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Monitoring Corrosion and Injectivity in Geothermal Plants with Digital Twin Technology

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ABSTRACT

Optimizing the performance of geothermal systems while minimizing operational risks, such as injectivity decline and corrosion, is essential for the global adoption of geothermal energy. These operational challenges significantly impact the operational costs for geothermal plants. However, that can be minimized using real-time data and predictive models which enable in-time decision making for an optimized operational scenario and scheduled maintenance. Therefore, digital twin is a need for this purpose that provides a tool for proactive decision making for complex operational systems. Digital twin of geothermal assets provides real time monitoring, predictive analysis and operational optimization.

This paper presents a digital twin framework for geothermal systems, focusing on two key challenges for long-term field and assets performance: injectivity and corrosion. Injectivity decline, caused by reservoir changes, scaling, and operational conditions, reduces operational efficiency, while incremental injectivity may occur due to factors like temperature effects. Corrosion impacts the integrity of facilities, leading to high maintenance costs and safety risks. By integrating sensors and real-time data, the digital twin enables monitoring and predictive maintenance, allowing for early detection of injectivity changes and corrosion, while optimizing system performance through operational scenario simulations.

In addition to the architecture of the digital twin, case studies will be presented to demonstrate the effectiveness of the injectivity and corrosion applications. The developed digital twin framework was tested on and integrated into a geothermal plant in the Netherlands for direct-use heating application.

The Injectivity monitoring application includes real-time calculation of the injectivity index, which provides insights into changes in injectivity. Moreover, Hall and skin factor plots are presented to enables scenario analysis in addition to the real-time monitoring. As a result, a decline in injectivity, due to scaling issues, is reflected in a decreasing injectivity index, an increased skin factor and a deviation of the Hall derivative from the Hall plot showing a steeper positive slope.

The corrosion monitoring application comprises real-time data collection from operational parameters and corrosion probes, combined with semi-real-time data from fluid chemistry analysis, enabling prediction of corrosion rates in geothermal wells. These predictive models are validated through physical inspections using calliper logs and coupon samples, providing a feedback loop that enhances model accuracy. The corrosion rate predictions are then used to optimize maintenance schedules by focusing resources on high-risk areas, adjust the frequency of logging activities, and facilitate proactive interventions, helping to prevent costly downtime and ensure integrity of geothermal well system.

1. INTRODUCTION

Geothermal energy is recognized globally as a critical resource for sustainable heating and power generation, due to its reliability and minimal environmental impact. However, geothermal operations often face challenges such as declining injectivity, corrosion, scaling and equipment degradation. Among these challenges, injectivity decline and corrosion are specially important because they significantly impact long-term performance, increase operational cost and create safety risks.

Injectivity decline in geothermal wells occurs due to various reasons, including reservoir changes, scaling formation, and operational conditions. Such declines reduce the effectiveness of fluid injection and overall plant efficiency. On the other hand, corrosion affects geothermal facility integrity, causing expensive maintenance needs and potential environmental and safety hazards. Both issues lead to increased downtime and operational costs, making it crucial to manage these problems proactively.

Recent developments in digital twin technology provide effective tools to tackle these operational challenges. A digital twin is a dynamic virtual representation of a physical facility built using real-time data. This virtual system allows for monitoring, predictive analysis, and optimized decision-making. Operators can proactively address injectivity and corrosion issues before they cause significant damage, therefore improving reliability and reducing costs (Mahmoud et al., 2023; Siratovich et al., 2022).

Previous studies have demonstrated the benefits of digital twins in geothermal applications. For instance, digital twins in geothermal steamfields increased annual energy production by 2–5% without additional infrastructure (Siratovich et al., 2022). The other study, (Mahmoud et al., 2023), found that applying digital twins improved the performance of ground heat exchangers. Digital twin technology, combined with machine learning and artificial intelligence, helps operators predict system behavior, understand complex interactions, and optimize maintenance schedules and operational scenarios (Buster et al., 2021). Moreover, open-source frameworks like GOOML have further increased the accessibility of digital twins for geothermal applications (Buster et al., 2021; Siratovich et al., 2022). Chityori et al. (Chityori et al., 2024) integrate a digital twin with augmented reality to simulate geofluid behavior for improved silica scaling control. Such advancements show clear potential for increased efficiency and reliability in geothermal energy production. An example of the digital twin development for geothermal heating applications is introduced in the literature (Shoeibi Omrani et al., 2024).

This paper presents a digital twin framework specifically developed to address the operational challenges such as injectivity decline and corrosion issues in geothermal systems. The proposed approach integrates standardized data management, multi-objective process control, real-time monitoring of injectivity and corrosion, predictive modeling, and scenario analysis for optimized operational decisions. This digital twin framework enables early detection of injectivity changes and corrosion risks, significantly reducing downtime and improving system reliability.

The effectiveness of the digital twin is demonstrated through practical case studies at a geothermal plant in the Netherlands. The injectivity monitoring application includes real-time calculation of injectivity index and uses Hall plots and skin factor analysis to identify and predict injectivity issues. Furthermore, the corrosion monitoring application involves integrating real-time sensor data and fluid analysis for corrosion prediction and maintenance optimization.

A key contribution of this work is the application of digital twin technology to the operational challenges in the geothermal industry, improving decision-making, reducing costs, and enhancing the operational efficiency of geothermal plants.

2. METHODOLOGY

This paper focuses on developing and implementing a digital twin technology framework for monitoring and optimizing injectivity and corrosion and automating multi-objective process control and reporting in geothermal systems. The developed solution integrates standardized data management, real-time data monitoring, and advanced modeling techniques, with a focus on open-source tools to ensure accessibility and adaptability. A set of models (mechanistic or data-driven) representing the equipment (e.g., wells, pumps, filters, heat exchangers) and processes (e.g., corrosion, scaling, erosion) within geothermal systems is incorporated into the digital twin technology, providing a comprehensive and integrated approach for monitoring and optimizing geothermal plants (Octaviano et al., 2022).

2.1 Architecture and framework

The digital twin architecture used in this paper, Figure 1, is structured into multiple interconnected layers designed for real-time monitoring, predictive analysis, and optimization. The architecture emphasizes simplicity, accessibility, scalability, and flexibility. It uses open-source programming languages and tools, making it easily accessible and adaptable.

The digital twin consists of four primary layers:

- *Frontend Layer*: Provides an easy-to-use graphical interface for project setup, real-time data visualization, and performing calculations via different applications. This layer uses HTML, CSS (Bootstrap), and JavaScript (React).
- *Backend Layer*: Connects all layers, performs calculations, and handles requests from the frontend. Developed using Python.
- *Workflow Manager Layer*: Organizes and schedules calculations at regular intervals to keep data and analysis continuously updated, managed using the open-source software Celery.
- *Database Layer*: Stores sensor data, calculated results, and user account details securely. The system supports databases like MySQL, InfluxDB, Redis, and MongoDB, allowing easy switching based on specific user needs.

The developed digital twin framework can run either locally at the geothermal site or remotely on cloud platforms such as Microsoft Azure, allowing multiple users access from various locations.

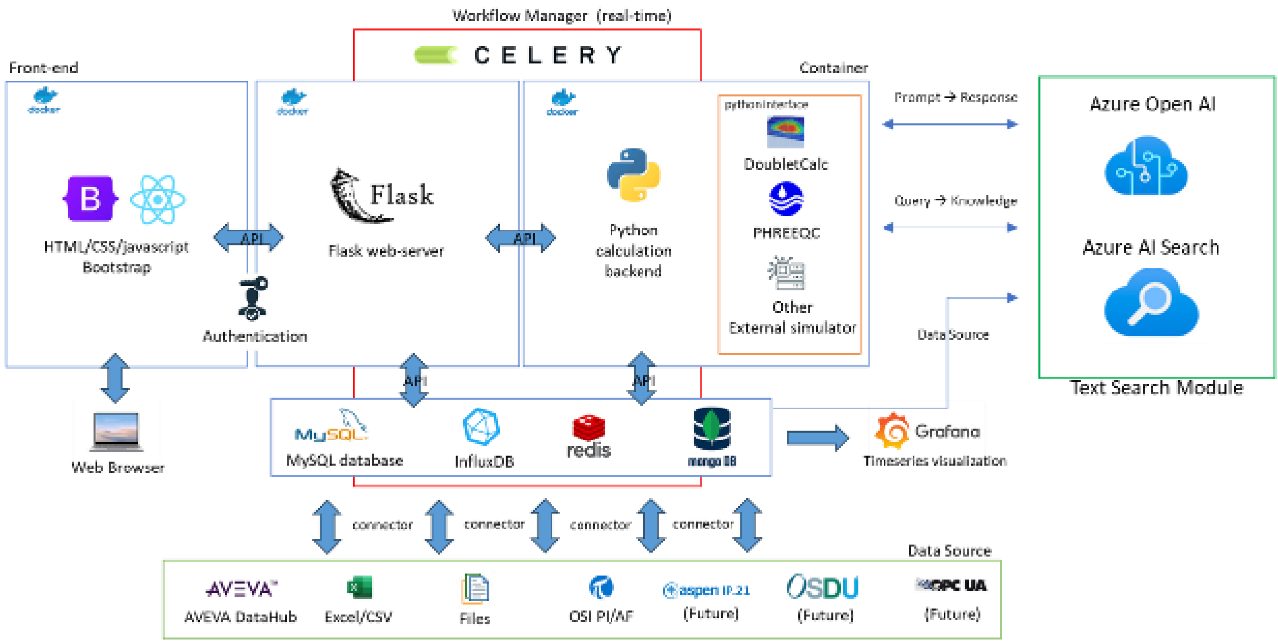

Figure 1: Proposed architecture for the open-source digital twin framework of geothermal assets.

2.2 Data management and model integration

Efficient handling of large amounts of real-time data is crucial for the performance of digital twins. Real-time data collected from sensors at the geothermal plant are integrated into external databases and then continuously retrieved for modeling and analysis. Calculations are regularly performed, and results are stored securely in local databases for analysis and decision-making purposes. User access to the data and projects is secured via username and password authentication.

Seamless integration of the models into the data infrastructure ensures accuracy and reliability. The workflow manager ensures that real-time and historical data needed by the models is updated continuously and allows for consistent and accurate results for improved operational decision-making.

2.3 Model and application development

2.3.1 Injectivity monitoring

Injectivity monitoring is necessary for maintaining optimal performance and sustainability of geothermal reservoirs. Effective monitoring and diagnostic tools help operators to identify and address injectivity issues proactively. The developed digital twin framework integrates three main techniques for injectivity monitoring: the injectivity index (II), Hall plot analysis and skin factor analysis.

<u>Injectivity Index (II)</u>

The injectivity index provides an immediate measure of injection well performance. It is calculated using the ratio of the injection rate to the pressure difference between the wellbore and reservoir pressure, equation 1 (Arnold, 2021). Real-time monitoring of injectivity index helps operators to identify performance declines or reservoir damage and allows for a quick response to address issues like scaling or plugging (Izgec & Kabir, 2007).

$$II = \frac{kh}{141.2\,\mu B\left(ln\left(\frac{r_{res}}{r_w}\right)+s\right)} = \frac{Q}{P_{bh}-P_{res}} \qquad [1]$$

<u>Hall plot analysis</u>

The Hall plot analysis is a powerful diagnostic tool for evaluating injection well performance and reservoir conditions. It plots cumulative injection pressure multiplied by injection time versus cumulative injected fluid volume. Hall plots can effectively indicate the cause of injectivity changes, distinguishing between reservoir effects and well completion issues (Silin, Holtzman, Patzek, Brink, et al., 2005). Moreover, incorporating Hall plot derivatives (rate of changes) to Hall integral (cumulative rates) provides better sensitivity, detecting subtle changes in reservoir conditions or near-wellbore issues like scaling or plugging (Silin, Holtzman, Patzek, & Brink, 2005). Within the developed digital twin, Hall plots and derivatives are generated from real-time data for a selected time period, allowing proactive management of injectivity issues.

Injection rate calculation (Izgec & Kabir, 2007):

$$Q = \frac{kh(p_{bh}-p_{res})}{\mu\left(ln\left(\frac{r_{res}}{r_w}\right)+s\right)} \qquad [2]$$

Modified Hall Integral (Izgec & Kabir, 2007):

$$\int_0^t (p_{bh} - p_{res})\,dt = \frac{\Sigma\,Q}{c}, \quad c = \frac{kh}{\mu\left(ln\left(\frac{r_e}{r_w}\right)+s\right)} \qquad [3]$$

Hall Derivative (Izgec & Kabir, 2007):

$$D_{HI} = \frac{d\int(p_{wf} - p_{res})dt}{d\,ln(\Sigma\,Q)} \quad [4]$$

Skin Factor analysis

Skin factor analysis quantifies formation damage or improvement around the wellbore area, which significantly influences injectivity. Positive skin factors indicate reduced injectivity due to issues like scaling or plugging, while negative values suggest improved permeability or stimulation. Combined with injectivity index and Hall plot analyses, real-time skin factor monitoring offers powerful diagnostic capabilities to manage geothermal reservoir conditions (Akin, 2019; Arnold, 2021; Mihcakan et al., 2005). The digital twin integrates skin factor analyses in real-time for a selected time period to provide critical information for operators to make proactive intervention decisions.

Skin pressure drop (Arnold, 2021):

$$\Delta P_{skin} = \frac{Q\,\mu\,s}{2\pi kh} \quad [5]$$

2.3.2 Corrosion monitoring

Corrosion is a relevant threat for the integrity of geothermal wells. The most relevant types of corrosion in Dutch geothermal wells are general or uniform corrosion (including galvanic), localised corrosion, erosion corrosion and environmentally induced cracking (Veldkamp, 2015). Carbon dioxide is the most important oxidizing element for the Dutch doublets.

Corrosion monitoring is essential for ensuring the long-term integrity and performance of geothermal well infrastructure. Accurate and continuous monitoring enables operators to identify corrosion trends, evaluate mitigation effectiveness, and prevent potential failures before they escalate.

To support proactive decision-making, corrosion monitoring systems should combine accurate data sources with practical analysis methods and prediction of future corrosion rates. This will also allow to optimize frequency and budget spent on well logging operations.

In this approach, the Well Integrity Management System (WIMS) toolbox plays a key role. As shown in Figure 2, the toolbox gathers data from multiple sources, such as configuration, monitoring, and surveillance, and calculated databases. The data is filtered and checked for quality before being used for well integrity monitoring. This allows the system to provide a more reliable and efficient way to predict and manage the risks such as corrosion and erosion.

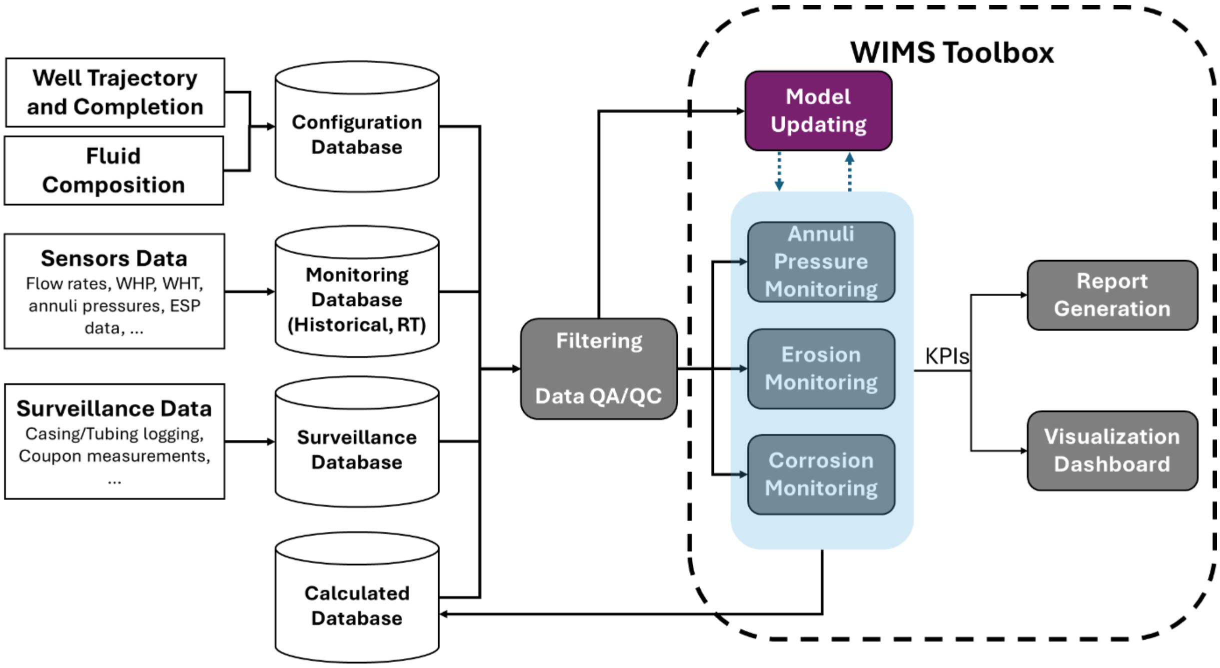

Figure 2: Flowchart illustrating the Well Integrity Management System toolbax that collects and processes data for well integrity monitoring

Corrosion prediction models have been developed mainly by the oil and gas industry for several decades. As most models were developed for the oil and gas industry, where oil or gas is the dominant phase, their applicability to geothermal is limited, and the results always uncertain. (Veldkamp, 2015). The approach developed here is to improve the reliability of the outcome of a corrosion prediction model by calibrating the model to align with measured data in particular wells. This incorporates direct corrosion probing (caliper and coupon measurements), real-time production data feed into a physics-based data-driven corrosion model, and systematic segment-by-segment calibration using historical measurements to align predictions with observed behavior. The result is a comprehensive and dynamic method for assessing corrosion conditions within the well environment.

Direct probing

Diagnostic tools are essential for quantifying in-situ corrosion rates in geothermal well systems. Downhole measurements are taken in regular intervals in wells to assess the condition of the tubulars. Typically, Multi-finger Caliper measurements, acoustic measurements and/or magnetic measurements are used to diagnose the tubular wall thickness over the length of a well. Downhole logging is typically performed prior to the commencement of production operations to establish a baseline of the wellbore's internal geometry. This baseline is relevant for identifying deviations over time that signify general or localized corrosion. High-resolution inner diameter or wall thickness data, when compared across operational intervals, enables accurate quantification of wall thickness reduction and early detection of structural anomalies. In parallel, corrosion coupons are installed in some geothermal systems in a dedicated side-stream loop, to replicate and downhole material exposure conditions, allowing more frequent corrosion rate assessment. The integration of measured downhole and coupon data provides a robust, field-validated approach to corrosion monitoring. It supports predictive modeling, the calibration of corrosion rate models and optimization of logging frequency — thereby improving asset integrity and reducing operational risk.

Downhole measurement logs are processed by extracting diameter or wall thickness measurements along each joint in the well and computing key statistics per tubular joint. Reason to calculate corrosion rate per joint is driven by practical considerations. Minor differences in actual depth vs indicated logging depth frequently occur due to wireline stretch or stick-slip motional behaviour of the measurement tool, making direct comparison of individual corrosion features problematic. Individual joints can however typically be identified in logs via distinct changes in diameter or via Casing Collar Locator information.

With multi-finger caliper logs, opposing caliper fingers,—mean, max, and min internal diameters—within each joint's depth interval are compared to the nominal casing dimensions or previous measurements to quantify wall loss and penetration.

Corrosion rate (CR) is then calculated in two ways:

- If only one log is available, the measured diameters are compared to the nominal ID. As the ID of new tubulars may be up to 12,5% larger than nominal, this may exaggerate corrosion rate.
- If multiple logs exist, the mean IDs of each log are compared chronologically. The difference in diameter is divided by the time between logs to give the corrosion rate in mm/year.

Physics-based Data-driven Corrosion model

Indirect corrosion monitoring in geothermal wells utilizes physics-based data-driven approach to estimate corrosion rates from operational data, offering a continuous, non-intrusive alternative to physical inspection methods. The core of this approach is the segmentation of well operation into intervals—typically from the installation date to the first caliper log, and between subsequent logs. Within each interval, time-series data such as flow rate, pressure, and temperature are filtered and coarsened using change-point detection algorithm (PELT). This coarsening process segments the data into periods where operational parameters remain relatively stable, ensuring that corrosion calculations reflect sustained conditions rather than short-term fluctuations as well as optimize modelling computational efficiency. The filtered and coarsened data are then fed into a corrosion modelling framework, which includes a Vertical Lift Performance (VLP) model for simulating downhole conditions, CO2 partial pressure and the DLD (de Waard, Lotz, Dugstad, 1995) models for corrosion rate prediction, however different corrosion models can be coupled with the proposed framework.

The DLD model was selected for this study based on the availability of the input parameter data. This model evaluates corrosion as a combination of reaction-controlled and mass transfer-controlled mechanisms. Reaction-controlled corrosion is governed by CO_2 fugacity and temperature, while mass transfer-controlled corrosion accounts for flow-induced effects using pipe geometry and fluid velocity. A scaling factor, dependent on system conditions, adjusts the result for potential scaling effects. The corrosion rate output is computed in mm/year for each joint over the interval and updated sequentially. This method provides a joint-by-joint corrosion estimate that evolves with operational conditions, making it ideal for predictive risk assessments and integrity management whilst direct downhole measurements are sparse.

Calibration

To ensure that the corrosion model accurately reflects real corrosion patterns observed in the well, a systematic calibration process is applied. This step is critical to align the output of the physics-based, data-driven corrosion model with measured corrosion rates derived from caliper logs. The calibration is performed on a joint-by-joint and interval-by-interval basis, enhancing spatial and temporal resolution across the entire wellbore.

Within each defined interval—bounded by successive caliper log dates—the model's predictions are compared to observed corrosion rates. The discrepancy between measured and modeled values is minimized by optimizing key DLD model parameters, such as reaction kinetics and flow dependent coefficients. To improve numerical stability and convergence, parameters are normalized and optimized using constrained solvers like SLSQP or COBYLA. These solvers iteratively adjust the parameter set to minimize the sum of squared errors (SSE) between predicted and observed corrosion at each joint.

The coarsened operational data, which already reflects stable flow, pressure, and temperature conditions, ensures that the calibration focuses on meaningful long-term trends rather than short-term fluctuations. Once optimized, the calibrated model provides more reliable predictions of future corrosion behavior under evolving well conditions. The calibration is inherently conservative, prioritizing the worst-case (maximum) corrosion scenario at each joint to ensure the model remains on the safe side of operational risk.

The result is a calibrated corrosion model tailored to the specific well environment, capable of producing more accurate predictions under dynamic flow and thermal regimes. This enhances the model's value in integrity management, supporting optimized inspection intervals, chemical treatment planning, and long-term risk mitigation strategies..

Following optimization, the calibrated model is integrated into a real-time corrosion monitoring system. It continuously processes live production data to provide updated corrosion rate predictions across all joints. This enables operators to track evolving integrity conditions without the need for immediate physical inspection. It also allows operators to forecast the effects of changes in operating conditions on corrosion and assess future integrity of the tubulars in these cases.

Recommendations

To confirm a well's integrity and validate ongoing predictions, a new downhole log will be acquired from time to time. If the measured corrosion profile aligns closely with the model's forecast—within an acceptable error margin— and the remaining wall thickness is sufficient, scheduling the next logging campaign can be optimized to a moment where the local wall thickness approaches the minimum value, considering an appropriate safety factor to account for uncertainties and response time for a well repair. This approach allows operators to shift from calendar-based to condition-based inspection scheduling, reducing unnecessary logging costs while maintaining confidence in well integrity.

Planned future developments include indicating areas in wells where prolonged high erosion conditions have occurred. This may help in assessing if erosion-corrosion of high-grade alloy steels (e.g. 13 Chrome) and erosion of corrosion barriers such as internal epoxy coating or GRE lining play a role of importance.

3. RESULTS

3.1 Injectivity monitoring

The injectivity monitoring method applied in this study uses three primary tools: the injectivity index (II), Hall plot analysis, and skin factor analysis. These methods were tested using data from geothermal operations to evaluate injectivity performance and identify potential issues. Two distinct operational periods were selected to clearly demonstrate the capability of the digital twin. The first scenario represents a period (January-March) experiencing injectivity issues due to plugging or scaling, while the second scenario represents stable operational conditions.

3.1.1 Injectivity decline due to plugging or scaling

In the first scenario (Figure 3, January-March), the injectivity index showed a notable decline of approximately 22%. This decline was also seen in the Hall plot, where the Hall derivative separated clearly from the Hall integral curve, indicating reduced injectivity. That could cause by scaling or plugging. Moreover, the skin factor analysis confirmed these observations, showing increased values consistent with decreased injectivity. Such injectivity decline could result from changes in temperature, scaling buildup, or mechanical damage.

The developed digital twins provide real-time monitoring capabilities that allow operators to detect injectivity problems early. As soon as injectivity decline is observed, operators can take corrective actions such as adjusting injection pressures and temperatures or applying chemical treatments to mitigate scaling.

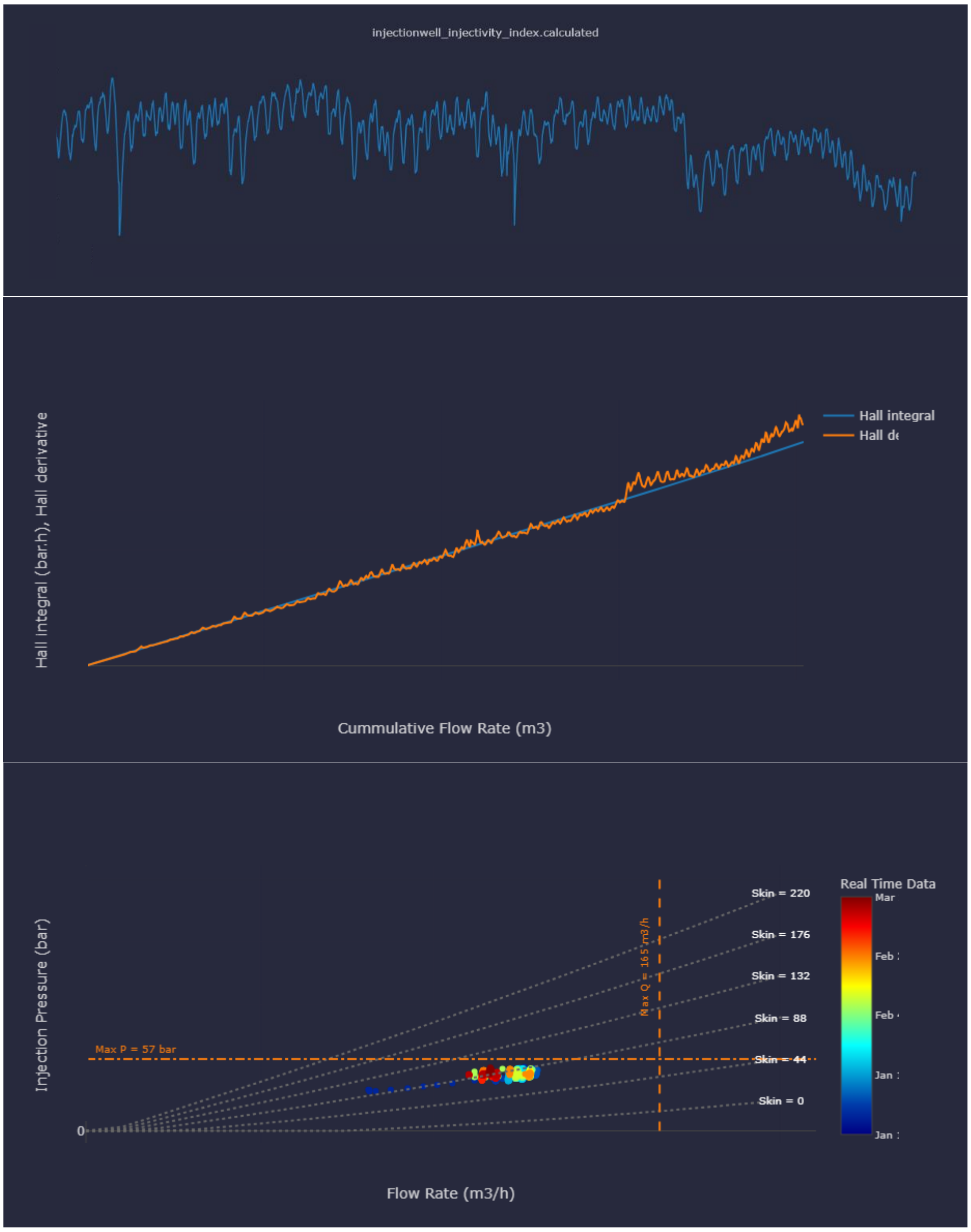

Figure 3: Injectivity monitoring during injectivity decline (Scenario 1). Injectivity index (top), Hall plot (middle), and skin factor (bottom) clearly show declining injectivity conditions due to plugging or scaling.

3.1.2 Stable injectivity conditions

In the second scenario, Figure 4, representing stable conditions, the injectivity index remained mostly constant, fluctuating by less than 7%. This stable injectivity was confirmed by the Hall plot analysis, where the integral and derivative closely matched, indicating no significant injectivity changes or reservoir issues. The skin factor remained stable, further confirming normal operational conditions without notable injectivity improvement or decline.

These results clearly demonstrate the value of real-time injectivity monitoring enabled by the developed digital twin framework. Injectivity changes can be caused by various operational factors, such as temperature variations, fluid composition changes, and injection pressures. By monitoring injectivity in real-time, operators can quickly detect deviations from normal conditions and proactively address emerging problems. This will significantly reduce operational risks, minimize downtime, and enhance overall reservoir management.

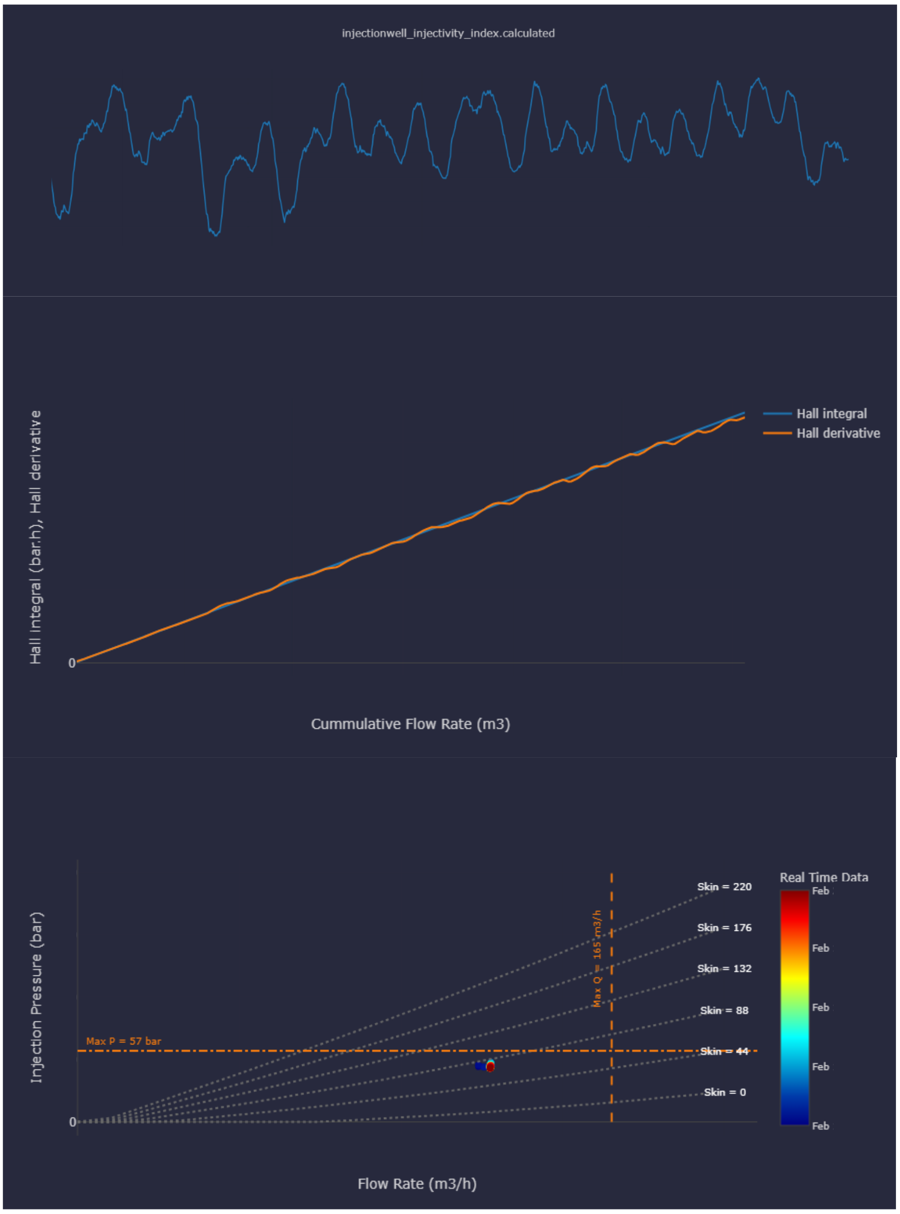

Figure 4: Injectivity monitoring during stable conditions (Scenario 2). Injectivity index (top), Hall plot (middle), and skin factor (bottom) demonstrate stability in injectivity with no significant changes.

3.2 Corrosion monitoring

This study presents an integrated approach to corrosion assessment combining caliper log processing, model calibration, and real-time corrosion monitoring. The methodology is designed to deliver accurate, joint-specific corrosion rates, supporting both historical evaluation and forward-looking integrity management in geothermal wells. Given workflow was tested on synthetic dataset consisting of a 3-month production period and arbitrary logging data presented below.

3.2.1 Log processing

The processed caliper logs (Figure 5) provide joint-by-joint assessment of casing condition, by calculating key metrics such as maximum penetration, wall loss, and internal diameter variations. These values are derived from opposing finger measurements and compared to nominal casing dimensions. The results are used to highlight areas of increased metal loss, enabling identification of high-risk zones and supporting corrosion model calibration and integrity management.

3.2.2 Calibration

The plot shown in Figure 6 illustrates the effectiveness of model calibration by comparing measured, un-calibrated, and calibrated corrosion rates along the wellbore, indexed by joint number.

The blue line represents the measured corrosion rate, derived from caliper logs between the date of the baseline measurement and 2 months after this date. The orange line shows the un-calibrated model output, which significantly underestimates corrosion across all joints, remaining nearly flat and failing to capture localized variations. In contrast, the green line, representing the calibrated model, closely follows the measured data, accurately reflecting the spatial variability and magnitude of corrosion along the casing.

Log 1 ▼

Processed Caliper Logs

Joint No.	Max. Pen. [%]	Max. Loss [%]	Max. Pen. Depth [m]	Min. Pen. Depth [m]	Max. ID [inch]	Min. ID [inch]	Mean. ID [inch]
1	18.8	8.2	3.4213	10.7113	12.595	12.359	12.497
2	16.6	6.4	14.0063	11.2513	12.574	12.351	12.478
3	19.3	7.9	26.8063	26.6863	12.6	12.359	12.493
4	17.7	7	44.9963	42.6663	12.585	12.365	12.485
5	17.9	7.1	49.4113	46.2813	12.587	12.343	12.486
6	18.9	7.9	59.8663	58.0213	12.596	12.345	12.493
7	18.4	7.3	72.3713	69.7663	12.592	12.328	12.488
8	18.6	8.9	84.3663	81.4263	12.594	12.356	12.503
9	19.1	7.9	94.4913	103.7713	12.598	12.367	12.494
10	20.8	9.2	108.7113	113.8363	12.615	12.375	12.507
11	20	7.8	123.3163	121.9413	12.607	12.346	12.493

Figure 5. Summarized processed caliper log data

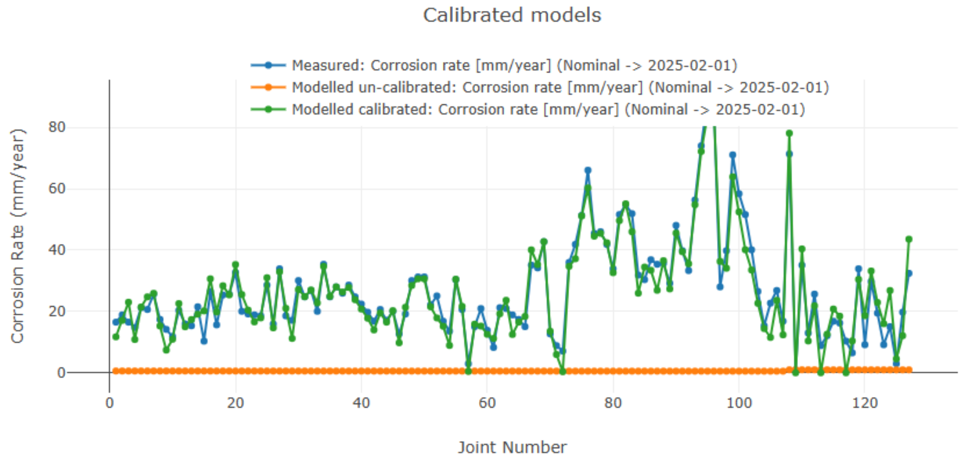

Figure 6 Corrosion rate per joint for a defined "training" interval between nominal/baseline and latest log date

3.2.3 Real-life monitoring

The next phase of the corrosion assessment framework is designed to enable real-time monitoring by integrating the calibrated model with live production data, including flow rate, pressure, and temperature. Although real-time deployment has not yet been carried out in this study, the system is fully equipped to support continuous corrosion rate estimation on a joint-by-joint basis. Once operational, the model's predictions can be validated against future caliper logs to assess its accuracy. If the predicted corrosion rates fall within an acceptable range of the measured values and remaining wall thickness is sufficient, including a safety factor, inspection intervals can be safely extended. This approach lays the groundwork for transitioning from traditional, time-based logging schedules to risk-based, condition-driven strategies, improving both inspection efficiency and long-term well integrity management.

4. CONCLUSIONS

The digital twin framework presented in this study provides effective real-time monitoring, predictive analysis, and proactive decision-making tools specifically for injectivity and corrosion challenges. Key findings from this study demonstrate that real-time injectivity monitoring effectively detects performance declines in geothermal wells, enabling early identification of operational issues such as scaling or plugging. For instance, the digital twin successfully identified an injectivity index decline of approximately 22% during the operational period tested, allowing for timely interventions to mitigate potential impacts on geothermal system performance. On the other hand, stable injectivity conditions were clearly distinguished, highlighting the effectiveness of digital twin in differentiating normal operations from problematic scenarios.

The corrosion monitoring framework developed in this study complements real-time injectivity analysis by providing a robust method for tracking wellbore integrity on a joint-by-joint basis. Through the integration of caliper-derived measurements, physics-based modeling, and parameter optimization, the system delivers high-resolution corrosion rate predictions. Although the real-time application is yet to be validated with live field data, the framework is fully designed to support continuous monitoring. Once operational data are available, model predictions will be compared with follow-up caliper logs to assess accuracy and reliability. This will enable a shift toward condition-based logging strategies, improving inspection efficiency while maintaining well integrity. Overall, this integrated approach holds strong potential for enhancing geothermal well surveillance and will be further validated through future field deployments.

Early detection of injectivity and corrosion issues significantly reduces operational risks, allowing operators to proactively manage reservoir conditions, minimize downtime, and optimize maintenance scheduling, thus reducing operational costs.

A significant advantage of this study is the use of a fully open-source digital twin framework for geothermal systems. The open-source approach promotes accessibility, adaptability, and knowledge-sharing across the geothermal industry, making the adoption of digital twin technology easier, faster, and more impactful.

REFERENCES

Akin, S. (2019). Geothermal re-injection performance evaluation using surveillance analysis methods. Renewable Energy, 139, 635–642. https://doi.org/10.1016/j.renene.2019.02.075

Arnold, R. (2021). Analytics-Driven Method for Injectivity Analysis in Tight and Heterogeneous Waterflooded Reservoir. JOINT CONVENTION BANDUNG (JCB) 2021, Ii.

Buster, G., Siratovich, P., Taverna, N., Rossol, M., Weers, J., Blair, A., Huggins, J., Siega, C., Mannington, W., Urgel, A., Cen, J., Quinao, J., Watt, R., & Akerley, J. (2021). A new modeling framework for geothermal operational optimization with machine learning (Gooml). Energies, 14(20). https://doi.org/10.3390/en14206852

C. de Waard, U. Lotz, A. Dugstad; March 26–31, 1995. "Influence of Liquid Flow Velocity on CO2 Corrosion: a Semi-Empirical Model." Proceedings of the CORROSION 1995. CORROSION 1995. Orlando, FL. (pp. 1-15). AMPP. https://doi.org/10.5006/C1995-95128

Chityori, A., Byiringiro, J. B., Ndeda, R., & Gathitu, B. (2024). Towards Digital Twin and Augmented Reality Modelling to Mitigate Silica Scaling in Geothermal Plants. SSRG International Journal of Mechanical Engineering, 11(5), 70–86. https://doi.org/10.14445/23488360/IJME-V11I5P107

Izgec, B., & Kabir, C. S. (2007). Real-time performance analysis of water-injection wells. Proceedings - SPE Annual Technical Conference and Exhibition, 2(2005), 1322–1330. https://doi.org/10.2523/109876-ms

Mahmoud, D., Tandel, S. R. S., Yakout, M., Elbestawi, M., Mattiello, F., Paradiso, S., Ching, C., Zaher, M., & Abdelnabi, M. (2023). Enhancement of heat exchanger performance using additive manufacturing of gyroid lattice structures. International Journal of Advanced Manufacturing Technology, 126(9–10), 4021–4036. https://doi.org/10.1007/s00170-023-11362-9

Mihcakan, I. M., Altinay, E. I., & Kasap, I. (2005). The Hall Plot Analysis of a Water Injection Test Affected by Geothermal Reservoir Response. Proceedings World Geothermal Congress, April, 24–29.

Octaviano, R., Dussi, S., de Zwart, H., Shoeibi Omrani, P., van Pul-Verboom, V., Elewaut, K., & van Schravendijk, B. (2022). Model-based monitoring of geothermal assets Case study: Electrical submersible pumps.

Shoeibi Omrani, P., Octaviano, R., Poort, J., Palochis, D., Hashemi, L., Egberts, P., & Hesari, H. D. (2024). Digital Twin of Geothermal Assets Assisting the Production and Operational Decisions. GeoTHERM Journal, 2. https://doi.org/https://doi.org/10.53196/gtj-2024

Silin, D. B., Holtzman, R., Patzek, T. W., & Brink, J. L. (2005). Monitoring waterflood operations: Hall's method revisited. SPE Western Regional Meeting, Proceedings, March 2005, 351–362. https://doi.org/10.2118/93879-ms

Silin, D. B., Holtzman, R., Patzek, T. W., Brink, J. L., & Minner, M. L. (2005). Waterflood surveillance and control: Incorporating hall plot and slope analysis. Proceedings - SPE Annual Technical Conference and Exhibition, January, 1191–1205. https://doi.org/10.2523/95685-ms

Siratovich, P., Buster, G., Taverna, N., Rossol, M., Weers, J., Blair, A., Huggins, J., Siega, C., Mannington, W., Urgel, A., Cen, J., Quinao, J., Watt, R., & Akerley, J. (2022). GOOML-Finding Optimization Opportunities for Geothermal Operations. PROCEEDINGS, 47th Workshop on Geothermal Reservoir Engineering, 1–10. https://pangea.stanford.edu/ERE/pdf/IGAstandard/SGW/2022/Siratovich.pdf

Veldkamp, J.G., Goldberg, T.V., Bressers, P.M.M.C., Wilschut, F. (2015) Final report Corrosion in Dutch geothermal systems. TNO 2015 R10160

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