Executive Summary

Oil production optimization has always been a challenging function in the petroleum industry. The search for effective production planning tools is an ongoing goal of many companies who are involved directly or indirectly in oil production.

The need for this research is to address a business problem related to the difference between the targeted production's theoretical capacity and what is actually produced in large oil fields. The business problem is known as lost production opportunity which is defined as the difference between the reservoir system and the surface facility's capabilities. This loss has impact on the profit as well as long term development plans for enhanced oil recovery. The objective for oil companies is to minimise this loss which is estimated at 15% in ADMA-OPCO (Abu Dhabi Marine Operation Company) and other companies (ref. Table 1-1 Lost production case studies).

In order to identify the reasons behind the loss in production opportunity, it is important to identify the key decision variables that contribute to production and include them in the production model. To achieve this goal, a survey with subject matter experts was conducted. The results of the survey identified a number of random variables which were not addressed in the current models or handled with specific assumptions. Examples of these assumptions are a steady well production or lift curve model which is subject to changes, the use of asset availability program in the absence of probabilities of failure, the use of constant separation models regardless of change in fluid characteristics, and ignoring stimulation activities which improves the well performance. A data collection and analysis was conducted on the defined decision variables. The information related to process flow diagrams and capacities were used to design and configure the simulation model parameters. The information related to production and operational activities were analysed for trending of polynomial or probability functions, in the case of random inferencing, and used to create material flow in the simulator.

The well production model, being a key decision variable, is found to be based on the latest well test available with the assumption of constant oil flow in the network between well tests. The well production volumes depicted poor correlation with

actual production. Therefore, the use of old well test data contributes to inaccurate production estimates. This can be attributed to the changes in the tubing back pressure, which is a key lift curve factor, as a result of operational changes of the other wells' flow rates across the field. To achieve accuracy, the research opted for production data mining to study the well performance and to obtain production trends without imposing more frequent well tests that are costly. The data mining to extrapolate future performance is found to be more correlated to actual production than the well lift curve model.

In a similar technique to reservoir simulation, the research uses the stochastic modelling and pattern recognition of the decision variables to configure a discrete event simulation model to represent the full production process. The simulation was run for a number of scenarios and produced less production losses than of the exiting model. The results of the findings of the new model are in the summary table below;

Period	Target Oil (Barrels) (LC basis)[1]	Current System (Barrels)	Sim. Model (Barrels)	Losses AEC[2]	Losses of sim. Model	Correl. Factor
Forecast 6 months	19,816,835	22,789,360	19,045,000	15%	3.9%	0.93
Forecast 14 months	44,918,159	51,655,883	41,830,000	15%	6.8%	0.79
Forecast 14 months (new wells)	44,918,159	51,655,883	44,403,000	15%	2.2%	0.92

The losses of the simulation model are expected due to natural decline over the elapsed time. The losses of the current model are caused by inadequacies of integer programming to handle random occurrences of field activities.

Chapter one explains the business problem and how a production system misaligns with the reservoir system capabilities. The chapter explains the need for the research as a result of competitive market, rise in local demand and the process of production planning that depicts poor correlation with the actual production. The production dynamics is described with respect to the pressure decline through the process chain.

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[1] LC is the Lift Curve basis considering latest production readings

[2] AEC is the Automatic Effective Capacity in use by the Company

Chapter two discusses the studied literature in detail and describes the achievements and methodologies timeline. The business problem of lost production opportunity and the research question is formulated in two parts. The definition of the variables and the model development. The well testing data that is needed to fine tune the model is infrequent. The dynamic nature of the oil field requires faster responsive optimization models to overcome the gap between planning and executing the work as described in (Amos, H.C., Jacob Bernedixen, J., and Syberfeldt A., 2010).

Chapter three describes the methodology for the decision variables questionnaire development and of building the simulation model. The research uses extrapolation analysis, inclusive of asset unavailability, resulting from unplanned shutdowns. The chapter describes the data collection and the parameters settings for the simulator.

Chapter four compiles the decision variables from the surveyed pool of experts in order to configure the simulation model. The model is configured to utilize trending and probability distribution functions when the variables are random. The results of the simulation were subject to hypothesis testing. The analysis of planned and targeted production produced good correlation resulting in models that are valid and more accurate than the current system.

Chapter five describes how a company can benefit from the results of the model to overcome the field performance decline. Companies can use simulation scenarios to devise a strategy and plans for short and long term development.

The underpinning theoretical premise of the research is to include stochastic variables in a model which were not possible to include in the previous models. Rndom variables can be modelled with stochastic programming. However, when the number of wells is large, the formulation becomes complex and encounters delays to achieve results through multivariate analysis. Hence, a discrete event simulator that is capable of using random and profiled events becomes more viable to model the process chain and produce timely results (Woo, J.H., Ho Nam, J. and HeeKo, K., 2014). Timely results are important to implement quickly while the field settings are still current.

The limitations of the research, such as simulating the water injection for pressure maintenance, flow diversion and well control on the basis of gas/water ratios are not addressed. They are options for future research.