Hybrid Thermodynamic & Machine Learning Model to predict Kawerau Geothermal Station Output Live

Lydia Hingston[1], Edna Lu [1], Theo Brehmer-Hine[1], and Shengnan Zheng [1], William Turner [1],

[1] Mercury, 283 Vaughan Road, Rotorua, New Zealand

lydia.hingston@mercury.co.nz

Keywords: *Geothermal Production Optimisation, Generation, Digital Twin, Hybrid Model, Machine Learning First Principles Thermodynamics*

ABSTRACT

Previously the Mercury Optimisation Engineering team has been able to predict a geothermal station's MW production to +/-0.5MW for one given time period, using station, steam field and integrated models. The Mercury Generation Optimisation Engineering and Decision Science teams saw an opportunity to create a digital twin to simulate various scenarios and accurately predict the net MW production at Kawerau live.

Using an agile approach, the joint team created a hybrid model that uses both engineering principles and Machine Learning (ML) to predict Mercury's geothermal flash plant Kawerau's net MW production live. The new model takes and predicts many inputs, including ambient weather forecasts (humidity and temperature), predicted available fuel, station derates, maintenance at the station and station operating states. The hybrid model has been tuned to be able to predict the net MW output to an accuracy of +/-0.3MW (Kawerau Gross MCR 113.67MW).

The production model provides:

1) A model that provides Operators with optimised set points to maximise generation, without putting the station into constant alarm.
2) A forecasting model that improves MW prediction accuracy. This provides Wholesale and Trading greater accuracy MW inputs for their Waikato River scheme model, particularly pertinent in dry years.
3) A hindcasting tool to help account for lost MW for various operating scenarios, which can be used to better prioritise projects to improve the station's efficiency and minimise downtime.

The optimised hybrid model helps maximise Mercury's geothermal baseload electricity generation, helping to address New Zealand's energy trilemma.

1. INTRODUCTION

Geothermal plant development requires large upfront investment and continuous reinvestment throughout a plant's life. There is also significant risk involved when developing geothermal stations as the deliverability and life of geothermal wells is uncertain. Often geothermal stations have to operate outside their original intended design specifications. Geothermal plants are complex in nature, with many systems, subsystems, relationships and noisy instrumentation signals. The Mercury Optimisation Engineering team saw an opportunity to combine first principal thermodynamics with empirical analyses and Machine Learning (ML) to model the Kawerau Geothermal plant (Maximum Continuous Rating 113.67MW) to manage and optimise the plant's production. "Digital KAG" is the bespoke hybrid model built from an agile collaboration between the Mercury Decision Science and Generation Optimisation teams in late 2024.

Combining both analysis methodologies provides a powerful approach to modelling complex systems. Building the model from first principles thermodynamics, such as incorporating Stodola's law of the ellipse to model the performance of multistage turbines, ensures that the model is robust and grounded in physics fundamentals (Jakobsson, 2024). A benefit of using model characteristics and ML models allows more accurate modelling particularly when a perfect thermodynamic model is not practical, and allows the model to be applied outside original design specifications of the plant (Tian & Horne, 2019). ML analyses have the major benefit of being able to capture complex non-linear relationships, such as the dynamic relationships of the cooling system through time interacting with the flash condenser, turbine and ambient conditions (Salins, Kumar, Ganesha, & Reddy, 2024).

Other hybrid models are being developed in geothermal settings. Siratovich et al. developed the Geothermal Operational Optimisation with Machine Learning (GOOML) modelling software that is an alternative digital twin and optimisation framework that uses ML confined by physics (Siratovich, et al., 2022). Siratovich et al. estimate 1% operational improvements in net generation with GOOML when implemented on geothermal steam fields (Upflow, 2025).

Digital KAG helps Kawerau operate and optimise production within today's operating limits. Optimising and managing production will become increasingly important into the future as geothermal reservoirs decline, and two-phase flow may become enthalpy and/or mass flow constrained. Short-term and long-term plant generation management and optimisation of electricity baseload is critical today, given the energy trilemma challenge: providing New Zealand with electricity that is secure, affordable and sustainable.

This article presents the hybrid model's architecture, as well as some key value streams that have eventuated from embedding Digital KAG into Kawerau Operations.

2. THE HYBRID MODEL

2.1 Overview of the Model

Digital KAG has been built on the Databricks platform, which takes live PI data (Process Information) from the station's PI historian, as well as plant planned maintenance, outage plans and external weather forecasts. To support accurate and dynamic modelling, 58 real-time PI tags are digested into Databricks at one-minute intervals. For model training, half-hourly averaged data was utilised to balance temporal resolution with computational efficiency. Through this

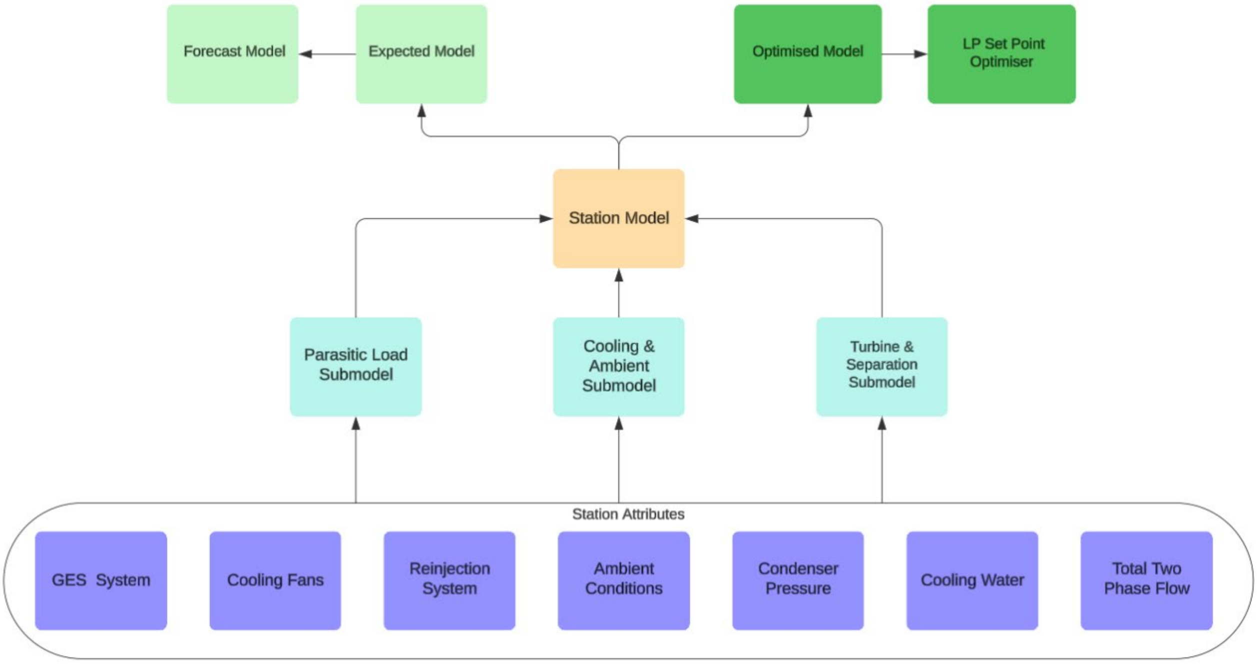

Figure 1: Overview of Digital KAG Architecture, Sub models and Models

process, 66 derived attributes were engineered to model the plant's operation and validate the model.

Digital KAG integrates multiple subsystems: the turbine and separation submodel, the cooling and ambient submodels, and the parasitic load submodel. The submodels combine to predict the station's net output in MW. Digital KAG has several models with various functions; these include the expected model and the optimised model. An overview of the Digital KAG's models, submodels and key attributes are illustrated in Figure 1.

2.2 Submodel: Turbine and Separator Models

The Kawerau geothermal plant is a double flash plant. The turbine model calculates the change in specific enthalpy for the High-Pressure (HP) and two Low-Pressure (LP) sections of the turbine. The turbine model assumes an isentropic efficiency based on design documentation for each turbine section.

The turbine expansion model is paired with the separation system model, which uses two-phase inlet enthalpy and mass flow to calculate the expected generation. This operates by adjusting the separator pressures to maximise steam flow within the turbine limits. Each separator has a lower pressure limit which is governed by the swallowing capacity of each stage of the turbine. Separator pressure limits are applied to this model to ensure that operational limits are maintained.

The key benefits of this approach are to:

- Allow for short-term generation optimisation by adjusting separator pressures within the limits of the station
- Relate Steamfield changes both current (offline well maintenance) and forecasted (steamfield decline)

2.3 Submodel: Cooling and Ambient Model

One of the key challenges in developing purely physics-based models is the inability to explicitly capture all system relationships through first-principles equations (Wang, Li, Gao, & Zhang, 2022). A notable example is the influence of ambient conditions on various station components. Heat transfer and fluid flow dynamics involve complex time-dependent behaviours and complex spatial variations, which are challenging to model even with partial differential equations, which require rigid assumptions (Klimanek & Bialecki, 2009). To address these multi-variable and non-linear relationships, a series of data-driven sub-models were developed using historical operational data to characterise the impact of ambient conditions on various station components.

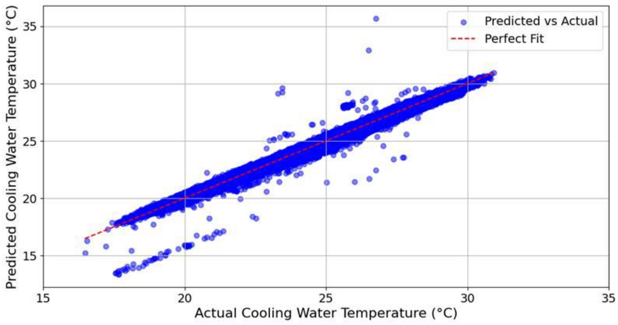

Figure 2: Cooling water model validation ($R^2 = 0.986$)

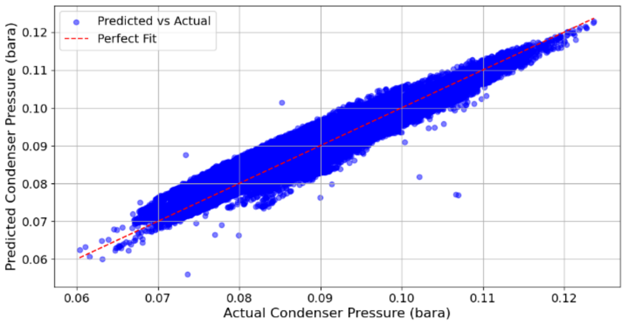

Figure 3: Condenser pressure model validation ($R^2 = 0.940$)

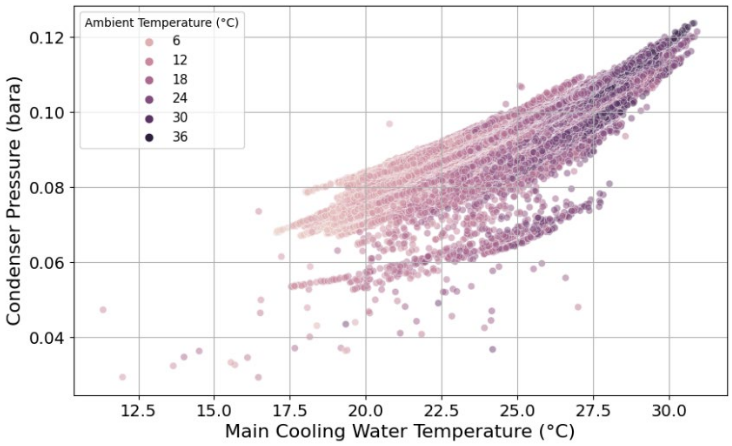

Figure 4: Condenser pressure by main cooling water temperature coloured by ambient temperature

These ML submodels were subsequently integrated into the broader hybrid station model. ML provides an accurate approach that predicts condenser pressure and cooling water temperatures that are dependent on many non-linear variables.

The first of these models predicts the main cooling water temperature based on attributes including wet bulb temperature, cooling tower fan current, high-pressure steam flow, and inlet cooling water temperature. Figure 2 shows the validation plot between actual main cooling water temperature and predicted main cooling water temperature in degrees Celsius with an R-squared of 0.986. These data are from January 2019 to April 2025, sampled at half hourly intervals.

The second model estimates condenser pressure using attributes from the Gas Extraction System (GES), turbine exhaust flow, and the predicted cooling water temperature. Figure 3 shows the actual condenser pressure versus the predicted condenser pressure using the model, with an R-squared of 0.940. These data are from January 2019 to April 2025, sampled at half hourly intervals.

These two models effectively simulate the impact of ambient conditions on the cooling system with a high degree of accuracy. Both models employ multiple linear regression, selected for its interpretability and ease of integration within the broader hybrid modelling framework. Lagged temperature effects and quadratic terms were incorporated to enhance model performance; allowing the models to capture non-linear and delayed responses of the system.

The selection of predictors in each model was guided by process knowledge of the causal relationships among cooling system components and further refined through exploratory data analysis and testing of various models. Figure 4 demonstrates the non-linear relationship between condenser pressure and cooling water temperature coloured by ambient temperature.

2.4 Submodel: Parasitic Load

The parasitic model forecasts parasitic load based on the GES, Brine ReInjection Pumps (BRIP), cooling tower fans, and wet bulb temperature. Figure 5 shows how Digital KAG predicts parasitic load overtime, compared to the measured parasitic load for various plant configurations, including both the 1st and 2nd stage BRIP with the 80% GES, and the 1st and 2nd stage paired with the 40% GES and 60% GES. The model yields an R-squared of 0.967.

A key challenge in developing this model lies in the sampling of the training data. To ensure generalisability, it is important to capture all relevant combinations of the GES and BRIP systems over the plant's history. However, certain configurations, such as the 40% and 80% GES operating with the 1st stage BRIP, have occurred less frequently. This can lead to a model biased toward more commonly observed system combinations, this can reduce predictive accuracy when the station operates under less frequent station configurations.

Conversely, incorporating the entire historical dataset without adjustment introduces another issue: the relationship between system operation and parasitic load has evolved over time due to equipment upgrades and operational changes. Using historical data considering the station context may thus introduce temporal biases and obscure current system dynamics. To address these challenges, a targeted sampling strategy was implemented. This approach ensures representation across all relevant system combinations while prioritising recent data for each configuration. As a result, the model is better equipped to account for both operational variability and evolving system behaviour, enhancing its robustness to future changes in station configuration.

Digital KAG has two main models that are built from the aforementioned sub-models; the Expected Model, which is the foundation of the Forecast Model and the Optimised Model, which is the foundation of the LP Set Point Optimiser.

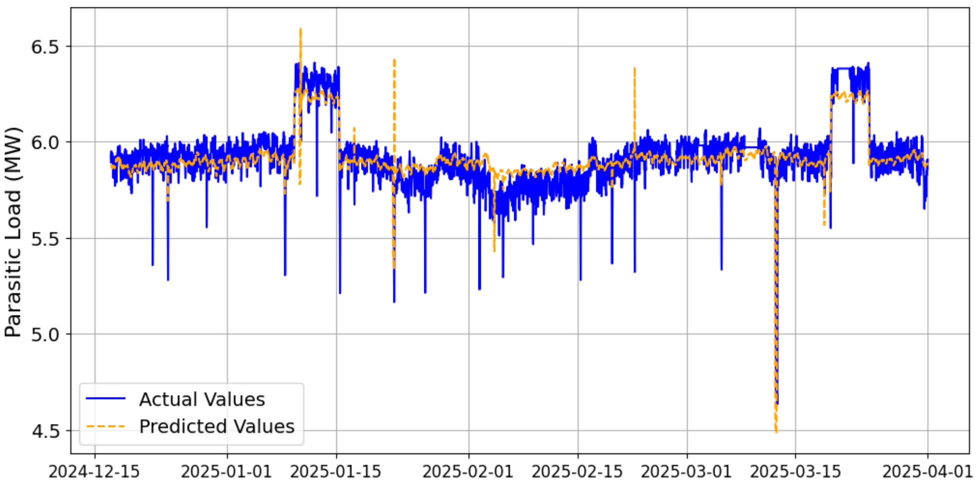

Figure 5: Parasitic load validation of the model versus the actual parasitic load in MW over time period 2024-12-15 to 2025-03-31 in half hourly frequency.

3. MODEL RESULTS

3.1 Expected Model

The expected model predicts the plant's actual output given the plant's operating configuration, conditions, and is used to predict production at any one time. Figure 6 shows the gross MW outputs over time; the actual generation in blue, the expected model in orange and the optimised model in green (refer to Section 3.3). The expected model has strong predictive performance for net power output predictions, achieving a Mean Absolute Error (MAE) of 0.27MW and Median Absolute Error (MedAE) of 0.23MW (in May 2025), highlighting the model's robustness and reliability in predicting Kawerau's behaviour.

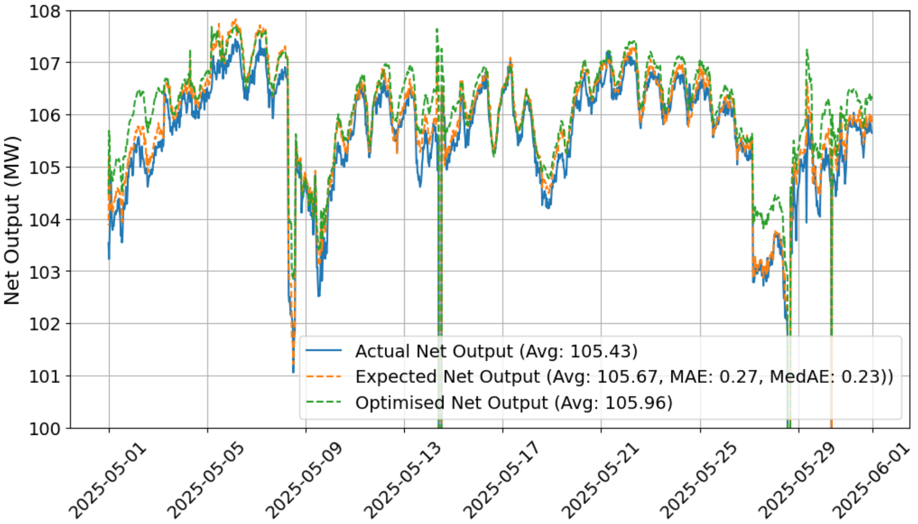

Figure 6: Production gross output in MW, actual output in blue, expected model in orange, and optimised model in green from 1 May 2025 to 31 May 2025

3.2 Forecast Model

Building on the expected model, the forecasting model is built with the same station-level digital twin skeleton and incorporates a short-term seven-day weather forecast sourced from a national meteorological service, which includes temperature and humidity. The model utilises a rolling inference dataset comprised of half-hourly operational data forecasting seven days in advance. Key operational parameters, such as steam flows, pressures, non-condensable gas content, and cooling system load—are held constant at their median values from the last 24-hour period. This assumption helps stabilise the model's baseline, to help ensure that the prediction is not affected by station events such as stem frees. Figure 7 shows Digital KAG's forecasted and actual net output in MW and temperature in degrees Celsius, for the last seven days and next seven days from 17 May 2025. The forecasting model demonstrates strong predictive performance, achieving a MAE of 0.48MW and MedAE 0.32MW for the forecasted net generation leading up to May 17, compared to the actual generation. A forecasting accuracy of 0.32MW MAE is remarkable considering that the model utilises external weather forecasts, with accuracy unlikely to exceed 97% (Ritchie, 2024). The low RMSE value attests to the model's capability to predict Kawerau's generation.

All forecast results are generated daily via scheduled jobs and stored in a centralised data repository for downstream analysis and operational planning. This integration of ambient forecasting into the digital twin framework enables proactive decision-making and supports more efficient geothermal power generation.

3.3 Optimised Model

The optimised model was designed to predict the maximum possible production at any given one time, by optimising input variables. The optimised model has an embedded iterative process that is executed across each time interval to

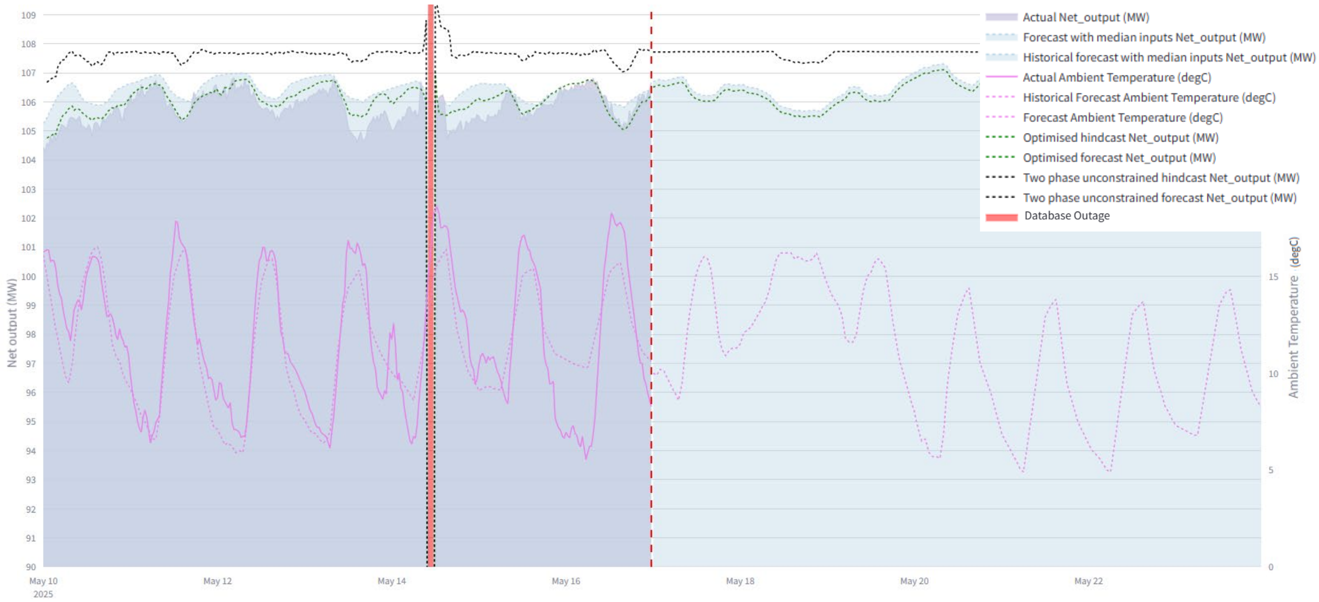

Figure 7: Forecasted net generation and ambient temperature for the seven days preceding and following 17 May 2025. With actual measured net generation and measured temperature overlaid for seven days preceding 17 May 2025. The forecast compared to actual net generation has an MAE of 0.48MW and MedAE of 0.32MW for the week preceding May 17.

estimate the optimal operating state of the station given the available mass flow and enthalpy. This iterative optimisation seeks to maximise HP steam flow and total turbine steam flow and, consequently, gross power output. This model is used to predict the best operating parameters live, at any one time.

3.4 LP Set Point Optimiser

While the station two-phase steam flow is abundant in both mass flow and enthalpy, optimising the LP separator pressure is less critical to maximising production, as the station can maintain HP steam flow to the steam turbine design limit. However, when the station is mass flow and/or enthalpy constrained, optimising LP separator pressure is critical to maximising production at any given time. The Digital KAG LP Set Point Optimiser, built from the optimised model foundation, was designed to bridge this gap, and solve for the optimised LP set point, live. Currently Kawerau's two-phase supply is both mass flow and enthalpy constrained. In this way, lower LP separator pressures are generally preferred, as they enable the extraction of a greater volume of steam from the same mass flow up to the turbine total steam flow limit and therefore extraction of work done on the turbine.

Achieving the maximised output requires optimising the steam flow from the separators, while accurately accounting for the impact of the pressure drop between the separator and the turbine. Geothermal wells naturally fluctuate in conditions though time (flow rate, well head pressure, line pressure) and so do conditions in the plant. The HP and LP set points and HP and LP separator pressures depend on the two-phase steam supply to the station. To determine the optimal LP setpoint, the LP setpoint optimiser calculates both HP and LP governor valve flow characteristics with a flashing steam calculation and iterates the calculations until it finds the optimal pressure setpoints. This method ensures that the selected LP pressure maximises steam availability while maintaining system efficiency and operational stability. A dashboard was developed with the Kawerau Operations team, which displays current operating conditions and the recommended LP Set Point to the Operator.

The Kawerau steam turbine has a total steam flow limit of 786t/h. Since the implementation of the dashboard, for a given mass flow and station enthalpy able to achieve the total steam flow limit, the station has seen an average increase in total steam flow limits of 3t/h; from 781t/h to 784t/h. To ensure the model is practical and useful to the station operators, the model has been tuned and optimised to recommend a set point that will result in a total steam flow just below the 786t/h limit. This ensures that the total turbine steam flow does not exceed the 786t/h limit and allows for any natural variance in steam, without sending the station into constant alarm.

Since the LP set point optimiser has been embedded into Kawerau operations, there has been an observed 0.2 MW gain in net generation, corresponding to an anticipated annual increase of approximately 1.752 GWh. This improvement was determined by comparing the historical difference between optimised and actual net generation before and post deployment.

Operator feedback on system limitations has been instrumental in guiding iterative improvements to the dashboard. As a result, several adjustments have been made to the optimiser to ensure its recommendations align more closely with real-time operating conditions as observed by station operators. Extensive validation of the LP setpoint optimiser was conducted, ensuring that steam flow and pressure estimations aligned closely with actual station measurements.

3.5 Gap-to-Potential – The Optimised Model

Mercury uses a "Gap-to-Potential" approach to account for MW generation and lost opportunity. This approach aims to attribute lost opportunity into categories that are monitored over time. Figure 8 illustrates the Gap-to-Potential approach as a waterfall diagram.

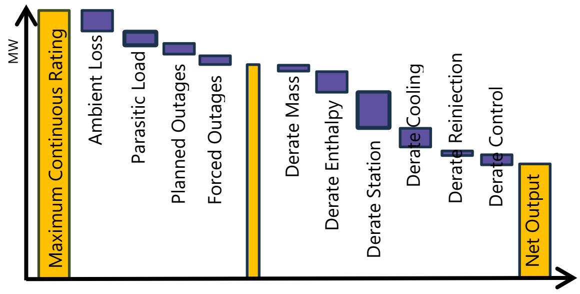

Figure 9: The Gap-to-Potential framework used to account for generated MW and lost opportunity.

The digital twin not only enables real-time monitoring and predictive analysis, but also supports scenario-based planning and decision-making. By integrating physical modelling with data-driven optimisation, this framework offers a powerful tool for enhancing the efficiency, reliability, and sustainability of geothermal power generation.

Using the Digital KAG optimised model live, actual station output can be compared to the maximum generation live, and lost opportunity accounted for as per the Gap-to-Potential framework. Figure 9 shows the optimised model surface plot. The surface plot illustrates the maximum MW that Kawerau can produce at any given one time, given the available two-

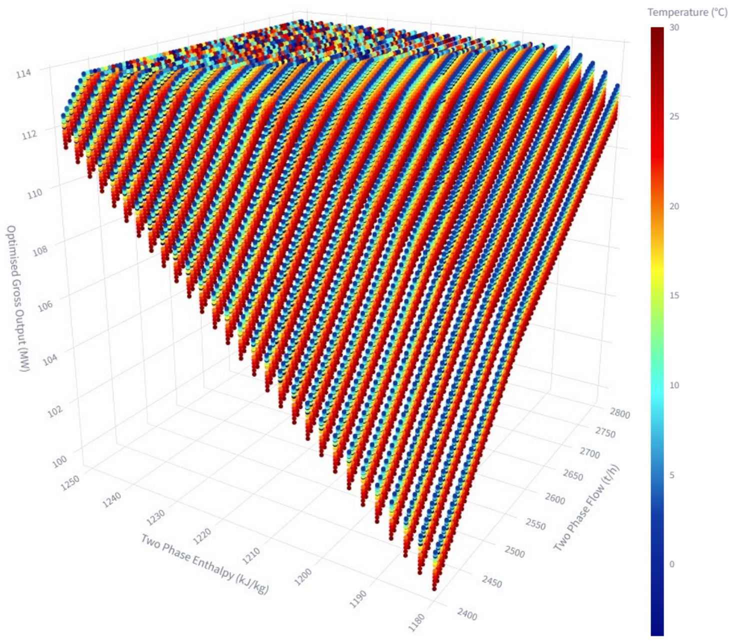

Figure 8: The Digital KAG's Optimised Solution used as a benchmark for production, given ambient conditions, plant configuration and available two-phase flow.

phase flow, station ambient conditions, and the optimal plant configuration.

The benefit of having an optimised model running live in the Kawerau control room has a twofold effect. Firstly, it provides a benchmark for station operators to cross-compare short-term plant operation and optimisation. Secondly, it provides a tool to help Operations and Engineering to better understand where the lost opportunity is and helps maintenance and capital investment opportunities to be more effectively prioritised at the station.

3.6 Gap-to-Potential – The Expected Model

The live expected model can also be used to account for lost opportunity in real time, as per the Gap-to-Potential framework. The expected model provides a flexible tool that allows engineers to easily conduct hindcast analyses. For example, in February 2025 one of the Kawerau production wells became shut in. Figure 10 shows the actual, the forecasted and the hindcasted (the expected model, assuming the production well had not been shut in) net MW outputs. The hindcast reveals that the production well shut in cost production 2.6GWh. The model can also be used to precisely predict generation outputs with different steam field arrangements and operating limits. Being able to hindcast expected net output allows lost opportunity to be quickly and easily quantified, to help inform decision making concerning prioritisation, spend, and risk.

It is also worth noting in Figure 10, how the forecast model recalibrates through time, as it reacts to changes in two phase flow to the station. In the same way, the LP Set Point Optimiser also recalibrates to the updated conditions, and will recommend the updated LP Set Point to the Operator.

4. DISCUSSION

4.1 Flow Meter Challenges & Future Opportunities

During the LP Set Point Optimiser validation process, certain discrepancies between model outputs and observed output were identified. The range, quality and error of flow, pressure and temperature meters onsite and/or instrumentation calibration float are thought to be a contributing factor to these discrepancies. The error associated with various on-site meters (such as venturis, Annubars, pressure transmitters) can have inherent error anywhere between +/-0.2-4.0%. It is acknowledged that tuning a model outside the error associated with the station's meters may have inherent limitations. The LP set point optimiser prompts the station operator to set the set point for the LP separators. When a set point is moved in the recommendation direction and does not result in the predicted MW increase, this can be a flag to investigate whether a meter calibration needs to be reviewed. This was the case for the GES motive steam Annubar flow meter which became uncalibrated during the LP set point optimiser testing. To mitigate noisy and/or erroneous instrumentation, the model often calculates key parameters in a myriad of ways and cross compares the results.

Bikmukhametov and Jäschke reviewed various case studies in oil and gas where ML has been used for virtual flow metering (Bikmukhametov & Jäschke, 2020). They note that virtual flow metering may improve flow accuracy estimates in dynamic state cases. There may be future opportunities to leverage ML to help predict two-phase steam flows to better accuracy than current methodologies.

4.2 Automated Process Control

The LP set point optimiser has had great implementation success with Kawerau operations. However, the recommended LP set point still needs to be manually inputted by the operator into the Distributed Control System (DCS). This process relies on the station operator being free and able to update the set point whenever plant conditions change. It is not realistic for the station operator to be paying attention to these station parameters at all times, as the operators are responsible for many other site tasks. Building on the success of the LP set point optimiser, the next step to improving the LP set point optimiser would be implementing Automated Process Control (APC). APC would use technology and ML tools such as reinforcement learning to automatically tune key station set points, removing the requirement for a human to be modulating small plant changes. Mercury is conducting an APC trial to test the success of having a machine modulate key set points.

4.3 Lessons Learnt

Engineering often requires waterfall project management styles to deliver projects. Additional to the realised MW improvements that the model has delivered, the agile project management style and collaboration between mechanical and process engineers with the decision science team has elevated our engineers' ways of working. Development of this model has allowed our engineers to improve their data science literacy skills and empirical analysis toolsets. We are starting to help shape the "engineer of tomorrow".

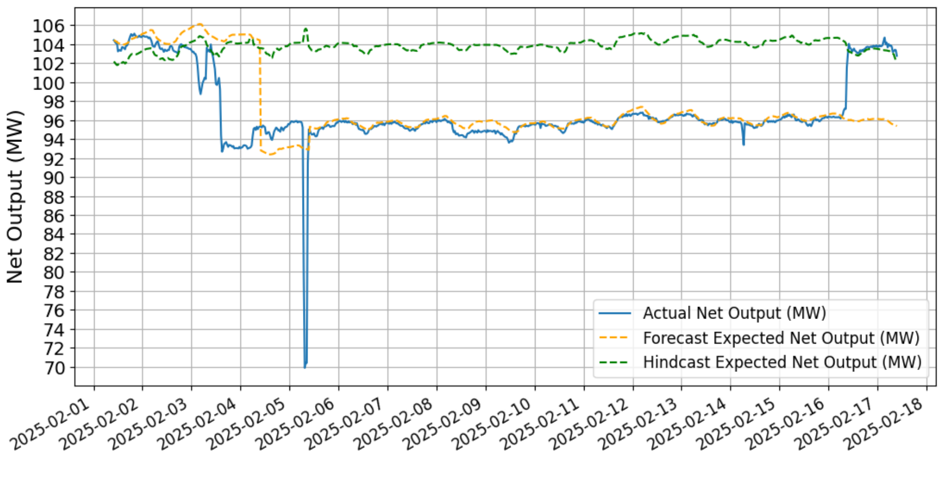

Figure 10: The actual, forecast model and hindcast model net output for the period Kawerau had one production well shut in February 2025.

4.4 Future Works

Building from the success of Digital KAG, the team are looking to pivot to Mercury's next geothermal plants and build the next hybrid thermodynamic ML models, with the aim to optimise plant set points in the short-term. Although many stations currently have an abundant two-phase supply, over time with geothermal reservoir decline, it will be essential to optimise two-phase take: taking the minimal amount of steam to produce maximised generation. Long-term reservoir management will become increasingly important to ensure that New Zealand's geothermal resources will be around for many generations to come. Additionally, as geothermal reservoirs decline, geothermal plants will increasingly be operating further from their original design limits. Hybrid models like Digital KAG will help maximise generation within new confines and plant configurations.

Modelling Mercury's full geothermal fleet will enhance forecasting of both intra-day and inter-day variation, which is critical to portfolio management across wind, hydro, and geothermal assets. This includes simulating upcoming plant constraints and derates to more accurately predict their impact. Mercury's generation portfolio is balanced using a flexible river hydro scheme. *Digital River* is an internal, planning focused, digital twin that can simulate the portfolio hydro response to changes in geothermal output, quantifying the impact and feeding back into geothermal decision making.

Managing production through the use of bespoke hybrid models built from thermodynamic first principles and ML will leverage New Zealand's capacity to produce electricity, committing to the energy trilemma, helping create more MW that are affordable, sustainable and secure.

5. CONCLUSION

The Mercury Optimisation Engineering and the Decision Science teams built the hybrid Digital KAG model with a predictive capability of +/-0.3MW for the 113.67MW MCR double flash plant, live.

Key benefits already realised from the model include:

1) A model that provides Operators with optimised set points to maximise generation, without putting the station into constant alarm. Since the deployment of the Digital KAG into daily station operations, the LP set point optimiser has helped improve production generally by +0.2MW.
2) A forecasting model that improves MW prediction accuracy. This can provide Wholesale and Trading greater accuracy MW inputs for their Waikato River scheme model, particularly pertinent in dry years.
3) A hindcasting tool to help account for lost MW for various operating scenarios, which can be used to better prioritise projects and maintenance to improve the station's efficiency and minimise downtime.

Digital KAG is a tool with greater accuracy, substantially greater computing power and greater flexibility than any tool developed prior. Plant production management and optimisation will become increasingly important, as geothermal reservoirs decline and plants are forced to operate further from their design limits. Optimising generation contributes positively to solving the energy trilemma in New Zealand and abroad.

6. ACKNOWLEDGEMENTS

We would like to thank:

- Matt Kedian and Dominic Miocevic for sponsoring and supporting this project, despite initial uncertainty about project impact and value.
- Paulo Gottgtroy and the Mercury Decision Science team for their support to build the model; with your help we have increased our capability by an order of magnitude.
- Kawerau Station and Operations for your support and testing while building the model. The testing and ongoing feedback has allowed us to improve the model and its uses.
- Richard Maginness who supported this idea from a small seedling, which has now blossomed into a flower.

7. REFERENCES

Bikmukhametov, T., & Jäschke, J. (2020). First Principles and Machine Learning Virtual Flow Metering: A Literature Review. *Journal of Petroleum Science and Engineering*.

Jakobsson, K. (2024). *Geothermal Flash Power Plant Modeling and Analysis.* Reykjavik: University of Iceland.

Klimanek, A., & Bialecki, R. (2009). Solution of heat and mass transfer in counterflow wet-cooling tower fills. *International Communications in Heat and Mass Transfer*, 547-533.

Ritchie, H. (2024). Weather forecasts have become much more accurate; we now need to make them available to everyone. *Our World in Data*. Retrieved from https://ourworldindata.org/weather-forecasts

Salins, S., Kumar, S., Ganesha, A., & Reddy, S. (2024). Machine learning-based optimization and performance analysis of cooling towers. *Journal of Building Engineering*.

Siratovich, P., Buster, G., Taverna, N., Rossol, M., Weers, J., Blair, A., . . . Akerley, J. (2022). GOOML - Finding Optimization Opportunities for Geothermal Operations. *Workshop on Geothermal Reservoir Engineering*.

Tian, C., & Horne, R. (2019). Applying Machine-Learning Techniques To Interpret Flow-Rate, Pressure, and Temperature Data From Permanent Downhole Gauges. *SPE Res Eval & Eng 22*, 386–401.

Upflow. (2025). *GOOML Geothermal Operation Optimization & Machine Learning*. Retrieved from Upflow: https://www.upflow.nz/projects/gooml

Wang, J., Li, Y., Gao, R., & Zhang, F. (2022). Hybrid physics-based and data-driven models for smart manufacturing: Modelling, simulation, and explainability. *Journal of Manufacturing Engineering*, 381-391.