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Geothermal Digital Twins

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Abstract

Maximising nett energy output of a geothermal system is essential to make geothermal energy successful. A Digital Twin of the system is an effective tool to optimise the performance and to gain control on well integrity risks.

This paper presents a digital twin framework for geothermal systems, focusing on two key challenges for long-term field and assets performance: injectivity and well integrity. Injectivity decline, caused by reservoir changes, scaling, and operational conditions, reduces operational efficiency, while incremental injectivity may occur due to factors like temperature effects.

The injectivity monitoring application of the digital twin includes real-time calculation of the injectivity index. 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.

Well Integrity Management Systems (WIMS) are becoming mandatory for deep geothermal systems several countries now. The digital twin can monitor the status of the WIMS compliance. A digital twin using real-time data and corrosion rate models enables in-time decision making for an optimized operational scenario and scheduled maintenance preventing expensive repairs, unplanned downtime or significant shortened well life and reputation damage. The WIMS Dashboard visualises the well integrity status using a real-time model to determine the corrosions rate. Corrosion rate predictions are then used to optimize maintenance schedules, adjust the frequency of logging activities, and facilitate proactive interventions. These predictive models are validated through physical inspections using calliper logs and coupon samples, providing a feedback loop that enhances model accuracy and are based on real-time data collection from operational parameters and corrosion probes, combined with semi-real-time data from fluid chemistry analysis.

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

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 fatal well integrity failures, leading to short lived projects and reputation damage.

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 well integrity 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 steam fields increased annual energy production by 2–5% without additional infrastructure (Siratovich et al., 2022). Another 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 behaviour, 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 behaviour 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. It enables early detection of injectivity changes and well integrity risks. 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 to update a WIMS dashboard.

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 modelling 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 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.

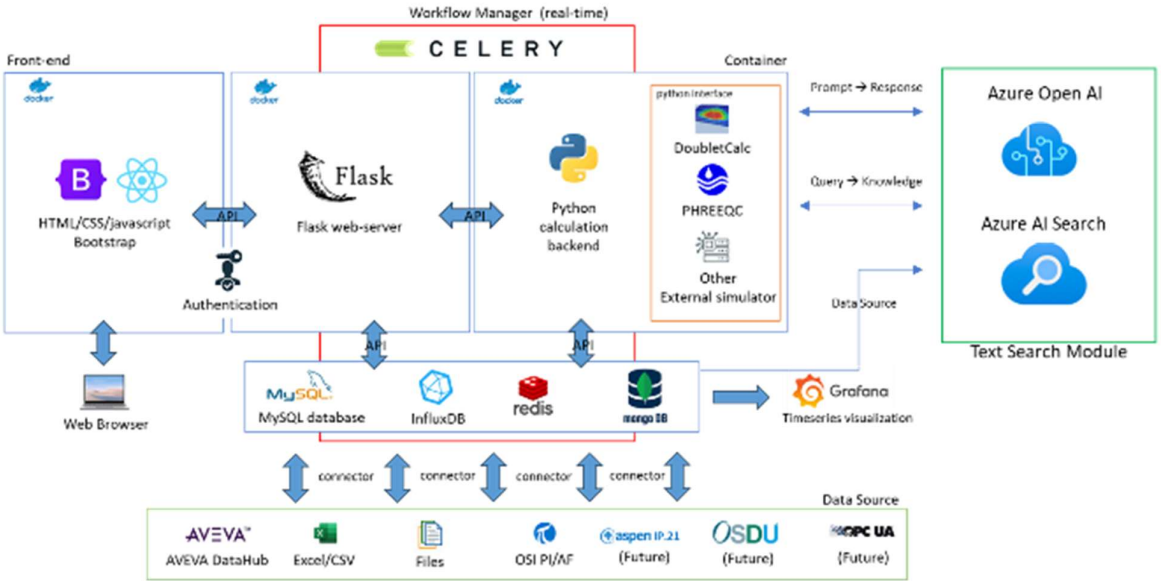

Figure 1. Architecture for the open-source digital twin framework of geothermal assets.

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 modelling 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.

Injectivity Index (II)

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).

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

Hall plot analysis

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 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):

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

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):

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

2.3.2 WIMS Toolbox

A Well Integrity Management System (WIMS) is a structured framework that ensures the safety, reliability, and environmental integrity of wells throughout their entire lifecycle — from design and construction to operation, suspension, and abandonment. It integrates technical, operational, and organizational controls to prevent the uncontrolled release of formation fluids or gases to the

environment, thereby protecting people, assets, and the environment. In the Netherlands, the WIMS are based on the ISO 16530-1 standard: Well Integrity – Life Cycle Governance and are mandatory for geothermal operators.

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.

Managing corrosion is an essential part of the WIMS and 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 based on expected production rates.

In this approach, the WIMS Toolbox plays a key role in the digital twin. As shown in **Error! Reference source not found.**, the toolbox gathers data from multiple sources, such as well configuration, monitoring, and surveillance, and calculated databases. This allows the system to provide a more reliable and efficient way to predict and manage the risks such as corrosion and erosion. The toolbox consists of various modules to cover various aspects of well integrity of which its relevance depends on the well design.

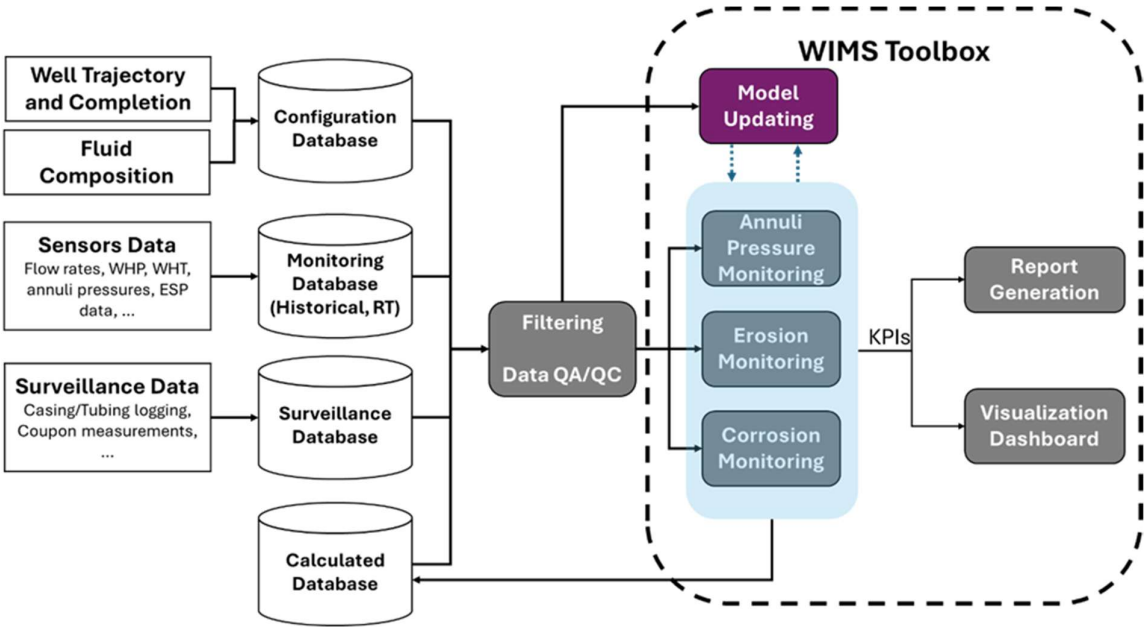

Figure 2. Flowchart illustrating the Well Integrity Management System Toolbox that collects and processes data for well integrity monitoring.

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 (calliper 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 behaviour. The result is a comprehensive and dynamic method for assessing corrosion conditions within the well environment.

Direct probing

Multi-finger Calliper measurements, acoustic measurements and/or magnetic measurements are used to diagnose the tubular wall thickness over the length of a well. Downhole logging requirements are defined in the WIMS and 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 downhole material exposure conditions, allowing more frequent corrosion rate assessment. The integration of measured downhole and coupon data provides a robust, field-validated approach for corrosion monitoring. It supports predictive modelling, 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 calliper logs, opposing calliper fingers measure inner diameter of a casing string. From this data mean, max, and min internal diameters are calculated within each joint's depth interval and are compared to the nominal casing dimensions or previous measurements to quantify wall loss and penetration. Corrosion rate (CR) is then calculated from this data.

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. Filtered and coarsened data are fed into a corrosion modelling framework, which includes a Vertical Lift Performance (VLP) model for simulating downhole conditions, CO_2 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. 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 calliper logs. The calibration is performed on a joint-by-joint and interval-by-interval basis, enhancing spatial and temporal resolution across the entire wellbore.

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.

WIMS improvements

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.

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 (**Error! Reference source not found.**, 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.

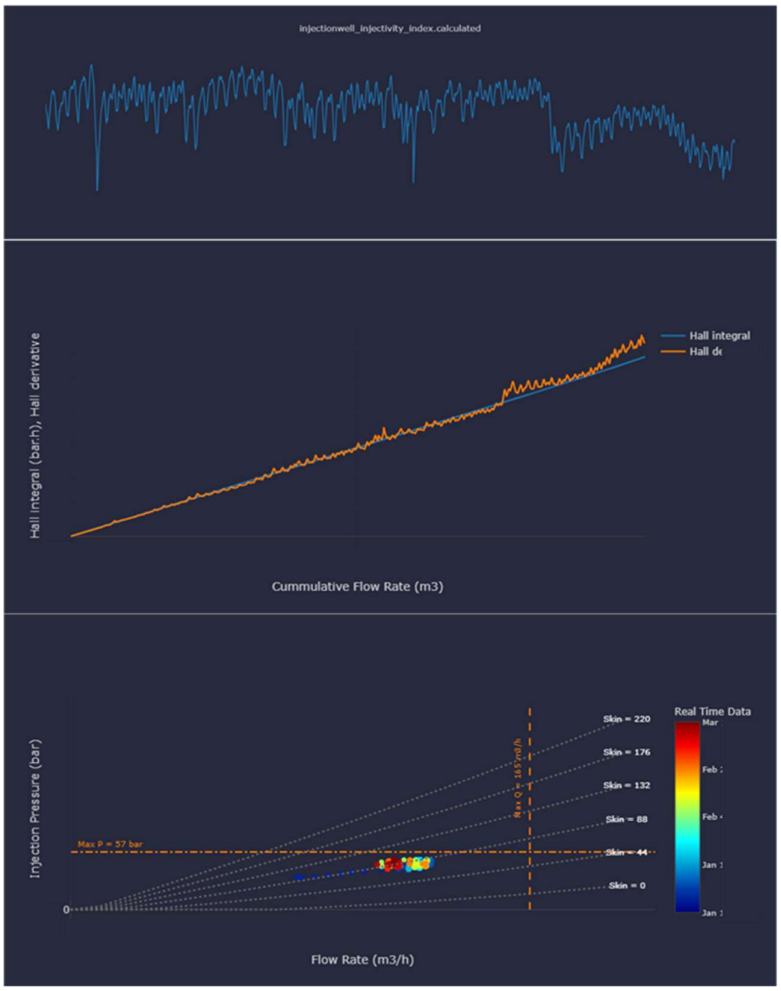

Figure 3. Injectivity monitoring during injectivity decline (Scenario 1). Injectivity index (top), Hall plot (middle), and skin factor (bottom) clearly show declining injectivity conditions due to plugging or scaling.

3.2 Well Integriy Monitoring

This study presents an integrated approach to corrosion assessment combining calliper 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 calliper logs 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 **Error! Reference source not found.** 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 calliper 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.

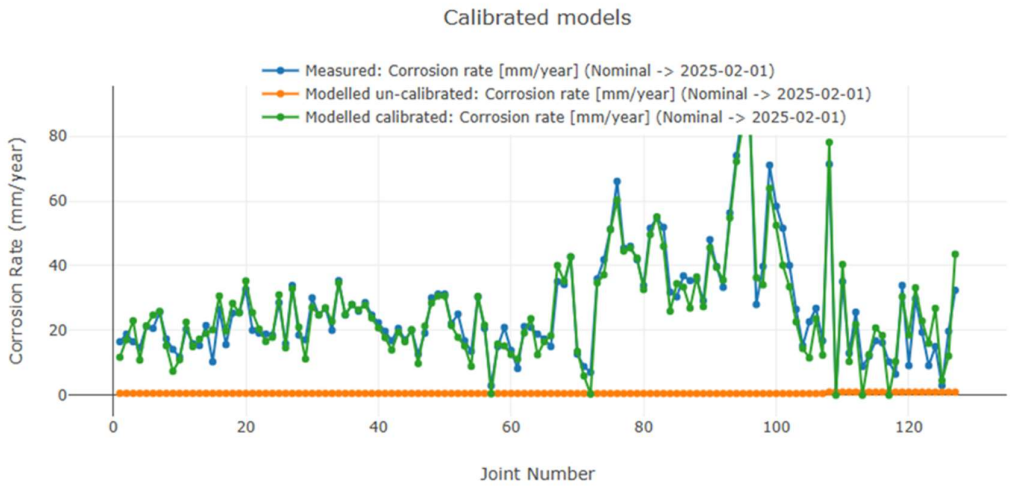

Figure 4. Corrosion rate per joint for a defined “training” interval between nominal/baseline and latest log date.

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 calliper 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.

3.2.4 WIMS dashboard

A "well barrier element" (WBE) is a physical element that, when combined with other well barrier elements into a Well Barrier Envelope, will prevent flow. The failure of a single WBE can cause the well barrier envelope to fail, resulting in an uncontrolled outflow of fluids or gasses. The corrosion modelling is used to determine the integrity of several of these barriers. The WIMS dashboard displays the status of the Well Barrier Elements (WBE) with a traffic light system to visualise if any

issues exist or maintenance actions need to be scheduled. This enables operators to track evolving integrity conditions without the need for immediate physical inspection. The WIMS dashboard can also be used to forecast the effects of changes in operating conditions on corrosion and assess future integrity of the tubulars in these cases.

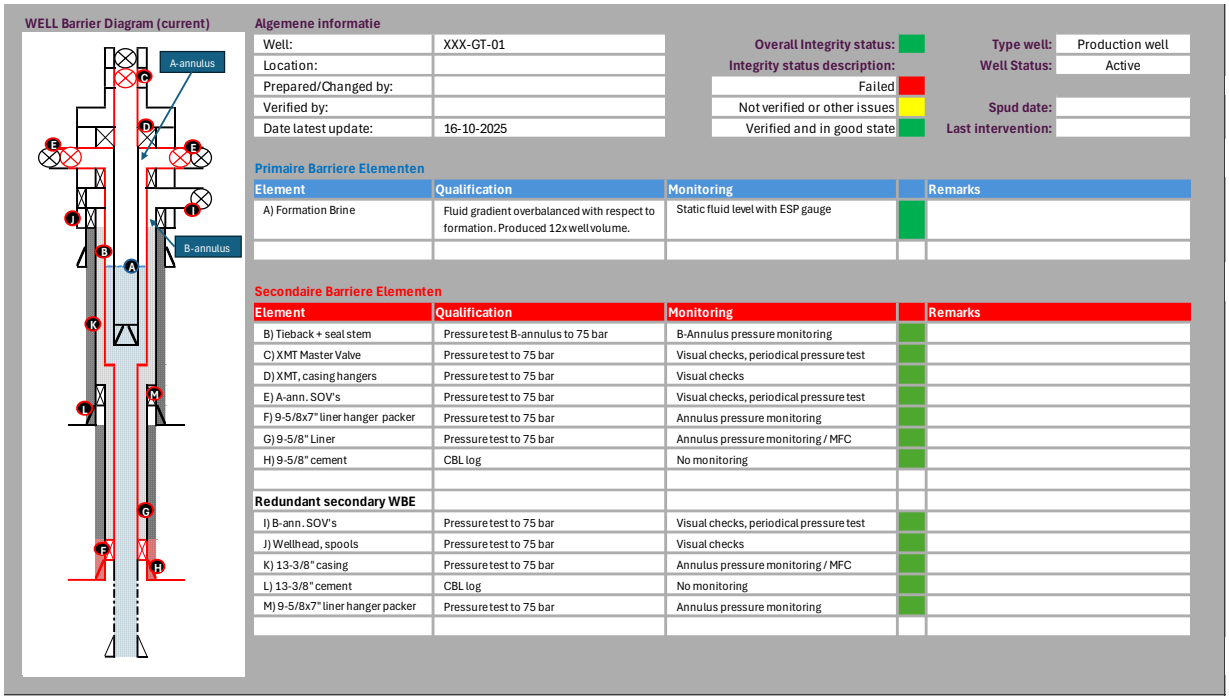

Figure 5. Example of the WIMS dashboard visualising the status of the various Well Barrier Elements.

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 well integrity management. 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.

Proper management of well integrity is essential to prevent expensive repairs. The WIMS dashboard is an effective tool to this end. 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 calliper-derived measurements, physics-based modelling, 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 calliper 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.

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