Chapter 2
Literature review

2.1 Barriers and achievements timeline

Historical production data shows that fluid ratios trending at the well-site was not used in production planning (Case studies section 1.2). Production planning is driven by the total field target and the lift curve model.

Production optimization is often researched as a subject of sustainability for long term field development during enhanced recovery state. The production during a steady state period is often researched on the basis of asset monitoring or the application of distributed simulation systems for day to day operational excellence (Dzubur, L. and Langvik, A., 2012). Table 2-1 briefs the optimization timeline in petroleum industry by (Khor, C. and Kamel, A., 1996) – (Production systems optimization methods for petroleum fields).

Table 2-1 Optimization timeline

1950s–1960s	Use of Linear Programming (LP) models in which the reservoir behavior (i.e. the relationship between flow rates versus pressures) was modeled to maximize production with-in known constraints for single and two well system - (Lee, A., Arnofosky, J., 1958)
1960s–1970s	Use of Non-Linear Programming (NLP) with single phase production advanced towards including facilities' maintenance programs in a discrete manner (Huppler, J., 1974).
1970s–1980s	Use of LP/NLP models combined with data obtained from numerical reservoir simulation for well development (McFarland, J., Lasdo, L. and Loose, V., 1984).

1980s–1990s	Use of discrete (integer) variables resulting in Mixed-Integer Programming (MIP) models for improved representation of the non-linear flow and pressure variables neural network and hybrid genetic algorithms (Bittencourt, A. and Horne, R., 1997).
1990s–2000s	Systems approach (FieldWatch, HYSIS, GAP, eProg, etc.)[3] in semi-automated optimization models to identify only the key decision variables to model the reservoir behavior which served overcoming operational constraints.
2000s-Present	Real Time Operations (RTO) to measure change of well flow and managing the choke for fast optimization ABB (ABB Automation Inc., 2001) and (Barber, A., Shippen, M., Barua, S., Hernanadez, A. and Montra, S., 2008). Geo chemistry was also piloted and yielded good results based on the oil samples originality (Mccaffrey, M., 2012).

2.2 Literature review models and limitations

The reviewed literature shows that studies have been using specialized simulation and Linear Programming (LP) based on well lift curve and network flow modelling. In the reviewed literature, a number of specific techniques have been used in studying the optimization of production variables to overcome the process constraints. Since the 1950s the optimization techniques went through several stages. The techniques used the constraints to formulate a model with variables that can be solved for maximum gains. Many LP techniques and computer solutions were developed to solve large numbers of equations pertaining to the large fields. Simulation emerged in the late 80s and evolved into specialized products to solve

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[3] Fieldwatch from ROXAR, Gap and eProg: scalable software products that can be configured for applications spanning from a diagnostics tool, through data validation and condition monitoring systems, to virtual instrumentation and simulation/control applications.

PVT models for subsystems in the production chains (e.g. HYSIS from Aspen Tech, GAP from PETEX, e-PROG from ABB, Eclipse from Schlumberger, Puma-Flow from Franlab, VIP-Decision Space from Landmark, RMS from ROXAR-EMERSON, etc.)[4].

The studied literature has identified a number of optimization modeling themes that are analyzed in the next sections while discussing the gaps of each;

2.2.1 Integer, linear and mixed integer programming

The referenced studies addresses artificial lift though gas compression to aid the flow of oil at the well site. Linear programming techniques are used to effectively recycle the available gas and optimize its use for multiple wells. Solutions are aimed at an individual well or a limited number of wells with steady state (constant flow rates) for the purpose of effective utilization and recycling of the gas used to lift the oil from the lower level of the well. (Camponogara, E. and Nakashima, P., 2006) and (Aronofsky J., Williams A., 1962). Applicability is valid when variables are controlled for a limited number of wells. The formulation becomes limited with a large number of variables and nonlinear constraints which require a stochastic approach.

2.2.2 Quadratic mixed integer coupled with numerical simulator

Integer programming handles the situations very well when the asset is either available or not. It has no mechanism to address situations in between when the asset is available with half efficiency. Coupling the model with numerical simulators supports subsurface considerations only, but does not give attention to the topside surface facilities' condition. The quadratic model is introduced at a stage of the oil recovery when the reservoir pressure is depleted mandating artificial lift and prior to the period of enhanced oil recovery. Gas lift optimization is used for enhanced recovery and effective gas recycling management using a limited number of wells (Dawson, R. and Fuller, D., 1999) which face challenges such as addressing the well

[4] Numerical Simulation software products designed for reservoir simulation, process simulation and used in oil companies to understand the reservoir characteristics to support the production system

natural oil lift, separation and water processing (Camponogara, E. and Nakashima, P., 2006). This methods falls short of meeting a complex field configuration.

2.2.3 Virtual metering, real-time data and DCS

This model relies on downhole gauges that read data in near real-time and are used to overcome operational constraints assuming steady state to overcome day to day flow assurance and pressure maintenance. The well performance and trends are not studied for a long strategy. Distributed Control Systems integration with real time data acquired from the digital instruments serves the purpose of solving operational problems rather than optimization (Bieker, H., Slupphaug, O. and Johansen, T., 2006).

The review concludes that the focus on monitoring and solving the production system does not serve the subsurface long term decisions. This is also common to digital oil fields, real time asset monitoring and neural network techniques as discussed by (Alimonti, C., Sapienza, L. and Falcone, G., 2002). They conclude that the diversity of the needed business skills and computing technologies to collaborate successfully makes an ideal model goal not easy to achieve.

2.2.4 Geochemistry based back allocation for optimization

Oil fingerprinting aims at enhancing the back allocations and not overcoming lost production opportunity. The oil samples provide volumes' estimates and sources on the basis of the chemical composition being unique for each zone. Geochemistry applications are good for zonal material balance and reservoir considerations with no added value to the well performance or contribution (McCaffrey, M., Ohms, D., Werner, M., Stone, C. and Baski, D., 2011).

2.2.5 Integer programming with planned maintenance optimization

The method shares the same drawbacks of section 2.2.1 in addition to missing actual asset availability estimation or failure probability. Outages of subsystems are configured with on/off conditions for online or in offline status. The model achieves operational short term results with a shortfall in meeting the full system production potential producing 15% losses to the production capacity (ADMA production annual report, 2014).

2.2.6 Specialized fit for purpose simulators solutions

Special fit for purpose simulators has been around and in use for specific tasks in the production chain. They work very well in silos but can't be expanded in a manner covering all the stages of the production chain. Case studies for production improvement encounters limitations due to the complex integration which requires assumptions of some variables as constants (Saputelli, L., Nikolaou, M. and Economides, M., 2006). Also, all simulation products have shortfalls in addressing the changing nature of key variables when they are deployed for the full production chain and incorporating probability distributions or extrapolation of future performance. Examples of these applications are Meerak PEEP and Avocet from Schlumberger, Field-Watch from Emerson, I-Do from Weatherford and GAP from PETEX[3].

2.3 Literature review in timeline

(Aronofsky J., Williams A., 1962) formulated a linear programming and mathematical models in managing underground oil production as one phase fluid excluding water and gas ratios. The study has decision variables' limitations related to flow constraints, facilities' capacities, and plant availability. The production model was presented in theoretical formulation without practical implementation.

(Clay, M., 1988) et al. introduced a practical approach to linear programming through quantitative online monitoring of daily operations for control purposes in the central gas facility at the Prudhoe Bay field. The use of real time data renders the approach as a process control system to monitor daily operations. It used limited decision variables related to overcoming production flow by alternating production wells without trending or probability considerations. (Gjesdal, A., Abro, E. and Midttveit, O., 1988) shared the same approach and introduced multiphase metering for gas and water measurement to allocate production for wells with high oil contents. The importance of accurate well allocation for reservoir management and production optimization is emphasized but was not targeting optimizing production capacity through trend analysis or process modelling for production forecasts.

A production optimization system for Alaskan Western Prudhoe Bay field (Muhlenberg, L., Barnes, D. and Humphrey, K., 1990) used the methodology of flow assurance based on high gas wells drive. This study shared the same purpose of the previous ones in overcoming operational difficulties irrelevant of the forecast, well performance or decline rates. The same focus was shared with the optimization of well rates under gas coning conditions by (Urbanczyk, C. H. and Wattenbarger, R. A., 1991).

A management schemes study (Lo, C.W. and Holden, W., 1992) used linear programing, decline curve analysis and simulation for fluid rate forecasts. The study doesn't use key decision variables (well contents ratios – GOR/WOR, plant availability or assets capacities). The study encountered limitations due to assumptions of constant gas/water ratios, and that each well can produce between the zero and the maximum flow. This does not reflect the reality where the well is shut-down prior to reaching a zero production rate. (Fang, W., Lo, K., 1996) added a generalized well management scheme which faced limitations related to field maintenance activities that impacts production opportunities and consequently results in missing the overall future estimation.

The introduction of a blended model of special purpose simulators to satisfy the total process chain complexity (i.e. GeoQuests, Eclipse, Pipesim, Prosper, PVTi, Eclipse 300) was under scrutiny by (Khor, C. and Kamel, A., 1996). It proved to be fragmented and lacked integration between the pressure system and the well system. However, when they were integrated through a distributed control system {e.g. (ABB Automation Inc., 2001), (Bonavita, N., Birkemoe, E., Slupphaug, O. and Storkaa, E., 2008), (Schlumberger, Abingdon Technology Center Training, 2005), (Cuacenetl, R., 2008), (Bieker, H., Slupphaug, O. and Johansen, T., 2006) and (Chowdary, S., 2016)}, they achieved the real-time objectives in overcoming daily operational problems based on current data provided by the numerical simulators.

Therefore, the embedded distributed control systems (DCS) helped more to overcome the operational constraints in steady state. However, the software models face limitations in data mining which are required for accurate estimates of production forecasts in a dynamically changing field. (Saputelli, L. A., 2003) study of blended models (real-time, numerical simulators and linear programming) debated that some key variables are often treated as constants. The blended model also faced limitations in the dynamic state where production priorities and settings change. The models also faced limitations with decision variables for changes of gas and water ratios as well as maintenance plans. The optimization works well for on-line order to overcome operational constraints in steady state, but faced limitations when random variables are encountered or readings are missed.

(Alimonti, C., Sapienza, L. and Falcone, G., 2002) introduced fuzzy logic and data mining to extrapolate missed readings and to correct wrong volumes' readings which were not correctly captured by the multiphase metering. However, the study admits the absence of an integrated model to handle dynamic changes for a better forecast. Additionally, the study's main gap is related to excluding decision variables for plant availability and facilities capacities.

While a number of optimizations addressed managing gas capacities for artificial lift (Wang, P., 2003); these models do not formulate the full process chain with stochastic variables. They work when all values are predetermined. Use of linear programming is limited to gas quantities utilization to sustain available gas lift capabilities (the gas is recycled to serve 4, 10 and 50 wells). The model become less practical when the field is larger and doesn't formulate a full process chain with all the variabilities in fluid contents, field maintenance activities and flow assurance.

Flow assurance was modeled by (Kosmidis, V., Perkins, J. and Pistikopoulos, E., 2004) by using mathematical programming for analyzing the flow in a pipeline network on the assumption that all of the wells are tied directly to a facilities' fixed-pressure systems. The drawback to this approach is that the assumption is not valid in an operating field. The dynamic condition was also missed by (Popa, C., Popa, A. and Cover, A. , 2004) and (Naus, M., Dolle, N. and Janson, J. D., 2004). They used a blend of numerical simulation and multivariate technique (sequential linear programing optimization) for optimization of comingled production with a high level of controls. The case study is limited to one reservoir and horizontal wells with four inflow control valves. Expanding the model for a full field would encounter limitations related to key decision variables (e.g. plant availability, and assets capacities) and hence the model was not designed to satisfy forecasting.

(Saputelli, L., Nikolaou, M. and Economides, M., 2006) reiterated that the use of multivariate analysis in oil and gas optimization has not been fully adopted in the hydrocarbon industry. The fields' dynamics resulting from flow and pressure changes was the main cause of the limitations for the long term optimization with these techniques.

(Goh, K.C., Muncor, C., Overschee, P. and Briers, J., 2007) in their data driven optimization models used software to substitute the missing readings from down-hole sensors. The study focused on understanding well performance, but was not aimed at a dynamic model for production forecast. The study also missed key variables (e.g. WOR/GOR, plant availability, and asset capacity) which are required for a global optimization model.

(Haavardsson, N. F., Huseby, A. B. and Holden, L., 2008) used a mathematical model for simplified production process that is constructed based on the specialized simulation output for wells, facilities and reservoir. The study does not address stochastic variables or extrapolation required for predictions of future well or assets performance.

(Palen, W. and Goodwin, A., 2008; Cuacenetl, R., 2008) addressed problems in flow assurance in the well-pipelines performance due to formation of gas condensation. The use of an integrated suite of applications enhanced the flow by 6%. The main solution is intended to handle operational constraints in a difficult terrain. This has added value for a specific solution for an operational problem such as a single bottleneck case, but not to a total optimization model.

(Palen, W. and Goodwin, A., 2008) addressed the debottlenecking of choke points by using a discrete event simulator for the process chain. It resulted in an increase in production with no extra budget through identifying bottlenecks and process chokes. A manual process recovered 4% of the estimated 15% loss in production opportunity. Later the process was simulated under a RAM simulator. The RAM didn't address well allocations and planning as key variables but enhanced topside assets efficiency by 10-15%.

Allocations were modeled by (Cramer, R., Scotanus, D., Ibrahim, K. and Colbeck, N., 2011) who used down-hole flow rates' meters and SCADA (supervisory control and data acquisition) systems to improve allocations and hydrocarbon accounting. The study came close to the use of accurate allocations for computing well allowable rates. But, the computations relied on the total flow without reflecting multiphase rates. It ignored other decision variables such as plant availability and assets' capacities. The purpose was to describe oil accounting improvement techniques used by Shell FieldWare software, but didn't address dynamic model or commingled production forecast.

(McCaffrey, M., Ohms, D., Werner, M., Stone, C. and Baski, D., 2011) studied the production allocations in commingled fields through oil geochemistry. The basis of the study was the use of oil samples geochemistry for back-tracing zonal contribution volumes (USA, Purdue Patent No. US20150309001 A1, 2012). It is effective for subsurface reservoir material balance management only, but not for surface facilities production optimization. It is applicable in a steady state, but it can't handle dynamic state for production forecast. The study recognizes inaccuracies in results due to imperfect sample representation. The study doesn't use key decision variables for plant availability, facilities capacities and unplanned downtime.

(Tucker, R., Straub, T. and Feng, S., 2012) analyzed the unplanned downtime in the Gulf of Mexico and highlighted the significant production loss opportunity through data mining of the company records between 2008 and 2012. The business problem identified two decision variables (unplanned downtime and well testing). Lost production opportunity was estimated at 12%.

(Shah, N. and Mishra, P., 2012) developed a mathematical model based on production rates decline and economics of maintenance cost, initial investment and leakage costs. While the model stays as a theory, it has limitations when it is implemented to account for a physical model.

Although production economics is conducted for every new field feasibility study, it relies on data obtained from initial subsurface exploration. (Jazayeri, T. and Yahyai, A., 2002), (Spencer, D., 2015) and many others evaluated the economics of production in isolation of an effective production optimization strategy. Economic studies focused on supply and demand, assuming certain production capabilities that are not a concern to the study. The study is complimentary to the optimization in the production chain, but is not intended for that purpose.

(ADMA production annual report, 2014) introduced a standalone economic component to a production model through special software tools to compliment the in-house application of the production forecast. The study relied on the lift curve and asset status (on/off) exploiting the Integer Programming technique. The asset is assumed to be in-service or off-service and without values in between. The results produced a 15% average production opportunity loss. Assumptions were made and not all decision variables are modeled.

Other reviewed case studies recognized the lost production opportunities. Among those are ZIFF Energy Group (Tucker, R., Straub, T. and Feng, S., 2012), British Petroleum (Burchel, S., 2014) and Schlumberger (Cuacenetl, R., 2008), where measures were taken to control this loss through a quasi-integer programming model and multiple simulators. This resulted in minor enhancements, but faced limitations in applying a systematic research method for identifying key decision variables (i.e. well productivity, asset availability, water rates, assets' capacities and market demand).

(Woo, J.H., Ho Nam, J. and HeeKo, K., 2014) and (DNVGL RAM Discrete Simulator, 2016) developed a simulation model for asset availability and for production optimization purposes. This constitutes the start of applying a discrete event simulator based on a reliability and availability model to optimize flow through constrained manifolds. It is used for random variables of operational nature (asset reliability) with no well data mining or trending to extrapolate future forecast or demand and economics.

2.4 Underpinning theory

In the reviewed literature, it was detected that a number of key random variables are assumed as constants in order to apply the existing models of mathematical programming. This was also concluded in (Saputelli, L., Nikolaou, M. and Economides, M., 2006) who went further and speculated why the use of multivariate optimization analysis has not been fully adopted in the hydrocarbon industry. They concluded that this approach lacks connection with real field dynamics. This is attributed to its reliance on steady-state conditions instead of the dynamic state, which represents the real status of the field.

The above case was emphasized by (Kosmidis, V., Perkins, J. and Pistikopoulos, E., 2004) in which a fixed pressure value was used for the separator with many wells tied directly to it. This was used as assumption for the pressure in the pipeline network which did not reflect the reality of flow changes.

In the multi-reservoir study optimization value chain, (Haavardsson, N. F., 2008) points out that the word optimization in the oil recovery industry is used in the sense of analyzing a few cases and choosing the best one. Hence, there is no model for optimization. He concluded that when many oil rates are involved, to an extent, the mathematical model "segments of quadratic equation formulation" would require expansion to a new subject of research altogether since quadratic equations will need to be reformulated iteratively (to cope with rate changes).

Therefore, the underpinning theory is that the multivariate models can handle limited steady state equations, but cannot account for the complex non-linear interactions between the wells that share common flow lines. The problem becomes more complex to solve when the constraints increase in large fields.

The mathematical programming and other models' limitations and shortcomings call for an alternative technique that can handle the equations as well as the random variables in a prompt and dynamic model. A Discrete Event Simulator (DES) is faster to configure and modify and can accept stochastic and polynomial based parameters. A (DES) based method is used in creating both a BP model (Burchel, S., 2014), (Codasa, A., Campos, S., Camponogarab, E., Gunneruda, V. and Sunjergae, S., 2012) and a general simulation product by (DNVGL RAM Discrete Simulator, 2016). All the developed models were relevant to the process chain asset availability for capacity planning (Woo, J.H., Ho Nam, J. and HeeKo, K., 2014) without an optimization objective.

2.5 The research question

Question number 1: What are the various decision variables that enhance offshore oil and gas production in the UAE?
Question number 2: Can a model be developed and adopted to fit all the decision variables and to forecast production?

An integer programming model used for status on or off does not give accurate results when the asset performance is partially efficient. A model will require key decision variables to be used as control parameters to the various simulated processes for executing different and new optimization scenarios.

The research problem

The gaps in the reviewed literature pointed out the main research problems:

To develop a unified single simulator that can overcome the gaps in the limitations of linear programming and to adjust production target forecasting (based on the lift curve) to a more accurate figure. The changes are due to the inflow dynamics and the operational nature of the oil fields. This is to be preceded by;

- Defining the decision variables for the overall production model that needs to be used, including production rates, phase behavior, accurate asset availability and missed readings of changes in the phase behavior at the well site.
- Study the decision variables' trends and rates of change over time with the impact on the dependent variables in order to configure the simulation model.

2.6 Chapter conclusions

The reviewed literature in section 2.2 revealed methods to improve production on steady state but faced challenges in answering the difficulties of the dynamic state of the field and the random activities that impact the production potential and the actual output (Khor, C. and Kamel, A., 1996). The case studies in Table 1-1 Lost production case studies) highlighted the losses and gains but did not provide impact analysis (What is the suitable choice? Would it be investing in new development or optimization?). In the absence of accurate losses calculations, the investments potential can't be measured accurately. Consequently, it can't answer whether the optimization can meet the market demand or an investment is required, nor can it quantify the investments needed to cope with market needs. (Intelligent Solutions, Inc, 2011) addressed data mining and pattern recognition as an alternative to traditional reservoir simulation to achieve accurate models. This research is adopting the same concept in addressing the optimization with consideration of facilities performance data mining to be used as input into an integrated simulator. It relies on modeling production facilities in one simulator that uses the key information related to assets capacities and performance history. It is important that the data change behaviour is understood by depicting trends and a dependency between the variables. One important function that can contribute to long term enhanced oil recovery is how the oil lift operations are managed and contained within the allowable limits.

The main gaps which are commonly shared are related to:

- The time to produce an optimization result and its implementation which renders the new settings ineffective due to the changes that took place in between.
- The accurate loss calculations and compensations are missing from all the reviewed literature.
- Most studies don't address data trending and at the same time are not capable of using recent information in the models. The impact of change over time on the well model is overlooked due to the duration between well tests.
- The short term production optimization remains unachievable due to focus on meeting operating challenges by alternating wells in a production stream.
- Studies that rely on down-hole sensors and virtual metering to obtain flow information in real time focus on instantaneous flow measurements, operational aspects and short term forecast or trending. But this technology falls short of tracking phase changes as part of the data mining.

- The long term objective focuses on reservoir management and known variables related to a fixed maintenance program of the facilities (pipelines, separators, plant availability, storage, etc.). Long term objectives ignore failure probability, wells performance and facilities efficiency.
- Demand fluctuation challenges are not modeled which can result in an unstudied reaction to the market (i.e. sudden accelerated plans for large investments or panic for drastic cuts in production and costs).
- The studies provide methods to improve production but do not provide an answer for overcoming the gap of a dynamic state of the field and the random activities that impact the production potential and the actual output.
- The studies do not provide impact analysis (what is the suitable choice? should it be investing in new development or optimization?).

This chapter describes the background and timeline of modeling to achieve production optimization.