Towards an Integrated Wide Approach for Sustainable Upstream Field Recovery

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Abstract

Integrated asset modelling (also known as integrated production modelling) is the modelling and simulation of an entire production facility consisting of both subsurface and surface elements. The intent is to holistically capture the complex interactions between the individual components of the system. The full benefits of these models however are not realised for several reasons, including extensive simulation time of complex models, siloed disciplinary approaches resulting in separate disciplines owning separate elements of the framework. This research study focuses on the development of surrogate models of an integrated field set up for both a gas producing and oil producing supplemented by water injection field. Surrogate models were developed via several techniques (traditional methods such as response surface models and regression and via more complex methods such as Artificial Neural Networks, SobolGSA Random Sampling High Dimensional Modelling Representation and ALAMO) and tested to determine the accuracy versus the fully integrated asset industry tool. Global sensitivity analyses were performed on a selected number of input (manipulated) field variables on the overall outputs from the surrogate models to validate the surrogate relationship postulations prior to attempting optimisation of the developed surrogates via several techniques with positive prediction results observed at a fraction of the simulation time of the industry state of the art tool. The developed surrogate models can be deployed to optimise and forecast production in a fraction of the simulation time; given the forecasted demand of hydrocarbons within the energy mix to meet the global energy demand in the short to medium term; optimising recovery from existing fields is critical especially given the reduced capex investments into new i.e. greenfield fields being developed.

**Keywords**: Integrated Asset Modelling; Optimisation; Surrogate model development; Reservoir modelling; Sustainable recovery

* 1. Methodology

Upon setting out on this research post review of the available literature which concluded that prime focus is on reservoir rather than integrated model simplification, attempting to construct an integrated asset model test case to use a basis and develop further understanding of these tools was deemed to be the first step. The following section outlines the industry tools assessed, the subsequent test cases built and the outputs from the simulation forecasts. These models would then be used as a basis for investigating surrogate model development methods. the most widely applied integrated asset modelling tool within the upstream industry was concluded to be the Petroleum Experts (PETEX ®) software suite; as such, this was selected as the basis for the research following application and receipt of education licenses at Imperial College London. An Intel i7 core CPU of 3.4GHZ with 8GB RAM workstation was used in this research study.

* + 1. Development of a Case Study Model within PETEX® Framework

Initially, a fully integrated field model (based on a central North Sea field) was developed within the industry state of the art tool, PETEX® integrated asset modelling suite to be utilised as a starting case for development of a proxy model representation. The system consisted of 3 black oil reservoir tanks within MBAL (PETEX® Material Balance zero-dimensional reservoir modelling tool), 8 producing wells across 2 production manifold, 3 production flow lines commingling at a landing host facility separator operating at 20bar. Following the construction of the test case within PETEX®, a simplified approach was adopted as a starting point for evaluating an integrated asset model proxy model proposal; 2 cases were proposed, a single gas well case coupled to an integrated network and an oil producing field supplemented by water injection drive.

* + 1. Global Sensitivity Analysis within SobolGSA and Generation of RS-HDMR Proxy Meta Model Representations

Utilising the SobolGSA [4] Proxy meta modelling software (developed internally by Imperial College London specifically for global sensitivity evaluation), a global sensitivity analysis was carried out utilising the input and output data extracted for 164 single solve simulation runs within GAP. The aim was to identify which of the selected 3 manipulated variables had the highest impact on the output (gas production). The input and output data structure was set up as follows:

* Input parameter 1: Separator landing pressure (barg)
* Input parameter 2: Roughness ratio of flowline (dimensionless)
* Input parameter 3: Gas well choke differential pressure (barg)
* Output parameter 1: Optimised gas production (MMScfd)

Within SobolGSA, the input distribution was generated by specifying a lower and upper bound with the distribution type for each parameter (selected as uniform for each of the three input parameters). This generated a random data set which was then used as specified inputs within the GAP model to generate an optimised (single solve) gas production forecast (MMscfd). Utilising this input and subsequent output generated data set, a sensitivity analysis was then run within SobolGSA utilising the RS-HDMR method (Li et al, 2002) of analysis with a Sobol sequence sampling strategy.

1.3 Development of a Gas Well Integrated Asset Model Incorporating a Coupled Numerical Reservoir Model (Eclipse® and Mbal)

Following the successful development of a test integrated field single well gas within GAP and Resolve (PETEX® integrator module to couple reservoir models and surface/well models), the subsequent step of the research was to attempt to develop a numerical reservoir gas model to couple to the integrated asset model via Resolve (PETEX® integrator tool) The aim was to firstly incorporate a detailed reservoir representation to compare simulation time and results versus the simplified integrated tank reservoir model. Secondly, the aim was to extend the research to a more representative reservoir model that is typically employed by subsurface teams within the upstream industry. Two full physics gas only reservoir models were developed in Eclipse® (3D reservoir modelling tool), a single well gas reservoir model without aquifer support and a single well gas reservoir model with numerical aquifer support incorporating water breakthrough after ‘X’ years of production. The developed 3D reservoir (full physics) models were subsequently coupled to a network GAP model consisting of a single flowline and arrival separator via Resolve. The coupled network was then used as a basis for further proxy modelling development and sensitivity analyses. In addition, a simplified tank reservoir model with a single gas well within Mbal (PETEX®) was developed and coupled to the integrated asset model via Resolve; this was used as a comparison to compare the output and performance of the full physics reservoir model against the simplified tank model.

1.4 Development of an Oil and Water Injection Integrated Asset Model Incorporating a Coupled Numerical 3D Reservoir Model

The Norne reservoir model obtained from NTNU [3] representing a segment of the Norne field was loaded into Eclipse®. The Eclipse® based Norne reservoir model was successfully run as a standalone simulation via the Schlumberger simulation platform. The subsequent step was to couple the reservoir model to an integrated asset framework utilising the PETEX® simulation suite. Within GAP, a network model was developed comprising of 3 producing wells, a common production flowline and a production separator set an arrival pressure of 22 barg. The water injection network comprising of 2 water injection wells and a common water injection manifold was configured in a separate GAP network model and coupled to the Norne Eclipse® Reservoir simulation deck via the PETEX® Resolve platform.

1.5 Sensitivity Analysis via SobolGSA and Subsequent Development of RS-HDMR Proxy Model Representations Incorporating Time Dependency

The SobolGSA sensitivity analysis software applied to the gas well case was deployed for the oil & water injection model case and used to analyse the key manipulated variables to determine which input parameter displays the most impact on the output parameters. The input and output data sets were based on the single solve optimisation results in GAP where the simulator forecasts the optimum oil and gas production respectively for the user specified inputs and hence is time independent. The input and output parameters for the sensitivity analysis was configured as follows:

* Input Parameter 1: Production choke setting, Xo (%)
* Input Parameter 2: Water injection choke setting, Xw (%)
* Input Parameter 3: Separator landing pressure, P (barg)
* Output Parameter 1: Oil production (bbl/d)
* Output Parameter 2: Gas production (MMscfd)

164 single solve simulation runs were executed in a batch manner in GAP to generate the input and output data sets. In the absence of any other information and in line with the maximum entropy principle, the input parameter distribution was specified as uniform, extracted, and run within the integrated asset model to generate the corresponding gas and oil production outputs. Following the generation of the time independent RS- HDMR meta model within SobolGSA, an extension to apply this to a time dependent meta model was investigated. The driver for this was to factor in that the production at different time steps varies particularly when comparing early field life to late field life. The simulation runs required at least 10 minutes per forecast run within PETEX® hence required considerable simulation time to generate the full forecasted data set. SobolGSA generates an output for each individual time step i.e. for each of the 215 time steps, a sensitivity per output parameter is reported for each of the three input parameters.

1.6 Generation of Artificial Neural Network (ANN) Proxy Model Representation

Following the successful coupling of the reservoir models (both material balance within Mbal and numerical models developed within Eclipse®), to the PETEX® GAP network via Resolve, these were then utilised as a template to develop further surrogate representations of the two selected key parameters, the change in reservoir pressure with respect to time and the gas production output as a function of key specified input parameters was postulated per Eq. (1) and Eq. (2):

**dP/dt f (G(t)) (1)**

dP/dt references the change in field pressure with respect to time and G(t) is the gas production at time t.

**G(t) f (dP,Xg) (2)**

dP represents the differential between the field pressure and landing i.e. separator pressure (barg) and Xg represents the choke setpoint on the producing gas well (%). An Artificial Neural Network (ANN) surrogate model was generated utilising the machine learning toolbox within Matlab utilising the data set for both the integrated tank reservoir model and outputs obtained from the coupled material balance reservoir model to the integrated asset model within PETEX®. This workflow was applied to both dP/dT and G(t) functions and both tank and Eclipse® reservoir model cases with the Baysian Regularization training algorithm selected due to its applicability for noisy and difficult data sets.

1.7 Refining of Differential Pressure Profile Utilising Smoothing Spline Fit (Gas Field and Oil Field supplemented by Water Injection Cases)

Following the development of the surrogate representation of both G(t) and dP/dT functions, the results obtained for the dP/dT profile were suboptimal in comparison given the R2 values obtained for the fit of G(t). On analysis of the differential pressure profile extracted from the PETEX® simulation forecast runs within Resolve, it was evident that there were significant oscillations within the data set that may have contributed to the sub optimal fit of the polynomial. Based on this, a smoothing spline approach was attempted to smooth out the oscillations. This data set was extracted and loaded in Matlab to generate a response fit as well as utilising the third-party surrogate modelling tool, ALAMO [3] to generate a surrogate representation between dPf/dt and G(t). Based on the revised spline differential estimate, ALAMO was used to generate a functional relationship between dPf/dt and G(t). Utilising the generated spline fit differential estimates and the extracted data profiles, an Artificial Neural Network (ANN) model was also derived for both functional relationships applied to the oil and water injection case per Eq. (3) and Eq. (4):

**O(t) f (Xw, dP) (3)**

O(t) represents the oil production at time t, dP represents the change in field pressure less landing pressure (barg), and Xw the choke setpoint on the water injection well (%)

**dP/dt f (Xw, O(t)) (4)**

dP/dt is the change in field pressure with respect to time and Xw represents the choke setpoint on the water injection well (%).

2.0 Results

The following section aims to summarise the key results from the conducted research at Imperial College London. The sensivity analysis carried out with SobolGSA (Imperial College London) for the gas well integrated asset model generated the following sensitivity analysis output per Figure 1 which displays Si, the first order sensitivity of each input parameter towards the output parameter; the higher the Si value i.e. closer to 1, the higher sensitivity towards the output. The separator landing pressure i.e. input parameter 1 demonstrated the largest sensitivity towards the gas production output.



**Figure 1:** Sensitivity Analysis of input parameters within SobolGSA; Si (Sensitivity Index) vs Input Parameters

The subsequent RS-HDMR meta model generated within Matlab was tested and this generated a positive R2 correlations at 0.90. The RS-HDMR model is deployed via Matlab to provide an accurate prediction of the production and field pressure profile; incorporation of time dependency demonstrated positive R2 correlations at early field life conditions but deteriorated at later field life. Figures 2-3 depicts the production and pressure profile predictions from the most optimal surrogate models developed (Response Surface Method, ALAMO, ANN, RS-HDMR methods were deployed in this research).

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| **Figure 2:** Gas Production prediction via surrogate model at varying water injection choke set points, Xw | **Figure 3:** Field differential pressure prediction (oil field) via surrogate model at varying water injection choke setpoints, Xw |
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A constrained non-linear optimisation framework (fmincon) based on the developed surrogate relationship for gas production and differential pressure profiles was set up utilising a custom ODE solver (adapted for stiff differential equations). The resultant cumulative gas production output compared favourably with the corresponding cumulative production output from the integrated asset simulator model. Further optimisation of the developed surrogate models (in addition to optimising the differential defined as epsilon, ε, between the output of the full physics reservoir coupled integrated asset model and the simplified tank reservoir integrated asset model) was investigated. Optimising the RS-HDMR and ANN models utilising metaheuristic methods was evaluated; genetic algorithms were employed to optimise the developed ANN’s. Sobol Opt (SobolGSA global optimiser which is designed to solve global non-linear optimisation problems) was deployed to optimise the RS-HDMR models which resulted in slight overpredictions in cumulative production and revenue at optimised conditions. An optimisation framework to minimise the differential term ε was deployed in Matlab to extract the corresponding input parameter, Xg which was subsequently played back to the surrogate model to evaluate the corresponding production, G(t). This workflow would enable to user to deploy the simplified tank reservoir model to propose operational decisions to maximise production in lieu of a full physics reservoir integrated model.

3.0 Conclusions

Development of surrogate models was attempted by utilising a number of integrated asset model frameworks (simplified gas tank model including acquifer support, full physics gas tank model and a full physics reservoir simulator). Having developed the integrated asset model test cases within the industry state of the art PETEX® suite and successfully run several global sensitivity assessments, several approaches were investigated to test fit a relationship for G(t), O(t) and the field/bottom hole pressure profiles, dPf/dt and dPb/dt. Response surface fitting of polynomials demonstrated good correlation for the production functions but less so for the field pressure profiles. Imperial College London’s proprietary meta modelling software, SobolGSA was deployed to determine whether extracted input and output datasets could be utilised to generate an RS-HDMR metamodel for predicting absolute production and pressure profiles for a given specified set of input parameters. Development and deploying Artificial Neural Networks (ANN) demonstrated a positive response when training the data sets utilising the Bayesian Regularization training regime; the developed ANN’s surrogate models predict the production and the pressure profiles for a given specified user set of inputs i.e. Xg, dP and Xw. Optimisation of the developed surrogates was attempted which was successful for a constrained non-linear optimisation framework; slight under predictions were noted when optimising the Artificial Neural Networks via gradient free methods such as a genetic algorithm. Lastly, machine learning was deployed to attempt to adapt the reduced order integrated asset model network to predict the performance of the full physics integrated asset model with similar findings i.e. deviations noted in later field life conditions which would caution the usage of the proxy models at these conditions.

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