SOLUTION MINING RESEARCH INSTITUTE
679 Plank Road
Clifton Park, NY 12065, USA

Telephone: +1 518-579-6587
www.solutionmining.org

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Emmanuel Sansusthy Tardio, University of Houston, Houston, USA

JoAnn Gage, Chevron U.S.A. Inc./ACES Delta, Salt Lake City, USA

Mahya Hatambeigi, WSP USA, Houston, USA

Scyller Borglum, WSP USA, Houston, USA

Sophie Minas, RESPEC Consultant to WSP USA, Montreal, Canada

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A COMPUTATIONAL MODEL FOR REAL-TIME BLANKET LEVEL TRACKING DURING SOLUTION MINING

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Abstract

During the salt cavern solution mining process, accurately monitoring the blanket-brine interface is essential for maintaining mechanical stability and ensuring that the cavern roof shape develops as designed. Although downhole density logging tools are commonly used to verify the interface location, they can be time-consuming, costly, interrupt solution mining operations, and create windows of uncertainty while waiting for logging to be completed.

To address these challenges, this paper introduces a robust computational methodology, implemented in Python, that combines advanced hydraulic calculations with machine learning algorithms to track gas and liquid blanket levels in real time. By using readily available surface data, such as pressure, density, and viscosity of leaching water and the blanket medium (e.g., nitrogen, diesel), the approach estimates downhole conditions and identifies the blanket-brine interface level with high accuracy.

Extensive validation with operational data from multiple salt cavern mining operations consistently demonstrates that this model maintains prediction errors of less than 1% in determining blanket levels. This high degree of accuracy enables operators to exercise tighter control over the leaching process and reduce the risk of unintentional upper-cavern dissolution.

In addition to providing continuous interface tracking, the proposed method can also be employed as a secondary verification tool that complements existing interface-logging techniques. Its smooth integration into current operational frameworks provides greater confidence in blanket-level measurements, promoting both safety and efficiency in salt cavern solution mining operations.

Key words: blanket-brine interface, nitrogen blanket, hydraulic calculations, machine learning.

1. Introduction

A critical aspect of cavern development and operation is the accurate management of the blanket-brine interface during both solution mining and injection-withdrawal cycles. This interface directly affects the geometry of the cavern roof, which is crucial for ensuring long-term structural stability. In recent years, nitrogen blankets have gained increased attention, largely driven by the growing global demand for hydrogen storage in salt caverns. Nitrogen offers several operational and environmental advantages that make it especially suitable for hydrogen storage: it is chemically inert, non-corrosive, non-contaminating, and environmentally safe.

Despite these advantages, nitrogen blankets pose unique challenges due to the compressibility of gas. Fluctuations in operational conditions such as leaching rate, fluid density, pressure, and temperature can destabilize the blanket level, increasing the risk of uncontrolled dissolution and undesirable changes to cavern geometry. Accurate and continuous tracking of the nitrogen-brine interface is therefore essential, yet difficult to achieve with conventional tools. Periodic logging techniques (e.g., gamma-gamma or neutron tools) interrupt operations and provide only snapshot measurements, leaving extended intervals of uncertainty.

To address this issue, permanently installed downhole measurement systems have been proposed for real-time monitoring of the blanket-brine interface. However, these wired systems present their own challenges, including high installation and maintenance costs and limited feasibility for retrofitting into existing wells. These limitations may restrict their broader adoption, particularly in operations with older infrastructure, technical complexities or budgetary constraints.

In parallel, spreadsheet-based computational methods are sometimes used to estimate interface levels from surface data. These models typically rely on simplifying assumptions such as fixed fluid properties and constant pipe roughness. Such assumptions reduce accuracy under dynamic leaching conditions, leading to interface estimation errors. Additionally, spreadsheet tools often struggle to manage the large volumes of time-dependent data required for continuous tracking.

Recognizing these limitations, we present a Python-based computational approach capable of continuously and accurately tracking the blanket-brine interface in real time using only surface-acquired data. The tool integrates hydraulic modeling with machine learning to estimate the interface level without requiring any downhole instrumentation or operational interruption. To evaluate the model's accuracy, it was applied to surface data from the leaching of two hydrogen storage caverns that are part of the Advanced Clean Energy Storage I (ACES I) Delta project in Delta, Utah. The results were subsequently compared with measured interface depths and pressure values to assess its performance under actual operating conditions.

2. Methodology and Computational Framework

The model integrates a deterministic hydraulic engine that simulates fluid behavior within the wellbore system, and a machine learning module (ML) that refines uncertain parameters such as pipe roughness and interface depth through optimization.

It operates using two categories of input data: dimensional parameters that define the geometry of the wellbore system, and operational variables collected at the surface. Dimensional parameters include the depth and diameter of the inner and outer hanging strings, production casing depth, and the most recent logged blanket level. Operational inputs consist of injection and return flow rates, water, brine and blanket pressures, and fluid-specific properties such as temperature and specific gravity. These inputs are typically recorded during solution mining operations and handled directly by the code, which automatically ensures unit consistency and applies necessary conversions. The graphical user interface (GUI) for entering these variables is provided in Appendix 1.

Key outputs of the method are the calculated injection pressure, blanket pressure, blanket interface depth, and casing shoe pressure gradient. These outputs are supported by intermediate calculations such as flow velocities, frictional pressure losses, dynamic viscosities, thermophysical fluid properties that vary with depth and operating conditions, and estimated pipe roughness values.

The ML module itself operates in two main stages: 1) Roughness finding and 2) Interface Tracking. The first stage estimates the absolute roughness of the inner and outer strings through an algorithm considering all the operational data available and the blanket depth, as of the last interface logging survey. The second stage utilizes the roughness found on the previous stage and the other parameters to perform the whole hydraulic balance, with the goal of estimating the blanket depth that best balances the hydraulic state of the system. Figure 1 shows the overall flow process of the calculations. The left wing performs calculations to find the pipes roughness, and the right one executes the logics to estimate the blanket level and related parameters.

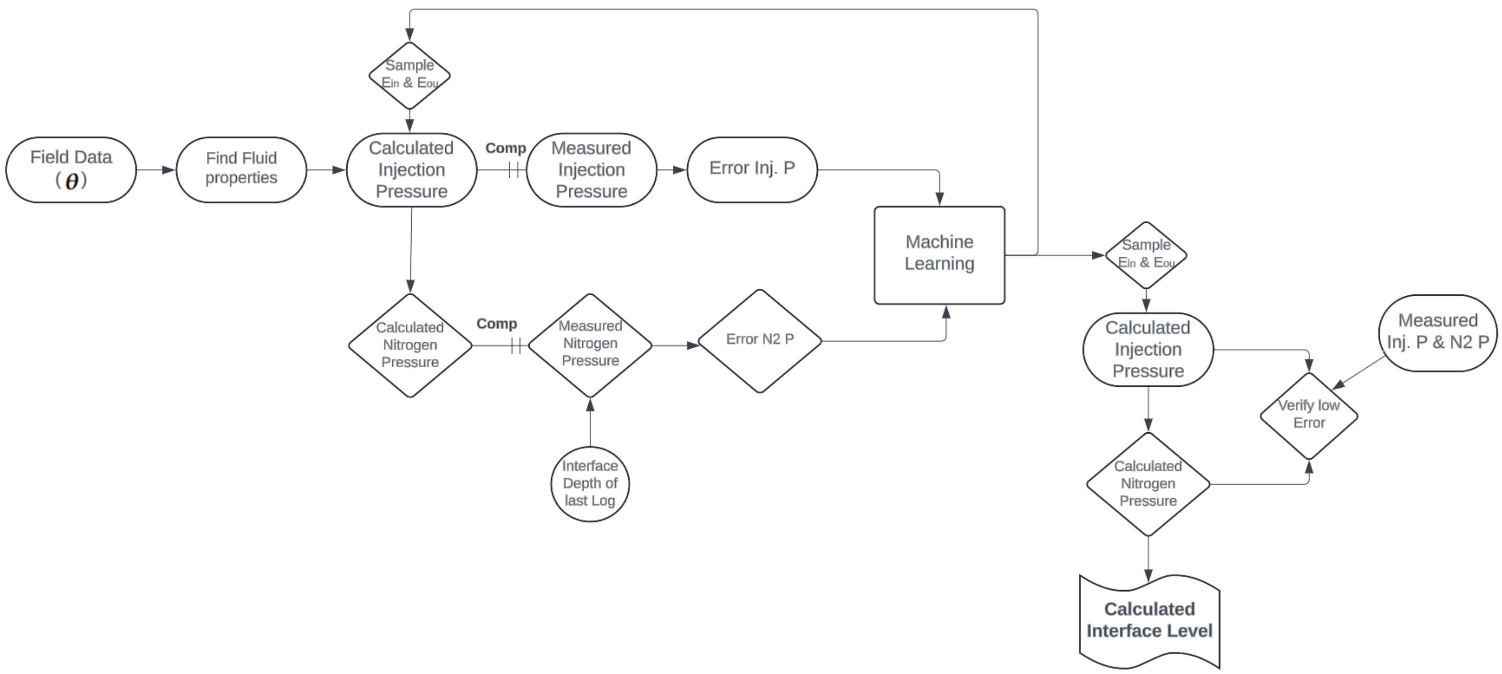

Figure 1. Global flow process of the computational model.

The following sections provide a detailed explanation of the hydraulic modeling framework and ML-based parameter estimation process.

3. Hydraulic Calculations

At the core of the computational engine is a set of hydraulic calculations based on the balance of static and dynamic loads within the inner tubing and annular spaces. Static components account for hydrostatic pressure from fluid columns, while dynamic losses arise from frictional effects influenced by flow rate, viscosity, pipes geometry, and surface roughness. The hydraulic calculations provide the basis for estimating injection pressure, interface pressure, and blanket pressure.

3.1. Injection and Interface Pressures

The injection and interface pressures are computed differently depending on the solution mining method employed.

For Direct Solution Mining:

$$P_{inj} = P_{br} + (H_{ou}\,\gamma_{br}) + (\gamma_{mx}(H_{in} - H_{ou})) - (H_{in}\,\gamma_{wt}) + \Delta P_{cent} + \Delta P_{ann} \quad (1)$$

$$P_{intf} = P_{br} + (H_{ou}\,\gamma_{br}) - (0.95\gamma_{br}(H_{ou} - h)) + \Delta P_{ann} \quad (2)$$

For Reverse Solution Mining:

$$P_{inj} = P_{br} + (H_{in}\gamma_{br}) - (\gamma_{mx}\,(H_{in} - H_{ou})) - (H_{ou}\gamma_{wt}) + \Delta P_{cent} + \Delta P_{ann} \quad (3)$$

$$P_{intf} = P_{inj} + (H_{ou}\gamma_w) - (1.2\gamma_w(H_{ou} - h)) - \Delta P_{ann} \quad (4)$$

where P_{inj} and P_{intf} are the injection and interface pressure, respectively, P_{br} is brine pressure at surface, H_{in} and H_{ou} are lengths of the inner and outer strings, h is the blanket-brine Interface depth, ΔP_{cent} and ΔP_{ann} are dynamic (frictional) losses in the center tubing and annulus and $\gamma_{br}, \gamma_{wt}, \gamma_{mx}$ are the specific weights of brine, injected water, and the fluid mixture.

The model automatically determines the fluids' specific weights as functions of temperature and pressure using the iapws package (Gomez Romera, 2017) and measured brine specific gravity at the surface.

3.2. Frictional Loss

Frictional losses (ΔP) are computed using Darcy-Weisbach relationships, with friction factors determined from Reynolds numbers (Re) and pipe roughness.

The friction factor determination follows established fluid mechanics principles, with different approaches for laminar and turbulent flow regimes. For laminar flow conditions (Re < 2000), the friction factor is calculated directly using the analytical relationship:

$$f = \frac{64}{Re} \quad (5)$$

Turbulent flow (Re > 2000) requires solving the Colebrook-White equation (Colebrook, 1939) iteratively to account for the combined effects of Reynolds number and relative surface roughness:

$$\frac{1}{\sqrt{f}} = -2log\left[\frac{\varepsilon}{3.7D} + \frac{2.51}{Re\sqrt{f}}\right] \quad (6)$$

where ε represents the absolute pipe roughness and D is the is the hydraulic diameter of the flow path. This implicit equation requires numerical iteration to converge on the correct friction factor value. The iterative process continues until successive approximations of the friction factor differ by less than a specified tolerance. The ε value used here is later estimated by the ML module described in Section 4.1, allowing friction losses to reflect evolving wellbore conditions.

3.3. Blanket Pressure

The model includes dedicated approaches for estimating Blanket Pressure depending on whether the blanket fluid is compressible (e.g., nitrogen) or incompressible (e.g., diesel).

For compressible blankets like nitrogen, the model treats the interface pressure, calculated as part of the hydraulic balance in Section 3.1, as a lower boundary condition for a discretized numerical simulation. The nitrogen column is divided into a series of vertical segments, and pressure is computed step by step from the interface up to the surface. At each step, temperature is estimated from a geothermal gradient, and nitrogen density is determined using either tabulated specific gravity values or the Peng-Robinson real gas equation of state (Peng and Robinson, 1976), which incorporates the pressure and temperature-dependent compressibility factor (z-factor). The updated density is then used to recalculate the pressure profile, and the loop continues until the calculated surface pressure matches the measured blanket pressure within a specified tolerance. This iterative sequence is summarized in Figure 2.

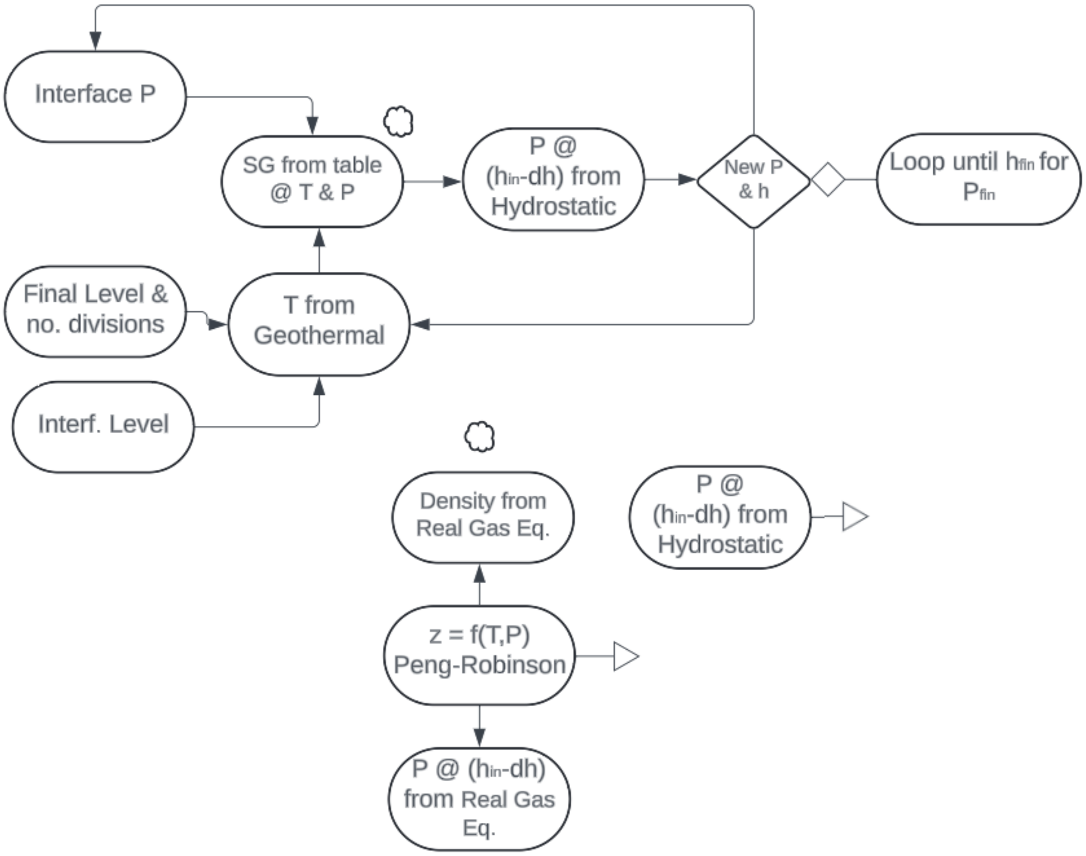

Figure 2. Nitrogen blanket pressure calculation flow process

For incompressible blankets such as diesel, the blanket pressure is calculated using a hydrostatic formulation based on the interface depth and the fluid's specific weight, adjusted for mid-column temperature and pressure. Because density variations with depth are minimal compared to compressible fluids, no iterative simulation is required. However, the calculation still accounts for annular friction losses and applies density corrections to maintain accuracy.

3.4. Casing Seat Pressure Gradient

Another key hydraulic output is the casing shoe pressure gradient, which serves as a critical regulatory and operational safeguard. Regulatory limits typically range from 0.7 to 0.9 psi/ft depending on local geological conditions. Exceeding maximum casing shoe pressure limits can accelerate micro-fracturing, compromise casing integrity, or trigger uncontrolled roof dissolution.

This calculation is a combination of the interface pressure described in Section 3.1 and hydrostatic pressure, but this time executed from the interface to the casing shoe:

$$P_{cg} = \frac{P_{intf} - \gamma_{mx}(h - H_c)}{H_c} \tag{7}$$

where P_{cg} is the casing seat pressure gradient and H_c is the production casing length.

4. Machine Learning: Roughness and Interface Depth Estimation

The hydraulic calculations described in the previous section provide a physics-based framework for determining wellbore pressures. Within the ML module, these calculated values are compared with measured operational data to quantify and reduce discrepancies. This process enables the estimation of two critical parameters of pipe roughness and interface depth, by minimizing the difference between predicted and observed values over time. The hydraulic model outputs serve as the foundation for the machine learning optimization, which is continuously updated using real-time surface data. The following sections describe the estimation logic and update routines in detail.

4.1. Roughness Calculation

Once all fluid properties are calculated, the absolute roughness of the inner and outer hanging strings can be determined through error minimization. A Bayesian optimization algorithm based on Gaussian process regression is implemented to find the pipe roughness values that best match calculated injection pressure with measured operational injection pressure. Additionally, the calculated blanket pressure is compared to measured blanket pressure. The algorithm evaluates various combinations of inner and outer string roughness values to determine which configuration best reproduces both pressure measurements.

Unlike a simple iterative search, the algorithm constructs a surrogate model of the system's response and uses an embedded acquisition function to select the next candidate values with the highest probability of reducing error, which accelerates convergence and avoids local minima. The calculation logic is visualized in the flowchart of Figure 3.

Once the optimal roughness values are determined, they are used in all subsequent calculations.

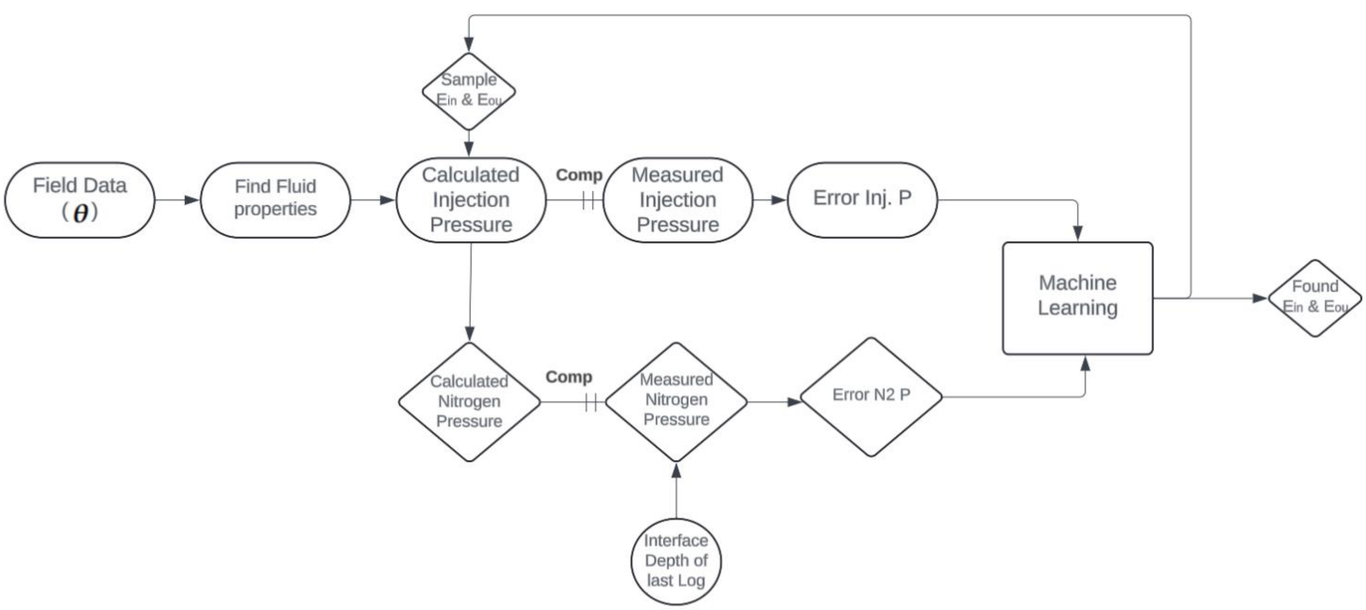

Figure 3. Tube Roughness calculation flow process

4.2. Interface Level

A similar Bayesian optimization algorithm is used to estimate the blanket-brine interface depth. The process begins with the measured blanket pressure at the wellhead and other operational parameters. The algorithm tests candidate interface depths, calculating the corresponding blanket pressure for each, and selects the depth that minimizes the difference from the measured value.

For compressible blankets such as nitrogen, the routine calls a nitrogen density function, which incorporates pressure and temperature-dependent compressibility, to model the gas column. The optimal interface depth is the one whose calculated surface nitrogen pressure best matches the measured blanket pressure.

The calculation logic is shown in Figure 4.

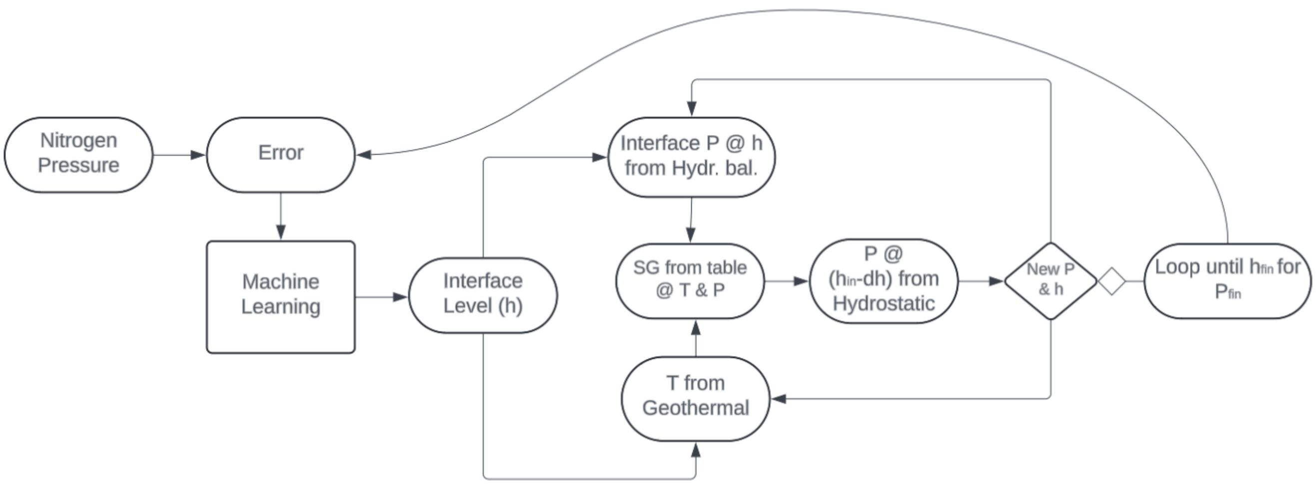

Figure 4. Blanket Level calculation flow process

5. Model Application: ACES I hydrogen caverns in Delta, Utah.

As part of the model validation process, the method was applied to two caverns (Cavern 1 and Cavern 2) under development for hydrogen storage through the ACES I project. This large-scale energy conversion and storage project will convert renewable power into green hydrogen , for storage in two 4.5 MMbbl (~7.15×10^5 m^3) salt caverns, each roughly the size of the Empire State Building. The caverns were solution-mined by WSP USA Inc. using nitrogen blanket, providing a technically demanding setting and valuable surface data across multiple leaching phases.

To evaluate the model, field data for Cavern 1 (including well geometry and operational variables) from direct leaching operations were processed in weekly intervals. Two specific one-week intervals were selected, each tied to interface logging events to ensure reference values for comparison and to avoid periods with missing or unstable data.

- First Interval: This week includes the interface logging performed on September 18, 2024. The model was based on the measured interface level of 4502 ft (1372.2 m), and leaching operations continued with a reduced flow rate during logging. This provided an opportunity to verify the model's consistency under quasi-stable conditions.
- Second Interval: The week immediately preceding the next intervention on November 9, 2024, during which both logging and sonar surveys were performed. In this case, no leaching activity occurred during the intervention, as operations were paused for sonar measurements. Because leaching data was

unavailable on the day of measurement, the model was applied to the week before the logging event. The goal was to assess whether the model could predict the expected upward movement of the interface, from 4502 ft to 4488 ft (1372.2 m to 1367.9 m), over the nearly two-month period since the last measurement.

Validation steps for each interval included:

1. Roughness Estimation: For each interval, the model estimated the absolute roughness of the inner and annular tubing strings. These values were compared to average values of tubes of the same material and monitored over time to assess trends related to tubing erosion or scaling during the leaching process.

2. Hydraulic verification: The model's calculated injection and blanket pressures were compared with field measurements. Good agreement between these values indicates proper resolution of the system's static and dynamic hydraulic balance.

3. Interface Level Estimation: The model-calculated blanket-brine interface depths were compared with logged measurements. In the first interval, the model was evaluated for short-term consistency using data from the same week as logging. In the second interval, the model was run using the prior logged interface (4502 ft) and surface data from the week before the November intervention to test whether it could predict the rise in interface position to 4488 ft.

The results of the model for both intervals are presented in Figures 5 through 8. Figures 5 and 6 show the comparison between measured and calculated injection and blanket pressures, while Figures 7 and 8 present the calculated vs measured interface depths and the casing shoe pressure gradients.

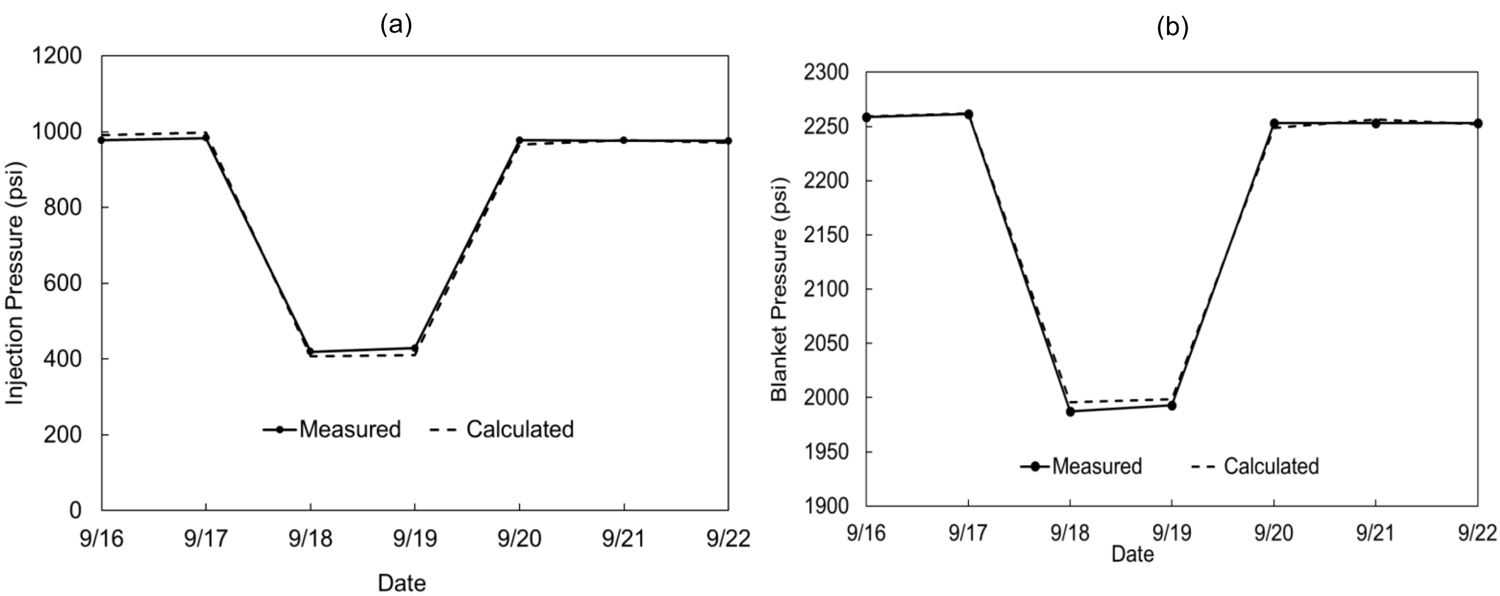

Figure 5. September 16-22 interval: (a) Measured vs. calculated injection pressure (b) Measured vs. calculated blanket pressure.

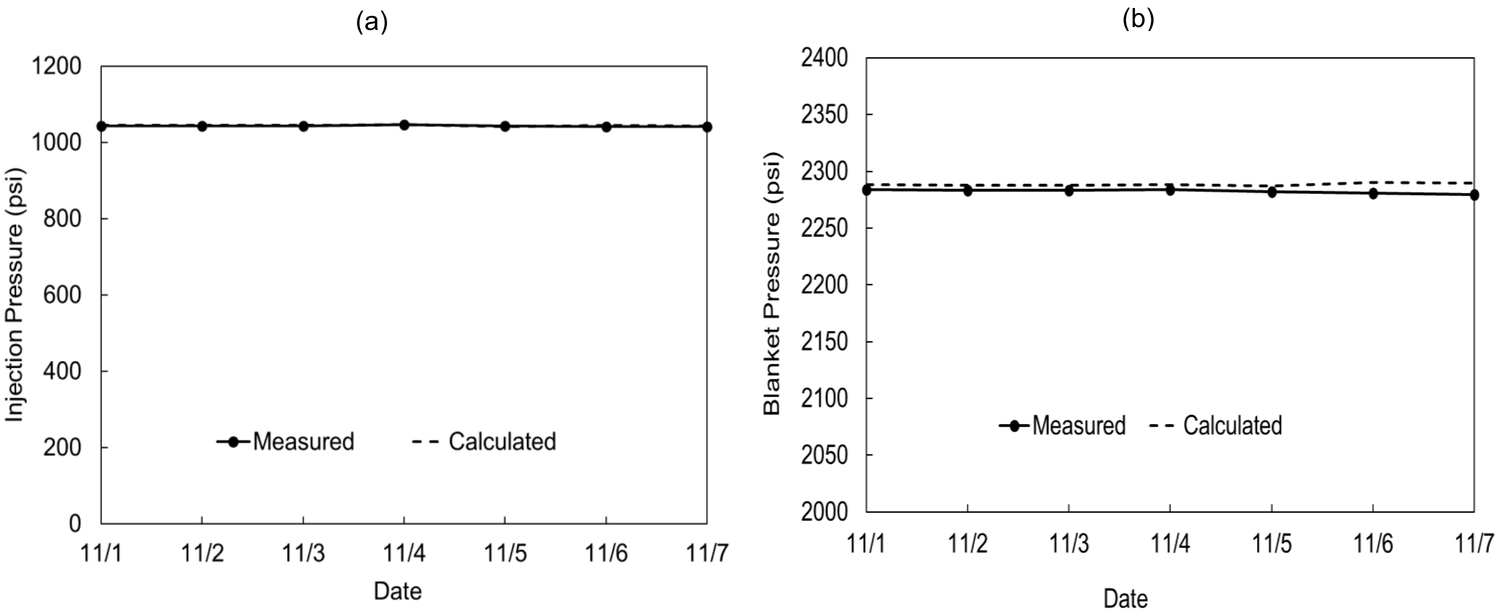

Figure 6. November 1-7 interval: (a) Measured vs. calculated injection pressure (b) Measured vs. calculated blanket pressure.

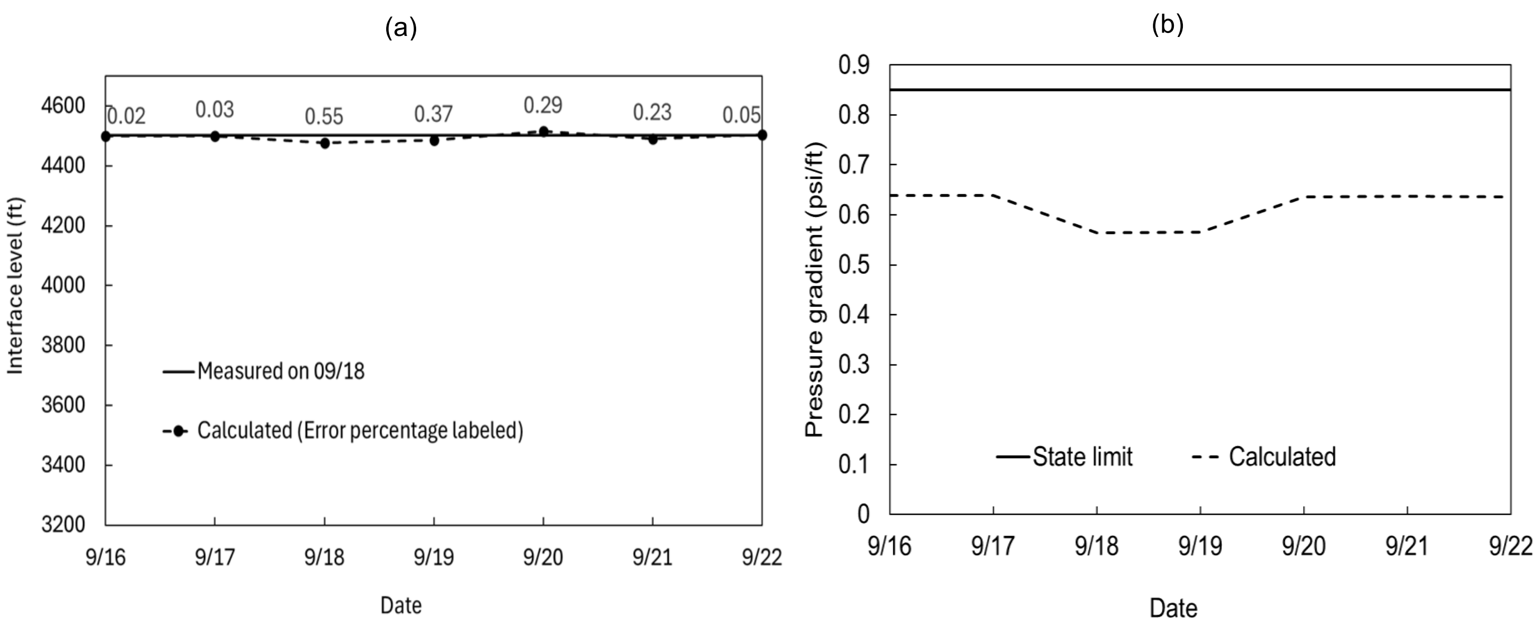

Figure 7. September 16-22 interval: (a) Calculated interface depth compared to the logged value (4502 ft). Percentage error values are labeled above each data point. (b) Calculated casing shoe pressure gradient, shown relative to the regulatory limit.

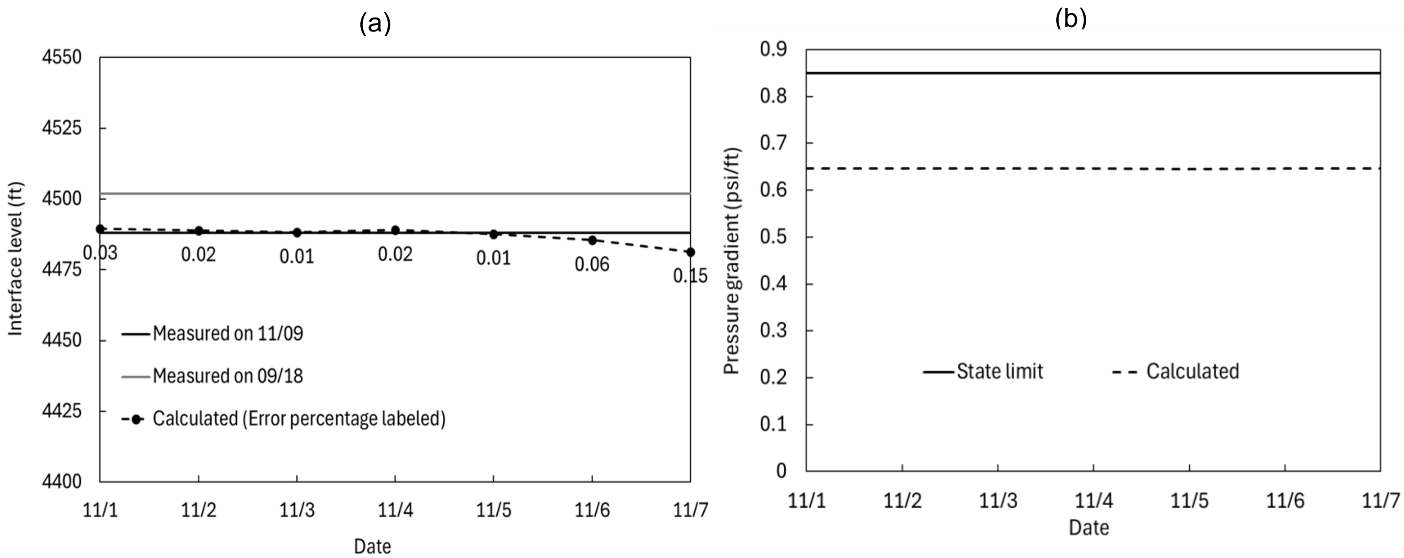

Figure 8. November 1-7 interval: (a) Calculated interface depth compared to the 09/18 logged value (4502 ft), and the subsequent logged value (4488 ft) from the 09/18 intervention. (b) Calculated casing shoe pressure gradient, shown relative to the regulatory limit.

In both intervals, the model demonstrated strong agreement with measured pressure data, capturing both steady-state and transient behaviors. During the September interval, the model successfully reproduced the sharp pressure drop and recovery associated with reduced flow rates during the logging, confirming the robustness of the hydraulic calculations even under dynamic conditions.

For interface depth estimation, the model showed high consistency with logged values in the first interval, with percentage errors remaining below 0.6%. In the second interval, despite the nearly two-month gap since the last measurement and the absence of leaching during the logging event, the model effectively predicted the upward shift in interface position, closely approaching the observed reduction in depth from 4502 ft to 4488 ft. This demonstrates the model's capability to track interface movement over extended periods using only surface data. The same analysis performed on Cavern 2 during comparable conditions yielded interface depth errors of less than 1%.

The casing pressure gradients in both cases remained well below the regulatory threshold, indicating safe cavern development.

The model-estimated roughness values are also presented for weekly intervals between September 16 and November 7, 2024 in Figure 9. Both the inner hanging string (IH) and outer hanging string (OH) show a clear increasing trend in absolute roughness, which is consistent with expected wall degradation due to fluid interaction, scaling, and abrasive flow effects. Notably, the outer string roughness increases more steeply, while the inner string roughness remains relatively stable at a higher value. This behavior is reasonable given the direct leaching configuration.

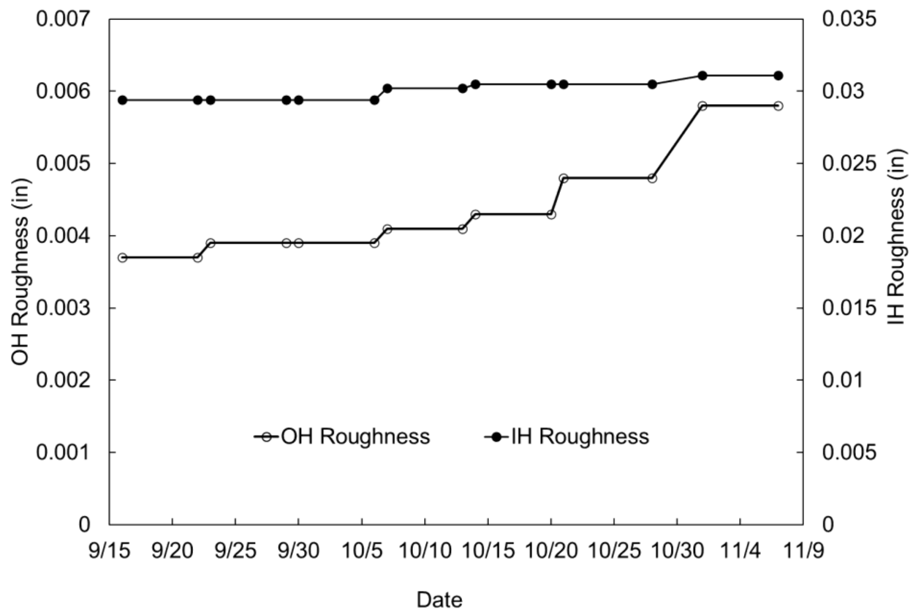

Figure 9. Evolution of Inner and Outer hanging strings absolute roughness in time

Although the persistently higher IH roughness may reflect physical factors such as different pipe materials, connection types, or greater exposure to turbulent flow, it is also shaped by the numerical optimization process. The model estimates roughness by minimizing the mismatch between measured and calculated pressures within a user-defined roughness range, where the initial guess and bounds are set based on expected surface conditions or material properties. As with most nonlinear regression and bounded optimization problems, results represent the locally optimal solution for the selected time interval and may vary slightly with different initial conditions or constraints. These values should therefore be interpreted in the context of engineering judgment and operational understanding.

Collectively, the results demonstrate the model's ability to reliably track blanket-brine interface movement and validate hydraulic behavior using only surface-acquired data, even under varying operational conditions.

6. Conclusions

The computational model presented in this work provides an accurate, non-intrusive, and operationally practical solution for real-time blanket-brine interface tracking during salt cavern solution mining. By combining deterministic hydraulic calculations with machine learning-based parameter estimation, the method successfully integrates routinely collected surface data into a robust predictive framework.

Validation using field data from hydrogen storage caverns in the ACES Delta project demonstrated that the model produced measured injection and blanket pressures, with interface depth prediction errors below 1%. The approach proved effective both in short-term verification against concurrent logging data and in forecasting interface movement over extended operational intervals without direct downhole measurements.

The model also effectively estimated the evolution of absolute roughness for both inner and outer hanging strings, capturing physically reasonable trends over time. This capability supports proactive maintenance and operational decision-making, particularly in hydrogen storage developments where non-invasive monitoring methods are preferred.

Some limitations remain. Estimated interface depth values during normal leaching operations may not fully represent the logged interface at shut-in logging conditions, and results are influenced by the range and quality of available field data. The range of defined roughness bounds in the optimization process can affect calculated results, and roughness outputs should be interpreted with engineering judgment. While the method produces quantitative predictions, these should be supported by qualitative context such as operational history, material properties, and cavern geometry to ensure correct interpretation.

For future work, the model's performance should be verified against continuous downhole measurements, such as fiber-optic sensors. Validation should be expanded to cover all stages of solution mining and a wider range of blanket types.

Overall, the proposed method offers a cost-effective and continuous monitoring capability that can complement or partially replace periodic logging surveys, reduce operational interruptions, and improve control over cavern roof development.

Acknowledgements

The authors would like to acknowledge the contributions and support of the ACES I project team, whose operational data from hydrogen caverns in Delta, Utah, were instrumental in validating the proposed methodology.

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Appendix 1: User interface

The dimensional parameters described in Section 2 are entered numerically in the code's graphical user interface (GUI). The same interface structure is used for both main calculation steps (Roughness Estimation and Blanket Interface Tracking) with additional inputs specific to each step. In both cases, the user must also specify the date range for analysis and the geothermal gradient parameters.

In the Roughness Estimation window, the minimum, maximum, and initial values for the inner and outer string roughness can be set. Defining realistic bounds helps the optimization algorithm converge more quickly to the most probable roughness values and avoids exploring low-probability areas of the parameter space.

In the Blanket Interface Tracking window, the only additional parameters are the roughness values obtained from the previous step.

All remaining inputs (operational parameters and fluid properties) are imported from a .csv file. The model calculates injection pressure, blanket pressure, blanket interface depth, and casing shoe pressure gradient for each row of the input file, maintaining the same time resolution (typically daily).

Outputs are generated both as plots, comparing calculated results to measured values or the most recent logged value, and as .csv files containing the estimated results and intermediate calculation steps. The intermediate variables, such as calculated fluid properties and interface pressures, allow verification of the underlying hydraulic model.

The Main Window (Figure A1) provides two primary options: Roughness Estimation and Blanket Interface Tracking.

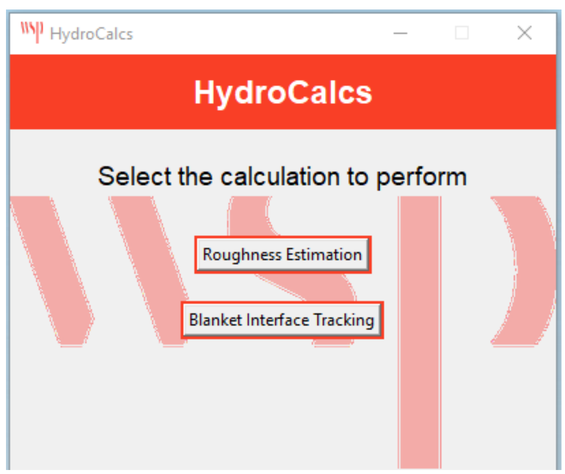

Figure A1. Main window

Key elements of the Roughness Estimation Window (Figure A2) are:

1. Select between direct or reverse solution mining and between nitrogen or diesel blankets.
2. Load the .csv file containing operational parameters and fluid properties, set the analysis date range, and enter dimensional parameters.
3. Input geothermal gradient parameters for the cavern location.
4. Define roughness search ranges for both inner and outer strings (minimum, maximum, and initial values).

Dimensional and geothermal parameters can be saved using the Save Project button, which also prompts the user to name the project. Saved projects can be reloaded later via the Load Project button.

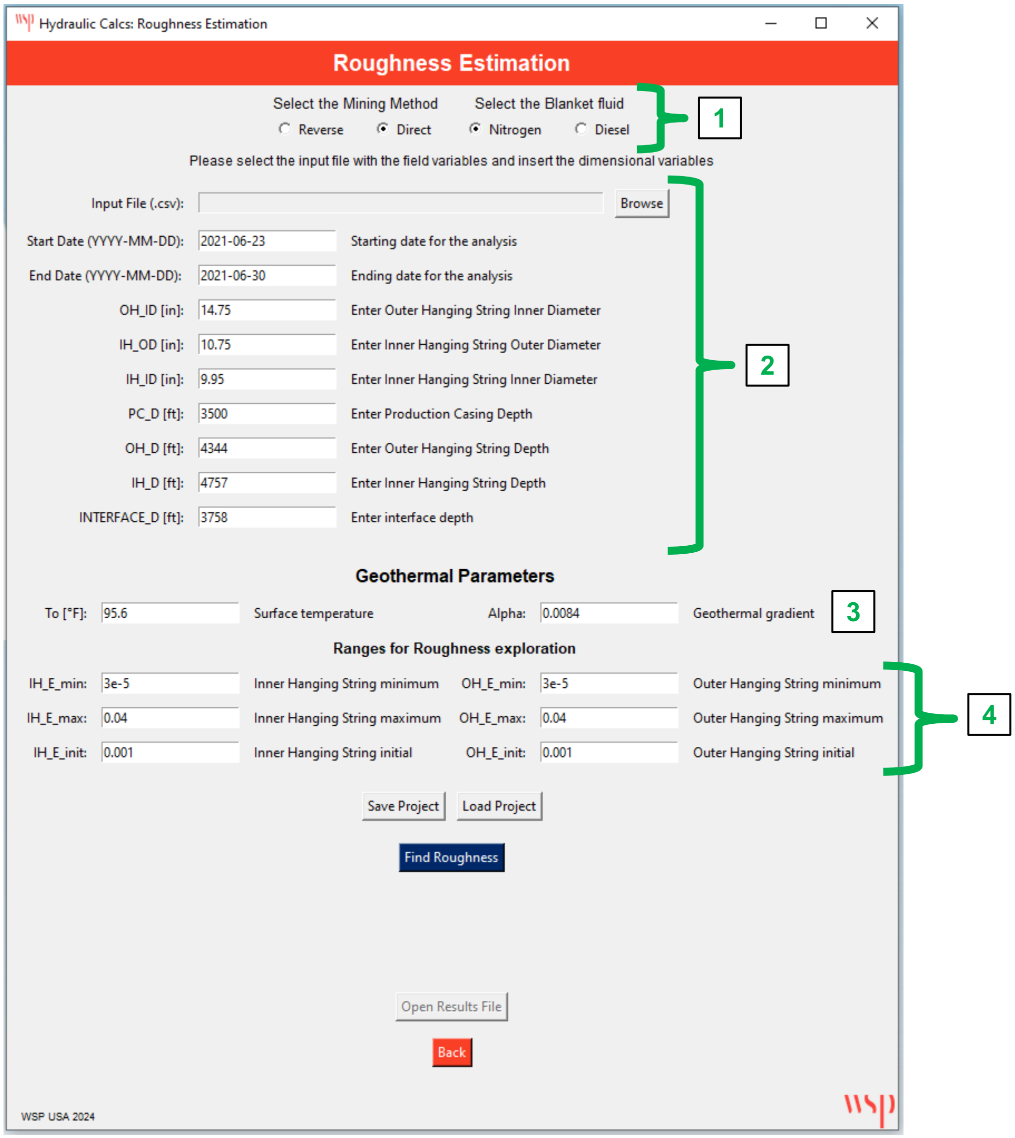

Figure A2. Roughness Estimation window

Blanket Interface Tracking Window (Figure A3) key differences are:

1. Input the roughness values obtained from the Roughness Estimation step.
2. Assign filenames for the output .csv and plot results.

Projects saved in either calculation step can be loaded in the other, though the same limitations on saved parameters apply.

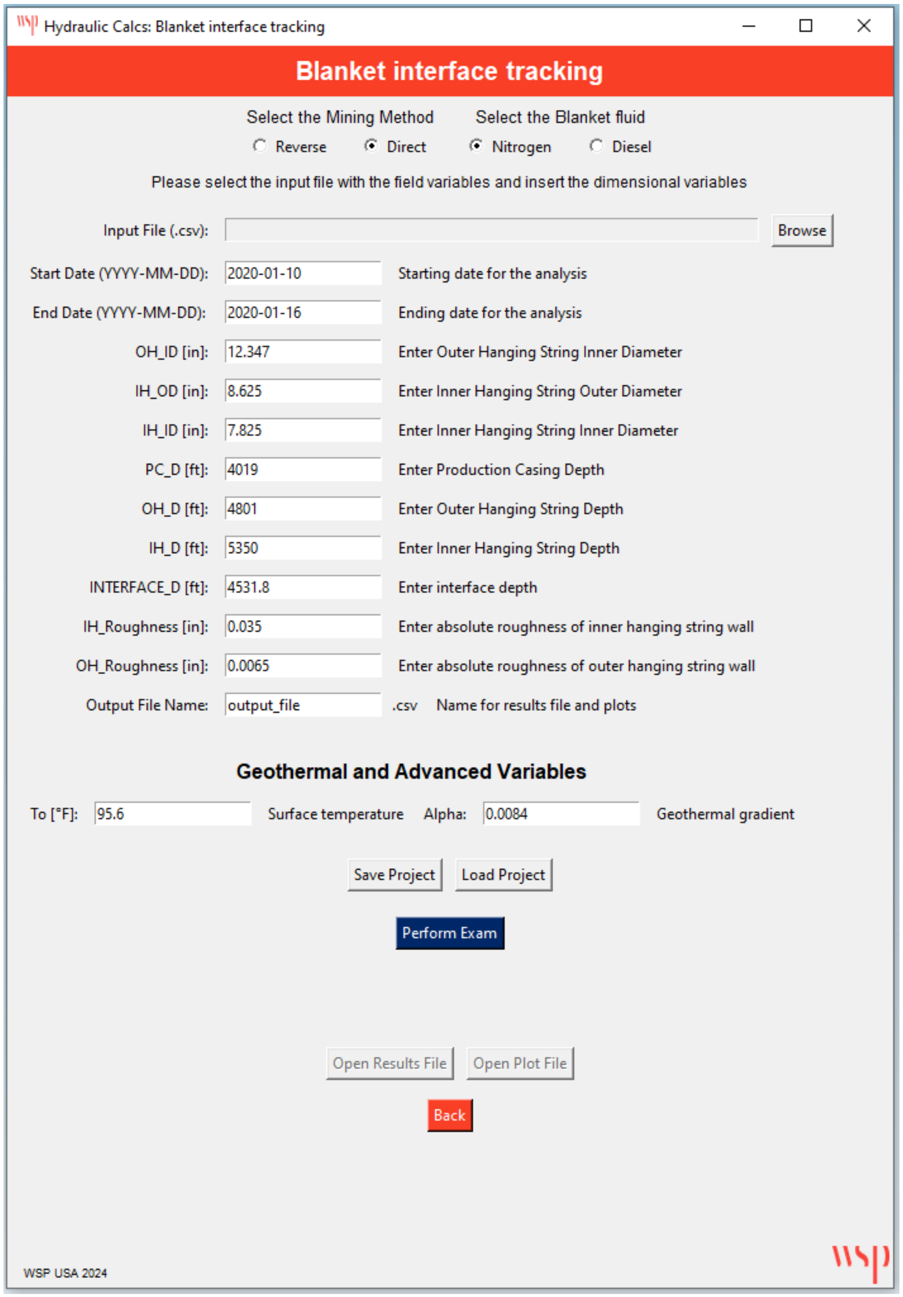

Figure A3. Blanket Interface Tracking window