

CHAPTER 4 – RESULTS AND DISCUSSIONS

4.1. Overview

This chapter presents the results and discussion of the multi-phase development of the GOOREMALE (Geothermal Operations Optimization, Reliability, and Efficiency through Machine Learning) system. The chapter is structured to reflect the progressive implementation of digitalisation and machine learning technologies across three major development stages: data centralization and visualization using Business Intelligence (Level 1), real-time data integration through historian systems (Level 2), and advanced predictive analytics via machine learning models (Level 3) in 3 aspects, Operation Optimization, Reliability, and Efficiency (ORE). Each section details the type of data collected, tools utilized, system architecture, key findings, and their implications for operational decision-making, reliability improvement, and production efficiency. The outcomes are then analyzed to evaluate how digital transformation and machine learning contributed to achieving the company's production targets and enhancing geothermal plant performance.

4.2. Data Obtained

The data used throughout the GOOREMALE project were collected progressively from 2022 to 2024, reflecting the multi-phase development of the digitalisation and machine learning initiatives. Each year marked a significant milestone in how data was acquired, structured, and utilized.

4.2.1 Foundation and Centralization (Business Intelligence Phase 2022)

The initial development began with centralizing operational data that had previously been scattered across various local systems and manual logs. Through the integration of Power BI Desktop with the existing data management platforms via Web API, operational data was imported and visualized. This phase laid the foundation for structured digital reporting by digitizing parameters across steam field and power plant. Table 3 presents the operational parameters collected, which were subsequently

visualized and analyzed based on the specific objectives of each development phase. In terms of production performance, the collected parameters specifically comprised gross generation, net generation, and parasitic energy consumption, providing a comprehensive overview of energy flow and operational efficiency.

The primary data source during this phase was an online Excel-based logbook, which was manually updated by field operators on a daily basis. By the end of 2022, an integrated dashboard was launched that visualized these data points, enabling the first round of centralized monitoring across all units.

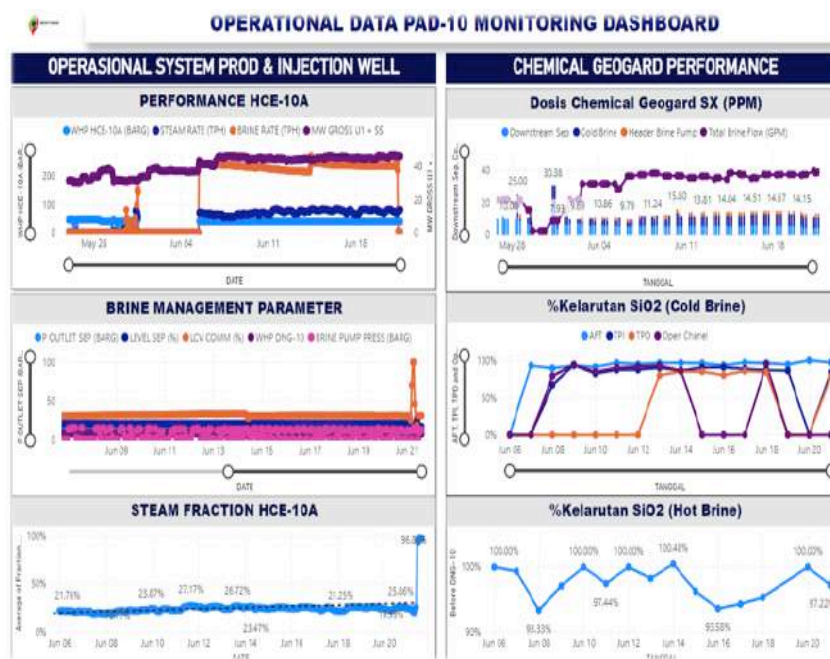


Figure 4.2 Steam Field Operational Parameter BI Dashboard

Figure 4.1
stakeholder

Figure 4.3 Steam Field Operational Parameter BI Dashboard

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and enables more efficient monitoring and data analysis.

4.2.2 Real-Time Monitoring and Historian System Integration (2023)

The focus in 2023 shifted toward real-time operation data acquisition. A historian system was implemented, enabling the continuous streaming of high-frequency data from upstream (steam field) and downstream (power plant) components. Data is currently streamed at intervals of seconds and stored in a time-series database.

With the integration of the historian system into the Distributed Control System (DCS) of each unit, a broader range of real-time operational parameters can now be collected. All sensor-captured data within the DCS are streamed, stored, and visualized through the historian platform. This advancement enables personnel at the head office to access and monitor comprehensive real-time data seamlessly, without latency. Furthermore, the ability to visualize a wider set of parameters allows for the development of more comprehensive and informative dashboards, which in turn simplifies analysis and supports faster, data-driven operational decision-making. The real-time dashboard featured automatic alerts and threshold warnings for operational deviations as shown in Figure 4.2. This infrastructure formed the foundation for anomaly detection and predictive modelling.

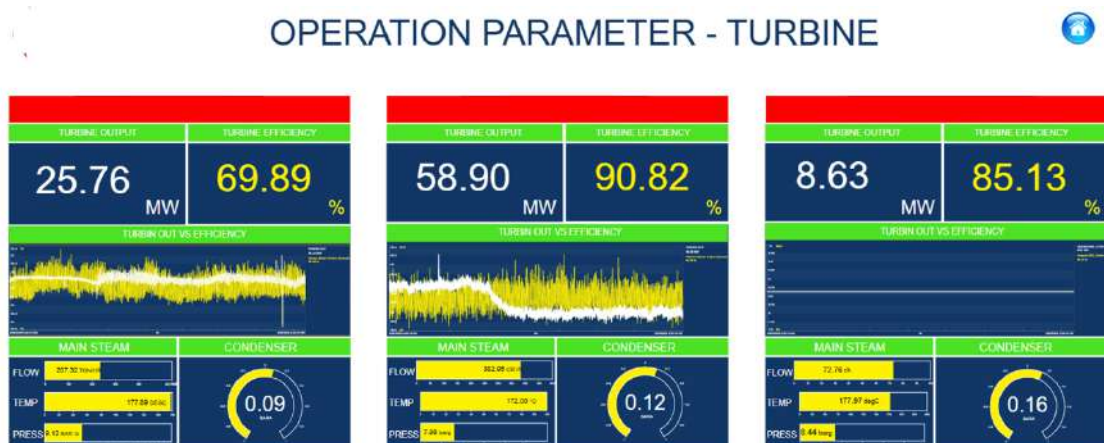


Figure 4.4 Real-time Dashboard using Historian

4.2.3 Machine Learning (ML) Development and Predictive Analytics (2024)

In 2024, the GOOREMALE system entered its third phase: leveraging the historical and real-time datasets to train and deploy machine learning models. Historical datasets from were preprocessed, cleaned, and used to train supervised ML models. Datasets were also expanded to include tagged anomaly events, maintenance logs, and operating conditions at failure onset. One of the primary objectives of the machine learning models is to detect anomalies as early as possible, providing asset owners with sufficient lead time to verify issues and plan necessary actions. In addition, the models

are capable to estimate the Remaining Useful Life (RUL) of critical equipment, thereby enhancing reliability and supporting more proactive maintenance strategies.

In parallel with the development of machine learning models, operational models were also constructed to enable what-if scenario simulations as part of the optimization effort. These models represent a digitalization of the end-to-end geothermal process—from upstream (steam field) to downstream (power plant). By simulating various operational scenarios, the models facilitate what-if analyses to evaluate the impact of alternative strategies or adjustments. Furthermore, they are instrumental in identifying inefficiencies within the system, such as energy losses or suboptimal operating conditions, thus supporting continuous process improvement and overall performance optimization. Figure 3.12 illustrates the diagnostic insights in the anomaly detection process, while Figure 4.3 presents the operational models developed for conducting what-if analyses and identifying process inefficiencies.

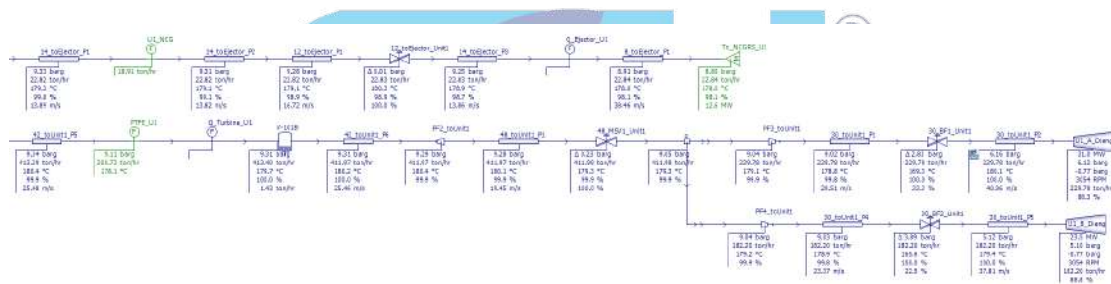


Figure 4.5 Operational Simulation Models

4.3. Data Analysis and Discussion

4.3.1 Plant Monitoring (Level 1)

Prior to the implementation of the GOOREMALE, the communication protocol between local operators and headquarter engineers was exceedingly complex, with frequent bad data quality. The use of a paper-based Operation Log Sheet resulted in superfluous but necessary work. Several reports were supplied individually and in a scattered way from each field. As shown in Figure 4.4, there were various manual daily operational data that were divided into three sections: steam field, power plant, and other reports. All reports were manually delivered to the headquarters using

communicator applications or corporate mail. The entire traditional file sharing workflow consumed about 14.5 hours each day. Late submission and compilation of data triggered an increase in non-productive time and obviously weak decision-making, resulting in tremendous effort for engineers in the headquarters.

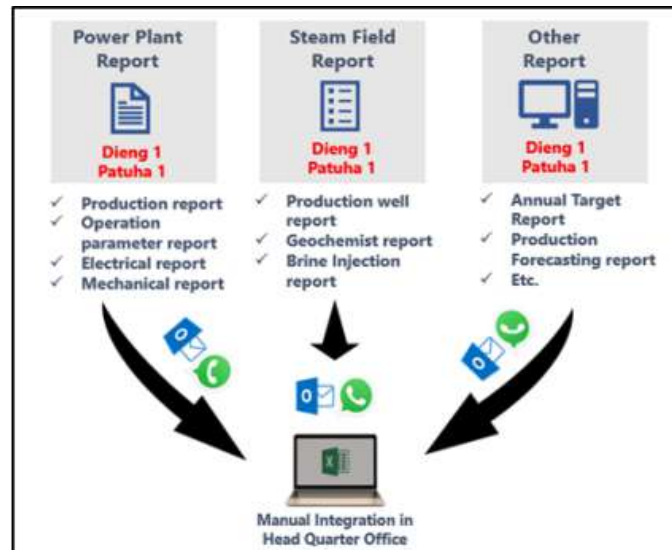


Figure 4.6 Traditional file sharing methods[®]

The GOOREMALE initiative was first launched by the end of 2022 with the digitization of the operational log sheet, which was stored in an online, widely accessible file that functioned as a preliminary information database management system (DBMS). Dashboards developed using Business Intelligence (BI) tools were constructed on top of this DBMS as the primary data source. These dashboards provided faster access to operational insights, thereby enabling quicker and more accurate decision-making (Obeidat, M et al. 2015). The adoption of this digital approach resulted in a 50% reduction in the previous decision-making cycle time. Additionally, this transformation yielded a soft-benefit in employee cost savings of approximately USD 2,245 per month, or around USD 26,940 annually.

Figure 4.5 presents a dashboard designed to optimize steam supply from production wells by analyzing pressure drops across wellhead pressure, line pressure, and main line pressure. A simplified nodal analysis was implemented in the Power Query Editor to identify inefficiency by automatically calculate the pressure drop for each steam line. As a result of this optimization, the system achieved a gain of approximately USD 233,280.

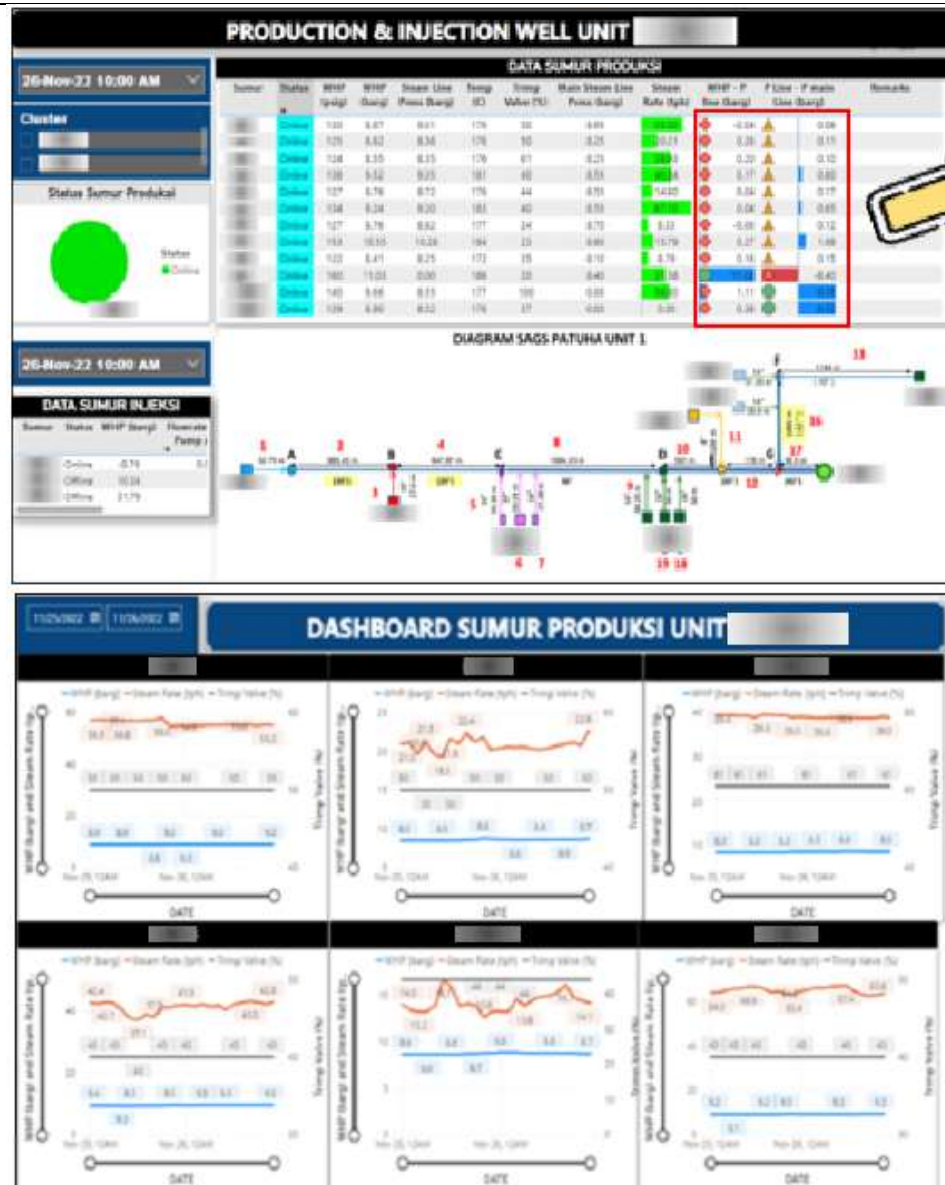


Figure 4.7 Steam supply optimization dashboard

One of the recurring challenges in the field is the formation of massive silica deposition, or scaling, which disrupts fluid flow and reduces system efficiency. To address this, condition monitoring dashboard (see figure 4.6), was implemented by integrating operational production data with geochemical brine analysis from the geochemistry team. This proactive approach enabled prevention of silica scaling within the brine line. As a result, the cleaning of the brine line—typically required due to severe scaling—was successfully avoided and the prevention of one day of lost production opportunity, leading to estimated cost savings of approximately USD 19,500.

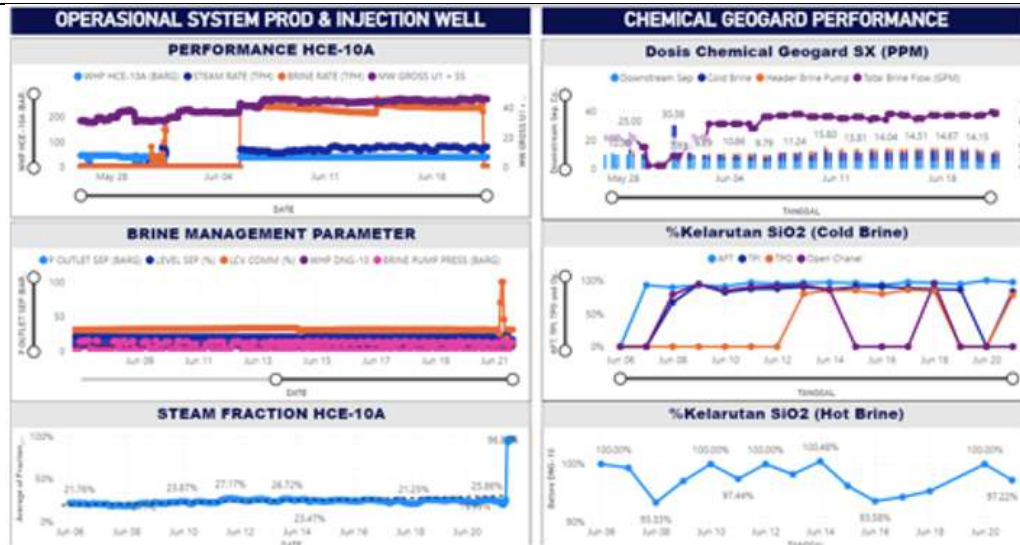


Figure 4.8 Integrated operational production and geochemist monitoring

4.3.2 Realtime/Periodic Performance (Level 2)

The ability to capture and utilize real-time data is a critical enabler for modern geothermal operations. Real-time data allows for continuous monitoring, faster response to anomalies, and more informed decision-making. It also forms the foundation prior to deployment of machine learning models for predictive maintenance, anomaly detection, and operation optimization, serving as the backbone for advanced analytics and intelligent decision-making. As a result, organizations are able to achieve operational excellence through digital transformation, driven by data intelligence and automation (Brous et al. 2020, p.120373, Oluwaseyi Ayotunde Akano et al. 2024, p.100222).

Operational excellence is also a key requirement for meeting ISO 55000 certification standards, which can be supported through the implementation of Enterprise Asset Management (EAM) (Amadi-Echendu et al. 2010, pp.3–16). To ensure the effective operation of EAM within the organization, GOOREMALE undertook structured data management and analytics initiatives. GOOREMALE leveraged Distributed Control System (DCS) communication protocols, including Open Platform Communication (OPC) and Modbus, to enable real-time data streaming over a secure private network—eliminating the need for manual data collection from log sheets. Furthermore, GOOREMALE has been positioned as an Asset Performance Management (APM) tool

to support the organization's broader objectives in achieving excellence in operations, maintenance, and efficiency.

Leveraging the Distributed Control System (DCS) enables a greater number of operational parameters to be streamed and captured from both the steam field and the power plant, thereby allowing for more comprehensive and integrated analysis. In addition to supporting advanced analytics, the system facilitates early-stage anomaly detection through predefined alarm set points, even prior to the implementation of machine learning models (Lee et al. 2015, pp.18–23). Figure 4.7 illustrates an example of early failure detection opportunity of the CHO pump using alarm set points. Furthermore, this digital infrastructure significantly accelerates the Root Cause Failure Analysis (RCFA) process in the event of a forced outage. In one documented case, a turbine trip occurred due to the closure of the main control valve, which was triggered by a loss of hydraulic pressure resulting from CHO pump failure. The accelerated RCFA process enabled by digitalisation contributed to a loss production opportunity (LPO) saving of approximately USD 53,526.

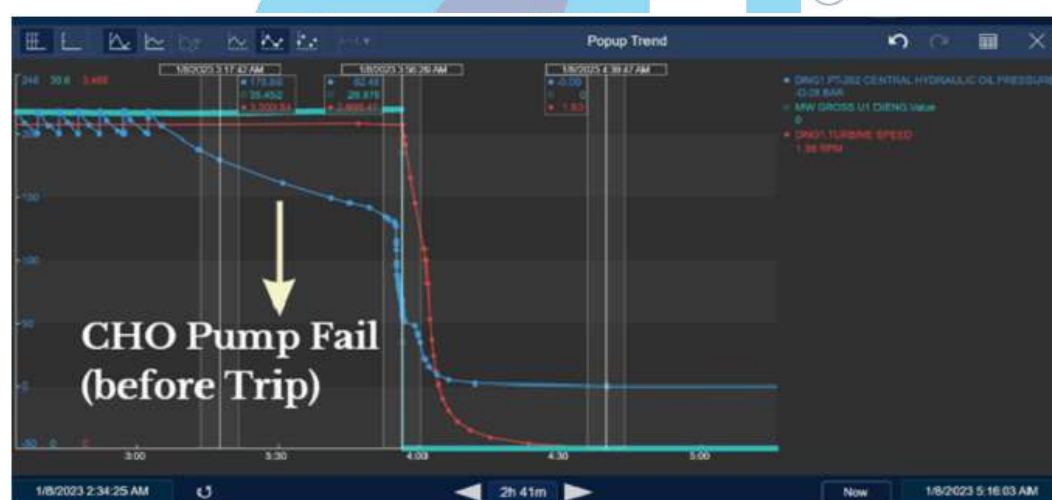


Figure 4.9 Early failure detection opportunity and accelerated RCFA process

The implementation of GOOREMALE Level 1 (end of 2022) and Level 2 (throughout 2023) also had a measurable impact on electricity production as seen in figure 4.8. From 2022 to 2023, actual production increased by 3.8%, demonstrating early gains from the digital transformation. Additionally, the production gap relative to the annual target was significantly reduced—from a shortfall of 8.1% in 2022 to just 1.8% in 2023. These improvements indicate that the benefits of GOOREMALE began to materialize during its first full year of implementation, particularly in enhancing operational performance

and reducing underproduction. Notably, 2023 marked the highest actual production level achieved within the 2019–2023 period, setting a new performance benchmark.

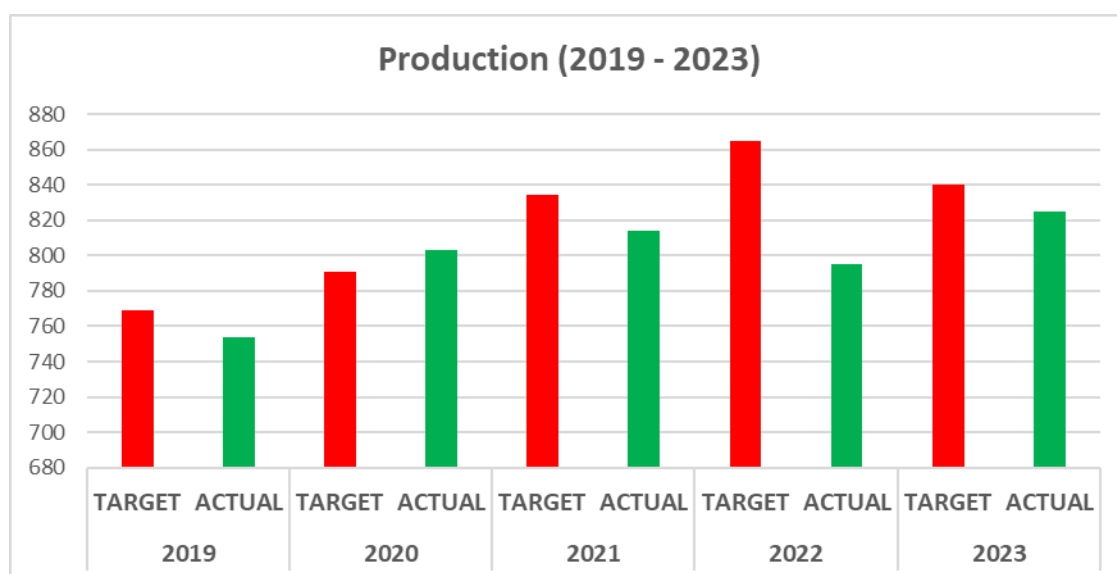


Figure 4.10 Target and actual production before implementation (2019-2021) and after implementation (2022-2023)

Furthermore, according to table 4.1, the revenue deviation trend shows consistent improvement from 2021 to 2023. While 2021 experienced a negative deviation of -4.7%, this shifted to -0.6% in 2022, and notably to a surplus of 6.3% in 2023, indicating that actual revenue **not only met but exceeded the annual target**. In parallel, operational cost control also improved—despite earlier years experiencing cost overruns, 2023 marked a significant turnaround with costs falling 11.6% below the planned target. This dual achievement in boosting revenue and reducing costs strongly supports the positive financial impact of digitalization through GOOREMALE.

Table 4.1 Deviation of Production Target 2019 – 2023

DEVIATION OF PRODUCTION TARGET		
YEAR	REVENUE	COST
2019	-7.4%	4.8%
2020	2.4%	-9.8%
2021	-4.7%	-8.4%
2022	-0.6%	0.6%
2023	6.3%	-11.6%

4.3.3 Machine Learning (Level 3)

After building the foundation by capturing and storing real-time data, machine learning models for predictive maintenance, anomaly detection, and operational optimization are ready to be developed and deployed. These models are capable of learning equipment behavior patterns from historical datasets, enabling earlier detection of anomalies that may indicate impending failures. As a result, asset owners and operators can take preemptive actions and plan maintenance activities more effectively, minimizing unplanned outages and improving reliability (Zhao et al. 2022, pp.2138–2148, Wuest et al. 2016, pp.23–45). In addition, operational simulation models allow for the execution of what-if analyses by replicating various operational scenarios in a risk-free environment. These simulations help identify inefficiencies, evaluate the impact of potential adjustments, and support data-driven decision-making for continuous process optimization (Hammond & Stapleton 2001, pp.141–162, Abdessadak et al. 2025, pp.5196–5218, Ricondo et al. 2021, pp.762–767).

In one documented case, see figure 4.9, the deployed machine learning model successfully identified anomalous behavior in the generator, which was primarily attributed to abnormal vibration patterns. Specifically, the model detected that vibration in Bearing #3 (Y-axis) contributed approximately 75% to the total anomaly score. A significant increase in peak-to-peak vibration values—nearly double the baseline—prompted the reliability team to collaborate with the field operations team for further validation. Subsequent verification using a vibration analyzer confirmed an increase in amplitude at both 1x and 2x RPM frequencies, which are commonly indicative of rotor unbalance or misalignment. As a result, this condition was closely monitored and designated as a priority item during the subsequent plant inspection, thereby enabling proactive maintenance planning.



Figure 4.11 Abnormal vibration patterns as anomaly detection

The gross power output of a steam turbine can be estimated using thermodynamic principles, derived from the first law of thermodynamics. The general formula used in the calculation is based on the product of mass flow rate and specific enthalpy drop across the turbine:

$$\text{Power Generation (kW)} = \dot{m} \times (h_{\text{inlet}} - h_{\text{outlet}}) \quad (2)$$

Where:

$\dot{m}$: mass flow rate (kg/s)

h_{inlet} : enthalpy inlet (kJ/kg)

h_{outlet} : enthalpy outlet (kJ/kg)

This formulation assumes steady-state operation and adiabatic expansion through the turbine. From this, the Specific Steam Consumption (SSC) can be calculated as the mass flow rate per unit of power output, commonly expressed as

$$\text{Specific Steam Consumption (SSC)} = \frac{\dot{m}}{\text{Power Output}} \quad (3)$$

Where:

$\dot{m}$: mass flow rate (ton/hour)

Power Output : enthalpy inlet (MW)

SSC serves as a key performance indicator, with lower values indicating more efficient turbine operation (DiPippo 2011, Dickson & Fanelli 2013).

The turbine is a double-flow type and, therefore, was modeled as two parallel turbines within the simulation framework. The simulation results yielded a gross power output ranging from 53 to 54 MW, with a mass flow rate of 410–414 tons per hour, an inlet pressure of 8.6 barg, an outlet pressure of -0.77 barg, and specific. For validation purposes, the simulation output was consistently cross-checked against actual plant data recorded by sensors. The actual gross power output ranged from 53.5 to 54.5 MW, with a mass flow rate of 400–405 tons per hour, an inlet pressure of 8.4–8.5 barg, and an outlet pressure of -0.7 barg. Given that the deviation between the simulated and actual values is less than 10%, the simulation model is considered valid and sufficiently accurate for operational analysis and decision support as seen in figure 4.10.

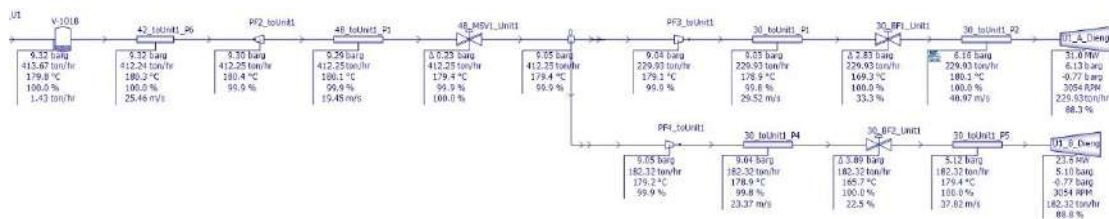


Figure 4.12 Operation Model Simulation

A comparison of Specific Steam Consumption (SSC) between actual and simulated data further supports the model's validity as seen in figure 4.11. For Asset 1, the actual SSC was recorded at 8.7097 tons/MWh, while the simulation yielded 8.6487 tons/MWh. For Asset 2, the actual SSC was 8.5724 tons/MWh, and the simulated value was 9.2963 tons/MWh. All values fall within a reasonable deviation—less than 10%—reinforcing that the simulation accurately reflects operational performance. However, slight differences between simulated and actual **gross power output**, as well as **SSC**, may be attributed to several factors, one of which is the steam well deliverability curve.

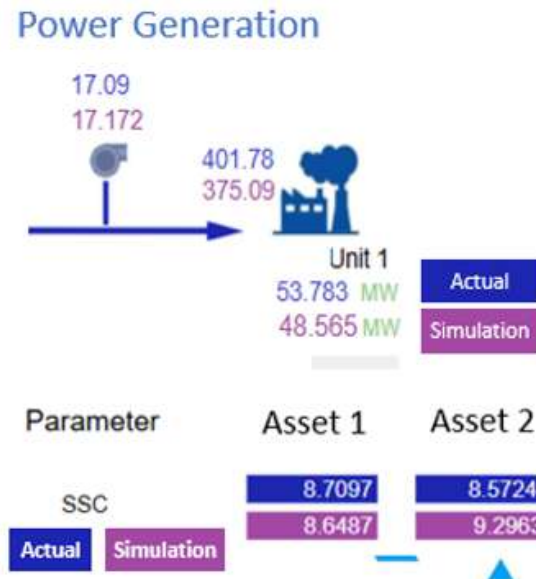


Figure 4.13 Power Generation and Specific Steam Consumption Actual and Simulation

Currently, the deliverability curve—used to represent the steam production capacity of each well—is not updated in real time. As a result, the mass flow rate assumptions feeding into the simulation model may not fully reflect the actual dynamic reservoir behavior at the time of measurement. This lag in deliverability data can influence the accuracy of both the mass flow rate and the estimated power output in the simulation, particularly under fluctuating well conditions. Incorporating real-time updates to the deliverability curve would therefore enhance model precision and allow for more responsive operational optimization.

The thermal efficiency derived from the simulation model ranges between 87% and 89% as seen in figure 4.12, while the actual calculated efficiency based on field measurements is approximately 87% to 89%. This indicates that the model maintains a deviation of less than 10% from actual performance, confirming its validity for operational analysis. Furthermore, the observed slight discrepancy in efficiency values may highlight potential performance losses in the actual system.

Turbine Status	
Actual	Simulation
PT-4061 8.49 BAR G	Pressure Sim 8.6425
TE-4101 177.54 DEGC	Temp Sim 176.66
FT-4062 404.70 TON/HR	Steam Flow Sim 376.17
Efficiency 87.76 %	Efficiency Sim 88.738 %

Figure 4.14 Actual and Simulation Operation Parameter

In 2024, the development and implementation of GOOREMALE demonstrated a significant impact on operational performance as seen in figure 4.13. Electricity production increased by 4.1% compared to the previous year—an improvement that surpassed the production gains observed in earlier stages of the project. Notably, for the first time in four years, the actual production exceeded the annual target by a solid margin of 1.6%. This milestone not only marked a return to target compliance but also represented the highest annual production ever recorded in the company's history.



Figure 4.15 Target and actual production before implementation (2019-2021) and after implementation (2022-2024)

From a financial standpoint, the revenue deviation showed a consistently positive trend from 2021 to 2024 as seen in table 4.2. After a deficit of -4.7% in 2021, the gap

narrowed to -0.6% in 2022, flipped to a surplus of 6.3% in 2023, and climbed even higher to 7.9% in 2024. This indicates that the actual revenue in 2024 not only surpassed the target but also exceeded the strong performance of the previous year. At the same time, cost management remained effective, with actual costs staying under the annual target by 2.0% in 2024—continuing the cost-saving trend initiated in 2023.

Table 4.2 Deviation of Production Target 2019 – 2024

DEVIATION OF PRODUCTION TARGET		
YEAR	REVENUE	COST
2019	-7.4%	4.8%
2020	2.4%	-9.8%
2021	-4.7%	-8.4%
2022	-0.6%	0.6%
2023	6.3%	-11.6%
2024	7.9%	-2.0%

These achievements underscore the effectiveness of digital transformation and machine learning in driving operational excellence. The continued integration of real-time data, predictive analytics, and automated monitoring enabled early identification of performance anomalies and supported timely interventions. Machine learning models played a critical role in detecting hidden inefficiencies, predicting equipment health trends, and informing strategic operational adjustments. Collectively, these advancements fostered a more agile, data-informed decision-making process, resulting in improved system reliability, optimized production output, and enhanced operational efficiency.

In early 2025, see figure 4.14, an abnormal vibration event was recorded in GOOREMALE in the generator system, prompting a detailed analysis using time-domain trending, spectral diagnostics, and post-validation. As shown in the vibration trend plot, the (X) and (Y) axis vibration levels for Generator #3 and #4 persisted following the disturbance, while the vibration levels for Turbine #1 and #2 in both axes returned to normal shortly after the incident. This divergence in behaviour indicated that the anomaly was localized to the generator rather than the turbine stages.

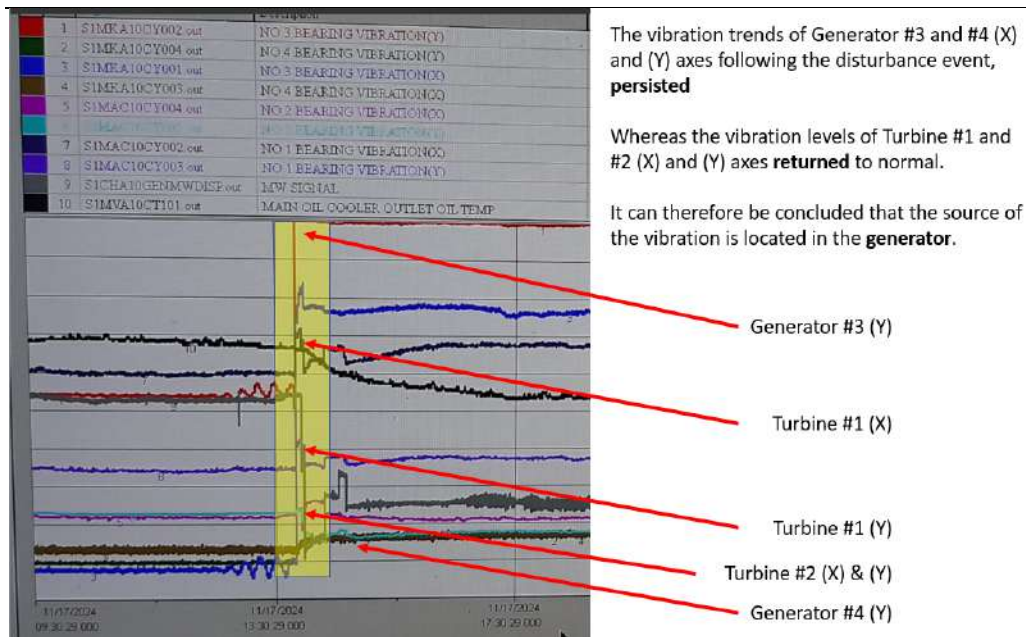


Figure 4.16 Generator abnormal vibration recorded in GOOREMALE

Spectral validation was conducted using a gearbox output horizontal waterfall plot as seen figure 4.15. The vibration spectrum aligned with the generator's rotational frequency (1×25 Hz), confirming that the observed vibration was likely a result of propagation from the generator. This finding was further supported by the significantly lower amplitude in the gearbox, suggesting it was not the origin of the disturbance. As a corrective action, the generator was shut down and reset. Post-validation confirmed that the generator vibration returned to normal, validating that the corrective intervention addressed the root cause effectively as seen in figure 4.16.

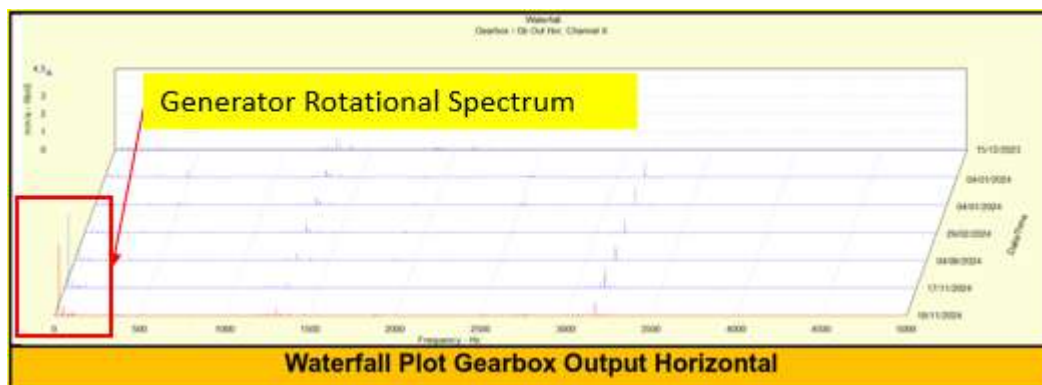


Figure 4.17 Generator Rotational Spectrum



Figure 4.18 Post-validation Confirmation

In 2025, the GOOREMALE implementation continued to be actively monitored and evaluated. One key focus was on optimizing operations by comparing simulation outputs with real-time field data. It was found that while the model readings—both in terms of wellhead pressure (WHP) and steam rate—remain relatively consistent with the deliverability curve projections, the actual field readings captured by field sensors show significant deviations as seen figure 4.17. Several wells exhibit steam rate differences of over 10% deviations, when comparing field sensor readings to the deliverability curve. These gaps suggest that the deliverability curves, although still aligned with simulation models, may no longer reflect true well performance in the field. To address this, a correction initiative has been carried out using offline Excel-based analysis to recalibrate the deliverability curves. The aim is to better align the simulation with real sensor data, thereby enhancing the accuracy of forecasting and production optimization.

				SENSOR			MODEL			Deliverability Curve				Steam Deviation	
1	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
2	Sumur	Tanggal	Separator	Valve	WHP	Steam Rate	Valve	WHP	Steam Rate	WHP Act	Steam Rate	WHP Sim	Steam Rate	Act vs DC	Sim vs DC
3				%	barg	t/h	%	barg	t/h	barg	t/h	barg	t/h		
4	I		V-158	4	59.65	10.94	4	36.8	115.29	59.65		36.8		190.88	466,2981
5	I		V-155	5	59.65	12.21	5	36.8	82.16	59.65	131.098	36.8			3,441953
6	I		V-154	10	49.66	23.15	10	30.83	94.92	49.66	45.058	30.83	65.05	94,63499	45,91852
7	I		V-159	13.7	20.67	89.92	13.7	22.22	71.81	20.67	82.48	22.22	80.27	8,274021	10,53943
8	I	03/06/2025	V-180	3.8	14.13	10.47	3.8	13.49	12.9	14.13	16.19	13.49	16.27	54,63228	20,71297
9	I		V-157B	17.5	38.88	0.35	17.5	31.32	22.97	38.88		31.32			
10	I		V-157A			13.99			57.61	38.88	66.96	31.32	72.55	366,9456	11,05823
11	I		V-102	20	51.66	0	20	47.59	25.75	51.66		47.59			
12	I		V-181	20	51.66	19.13	20	47.59	17.43	51.66	44.17	47.59	52.87	130,8939	18,32797

Figure 4.19 Actual and Simulation Readings Compared with Deliverability Curve

In the first half of 2025 (January to June), actual electricity production reached only 374.5 GWh compared to a target of 452.1 GWh, resulting in a notable shortfall of approximately 17.2% as seen in figure 4.18. This significant deviation was primarily attributed to the unexpected breakdown of a turbine unit, which was later confirmed to be caused by corrosion-related damage. The unplanned outage disrupted generation for

a prolonged period, limiting the plant's ability to meet its production target despite otherwise stable operating conditions.

This incident highlights the critical importance of incorporating reliability-focused analyses into ongoing digital transformation efforts. Consequently, one of the key recommendations going forward is to enhance asset reliability forecasting by conducting RAM (Reliability, Availability, Maintainability) analysis and applying Weibull distribution modeling. These methods are expected to provide deeper insights into equipment failure behavior, improve lifecycle planning, and help mitigate the risk of future unanticipated breakdowns that could jeopardize production objectives.

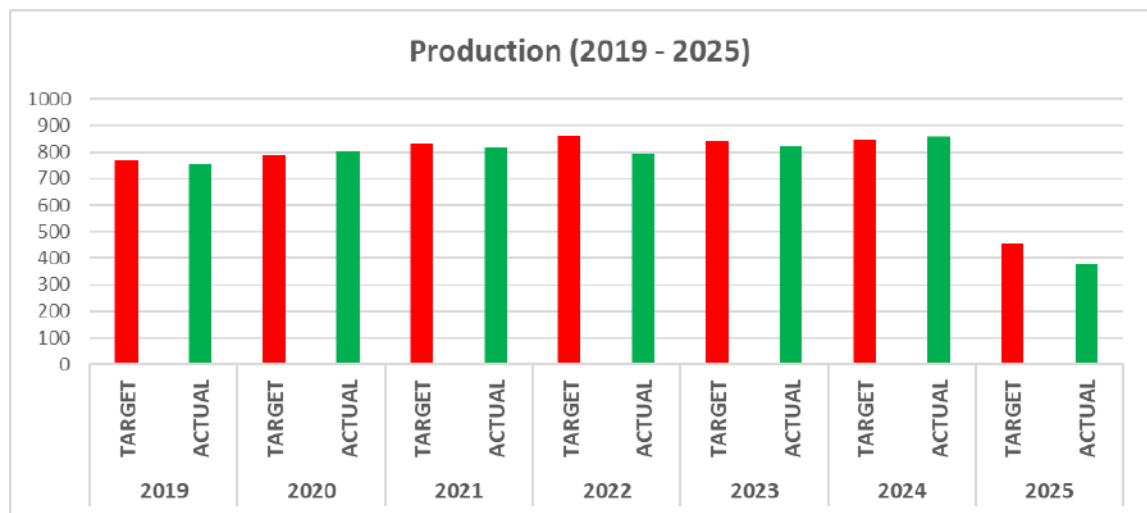


Figure 4.20 Target and actual production in 2019 until 1st half of 2025