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SINTEF A19402- Unrestricted

Report

Simple near well models for fast generation of dynamic GOR

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SINTEF ICT
Applied Cybernetics
2011-12-05

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Simple near well models for fast generation of dynamic GOR

KEYWORDS:
Identification,
autoregressive models,
gas reservoirs,
production optimization

VERSION
1

DATE
2011-12-05

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Center for Integrated Operations in the Petroleum Industry

CLIENT'S REF.
Bjarne Foss

PROJECT NO.
90G337

NUMBER OF PAGES/APPENDICES:
25

ABSTRACT

This report presents the use of auto regressive models as simplified near well models for fast online generation of rate dependent gas oil ratios (GOR) used in offline and real time production optimization and reservoir management. The main aim of this work is to investigate the use of simple linear and non-linear models applied to oil field data. Fast generation of GOR may improve reservoir optimization schemes, production optimization and allocation calculations, as this enable continuous access to GOR estimates. The main contribution of this work is the application of modified auto regressive models with exogenous variables (ARX) in order to generate GOR estimates for use in production optimization. The models are planned to be applied in the commercial reservoir optimization software

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REPORT NO.	ISBN	CLASSIFICATION	CLASSIFICATION THIS PAGE
SINTEF A19402	9788214049800	Unrestricted	Unrestricted

Document history

VERSION	DATE	VERSION DESCRIPTION
Version No. 1	2011-12-05	

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SINTEF

1 Introduction

Mathematical models are important tools as an aid for a variety of decision processes in reservoir management. Long term decision support is usually based on large scale dynamic reservoir simulators, e.g. ECLIPSE©, whereas short term decisions, typically days to weeks, are based on much simpler reservoir representations. Applications of the latter may include short term rate allocation between wells using software like *GAP™* or ***FlowManager™ MaxPro***. Such model-based decision support tools require models of the reservoir, typically the near well region, wells, manifolds and pipeline system. A key challenge for widespread use of these decision support tools is model maintenance, in particular updating the near well models to account for long-term depletion effects. This is seldom discussed in published papers, but frequently a central theme among practitioners.

In this paper we present a new method and concept for generating and updating empirical, near well reservoir models for on-line generation of dynamic gas oil ratios (GOR). The prime use for such models is in short term production optimization, also denoted real time production optimization (RTPO). Detailed knowledge of GOR is especially important for RTPO when the wells are located in thin oil rims beneath a large gas cap as the system may have limited capacity for gas processing. We generalize our description by including transient models since fast dynamics is an issue when the GOR changes rapidly e.g. after choke position changes. An example of the latter is re optimizing a well after a shut in period.

There are a number of papers on model based techniques for long term reservoir management. These will not be discussed here apart from mentioning a comprehensive survey paper by (Jansen, Bosgra et al. 2008). Further, there has been a steady flow of papers on RTPO, see for instance (Saputelli, Nikolaou et al. 2003), (Bieker, Slupphaug et al. 2006), (Kosmidis, Perkins et al. 2005) and (Foss, Gunnerud et al. 2009).

Models of near well systems may be categorized into physics based models and black box models. Physics based well models including gas coning date far back, see (Muskat 1938). Konieczek (1990) constructed a simplified model to identify the critical rate for gas coning in thin oil layer reservoirs. More recently a dynamic simulation model, based on Darcy’s law, was developed in order to predict how the GOR varies with the production rate (Mjaavatten, Aasheim et al. 2006). This model was developed for RTPO at the Troll field on the Norwegian Continental Shelf. The Troll field has a thin oil layer between the aquifer and a large gas cap. A dynamic model was developed to describe the essential reservoir dynamics using a simplified description of the interaction between the well and the surrounding reservoir, and it was reported that the prediction of the rate dependent GOR was essential for successful optimization of oil production.

A near well model based on black box techniques may be automatically generated based on simulator data or a real production history through training and verification. Such models could be updated more easily, and may therefore be suitable for online applications. (Saputelli, Malki et al. 2002) gives an overview on artificial neural network (ANN) applications in the petroleum industry. ANN has been applied in reservoir characterization, virtual measurements and optimization of field operations. The article refers to work being done in the late 1990's. Moreover, (Bertrand, McQuaid et al. 2005) uses three seismic attributes from the Troll field to train a neural network for estimation of gas oil contact movement, in order to identify un-drained zones. Similar work has been done at TU-Delft, where a model describing the oil and gas flow towards the wellbore and the dynamic flow inside a vertical well was developed. Water and gas coning could be predicted using this model (TU-Delft 2008).

The main advantage with black box models is that they can be established without detailed knowledge of the underlying physics and system dynamics. This implies that efficient and accurate models may be generated, but at the expense of a reduced region of validity. Such models are only valid locally in time and space, depending on the training data. By incorporating assumptions related to physical laws in the black box representations, the region of validity of the simple near well oil reservoir model may be improved. This approach is often presented as *grey box* modelling or semi-physical modelling, and is the approached which will be pursued in this work.

Short term production optimization schemes require models that facilitate a closed loop decision structure, hence the models must contain quantitative relationships between the variables subject to optimization. If for example gas flow is chosen as a decision variable, the model output can be a prediction of downhole pressure and oil/water inflow rates in order to generate dynamic GOR tables for use in RTPO. Furthermore, the models should facilitate a description of constraints, e.g. GOR and sand production, required in the optimization program. In this work we present a methodology for developing and validating simple grey box models based on historical data from real or simulated field production in an online production optimization scheme.

The outline of the paper is as follows. Section 2 holds a description of the concept in focus. In Section 3 and 4 the methodology is exemplified and validated. Section 5 and 6 contains the discussion and conclusions.

2 Concept and problem statement

The proposed concept is based on the assumption that near well reservoir models are sufficient for characterizing reservoir conditions in RTPO, and that such models should be simple to generate and to be kept alive over time. In our concept near well models will imply rather simple dynamic grey box models.

Simplicity comes from the fact that RTPO models only need to consider short term effects. Further, simple models may be easier to maintain, i.e. adjust, with time to account for long term effects.

In general, a RTPO system includes a partially or completely automated decision making system. It typically includes data validation, model updating, model based optimization and a structure for validation and control effort calculations based on the solution from the optimization, see (Xiong and Jutan 2003) and (Darby and White 1998) for details.

In this work we limit the scope to a RTPO system defined by three main parts; the data source, the production optimization tool and the near well model, and the interaction between them. This system structure is shown in Figure 1 (see Section 2.4 for details).

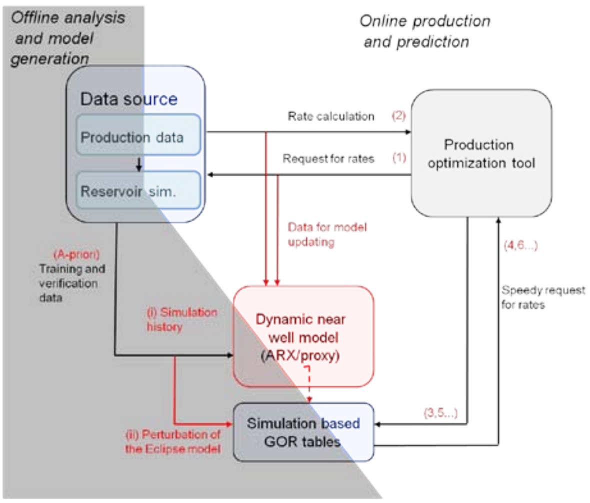

Figure 1. The system structure and the link between the data source, the production optimization tool and the near-well model.

In the following each of the components of the RTPO system is first explained in some detail, and subsequently the operator interaction and the totality of the system are explained. The formal problem statement for this work is given at the end.

2.1 Data source

A key component of the concept is flexible use of data sources. In this context this means the use of real production data or simulation results from a high fidelity simulator. This opens for a variety of data generating structures, where pure production based and pure simulator based data, define the extremes of these structures. In Figure 2, two such scenarios are visualized.

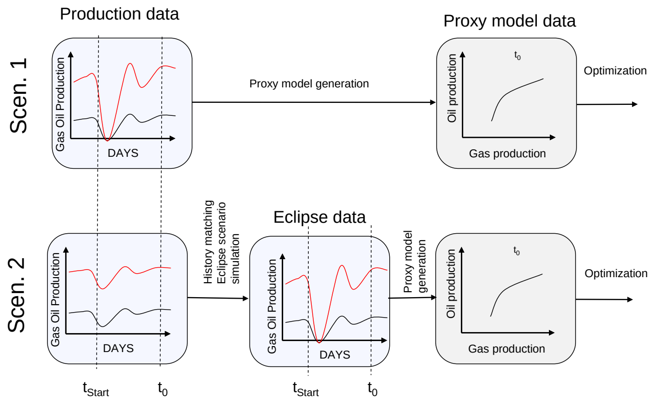

Figure 2. Examples of data sources for near well model generation

The understanding of how combinations of production and simulator data sets can be generated and applied is especially important when optimization algorithms are part of the decision support system (for deciding well production rates).

Typically, the optimisation algorithm will suggest a steady state or slowly varying optimal production trajectory for each well. In an ideal situation the real production rates from each well will converge to the optimal solution. Over time the "quality" of the near well model will decay since

- The data will not be sufficiently rich in the sense of perturbations
- The data will not sufficiently span the region of validity of the model (the persistence of excitation[1] (PE) condition)

One way around this problem may be to utilize data from simulators matched with the real production, given that the simulators can provide data with sufficient resolution and accuracy. In this case a virtual production scenario that satisfies the PE condition may be generated, and the simplified model updated online as shown in the second scenario in Figure 2.

2.2 Near well model

The near well model identification process includes the definition and identification of a model structure and training of the model parameters. The model structure and parameters can be changed both by *offline analysis* and *online algorithms*.

By *offline analysis* is meant the process of choosing the model structure based on available training data, geological information and operation knowledge.

[1] For a technical definition of PE, see for example (Ljung 1999)

The term *online algorithms* refer to recursive algorithms which manage and incorporate real-time information by adjusting model parameters. The model structure and methods for updating the models are further presented in Section 3.

2.3 Production optimization tool

A production optimization tool requires models of the transportation properties of the field as well as the process plant fluid, gas and sand capacities. Furthermore, for each well in the field, the well performance characteristics over a certain time horizon need to be estimated in order to reach the production optimum for the oil field. The main topic of this work is to give a description of the well properties by use of simple and easy maintainable near well models.

2.4 Complete system and operator interaction

In Figure 1 the information and operation flow in the complete system is divided into an offline and an online mode.

Online operation

The production optimization tool sets the well production rate based on a GOR table which is derived for the current state of the system, see (1) in Figure 1. Then the well production is simulated by the reservoir simulator, or given directly by production data, and sampled accordingly (2). Based on this the dynamic well model is trained and updated and new GOR values are derived and extracted by the optimization tool (3,4 ...).

Offline model identification and validation

Based on the data history from the simulator or plant, (i) in Figure 1, the near well model is identified, see section 3 for details. As the intention of this work is to define simple near well model structures that are easy to maintain, a production engineer should have the possibility to interact with each of the components in the complete system.

- Data source selection. In order to provide a good basis for the near well model identification, relevant data for a particular operation scheme should be considered.
- Model structure manipulation. The model structure can be manipulated by adding or removing significant and insignificant mechanisms based on the operators' understanding of the reservoir. This knowledge serves as an important information source at a high level of understanding of physical phenomena in the reservoir. Examples of such information are well start up transients, coning effects and long term reservoir depletion.
- Optimization program properties. The optimization program depends on the identification process both through the model structure and the identification data. Further, both the constraints and cost function of the program may be updated with respect to the model region of validity.

In order to give an exact, detailed validation of the proposed near well model methodology, a data set based on repeated simulations of different inputs at the same time instant need to be considered, see section 4. In principle such validation is not possible in real production, but by considering well tests that are significantly varying (PE) and spanning the domain of relevant production, the data may be analyzed and the model indirectly validated.

2.5 Problem statement and main assumptions

With relation to Figure 1 the main task is to define and maintain a simple dynamic near well model which can generate rate dependent, or more generally time dependent, GOR values for production optimization.

Our main assumptions relate to the data used for generating the models. They need to have the following properties

- Realistic data source. The data represents the true/real mechanisms (real experimental data or data from realistic detailed models) of the reservoir and the near well.
- Persistence of excitation. Over time the data needs to be sufficiently rich in the sense of perturbations. Furthermore, the data needs to span the region of which the dynamic near well model is required to be valid.

3 Methodology

In the following we generate a simplified grey box model which based on the gas production (the model input) predicts the oil production (the model output) from which the dynamic GOR values may be calculated. Furthermore, it is described how the initial model structure may be identified.

3.1 Model development and identification

System identification based on input-output data, is a procedure where various model structures and model orders are tested in order to find the model which gives the best fit to the dataset. Figure 3 (Ljung 1999) shows a diagram of this processes.

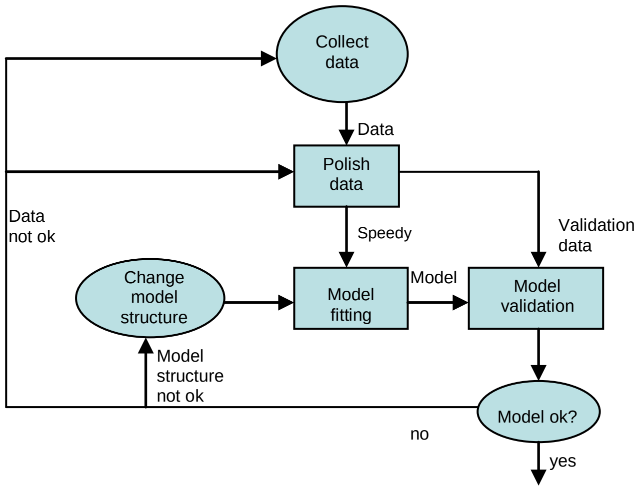

Figure 3. Typical identification cycle (Ljung 1999)

In general the system identification procedure involves working processes that relates to:

(I) A priori considerations: the recording of the data set that represent the system

(II) Defining the model structure: the choice of model structure

(III) Model prediction based on measurement updates: the determination of the parameter set for the model that describes the dataset in some optimal way

3.1.1 A priori considerations (I)

The main property of the simplified near well model is to provide good estimates of oil production based on changes in the gas production. A good understanding of the reservoir/well system and the production optimization tool, together with the provided data will help in defining a suitable model structure for the system.

The following issues need to be considered.

Choosing inputs and outputs

Depending on the decision parameters used in the production optimization software, the prediction of oil and water should be calculated such that the error between the estimated and the real decision parameter is as small as possible. Thus, the knowledge of the structure of the optimization program parameters is of importance in the process of defining a model structure and identifying the parameters of such models. For example, in this case study, the oil flow is considered to be an optimization variable, then identifying the oil flow model directly may offer a more systematic approach for handling transients in optimization variable errors, than identifying a GOR model.

Model structures for GOR calculations

In the presented work a nonlinear **auto regressive model with exogenous variables** (NARX) parameter affine structure is chosen as a basic structure for the near well model

$$y_{(k)} = \sum_{i=1}^{n_x} a_i y_{(k-i)} + \sum_{i=1}^{n_u} b_i f_i(u_{(k-i+1)}) \qquad (1)$$

where y is the model output (oil flow) and u is model inputs (gas flow) at discrete time. a_i and b_i are parameters, and f_i is a continuous function. n_x and n_u are the output and input orders.

The reason for choosing a nonlinear function f_i instead of a linear term is to account for nonlinear behaviour. Hence, provided f_i is a good approximation the parameters b_i need only adjust for long term effects like reservoir depletion.

Slow transients

Slowly varying transients, offsets and drifts in the dataset due to oil depletion can be handled in different ways. The data can either be explicitly pre-treated by subtracting the signal mean, or, preferably, the drift can be estimated in the defined model structure by incorporating integral action, offset parameter estimation or parameter adaptation.

Interpolation/extrapolation and handling bad or missing data.

Varying time-steps in the historical gas production data need to be handled in a systematic way, i.e. by interpolation. Moreover, algorithms for detecting and replacing erroneous data need in general to be considered.

Data for model identification and validation

Depending on the model region of importance, the near well model should be trained and validated with data confined to a set that represents this region. Fitting data from other operation modes will require a more complex structure in order to give a good representation of the total dataset. A black or grey box model trained on data from a wide range of operating modes will result in an "averaging" model of poor performance. By including active data selection, the model size can be kept small, and the parameter set can be reduced. The data applied in the validation of the model should, if possible, be different from the data applied in the model identification.

3.1.2 Defining the model structure (II)

The basis for the grey box models is the NARX model structure (1). This model can be purely static (n_x=0) or include dynamics. By incorporating the previously mentioned a-priori considerations in the equation structure and evaluating its simulation and prediction properties, a *grey box model* is defined.

The grey box model structure (2) consists of a linear dynamic part that incorporates transients in the reservoir and well and a part that involves a nonlinear steady state relation between the input and the output.

$$x_{(k)} = \sum_{i=1}^{n_x} a_i x_{(k-i)} + \sum_{i=1}^{n_u} b_i u_{(k-i+1)}$$
$$y_{(k)} = x_{(k)} + f(u_{(k)}) - \frac{\sum_{i=1}^{n_u} b_i}{1-\sum_{i=1}^{n_x} a_i} u_{(k)} \quad \text{......................................(2)}$$

Determination of model size, the input function *f(u)* and the model structure parameters are based on simulation and prediction performance evaluation according to the identification process shown in Figure 3.

3.1.3 Model prediction based on measurement updates (III)

In the described grey box model approach, the model construction is heavily based on the identification data. As this data is time dependent the validity of the model (parameters and structure) will only hold locally in time, and a model update system should be defined.

As new identification data becomes available; (i) the states in the model, which are old outputs, may be replaced with the new measurements, (ii) the parameters in the model may be updated or (iii) the model structure may be updated or changed according to the data trends. Typically the state dynamics are faster than the parameter dynamics and changes in the parameters will occur more often than the structural changes in the model. This implies that new data should be used for updating the prediction model in three loops, two state and parameter estimation loops (online algorithm based update) and one slow offline model structure analysis loop including the production engineer and a new analysis.

New data can be used in the model without any updating of the model parameters or in an adaptive structure which handles time-varying model parameters. Given an affine model parameterization:

$$y_{(k)} = \eta_{(k)}^T \theta$$
$$\eta_{(k)} = \Phi(y_{(k-1)}, \ldots y_{(k-ny)}, u_{(k)}, \ldots u_{(k-nu)}) \quad , \quad \text{......................................(3)}$$

a standard recursive least squares algorithm can be used in order to update the parameter estimates, for example a Newton based algorithm (Ljung 1999). Other common algorithms that can be used are the Kalman filter and standard gradient based algorithms derived through for example Lyapunov analysis. On a higher level “sliding windows” of data (not necessarily continuous), where old data is replaced by new data, as the new the data becomes available (not necessarily at each sample but dependent on operation) and use standard regression methods for identifying the parameters of the model. Since the dynamic properties of a reservoir may change significantly over time, the initial near well model structure may no longer be suitable. In such cases (particularly if the model should have bad predictions over a longer prediction horizon) a new analysis of the data is necessary. The challenge is then to define the quality of the models ability to predict, and construct a criterion that will initiate the process of updating the model structure.

3.1.4 Possible model extensions and modifications

The production engineers experience and know-how with the mechanisms in the well must be exploited when choosing the model structure, in order to increase prediction precision and the region of validity. Extensions that handle slowly varying bias, start up and shutdown transients may also reduce the number of parameters to be adapted. In the following three such mechanisms are presented and included in the model in order to exemplify how the production engineer may manipulate the model structure.

A slowly varying bias may be introduced by the accumulated production (integral) of the gas input *u* to the model

$$u_{(k)}^{decay} = u_{(k-1)}^{decay} + u_{(k)} \quad \text{......................................(4)}$$

Start and shutdown transients can be modelled by recording the gas production below a defined reservoir production equilibrium, such that an estimate of the reservoir oil accumulation (reservoir dynamics) can be made. This estimate can be used to calculate the transients in the start-up phase of a reservoir well.

$$\begin{aligned} u_{(k)}^{start} &= u_{(k-1)}^{start} + (EQ - u_{(k)}), \quad if \quad u_{(k)} < EQ \\ u_{(k)}^{start} &= e_I u_{(k-1)}^{start}, \quad else \end{aligned} \quad \text{......................................(5)}$$

where *EQ [Sm3/day]* is the reservoir production equilibrium parameter and e_I*[-]* is the integration input discharge parameter.

In the shutdown phase, large transients may not necessarily occur, thus start up and shut down events do not give linear and symmetric responses. A nonlinear gas production weighting term may be introduced in the model in order to take care of such asymmetry:

$$u_{(k)}^{shutdown} = \frac{u_{(k)}}{u_{(k)} + h} \quad \text{......................................(6)}$$

where *h [Sm3/day]* is an on/off symmetry parameter.

Other reservoir mechanisms or operating modes may be considered in general, and added to the model according to an experienced operator with special knowledge of the particular well.

Based on the model elements in equations (2)-(6), the following structure of a simplified oil production model can be made

$$\begin{aligned} y_{(k)} &= \sum_{i=1}^{n_x} a_{1i} y_{(k-i)} + b_5 u_{(k)}^{decay} + b_6 u_{(k)}^{start} + u_{(k)}^{shutdown} \\ &+ \sum_{i=1}^{n_x} b_{1i} f(u_{(k-i+1)}) + \sum_{i=1}^{n_u} b_{4i} u_{(k-i+1)} \\ &+ \sum_{i=1}^{n_x} b_{2i} \left(f(u_{(k-i+1)}) - f(u_{(k-i)}) \right) + b_3 \left(-u_{(k)} + u_{(k-1)} \right) \end{aligned} \quad \text{......................................(7)}$$

The above mentioned phenomena have not been included in the presented simulation study as these structural choices are dependent on the reservoir, and thus need to be considered for every well.

4 Simulation study

In the following a study is presented to exemplify and validate the presented methodology. The simulation study is based on reservoir data from the second SPE comparative project (SPE'cp 2). The data from the SPE'cp 2 project is relevant to this work since it includes the main properties from a gas and water coning well. A schematic description of the reservoir and well is given by Figure 3 with the following features:

- Single vertical radial well based on an actual field
- Grid: 10 (radial layers) x 15 (vertical layers)
- Variable net thickness, porosity, and permeability
- Oil and water density nearly equal

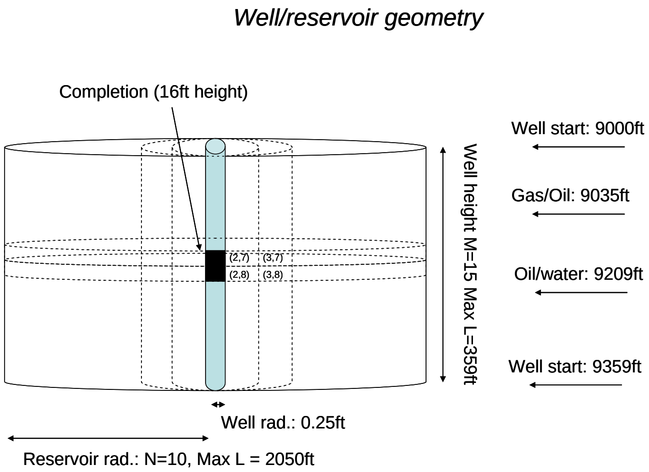

Figure 3. The geometry of the reservoir/well from SPE'cp 2

The ECLIPSE implementation of this model can be found at **http://www.ipt.ntnu.no/~kleppe/**, and for more details on the model and program in general see (Weinstein, Chappelear et al. 1986).

The process of generating a grey box models involves an iterative process in order to identifying the model size and structure. In order to organize the verification and validation process, an analysis tool was developed in MATLAB. Moreover a communication structure between an ECLIPSE server and a MATLAB client was set up in order to gather the simulation and validation data. The simulation study includes the generation of data for model training and validation, the definition of the near well model structure and the model validation scheme.

4.1 Data generation for training and validation

Production data is required to identify, train and validate grey box models. The data applied in this work was generated by simulating the ECLIPSE model (SPE'cp 2) over a prediction horizon with a perturbation of the reference production nominal gas input and given the reference production time, dependent on initial conditions as illustrated in Figure 4.

The gas oil ratios will in this case incorporate the transients (constrained by the prediction horizon) which are important information for the production optimization software in order to avoid violating critical constraints. The perturbation inputs are generated by adding and subtracting a defined amount from the nominal input at the initial time, and held constant during the prediction horizon as shown in equation (8).

$$u_{new}(i,t) := u_{nom}(t) + \delta_u$$
$$\delta_u := \frac{TotVar}{Data\,Res}(i-0.5) - \frac{TotVar}{2} \qquad \forall i \in [1..Data\,Res] \quad \text{......................................(8)}$$

Based on the calculation of gas oil relation presented above, the main design parameters are:

- *PredH, Δt [day]*, describes the horizon for which predicted oil-gas ratios should be valid (this parameter is related to the oil field management i.e. the time elapsed between running the production optimization program of the field)
- *TotVar [Sm3/day,]* describes the region of assumed valid inputs (the parameter is related to the dataset that was used to compute the black box models)
- *DataRes [-]*, describes the resolution of oil-gas ratios.

Note that *the* perturbation δ_u is bounded, by the PE assumption, with respect to the reference input. In Figure 4 this setup is graphically visualized.

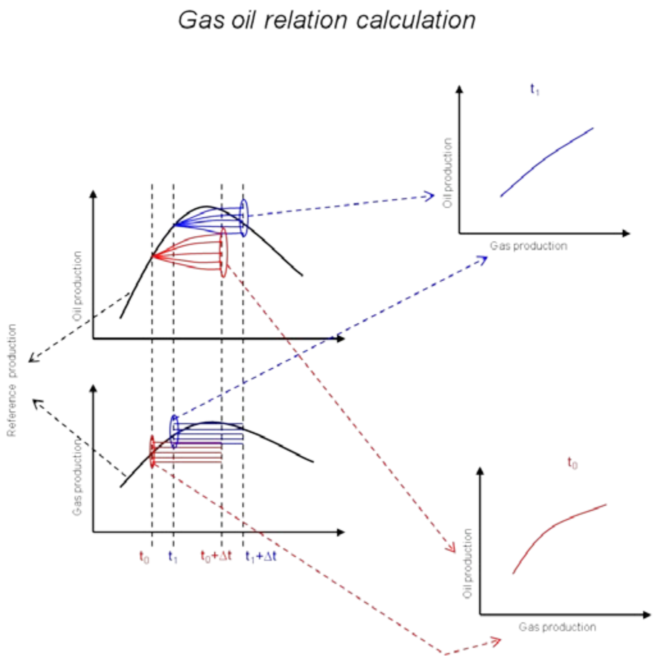

Figure 4. The setup for calculation of the gas oil relation

4.2 The near well model structure

Equation (2) can be written in the following model structure

$$\begin{aligned} y_{(k)} &= a_1 y_{(k-1)} \\ &\quad + b_1 f(u_{(k)}) + b_4 u_{(k)} \\ &\quad + b_2 \left(f(u_{(k)}) - f(u_{(k-i)}) \right) + b_3 \left(u_{(k)} - u_{(k-1)} \right) \end{aligned} \qquad \text{.......................................(9)}$$

$f(u) := \sqrt{u}$ – This function is defined by the identification data

where y is the model output representing the oil rate, u is the model input representing the gas production, a_i and b_i are scalar model parameters and f is defined based on a intuitive assessment of the training data. Operator experience is essential in the process of identifying f.

By the notation given in (3) a recursive least squares algorithm, in this case a Kalman filter, is used as an adaptive update law for the near well model parameters a_i and b_i:

$$\begin{aligned} \hat{\theta}_{(k)} &= \hat{\theta}_{(k-1)} + K_{(k)} \left(y_{(k)} - \eta^T{}_{(k)} \hat{\theta}_{(k-1)} \right) \\ K_{(k)} &= \frac{P_{(k-1)} \eta_{(k)}}{R_{2(k)} + \eta^T{}_{(k)} P_{(k-1)} \eta_{(k)}} \\ P_{(k)} &= P_{(k-1)} + R_1 - \frac{P_{(k-1)} \eta_{(k)} \eta^T{}_{(k)} P_{(k-1)}}{R_2 + \eta^T{}_{(k)} P_{(k-1)} \eta_{(k)}} \end{aligned} \qquad \text{......................................(10)}$$

$\hat{\theta}$ holds the estimated model parameters. R_1 and R_2 represent the process and measurement covariance. We use $R_1/R_2=1e\text{-}6$ to reflect a relatively slow update algorithm. $P_{(1)}$ and $K_{(1)}$ are initialized by the identity matrices of sizes 5 and 3.

The GOR calculations are given by the following perturbation scenario parameters:

PredH, Δt [day]	15 *days*
T*otVar [Sm3/day]*	3000 *Sm3/day*
DataRes [-]	9

4.3 Near well model performance and validation

A reference production scenario is generated to identify and validate the near well model, by simulating the ECLIPSE model implementation of the SPE’cp 2 project. The production scenario is generated by controlling the gas production as presented in Figure 5. The historical gas oil relation (filtered) is shown in Figure 6.

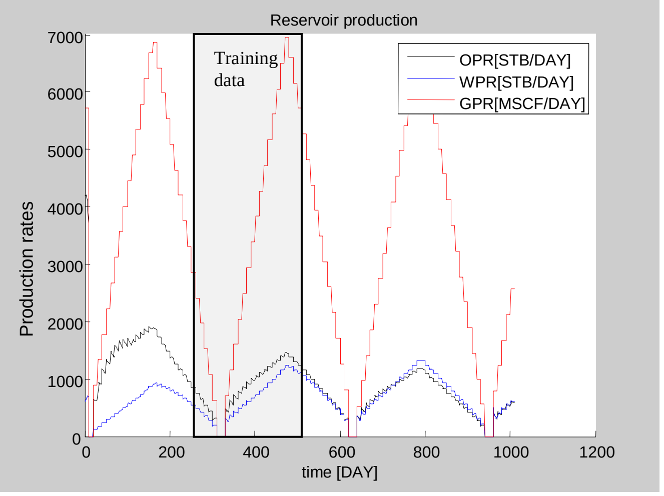

Figure 5. The production scenario (ECLIPSE simulation based on SPE'cp 2) that defines the nominal reference data for this example. Oil Production Rate (OPR), Water Production Rate (WPR) and Gas Production Rate (GPR)

The simulation scenario does not represent a normal production scenario since the production rate is highly varying, but it is considered in order to validate the prediction capability of the model (satisfy the main assumption from section 2).

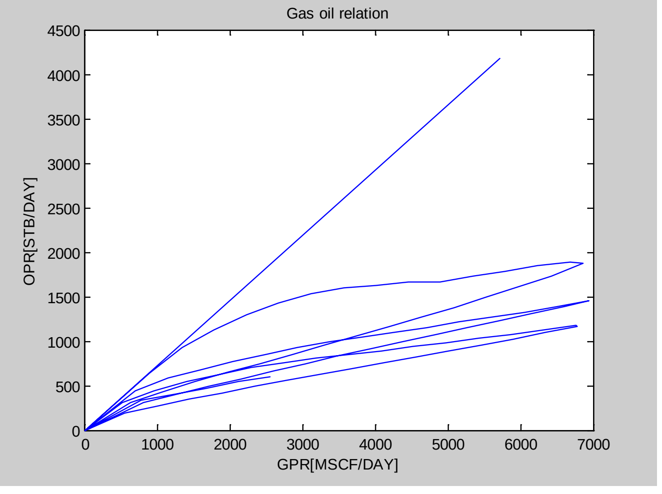

Figure 6. Historical (1-1000 days) gas vs. oil production

By seeing the historical gas oil relation (Figure 6) together with the production scenario (Figure 5), both time-dependence and production dependence is evident. Typically mechanisms like hysteresis and the decaying production capability of the well, as a result of near well oil drainage and charge, can be seen in Figure 6.

4.3.1 Model performance

It is important to distinguish between validating the model with respect to the production reference and validating the model with respect to the assumptions from section 2. The first case (model performance validation) mainly validates the existence of a good parameter set for the model structure. While in the second case (hypothesis validation) the model structure itself is validated with respect to the assumptions from section 2.

An important parameter for calculating the quality of the model is a suitable metric defined by:

$$\text{fit:=}100\frac{1\;-\;\left|Y_m-Y\right|}{\left|Y-\text{mean}\left(Y\right)\right|},\quad ....(11)$$

where Y and Y_m are time series of the real and the predicted output. In Figure 7 - Figure 9, the performance of the near well model is shown by a one day ahead prediction of the oil production based on the gas production. There is little difference in the fit percent by applying the adaptive approach. However, the adaptive near well model performs significantly better when it comes to GOR predictions as shown in Figure 10-Figure 11.

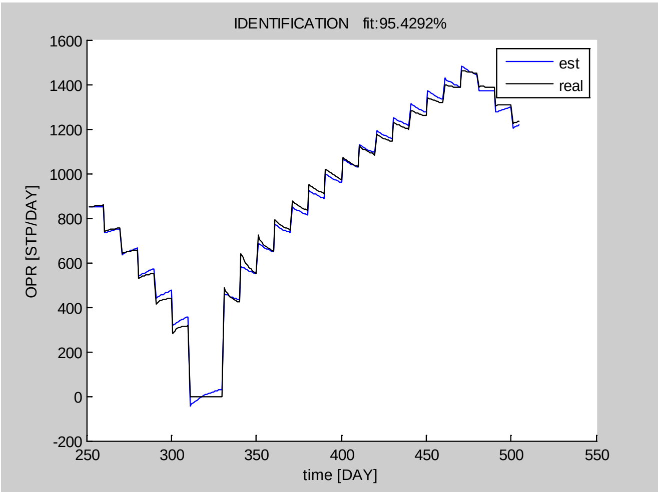

Figure 7. Plot of the model performance, based on the training data. Fit value 95,4%

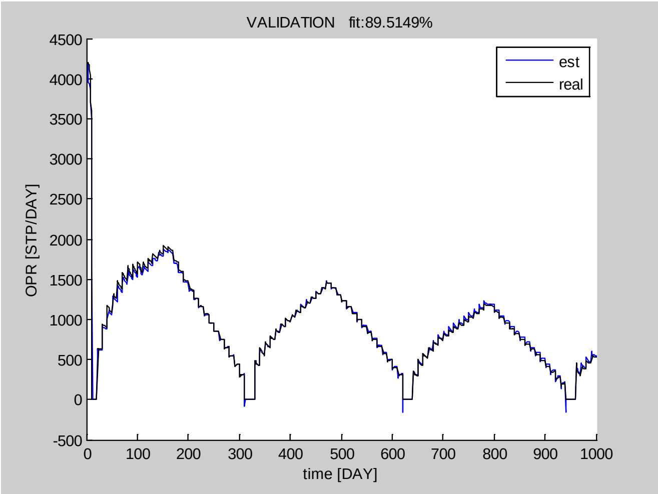

Figure 8. Plot of the model performance, based on validation data. Fit value 89,5%

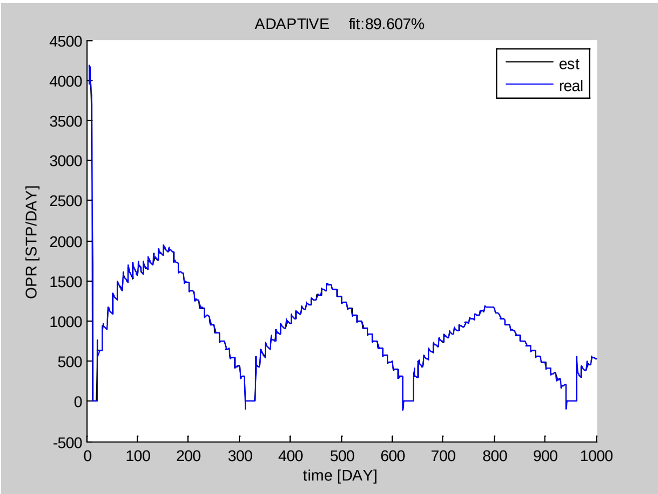

Figure 9. Plot of the model performance with parameter adaptation, based on validation data. Fit value 89,6%

4.3.2 Validation and discussion

Since the nature of the well is dynamic in the sense that the production rates will not change instantly according to new production set points, but rather go through a transient phase, it is of interest to investigate the gas oil relation with respect to different prediction horizons. In the following a 15-day prediction horizon is considered in order to catch the assumed linear dynamics of the transients and the more steady state nonlinear response of the well.

The red lines in Figure 10-Figure 14 represent various oil vs. gas production rates for a 15 day prediction horizon generated by ECLIPSE model simulations. The black lines in Figure 10 are predictions by use of the near well grey model without adaptation, while Figure 11 shows the adaptive approach. The numbers that are plotted in the figures denotes the days from which the prediction was calculated.

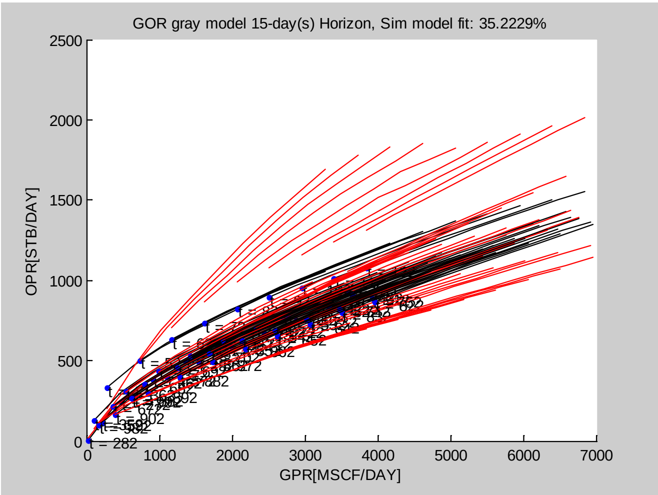

Figure 10. Model generated (15-day prediction) gas vs. oil production (black) denoted by initial prediction time (t) and compared with the ECLIPSE prediction (red). Fit value 35.2%

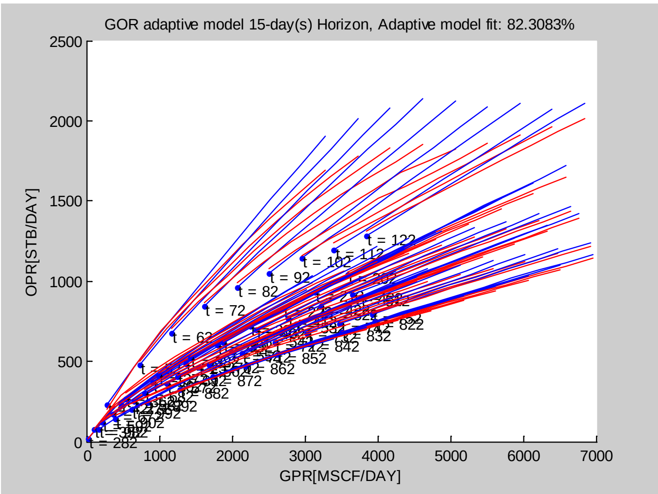

Figure 11. Adaptive model generated (15-days prediction) gas vs. oil production (blue) denoted by initial prediction time (t) and compared with the ECLIPSE prediction (red). Fit value 82.3%

Comparison of the fit values from Figure 10 and Figure 11; shows that the adaptive model has an overall better GOR table estimate performance (time dependent). This is intuitive since the adaptive model utilizes more data, but it is also a consequence of not including the oil depletion effect in the model structure (5). This shows the typical trade-off between a general model that will require more variance in production data in case of parameter updating, and a simpler model that may be updated based on less “rich” data. This is typically something that an experienced field operator would need to evaluate.

An ad hoc approach was also considered for predicting the gas oil relation based on the following equation:

$$\hat{y}_{(k)} = \frac{y_{(k-1)}}{u_{(k-1)}} u_{(k)} \text{ ,.......................................(12)}$$

where $\hat{y}_{(k)}$ is the predicted oil production, and $u_{(k)}$ is the gas production for time k, and $y_{(k-1)}$ and $u_{(k-1)}$ are the actual oil and gas production from the previous time-step.

The results are presented in Figure 12, with the red lines representing the Eclipse simulator predictions, while the green lines denote an ad hoc approach. This approach gives a better prediction than the developed near well grey model without adaptation (Figure 10), but since it is a linear implementation the marginal GOR will be constant and provides low value information to the production optimization algorithm.

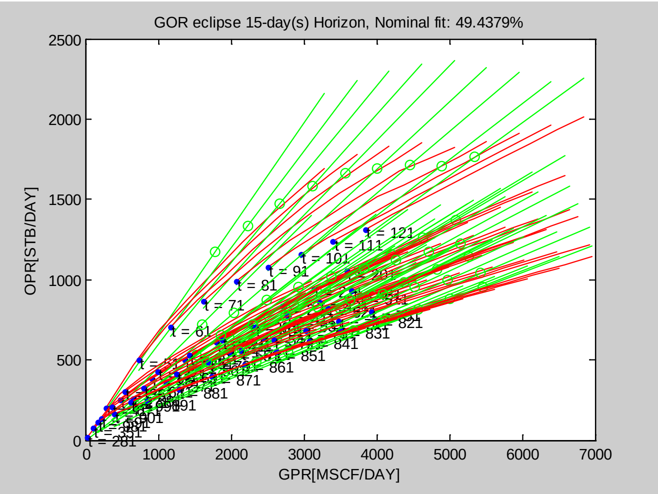

Figure 12. Ad hoc (15-days prediction) gas vs. oil production (green) denoted by initial prediction time (t) and compared with the true ECLIPSE prediction (red)

The ad hoc approach has a good fit percentage in this particular scenario, but will in general perform badly for wells with a more nonlinear gas oil relation (longer prediction horizons are expected to be more nonlinear since the production process has time to stabilize and the steady state effect is becoming more significant). A field operator might consider including this effect in the model structure, giving an additional relation parameter to estimate on.

Figure 13 shows one single 15-day ahead prediction from day 541. A good fit value (86,6%) is achieved using the adaptive approach compared to the model without adaptation (78,1%). The fit value for the ad hoc approach was 63,9%.

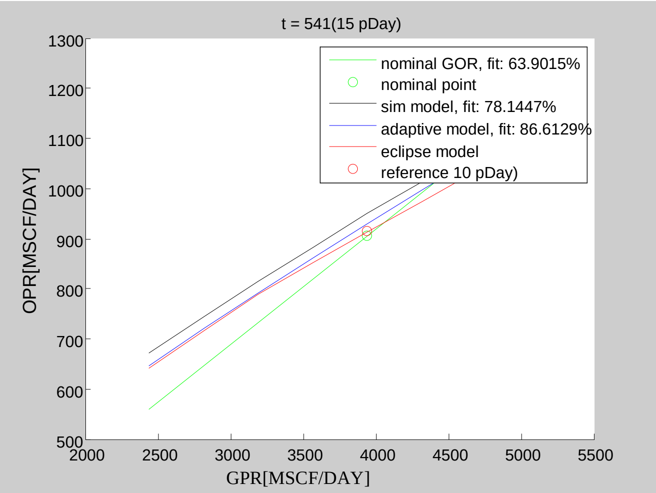

Figure 13. 15-days GOR at day 541, best fit with adaptive approach, fit value 86,6%

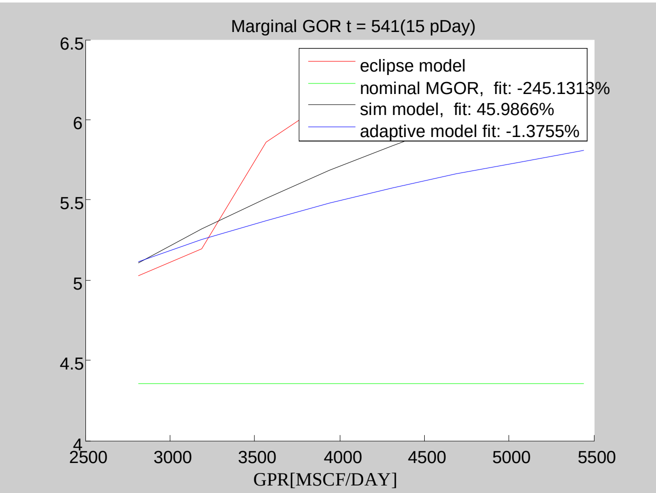

Figure 14. 15-days marginal GOR relation at day 541

In the marginal GOR (MGOR:=dq_{gas}/dq_{oil}) plot, Figure 14, the nonlinear tendency of the models is shown. This value is important for the optimization routine, in order to balance the production from different wells in an oilfield. Also note that at day 541 the 15-days prediction of the MGOR based on the adaptive model performs worse than the non-adaptive model. This is due to the proximity of the model training data (250-500 day). While the initial parameter set of the non-adaptive model is kept, the initial parameter set of the adaptive model is updated according to the production data starting at day 1. This means that more data is considered in the parameter selection, which in other terms means that the simple model will suffer from an averaging effect. In general this may be coped with by introducing a forgetting factor in the adaptive algorithm.

5 Summary

The main advantage of considering a grey box model, based on an auto regressive structure for use in RTPO, is its simple and flexible representation. This implies that a near well model structure easily can be updated by new data and manipulated to incorporate relevant physical phenomena. The model construction is heavily based on the identification data, and as this data is time-dependent the validity of the model (parameters and structure) will only hold locally in time. Model updating and maintenance is therefore important in order to keep the oil and gas rate prediction precision. Adaptive algorithms for automatic parameter adjustment are essential as well as the interaction with a production engineer whom will have a good understanding of the production well behaviour. As the simulation result presented in Figure 10-Figure 14, the grey box model structure provides a channel for implementing this knowledge.

When adaptive algorithms are implemented, it is important to bear in mind that in order to uniquely identify a set of model parameters, the requirements on the identification data variation will increase with the number of parameters to be estimated. For steady state production wells (little variance in the production, no PE) this means that only the main mechanisms should be considered in the near well model. If a detailed reservoir simulator is available for analysis of the production, but not application for instance due to computational constraints for the production optimization software, the simulator may be used to generate virtual production scenarios (identification data) in order to increase the region of validity of the grey box near well model. Section 2 discusses a framework for this setup.

When black box and grey box models are constructed, the validation process is very important in order to ensure the model performance and range of validity. In the simulation study the validation data was generated by repeated simulations of the ECLIPSE simulator with different gas rate production for a given time-step. Since this is not a causal process, such validation is in principal not possible to perform for real production. But by considering well tests that are significantly varying (identifying the theoretical constraint from the PE assumption) and spanning the domain of relevant production, the near well model may be indirectly validated by the data analysis as is shown in the previous section.

This study shows pros and cons of the proposed model. The need for informative data and limitations in terms of the validity region is clearly a limitation compared to high fidelity models. This has certain consequences when applied in an optimization tool. In particular a production allocation recommendation should if possible be in the vicinity of the current allocation. By this a new operating point will most probably stay within the validity region of the model. Such a strategy will be similar to the strategy of most production engineers since they tend to prefer small variations rather than large changes in well allocation.

The model methodology seems promising. Furthermore, the proposed methodology could simplify long term reservoir planning and increase production efficiency and precision.

Further work will involve validation of this methodology on real, publically available production data and analyse its properties in an optimization tool.

6 Acknowledgements

This work was financed by the NTNU Centre for Integrated Operations in the Petroleum Industry and the SINTEF research program Optimal Gas Processing. The authors are thankful to Bjarne Foss at NTNU, Dag Ljungquist and Knut Vannes from FMC Technologies for insightful comments and many suggestions for improvements.

7 References

Bertrand, A., S. McQuaid, et al. (2005). "A high resolution workflow for 4D friendly analysis: application to gas oil contact monitoring at Troll West."

Bieker, H., O. Slupphaug, et al. (2006). Real Time Production Optimization of Offshore Oil and Gas Production Systems: A Technology Survey.

Bieker, H. P. (2007). Topics in offshore oil production optimization using real-time data. Department of engineering cybernetics. Trondheim, Norwegian university of science and technology. **PhD**.

Darby, M. L. and D. C. White (1998). "On-line optimization of complex process units." Chemical Engineering Progress **84**(10): 51-59.

Foss, B., V. Gunnerud, et al. (2009). "Lagrangian Decomposition of Oil-Production Optimization Applied to the Troll West Oil Rim." SPE Journal **14**(4): 646-652.

Jansen, J., O. Bosgra, et al. (2008). "Model-based control of multiphase flow in subsurface oil reservoirs." Journal of Process Control **18**(9): 846-855.

Konieczek, J. (1990). The concept of critical rate in gas coning and its use in production forecasting.

Kosmidis, V., J. Perkins, et al. (2005). "A mixed integer optimization formulation for the well scheduling problem on petroleum fields." Computers & chemical engineering **29**(7): 1523-1541.

Ljung, L. (1999). System identification: Theory for the user (2nd ed.). Upper Saddle River, NJ, Prentice-Hall.

Mjaavatten, A., R. Aasheim, et al. (2006). A Model for Gas Coning and Rate-Dependent Gas/Oil Ratio in an Oil-Rim Resevoir.

Muskat, M. (1938). "The flow of homogeneous fluids through porous media." Soil Science **46**(2): 169.

Saputelli, L., H. Malki, et al. (2002). A Critical Overview of Artificial Neural Network Applications in the Context of Continuous Oil Field Optimization.

Saputelli, L., M. Nikolaou, et al. (2003). Self-learning reservoir management.

TU-Delft (2008). "ISAPP Smart wells and smart fields, www.isapp.nl."

Weinstein, H. G., J. E. Chappelear, et al. (1986). "Second Comparative Solution Project: A Three-Phase Coning Study " Journal of Petroleum Technology **38**: 345-353.

Xiong, Q. and A. Jutan (2003). "Continuous optimization using a dynamic simplex method." Chemical engineering science **58**(16): 3817-3828.

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