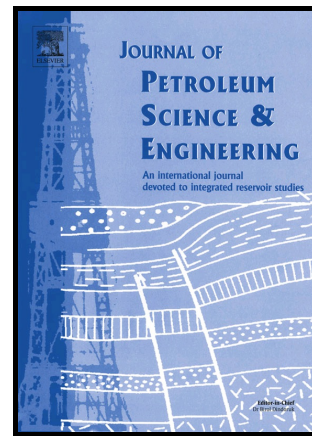


# Author's Accepted Manuscript

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## Automatic Optimisation of Oilfield Scale Inhibitor Squeeze Treatment Designs

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## Automatic Optimisation of Oilfield Scale Inhibitor Squeeze Treatment Designs

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### Abstract

Squeeze treatments are one of the most common methods to prevent oilfield scale deposition, which in turn is one of the most significant flow assurance challenges in the oil industry. Squeeze treatments consist of the batch injection of a chemical scale inhibitor (SI), which above a certain concentration, commonly known as MIC (Minimum Inhibitor Concentration), prevents scale deposition. The most important factor in a squeeze treatment design is the squeeze lifetime, which is determined by the volume of water or days of production where the chemical return concentration is above MIC, which commonly is between 1 and 20 ppm. Typically, squeeze treatment designs include the following four stages: a preflush, acting as a buffer; the main slug, where the main chemical slug is injected; the overflush, which will displaced the chemical pill deeper into the formation and finally, a shut-in stage, which allows the chemical to be further retained in the formation.

The main purpose of this paper is to describe the automatic optimisation of squeeze treatment designs using an optimization algorithm, in particular, using particle swarm optimization (PSO). The algorithm provides the optimum design for a given set of criteria that are used in a purpose built reactive transport model of the near-wellbore area. Every squeeze design is fully determined by a number of parameters; namely, injected inhibitor concentration, main slug volume, overflush volume and shut-in time. The parameter space is bound to certain limits, which will be determined by the maximum injected concentration, main slug and overflush volumes. The maximum injected concentration might be determined by, amongst other issues, logistics, economics and/or compatibility with other chemicals. The main slug and overflush maximum volumes may be identified by the well engineer based on concerns of water formation damage, hydrate formation and/or gas lifting limitations, which might be lower for high value wells. This approach still requires engineering input and review, but speeds up the process of finding an optimum design, and reduces risk of non-optimal squeeze treatments being performed.

Keywords: Optimisation; Squeeze treatments; Scale

### 1 Introduction

Oilfield scale is one of the most significant flow assurance challenges in the oil industry; it is defined as the deposition of organic and inorganic material compounds present in the produced brine, the deposition may occur in the surface facilities, wellbore or near wellbore areas. The deposition in the near wellbore area may block the porous medium and clog the perforations reducing well inflow. Deposition in the tubing and surface facilities will significantly reduce the well inflow deliverability. The deposition due to the precipitation of a number of compounds present in the produced brine is triggered by a disruption of the original geological equilibrium which was obtained over geological times (Crabtree, et al., 1999).

The most common inorganic scales that can be found in oilfields worldwide are sulfate and carbonate scales, which are formed by two different mechanisms. Sulfate scales, namely Barium Sulfate ( $\text{BaSO}_4$ ), Strontium Sulfate ( $\text{SrSO}_4$ ) and Calcium Sulfate ( $\text{CaSO}_4$ ), precipitate as the result of mixing of incompatible brines, specifically injected seawater and formation brine. Carbonate scales, on the other hand, precipitate due to the pressure reduction in the production wells, which releases the dissolved  $\text{CO}_2$ . Also, NaCl salt precipitation is becoming more common; this is due to

the cooling of well fluids and evaporation of saturated brines. Finally, previously termed “exotic” scales, such as Iron, Lead and Zinc Sulfide, nowadays are becoming more common as the number of HPHT (high pressure high temperature) reservoirs being produced is currently increasing.

Oilfield scale deposition is a significant flow assurance problem, and once it has occurred in a producing reservoir, it may seriously compromise hydrocarbon production and system safety, should key safety equipment, such as Sub Surface Safety Valves (SSSVs) be damaged. Scale removal can be very difficult; in some cases, such as for barium sulfate, which has a very low solubility, it generally has to be removed by well intervention. Other scales, with higher solubilities, particularly carbonate scales, can be removed by acid washes. The economic consequences of scale deposition can be very serious, because the well has to undergo some form of intervention, where the well has to be shut for a period of time with the consequently deferred oil production. In the next section, a number of mitigation and solutions will be described.

### 1.1 Oilfield Mitigation and Solutions

The most common methods to mitigate oilfield scale deposition applied in the oil industry are as follow: First, fluid modification, which includes sulfate reduction of the injected seawater and produced water reinjection to reduce the risk of sulfate scales. Second, flow modification or water shut-off, to reduce water flow and hence minimize the mass of scale depositing. Third, damage removal such as dissolvers, fracturing, milling and re-perforating. Finally, inhibition is used to prevent scale damage in the first place. If a severe risk of sulfate scale deposition, in particular Barium Sulfate, is predicted, it is particularly advisable to inhibit scale deposition, because once formed it is very difficult to remove. Inhibition consists in the injection of a chemical which prevents crystal nucleation or retards the crystal growth. It is deployed where the scaling deposition is expected to occur. Normally, the chemical is placed in the wellbore by continuous injection through a dedicated chemical flow line, or by bull-heading a batch treatment into the formation. This latter is commonly known as scale inhibitor squeeze treatment. The chemical then will be back produced protecting all locations from the wellbore to the topside facilities. Inhibition is considered to be one of the most effective mechanisms to prevent scale formation (Brod, 1991).

### 1.2 Scale Squeeze Treatments

Scale squeeze treatments have been commonly applied in the North Sea fields for controlling/preventing the formation of oilfield mineral scale. The success of the treatment is mainly based on the interaction between the chemical and the rock formation, which retains the chemical, allowing a gradual release in the produced brine over an extended period, (Sorbie and Gdanski, 2005). The chemical will be capable of inhibiting scale as long as the return concentration is above a certain level, commonly known as MIC (Minimum Inhibitor Concentration). The performance of squeeze treatments is given by the squeeze lifetime, which is the time taken until the SI return concentration falls below MIC. Squeeze lifetime might expressed in terms of time, normally in days, or in terms of volume of protected water produced.

Generally, a squeeze treatment consists of the following stages: preflush, main slug, overflush and shut-in. The preflush is injected as a buffer to displace any formation fluids and prepare the formation and clean the rock surfaces before injecting the main chemical slug. The main slug is where the main pill of chemical is injected. The overflush displaces the chemical deep into the formation allowing further retention on clean rock. Finally comes the shut-in stage which is a soak period that allows the chemical to retain at a higher level. Figure 1 shows a schematic of the three stages outlined above (from Jordan et al, 2008).

The main goal of this paper is to present an algorithm capable of optimizing a squeeze treatment design automatically. Optimizing does not necessarily mean the best design in terms of the longest squeeze lifetime, but the design that achieves the target squeeze lifetime at the lowest cost or using the lowest volume of water injected. In wells with a high water cut, above 80%, the volume of water injected might not be the most important factor, but the treatment cost will be. On the other hand, in low water cut wells there may be a risk of formation damage and so loss of productivity, so minimizing the volume of the aqueous solution may be desirable.

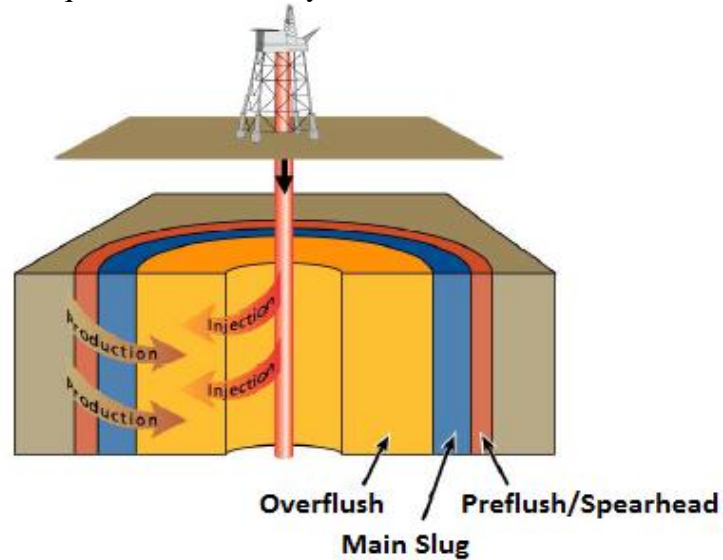


Figure 1 Schematic of the principal stages of a scale squeeze treatment (Jordan et al, 2008).

## 2 Optimization Techniques

In a simple scenario, optimization consists of maximizing or minimizing an objective function: the value of the objective function is determined by a number of input parameters. This process may be attempted by varying the parameters by hand until a desired match is obtained; however, this approach might be extremely time consuming, onerous and error prone. There have been various studies that described sensitivity analysis (Mackay and Jordan, 2003; Vazquez et al., 2015). These studies provided very valuable information at the time, although the calculations were set up manually. This novel approach not only aims to automate the process, but it also uses an optimization algorithm to assist and speed up the search.

There are a great variety of optimization algorithms or techniques, which can be clearly classified as deterministic and stochastic. A deterministic search uses the objective function in every stage of the algorithm to establish the search direction towards the global optimum solution (Vazquez et al., 2013a). Examples of deterministic search algorithms are the bisection method, Newton Raphson, and the steepest descent or gradient method, (Spall, 2003).

Although the deterministic search techniques will provide the optimum global solution, they might achieve this at high computational price and, maybe more significantly, they are not always applicable when the functional relationship between input variables and misfit is not clear (Onwubolu and Babu, 2004), such as in complex real life problems, where the surface or fitness landscape is jagged, or even discontinuous. Due to the nature of stochastic searches that are much more flexible and easy to implement, they are preferred in this particular problem.

Stochastic search algorithms can be classified between local search and population search. The hill climber algorithm, a well-known local search algorithm, has been successfully used for the

automatic adsorption isotherm matching, (Vazquez et al., 2013a). However, the population search algorithm has been extensively used in automatic reservoir history matching, due to its flexibility to accommodate complex real life problems. There are various population based algorithms such as the Genetic Algorithm (Goldberg, 1989), Differential Evolution, (Storn and Price, 1995) and Particle Swarm Optimisation (PSO), (Kennedy and Eberhart, 1995).

### 3 Proposed method

It seems reasonable to use a stochastic optimization algorithm to find the optimum scale squeeze design, because it is a complex real life problem, where the surface or fitness landscape is likely to be jagged. Among all the stochastic optimization algorithms available the population based ones seem to be the best candidates, and although any of these algorithms would have shown similar results, PSO has been used effectively to find well history matched reservoir models (Mohamed et al., 2010a, 2010b) and to find the layer flow rate distribution to match tracer return in a squeeze treatment (Vazquez et al., 2014). It is not the objective of this paper to compare the performance of different algorithms.

The PSO algorithm is inspired by the flight of flocks of birds: PSO is a set of agents (particles), which is described by a simple law of motion, where each particle motion is updated based on the best solution the particle has seen, (pbest), and the best solution across the whole population, (gbest). The main computational steps have been described before by (Mohammed et al, 2010a; Vazquez et al., 2013b):

- Step 1.** Initialise the algorithm with a population of particles of N designs randomly generated from the parameter space, where each particle is assigned a random velocity.
- Step 2.** Evaluate the fitness for every particle.
- Step 3.** Find pbes and gbest.
- Step 4.** Update the velocity of each particle i using Equation 1

$$v_i^{k+1} = w \cdot v_i^k + c_i^1 \cdot r_1 \cdot (pbest_i - x_i^k) + c_i^2 \cdot r_2 \cdot (gbest^k - x_i^k) \quad (1)$$

where:

- $v_i^k$  is the velocity of particle i at iteration k
- $x_i^k$  is the position of particle i at iteration k
- w is the inertia parameter
- $r_1, r_2$  random number in the range [0,1]
- $c_i^1, c_i^2$  are the acceleration terms

- Step 5.** Update the motion of each particle i motion using Equation 2

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (2)$$

- Step 6.** Repeat steps 2 to 5 until the maximum number of iterations is reached or another stopping criterion is met.

The fitness of each particle is calculated using the conventional L1 norm, see Equation 3, which calculated the normalized difference between the target (T) and the suggested design squeeze (S) lifetime. The closer the suggested design is to the target, the closer the design is to the objective and so the fitness.

$$\text{Objective} = |T - S|/T \quad (3)$$

### 3.1 Parameter space

As mentioned before, a scale squeeze treatment consists of a number of stages; in these calculations the main treatment and overflush will be considered, the shut-in time is not considered, since normally it is not exclusively a part of the squeeze design strictly speaking, i.e. the shut-in time may be determined by secondary factors such as the time necessary to put the well back in production. Therefore, three parameters will be considered, specifically the main treatment volume, the injected inhibitor concentration and the overflush volume. The ranges of these parameters are determined by an initial squeeze design, and by a low and high multiplier.

### 3.2 Multi-objective Optimization

Although it may appear that the optimum squeeze design is the one with the longest squeeze lifetime, it might not be the most effective treatment design, considering the operator management philosophy in question. It has been shown before that the overflush volume, coupled with the main treatment volume, is the most effective parameter in squeeze designs; however, other engineering considerations must be also considered, such as the impact of lifting all the water injected and deferred oil production (Mackay and Jordan, 2003; Vazquez et al., 2008). Also, it has been reported that although injected SI concentration increases the squeeze lifetime, it is not as effective as the overflush, due to the nature of interaction between the SI and the rock formation, increasing the total expense. Therefore, it seems that not only one objective (squeeze lifetime) should be considered, but three objectives: the total design cost, the total injected water and the squeeze lifetime.

Therefore, the problem becomes a multi-objective optimization, where there might not be a single design that optimizes each objective. In this case, the objectives are said to be conflicting objectives and there exists a number of Pareto optimal solutions or squeeze designs. A design will be part of the Pareto front if it is not dominated by other design. A solution  $v$  strictly dominates  $w$ , if  $v_i \leq w_i$  for every objective  $i$ , and at least one inequality is strict. In this paper, the optimization exercise assumed one objective (squeeze lifetime), but in the analysis we considered the Pareto front of the suggested designs, because the three objectives are important: the priority is to find a design that achieves the target squeeze lifetime. Then, from among the suggested solutions the most effective design, in terms of the operator management criteria, can be identified.

## 4 Field cases

Two cases will be considered in the study: both cases are field applications. The first case, Case 1, consists of one layer of 20 ft completion interval. The original squeeze design is shown in Table 1, the SI adsorption process is under kinetic conditions with a rate of 0.1 1/d and described by the following Freundlich isotherm,  $\Gamma = 750 * C^{0.4}$ , which was determined by matching the scale inhibitor return concentration profile from field treatment, as shown in Figure 2. The match was obtained using a purpose built near wellbore simulator (Sorbie et al., 1991; Vazquez et al., 2006, 2012).

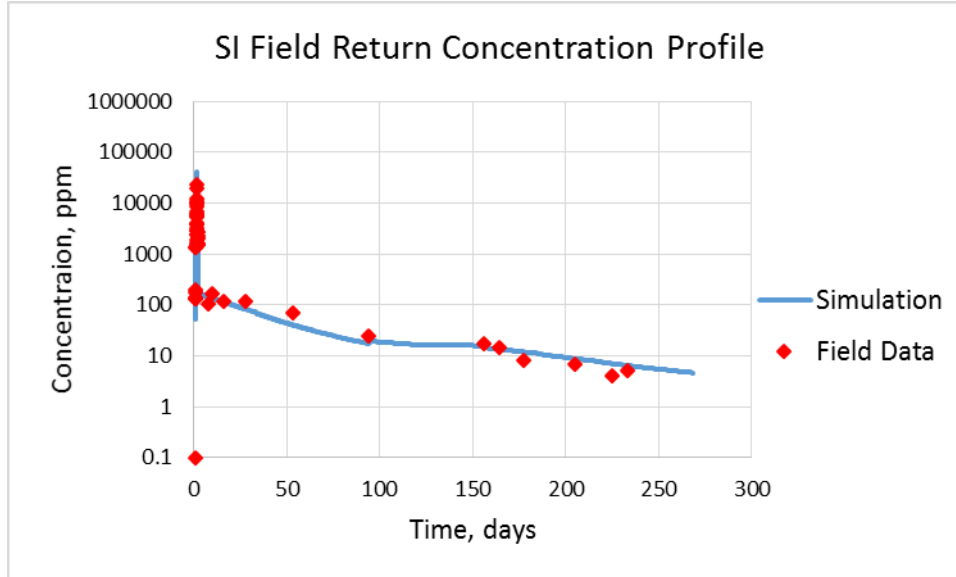


Figure 2 Case 1, SI field return concentration match.

The second case, Case 2, consists of three layers with a total completion interval of 70 ft, the squeeze design can be found in Table 2, the SI adsorption process is under kinetic conditions with a rate of 0.1 1/d and described by the following Freundlich isotherm,  $\Gamma = 501.1 * C^{0.4}$ , as shown in Figure 3.

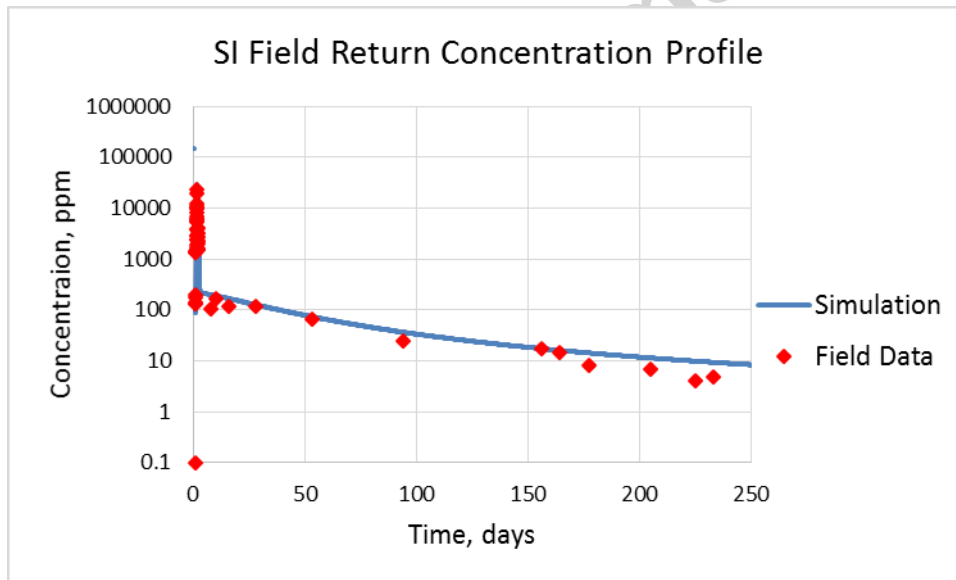


Figure 3 Case 2, SI field return concentration match.

Deriving an isotherm from the SI field return concentration profile is a common procedure which has been applied a number of times before (Lopez et al., 2005; Mackay and Jordan, 2003; Poynton et al., 2004; Vazquez et al. 2011, 2013a). Due to the fact that generally, the isotherm derived from a coreflood does not match accurately the field return concentration profiles (Mackay and Jordan, 2003; Sorbie et al., 1992; Yuan et al., 1994). Due to among other factors, variations in lithology in

the formation, assumptions about SI placement, and changes in brine chemistry of the produced fluid (Mackay and Jordan, 2003). The derived isotherm from the field return profile describes accurately the interaction of the particular scale inhibitor and the well formation. This isotherm provides excellent predicting results for the subsequent treatments, as long as the same SI is injected in the same well (Mackay and Jordan, 2003, Vazquez et al., 2011, 2013a).

#### 4.1 Optimization results

In this section, the optimization results from Case 1 and 2 will be analysed. To determine the parameter space limits for both cases the low and high multipliers for the three parameters are 0.05 and 3, respectively. As mentioned before, although the optimization exercise considered one objective, in particular the squeeze lifetime, which is described as the relative error against the target squeeze lifetime. The Pareto front was calculated considering two objectives, the squeeze lifetime (OBJECTIVE) and the total injected SI (SI BBL). In a future publication multi-objective optimization will be strictly considered, such as multi-objective approaches considering the Pareto envelop (Knowles et al., 2009; Corne et al., 2000).

##### - Case 1

Figure 4 shows the suggested designs by the optimizing algorithm, including the Pareto front. Also, each design is colour matched with the total injected volume of water, i.e. the main treatment and overflush water volume; the plot encapsulates the three main criteria for an effective squeeze design. The results identified a more effective design than the original, not only in terms of squeeze lifetime, but also requiring less total SI, reducing the total design cost. To assist in the analysis, the squeeze designs part of the Pareto front and the original design are listed in Table 3. The algorithm suggested that designs 8 and 9 are more effective than the original, although the total water injected is slightly higher. As expected, to achieve the desired squeeze lifetime the total injected SI and water volume has to increase; however, among the designs with similar squeeze lifetime the more effective ones can be identified by the Pareto front.

##### - Case 2

As for Case 1, Figure 5 shows the suggested designs by the optimization algorithm, and as before the algorithm identified designs 6, 7, 8 and 9, which are part of the Pareto front, see Table 4, more effective than the original design, where a lower amount of SI is necessary, although the volume of water injected has to be increased significantly.

## 5 Conclusions

The application of the Particle Swarm Optimization algorithm, which is a population based stochastic algorithm, has been applied to identify the most effective squeeze designs in two field cases. The effectiveness of a squeeze treatment design is determined by the following criteria: squeeze lifetime, total SI injected, i.e. total operation cost, and finally, total injected water volume. The last criterion is particularly relevant to water sensitive formations or valuable wells producing at low watercuts. Despite the existence of three possible conflicting objectives, the optimization exercise accounted for squeeze lifetime a single objective, due to the fact that among the three it is the most important.

Despite only a single objective being included, the Pareto front was calculated for the suggested designs on two objectives, the squeeze lifetime and the total SI injected, and in addition,



every design was colour matched to the injected water volume. Therefore, the three objectives were accounted for to identify the most effective design.

The algorithm described in the paper was capable of identifying more effective squeeze designs in terms of total injected SI, which will minimize the total operational cost. However, the total injected water was increased in all the cases, which is expected based on the nature of the interaction of the SI and the rock formation. The squeeze lifetime is enhanced if the overflush is increased, as has been previously reported, (Mackay and Jordan, 2003; Vazquez et al., 2008).

From the results, it can be concluded that to achieve the target squeeze lifetime the total SI injected, but also the injected water volume, need to increase. However, using the suggested plotting technique it is easy to identify among the designs close to the target squeeze lifetime the most efficient one with particular requirements, i.e. reducing costs or reducing injected water volume. For both cases the algorithm was capable of finding more effective squeeze designs in terms of the total injected SI.

The methodology was applied successfully to two field examples, which may be applied to any other field scenario.

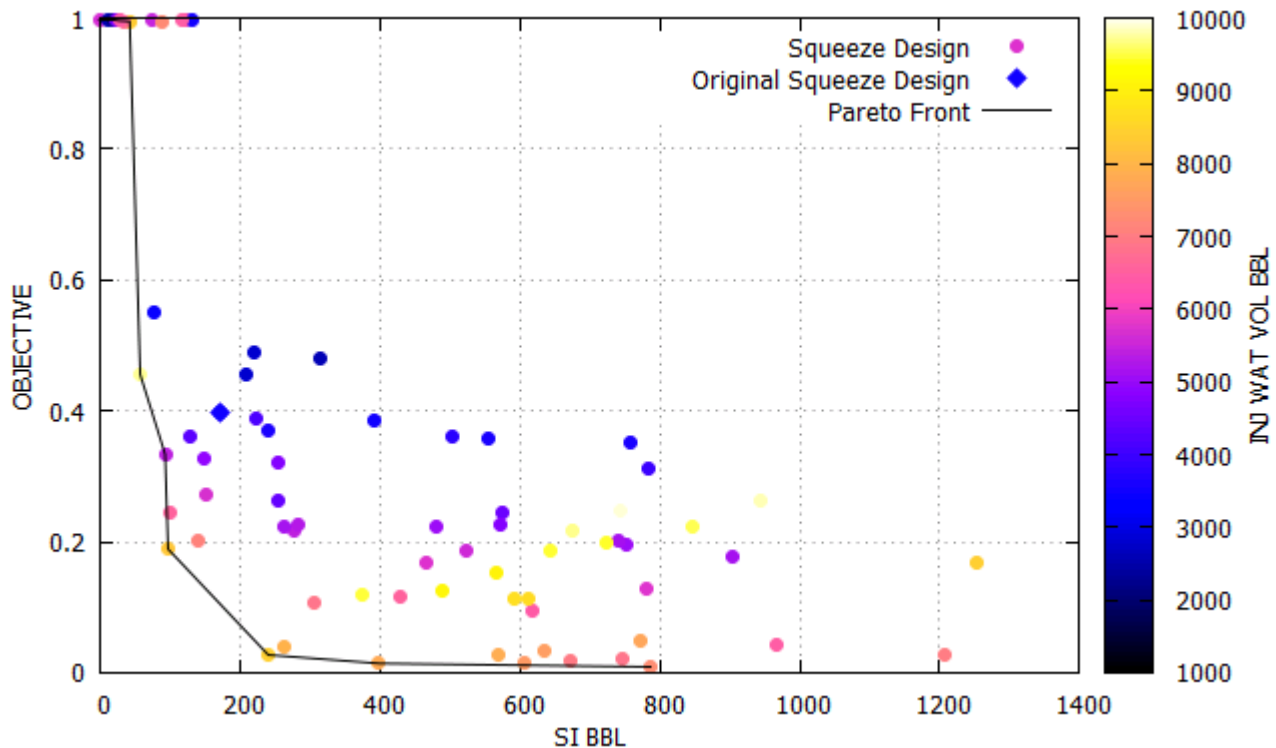


Figure 4 Case 1 optimization results, where the data are normalised against the original design.

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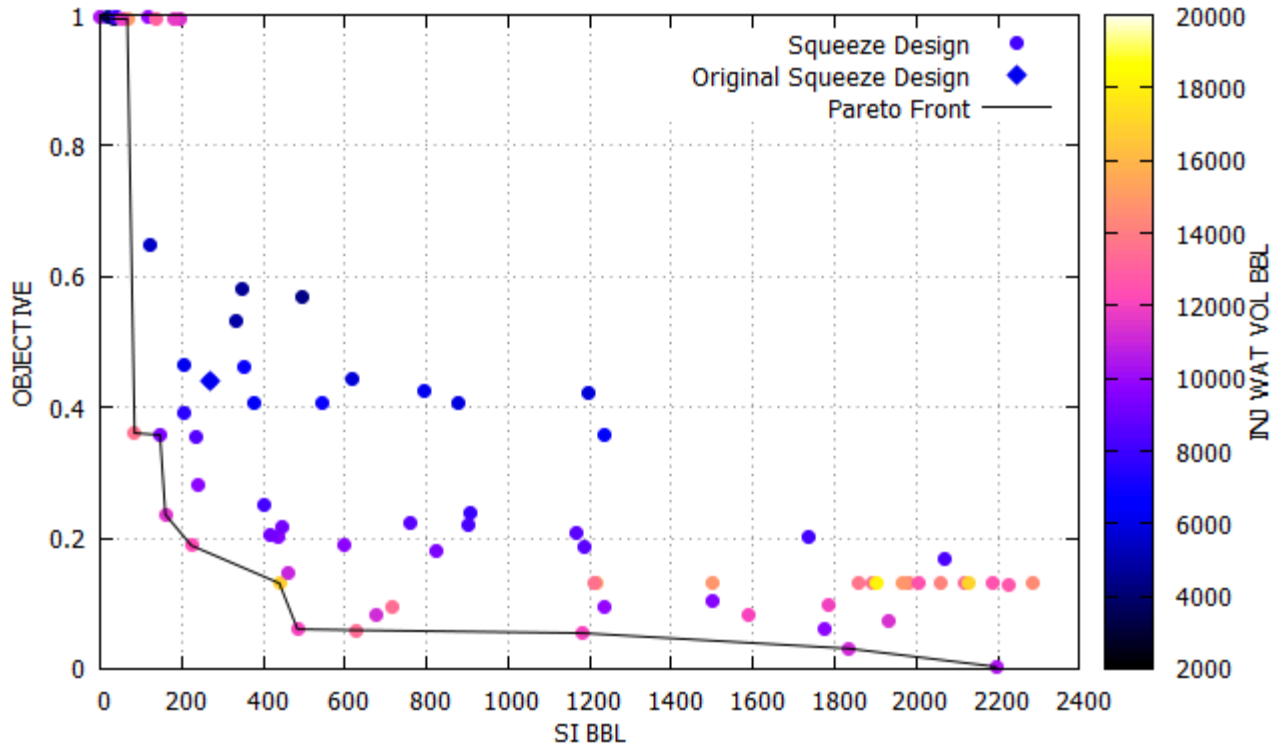


Figure 5 Case 2 optimization results, where the data are normalised against the original design.

Table 1 Case 1 Original Squeeze Design.

Parameter	Value
Main Treatment Volume (bbls)	1,140
Inhibitor Concentration	15%
Overflush Volume (bbls)	2,340

Table 2 Case 2 Original Squeeze Design.

Parameter	Value
Main Treatment Volume (bbls)	1,800
Inhibitor Concentration	15
Overflush Volume (bbls)	4,320

Table 3 Case 1 Pareto front designs, squeeze lifetime target is 400 days.

Design	MT Vol (bbls)	[SI] %	OF Vol (bbls)	SI (bbls)	Squeeze Lifetime (days)	%(Tar-Obj)/Tar
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1	1140.0	15.0	2340.0	171.0	241.1	39.7
2	179.8	0.8	5436.1	1.4	1.5	99.61
3	540.1	3.8	1445.2	20.7	1.5	99.61
4	3039.4	0.9	3362.8	27.8	1.6	99.59
5	2850.8	1.2	3917.9	34.9	1.7	99.56
6	1851.6	2.3	6483.9	42.5	2.0	99.5
7	3303.0	1.7	6403.2	57.4	217.7	45.57
8	2099.7	4.4	3249.8	93.1	266.5	33.39
9	3264.0	3.0	5027.0	97.3	324.4	18.91
10	3383.3	7.1	5011.3	240.6	389.1	2.73
11	3300.1	12.1	4440.6	399.1	394.3	1.43
12	3413.8	23.0	3838.1	786.9	403.6	0.9

Table 4 Case 2 Pareto front designs, squeeze lifetime target is 400 days.

Design	MT Vol (bbls)	[SI] %	OF Vol (bbls)	SI (bbls)	Squeeze Lifetime (days)	%(Tar-Obj)/Tar
1	1800.0	15.0	4320.0	270.0	223.9	44.0
2	283.9	0.8	10035.8	2.2	1.7	99.6
3	852.8	3.8	2668.0	32.7	1.9	99.5
4	4501.3	1.2	7233.0	55.0	1.9	99.5
5	2923.6	2.3	11970.3	67.1	2.2	99.4
6	5320.1	1.6	8264.6	84.8	255.7	36.1
7	3315.2	4.4	5999.6	147.0	256.9	35.8
8	3537.4	4.5	7930.7	160.5	305.7	23.6
9	5338.1	4.2	6808.3	223.8	324.5	18.9
10	5380.4	8.2	11465.3	439.3	452.4	13.1
11	4649.9	10.4	7275.7	483.8	375.7	6.1
12	5210.6	12.1	8198.1	630.2	423.7	5.9
13	4727.0	25.0	7161.3	1180.9	421.9	5.5
14	5391.7	34.0	5660.9	1834.7	412.5	3.1
15	5396.4	40.7	4946.0	2194.9	398.6	0.3

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#### Highlights

- Automatic optimisation of scale squeeze treatment design
- Multi-objective Optimization of scale squeeze treatment design
- Identify most optimum design based on considering the operator management philosophy

Accepted manuscript