Optimal Scheduling of Field Activities Using Constraint Satisfaction Problem Theory

Faraj Zarei

A thesis submitted for the Degree of Master of Philosophy
School of Energy, Geoscience, Infrastructure and Society
Heriot-Watt University
Edinburgh, Scotland, UK

May 2021

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The challenge of identifying problematic wells and planning their workover operations is common in oil and gas fields. On top of this, the well intervention resources are seldom easily accessible so it is crucial to target the right set of wells at the right time. Oil and gas reservoirs are complex dynamic systems the production and injection patterns of which can significantly affect the reservoir and well response. This represents a complex mathematical optimisation problem where the overall life performance of the field strongly depends on the workover planning decisions.

This work presents a reliable and effective tool that is able to screen and explore the large search space of the potential work-overs that adds value to the reservoir management process. The proposed solution considers the overall performance of the field throughout a specified period while respecting all operational limitations as well as considering the risks and costs of the interventions. The proposed workflow combines the commercial optimiser techniques with constraint satisfaction problem optimiser to identify the optimal workover scheduling. The schedule found is guaranteed to satisfy all predefined field constraints. The presented results showed better performance achieved by the proposed hybrid optimiser compared to classical gradient-free optimisation techniques such as Genetic Algorithm in maximising the defined objective function. The suggested workflow can greatly enhance the decisions related to field development and asset management involved with large number of wells and with limited intervention resources.

Dedication

This thesis work is dedicated to my wife, Behnaz, who has been a constant source of support and encouragement during the challenges of graduate school and life.

Acknowledgements

I owe my deepest gratitude to my supervisors Dr. Khafiz Muradov and Prof. David Davies

For countless hours of reflecting, reading, encouraging, and most of all patience throughout the entire long process.

I wish to thank the examiners Prof. Vasily Demyanov and Dr. Gbenga Oluyemi for spending their time in reading this thesis and valuable comments given during the thesis examination.

My sincere gratitude to my colleagues in IWFsT and VAWE JIP projects: Dr. Reza Malakooti, Dr. Morteza Haghighat their moral support and invaluable discussions.

I would like to thank all sponsors of IWFsT and VAWE JIP projects for the financial support, data provided for my study and valuable discussions and suggestions during JIP meetings as well as CNOOC (Previously Nexen UK) and Schlumberger Information Systems for access to their software.

I greatly acknowledge the Heriot-Watt University staff for continuous support throughout this study.

ACADEMIC REGISTRY
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School/PGI:	School of Energy, Geoscience, Infrastructure and Society		
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Chapter 1 Introduction

1.1 Motivation

The ultimate goal of any field development optimisation is to maximise the recovery and profit with minimum associated costs. The field development plans are usually presented in the form of long-term decisions which result in improved hydrocarbon production over the life time of the field. These decisions may include scheduling workover operations, infill drilling, changing surface processing facilities, deploying EOR/IOR techniques and etc.

Selecting the suitable wells at correct time to carry out the workover operation is a very complicated task when workover resources are not enough for the existing number of producers and injectors in the field. This task will be even more challenging when the workover scheduling is implemented as part of the development study of mature fields in which hydraulic interactions between the reservoirs and wells make complex downhole fluid flow phenomena and brings additional uncertainty to the field project.

The optimal workover scheduling has become demanding over the last 5 years during the all times of low oil price as many companies have started to apply cheaper ways of producing oil and gas from the fields. Workover operations allows additional barrels of oil with less resources and cost in comparison to drilling new wells (Eze et al., 2016). The workover projects may include various jobs such as replacement of tubing strings, installation of subsurface safety valves; re-perforation or shutting the perforated zones, restoring the well integrity and etc. A mature well may face one or a combination of following issues and well intervention is recommended to deploy the well reconstruction solutions (Canny, 2016):

- Restrictions in tubing caused by deposition
- Corrosion and failure of tubing
- Corrosion and failure of casings
- Corrosion and integrity problems of tubulars caused by Non-CRA materials
- Collapse/instability of the wellbore
- Degradation of the cement integrity
- Degradation of metallic and elastomer sealing

- Sustained annular and casing pressure

Optimal planning of the workover operations compared to infill drilling approach can significantly save the CAPEX for operators who especially intend to maximise the mature field profit at this downtime of the oil and gas industry.

Field workover screening algorithms have been proposed to identify the workovers with the highest added values. Popa et al. (2005) used the artificial intelligence and lean sigma techniques for field planning on a large scale, based on the wells' current production signatures. Ugbenyen et al. (2011) analysed the economic effects of current production profiles to identify the wells with the most urgent intervention need. These workflows focus on the individual wells and only the well's current status is used to make the decision. No consideration was given to the long-term effects of the work-over on the overall well/field performance. Another published approach (Sumaida, 2013, R.O.Paiva, 2000, Lasrado, 2008) for workover planning is operation-oriented with the well priority being determined by optimising the workover rig mobility (a problem similar to the classic "Travelling Salesman" dynamic optimization problem). This perspective also lacks integration with the reservoir performance and the well intervention results.

It is clear from the above that a reliable and effective tool that is able to screen and explore the large search space of the potential workovers that adds value to the reservoir management process is not currently available. The search will need to consider the overall performance of the field throughout a specified period while respecting all operational limitations as well as considering the risks and costs of the intervention. This could be (1) a reactive choice of the currently most profitable option or (2) a proactive procedure to identify a workover sequence that yields the maximum added value by making forecasts of future events based on the current reservoir simulation model.

1.2 Thesis Outline

The organization of this thesis can be summarised as follows:

Chapter 2 starts with presenting the principles of work-over planning and implementation. Then it reviews concepts of computational modelling and optimisation in the context of job scheduling. The methods of translating of an engineering problem into sets of mathematical equations are discussed and an available search algorithm is reviewed. Classic definition of the scheduling in

Operational Research (OR) is followed by re-iterating of the limiting role of computationally expensive objective function and lack of an appropriate, analytical scheduling method. Applications of scheduling techniques in the asset management are listed. Limitations of these techniques in high levels of interdependencies are addressed to emphasise motivations to develop a helper to reduce such levels of interdependencies and a novel dynamic programming technique to maintain them.

Chapter 3 introduces the reservoir simulation model used in this study to validate the proposed algorithm. Then the list of various well intervention jobs that may be conducted during the workover operation are listed.

Chapter 4 introduces the Constraint Satisfaction Problem (CSP) as a robust methodology to solve the workover scheduling problem. This chapter presents a hybrid methodology by combining CSP and search algorithms. The proposed workflow is applied in both reactive and proactive modes of the workover planning.

In **Chapter 5** a Genetic Algorithm (GA) optimisation search procedure - one of the most commonly used algorithms in proactive optimisation of intelligent wells – is used to find the optimal control strategies by considering both the well and field scale to assign workovers optimally at the full-field level. It is discussed how engineering knowledge of the field production conditions allows us to create additional sampling tools to decrease the dimensions of the proactive optimisation problem and increase the likelihood of the optimiser reaching a significant improvement in the project value within a limited number of iterations.

Chapter 6 concludes the thesis with a summary of the findings and recommendations for future study.

Chapter 2 Numerical Optimisation and Scheduling: Concepts, Optimal Field Planning Applications

2.1 Workover Operation

Workover operation refers to any well intervention activity which is planned on an oil or gas well to extend its producing life by either improving the performance or providing additional hydrocarbon reserves. The workover operation does not only solve the well and reservoir problems but also provides information on lateral and vertical fluid movements and current location of oil, gas and water within the reservoir.

2.1.1 Reasons for Workover

Number of reasons can be listed for low production rate that requires workover implementation to increase economically the field's recovery (Allen & Roberts, 1982):

- Formation damage: Operations such as clean-out, reperforating, chemical treating, acidizing or a combination of these methods can be used to reduce the effect of formation damage and presence of any sand or mud in the wellbore.
- Low permeability: It is preferred to conduct a hydraulic fracturing treatment to increase the productivity of wells drilled in the naturally low permeable formations.
- Low reservoir pressure for reservoir depth: The stimulation is not effective in these type of reservoirs as less drawdown pressure is available to capitalise the increases productivity index. Thus, perforation of new zones or artificial lift installation may be a practical solution for this problem.
- Excess water production: The water path production originates from reservoir, casing leaks or primary cement failures. This problem results in costly lifting approaches and disposal treatments. However, the costs can be reduced by squeeze cementing or plugging back the contaminated intervals.
- Excess gas production in oil wells: The gas may be produced from dissolved gas in the oil or from the gas cap which has been trapped above the oil zone. It is also possible to have excess gas production from a gas zone separated from oil zone through the channels as a result of casing leaks or poor cementing jobs. The workover operation may not be

successful to reduce the high gas oil ratio in these wells as the issue is a reservoir related problem as a whole rather than to be a well problem.

- Scale, paraffin or asphaltene deposition: Acidizing or chemical treatments are usually considered to remove scales from the well and open holes. There might be cases in which the scales are drilled out from the wellbore. Steam, hot oil, hot water and solvents are used to remove the wax from the tubing.
- High viscosity fluid: Thermal techniques are effectively reducing the oil viscosity and increase the oil mobility near the wellbore and in the drainage area.
- Mechanical failure: This includes primary cement failures, casing, tubing and packer leaks, wellbore communication in multiple completions and other downhole failures.

2.1.2 Workover Equipment

A typical workover operation is conducted using either conventional workover rigs, concentric workovers or wireline techniques. A conventional workover is usually required when 1) production tubing and other retrievable downhole equipment must be removed, 2) the permanent downhole well configuration needs to be repaired or changed, 3) Additional perforations or completion of new intervals requires to be implemented and 4) improvement of retrievable downhole equipment or artificial lift should be applied. During the conventional workover, the well is killed, and production tubing is removed. There are number of rig types to handle this job such as drilling rigs, conventional workover rigs and snubbing units. These facilities usually offer all the rotation, circulation and well control capacities.

A small tubing or drill pipe is run inside the existing production tubing in the concentric workover system and the well is not required to be dead. This eliminates the additional formation damage by injection of killing fluid into the wellbore. If rotation and fluid circulation is not needed in a workover job, the wireline option is preferred to minimise the workover costs. The concentric tubing methods are cheaper than conventional workovers due to their reduced workover time, no need of moving of well tubing and use of smaller size of workover rig.

Coiled tubing and snubbing hydraulic units are the most widely concentric workover options used. Coiled tubing is commonly used for well cleaning, washing sand, acidizing, well kick-off, and sand consolidation treatments. However, it’s not suggested for heavy workover services because of limited tensile capacity of the tubing and hoisting capacity of the rig and inability of tubing rotation. In contrast, hydraulic workover equipment provides higher lifting capacity and rotary capabilities to perform light drilling.

2.1.3 Workover Equipment Selection

The selection of workover system depends on the type of operation involved in the workover job. These operations are listed as:

- Drilling and milling: Conventional rigs are typically used for drilling and milling operations since they provide required penetration rates and high torque. The conventional rig is also suitable to complete new downhole completion which is usually required after any drilling operation. Concentric rigs are instead used for light drilling, milling up very hard sand layers and removing deposits such as paraffin or plastic consolidation materials from inside the tubing string.
- Squeeze cementing: This operation can be conducted using both conventional and concentric workover systems. However the selection may depend on the specific requirements of the well and the job. There are circumstances where the conventional rigs are more suitable such as 1) when the cementing is performed in the production string above the packer, 2) the packer needs to be removed to keep pressure off the casing or 3) when cement needs to be milled out of large-diameter casing.
- Recompletion: If the new completion interval is above a retrievable packer, a conventional rig is used to pull out both packers and tubing string. If the interval is below the existing perforations, both concentric techniques or a conventional rig can be selected based on depth, hole angle, casing and tubing size, and ability to drill the cement plug.
- Repair/replace downhole equipment: Wireline workover is suggested when the equipment (e.g. subsurface safety valve, gas-lift valve, tubing patches, etc.) is suspended in the tubing string. If it is necessary to pull out the production tubing (e.g. replacement of the packer, retrieval of the screen in a gravel packed completion, retrieval of corroded tubing, etc.), then a conventional rig is usually used.
- Sand Control: The choice of workover rig depends on the sand control technology used in the wellbore. The screens and gravel pack are normally installed in the well during the initial completion with the drilling rig. However, a conventional workover rig must be used if it is decided to run these mechanical devices later in the well's history. A concentric workover system may be used in the case of running the gravel pack designed for a tubingless completion. When sand production is controlled by chemical consolidations or resin coated sands, either a concentric workover or bullheading down the existing tubing is

used to pump the chemicals into the target interval. Although the concentric rig option results in additional cost and a risk of pipe sticking in the hole, it reduces the fluid mixing and contamination problems.

- Stimulation: Three choices of workover are available to carry out a stimulation treatment named as bullhead, concentric and conventional. Bullhead method is able to inject small volumes of chemicals (such as solvents, surfactants, and small acid jobs) to short intervals. It requires divergent techniques if the production interval is fairly long. This option is also used to perform large hydraulic and acid fracturing if the tubing diameter is large to provide low friction pressure and the packer can withstand the high injection pressure. If the tubing diameter and packer is not appropriate to conduct the fracturing job, a conventional rig is required to remove the existing completion. The concentric workover rig is suggested for matrix acidizing treatments where the acid is pumped throughout the smaller work string and its reciprocating movement improves the coverage of the sand face by the acid.
- Clean-up: Depending on size of the casing, the scale materials and the available fluids, both conventional and concentric workover options can be used for cleaning treatments. The reverse circulation through the production tubing is sometimes preferred as it provides high velocity to improve the solids transport.

Generally, workover is planned based on the well problem type, the appropriate workover technique for the given well problem and available workover systems in the field. It is important to perform the number of critical steps in order to complete a workover job: the steps such as economic evaluation, assessment of advantages and disadvantages of the workover technique, selection of the most optimum workover system, ensuring safety, analysing, recording and filing the workover procedure and results.

2.2 Workover Scheduling

The previous section summarised possible well problems and discussed how to do the selection of workover operation for each type of the problem. In real fields, the workover plan should present an integrated solution to all possible problems during the life time of the wells. However, the number of available workover rigs is less than the number of the wells requiring service due to their high operational expenses.

Smith (1956) proposed a "natural order" of well scheduling when only one rig is available and no time windows are considered. Based on his work, the wells are ordered in decreasing values of their $P_i/\Delta t_i$where P_i is the production loss per day for the well i and Δt_i is the estimated workover time. Two other strategies may also be used to schedule workovers: 1) arrange the workovers by descending values of P_i and 2) plan the workovers by ascending values of Δt_i (Barnes et al., 1977). Barnes et al. (1977) showed that there is a lower bound (LB) of total production loss ($LB = \frac{1}{2}m[(m-1)B(n) + 2B(1)]$) for this type of problem with m rigs and n wells. $B(1)$ and $B(n)$ presents the total production losses when 1 and n rigs are available respectively. They also proposed a two-step approximate technique to plan the workover if more than one rig is available. Step one includes scheduling the wells one at a time in the reverse of natural order (in order of decreasing values of their $P_i/\Delta t_i$) and assigning the next well to the rig with the least processing time already assigned. The assigned wells on each rig are reordered again in their natural order in step two. These traditional aforementioned strategies may result in a schedule that fails to maximise total production from all wells during the workover period. Since several efficient optimisation methods are available, researchers prefer to apply these techniques instead to obtain the optimum schedule. A number of factors such as well production, the current location of the workover rigs, operation time window and the type of workover treatment affects the workover scheduling optimisation problem.

Aronofsky's work (1962) can be mentioned as one of the earliest drilling rig scheduling studies that were using linear programming. that the rig scheduling problem dealt eith the production from a given well follows a specified production decline curve. Irregular reservoir shape was modelled with known size and dimensions and uniform thickness which was subdivided into number of cells with no crossflow to simulate a typical production rate decline curve. Hartsock, and Greaney (1971) formulated a mathematical model to schedule the development drilling of an oil field in which the objective function was the total discounted cost of the development operation and the control variable was the number of drilled wells as a function of time. Unlike Aronofsky's approach (1962) in which he treated both the field producing capacity and the crude oil demand deterministically, they considered these two parameters as log-normally and normally distributed random variables. Therefore, the cost function resulted in a nonlinear unconstrained minimisation problem which was solved by the pattern search technique of Hooke and Jeeves.

Pavia et al. (2000) tested four algorithms: 1) follow the next closest well, 2) follow the next best payoff, 3) deep search and 4) simulated annealing – to determine the optimum workover schedule for the list of wells waiting for the workover rig. The objective function cost considered both the rig expenses (transport, assembly and operation) and the well's production losses. The study used reservoir simulation to include the effect of wells shutdown on the field production performance.

Aloise et al. (2006) proposed a variable neighbourhood search (VNS) heuristic to solve the workover scheduling problem for known number of days available for workover operations in Brazilian oil fields. The workover operations included cleaning, artificial lift re-installation and stimulation. They assumed the workover rigs are spread throughout the field rather than to be located in the field centre. The travel times between the wells and their daily oil production were also known in this study.

Ribeiro et al. (2011) used simulated annealing approach for workover scheduling problem in real Brazilian cases. They obtained the best workover plan for cases of 25, 50, 75, 100 and 125 wells for the condition of 2, 4, 6, 8 or 10 rigs available for individual cases. The simulated annealing method provided better results compared to the one published in the literature using other non-derivative search methods such as the greedy randomized adaptive search procedure, genetic algorithm and scatter search.

There are a number of studies to address the workover planning issue through using heuristic search algorithms (Ribeiro et al. (2012a); Ribeiro et al. (2012b); Ribeiro et al. (2014); Monemi et al., 2015). Similar to Ribeiro et al. (2011) work, these researches are based on a data set from Petrobras and within the Brazilian field. Sumaida et al. (2013) presented a systematic rig movement approach. They used two possible operations to move the rigs, 1) mast-up when the road is allowed to do that, or 2) conventional mast-down movement if there are obstacles in the way. c) presented a comprehensive review of works addressing the workover rig scheduling problem. They proposed a 0-1 integer linear programming model to efficiently solve the complex and large instances reported by Petrobras for which only approximate heuristic or multi-heuristic solutions were available from previous works. These all mentioned studies lack the integration with the reservoir performance and well intervention results. No consideration was given to the long-term effects of the workover on the overall well/reservoir performance.

If reservoir simulation is used along with optimisation technique in workover scheduling problem, it is possible to maintain field production rate by increasing flow from other wells when production is lost from a well during the workover period. Reservoir simulation results are sent to the optimiser to find the best optimum workover solution. Lasrado (2008) work was based on this approach while he did not incorporate any optimisation method in his workflow. However, this scenario is not achieved in the studies in which rig scheduling optimisation problem is based on the well production loss for the duration of the workover. Aponte et al.

(2016) developed a stochastic approach in which the sequence of top twenty workovers with higher NPV was obtained through running hundreds randomly generated sequences. They integrated multiple geological reservoir realisations, well timing, operational risk and differential scenarios for capital and operating costs. Proxy models were generated using a multivariate linear regression for each intervention. Their work was more focused on finding the best group of workover schedules respecting the reservoir uncertainties and operational constraints rather than determining the global optimum solution.

It is clear from the above that a reliable and effective tool that is able to screen and explore the large search space of the potential work-overs that adds value to the reservoir management process is not currently available. The search will need to consider the overall performance of the field throughout a specified period while respecting all operational limitations as well as considering the risks and costs of the intervention. This could be (1) a reactive choice of the currently most profitable option or (2) a proactive procedure to identify a work-over sequence that yields the maximum added value by making forecasts of future events based on the current reservoir simulation model.

2.3 Planning and Scheduling in Operational Research

2.3.1 Job Shop Scheduling Problem

The scheduling problem particularly in its most common industrial form of job shop scheduling (JSS) has gained a lot of attentions in the fields of industry, economics and management. JSS is a type of combinational optimisation problem known as NP-hard and is recognised as the nearest problem to field workover scheduling. The JSS problem components are a shop, jobs and machines. Each job includes a number of operations and each operation should be performed by only one machine with a predefined processing time. Mathematically, JSS problem consists of:

- n jobs: $J_1, J_2, \ldots J_n$
- m machines: $M_1, M_2, \ldots M_m$
- mj operations: $O_{j1}, O_{j2}, \ldots O_{jmj}$ (Operations of each job should be scheduled in this order and each O_{jk} has a processing time of P_{jk}.)

Based on above parameters, JSS attempts to find the optimum operating sequence for each machine to minimise a certain criterion such as makespan (required time to complete all of the jobs), maximum lateness and total weighted tardiness (Abdolrazzagh-Nezhad and Abdullah, 2017).

The JSS problem was initially addressed by Johnson (1954). Later several works were published to address the JSS problem solution (Smith, 1956; Jackson, 1957; Brooks and White, 1965; Conway et al., 1967; Rinnooy Kan, 1976; Baker, 1998). A number of techniques has been proposed to solve the scheduling problem. Arisha et al. (2001) presented a summary of these solutions classed into two groups of traditional techniques and advanced techniques. Figure 2-1 shows the number of traditional techniques while the advanced ones include simulation, artificial intelligence and repair-based methods.

2.3.2 Revisions of Job Shop Model for Field Scheduling

The field scheduling is an advanced variant of the problem with additional complexities:

- Cost/Profit vs. Makespan: While job scheduling problems try to minimise makespan, in field scheduling problem all the scenarios have the pre-fixed makespan which is equal to the operation period e.g. work-over. Instead the goal is to find the schedule(s) that bring the highest net profit.
- Sequence-Dependent Setup: Unlike classic version, in well scheduling cost/profit for a particular job (machine's setup time) depends not only on that particular job but also on previous jobs that the machine has completed. For example, well production after any particular operation depends on the history of the well and the way well(s) has been operated.
- Job Selection: not all the jobs are done. Only a limited number of jobs depending on the defined optimisation period are selected to be carried out. It means only selections of work-overs that can be done are actually planned.
- Dynamic constraints on jobs: The list of jobs dynamically changes based on selected choice in the previous step. If you alter a well’s completion at this date, choices for the future interventions also change.
- Sequence Dependent Objective Function/Machines can have sequence-dependent setups: While in the classic job shop the objective is to minimise the makespan the ultimate goal of work-over is to maximise the production performance. The same set of workovers applied in different sequences will result in a different production profile which can only be quantified with reservoir simulation.

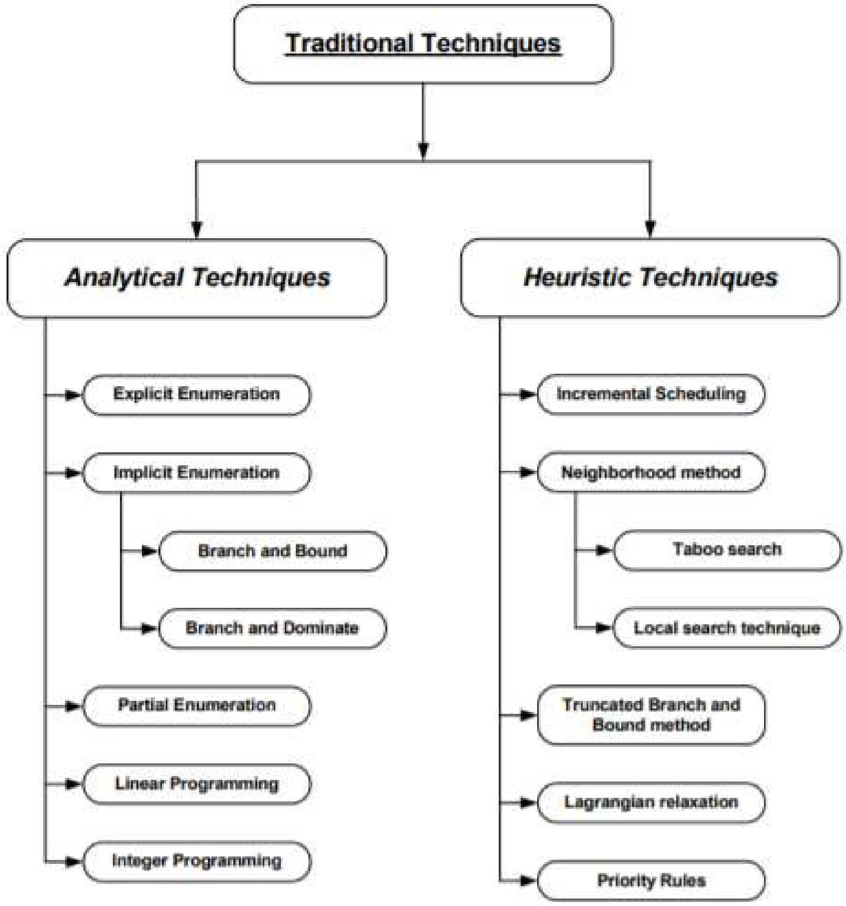

Figure 2-1: Traditional methods to solve the JSS problem (Arisha et al., 2001)

2.4 Constraint Satisfaction Problems

Constraint satisfaction problem (CSP) defines a number of variables (objects) whose values (domain or state) must be satisfied under a number of constraints (limitations). In other words, a value for each of the variables is found that satisfies all of the constraints. The N-queen puzzle is a very good example of CSP in which it is attempted to place n queens on an $n \times n$ chess board so that no queen can attack any other queen in this problem. The components of this problem are defined as:

- Variables: n number of queens on a $n \times n$ chess board
- Values: The set of values for each queen is $\{1, 2, \dots, n\}$. Any two queens cannot be placed in the same column. Therefore, it is only required to find out which row must be assigned to each queen.

- Constraints: Qi cannot attack Qj ($i \neq j$)
    - Qi is a queen in column i and Qj is a queen in column j.
    - The value of Qi and Qj are the rows the queens must be placed in.
    - There is a constraint Cij for every pair of variables (Qi,Qj). The assignment of values to the variables Qi = A and Qj = B satisfies this constraint if and only if
        1. $A \neq B$
        2. $|A - B| \neq |i - j|$

A solution to this problem is any assignment of values to the variables $Q_1, \ldots, Q_n$ that satisfies the above constraints. Constraints can be defined over any group of variables. However, constraints over pairs of variables (binary constraints) were used in the N-queen problem.

2.4.1 Constraint Satisfaction Problems in Workover Scheduling

The CSP concept can also be applied to solve the workover scheduling problem. The workover scheduling problem is defined in this study in a way to assign the workover rig to the most optimum well in order to conduct the workover operation monthly while this process occurs for a number of months. It is assumed each well may have been completed, re-completed or isolated on a number of zones.

According to CSP definition, this particular workover scheduling problem is defined mathematically as follows:

- N (number of variables) equals the summation of all zones of all wells which can be entitled for workover operations.
- The set of values of above variables include {1, 0, -1}. Perforated (open), closed and unperforated zones are assigned with values of 1, zero and -1 respectively.
- The constraint implies that the closed (shut) zones can be reperforated during the schedule of workover rig

2.4.2 Solutions to Constraint Satisfaction Problems

Sequence of variables X in CSP can be assigned to each finite, search tree of P such that:

- P_0 is its root
- Its nodes are CSPs,

- At each level, only one node is extended and there is one single descendant.
- If $P_1,\ldots,P_m$, where $m \geq 1$, are direct descendants of P_0, then the union $P_1,\ldots,P_m$ is equivalent w.r.t. X to P_0.

Figure 2-2 shows a sample search tree. Odd levels correspond to constraint propagation and splitting happen at even levels. For instance, imagine a decision is to be made on Zone A of Well B. Originally it can be perforated (P_0), and stays so until the next workover season, during which it can either 1) stay perforated or 2) be isolated. These two branches are extended until yet the next workover season, when they in turn branch out with new options, etc. The tree may become very dense if several zones and/or multiple other workover options are considered simultaneously.

If the CSP is consistent the tree creation continues until CSP is solved. For inconsistent CSP none of the leaves can be extended until all the variables are assigned. It means there is no solution for the CSP.

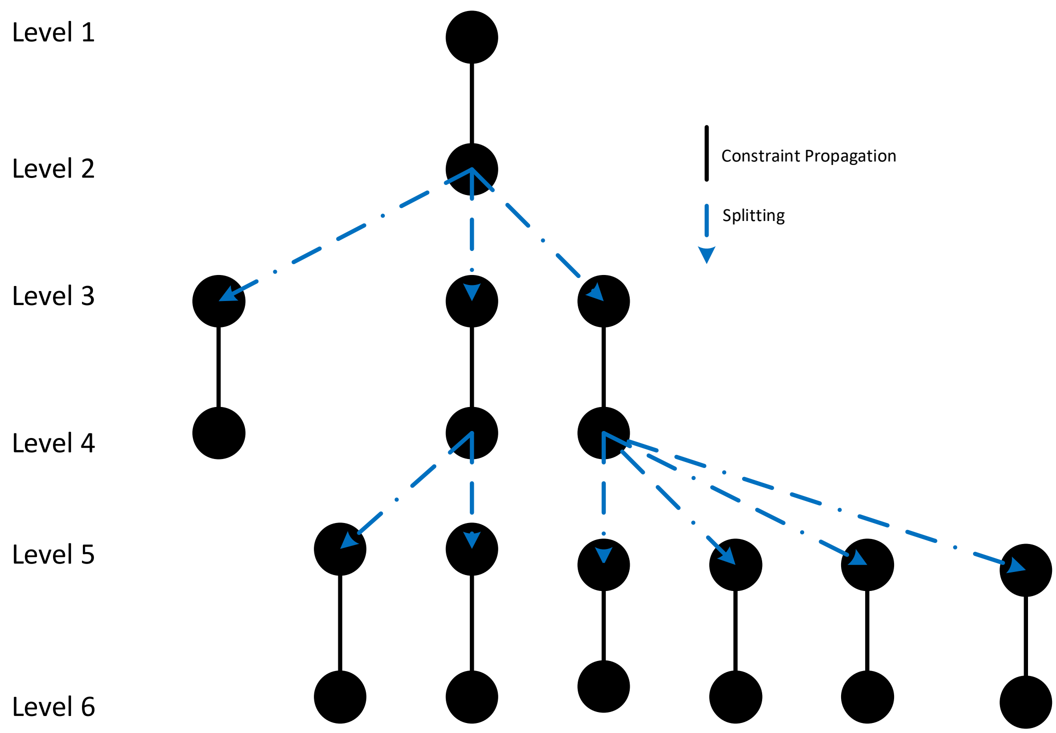

Figure 2-2: Search tree example

The concept of a decision tree is widely used in CSP. The choices and made decisions create the tree. Search algorithms try to effectively explore the tree with partial constructing the tree in optimised progresses.

a) Backtracking

Backtracking is known in literature under different names, e.g. the top-down search or depth-first search algorithms are used to create the full extent decision tree. Lowest level node in a tree is expanded until a dead-end or failure is reached which means the variable domains becomes empty. At this stage there is at least one unassigned variable and the CSP is still unresolved. Taking one step back, the expansion continues from another node.

In these algorithms one repeatedly expands a node at the lowest level in the tree until a failure arises, upon which one returns (backtracks) to a higher level at which one resumes the node expansion.

b) Forward Tracking

Forward tracking algorithm looks ahead. The assignment of any problem updates all the connected variables and the domains of the affected variables are updated to make sure they are consistent with the assignment. If the assignments leave the domain of any unassigned variables empty the search has to take a step backward and select the next value. Domains of unassigned variables are reset accordingly and re-evaluated with respect to the newly selected value. The algorithm is able to predict the inconsistencies earlier than backtracking and results in the more effective search.

2.4.3 Concept of "Constrained Optimisation Problem" and the solution approach

In some cases, the mere finding a valid solution is not enough. The allowed solutions are associated with an objective function which compares how good they are. If the number of solutions is limited, one can find all the possible solutions. Ranking the solutions based on the objective function values allows the best solution be identified.

Field scheduling is an example of CSP with a large number of solutions. In essence it is a maximisation problem which aims at boosting a selected objective function e.g. Field Oil Production, NPV or any other selected parameter. In such condition, using the right algorithm each new CSP solution which brings higher objective function value replaces the old solution. Optimisation is terminated when the selected stopping criteria are reached.

This study suggests hybrid Genetic algorithm (GA) and Stochastic Gradient Decent (SGD) that uses the feasible traits of two optimisation algorithms in CSP environment:

a) Stochastic Gradient Decent

Gradient decent or Steepest Descent is a deterministic/trajectory based/local optimisation algorithm which uses the gradient information at each step to move toward the local minimum. For high number of variables, calculation of the gradient can be computationally expensive. The Stochastic Gradient Decent is a modification of the basic gradient decent algorithm which deals with such large problems and aims at finding global minima.

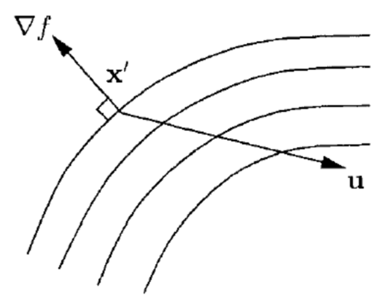

Figure 2-2-3: Search direction u relative to gradient vector at x'

For a n-dimensional problem when the iterative mode is used the algorithms randomly perturbs m subset (m<n) of variables and uses the calculated gradient to move (and generally descend) in the n-dimensional space.

In the problem of field scheduling due to difficulties of obtaining the gradient from the numerical simulation, the partial perturbation trait of the algorithm is used. Subset of the variables will be altered, and the final objective function will be monitored in order to be maximised. More details of the mathematical background of the technique can be found in (Bottou 2010).

b) Genetic algorithm

Genetic Algorithms are a subset of metaheuristic evolutionary algorithms. Because they are population based and gradient free, these algorithms can be a strong candidate for many simulation-based problems. GAs use two mechanisms to evolve the population of individuals and converge to optimal points:

- Cross over is used to exchange information between the good individuals. The idea is to find building blocks of good solutions and combine them to create better solutions. Unfortunately, application of cross over affects the feasibility of CSP solution. It is likely to come up with unacceptable solutions when two acceptable solutions are combined.

- Mutation is used to alter one or more genes in chromosomes. This might change the focus of the search to a completely different area in the search space. This study uses this mechanism to change the values of selected subset of variables. The workflow is created in a way that any alteration does not affect the feasibility of CSP.

More details can be found in (Kramer, Ciaurri et al. 2011)
Combination of random set of variables for perturbation and mutation create a hybrid algorithm compatible with CSP optimisation which will be discussed further in next chapters.

Chapter 3 Field Workover Problems – Real Case Study

3.1 Field Introduction

A large, dead-oil field reservoir simulation model (Field A) that had been history matched to the first six years of production data has been selected in this project to apply the proposed optimal work-over scheduling algorithm. The model geology shows four reservoir formations composed of highly permeable sand layers with thin, interbedded shale layers where the shale layers thicken into shale zones in some horizons. There is an active aquifer supported by a water injection scheme to maintain the field pressure. The combination of faults and heterogeneous reservoir properties make it difficult to achieve an effective sweep of the oil flow towards the production wells. More than 30 oil producers have been placed within the reservoir. A limited volume of gas is available to allocate between the producers for the purpose of gas lift operation.

Producers are controlled by the minimum Bottom Hole Pressure (BHP) and Tubing Head Pressure (THP) as well as the Group Liquid Rate. Wells are grouped based on the location and the produced water cut. The capacity of the surface facilities is limited to handle the treatment of the produced water. The internal optimiser provided by a commercial reservoir simulator was used to optimally distribute the gas among the production wells.

This history matched model suggests the field is able to maintain the maximum oil rate limit in the short term with a gradual decline starting from (the fictitious date of) the third quarter of 2001. A recommendation for a work-over of conventional well during the plateau period is unlikely to be approved by the operator company due to the associated costs and operational risks without any gains in oil production. The contribution of individual conventional wells can only be managed by adjustment of surface chokes during the plateau period.

The proposed methodology in this work will be tested during the gradual decline period to find the optimum, 3-year, work-over program for the duration of 01-Jan-2003 to 01-Jan-2006. (see Figure 3-1):

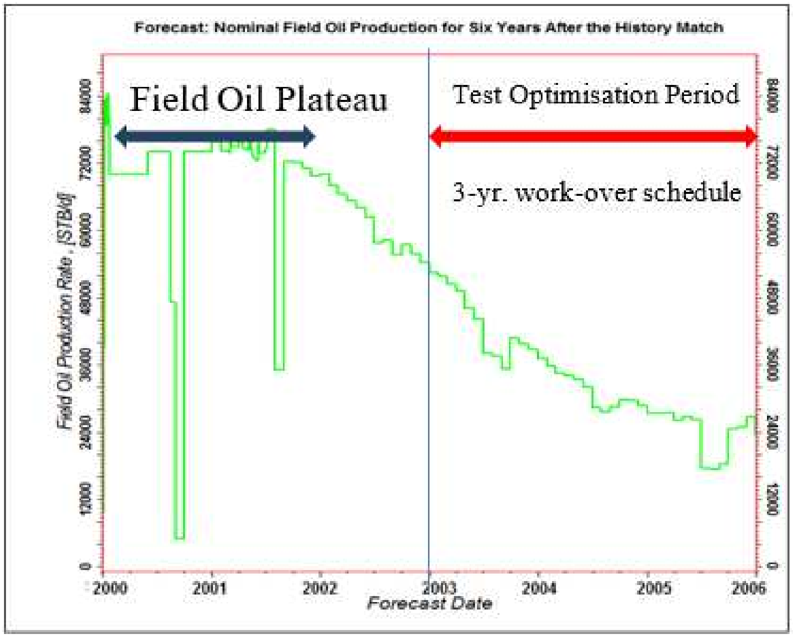

Figure 3-1: Field 'A' Oil Production Forecast

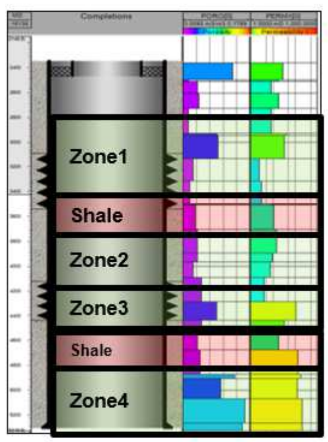

Figure 3-2: Well schematic for a 4-zone, completion

The individual oil-bearing geological zones are treated as a distinct intervention units in this study. Each zone includes several grid layers in the simulation model (Figure 3-3).

3.2 Well Services and Interventions

3.2.1 Stimulation

Stimulations are carried out to remove the well skin, clean-up sand face and enhance the properties of well's drainage area. It is performed in the form of acidizing, fracturing. Bull heading or coiled tubing are used to pump the fluid into the formation.

3.2.2 Zone Shutting

The fluid contacts eventually move toward the perforations depending on driving mechanism in reservoirs, during the production history. As sweeping efficiency is merely perfect, the water/gas will probably by pass the oil and reach the perforations earlier than the contact. Early breakthrough is caused by heterogeneities in petrophysical properties as a result of different rock quality, permeability and fractures and fissures. Poor cementing around the production casing may also create a channel for the water to reach to the perforations. While early unwanted breakthrough affects the productivity of the well, it also drains the reservoir energy and negatively impacts the long term recovery from the reservoir by (Tarek Ahmed 2006):

- Extra cost of handling unwanted fluid (water/gas) especially for water which is usually corrosive.
- Excessive free gas production from the gas cap will drain the reservoir energy in a short period of time without obtaining the associated oil sweep effect.
- Producing water instead of hydrocarbon impacts the overall recovery of the reservoir.
- If not properly controlled, the afflicted well may have to be abandoned.

Zone shutting off may be performed through tubing intervention including cement and gel squeezes, slugs, straddles, patches or valve closing when Interval Control Valves (ICVs) are available.

3.2.3 Perforating

Candidate producing zones are identified with reservoir characterisation techniques and production logs. The perforation is used to re-establish the best possible connection (through the casing/liner and cement) between the borehole and the pay zone when the well design is cased hole. Shaped charges are the most commonly used technique for the perforation (Perrin, Caron et al. 1999). Reperforating existing open zones may also be considered for the operation in such cases the perforation through the tubing is preferred (Van Dyke 1997).

3.2.4 Stacked Oil Rim reservoirs

In oil rims a producer might intersect different separate reservoirs. In conventional wells these reservoirs are produced one by one starting from the deepest reservoir. When it is depleted the deeper section is plugged and a new shallower reservoir is perforated (Figure 3-3).

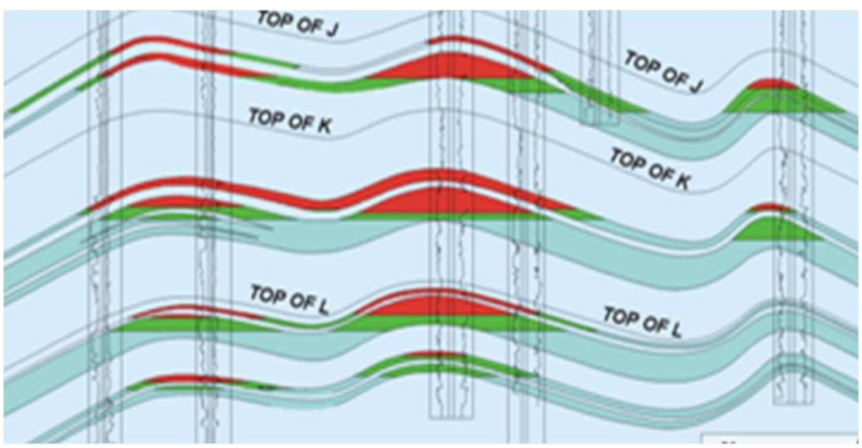

Figure 3-4: Sequential production from oil rims

3.2.5 Work-over to limit excessive water production

Before planning to eliminate excessive water production, well production troubleshooting has to identify the source of water. Production logs are able to detect flow behind casing from a water zone due to cementing problems. The flow can be blocked by remedial cement squeeze. Water fingering occurs when production is limited to one stratified reservoir. Production logs are able to identify the invaded zone where then work-overs are planned to plug-back the lower zone or selectively shut-in the other offending zone(s).

Water coning often happens due to high vertical permeabilities. These high permeability rocks create a water channel to the well. A common work-over planning approach based on the actual well performance is to employ a bottom-to-top (re)perforation policy. The deepest oil layers are brought to production first with the priority given to the most productive zones, and then with the gradual movement of the Oil Water Contact (OWC) the watered zones are plugged and the shallower oil zones are perforated. Such a planning process may result in a less efficient sweep of the reservoir oil and a reduced project value in fields which have complex geologies, e.g. compartmentalized by faults and/or with heterogeneous reservoir properties. The well's total in- and out-flow performance at a particular time is not optimised.

3.2.6 Work-over to limit excessive gas production

High gas production is controlled similar to the excessive water problem. The invaded zone that produces high Gas Oil Ratio (GOR) is plugged and a new lower GOR zone which normally is deeper is recompleted.

Gas channelling can also be the result of poor cementing. Cement squeezing can block the flow channel and control the excessive gas production.

3.2.7 Work-over for Sand Control

Sand control completion can be:

- Mechanical: which implies installing a filter including screens alone or gravel packing (the most common approach)
- Chemical: which tries to stabilise the grains and reinforce the integration bonds.

For long production sections gravel packing is the common choice. Correct sizing of the gravel is essential for successful gravel packing. If the sand zone is unconsolidated then the gravel pack should be installed at the beginning.

Chapter 4 Novel Hybrid Optimisation Algorithm Coupled with Constraint Satisfaction Problem for Optimal Workover Scheduling

Field workover planning is a complex dynamic programming problem with a large number of variables in the search space. The limited resources to perform the workover operations adds complexity to this problem as the feasible workover options depend on the resource availability. Constraint Satisfaction Problem (CSP) is a robust methodology to solve the workover scheduling problem. This chapter presents a hybrid methodology by combining CSP and search algorithms. The proposed workflow is applied in both reactive and proactive modes of workover planning.

4.1 Variable Definition and Handling

The scheduling problem is defined as:

- (X or variables) allowed dates to perform interventions
- (D or domain of each variable): allowed interventions at that particular date

Well interventions are normally planned periodically. The number of optimisation problem variables in this study depends on the duration of workover period and frequency of conducting workover operations throughout the planned period. The domain of each variable is obtained by CSP search tree (refer to section 2.4.2). The size of the domain depends on the range of possibilities (largely dependent on the number of wells to be considered). With any decision made at the date 1, the domain for the date 2 is updated based on constraint propagation of the CSP. The process continues until the decision is made for the last date and a valid solution for the CSP is achieved.

Raw domain of variables (Before CSP) is defined by the zonal control concept. The wellbore interval in the reservoir section may be described as a certain number of zones due to geological stratigraphy and presence of barriers such as faults, impermeable layers, etc. It is recommended to keep the number of zones as low as possible since the complexity of the search space increases exponentially with the number of variables. The initial state of zones (open or close) are defined in a matrix.

4.2 Workover Operation Modelling

The workover operation algorithm includes three modules: input, machine and output. Each individual zone is assigned a value to be used in this algorithm, as defined in Table 1.

Table 4-1: Assigned values for individual zones in workover operation algorithm

Well status / Section	Unperforated	Perforated	Already Shut
Input: Initial State of Variable	1	0	-1
Machine: Conducting Workover	N/A	N/A	-1
Output: New State of Variable	1	0	-1

Pinch-out zones or any other zones that might not be suitable candidate for optimisation purpose are presented by -99. Only zones with positive or zero assigned values are considered for workover operation. It is also assumed that the shut zones are not considered for reopening in the next dates of the well intervention.

4.3 Reactive vs. Proactive Workover Optimisation

The well with the lowest productivity at any particular date is selected for the intervention in the reactive workover operation approach. A brute-force search algorithm is used to identify all the possible interventions at any particular date. The number of simulations runs at any date equals the number of feasible combinations of zonal changes. These simulations are carried on until the next intervention date. Search algorithm tracks the change in the objective function and the one associated with the highest positive change is selected for at the corresponding date. The assignments continue until the last intervention date. Figure 4-1 shows the optimisation loop.

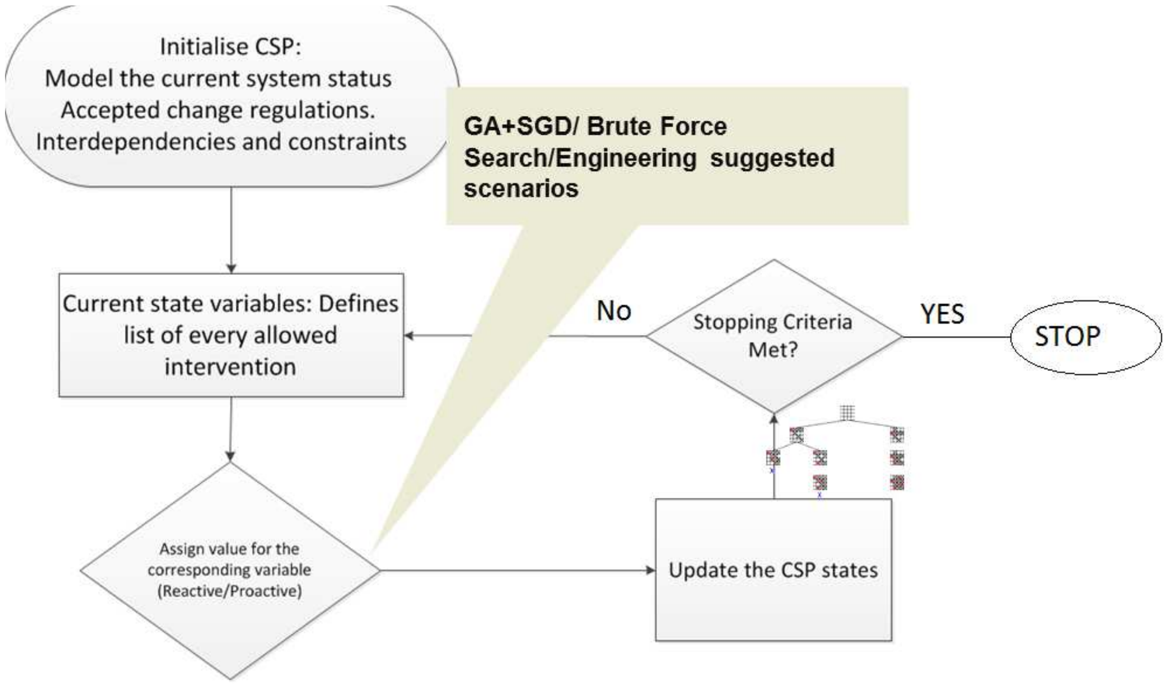

Figure 4-1: Work-flow Structure

In the proactive mode all the possible, current and future interventions are considered. There might be solutions with the objective function values initially lower than the corresponding reactive values, but expected to have higher values at the end of the forecast. In proactive mode CSP is partially created based on the selected job from the previous steps. The hybrid algorithm of combined SGD and GA is used as a search engine.

The concept of proactive optimisation looks ahead of the current conditions. It is necessary to keep the concept constituent regardless of the order of assignment being earlier or later. This is maintained with extended forecast beyond the last operation to allow reflecting positive or negative contributions in the overall changes of the objective function.

4.4 Application of Hybrid Optimisation Algorithm in a Case study "Field A"

The discussed workflow has been applied to the Field "A" described in Chapter 3. Optimal scenarios in both reactive and proactive strategies were found.

4.4.1 Definition of the CSP

Due to limited information available from reservoir characterisation this study assumes four distinct reservoir subzones as individual control zones. Each zone includes several grid layers in the simulation model (Figure 4-2).

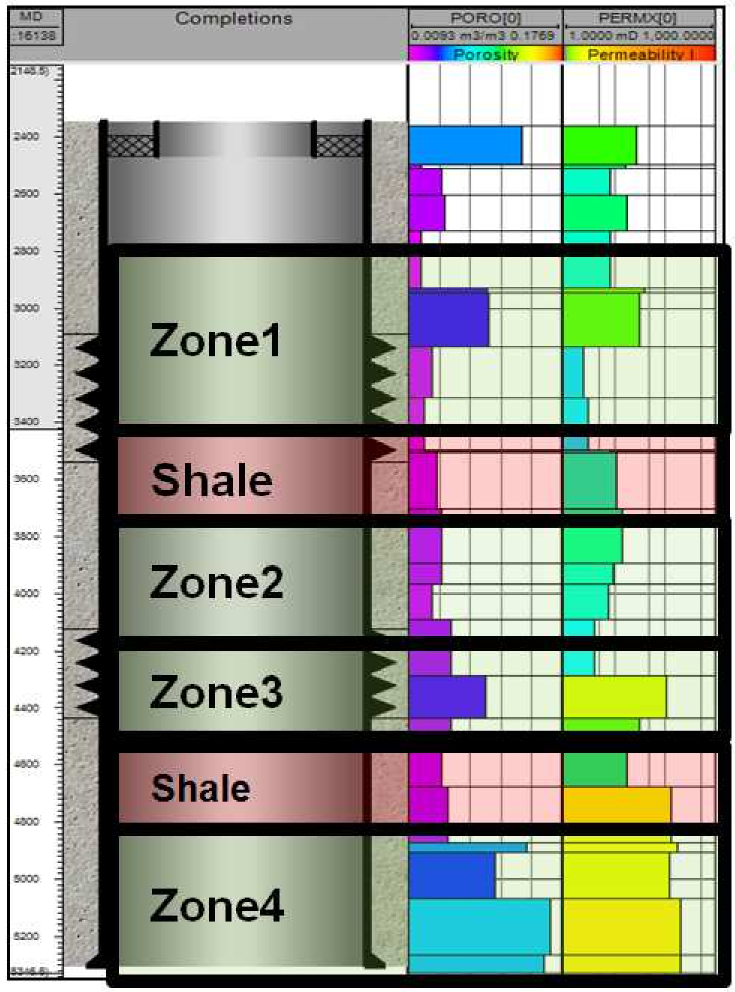

Figure 4-2: Porosity and horizontal permeability log for each individual zone

A table of 107 possible workovers was created based on the drilling trajectories and the current production intervals at the time of the start of the optimisation period (01-Jan-2003). They consist of perforating zones that have not previously been produced, fully perforated zones and partially perforated zones as shown in Table 4-2. The zone thickness is reduced due to pinch-out problem in number of wells and cannot be considered as a “stand-alone” completion zone.

Table 4-2:Zone operational status within the optimisation process

Well name	Z1	Z2	Z3	Z4
A2	UnPerf.	UnPerf.	Not Drilled	Not Drilled
A4	UnPerf.	Perf. Already	Not Drilled	Not Drilled
A7	UnPerf.	UnPerf.	Partial/UnPerf.	Not Drilled
A8	Perf. Already	Perf. Already	Not Drilled	Not Drilled
A9	Perf. Already	Partial/UnPerf.	UnPerf.	1 Act. Layer: Ignored
A10	Perf. Already	Perf. Already	Partial/UnPerf.	UnPerf.
...				
A30	Perf. Already	Perf. Already	UnPerf.	Perf. Already
A31	Perf. Already	Perf. Already	UnPerf.	UnPerf.
A32	Perf. Already	Perf. Already	UnPerf.	UnPerf.

Green & Brown: Subject to Optimisation White: Not included in Optimisation

Work-over capacity is limited to one well per month. Multiple zones in this well can be altered once the well has been accessed.

Table 4-3:Coded initial zonal status of the producers

Well name	Z1	Z2	Z3	Z4
A2	1	1	-99	-99
A4	1	0	-99	-99
A7	1	1	1	-99
A8	0	0	-99	-99
A9	0	1	1	-99
A10	0	0	1	1
...				
A30	0	0	1	0
A31	0	0	1	1
A32	0	0	1	1

Table 4-2 is converted to Table 4-3 according to the criteria given in Table 4-1. The Tables 4-2 and 4-3 actually reflect the current domain for the next date of intervention. Based on field intervention capacity, only one line of Table 4-3 can be altered. Table 4-4 presents the regular alterations of the variable's domains. Each row of the Table 4-4 represents a date of intervention.

Table 4-4:Field zonal status during the work-over operation

	1	2	3	4	5	6	7	8		205	206	207	208
	Well A2				Well A4					Well A32			
	Z1	Z2	Z3	Z4	Z1	Z2	Z3	Z4		Z1	Z2	Z3	Z4
Initial State	1	1	-99	-99	1	0	-99	-99	…	0	0	1	1
WO-1	1	0	-99	-99	1	0	-99	-99		0	0	1	1
WO-2	1	0	-99	-99	0	-1	-99	-99		0	0	1	1

Figure 4-3 shows the decision tree used to search for CSP solution according to changes reflected in Table 4-4. Purple boxes are the selected scenarios and while yellow ones present the resulting constraint propagation. Note that no action scenario is an option at all potential work-over dates to eliminate the chance of assigning unnecessary interventions when they are not justified by the objective function.

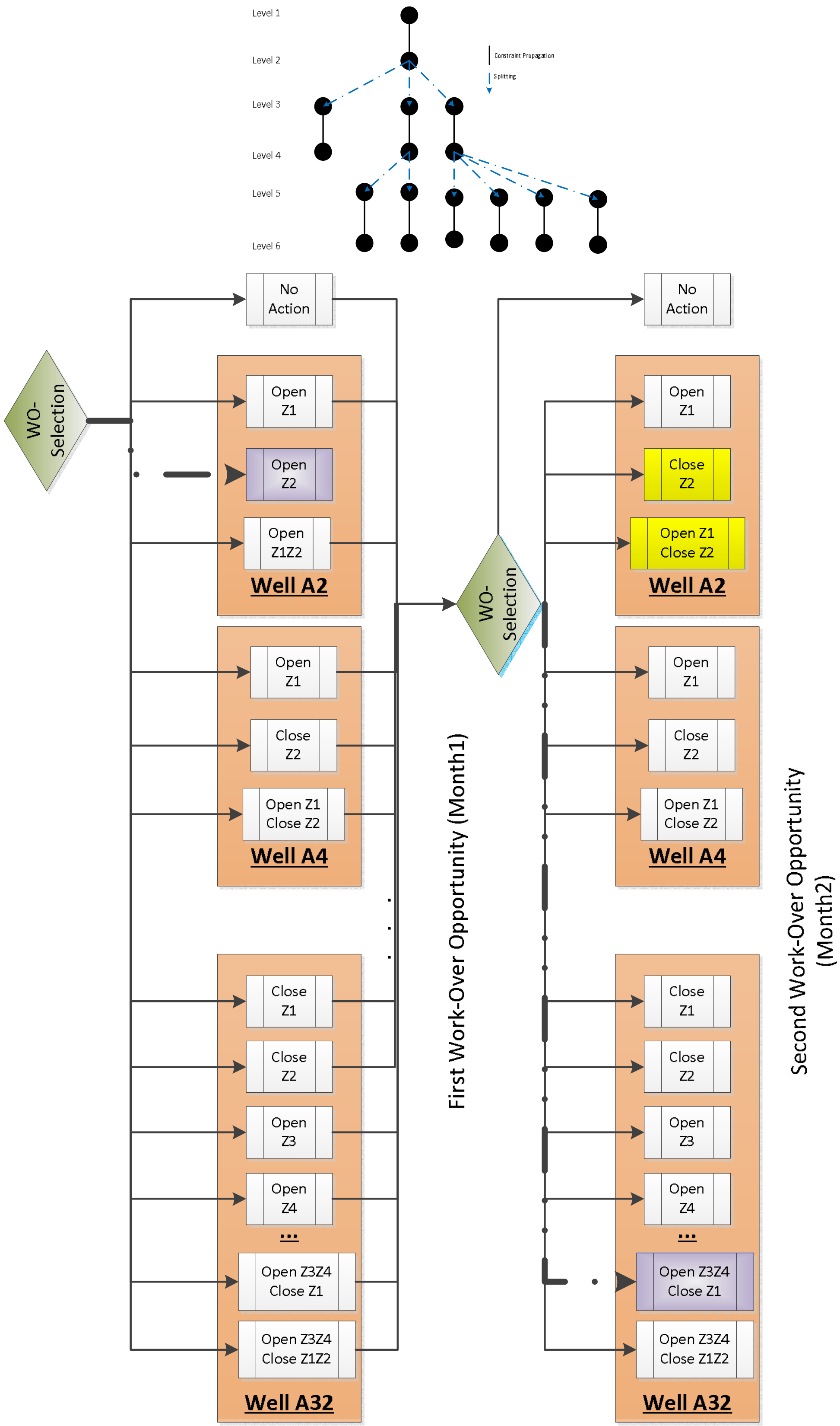

Figure 4-3: Decision tree expansion during the CSP resolution

4.4.2 Objective Function and Economic Model

Improvements of the field economic by conducting suggested interventions can be achieved in the short-term with a reactive mode strategy or in the long-term with a proactive strategy. Depending on the selected strategy different objective functions are defined. Instantaneous Cash Flow is selected as the objective function in the reactive control mode and is calculated as:

$$\text{Cash Flow} = \\ \text{Oil Price}\left(\frac{\$}{\text{BBL}}\right) \times \text{Net Total Oil Produced} - \text{Water Handelling Costs}\left(\frac{\$}{\text{BBL}}\right) \times \text{Total Water produced}$$

Where:

- $\text{Oil Price}\left(\frac{\$}{\text{BBL}}\right): 60\ \mathit{in\ this\ case}$
- $\text{Net Total Oil Produced}$: Until the next allowed work-over date
- $\text{Water Handelling Costs}: 2\ \mathit{in\ this\ case}$
- $\text{Total Water produced}$: Until the next allowed work-over date

Parameters included:

I. Improvements through the recovered extra oil or reduced water handling cost.
II. Delayed production due to the well closure during the operation, equivalent of seven days of lost production

Following any intervention and after agreed seven days of production stoppage, total water and oil production for the remaining days of the month is calculated using reservoir simulation. The objective function is evaluated with the above equation. In the proactive mode, the Adjusted Cash Flow at the end of the forecast (01-Jan-2003 to 01-Jan-2006) is defined as the objective function.

In addition to the parameters already included in the reactive mode, the proactive mode includes:

I. Direct costs of the work-over operations.
II. Penalties equivalent to the risk of operation failure or even a complete loss of a well.

In proactive mode Net Oil Production is replaced with of Equivalent Total Field Oil Production (EFOPT). The new terms adjust the FOPT according to the costs and risks associated with a given scenario. The conversion factor (32.67 Stock Tank Barrels of Oil (STBO)/1000 USD) is used to cover the costs and penalties in EFOPT:

$$\text{EFOPT} = \text{FOPT} - \text{Total Costs/Penalties of All the Interventions (1000 USD)} \times 32.67$$

Any well intervention adds risks to the project. A risk penalty of 1% of 10 million USD (the estimated well replacement cost) is added to represent the possibility of losing a well during an intervention. The assumed work-over costs per operation, advised by the field operator, are:

- Perforation : 250,000 USD
- Plug : 100,000 USD
- Remove Plug : 300,000 USD
- Straddle : 250,000 USD

4.4.3 In-House MATLAB/Python Platform

Limitations of commercial optimisers in handling complex variable constraints motivated me to create an In-House MATLAB optimiser. The Optimiser remains under the control of online CSP. The code creates the parallel scenarios according to the selected optimisation techniques and upon reading the simulation results the objective function is calculated with necessary adjustments. There is also a Python code involved which translates the numerical solutions suggested during the solution process to the field simulation schedule and modifies the corresponding data files.

4.4.4 Results of Applying the Hybrid Algorithm in the Field Case Study

Workflow was tested in two modes and results are compared against each other and against the NO Action scenario. Unfortunately, there is no externally proposed schedule to compare our solution with.

a) Reactive mode

Figure 4-4 shows the flow chart of reactive optimisation.

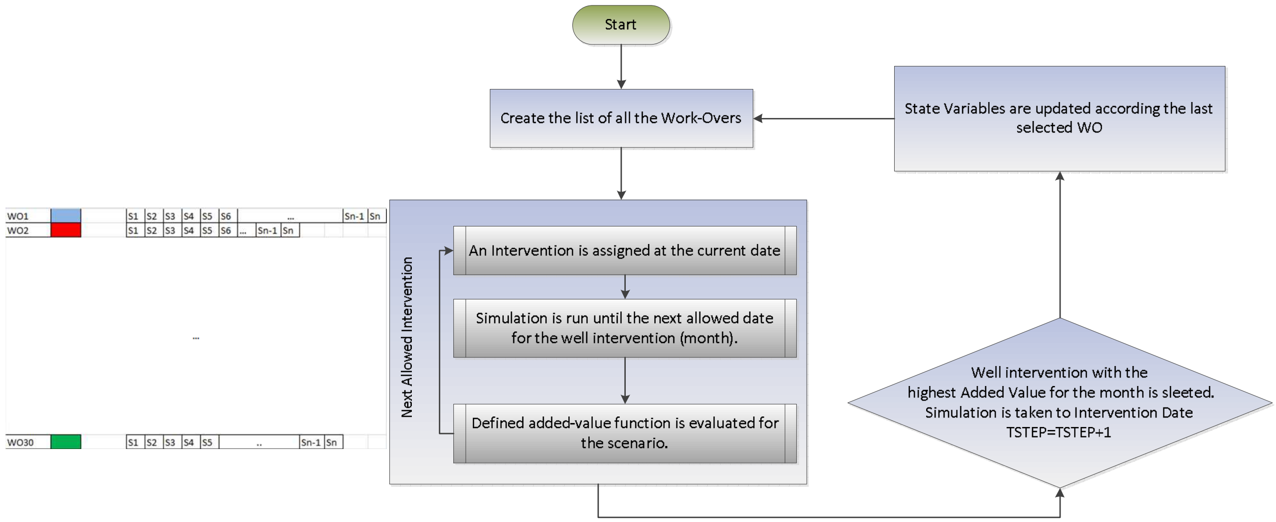

Figure 4-4: flow chart of Reactive optimisation

Using the brute-force algorithm at any date all the feasible options which are identified by the CSP are checked with reactive optimisation objective function. Once the best scenario is found the CSP is reflected and constraint satisfaction is carried out. Restating from the last simulation date keeps the CPU time low and the simulations at each step are done only until the next date of intervention.

Cumulative production values are reset to zero at the start of the scheduling date. This allows accurate quantifying of any incremental improvement.

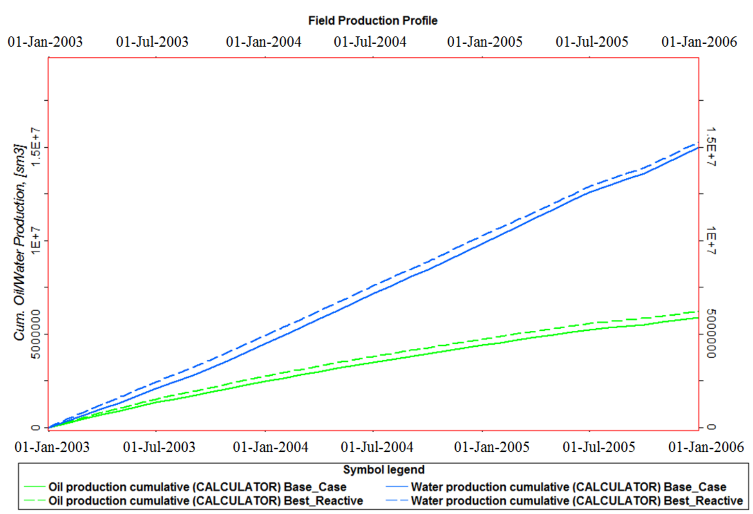

Figure 4-5: Cumulative production of oil and water for the field

Running the simulation for 5433 single time steps with 14 parallel, runs take 5 hours. Results showed the global optimal scenario increased the cash flow by 9.9%. With respect to the FOPT a 9.7% increase during the simulation period is achieved (Figure 4-5).

b) Proactive mode

The proactive mode of scheduling is much more challenging. Figure 4-6 shows the details of the work-flow and the way it is handled by CSP+ Search.

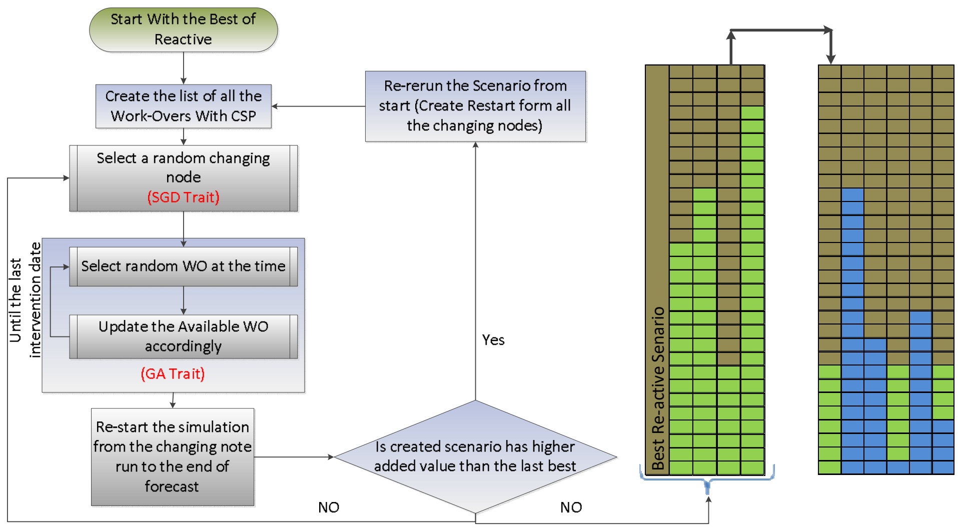

Figure 4-6: Proactive Optimisation Work-flow

In this case the global reactive schedule is selected as the starting point. The schedule is composed of a sequence of distinct interventions at different dates. Assuming that all the previous work-overs until the date of interest are confirmed, using the partially completed of decision tree, the feasible search domain (feasible scenarios) at any date is identified. This allows the SGD trait of the hybrid search algorithm to start changing the schedule from any date while the feasibility of the schedule as a whole is maintained.

When the changing date is selected the GA part of the algorithm becomes active. Using the mutation, the reaming sequence of the partial schedule is completed until the last date of intervention which is 01-Jun-2005 in this case. The completed schedule is submitted to the simulator and the Adjusted Cash Flow is calculated. If the new objective function value is lower than the one from the initial schedule, the process is repeated until a plan with a higher objective function is achieved. At this stage the base case is replaced with the current best scenario. The iterations continue until the stopping criteria are met.

Figure 4-7 presents the optimisation progress using the hybrid algorithm. Different colours show the stages when the search switched to a better base case. Changes of the objective function are quantified against the No Action scenario.

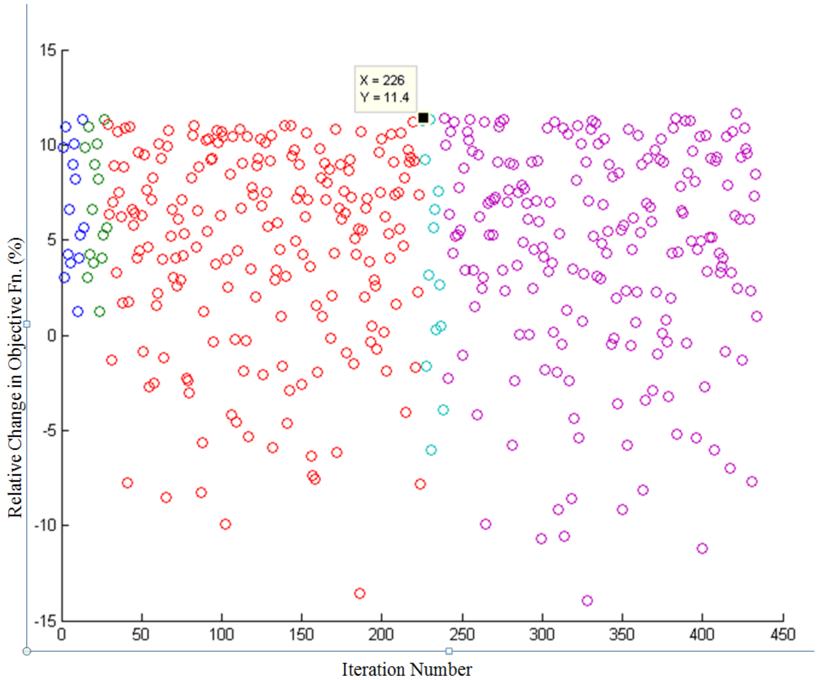

Figure 4-7: Optimisation progress in pro-active mode using SGD+GA

The optimal proactive scenario at the end of 450 iterations increased the objective function by 11.7% while the net oil production increased by 11.4% (Figure 4-8). The search used the 14-cores parallel simulation and the total search time was 58 hours (less than three days).

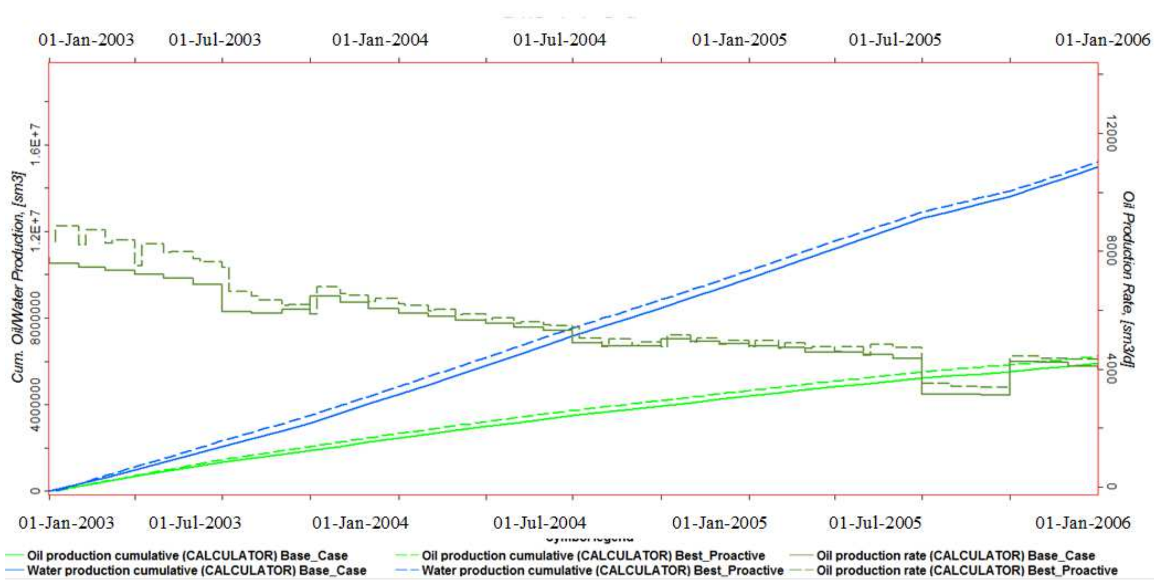

Figure 4-8: Comparison of the optimal proactive scenario against No Action Scenario

c) Reservoir Engineering Implications

According to Figure 4-7 a range of the near optimal scenarios can be identified which are expected to have the performance similar to the best scenario. These scenarios allow the reservoir management team to choose from these scenarios where required.

Understanding the similarities between the near optimal scenarios helps engineers to understand the reasoning behind the design and identification of dominant production processes. In the case of Field A with several major faults and heterogeneous property distribution, wells at the upper panel tend to be earlier work-over targets as a result of the changing dynamic properties individually. Also wells initially completed across the shallower zones tend to be perforated at the lower zones as delaying in production might leave oil upswept.

Methods of high dimensional projection are available in the literature which can help to understand the pattern of optimality (Paulovich, Oliveira et al. 2007). These methods work on the basis of relative distance of the variable sets from each other. Scheduling can be plotted by:

- Variables: Intervention Dates {DX1, DX2, DX3…, DX30}
- Variable domain: Distinct numbers assigned to each distinct intervention.

As the different jobs can be included or excluded depending on the decision being made, the task of job numbering is difficult. Even the assignment of the values should be in such a way that logically similar interventions end up having closer values. For example, if the first well in the table has three open zones any combination of these can be closed at the date of intervention thus eliminating one, two or three closing jobs for the next work-over date. This means some of the variables will be discarded and reaming variables will have got a different name tag. The same principle applies when a new set of zones are opened.

We use a numbering scheme which is based on intervention location in changing Table 4-1. With any table the top left scenario is assigned 1 and then the number is increased left to right and top to bottom. The results of projection are presented in Figure 4-9 clustering of red dots shows the area of optimality. Several local optima can be spotted in the pattern.

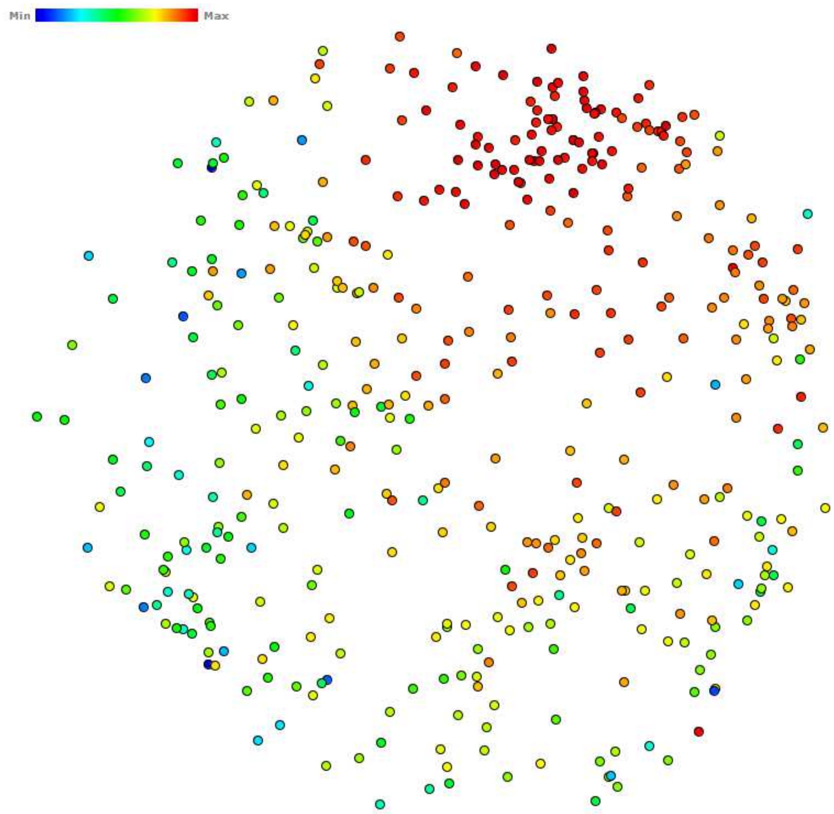

Figure 4-9: Projection of optimal pattern scenarios

Chapter 5 Optimal Work-over Scheduling with Genetic Algorithms and Constraint Repairing

5.1 Introduction

Well interventions are planned to enhance the production profile of wells and they involve full scale rig setup. High costs and complex logistics of work-over operations necessitates evaluation of the long-term/short-term impacts.

Long-term optimisation of the production plan is an established topic in the petroleum engineering literature. Several research projects have looked into the highly complex and iterative problem of field development design. Friedel et al. (2009) proposed iterative linking of the elements of a dynamic field model (from geo-model to production network) to maximize the value of available information in well planning. They successfully improved the production scenario in a stacked oil reservoir. Abdollahzadeh et al. (2012) applied Bayesian algorithms to use the explicit interactions between the field design variables for the improved search. Efficient, reservoir production planning requires a degree of the well control flexibility. Intelligent wells equipped with down-hole flow control devices and sensors inherently have a greatly increased flexibility to respond to (often unexpected) changes in the well and reservoir performance. Down-hole, Inflow control valves (ICVs) are used to control the well zonal flow rates. They allow the operator to respond to the changes in the production profile at the zonal level in the reactive control mode {e.g. to zonal Water Cut (Grebenkin and Davies, 2012); or even take action in advance applying the Proactive control mode. These valves are available in Open/Close, Multiple Position Discrete or Infinitely-variable Position types.

The Completion Design team is tasked with selecting an appropriate valve type according to the selected production scenario. Model uncertainties and difficulties in finding the optimal ICV control strategy for a dynamic reservoir model often result in the application of reactive control when operating the ICVs despite the fact that a proactive strategy potentially delivers the highest added value during the field's life.

However, the only option available for the conventional wells -that still include majority of the active ones- is a workover operation. They provide a similar but reduced level of well and reservoir management flexibility to that achieved by an intelligent well. Workovers allow the well to either increase or maintain its oil rate by controlling unwanted (water and gas) fluid production or perforating additional zones.

This chapter uses a Genetic Algorithm (GA) optimisation search procedure - one of the most commonly used algorithms in proactive optimisation of intelligent wells - to find the optimal control strategies by considering both the well and field scale to assign work-overs optimally at the full-field level. Use of the most up-to-date dynamic reservoir model ensures that the effects of any work-over are captured while considering both the long and short-term perspective.

Genetic Algorithms suffer from the difficulties of long calculation times and, sometimes, convergence problems when a large number of variables are being analysed simultaneously. Engineering knowledge of the field production conditions allowed us to devise additional sampling tools which have been incorporated into the workflow. These tools decreased the dimensionality of the proactive optimisation problem and increased the likelihood of the optimizer reaching a significant improvement in the project value within a limited number of iterations.

5.2 Improved Optimisation Tools

It was suggested that the sampling-based methods are ideal candidates for this type of scheduling problems. The following, selected techniques are combined to maximise performance and eliminate disadvantages:

5.2.1 Genetic Algorithm

GA is a subcategory of evolutionary algorithms that combine a structured information exchange with a "survival of the fittest" approach similar to natural evolutionary mechanisms (Goldberg, 1989). GA is capable of working with discrete and continuous variables and has the advantage of being easily modified for different problems. Hybridization with surrogate models (e.g. Artificial Neural Networks, Neuro-Fuzzy, etc.) can be added to speed up the optimisation. Three advantages of GAs that are important in engineering problems similar to the one described here are:

1. The algorithm returns multiple solutions - this is important when the prediction model is not entirely correct.
2. The algorithm is robust - this is important if it cannot be guaranteed that the objective function can always be evaluated successfully. During the iterative solution process, some intermediate scenarios might be unacceptable for e.g. logical or technical reasons and the objective function value might be missing for them.

3. Parallel processing is possible - resulting in a more effective use of the today's computing facilities (Nikravesh et al., 2003).

GA's working principle is based on representing a population of individuals (i.e. model solutions) as chromosomes, each of which has an importance (i.e. the objective function's) value. These chromosomes are then introduced into an evaluation procedure where selection, reproduction, crossover, and mutation are applied in several iterative sequences. At the end of the evaluation procedure, the best chromosome is taken as the optimized solution. Further details about the fundamentals of the algorithm can be found in (Goldberg, 1989, Mitchell, 1998).

A major advantage of the algorithm in field design is its generation of multiple sub-optimal scenarios. This feature offers extra flexibility to the reservoir management decision making process of selecting alternative plans that satisfy other limitations than those included in the simulation model / optimisation work-flow. As new information/history from the model becomes available, the model behaviour can be updated.

5.2.2 Latin Hypercube Sampling

The starting point of the search plays an important role in finding the global optimum (Haupt and Haupt, 2004). Traditionally, GA uses a uniformly distributed population to start the algorithm. Introduction of the sampling methods already at the initial stage ensures the search starts in a genetically rich and diverse environment. This encourages the exploration throughout the search space and speeds up the discovery of the global optimum in the solution space.

We used the Latin Hypercube Sampling (LHS) method for gathering information from the search space. The basic idea of this technique is to divide the N-dimensional $(\mathrm{N\ possible\ Interventions})$ sampling space into M segments. This way, the whole N-dimensional space can be segmented differently (M^{N} times) followed by randomly selecting one of these segmentations. The process is as follows: a sample point is randomly chosen from the selected cell. All cells in the selected row and column are then eliminated (Figure 5-1a). The second point is selected from the remaining $(\mathrm{M}-1)^{\mathrm{N}}$cells and one sample point is randomly selected inside the selected cell. The process continues until there is only one cell left, the final sample point is randomly selected inside the last cell. (Preechakul and Kheawhom, 2009).

(Figure 5-1b) shows the sampling process in 2D (N=2) design where each variable is divided into 5 segments (M=5). First sample has 5 choices. The second sampling is limited to 4 unselected values and so on.

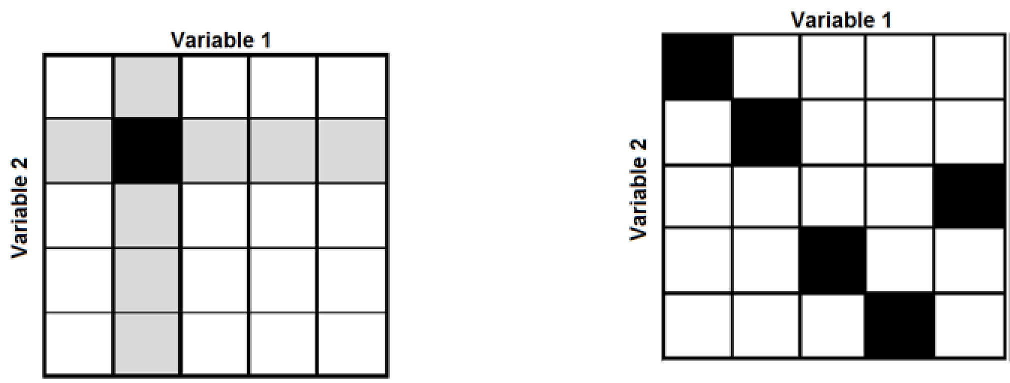

Figure 5-1: a. LHS forming process, excluding the row and the column b. Final LHS design

Non-uniform probability distribution functions (PDFs) of variables are used to encourage a denser sampling within the areas where better solutions are expected. Probable outcomes of the intervention (the oil production during the period under consideration) are used to assign the PDFs.

5.3 Variables Definition

Application of the artificial Intelligence methods to petroleum engineering problems often requires an appropriate degree of engineering insight to guide the optimiser and to reduce the problem's dimensionality. This is especially important when the objective function evaluation is time consuming, for instance when a dynamic reservoir simulation is being employed. On the other hand, an unnecessarily strong steering of the search algorithm by the engineering knowledge can adversely affect the search and might lead to a local rather than a global optimum being identified.

Representative variable definition is essential for mathematical modelling of the problem. Also, since the problem can be highly complex and objective function evaluations mathematically expensive, it is necessary to limit the number of variables to the minimum that still keeps the problem realistic.

The optimisation starts with defining the global search space. The global search space in smart work-over optimisation includes all possible, distinct interventions that can be carried out throughout the complete optimisation period. Interventions are applied at the level of the smallest recompletion target. These targets can be: reservoir flow units, oil bearing horizons, separate layers or net-pay intervals. Defining the range of feasible work-overs and work-over targets is done according to the engineering knowledge (Geology/Petrophysics/Reservoir) as well as any limitation on the field operations/logistics etc.

This study only considers the interventions that involve opening or closing of zones. A revised Kh-map methodology is used to increase the chance of a more productive zone being considered first for opening. Kh maps are frequently used for predicting the volume of hydrocarbon production in a well location problem. The standard workflow has been modified to account for the effect of depleted zones by inclusion of the current oil saturation. The oil saturation's numerical value ranges from 0 to 1 while the permeability variation is much broader (1 to 5000 mD). Logarithmic permeability dampens the effects of these high permeability values and allows the other parameters to exert an equal influence on the search process. The resulting parameter, $\mathrm{Log(K)hS_{oil}}$, was used to map the reservoir quality of individual zones. Non-productive zones were excluded from consideration by applying a $\mathrm{Log(K)hS_{oil}}$ cut-off value based on well test data and the current information from the producing wells.

Wells which will benefit most from an early intervention can be identified using engineering analysis of their current production profile. Data such as liquid rates, oil rates, water-cuts (WCs), and Gas Oil Ratios (GORs) can be used to decrease the probability of the GA closing a good zone while at the same time increasing the chance that the poorer production zones will be worked-over.

The above filters reduce the size of the search space (Figure 5-2), minimising the number of variables and increasing the speed of the convergence. Other filters can be added as appropriate in a case by case basis.

The definition of the variables and the screening process is further discussed below and illustrated in a field case study later on in this chapter.

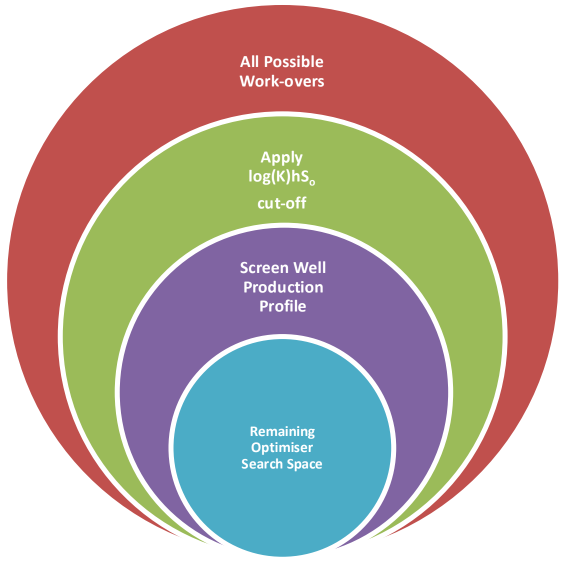

Figure 5-2: Search space reduced through the application of case specific knowledge.

5.4 Modelling of Work-over Planning Problem

This chapter provides two levels of the results comparison in order to investigate the value of work-over planning. The first level will aim to compare the no work-over program with the work-over program during the target, 3-year period. The "no work-over" program will be referred to as the base-case scenario. The second level will compare differently developed work-over programs: a conditional stochastic optimisation vs. an unconditional stochastic optimisation.

5.5 Screening Variables and Steering the Optimiser Using Case Specific Knowledge

Several modified sampling approaches and variable screening techniques are proposed to decrease the problem dimensionality and improve the optimisation efficiency. These approaches are based on prior field knowledge. They include:

5.5.1 Minimum Payzone

A table of 107 possible workovers (Table 5-1) was created based on the drilling trajectories and the current production intervals at the time of the start of the optimisation period (01-Jan-2003). Green entries show the possible zone openings. They consist of perforating zones that have not previously been produced or fully perforating partially perforated zones. The workflow was modified in a number of wells to account for layer pinch-outs reducing the reservoir layer' thickness to such a low value that it affected the viability of becoming a "stand-alone" completion zone.

Table 5-2:Zone Operational status within the Optimisation Process

Well name	Zone1		Zone2		Zone3		Zone4	
	Open	Close	Open	Close	Open	Close	Open	Close
A2	Sub.to Opt.	NA	Perf. Already	Sub.to Opt.	Not Drilled	Not Drilled	Not Drilled	Not Drilled
A4	Perf. Already	Sub.to Opt.	Perf. Already	Sub.to Opt.	Not Drilled	Not Drilled	Not Drilled	Not Drilled
A5	Perf. Already	Sub.to Opt.	Perf. Already	Sub.to Opt.	Perf. Already	Sub.to Opt.	Not Drilled	Not Drilled
A6	Sub.to Opt.	NA	Sub.to Opt.	NA	Not Present	Not Present	Sub.to Opt.	NA
A7	Perf. Already	Sub.to Opt.	Not Drilled	Not Drilled	Not Drilled	Not Drilled	Not Drilled	Not Drilled
A8	Sub.to Opt.	NA	Sub.to Opt.	NA	Sub.to Opt.	NA	1 Act. Layer: Ignored	Sub.to Opt.
A9	Perf. Already	Sub.to Opt.	Sub.to Opt.	NA	2 Act. Layer:Ignored	NA	Sub.to Opt.	NA
A10	Perf. Already	Sub.to Opt.	Sub.to Opt.	NA	Sub.to Opt.	NA	Sub.to Opt.	NA
A11	Perf. Already	Sub.to Opt.	Sub.to Opt.	NA	Not Present	Not Present	Sub.to Opt.	NA
A12	Not Present	Not Present	Perf. Already	Sub.to Opt.	Perf. Already	Sub.to Opt.	Perf. Already	NA
A13	Sub.to Opt.	NA	Perf. Already	Sub.to Opt.	Not Drilled	Not Drilled	Not Drilled	Not Drilled
A14	Perf. Already	Sub.to Opt.	Not Drilled	Not Drilled	Not Drilled	Not Drilled	Not Drilled	Not Drilled
A16	Perf. Already	Sub.to Opt.	Perf. Already	Sub.to Opt.	Perf. Already	Sub.to Opt.	1 Act. Layer: Ignored	Sub.to Opt.
A17	Perf. Already	Sub.to Opt.	Perf. Already	Sub.to Opt.	Not Drilled	Not Drilled	Not Drilled	Not Drilled
A18	Perf. Already	Sub.to Opt.	Sub.to Opt.	NA	Sub.to Opt.	NA	Sub.to Opt.	NA
A19	Perf. Already	Sub.to Opt.	Perf. Already	Sub.to Opt.	Partial/Sub.to Opt.	NA	Sub.to Opt.	NA
A20	Perf. Already	Sub.to Opt.	Partial/Sub.to Opt.	NA	Sub.to Opt.	NA	1 Act. Layer: Ignored	Sub.to Opt.
A21	Perf. Already	Sub.to Opt.	Perf. Already	Sub.to Opt.	Not Drilled	Not Drilled	Not Drilled	Not Drilled
A22	Sub.to Opt.	NA	Sub.to Opt.	NA	Partial/Sub.to Opt.	NA	Not Drilled	Not Drilled
A23	Perf. Already	Sub.to Opt.	Perf. Already	Sub.to Opt.	Not Drilled	Not Drilled	Not Drilled	Not Drilled
A24	Sub.to Opt.	NA	Perf. Already	Sub.to Opt.	Not Drilled	Not Drilled	Not Drilled	Not Drilled
A26	Sub.to Opt.	NA	Perf. Already	Sub.to Opt.	Not Drilled	Not Drilled	Not Drilled	Not Drilled
A27	Sub.to Opt.	NA	Sub.to Opt.	NA	Sub.to Opt.	NA	Sub.to Opt.	NA
A28	Sub.to Opt.	NA	Sub.to Opt.	NA	Not Drilled	Not Drilled	Not Drilled	Not Drilled
A29	Sub.to Opt.	NA	Sub.to Opt.	NA	Sub.to Opt.	NA	Sub.to Opt.	NA

Green & Brown: Subject to Optimisation White: Not included in Optimisation

5.5.2 Eliminate closing scenario for recently opened scenario

Brown entries denote possible zone closings. Field A, with 30+ producers & 107 zones, has limited work-over resources. To further reduce the number of the optimisation variables (i.e. the number of possible work-over operations) we prohibited closures of the zones opened during the optimisation period. This condition reduces the number of possible work-over operations to 69. The validity of this condition was subsequently verified by checking that none of the optimised wells had produced the amount of water large enough so that its processing would cost more than either the revenue from the zonal oil produced or the cost of the shut-in work-over. Note that at a later stage of the field development, when higher water rates are expected, this condition may no longer be valid.

5.5.3 Minimum Oil Saturation

The oil saturation values at 01-Jan-2003 were used in the Log(K)hS_{oil} maps to screen for the potential increase in oil production by further perforating. Use of the 01-Jan-2003 values ensures that depletion of the producing zones is properly considered by the optimiser. Figure 5-3, the map for Zone-1, is an example of the maps that were generated for all zones. Perforating zones with a higher $\mathrm{Log(K)hS_{oil}}$ value are expected to yield a higher oil production rate. A $\mathrm{Log(K)hS_{oil}}$ cut-off value of 40 was used to screen out potential perforation zones. The value of 40 was used since both the field data and the reservoir simulation model indicated that lower values result in higher water-cut production or negligible additional oil production rates. This cut-off value eliminated 6 potential, opening work-overs that were mostly situated in the highly depleted zone-1.

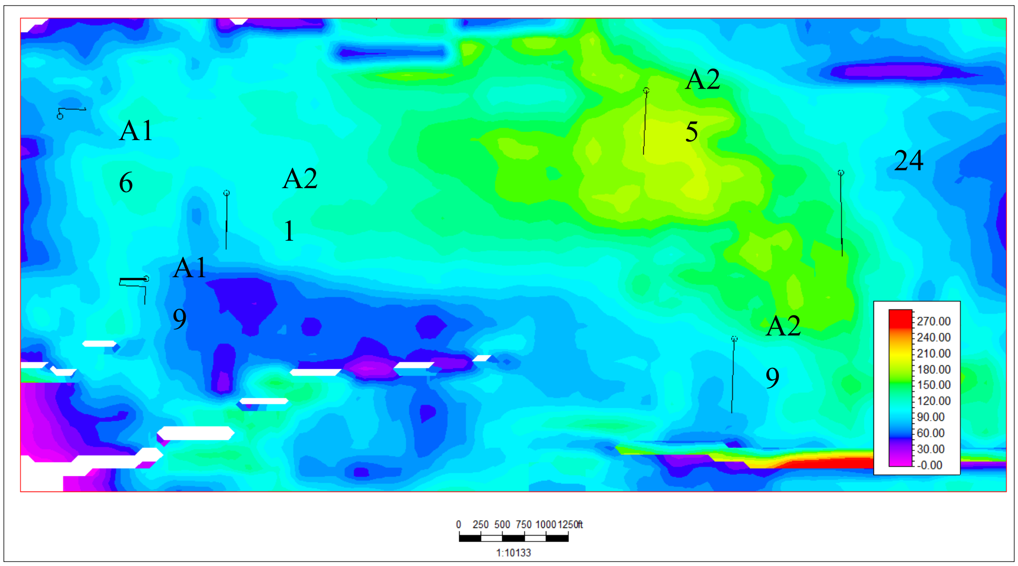

Figure 5-3: $\mathbf{log(K)hS_{oil}}$ map for Zone-1 as of 01-Jan-2003

5.5.4 Production Disruption on High Quality Producers

Analysis of the individual production profiles of the producers can also help to exclude the good producing zones in productive wells from the list of potential closings. Producing zones in the wells with less than 60% water cut are excluded from the list of potential closings. This can be explained using the same logic as in Point 2 above: the water treatment costs from such zones are lower than the additional oil revenue since the maximum produced liquid constraint is not breached. Hence their closure would have been unprofitable. This cut-off eliminated 7 wells with 19 producing zones from the "closing" list, decreasing the total number of variables to 44.

5.5.5 Minimum Allowed Production Window after the Last Work-Over

Work-over operations involve a production stoppage, increased cost, and risk of loss of the well. They adversely affect the cash-flow in the short-term. The positive contribution of the intervention only emerges as the production profile improves. The greater the increase in oil production after the work-over the earlier the cash flow becomes positive. This also implies that sufficient time must be allowed between the last work-over and the date of the final economic analysis to allow the work-over to become profitable. Interventions were therefore only considered during the first 30 months of the 36-month period being considered. The (final) six-month period after the last intervention was only modelled to provide the production data for the economic analysis.

5.6 Steered LHS

Latin Hypercube Sampling divides the Cumulative Distribution Function (CDF) of the control variables into equally large compartments. The zones with the higher $\mathrm{Log(K)hS_{oil}}$ value have better productivity and richer oil saturation; therefore, they are likely to generate more incremental oil when opened as compared to the zones with a lesser $\mathrm{Log(K)hS_{oil}}$ value. Therefore, $\mathrm{Log(K)hS_{oil}}$ can be used to moderate the zonal opening probability during the LHS sampling stage. Analysis of the $\mathrm{Log(K)hS_{oil}}$ values indicates that they are distributed normally. During the LHS sampling stage these values are normalized, and a normal distribution with the mean value of the normalized index is assigned to represent the weighting mechanism. This allows helping the LHS to generate the range of good initial work-over scenarios, which are already close to the optimum. As a result, further optimisation takes less time to converge to the optimum solution. Note that one should carefully check the assumption that $\mathrm{Log(K)hS_{oil}}$ values relate to the highly profitable intervals – sometimes other factors (e.g. proximity to an aquifer) can take effect as addressed later in this chapter.

5.7 Integrated Economic Model

Optimal well interventions improve the field’s economic value, but they bring costs and add risk to the project. Elements of the integrated economic model include:

- Improvements through the recovered extra oil
- Delayed production due to the well closure during the operation
- Penalties equivalent to the risk of operation failure or even a complete loss of a well
- Direct costs of the work-over operations.

The objective function selected for the optimisation in this paper is the Equivalent Total Field Oil Production (EFOPT) at the end of the 3-year optimisation period (01-Jan-2006). Equation 1 adjusts Field Oil Production Total (FOPT) considering direct/indirect costs and total risk penalties. The conversion factor (32.67 Stock Tank Barrels of Oil (STBO)/1000 USD) is used to cover costs and penalties to EFOPT:

$$\text{EFOPT} = \text{FOPT} - \text{Total Costs/Penalties of All the Interventions } (1000\text{ USD}) \times 32.67$$

Equation 1

Any well intervention brings risks to the project. A risk penalty of 1% of 10 million USD (the estimated well replacement cost) is added to represent the possibility of losing a well during an intervention. The work-over costs are:

- Perforation : 250,000 USD
- Plug : 100,000 USD
- Remove Plug : 300,000 USD
- Straddle : 250,000 USD

Work-over capacity is limited to one well per month, although multiple zones can be altered once a well has been accessed.

Note that for simplicity the water treatment costs are not being included in the final EFOPT calculations. This is because all cases produce the same volume water (±0.05% difference), resulting in minor contributions to the EFOPT calculation.

5.8 Field-Scale Optimisation

Two workflows to illustrate the integration of the engineering knowledge into evolutionary algorithms are discussed in this section. The initial test considered 107 variables when GA was used without any engineering knowledge-driven screening (referred to as “pure” GA). The large number of constrained variables with interdependencies negatively affects the performance of the GA search algorithm. This interdependency is especially visible when the shut-in time for a newly opened zone is sought. The closing date of a zone that is opened during the period under consideration can only fall between the opening date and 30th month (Figure 5-4).

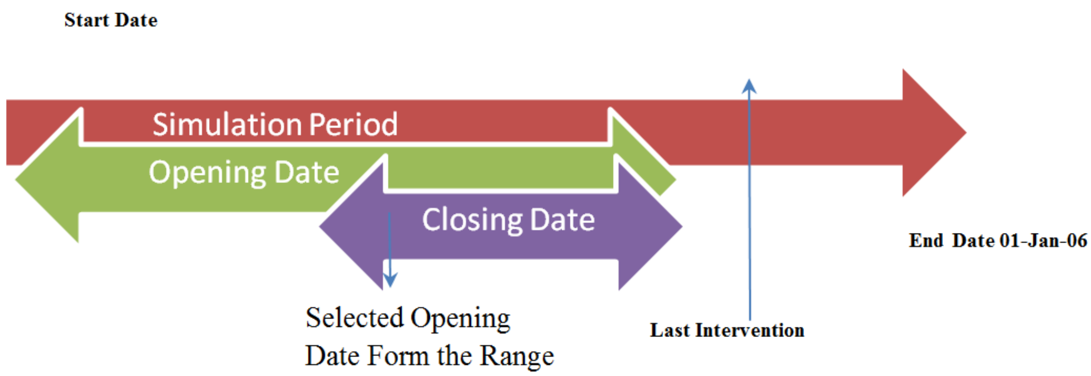

Figure 5-4: Optimisation, Simulation and Economic Analysis Periods compared

Figure 5-5 shows the search performance of this initial test with "pure" GA that did not include any of the engineering guidance or cut-off values described above. Hence all the 107 well interventions including dependent closing variables were included.

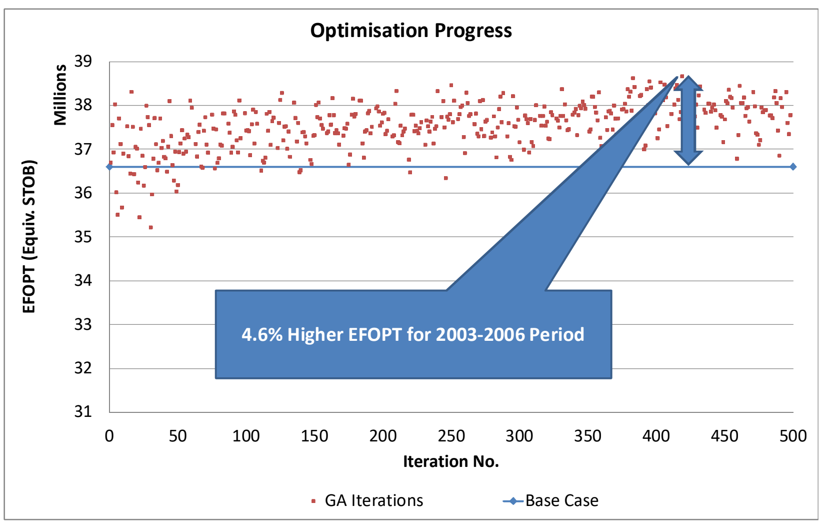

Figure 5-5: "Pure" GA iteration results (>500 runs). Improvements are observed, but search results are scattered

More oil is recovered in the optimal scenario as compared to the base "No Action Scenario" Case. The optimisation progress (Figure 5-5) indicates a scattered search that shows little sign of identifying an optimum value. A number of the iterations had values less than, or close to, the base case. This is due to the fact that the optimizer, trying to explore the search space, has shut zones with a high oil production rate.

The base case FOPT for the three years period is 36.6 MMSTBO. Optimisation shows that the maximum direct cost of the work-over operations can reach 6.9 million USD, even after inclusion of risk penalties of 2.3 million USD. Note that the total maximum cost (in equivalent STBO) of work-over operations is equivalent to only 0.8% of the base-case FOPT, which means that the incremental oil value is far larger than the associated work-over costs. Also note that FOPT value for the base case is the "Do nothing" scenario that represents continuity of oil production without the risk and cost elements of a work-over.

Later on the workflow is equipped with engineering knowledge-based conditions to "steer" the GA optimiser as was explained in Section "Work-over Planning in a Real Field" above. Figure 5-6 charts the Work-over Optimisation workflow when coupled with the field knowledge. It illustrates the coupling of the various screening techniques and Latin Hypercube Sampling with the Genetic Algorithm. Applying the $\mathrm{Log(K)hS_{oil}}$ index, 100 initial simulations were run to explore the search space and create a genetically rich initial population for the GA to optimise. The efficiency of the available work station's 16 CPUs was maximised by setting the population number to 50 with a replacement factor of 0.28 i.e. each generation initiates 14 new simulation runs, which could be run in parallel mode on the available high-end, single PC. The crossover rate was set at 0.9 and the mutation rate was 0.05, meaning that 90% of the individuals are combined to generate a new population converging to the optimal point ("Exploration of the search space around the best solutions" case) while 5% mutate to ensure a sufficiently wider exploration area.

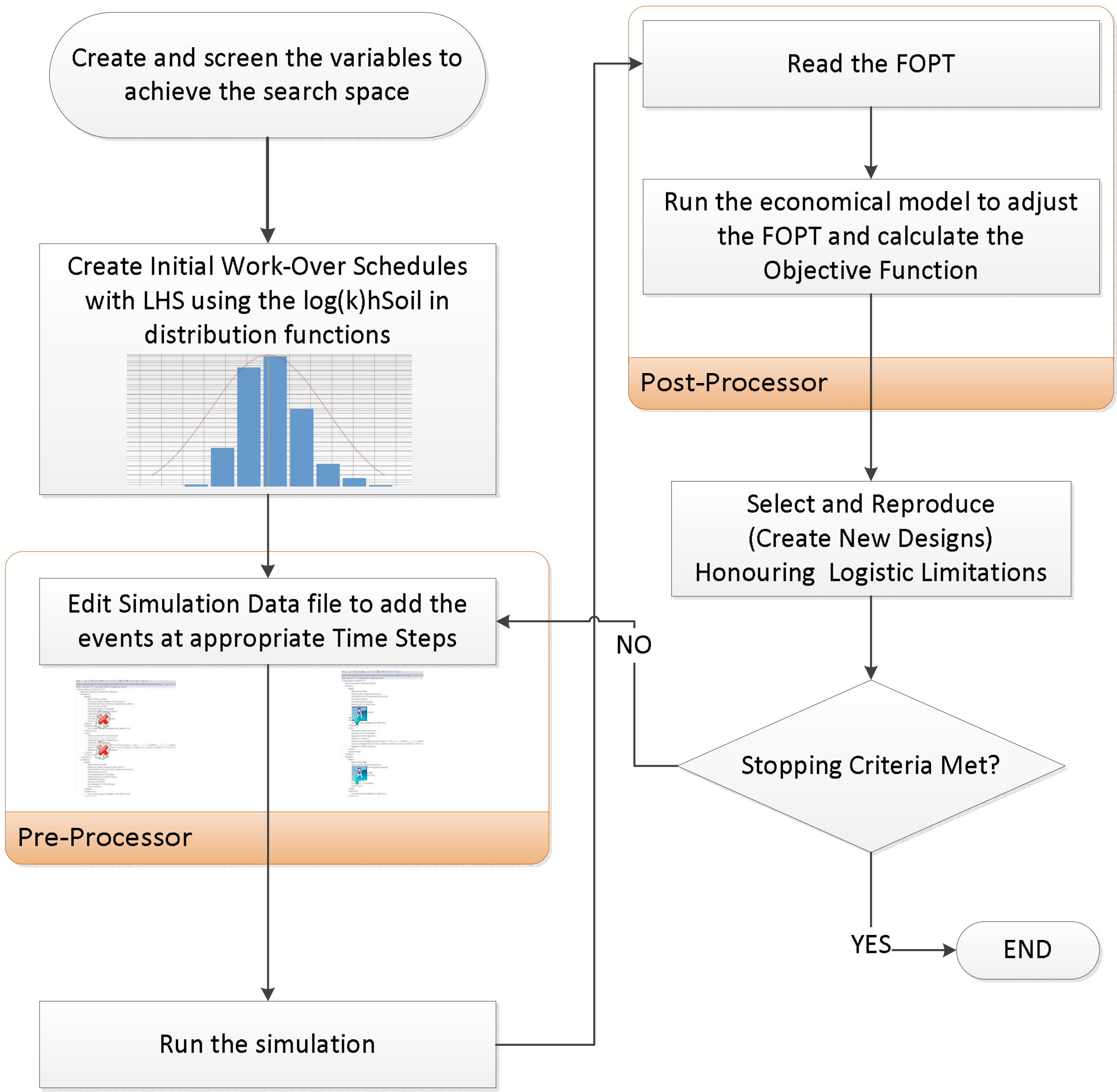

Figure 5-6: Global Work-Flow for Smart Work-Over Planning (Steered GA approach)

Figure 5-7 shows the optimisation performance over 500 iterations. A maximum of 6.4% higher EFOPT is achieved as compared with the base case scenario. After 700 runs were completed less than 0.5% variation on the objective functions of the last 14 sets of simulations were seen and this was deemed an acceptable level of convergence for the optimisation. With an average run time of 80 minutes and 14 parallel runs the whole optimisation process took less than three days to complete. Table 5-2 compares the structure and the performance of two methods over the same computation efforts.

Table 5-3: Comparison of the Pure GA and Steered GA performance over 500 runs

	"Pure" GA	"Steered" GA
Total Number of Variables	107	Stage 1: 44/ Stage 2: 29
% of solutions better than the base case	28	93
Average added Nominal FOPT per simulation (STBO)	3400	4700
Maximum added FOPT (% of base case FOPT)	4.6	6.4
Total run time (hrs.) for 500 runs	47	
Ease of the Setup	High	Low

The "steered" GA optimisation started with sampling of 100 points in the search space made up of the potential 44 zones which could be opened or closed. The modified LHS uses $\mathrm{Log(K)hS_{oil}}$ values to change the CDFs as was explained above. The GA optimisation stopped after 32 generations (448 iterations). Analysis showed that the best solutions were the ones which consisted of only opening formations ranked by added value. This can be explained by the field production constraints since excess liquid processing capacity is available and it is always economically advantageous to open new zones if the oil production is sufficient to pay for the risked cost of the work-over. This allowed a further reduction in the number of variables by excluding all possible closing operations; leaving only 29 variables to be optimised by the GA. (Figure 5-8)

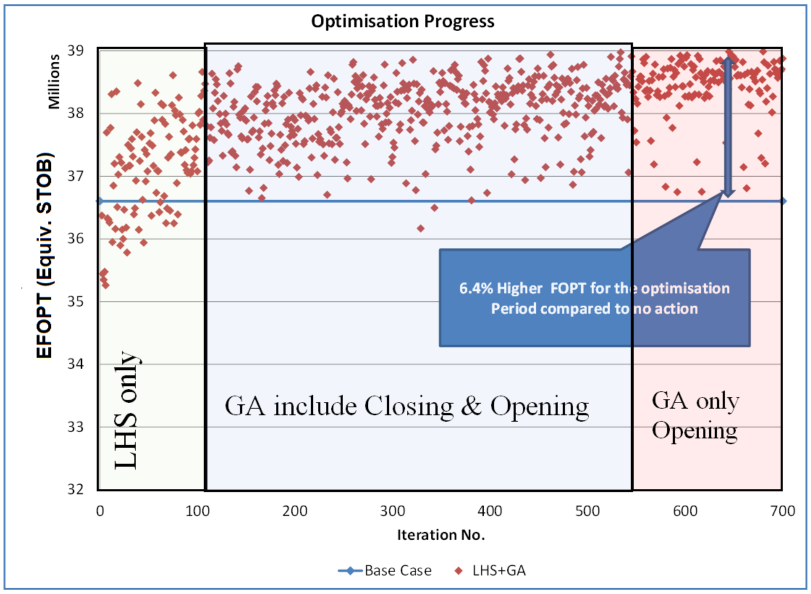

Figure 5-8: GA iterations results for 700 runs. A satisfactory optimisation was observed with convergence towards a maximum value

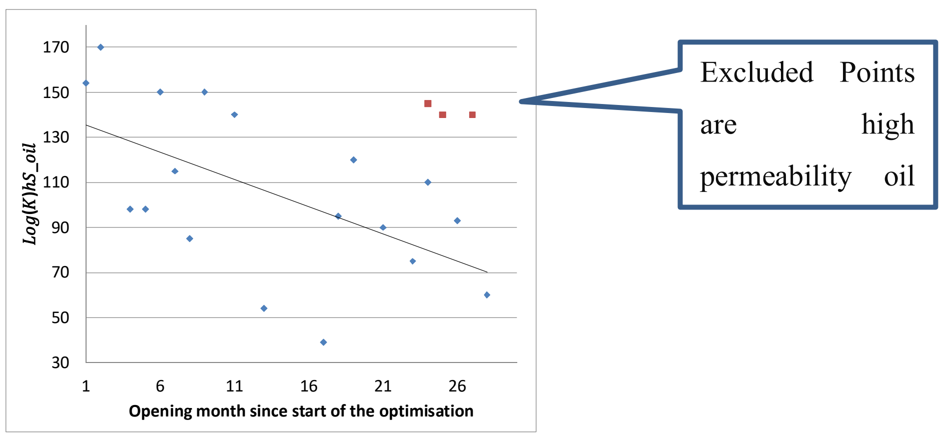

Figure 5-9: Zone quality index inversely related to the opening month

The optimal scenario included 22 well interventions on 13 different wells to open new zones. The Log(K)hS_{oil} parameter was only used to create the distribution function during the LHS stage. However, one can see that the poorest zones as measured by Log(K)hS_{oil} are unlikely to be opened (Figure 5-8). This confirms our earlier screening assumption, that higher values of Log(K)hS_{oil} zones should be tried first. Note that the quality index and the opening months are inversely related if the three points representing high permeability oil bearing zone close to the aquifer at the edge of the reservoir are excluded. They were quickly drained, illustrating that the Log(K) index should be used carefully as it is case-specific.

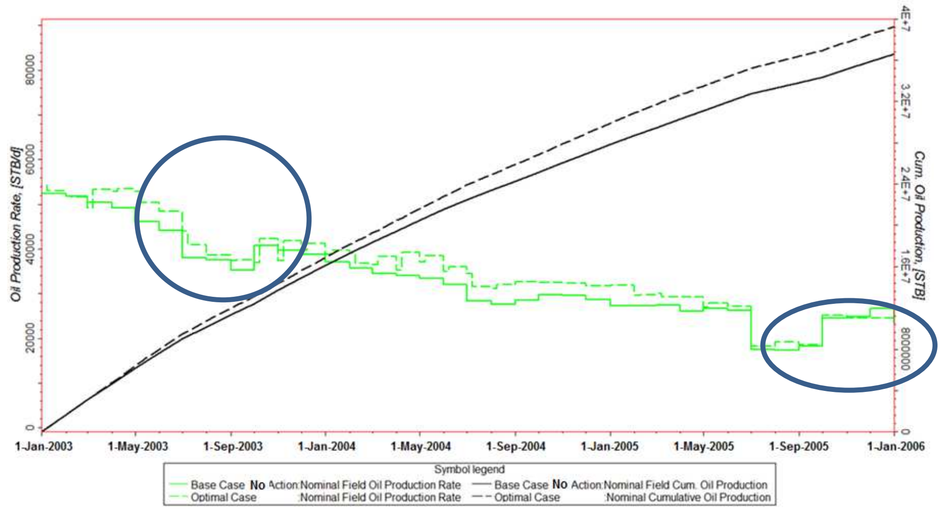

Figure 5-10: Comparison of the production forecast for the base case (No-Action) and the optimal 3-year work-over schedule Higher oil rates are observed (e.g. in the left circle) with some exceptions (right circle)

Figure 5-11 compares the base case ("No action" Scenario) against the scenario with the optimum series of the work-overs. It shows that the optimiser gave priority to the better zones, opening the early in the optimisation period with poorer zones being delayed. (Compare the circle on the left with the one on the right. The added cumulative oil continued to increase over the optimisation period while the only times that the current optimal production rate fell below the base case value (Mar-2003 and Nov-2004) occurred when work-overs were being performed on the best producers.

5.9 Analysis of the Results

This chapter presented a work-over allocation workflow which assigns limited well intervention resources to the work-over options that generate the greatest profit within the relatively limited time period that is considered during work-over planning. Our optimisation workflow uses a GA engine to set the date of individual work-overs and evaluates the total field performance throughout the work-over planning period. The economic analysis employs an integrated model that includes both the risks associated with well intervention work in addition to their direct and indirect costs.

The simplest version of this workflow employed the available GA optimisation package, identified as "pure" GA in this paper. Its performance proved to be less than desired in terms of the optimisation efficiency and the required computation time due to the:

- Large number of variables
- Large search space without any mechanism to direct its search to the potentially optimal areas
- Interdependency between the two sets of variables (i.e. between the zonal opening and closing dates)

An enhanced workflow, called "Steered GA", was therefore developed to evaluate if the inclusion of engineering knowledge into the optimisation process together with Latin Hypercube Sampling was able to guide the GA to search within the most optimum areas. The engineering expertise included:

- *Opening zones.* Apply cut-offs to a $\mathrm{Log(K)hS_{oil}}$ map which:
    1. Excluded non-productive and depleted zones.
    2. Ensured that the potentially optimal areas were included in the search space.
- *Closing zones.* Remove from the "closing" search all:
    1. Opened zones identified above.
    2. Highly productive zones.

  Closing the above zones is likely to reduce the total oil production since the field's production is not liquid rate constrained.

- Additional constraints can also be added to the workflow where necessary with the possible advantage of a reduction in the problems dimensionality at the expense of introducing additional interdependencies.

"Steered" GA showed an increased rate of convergence with better results being achieved with a reduced computational time. Application of the "Steered" GA to a large, real field, simulation model delivered an extra 1.8% in FOPT over the three year work-over time period when compared with the optimisation by "pure" GA. The maximum increase in FOPT was 6.4% when compared to the "No work-over" scenario over the same time period.

Chapter 6 Conclusions & Recommendations

The main findings of this work are summarised as:

- The common work over planning approach is generally a reactive process. The jobs are assigned to intervene on the worst offending wells or to add some new layers as the hydrocarbon production rates drops. Albeit being easy to implement, this fails to create a mid/long-term work over program and might result in profit loss when long-term objectives like field total oil production, net present value or ultimate recovery are concerned.
- A novel hybrid algorithm coupled with constraint satisfaction problem was proposed to optimise the work-over scheduling over the long-term field performance. Comparing to commercial optimiser using standard genetic algorithm search engines, the new algorithm resulted in an increase of added-value (relatively) if Field Total Oil Production is selected as the objective function. The workflow is also able to satisfy all pre-defined conditions by using the CSP iteration scenarios. This can be of significant value as operational constraint are usually driven by complex logistics.
- The developed algorithm was tested successfully in a real dataset considering both reactive and proactive search spaces. In reactive mode, the search algorithm finds the most favourable intervention at the time of the forecast which is allowed based on the operational conditions. Those depend on individual well/layer conditions and workover fleet availability. In proactive mode, the algorithm sets the first and ALL the subsequent interventions at the start of the simulation. This method still considers all the operational conditions mentioned. The proactive method was tested using metaheuristic techniques. While it did not show an effective search near the optimal solution, we observed some small increments in objective functions (<2%) within 450 iterations in comparison to what reactive method achieved in single iteration.

The future studies are recommended as follows:

- Further investigations are required on other heuristic methods better compatible with workover planning problems. A major factor will be the ability of these algorithm to adopt to fast changing search space and the variables. For example, in field with a number of producers, after several rounds of workovers the number of open layers will be significantly lower than the initial date and the search has to focus on finding where to shut-in to control high water cuts i.e. the number and the types of variables will be fast changing.

- With minor changes, the workflow can be applied for other resource allocation problems where the numerical simulation is the only tool to predict the long-term performance. EOR Operations with repeating cycles are examples of such processes e.g. the workflow can be applied to find the right sequence in WAG process over several years setting the right duration for each sequence at each cycle. The one-month water injection for the first cycle might not be optimal for the second cycle or to improve the recovery the WAG process might have to move to another well.

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