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Thermodynamic performance evaluation of a steam turbine at kamojang geothermal power plant using operational data

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Abstract

Geothermal power plants play a significant role in sustainable energy systems due to their ability to provide stable baseload electricity with relatively low carbon emissions. This study investigates the thermodynamic performance of the steam turbine at Kamojang Geothermal Power Plant Unit X using operational data collected over 29 days and processed into 6-hour averages to represent the local operating envelope around the turbine design point. A multiple linear regression model was developed to evaluate the effects of steam mass flow rate, inlet steam pressure, inlet steam temperature, and condenser pressure on turbine isentropic efficiency. The results indicate that inlet steam pressure, inlet steam temperature, and condenser pressure significantly influence turbine efficiency, whereas steam mass flow rate has no significant effect. The model explains 43.8% of the variation in turbine isentropic efficiency (R^2=0.438) and yields a low in-sample prediction error (MAPE=0.12%), indicating that the regression closely reproduces the observed data within the limited operating range. In contrast, a considerable portion of the variation remains unexplained. Condenser pressure was identified as the dominant influencing parameter. These findings suggest that local deviations from the design point may contribute to off-design operation and additional thermodynamic irreversibility, providing practical implications for performance monitoring and operational optimization in geothermal power plants.

Keywords:
Geothermal power plant, steam turbine, efficiency, statistic, multiple linear regression

1 Introduction

Energy is one of humanity's most basic needs, supporting daily activities ranging from household use to industry and transportation. Globally, energy demand continues to rise in tandem with population growth and industrial development. However, the majority of energy currently used still comes from fossil fuels, which produce massive carbon emissions. The International Energy Agency (IEA) reports that over 60% of the world's energy is still supplied by coal, oil, and natural gas [1]. Heavy reliance on fossil fuels not only accelerates climate change but also threatens the long-term sustainability of energy supplies. Therefore, the transition to clean and sustainable energy has become a global priority, with the expansion of renewable energy utilization serving as a strategic step [1].

As a country with high economic growth, Indonesia naturally faces similar challenges in meeting the continuously increasing national electricity demand. Meanwhile, fossil fuel-fired power plants still dominate the national electricity supply, making emissions and supply security major concerns. The Ministry of Energy and Mineral Resources (ESDM) reports that the national energy mix is still dominated by fossil fuels at around 85%, while the contribution of renewable energy has only reached about 15% [2]. The Indonesian government has strengthened its commitment to reducing emissions through the Net Zero Emission 2060 policy, and the target for renewable energy utilization is expected to reach 23% by 2025 [2]. As a new renewable energy source, geothermal energy plays a crucial role because it is sustainable, stable, and independent of weather conditions [3]. Therefore, increasing the utilization of geothermal energy and optimizing the performance of existing power plants are crucial parts of achieving the energy mix targets.

As a country located within the Ring of Fire, Indonesia possesses enormous geothermal potential. This potential amounts to approximately 23.9 GW, or nearly 40% of the world's total potential, making it the second-largest in the world [2]. However, the installed capacity of geothermal power plants has reached only about 2.4 GW, leaving a gap between potential and actual utilization [2]. The low utilization of geothermal energy is driven by factors such as high initial investment costs, geological complexity, and suboptimal energy conversion system efficiency. Therefore, in addition to building new capacity, increasing the contribution of geothermal energy can also be achieved by improving the performance of existing units. Optimizing the performance of operating power plants is crucial to ensure that available geothermal energy is utilized more effectively and generates a more reliable electricity output. Consequently, a systematic evaluation of the performance of key equipment at geothermal power plants is necessary to accurately identify opportunities for improving efficiency.

In geothermal power plants, steam turbines are the primary components that convert the thermal energy of geothermal fluids into mechanical energy and, subsequently, into electrical energy via a generator [3], [4]. Steam turbine performance is generally evaluated using isentropic efficiency, which is the ratio of the actual work done by the turbine to the work that would be produced if the expansion process occurred isentropically [5], [6]. The isentropic efficiency is influenced by various operating parameters, including inlet steam pressure and temperature, steam mass flow rate, and condenser pressure. Value changes in operating parameters can affect the thermodynamic conditions of the turbine, thus impacting the turbine's specific work and efficiency [4], [5], [6], [7]. Based on the design specification of Kamojang Unit X, the turbine was designed to operate with a rated steam inlet pressure of 6.5 bar, a rated steam inlet temperature of 161.9°C under saturated steam conditions, a condenser pressure of 0.10 bar, and a rated steam mass flow rate of approximately 107.86 kg/s. These parameters represent the thermodynamic design point at which the turbine is expected to achieve optimal energy conversion efficiency. In actual conditions, a decline in the performance of geothermal power plant steam turbines is triggered by operating conditions that deviate from the ideal state, whether due to steam supply dynamics or the exhaust-side system. Therefore, turbine performance monitoring based on operational data plays a crucial role in maintaining power plant efficiency and power output stability.

Previous studies on turbine performance at geothermal power plants in Indonesia have consistently identified turbines and condensation systems as the primary sources of energy loss. Amrita and Nugroho at the Kamojang Unit II geothermal power plant and Qurrahman et al. at the Dieng geothermal power plant both found that the greatest exergy losses occur in the turbine components, confirming that the turbine is the primary determinant of overall energy conversion efficiency [3], [7]. Similar findings were reported by Musa et al. at the Lahendong geothermal power plant, where a gradual decline in steam quality was directly correlated with a decrease in turbine power output [5]. From the perspective of operational parameter optimization, Aloanis et al. demonstrated that adjusting the separator pressure at Lahendong Unit 2 can significantly increase turbine power, while Perdana and Akhiriyanto at the Patuha Geothermal Power Plant identified variations in steam mass flow rate as a more influential factor on electrical power compared to variations in pressure and temperature [4], [8]. On a broader scale, Başaran et al. demonstrated that environmental factors, such as air temperature, also affect the performance of cooling systems and power output in binary-cycle geothermal power plants [9]. Nevertheless, most of these studies are based on static thermal and exergy analyses or theoretical models with assumed constant operating conditions, and thus are unable to capture the dynamic variability observed in actual operations.

Recently, developments in power plant system analysis have shown a significant methodological shift toward approaches based on operational data. A study by Cheng et al. revealed that the adoption of machine learning and deep learning methods has increased significantly since 2018 for turbine performance diagnosis and prognosis, but also emphasized that challenges related to model interpretability and the availability of representative data remain major barriers to implementation [10]. Ling et al. demonstrated that an Artificial Neural Network model trained on field operational data can predict geothermal power plant's power output with high accuracy, while acknowledging that the model's reliability depends heavily on the quality and representativeness of the available training data [11]. Dutta et al. further assert that integrating thermodynamic parameters and machine learning algorithms yields a more reliable analysis system, provided that the system's underlying physical relationships are first understood as foundation for feature selection [12]. All three studies consistently demonstrate that a solid quantitative understanding of the relationship between macroscopic operating parameters and system performance is a critical prerequisite for meaningful development of more complex models.

Based on previous research, there is a significant gap in the foundational aspects of this research. Previous studies on the performance of geothermal power plants in Indonesia generally employ thermal and exergy analysis approaches based on steady-state operating conditions, thus failing to produce quantitative models capable of statistically describing the relationship between variations in daily operating parameters and isentropic turbine efficiency. Conversely, studies using data-driven approaches, such as those by Ling et al, focus on power output prediction using black-box methods, so the resulting coefficients cannot be thermodynamically interpreted to understand the underlying physical mechanisms of each variable's influence [11]. This complexity is further compounded by variables that have a significant physical impact on turbine efficiency but cannot be measured during routine operations, such as steam quality (dryness fraction). According to Baumann's Rule, every 1% increase in average moisture content during the expansion process results in a roughly 1% decrease in the turbine's isentropic efficiency [13]. Therefore, dynamic variations in steam quality resulting from fluctuations in geothermal reservoir conditions represent a source of uncertainty that must be accounted for in any model based on macroscopic parameters. This gap is particularly evident in dry steam systems such as the Kamojang geothermal power plant, which has working fluid characteristics and NCG dynamics that are different from binary cycle geothermal systems.

This study aims to address this gap by developing a quantitative model based on multiple linear regression that explicitly integrates statistical analysis and thermodynamic interpretation, using actual operational data from the Kamojang Geothermal Power Plant Unit X over a 29-day period. It should be emphasized that this study deliberately adopts an approach based on macroscopic operating parameters measurable in routine monitoring systems, namely inlet steam pressure, inlet steam temperature, steam mass flow rate, and condenser pressure. This approach was chosen not because it ignores the system's complexity, but because it yields a model with coefficients that can be directly interpreted and applied in operational decision-making, something that black-box models cannot provide. Thus, this study contributes an interpretive-quantitative foundation that maps dominant variables based on real field data while simultaneously establishing the knowledge base required for the development of more advanced approaches in the future, including integration with thermodynamics-based machine learning methods and Digital Twin technology.

2 Research methodology

This research analyzes the thermodynamic performance of the steam turbine at the Kamojang Geothermal Power Plant Unit X, focusing on isentropic efficiency as an indicator of the turbine's internal performance. This research objective is to identify the operational parameters that most significantly influence isentropic efficiency and to develop a quantitative model based on operational data to support performance monitoring. This research used actual operational data collected over 29 days. The dependent variable in this research is the turbine isentropic efficiency (ηis), while the independent variables include the steam mass flow rate ($\dot{m}$), steam inlet pressure (Pin), steam inlet temperature (Tin), and condenser pressure (Pcond). Data processing was performed using Microsoft Excel, while statistical analysis was conducted using SPSS, following the stages of classical assumption testing as a prerequisite for the model, regression modeling, and hypothesis testing to assess the partial and simultaneous effects of operational variables on η.

2.1 Geothermal power plant system

The Geothermal Power Plant is a power generation system that uses geothermal steam to generate electricity by converting thermal energy into mechanical energy [13]. In general, geothermal steam from the reservoir is brought to the surface and processed through a separation system to obtain steam that meets the ideal conditions for entering the turbine. The steam is then expanded in the steam turbine to rotate the rotor shaft, which, in turn, drives the generator to produce electrical power. The remaining steam on the turbine exhaust side is condensed in the condenser, creating low-pressure conditions that help increase the turbine expansion ratio. Therefore, turbine performance and condensation system performance are critical factors determining energy conversion efficiency in geothermal power plants, as shown in Fig. 1.

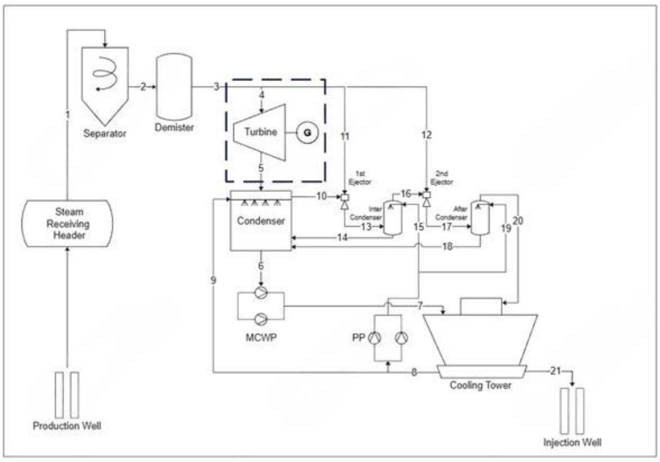

Fig. 1. Process flow diagram PLTP kamojang unit X

Fig. 1 shows a process flow diagram of a geothermal power plant, which includes a separator, steam turbine, generator, and condenser as the primary energy conversion components. The separator separates steam from the geothermal fluid mixture so that the steam entering the turbine has specific operating characteristics tailored to power generation needs. Steam from the separator enters the turbine to generate shaft work, and this mechanical energy is then converted into electrical energy via the generator. The steam exiting the turbine is directed to the condenser for condensation, thereby creating low pressure on the turbine exhaust side, which supports an increase in the expansion ratio [13], [14]. Based on Figure 1, this research is limited to the steam turbine and condenser subsystems, with a focus on inlet and outlet operating parameters, which are assumed to be most relevant to changes in the turbine's isentropic efficiency.

2.2 Data preprocessing

The initial operational dataset consisted of 695 hourly records collected from the steam turbine operating log. Prior to statistical analysis, the data were preprocessed to improve consistency and reduce high-frequency fluctuations that could affect the validity of the classical assumption tests. Since the objective of this study is to evaluate the thermodynamic relationship between operational variables and turbine isentropic efficiency under relatively stable operating conditions, the hourly data were aggregated into 6-hour averages. This procedure reduced the influence of short-term measurement noise and transient disturbances that are common in real plant operation. After aggregation, the final dataset used for regression analysis consisted of 116 observations.

The averaging process was applied to obtain data that better represent quasi-steady operating behavior rather than instantaneous fluctuations. This step is important because classical regression assumptions, especially the normality of residuals and the independence of autocorrelations, can be sensitive when the data exhibit rapid temporal variation. By converting hourly observations to 6-hour intervals, the analysis becomes better suited to capturing the overall thermodynamic trend of the turbine while minimizing the effects of local spikes that are not representative of the general operating condition. In addition, the aggregation process helps reduce the potential influence of duplicated patterns within closely spaced hourly measurements. Therefore, the processed dataset is more appropriate for multiple linear regression analysis and classical assumption testing.

Although the final number of observations is smaller after aggregation, the dataset remains sufficient for the scope of this study. The regression model uses four independent variables, and the final sample of 116 observations provides an adequate observation-to-predictor ratio for stable parameter estimation. More importantly, the data were taken from actual plant operations under a real operating envelope, so the study reflects practical turbine behavior rather than artificial laboratory conditions. The limited dataset should therefore be understood as a realistic representation of the available operating records within the observation period, not as an arbitrary reduction. In this context, the preprocessing step improves the reliability of the statistical interpretation while preserving the thermodynamic meaning of the data.

2.3 Calculation of turbine isentropic efficiency

The isentropic efficiency of the turbine is calculated using the approach of comparing the actual power to the isentropic power, as stated in Equation (1) [15]. The actual power of the turbine ($\dot{W}_{act}$) is obtained from the electrical power of the generator ($\dot{W}_{gen}$) corrected using the generator efficiency (η_{gen}) as shown in Equation (2). The isentropic power ($\dot{W}_{is}$) is calculated based on the ideal enthalpy drop in the isentropic expansion process, as shown in Equation (3). In the Eq. (1) and Eq. (3), $\dot{m}$ is the mass flow rate of the steam, h_1 is the enthalpy of the steam entering the turbine, and h_{2s} is the enthalpy of the steam exiting under isentropic expansion conditions [15].

$$\eta_{is} = \frac{\dot{W}_{act}}{\dot{W}_{is}} = \frac{\dot{m}(h_1 - h_2)}{\dot{m}(h_1 - h_{2s})} = \frac{h_1 - h_2}{h_1 - h_{2s}} \tag{1}$$

$$\dot{W}_{act} = \frac{\dot{W}_{gen}}{\eta_{gen}} \tag{2}$$

$$\dot{W}_{is} = \dot{m}(h_1 - h_{2s}) \tag{3}$$

2.4 Statistical model

Statistical modeling in this research is used to quantify the relationship between turbine operating parameters and isentropic efficiency based on actual operational data. The dependent variable used is the isentropic efficiency of the turbine (η_{is}), while the independent variables include the steam mass flow rate ($\dot{m}$), steam inlet pressure (P_{in}), steam inlet temperature (T_{in}), and condenser pressure (P_{cond}). The relationship between variables is analyzed using multiple linear regression, so that the influence of each independent variable can be evaluated while the other variables are held constant [16], [17]. The general form of the model used is shown in Equation (4), with α as the constant, β1 to β4 as the regression coefficients, and e as the error. Modeling is conducted to produce a quantitative equation that can be used to identify dominant factors and to develop a model to predict isentropic efficiency under observed operating conditions.

$$\eta_{is} = \alpha + \beta_1 \dot{m} + \beta_2 P_{in} + \beta_3 T_{in} + \beta_4 P_{cond} + e \tag{4}$$

2.5 Statistical test

Statistical testing is conducted to ensure that the model used meets the analysis prerequisites and that the results can be reliably interpreted. The first stage is the classical assumption test of the model residuals, including tests for normality, multicollinearity, heteroscedasticity, and autocorrelation [16]. This testing is necessary because operational data is time series in nature and may contain variations that affect the validity of the regression model. Once the classical assumption tests were fulfilled, the analysis proceeded with hypothesis testing to assess the significance of the independent variables' influence on isentropic efficiency. All tests were conducted at a 5% significance level as the foundation for statistical decision-making.

2.5.1 Normality test

The normality test is a statistical procedure used to verify the distribution of residuals in a regression model. Specifically, this test is used to determine if the residuals of a regression model follow a normal distribution [17], [18]. In this research, the Kolmogorov–Smirnov test was applied to the residual values. Residuals are considered normally distributed if the significance level is less than 0.05. Fulfilling the assumption of normality is crucial for ensuring the validity of parameter significance tests in regression analysis. Once this requirement is met, the analysis can proceed to the next prerequisite test.

2.5.2 Multicollinearity test

The multicollinearity test was conducted to ensure that the independent variables were not highly correlated enough to compromise the stability of the regression coefficients 17]. Multicollinearity was assessed with tolerance and the Variance Inflation Factor (VIF). The model is considered exempt from serious multicollinearity if the VIF values are below an acceptable threshold and the tolerance values are not close to zero. This means that each independent variable still provides independent information to explain variation in isentropic efficiency, thus allowing for a more robust interpretation of each variable's partial effects.

2.5.3 Heteroscedasticity test

The heteroscedasticity test is a statistical procedure used to determine whether the variance of the residuals remains constant across the range of predictor values 17]. This research uses the Glejser test, which performs a regression of the absolute residuals on the independent variables. The model is assumed to be homoscedastic if the significance value for each predictor is greater than 0.05. Fulfilling this assumption is important because unequal variances can introduce bias in standard errors and coefficient significance tests. When the residual variance is constant, the regression estimates and their significance become more trustworthy.

2.5.4 Autocorrelation test

The autocorrelation test was conducted time series nature of the operational data, which can lead to autocorrelation in the residuals across observations [17]. At first, the Durbin-Watson statistic was used to detect autocorrelation in the residuals. To confirm this result, a run test was also conducted to assess whether the residuals are random. Residuals are deemed random when the run test returns a significance level above 0.05. When this condition is satisfied, the model is considered free of serial correlation in the residuals, which might distort the regression results.

2.5.5 Hypothesis and model fitness test

Hypothesis testing is applied to determine whether the independent variables significantly influence the turbine's isentropic efficiency. Individual effects are evaluated using t-tests; a p-value below 0.05 indicates a significant predictor [16]. The combined effect of all predictors is assessed with an F-test; the model is considered significant if the p-value is less than 0.05 [16]. The model's explanatory power for variation in η_{is} is measured by R^2 and adjusted R^2, which indicate the share of ηis variance accounted for by the included operational variables [16].

2.6 Model validation

Regression model validation was performed to assess the model's accuracy in predicting turbine isentropic efficiency values based on the operational data used. In this study, the validation parameter is the Mean Absolute Percentage Error (MAPE), a widely used measure of prediction error in empirical model analysis. MAPE is defined as mean absolute percentage error between the actual values and the model's predicted values relative to the actual values [19]. Mathematically, MAPE is expressed as shown below in Equation (5):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_{actual,i} - y_{predicted,i}}{y_{actual,i}}\right| \times 100\% \quad (5)$$

where y_{actual} is the observed value, $y_{predicted}$ is the model-estimated value, and n is the number of observations. Absolute values are used to eliminate the effect of sign, so that all errors are calculated as deviations without regard to the direction of the error.

MAPE provides a percentage measure of error, making it easier to interpret the model's accuracy. The smaller the MAPE value, the higher the model's accuracy in predicting actual values [19]. Conversely, a large MAPE value indicates that the model has a high deviation from the actual data. Thus, MAPE is used as a quantitative indicator to assess whether the developed regression model has adequate predictive capability in representing the conditions of the analyzed system.

3 Result and discussion

3.1 Descriptive statistics

The operational data characteristics of the steam turbine at the Kamojang Geothermal Power Plant Unit X were first analyzed using a descriptive statistical approach to provide an overview of the distribution and variation of each research variable. The variables analyzed included steam mass flow rate ($\dot{m}$), steam inlet pressure (P_{in}), steam inlet temperature (T_{in}), condenser pressure (P_{cond}), and isentropic turbine efficiency (η_{is}) as dependent variables.

Table 1. Descriptive statistics

	N	Minimum	Maximum	Mean	Std. Deviation
m uap (kg/s)	116	88.194444	119.444444	97.90189974	9.482361680
p uap (bar)	116	6.00	6.40	6.1462	.08137
t uap (°C)	116	160	165	161.78	.775
p kondensor (bar)	116	.074	.113	.10475	.003886
efisensi isentropik (%)	116	69.451079	78.712118	74.73690851	1.449197117
Valid N (listwise)	116				

As shown in Table 1, the isentropic efficiency of the turbine has an average value of 74.74%, with a range of values between 69.45% and 78.71% and a standard deviation of 1.45%. This relatively narrow range of variation indicates that the turbine's performance during the observation period was generally stable, although fluctuations still occurred, reflecting the dynamics of actual operating conditions. On the other hand, the steam mass flow rate exhibits the widest range, from 88.19 kg/s to 119.44 kg/s, with a standard deviation of 9.48 kg/s, indicating significant changes in operating load during the observation period. Meanwhile, the steam inlet pressure and temperature variables showed relatively small variations, indicating that the steam supply conditions tended to remain within a narrow operating range.

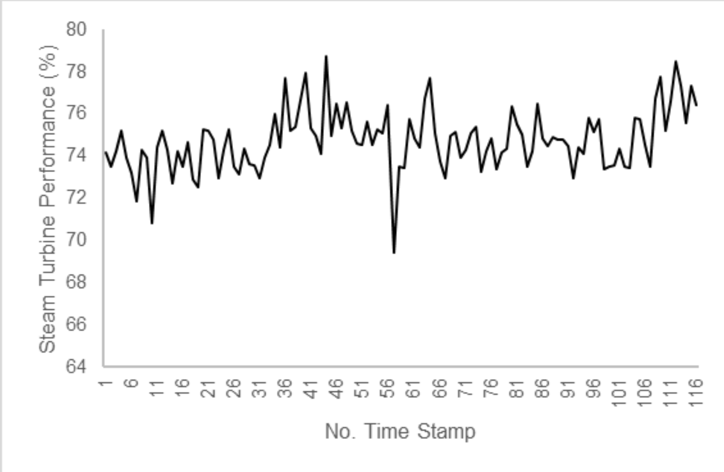

Fig. 2. Steam turbine performance

As shown in Fig. 2, turbine efficiency exhibits a fluctuating pattern, generally ranging between 73%-76% throughout the observation period. Although no significant upward or downward trend is apparent, several instances of sharp drops in efficiency indicate disturbances or temporary changes in operating conditions. These fluctuations reflect the characteristics of geothermal power generation systems, which are influenced by the variability of working-fluid conditions and interactions among system components.

3.2 Classical assumption test

3.2.1 Normality test

Normality tests are performed to assess whether the residuals from the regression model are normally distributed, a key assumption in linear regression analysis. The test is conducted using the Kolmogorov–Smirnov test on the unstandardized residuals.

Table 2. Normality test result

		Unstandardized Residual
N		116
Normal Parameters	Mean	.0000000
	Std. Deviation	1.08619518
Most Extreme Differences	Absolute	.060
	Positive	.060
	Negative	-.055
Test Statistic		.060
Asymp. Sig. (2-tailed)		.200

According to the test results shown in Table 2, a significance value (Asymp. Sig.) of 0.200 was obtained, which is greater than the significance level of 0.05. This result indicates that there is insufficient evidence to reject the null hypothesis; therefore, the model residuals are not significantly deviating from a normal distribution. Thus, the assumption of normality in the regression model can be deemed satisfied. The fulfillment of this assumption indicates that the regression model has an adequate statistical basis for further testing, particularly for interpreting regression parameters and conducting hypothesis tests. Additionally, the near-normal distribution of the residuals also indicates that the model does not exhibit significant systematic deviations in representing the relationship between the independent variables and the isentropic efficiency of the turbine.

3.2.2 Multicollinearity test

Table 3. Multicollinearity test result

Independent Variable	Tolerance	VIF	Result
Steam mass flow rate ($\dot{m}$)	0.341	2.934	No Multicollinearity
Steam inlet pressure (P_{in})	0.371	2.692	No Multicollinearity
Steam inlet temperature (T_{in})	0.924	1.083	No Multicollinearity
Condenser pressure (P_{cond})	0.859	1.164	No Multicollinearity

The multicollinearity test is used to determine whether the independent variables in the regression model are highly correlated. The multicollinearity test is performed using the tolerance value and Variance Inflation Factor (VIF) indicators. Table 3 shows that all independent variables have tolerance values above the minimum threshold and VIF values below the critical limit, indicating that there is no excessive linear relationship among the independent variables.

Although the VIF values indicate that no statistically significant multicollinearity exists among the predictor variables, steam inlet pressure and steam inlet temperature remain thermodynamically coupled in saturated steam systems. Both variables are physically governed by saturation characteristics and therefore cannot be considered completely independent from a thermodynamic perspective. Thus, the statistical result indicates coefficient stability rather than complete physical independence.

3.2.3 Heteroscedasticity test

Table 4. Heteroscedasticity test result

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-4.095	16.638		-.246	.806
	m uap (kg/s)	.006	.012	.084	.521	.603
	p uap (bar)	.004	1.309	.000	.003	.998
	t uap (°C)	.022	.087	.025	.256	.799
	p kondensor (bar)	6.756	18.033	.038	.375	.709

a. Dependent Variable: ABS_RES

The Glejser test in Table 4 shows that all independent variables are not significant at the 0.05 level for the absolute residuals. The results imply that the model satisfies the homoscedasticity assumption, since the residual variance appears relatively constant across all predictor values. A constant residual variance indicates that the model is not biased toward certain predictor values.

3.2.4 Autocorrelation test

The obtained Durbin–Watson value in Table 5 falls within the inconclusive region as shown in Fig. 3, so it cannot be directly concluded whether there is autocorrelation or not. Considering the data is of an operational time series nature, a further test using the runs test was conducted to examine the randomness of the residuals. The results of the runs test in Table 6 showed a significance value greater than 0.05, indicating that the residuals are random. Thus, the regression model is not affected by significant autocorrelation between observation periods. This condition strengthens the validity of the model in representing the relationships between variables.

Table 5. Durbin-watson value

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.662	0.438	0.418	1.10559306	1.656

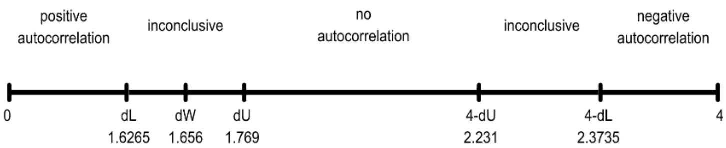

Fig. 3. Durbin-watson test

Table 6. Runs test result

	Unstandardized Residual
Test Value[a]	.00352
Cases < Test Value	58
Cases >= Test Value	58
Total Cases	116
Number of Runs	52
Z	-1.306
Asymp. Sig. (2-tailed)	.192

a. Median

3.3 Multiple linear regression model

Table 7. Multiple linear regression result

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta
1	(Constant)	155.184	26.415	
	m uap (kg/s)	-0.011	0.019	-0.07
	p uap (bar)	-6.145	2.079	-0.345
	t uap (°C)	-0.367	0.138	-0.196
	p kondensor (bar)	168.789	28.63	0.453

a. Dependent Variable: efisensi isentropik (%)

As shown in Table 7, the multiple linear regression analysis produces an empirical model that represents the relationship between operational parameters and the turbine's isentropic efficiency. The obtained model is shown in Equation (5) below:

$$\eta_{is} = 155{,}184 - 0{,}011\dot{m} - 6{,}145P_{in} - 0{,}367T_{in} + 168{,}789P_{cond} \tag{5}$$

where η_{is} is the isentropic efficiency of the turbine (%), $\dot{m}$ is the mass flow rate of steam (kg/s), P_{in} is the steam inlet pressure (bar), T_{in} is the steam inlet temperature (°C), and P_{cond} is the condenser pressure (bar).

The regression coefficient indicates the direction of the relationship between turbine operational variables and isentropic efficiency. The negative coefficients for steam pressure and steam temperature indicate that, under certain operating conditions, increases in these parameters can be followed by decreases in turbine efficiency. This phenomenon can occur if the increase in inlet conditions is not fully reflected in an improvement in steam expansion quality, due to irreversibility losses in the turbine system. Meanwhile, the relatively large positive coefficient for condenser pressure indicates that this parameter is highly sensitive to changes in turbine efficiency in the generated model.

3.4 Hypothesis test

3.4.1 F-test

Table 8. F-test result

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	105.841	4	26.460	21.647	.000[b]
	Residual	135.679	111	1.222		
	Total	241.520	115			

a. Dependent Variable: efisensi isentropik (%)

b. Predictors: (Constant), p kondensor (bar), t uap (°C), p uap (bar), m uap (kg/s)

The F-test is used to assess the joint effect of independent variables on the turbine's isentropic efficiency. The analysis results in Table 8 show that the calculated F value is 21.647, with a significance level of $p < 0.001$. A significance value of less than 0.05 indicates that, simultaneously, the variables of steam mass flow rate, steam pressure, steam temperature, and condenser pressure have a significant influence on the turbine's isentropic efficiency. This indicates that the overall variation in turbine operating parameters contributes to determining the thermodynamic performance of the steam turbine. Physically, the turbine's operating conditions are indeed strongly influenced by pressure, temperature, and condenser vacuum, which determine the magnitude of enthalpy reduction during the steam expansion process.

3.4.2 Partial test

Table 9. t-test result

Model		t	Sig.
1	(Constant)	5.875	0
	m uap (kg/s)	-0.577	0.565
	p uap (bar)	-2.956	0.004
	t uap (°C)	-2.65	0.009
	p kondensor (bar)	5.895	0

a. Dependent Variable: efisensi isentropik (%)

Partial analysis was conducted to determine the contribution of each independent variable to turbine efficiency. The results in Table 9 show that inlet steam pressure significantly affects turbine efficiency, with a significance value of 0.004. The negative regression coefficient indicates that higher inlet pressure under actual operating conditions tends to reduce efficiency when the expansion process is not optimal. Inlet steam temperature also has a statistically significant effect, as indicated by a p-value of 0.009. This finding suggests that changes in steam temperature influence the thermodynamic properties of the steam and affect turbine expansion.

In contrast, the steam mass flow rate does not have a significant effect on turbine efficiency (p-value = 0.565). These results indicate that variations in mass flow rate within the observed operating range insignificantly affect efficiency. Across all variables, condenser pressure has the greatest influence on turbine efficiency, with a p-value of $p < 0.001$ and the largest regression coefficient. These findings identify condenser pressure as the most dominant operational parameter influencing turbine performance. Thermodynamically, lower condenser pressure increases the available enthalpy drop during expansion, which ultimately results in higher turbine efficiency.

3.4.3 Coefficient of determination

Table 10. Coefficient of determination result

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.662	0.438	0.418	1.10559306

According to the analysis results shown in Table 10, the coefficient of determination (R^2) was found to be 0.438, indicating that 43.8% of the variation in isentropic efficiency can be explained by the variables steam mass flow rate ($\dot{m}$), steam inlet pressure (P_{in}), steam inlet temperature (T_{in}), and condenser pressure (P_{cond}). Meanwhile, the adjusted R^2 value of 0.418 indicates that after accounting for the number of variables in the model, the model's explanatory power remains at a relatively consistent level.

The coefficient of determination value in the moderate category indicates that the developed regression model is not yet fully capable of representing the complexity of the steam turbine system in geothermal power plants. This is reasonable considering that turbine performance is influenced not only by the primary operating parameters used in the model but also by various other factors not included in the analysis, such as steam quality (dryness fraction), non-condensable gas (NCG) content, equipment condition, and irreversibility phenomena occurring during the expansion process. These factors contribute to variations in efficiency but are not fully captured in the constructed regression model.

In addition, the dynamic nature of geothermal power generation systems, influenced by reservoir conditions, leads to performance variations that cannot be fully explained by a simple linear regression approach. Therefore, the moderate R^2 value in this study does not necessarily indicate a weakness in the model, but rather reflects limitations in variable representation and the complexity of the thermodynamic phenomena in the actual system. Thus, the regression model in this study is more appropriately used as a tool to identify relationships between variables and determine the dominant factors affecting efficiency, rather than as an absolute predictive model that covers all aspects of the system.

Furthermore, the use of Multiple Linear Regression (MLR) introduces an additional limitation, as it primarily captures first-order linear relationships between predictors and responses. Steam expansion processes in geothermal systems may exhibit nonlinear behavior, particularly near saturated and superheated regions where phase transitions occur. Consequently, hidden nonlinear interactions among operational variables may exist and cannot be captured by standard diagnostics such as VIF or linear regression coefficients. The moderate coefficient of determination observed in this study therefore reflects not only the influence of unmeasured operational variables but also the limitations of representing complex thermodynamic processes using a simple linear model.

3.5 Model validation

Regression model validation was performed to evaluate the model's accuracy in predicting turbine isentropic efficiency based on the operational variables used. Based on calculations using the Mean Absolute Percentage Error (MAPE) method, a MAPE value of 0.12% was obtained. This value indicates that the average deviation between the model's predicted results and the actual data is very small, meaning the model has a very high level of accuracy in representing the turbine's operational conditions. To reinforce this evaluation, a visual analysis was conducted using a comparison graph of the actual values and the model's predictions.

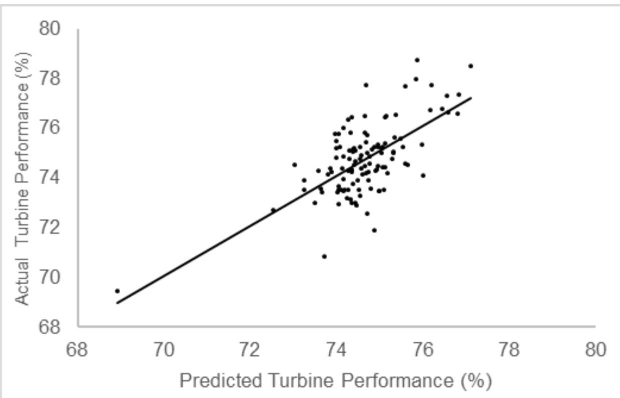

Fig. 4. Comparison of actual and predicted value of turbine isentropic efficiency

As shown in Fig. 4, most data points are distributed around the gradient line, indicating that the model's predicted values closely align with the actual values. The distribution pattern, which generally follows this linear line, indicates that the regression model consistently captures the relationship between the independent variable and isentropic efficiency. Although there are some deviations at certain points, these deviations are relatively small and do not show a systematic pattern, so they can be considered natural variations in the operational data.

The obtained MAPE value of 0.12% indicates a low average relative prediction error within the observed operating range. However, this result should be interpreted with caution, as MAPE and R^2 assess different aspects of model performance. While R^2 represents the proportion of variability explained by the model, MAPE measures average prediction deviation relative to observed values. Because turbine efficiency values fluctuate within a relatively narrow operating range, small prediction deviations may still occur even when substantial variability remains unexplained. Therefore, the low MAPE value should be interpreted as evidence of good in-sample fitting performance rather than as evidence of universal predictive capability.

3.6 Thermodynamic discussion

3.6.1 Condenser pressure

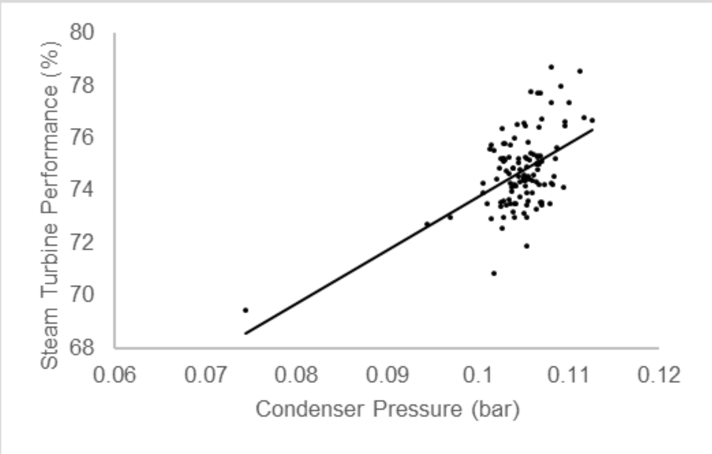

Fig. 5. Relationship between turbine isentropic efficiency and condenser pressure

Condenser pressure is the most dominant variable in the regression model, with a positive coefficient of 168.789, a standardized beta of 0.453, and a significance value of $p < 0.001$. The observed condenser pressure ranges from 0.074 to 0.112 bar, which indicates that the turbine operates within a relatively narrow band around the nominal exhaust condition. Thermodynamically, condenser pressure defines the exhaust boundary condition of the turbine and directly controls the pressure ratio across the expansion process. In an ideal Rankine cycle, lower condenser pressure would normally increase the available enthalpy drop and improve turbine efficiency. However, the operational results in this study indicate that the actual geothermal system does not follow this ideal trend in a simple linear manner.

This behavior can be explained by the actual conditions in geothermal condensers, where non-condensable gases may accumulate and affect vacuum stability. When the condenser pressure is too low, gas accumulation and heat-transfer limitations may reduce condensation effectiveness and increase exhaust-side losses. In that case, a slight increase in condenser pressure may reflect a more stable operating state with better gas-removal performance. Because of this, the positive coefficient should not be interpreted as a violation of thermodynamic theory, but rather as a local response within the observed operating envelope. The result suggests that condenser pressure here functions not only as a thermodynamic variable, but also as an integrated indicator of condenser health and exhaust-side irreversibility. This is why condenser pressure emerges as the dominant predictor of turbine efficiency in the model.

3.6.2 Steam inlet pressure

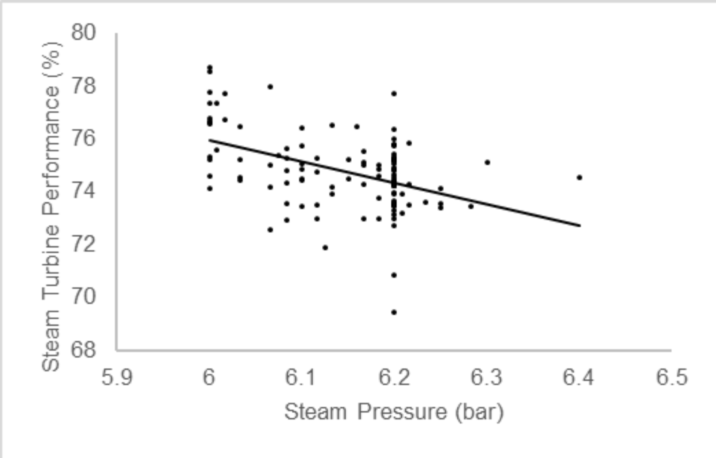

Fig. 6. Relationship between turbine isentropic efficiency and steam inlet pressure

Steam inlet pressure shows a significant negative effect on turbine isentropic efficiency, with a coefficient of -6.145, a standardized beta of -0.345, and $p = 0.004$. The observed pressure range is 6.00 to 6.40 bar, which remains relatively close to the turbine's design condition. This means the regression coefficient should be understood as a marginal effect around the design point rather than a broad operating trend. Thermodynamically, inlet pressure directly influences the pressure ratio and available expansion energy across the turbine stages. Therefore, variations in steam pressure can potentially affect the conversion process occurring within the turbine.

From a theoretical perspective, increasing inlet pressure generally increases the available expansion work and improves turbine performance. However, the operational data analyzed in this study indicate an opposite tendency within the observed operating range. This difference may be explained by considering actual turbine operation under off-design conditions. Steam turbines are designed to achieve optimum performance at specific operating parameters, and deviations from these conditions may introduce additional aerodynamic losses. Consequently, an increase in pressure may not necessarily lead to a proportional increase in energy conversion efficiency.

Another possible explanation is changes in the steam characteristics entering the turbine. Variations in steam pressure may alter upstream steam separation behavior and, in turn, affect the steam quality entering the turbine. Increased moisture content may increase flow disturbances and generate additional irreversibility during the expansion process, which directly increases erosion and turbulence losses on the turbine blades. According to the Baumann relation, increasing moisture content reduces turbine efficiency because part of the available energy is dissipated through wet-steam losses. Therefore, the negative coefficient observed in this study likely reflects the combined influence of pressure variation and unaccounted-for thermodynamic effects.

3.6.3 Steam inlet temperature

Steam inlet temperature also shows a significant negative effect on turbine isentropic efficiency with a coefficient of -0.367, a standardized beta of -0.196, and $p = 0.009$. The observed temperature varies between 160 and 165°C, indicating that the operating condition remains relatively close to the saturated steam region. This narrow range suggests that the coefficient from the regression model reflects local variations in steam properties rather than substantial temperature changes, as in superheated steam systems. Thermodynamically, the inlet temperature influences the steam enthalpy and the state of steam entering the turbine stages. Consequently, temperature variations may influence the expansion behavior and turbine performance.

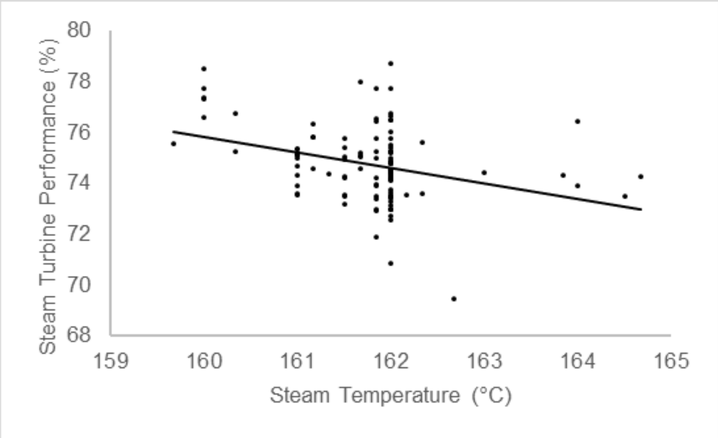

Fig. 7. Relationship between turbine isentropic efficiency and steam inlet pressure

In conventional steam power systems, increasing the inlet temperature often improves turbine performance by increasing the available thermal energy. However, geothermal steam systems generally operate near saturated conditions, where the relationship between temperature and performance becomes more complex. Small temperature variations near the saturation boundary can produce noticeable changes in steam properties, such as density, specific volume, and moisture content. These changes may alter the expansion path inside the turbine and shift operating conditions away from the intended design state. Therefore, a temperature increase does not necessarily correspond to improved turbine efficiency in actual geothermal applications.

Another important aspect is that temperature in geothermal systems is strongly coupled with pressure and steam quality. Therefore, temperature changes may indirectly reflect variations in other thermodynamic parameters not explicitly included in the present model. Such interactions may increase entropy generation and reduce the effectiveness of energy conversion. Consequently, the observed negative coefficient should not be interpreted as a general statement that higher temperatures always reduce turbine efficiency. Instead, the result likely reflects local operating behavior associated with deviations from the optimum steam condition.

3.6.4 Steam mass flow rate

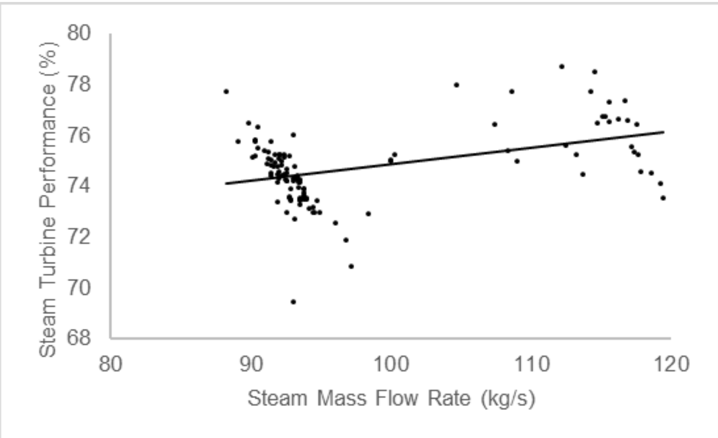

Fig. 8. Relationship between turbine isentropic efficiency and steam mass flow rate

Steam mass flow rate does not show a statistically significant influence on turbine isentropic efficiency, with a coefficient of -0.011, a standardized beta of -0.070, and p = 0.565. This indicates that, within the operating range observed in this study, changes in flow rate were insufficient to produce a measurable direct effect on efficiency. This finding is thermodynamically understandable because the isentropic efficiency of a turbine is conceptually the ratio of actual work to isentropic work, which is intensive and independent of the magnitude and mass flow rate as long as the turbine operates within the specified design flow range. This helps explain why the statistical effect of steam flow is weak compared with pressure and temperature.

The insignificance of mass flow rate also suggests that the turbine performance is more sensitive to boundary state conditions than to the amount of steam passing through the machine. In other words, the thermal quality of the steam and the exhaust condition appear to matter more than flow magnitude alone. The observed flow variation may still affect output capacity, but it does not necessarily disturb the ratio between actual and ideal work to a large extent. This implies that flow rate in this study functions more as a supporting operational variable than as the main thermodynamic driver. It also strengthens the interpretation that the dominant losses arise from inlet and exhaust state deviations rather than from steam quantity. Therefore, the regression result is consistent with the intensive nature of turbine isentropic efficiency.

4 Conclusion

This study evaluates the thermodynamic performance of the steam turbine at Kamojang Geothermal Power Plant Unit X using a multiple linear regression model based on operational data. Based on the results obtained, several conclusions can be drawn:

1. The developed regression model adequately represents turbine performance within the observed operating range. The model passed the classical assumption tests and produced a coefficient of determination (R^2 = 0.438), indicating that the selected variables explain a moderate portion of the efficiency variation. The low prediction error (MAPE = 0.12%) shows that the model closely follows the observed operational data.
2. Operational parameters influence turbine efficiency differently. Statistical analysis shows that condenser pressure, inlet steam pressure, and inlet steam temperature significantly affect turbine isentropic efficiency, whereas steam mass flow rate does not. Among these variables, condenser pressure has the strongest influence.
3. The thermodynamic interpretation indicates the presence of off-design effects. Local deviations from the turbine design point may introduce additional irreversibility during steam expansion, affecting efficiency performance.
4. The developed model provides practical operational value. Maintaining stable condenser performance and consistent inlet steam conditions is important for reducing efficiency losses. The model can support performance monitoring and early detection of operational deviations.

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