# System Analysis of a Numerical Well Design Optimization Process

by

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## Abstract

The emergence of advanced engineering technologies creates the opportunity to improve existing manual and silo-ed workflows within integrated energy companies. The processes used for drilling engineering have not evolved at the pace of cutting-edge technology advancements over the last 20 years. The most significant shifts in classical well development are standardized design methods, advanced disciplinary analysis, improved knowledge transfer systems, excel-based workflows, and structured employee training.

As the Industrial Revolution 4.0 progresses, technologies in Model-Based Systems Engineering are emerging to enhance existing well design processes, yet the step change is insufficient to close the technology gap. This research contributes to existing drilling engineering and well design advancements by developing a system optimization architecture for the well design process. A random search algorithm coupled with a stochastic optimization methodology for multi-objective optimization emerges through the relationships defined within a system Design Structure Matrix (DSM). The optimization method includes the evaluation of the algorithms' computational efficiency, design diversity, and convergence. The development of a numerical solution for well design, will provide the framework necessary to implement advanced analysis of well design that can accurately predict the quality of engineering decision-making.

Thesis Supervisor: Eric S. Rebentisch
Title: Research Associate

# Acknowledgments

The endeavor to successfully meet the requirements for the Systems Design and Management Program pushed me further than I ever imagined. It gave me a new focal point to further my systems thinking and design knowledge. I am grateful for the opportunity to embark on this journey, and I look forward to the world ahead as I work to integrate systems thinking into complex problems.

First, I thank my family for their continued motivation and support. My lovely wife, Jasmine Hicks, supported me throughout the year and was critical in the level of commitment and time I put into my learning. Your continued motivation was a significant contributor to my success. I would also like to thank my son Wesley, who reminded me repeatedly that I needed to "work on my Thesis." I would like to thank the rest of my family for cheering me along and having continued support for the endeavors in my life.

I would like to thank Chevron for providing me with the opportunity to attend MIT as part of the third Cohort of Digital Scholars. I was one of 15 valued individuals selected for this once-in-a-lifetime opportunity, and I hope to be a valued contributor in the future. I would especially like to thank the people, supervisors, co-workers, and mentors who have supported my journey of learning and transformation throughout my career. I am truly thankful to have the opportunity to work for such a great company and group of people.

Lastly, I'd like to thank Dr. Eric Rebentisch for his guidance through this Thesis process, working through the countless iterations of thoughts to pushing for the right level of complexity within the analysis. Your guidance and confidence in my abilities to deliver cohesive research are appreciated.

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# Chapter 1

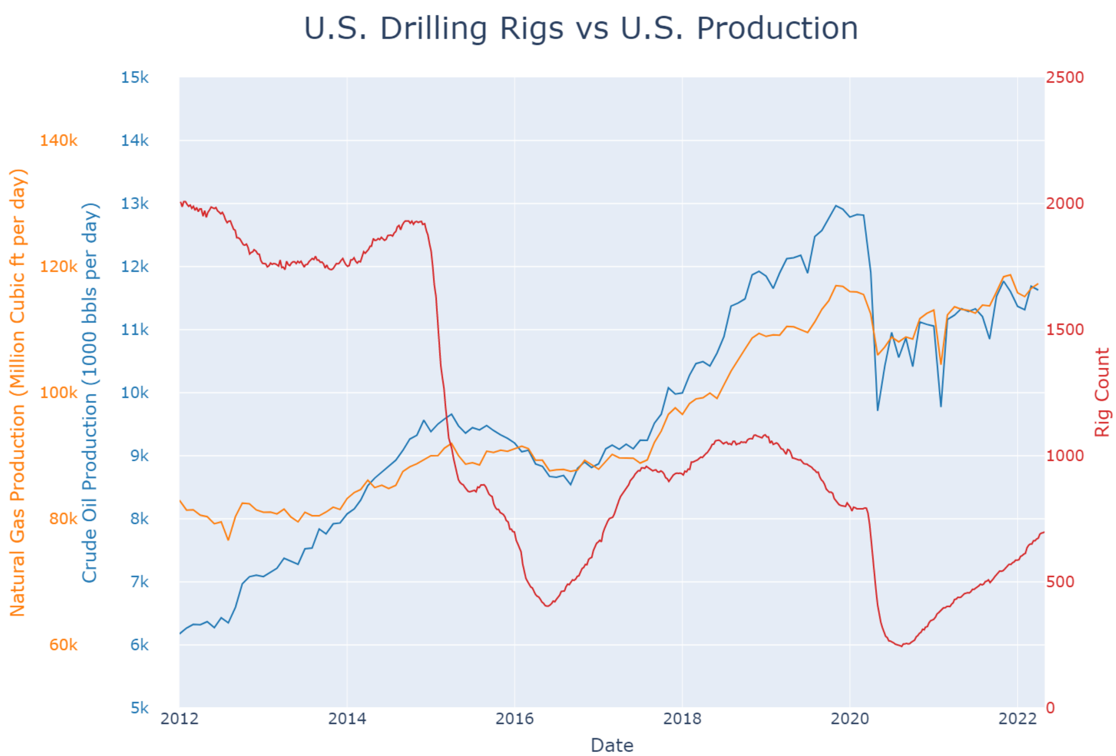
# Introduction

## 1.1 Motivation

### 1.1.1 Industry 4.0

The overall progression in the oil and gas industry since the oil price drawback starting in 2015, was to do more work with less resources. This is evident in the active rig counts for the U.S. compared to the U.S. Production of Oil and Gas shown in Figure 1-1. Although many other factors can be attributed to this relationship, such as the emergence of unconventional resource development, well design is vital in driving significant improvements. The growth in operational efficiency of drilling can be attributed to increased personnel experience, minimal growth-related disruptions, and standardization of designs and processes within the oil and gas industry. "Lower commodity prices drive the need to restore profitability through lowering the total cost of exploration and production. The generational change in the workforce requires attracting, training, and challenging the next influx of professionals. New innovations and sources of competition force us to rethink, adopt, and push technological boundaries" [60]. The push for increased capital and environmental discipline will require additional tools for engineers to explore and develop new, reliable, predictable, and creative well designs. By adopting advanced analytical techniques, improved project management practices, and Industry 4.0 digital technologies, oil and gas projects can see a 15 to 30 percent reduction in capital expenditures in major capital project from reduced development time alone, as reported by McKinsey and Company [29]. Bound by consistent cost overruns, schedule delays, and reduced profitability due to long development duration, major capital projects in the oil and gas industry have been significantly reduced as shale oil projects improve returns through low complexity production.

**Figure 1-1:** U.S. Rig Count vs Oil and Gas Production




*Data Source: Energy Information Agency [23], Baker Hughes Rig Count* [33]

### 1.1.2 Financial Discipline and Efficiency

The requirements for engineering design have become more complex, design tolerances reduced for capital expenditure efficiency, and visibility into design failures are highlighted for company and industry learning. The energy industry is undergoing a significant shift in asset valuation due to challenges from investors and Environmental, Social, and Governance (ESG) objectives. Many of the existing exploration areas for oil and gas are considered mature, have moderately low levels of subsurface uncertainty, and are expected to maintain the necessary production output needs for future demand. The shift to more sustainable energy sources will require the exploration of immature areas to develop carbon sequestration reservoirs and second-generation geothermal wells using technology historically applied to oil and gas production [67]. The significant difference for new field development is that the return on investment is uncertain, geological parameters are uncertain, and operational and design efficiencies are uncertain. Drilling Engineers must develop high-quality wells at competitive economics early in asset development plans under these uncertain conditions. Engineers will require tools to aid in well design and decision-making to develop optimal designs at low costs while preserving environmental, safety, structural, and operational integrity. Well development costs naturally tend to reduce over time as the magnitude of uncertainty reduce. Developing sound strategies to accelerate cost reductions while maintaining well design and operational integrity is critical to the future of subsurface asset development.

### 1.1.3 Advancements in Engineering Requirements and Objectives

As many legacy industries move through organizational shifts in technology adoption and Digital Transformations, engineers are at the limits of human capabilities and disciplinary expertise. Engineers leverage fit-for-purpose tools to assist with managing complexity, typically simplified in programs such as Excel. The use of spreadsheet-based tools has been helpful but can be an impairment to new technology implementation, as described by Schuman [52]. Engineering progress using the simplified approach is steady, has a manageable level of complexity, the results are discernible by large groups of peers, and does not have a recurring overhead often associated with complex systems software tools. "Every system is analyzed at a particular level of complexity that corresponds to the interests of the individual who studies the system" [47]. Managers accept the status quo, but have aspirations for more creativity.

Investors are increasingly anxious for portfolio profits and modest improvements in operational efficiency. To meet and exceed these expectations a technological shift is needed.

Before understanding the significance of systems thinking, the importance of understanding how the changes in one system would impact downstream results is highlighted. As one discipline makes major decisions to change a design objective, what does it affect? How does it change the overall project deliverables? Will the realized savings be lost as the change propagates through the system? The mental models developed through years of experience are not as prevalent in today's disciplines. Advanced foundational principles are embedded into simulation software and abstractions based on experimentation and experience. With the increasing complexity of well design, the capabilities of rational human understanding of the system are limited. The reliance on Subject Matter Experts (SME) has reduced the knowledge necessary to be considered a competent Wells Engineer. A significant portion of tacit knowledge has been recorded in the form of requirements, standards, and standardized tools, which can be, and has been a source of failure as designs change.

## 1.2 Significance of Research

The integration of System Engineering tools in Well Design is a prevalent topic. Multiple energy service companies have created tools to integrate drilling planning workflows. Software applications such as Schlumberger DELFI, Oliasoft, and Dynamic Graphics WellArchitect contribute to the adoption of Systems Engineering for Drilling Engineers and Geologists. These tools focus on design coupling and validation through industry-accepted well analysis and modeling methods. *Designing* is a decision-making process to derive the best possible alternative [47]. The iterative nature required to explore alternatives is a function of the engineers and organization's time, effort, and efficiency. The optimal design in any state is, therefore, a function of the patience of the engineering organization to perform the necessary iterations to obtain an optimal solution. The proposed contribution to well design methods is to formulate a mathematical model for well design that is reliable, feasible, and tractable under uncertain conditions.

The well design process varies in form by the organization, but the overall function of the well design process is to provide a detailed design summary that can be used to complete the operation with minimal deviation. Azar describes the summary of the well construction plan as the "Drilling Program", and is composed of [7]:

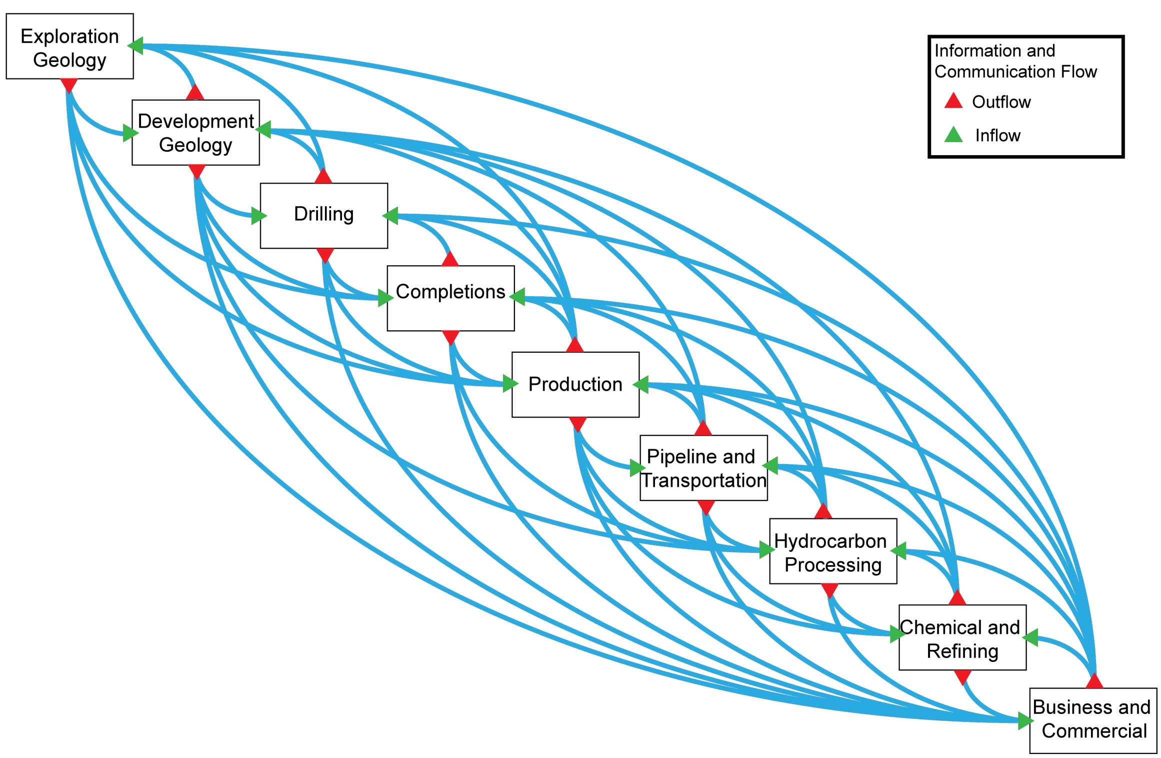
- Summary of the overall well information
- Details regarding fluid, casing, drill pipe, and cement design
- Listing of tangible equipment needed for the well
- Drilling rig details most relevant for the project
- Formation evaluation objectives
- Emergency and contingency plans
- Time and Cost estimations
- Regulatory and Permitting Details

Software applications used for well design take a Model Based Systems Engineering (MBSE) approach to establish relationships needed to formulate the drilling program efficiently. Szemat-Vielma et al. describe the current process as engineers "working in disconnected silos" [60], which leads to the inefficiency and error propagation observed over decades of drilling planning. The drawback for pure MBSE for well design optimization, is that the resultant well designs are an engineers' assumptions of a good design, but often ignore the complex relationships that can be modified to create emergent systems. An exploration of many designs requires exploration of design sensitivities, and in many cases is a slow process to make impactful change. Utilizing advanced optimization techniques can take advantage of the relationships derived from MBSE, and further explore possibilities for better solutions.

"Industry 4.0 is understood as a new industrial stage in which there is an integration between manufacturing operations systems and information and communication technologies (ICT) – especially the Internet of Things (IoT) – forming the so-called

Cyber-Physical Systems (CPS)" [20]. Large, integrated companies leverage scale to maintain a competitive advantage over their smaller counterparts. Industry 4.0 highlights the need for accelerated systems development to take advantage of these inherent competitive advantages. Optimized and interconnected strategy, design, construction, and operation within the oil and gas industry can lead to capital and operational expense reductions if managed at the proper level of abstraction.Using a systematic approach to developing well design concepts and engineering, best practices can be implemented using numerical optimization for efficient and predictable results. Figure 1-2 shows the interconnections of the oil and gas system. "The lifecycle of petroleum operations includes exploration and development, production , refining, marketing, transportation/distribution to the end user and final utilization" [31]. Each discipline is dependent on information in some form from other disciplines, and the strongest connections require complex systems to ensure the shared information is accurate and precise. Uncertainties must be defined, and effective communication of risk must be quantified.

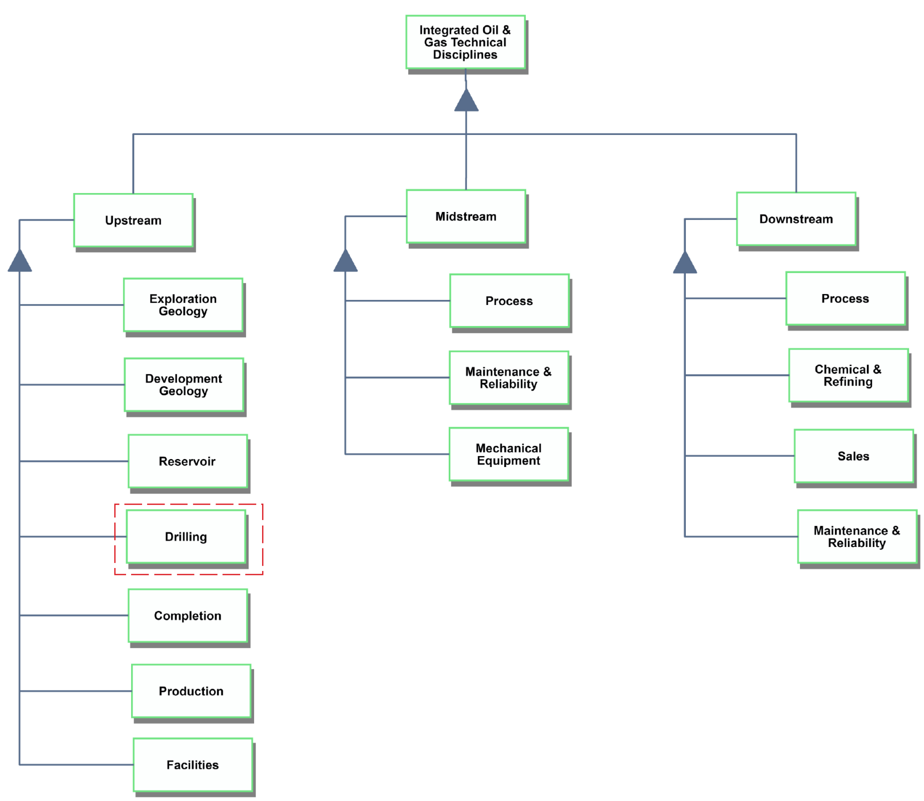
**Figure 1-2:** Network Representation of Oil and Gas Discipline Dependencies



## 1.3 System Boundary Definition

The remainder of this work will explore the optimization of the well design system setting the system boundary strictly around the well construction parameters. Geological, completion, and production inputs will be considered fixed and serve as boundary conditions and constraints. Figure 1-3 highlights the technical functions involved in an integrated oil company. The red box indicates the system boundary for this optimization and will receive inputs from other technical disciplines as static inputs.

**Figure 1-3:** Technical Decomposition of an Integrated Oil Company




Management of the interactions within the system can be managed using a Design Structure Matrix, "The DSM is a network modeling tool used to represent the elements comprising a system and their interactions, thereby highlighting the system's architecture" [24]. Management of the interactions at the system boundary and within the drilling system, which are represented in a visual tool, can reduce the analytical complexity of identifying possible solutions for optimization of the system.

## 1.4 Research Questions

1. Does the use of a Design Structure Matrix (DSM) assist in identifying the ability to modularize or couple sub-optimization algorithms?
2. Are any existing algorithms capable of handling the mixed variable nature used in well design?
3. How can a the well design process be modeled as a numerical optimization problem?
4. What optimization formulation will provide efficient exploration of the feasible region of the design space?

## 1.5 Thesis Outline

The eight chapters of this thesis will develop a framework for optimizing a well design system using a hybrid optimization approach. Chapter 2 will explore current oil and gas optimization processes along with known optimization methods and functionality. Chapter 3 will review possible optimization methods that can be used to solve well optimization problems, with varying complexity. Most new research focused on accuracy, speed, tractability, and scale. Chapter 4 will discuss the development of definitions of the architecture and interactions of the well system. In Chapter 5 the architectural analysis discussed in Chapter 4 will be use used to determine a suitable optimization architecture and framework to optimize the well system using a hybrid optimization technique. Chapter 6 will detail the model construction, data sources, and methodologies used to derive a numerical optimization model. Chapter 7 will perform a comparative analysis of designs generated in a trial optimization formulation using a Genetic Algorithm. We will explore possible use cases and failure modes associate with the numerical optimization technique. Chapter 8 will summarize the results of this research with an explicit discussion on the limitations of the research, suggestions for future work, and overall contributions to Systems Engineering for subsurface exploration and development.

# Chapter 2

# Optimization in Oil and Gas Exploration

Optimization in Exploration and Production involves numerical decision-making processes that help to determine subsurface design parameters to maximize the production and profitability of the assets of concern. A review of existing optimization offerings in the exploration and production industry reveals that well design optimization is treated as an abstraction in subsurface models and can introduce significant uncertainty in well design feasibility and cost. Existing well design optimization is isolated to disciplines such as directional trajectory design, fluid design, or real-time drilling rate of penetration optimization. Each optimization formulation requires fixed input parameters and manages improvement through sensitivity analysis. Integration of existing optimization models could provide valuable insights and the emergence of new well design solutions.

Optimization in well design is centered on time and cost, but must be balnaced with risk and safety. Optimization of casing design, well trajectory design, discussed in Section 2.3, drilling fluid design discussed in Section 2.4, and rate of penetration optimization, are key parameters of the drilling process, and could improve the cost and duration of well construction.

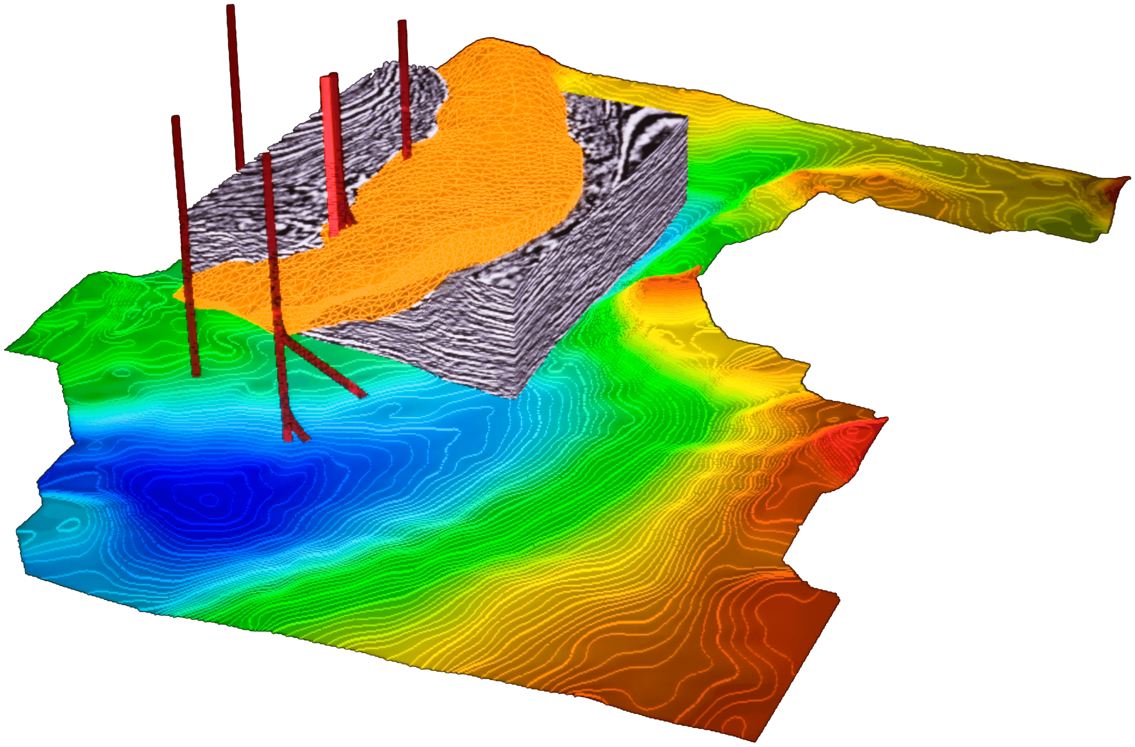
## 2.1 Optimization of Reservoir and Production Systems

Optimization in reservoir and production systems for intelligent resource extraction and Enhanced Oil Recovery (EOR) is the most commonly used process in the energy industry. "EOR processes are oil recovery strategies that use the injection of fluids, chemicals, and heat into a reservoir that alter the thermo-physical or chemical properties of the multi-phase fluid–rock system" [11]. The process of modeling reservoir mechanics is computationally intensive, even by today's standards. Historically, oil and gas exploration companies used differentiation of this technology as a technical advantage and considered the information contained in the reservoir models highly proprietary. The petroleum experts company, PETEX, started in 1990 developed a suite of tools to optimize the production, fluid routing, and well development system using numerical analysis, simulation, and optimization techniques [49]. The work in reservoir and production optimization is continuously studied due to the complexity of model simulation, approximation, and cost-benefit.

Khor et al. defines optimization methods used in oil and gas production using various known and well-understood techniques. Sensitivity analysis is the easiest to implement, but the least useful at finding good or optimal solutions compared with heuristics and mathematical programming techniques [39]. "Heuristic optimization algorithms seed good feasible solutions to optimization problems in circumstances where the complexity of the problem or the limited time available for its solution do not allow exact solution" [51]. In many cases, the optimizations of the reservoir management systems utilize data with known uncertainty to derive reasonable solutions. Therefore, developing an exact reservoir fluid and mechanical model is not tractable. The scale of interactions within the rock structure, transient pressure changes, and undetected natural fractures contribute to the complexity of the reservoir production system, and prevents the development of an exact model.

Zhao et al. proposed the classification of production under uncertainty using Genetic Algorithms based on a modified formulation of the Non-Sorting Genetic Algo-

**Figure 2-1:** 3D Reservoir Model



Note. From Chevron Energy Technology Company.(2009).3-D Reservoir simulation model.

rithm using a "Classification-Based Surrogate-Assisted" model [69]. Figure 2-1 helps to visualize the well placement in relation to reservoir features highlighted by a variation in color, where the objective of the classification model is to optimize the well placement and classification for maximum production and injection efficiency. Many genetic algorithms have good first-pass solutions, but can become very expensive as the solution moves toward a global optimum. Meta-heuristics cannot guarantee optimality, and therefore are used in applications where the non-optimality is acceptable. Proposed formulations such as that published by Zhao, looks to accelerate the evaluations of possible solutions, and promote efficient design space exploration [69]. Problems in reservoir and production modeling require complex transient non-linear analysis, which lead most software and services to utilize sensitivity analysis instead of heuristics or mathematical optimization. The utilization of model approximations is important in the progression of meta-heuristics.

Optimization of production and reservoir systems is a developing discipline with mature capabilities. "The combination of large-scale numerical reservoir simulation models and optimization algorithms for parameter estimation (using historical production data as input) has been developed in the oil industry since the 1970s. Under the names 'computer-assisted history matching', 'automatic history matching' or 'data assimilation" [62]. Emerging computational capabilities such as neural networks, parallel processing, and quantum computing will provide an additional springboard to this field of study. The significance of reservoir and production optimization applications of water, oil, gas, heat, and carbon capture will continue to develop with computational capabilities, and serve as the most valuable form of optimization for oil and gas operators.

## 2.2 Optimization of Well Spacing

In the mid-2010s, horizontal drilling and hydraulic fracturing of low permeability, low porosity rock began to emerge as a strategic development strategy. Conventional reservoirs are hydrocarbon-containing rock that can be produced at a measure related to its' porosity and permeability and where oil is held in place by geological structures. Unconventional wells produce oil from reservoirs that do not easily flow, have micro-Darcy permeability, and must be fractured for commercial production.

The development of an unconventional or tight rock reservoir does not produce if it is not stimulated or fractured. Overstimulation or fracture interaction of adjacent wells can be inefficient due to lost or inaccessible productivity [6]. Ineffective fracture treatments are an improper use of capital or resources and can decrease the overall well productivity and thus reduce the profitability. The work of well spacing is directly related to reservoir production and stimulation. Similar to the studies performed by [45] and [59], which are primarily sensitivity studies of the complex reservoir interactions in hydraulic fracturing. The studies explore numerical methods to evaluate the transient results provided by rock mechanics and production models in unconventional reservoir systems. They also utilize data matching to tune models and verify result accuracy. The optimization of these systems has been defined as a workflow to achieve acceptable or near-optimal solutions.

Uncertainty of reservoir characteristics can only be reduced through expensive analysis such as drilling new wells, extracting large contiguous samples of rock (coring), advanced seismic technologies, drill stem testing, and subsurface fracture monitoring. Even with these technologies, the information gathered will remain an estimate. In unconventional reservoir systems, natural fractures play a significant role in the dynamics of the fracture treatment, impact the optimal well spacing, and ultimately affect the system's overall productivity. Cheng et al. developed a numerical simulation to study the effect of natural fractures in an unconventional reservoir and found that the relationships to well spacing, natural fractures, and productivity have non-linear correlations, thus making it challenging to correlate or implement in tractable optimization formulations [15].

## 2.3 Optimization of Directional Well Trajectory

Well Trajectory optimization optimizes a directional well path to minimize the measured depth while intersecting all targets. The constraints on well design, such as the dogleg severity limitations, rate of penetration (ROP) variations, minimum separation distance from neighboring wells, and reservoir contact objectives, as described by Cao, Wiktorski and Sui, add significant complexity to the optimization of the well path [13]. The lens of the optimization objectives are dependent on the discipline of concern. Optimization of multiple targets or reservoir models focuses on the target placement, not the estimated well path, as described in the Particle Swarm Optimization algorithm developed by Jesmani et al. [36].

Trajectory plans are designed to maximize drilling efficiency in parallel with meeting the other constraints related to well design. Using the principles defined by Shokir et al., the trajectory design must consider the casing points to determine inflection points or as most works state, build, hold, and drop points [55]. The inflection points are significant objective parameters to trajectory optimization, and the number of individual inflections should be minimized to allow for more efficient drilling. A well with a continuous directional profile is challenging to drill, and is not an accepted practice using current technology. Therefore, all well trajectories should follow the principle defined by Shokir.

## 2.4 Drilling Fluid Design Modeling

Drilling fluid is a primary component in any well design. Azar lists the major and minor functions of drilling fluid shown in Table 2.1. Varadarajan et al. developed a numerical formulation for real-time optimization of drilling associated with the drilling fluid [5]. Varadarajan used a transient formulation to estimate and model the equivalent circulating density and pipe movement friction pressure changes or surge and swab pressure. The development of this formulation is a single discipline approach to optimizing the planned system variables while drilling. Accurate development of this formulation could be used to simulate or model specific parameters within an optimization problem.

**Table 2.1:** Drilling Fluid Functions

| **Major Functions** | **Minor Functions** |
|---|---|
| Drilling-cuttings removal | Cooling and lubrication of the bit |
| Containment of subsurface fluid pressure | Removal of drilled solids |
| Hole stabilization | Reduction in casing and drill string weight, buoyancy |
| | Aid in formation evaluation |
| | Cleaning of drill bit |
| | Power downhole equipment |

*Information adapted from [7]*

# Chapter 3

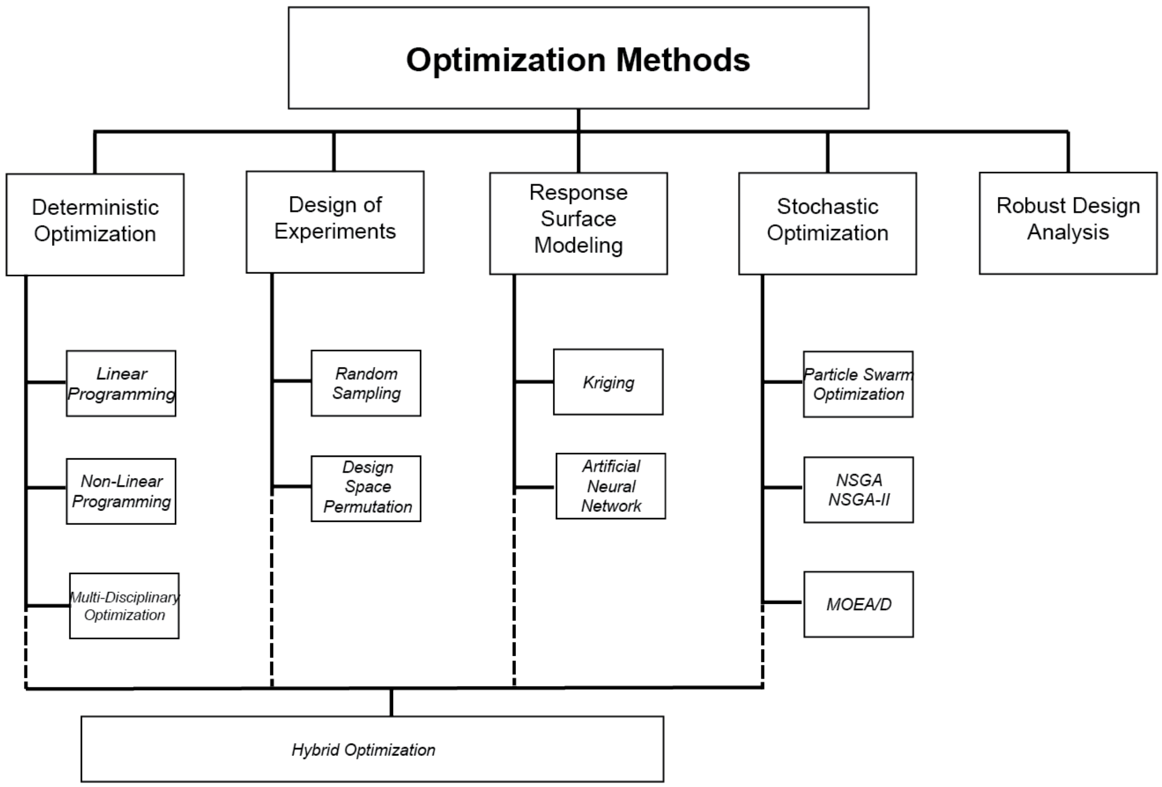
# Optimization Methods

This section covers algorithms that have the potential to solve complex engineering problems. Each algorithm has advantages, but there is not a numerical solution that is the best in all scenarios. "In engineering design of systems with realistic complexity we rarely demand the identification of the mathematical optimum with precision, and we often will settle for a design that represents a substantial improvement over an existing one" [47]. Numerical optimization can be distributed into Design of Experiments, Response Surface Modeling, Deterministic Optimization, Stochastic Optimization, and Robust Design Analysis [14]. Figure 3-1 organizes the optimization methods discussed in this section into their respective categorical class of optimization.

## 3.1 Deterministic Optimization Methods

Deterministic optimization or mathematical programming is a form of global optimization that finds the optimal solution using analytical, mathematical, and combinatorial tools concurrently [30]. This process uses gradient-based optimization techniques to solve for optimal solutions. The most common form of mathematical programming is linear programming and is described along with non-linear programming and Multidisciplinary Optimization in this section.

**Figure 3-1:** Optimization Methods and Examples Discussed in This Section




### 3.1.1 Linear Programming

Linear programming is an efficient form of optimization that guarantees a global optimum under linear conditions. Linear programs can be described as "minimizing a linear cost function subject to linear equality and inequality constraints" [9]. Linear programs can be represented using the standard notation:

$$\begin{aligned} &minimize && c'x \\ &subject\ to && Ax = b \\ & && x \geq 0 \end{aligned}$$

The formulation of linear programming problems must be linear for all objectives and constraints. The simplex method can be used to solve problems where "x" is a continuous variable. If "x" is an integer value, then the problem is a harder to solve integer program, and in some cases, exponentially difficult to find optimal solutions within the feasible region.

### 3.1.2 Non-Linear Programming

An optimization problem where any equation in the objective or constraints is non-linear, then we have a non-linear programming problem. A non-linear problem can have any of the properties listed below [17]:

- The presence of at least one non-linear function.
- One or more variables all of which are continuous.
- Inequality constraints, equality constraints, or no constraints.
- Properties of the functions, which may include continuity, differentiability, or convexity.
- Occasionally intricate optimality criteria.
- Convergent (but not usually finite) solution algorithms with associated rates of convergence, such as linear, superlinear, and quadratic.

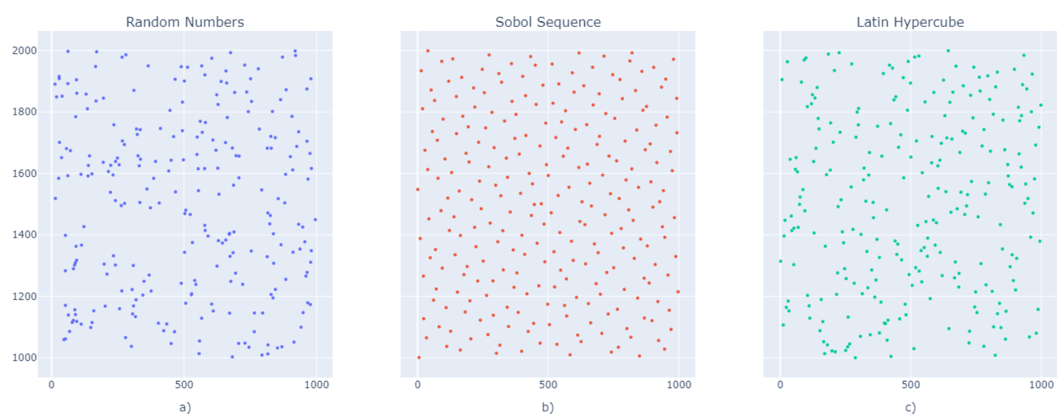
### 3.1.3 Multi-Disciplinary Optimization

"Multidisciplinary design optimization (MDO) is a field of engineering that focuses on the use of numerical optimization for the design of systems that involve a number of disciplines or subsystems" [43]. The development of MDO solutions is not a one-size-fits-all. The concepts of MDO utilize fundamental continuous, integer, and discrete optimization to solve and couple multiple optimization problems into one solution. This concept has been utilized primarily in "aviation, bridges, building, railway cars, microscopes, automobiles, ships, propellers, rotor-craft, wind turbines, and spacecraft" [43]. The architectures used to solve MDO problems vary in complexity, speed, and accuracy. The use of MDO is a broad family of solution architectures that can take advantage of distributed computing systems, complex coupled analysis, and surrogate-based optimization. The main drawback of MDO is its complexity, low speed of execution, relatively low level of adoption, and complex configuration and maintenance. Alexandrov and Lewis describe one of the challenges for the development of MDO is the complexity of integrating components to create tractable solutions while maintaining as much autonomy of each discipline as possible [4]. OpenMDAO developed in partnership with NASA is "an open-source MDO framework that uses Newton-type algorithms to solve coupled systems and exploits problem structure through new hierarchical strategies to achieve high computational efficiency" [27].

## 3.2 Design of Experiments

The goal of Design of Experiments (DOE) is to intelligently guide the evaluation of a set of designs to solve for the best designs efficiently [14]. There are numerous techniques used to perform DOE. Full Factorial designs require an evaluation of a full permutation of design possibilities, which is not possible. A design with 20 variables, having 5 distinct parameters for each variable, has $20^5$ or 3.2 million possible design combinations as an example of the scale of computation

**Figure 3-2:** Sample Selection of a 2D Design Space for DOE




a) Random Numbers, b) Sobol Sequence, and c) Latin Hypercube Selection

Depending on the design space complexity, it may not be possible to evaluate the design space efficiently. Methods such as the Randomized Complete Block Design, Box-Behnken, Taguchi Method, Random Sample, and Latin Hypercube Sampling have been developed to efficiently explore the design space [14]. The Latin Hypercube breaks the design space into sections and selects a subset of samples from each section. This enables random subsets to be more dispersed throughout the design space. A uniform distribution function such as that proposed by Sobol has the most distributed combination of design space variables of the described methods, and uses a numerical formulation to develop an evenly distributed set of solutions [58]. A comparison of a design set using a full factorial, Latin Hypercube, and Sobol Sequence is shown in Figure 3-2. The Sobol Sequence shows the most evenly distributed set of sample points, while the Latin Hypercube looks like a marginally improved distribution from the random number sample.

## 3.3 Response Surface Modeling

A Response Surface Model (RSM) is an approximation of a design space based on the outputs of a DOE [14]. RSM is commonly referred to as a meta-model, which is known to be implemented to accelerate design evaluations. RSM methods include: Least Squared Method, Optimal RSM, K-Nearest, Kriging, Radial Bias Methods, and Neural Networks [14]. Kriging is a popular option to develop response surfaces for multi-variate problems such as well design, and Neural Networks have broad capabilities for accurately approximating the most complex problems.

### 3.3.1 Neural Network

Neural Networks (NN) are designed to mimic the central nervous system [14]. The connections between neurons are trained to have predictive responses based on input conditions. For a response surface, supervised learning is applied by training the neurons from DOE data points, where "the learning process aims at finding the weights of the neural connections so that a cost function C is minimized" [14].

### 3.3.2 Kriging Response Surface

Kriging is a linear least squares algorithm that estimates the result of an input vector using a linear combination of the results of a DOE [14]. The Kriging estimation can be represented using the linear formulation:

$$\hat{f}(\mathbf{x}) = \sum_{i=1}^{N} \lambda_i(\mathbf{x})\ y_i$$

where

$\lambda_i$ is a weight vector or system of linear equations

$y_i$ is the response of a DOE data point

## 3.4 Stochastic Optimization

Stochastic optimization uses random or evolutionary selection to find the best solution [14]. Each respective algorithm uses the best points from each iteration through selection, evaluation, and iteration to describe the best known solution. This class of algorithms is used when there are many discrete decision variables with a non-convex decision space. This section explores common stochastic optimization algorithms that are used for optimization, primarily using Evolutionary or Genetic Algorithms.

### 3.4.1 Particle Swarm Optimization

The formulation of the Particle Swarm Optimization (PSO) proposed by Kennedy and Eberhart uses the ideal of natural swarming to generate solutions that "swarm" to the global optimum solution [38]. This algorithm uses, N, number of particles, and each particle flocks to the current global optimal solution. As the global optimum solution evolves, the direction of the flock also changes. If the global best solution does not change, the flock will eventually converge to the global optimum solution of the swarm. Poli describes several improvements to PSO [50]. Based on the exploration of Poli, the original PSO method proposed by Kennedy and Eberhart has seen improvements in swarm dynamics and particle interactions.

### 3.4.2 Non-Sorting Genetic Algorithm (NSGA)

The NSGA Algorithm, developed by Srinivas and Deb, is an Evolutionary algorithm that advances the Evolutionary Algorithm used to encompass multi-objective optimization by giving each member a fitness assignment and works to preserve diversity among Pareto solutions [21]. Sloss and Gustafson describe the fitness function used in Evolutionary algorithms as "the measure of how close a result is to the desired goal" [57]. The calculation of the fitness function and the determination of diversity is an expensive calculation. Therefore, many experts did not find the original NSGA formulation to be advantageous to other Heuristic methods. Deb describes the NSGA as an expensive formulation that lacks elitism with an expensive Non-Dominated sorting process. In each iteration, "the chosen parents remain in the next population or iteration rather than being discarded" [57], and a sharing parameter had to be specified to gain sufficient diversity of the results.

### 3.4.3 NSGA-II

Deb's proposal of the NSGA-II formulation improved upon the original NSGA formulation based on criticism as compared to other Evolutionary Algorithms. NSGA-II is frequently used as a baseline comparison for multi-objective optimization problems due to the computational success and ease of formulation implementation. It is the benchmark comparison of other statistically significant methods such as Particle Swarm Optimization [16] and MOEA/D [68]. In the NSGA-II formulation, the non-dominated sorting is improved by a systemic discounting of Pareto rank solutions. Each solution in a population is assigned to a Pareto ranking. For each Pareto front p, solutions in the population are evaluated for each non-dominated Pareto solution. If a solution in the Pareto front is dominated by a any solution in the population, the dominated solution is moved up into the next Pareto front, $p+1$, and the current solution is added to the Pareto front, $p$. This formulation is the determination of solution fitness. The solution that is placed in the Pareto front, $p$, is not evaluated for domination again. This prevents the need to revisit previously evaluated solutions in each population evaluation, which limits the computational requirements needed to perform the non-dominated sorting function. Additionally, the NSGA-II formulation uses the concept of crowding distance to replace the need to develop a user-defined sharing parameter. The non-dominated Pareto solutions within each population are evaluated for the crowding distance or concentration of non-dominated solutions to maintain solution diversity within each Pareto rank. The solution space of the NSGA-II solution works well for problems with two objective functions, but begins to slow down significantly as the number of objective functions increases. Deb describes the complexity of the algorithm as $O(MN^2)$, where M is the number of objectives, and N is the population size [21]. Therefore, we see that increasing the number of objectives, M, will increase the formulation complexity. As this increases, so does the expense of the computation.

### 3.4.4 NSGA-III

The formulation of NSGA-III is similar to that of the NSGA-II formulation. The main differences in the two algorithms are the selection operator used to select populations, and the removal of the crowding distance parameter for the Pareto front [22]. The NSGA-III is developed as a many objective optimization formulation, indicating that it is designed to handle more than three objectives functions for one formulation. Experiments for problems with more than 3 objectives outperformed the NSGA-II formulation. The use of reference directions or reference points is an advantage of the NSGA-III formulation, and the performance compares with that of the Multi-Objective Evolutionary Algorithm with Decomposition discussed in the next section.

### 3.4.5 Multi-Objective Evolutionary Algorithm with Decomposition

The Multi-objective Optimization formulation proposed by Zhang and Li [68] decomposes a Multi-objective problem into multiple scalar optimization sub-problems, and uses pareto front methods such as Weighted Sum, Techebycheff, or Boundary Intersection approaches to evaluate the problem space. This method has a similar approach to the principles used in MDO, where each discipline would be it's own sub-problem. The drawback to this method is that the coupling created within most MDO architectures is not present in MOEA/D. MOEA/D is an advancement from a multi-objective optimization problem through it's use of a genetic reproduction and mutation operations of neighboring solutions. The process of executing the MOEA/D is shown in Figure 3-3.

## 3.5 Hybrid Optimization

Optimization of complex non-linear problems in engineering strive to solve the solution for the global minimum. Hybrid optimization algorithms look to utilize the Wolpert and Macready "no free lunch theorem" [66] to develop combinations of algorithms that outperform the conventional standalone algorithm. "The no free lunch theorem states that no individual optimization algorithm is better than all the other optimization algorithms for all classes of optimization problems" [28]. Indicating that the best optimization algorithm does not exist for every situation. Combinations of individual algorithms in some form of concurrency have shown improved convergence rates and better solutions

In this text, the objective function for the optimal well design is a multi-objective function; therefore, any Hybrid Optimization formulation must be able to compute more than one objective function. Greiner et al. describe the two classes of hybrid multi-objective algorithms as "High-level Relay Hybrid (HRH) algorithms where each of the constitutive algorithms run on its own in a sequential non-parallelized scheme,

**Figure 3-3:** Process Flowchart for MOEA/D Algorithm

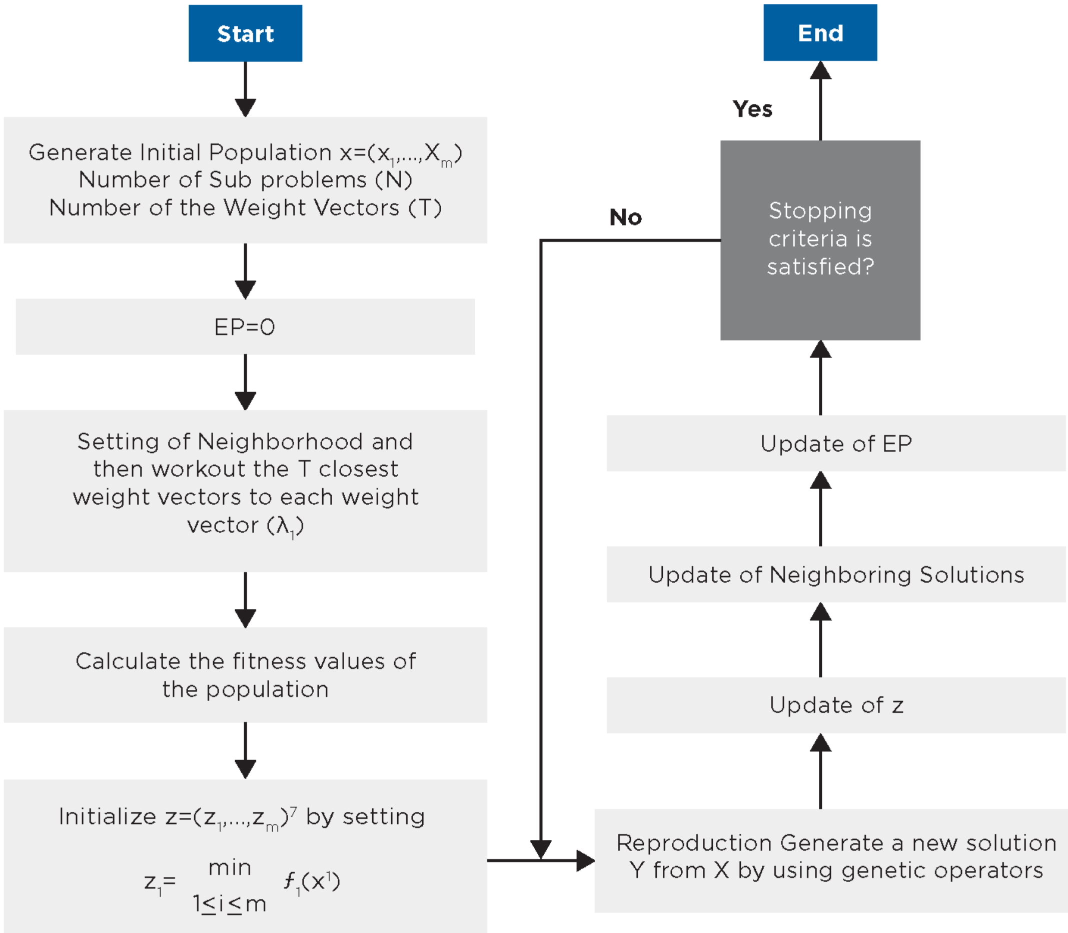



Image adapted from [2]

or as High-level Teamwork Hybrid (HTH) metaheuristic algorithms where constitutive optimization algorithms run in parallel and contribute a portion of each new generation's population" [28].

Vrugt and Robinson developed AMALGAM or A Multi-Algorithm, Genetically Adaptive Multi-objective to take advantage of the strengths of multiple algorithms to create a robust hybrid optimization algorithm [64]. The AMALGAM algorithm substantially outperformed each individual algorithm, and converged to the Pareto optimal solutions much faster and more distributed than the individual counterparts. AMALGAM is an HTH algorithm that runs NSGA-II, Particle Swarm Optimization, Differential Evolution, and Adaptive Metropolis Search in parallel. Each algorithm contributes a portion of the offspring, and the weights or ratio of each generated population is evaluated for each iteration. The adaptive ratio can be defined by the formulation [64]:

$$N_t^i = N \cdot \frac{(P_t^i / N_{t-1}^i)}{\sum_{i=1}^{k} (P_t^i / N_{t-1}^i)} \quad \forall i \in k$$

*such that*

- N is the number of offspring in the population
- The ratio $P_t^i / N_{t-1}^i$ is the number of offspring points an algorithm contributes to the new population, $P_t^i$
- $\sum_{i=1}^{k} (P_t^i / N_{t-1}^i)$ scales the success of a single algorithm to the combined success of all the algorithms
- $\{N_t^1,\ ...,\ N_t^k\}$

An HRH algorithm also utilizes multiple algorithms run in series to create a diverse optimization set that outperforms the individual algorithms. Unlike AMALGAM, the Multi-Objective Hybrid Optimizer (MOHO) developed by Moral and Dulikravich uses three algorithms with a switching algorithm that determines which optimizer handles the next generation [46]. Results of the work show an improvement of the solution to convergence ot the optimal Pareto front over the individual algorithms. A comparison performed by Moral and Dulikravich shows that the AMALGAM algorithm outperforms the MOHO algorithm in most cases, and the MOHO algorithm fails to outperform the NSGA-II algorithm in all scenarios [46]. The results of the algorithm use the convergence ($\gamma$) and diversity ($\delta$) metrics defined by Deb, where the convergence asymptotically approaches 0 as solutions approach the Pareto optimal solution, and the diversity metric, is a measure of how the solutions span the optimal Pareto front [21]. In Table 3.1 below, the results for NSGA-II, AMALGAM, and MOHO algorithms run for 15,000 function evaluations.

**Table 3.1:** Hybrid Optimization Comparison of NSGA-II [21], AMALGAM [64], and MOHO [46]

| | **NSGA-II** | | **AMALGAM** | | **MOHO** | |
|---|---|---|---|---|---|---|
| **Problem Name** | $\gamma$ | $\delta$ | $\gamma$ | $\delta$ | $\gamma$ | $\delta$ |
| **Fonseca and Fleming** | 0.0026 | 0.38 | 0.0017 | 0.33 | 0.006 | 0.33 |
| **Kursawe** | 0.0108 | 0.48 | 0.0099 | 0.47 | 0.037 | 0.37 |
| **ZDT1** | 0.0053 | 0.34 | 0.0011 | 0.33 | 0.0158 | 0.35 |
| **ZDT2** | 0.0068 | 0.36 | 0.0009 | 0.35 | 0.0128 | 0.34 |
| **ZDT3** | 0.0027 | 0.56 | 0.0010 | 0.55 | 0.600 | 0.62 |
| **ZDT4** | 0.0523 | 0.73 | 0.0022 | 0.32 | 14.6 | 0.99 |
| **ZDT6** | 0.0504 | 0.53 | 0.0011 | 0.40 | 0.289 | 1.00 |

*Data source: [46]*

## 3.6 Best Practices for Optimization

Numerical optimization requires strategic planning and organization to ensure the accuracy of the numerical representation of the physical system. As the saying goes, "garbage in, garbage out", and mismanaged or sloppy system design can lead to inaccurate and useless results. "The early stages of an optimal design project are critical for the success of the entire effort" [47]. Papalambros and Wildeprovide an outline for developing an optimization formulation and some applicable best practices include the following [47]:

- The formulation of an optimal design requires a sound problem statement prior to a definition of the system. The use of physical or graphical tools can assist in the problem definition, followed by an accurate representation of the physics, assumptions, constraints, inputs, and objective functions.
- The selection of an algorithm or architecture used for optimization is naturally subjective, and the tool with the most familiarity is typically the tool of choice. A detailed search of existing models and how they are used in the field of study is a great point of reference for the selection of an optimization model.

- It is best to manage discrete variables as a continuous parameter, which can provide opportunities to use more gradient-based or meta-heuristic methods.
- Continued effort into problem complexity reduction in the number of variables, noisiness, and scale helps to simplify the model.
- Once a final model is generated, validate the results with existing systems or other mature forms of analysis.

The optimization of a well design system is a factor of the stage of the well planning process. Through the literature exploration, optimization of well disciplines such as well location, trajectory, and fluid system exist in isolation, and there is no known optimization method for the system optimization of the well design process. Developing an integrated optimization system will require using multiple optimization methods coupled to function as a hybrid optimization algorithm. Due to the historical context of oil and gas development, it is infeasible to replace all discrete parameters in exchange for continuous variables, as described by Papalambros and Wilde [47]. In Chapter 5, an exploration of the selection of an optimization framework will be detailed based on the numerical relationships and parameter type.

# Chapter 4

# Well Design System Analysis

Developing an analytical solution for well design requires the conversion of mental models for standard drilling design practices into a numerical system of equations. The system described by [60] is a model-based systems engineering process that integrates the workflows of geologies, subject-matter experts, and drilling engineers into a seamless process that cascades changes and information for more efficient and reliable well designs. Szemat defines several workflow categories, shown in Table 4.1 are expanded throughout the remainder of Chapter 4 for the development of an optimization architecture. By expanding categories in terms of an optimization model, a generalized Pareto solution can provide a comprehensive well design. With further analysis and verification, it may be used as a primary well design. Many of the categories provided by Szemat have significant interdependence, and a DSM is used to evaluate the interconnectivity in Section 4.3.

## 4.1 Well Design Workflow

### 4.1.1 Input Parameters

The interface parameters needed to develop a robust well are provided to the drilling engineers during the well design process. These interface parameters define the system boundary conditions and contribute to strategic decisions primarily based on

**Table 4.1:** Drilling Program Workflow Categories

| Workflow Categories | | |
|---|---|---|
| Regulatory Requirements | Drilling Fluid | Bottom Hole Assembly |
| Geological Parameters | Casing Design | Bit Design |
| Financial and Supply Chain | Well Control Requirements | Rig and Surface Equipment |
| Well Properties | Cementing | Dynamic Drilling Properties |
| Directional and Trajectory | Drill Pipe | |

*Data adapted from [60]*

geographical location, design and operational risk tolerance, and organizational and technical capabilities.

#### Regulatory Requirements

The regulatory body makes appropriate standards based on environmental impacts, groundwater protections, land and lease obligations, and political pressure. Regulatory requirements for well design for the Continental Shelf and Deepwater Gulf of Mexico are listed in Title 30 of the CFR [1], and is enforced by the Bureau of Safety and Environmental Enforcement (BSEE) in the United States.

#### Regulatory and Political Environment

Separate from the regulatory bodies, the political environment can impact the design regulations. Heavy influences from the political environment can exacerbate rulings and determinations of minimum design standards, which push regulations to be more stringent. The differences in California and Texas rules and regulations for drilling activities highlight the differences based on political impact and geographical location. Although both areas benefit from the profits of the hydrocarbon industry, the reporting, regulations, and requirements are different due to political motivations and geographical location. California has a more significant risk of earthquakes and tectonic plate movement, which requires careful exploration of the subsurface formations.

### Geological Properties, Hazards, Surface Location, and Targets

Geological properties include lithology, pore pressure, fracture gradients, and estimated well stability analysis. The expected geology's simplified characteristics are derived using geotechnical engineering and provided as a probabilistic range of expected values.

Geological hazards help drilling engineers to plan for abnormalities with varying degrees of uncertainty. The hazards are significant deviations from the normalized geological properties due to faulting, water injection formations, unconsolidated formations, caverns, and many other factors. Drilling engineers use the identified hazards for contingency planning or providing feedback for alternative well designs or drilling locations.

Drilling targets are provided as the desired production location or injection interval location based on reservoir simulations or best practices. The targets are used to determine a possible drilling path or trajectory to reach the geospatial location. The feasibility of a well path must be thoroughly evaluated, which makes trajectory optimization a challenging task.

### Overall Well Value

The budget of many wells, or the economic threshold, is based on the resources' profitability over the well's life. Wells with long lifespans may have a higher value for quality and reliability, whereas wells with short expected lifespans may look for lower-cost wells. Wells with higher costs are typically high productivity, resulting in higher consequences of failure. Trade-offs must be made to ensure the well design is able to balance the total well cost and risk of failure.

### Material Availability

Some well designs' feasibility depends on the current supply of items such as mud systems, drilling rigs, and tubular goods such as drill pipe and casing. Tubular goods availability can be restricted based on geological location, supply chain constraints, and industry partnerships for common or shared goods. The entire catalog of standard and premium tubular components is unlikely to be available for all locations. The availability is critical to consider in optimizing potentially feasible solutions.

#### Drilling Technology Implementation

Several advanced technologies are available for installation on the surface, such as Managed Pressure Drilling, Bottom Hole Assembly logging tools, and wired drill pipe, which are designed to decrease risk and increase drilling performance. "A technology is selected based on criteria such as technical feasibility, cost-effectiveness, regulatory requirements, and environmental impacts" [31]. These technologies can create complex inter-dependencies and costs but can alter Pareto solutions if implemented.

### 4.1.2 Well Constraints

Wells are constructed using geology, production engineering, and completions engineering requirements. These constraints identify where the rig will start drilling, how deep it must drill, and how the well should intersect production zones. Furthermore, the drilling engineer is given a minimum feasible diameter from the production and completions engineers, while the geologist assists in providing a safe and advantageous surface location for drilling. With this information, the Drilling Engineer can begin designing the well to fit within the well design boundary conditions. A failure to meet any of these could result in a well with a reduced or negative value.

### 4.1.3 Drilling Fluid System

Drilling fluid in well construction operations performs multiple functions and must consider several competing factors. The fluid system in oil and gas operations is one of the most complex systems to manage while drilling. Engineers must design the system to accomplish the necessary tasks for safe and efficient operations while working within geological, regulatory, supply, and cost constraints. "The correct selection, properties and quality of mud is directly related to some of the most common drilling problems such as rate of penetration, caving shales, stuck pipe and loss circulation etc." [31]. Failure to implement and practice safe fluid design and monitoring practices could lead to costly, fatal, or environmental consequences.

Azar uses the definition of "major functions" and "minor functions" to determine the value the drilling fluid serves [7]. Major functions include hole cleaning, formation fluid containment, and wellbore stabilization. Minor Functions include powering, cooling, and lubricating downhole components, suspending solids during connections, reducing tubular weights, enabling formation evaluation, and cleaning of the drill bit [7]. The drilling fluid interactions involve complex rock chemistry, rock mechanics, operational efficiencies, and requirements to reach the desired drilling target safely. In general, the design process for drilling mud aims to have the lowest density fluid, minimal proprietary chemical additives, and the lowest cost base fluid. A base fluid for drilling mud can be air, freshwater, brackish water, seawater, diesel, or synthetic base oil. The selection of base fluid is derived from the evaluation of rock chemistry, fluid cost, formation interactions, local mud supply, and environmental risks. Detailed engineering and subject matter experts can discern these interactions using best practices and generalizations of experienced-based learning.

During early planning and conceptual design, drilling engineers will use the mud system as an abstraction and perform estimations using historical averages. Drilling engineers and operations personnel must have a good understanding of the mud system, but do not need to know all of the complex details [31]. Most drilling engineers understand the chemical composition of drilling fluids, how chemicals function, and how to independently identify common problems in the fluid system. The detailed design, thresholds, and interactions of chemicals within the fluid are often tasks that are not significant to the drilling plan at the drilling program level, but are important for proper mud system development.

### 4.1.4 Well Trajectory and Directional Drilling

In drilling, vertical wells may not be able to meet well objectives [31]. Directionally drilled wells are implemented when vertical wells are infeasible due to: surface constraints, if using an existing well to deviate to a reservoir some specified distance from the current wellbore, or where the production section has optimal production if the well is drilled at an angle through the reservoir. Hossain lists common functions for directional or deviated wells [31]:

- A single surface or platform location with more than one well requires deviated drilling to avoid collision and to reach the desired target locations.
- Using a land drilling rig to drill under a body of water.
- Drilling to subsurface locations inaccessible for a drilling rig, such as environmentally sensitive areas or city centers.
- Emergency wells drilled to intersect a well that has lost integrity.
- Drill through an existing wellbore, but away from an exiting branch.
- Avoidance of subsurface features such as shallow faulting or subsurface salt.
- Horizontal drilling for unconventional well production.
- Directional targets are aligned in a non-vertical path, but can be reached with a single well.

### 4.1.5 Casing and Liner

The casing is a critical component used in the well construction process, as it serves multiple functions such as well stability and isolation. The design and installation of casing strings are treated as milestones for well construction. The installation of casing that is secure and tested is an indication of a static situation. The wellbore becomes a closed system upon successfully installing and testing a casing string. Hossain identifies several key functions of casing strings [31]:

1. The casing provides the support needed to maintain the geometry of the well-bore. When drilling, the removal of the volume of rock creates an imbalance of internal stress, which can cause fracturing or caving of the nearby rock.
2. Isolates the target interval from being contaminated by fluid from other intervals when coupled with cementing.
3. Eliminates fluid communication between intervals or zones.
4. Protects the freshwater system from contamination of produced or drilling fluids.
5. Protects the oil bearing zones from surrounding water containing intervals.
6. After casing is set in place, it will prevent interactions with previously drilled intervals.
7. Creates a structural conduit for installing an inner string, tubing, to be installed for hydrocarbon production.
8. Structural and pressure-containing system that can hold the wellhead and Blowout Preventer (BOP).
9. Reduces the formation damage created by drilling fluids. This is an important factor for some well designs within the target intervals.
10. Structural conduit is known, measurable, and consistent in well-designed situations. If the geometry of a casing string changes subsurface, this is considered a casing failure.
11. Required for the subsequent completion and production operations.

Each casing string is designed for a specific set of expected load conditions. For land-based wells, casing sections are defined as: Conductor, Surface, Intermediate, and Production casing strings. Figure 4-1 depicts each string's relative position in the well, where the Conduction Pipe is the first string installed, and the Production Tubing is the last string installed. Interestingly, the casing design process follows a bottom-up approach, where the production tubing and production casing selections are selected before strings at shallower depths.

**Figure 4-1:** Wellbore Casing Schematic

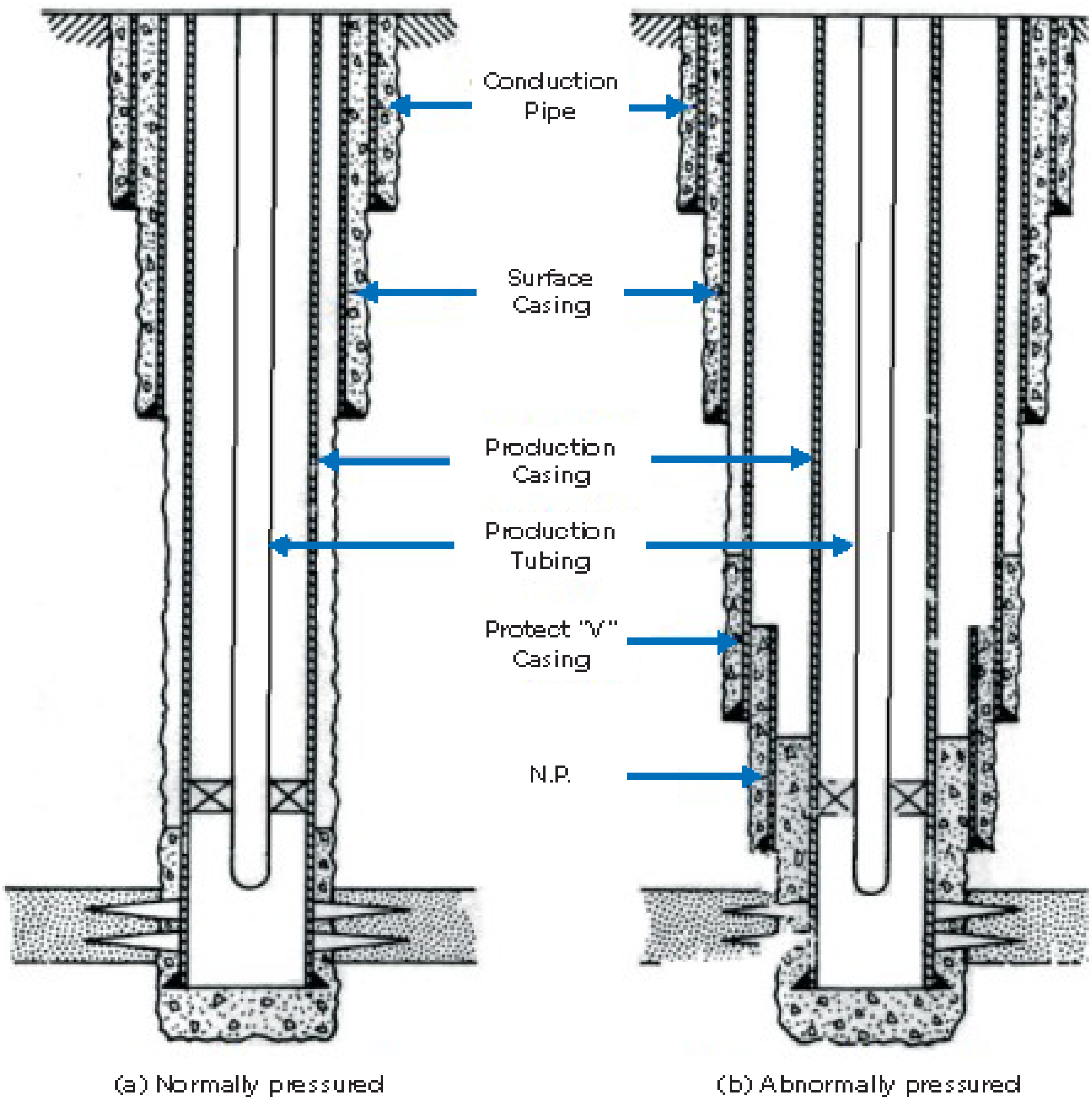



Image Adapted From [31]

### Conductor Pipe

Conductor pipe is used as the first structural pipe and is used to isolate unconsolidated, soft and unstable topsoil and rock, water zones, and shallow gas zones [31]. This string is not used as a pressure-containing string. It is a critical structural component for supporting the load of subsequent sections and in some cases, production rig loads. The design of the conductor casing string is driven by the setting depth, installation method, wellhead configuration, and ID requirements needed for the well.

### Surface Casing

The surface casing string is the first pressure-containing string, and is drilled without a BOP. This string is installed after the conductor pipe, is cemented to the surface, and protects shallow zones and the migration of fluids to the surface [7].

### Intermediate Casing

The intermediate casing can be one or multiple sections of string. In Figure 4-1 the intermediate string is set deeper than the surface casing, and before the last string is set. It is installed to isolate zones needed for drilling to the final interval. Well profiles can range from 0-3 intermediate casing string sections. A casing string must be installed or set in a specialized profile, at or near the surface, therefore the technical limit to the number of intermediate strings is based on the feasibility of multiple casing strings installed in the wellhead. Cementing for this string is not required to reach the surface. As the temperature of the well increases, trapped fluid in the annulus could increase the annulus pressure significantly during production. As shown in Figure 4-1.b, the exposed formation below the surface casing string, and above the intermediate casing cement, can be used to maximize the possible annulus pressure theoretically. The exposed formation will allow fluid to flow into the rock as the fluid expands due to rising temperatures from produced fluids.

### Intermediate Liner

A string not installed at or near the surface is a liner [7]. Liners are used to isolate formations to continue drilling to subsequent sections or simply to reduce the volume of material in a well. Secondary benefits to liners are reduced surge pressures when running the string into the well, faster installation time, and reductions in circulation pressures. Liners do not protect the casing strings above it, so the casing strings are exposed to more loads following the installation of a liner.

### Production Casing

Production Casing is the last casing string to be installed and cemented in the well. In cased hole completions, which is shown in Figure 4-1, the production string intersects the production interval, but in open-hole completions, the production casing string is installed above the production interval. The production casing string is designed for the worst-case loads that could occur during production. This string must contain all fluids throughout the life of the well, and irreparable failures of this casing string lead to the loss of the well. The design and qualification criteria for the production string are the most stringent of all casing strings.

## 4.1.6 Drilling Rig and Surface Equipment

A drilling rig is a package of equipment needed for circulation, control, hoisting, power, data acquisition, and storing equipment needed to construct a well [7]. The surface environment of the well location, expected drilling depth, maximum string weights expected, and circulation and fluid storage capabilities are the drivers for rig selections. A rig type referred to as a Jack-up rig is used for drilling in shallow offshore water, typically up to 500 ft. The rig has all equipment, including the BOP, installed above the water line and is fixed to the sea floor using three truss-supported pylons. A common land-based rig is referred to as a "triple" due to its ability to utilize a three joint drill string, measuring approximately 130 ft. The rig package comprises a modular system that can be moved to a new rig site on public roads with regulatorycompliant vehicles and minimal infrastructure disruptions. A typical rig can relocate within one week to begin work in a location in the same development region. The most advanced and complex class of rigs operates in water approximately 10,000 ft deep, houses more than 150 crew members, maintains position using satellite-based dynamic positioning system, has a hoisting capacity greater than 1,500,000 lbs, is a fully integrated system with multiple fixed cranes, and drills up to 40,000 ft. The most recent class of deepwater drillships has a 3,000,000 lb hoisting capacity [40]. Table 4.2 shows a comparison of capabilities, which are not all-encompassing, but show a glimpse of some of the major differences in rig types, such as water depth, circulation system horsepower, and hook load capacity.

**Table 4.2:** Sample Drilling Specifications

| **Specification** | **Rig Type** | | |
|---|---|---|---|
| | **Land** | **Jackup** | **Drillship** |
| **Hookload Capacity** (lbs) | 1,000,000 | 2,000,000 | 2,500,000 |
| **Circulation System** (hp) | 4,800 | 6,600 | 7,260 |
| **Circ. System $\Delta$P Rating** (psi) | 7,500 | 7,500 | 7,500 |
| **Circ. System Max Q** (gpm) | 1,200 | 1,500 | 5,170 |
| **BOP Rating** (psi) | 10,000 | 15,000 | 15,000 |
| **Fluid Storage Capacity** (bbl) | Variable | 26,420 | 63,203 |
| **Crew Capacity** | N/A | 150 | 200 |
| **Maximum Drilling Depth** (ft) | 30,000 | 35,000 | 40,000 |
| **Operating Water Depth** (ft) | 0 | 400 | 10,000 |
| **Relative Cost** | 1x | 5x | 20x |

### 4.1.7 Drilling Assembly

The design of the drilling components used to create the borehole, with acceptable curvature or deviation, proper gauge diameter, ensure depth measurement, measure and transmit signal, and create localized stress to break the rock are essential functions of the drill string assembly. The drill string assembly consists primarily of the kelly, drill pipe, bottom hole assembly (BHA), and drill bit shown in Figure 4-2. "The drilling fluid and rotational power are transmitted from the surface to the bit through the drill string" [31]. The drill bit, measurement while drilling (MWD), logging while drilling (LWD), directional control, and centralization configuration help control, measure, and direct the tools to their desired targets. Drilling engineers work to optimize the trade-offs for bottom hole assembly design and selection to lower the costs needed to deliver the most value for each well. Hossain [31] describes the design of the drill string as a function of the well depth, hole diameter, fluid density, safety factors required, and bottom hole assembly configuration. The string is evaluated for tension, torsion, shock, collapse, and pipe stretch.

**Figure 4-2:** Drill String Components Schematic

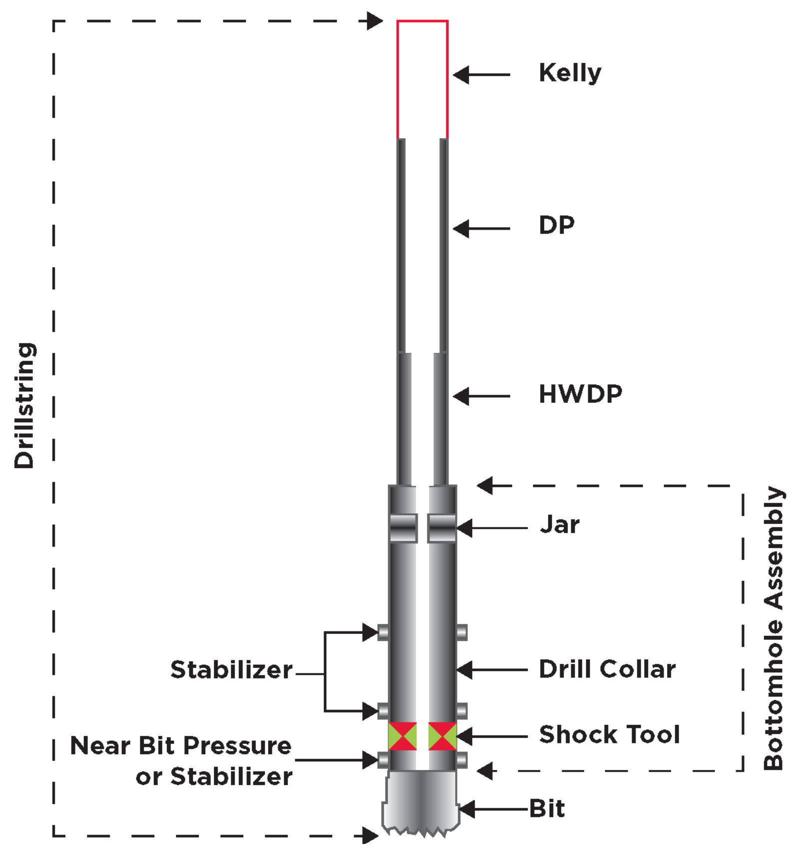



Image Adapted from [31]

### Drill Pipe

Drill pipe is the primary component used to convey the drill bit into the hole along with the BHA. It transmits torque and provides a conduit to pump fluid throughout the wellbore. A typical configuration in a 20,000 ft well would have 1,000 ft of BHA and 19,000 ft of drill pipe. Therefore, the drill pipe is a critical point of failure, a major contributor to the Equivalent Circulating Density (ECD), and increases the friction pressure in the drill string as a function of its length. The drill string connections are called tool joints, and the tool joint OD must be less than the hole and casing diameters it will pass through. Drill string design is a factor of well trajectory, bit, casing, and pipe diameter diameters, pump rates need for hole cleaning, ECD limitations, rig hoisting capacity, formation fluid composition, and drilling depth. Drill strings for deep applications are often tapered to allow for a higher axial tension safety factor when additional tension is required on the drill string. The material selection of drill pipe is important for sour service wells, as Hydrogen Sulfide causes significant pitting in cracking over time, leading to frequent failures while drilling.

### Bottom Hole Assembly

As shown in Figure 4-2, the BHA is located below the drill pipe and above the drill bit. It provides weight to the bit, using large diameter, heavy pipe along with some directional control mechanism. Directional control can be provided using stabilizer configurations or other bit directional tools such as a rotary steerable system or directional mud motor. Possible components of the bottom hole assembly could include:

- Jars - device used to store and release energy in the direction of the bit if the BHA becomes stuck.
- Drill Collars - Heavy, large OD, small ID pipe with high compressive strength.
- Stabilizers - Well Gauge OD component used to centralize the pipe and increase the BHA stiffness.

- Mud Motor - Hydraulically driven "positive displacement motor (PDM) or a drilling turbine." [31].
- Measurement While Drilling - Specialized tool used to provide directional measurements through geomagnetic or gyroscopic measurements and radioactive responses of the rock. This signal can be transmitted to surface manually, as a pulsating shock wave, or through wired drill pipe.
- Logging While Drilling - Measurement tool for formation evaluation using sensors to detect changes in formation properties and lithology [31].

**Drilling Bit**

Drill bits are used to break or chip the rock to create a deeper wellbore. The design of the drill bit is dependent on the expected lithology in each interval, desired ROP, and vibration and shock tolerance of the bottom hole assembly, and the operational risk associated with failed drill bits. Bit selection is different for each drilling area, and minimal changes in lithology, operational parameters, and bit life cycle drive final bit selections by engineers. The selection of a bit is not trivial, but it does not significantly affect the overall system design.

### 4.1.8 Cementing

Cementing in well operations is used for impermeable isolation of well fluids and structural support within the wellbore. The unique properties of cement, which flows as a liquid, and sets as an ultra-low permeability rock that does not degrade or decay under extreme conditions, make it well suited for wellbore operations. During well design, primary cementing is the pumping of a cement slurry after the casing is run. The goal of the cement is to isolate the casing shoe, and formations that have been drilled and cased in previous sections. Failure of a primary cement job could lead to costly remediation and, in some cases a loss of the well. During primary cementing, a critical design component of the cementing operation is the timing and duration of the cement transition. During the cement transition period, the density of the cement slurry is equivalent to the fluid in the slurry and can lead to an underbalanced well, which allows the formation fluid to contaminate the cement slurry. Strategic design of the fluid hierarchy must be considered when designing the cement slurry to prevent fluid mixing during the cement setting periods. Cementing follows a hierarchal relationship where each pumped fluid has a higher density. Careful selection of wellbore fluid, spacer fluid, and cement densities must be selected to ensure the well remains overbalanced at all times while minimizing the possibility of lost circulation or exceeding the fracture stress of the rock.

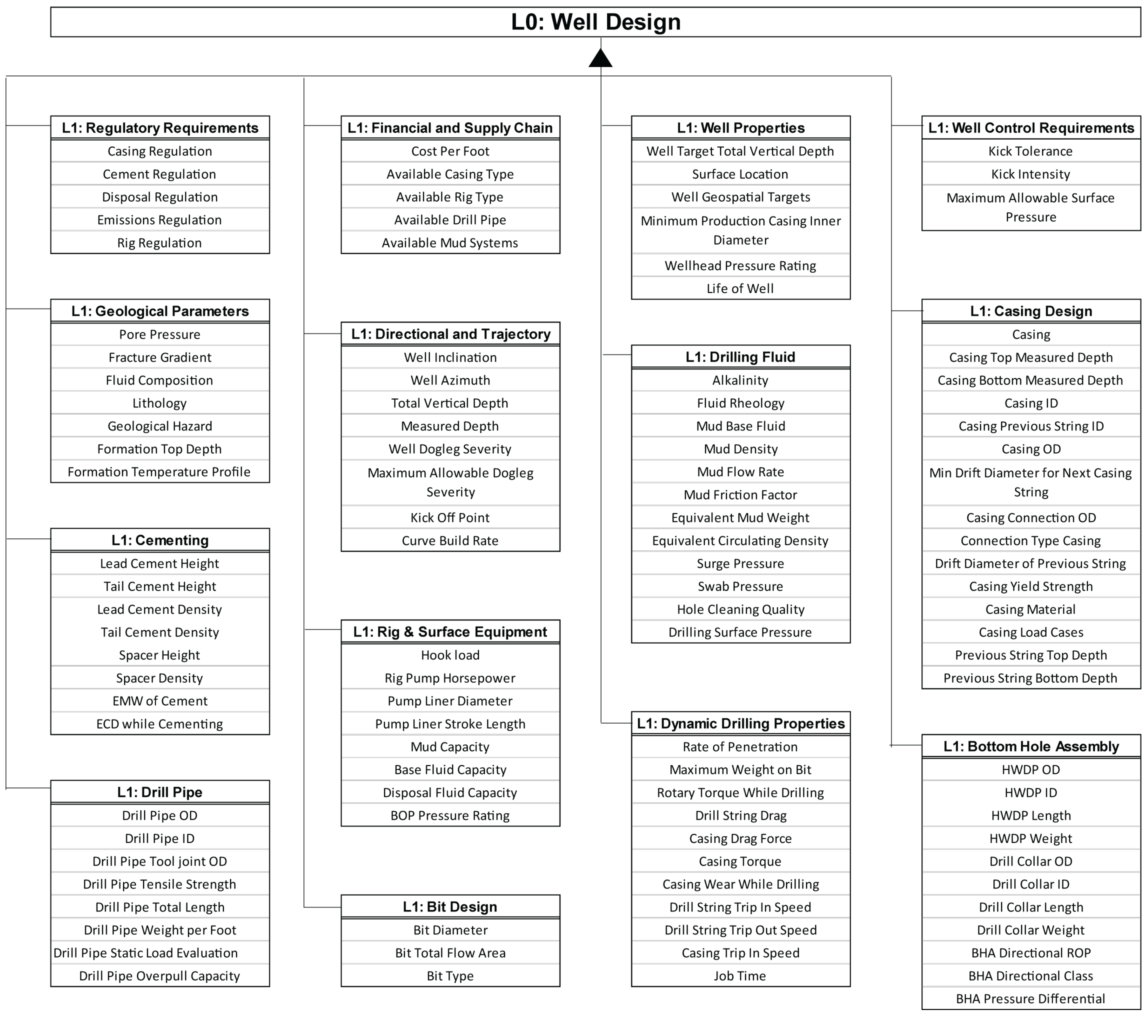
### 4.1.9 Well Barriers

Well barriers are the most important constraint for all phases of work. As defined by API Standard 65 Part 2, a barrier is a physical or operational system that inhibits the flow of uncontrolled wellbore fluids. Barriers can be physical such as fluid, mechanical plugs, or solid cement [34]. Throughout the drilling process, barriers must be clearly defined and monitored for the safety of the people and the environment. When barriers fail, a blowout occurs when uncontrolled wellbore fluid is released. Once a blowout occurs, the wellbore is considered a lost asset, and hydrocarbon releases and death are likely. The Blowout preventer must be rated to contain the maximum expected reservoir pressure minus some standardized fluid gradient, the wellhead must contain the maximum possible pressure of production fluids, and the wellbore fluid must be monitored for abnormalities indicating an influx of wellbore fluid while drilling. CRF-250 Subpart B states that two barriers must be maintained so that if one barrier fails, a second is likely not to fail [1].

## 4.2 System Decomposition

To develop a proposed numerical simulation, the decomposition of the parameters used for numerical and logical engineering help manage the complexity of the interactions. A *system decomposition* is a tool used to divide the parameters into individual entities for further evaluation [19]. The numerical relationships of the system decomposition use parameters with clear and logical numerical relationships. In Figure 4-3 the system is divided into a Level 2 architecture. The level two items are input variables, constraints, decision variables, or optimization parameters based on contextual knowledge principles for drilling engineering. Although these variables are not represented in the Level 2 descriptions, it is important to note that these parameters are ordered and labeled based on a Drilling Engineers perspective. To avoid increasing

**Figure 4-3:** Well Design Level 2 Decomposition




the complexity of the Level 2 Decomposition, it is critical to clearly understand the use of abstractions, which can be defined as an "expression of quality apart from the object or as a representation having only the intrinsic nature rather than the detail" [19]. The job of a drilling engineer is to work with and manage abstractions within the complex nature of the materials used in well construction. Abstractions of fluid mechanics, metallurgy, rock mechanics, and geomagnetic properties are critical items managed as an abstraction for most well construction processes. For example, determining the fluid viscosity in a Non-Newtonian fluid is a transient property that changes when starting pumps and moving the drill pipe. The chemistry required to reach the desired rheological properties is treated as an abstraction for many processes. An external party, fluids engineer or contracting company, manages the details and provides expert analysis using the well conditions as inputs and rheological dynamics as outputs. The importance of precision of the fluid properties is conditional on the risk of well failures but must accurately represent the expected parameters during operation. These challenges are natural occurrences for the neurological processing of a Drilling Engineer but can be difficult to implement into a numerical solution. Appendix A expounds on the details of the parameters used in the Level 2 decomposition.

When representing the system as a numerical model, it was a challenging task to avoid over-constraining system variables. In the well engineering process, the term "consider the..." is used frequently to describe a cause and effect relationship of parameters. Changing the casing diameter causes one to consider the ECD of the subsequent section. However, in a numerical optimization process, these relationships are inherently built into the mathematical formulation and therefore do not require symmetric relationships within the DSM. The reduction of the symmetric relationships personifies the strength of how numerical analysis allows logical modularization of the DSM, and could significantly improve the design process.

Using a Design Structure Matrix (DSM), the well design numerical relationships can be visualized in an organized manner. The DSM has the input parameters on the horizontal axis and output variables on the vertical axis. An ideal DSM would have a "bottom-left" design, which indicates the ability to develop a waterfall or series-based optimization algorithm. The cross-entity interaction increases the complexity of optimizing the well design process significantly. In terms of MDO, these cross entity interactions are "shared variables" [43].

## 4.3 Development of a System DSM

Developing a system DSM required a methodical identification of the level 2 items shown in Figure 4-3. The relationships of the level 2 items are developed using physical equations, tabular relationships, or process design relationships that are best practices. During the development of the DSM, all relatiohips that did not have a direct numerical relationship, but instead were typical considerations were not labeled within the DSM. The goal was to limit the interactions to numerical formulations only. By using numerical relationships only, the DSM would represent the resulting numerical model that is created. For example, the relationship of the rate of penetration to the casing diameter has an indirect relationship. Increasing the casing diameters size reduces the rate of penetration, but the numerical relationship does not exist for the relationship, therefore should not be identified within the DSM. However the hole diamter or bit size does have a numerical relationship to the rate of penetration, and therefore is identified as a non-symmetric relational item within the DSM.

## 4.4 Modularization for Numerical Analysis

Modularization or clustering is used to group the level 2 decomposition items into clusters that penalize interactions that are not in an optimal location. Using "the Principle of 2 Down, 1 Up" [19], a feasible strategy for implementing an optimization algorithm emerges from the modularization of the DSM. The three main objectives of the modularization of a numerical evaluation of a well design are:

1. Identify the input parameters passed from boundary disciplines, such as Production, Geology, and Completions. These parameters are not decision variables for a Drilling Engineer. Changing the input parameters requires communication or a feedback loop to an external discipline to modify the well design boundary conditions. In practice, this process is naturally a component of early phase design decisions.

2. Assume selection parameters are static values generated by an outer iterative optimization algorithm, with a preference for discrete values. In Chapter 5 we will explore outer algorithm selection concepts to generate feasible design sets. The outer algorithm encompasses the well architecture, which includes the casing and trajectory information. Optimizing the well trajectory is an expensive formulation, and improper coupling with the optimization algorithm could lead to an infinitely large design space.

3. Modularize the remaining constraints and parameters by minimizing the number of shared variables above and to the right of the modules, which can be considered feedback loops or wait-and-see variables. The sub-modules are evaluated for each well section; therefore, the expense of the evaluation is multiplied by the number of hole sections in the well. The relationship for well sections is not explicitly displayed in the DSM, but is a critical part of the well design process. The volume of interactions across disciplines is significant, and the numerical formulation must result in a tractable optimization solution.

The clustering of the DSM groups highly interactive components of the system into groups, penalizing elements that are not within clusters [24]. The clustering of the system for well design looked to group elements with the least amount of interaction in the upper right diagonal of the DSM. A manual clustering process was completed through the movement of variables to attain a reasonable reduction in upper right interactions while maintaining a logical grouping of the design parameters. The Boundary Parameters and Well Architecture Parameters were allocated first; then remaining disciplinary components were moved to develop a flow of reduced feedback dependencies in the upper right diagonal. The objective of making the clusters small did not work for the Circulation System and Drill String group. This highly integrated analysis was designated as one large integrated cluster with two disciplinary processes for evaluation. One of the significant advantages of numerical optimization, both principles of design will be integrated to formulate the best solutions. The addition of the Well Performance and Objectives clusters have the most interactions with the outputs of the above clusters and are primary parameters for feasibility and optimality. The modularization of the DSM reduces outer disciplinary interactions. It moves the complexity of the decision-making to the performance and objective disciplines, which provide feedback to the disciplinary modules to search for optimal and feasible combinations of the variables.

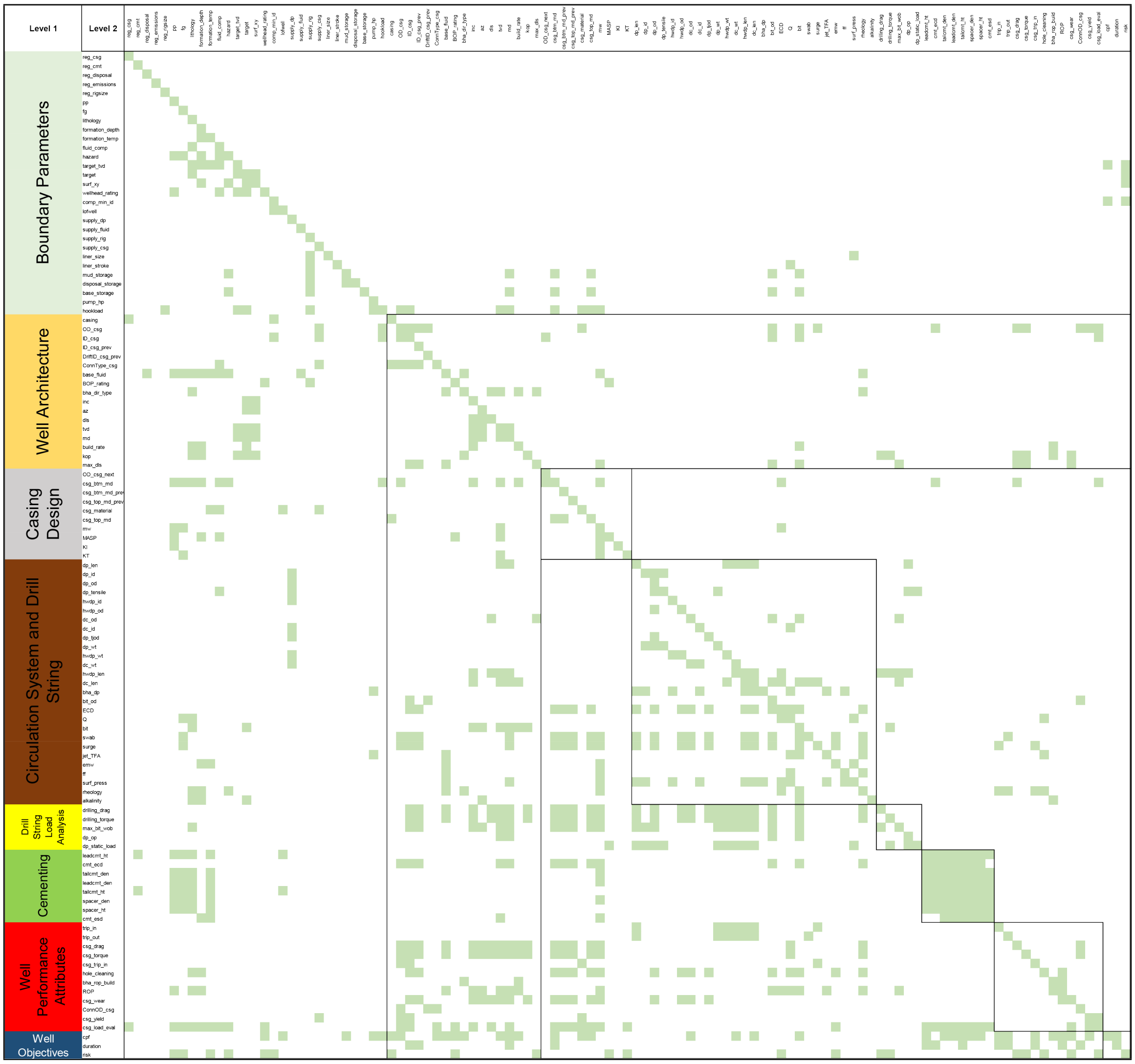
### 4.4.1 Well Design Decomposition

After modularizing the DSM into categories, the quality of clustering can be considered sufficient for use in a numerical optimization formulation. The three main objectives are sufficiently met to assist the evaluation of numerical optimization techniques explored in Chapter5. The Level 1 decomposition for the well design process are listed in Table 4.3 and in the DSM diagram in Figure 4-4. Section 4.4.2 discusses the details and strengths of each modular section.

**Table 4.3:** Sample Drilling Specifications

| **Initial Level 1 Before Modularization** | | **Final Level 1 After Modularization** |
|---|---|---|
| Regulatory Requirements | | |
| Geological Parameters | | |
| Financial and Supply Chain | | Boundary Parameters |
| Well Properties | | Well Architecture |
| Directional and Trajectory | | Casing Depth |
| Drilling Fluid | $\rightarrow$ | Circulation System and Drill String |
| Casing Design | | |
| Well Control Requirements | | Drill String Load Analysis |
| Cementing | | Cementing |
| Drill Pipe | | Well Performance |
| Bottom Hole Assembly (BHA) | | Well Objectives |
| Bit Design | | |
| Rig and Surface Equipment | | |
| Dynamic Drilling Properties | | |

**Figure 4-4:** Modularized DSM for a Numerical Well Optimization Process




## 4.4.2 Modularized Level 1 Decomposition

The final level 1 items for the well design numerical representation will be discussed in detail in this section. The order and clustering of each Level 1 item follows the logic of an optimization problem, where the problem constraints and input parameters are first. The DSM shows these input parameters having feedback items from the optimization elements, which reflect the information presented in Figure 1-2. Well architecture is considered a component of the outer function, which provides an architecture for a subset within the design space. The subsequent items are treated as the well system's constraints, decision variables, and optimization parameters. The well performance attributes are mostly optimization parameters and provide feedback to the well design system, for the quality of the design selection.

### Boundary Parameters

The information given to a drilling engineer is treated as the drilling scope and drives many of the trade-offs to creating well designs. Static conditions for regulations and geological properties are things that cannot be easily modified for design optimization. Geology is considered to carry the most uncertainty, as the predictability of geological properties of even the most understood geological regions changes in unpredictable manners. Geotechnical Engineering uses estimations of geological properties to develop probabilistic and stochastic models with a range of certainty that is a function of the expense of data collection of actual, nearby subsurface data [26]. In drilling, this uncertainty can equate to risk, and the drilling design must remain within the risk tolerance of the geographical and political environment, operation company, the consequence of failure, and well value.

Other boundary parameters such as the well surface location, targets, supply chain availability, and rig availability are fixed for a single design. Changes to material availability can be modified if the value of the change is warranted. However, in many cases, the cost of a change can significantly affect the development cost of a well. As shown in Table 4.2, rig capabilities are static values, and operations that fall outside of current availability require the engineering and construction of a new rig class or global sourcing for a drilling rig.

### Well Architecture

The architecture of a well is the structural makeup of a well. Drilling engineers reference the architecture of a well, using references to the number of casing strings, the size of the casing strings, and the directional trajectory [56]. The geometric properties of the casing are selected, along with the development of a potential well trajectory. Casing diameters cannot be reasonably relaxed. Casing OD's are standardized throughout the industry, and the sequence of casing sizes creates a large discontinuous design space.

### Casing Design

Determining the casing attributes is a primary feedback sequence within the well design process. The casing setting depths and material selections are functions of subsequent optimization processes according to the process methodology described in Figure 4-4. Through the optimization of the casing points, fluid density, formation fluid concentration of corrosive elements, and geological changes, the casing must maintain integrity for all applicable load cases. Failure of any single load case results in an infeasible design.

### Circulation System and Drill String

The parameters identified for optimization include two subsystems, the drilling fluid and the circulation system. The drill string and circulation system selection are tightly coupled, as the drill string and bottom hole assembly are the primary driver for system friction pressure. Although the complexities of drilling warrant significant attention, decoupling the system could add to the complexity of the problem as critical interactions occur on the subsystem boundaries.

### Drill String Load Analysis

The analysis of the drill string is a determination of "drillability", which indicates if a design is physically possible to drill. The drill string load analysis could be considered a constraining component of the Circulation System and Drill String decomposition but is separated to allow optimal parameters to be explored without the relatively expensive evaluation for feasibility. Any feasible design shall meet the constraints necessary for drilling each hole section.

### Cementing

In Figure 4-4, Cementing is represented as a highly coupled system with limited interaction with external systems. Cementing has the complexity and importance to be considered a critical operation. However, the details associated with cementing design optimization are represented as an abstraction for this numerical model. This information remains unchanged from the original model decomposition and will be calculated for feasibility within the existing well architecture.

### Well Performance Attributes

Well performance factors directly correlate to a drilled well's efficiency and quality. The challenge of meeting the constraints of the operating environment, coupled with the cost to drill a profitable well, leads to engineered trade-offs for optimal well design. This section is a result of the decision made on optimal conditions and will implement significant feedback throughout the system. An optimization formulation should focus on the computational efficiency of the well performance attributes, as they are not treated as constraints but as optimal or beneficial parameters used to calculate the objective functions.

### Well Objectives

Drilling Engineers use Well Cost, Drilling Risk, and Drilling Job Duration to design wells under provided constraints. Minimizing tangible items, well depth, drilling complexity, and minimizing safety factors for casing designs ultimately reduce cost per foot. The well duration is a summation of distinct operational activities, each of which has a duration associated with it. The time intervals result from equipment installation times, maximum pipe speed (surge/swab) for running casing and drill pipe, and the rate of penetration. Identification of risk can be complex to translate into a numerical model. The numerical identification of risk using a probabilistic approach to quantify the risk of an operation, given an uncertainty set, is described by Sheng et al., which highlights how geological uncertainty propagates and is managed for well design [54].

### 4.4.3 Utilization of DSM For Optimization Architecture

The development of the DSM representing the well design system provided a visual representation of the problem variables and their interconnectivity. In an analysis of the problem using the principle of two down one up to develop a modular decomposition, a system modularization for use in algorithm development. In Chapter 5, the generalizations of the Level 1 decomposition from Figure 4-4 will be used to generate a reasonable architecture for a numerical optimization formulation.

## 4.5 System Representation of the Well Design Process

The DSM produced in this chapter is a useful tool in simplifying the complex interactions in the well design. The development and identification of the numerical relationships within the design help identify which variables are decision variables, constraints, or parameters. Future evaluation of the DSM leads to modularization, which further simplifies the system representation for analysis of the system interactions in their most efficient form. The modularized DSM can be implemented into disciplinary optimization formulations such as Multi-Disciplinary Design Optimization or Multi-Objective Evolutionary Algorithm with Decomposition to develop a multi-objective optimization problem. The final clustered DSM can be used to communicate and construct the system optimization model using the input variables on the horizontal axis to generate a feasible optimization formulation. As the number of top-right dependencies decreases, the complexity of the algorithm needed to represent the numerical system decreases. The newly constructed modularized DSM represented by the three divisions of boundary parameters, outer optimization parameters, and continuous or integer optimization parameters can be used as a tool for possible optimization formulations.

### 4.5.1 Utilization of DSM For Optimization Architecture

The development of the DSM representing the well design system provided a visual representation of the problem variables and their interconnectivity. An analysis of the problem using the principle of two down one up to develop a modular decomposition, a system modularization for use in algorithm development. In Chapter 5, the generalizations of the Level 1 decomposition from Figure 4-4 will be used to generate a reasonable architecture for a numerical optimization formulation.

# Chapter 5

# Numerical Well Design Architecture Analysis

This chapter evaluates the modeling methodologies for design space exploration of a well design. Developing a numerical optimization model for well design requires the creation of numerical models using decades of information from best practices, physical principles, and operational limitations to derive reasonable solutions. An analytical system architecture is proposed for optimal well design through an analysis of the DSM constructed in Chapter 4. The objective of the numerical optimization is to provide a set of Pareto optimal well designs derived from a comprehensive exploration of the well design space by developing a tractable numerical formulation of the design system using a hybrid optimization algorithm.

Numerical simulations using Genetic Algorithms enable the complex development of continuous, discrete, discontinuous design spaces. In well design, multiple architectures can be explored by modifying the number of casing strings or hole sections within the well construction parameters. The change in hole sections generates a new set of decision variables within the optimization framework. For this study, we will set the number of hole sections available for evaluation to a reasonable maximum for the well boundary conditions. For a single architecture, multi-objective function system with mixed continuous, integer, and discrete variables, evolutionary algorithms (EA) can search the feasible solution space for Pareto optimal solutions in one optimization run [21].

## 5.1 Well Design as a Numerical Method

The development of any model is a numerical representation of a physical system [47]. The well design development process is represented as an abstraction throughout the development phases of the project design. This section will explore the development of an early phase well development plan using an optimization formulation. In the early design phases, the well design is generally treated as a cost object, and receives minimal input on detailed design variables. High fidelity rock mechanics, fluid design, and ROP dynamics are developed in the late design phases to reduce the operational well construction risk. During the drilling phase of the well construction process, the goal is to have zero deviations from the planned well design, with the exception of tuning parameters to manage geological and lithological uncertainties. The best operations personnel are inherently those who can quickly analyze the system interactions and develop logical solutions based on physical principles and industry best practices.

### 5.1.1 Drilling Process and Source of Inputs

Within the subsurface exploration and production discipline, the construction of the conduit used to access fluids beneath the surface, generally requires the construction of a well. The depth, hazards, cost, and consequence of failure determine the value and rigor of engineering for well design. Drilling engineers are given a list of inputs ranging from locations to available equipment and cost. Appendix A details the design inputs and how they relate to the numerical design functionality.

Drilling Engineers receive a package of information generated by an asset owner, which defines the well objectives, geologic or geospatial targets, and cost limitations. The asset owner receives information from other disciplines for reservoir characterization, geological interpretation, and production estimation to generate the well constraints and field development plan. Figure 1-2 highlights the complexities of the disciplinary interactions within the development of hydrocarbons. In Chapter 2, a software package, PETEX, is described as a tool used to assist in field optimization and planning. This software does not involve the optimization or design attributes of the well that must be drilled, so the drilling engineering team must use the provided constraints to generate the well design. In a numerical model of a drilling-specific optimization process, the input information or boundary parameters are static parameters. The design variables must conform to those parameters while making knowledgeable tradeoffs for optimal design.

### 5.1.2 Requirements and Assumptions

The diversity of well design solutions is a function of the interpretation of government regulations, adherence to minimum recommended API specifications, and the risk profile of the operating organization. Integration of complex interactions of social impact, uncertainties in the regulatory environment, and location-dependent political risks will not be in scope for developing the numerical method. Sheng and Guan developed a probabilistic numerical risk ranking process that improves the numerical evaluation of drilling risk with simplified rankings of safe, transitional, and dangerous regions based on the probability of failure [54]. Comprehensive development of well design risk is subjective and remains operator and location dependent. The operator of the numerical evaluation must use an internal risk register that has been converted into a numerical model for proper drilling and well design risk evaluation.

The numerical evaluation assumes that the input information are static parameters and there will be a constrained set of casing, drill pipe, drilling rigs, and drilling fluid available for use. This limitation of options intentionally reduces the design space options and is a phenomenon realized by all drilling engineers during the design process. Design options are essential when considering tradeoffs not included in the numerical model, mainly where the bounding parameters are highly uncertain.

### 5.1.3 Design System Constraints

All well designs must meet an acceptable determination of well construction duration, total well cost, well objectives, and risk of operational failures. The iron triangle constraints concept, developed by Barnes [8], and later expounded by several others to include more project constraints, applies to developing the well design system and drives the solution space to make tradeoffs for design quality. A commonly referenced tradeoff are those made for shallow water offshore wells and deepwater offshore wells. The rate of production, cost of failure, and risk of catastrophic consequences modify the constraints for deepwater wells, and allow cost to increase at the expense of well integrity failures. For shallow water wells, the cost of well integrity failures over the life and during the well construction process of the well is much lower and can withstand some design risks. The well development solution must fit within the design boundaries defined by the input parameters and boundary interfaces. Any numerical solution developed for the design and construction of a well must quantitatively evaluate the ilities within the design space, which currently exist as best practices, rules of thumb, and corporate recommended practices. Operational best practices such as changes in mud density, base fluid, and chemistry are significant to operational feasibility but can be challenging to implement into a numerical simulation.

### 5.1.4 Early Phase Well Design Output

The use of an optimization process in a new area or reservoir target serves the most advantage for drilling engineers, as the initial well design is a knowledge-based assessment of the best option. The best option is a conservative estimation of an existing, well-understood well architecture that is iteratively improved as more information on the performance of the well architecture is generated. Ullah et al. describes the rate of improvement as a learning curve. The learning curve approaches some subjective technical limit as the feedback of new knowledge is implemented into the well engineering process [61]. Utilizing an optimization process in the early well design process would provide solutions that are valid options for implementation into a well design.

Developing a numerical optimization model in the well engineering process will improve the initial cost estimates, initial well construction designs, and the existing well architectures. Shokry and Elgibaly's removal of a casing section saved more than 25% of drilling time and cost using a numerical approach to optimal design [56]. Integration of ilities is a challenging but necessary requirement to move past a minimum viable product numerical design strategy. Considerations for non-standard equipment and processes, such as managed pressure drilling or foam cementing, produces much of the time and cost improvements in current well designs. New technology and detailed analysis on formation evaluation, specialized equipment, and field experience can affect the numerical tractability, but serves as a barrier to entry into the engineering process.

The design architecture is the most critical component for a detailed analysis of a well design. Casing setting depths, casing string dimensions and strengths, bit and hole sizes, and well trajectory are major architectural decisions that drive the design possibilities in a well. The MBSE system described by Szemat-Vielma et al. requires the input of a well design, and the integrated system verifies the design and can run higher fidelity analysis on the selected design [60]. The drilling engineer can perform a detailed well design exploration by coupling a low fidelity numerical optimization process with a higher fidelity MBSE formulation through the supply of optimal, feasible solutions. The process design integration would enhance the drilling engineering workflow's time, efficiency, and quality.

## 5.2 Optimization Architectures for Well Design

The selection of an optimization architecture for well design must be able to manage the interdependencies shown in the well design DSM, Figure 4-4. The optimization of feedback mechanisms or causal effects are strengths of Multi-Disciplinary Design optimization. Stochastic optimization methods can utilize the random search methods to find and search local minima to iterate or progress toward optimal solutions and eliminate numerical feedback within the mathematical model. This section will

**Figure 5-1:** Well Design Engineering Inputs

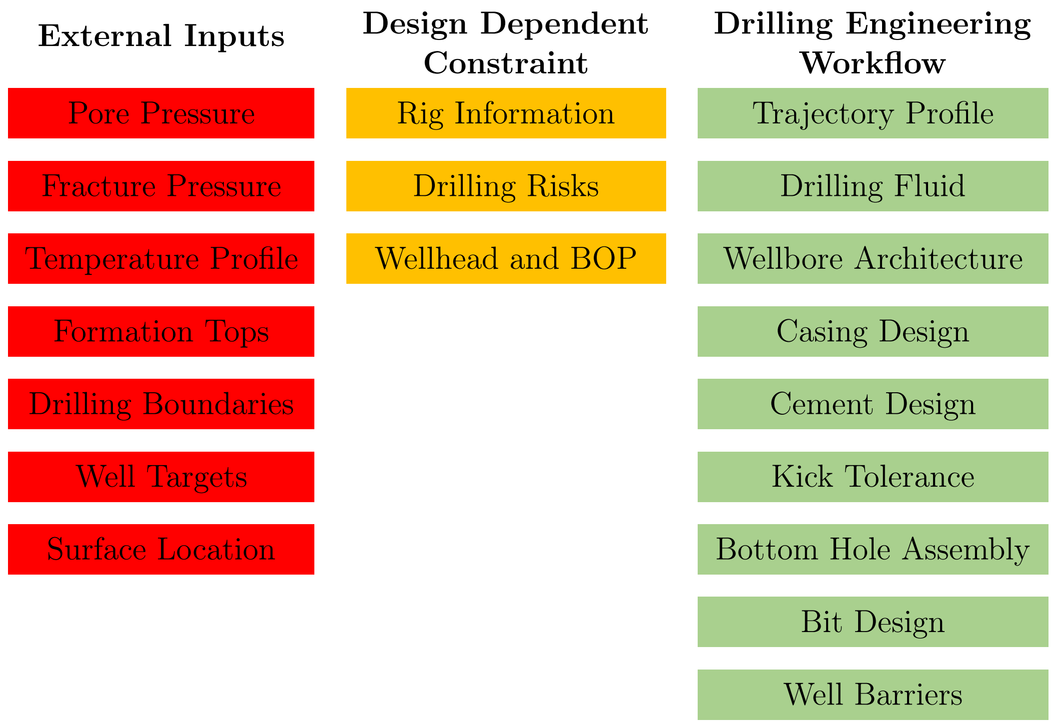



Image adapted from [60]

explore the feasibility of using MDO and the Evolutionary Algorithms as a subset of stochastic optimization for use in the numerical well design optimization formulation.

### 5.2.1 Utilization of Evolutionary Algorithms

Evolutionary Algorithms use the principles of biological processes to develop optimization methods. Many of these techniques use stochastic and probabilistic methods to make selections and mutations to find good potential solutions [37]. Many proposed solutions are benchmarked with the Non-Sorting Genetic Algorithm (NSGA-II) [21] for a comparison using standardized metrics for diversity, convergence, and Pareto optimality. The goal of the evolutionary algorithms in multi-objective optimization of non-linear, non-convex, discrete, continuous design spaces is to find the local minima of the design space solutions efficiently. No known algorithms exist to guarantee the global minima in non-linear optimization, with the exception of theoretical quantum computing. Therefore most algorithms for complex optimization formulations efficiently explore local minima for the best known solution.

**Figure 5-2:** Basic Evolutionary Algorithm

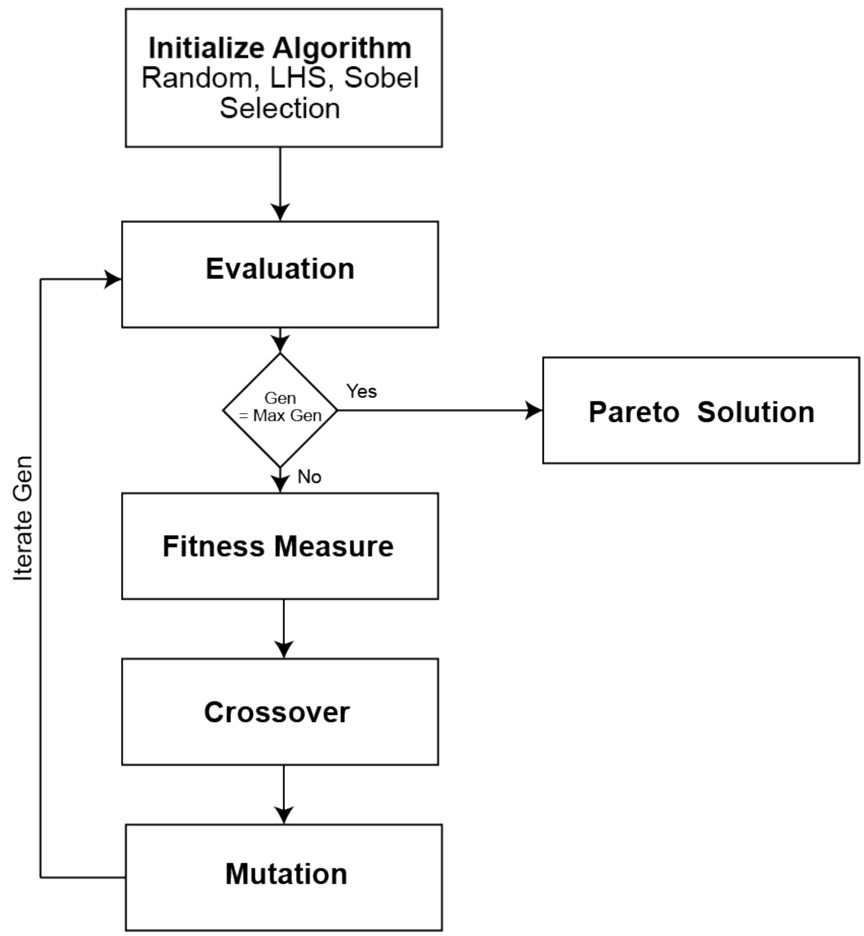



Image adapted from [57]

The initialization of an Evolutionary Algorithm generates a sample or initial population as the first iteration. The initial population is random selection of the permutation matrix or design space, constrained to an upper and lower limit. More advanced methods of sample set generation of evenly spaced data points is highlighted in Figure 3-2. "Healthy populations are important for discovering good solutions" [57]. The initial population set will evolve with each generation or iteration of the algorithm.

Following the selection of a population, evolutionary algorithms use some form of evaluation to determine if a solution is a good evolution. The good solutions, or those with the highest fitness, are used to generate more offspring, which share part of the parent population. Note that evolutionary algorithms use the principle of fitness, mating, and offspring to describe the natural evolution of organisms to formulate the algorithm. In well design, these changes or exchanges in design variables create possibilities for random variable selections that may completely change the architecture, which describes diversity. Diversity is a variation within the numerical optimization objective function and design variables.

### 5.2.2 Multi-Disciplinary Optimization

Based on the analysis of the DSM in Figure 4-4, optimizing each discipline with independent decoupled gradient optimization would be inferior and would not provide solutions within the optimal disciplines. The utilization of a full MDO, All-at-once gradient-based optimization formulation is nearly impossible based on the number of discrete variables in the design space. Due to equipment supply and standards constraints, the relaxation of all discrete variables would introduce extreme uncertainty, making the solution unrealistic. Suppose the DSM is interpreted as having an outer function that manages the discrete variables. In that case, MDO is a good solution to manage the coupled design parameters for optimal well design.

Design optimization using MDO has been proven to be effective in physics-based aviation applications and is used extensively in improving designs associated with mechanical structural analysis coupled with fluid mechanics [44] [53]. Sgueglia et al. compared the computational expense of generating a Pareto set of solutions using a sensitivity approach to Multi-Objective Optimization with an NSGA-II model. The experiment found that although the NSGA-II model generated more solutions on the Pareto, the MDO model generated a good set of Pareto solutions in less time. Utilization of parallel computing could improve the rate of convergence for Multi-Objective MDO, and would be a viable option for evaluation.

### 5.2.3 Design of Experiment

The use of DOE as a design optimization strategy is the most robust method for finding and evaluating feasible solutions but is the least efficient in exploring solutions to improve the Pareto front. The evaluation of a complex solution using a DOE approach decreases in effectiveness as the design and solution space increases [25]. Using a design space exploration algorithm based on the NSGA-II framework will generate more Pareto optimal solutions as the number of variables and complexity of the design space increases. The random, or stochastic nature of DOE formulations, is a simple approach to constrained optimization, but can be computationally inefficient when continuous variables are present in the formulation.

### 5.2.4 Challenges for an Out of the Box Algorithm

The principle of the "No Free Lunch Theorem" highlights that optimization algorithms are not one size fits all, and for any optimization, it is difficult to determine the best solution [66]. Determining a single best algorithmic formulation is a function of the problem development, scale, computational capabilities, and design objectives. For optimization of the entire well design space, managing the constraints and relationships within the design space are critical considerations for an algorithm. Monolithic algorithms for a complex optimization algorithm in a discrete, integer, continuous, non-linear, and non-convex design space is a challenging problem. Due to the discontinuous design space, gradient-based algorithms in monolithic systems are infeasible options. The benefit of MDO is the distinction of disciplines allows the separation of disciplines, which can help eliminate the effects of discontinuity in the design space. Stochastic optimization is an attractive alternative and features many benefits that could lead to a set of good outputs for well design. Suppose the well architecture is optimized using stochastic optimization on a well that will drill four sections. In that case, the resulting design space has $19^{17}$ potential combinations of solutions. Even with advanced evolutionary algorithms, exploring a very small percentage of this design space does not yield promising logic.

Management of the discrete design space for the casing dimensions using standard API pipe [35] yields 21 and 121 casing ODs and IDs, respectfully. The combination of the discrete values for the casing design problem will require the use of a conditional selection algorithm to limit the evaluation of infeasible design options. The standardized casing IDs are provided as ranges, within a specified tolerance, and could be relaxed to a continuous design variable within optimization formulations. Considering the standard best practices shown in Figure 5-3, which represents a rule of thumb selection for Casing OD and bit diameters, the casing design problem can be considered a minimum cost flow problem, where the objective is to minimize an objective associated with each respective casing and bit node. The network representation in Figure 5-3 does not capture the use of the various constraints binding the relationship but gives reliable and consistent solutions that are well accepted throughout the industry.

**Figure 5-3:** Casing and Bit Size Selection Chart

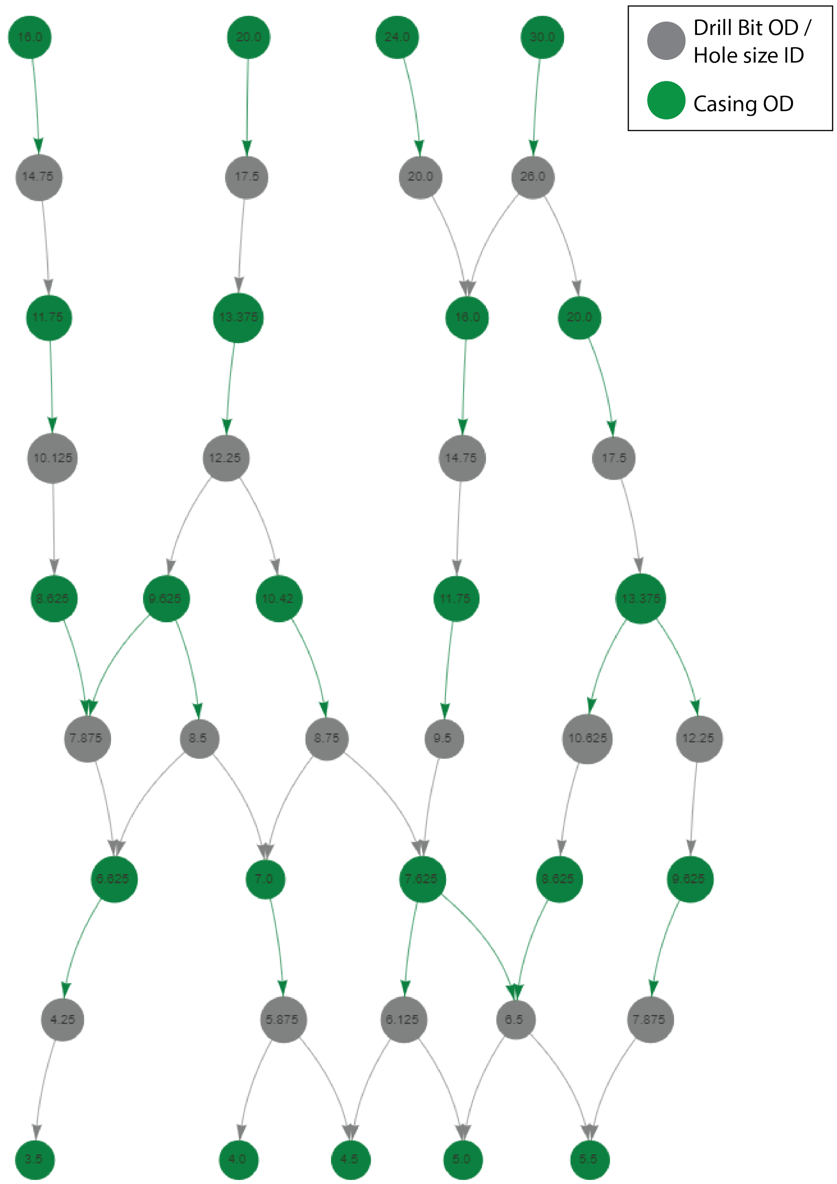



Image adapted from [7]

**Note:** *The casing and bit OD selection is a conservative estimate and does not comprehensively demonstrate the feasibility of all solutions.*

## 5.3 Research Methods

The optimization algorithm will have a population of at least 2500 members, which indicates 2500 distinct designs will be evaluated for 120 generations or iterations. There will be a total of 5 casing combinations for a three string design, and 4 combinations for a four string design generated at random intervals for consideration. Each casing architecture generated will evaluate 175,000 potential design options using the NSGA-II and NSGA-III Genetic Algorithms to determine a set of Pareto optimal solutions. The formulations are evaluated for the quality of solutions, rate of improvement throughout the algorithm, and a subset of the genetic formulation will measure the design space diversity throughout the iterations. The use of diversity and rate of convergence are used in various forms for algorithm comparison and effectiveness.

### 5.3.1 Well Design Validation

Well design validation will be performed using a visual to come in well designed and construction. the casing point or plotted with the mud density and estimated changes in operational mode density to ensure the casing architecture fit within the geological envelope. for the purpose of this research, one Pareto optimal design from the three section optimization, and one four section Pareto optimal design will be published within Chapter 7. The valuation of feasibility for all solutions is not necessary if it is understood that the constraints in the evolutionary algorithm hold true.

### 5.3.2 Design Feasibility

The important feature for the efficiency of an evolutionary algorithm is to measure the rate of feasible solutions evaluated through each generation. Feasibility of the designs within the optimization algorithm are defined as the set of design variables that meet all constraints defined within the optimization formulation. As the algorithm evolves the number of feasible solutions per generation should increase through the combination of the feasible population crossover and mutation performed by the genetic operator. An algorithm that does not show and increase infeasible solutions shall be considered a sub-optimal objective process. An algorithm that shows an increasing to plateauing solution will be further evaluated for pareto improvement and convergence. Li notes that an algorithm that forces populations into the feasible region have a higher propensity to land in a feasible region, and and not explore additional optimality within the design space or only evaluate feasible regions with high concentrations of solutions [41]. Therefore, a measure of solution diversity and convergence must be used in congruence with evaluation of feasibility.

### 5.3.3 Design Space Diversity

The well design space is a discontinuous optimization problem, with many design variables and constraints. The measurement of design space diversity helps provide confidence in the algorithms ability to search many local minima for the best solution. The factor used to approximately measure design space diversity, $\mathbf{D}_k$, for each design space variable in the total design space population, $\mathbf{X}$. Within each generation the approximation of the diversity, $d_k$, for each design variable,$x_k$ is described in the equation below [48]:

$$d_k = \sqrt{\frac{1}{l} \cdot \sum_{i=1}^{l} \left( \frac{c_k - x_i}{b_k - a_k} \right)^2} \qquad \forall\ k \in \mathbf{X}$$

$$\begin{aligned} &where: \\ &\quad k = \text{a design variable in the population d} \\ &\quad c_k = \text{centroid for k} \\ &\quad b_k = \text{minimum of variable k} \\ &\quad a_k = \text{maximum of variable k} \end{aligned}$$

### 5.3.4 Pareto Analysis

The Pareto front are the non-dominated data points of the solution set. The theory of non-dominated solutions are data points in a 2-D solution space, that have no solutions with an objective function $f_1(i)$ less than $f_1(0)$ and $f_1(i)$ less than $f_2(0)$. The definition of Pareto optimality means you can simply draw a line to each Pareto optimal point, and will not intersect any other solutions. In a numerical computation, the method developed for this research uses an iterative slope approach to find the next Pareto optimal point.

---

**Algorithm 1** Computation of the Non-Dominated Pareto Front

---

**Require:** *Sort Solution Set*, $S$, *in Ascending Order*
  $P(0) \leftarrow S(0)$
  $R \leftarrow rows\ in\ S$
  $r \leftarrow 1$
  $p \leftarrow P(0)$
  **while** $r \leq R$ **do**
    $s \leftarrow S(r)$
    **if** $s_1 > p_1 and s_2 < p_2$ **then**
      $dom \leftarrow False$
      $f(s_1) \leftarrow linear\ curve\ for\ p \rightarrow s,\ where\ f(s_1) = s_2$
      $i \leftarrow r$
      **while** $dom = False$ **do**
        **if** $S(i)_2 > p_2\ or\ S(i)_2 > s_2$ **then**
          $i = i + 1$
        **else if** $f(S(i)_1) < S(i)_2\ and\ S(i)_1 > s_1$ **then**
          $dom \leftarrow True$
        **end if**
      **end while**
      **if** $dom = False$ **then**
        $s \in P$
        $p \leftarrow s$
      **end if**
    **end if**
    $r \leftarrow r + 1$
  **end while**

---

### 5.3.5 Optimization Convergence

Convergence of the well design formulation to a known Pareto solution can be performed empirically using a Euclidean distance formulation. A measure of convergence can be generated using the average Euclidean distance of the parental optimal solutions to the solution Pareto. The solution pareto is the best Pareto set generated by all design architectures. There will be no solutions that have a pareto line better than the optimal solution Pareto. From this, a modified Inverse Generational Distance (IGD) metric will be used to measure Pareto improvement through each generation. Deb and Jain define IGD as [22]:

$$IGD(\mathbf{A}, \mathbf{Z_{eff}}) = \frac{1}{\mid \mathbf{Z_{eff}} \mid} \cdot \sum_{i=1}^{|\mathbf{Z_{eff}}|} \min_{j=1}^{|A|} \parallel z_i - a_j \parallel_2$$

where $\mathbf{Z}$ is the optimal Pareto and $\mathbf{A}$ is the generational Pareto front. The function uses the minimum distance of a non-dominated solution to the nearest optimal pareto solution. The IGD measure is a scalar comparison of all solutions to the best pareto solutions, and provides a measure of improvement through the generations. As the generations converge to the solution optimal Pareto, the IGD metric will approach zero. The IGD measure will use the solution Non-dominated points as Z, and each architecture will be evaluated individually for A. The major advantage for this method is that it does not need to be subjectively scaled, and it is able to compare each generated solution architecture with a unifying metric.

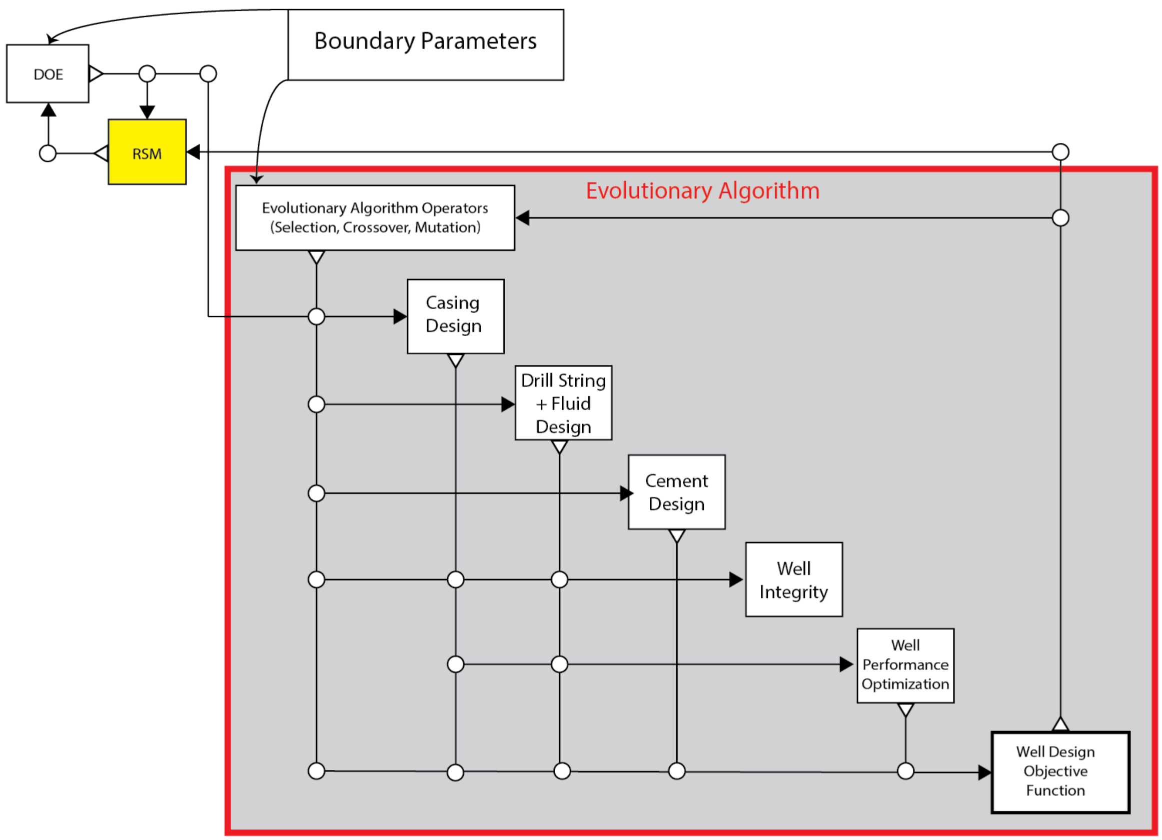
## 5.4 Proposed Well Optimization Architecture

The well optimization formulation should develop a small set of solutions that can be evaluated in a high fidelity model or engineering process for ultimate implementation into the well construction process. This research proposes the development of a hybrid Evolutionary Algorithm, developed using the Pymoo library [10], integrated into a Design of Experiment. The design of experiment algorithm generates possible feasible architectures of casing and trajectory design, while the Evolutionary

Algorithm works to find Pareto feasible solutions. The computed solutions for each architecture generation will be sorted, and a Pareto optimal design curve is generated. This method is a generalization of the architectural exploration of an infinite design space developed by Frank et al. [25].

Developing the Pareto optimal solution set using an Evolutionary Algorithm will be inefficient. However, integration of the Evolutionary Algorithm with the existing representation of well design is an advantage to the optimization framework. An exploration of the NSGA-II and NSGA-III algorithms' solution exploration efficiency, population diversity, and rate of convergence or improving solutions will be performed in Chapter 7. The proposed architecture in Figure 5-4 uses the outer algorithm to generate the Casing OD dimensions, with each casing string following a set of generalized design rules. The casing ID is relaxed for allowance into the evolutionary algorithm evaluation. If Figure 4-4 is compared with the proposed architecture in Figure 5-4, the bottom left dependency structure is maintained, but all upward dependency is handled using the evolutionary operator. The evolutionary measure of fitness, which is proportional to the objective function, is used to generate new solutions and improve upon the existing Pareto optimality.

**Figure 5-4:** Proposed Architecture for Well Design Optimization



# Chapter 6

# Numerical Well Optimization

## 6.1 Numerical Well Design Architecture

The formulation of a comprehensive well optimization process is a multi-discipline problem, that as shown in Figure 4-4, has significant interdependencies that must be managed within a numerical formulation. The proposed algorithm in Figure 5-4 manages the feedback dependencies throughout the genetic algorithm operators. This section will discuss the formulation of a numerical well design solution that is designed based on the data presented in Chapter 4, and optimization algorithms selected in Chapter 5. The discussion of the optimization formulation within section 1 is based on using a detailed representation to develop well design options. Section 2 will discuss the algorithm as developed for the purpose of this research, and uses a minimum viable constraint design approach to evaluate the feasiblity of using a genetic algorithm for optimization.

### 6.1.1 Input Parameters

The initialization of the well design optimization requires the well design objectives, fixed tables, and parameters to be defined as input parameters. Table 6.1 lists the boundary parameters for the well design optimization formulation. Independent of the optimization algorithm, the requirements for the well design process are constrained

**Table 6.1:** Input Parameters

| | |
|---|---|
| Lithology | Formation Top Depth |
| Formation Temperature Profile | Fluid Composition |
| Well Target Total Vertical Depth | Well Geospatial Targets |
| Surface Location | Life of Well |
| Available Drill Pipe | Available Mud Systems |
| Available Rig Type | Available Casing Type |

by the boundary parameters. The bounding disciplines provide the boundary parameters as highlighted in Figure 1-2.

### 6.1.2 Decision Variables

The well optimization process aims to select a combination of decision variables, or sets of numbers or indices that are changed to represent distinct options within a design space. Changes to the decision variables ultimately affect the design constraints, feasibility, and objective functions. It is worth noting that this list is not comprehensive of all well design parameters. Implementation of technology options such as bottom hole assembly components, logging technologies to reduce uncertainty, and surface equipment such as managed pressure drilling, will increase the size of the design space. Careful consideration should be taken when introducing additional decision variables. A minimum feasible design approach was taken for this research and does not include the technology-specific variables. As the number of decision variables increases, there is a non-linear relationship between computational expense and complexity vs. the number of decision variables for optimization. For well design optimization, the 33 decision variables listed in Table 6.2 are evaluated for each well section. Therefore a three-section well, which is a seemingly basic well design, could have more than 99 design variables. Intelligent or adaptive design space exploration is critical to solution convergence. The relationships for the Casing Dimensions OD are generated in a random generator to limit the number of infeasible solutions explored. This strategy also allows the Genetic Operator to use the fitness of existing solutions

**Table 6.2:** Well Optimization Decision Variables

| | | |
|---|---|---|
| Casing | Casing Top Measured Depth | Bit Type |
| Casing OD | Mud Density | Bit Total Flow Area |
| Casing ID | Drill Pipe ID | Fluid Rheology |
| Connection Type Casing | Drill Pipe OD | Lead Cement Height |
| Mud Base Fluid | Drill Pipe Tensile Strength | Tail Cement Density |
| Bottom Hole Assembly Directional Class | Heavy Weight Drill Pipe OD | Lead Cement Density |
| Well Inclination | Drill Collar OD | Tail Cement Height |
| Well Azimuth | Heavy Weight Drill Pipe Length | Spacer Density |
| Kick Off Point | Drill Collar Length | Spacer Height |
| Casing Bottom Measured Depth | Bit Diameter | Casing Connection OD |
| Casing Material | Mud Flow Rate | Casing Yield Strength |

to generate and improve upon the existing feasible Pareto front solutions. In Chapter 7 this research explores the effectiveness of the Genetic Algorithm and determines if the convergence rate can lead to efficient design exploration.

### 6.1.3 Design Constraints

The well design constraints are physical, numerical, and logical constraints on the well design formulation. The constraints for well optimization are used to set limits and thresholds for fluid mechanics, equipment limitations, formation integrity limits, directional drilling limitations, and metallurgical bounds for casing and drill pipe. All design constraints must hold true for a well design to be considered feasible.

Optimizing with a genetic algorithm requires the explicit selection, crossover, and mutation of design variable combinations that approach the boundary conditions of the well design. Genetic algorithms rely on randomness to reach the best solution in a fixed or set number of generations or iterations. Li et al. describe the management of constraints by evolutionary algorithms in three classes [41]:

1. Preservation of Feasible Solutions: The feasible solutions are prioritized and kept for future iterations. This can limit the exploration of the design space if the selection and mutation areas become biased to a feasible region.

2. Convergence to Feasibility Tradeoff: The feasible solutions are used to drive convergence to the Pareto front, while the infeasible solutions are driven to feasibility.

3. Solution Repair: Optimization of the solution to the Pareto Front is given a lower priority than repairing infeasible solutions. As the infeasible solutions enter the feasible region, the thought is that the boundary of the infeasible to the feasible region will contain optimal solutions.

There is ongoing research to manage complex constraints, which involve more than upper and lower limits of design variables. The parameters in Table 6.3 can be considered complex constraints due to the multi-variant interactions described in the System DSM, Figure 4-4. The generalized process of random crossover and mutation by the NSGA-II and NSGA-III formulations indicates that the proposed formulation uses class 1, Preservation of Feasible Solutions, which can lead to insufficient design space exploration.

**Table 6.3:** Well Optimization Constraint Variables

| | | |
|---|---|---|
| Casing Regulation | Available Mud Systems | Maximum Allowable Dogleg Severity |
| Cement Regulation | Available Rig Type | Maximum Allowable Surface Pressure |
| Disposal Regulation | Available Casing Type | Kick Intensity |
| Emissions Regulation | Mud Capacity | Kick Tolerance |
| Rig Regulation | Disposal Fluid Capacity | Surface Pump Pressure |
| Pore Pressure | Base Fluid Capacity | Maximum Weight on Bit |
| Fracture Gradient | Rig Pump Horsepower | Drill Pipe Overpull Capacity |
| Geological Hazard | Hook load | Drill Pipe Static Load Evaluation |
| Wellhead Pressure Rating | Blow Out Preventer Pressure Rating | Hole Cleaning Quality |
| Minimum Production Casing Inner Diameter | Well Dogleg Severity | Casing Load Cases |
| Available Drill Pipe | | |

## 6.2 Well Design Objectives

The objective of the numerical well design process is a multi-objective optimization formulation, summarized into three objective functions for total project duration, well cost, and design and operational risk. Table 6.4 details the factors of each well design objective function. Pareto front optimization with more than two objective functions can be solved more efficiently using the NSGA-III formulation than the NSGA-II formulation [22]. Although the use of three objectives will not be evaluated in this research, it is essential to note that NSGA-III is considered to significantly improve problems with more than two objective functions. When using the average weighted sum method to manage multiple objectives, each sub-optimization parameter must be scaled and weighted for use in the shared objective parameter. The weighting and scaling process is a subjective determination of which factors are most important but could serve as a helpful tool for the drilling engineers' input or preference for valuable solution searches. The use of the average weighted sum formulation for the Project

Table 6.4: Well Design Objectives

| **Project Duration** | **Project Cost** | **Risk** |
|---|---|---|
| Maximize ROP | Minimize Casing Volume | Well Control |
| Maximize Drill Pipe and Casing Tripping Speed | Minimize Mud Cost | Safety Factors |
| Minimize the Number of Hole Sections | Minimize Cementing Cost | Uncertainty |
| | Minimize the Energy Input for Drilling | |

Duration can be described as:

$$
\begin{aligned}
Project\ Duration = \quad & \lambda_1 \cdot Scaled\ ROP \\
& + \lambda_2 \cdot Pipe\ Running\ Time\ Scaled \\
& + \lambda_3 \cdot Casing\ Running\ Time\ Scaled \\
Where: & \\
& \lambda_1 + \lambda_2 + \lambda_3 = 1
\end{aligned}
$$

The objective functions must be architecturally agnostic, which requires the normalization of design vector and parameters within the design space. For the scope of this research, the objectives evaluated are limited to simplified normalization of factors such as cost. The rate of penetration is challenging to estimate and is only optimized in a predictive form while drilling. The information and insights generated while drilling is used after wells have been drilled, but the information in new fields is not available. There are geological and dynamic uncertainties in bit wear, geology, lithology, and drilling parameters, which have significant impacts on the drilling performance [12]. Minimizing the project cost is, in most cases, directly correlated to the project duration but inversely correlated with the project risk. The value of each respective objective is valuable when considering options for an optimal well design.

## 6.3 Well Design Optimization Formulation

The exact formulation of an optimal well design can be described in a generalized format using the objectives, design variables, and constraints as abstractions to the mathematical formulation. The true numerical representation of an optimal well design can involve implementing domain-specific technologies and methods, integrating design approximations, and reducing design space by identifying suitable equipment options.

The objective of the well design process is to minimize the project duration, project cost, well construction, and operational risk. Well architecture is defined as a fixed design for the number of hole sections, directional profile, and casing ODs. A genetic algorithm is utilized for each well architecture to find a set of Pareto front solutions to the well design. The well design vector feasible region must ensure the following constraints are fulfilled to qualify as a feasible solution within the design space:

- Well Barrier Design
- Casing Architecture
- Casing and Tubing Integrity
- Fluid Design
- Geological Control and Stability
- Drill String Design
- Directional and Trajectory Design
- Cementing Integrity
- Drilling Assembly and Bit Design

The sub-optimization process Pareto optimal solutions generated from the Genetic Algorithm are evaluated as a set of solutions to the well architecture and determine an overall Pareto front. As shown in Figure 5-4, a Response Surface Model (RSM) will be developed and used for well architecture approximation. The approximations can be used to select a small subset of well architectures that have estimated solutions near an approximate Pareto front. This will be a significant advantage to the random selection process used in this research. The RSM will be developed, trained, and deployed on a program level, increasing the likelihood of finding solutions at or near the system Pareto front. However, this research will not explore the development of the RSM.

## 6.4 Algorithm Development for Analysis

The algorithm developed for this research uses a random conditional selection process to generate a possibly viable set of casing OD configurations, which initializes the stochastic algorithms under evaluation. A subset of decision variables are selected to test the feasibility of using the NSGA-II and NSGA-III optimization algorithms. The generated populations will measure the quality of feasible solutions and the diversity of the design space as the algorithm progresses through each generation.

Innovative methods for optimizing a complex, constrained system requires a strategic formulation of the system, represented as a numerical model. The development of the system model generated within this analysis highlights the interdependencies in the functional disciplines of well design. The analysis of the classical Genetic Algorithm, NSGA-II [21] and NSGA-III [22] will explore avenues for future integration of numerical optimization in well design.

The approach for this research uses a subset of all design variables and constraints to explore the development of a constrained evolutionary algorithm for well design optimization. The number of design variables generated by the algorithm is dependent on the number of sections defined within the random architecture generation of the outer algorithm. The proposed well design will be a vertical well, and will not include the development and optimization of a directional profile. Table 6.5 describes the remaining boundary conditions and assumptions. These conditions are used as input variables to the optimization algorithms and remain constant throughout the analysis.

**Table 6.5:** Well Design Boundary Parameters and Assumptions

| Well Design Boundary Parameters | Boundary Condition | Resulting Action |
|---|---|---|
| **Directional Profile** | Vertical Well Trajectory | Considerations for deviated wells are not applicable. Indicates the surface location is directly above the target location. |
| **Total Vertical Depth** | 8,720 ft | The total well or target depth is set |
| **Pore Pressure and Fracture Gradient** | Pore Pressure and Fracture Gradient | Formation pressure and integrity limits |
| **Drilling Rig Max Hookload Capacity** | 800,000 lbs | Maximum casing load that can be handled by the drilling rig |
| **Maximum Hole Volume** | 11,800 bbls | Due to mud system constraints, the maximum well fluid volume is defined |
| **Maximum Number of Hole Sections** | 4 | The maximum number of distinct drilling intervals is set |
| **Minimum Production Casing ID** | 4 inches | Value set by production engineers as the minimum ID limit to the well construction |
| **Regulatory** | Surface Casing must be set Below 800' TVD | Regulatory requirement that the surface casing is set in the first structurally competent interval. |

### 6.4.1 Selection of Decision Variables

The subset of decision variables used in this research are primarily functions of architectural feasibility and basic casing point selection. The decision variables generalize the functionality of the Genetic Algorithm as a strategy for a constrained well optimization framework. A three-casing string well design has 57 design variables, while a four-string well has 76 design variables. The subset of variables is approximately two-thirds of the design variables identified in Table 6.2. Table 6.6 summarizes the decision variables used for each casing section for the well design optimization. The major modification to the design variables is the relaxation of the casing ID or wall thickness as a continuous variable. The wall thickness range is defined as the minimum and maximum wall thicknesses defined in the API TR 5CE Table K1 [35]. The relaxation of the casing ID allows the optimization process to select an optimal casing wall thickness without restricting the algorithm to a discrete OD and ID combination of the casing string sizes. Actual casing wall thicknesses will be evaluated using stochastic or robust design methods to determine the feasibility of each casing string for a range of casing thicknesses expected or through a higher fidelity model. Casing design standards have tolerance allowances for changes or variability in pipe wall thickness, and all casing typically meet minimum tolerance values defined within the API standards. Therefore the robust evaluation will help understand the impact of the uncertainty.

**Table 6.6:** Algorithm Decision Variables

| **Design Variable** | **Variable Type** | **Range** |
|---|---|---|
| OD | Discrete | |
| Casing Wall Thickness | Continuous | [0.2,0.8] |
| Casing Yield Strength | Discrete | [0,5] |
| Casing Shoe Depth | Discrete | [1,# of formations] |
| Drill Pipe OD | Discrete | [1,4] |
| Drill Pipe ID | Discrete | [1,3] |
| Drill Collar OD | Discrete | [1,4] |
| Drill Collar ID | Discrete | [1,2] |
| Heavy Weight Drill Pipe Length | Integer | [0,1000] |
| Drill Collar Length | Integer | [100,500] |
| Bit Diameter | Integer | [5,15] |
| 300 RPM Viscocity | Integer | [10,35 |
| 600 RPM Viscosity | Integer | [20,45] |
| Minimum Annular Flow Rate | Integer | [80,250] |
| Mud Density | Continuous | [8.6,13.5] |

### 6.4.2 Constraints

The design constraints for formulating the optimization algorithm are to develop valid architectures that meet the basic requirements of well design. With the random nature of stochastic optimization decision vector selection, the feasibility of the design architectures is managed using constraints within the optimization formulation. The formulation used for this research does not encompass all possible constraints; therefore, the design results may not be feasible when analyzed in a higher fidelity model.

**Model Constraints:**

- The Surface casing must be set within 1750' of the surface, which in this specific case, limits the surface casing to one setting depth. This is a common practice for freshwater aquifer protection.
- The casing setting depth for each section must be at least 500' difference, the depth order of the casing strings must go from shallowest to deepest.
- The mud density must be above the Pore Pressure and below the frac gradient by a 0.5 pound per gallon (ppg) generalized safety factor for each open hole section.
- The casing string must not exceed 800 klbs, which is the drilling rig hookload limitation for a small land-based drilling rig.
- The casing integrity must withstand a casing test, a potential worst-case gas kick, a loss of fluid while drilling, and the production string must withstand a fully evacuated string with gas.
- The kick tolerance of the drilling design must be at least 0.75 ppg.
- The weight on bit (WOB) for the drill string drill collar and heavy weight drill pipe buoyed weight must exceed 500 $lbs/in^2$.
- The drill pipe and bit must be less than the drift diameter of the casing string
- The ECD may not exceed the fracture gradient for a minimum annulus flow rate defined within the decision vector.

- The rheological factors for the Power Law formulation for a given fluid must be a reasonable ratio for a non-Newtonian fluid.

The optimization constraints are a good set of design limitations for testing the functionality of the optimization formulation. Additional constraints for cementing, drilling pump rate limitations, surge and swab determinations, and rate of penetration estimation are critical items that should be considered in future research.

### 6.4.3 Objective Functions

With the limited set of provided information, it is important to highlight and utilize objectives that are constrained within the design space. One of the most significant cost measures for drilling is the size and depth of the casing strings run into the well. Therefore, one objective function minimizes the volume of casing and the total open hole volume which directly correlates with total well cost. The second objective function minimizes the difference in mud density and pore pressure with an additional penalty factor that includes the apparent viscosity, using Moore's Correlation [12] multiplied by the minimum annulus flow rate in ft/s. The combination of fluid density with Moores correlation balances the need for minimum fluid density for drilling and flow rate and viscosity required for proper hole cleaning. Without the addition of the penalty factor, the optimization formulation minimizes the difference in the N600 and N300 decision variables, if the well design is not limited by the ECD and fracture gradient constraint.

**Objective #1**

$$\min \sum_{section} (Casing\ Cross\ Section \times String\ Length)_{section} + Annulus\ Volume_{section} \quad \forall\ section \in well$$

**Objective #2**

$$\min \frac{1}{sections} \cdot (Mud\ Density_{shoe} - Pore\ Pressure_{shoe} - \frac{Apparent\ Visc \cdot Min\ Flow\ Rate_{section}}{50000}) \quad \forall\ section \in well$$

The objective function defined for this formulation remains in two dimensions for the benefit of visual analysis of the Pareto front, design space exploration. The objective function also utilizes the available information to generate a reasonable set of designs for evaluation. Minimizing material and well size is a typical cost and time reduction strategy, while minimizing the mud density reduces cost and can improve drilling time due to a reduction if formation pore pressure and fluid density differential. Bourgoyne et al. show that the drilling rate relationship to the differential pressure of the drilling mud density and pore pressure has a logarithmic relationship to the pressure differential [12].

# Chapter 7

# Evaluation of the Optimized Well Design Formulation

This chapter will evaluate the solution space of the NSGA-II [21] and NSGA-III [22] optimization formulations developed by K. Deb. The results are evaluated for feasibility, design space diversity, Pareto convergence through the use of the inverse gradient distance, and a discussion on computational expense. The resulting analysis will determine if using a genetic algorithm for constrained well design optimization is feasible for the implementation of the well system optimization problem at scale. There is no known optimal solution to the optimization problem provided; therefore, all comparisons to optimal are in reference to the known optimal solutions generated within the algorithm.

## 7.1 Validation of Results

Optimizing the well designs using the process described in Section 6.4 generated 1,796,355 feasible design options of 9 architectures generated through the DOE. There are 29 Non-Dominated solutions in the design space, 100% of the non-dominated solutions are three-section casing architectures generated by the DOE, the first step in the optimization formulation shown in Figure 5-4. The dominant designs will be used to validate the optimization model results based on the design constraints and objective functions used within the optimization algorithm.

### 7.1.1 Optimal Well Design for Three and Four Section Well

The well design meets the minimum dimensional and mud density design constraints provided to the algorithm. A drilling engineer would, however, have many questions about the casing wall thickness, which is near the minimum design vector wall thickness for the casing string, which was set to 0.20 inches. The casing grade is also a minimum value, using the J-55 casing grade, which has a 55,000 psi yield strength. The algorithm did not provide guidance on appropriate casing points, hole stability, or hazardous zones. Therefore, the casing point selection is a function of the pore pressure, fracture gradient, and Kick Tolerance. The results of the designs shown in Figures 7-1 and 7-2 meet the design constraints of the constructed algorithm. However, they would likely fall short as other design constraints and objectives are integrated into the model. The four-section well design also meets the design objectives of the algorithm, which has a fixed string architecture and looks to minimize the volume of casing run into the well. As the casing selection points are selected, the algorithm minimizes the casing sections' length to ensure the design meets the design requirements.

The equivalent circulating density function for the well did not perform as a dynamic variable. It would fail to meet minimum specifications if the calculation was performed for each drilled depth vs. the simplified formulation performed at the base of the well. Decreasing the fluid flow rate would decrease objective function #2 and could remove Figure 7-1 from the Pareto. If this scenario was encountered by a drilling engineer, there are a multitude of solutions, but for this scenario, the engineer would simply reduce the maximum allowable pump rate as the bottom hole assembly reaches the weaker section. There are no rational reasons to install a casing string at that depth if this is assumed to be a vertical wellbore. The four-section wellbore shown in Figure 7-2 could also fail to remain below the fracture gradient, but the corrective action would remain the same. Although corrective actions exist, future models must address the dynamic equivalent circulation density measurement.

**Figure 7-1:** Schematic of a Three-Section Pareto Designs

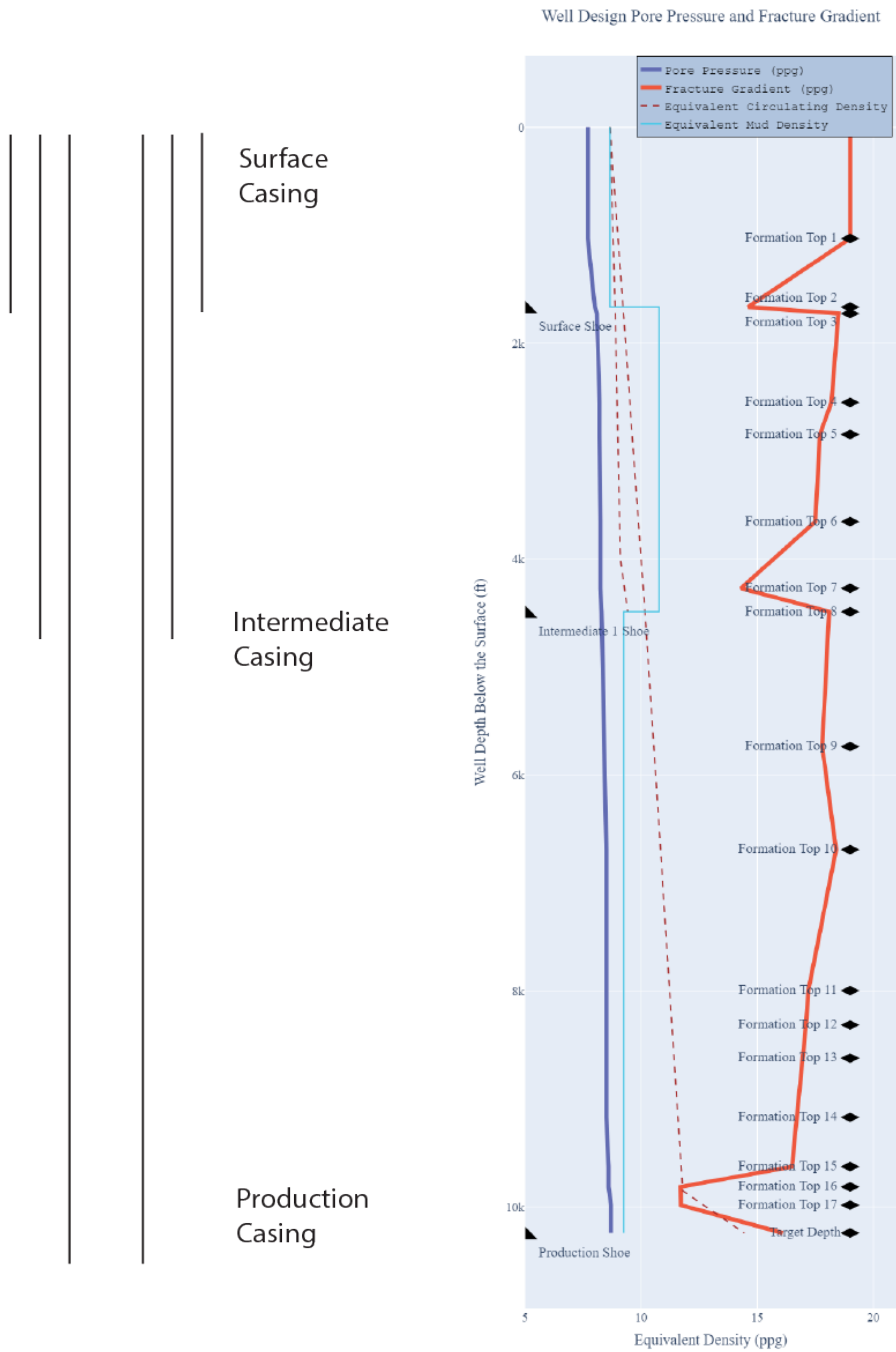
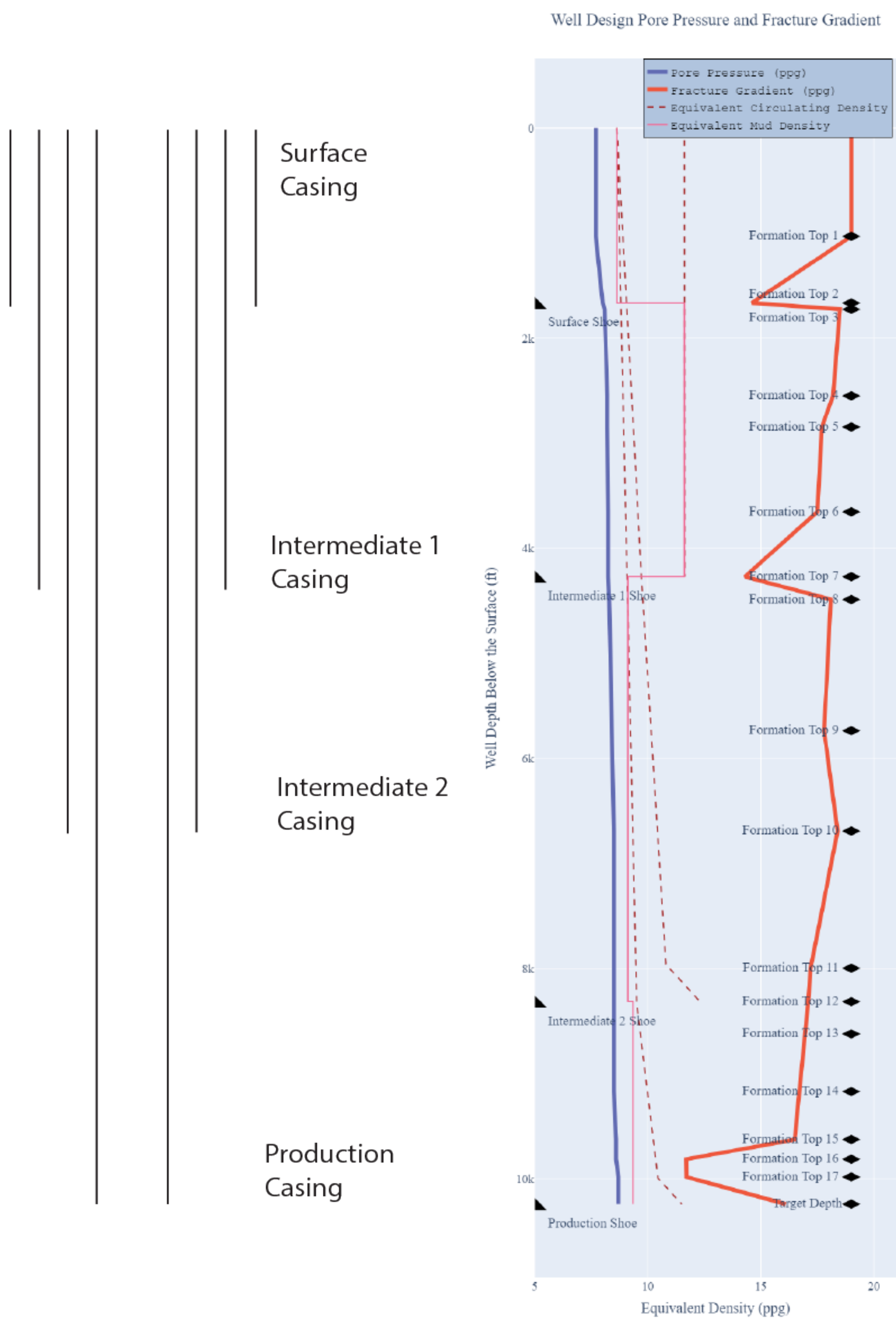


**Figure 7-2:** Schematic of a Four-Section Pareto Design



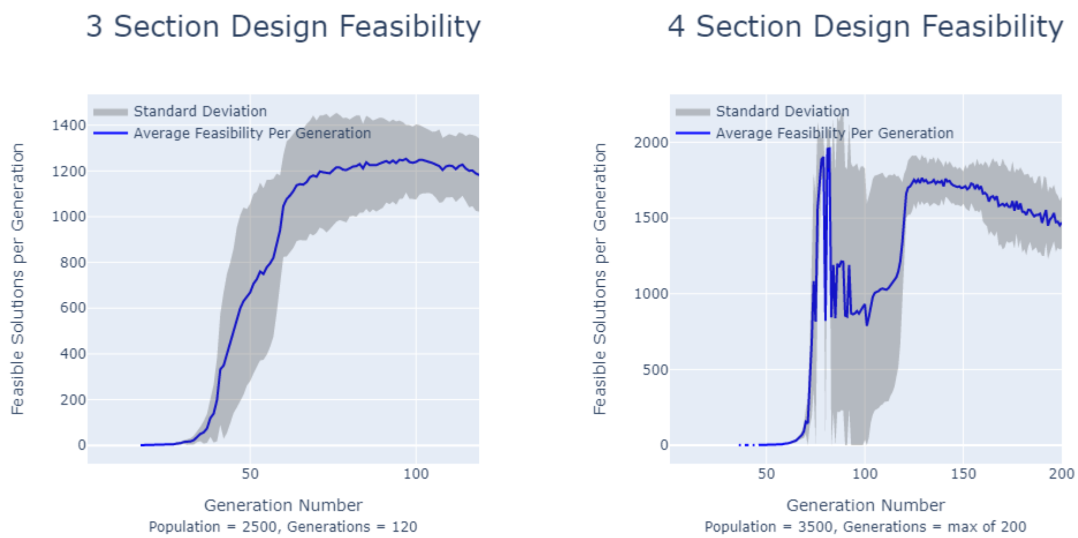
## 7.2 Model Evaluation

The development of the well design optimization model uses two genetic algorithms, NSGA-II and NSGA-III, to evaluate the feasibility of the design choices produced by the optimization algorithm for three and four-section well designs. The algorithm evaluates five three-section and four four-section well designs with varying casing OD's, selected by the random selection algorithm. This section will review the design outputs as a measure of design feasibility rate, design variable diversity, overall Pareto front for the well optimization process, and convergence rate computed using the Inverse Generational Distance formulation described in Section 5.3.5.

### 7.2.1 Feasibility

The set of feasible solutions within the design space indicates that the algorithm can provide a solution space that evolves through multiple generations and provides many solutions to develop the Pareto front. No penalty functions constrain the well design or significantly reduce the objective function within this formulation; therefore, all factors of feasibility are binary values. As the number of well sections increases, the total number of design variables and constraints increases exponentially and results in the feasibility reduction seen in Figure 7-3, which highlights the change in the rate of feasible solutions to evaluate within the optimization algorithm. The four-section algorithm is increased to a population size of 3000 individuals, with 150 generations. With this increase, the possibility of finding solutions improved and developed solutions that are at or near the optimal Pareto front. A detailed look into constraining variables shows that if no feasible solutions are found, future generations continue to search a wide range of combinations for a possible feasible solution, utilizing variable combinations that show feasibility. The feasibility analysis varied throughout the design exploration for each architecture and shows a significant difference in the four section architecture in Figure 7-3. The four-string casing designs have a lower percentage of feasible designs, as the feasibility rate is challenged when the number of constraints and design variables increases. The combinations and relationships of

**Figure 7-3:** Feasibility of Solutions By Number of Hole Sections




the constraining variables show a reduced rate of solution feasibility and drive the requirement to increase the population size with an increase in constraints and design variables. The low level of feasibility shown with the addition of one well section indicates the necessity to modify or limit the design space, if possible. The population size required to find feasible solutions is directly correlated to the number of design variables and constraints. As the algorithm begins to find feasible solutions, there is an increase in the feasible solution rate. The fitness, crossover, and mutation of the NSGA formulation continues to search for feasible solutions through genetic evolution.

The differences in the rate and occurrence of feasible solutions for the three and four-section well designs indicate that adding more design variables and constraints will require carefully selected reference directions in the NSGA-III formulation. As performed in this research, the four-section design required a more extensive design space exploration to reach the feasible solution phase. Performing the analysis for the four-section design yielded inconsistent and non-optimized solutions.

### 7.2.2 Decision Space Diversity

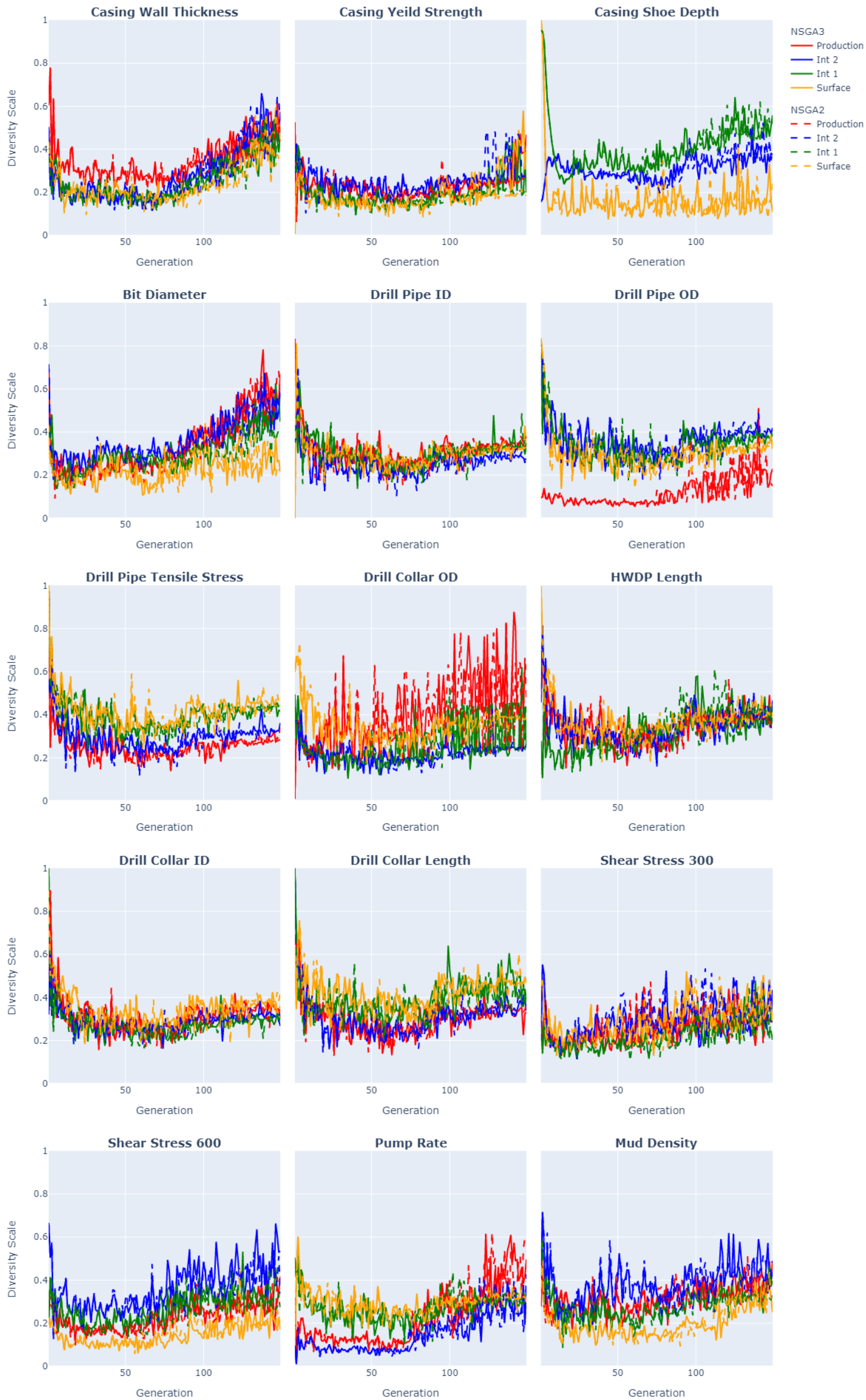
Large continuous feasible regions can lead an optimization formulation to remain in local minima and limit the design space diversity early in an algorithm [41]. Decision variable diversity is evaluated to understand the source of diversity within the algorithms' population and objective functions. It indicates the quality of solutions provided by the algorithm. The diversity measure also indicates which variables strongly influence the design objective, as the most influential variables maintain low levels of diversity. Using the diversity approximation formulation in Section 5.3.3, a computationally efficient means of calculating the sum of the difference of all individuals in the population, a reduction in diversity is seen in Figures 7-4 and 7-5. The diversity measures for the three-section and four-section designs are different and separated for clarity. As the algorithm finds feasible solutions, several design variables' diversity decreases to optimize the feasible region. The NSGA-II and NSGA-III algorithms are also separated by line marker style to highlight the differences in the evolutionary variability. As the four-section well design searches for solutions, the diversity is vast, but as the set of feasible solutions grows, the diversity decreases rapidly. Although searching for a feasible solution takes many iterations, the rapid reduction in variable diversity could signal minimal design space exploration, which may lead to sub-optimal design choices.

The convergence of the decision variables that have the most significant impact on the objective function shows an apparent decrease in diversity as the number of generations increases. It is worth noting that feasible solutions did not begin to appear until generation 25 for the three-section design, and generation 65 for the four-section design, which Figures 7-4 and 7-5 highlights that the genetic algorithm gradually decreases the variance in the design space as it approaches a feasible region. Once the feasible region is reached, the decision variables responsible for tuning the objective function continue to indicate higher levels of diversity, meaning the design variables are exploring localized regions for feasible solution improvement. The variables that converge to lower diversity values will be considered feasibility variables, while variables that maintain a higher level of diversity are optimization variables. The difference in the feasibility variables is that they are highly coupled with the design constraints and are likely at or near the design space boundary. The optimization variables, on the other hand, have the ability to move throughout the design vector to improve the objective function.

The information generated through the evaluation of the design vector feasibility rate can provide insight for developing an alternative optimization algorithm, which only looks at the changes in the optimization variables. The alternative algorithm will convert the feasibility variables into variables or values with limited variability or set them to static values. Alternative methods of using single objective optimization methods such as Particle-Swarm Optimization could also generate additional feasible solutions to the Pareto front using only the optimization variables in the design space.

**Figure 7-4:** Decision Variable Diversity with Three Sections

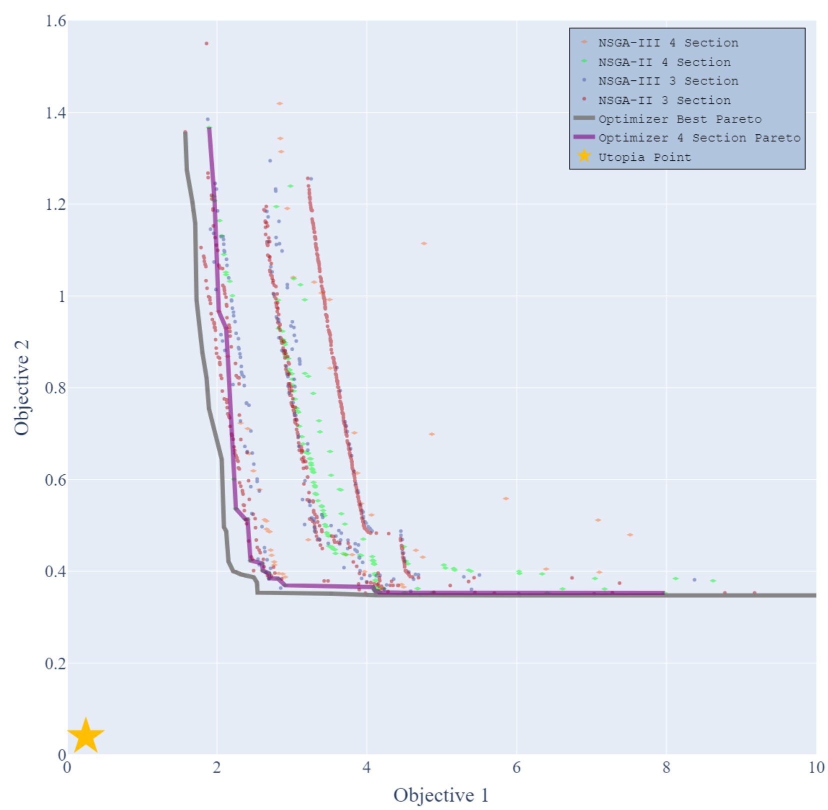
**Figure 7-5:** Decision Variable Diversity with Four Sections



### 7.2.3 Pareto Comparison

The Pareto solutions for 40 architectures are generated through the well optimization algorithm using the NSGA-II and NSGA-III modules using the Pymoo open source library [10]. Each three-section optimization formulation used a population size of 2,500 individuals and 70 generations, while the four-section designs used 3,500 individuals with 100 generations to develop the Pareto front described in Figure 7-6. Using the objective functions for the Multi-Objective Evolutionary Algorithm detailed in Section 6.4.3, a total of 1081 individual Non-dominated solutions from all evaluated architectures are produced and showin in Figure 7-6.

**Figure 7-6:** Pareto Solutions Generated by All Designs




The NSGA-II formulation found solutions that outperformed the NSGA-III formulation in nearly all architectures. The NSGA-III formulation is designed for many-objective problems and only has small variations from the NSGA-II formulation [22]. The three-section casing designs heavily outweigh the Pareto optimal designs for the four-section well designs. An individual evaluation of the four-section Pareto is developed to compare the two well section designs. Using the information provided through the Pareto analysis, it is concluded that the four-section well design is inferior to the three-section well design.

### 7.2.4 Model Convergence

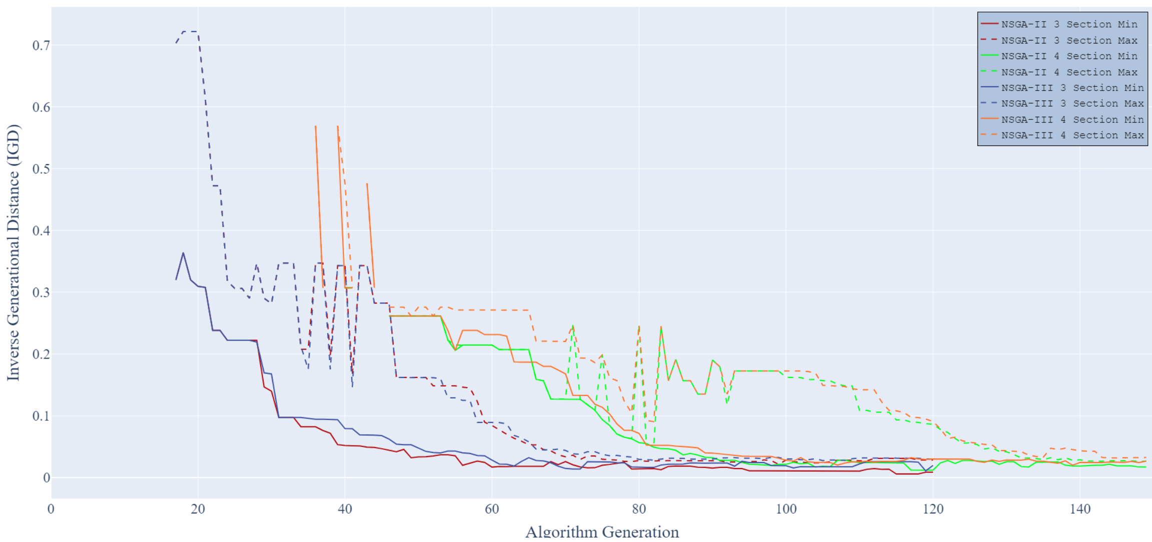
The algorithm's convergence occurs when all feasible architectures show improvement through each algorithm generation. The non-dominated Pareto of all architectures evaluated is considered the optimal front and determines the zero distance point for the IGD calculation. If a single architecture holds all non-dominate solutions, then the IGD value for the architecture at some iteration will equal zero. If an architecture converges but is not near the optimal Pareto, the IGD value will be relatively larger than the average IGD metric.

Evaluation of the IGD is presented as a minimum and maximum range to show that the worst algorithm converges to a reasonable IGD, indicating that convergence occurs for all architectures of the three and four section well designs. The three-section well designs begin to converge at earlier generations and fully converge near 70-80 generations. In comparison, the four-section design converges after 90 generations for the best architecture but requires 130 generations for the worst. The additional generations required to reach a reasonable IGD value shows how increasing the number of constraints and design variables requires additional generations to reach convergence.

## 7.3 Computational Expense

An optimization algorithm's acceptable computational expense is directly correlated to the value it provides to the end-user or process. The question managers will ask before accepting to develop the solutions is, what can it do that the Engineers cannot? The realization is that the theoretical designs it produces are simply the best reasonably generated solutions within the constraints of the optimization formulation.

**Figure 7-7:** Algorithm Inverse Generational Distance by Function and Well Section




An engineer can conclude that a single design is better than the rest, but at what level of effort?

The computational time to run the algorithm discussed in this research was performed using Python, run on a 64-bit 1.8GHz processor with no concurrent functionality in the Python computations. The three-section well design performed at 11.5 seconds over 70 iterations and 16 seconds over 100 iterations for the four-section design. The increase in the population size, decision variables, and constraints significantly impacts each iteration's performance, as the algorithm actively scales to meet the desired number of well sections. The total duration of the optimization algorithm on a single-thread machine takes approximately 9 hours to complete 20 casing architecture design evaluations for a three or four-section casing design. Evolutionary algorithms must be run in sequence to allow the evolution of the population to occur. Therefore, parallelization may only occur outside of a single casing architecture but could result in a total reduction of run-time for the algorithm to be equivalent to the equation below.:

$$Time = \frac{Duration\ Per\ Casing\ Architecture \times Number\ of\ Architectures}{Number\ of\ Parallel\ Resources}$$

Based on the estimated time to run the algorithm, the expense to run the optimization is a factor of the value the results can generate through well design improvements and engineering time savings. Suppose the numerical formulation is searching for design improvement to an existing design. In that case, the length of the computation may not be critical. However, if the process is used in tandem with engineering development, the process may require generating good designs in a fixed duration. Within the oil and gas industry, the simulations performed in reservoir optimization can extend to hours and days of computation for the transient analysis of reservoir mechanics. The extended time is accepted due to the value of the results for asset development. A well design optimization process that provides consistent results that increase the speed of cost reduction strategies in exploration and development wells, the cost of computation will not hinder the process integration.

## 7.4 Analytical Conclusion

The analysis of the resulting feasibility, diversity, and convergence of the well optimization formulation shows that the Genetic Algorithms NSGA-II and NSGA-III have similar performance on solution feasibility, diversity, and convergence, with NSGA-II showing a small advantage in Pareto front generation. It was observed that as the number of design variables or constraints increased, the ability of the algorithms to find the feasible region grew exponentially and resulted in an increased population and generation size for the four-section well design over the three-section well design. The smaller design space converged faster, even though the population size was smaller, indicating that a complete well design problem would require a significant increase in the population size and number of generations to ensure the optimization algorithm can find the feasible region.

By analyzing the solution feasibility and diversity together, one could infer that the solution diversity significantly lowered after the first feasible region was discovered. The optimization algorithm generates feasible solutions wherever it finds the first feasible region. However, the diversity of the design variables never reached zero in

Figures 7-4 or 7-5, so the diversity of feasible solutions for this optimization problem could be more continuous than one would initially believe. Plotting the feasible region for a visual representation is impossible; therefore, additional analysis is required to understand the design space's continuity. If the design space is continuous, then the concern with low levels of diversity would lead one to believe that there is limited exploration of local minima to find the best solution. The convergence of the plots developed in this research show minimal improvement in later generations, which indicates the formulation does, in fact, find good solutions while continuing to explore infeasible regions for improved local minima.

Proper tuning of the genetic algorithms' population size and number of generations is critical to confidently finding the local minima data points, as indicated in Figure 7-7. The difference in population size and number of generations for the four-section design nearly generated a non-dominated solution. This increase does not come without consequence, as the computational expense for the increase in the design space size and constraints adds additional time for computation. Due to the non-parallelization of Evolutionary Algorithms, the time required for optimization will remain factors of minutes for unique architectures. Therefore, any application of the optimization algorithm will require the end user to wait for optimal results. The use of the NSGA-II or NSGA-III formulation are possible feasible options for a two-objective optimization formulation. However, they may be an expensive calculation as the well design formulation is scaled to encompass all design variables and constraints.

# Chapter 8

# Conclusion

## 8.1 Summary of Research and Analysis

An analytical model evaluation using the Design Structure Matrix for identification of system inter-dependencies lead to the development of a hybrid optimization model show in Figure 5-4, which utilizes an outer Design of Experiments and Response Surface Model and the Evolutionary Optimizer for system design optimization. A genetic algorithm formulation was utilized to conduct the evolutionary optimization using the open source Pymoo library [10] to develop and optimize the system design. A comparison of the NSGA-II [21] and NSGA-III [22] algorithms did not indicate a clear winner as the best option, even though the NSGA-II formulation provided the best objective functions for the corresponding designs. The algorithms displayed similar feasibility, convergence, and design variable diversity levels.

A limited set of design architectures are tested using the Genetic Algorithms. The three-section well design evaluated 300,000 design alternatives to develop a Pareto optimal design set. In contrast, the four-section well design required 525,000 solution evaluations to reach an acceptable level of convergence, measured using the Inverse Generational Distance Method [22] as the primary success measure for the determination of generational improvement. Utilizing a single thread computing process shows limited feasibility of real-time design improvement, but parallel or batch computing could improve the rate of architectural iteration. The Genetic Algorithms showed an acceptable convergence rate, indicating tractability of the formulation of a partially constrained well design. Expansion of the model to include more design variables and constraints will require a significant increase in computation and should utilize adaptive or selective design space generations for efficient computation. As the design space diversity decreases, adapting the design variable search region to a possible feasible region could increase the feasibility rate and decrease the number of generations required to reach a convergence point.

## 8.2 Discussion of Research

The numerical representation of the well design system for this research is a reduced order formulation to explore the feasibility of utilizing a numerical optimization formulation for the well design process. Through analysis of the resulting design feasibility, computational efficiency, and design convergence, it is determined that this formulation will assist in the improvements to development and exploratory well designs. As the number of decision variables reduces, the efficiency of computations will increase and can provide reasonable alternatives for design improvements. The integration of this method into practice will involve the development of a quality numerical formulation (Section 8.2.1), utilizing the strengths of Evolutionary Optimization development (Section 8.2.2), and utilizing existing strategies and processes to integrate into the Drilling engineering workflow (Section 8.2.3).

### 8.2.1 Production Ready Formulation

Well design and development is a capital-intensive and risky operation. An optimization system's resulting safety and reliability must utilize engineering and operational best practices and standards when optimizing a system. Generation of designs with simple, hidden errors could lead to catastrophic loss of assets or life. The care and rigor placed on the well design processes are guided by the experiences of the individuals, their knowledge repositories, and the collective mental models of the industry. Breakthrough applications and new technology must integrate the existing new methods and processes with existing mental models with seamless and reduced error integration.

To accomplish the objective of developing and deploying a reliable optimization formulation, the most valuable attribute is safety and efficiency coupled into one program. A numerical representation of the well design process that provides engineers with insights and metrics on the generated well designs ensures the numerical representation is a feasible option. It is imperative to strategically identify the dependencies and constraints that drive well design, and ensure preferences and rules of thumb are minimized to allow the physical representation of the model to calculate and formulate numerical rules. The analysis performed using the DSM in Chapter 4 helps to identify unnecessary circular dependencies that could introduce unnecessary complexity into an optimization formulation.

The method proposed within this Thesis does not represent all industry standards and design practices necessary to design optimal well design alternatives, but the expansion of the design constraints, objective functions, and best practices can lead to a formulation that could provide helpful insights for well design optimization and architecture exploration.

### 8.2.2 Strengths of Method

Utilizing Evolutionary Algorithms for complex optimization to find good solutions using a stochastic genetic search is advantageous due to the genetic operator's efficiency in finding and improving feasible solutions. The natural evolution of the crossover and mutation sequence works to preserve good solutions through combinations of population solutions or crossover and mutation of the design space. A combination of Figure 7-7 and 7-4 help describe how the evolutionary algorithm progresses to find the Pareto optimal solutions while maintaining a diverse combination of variables for efficient, multi-objective optimization.

Evaluation of the evolutionary algorithm for the system optimization of a well design shows that the complexity depicted within the system DSM, Figure 4-4, is evident in the rate of feasible solutions, Figure 7-3, and rate of convergence, Figure

7-7. As the algorithm progresses, it can find and continuously optimize objective functions in all cases with feasible solutions. The Pareto optimal design set also highlights the concentration of architectural designs. It gives an insight into how challenging it can be to determine the value of changes in design architecture. If a numerical system model is developed and validated against existing data, exploring the design space will become incredibly useful. Exploration of design improvements, weaknesses, and sensitivities could emerge from a comprehensive system formulation.

Integrating best practices can be introduced into the optimization formulation as penalty functions, parameters that can penalize or reward the objective functions for preferred designs. The introduction of Moore's correlation for the apparent viscosity of the drilling fluid as it relates to the fluid density for objective #2, rewards higher viscosity fluid, which helps to clean the wellbore, but increases the constraining formulation for equivalent circulating density. Utilizing the principles of optimal design, total flexibility in design options and principles is possible.

### 8.2.3 Drilling Engineering Process Integration

Integration of this process into existing model-based systems engineering programs, such as the process described by Szemat [60], will increase the effectiveness and rate of design improvements in drilling programs. Standardizing well construction designs, processes, and supply chains is a competing objective to well design optimization and could limit the implementation without strategic integration. In high-volume development scenarios, such as unconventional drilling, optimization of a single design must be robust for repeatable and predictable implementation to meet design standardization and well construction simplification. The optimization algorithm should work within the confines of the supply and design constraints to optimize designs where possible but maintain a cycle of continuous improvements for system optimization.

Using a numerical simulation tool is a valuable method for integrating knowledge requirements, where best practices, standards, and design requirements are represented within the algorithm as constraints of feasibility or penalties for the objective function. The numerical model is only feasible where the "disconnected silos" [60], as referred to in Chapter 1, are removed in an analytical process. The variability of information presented as best practices or design improvements must be converted into a numerically representative form to be used by the model or stored for future integration. By requiring applicable information integrated into the numerical representation in a mathematical form specific to the model, storage, modification, and replication of knowledge are configured to represent various scenarios, disciplines, and teams.

Developing a complex constrained optimization algorithm shows that this process can be used to find improvements to existing designs and perform a broad search of possible feasible designs. The computational expense for a high-fidelity design restricts a deterministic or stochastic systems optimization process to being used infrequently within the project development process. The use of an optimization tool would serve the best value in early conceptual planning or as a tool for improvements to existing engineered well designs. Early conceptual planning would utilize a low-fidelity model with a large design space and generalized constraints. Methodical design variable reduction in a high fidelity analysis, with emphasis on parameters such as the rate of penetration and operational efficiencies, could serve as an improvement to sensitivity studies to assist in improvements to existing well architectures. The construction and function of the optimization process will not be suitable for use in an active graphical user interface with real-time decision-making or modeling due to the computational expense of the optimization process. Additional research into the feasibility of deep learning and neural network development as a catalyst to design optimization is required. This research shows that reducing decision variables constraining the design space is optimal for a scalable solution. The method used within this Thesis could be a good tool for identifying non-optimal decisions in a well design, and through that exploration, design improvements may be recommended.

## 8.3 Limitations of Research

The system optimization of the well design and construction process is a complex problem that multi-disciplinary teams of teams must solve to ensure the objectives of well construction can be met with numerical representation. The information of this Thesis is limited to an arbitrary set of information generated using a normally pressured reservoir in a mid-sized vertical well. The introduction of trajectory optimization as a measure of feasibility and design options can exponentially increase the design space's size. To maintain a reasonably sized design space and problem formulation, the design constraints are not comprehensive and may not represent a feasible well design in reality. The research does not include constraints such as the casing connection diameters, drill pipe tool joint dimensions, and geological interactions with the mud system. For further exploration into the feasibility of this method, additional feasibility constraints should be added to the problem space for a realistic representation of the design. The algorithm used for this research had 34 constraints for a three-section design and 47 constraints for a four-section design, all of which have varying weights on the feasibility of designs.

In Chapter 5.4 implementation of a Response Surface Method for the Design of Experiment selection is proposed to enhance the likelihood of selecting favorable architectures within the DOE generation of Casing OD architectures but was not explored as part of this research. The DOE generation used a Random set of solutions generated with dimensional constraints to help achieve feasibility but did not guarantee the optimizer to find a solution or an architecture that would produce a competitive solution for the Non-Dominated Pareto set. The computational expense to run one architecture did not provide sufficient training information to construct a response surface, for use with the DOE.

Geographical information used for the optimization process utilized the minimum practical information for the well construction boundaries. Inclusion of formation fluid, geo-hazards, lithology and their impacts to drilling, and formation fluid content are geological constraints that are not defined in this research. The objective function used for design does not consider risk and does not capture risks of wellbore failures or significant uncertainties in the geological estimations.

## 8.4 Future Research

Implementing an Optimization formulation is feasible and possible at scale with advanced computing and parallel processing. This research finds that the solution improvement using the Non-Sorting Genetic Algorithm provided usable solutions. Future research into well design optimization through a focus on speed, scalability, and process integration will allow this work to progress to the point of implementation.

#### Many Objective Evaluation

As the complexity of the algorithm increases, the utilization of many objective algorithms for optimal design development. The utilization of the additional objective function within the NSGA-III algorithm could yield different sets of Pareto solutions using decision variables and design parameters normally not considered for optimality.

#### Integration of Neural Networks

Integrating a neural network, deep learning, or response surface methods will increase the scaleability of the optimization formulation by utilizing trained data models for increased computing efficiency. Although the scalability of the Stochastic optimization performed within this research is not feasible for advanced well design, implementing methods to increase evaluation efficiency and design selection will significantly improve the optimization process.

#### Cloud and Parallel Computing

Well design and construction is a capital-intensive process that ranges from $500,000 USD for shallow development wells to $250,000,000 USD for complex exploration wells. Utilization of cutting-edge computational techniques such as parallel computing, caching methods for increased efficiency of Optimization Archiving, and machine swarms are viable options if the value of the results generated through the optimization formulation consistently exceeds the computation cost.

#### Socio-Technical Evaluation for Adoption and Value

The integration of a complex optimization process must be accepted by the incumbent individuals developing well designs. A study into the process integration of an optimization method must be completed to ensure the safe and reliable development of wells. The ilities of well design are complex and require the re-tuning of models to ensure best practices, failures, and regulatory changes are captured immediately. The optimization process must have a minimum level of knowledge for integrity measures, and proper audit and review of the model performance.

## 8.5 Closing Remarks

The process used in this research is a basic approach to well design, and introduces the use of optimization to improve the processes used in well design and construction. Although the research does not represent realistic designs and outputs, the value of information presented is a strategic approach to optimal well design. I am confident that the methods expressed within this research will be useful in generating advanced methods of engineering well design.Integration of technical disciplinary engineering, mathematics, and computational techniques can improve the accuracy, speed, and robustness of the designs.

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# Appendix A

# Well Design Parameters

## A.1 Design Structure Matrix Inputs

### A.1.1 Regulatory Constraints

**Casing Regulation**

Casing Regulations are developed by the government, the Nomenclature of Economic Activities (NACE), and API standards. Casing regulations sanctioned by the government are required, while if not specifically specified, API and NACE standards can be considered recommendations. Casing standards define casing design parameters that must be met, such as: depths, safety factors, and worst-case load definitions.

**Cement Regulation**

Cementing regulations define specific subsurface zones that must be isolated with cement. These can include freshwater zones, Hydrogen Sulfide containing zones, or oil containing zones. The cementing regulations define the minimum cement heights or zones which must be isolated based on potential hazards.

**Disposal Regulation**

Fluid disposal regulations can eliminate potential design considerations. For example, north sea regulations do not allow any fluids to be discarded overboard vs. the Gulf of Mexico allows tested fluid to be discarded. This seemingly simple regulation creates an increase in operating costs, as all waste in the North Sea must be discarded into disposal wells or landfills. On land, a major drawback in some areas is the inability to use man-made ponds or pits. These are cheap options for storing water and disposing of waste while drilling. If these pits cannot be used, then all cuttings must have alternative disposal methods.

**Emissions Regulation**

Emissions regulations are new in the Oil and Gas Industry, and many operators have taken a self-governance approach to potential future regulations. For the drilling function, these regulations only require reporting total emissions.

**Rig Regulation**

The rig size regulations are essential on land. The rig configurations are bound by component weights to meet Transportation Departments regulations. Other factors could be, the inability to have the rig as an open structure in areas such as Los Angeles, CA. If the rig must be behind containment, then you could be limited in total rig height.

### A.1.2 Geological Inputs

**Pore Pressure**

Pore pressure is the pressure of the fluid within the formation and is a function of depth. Normal, abnormal, and subnormal pressure gradients are greater than, less than 0.433 psi/ft of depth, respectively [7].

**Fracture Gradient**

The fracture pressure is the maximum fluid pressure the formation can hold before losing its integrity. It can be defined using the Hubbert and Willis Equation: "The minimum wellbore pressure required to extend an existing fracture was given as the pressure needed to overcome the minimum principal stress" or $p_{ff} = \rho_{min} + p_f$ [12]. Where $p_{ff}$ is the wellbore pressure less than or equal to the ECD, ESD, ESD + Surge Pressure, or Cementing ECD, depending on the defined operation.

**Fluid Composition**

The fluid composition in this system is defined as the fluid medium in the pore spaces of the rock. This could be water, gas, oil, and other substances such as Hydrogen Sulfide or Carbon Dioxide.

**Lithology** Subsurface lithology is an abstraction of the rock minerology and is vital for quantifying the type and composition of minerals within each formation.

**Geological Hazard**

In drilling, areas with increased or undefined uncertainty are termed hazards. These areas are at times unavoidable and introduce significant risk into the operation. Hossain states that any drilling operation is measured by its ability to identify and mitigate these uncertainties [32]. Some problems that can be encountered include "drill pipe sticking, stuck pipe, drill string failures, wellbore instabilities, hole deviation and well path control, mud contamination, kicks, hazardous and shallow gas release, lost circulation, formation damage, loss of equipment, personnel, and communications" [32].

**Formation Top Depth**

The expected formation transitions separate the formation depths provided to drilling engineers. This is where geological properties encounter shifts in geological age and lithology.

**Formation Temperature Profile**

The formation temperature naturally increases with depth below the mud line, or surface. The rate of change is variable and is an important factor for fluid, cement and casing design. In cases of extreme heat, the bottom hole temperature can be a limitation of drilling tools used for formation evaluation and directional control.

### A.1.3 Well Cost and Material Supply

**Cost Per Foot**

The well cost per foot of drilled depth is the sum of all total costs for well construction divided by the total well depth. This function is relative to the geographical area and expected profitability and is only a measure for normalizing localized drilling costs.

**Available Casing Type**

The casing is offered in both standard API and non-standard sizes, grades, and thicknesses. This term can be used to limit the number of casing strings evaluated to define which casing string could be possible. This limits the design space to possible solutions.

**Available Rig Type**

Drilling Rigs are limited in size and capability. Designing a well that cannot be drilled, for example, a well that requires a 20,000 psi BOP on a shallow water Jack-up, may not exist and would render a design option infeasible.

**Available Drill Pipe**

Drill pipe grades and sizes are limited in availability and this table will define the drill pipe size and grades available.

**Available Mud Systems**

Drilling fluid availability is an industry norm. The availability of drilling fluid can be driven by regulatory restrictions, geological anomalies, or industry best practices. Using fluids not readily available can increase costs but may not always lead to infeasible solutions.

### A.1.4 Well Design and Construction Constraints

**Well Target Total Vertical Depth**

The target total vertical depth is the depth in which the well will be placed for optimal injection or production. There are generally multiple targets within a well, which drive the inclination and azimuth needed to intersect each. The targets can be in single or multiple formations, and have a defined inclination and azimuth between them. The target TVD is the vertical distance from a reference point, typically the rig floor or surface, that defines the depth of the formation target.

**Surface Location**

A rig system's surface location is selected carefully considering expected drilling hazards, surface topography, surface environmental attributes, field design, production, and subsurface targets. This can be considered an interface condition for drilling, but the feasibility of a selected surface location can change as drilling details are explored. Cox et al describe the surface location as critical to reducing the possibilities of encountering shallow hazards, and possible deeper hazards such as fractures or unconsolidated material [18].

**Well Geospatial Targets**

Factors outside of the well design define the target selection of a well. The well targets are a function of time-dependent data for production, reservoir mechanics, and rock and fluid interactions [11].

**Minimum Production Casing Inner Diameter**

The minimum production casing ID is the starting constraint for any well design. The completion design determines the equipment installed in the well, so this is a boundary variable with the completion design process. The completion equipment defines the minimum ID of any production casing or liner. "Successful completions recognize the flow characteristics of the reservoir" [7]. The completion design is a function of well profitability, lithology, fluid composition, pore pressure, cementing capabilities, directional profile, expected production rates, and total well life [7].

**Life Expectancy of Well** The design of a well must take into consideration the expected production duration of the well. Installed well components should consider the transient corrosion effects to ensure the well design will meet the expected loads during production. Most wells cannot be significantly modified once constructed. The ilities associated with well productivity duration are the casing material and thickness, surface equipment material specifications, the minimum diameter of the wellbore, and cementing quality of the casing string. The numerical representation can be presented as penalty factors or, in complex cases, additional design constraints.

### A.1.5 Well Barriers and Well Control

**Wellhead Pressure Rating**

The wellhead rating is the maximum pressure expected at any point in the life of the well. The minimum wellhead pressure is typically a function for the pore pressure of the producing interval minus some fluid and gas gradient mixture. This term is considered to be the worst case discharge.

$$\begin{aligned} WH\ Rating \geq\ & Pore\ Pressure * 0.052 * TVD \\ & - Liquid\ Oil\ Gradient * TVD * Fluid\ Fraction \\ & - Gas\ Gradient * TVD * (1 - Fluid\ Fraction) \end{aligned}$$

*where*

*TVD is the True Vertical Depth of the highest pressure perforation*

*The Oil Gradient is dependent on formation characteristics*

*The fluid fraction is dependent on the design criteria of the well*

**Kick Tolerance**

The kick tolerance factor is the allowable increase in equivalent circulating density due to a fluid influx. It should always be greater than 0, to ensure there is a margin for a well influx. The formulation for kick tolerance factor is defined below [42].

$$Kick\ Tolerance = \frac{csgshoe_{sec-1}}{csgshoe_{sec}} \cdot (fg_{sec} - mw_{sec})$$

### A.1.6 Well Trajectory and Directional Drilling

**Well Inclination**

The planned directional survey is constructed typically with a minimization of the total well depth or Measured Depth (MD). The directional profile of a well has the objective of minimizing drilling time and cost, minimizing the total well length, optimizing target intersections for production, considering hole cleaning and fluid flow, and maximizing the rate of penetration [13].

The well inclination vertical displacement of the wellbore from a reference point of zero degrees indicates a direction perpendicular to the earth's gravitational center. The inclination changes to meet the objective to reach the target objectives and starts from the designated surface location.

**Well Azimuth**

The well azimuth is the direction of the wellbore in relation to the magnetic north pole, where zero degrees directly aligns with the magnetic north pole.

**Total Vertical Depth**

The total vertical depth is the vertical displacement of the well, interpolated using the well length, inclination and azimuth.

**Measured Depth**

The well's measured depth is the wellbore's length independent of the inclination, azimuth, or depth. The measured depth can be measured using a device such as a wired tool string, drill pipe, or casing. The measured depth of the well is a function of the inclination, azimuth, TVD, in relation to the directional objectives from the surface location to the well targets.

**Well Dogleg Severity**

Dogleg Severity is a term that describes the triaxial change in the well trajectory over a specified length. The dogleg severity is typically represented in degrees per 100 ft in US units. The change in inclination and azimuth over a section of the well determines this scalar factor. Abnormal increases in dogleg severity can be catastrophic, and cause unplanned failures in the drilling string, increased torque and drag, and possibly stuck pipe.

**Maximum Allowable Dogleg Severity**

The maximum dogleg severity is generally a function of the well section. This variable changes over the wellbore. It is a function of the well depth, casing analysis, torque and drag, and tubular diameters.

**Kick Off Point**

The kick-off point is where a curve or change in planned inclination and azimuth begin. Well are not continuous curves due to equipment limitation and rate of penetration optimization; therefore each change in geometry requires a designated point (kick-off point) to make major changes in the planned trajectory. The selection of kick-off points depends on the relative distance to the well target, expected lithology encountered while drilling, the bottom hole assembly, casing wear analysis, and the torque and drag analysis of the casing and drill pipe at deeper intervals.

**Curve Build Rate**

The build rate is the maximum inclination change a bottom hole assembly can achieve. The selection of build rate has the objective to occur with the fastest rate of penetration but at the lowest cost. Excessive build rates can affect the torque and drag analysis and, therefore, can be infeasible. This value is different for build sections, and wells could have as many as 5 build sections in a single well.

**Bottom Hole Assembly Directional Class**

The type of directional assembly could be separated by a straight assembly, downhole motor, and rotary-steerable systems. Rotary-Steerable systems rely on the drilling fluid to provide power to the downhole tools, including higher viscosity fluids.

### A.1.7 Drilling Fluids

**Fluid Rheology (Needs to Update for better description as Abstraction of properties)**

Drilling fluid has many parameters that can improve the Rate of Penetration and hole cleaning efficiency. In many cases, it can be best to drill with fluid with the lowest shear rate and fluid loss. In such cases, fresh, brackish, or salt water can be used as the primary drilling fluid. The rheology will in this research uses the Power Law Model [7]:

$$\tau = K\gamma^n$$

where

$\tau$ is the Shear Stress

$\gamma$ is the Shear Rate

$K$ is the consistency index

$n$ is the power law index

**Mud Base Fluid**

Azar describes drilling fluid selection parameters and attributes to the base fluid selection listed below [7]. For use in optimization, the parameters marked with an asterisk can be used as a component of the objective function.

**Mud Density**

The objective of the mud density is to achieve a value that is as low as possible.

$$Pore\ Pressure \leq Mud\ Density \leq Fracture\ Pressure$$

**Mud Flow Rate**

In many cases, the objective of a well operation is to achieve the maximum flow rate whenever possible. The drilling pump rates are limited by pump capabilities and the wellbore fracture pressure. Circulation pressures must be high enough to remove cuttings from the wellbore. There is an increased risk

**Table A.1:** Base Fluid for Drilling Fluid Optimization

| **Influencing Parameters** |
|---|
| Production Concerns |
| Rate of Penetration * |
| Circulating Friction Pressure |
| Torque and Drag * |
| Lithology and hole stabilization |
| Safety and Environmental |
| Solids Removal or Hole Cleaning * |
| Wellbore Temperature |
| Potential for Mud Losses - Low Fracture Gradient |
| Potential for Mud Contamination - High Pore Pressure |
| Drilling Rig Capabilities |
| Bottom Hole Assembly |
| Formation Evaluation Requirements |

Data Table Adapted from [7]
* Indicates parameters that are defined in an objective function.

of pipe sticking due to excess debris in the well without a sufficient flow rate. The mud pumps have a fluid displacement volume per stroke as a function of "the piston diameter, the liner diameter, and the stroke length" [31]. The total pump horsepower needed for a given circulation system is a function of the rate and pressure. Drilling rigs can have multiple pumps with various liner and piston sizes; therefore rate is dependent on the friction pressure encountered in the system and the total available horsepower. This can be represented as [31]:

$$P_{hp} = \frac{P_f \times Rate}{1714}$$

The circulating rate must be less than system friction pressure as a function of the pump horsepower. Azar details the total friction pressure or pump pressure while drilling as [7]:

$$P_f = P_{fdp} + P_{fdc} + P_{fadp} + P_{fadc} + P_{fs} + P_{bha} + P_b$$
$$Rate \leq \frac{1714 \times P_{hp}}{P_f}$$

Where:

$P_{fdp}$, $P_{fdc}$ are the respective pressure friction losses inside drill pipe and drill collar

$P_{fadp}$, $P_{fadc}$ are the respective pressure friction losses in the annulus around the drill pipe and drill collar, respectively

$P_{fs}$ is the pressure friction loss inside surface connections

$P_{bha}$ is the pressure friction loss through the bottom hole assembly

$P_b$ is the dynamic pressure change across the bit

The flow rate while drilling must also exceed the recommended velocity for circulating in a wellbore. The hole cleaning index developed by Al-Rubaii [3] must be greater than 1 to indicate good hole cleaning.

**Mud Friction Factor**

The Doge and Metzner correlation for use with their calculation of the Reynolds number of a Power Law fluid yields an equivalent Reynolds number for pipe and annulus fluid [12], with an approximate formulation for the friction factor [63] :

$$
\begin{aligned}
a &= 2 * \log \frac{R}{2.51} \\
c &= \left( \frac{\epsilon R}{9.287D} + a \right) \\
d_e &= 0.816 * (OD - ID) \\
\sqrt{1/f} &= a + 2 \log c \left( \frac{d_e}{c} + 1 \right)
\end{aligned}
$$

$where:$

**Pipe Reynolds Number**

$$N_{Re} = \frac{89,100 \rho \nu^{2-n}}{K} \cdot \left( \frac{0.0416 \cdot d}{3 + 1/n} \right)^n$$

**Concentric Annulus Reynolds Number**

$$N_{Re} = \frac{109,000 \rho \nu^{2-n}}{K} \cdot \left( \frac{0.02089 \cdot (OD - ID)}{2 + 1/n} \right)^n$$

**Equivalent Static Density**

The equivalent static mud density can be represented using the simplified formulation below.

$$Hydrostatic\ Pressure = 0.052 \times True\ Vertical\ Depth \times Fluid\ Density$$

**Equivalent Circulating Density**

Newtonian and Non-Newtonian fluids can separate the determination of the annulus pressure loss formulation. The fluid is in the laminar flow state for fluids with a Reynolds number less than 2100. For the Power Law, the annulus pressure drop can be estimated for drilling ECD as turbulent flow.

Using the equations derived by [12]:

**Laminar Fluid ECD, RE<2500**

$$ECD_{laminar} = \frac{K \upsilon^n \left( \frac{3+1/n}{0.0416} \right)^n}{144,000 \cdot d^{1+n}} * len_{section}$$

**The Turbulent Fluid ECD, RE>2500**

$$v = \frac{Q}{2.448 * (ID_{outer}^2 - OD_{pipe}^2)}$$
$$n = 3.32 * log\frac{\theta_{600}}{\theta_{300}}$$
$$K = \frac{510 * \theta_{300}}{511^n}$$
$$ECD_{turbulent} = \frac{f * \rho * v^2}{21.1 * (ID_{outer} - OD_{pipe})} * len_{section} + EMW$$

$where:$

$\theta_{600}$ & $\theta_{300}$ are rheological relationship of the shear rate vs. shear stress

$Q$ is the fluid flow rate in gal/min

$ID_{outter}$ is the ID of the previous casing string(s) or the hole diameter

$\rho$ is the mud density

$f$ is the friction factor correlations generated using the friction factor approximation [63]

**Surge and Swab Pressure**

For moving pipe, the equation derivations from Bourgoyne apply for laminar flow in the well annulus [12]. When moving pipe into the hole, the term "surge" is used to describe an increase in wellbore pressure from the added frictional pressure of moving fluid. Bourgoyne uses a formulation to estimate the fluid velocity as a function of pipe speed in the open-ended pipe and estimates the rate of fluid movement in closed-ended pipe [12].

For open ended pipe:

$$\nu_a = \nu_p \cdot \frac{3d^4 - 4d_1^2(d_2 - d_1)^2}{-6d^4 - 4(d_2 - d_1)^2(d_2^2 - d_1^2)}$$

For closed ended pipe:

$$\nu_a = \frac{d_1^2 \cdot \nu_p}{(d_2^2 - d_1^2)}$$

$$\left(\frac{dP_f}{dL}\right)_{sec} = \frac{\mu\,(\nu_a + \nu_p/2)}{1000(d_2 - d_1)^2} \quad \forall\ sec \in Well$$

Surge pressure can be calculated when $v_p \geq 0$ :

$$fg \geq \sum_{sec} \left(\frac{dP_f}{dL}\right)_{sec} + EMW$$

Swab pressure can be calculated when $v_p \leq 0$

$$pp \leq \sum_{sec} \left(\frac{dP_f}{dL}\right)_{sec} + EMW$$

**Hole Cleaning Quality**

Using the hole cleaning index developed by Al-Rubaii et al. [3] we can develop a numerical estimation of hole cleaning quality as a function of rheology, flow rate, hole geometry, cutting size, rate of penetration, and hole angle.

**Drilling Surface Pressure**

The drill pipe, BHA, and Bit friction pressures are the main contributors to surface pressure. The summation of system friction pressures is equivalent to the surface and mud pump pressures. Using correlations for the Power-Law Model of fluid flow in turbulent fluid space the surface pressure estimation can be determined using the equations below [12].

$$P = \sum_{s}^{String} \frac{dP_f}{dL_s} \cdot L_s + dP_{bha} + dP_b + \sum_{a}^{annulus} \frac{dP_f}{dL_a} \cdot L_a$$

*where*

$$\frac{dP_f}{dL_s} = \frac{f\rho\nu^2}{25.8\ d_s} \quad \forall\ s \in string\_sections$$

$$\frac{dP_f}{dL_a} = \frac{f\rho\nu^2}{21.1\ (d_{1,a} - d_{2,a})} \quad \forall\ a \in annulus\_sections$$

$P_f$ is the friction pressure

$f$ is the friction factor

$\rho$ is the fluid density

$\nu$ is the fluid velocity

$d$ is the diameter

### A.1.8 Casing Design

**Casing**

This integer value is used to determine if a string will be rated as casing or liner. Liners are cheaper and serve advantages in deeper wells. An evaluation of the casing regulations, casing load analysis, hole cleaning, and casing wear will determine the possibilities of a string becoming a liner. This is a binary variable of 0,1. There are no defined dependencies other than regulatory requirements. The evaluation of the casing load cases will determine if the use of the liner string is a feasible option. The numerical evaluation will treat the casing parameter as a binary variable that is an input parameter.

**Casing Top Measured Depth**

The top of the string is the reference point closest to the surface. For strings that are casing, this will always equal 0. For liner strings, this depth is variable but must meet the constraint of being shallower than the previous string minus some required liner x casing overlap. This overlap distance is typically a minimum of the previous strings shoe track, which is not discussed in this research.

$$
\begin{aligned}
(1 - Casing) * Csg_{top} + Casing * Csg_{top} \quad &\leq Casing * (Csg_{btm,i-1} - Liner\ Overlap) \\
where & \\
Casing \ &\in \{0, 1\}
\end{aligned}
$$

**Casing Bottom Measured Depth**

In simple terms, the selection of casing depths is based on a static mud weight greater than the pore pressure and less than the fracture gradients for the drilled section. The casing bottom is approximately equal to the depth of a formation break. The depth is also a function of operational parameters drilling hazards, ECD, Hole cleaning, surge and swab pressures.

$$\rho_{sec} \geq pp_{sec}$$
$$swab_{sec} \geq pp_{sec}$$
$$\rho_{sec} \leq fg_{sec}$$
$$surge_{sec} \leq fg_{sec}$$
$$ECD_{sec} \leq fg_{sec}$$

**Casing ID**

The inner diameter (ID) of the casing string should be maximized to meet the constraints of the load cases of the evaluated section. Increasing the ID results in a reduced wall thickness. In a bottom-up design strategy, the casing ID must be greater than the bit diameter of the previous section.

$$\begin{aligned} &\textbf{Objective}: max\ ID_{csg}\ or\ \ min\ wall\ thickness \\ &\textbf{such that}: \\ &\qquad \text{Casing Load Evaluation Passes} \\ &\qquad ID_{csg} \geq OD_{bit,\ sec+1} \\ &\qquad ID_{csg} \geq OD_{csg\_conn,\ sec+1} \end{aligned}$$

**Casing OD**

The outer diameter of the casing string is driven by the bit size, minimum ID allowance, next casing string ID, maximum allowable OD, connection type, and the satisfaction of applicable load cases. "The size of the casing string is controlled by the necessary ID of the production string and the number of intermediate casing strings required to reach the depth objective" [12].

$$\textbf{Objective} : \min OD_{csg,sec} \ \forall \ sec \in Casing\ Sections$$

$$\textbf{such that} :$$

$$\text{Casing Load Evaluation Passes}$$

$$OD_{csg,sec} \leq ID_{csg,sec+1}$$

$$OD_{csg,sec} \geq OD_{csg,sec}$$

**Min Drift Diameter for Casing String**

The Drift diameter for any string is the minimum allowable ID that will allow the passage of an object with a fixed OD and length. This factor is important when considering the diameter clearance, tolerances, and bending angles. This is an input parameter that is specified by API standards or the tubular manufacturer and is a property of the discrete selection of a casing string. The drift ID is approximately equal to $ID_{csg} - OD_{csg}/64$. All equipment that will pass through the casing must be less than the drift diameter.

$$DriftID_{csg} \geq OD_{csg\_conn,sec+1}$$

$$DriftID_{csg} \geq OD_{bit}$$

$$DriftID_{csg} \geq OD_{csg,sec+1}$$

**Casing Connection OD**

Most connections used have standardized dimensions or can be interpolated from a table. For this research, we will leverage the standardization of API connections in API Spec 5CT to define the OD of the casing connections, which are lookup values to standard OD pipe for the diameter and length from API Round and Buttress Connections.

**Casing Connection Type**

The connection type is selected as a factor of the lowest cost connection that will meet the ultimate well objectives. The well objectives that determine the type of connection used could include: the total well cost, the total life expectancy of the well, the risk and cost of failure, regulatory requirements, operational time per connection, equipment availability for special operations, formation fluids, well architecture limitations, and if the string is a casing string or liner.

$$\begin{aligned}
&\textbf{Objective}: \min\{conn_time, cost, OD\} \\
&\quad \textbf{such that}: \\
&\qquad \text{Casing Load Evaluation Passes} \\
&\quad OD_{conn,\ sec} \leq ID_{csg,\ sec-1} \\
&\quad OD_{conn,\ sec} \geq OD_{csg,\ sec} \\
&\qquad \text{Isolates Formation Fluids}
\end{aligned}$$

### Casing Yield Strength

The casing yield strength is the primary material factor of casing load analysis. The geometry of a casing string can be modified with allowances for higher yield pipes.

### Casing Material

In well design, the casing material selection is essential for the life of the well. The material selection is based on the casing yield strength, wettability or in direct contact with oil, and corrosion resistance if placed in corrosive environments. Using Figure 8.27 from [31], the material selection for casing corrosive environments can be implemented into a numerical simulation, where the $CO_2$ and $H_2S$ concentrations in parts per million in combination with the highest expected fluid temperature, designates material classes suitable for the environment.

### Casing Load Cases

The evaluation of casing string evaluates the possible failure modes of the casing string under the highest expected loads, such as pressure testing, a loss of internal fluid, or production pressure and temperature limitations. The casing load analysis evaluates burst, collapse, axial, and bending stresses for each casing string at the most extreme, but controlled, data points possible during the well construction operation [31]. Occurrences such as well blowouts, damaged equipment, or subsurface anomalies such as unexpected caving or tectonic movements are not evaluated. Using the tri-axial formulation defined in API Technical Report 5C3 [35], the combined stresses must remain less than the pipe yield strength.

$$\sigma_e \leq pipe\_yield$$

$$where$$

$$\sigma_e = [\sigma_r^2 + \sigma_h^2 + (\sigma_a + \sigma_b)^2 - \sigma_r\sigma_h - \sigma_r(\sigma_a + \sigma_b) - \sigma_h(\sigma_a + \sigma_b) + 3\tau_{ha}^2]^{1/2}$$

$$with$$

$$\sigma_a = \frac{F_{axial}}{\frac{\pi}{4}(OD^2 - ID^2)}$$

$$\sigma_b = Ecr$$

$$\sigma_h = \frac{(p_{int} * d_{wall}^2 - p_{ext} * OD^2) + (p_{int} - p_{ext}) * d_{wall}^2 * \frac{OD^2}{d_{wall}^2}}{OD^2 - d_{wall}^2}$$

$$\sigma_r = \frac{(p_{int} * d_{wall}^2 - p_{ext} * OD^2) - (p_{int} - p_{ext}) * d_{wall}^2 * \frac{OD^2}{d_{wall}^2)}}{OD^2 - d_{wall}^2}$$

$$\tau_{ha} = \frac{Tr}{J_p}$$

*where*

| | |
|---|---|
| $A_p$ | is the area of the pipe cross-section, $A_p = \pi/4(D^2 - d^2)$ |
| $c$ | is the tube curvature, the inverse of the radius of curvature to the centerline of the pipe |
| $D$ | is the specified pipe outside diameter |
| $d$ | is the pipe inside diameter, $d = D - 2t$ |
| $d_{wall}$ | is the inside diameter based on $k_{wall}t, d_{wall} = D - 2k_{wall}t$ |
| $E$ | is Young's Modulus |
| $F_a$ | is the axial force |
| $I$ | is the moment of inertia of the pipe cross-section, $I = \pi/64(D^4 - d^4)$ |
| $J_p$ | is the polar moment of inertia of the pipe cross-section, $J_p = \pi/32(D^4 - d^4)$ |
| $k_{wall}$ | is the factor to account for the specified manufacturing tolerance of the pipe wall e.g. for a tolerance of $-12.5\%,\ k_{wall} = 0.875$ |
| $M_b$ | is the bending moment |
| $p_i$ | is the internal pressure |
| $p_o$ | is the external pressure |
| $r$ | is the radial coordinate, as follows: $(d/2) \leq r \leq (D/2)\ for\ \sigma_a,\ \sigma_b,\ and\ \tau_{ha}$ $(d_{wall}/2) \leq r \leq (D/2)\ for\ \sigma_r\ and\ \sigma_h$ |
| $T$ | is the applied torque |

### A.1.9 Cementing

**Lead Cement Height** The lead cement height is the lower density cement pumped between the cementing spacer and tail cement. The height of the slurry should be designed to meet the regulatory or cementing objectives, and should account for eroded rock sections, termed "washout."

**Tail Cement Height** The tail cement is the last cement slurry pumped downhole, and has the highest density of all fluids within the wellbore. The height of the tail cement slurry should be greater than the casing shoe track length, but the hydrostatic pressure contribution must remain below the well fracture gradient.

**Lead Cement Density** This cementing mixture should have a density greater than the cementing spacer and drilling mud to prevent fluid mixing. The density of the lead cementing slurry must be large enough to maintain the hydrostatic pressure as the lead cementing slurry transitions to a solid, but allow the cementing spacer to maintain hydrostatic pressure as the lead cement transitions to a solid.

**Tail Cement Density** This slurry is used to isolate the casing shoe when drilling the next hole section and should be designed to obtain a high compression load at the fastest rate. The tail cement density should be greater than the lead cementing density, and must balance the setting time and compression strength for casing shoe structural integrity.

**Cementing Spacer Height and Density** A properly designed cementing spacer is critical to a successful primary cementing operation. The cementing spacer is a water-based fluid that has low reactivity to the cementing slurry and serves several purposes:

- Removes mud filter cake from the wellbore walls
- Displaces drilling mud away from cementing slurry
- Assists in maintaining hydrostatic integrity during cementing transition

times. As cement transitions from a liquid to a solid, there is a transitional period where the density of cement is equivalent to its base fluid, water.

– Carries corrosion prevention chemicals into the wellbore annulus

**Equivalent Mud Density while Cementing** The equivalent mud density (EMW) of cement is equivalent to the sum of all hydrostatic pressures of all fluids in the annulus. The sum of the pressures must remain below the well fracture gradient.

$$\begin{aligned} EMW_{cement} =& (mw * Height\ of\ Mud \\ & + spacer\ density * Height\ of\ Spacer \\ & + Lead\ Cement\ Density * Height\ of\ Lead\ Cement \\ & + Tail\ Cement\ Density * Height\ of\ Tail\ Cement) \\ & \div TVD_{Depth} \\ EMW_{cement} \leq & \ Frac\ Gradient_{Depth} \end{aligned}$$

**Equivalent Circulating Density while Cementing** The ECD while cementing calculation is similar to the mud ECD calculation. Cement is pumped at a much lower flow rate to allow for proper mixing, and is limited by the ECD while pumping. The viscosity of cement is significantly higher than the fluid used to drill, and is a critical structural integrity component that could result in significant cost implications for failure.

### A.1.10 Drilling Assembly

**Drill Pipe OD**

Drill pipe is supply constrained to standard API drill pipe grades. The Drill Pipe OD, ID, and tool joint OD will be distinct table values that depend only on the supply capabilities and material grade. Externally upset drill pipe is the most common grade of drill pipe, making the tool joint's OD larger than the pipe's OD. The drill pipe OD is a discrete decision variable that will not have direct inputs. The standard drill pipe OD's are 2.375", 2.875", 3.5", 4.0", 4.5", 5.0", 5.5", and 6.625".

**Drill Pipe ID**

The drill pipe ID depends on the OD and weight of the drill pipe. The ID of the pipe is a significant contributor to the friction pressure of the drilling fluid circulation system. A balance in pipe tensile strength, weight, ECD, and pipe availability must be managed during the well design and construction process.

**Drill Pipe Tool Joint OD**

The tool Joint OD is a function of the drill pipe OD. The tool joint is designed to be the weakest link in the drill pipe, which makes string retrieval easier. The limits of the tool joint OD indicate that the tool joint OD must be less than the drift ID of the previous casing string and the bit diameter.

$$OD_{TJ} \leq DriftID_{csg,sec-1}$$
$$OD_{TJ} \leq bit\_diameter$$

**Drill Pipe Tensile Strength**

The drill pipe tensile strength is a tabular value of the pipe OD and grade selected. The tensile strength of the drill pipe is determined by evaluating the total string weight expected, the necessary overpull needed for safe operations, and the fluid composition of the drilled formations. Formations with highly corrosive fluids can cause stress cracking and premature failures and require a pipe with lower tensile stress to withstand the corrosive environment. For numerical optimization, the minimum tensile stress for pipe will be calculated using a summation of all weights in the drill string plus the required overpull shown below.

$$overpull_{dp} \geq pipe\_tensile - [wpf_{dp} + wpf_{hwdp} + wpf_{dc}]$$

**Drill Pipe Total Length**

The total length of drill pipe is a function of the heavy-weight drill pipe (HWDP) and Drill Collar (DC) lengths. When drill pipe limits are near the maximum allowable tensile limit, two to three diameters of drill pipe may be used. The length limit of the bottom (dp2) and top (dp1) drill string segments are defined below [7], where the maximum tensile limit is 90% of the published tensile limit.

$$\begin{aligned}
Len_{dp2} \leq & \frac{0.9 * Tensile_{dp2} - Min_Overpull}{wpf_{dp2} * BF} \\
& - \frac{wpf_{hwdp} * Len_{hwdp}}{Wpf_{dp2}} \\
& - \frac{wpf_{dc} * Len_{dc}}{wpf_{dp2}} \\
Len_{dp1} \leq & \frac{0.9 * Tensile_{dp1} - Min_Overpull}{wpf_{dp1} * BF} \\
& - \frac{wpf_{dp2} * Len_{dp2}}{Wpf_{dp1}} \\
& - \frac{wpf_{hwdp} * Len_{hwdp}}{Wpf_{dp1}} \\
& - \frac{wpf_{dc} * Len_{dc}}{wpf_{dp1}}
\end{aligned}$$

**Drill Pipe Weight per Foot**

The drill pipe weight per foot metric is the average dry weight of the drill string before introducing the buoyancy factor. This value is generally given as a table value, but could be be numerically calculated using $f(OD_{dp}, ID_{dp}, Density_{dp})$. The tool joints add a relatively small amount of weight, but it can be significant when the error is scaled on an entire drill string. ‘

**Drill Pipe Static Load Evaluation**

Drill pipe load analysis evaluates torque, compression, tension, burst, and BOP closure with MASP or BOP test pressures. These loads will ensure the drill string can achieve a desired level of torque while drilling, pull the string if it becomes stuck, and contain internal and external pressures.

**Drill Pipe Overpull Capacity**

The drill pipe overpull allowance is the minimum difference in the calculated axial tension and the allowable axial tension [7]. This value is given as a constant for each hole section.

**Heavy Weight Drill Pipe OD**

The heavy-weight Drill Pipe OD is equivalent to the smallest drill pipe in the hole. The smallest OD drill pipe is also the deepest.

**Heavy Weight Drill Pipe ID**

The ID of the heavy-weight drill pipe is a lookup value and must be greater than the minimum allowable ID in the drill string.

**Heavy Weight Drill Pipe Length**

The use of heavy-weight drill pipe in drill string design serves as an intermediary to drill collars and drill pipe. The pipe length can be represented as a function of maximum weight on bit, hole cleaning, ECD, and maximum angle. Heavy weight drill pipe can be used in both tension and compression and is used in the transition zone between drill collars and drill pipe. Furthermore, the HWDP reduces the torque and drag and limits differential sticking [7]. The length of the heavy-weight drill pipe is a decision variable that can be applied to cost and performance objective functions.

**Heavy Weight Drill Pipe Weight**

The weight of the heavy-weight drill pipe is a function of the OD and ID of the pipe. As the ID of a set heavy weight drill pipe OD string decreases, the weight of the string in lbs/ft will increase. The string's buckling strength will also increase due to the increasing Bulk Modulus.

**Drill Collar OD**

Drill collars have standardized sizes, and the diameter is dependent on the hole section diameter.

**Drill Collar ID**

The drill collar ID is generally the smallest ID of the drill string. The ID is limited by the minimum allowable diameter for objects that must pass through the Bottom Hole Assembly, such as fishing tools and balls used for various functions.

**Drill Collar Length**

The desired weight on bit primarily drives the length of drill collars, and in deviated wells, the maximum deviation can impact the length of drill collars. Long drill collar sections can make drilling highly deviated wells difficult due to the stiffness of the drill collar assembly. The length of the drill collars and the heavy-weight drill pipe is determined by the desired weight on bit in a vertical well and can follow the equation below.

$$max\_wob \leq wpf_{dc} \times len_{dc} \times BF + wpf_{hwdp} \times len_{hwdp} \times BF$$

**Drill Collar Weight**

Similar to the heavy weight drill pipe weight, the drill collar weight is driven by the OD and ID of the pipe. The weight of the drill collars are used as the primary source of bit weight, so there must be a sufficient balance in drill collar weight to ensure drilling can occur with the bottom hole assembly configuration.

**Bottom Hole Assembly Directional ROP**

The ROP of any BHA is a complex function of the BHA and bit design. Using the principles discussed by Witktorski, Kuznetcov and Sui, we can use a linear relationship of the Rate of penetration of directional drilling to the Rate of Penetration of the non-directional rate of penetration [65].

**Bottom Hole Assembly Pressure Differential**

The maximum allowable BHA differential pressure is used to determine the type of equipment that can be used in the BHA. This value is the remaining pump pressure and rate that can be achieved with existing equipment [7].

$$MaxP_{bha} \leq \frac{1714 \times P_{hp}}{Rate} - (P_{fdp} + P_{fdc} + P_{fadp} + P_{fadc} + P_{fs} + P_{b})$$

**Bit Diameter**

The bit OD is a discrete set of values that is driven by an upper and lower limit of the casing of the current and previous sections. To limit the number of possible solutions, additional clearance can be added to the upper and lower bounds for more realistic solutions and to limit the feasible design space. Therefore, for this research, a diameter difference of 1/4" will be applied to all sections.

$$OD_{bit} \leq MinID_{prev\_csg} - 0.25$$
$$OD_{bit} \geq MaxOD_{csg\_conn} + 0.25$$

**Bit Total Flow Area**

The bit total flow area (TFA) is the sum of area of all jets in the bit. The small area is the outlet to transfer fluid from the drill string to the drilling annulus. The bit TFA is limited by the system friction pressure. The goal in TFA optimization can be to maximize the Bit Nozzle Velocity, Bit Jet Force, and Bit Hydraulic Horsepower [12]. The formulation below describes the process used to maximize the hydraulic horsepower, where Azar uses an absolute maximum as the optimal point. However, for this integrated approach, the maximum will be treated as an objective function [7].

$$P_f = P_{fdp} + P_{fdc} + P_{fadp} + P_{fadc} + P_{fs} + P_{bha}$$
$$P_b = max(P_{surf} - P_f) * Q$$
$$TFA = \sqrt{\frac{(8.3 \times 10^{-5}\gamma Q}{C_d^2 P_b}}$$

**Bit Type**

The bit type will be defined as a selection of Polycrystalline Diamond Cutter, Tri-Cone Roller, or Diamond Impregnated Bits. A data table of reliability, vibration, cost and Rate of Penetration would need to be developed to perform proper bit type selection in an optimization problem.

### A.1.11 Drilling Rig and Surface Equipment

The drilling rigs are designed and manufactured to drill small wells subsets at economical costs. When designing a drilling program, it is a best practice to use a drilling rig that is at or near the limitations of the well design. Drilling rigs with advanced or exceeding capabilities are not cost-efficient. As described in the drilling specifications Table 4.2, there are a wide array of drilling specification, many of which focus on the drilling environment. The list of items below should be considered when designing a well plan.

- Hoisting Capacity
- Rig Pump Horsepower
- Pump Liner Diameter
- Pump Liner Stroke Length
- Mud Capacity
- Base Fluid Capacity
- Disposal Fluid Capacity
- Blow Out Preventer Pressure Rating

### A.1.12 Performance Parameters

**Rate of Penetration**

The Penetration rate is a complex, non-linear calculation that must consider all factors of drilling. During well planning the range of Rate of Penetration prediction is generalized through the analysis of historical data, and supplied as probabilistic values rather than simulated approximations. The Bourgoyne-Young drilling model uses the product of functions to estimate the drilling rate. Bit weight, rotary and bit speed, drill bit wear, formation depth, hole diameter, pore pressure to mud density differential pressure, lithology correlations, and impact force combine to estimate the drilling rate of a given formation [12]. This calculation is used for real-time predictions and uses correlation and history matching to define the constants within the algorithm.

**Maximum Weight on Bit**

The maximum bit weight is the maximum possible weight that can be applied to the bit before the drill pipe is in compression or the technical specifications for the axial load limit of the drilling bit is reached. Based on the Bourgoyne-Young model, the drill bit weight has a positive correlation to the rate of penetration [12].

$$f_5 = \left[ \frac{\frac{W}{d_b} - \frac{W}{d_b}_t}{4 - \frac{W}{d_b}_t} \right]^{a_5}$$

*where*

$W$ – Weight on Bit

$d_b$ – Bit Diameter

$a_5$ – Location drilling constant

$\frac{W}{d_b}_t$ – Threshold bit weight,

weight in which the bit begins to drill

**Rotary Torque While Drilling**

The rotary torque is a limiting measure for drilling torque. Bit torque has a positive effect on drilling rate, but depending on the lithology of the drilled rock, could reduce the drilling bit reliability, and result in premature failures. The rotary torque is equivalent to the summation of the torque required to drill rock, plus the frictional system torque. This value must be less than the drill pipe make-up torque, or drill pipe reliability is reduced.

### Drill String Drag

Drill string drag is the sum of the forces opposing movement in the axial direction of the pipe. In directional drilling drag can limit the horizontal distance achievable. The increase in drag results in decreased weight transferred to the drilling bit. During drilling operations the drill string drag force can be an indication of drilling anomalies, such as insufficient wellbore cleaning, failed wellbore integrity, or differential sticking of the drill pipe to the wellbore walls.

### Casing Torque and Drag Force

The casing drag force is summation of the opposing force to move the casing into the well. This value is similar to the drill string drag, without the additional bit torque. Most torque and drag simulations utilize arbitrary friction factor values to represent friction reduction technologies, and is an acceptable method for modeling.

### Job Time

The duration for drilling is associated with the operational order of the well, the time requirement to transition between activities, and the time required to drill the well. An example of a well phase description for the total time required to drill a well is described in Table A.2.

**Table A.2:** Drilling Job Activity and Duration for a 3 Section Well

| **Activity** | **Duration (days)** |
|---|---|
| *Drilling Rig Moves onto a Well and Configures the Rig for Drilling* | 7 |
| *Drill the Surface Section of the Well* | 0.25 |
| *Pull the Drill String and Drilling Bit out of the Well* | 0.1 |
| *Run the Surface Casing into the Well* | 0.3 |
| *Cement the Surface Casing* | 0.3 |
| *Install the Wellhead and Blowout Preventer* | 0.5 |
| *Pressure Test Blow Out Preventer and Surface Equipment* | 0.2 |
| *Drill the Intermediate Well Section* | 1.5 |
| *Pull the Drill String and Drilling Bit out of the Well* | 0.3 |
| *Cement the Intermediate Section* | 0.6 |
| *Drill the Production Well Section* | 1.5 |
| *Pull the Drill String and Drilling Bit out of the Well* | 0.5 |
| *Cement the Production Casing* | 0.6 |
| *Test the Well Integrity and Dismantle the Drilling Rig* | 3 |
| **Total Job Duration** | **16.65** |