Forecasting Performance of Production Wells in the Maibarara Geothermal Field using Artificial Intelligence

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ABSTRACT

Reservoir modeling is the current industry practice used to forecast the response of the geothermal resource to production and in predicting the power plant's future generation. However, building and running numerical reservoir model is costly and time-consuming. Due to these limitations, Artificial Intelligence techniques are being explored as an effective alternative using their strong learning capabilities and computational efficiency. This study aims to predict future production trends using artificial intelligence and the field's historical data. The two machine learning models, multivariate linear regression (MLR) and multilayer perceptron (MLP), were built and trained for three Maibarara production wells. The model performance was compared using two error metrics, root mean squared error and coefficient of determination score. This study showed that MLP performs better than MLR using 80% training data and 20% testing data. The forecasts using the MLP model showed decreasing steam flow trends of varying magnitude for each well. Results also showed that model performance is influenced by the training-and-testing ratio, model type, and data imbalance, e.g. data size and distribution. For further evaluation, it is recommended to acquire more data for improvement in long-term forecasting accuracy, incorporate other data types, e.g. temperature-related data, enthalpy, and tracer test data, and explore and integrate other AI models, such as recurrent neural networks and long short-term memory.

Keywords: Maibarara, machine learning, artificial intelligence, modeling, forecasting

1. INTRODUCTION

The Maibarara Geothermal Field is situated at the western foot of the inactive stratovolcano, Mt. Makiling in Luzon Island (Figure 1) and is one of two geothermal fields on Mt. Makiling, the other being the Makiling-Banahaw (Mak-Ban) field (Buban et al., 1994). Exploration of the Maibarara field began in the 1970s by Philippine Geothermal Inc. (PGI). Consequently, 12 wells were drilled into the Maibarara field between 1977 and 1983, and 5 were found commercially viable at the time (Olivar et al., 2011). The development of the Maibarara field only resumed in 2010 after the Maibarara service contract had been awarded to PetroEnergy Resources Corp. (PERC) and the joint venture of Maibarara Geothermal Inc. (MGI) was formed.

The Maibarara Geothermal Power Project (MGPP) currently produces 32 MWe gross power from its two generation plants: 20-MW Maibarara-1 Geothermal Power Plant (M1GPP) and 12-MW Maibarara-2 Geothermal Power Plant (M2GPP). starting commercial operations in February 2014 and April 2018, respectively (Olivar et al., 2011; Maturgo et al., 2015). As of 2024, five wells are used for the 32-MW power facility, comprising three production wells (PW-1, PW-2, and PW-3) and two reinjection wells (RI-1, RI-2).

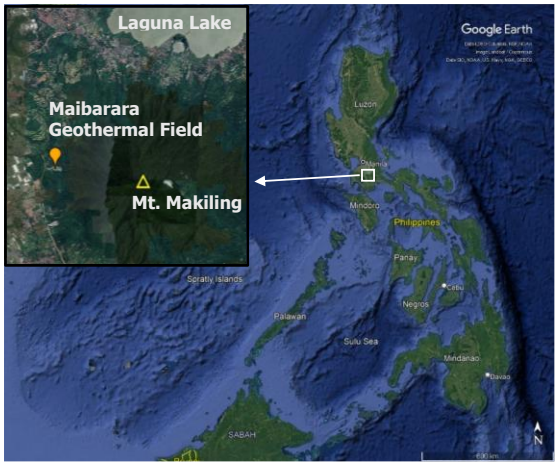


Figure 1: Location of the Maibarara Geothermal Field in the Philippines

Reservoir modeling is an industry practice used to understand the nature and properties of the resource, as well as forecast the response of the resource to production (Axelsson et al., 2005). Thus, making it vital in predicting the power plant's future power generation. Comprehensive monitoring and subsequent forecasting are essential for the sustainable management of geothermal utilization. Proper monitoring programs yield essential data, providing the basis for future predictions. Consequently, these support proper resource management and the mitigation of resource depletion. The monitoring data are typically used to calibrate numerical reservoir models to provide an adequate understanding of the geothermal system and to enable changes in the reservoir to be seen in advance through predictions (Monterrosa and Axelsson, 2013).

However, the complexities of a geothermal reservoir, e.g. not static, non-isothermal fluid, non-uniform fluid compositions, unknown reservoir boundaries, etc. can exacerbate the challenges associated with building and running reservoir models (Ariturk, 2019). Thus, detailed subsurface modeling requires significant time and large amounts of data and uses huge computational overhead to build and run. Due to these limitations, Artificial Intelligence (AI) techniques are being explored as an effective alternative with their strong learning capabilities and computational efficiency.

Okoroafor et al. in 2022 reviewed the application of AI in geothermal subsurface studies, particularly machine learning applications, and showed an increasing trend over the past 20 years (Figure 2). The trend also showed an exponential increase from 2018 to 2021, possibly aided by the introduction of programs and frameworks, such as TensorFlow and Keras, in 2015. There has been a significant increase over the last three years, especially in reservoir management and modeling. These reservoir engineering studies use machine learning to predict production data, e.g. flow rate, temperature, pressure, etc. (Shi et al., 2021; Aydin et al., 2020; Ariturk, 2019; Wardoyo et al., 2021; Hosseini and Akilan, 2023).

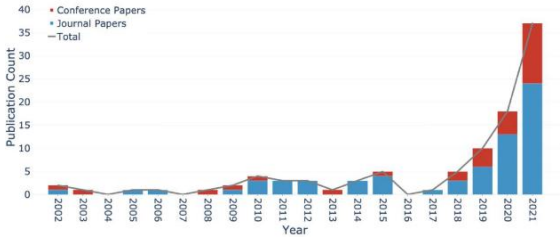


Figure 2: Histogram plot of the yearly publication count or articles on machine learning applications for subsurface geothermal resource development (Okoroafor et al., 2022)

This study aims to predict future well production, specifically well outputs of the Maibarara field, using the techniques and algorithms of AI, particularly machine learning, based on the field's historical data. A background on artificial intelligence, the methods developed for model evaluation, including construction, verification, and prediction, are detailed in this study, along with corresponding results.

2. ARTIFICIAL INTELLIGENCE

McCarthy (2007) refers to artificial intelligence (AI) as the science and engineering of intelligent machines, i.e. intelligent computer programs. In other words, it is a discipline that tackles problem-solving by integrating computer science with extensive datasets.

Machine learning is a branch of AI involved with the creation and implementation of algorithms used for data-driven prediction, classification, and optimization, among other applications (Mlhanga, 2007). Supervised machine learning uses data with known independent variables and known dependent variables. In the training stage, the algorithm looks for patterns in the input data associated with the target output. In this study, supervised machine learning is applied to estimate future production well outputs, since the field's historical data includes known independent and dependent variables.

Various regression algorithms or machine learning model designs can be used. Linear Regression is the simplest type and performs similarly to other statistical models with slight inaccuracies. For this model, the training time is significantly shorter and is often considered as the baseline model. A more complex model is the Neural Network, with higher accuracy than simpler models. The simplest neural network has at least three layers: an input layer, a hidden layer, and an output layer, with feed-forward processing. An example is the Multilayer Perceptron (MLP) model, a feed-forward neural network comprised of an input layer, two or more hidden layers, and the output layer. In the MLP model, data processing only occurs in one way but can travel through a number of hidden layers (Tufail, 2023).

3. METHODOLOGY

The research methodology is outlined in the process flow diagram in Figure 3. The approach consists of the following steps: 1) data gathering, 2) data preparation, 3) building & configuration of the model, 4) training the model, 5) testing the model, 6) model selection, and 7) prediction using the selected model.

The data used for this study includes the following production and/or reinjection data from the 3 operating wells in the Maibarara field from 2021 to 2024: 1) Wellhead Pressure (WHP; input feature), 2) Wellhead Temperature (WHT; input feature), 3) Reservoir Pressure (RP; input feature), 4) Steam Flow Rate (SF; target output), and 5) Reinjection Load (RI-1, RI-2; input feature).

The data preparation stage is comprised of cleaning and preprocessing of the collected data. Shut well data and outliers were removed from the dataset before data scaling using MinMaxScaler.

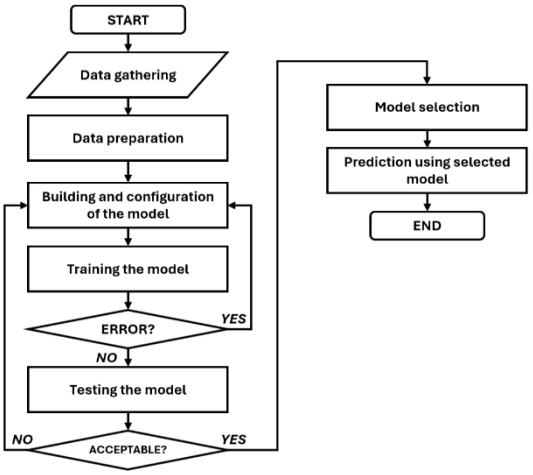


Figure 3: Process flow diagram for construction, verification, and prediction of the artificial intelligence model

Two AI models were built and compared in this study: the Multivariate Linear Regression Model (MLR) and the Multilayer Perceptron Model (MLP). The degree of complexity involved in building each model varies, where MLR is the simplest and MLP is more complex. The model is trained using a percentage of the dataset, referred to as training data, while the remaining data, i.e. testing data is used to assess the model's performance. Table 1 shows the scenarios used in the training and testing stage.

The predicted outputs were compared with the actual outputs from the dataset. Root mean squared error (RMSE) and coefficient of determination (R^2) was used to measure the model's accuracy and goodness of fit. The model and scenario with lowest RMSE and highest R^2 were selected to use for the forecasting. In this forecast phase, the model is trained using 100% of the dataset. Then, the trained model is used to predict the well output for the forecast.

Table 1: Scenarios for training and testing the model

Scenario	Dataset for training the model, %	Dataset for testing the model, %
a	50%	50%
b	60%	40%
c	80%	20%

4. RESULTS AND DISCUSSIONS

AI models rely heavily on the data fed to them, so it is important to use good and accurate data. The presence of outliers in the dataset can distort the data distribution, possibly leading to erratic predictions and higher errors. Data cleaning is also vital for the data scaling step, which transforms the data to synchronize with the algorithm's transfer function. Data scaling also helps minimize bias, ensuring fairer model performance across all features.

The correlation of the input features with each other and the target output is illustrated in the Pearson correlation matrices for PW-2 before and after data cleaning (Figure 4). An improved correlation is observed after data cleaning, except for RI-1 and RI-2. This correlation is well-suited for identifying linear relationships and is useful for linear regression models, e.g. MLRs. However, it may not capture the non-linear relationships that MLPs are designed to learn. Still, this correlation can be used as a preliminary tool to highlight potentially important features and low-impact features that can be omitted. WHP, CV, and RP appear to have a strong correlation (Figure 4) with the target. This suggests pressure is a key factor for well output, whereas WHT may be omitted in future studies. Wardoyo et al. (2021) and Ariturk (2019) studies on AI applications for well forecasting also incorporated pressure-related input features such as wellhead pressure, reservoir pressure, and bottomhole pressure.

There are difficulties in matching the actual and predicted values at lower target values (Figure 5). This is addressed by using a bigger dataset as seen in scenario c (Figure 5.c), which covers a broader range of features and the target. While scenarios a and b capture only a narrow range of the data distribution (Figure 5.a; Figure 5.b), the larger training dataset likely enabled the model to effectively learn more patterns between features and target (Figure 5.c). Wardoyo et al. (2021) reported similar findings on the effect of the training and testing ratio. It is equally important to have an adequately sized dataset remaining for testing the model's generalization on unseen data during the training and testing stage.

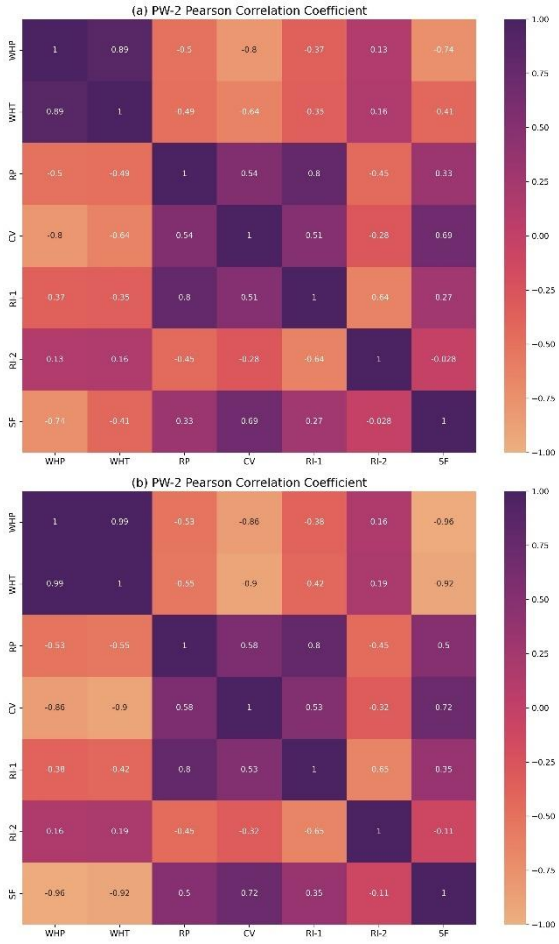


Figure 4: PW-2 Pearson correlation matrix for six input features [WHP, WHT, RP, CV, RI-1, RI-2] and one target output [SF] (a) before and (b) after data cleaning

MLR model performance is relatively good with low RMSE and high R^2 for the three scenarios based on the results in Table 2. This is likely influenced by the strong

correlation between input features and target output (Figure 4). Nevertheless, PW-2 model improved when using the MLP model, resulting in a better calibration of predicted and actual values than the MLR model (Figure 6) and also apparent in the RMSE and R^2 values.

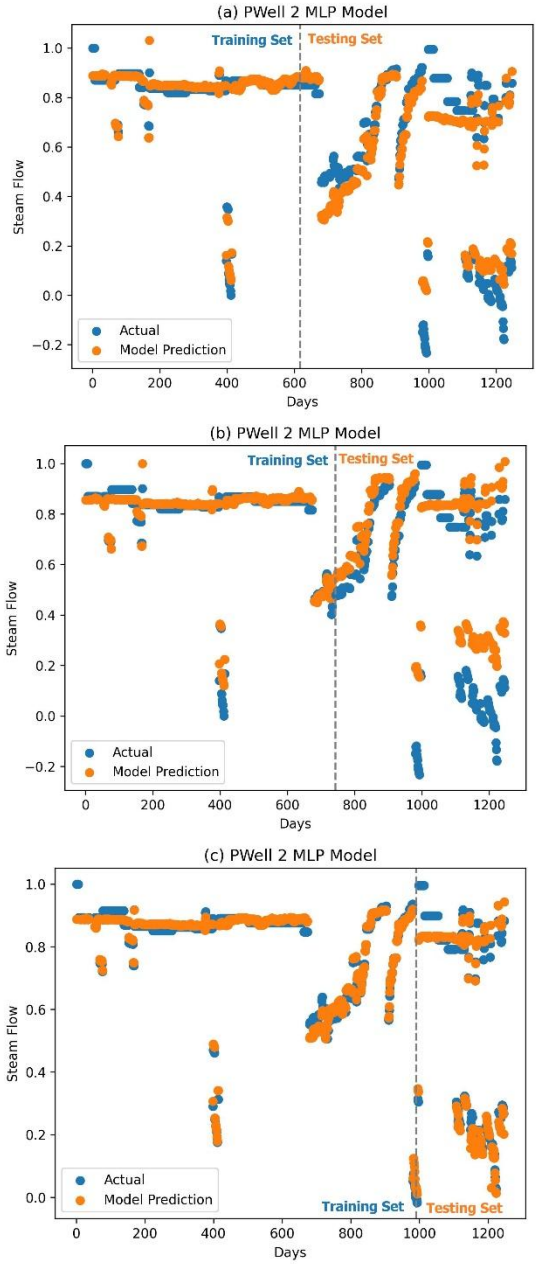


Figure 5: PW-2 Multilayer Perceptron (MLP) Model for scenarios (a), (b), and (c).

Also, the MLR model exhibited the highest RMSE and lowest R^2 score. This aligns with Tufail's (2023) findings, which suggest that the MLR model can serve as a baseline model in machine learning. This model type is only capable of learning linear relationships and patterns, whereas the geothermal reservoir entails several complexities that may not be easily analyzed linearly.

Table 2: PW-2 Model Performance for each model and scenario

Model	**MLR Model**	
Error Metrics	**RMSE**	**R^2**
Scenario a (50%-50%)	0.09	0.91
Scenario b (60%-40%)	0.12	0.87
Scenario c (80%-20%)	0.08	0.94
Model	**MLP Model**	
Error Metrics	**RMSE**	**R^2**
Scenario a (50%-50%)	0.10	0.89
Scenario b (60%-40%)	0.16	0.75
Scenario c (80%-20%)	0.06	0.96

On the other hand, the MLP model is an artificial neural network capable of learning non-linear relationships through non-linear activation functions since data in reality is rarely linear. In the MLP model architecture, all neurons in the hidden layers are connected to input neurons, implying all input features can influence the hidden layer and learn the complex relationship between features. Such capabilities are vital for capturing the complexities associated with a geothermal reservoir and interactions among the input features. Yet, one limitation of this neural network model is its feed-forward structure. This means that MLP models cannot capture sequential or time series data.

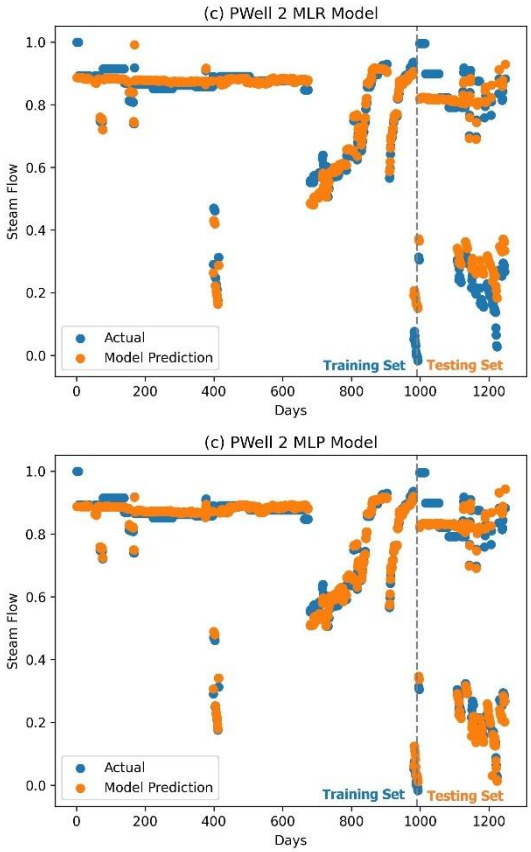


Figure 6: Comparison of PW-2 MLR Model (top) and PW-2 MLP Model (bottom) for scenario (c)

With these findings, the PW-2 well forecasts used the MLP model at scenario c as the optimal model and scenario based on the error metrics (Table 2). In the forecast, the well shows relatively stable output with a slightly decreasing trend during the forecast period (Figure 7). It is noted that the model forecast did not exhibit great fluctuations since the input parameters were maintained at normal operating conditions for simplicity.

The forecast predictions were intentionally limited to avoid overextension and maintain model accuracy, consistent with the training and testing steps. This approach avoids optimistic and unrealistic forecasts beyond the range of the training data. It was observed that the model performed poorly when trained with a smaller dataset, as it did not calibrate effectively for scenarios a & b. Additionally, since machine learning models rely heavily on historical data, possible changes in the geothermal system may not be accounted for. As a result, the longer the forecast, the more errors may accumulate if the training is not comprehensive. This may be comparable to any model behavior using conventional modeling methods, wherein forecasts will not be reliable if model calibration is inadequate.

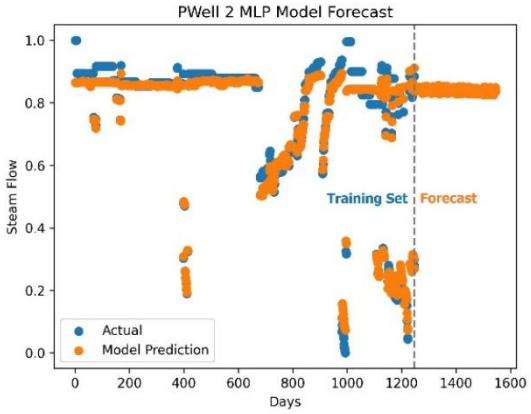


Figure 7: Well forecast using MLP model for PW-2. The dashed line represents the end of training and start of the forecast

Forecasting the wells' output is an inherent part of the management of geothermal resources during utilization and vital in determining the power plant capacity and efficiency (Ariturk, 2019). The forecasts provide insights into how the reservoir responds to different production schemes and reinjection strategies and its sustainability in the long term (Axelsson, 2010). The forecasts resulting from the AI models can be applied to Maibarara field's future utilization, such as foreseeing the need for a well intervention, makeup well(s), and changes in the production and reinjection schemes. Although these forecast results must be updated with new field data, production, and reinjection schemes to be fully applicable to the Maibarara field, the methodologies employed in this study provide a useful foundation for using AI in forecasting Maibarara wells' output.

While this study provides insights into the application of artificial intelligence in geothermal reservoir engineering, particularly well forecasting, it is recognized that it is likely limited by data imbalance and model type. Consequently, it is recommended to acquire more data to

improve model performance and long-term forecasting and address the data imbalance limitation. Moreover, incorporating other types of data affecting the geothermal resource should be explored. This may include the reservoir temperature, enthalpy, tracer test data, brine reinjection temperature, just to mention a few. The integration of temperature data aims to tackle changes in temperature, such as the possibility of cooling due to reinjection returns.

In addition, other model types, such as recurrent neural networks (RNN) and long short-term memory (LSTM) can be evaluated for their suitability in well forecasting. RNNs and LSTMs can retain memory and process inputs sequentially, possibly addressing the limitations of the MLP model used in this study. Furthermore, since AI technology is relatively new for forecasting wells, the reliability of the AI models can also be explored through comparison with conventional modeling methods, such as numerical reservoir modeling and lumped parameter modeling. The AI models can be compared to wellbore simulators coupled with the numerical model. Integration of AI models with lumped parameter models can further expand the results and analysis to include the well output flows.

5. CONCLUSIONS AND FUTURE WORKS

The project aims to predict the production output of the Maibarara production wells using artificial intelligence. Two models, MLR and MLP, were built and trained, and the model performance was compared using the selected error metrics, RMSE and R^2 score. Results showed that the model performance can be influenced by the training and testing ratio, model type, and data imbalance, such as data size and distribution. This study concludes that a sufficient amount of data is required for training the models to effectively capture the relationship between the features and target variables, compared to a smaller dataset percentage for training, while having adequate data remaining for testing the model's performance is required. In addition, the MLP model proved better than the MLR model for the well evaluated in the study based on the error metrics. For PW-2, the RMSE and R^2 scores are 0.06 and 0.96, respectively. The forecast showed a decreasing trend in the steam flow output resulting from production.

Further development of AI-based techniques is needed for forecasting geothermal production. This includes the incorporation of other data types affecting the geothermal resource, such as temperature-related data, enthalpy and tracer test data, to address possible changes in temperature. Other types of AI models, such as recurrent neural networks (RNN) and long short-term memory (LSTM) can be evaluated for their applicability in subsurface modeling. Conventional modeling methods, such as numerical reservoir modeling, and lumped parameter modeling, can be integrated with artificial intelligence methods for future reservoir engineering research. In addition, results from each model can be used to corroborate the reliability of the models.

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