. Moreover Figure 62 helps to find specific locations with high uncertainties. For example Location 40 seems to have three surrounding wells with high End rate uncertainties. Location 77 and Location 118 seem to have a general problem with their forecasts, since all three uncertainty values are high.

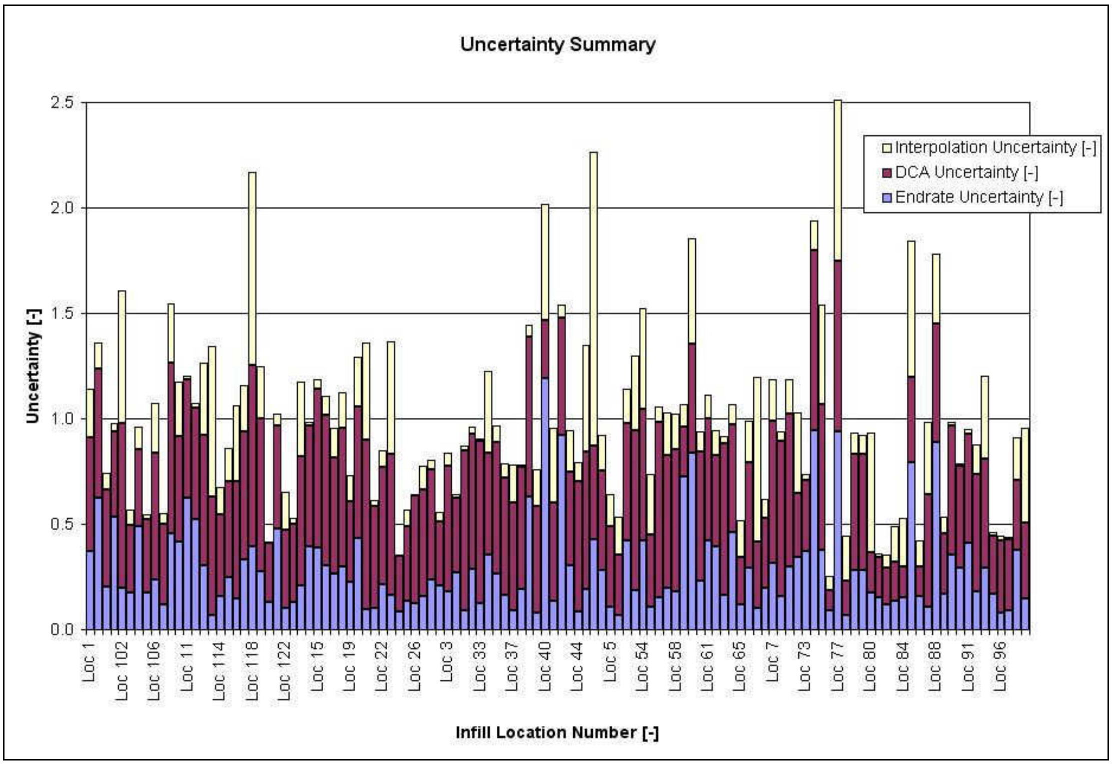


Figure 62: Uncertainty Summary

Figure 63 shows a bubble map of total uncertainty for the input $w_1 = w_2 = w_3 = {}^1/_3$. The larger the bubble the higher the associated forecast uncertainty and therefore the higher the user's cautiousness in analyzing this location should be.

The total uncertainty is a very important parameter in the subsequent workflows. Especially in the workflow to find potentially good infill locations it is highly influencing the results. Since workflows as finding reactivation candidates, finding work over candidates, etc. are less capital intensive, the influence of uncertainty on these workflows is less.

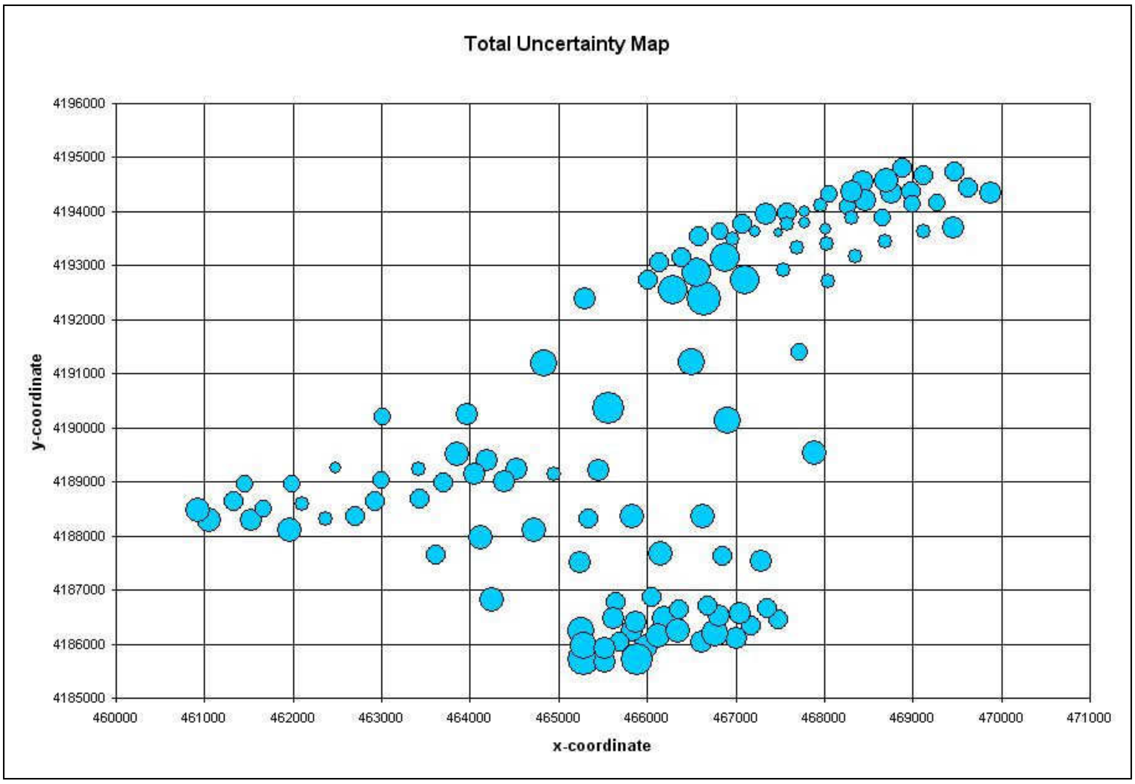


Figure 63: Total Uncertainty Map

3.10 Reasoning

All workflows in BRIGHT described so far are preprocessing the data so that they can be used in the reasoning workflow that finally applies the expert knowledge to evaluate the projects. The purpose of the reasoning in BRIGHT is to process the multidimensional and maybe probabilistic input data that are generated in the precedent workflows (e.g. all forecasted performance indicators that have been created for an infill location) and output a single numeric score between zero and 100. The reasoning's underlying algorithm is the marginalization algorithm and the Bayesian network evaluation algorithm as described in Chapter 2.1.4. The conditional probability tables (CPT) that are used for the reasoning procedure have been set up together with experienced RAPID engineers in the Schlumberger office in Calgary, Canada. The objective of this knowledge capturing procedure was to create a Bayesian Belief network that is able to draw conceptually the same conclusions as the engineers involved in RAPID studies. After setting up the CPT the reasoning algorithm was checked by comparing its result to former RAPID studies.

This Chapter presents the reasoning procedure as applied in the infill location selection workflow. The Bayesian Belief network applied to the infill location selection workflow, the associated knowledge capturing process, the parameters and their origin and the way how the algorithm can be modified to obtain the desired results are introduced to the reader.

3.10.1 Infill location selection

The purpose of the infill location selection workflow is to process the multiple forecasts for the infill locations, as generated in the previously explained workflow steps and determine an output score between zero and 100. Zero denotes an infill location that when drilled will very likely not be a successful project, whereas a score of 100 attributes a very good chance of success for and infill project. The Bayesian Belief network used for the infill location selection workflow is depicted below in Figure 64.

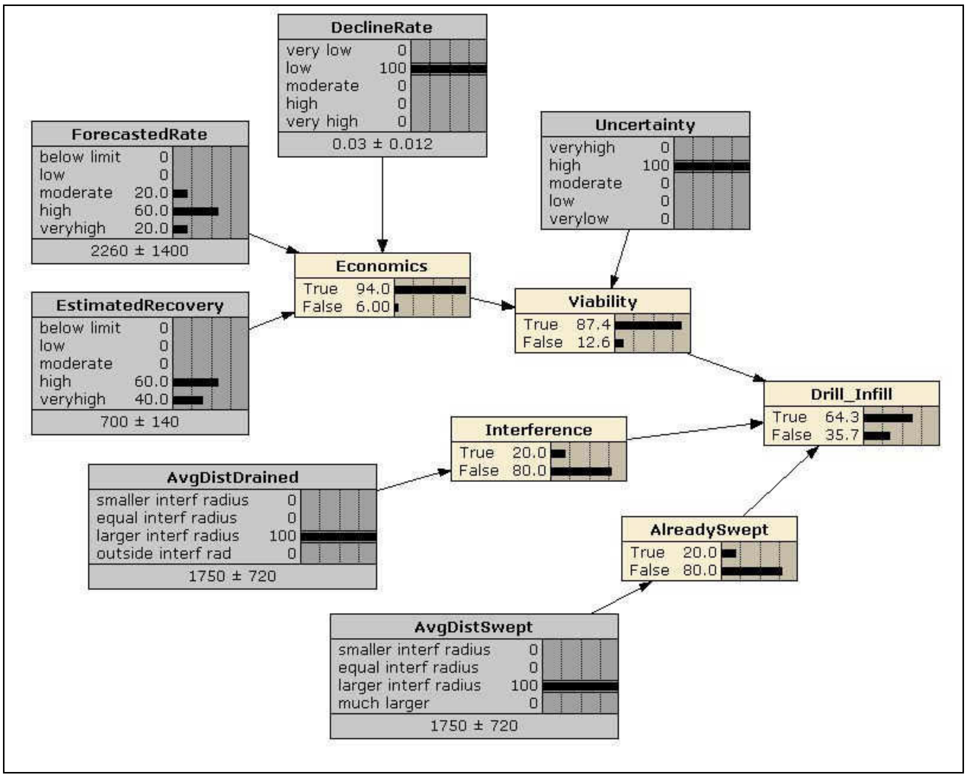


Figure 64: Infill location selection Bayesian Belief Network

The parameters used for the infill location selection workflow are:

- *Forecasted Rate [STB/d] or [Mscf/d]:* As given in Equation 26 forecasted rate summarizes the initial rate determined by interpolating on the last measured daily rate [STB/d] or [Mscf/d], the last calculated average 4 months daily rate [STB/d] or [Mscf/d] and the rate given by the decline curve at forecast start date [STB/d] or [Mscf/d].

- *Estimated Recovery [STB] or [Mscf]:* As determined in the automatic decline curve module the forecasted rate and the decline rate are spatially interpolated in the infill locations and used in the equation for exponential decline to determine the Estimated Recovery in the next three years. This value is a good performance indicator for the upcoming forecasted production profile.
- *Decline Rate [1/d]:* The decline rate for each existing well's decline curve has been determined in the automatic decline curve module and is here used as a performance indicator for the future performance. The smaller the value for the decline rate, the better, since this allows longer production.
- *Average Distance to drained area [ft]:* This parameter expresses the average distance of the infill location to the drained areas of the existing wells that are given in the corners of the triangle as described in Chapter 3.6.2. The drained areas for the existing wells are determined by calculating their drainage radius as defined in Equation 20. A schematic diagram of the average distance to the drained area of the neighboring, existing wells is depicted below:

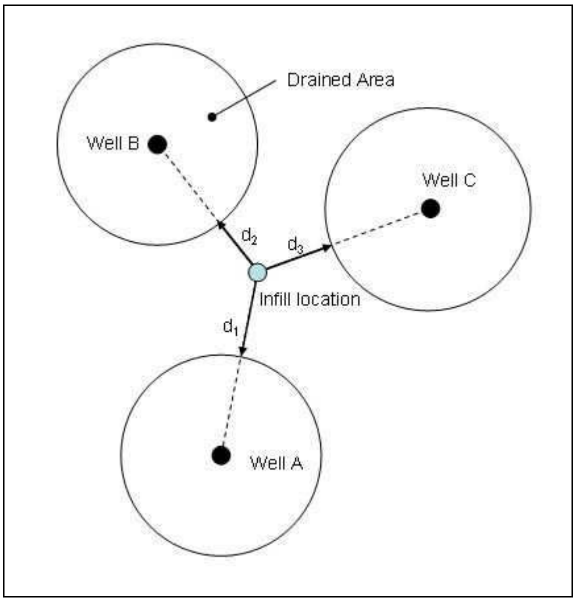


Figure 65: Average Distance to Drainage Area

The value for 'Average Distance Drained' is thus calculated as:

$$\bar{d} = \frac{d_1 + d_2 + d_3}{3}$$ **Equation 37**

Where $\overline{d}$ is the average distance to the drained areas [ft]; d1, d2, and d3 are the distances to the respective neighboring wells [ft].

- *Average distance to swept area [ft]:* In concept this parameter refers to the same idea as the parameter 'average distance to drained area'. Since water movement cannot yet be modeled in BRIGHT, the average distance to the injectors sweep radii is used as an indicator of whether the area around the infill location might already be swept (i.e. oil saturation reduced to residual oil saturation due to displacement of oil by water). The average distance to the swept area is calculated as given by Equation 37.
- *Uncertainty [-]:* Especially for the infill location selection the associated confidence at a certain location is a very important parameter. Since drilling costs are usually higher than the costs for any other common Brownfield operation, a high uncertainty would significantly downgrade the score of an infill location. The uncertainty calculation has been described in detail in chapter 3.9 and is normalized regarding the maximum total uncertainty value in order to only obtain values between zero (no uncertainty) and one (very high uncertainty).

The current version of BRIGHT does not allow multiple forecasts, however this feature will be implemented soon. Multiple forecasts would gain several values for the same parameter (e.g. three different forecasting techniques give three different values for decline rate, forecasted rate, etc.). As explained, Bayesian Belief networks can cope with probabilistic input and would process that information to an output that would still be a single numeric value. The advantage of this approach would be that the uncertainty is not only captured through the presented 'uncertainty' parameter but also in the standard deviation of the respective forecast parameter due to the different forecasting techniques.

3.10.2 Implementation in BRIGHT

After calculating the numeric score for each infill location a bubble map is presented as shown in Figure 66. Each black dot represents an infill location, the larger and the greener the bubbles, the higher the score and therefore the higher the estimated probability of success if a well is drilled in an area with a lot of green bubbles (e.g. as the northern edge of the presented field). This screen is mainly an analytical tool that presents the results as well as gives the user the opportunity to perform a simple sensitivity analysis by modifying the slider settings on the bottom of the screen. For each parameter presented in Chapter 3.10.1 a slider exists that is preset to the value as determined in the precedent forecasting steps. The score is presented in the pie chart to left of the sliders, where the green area is proportional to the score. If the user decides to change the sliders in order to investigate the influence of an e.g. changing Estimated Recovery, the score will be updated simultaneously and the pie chart will be altered accordingly.

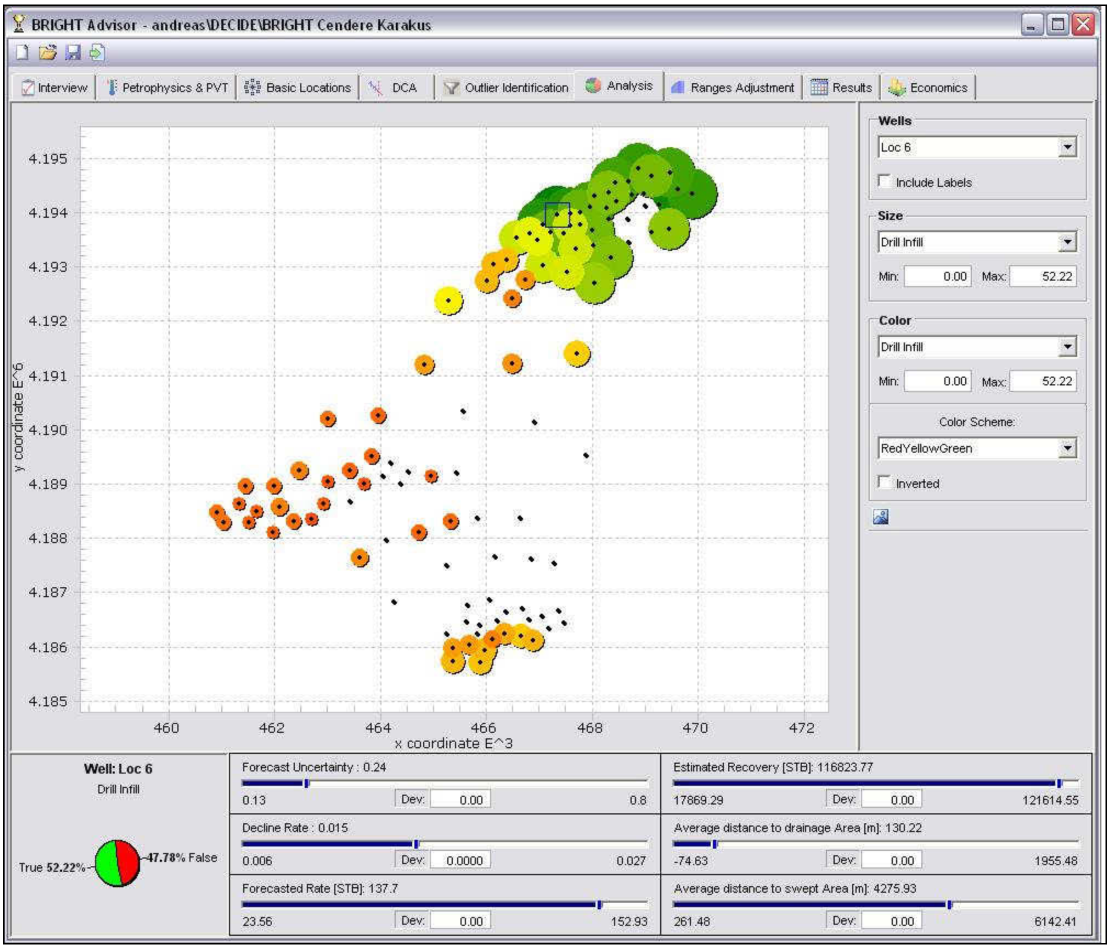


Figure 66: Analysis Screen

In the boxes below the sliders the user has the option to enter a standard deviation. If the user decides to enter a deviation, the score will most probably change, since the input is not a numeric value but a probability density function for a normal distribution; the mean is the calculated forecast value and the standard deviation is the value entered in the box. The final score will change, since this function will most probably range over several states (as discussed in Chapter 2.1.3.3) and the discretization of the function will therefore lead to different results.

Below an example has been set up to demonstrate the influence of the deviation on the result. The analysis of an infill location has resulted in the following forecasted values:

	Expected Value		Deviation	
Forecasted Rate	108.5	[STB/d]	42.5	[STB/d]
Estimated Recovery	79	[MSTB]	30.9	[MSTB]
Decline Rate	0.0136	[1/d]	0	[1/d]
Uncertainty	0.35	[-]	0	[-]
Average distance to drained Area	116.98	[ft]	10	[ft]
Average distance to swept Area	no injectors	[ft]	0	[ft]

Table 7: Infill Location, Forecasted Values

In the current version of BRIGHT only the expected values are used in the analysis. The values for the deviation were determined manually in individual forecast runs. If no deviation is taken into account the final result score would be 63 [%], thus giving that particular location a rather good chance of being a successful infill location. It has to be noticed that if the deviation is not considered, the discretization procedure that has been described in Chapter 2.1.3.3 would only lead to one state that is encountered by hundred percent and all other states are set to zero [%].

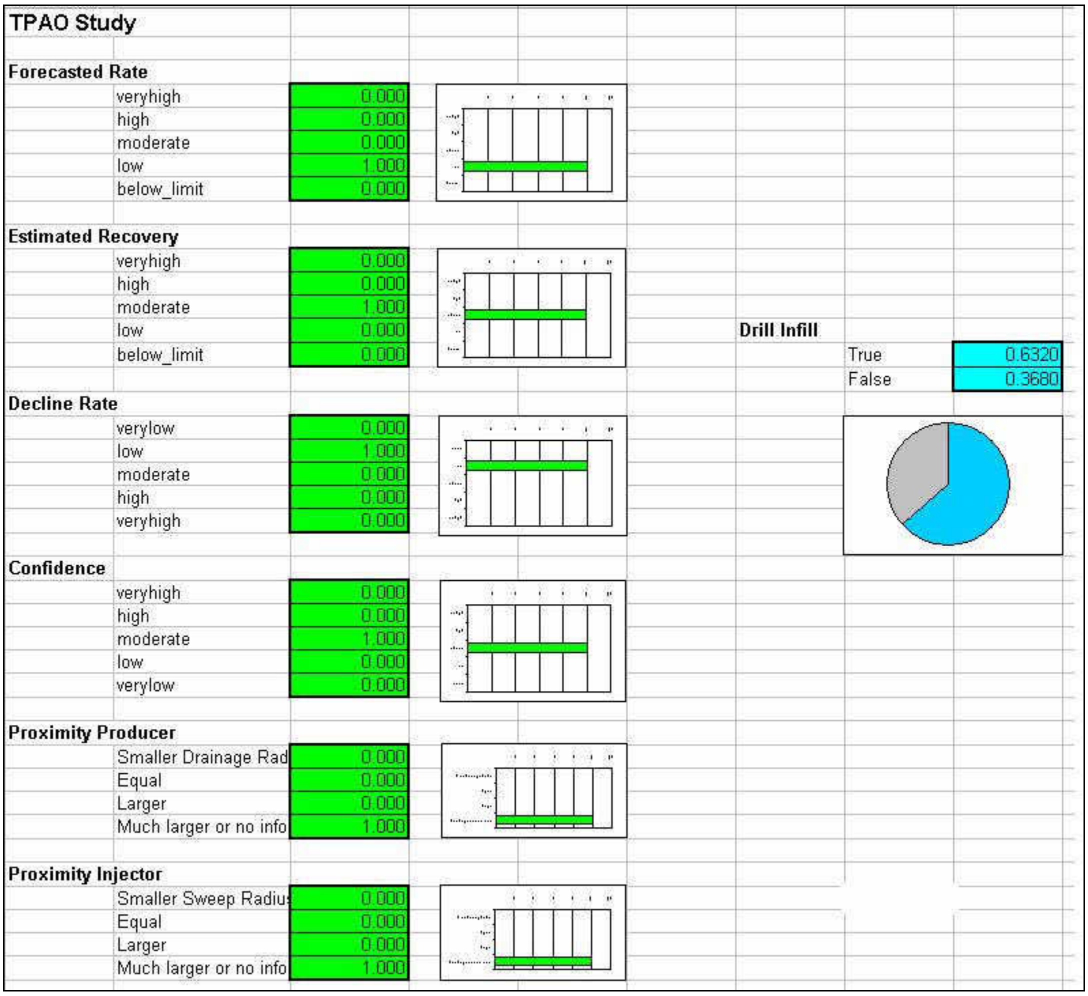


Figure 67: Score without deviation

If the deviation is taken into account that situation changes. The *inputfunction(x)* in Equation 7 would be a normal distribution density function with the mean at the value that is given in the column 'Expected Value' in Table 7, and the standard deviation given in the column 'deviation'. The application of Equation 7 would lead to a state distribution that follows the normal distribution density function according to the state limits. Therefore several states will be encountered with fractions between 0 and 100 [%] which would change the result score significantly. The example well in Table 7 would gain a result score of 54 [%] when the deviation is taken into account in contrast to 61 [%] if the expected values are taken as numerical values rather than as parameter of a density function.

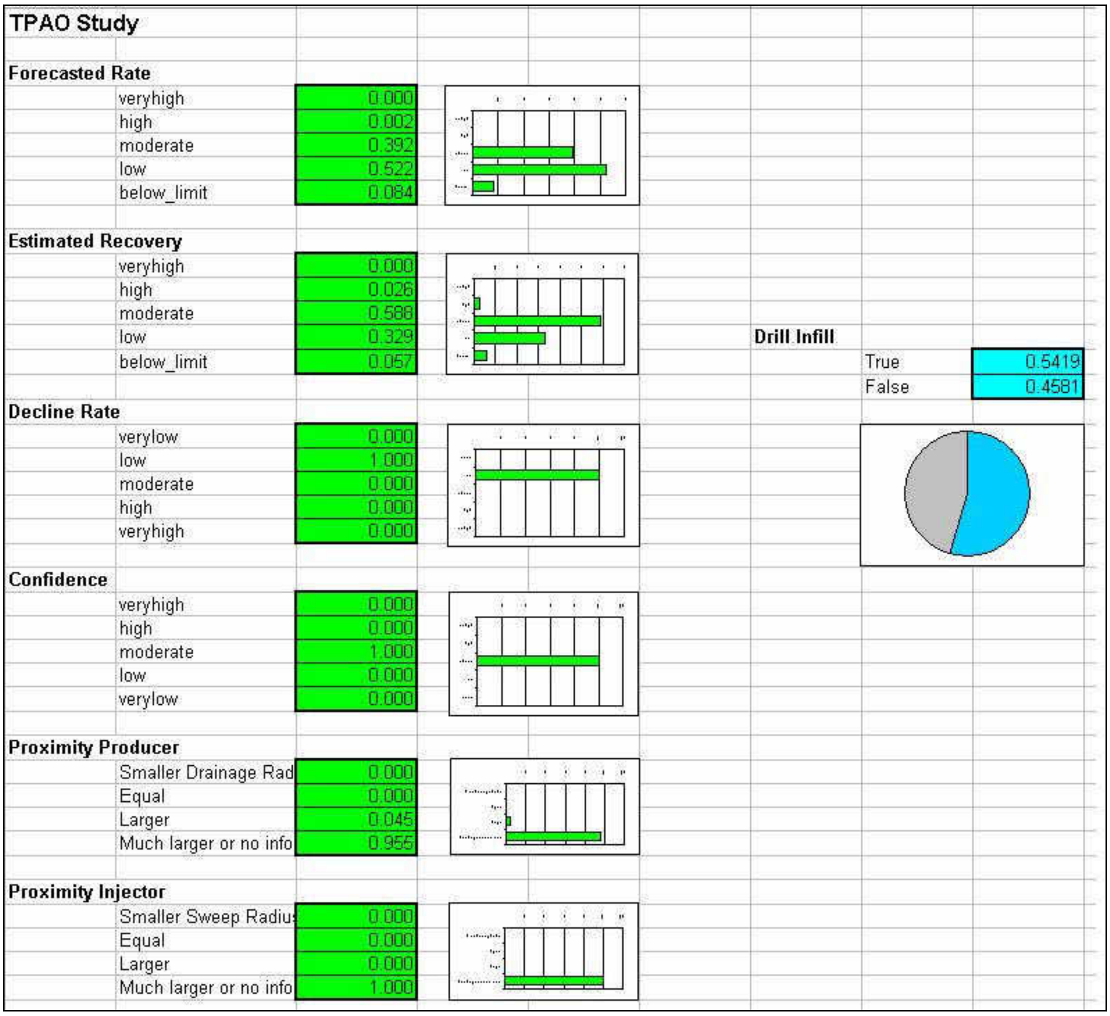


Figure 68: Score with deviation

A sensitivity study in Crystal Ball, a statistical tool that performs Monte Carlo simulations, has been performed to investigate (a) the effect of the deviation on the score and (b) the sensitivities of the score on ‘Forecasted Rate’ and ‘Estimated Recovery’. The input were the values given in Table 7 as a normal distribution’s mean (column: Expected Value) and standard deviation (Column: Deviation).

As expected, the deviation leads to a higher spread in the results. Figure 69 shows the scores on the x-Axis and the respective frequencies of the individual scores on the y-axis. The mode in the diagram below is around 58 [%]. The minimum occurring score value is zero [%] and the maximum value is 69 [%], which is a very large spread.

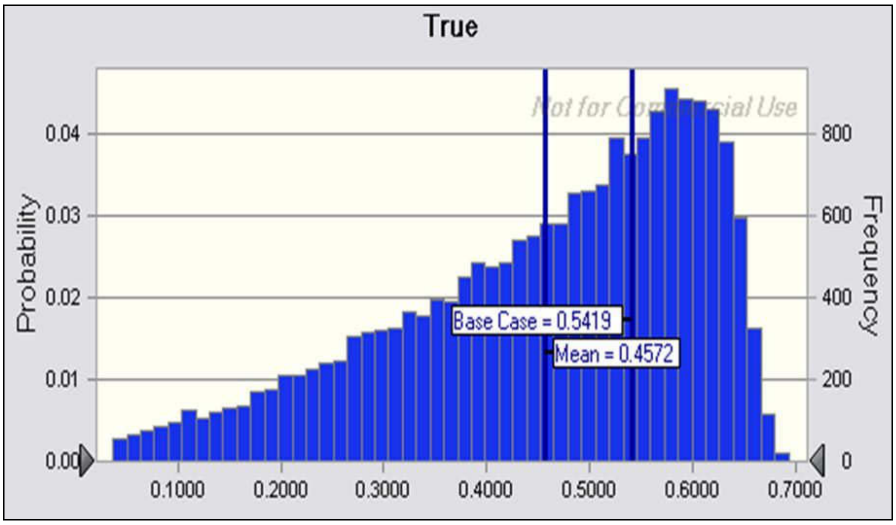


Figure 69: Monte Carlo Analysis, Score

By reducing the deviation of ‘Estimated Recovery’ from 42.5 [MSTB] to 20 [MSTB], the frequency plot looks as depicted below. All other forecasted values for the infill locations stayed the same. Again the scores are depicted on the x-axis and the frequencies on the y-Axis. It can be seen that the resulting mode is at 63 [%], which already is much closer to the value obtained in the very first calculation, where the score was computed without regarding the deviations at all. The spread is lower with decreasing deviation; the minimum value in that case is at approximately 20 [%], which is closer to the maximum score of 70 [%] than in the prior case.

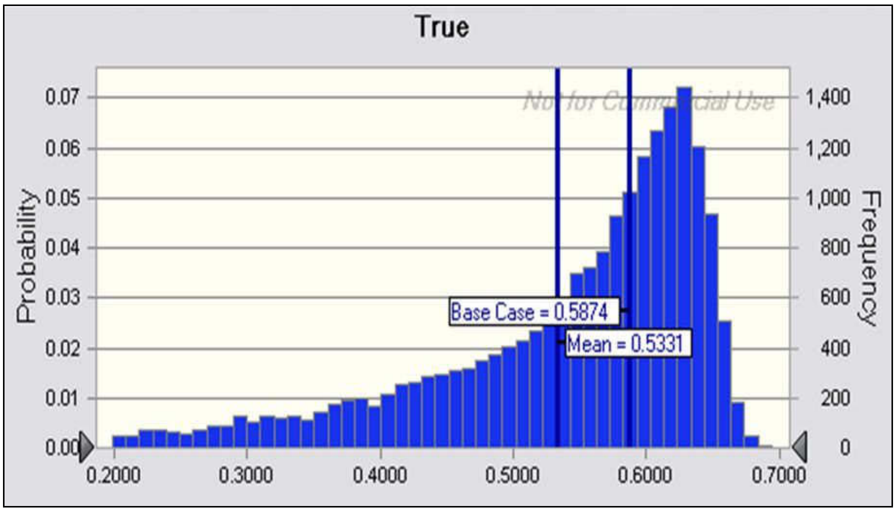


Figure 70: Monte Carlo Analysis, Scenario 2

The reduction of deviation leads to a change in sensitivities. It has to be noted, that a change of state for ‘Estimated Recovery’ leads to the largest change of the multiplier in Baye’s Theorem as applied in BRIGHT (e.g.

$\sum_{States} p\left(Economics = true \middle| \begin{array}{l} ForecastedRate = State_i, \\ Estimated\,Recovery = State_j, \\ DeclineRate = State_k \end{array} \right)$ in Equation 9). Therefore all changes in influence on the score are mainly dependent on the behavior of ‘Estimated Recovery’. The ‘Estimated Recovery’ did not have too much influence on the output in the first case. However, in the second example the influence of ‘Estimated Recovery’ on the score was rather high. The change in the influence of ‘Forecasted Rate’ was even more severe. In the first case it was highly influencing the result whereas in the second case its influence decreased to almost zero. The reason for that is, that due to the higher deviation of the ‘Estimated Recovery’ in the first case, the multiple possible parameter combinations lead to a lot of different score results, thus leaving the parameter ‘Forecasted Rate’ with a rather high influence on the score. However, in the second case, ‘Estimated Recovery’ did not fluctuate too much between the states since its deviation was a lot lower. Therefore, not as many different parameter combinations with ‘Forecasted Rate’ were possible. Therefore the influence of ‘Forecasted Rate’ was decreased.

It is apparent that the evaluation of a Bayesian Belief Network is generally similar to a Monte Carlo analysis. The main differences is that Monte Carlo Analysis use the classical statistical approach of using frequencies but BRIGHT is using Baye’s Theorem. Moreover in BRIGHT’s case the marginalization technique leads to a single numeric value as an output, which makes it a lot easier to rank the values instead of ranking density functions. The computational time is reduced significantly. The above investigations have been performed with 10,000 iteration runs. In a field with hundred or more potential infill location that would lead to more than ten million iterations. The Bayesian Belief network incorporates the deviations already in the first computation run, thus making iterations because of deviations obsolete.

3.10.3 Range setup

It has been mentioned several times that the conditional probability tables have been set up together with experienced engineers in the field of Brownfield studies. Since the CPTs have a very critical influence on the result and its soundness it was decided that in BRIGHT the user should not have the option to modify the value in the CPT. That lead to another issue about how an engineer in an arbitrary field can modify the assessment and evaluation logic of BRIGHT according to his or her perception of the field and the project. It has been decided that the best influence for a user on the output is in the change of ranges of the states. Chapter 2.1.3.3 and 2.1.3.4 explain the states of the nodes, their ranges, the discretization of the input function and the result on the output in detail. Here it will be demonstrated, how the user can modify the range limits to change the assessment logic according to the project requirements.

Figure 71 shows the state ranges setup screen. Each area plot displays a sorted histogram for a certain parameter. E.g. the area plot on the top right is a sorted histogram of ‘Estimated Recovery’. In a sorted histogram all calculated mean values for ‘Estimated Recovery’ are displayed in an ascending order from left to right. The x-Axis stands for the well and the y-Axis displays the value for the respective parameter. It has to be pointed out that a well, which is located on e.g. spot 55 in the ‘Forecasted Rate’ plot is not necessarily on the same spot in the ‘Estimated Recovery’ diagram, since each diagram is sorted separately.

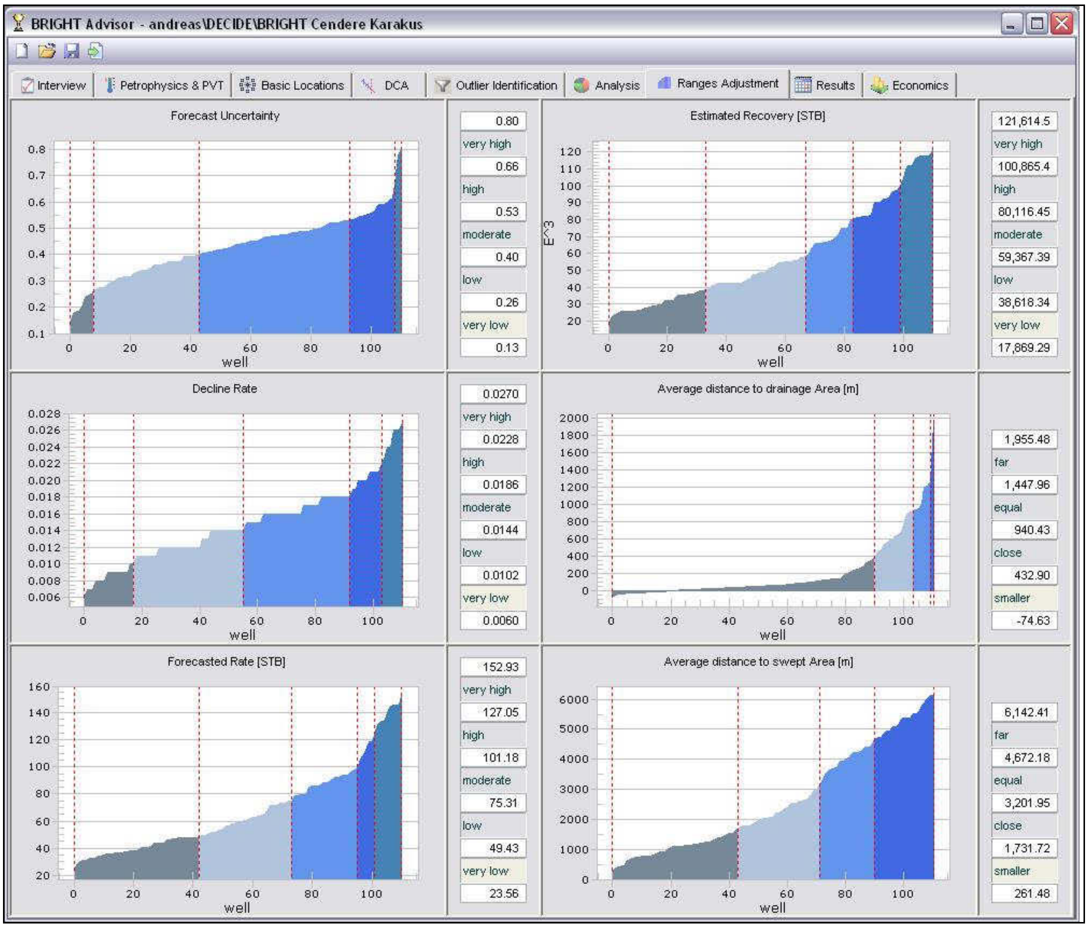


Figure 71: State range setup

As explained in Equation 7 the upper and lower limit of the state determine what fraction of the input distribution can be assigned to a certain state. A larger range for a state will most probably lead to a higher fraction for that state. This will have direct consequences on the computation of the output score as can be seen in Equation 9, since the values for *p('Parameter'=state$_j$)* change. Since it is a fact, that 'good' parameter states (e.g. 'Estimated Recovery' = 'high', 'Forecasted Rate' = 'high', etc.) are given a high score, the user can generally increase the score by increasing the range of the 'good' parameter states. Vice versa the user can take a more pessimistic look on the field by reducing the range of the 'good' states and increasing the 'bad' parameter states, such as e.g. 'Estimated Recovery' = 'very low', 'Forecasted Rate' = 'low', etc. Hence, the user has a tool to change the weight and the influence of specific parameters. By changing the parameter range limits to his or her understanding. The effect of the parameter state ranges is demonstrated for the northern part of the example field:

(a) Pessimistic view on the reservoir:

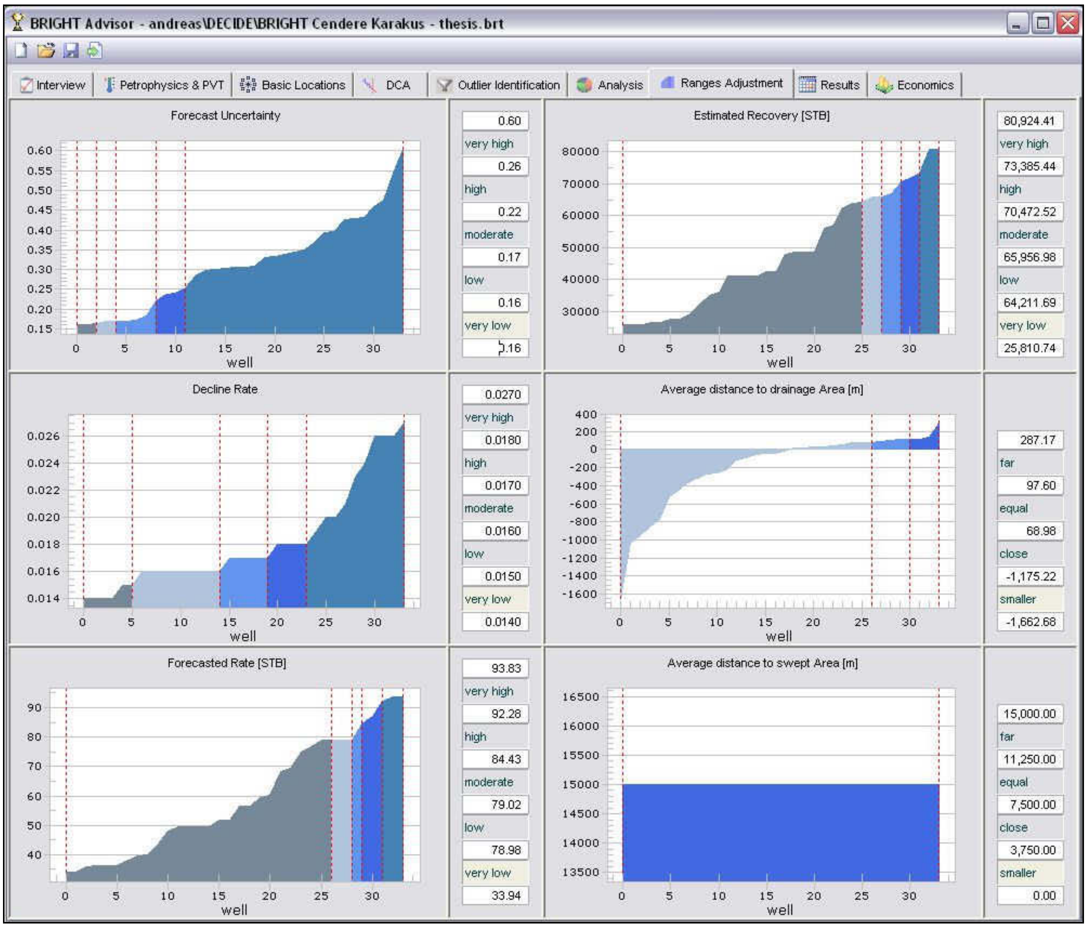


Figure 72: Pessimistic Range setup

The parameter range setup as presented in Figure 72 is a rather pessimistic view on the reservoir. The ranges for ‘Estimated Rate’ = ‘very low’ and ‘Forecasted Rate’ = ‘very low’ are rather large thus increasing the number of inputs that are classified in these two states. An infill location with one of these to parameters classified as ‘very low’ is automatically given a score of zero [%], because they are not assumed to be economically producible. A lot of infill locations will therefore be given a score of zero [%] or otherwise a very low score. An infill location that is determined to be a good location even though the parameter range setup is making it really hard for an infill location to be evaluated with a good score, is very probable a good infill location to go for.

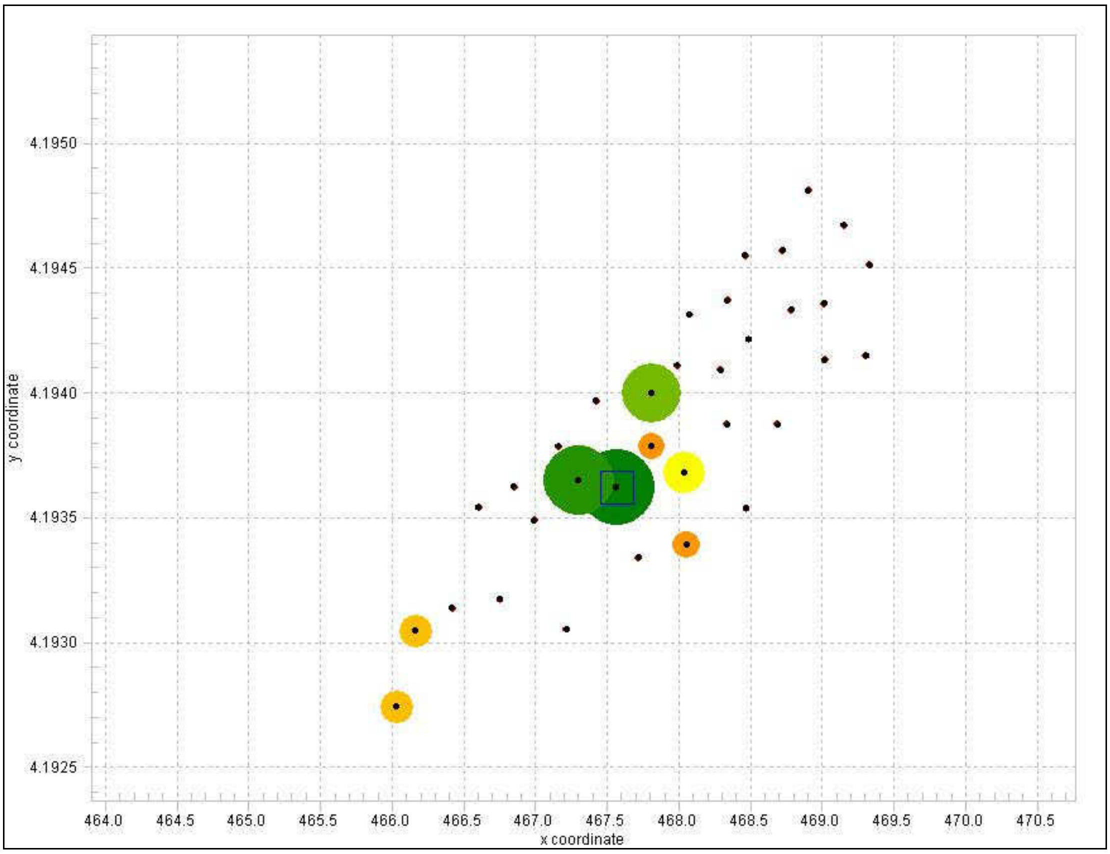


Figure 73: Infill Location map

Figure 73 shows an infill location bubble map, with the x-coordinate of the infill location on the x-axis and the y-coordinate of the infill location on the y-axis. The bubble size and the greenness is proportional to the score; the larger and the greener the bubble the better. According to Figure 73 only three wells correspond to the high standards set by the parameter range setup.

(b) Optimistic view on the reservoir

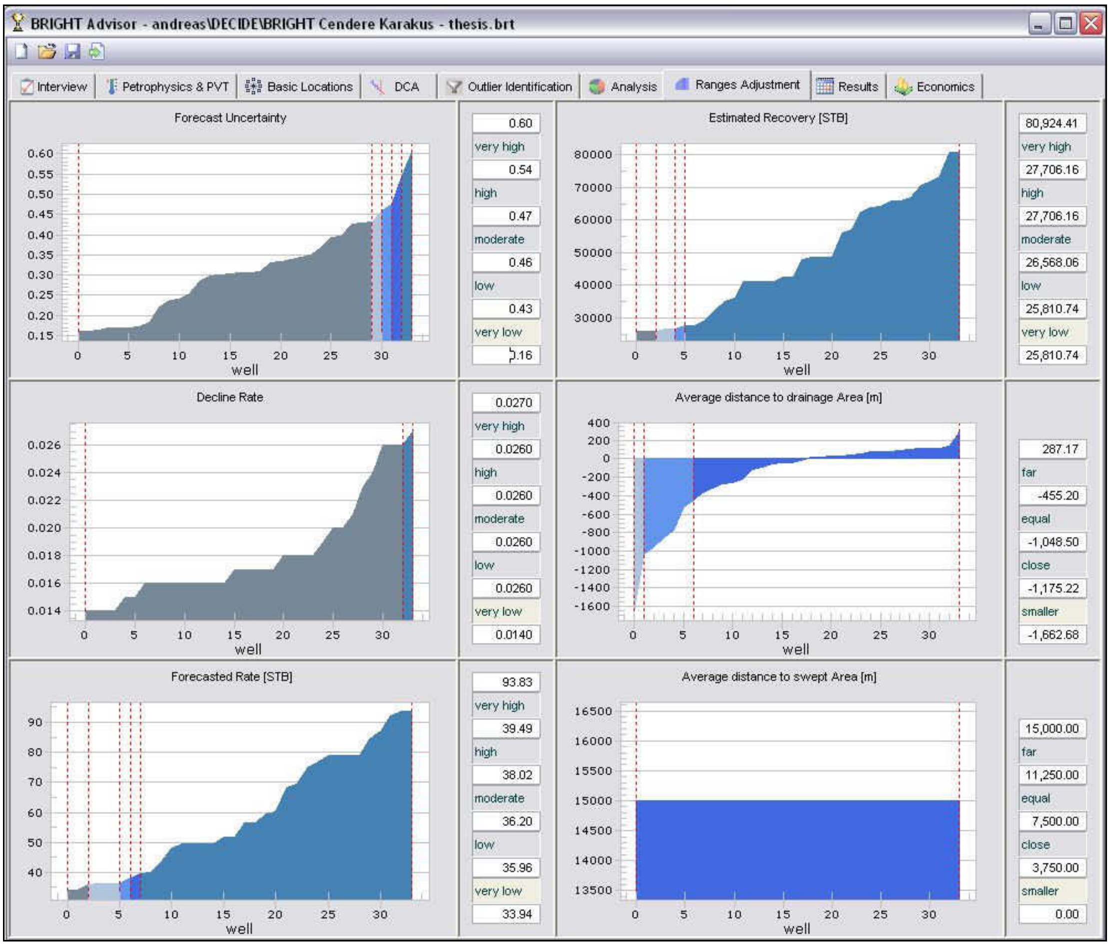


Figure 74: Optimistic Range setup

Figure 74 shows an optimistic range setup where very well visible the ranges for 'Estimated Recovery'= 'very high' and 'Forecasted Rate' = 'very high' have been increased significantly, leaving the 'very low' states with only a very narrow margin. Thus, a lot of wells will be classified as very good infill locations, since their forecast values are binned into 'very high' states. The map of the same example field is displayed in Figure 75. Again the same diagram setting as explained in the prior example has been used to display the result. The result has changed significantly presenting much more locations with a probably very good chance of being a well performing infill location.

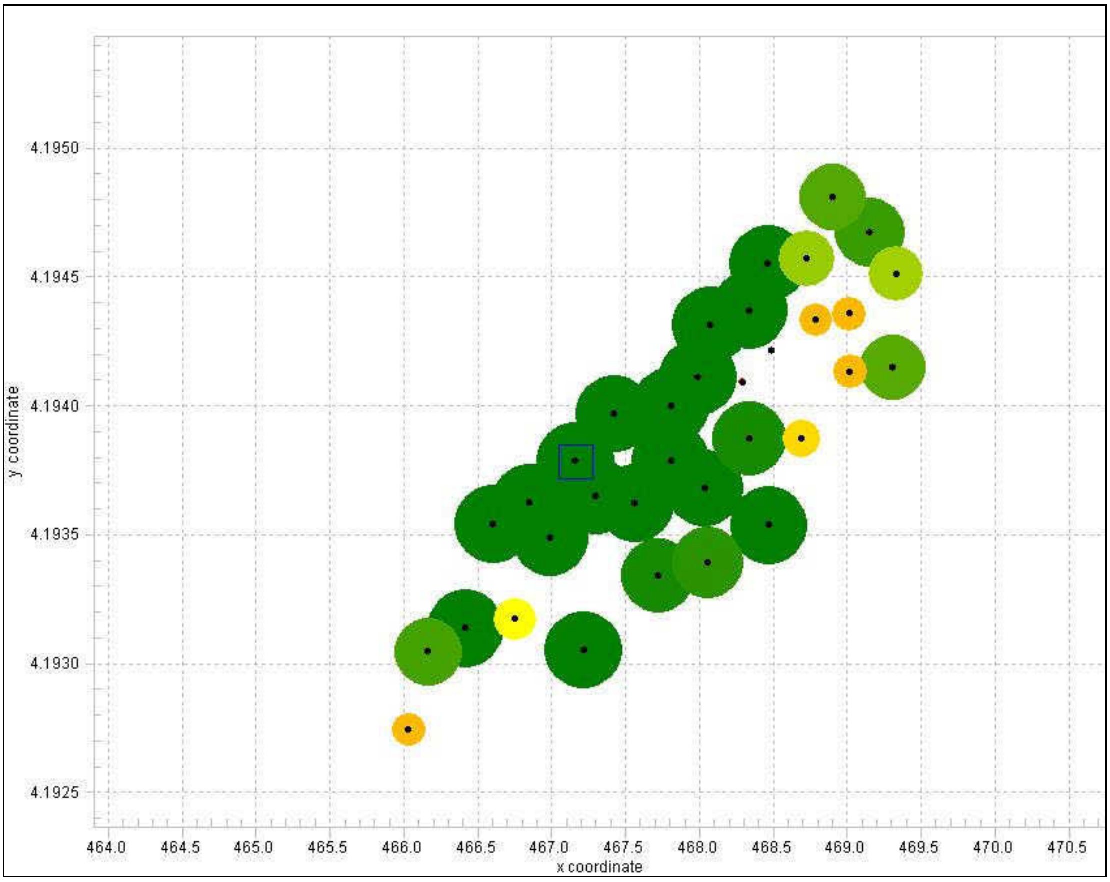


Figure 75: Infill location map

3.11 Workflows

The only workflow that will be implemented in BRIGHT's first version is the infill drilling location selection workflow. In this chapter the workflow schematic is presented and all processes are summarized and integrated. Chapter 3.11 will also inform about how BRIGHT accounts for interference of selected infill well projects with existing wells.

All steps in the process have been described in the earlier chapter. In this chapter they shall be integrated and presented in the process flow so that the reader gets an insight into the workflow.

1. Monthly production rates for the phase to be investigated are retrieved from the database as well as the x and y coordinate for each well. These three parameters are mandatory and cannot be left without values.
2. All available petrophysical parameter (Porosity ϕ [-], Water saturation s_w [-], average net pay thickness h [-])

3. Voronoi Grid: To allocate an amount of hydrocarbons in place (HCIP) [STB] or [Mscf/d] to a certain well the Voronoi grid is applied (as explained in Chapter 3.6.1). It is very important to notice, that the calculation of the hydrocarbons in place is only based on geographic information of the well locations and not on actual drainage areas. Therefore a rather elliptical drainage area of an inclined well cannot be modeled adequately in BRIGHT's first version (remark: that is the reason why BRIGHT claims to not be yet applicable for reservoirs with many inclined or horizontal wells). Also another restriction applies: The differences in pressure drop from reservoir to Wellbore among the wells cannot yet be regarded in the calculation of allocated hydrocarbons in place. Therefore a well with a higher pressure drop from reservoir to Wellbore is not necessarily allocated a larger drainage area and subsequently a larger amount of allocated HCIP, as would be the case when strictly using Darcy's equation.
4. Spatial Interpolation of Petrophysical Data: The petrophysical values for unsampled wells are determined through a method that can be chosen by the user (either averaging, ordinary Kriging or user input). The user has to decide, which method is the most applicable based on the number and of the spatial density of the locations with petrophysical measurements.
5. Automatic Decline Curve Analysis: As explained in Chapter 3.7 the automatic decline curve procedure is applied to determine Forecasted Rate [STB/d], 3 Year estimated recovery [STB], Decline Rate [1/d] and – incorporating the petrophysical data – 'Recovery Factor' [-] for existing wells.
6. Outlier Identification through Exclusion Mapping: In Chapter 3.8 the term outlier was defined and the procedure to detect outliers was introduced. In the process workflow the outlier detection is a precedent step prior to the generation of infill locations, to make sure that the outliers are not regarded in the infill location selection workflow.
7. Generation of Infill Locations: In Chapter 3.6.2 the Delaunay Triangulation procedure was presented that is applied here to – after the outlier detection has tossed out significantly different behaving wells – the remaining existing wells. The coordinates of the inner circle center point of each triangle are stored as the infill location's coordinates.

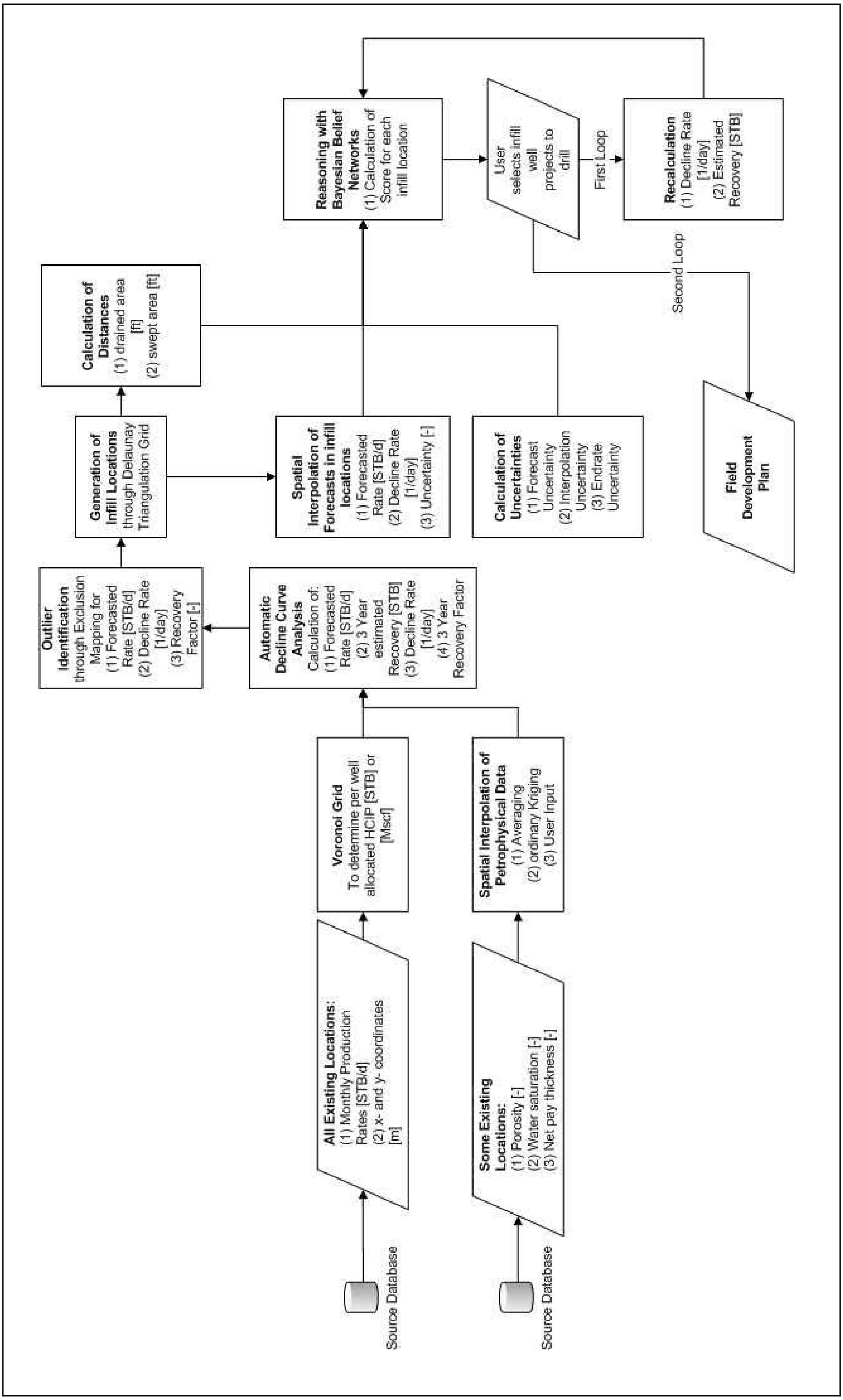


Figure 76: Infill Location Selection Workflow schematic

8. Spatial Interpolation of Forecasts in Infill Locations: After the automatic decline curve analysis module has determined the forecast for all wells and the outlier wells have been removed from the workflow, the production performance forecasts can be interpolated in the infill locations. In the spatial interpolation step for the petrophysical data, the user had to choose the type of estimation technique BRIGHT should apply. Since the availability of a statistically reasonable amount of well data is one of the prerequisites for a BRIGHT study, it is now safe to go on with ordinary Kriging by default. Interpolated parameters are Forecasted Rate [STB/d] or [Mscf/d] (see Equation 26) and Decline Rate [1/d]. The other performance indicators (e.g. 3 Year estimated recovery [STB] or [Mscf], estimated ultimate recovery [STB] or [Mscf]) are calculated based on Forecasted Rate and Decline Rate using the equation for the exponential decline of the production rate as given in Equation 11on page 42.
9. Calculation of Distances: Based on the coordinates of the existing wells (without outliers) and the coordinates of the infill locations the average distance to drained area and the average distance to swept area is calculated (see Equation 20 and Equation 37).
10. Calculation of Uncertainties: Now that all forecasts and spatial interpolations for the infill locations have been performed the uncertainties as described in Chapter 3.9 are calculated for the infill locations.
11. Reasoning with Bayesian Belief networks: Every infill location has now been assigned their coordinates, their forecasted values and their uncertainties. The reasoning part of BRIGHT now has to combine all the information process it according to the captured expert knowledge in the Conditional probability tables and the rages setup for the states of the parameters and compute a single numeric value as the output score for each location. The results are presented (1) in a bubble map, where the x- and y-axis correspond to the respective coordinates and the bubble color and bubble size correspond to the score and (2) in a table that is sorted according to a descending score (i.e. best scores are on the top of the table).
12. The user now has to select the infill locations that should be drilled. By doing that BRIGHT of course has to account for interference of the potentially infill well with the surrounding existing wells. The interference effect is calculated

with a very basic principle in mind: There are no new reserves added. An infill well therefore can only increase production rates but not add any new reserves. This is a valid assumption for Brownfields since the well density is usually very high.

BRIGHT therefore calculates the total estimated ultimate recovery (EUR) of the three existing wells that have been used in the Delaunay triangle for the selected infill location. Since the infill location is selected and therefore going to be drilled, the EUR of all three wells is now redistributed among all four wells, including the new well to be drilled. This consequently leads to lower values for the EUR for the three Delaunay triangle wells, which in turn increases their decline rates. BRIGHT calculates this reduction in EUR and increase of Decline rate and starts a new interpolation (ordinary Kriging) of the Decline rate for the infill location. The value for the Decline rate in the infill location will thus also be a little higher, which reduces the estimated recovery for the infill location. BRIGHT will use the new forecasted values again in the Bayesian Belief Network and reevaluates the well giving it a new score, which will most probably be slightly lower than the score given at first. The user can now take well production interference into account when deciding whether that infill location should still be drilled or not.

13. A Field Development Plan is automatically generated based on a project ranking logic that evaluates basic economic parameters and ranks the selected projects according to their positive economic impact on the field development.

4. Examples

In this chapter the introduced workflow is presented on the basis of a real field example. The presented field is a gas field in the north eastern part of Alberta, Canada. Most of the wells in that region are operated by BP Canada. This field was one of the fields to test the applicability of BRIGHT.

The field contains more than thousand completions, however only 472 have been brought on stream to produce gas. The project scope contained 178 of these 472 wells. The field was discovered in 1967 and started production in the late seventies. A summary plot about the number of producing wells and the cumulative gas production is depicted below.

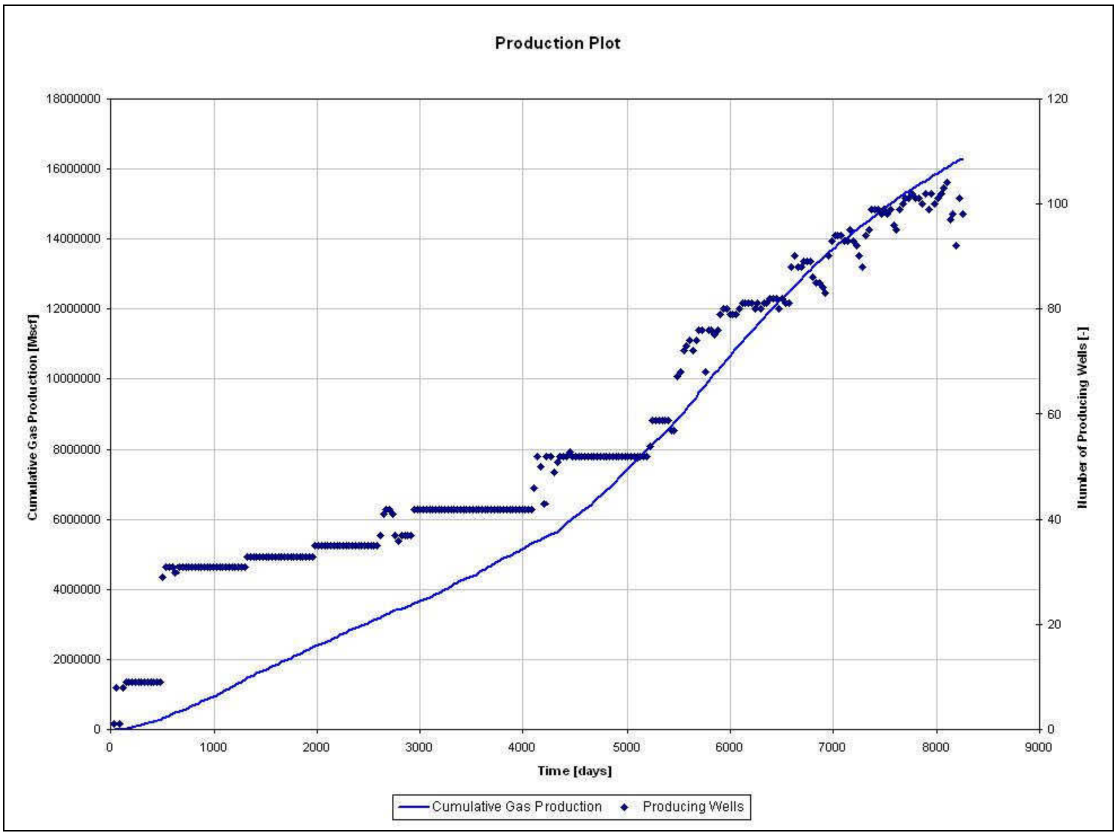


Figure 77: Production Plot

BP is interested to know about the best infill drilling locations.

4.1. Application of BRIGHT

The named conditions indicate a good application area of BRIGHT. However, the interview screen questions are answered in order to have confirmation.

The production data are reliable. They are obtained from a public domain database, which are used in North America to store and query the production volumes of national oil and gas companies. The primary produced phase is gas and the secondary phase is water. The fluid check is therefore OK and it is safe to go on. The Reservoir Characterization check also is OK, since the reservoir is neither unconventional nor is a complex reservoir system apparent. The ‘Operating Strategy’ check was OK since the operating conditions have not changed recently (e.g. installation of compression units) and there were no recent new fracturing jobs performed. This is important to know, because recent changes in the operating strategy would introduce a transient production profile, which is currently not manageable with BRIGHT. The data availability check was OK as well, since the production history of 178 wells is given in a monthly time increment over 30 years. This is enough to justify the application of statistical techniques and extrapolation techniques as used routinely in BRIGHT.

All of the wells have values for average reservoir porosity, average reservoir permeability (which is currently not used in BRIGHT), average reservoir net pay thickness and average reservoir water saturation. This indicates that probably a numerical reservoir simulation model has already been set up and the data might come from a geologic model that has been used as an input for that simulation model. Therefore no interpolation of geophysical properties is necessary.

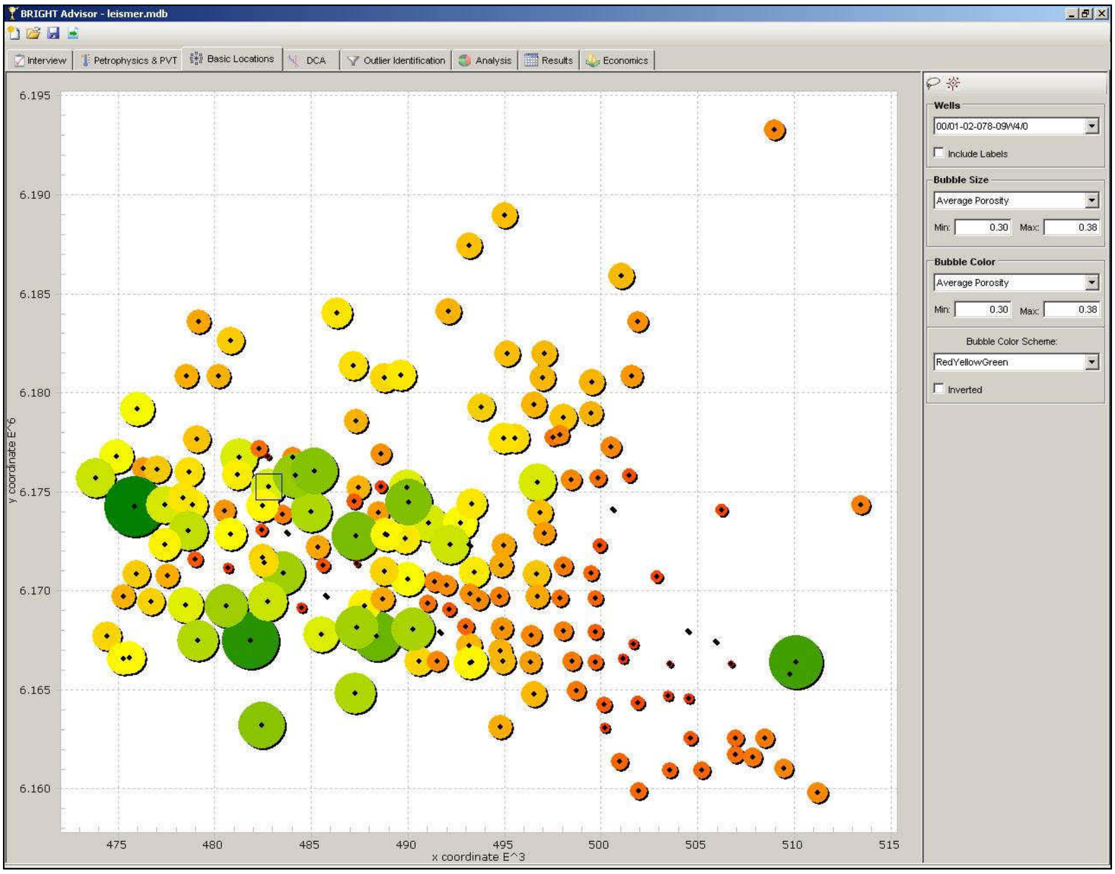


Figure 78: Porosity Bubble Map

The next workflow step shows a map of the field. Each point in the map represents a well. In the depiction in Figure 78 the porosity was chosen as the parameter to be displayed as bubble size and bubble color. The larger and the greener the bubbles the higher the porosity. Already now a relatively better area – regarding Petrophysics – is identified in the western part of the field.

The next step is to create the Voronoi grid. Since the internal algorithm does not crop the Voronoi cells on the edge and makes them infinitely large – which in turn would lead to an infinitely large drainage area and subsequently to a recovery factor of zero-, the bounding radius option has to be applied. It has to be clear to the user that the current application is gas field; therefore the bounding radius can be larger than the bounding radius of a common oil field.

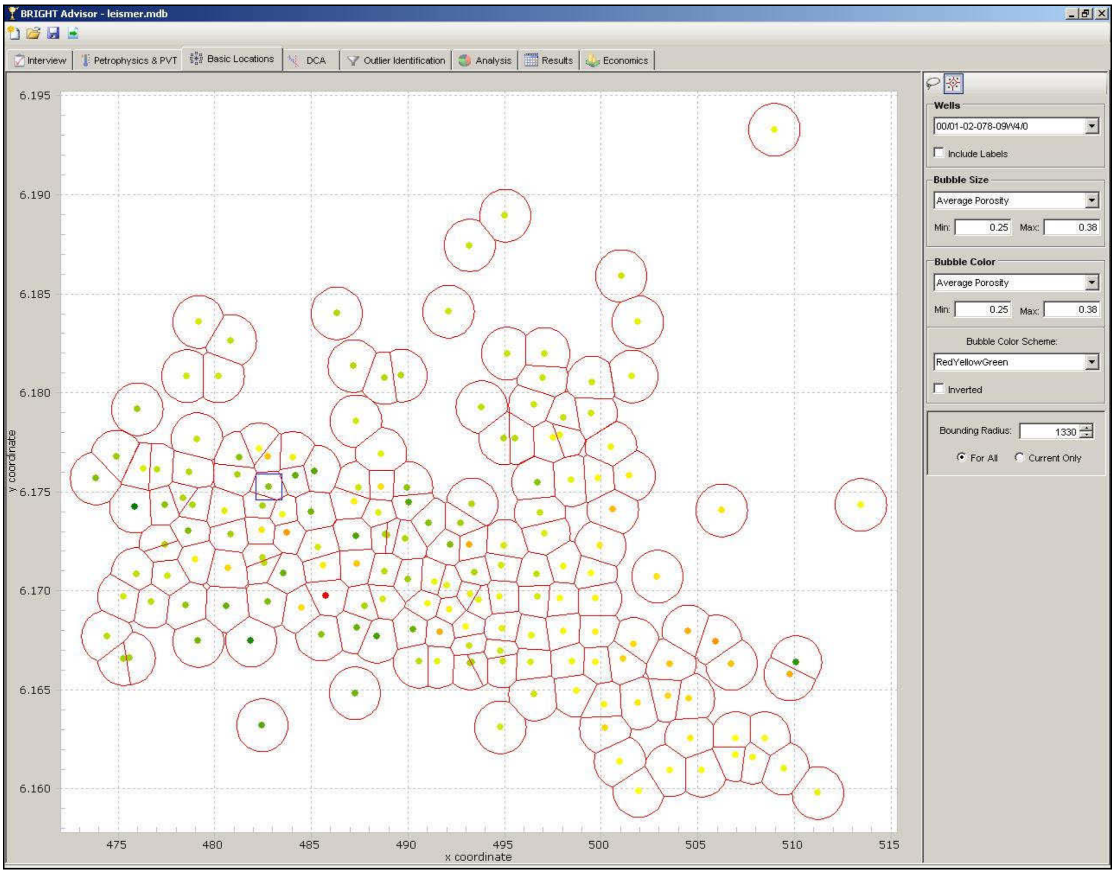


Figure 79: Voronoi Grid

Now that the drainage area is determined and the area of interest is located the automatic decline curve analysis can be started. Since a lot of production rate data are available the user can expect a good performance of the decline curve algorithm.

When browsing through the decline curves, there are a lot of wells that have stopped production long before the forecast start date, which is in 10/1/2001. These wells have to be identified in the outlier detection workflow steps. In later versions of BRIGHT these wells will be analyzed separately for work over and recompletion potential. The user is advised to browse through all decline curves in order to find misfits due to severe outliers. The better the forecast of the decline curve analysis the more accurate the field development plan is.

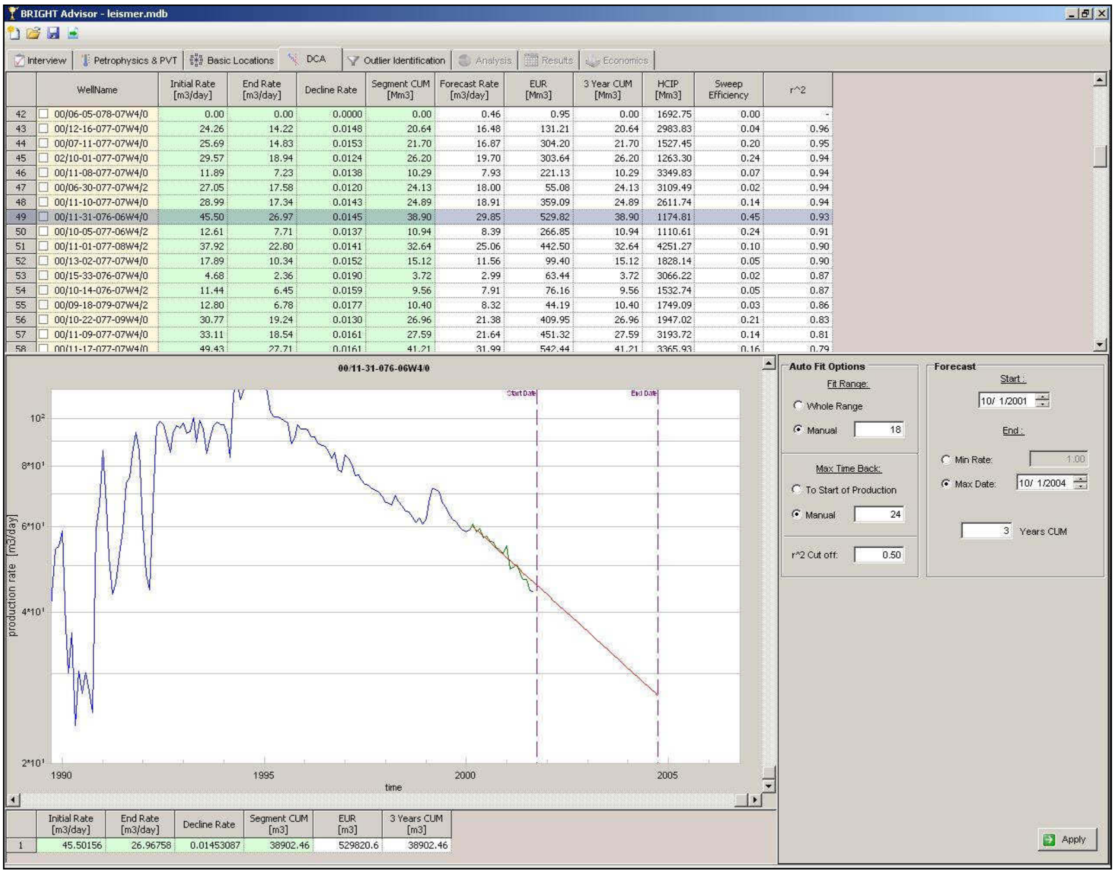


Figure 80: Decline Curve Analysis

After a few corrections for several decline curves it is possible to go on to the outlier detection workflow step. In the list of the outlier it is obvious that most of the 71 outliers are outliers because of their too long shut-in time. About 51 of the 71 outliers can therefore for sure be tossed out for further performance interpolation operations. The remaining 20 wells either have a positive decline curve slope (15 wells) or are outliers because two of their performance indicators are significantly different than their surrounding well's performance indicators (5 wells). The user can now chose if she or he wants to go back to the DCA step and manually correct those 15 decline curves. For the purpose of this work the decline curve of these 15 wells have been corrected.

The analysis of the results is the next step. Before having a look on the result values, the advanced setup of the range limits has to be done. BRIGHT automatically finds suitable range limits, however it should be checked, whether the automatic limits correspond with the engineer's perception of the situation. As can be seen in Figure 81 the range setup looks very reasonable and will therefore not be changed manually.

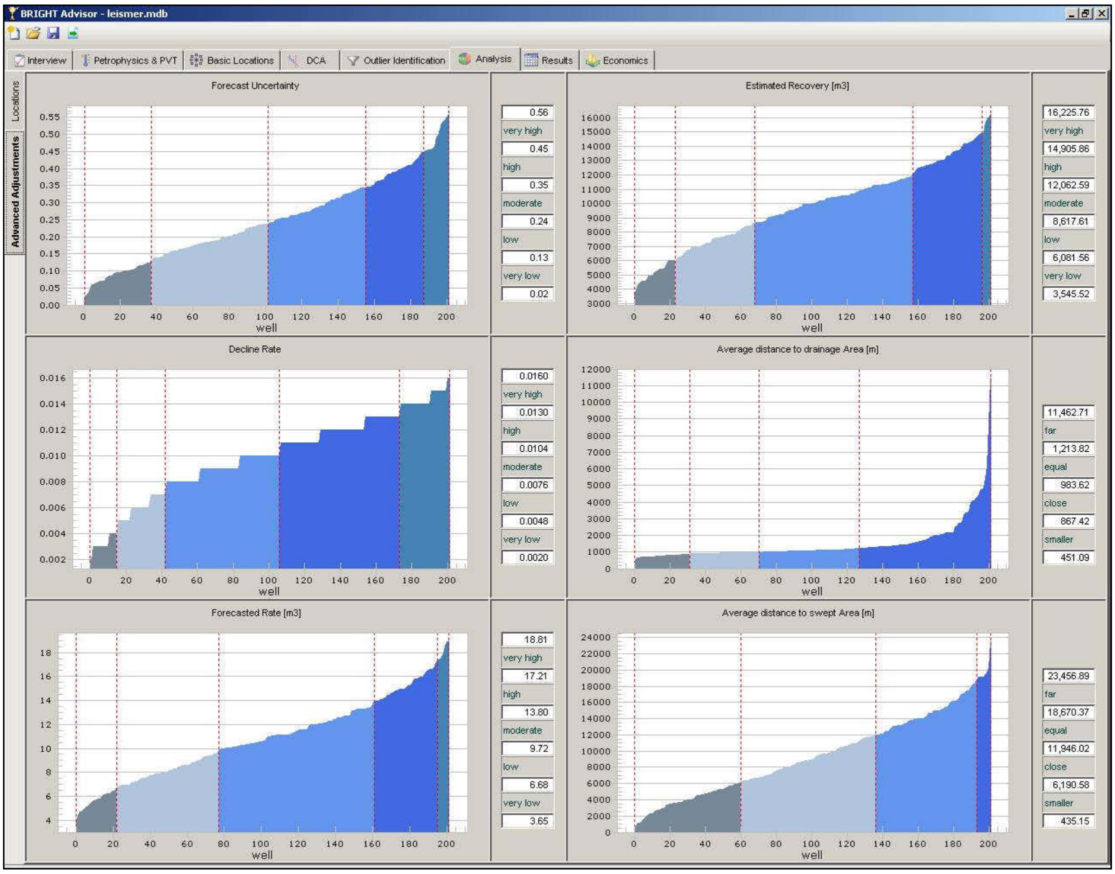


Figure 81: Range Setup

The results look very interesting. BRIGHT has clearly identified a cluster of very promising infill locations in the northwestern part of the field. This result is not so much surprising as the high porosity part of the reservoir has already been identified in that area of the reservoir. There is also a very promising cluster in the eastern part of the field, which can be comprehended after looking on the forecasts. The wells in that part of the field showed the best values for forecast rate and estimated recovery, as well as the smallest values for decline rates. However, the infill locations generally show a higher uncertainty in their forecasts, which lead to the worse scoring. This might be due to the difficult situation since a few water injectors are located close to the eastern edge of the reservoir. A surprising fact is that the central part of the field has a high density of wells with high rates, but no high quality infill location. However, when taking a closer look it can be seen, that the locations in the central part of the field all have a high decline rate and therefore are to be penalized regarding the better performing wells in the western part of the field.

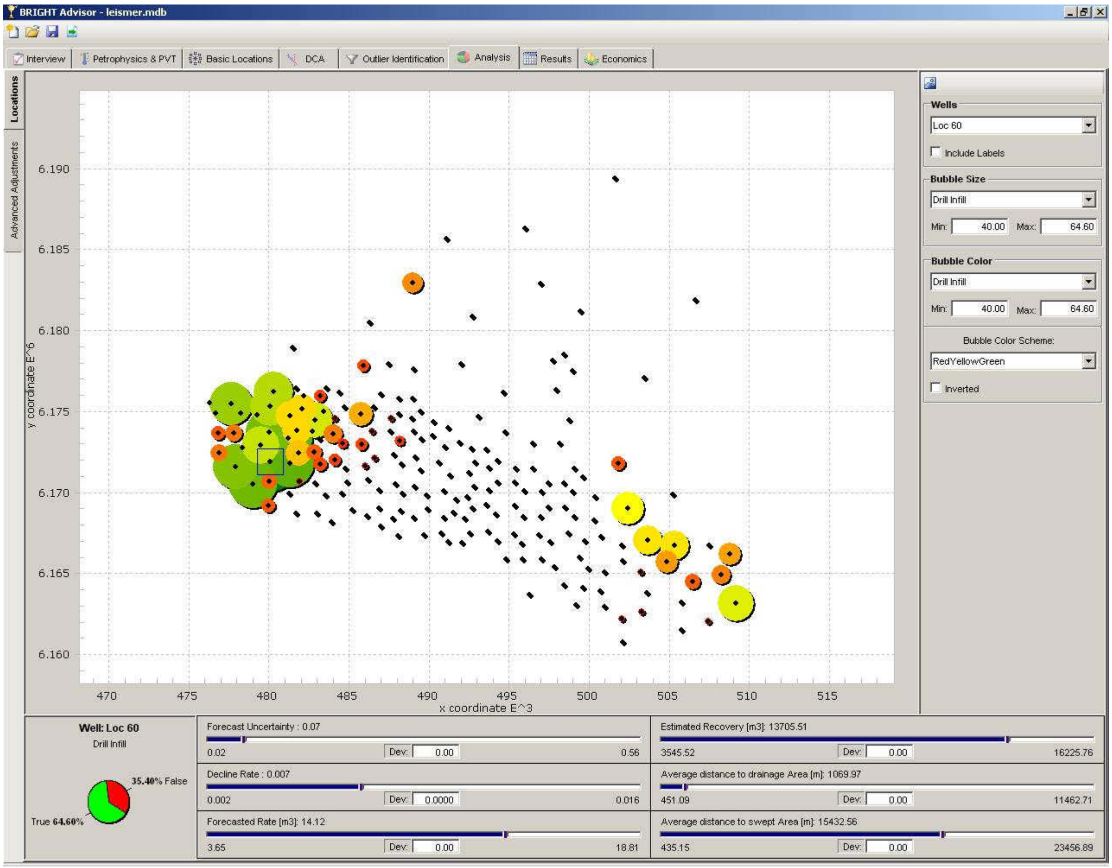


Figure 82: Infill Locations Scoring

Figure 82 shows a bubble map of the scoring. The x and y axis correspond to the x and y coordinates, respectively. The bubble size and the bubble color correspond to the score (the larger, the higher the score and the greener, the higher the score). It can be seen very clearly that the main cluster is in the western end of the field and an also promising cluster is to be found on the eastern side of the field. The most probable suggestion the engineer will make to the executive board will be to drill a well in the western region of the reservoir.

5. Conclusions and Future Outlook

The first version of BRIGHT is about to be released to Schlumberger internally in December 2006. The main concern of BRIGHT's development team is to distribute a stable and effective BRIGHT version. However, there is still a lot to do to improve the quality and the applicability of BRIGHT. The current version is capable of suggesting the best infill locations in a mature oil or gas field; it is able to process a sparsely populated dataset (minimum data requirement: geographical well locations, monthly production rates) and to suggest the best infill locations. This is achieved by a series of geologic interpolations, recovery predictions and forecast interpolations on an automatically quality controlled well data set. Moreover BRIGHT - in the current state - can identify outlier wells, which in general are wells that are either performing significantly better or significantly worse than the surrounding wells. It is not yet possible to process that information to automatically suggest work over or stimulation candidates; however, it can be used as a guideline or as a suggestion as of which wells should be investigated manually in more detail.

In the end of a BRIGHT study, a field development plan will be presented based on the expected performance of the field after the suggested projects have been performed. A rough economic evaluation will calculate the main economic project parameters, such as Net Present Value or the Internal Rate of Return to roughly estimate the economic potential of a proposed field development plan.

5.1. Current Limitations

BRIGHT is a tool that has its place in the Brownfield development process as a screening tool and a quick evaluation tool. Within the current scope of its capabilities, it performs extremely well and can finish an analysis very quickly. In the current state it is neither replacing numerical reservoir simulation nor analytical material balance equations. It is intended to quickly evaluate whether a field is worthy of being fully and thoroughly investigated; therefore it will essentially give a guideline about which fields bear a development potential and which fields should not be further developed. This is especially of interest for Schlumberger clients that are about to take over mature fields and want to know about the production potential of their probable acquisition.

The main limitations of the first release are:

- The *other RAPID workflows* such as finding the best reactivation candidates, suggesting better completion intervals or suggesting work over candidates have not yet been implemented. This is due to the fact that the four workflows are very similar and it was determined that the best way to expand the workflow selection offered by BRIGHT is to guarantee a single, very stable workflow implementation that can be used as a basis for the other workflows. Most probably the reactivation candidate workflow will be implemented next, since its forecasting and parameter requirements are very similar to the infill location workflow presented in this work. Moreover, the identified outliers in the infill location selection process can be used to automatically suggest work over candidates and present 'best practice' wells.
- A big concern among BRIGHT's developers is to provide the workflows for *multiphase cases* (especially if a second phase, e.g. water, is present). Of course the relative permeabilities of the hydrocarbon phase and water will play an important role in determining the expected hydrocarbon recovery. The forecasts in a multiphase environment will most probably decrease the expected hydrocarbon recovery (due to the non linear relative permeability functions of hydrocarbons and water) to account for increasing water production during the life of a field.
- *Horizontal or deviated wells* cannot be handled by the current implementation of BRIGHT. The reason is that in evaluating drainage areas BRIGHT is only using the geographic information of the bottom hole locations. Therefore the Voronoi grid cells that are used to determine the reservoir aerial cross-section that can be allocated to a specific well and subsequently the Hydrocarbons in Place for that well are created solely based on the coordinates of the bottom hole locations. In order to process horizontal wells or highly deviated wells, the well path would have to be loaded and the Voronoi areas would have to be modified in order to account for the elliptical rather than circular drainage area of a horizontal well.
- *Transient behavior of the well's production* bears a high degree of uncertainty and would lead to less reliable results of BRIGHT. This is especially true when looking at the forecasting techniques BRIGHT is using. The decline

curve analysis depends heavily on the steady state-ness or pseudo steady state-ness of the well's production profiles and since this is the only forecasting technique in BRIGHT, it would severely downgrade the reliability of BRIGHT's results. To deal with transients in the production profile, the user should use an analytical formulation (e.g. Tarner's formulation of the Material Balance equations) or a numerical tool (e.g. Numerical Reservoir Simulation).

- *Multi Layered systems* with commingled production systems are not handled by BRIGHT. It is compulsory to accurately allocate the production to each layer prior to starting the BRIGHT analysis, to avoid comparing wells that produce in highly productive layers with wells that are perforated in less productive reservoir layers. As long as Multi Layer systems cannot be handled, BRIGHT will not be able to suggest the perforation in another layer.

5.2. Future Developments

The future development plans are set to meet the requirements imposed by the mentioned limitations. The most important next development steps are:

- It is compulsory to implement the *other RAPID workflows* as soon as possible. The basis for the workflow to identify reactivation candidates is already present since this workflow basically uses the same forecasting techniques as the infill drilling workflow. The other workflows such as identifying recompletion candidates or work over candidates need further modifications of the workflow (e.g. handling of multi layered systems, incorporating work over data, etc.). The conditional probability tables however are already provided and can be used as soon as the forecasting workflow is delivering the necessary parameters for the other workflows.
- *Secondary phase analysis* BRIGHT has to be able to analyze the performance of a well in the presence of a second phase (as for example water). A set of key performance indicators has to be identified to be able to evaluate the performance of a well that is producing more than one phase. The computation of Estimated Ultimate Recovery has to be adjusted as well, since in a multiphase environment the production profiles do not behave as calculable as for single phase production profiles. In water flooded reservoirs Ershagi's X-plot of the natural logarithm of Water oil ratio versus cumulative oil

production[30] could be an excellent tool to predict oil production in the presence of a mobile water phase. Also the simultaneous solution of multiphase flow equations for the Voronoi grid blocks incorporating the relative permeability functions of oil, water and gas could be an applicable tool. This has to be tested and developed in future BRIGHT versions.

- Since BRIGHT is applying forecasting methods, an automated history match procedure has to be implemented in order to validate the forecasts and to increase the confidence of users of the tool. A method to meet that requirement could be the CFD plot mentioned in Chapter 3.1.9. Another possible technique is to perform a BRIGHT run disregarding the latest three wells and verify the accuracy of the forecasts for those wells.
- Another very important point is the *handling of horizontal and highly deviated wells*. Future versions of BRIGHT will be able to handle horizontal and highly deviated wells and allocate the Hydrocarbons in Place considering the modified drainage area of a horizontal well. This requires a modification of the Voronoi algorithm to account for the respective well paths and irregular drainage area. A deep investigation of available unstructured grid techniques has to precede the implementation of a solution for that problem.

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