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Maximizing Steam Turbine Efficiency in Coal Fired Power Plant Through Artificial Intelligence-Based Digital Turbine Optimization (D-TOP)

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***Abstract*— Optimizing steam turbine operating parameters is crucial for improving the performance of coal-fired power plants, as even minor adjustments can significantly impact the net plant heat rate. However, manual parameter optimization becomes ineffective due to the intricate nature of the steam turbine system and the complex interactions among various operating patterns. An artificial intelligence-based Digital Turbine Optimization (D-TOP) application will determine the best operating parameters to address this challenge. D-TOP involves the analysis of turbine operational data, functional simulation, integration of PI communication with Python, and an artificial intelligence program model, incorporating fuzzy logic for root cause analysis of heat rate discrepancies. Utilizing D-TOP, optimal values for controllable operating parameters, including steam pressure, temperature, water heater level, and others, are provided in real-time at each alteration in electricity production and fuel usage, ensuring the most efficient turbine heat rate. Consequently, D-TOP significantly reduced the turbine heat rate to 79 kcal/kWh, equivalent to a commendable net plant heat rate of 36.55 kcal/kWh, resulting in remarkable energy cost savings of $1,392,552.47 annually. These substantial energy savings correspond to a reduction of 0.0208 cents/kWh and a notable decrease in carbon emissions by an average of 298,14 tons of $CO2eq$.**

Keywords— Steam turbine, Turbine system optimization, Coal-fired power plant, Net plant heat rate, Operating parameters, Fuzzy logic, Carbon emissions, Energy efficiency

I. INTRODUCTION (*HEADING 1*)

The turbine system in a Coal Fired Steam Power Plant comprises several main subsystems: a steam turbine responsible for converting thermal energy into mechanical energy, a feed water heater utilized to elevate the feed water temperature, and a condenser that transforms steam back into water. During operation, various controllable parameters, such as water and steam pressure, temperature, flow and level, are essential for optimising the heat rate. The optimisation of these operating parameters is crucial to enhance the turbine system's performance, as even minor adjustments can significantly impact the heat rate. However, the existing turbine operation method is done without any guidance to optimise its performance, so it will require substantial time, effort and differences in operating pattern. For example, the main steam pressure operating pattern at 330 MW is illustrated in Figure 1, where each team implements different main steam pressure operating patterns ranging from 13.7 to 16 MPa, leading to variations in the heat rate. This is also evident from the main steam operating capability curve shown in Figure 2, indicating Cpk << Cp, which implies high operating variation deviating from the baseline constraints.

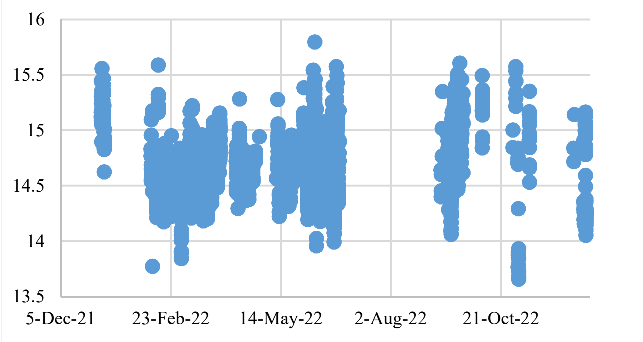


Fig. 1. Main steam pressure operating pattern

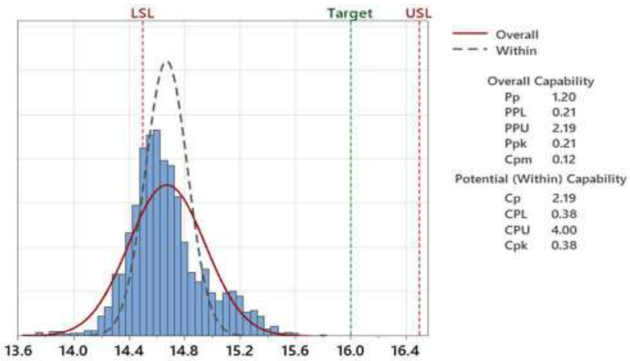


Fig. 2. Main steam pressure capability curve

A fishbone diagram in Figure 3 illustrates several losses that influence the turbine's performance. Among them, the main causes of losses within the turbine system are attributed to the Methods aspect, namely non-uniform operation patterns between teams, the absence of a baseline operation, and the lack of routine and real-time operational monitoring.moisture reaches> 35%wt. According to this problem, it needs a method to set the fuel and combustion for optimum conditions.

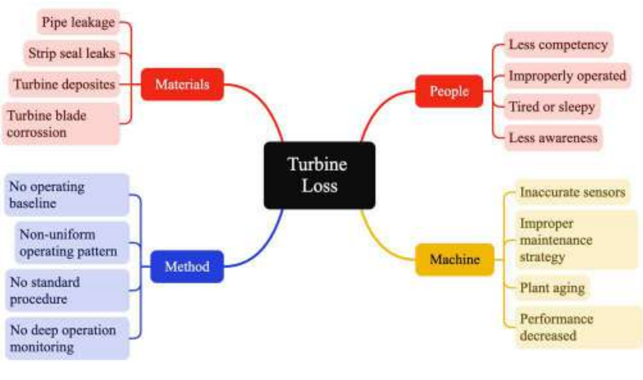


Fig. 3. Turbine losses fishbone diagram

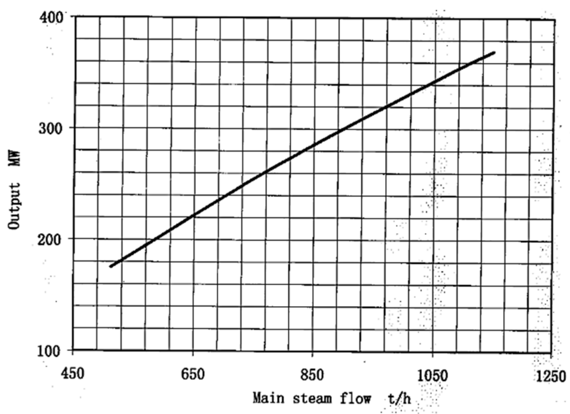
To tackle these challenges, implementing artificial intelligence (AI) can prove beneficial in optimizing the turbine system's operating parameters. Using AI, the turbine system can autonomously learn and identify optimal solutions based on historical data. Consequently, the operating parameters can be automatically adjusted and continually refined to achieve maximum efficiency.

II. Methodology

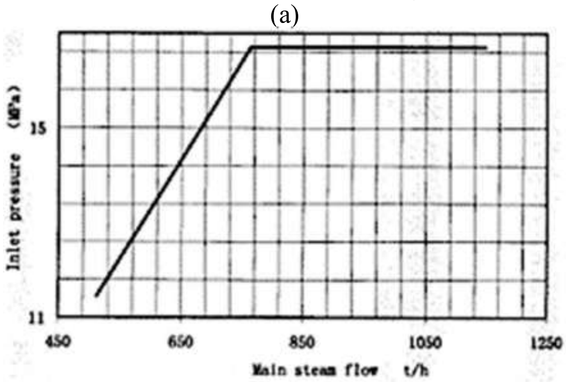
The development of D-TOP involves five main stages, namely: (1) Identification of Operating Patterns on Turbine System Performance, (2) Experiment Design and Simulation, (3) Dashboard Setup and PI System communication, (4) Creating an Artificial Intelligent Program Model Using Python, and (5) data validation.

A. *Identification of Operating Patterns on Turbine System Performance*

The objective of identifying the operating parameter patterns' impact is to objectively assess the consistency of the turbine operation process and acquire essential information to enhance process quality. This improvement aims to improve efficiency and productivity and minimize unnecessary production costs within the operation process.



(a)



(b)

Fig. 4. (a) Load output curve against the main steam flow (b) Operating parameter curve of sliding pressure against the main steam flow

For instance, the main steam pressure operation follows the semi-fix-sliding method, as depicted in Figure 5. However, during actual process at a load of 300 MW, determining the main steam pressure tends to vary among different teams, as illustrated in Figure 5.

The main steam pressure tends to be higher when a lower Specific Fuel Consumption (SFC) or higher-quality coal is used. Nevertheless, at the same SFC, the main steam pressure (MSP) exhibits distinct values with a gap of up to 1.5 MPa.

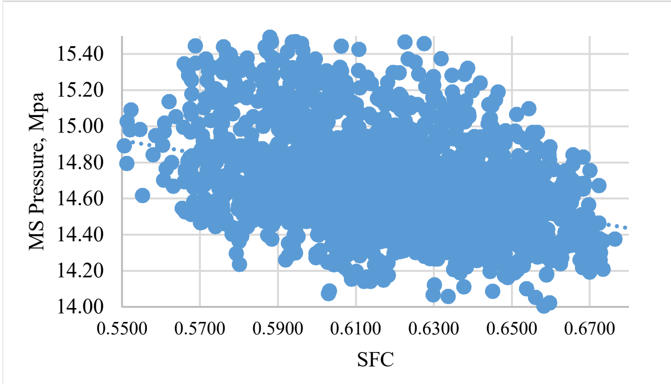


Fig.5. Main steam pressure operating pattern at 300 MW

Addressing this issue can improve the heat rate, as per theoretical expectations that a higher main steam pressure would result in a lower heat rate, given the appropriate limits and combination with the main steam temperature.

B. *Design Experiment and Simulation*

To simulate the improvement process, a series of tests are conducted by varying several turbine operating parameters (controllable factors) to assess their impact on performance. As an illustration of the design of experiments and simulations in high-pressure turbines, certain variables, such as pressure and temperature, are manipulated to observe their effects on isentropic efficiency and heat rate.

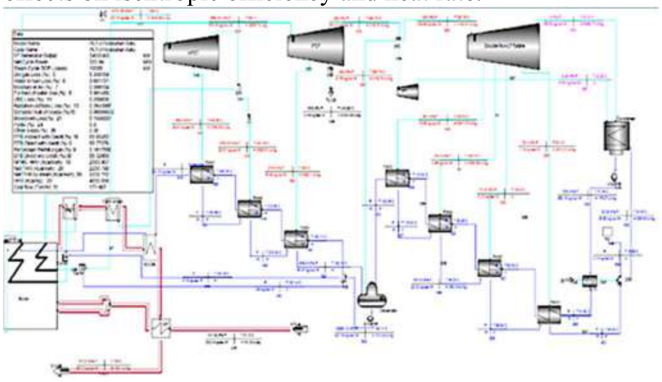


Fig.6. Turbine operation simulation using GateCycle

Due to the impracticality of actual testing on the generating unit with these parameter variations, a heat balance simulation is performed using a Gate Cycle, which follows the current unit conditions, as depicted in Figure 6. This simulation yields a combined relationship of the high-pressure turbine's parameters, as shown in Figure 7.

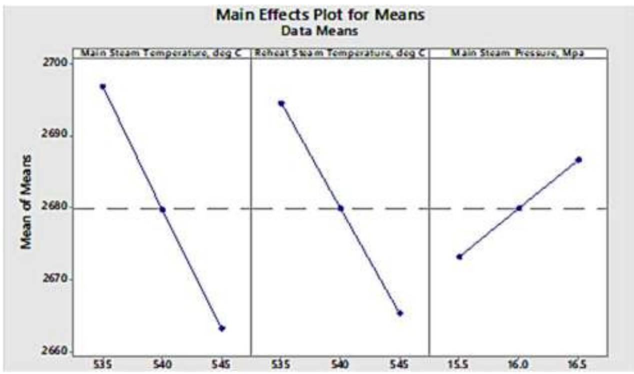


Fig.7. Effect of main steam operation on the heat rate

Since a lower heat rate indicates better performance, Figure 8 serves as the basis for identifying the optimal operating parameters to be applied at a 350 MW load on the high-pressure turbine. The optimal parameters include a main steam pressure of 15.5 MPa, main steam temperature of 545 °C, and reheat steam temperature of 545 °C, resulting in a low heat rate of 2643 kcal/kWh. Additionally, controllable parameters related to the feed water heater, condenser, and others are optimized to maximize energy savings during the process.

C. *Dashboard Setup and PI System communication*

To facilitate the monitoring and control process by the unit operations team, the subsequent step involves creating a dashboard on PI Vision as depicted in Figure 8.

Fig.8. D-TOP dashboard

The displayed operating parameters on the dashboard will automatically adjust in response to changes in load (MW) and variations in fuel quality (cofiring) indicated by SFC in kg/kWh. Whenever the actual values of the operating parameters deviate from the recommended values, D-TOP will indicate this with a red indicator, while green and yellow indicators will be shown if the parameters follow or fall within the tolerance limits.

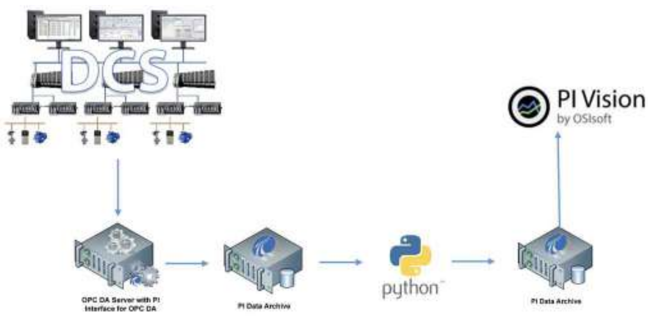


Fig.9. D-TOP flow communication

The flow of communication and data transmission within D-TOP is illustrated in Figure 9. Generally, Integrating PI communication with Python to a Distributed Control System (DCS) involves connecting Python to the PI System, retrieving and processing data, connecting to the DCS, potentially sending commands, and implementing error handling and security measures. Thorough testing, documentation, and ongoing monitoring are essential for a successful integration.

For example, as the sensors read, data from the turbine system, including pressure, temperature, flow rate, and level, is transmitted to the Distributed Control System (DCS). Subsequently, the data present in the DCS is sent to the PI Server (PI Data Archive) via the PI Interface. The selected and necessary data for optimization calculations are then retrieved into Python. Within Python, machine learning calculations, specifically multiple linear regression, are performed. The calculation results are subsequently returned to the PI Server and stored as tags for visual display on the PI Vision dashboard.

D. *Artificial Intelligent Program Model Using Python*

The D-TOP programming model algorithm is done by multiple linear regression using Python. This AI technique optimizes processes and controls variables (such as temperature, pressure, and flow rates) and turbine efficiency or performance, exemplifying the programming stages for main steam pressure optimization in Figure 10.

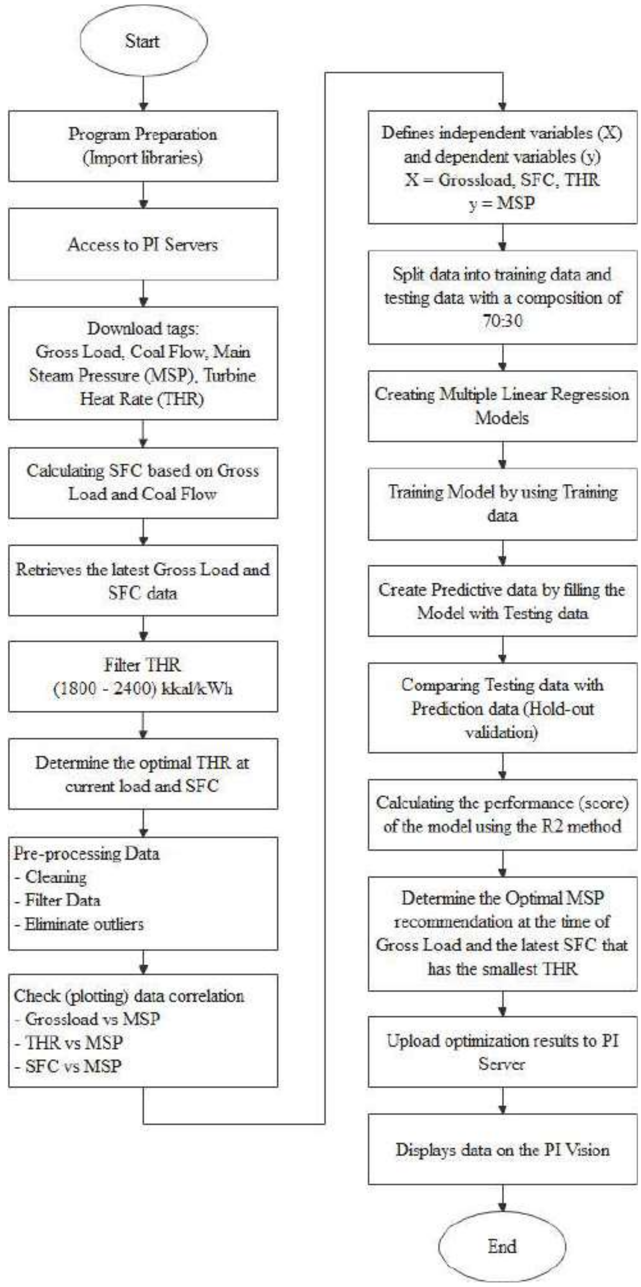


Fig.10. Programming flowchart

The stages are: (1) Importing the required libraries for optimization calculations, including pandas, numpy, matplotlib, seaborn, urllib3, time, OSIsoft, and sklearn. (2) PI Server access to retrieve data and send data to and from the PI Server. It needs to access the webapi with a registered username and password. (3) The tags taken are Gross Load, Coal Flow, Main Steam Pressure, and Turbine Heat Rate. Data was taken from the past 15 days at 5 minutes intervals. (4) Performing SFC calculations using Coal Flow and Gross Load data. (5) Retrieving the latest load and SFC data to determine the optimal MSP concerning the Turbine Heat Rate (THR). (6) Filter THR data to get the most optimal THR in the 1800 – 2400 kcal/kWh range. (7) Determining the optimal turbine heat rate at the current load and SFC based on past data. (8) Pre-processing Data (Cleaning Data, Filtering Data, Eliminating Outliers), where cleaning is used to delete non-integer and non-float data, so the data displayed is only integer and float data. Filtering determines the data range for each parameter used in optimization. Where Gross load (5 – 350 MW), SFC (0.45 – 0.8 kg/kWh), Main Steam Pressure (0 – 16.5 Mpa), Turbine Heat Rate (1600 – 2400 kcal/kWh). Removing outliers removes data whose value is quite far from the average data downloaded from the PI Server. Determination of outliers data based on the Inter Quartile Range (IQR) with the following formula:

$$IQR = Q3 - Q1 \tag{1}$$

$$\text{Lower limit} = Q1 - (1.5 * IQR) \tag{2}$$

$$\text{Upper limit} = Q3 + (1.5 * IQR) \tag{3}$$

Data smaller than the lower limit and larger than the upper limit will be discarded. (9) Checking data correlation between Gross Load and Main Steam Pressure (MSP), SFC with MSP, THR with MSP. (10) Defining the independent (X) and dependent (y) variables, where: X = Grossload, SFC, THR and y = MSP. (11) Split data into training and testing data with a composition of 70:30. (12) Create a machine learning model using Multiple Linear Regression where X = Main Steam Pressure and Y = Grossload, SFC, and Turbine Heat Rate. (13) Perform Model Training using Training data. (14) Create Predictive data by filling in the Model that has been made with Testing data. (15) Comparing Testing data with Prediction data (Hold-out validation). (16) Calculating the performance (score) of the Model using the R2 method. (17) Determines the most optimal MSP recommendation at the latest Gross Load and SFC that has the smallest THR, illustrated by the algorithm in Figure 11.

```
# MSP Optimal berdasarkan Load dan SFC saat ini dan THR optimal

predictedMSP = model_reg_MSP.predict([[Current_Load, Current_SFC, Optimal_THR]]) #Optimal_THR
print(predictedMSP)
```

Fig.11. Main steam pressure optimization algorithm.

(18) The Python optimization result data is subsequently transmitted to the PI Server and visualized on the PI Vision dashboard alongside the optimization of other operating parameters.

E. Parameter Validation

The method utilized to validate the optimization results from D-TOP is the hold-out validation method, where the dataset obtained from PI is divided into two groups: training data and test data, with a proportion of 70% and 30%, respectively. The training data is utilized for training the Machine Learning (Multiple Linear Regression) models, while the test data is employed to evaluate the Model's performance. First, the Multiple Linear Regression models are trained using the train data to learn the relationships between the input features and the target variable. This allows them to make accurate predictions on new, unseen data.

```
# Menghitung nilai R2
from sklearn.metrics import r2_score
R2 = r2_score(y_test,y_pred)
print("Nilai R2: ", R2)
```

```
Nilai R2:  0.8571470063708233
```

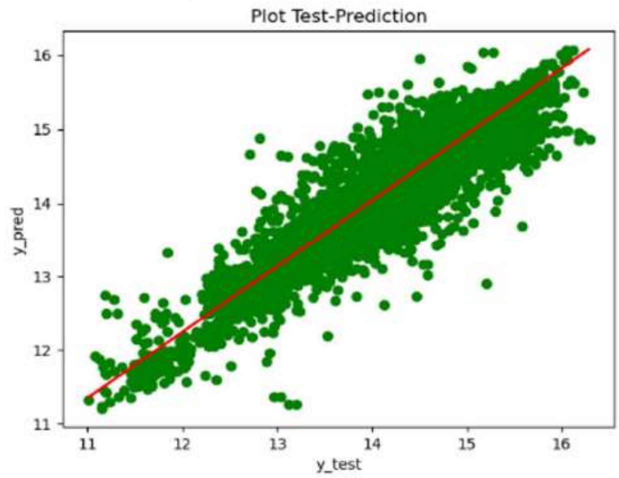


Fig.12. Parameter validation.

Subsequently, the trained Model is used to predict the test data. The prediction results are then compared with the test data, which represents the real data, to validate and evaluate the accuracy of the developed Model. The linear regression model is evaluated using the coefficient of determination (R2). The coefficient of determination (R2) measures how well the regression line matches the actual data, indicating the goodness of fit. R2 quantifies the percentage of the total variance of the dependent variable Y that can be explained by the independent variable in the regression line. The value of R2 falls within the interval of 0 and 1 (0 < R2 < 1), as illustrated in Figure 11. The closer the value of R2 to 1, the better the results. Conversely, if R2 is closer to 0, it suggests that the independent variable cannot adequately explain the variation in the dependent variable.

F. Heat Rate Cause Analysis

D-TOP has been equipped with a root cause analysis based on fuzzy logic as the first course of action when encountering issues, as depicted in Figure 13.

Fig.13. Dashboard for heat rate root caused

The root cause heat rate dashboard is presented in the form of a matrix, facilitating the identification of the source of the cause whenever a red heat loss mode appears. The calculations for both turbine system performance and heat rate loss mode adhere to ASME PTC standards, best practices from EPRI, and the expertise of certified employees.

The function of this feature is: (1) Data collection includes sensor readings, system parameters, and historical data. (2) Fuzzy Logic Modeling that represents the relationships between input variables (data) and potential root causes. (3) Fuzzy Interference to determine the likelihood of each root cause. (4) Aggregation and Defuzzification to determine the overall likelihood or degree of certainty of each potential root cause. (5) Root Cause Identification to select the root cause(s) with the highest likelihood based on the fuzzy inference results. (6) Implement a feedback loop to continuously collect and analyze data, update the fuzzy logic model, and improve the accuracy of root cause analysis over time.

III. RESULTS AND DISCUSSION

A. *Heat Rate Impact and Benefit*

The energy performance indicator used to evaluate the success of this innovation is the Turbine Heat Rate (THR), which measures the amount of heat required by the turbine to generate electricity (kcal/kWh).

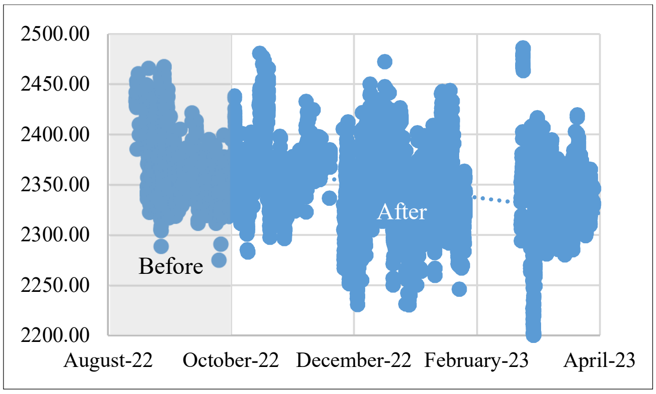


Fig.14. Turbine heat rate impact

TABLE 2. BENEFIT CALCULATION

Total Project Time	1 year
Total manpower	Five people
Energy Performance Improvement Period	One year
Fuel Cost	347 cents/kg
Calorific Value	4400 kcal/kg
Energy saving due to decreasing turbine heat rate	36,5 kcal/kwh
Fuel consumption saving	2,95 ton/hour
Fuel cost saving	$1,392,552.47
Manpower costs three people @ $ 928.57	$2,785.71
Additional devices, tools, or software	$0
The total benefit over the improvement period	$1,392,552.47
Decreasing the cost of Electricity Generation Cost (Fuel Component)	0.0208 cents/kWh
The payback period on implementation (years)	0,032

Following the implementation of D-TOP, as illustrated in Figure 14 and calculated in Table 1, there was an average reduction in turbine heat rate by 79 kcal/kWh or a decrease in net plant heat rate of 36.5 kcal/kWh. This translates to an annual cost savings of $1,392,552.47 and a 0.0208/kWh reduction in the Electricity Generation Cost (Fuel Component). These savings positively impact the economy of the community and the country, especially in the efforts to recover from the effects of the COVID-19 pandemic.

B. *Influence on Society and the State*

Through the enhancement of turbine system performance and the subsequent reduction of the Electricity Generation Cost (Fuel Component) by 0.0208 cents/kWh, this improvement has significantly contributed to the government's initiative to lower the electricity price for the community up to 2.96 cents/kWh.

TABLE 2. ELECTRICITY PRICE

No	Coal Fired Power Plant	Price, cent/kg	Calorific Value, kcal/kg	Inc Cost, cent/kwh
1	Tanjungjati 3-4	224	5.479	80
2	Tanjungjati 1-2	221	5.501	82
3	Tanjung Awar	191	4.442	84
4	Banten	179	4.200	84
5	Cilacap 4	172	4.205	85
6	Jawa 4 (2 Unit)	202	4.939	85
7	Jawa 7	184	4.145	88
8	Suralaya 5-7	206	4.711	88
9	Jawa Power	206	5.000	90
10	PEC 3	211	5.000	90
11	**Pelabuhan Ratu**	**202**	**4.824**	**90**
12	Paiton 9	172	4.097	90
13	Jawa Tengah	204	4.500	91
14	Adipala	196	4.063	94
15	Cilacap 3	181	4.200	94
16	Paiton	180	4.259	95
17	Jawa 1	204	4.500	95

As shown in Table 2. According to the annual report organized by Indonesia state-owned energy utility PT PLN (Persero), Pelabuhan Ratu Coal Fired Power Plant remains ranked 11th among the Java-Bali Power Generation. It is worth noting that despite competing with power plants boasting a capacity of over 600 MW and equipped with supercritical technology, the advancements in the turbine system have allowed Pelabuhan Ratu to maintain its competitive position.

C. *Influence on the Environment*

The impact indicators of D-TOP are calculated from air pollution indicators, like CO_2, SO_x, and NO_x. Based on the equation to calculate emission reductions CO_2 namely $ECO_2 = \sum F\, x A_c CCxOFxMWCO_2 xANC$, where $\sum F$ =Coal reduction; $A_c CC =$ Actual carbon content (57 ton C/kton); $OF =$ Oxidation factor (0,987); $MWCO_2$=Molecular weight CO_2 (44); ANC= Atomic weight of C (12), obtained the trend of reducing tons of CO_2eq from D-TOP, shown in Figure 15. The average reduction of CO_2 is 298,14 tons of CO_2eq.

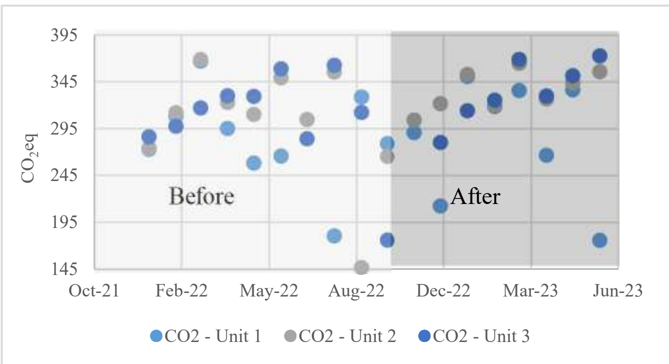
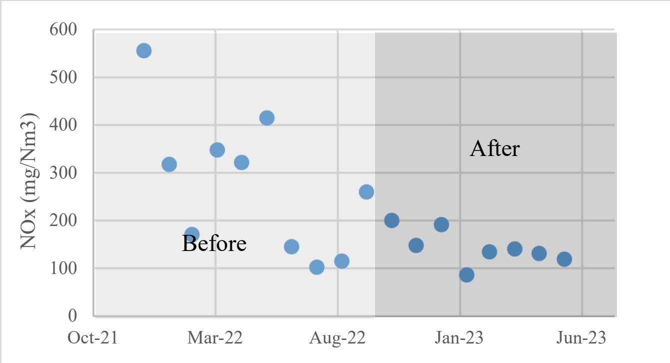
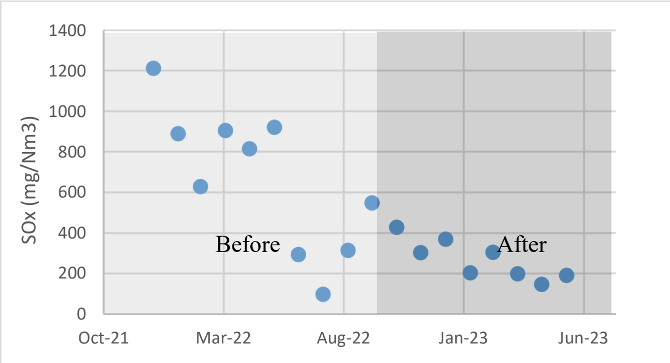


Fig.15. Reduction of tons CO_2eq eq at Pelabuhan Ratu CFPP.



(a)



(b)

Fig.15. a) Trend of NO_x, (b) Trend of SO_x

While the trend of ton greenhouse gas after the improvement is shown in Figure 16. Where the average of NO_x Reduce up to 170 mg/Nm3 and SO_x up to 250 mg/Nm3. These values indicate a significant improvement compared to the standards set by The Indonesian Ministry of Environment and Forestry, which requires NO_x and SO_x level to be maintained below 550 mg/Nm3.

IV. Conclusion

Digital Turbine Optimization (D-TOP) is an innovative application that harnesses artificial intelligence to optimize steam turbine operating parameters in coal-fired power plants. By employing advanced data analysis, simulation techniques, and real-time monitoring, D-TOP achieves a remarkable reduction of 79 kcal/kWh in the turbine heat rate. This significant improvement translates to substantial energy cost savings, amounting to $1,392,552.47 annually while achieving an impressive net plant heat rate of 36.55 kcal/kWh. Beyond its economic benefits, D-TOP contributes to environmental preservation by reducing carbon emissions by an average of 298.14 tons of CO2 equivalent. This demonstrates the application's vital role in promoting sustainable power generation and supporting global efforts to combat climate change.

The successful implementation of D-TOP showcases its importance in enhancing power plant performance and highlights the potential of artificial intelligence in revolutionizing energy optimization processes. As a cost-effective and environmentally friendly solution, D-TOP paves the way for a more efficient and greener future for the energy sector.

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