Proceedings World Geothermal Congress 2026
Calgary, Canada, June 8 – 11, 2026

Geothermal Well Interconnection Analysis using Stock Reservoir Modeling

Arkaitz Manterola Donoso[1]*, Hlynur Stefánsson[1], Egill Júlíusson[2] and María Gudjónsdóttir[1]
Reykjavik University[1]*, Arctic Green Energy[2]
arkaitz23@ru.is

Keywords: Stock Reservoir Modeling (SRM), Geothermal Production Planning, Well Interconnection, Production Optimization, Reservoir Simulation, Krafla Geothermal Field

ABSTRACT

Understanding and optimizing geothermal well performance is essential for sustainable and efficient reservoir utilization. Building on previous work done on stock reservoir modeling (SRM), this study presents an expanded methodology that aims to incorporate interconnected geothermal wells to further enhance production planning for geothermal systems. SRM offers a fast, data-driven approach that requires only historical production data to estimate individual well behavior, without requiring physical reservoir characterization. It has proved effective for wells with reduced interactions; however, for most geothermal fields, well-to-well interactions are frequent, which makes understanding these interactions important when optimizing the production of geothermal fields. This research proposes an expanded SRM methodology that further studies subsurface interactions between wells based on production trends and pressure responses by including data from pressure monitoring of a field. The main objective is to identify the dependencies between wells and provide insight into whether or not considering their interconnectivity would improve the model and the optimization process. By improving SRM's interaction analysis, the approach aims to improve short- and mid-term forecasting accuracy for geothermal fields. This contributes to making geothermal production models more flexible and robust, especially in fields where operational data is available but detailed subsurface models are not as accessible.

1 INTRODUCTION

The development of accurate reservoir models is a cornerstone of geothermal energy utilization, as they allow forecasting production, optimizing resource allocation, and contributing to the long-term sustainability of geothermal systems. By reliably and efficiently representing reservoir dynamics, these models support decision-making under geological uncertainty while balancing technical, economic, and environmental objectives. Their role is becoming increasingly critical as geothermal developments expand to more complex and interconnected systems.

Traditionally, geothermal reservoir modeling approaches range from detailed physics-based numerical simulations to simplified lumped parameter modeling (LPRM). While numerical models provide detailed subsurface characterizations, they require trained professionals and extensive geological, geophysical, and hydrological data, which may not always be available or reliable (Barton et al., 2025). By contrast, LPRM simplifies the geothermal system into different interconnected zones that approximate its overall behavior, for fast initial assessments and less detailed monitoring of the system using a fraction of physical data (Axelsson, 1989). Building on insights from other energy technologies, Stock Reservoir Modeling (SRM) emerged as a promising alternative. SRM offers a data-driven methodology that relies solely on historical production records to estimate well performance, providing a fast and practical framework that avoids the complexities of full physical characterization (Manterola Donoso et al., 2025).

Although SRM has shown promise in fields with limited well interconnection, its applicability in geothermal systems with interconnected wells remains an open question. In most operating fields, wells do not behave independently: production from one well can influence the pressure and output of neighboring wells. This interconnectivity introduces additional complexity that has yet to be fully captured in SRM. The present research addresses this challenge by exploring whether SRM can be extended to account for well-to-well interactions and whether such an extension improves its predictive capabilities for production optimization.

This study, therefore, investigates whether SRM can be adapted to capture production interactions between interconnected wells and whether pressure monitoring data can be used to validate such interactions and enhance model robustness. These objectives are addressed through a case study in the Krafla geothermal field in northern Iceland, where three wells are suspected to exhibit strong interconnection effects. Building on the authors' previous SRM applications in Iceland (Manterola Donoso et al., 2025, Manterola Donoso et al., 2024),

this work investigates whether considering well interaction enhances short- to mid-term forecasting, thereby contributing to more flexible and robust geothermal production planning.

2 BACKGROUND

Production optimization is one of the main objectives of geothermal reservoir management, as it balances maximizing energy output with sustaining long-term reservoir pressure and temperature. Achieving this requires reliable models that can provide forecasts under different production scenarios, guide operational decisions, and help mitigate reservoir decline. A key challenge lies in selecting a modeling approach that applies to available data and the operational objectives of the geothermal project.

Reservoir models can be grouped into three categories: numerical models, lumped parameter models (LPRM), and stock reservoir models (SRM). Numerical models offer the highest level of detail, representing the subsurface using discretized grids and solving equations that describe fluid flow and heat transport. However, their complexity demands trained professionals and extensive geological, geophysical, and production data as well as a significant computational effort (Barton et al., 2025; Scott et al., 2025). LPRM offers a simpler alternative, simplifying the system into a small set of interconnected tanks to estimate broad reservoir dynamics, making them easier to implement in data-limited conditions, but they often lack spatial resolution (Axelsson, 1989; Qin et al., 2017). SRM is built with the aim of studying production economics, conceptually similar to lumped representation, but only focusing on historical production data to assess the geothermal system. Instead of relying on geological and geophysical inputs, it treats each well as an individual "stock," whose output is characterized solely by historical production data. This makes SRM computationally light and well-suited for rapid forecasting, avoiding complex physical characterization (Júlíusson and Axelsson, 2018; Manterola Donoso et al., 2025). A comparative summary of these approaches is provided in Table 1.

Table 1. Summary and comparison of geothermal reservoir engineering approaches. (from Manterola Donoso et al., 2025)

	Numerical modeling	LPRM	SRM
Complexity	Very detailed	Less detailed	Less detailed
Study area	Both field-wide and individual well focus	Field-wide focus	Individual well-focus
Data	Physical data and operational data	Simplified physical data and operational data	Operational data only
Solving time	Very slow	Fast	Very fast
User accessibility	Expertise required	Some knowledge required	Easy to use
Main applicability	Detailed reservoir management and long-term planning	Quick assessment of reservoir-wide trends	Quick well-to-well assessment

The extension proposed in this research focuses on introducing interconnections between "stocks", representing well-to-well interactions. Instead of treating each well as being fully independent, production from one well can influence the behavior of another through shared pressure changes. This requires incorporating additional input data, specifically from field pressure monitoring, to be able to validate and quantify the strength of interactions between wells. The formulation of the model builds on the structure presented in earlier works (Manterola Donoso et al., 2025; Manterola Donoso et al., 2024), with modifications to include inter-stock flows that reflect interconnectivity effects. While the detailed mathematical equations and parameterization are described in the following section, the conceptual update involves transitioning SRM from a set of isolated stocks (Júlíusson and Axelsson, 2018; Manterola Donoso et al., 2025) to a partially coupled system.

Finally, this methodology is applied to a case study in the Krafla geothermal field, located in northern Iceland, where three wells that show potential for strong interconnection were selected. This case study aims to assess the feasibility of using SRM to capture well interactions and explores how this model adaptation may influence its application for geothermal production optimization.

3 METHODOLOGY

Stock Reservoir Modeling (SRM) provides a fast, data-driven method for forecasting geothermal production by only using historical well data. In its conventional form, however, SRM studies each well as an independent unit, without accounting for possible subsurface interactions where pressure and production are interconnected. This simplification limits its applicability in settings where well interconnection affects the performance of the production and the model (Manterola Donoso et al., 2025).

To address this limitation, we extend SRM by introducing a way to study well interconnection. The modified model retains the original SRM structure but adds parameters that account for shared storage and transmissibility between wells, providing a more realistic basis for production optimization. Therefore, the new model needs to solve additional decision parameters that account for these changes. See Table 2 for all the decision parameters of the model. See Figure 1 and Figure 2 for the conceptual diagrams of an individual SRM and a three-well interconnected SRM.

Table 2. Key decision parameters of the extended SRM.

Symbol	Parameter	Units
$Q_{i,MAX}$	Maximum thermal energy output	MWth
$P_{i,MAX}$	Maximum wellhead pressure	bar
$S_{i,MAX}$	Maximum well stock	MWyr
$R_{i,MAX}$	Maximum recharge rate	MWth
$S_{0,MAX}$	Connecting reservoir's maximum stock	MWyr
$R_{0,MAX}$	Connecting reservoir's recharge rate	MWth
α_i	Transmissibility coefficient	-

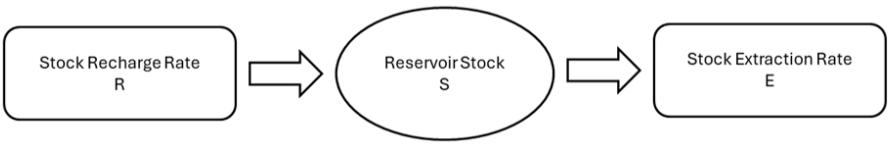


Figure 1. Conceptual diagrams of SRM for an individual well (Adapted from Júlíusson and Axelsson, 2018).

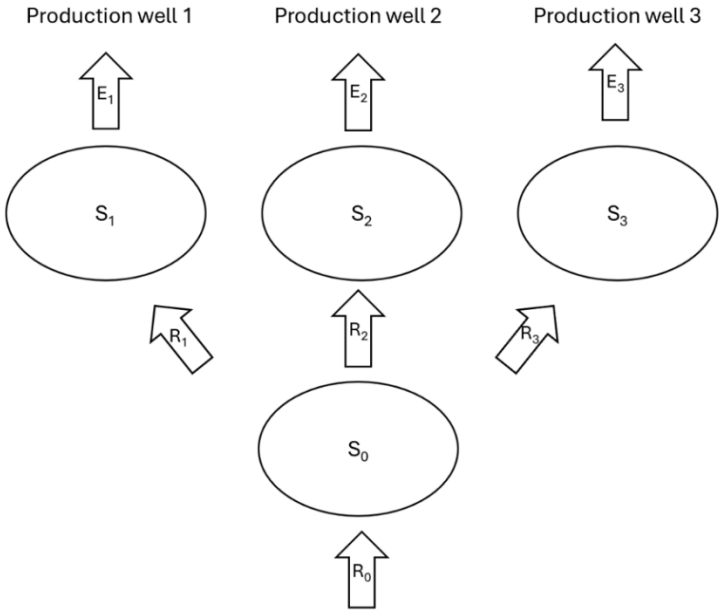


Figure 2. Conceptual diagrams of a three-well interconnected SRM.

The decision parameters describing each well ($Q_{i,MAX}, P_{i,MAX}, S_{i,MAX}, R_{i,MAX}$) are kept the same as in individual SRM (Manterola Donoso et al., 2025). However, as shown in Table 2 and Figure 2, three new parameters are required. First, a common reservoir stock, denoted as S_0, accounts for the portion of thermal and pressure storage that can be accessed by multiple wells. Second, a corresponding recharge term, R_0, describes the inflow into this shared reservoir that can be subsequently distributed among the interconnected wells. Finally, to capture the degree of well-to-well influence, a transmissibility coefficient, α, is introduced for each well. This parameter modulates how changes in pressure or recharge in one well affect the performance of neighboring wells in comparison to the primary production well, adapting principles previously applied in lumped parameter reservoir modeling (LPRM). All parameters are bound to have positive values.

Considering all the new parameters, the extended SRM is formulated through six equations. As in the individual SRM (Manterola Donoso et al., 2025), Equations 2, and 4 describe extraction (E) and stock (S) for each well, and are incorporated here without modification. The objective function (Equation 1) is also retained but extended to consider all production wells simultaneously by minimizing the difference between the estimated extraction (E) and the measured extraction data (Ed) across all time steps.

The main innovations arise in three additional formulations. First, Equation 3 introduces the transmissibility coefficient (α), which determines the recharge of non-primary wells based on the behavior of the primary production well. The distinction between primary ($i = 1$) and non-primary ($i > 1$) is based on productivity data and is introduced to simplify the formulation by connecting all wells at the recharge level through the primary one. Selecting the primary well is an operator or modeler decision, typically guided by productivity. The most productive well is expected to have the highest recharge, while the remaining wells' recharge is modeled as proportional to it. This proportionality is a key relationship captured by the model.

Second, Equation 6 describes the stock of the shared reservoir, and third, Equation 5 defines the recharge of this common reservoir. Both are adapted directly from the structure of Equations 3 and 4 but applied at the system level rather than the individual well level.

Together, these modifications enable the model to characterize not only well-specific parameters ($Q_{MAX}, P_{MAX}, S_{MAX}, R_{MAX}$) but also the shared reservoir dynamics ($S_{0,MAX}, R_{0,MAX}$) and the transmissibility between wells (α_i). This structure preserves the simplicity of SRM while extending its applicability to interconnected geothermal systems where well interactions play a significant role. The parameters used in the model equations are summarized in Table 3.

$$\underset{Q_{i,MAX},P_{i,MAX},S_{i,MAX},R_{i,MAX},S_{0,MAX},R_{0,MAX},\alpha_i}{minimize} \sum_t \left(Ed_{i,t} - E_{i,t}\left(P_{i,t}, S_{i,t}\right)\right)^2 \quad \forall\, i \in N, t \in T \tag{1}$$

$$E_{i,t}(P_{i,t}, S_{\mathrm{i,t}}) = Q_{i,MAX} \cdot \frac{S_{\mathrm{i,t}}}{S_{i,MAX}} \cdot \sqrt{1 - \left(\frac{P_{\mathrm{i,t}}}{P_{i,MAX}}\right)^2} \;\forall\, i \in N, t \in T \tag{2}$$

$$\begin{cases} i = 1 & R_{1,t}(\mathrm{S_{i,t}}) = R_{i,MAX} \cdot \left((S_{i,MAX} - S_{i,\mathrm{t}})/S_{i,MAX}\right) \\ i > 1 & \mathrm{R_{i,t}}(S_{\mathrm{i,t}}) = \alpha_{\mathrm{i}} \cdot \mathrm{R_{1,t}} \cdot \left((S_{\mathrm{i},MAX} - S_{\mathrm{i,t}})/S_{\mathrm{i},MAX}\right) \end{cases} \forall\, i \in N, t \in T \tag{3}$$

$$S_{\mathrm{i,t}} = S_{i,(\mathrm{t}-\Delta t)} - \mathrm{E_{i,t}}(P_{\mathrm{i,t}}, S_{i,(\mathrm{t}-\Delta t)}) \cdot\ \Delta t + \mathrm{R_{i,t}}(S_{i,(\mathrm{t}-\Delta t)}) \cdot \Delta t\ \ \forall\, i \in N, t \in T \tag{4}$$

$$R_0(S_{0,t}) = R_{0,MAX} \cdot \left(\frac{S_{0,MAX} - S_{0,t}}{S_{0,MAX}}\right) \;\forall\, i \in N, t \in T \tag{5}$$

$$S_{0,\mathrm{t}} = S_{0,(t-\Delta t)} - \sum R_i(S_{\mathrm{i},(t-\Delta t)}) \cdot \Delta t + R_0(S_{0,(t-\Delta t)}) \cdot \Delta t\ \forall\, i \in N, t \in T \tag{6}$$

$$Q_{\mathrm{i},MAX} \geq 0;\ P_{\mathrm{i},MAX} \geq 0;\ S_{i,MAX} \geq 0; R_{i,MAX} \geq 0; S_{0,MAX} \geq 0; R_{0,MAX} \geq 0;\ \alpha_{\mathrm{i}} \geq 0$$

Table 3. Summary of parameters used in the SRM formulation.

Symbol	Parameter	Units
$E_{i,t}$	Calculated extraction rate	MWth
$Ed_{i,t}$	Measured extraction rate	MWth
$P_{i,t}$	Wellhead pressure	bar
$S_{i,t}$	Reservoir stock	MWyr
$R_{1,t}$	Primary well recharge rate	MWth
$R_{i,t}$	Non-primary well recharge rate	MWth
$Q_{i,MAX}$	Maximum thermal output	MWth
$P_{i,MAX}$	Maximum wellhead pressure	bar
$S_{i,MAX}$	Maximum reservoir stock	MWyr
$R_{i,MAX}$	Maximum recharge rate	MWth
$S_{0,t}$	Shared (connecting) reservoir stock	MWyr
$R_{0,t}$	Shared reservoir recharge	MWth
$S_{0,MAX}$	Maximum shared reservoir stock	MWyr
$R_{0,MAX}$	Maximum shared reservoir recharge	MWth
t	Time step index	-
Δt	Time interval between steps	yr
T	Total time	yr
i	Well index	-
N	Total number of wells	-

3.1 Case study

To apply the extended SRM, we use field data from the Krafla geothermal system in northern Iceland, where three production wells are suspected to exhibit strong interconnection effects. The site provides an ideal testing ground due to the availability of production data and the evidence of subsurface interactions.

The dataset includes data for three wells with 180, 208, and 242 data points, respectively, each data point representing the wellhead pressure, production rate, and enthalpy at the measured date, corresponding to approximately 10–14 years of production history. Considering that the model compares multiple wells simultaneously, the datasets first required preprocessing to standardize time steps. After removing incomplete records, the data were resampled to provide one representative value per tenth of a year, calculated as the average of production over that interval. Missing values were filled in using interpolation to ensure a consistent time series across wells.

Additionally, a small adjustment was necessary for Equation 3, which incorporates the transmissibility coefficient. In the Krafla dataset, the most productive well, designated as the primary well (index 1 for i); only began producing after the less productive wells had already entered operation. To account for this, the recharge term was reformulated to exclude transmissibility during the period in which the primary well was not in production. By doing so, for this specific case study, both non-primary wells were considered as individual and not interconnected until the primary well data became available (year 2015 or t=5.4), where the transmissibility parameter was used to interconnect primary and non-primary well recharge rates. See below the reformulated Equation 3a for the case study.

$$\begin{cases} i = 1 & R_{i,t}(\mathrm{S_{i,t}}) = R_{i,MAX} \cdot \left((S_{i,MAX} - S_{i,\mathrm{t}}) / S_{i,MAX} \right) \\ i > 1; t < 5.4 & R_{i,t}(S_{i,t}) = R_{i,MAX} \cdot \left((S_{i,MAX} - S_{i,t}) / S_{i,MAX} \right) \\ i > 1; t \geq 5.4 & R_{i,t}(R_{1,t}) = \alpha_i \cdot R_{1,t} \end{cases} \quad (3a)$$

The optimization problem was implemented in Python using the SciPy optimize library (Virtanen et al., 2020) where the limited-memory Broyden–Fletcher–Goldfarb–Shanno algorithm with bounds was employed (L-BFGS-B). This algorithm handles variable bounds efficiently without requiring inequality constraints and uses a gradient-based approach to improve the accuracy of the optimized parameter values (Byrd et al., 1996).

4 RESULTS

Using the individual SRM (Manterola Donoso et al., 2025), each well was first analyzed to calibrate its decision parameters. The resulting values, summarized in Table 4, show the performance and mean square error (result of the objective equation, Equation 1) for each well. The results show the applicability of individual SRM and provide the initial conditions for the extended SRM, allowing for direct comparison between the two approaches. To protect sensitive information, the maximum output parameter (Q_{MAX}) is not shown.

Table 4. Optimized parameters for selected wells in the Krafla field using individual SRM.

Well	P_{MAX}	S_{MAX}	R_{MAX}	Error	Nº datapoints	Corrected error
Well 1	8.36	315.88	572.35	43.40	115	0.38
Well 2	6.07	204.23	149.30	12.87	146	0.09
Well 3	27.52	176.46	333.13	58.12	162	0.36

Applying the extended SRM with interconnected wells results in updated decision parameter values, as shown in Table 5. As before, the maximum output parameter (Q_{MAX}) is not shown. The overall objective error is 11306.57, which, given the 160 timesteps, corresponds to a corrected value of 70.75. Figures 3, 4 and 5 compare the modeled production with observed data for each well, along with changes in stock and recharge rates for each well. The thermal output values are shown as a percentage to protect any sensitive information.

Table 5. Optimized parameters for selected wells in the Krafla field using the extended SRM.

	P_{MAX}	S_{MAX}	R_{MAX}	α
Well 1	8.00	241.02	382.00	-
Well 2	5.79	99.45	95.50	0.25
Well 3	104.67	6196.26	343.80	0.9
Connecting reservoir		1022.54	711.45	

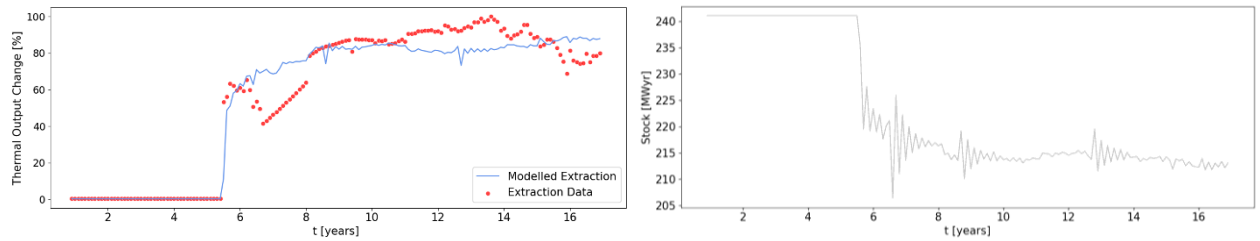


Figure 3. Stock model variables for Well 1. Left: recharge rate, extraction rate, and production data over the studied period. Right: Reservoir stock over the studied period.

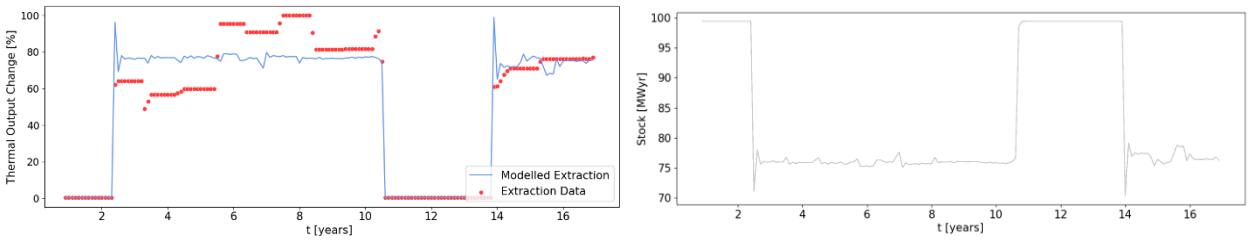


Figure 4. Stock model variables for Well 2. Left: recharge rate, extraction rate, and production data over the studied period. Right: Reservoir stock over the studied period.

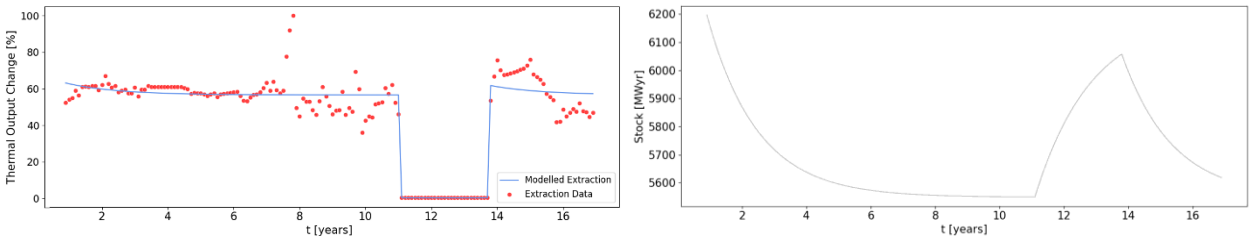


Figure 5. Stock model variables for Well 3. Left: recharge rate, extraction rate, and production data over the studied period. Right: Reservoir stock over the studied period.

The role of the connecting reservoir is illustrated in Figure 6, which shows its stock variations throughout production. Considering the availability of pressure measurements from a monitoring well in the system, these changes are compared with those of said monitoring wells. Figure 6 also shows that the modeled reservoir stock (grey line in Figure 6) follows the same trend as the measured pressure, supporting the ability of the extended SRM to capture inter-well interactions and overall reservoir dynamics, thereby providing the model with a form of validation. The comparison between measured pressure and modeled reservoir stock changes yields a mean square error of 1.21, supporting the validity of the approximation. The largest deviations occur in the initial time steps, before production from Well 1, which is both the most productive and the primary well in the model.

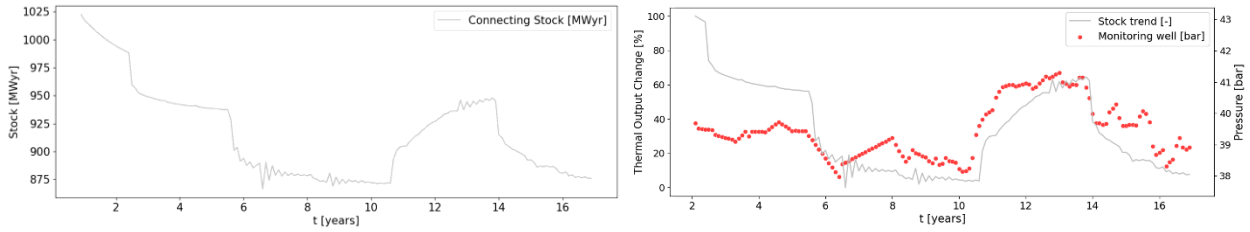


Figure 6. Left: Stock level throughout production for the connecting tank. Right: Trend comparison between the stock changes and the monitoring well pressure changes.

5 DISCUSSION

The results demonstrate that extending SRM to include well interconnection is a promising approach to represent in a simplified way how extraction affects both production wells and the geothermal system as a whole. While the individual SRM reproduces well-level production trends with higher accuracy in capturing small changes, the extended SRM provides a broader perspective by analyzing all wells simultaneously. Despite the need for data normalization and the increase from four to sixteen parameters in the three-well case, the model

achieves acceptable error levels, showing that SRM can successfully be scaled to study interconnected systems.

Considering the resulting parameters shown in Tables 4 and 5, we can see how the resulting parameters for Wells 1 and 2 stay consistent, with small deviations between both models, whereas Well 3 has quite a deviation in its values. This can not only be due to the nature of the wells themselves, but also to the consideration of the interconnection. We can also see that Well 3 shows higher transmissibility, meaning its production and specifically, its recharge, are more connected, as Wells 1 and 2 show similar production trends (Figures 3, 4 and 5).

A key strength of the approach is its validation against independent data. Validation of the individual SRM was challenging, as a separate test dataset was needed. However, the availability of monitoring well enabled direct comparison between modeled reservoir stock and measured pressure, offering a more robust assessment. Moreover, the low error and the alignment between the modeled reservoir stock and monitoring well pressure (Figure 6) suggest that the model captures subsurface processes successfully. This provides confidence that the extended SRM could serve as a reliable tool for forecasting future system behavior under different production scenarios.

Beyond accuracy, the model retains simplicity that makes SRM attractive for operational applications. It requires only historical production and pressure data, avoiding the computational cost and data intensity of full numerical simulations. This makes it particularly useful for fields where rapid forecasting and decision-making are needed, or where detailed geological information is limited.

Nonetheless, several limitations should be acknowledged. The current formulation assumes a single primary well, which may oversimplify interconnection patterns in more complex geothermal fields. The model also depends on the availability of long-term, high-quality datasets for calibration, and preprocessing steps such as data normalization and interpolation can influence outcomes. Addressing these issues will be important for extending the applicability of the method.

Overall, the extended SRM shows a practical and efficient way of modeling interconnected geothermal systems. By improving the representation of well interactions while maintaining a lightweight, data-driven structure, it provides a valuable basis for production optimization.

6 CONCLUSION

This study introduced an extension of Stock Reservoir Modeling (SRM) to account for well interconnections through a shared reservoir and transmissibility coefficients. Applied to three wells in the Krafla geothermal field, the extended SRM successfully modeled production changes in an interconnected reservoir and reproduced reservoir pressure trends observed in the monitoring well. These results indicate the method's potential as a lightweight, data-driven alternative to numerical simulations, requiring only historical production and pressure data. While current limitations include the assumption of a single primary well and dependence on mid-term datasets, the approach demonstrates strong promise for supporting production forecasting and optimization in interconnected geothermal systems. Future work might explore more complex systems or their further integration with production models.

Acknowledgements

The study received financial support from the Reykjavik University Sustainability Institute and Forum (SIF), from Rannis Technology Development Fund (project: 2321574-601), and the Landsvirkjun Energy Research Fund.

The authors would also like to specially thank Landsvirkjun, which provided the required data to perform the work.

REFERENCES

Axelsson, G.: Interpretation of pressure changes in hydrogeological reservoir engineering, Proceedings, 14th Workshop on Geothermal Reservoir Engineering, Stanford University, Stanford, California, USA (1989).

Barton, C., Scott, S., and Rivera, J.: Advances in numerical reservoir modeling for geothermal fields: Case studies and challenges, Proceedings, 50th Workshop on Geothermal Reservoir Engineering, Stanford University, Stanford, California, USA (2025).

Byrd R.H, Peihuang L, Nocedal J. A limited-memory algorithm for bound-constrained optimization [report]. University of North Texas Libraries, UNT Digital Library. 1996 Mar 1; Illinois. [Accessed 2023 October 20] Available from: https://digital.library.unt.edu/ark:/67531/metadc666315/m1/2/.

Júlíusson E., and Axelsson G. “Stock models for geothermal resources.” Geothermics: 2018. 72:249–57. Available from: https://doi.org/10.1016/j.geothermics.2017.11.006.

Manterola Donoso, A., Guðjónsdóttir, M.S., Stefánsson, H., and Júlíusson, E.: Optimizing Geothermal Resource Management: Insights from Stock Reservoir Modeling Analysis in Icelandic Fields, Proceedings, Geothermal Rising Conference 2024, Kona, Hawaii, USA, GRC Transactions, Vol. 48 (2024). Available from: https://doi.org/10.1016/j.geothermics.2025.103430.

Manterola Donoso, A., Guðjónsdóttir, M.S., Júlíusson, E., and Stefánsson, H.: Reservoir impact optimization of geothermal utilization using stock reservoir modeling, Geothermics, Vol. 132 (2025).

Scott, S., and Barton, C.: Numerical modeling for geothermal energy: From conceptualization to field-scale applications, Proceedings, 50th Workshop on Geothermal Reservoir Engineering, Stanford University, Stanford, California, USA (2025).

Virtanen P. et al. SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. Nature Methods. 2020.

Qin, Z., Zhang, Y., and Chen, L.: The lumped-parameter model on two-phase and superheated geothermal reservoir, Proceedings, 42nd Workshop on Geothermal Reservoir Engineering, Stanford University, Stanford, California, USA (2017).