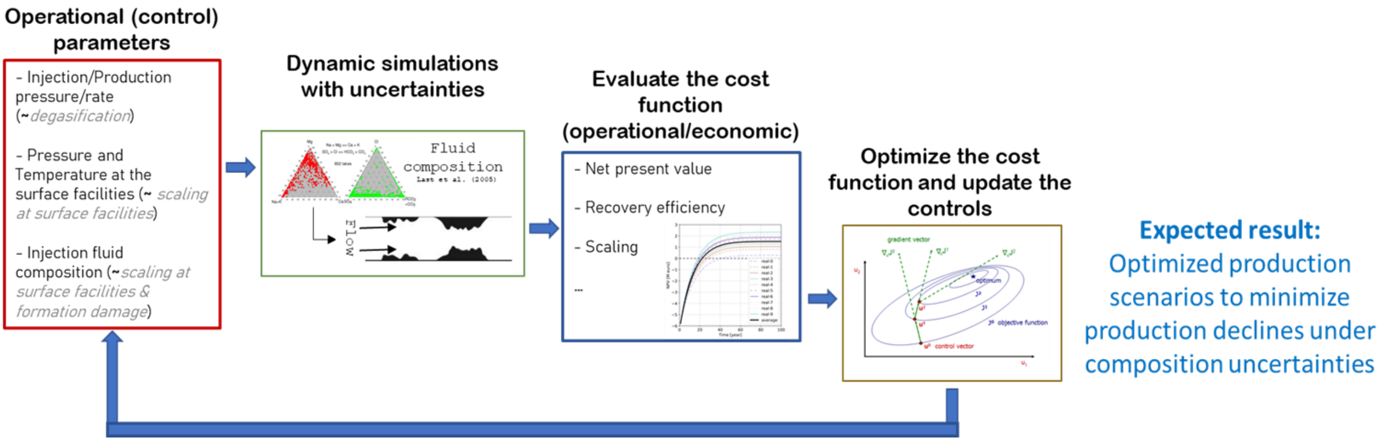
REFLECT DELIVERABLE D4.5

DECISION SUPPORT WORKFLOW FOR OPERATION OPTIMISATION UNDER FLUID COMPOSITION UNCERTAINTY



Summary:

This deliverable summarizes the optimization workflow to determine the optimum operational controls for the geothermal assets operation considering the uncertainties in the brine composition. The developed models for coupling hydrodynamics with chemistry and uncertainty quantification workflow for estimating the risk of scaling in geothermal plants were integrated with a stochastic optimization model. Results showed the demonstration of such an integrated workflow applied to a scaling precipitation case study and possible variations in operational decisions due to uncertainties in the brine composition.

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This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement nº 850626.

Title:	Decision support workflow for operation optimisation under fluid composition uncertainty		
Lead beneficiary:	TNO		
Other beneficiaries:	-		
Due date:	April 2023		
Nature:	Public		
Diffusion:	All project partners and general public		
Status:	Final		
Document code:	REFLECT_D4.5		
DOI:	https://doi.org/10.48440/gfz.4.8.2023.007		
License information:	CC-BY 4.0		
Recommended citation:	*Gonçalves Machado, C., de Zwart, H., Gonçalves Dias Barros, E., Shoeibi Omrani, P. (2023), The H2020 REFLECT project: Deliverable 4.5 - Decision support workflow for operation optimisation under fluid composition uncertainty, GFZ German Research Centre for Geosciences, DOI:* https://doi.org/10.48440/gfz.4.8.2023.007		
ORCID:			
Revision history	Author	Delivery date	Summary of changes and comments
Version 01	*C. Gonçalves Machado*	21/04/2023	First draft
Version 02	Shoeibi Omrani	27/04/2023	Improvements based on reviewer comments
Final version			

Approval status			
	Name	Function	Date
Deliverable responsible	Cíntia Gonçalves Machado	Scientist (TNO)	21/04/2023
WP leader	Laurent André	Hydrogeochemist (BRGM)	21/04/2023
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1 EXECUTIVE SUMMARY

Scaling is a major challenge in the operation of geothermal plants. The accumulation of scale can reduce the efficiency of the plant, increase maintenance costs and lead to frequent intervention and loss of production. One factor that can significantly impact scaling in geothermal plants is the composition of the brine used in the plant. Brine is a key component in the heat transfer process in geothermal plants, and variations in its composition can affect the solubility of minerals and the deposition of scale. However, there is often uncertainty regarding the composition of brine, which can be influenced by factors such as well depth, temperature, and geological formations which can impact the prediction of scaling risk in the system. In order to support operators in making operational decisions to deal with all these unwanted production challenges, including scaling, a workflow is required to accurately predict the system behaviour and performance and to provide advise to the operators on the optimum settings of the operation considering the uncertainties impacting the system.

This report summarizes the optimization workflow to determine the optimum operational controls for geothermal assets considering uncertainties in the brine composition. As a case study, a geothermal asset with barite precipitation in the heat exchanger was used to demonstrate the workflow. An optimization case to maximize the coefficient of performance (COP) of the geothermal doublet was conducted to find the optimum outlet temperature of the heat exchanger given an uncertain brine composition. Such a workflow can be used to derive optimum decisions for different operational tasks such as corrosion management, production-injection optimization and pump control.

The goal of this work was to show the added value of using robust optimization as the decision support of geothermal operators. It should ensure that geothermal sector is aware of the importance of integrating uncertainties in their modelling (Deliverable 4.3) and robust optimization workflows (as shown in this report). In this work we use the optimization toolbox Everest (Everest, 2023). However, the workflow we show for robust optimization is not limited to the use of Everest and in principle any other robust optimization algorithm can be used.

2 INTRODUCTION

In geothermal operations, mineral precipitation is a common problem that occurs when hot brine is extracted from underground reservoirs and brought to the surface for energy production. The hot brine typically contains high concentrations of dissolved minerals, which can precipitate out of solution due to the changes in the temperature and pressure during its journey through the production and injection system. This mineral precipitation can cause several issues, including fouling of heat exchangers, blockages in pipelines, and reduced system efficiency. The fouling of heat exchangers is one of the most significant issues caused by mineral precipitation in geothermal operations. These deposits can reduce the heat transfer efficiency of the heat exchanger, leading to decreased energy production and increased operating costs. Furthermore, the deposits can create a barrier that prevents further heat transfer, which can cause overheating and damage to the system. To mitigate the problem of mineral precipitation, various approaches have been developed, including chemical treatments, mechanical cleaning, and thermal treatments. Chemical treatments involve the use of chemical inhibitors to prevent mineral precipitation or dissolve existing deposits. Mechanical cleaning involves physically removing the deposits from the heat exchanger surface using brushes, high-pressure water, or other cleaning methods. Thermal treatments involve heating the heat exchanger to a high temperature to dissolve the salt deposits.

Next to the treatments mentioned above, changing the operation and process conditions in the geothermal system could have an impact on the initiation or rate of scaling in the system. Such decisions in the operation need to be made fast (in operational time-scales) and often the operator requires support to make such decisions. Several models and methods were developed to quantify the risk of scaling in geothermal plants which can potentially be used to identify optimum control settings of the system (Wasch et al. 2019).

This report summarizes the activities related to the decision workflows for geothermal operation under uncertainties. The next chapter demonstrates the methodology of robust optimization which was applied for the optimization of operational decisions. Afterwards a case study is defined for the optimal control of the heat exchanger in order to maximize the thermal energy produced. The models developed in Task 4.2 of the H2020 REFLECT project are used for the prediction of mineral precipitation under brine composition uncertainties. The results of the case study are shown and analyzed. Since the application of such a decision support framework is generic, other case studies in geothermal systems which can be applied in this framework are discussed in the final chapter.

3 METHODOLOGY

Robust optimization is a methodology for solving optimization problems that accounts for uncertainty in the problem input parameters (Figure 1). One approach to robust optimization is to use Stochastic Simplex Gradients (StoSAG), which is an algorithmic framework that combines robust optimization with stochastic gradient descent. StoSAG was first introduced by Chen (2008, 2009) as a robust optimization approach that could handle uncertain, noisy, and high-dimensional optimization problems. StoSAG uses a simplex gradient descent approach to compute the stochastic gradient of the objective function (Fonseca et al, 2016). The stochastic gradient is then used to update the solution in a way that accounts for the uncertainty in the problem parameters. At each iteration, a random sample of the problem parameters is generated, and the objective function is evaluated at the current solution. The stochastic gradient of the objective function is then computed using a simplex gradient descent approach, and the solution is updated accordingly. StoSAG has been shown to be effective in solving various robust optimization problems, including large oil field developments problems.

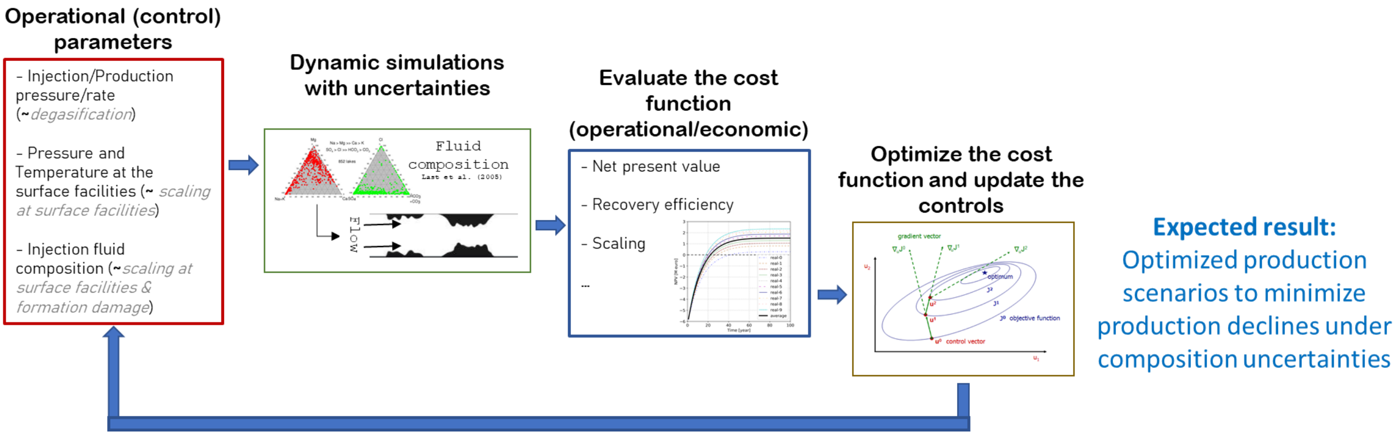


Figure 1. Optimization workflow.

In this work we use the optimization toolbox Everest (Everest, 2023). Everest is a decision making tool developed for use with multiple realization models/ensemble models to account for uncertainty, but Everest can be used both for optimization on single realizations and multiple realizations. The main advantages of our robust optimization tool are:
- Multi-objective function and constraints
- Account for uncertainty
- No need for gradient to be available
- Flexible (can be coupled to any model easily)
- Scalable to large number of controls variables: can easily become more complex

In Fig. 2, we present Everest robust optimization framework written in Python. Everest applies the StoSAG method described above together with optimizers from Dakota library (Adams et al, 2009). Robust optimization is an iterative optimization algorithm which incorporates uncertainties. In our workflow, we use the mean of an objective function value ($\widehat{OF}$) - for a single strategy for controls ($\mathbf{u}$) - evaluated over an ensemble (with N discrete scenarios) of models ($\mathbf{c}$) to describe the known uncertainty:

$$\widehat{OF}(\mathbf{u}) = \frac{\sum_{i=1}^{N} OF(\mathbf{u}, \mathbf{c}_i)}{N}$$

subject to

$$\mathbf{low\_bounds} \leq \mathbf{u} \leq \mathbf{upper\_bounds}$$

and

$$\widehat{OF}(\mathbf{u}) \geq \widehat{OF}_{min}.$$

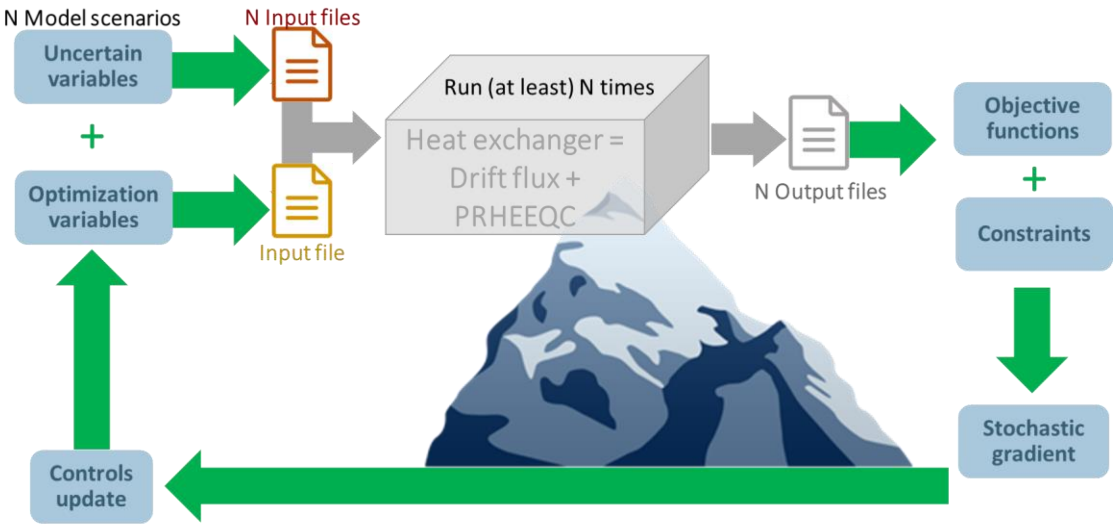


Figure 2. Everest Robust Optimization Framework.

4 CASE STUDY

4.1 CASE STUDY DESCRIPTION

The case study to demonstrate the robust optimization framework in this work is Barite precipitation in the heat exchanger of a geothermal doublet for direct use application. We assume that the brine composition is uncertain which can lead to different scaling index and amount in the heat exchanger at the same process conditions. The base composition of the brine is shown in Table 1. The aim of the case study is to find the optimum temperature control scheme in the heat exchanger to maximize the coefficient of performance in the geothermal plant.

Table 1. List of brine elements in the case study

Elements	Concentration [mg/l]
Na	85000
K	2200
Ca	7450
Mg	1150
Ba	5.5
Sr	290
Fe	175
Cl	145000
S(6)	585
Mn	9.25

The coefficient of performance (COP) is a measure of the efficiency of a heating, cooling, or refrigeration systems. It is defined as the ratio of the desired output of the system (heating or cooling capacity) to the required input (energy consumption or work done) to achieve that output. For a heating system, the COP is defined as the ratio of the heat output (in units of energy, such as Joules or BTUs) to the energy input (in units of energy, such as Joules or BTUs) required to produce that heat output. A higher COP indicates a more efficient system that produces more heat output for a given amount of energy input. We define the COP as:

$$\mathrm{COP} = \frac{Q_{\mathrm{Transfer}}}{W_{\mathrm{ESP}}},$$

where Q_{Transfer} is the energy extracted from the system in the heat exchanger

$$Q_{\mathrm{transfer}} = \sum_{\mathrm{Cell}} \left[\frac{1}{R_{\mathrm{thermal,cell}}} * \Delta T \right]$$

and W_{ESP} is the power consumed by the Electrical Submersible Pump (ESP), given by

$$W_{\mathrm{ESP}} = \frac{Q_{\mathrm{volumetric}}}{3600} \left(\rho_{\mathrm{brine}} * g_{\mathrm{earth}} * h_{\mathrm{hydro.head}} + P_{\mathrm{HEX,\,in}} \right)$$

with

$$R_{therm} = \frac{1}{2 * \pi * L_{cell}} * \left(\frac{1}{(r_{I.D.} - t) * h_{conv,\,in}} + \frac{\ln\left[\frac{r_{I.D.}}{r_{I.D.} - t}\right]}{k_{barite}} + \frac{\ln\left[\frac{r_{O.D.}}{r_{I.D.}}\right]}{k_{stain.steel}} + \frac{1}{r_{O.D.} * h_{conv,\,out}} \right)$$

and

$$h_{conv} = \frac{k_{barite}}{2 * \left(R_{pipe} - t_{precip.\,layer}\right)} * \left(\frac{\frac{f}{8}(Re_D - 1000)Pr}{1 + 12.7\left(\frac{f}{8}\right)^{0.5}\left(Pr^{\frac{2}{3}} - 1\right)} \right)$$

Note; the COP depends on the temperature and pressure in the heat exchanger, and on the volumetric flow rate since these parameters will impact the scaling behaviour.

As the forward model we use a multiphase flow solver coupled with PHREEQC (Figure 3) developed in WP4 (Poort et al, 2022). In this model, the mineral precipitation amount (in mol/L) is given by PHREEQC, following from flow properties calculated by the Drift-Flux model (multiphase flow). A precipitation model was created, which converts precipitation quantities into a deposition profile along the pipe wall of the heat exchanger. The heat exchanger pipe is divided into 25 cells of equal length. The deposition profile affects following parameters: Surface roughness, which affects the friction factor, Flow velocity, Pressure drop and Heat transfer to secondary flow. This process is iterated over a time period (now 25 days, up to 100 days) in order to capture effects over time. The details of the model can be found in Poort et al 2022 and Reflect Deliverable D4.3.

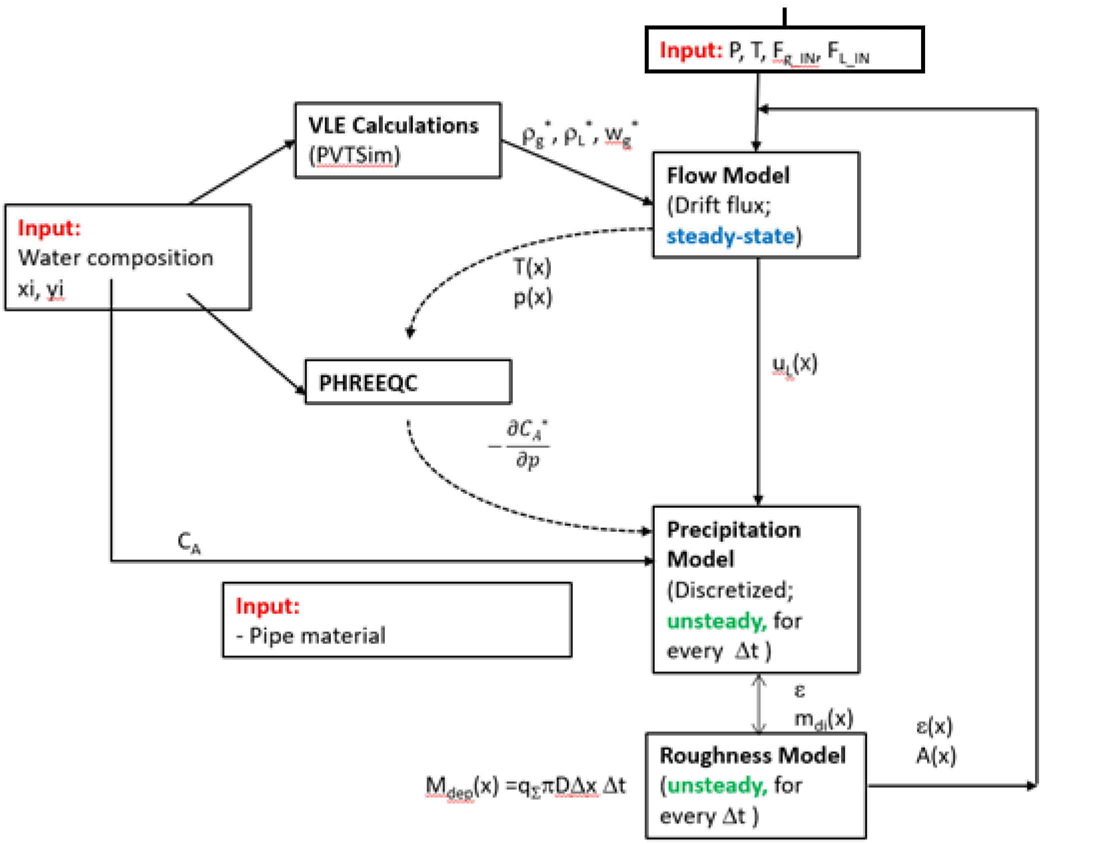


Figure 3. Forward model framework or the coupled flow and chemistry. Image adapted from Twerda 2014

4.2 OPTIMIZATION PROBLEM

Due mineral precipitation which decreases the heat exchanger pipe radius, eventually the heat production rate over time will decrease. Barite precipitation in the heat exchanger can be controlled by controlling the heat extraction at the heat exchanger which in turn will decrease thermal energy produced. However, by keeping the heat extraction from the heat exchanger high, the precipitation in the heat exchanger will lead to a higher resistance in the system and higher power is required to transport the production. In addition, uncertainty in the geochemical composition and gas concentrations in the produced water makes the precipitation prediction/control a challenge. The goal is to optimize the heat exchanger outlet temperature to maximize energy flow rate produced while minimizing the barite precipitation and power consumption of the pumps. For the case study described above, we have defined our objective function as

$$\mathbf{u}_{max} = argmax\, \widehat{COP}(\mathbf{u})$$

subject to

$$T_t^{\,out} < T_t^{\,in},$$

where u are the control variables and the expected COP is

$$\widehat{COP}(\mathbf{u}) = \frac{\sum_{i=1}^{N} COP(\mathbf{u}, \mathbf{c}_i)}{N}$$

and w is the uncertainty parameters. $COP(u, w_i)$ is the total heat produced:

$$COP(\mathbf{u}, \mathbf{c}_i) = \frac{\int_0^{t_p} q_{heat}(\mathbf{u}, \mathbf{c}_i, t)dt}{\int_0^{t_p} \mathrm{W_{ESP}}(\mathbf{u}, \mathbf{c}_i, t)dt}.$$

In this case, the brine contains Barite. The control is the heat exchanger outlet temperature, $\mathbf{u} = [T_0, \dots, T_t]$, at each time t, and the uncertainty is the amount of barite in the brine. $\boldsymbol{c_i}$ is the concentration of salt in the brine for each realization i.

4.3 ANALYSIS

In Figure 4, we show the COP versus time and outlet temperature for two Ba concentrations of 2.25 and 5.5 mg/L in the brine. We can see that when the outlet temperature goes towards the inlet temperature value (100.15°C), COP tends to null. Since as temperature difference goes towards zero, no heat is produced and COP is zero as well. When the outlet temperature drops in this case, barite precipitates, creating an insulation barrier, increasing the power consumption of the pump and decreasing the COP over time. In this case, the optimum is around 30°C during the whole period simulated (100 days). For the case with barite concentration of 2.25, the optimum solution is $\mathbf{u} = [27.0, 27.4, 27.7, 28]$, with a $COP = 21.0132$ at 100 days. For the case with barite concentration of 5.5, the optimum solution is $\mathbf{u} = [27.3, 27.9, 27.9, 27.9]$, with a $COP = 19.0120$ at 100 days.

In Figure 5 we show the amount of barite precipitated in the heat exchanger. As expected, we can see that, higher the initial amount of barite, higher the precipitated volume over time.

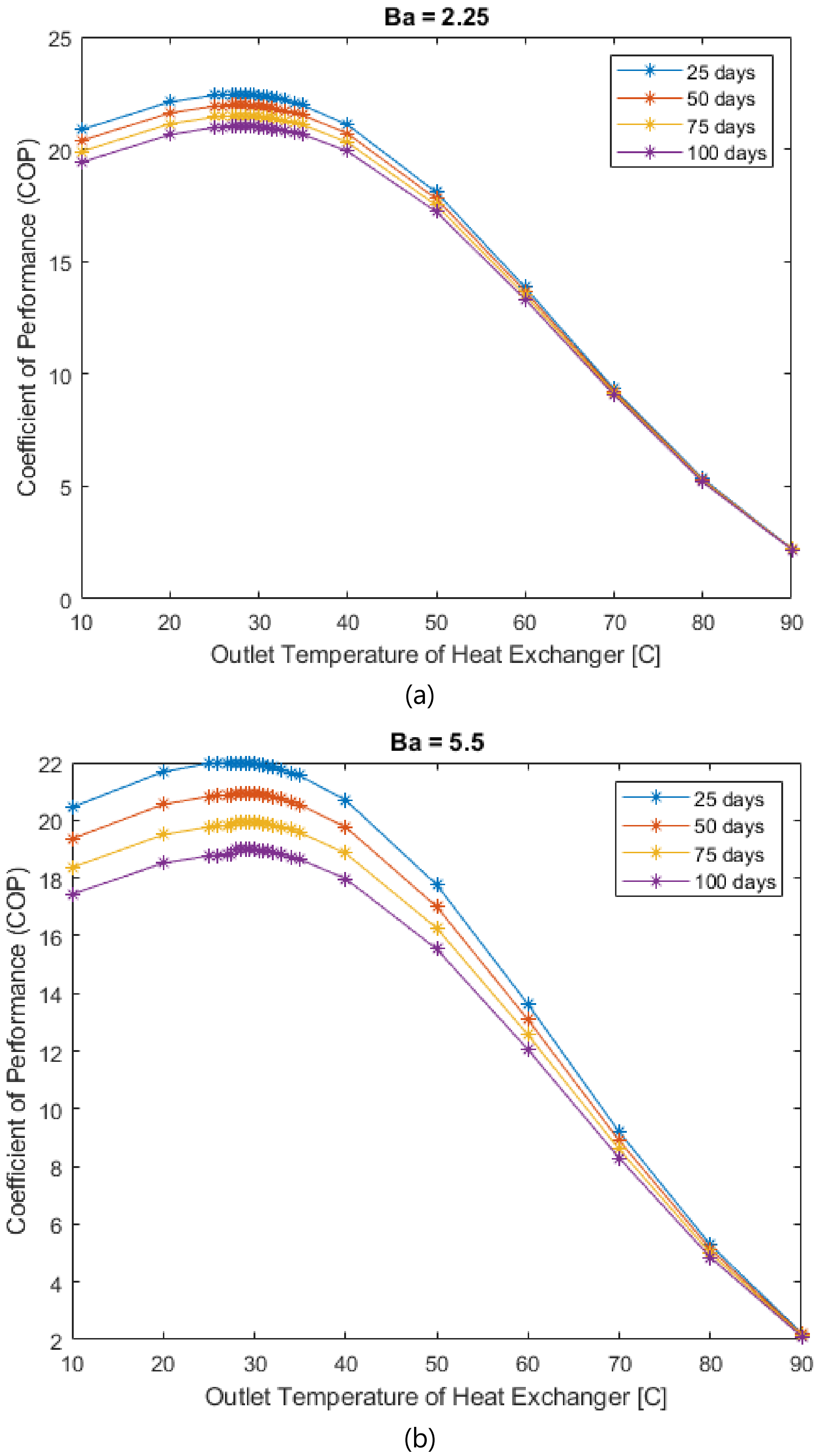
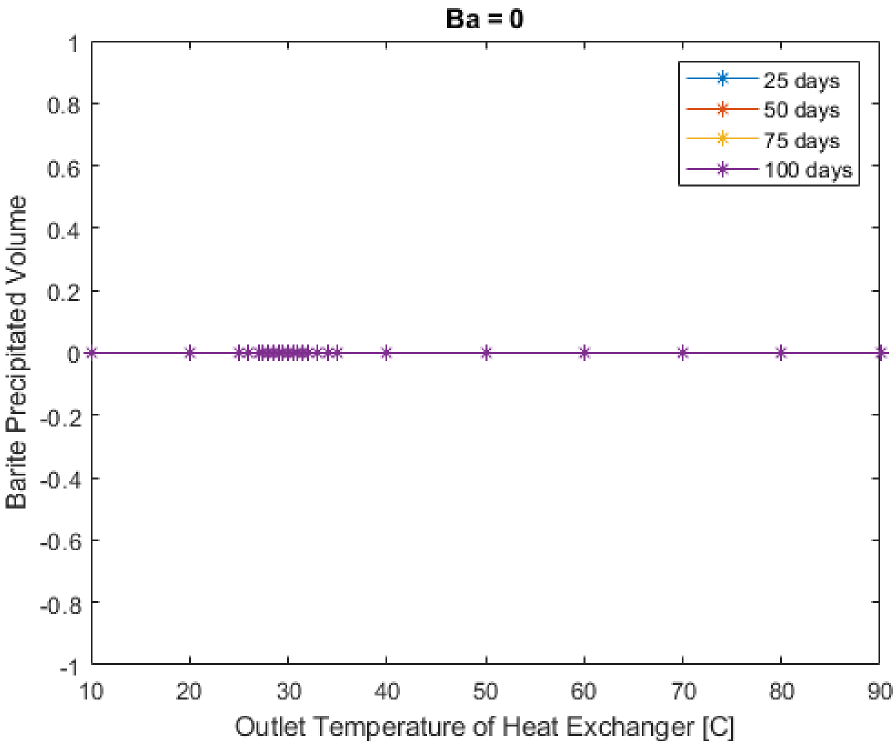
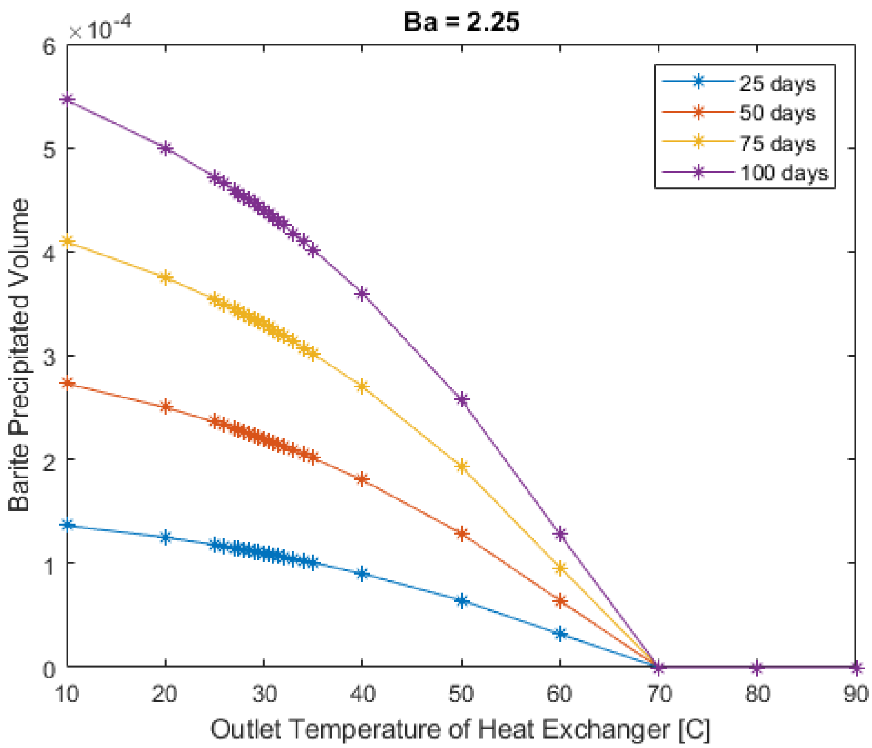


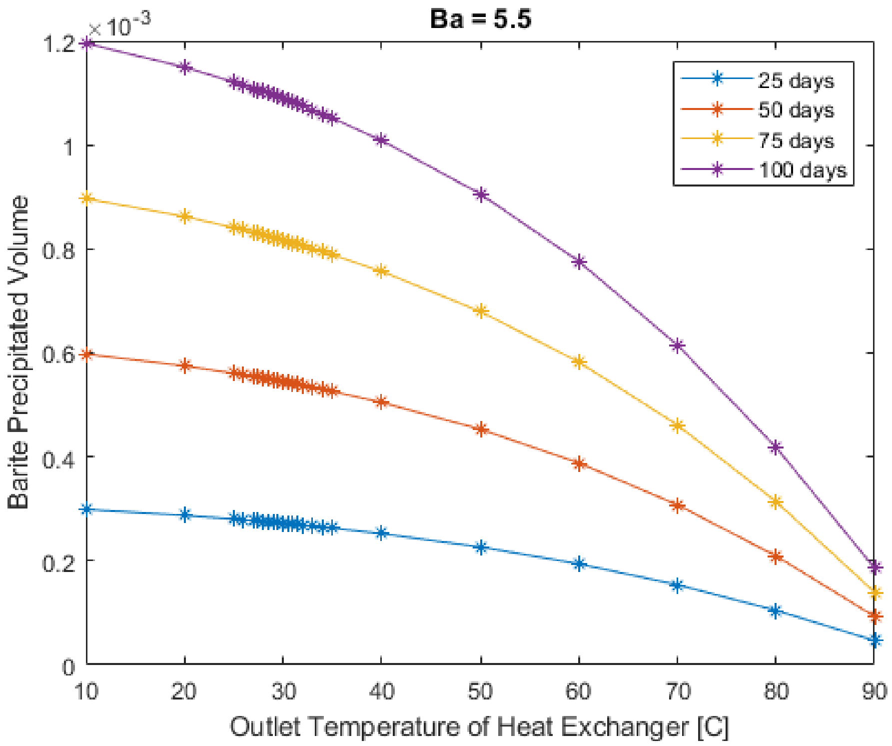
Figure 4. COP vs. outlet temperature at different times for a barite concentration of 2.25 (a) and 5.5 (b), with an inlet temperature of 100.15C. Optimum outlet temperature is around 30°C; optimum control is $\mathbf{u} = [27.0, 27.4, 27.7, 28]$ for (a) and $\mathbf{u} = [27.3, 27.9, 27.9, 27.9]$ for (b).


Ba = 0
25 days
50 days
75 days
100 days
Barite Precipitated Volume
Outlet Temperature of Heat Exchanger [C]
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
10
20
30
40
50
60
70
80
90

(a)


Ba = 2.25
×10-4
25 days
50 days
75 days
100 days
Barite Precipitated Volume
Outlet Temperature of Heat Exchanger [C]
6
5
4
3
2
1
0
10
20
30
40
50
60
70
80
90

(b)



(c)

Figure 5. Volume precipitated of barite in the heat exchanger over time for different outlet temperatures for different initial concentration of barite in the brine: 0 (a), 2.25 (b), 5.5 (c).

When we added uncertainty to the barite concentration around ±3% (Figure 6) and we compute the average COP using the equation described in the optimization subsection for robust optimization. Here we have also an optimum around 28°C for all times. In this case, $\mathbf{u} = [27.0, 27.9, 27.9, 27.9]$, with a $\widehat{COP} = 20.6584$ at 100 days. In Figure 7, the average volume of barite precipitated is shown. In Table 1, we present a summary of all experiments done.

Table 1. Summary of optimization experiments, in the case of no Ba the optimum was found at the lowest temperature at the outlet of the heat exchanger.

B_a	0*	2.25	5.5	$\widehat{B_a}$
$\mathbf{u}$	10	$[27.0, 27.4, 27.7, 28]$	$[27.3, 27.9, 27.9, 27.9]$	$[27.0, 27.9, 27.9, 27.9]$
COP at 100 days	24.1	21.0132	19.0120	20.6584 ($\widehat{COP}$)

* is a deterministic case

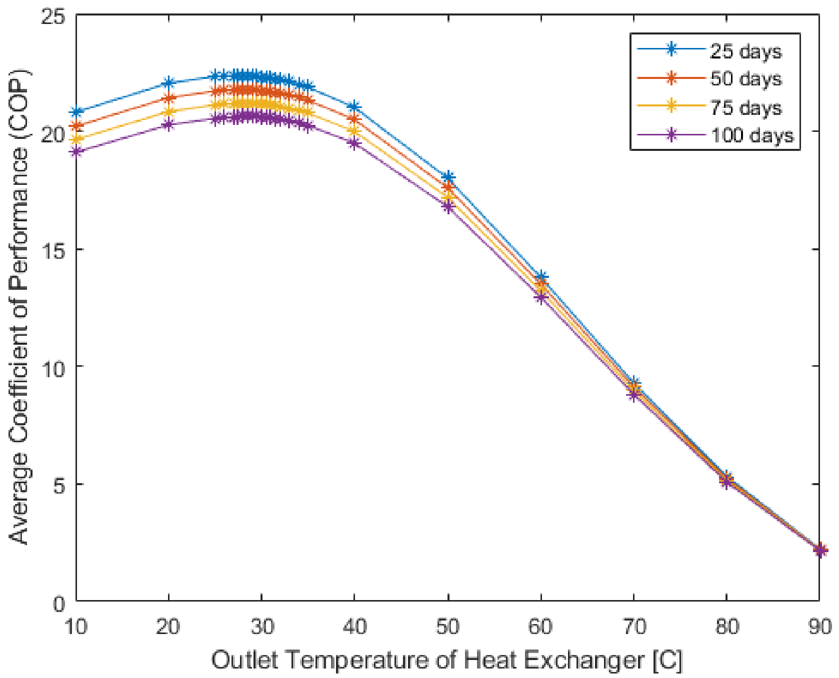


Figure 6. Average COP vs. outlet temperature at different times for a barite concentration between [0-5.5] and inlet temperature of 100.15C a time 100 days. We have used 3 realizations, c=[0,2.25,5.5]. In this case, $\mathbf{u} = [27.0, 27.9, 27.9, 27.9]$.

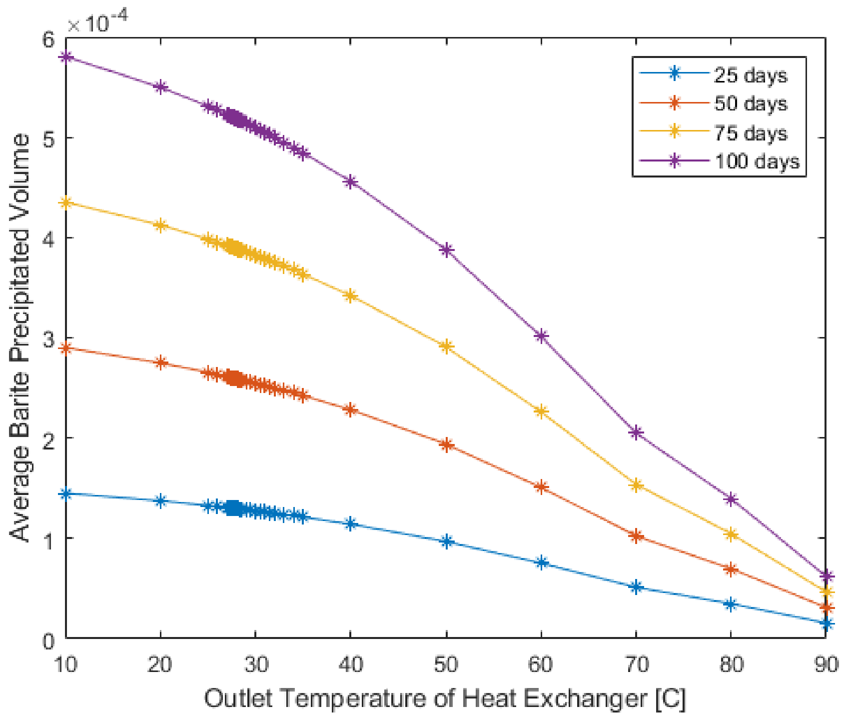


Figure 7. Average barite precipitated volume vs. outlet temperature at different times for a barite concentration between [0-5.5] and inlet temperature of 100.15C a time 100 days. We have used 3 realizations, c=[0,2.25,5.5].

4.4 OPTIMUM RANGE OF CONTROLS

Another point to be looked at is to find not one optimum, but an optimum range of temperatures where the system would lead to an acceptable COP. We can formulate this problem as a weighted multi-objective optimization problem where we try to optimize the COP of the lower and upper outlet temperatures ($\mathrm{T} = [\mathrm{T_l},\ \mathrm{T_u}]$) of the range while also optimizing the temperature difference between upper and lower limit, i.e., the size of the range.:

$$\mathbf{T}_{max} = argmax(w_1(\widehat{COP}(T_l) + \widehat{COP}(T_u)) + w_2\frac{T_u - T_l}{T_{in}})$$

subject to

$$T_u > T_l,$$

$$T_u < T_{in},$$

and

$$T_l > T_{min}.$$

The weights must sum to 1, $w_1 + w_2 = 1$ and the objective functions must be scaled properly and dimensionless (i.e., $\widehat{COP}$ here is dimensionless). Note, the third objective function serves as a penalty function that penalize the objective function as $T_l \to T_u$, there is, the range bounds collapses. T_{min} should be at least above freezing temperature of brine. Note, this formulation is only valid for convex optimization problems.

We run two optimization experiments with $\mathbf{c} = 5.5$: (1) optimize only an optimum value vs. (2) an optimum range. In this case, for the experiment (1), the optimum control $\mathrm{T_{out}} = 28.1953$, which gives a COP of 18.9380. For the experiment (2), $\mathbf{u} = [18.0349, 35.4192]$, with a $COP = [18.2652, 18.6486]$, respectively, at 100 days (Figure 8). For experiment (2) we used $\mathbf{w} = [0.7,0.3]$ and normalized the $\widehat{COP}$ by dividing by the COP by a constant equal 23.

The penalty function may be worked out such that its weight decreases as the range size increases, or use a barrier function, so that the range does not collapse or goes towards the maximum allowed range ($T_{in} - T_{min}$).

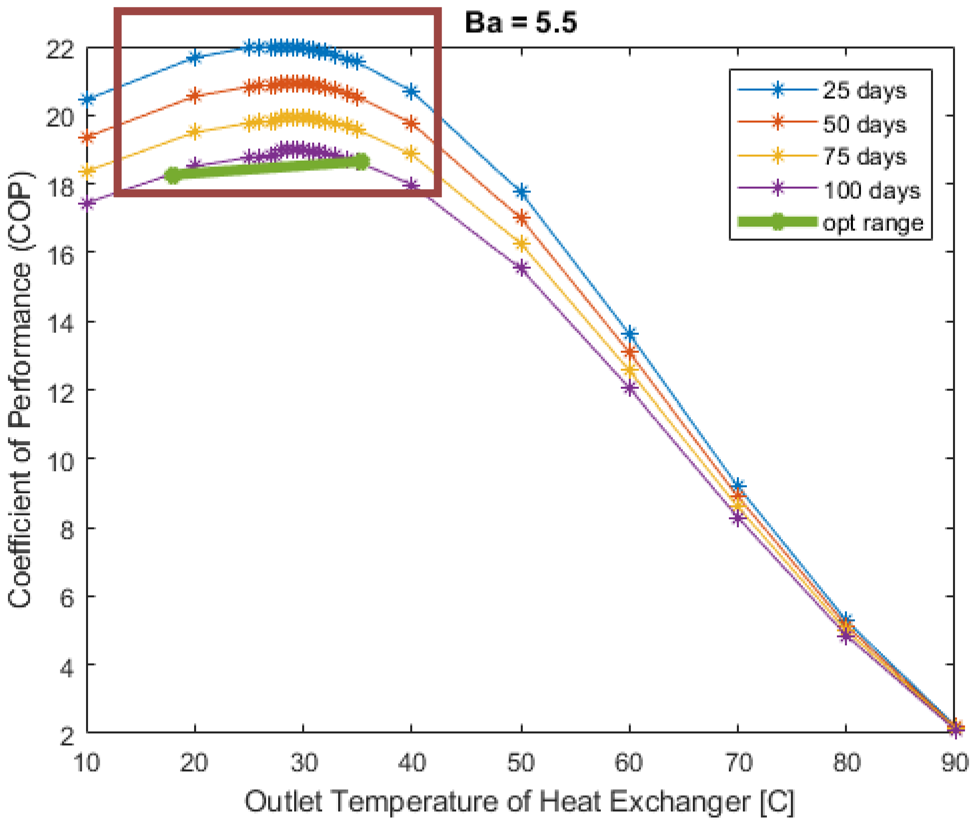


Figure 8. COP vs. outlet temperature at different times for a barite concentration of 5.5 with an acceptable range for outlet temperature between 18 and 35 C to have a COP above 18. In this case, the optimum range for the outlet temperature is between 18 and 35 C ($\mathbf{u} = [\mathbf{18.0349}, \mathbf{35.4192}]$).

5 FINAL REMARKS

The numerical models used to describe the geothermal fluid and heat transfer in the geothermal plant need to include brine composition uncertainties. Model-based optimization workflows for design and operation geothermal systems would be incomplete if uncertainty is not accounted within the optimization process. In this work, we have developed a workflow for operational decision support under uncertainties using a robust optimization algorithm. The objective of the workflow is to determine the optimum production decisions to obtain the best performance protocols for geothermal system operation. Robust optimization is an optimization process that incorporates uncertainty.

The developed workflow was demonstrated in a case study of optimum temperature control of the geothermal plant, downstream of the heat exchanger, which suffers from barite precipitation. The optimum operation point that gives the highest COP is the outlet temperature that gives the highest temperature drop across the heat exchanger, while maintaining the temperature of the system high enough to avoid mineral precipitation (in this case barite). We have run several deterministic and robust optimization experiments to show how we can use our optimization workflow to find the optimum operational range of temperatures. The results demonstrate that a single value for the control of temperature in the heat exchangers will not provide the optimum for the plant and the mean of the optimum values for each realization will provide an improved strategy for the plant.

5.1 FUTURE WORK

The generic workflow to account for uncertainties in the modelling and optimization has several applications for the design and operation of geothermal plants. As an example, in case of other precipitations were several parameters will impact the scaling in different locations, as an example calcite, to avoid scaling, we have to control the pressure and temperature across the plant. In addition, other parameters can act as inhibitors such as CO2 dosing and pH control. In this scenario, we need to optimize the plant by controlling pressure, CO2 dosing and inhibitor dosage (e.g. HCl) and we have as control variables $\mathbf{u} = [p, CO2, HCl]$, at each time t, and the uncertainty is the amount of minerals and gas in the brine, $\mathbf{w} = [c, g]$.

In addition, the workflow can be used to control the injection and production rates to account for other production issues such as corrosion, erosion and pump failures. For the design aspects, the efficiency and design of ion exchange filters under brine composition can also be estimated using the current workflow.

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