Journal of Artificial Intelligence and Engineering Applications

Website: https://ioinformatic.org/

15th February 2025. Vol. 4. No. 2; e-ISSN: 2808-4519

Optimization of Machine Learning Models for Jiwa Garuda in Predicting Geothermal Well Flow Rates

Aldo Dwi Putra Pasaribu

Universitas Pembangunan Nasional "Veteran" Jawa Timur
aldopasaribu021@gmail.com

Abstract

The accurate prediction of geothermal well flow rates is critical for optimizing resource utilization and ensuring sustainable energy production. This study focuses on the optimization of machine learning models, termed "Jiwa Garuda," specifically designed for geothermal applications. The research aims to develop a robust predictive framework by leveraging advanced machine learning techniques to model complex thermodynamic and fluid dynamic behaviors within geothermal reservoirs. The outcomes of this research provide actionable insights for geothermal field operators, including predictive capabilities for well flow rates under varying operational scenarios. Furthermore, the Jiwa Garuda model offers potential scalability to other geothermal sites, contributing to the broader adoption of machine learning in sustainable energy development.

Keywords: *Machine Learning, Geothermal Flow Rate Prediction, Jiwa Garuda, Model Optimization, Sustainable Energy*

1. Introduction Jiwa Garuda

Jiwa Garuda is software provided by PT Anugrah Indonesia Lima (Ailima) aimed at framework designed to support data management and analysis in geothermal well operations, with a focus on intelligent technologies powered by machine learning. One of its primary applications is to predict critical parameters such as wellhead pressure, a key indicator for assessing operational performance and production efficiency in geothermal energy. In the context of research on machine learning model optimization, Jiwa Garuda serves as an ideal platform due to its ability to integrate advanced algorithms and deliver accurate, relevant predictions. This framework collects operational data from various field sensors, including reservoir pressure, fluid flow rates, temperature, and physical characteristics of the wellbore. The gathered data is processed through an analytical pipeline equipped with feature engineering capabilities to enhance the quality of inputs for machine learning models. Jiwa Garuda employs a modular approach, enabling algorithms such as Gradient Boosting, Random Forest, and Neural Networks to be efficiently implemented and compared for determining the best model to predict wellhead pressure. [1]

Fig. 1: The logo of Jiwa Garuda software by Ailima

Model optimization within Jiwa Garuda is achieved through hyperparameter tuning and cross-validation techniques, ensuring that the resulting models exhibit high performance and can address operational challenges such as dynamic reservoir conditions. By leveraging comprehensive datasets and relevant features, this optimization process not only enhances prediction accuracy but also aids operators in making better-informed decisions regarding well management, such as determining optimal production levels or identifying potential issues at an early stage. Furthermore, the framework is supported by an intuitive interface, allowing users to monitor prediction outcomes and model implementations directly. Thus, Jiwa Garuda serves not only as an analytical tool but also as a strategic platform capable of advancing sustainable geothermal operations. In this study, the optimization of machine learning models within Jiwa Garuda offers opportunities to develop more sophisticated predictive solutions, strengthen geothermal energy management, and support the development of environmentally friendly technologies to meet future energy needs.

2. Literature Review

2.1. Parameter Review

Geothermal flow rate refers to the volume of fluid (typically water or steam) flowing through a geothermal reservoir system per unit of time. It is one of the critical parameters for evaluating the energy potential of geothermal resources. This flow rate directly impacts the amount of energy that can be extracted from the reservoir, where a higher flow rate translates to greater energy production. Flow rate measurements are typically conducted at the wellhead, the point where the fluid exits the geothermal well.[2]

Meanwhile, wellhead pressure (WHP) is the pressure measured at the wellhead, representing the conditions at the fluid discharge point. WHP provides valuable insights into the operational status of the well and the geothermal reservoir. It serves as an indicator of production potential, well integrity, and operational sustainability. A low wellhead pressure may signal issues with the reservoir or well, while excessive pressure could pose risks of system damage.[3]

These two parameters are closely interrelated. Generally, higher wellhead pressure (WHP) correlates with a greater capacity of the well to produce fluid at higher flow rates, leading to an increase in flow rate. Conversely, a drop in wellhead pressure typically corresponds to a decline in flow rate, as lower pressure reduces the ease of fluid production. Therefore, balancing these parameters is essential for optimizing geothermal energy production. Excessively high or low pressure can compromise production efficiency or damage the system. Effective management, such as employing machine learning models to predict the dynamic relationship between WHP and flow rate, can significantly enhance well operations. This approach facilitates more efficient and sustainable geothermal well management, ensuring long-term energy production.[3]

2.2. Well Decline

In the geothermal industry, well decline refers to the reduction in energy or fluid production rates from a geothermal well over time. This process occurs due to various factors, including reservoir pressure depletion, reduced fluid flow rates, or changes in the physical properties of the reservoir itself. In this context, wellhead pressure (WHP) and geothermal flow rates play critical roles in illustrating the dynamics of decline. As a well is continuously exploited, the WHP gradually decreases over time. This pressure drop makes it harder to push fluids out of the well, leading to a reduction in geothermal flow rates. This decrease in flow rate directly correlates with a decline in energy production, as lower flow rates result in less energy being extracted from the well.[4]

Well decline over time is often marked by reductions in both WHP and flow rate. As wellhead pressure diminishes, fluid becomes more challenging to produce, ultimately affecting energy output. Additionally, reservoir temperature decline and other technical issues, such as blockages or well damage, can accelerate this decline process. Consequently, close monitoring of WHP and flow rate is crucial for understanding and managing well decline. Techniques such as reinjection to restore reservoir pressure can help mitigate the reduction in fluid flow, while predictive models or machine learning approaches can assist in forecasting and developing more effective management strategies. Thus, the close relationship between geothermal well decline, WHP, and flow rate is a determining factor in the operational efficiency and sustainability of geothermal energy production.

2.3. Deliverability curve

The geothermal deliverability curve illustrates the relationship between wellhead pressure (WHP) and the flow rate of a geothermal well under varying operational conditions. This curve is used to model the production capacity of a well in generating fluid, whether steam or hot water, across a range of wellhead pressure values. It provides insights into how a well can supply fluid at specific WHP levels and aids operators in predicting well performance over time The connection between the deliverability curve and WHP is highly significant, as WHP is a primary factor influencing fluid flow from the well. At higher points on the curve, the well can deliver greater flow rates at higher WHP levels. Conversely, if WHP decreases, the achievable flow rate also diminishes. A drop in WHP can occur due to sustained production increases or declining reservoir pressure over time. By utilizing the deliverability curve, operators can predict the extent to which declining WHP may impact a well's fluid production capacity and plan appropriate strategies, such as reinjection or well maintenance, to sustain well performance.[5]

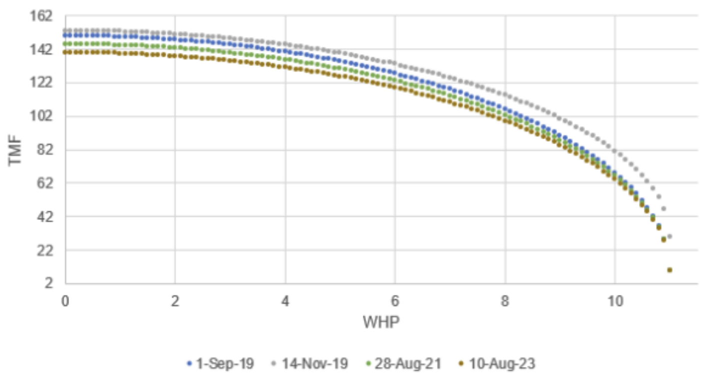

Fig. 2: Deliverability Curve Model by Ailima

Deliverability curve also helps forecast how a well will perform under different pressure conditions, enabling operators to anticipate declines in well capacity and make informed decisions about when and how to intervene in well operations. Additionally, by understanding the relationship between flow rate and WHP, operators can optimize production by maintaining pressure at optimal levels to maximize geothermal energy output. They can also develop long-term plans to sustain production with suitable maintenance strategies. Overall, the deliverability curve is a crucial tool in geothermal well management, with its clear relationship to WHP playing a critical role in determining the flow rates that can be achieved from the well.

3. Optimization of Jiwa Garuda Software

3.1. Building the Jiwa Garuda Algorithm

Before Jiwa Garuda is used to predict parameters related to WHP, the algorithm must first be built by inputting existing data. The input data pertains to the discussed parameters. The data to be input consists of 1,000 surface production well data entries, which include time, wellhead pressure (WHP), and flowrate, provided by the Ailima team

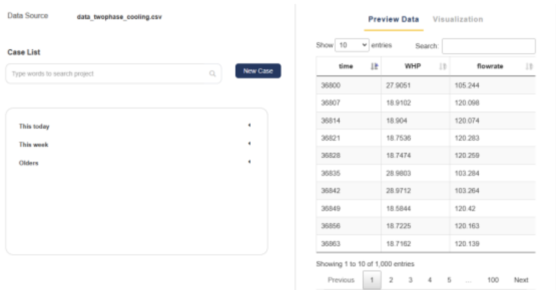

Fig. 3: Training Model Input Data in Jiwa Garuda

Subsequently, a machine learning model was selected from the available options in Algorithm Selection. Based on various experiments and analyses, the most suitable machine learning model is Random Forest Regression. This model was chosen to predict the "flowrate" using "time" and "WHP" as predictors. Furthermore, based on the experimental analysis, the algorithm's parameter settings shown in the image below were determined to be the most appropriate.

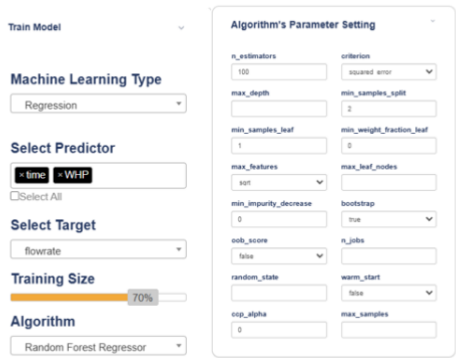

Fig. 4: Train Model Settings (left) and Algorithm Parameter Settings (right)

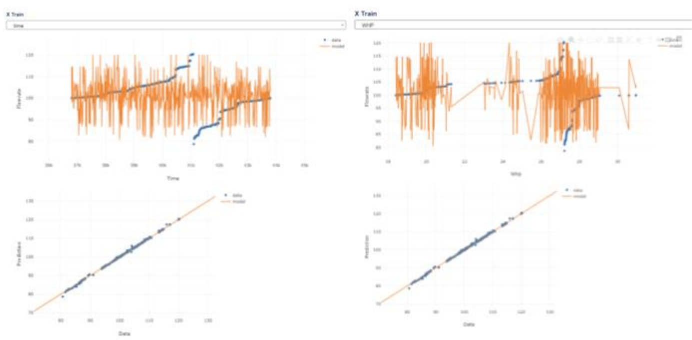

Fig. 5: Prediction Flowrate Modeling Graph

Once the algorithm modeling results are available, as shown in Fig 5, use the prediction tab to predict the flowrate at a WHP pressure of 27 bar for each time step. This step represents the normalization of the flowrate. After successfully predicting the flowrate, an exponential regression is performed on the normalized flowrate. Subsequently, the annual decline rate of the well can be identified.

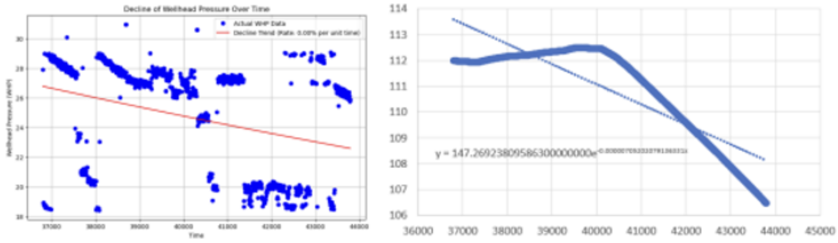

Fig. 6: Exponential Regression Plot in Python (left); Exponential Regression Plot of Jiwa Garuda (right)

However, to validate the results from Jiwa Garuda, a comparison needs to be made. Using the available surface production well data, a well decline model is developed, and the results can be seen in Fig 6. The output from Python shows that the well experiences a decline of Decline Rate: 0.0024331136418508786 % overall. From Jiwa Garuda's results, the following exponential equation is obtained: $y = 147.26923809586300000000 \times e^{(-0.000007052020791 36331 \times 365),}$ with a decline of 1.4689065634616938% per year. The results indicate that Version 2 is more accurate, as it uses wellhead pressure (WHP) data as a validator, which enhances the precision of calculations and generates a more complex model that takes external factors into account. Additionally, the machine learning visualization is more realistic in producing a model of the well's condition.

3.2. Adjustment of the Deliverability Curve with Wellbore Simulation Data

After the machine learning model in Jiwa Garuda has been built, it is necessary to test it using a deliverability curve simulation. The Deliverability Curve is created from the Jiwa Garuda model with test data from October 1, 2000, April 18, 2010, and November 24, 2019, and the following are the results of the simulation.

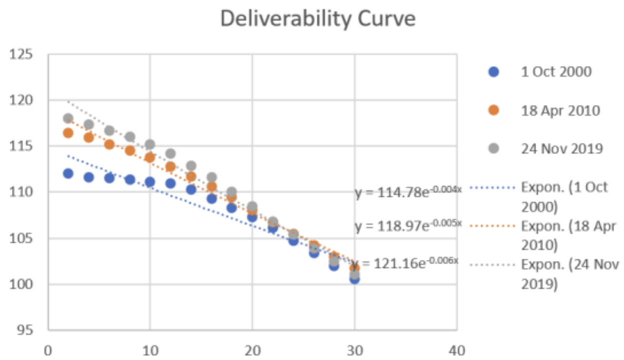

Fig. 7: Deliverability Curve from Jiwa Garuda Flowrate Prediction Data

The accuracy of Jiwa Garuda is compared with the wellbore simulation data provided by Ailima. The normalization results from the existing machine learning model are compared with the normalization results obtained using the wellbore simulation. This comparison allows for an assessment of how closely Jiwa Garuda's predictions align with actual wellbore conditions, providing insight into the model's performance. If the results from Jiwa Garuda closely match those from the wellbore simulation, it demonstrates the effectiveness and accuracy of the machine learning model in predicting well behavior and fluid flow dynamics under varying conditions. Conversely, discrepancies may highlight areas where the model can be further refined or adjusted.

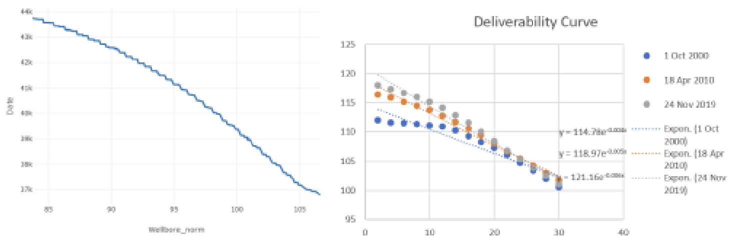

Fig. 8: Wellbore Simulation Plot (left), Jiwa Garuda Deliverability Curve (right)

From the machine learning results, a decline reduction is observed, decreasing from 1.76% to 0.60%, while the wellbore simulation normalization results show a decline of 1%. Therefore, the difference between the two methods is approximately 0.4% to 0.8%. This comparison highlights the accuracy and potential improvements that Jiwa Garuda's machine learning model provides in terms of predicting well decline, with the model offering a somewhat lower decline prediction compared to the wellbore simulation. The difference in decline values indicates a potential area for further refinement in the model to match real-world simulation results more closely.

4. Conclusion

Based on the deliverability curve, the model developed shows inaccurate results due to significant differences in decline patterns between the periods (2000, 2010, and 2019). This discrepancy is likely caused by several factors, such as insufficiently diverse data, the use of a model that does not align with the parabolic nature of the decline, and the lack of integration of well physical factors into the model. To improve accuracy, it is recommended to collect more comprehensive data covering a broader range of operational conditions and time periods. Additionally, testing with nonlinear or hybrid models that better match the actual decline pattern should be considered. Finally, validating the prediction results with wellbore simulation data is essential to ensure the model's predictions align with real-world conditions.

These steps are expected to enhance the model's performance, making it more reliable for geothermal well management and predictive analysis.

Furthermore, Jiwa Garuda's ability to incorporate external factors and improve predictive accuracy through machine learning-based models makes it an invaluable tool for geothermal well management. The normalization process and the subsequent use of the deliverability curve to validate model predictions highlight the robustness of this approach. This work emphasizes the importance of continuous optimization and validation to enhance well performance and ensure the sustainability of geothermal energy production. Overall, Jiwa Garuda offers a reliable framework for forecasting well behavior and optimizing geothermal operations, with potential for future advancements in model accuracy and predictive capabilities.

References

[1] Ailima, "Ailima Jiwa System," 2024. [Online]. Available: https://ailima.co.id/jiwa-garuda/. [Accessed 23 12 2024].

[2] M. Mohammadpour, P. Behnoud, M. Reza, and K. Movaghar, "Develop an empirical flow rate correlation to model wellbore storage phenomenon for wells produced at a constant wellhead pressure," *Sci. Rep.*, pp. 1–19, 2023, doi: 10.1038/s41598-023-44678-3.

[3] M. Liu, B. Bai, and X. Li, "A unified formula for determination of wellhead pressure and bottom-hole pressure," vol. 37, pp. 3291–3298, 2013, doi: 10.1016/j.egypro.2013.06.217.

[4] DECLINE CURVE ANALYSIS OF PRODUCTION DATA FROM THE GEYSERS GEOTHERMAL FIELD," pp. 23–27, 1987.

[5] H. Alberto and D. José, "Two-Phase Geothermal Well Deliverability Output Curve Linearization Analysis," vol. 0, no. 3, pp. 1–8, 2016.