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Energy Performance Monitoring Framework for Dual-Shaft Gas Turbine-Driven Gas Compressors in Processing Plants

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Abstract

The paper presents a novel methodological framework for monitoring the energy performance of dual-shaft gas turbines-driven centrifugal compressors in gas processing plants. The framework specifically addresses the complexities and challenges associated with gas compressor operation. To achieve this, a comprehensive performance analysis was conducted using real industrial data obtained from five gas processing plants located in different regions and collected at various time intervals. The Cumulative Sum of Difference Analysis technique was utilized to identify deviations in energy consumption levels, effectively highlighting significant deviations from the expected data. Furthermore, a sensitivity analysis was performed to identify and analyze the key factors that impact energy consumption, including process gas temperature, pressure, efficiencies, gas composition, fuel gas quality, load factor, aging, and ambient conditions. A regression analysis was carried out to identify significant predictor variables that accurately represent the compressor's performance, and a steady-state simulation model was developed for a commonly employed compressor package. The resulting regression equation was validated through comparisons with both simulated and actual data. The results demonstrate that the regression equation provides a robust representation of the actual data, closely matching it. The cumulative sum of difference between the actual and regression equation was found to be 1.81 MMSCFD based on a dataset comprising 60 measurements, indicating a relatively small deviation. Moreover, the CUSUM between the actual and the simulation results was 9.06 MMSCFD..

Keywords: *Gas compressors; Gas turbines; Gas processing plant; Energy performance monitoring; Regression analysis.*

1. Introduction

Gas compressors play a vital role in gas processing plants, but their energy consumption poses challenges in terms of efficiency and sustainability [1]. Over the past decade, a significant innovation has been the shift from fixed-speed drivers to variable-speed dual-shaft gas turbines and variable-speed electrical drives [2]. This transition to variable-speed driven compressors has expanded the operating range and flexibility, resulting in improved efficiency. However, it has also introduced complexities in controlling compression stations [3].

Optimizing the operation of gas compressors can further reduce the overall energy consumption, thereby impacting the operational and maintenance costs of gas processing plants [4]. Although advanced optimization techniques show promise, their implementation is hindered by the lack of accurate information on the performance map of individual compressors, which is crucial for system optimization [5]. The performance map of a compressor can undergo significant changes due to external and unknown factors. Therefore, for effective compressor system optimization, it is essential to have an efficiency model that is continuously monitored and updated with accurate parameters [6].

In general, the compressor map, which shows the relationship between head and flow at different speeds, and the performance map, which indicates efficiency at various operating points, are only tested periodically to minimize downtime and associated economic losses. Unfortunately, these tests are often limited in scope, resulting in incomplete or unreliable information regarding the compressor and performance maps. This lack of accurate information poses a significant challenge when it comes to optimizing the energy performance of gas compressors [7-8].

Given the importance of energy efficiency in gas processing plants, there is a pressing need for a methodological framework that enables comprehensive energy performance monitoring of gas compressors driven by dual-shaft gas turbines. Such a framework would facilitate the accurate measurement, analysis, and evaluation of energy efficiency, thereby allowing for the identification of areas for improvement and the implementation of targeted energy optimization measures. This research paper aims to address this gap by proposing a robust methodological framework for energy performance monitoring [9-12].

This paper draws upon a range of existing research contributions to achieve its goals. Cortinovis *et al.* propose an online adaptation method using a Kalman filter to improve the accuracy of performance maps for centrifugal gas compressors [7], while Hanachi *et al.* employ a physics-based modeling approach to monitor gas turbine engine performance and identify performance degradation [13]. Zagorowska *et al.* introduce a real-time feedback optimization technique using Gaussian Process Regression (GPR) for compressor stations, resulting in significant power consumption reductions [14]. Ferraeu *et al.* propose an online active set strategy to optimize model predictive control (MPC) in gas turbine systems, reducing computational costs [15]. Wei *et al.* introduces a Bayesian calibration method for predicting performance degradation in gas turbine-driven compressor units [16]. Oyedepo *et al.* conduct a performance and economic analysis of a gas turbine power plant in Nigeria, identifying subpar performance indicators and suggesting improvements for enhanced operational efficiency and economic viability [17]. A study conducted by El-Eishy *et al.* offers valuable insights into the factors influencing the performance of condensate stabilization units. Furthermore, the authors utilized genetic algorithm optimization to identify the most favorable operating conditions for the condensate stabilization unit. The study's findings hold the potential to enhance the operational parameters of these units and maximize the production of C_{5+} [18].

Gülen *et al.* introduce a real-time, on-line performance monitoring system for heavy-duty industrial gas turbines, which detects and diagnoses performance issues, optimizing maintenance schedules and improving plant availability [19]. De Sa., and Al Zubaidy [20], Fernandez *et al.* [21], and Erdem *et al.* [22] collectively investigate the impact of ambient conditions, including temperature, on gas turbine and compressor systems, revealing that higher ambient temperatures reduce electricity production and increase fuel consumption. Burnes and Camou [23] and Agbadede *et al.* [24] explore the effects of fuel composition and associated gas utilization on gas turbine engine performance and durability. Tsoutsanis and Meskin [25] propose a derivative-driven regression method for gas turbine performance prognostics, and Haglind and Elmegaard [26] develop methodologies for predicting aero-derivative gas turbine performance. Tsoutsanis *et al.* [27] propose a method for diagnosing transient gas turbine performance problems by adapting compressor and turbine maps. Razak's [28] chapter on gas turbine performance modeling, analysis, and optimization covers various aspects of gas turbine technology, Fasihizadeh *et al.* demonstrate the effectiveness of simulation algorithms in optimizing the operation of gas transmission networks [29], Marjani and Baghmolai investigate the modeling of non-isothermal and steady-state gas transportation networks, employing analytical, numerical, and artificial intelligence (AI) approaches [30]. Finally, Chacartegui *et al.* introduce a real-time simulation method for medium-size gas turbines, utilizing a thermodynamic model coupled with a control system implemented in MATLAB-Simulink [31].

2. Experimental

2.1. Performance analysis of the gas compression package

In this section, the performance of five centrifugal gas compressors driven by dual-shaft gas turbines was investigated as in the following steps:

Data collection. The compression packages utilized in this study were commissioned at various locations and times. To acquire accurate energy consumption data and identify process variables that directly impact energy usage, data from daily plant operating condition log sheets was gathered for a one-year period preceding the study. Figure 1 displays the monthly feed gas flow rates for each compressor, while Figure 2 illustrates the monthly fuel gas consumption. Design data for each compression package is presented in Table 1.

Table 1. Design data for the selected compression packages.

Package	Start-up Year	Compressor		Driver (gas turbine)	
		Design capacity MMSCFD	Design efficiency % at 45 °C	Rated power MW at 15° C	Design efficiency % at 15 °C
1	1985	50	72	3.20	25.7
2	1990	90	74	4.00	26.1
3	2004	110	77	4.72	28.2
4	2009	100	78	4.19	29.5
5	2010	95	79	4.64	31.1

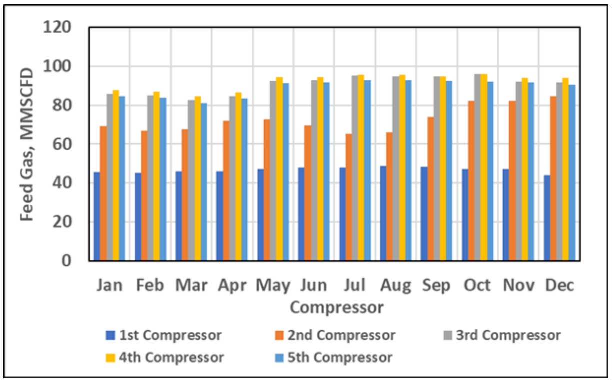

Figure 1. Monthly feed gas flow rates for each compressor.

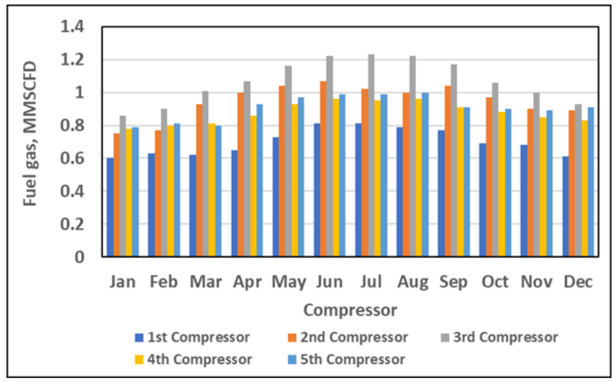

Figure 2. Monthly consumed fuel gas, MMSCFD.

Data verification. To ensure the accuracy and reliability of the collected data, the consumed energy and compressed gas power were calculated and then the overall cycle efficiency were determined. The consumed energy against the gas power was plotted to determine the functional relationship between energy consumption and the key determining parameters, which is shown in Figure 3. From Figure 3, the linear regression equation that used to model the relationship between the dependent variable "consumed power" and the independent variable "gas power" was presented in equation 1 as follow:

Equation 1: Equation for measured data of compression packages

$$y = 0.2165x + 575.03 \quad (1)$$

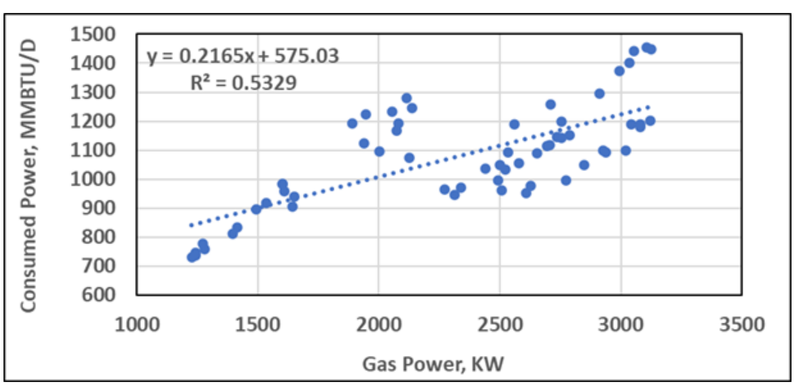

Figure 3. Measured data for compression packages.

Preliminary examination of Figure 3 suggests that the energy/gas power points do fall into a roughly linear pattern, energy increasing with gas power, however, The R^2 value of 0.5329 suggests a relatively weak relationship between the variables, indicating that the regression line may not be a good predictor of the consumed power based on the gas power.

Measurement errors can affect data accuracy, but it is crucial to differentiate significant factors from random noise. To address this, a cumulative sum of difference analysis (CUSUM) was conducted to assess if the measured energy consumption significantly deviates from the expected level or is merely random noise.

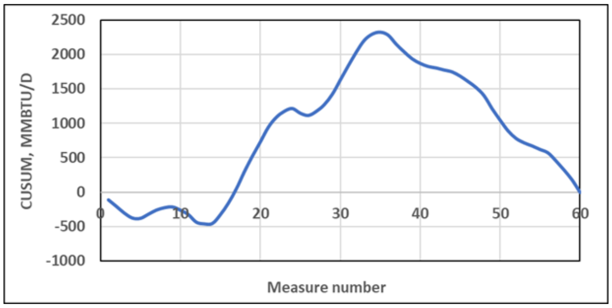

Figure 4. Compressor package CUSUM plot.

To obtain the CUSUM, the expected energy consumption for each package was calculated using Equation 1. This establishes a baseline for comparison against any deviations. Figure 4 illustrates the CUSUM chart, plotting the cumulative sum of differences between expected and actual data points. The substantial deviations from the expected data indicate the need for further investigation into the relationship between variables, aiming to identify and analyze significant factors impacting the energy consumption of the selected modules.

2.2. Sensitivity analysis of the compression package

Due to the limitations of the linear regression model with a low R^2 value and potential lack of linearity, further investigation on the nature of the relationship between the variables was necessary. In this section, the operating parameters that affect the compressor package energy consumption were investigated.

2.2.1. Effect of the ambient temperature on the package performance

By varying the ambient temperature between 0°C and 59°C while keeping other operating parameters constant (as listed in Table 2), the impact of ambient temperature on energy consumption and cycle efficiencies were evaluated, as depicted in Figure 5. We also examined the effect of ambient temperature on the efficiencies of compressors and turbines, which are illustrated in Figure 6. The results indicated that increasing the ambient temperature resulted in a corresponding increase in fuel gas consumption and a decrease in compressor, turbine, and cycle efficiencies.

Table 2. Operating parameters values while varying the ambient temperature

	Gas turbine (driver)				Compressor				
Years of operation	Design η% @15C	Load %	Fuel gas HHV, BTU/SCF	Fuel gas temp., °C	Design η% @T	Load %	Gas flow rate, kg/hr	Delta P, Bar	Feed gas MW, g/mol
23	28.2%	74.9%	1201	37	77%	88%	3136	47	21.71

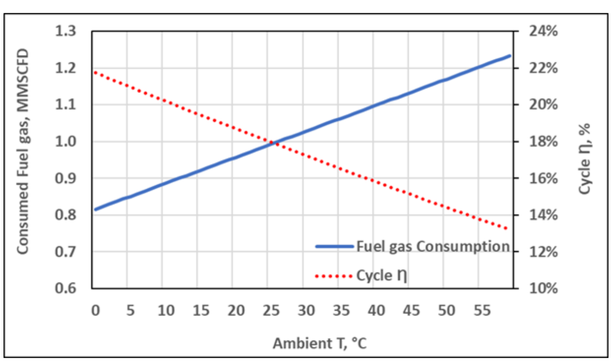

Figure 5. Effect of ambient temperature on Compression package performance.

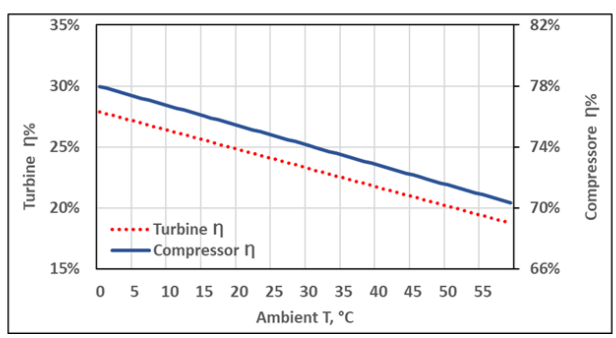

Figure 2. Effect of ambient temperature on compressor and turbine efficiencies.

2.2.2. Effect of the number of operating years on the package performance

By manipulating the duration of operation across a range of 0 to 60 years, while keeping all other operating parameters constant, an extensive evaluation to investigate the effects of the number of operating years on energy consumption and cycle efficiencies was conducted. These findings are visually depicted in Figure 7. Additionally, the implications of varying operating years on the efficiencies of compressors and turbines were explored, as illustrated in Figure 8. The outcomes of the analysis consistently revealed a clear trend: an increase in the number of operating years corresponded to higher fuel gas consumption and decreased efficiencies in compressors, turbines, and the overall cycle.

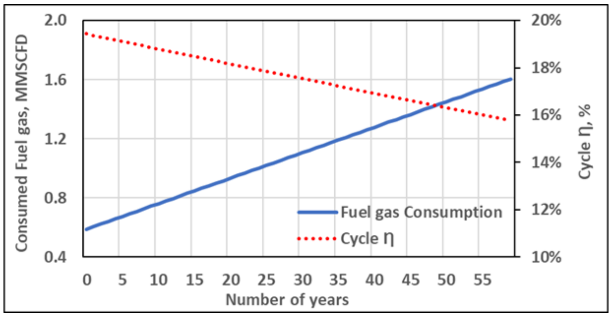

Figure 7. Effect of operating years on compression package performance.

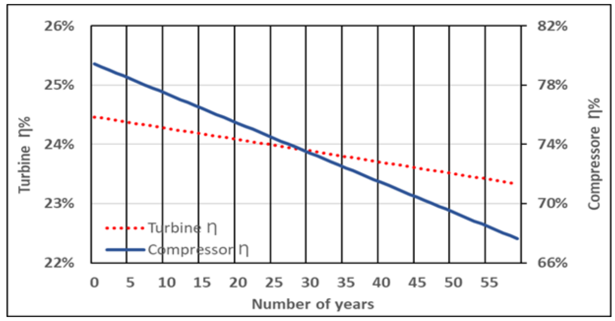

Figure 8. Effect of operating years on compressor and turbine efficiencies.

2.2.3. Effect of turbine design efficiency on the package performance

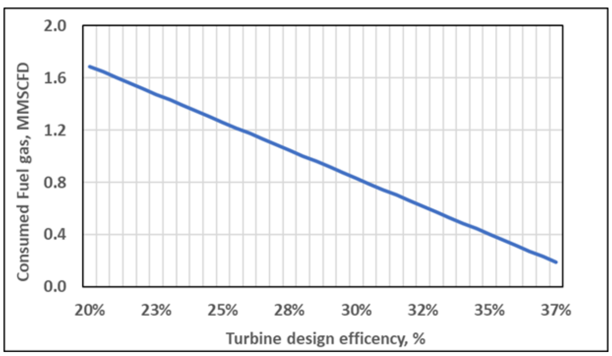

Figure 3. Effect of turbine design efficiencies on fuel consumption.

Through the manipulation of turbine design efficiency within the range of 20% to 37%, while maintaining consistency in other operating parameters, a thorough assessment of the impact of turbine design efficiency on energy consumption was conducted. The findings of the analysis consistently revealed that as the turbine efficiency increased, there was a concurrent reduction in fuel gas consumption, as shown in Figure 9.

2.2.4. Effect of turbine load percent on the package performance

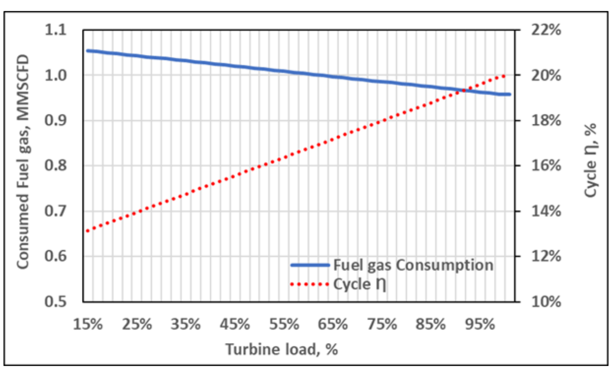

Figure 4. Effect of turbine load on cycle efficiency.

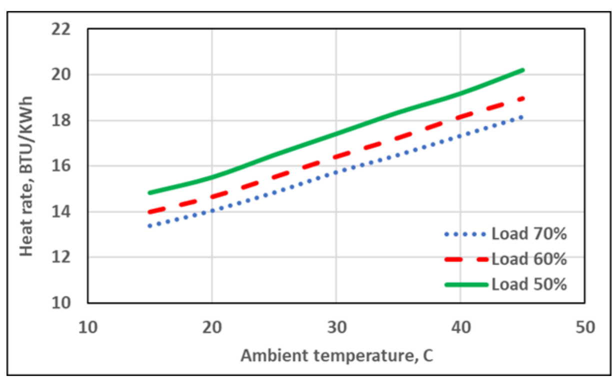

Figure 5. Impact of ambient temperature and load factor on turbine performance.

Through the manipulation of turbine load within the range of 15% to 100%, while maintaining consistency in other operating parameters, a thorough assessment of the impact of turbine load on the cycle performance was conducted. The findings of the analysis consistently revealed that as the turbine load increased (at a constant feed flow rate and different turbine capacities), there was a concurrent enhancement in the cycle performance, as shown in Figure 10.

Figure 11 presents the relationship between ambient temperature, load factor, and turbine performance. The data clearly demonstrates that as the ambient temperature rises and the load factor decreases, there is a corresponding decrease in turbine performance.

2.2.5. Effect of fuel gas heating value on the package performance

By systematically adjusting the fuel gas heating value within the range of 820 to 2000 btu/scf, while ensuring the other operating parameters remained constant, a comprehensive analysis to explore the influence of heating value on cycle performance was conducted.

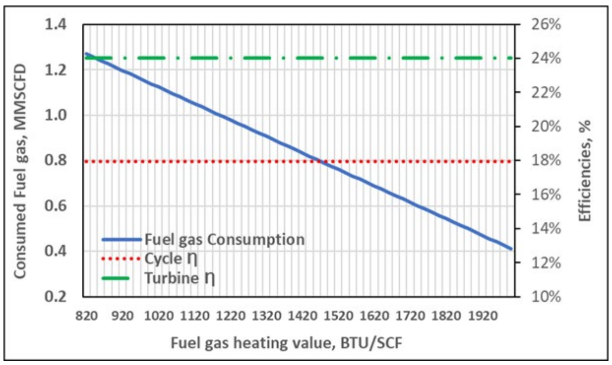

Figure 6. Effect of fuel gas heating values on cycle performance.

The outcomes of the study consistently revealed that as the fuel gas heating value increased, there was a noticeable decrease in the amount of consumed fuel gas. However, it is important to note that this increase in heating value resulted in the loss of valuable byproducts. These findings highlight the trade-off between enhanced fuel efficiency and the loss of valuable products. Additionally, the analysis indicated that the turbine efficiency remained unaffected by variations in the fuel gas heating value. These findings are visually depicted in Figure 12.

2.2.6. Effect of fuel gas temperature on the package performance

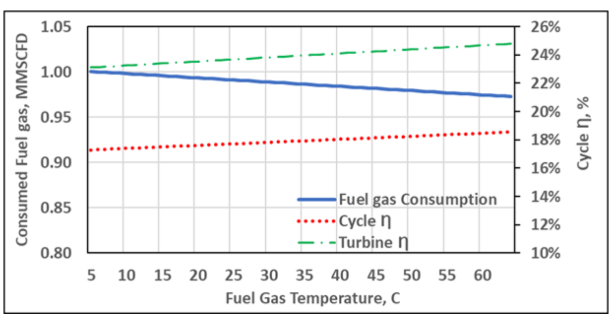

Figure 7. Effect of fuel gas temperature on cycle performance.

A comprehensive analysis was conducted by systematically adjusting the fuel gas temperature within the range of 5 to 60 degrees Celsius while keeping other operating parameters consistent. The findings consistently demonstrated that increasing the fuel gas temperature resulted in a slight decrease in fuel consumption. Moreover, a marginal improvement was observed in both turbine efficiency and cycle efficiency, as illustrated in Figure 13.

2.2.7. Effect of compressor load percent on the package performance

A comprehensive analysis was conducted by systematically varying the compressor load between 25% and 100% while maintaining all other operating parameters constant. The results consistently indicated a slight but discernible effect: as the compressor load increased, there was a corresponding modest enhancement in both compressor and cycle performance, as illustrated in Figure 14.

2.2.8. Effect of the process gas mass flow rate on the package performance

An extensive analysis was conducted by systematically manipulating the process gas mass flow rate within the range of 2500 to 5450 kg/hr, while maintaining all other operating parameters consistent. The results consistently indicated that as the process gas mass flow rate increased, there was a corresponding rise in fuel gas consumption. However, the performance of both the compressor and the overall cycle remained unaffected, as illustrated in Figure 15.

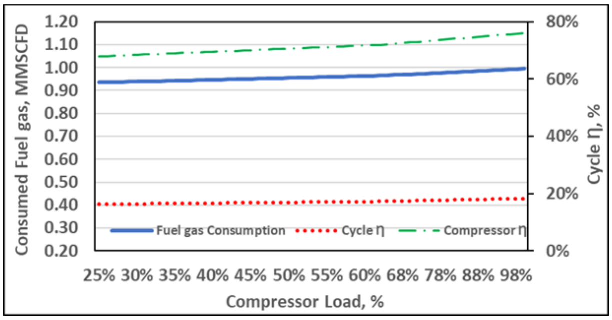

Figure 8 Effect of compressor load on cycle performance.

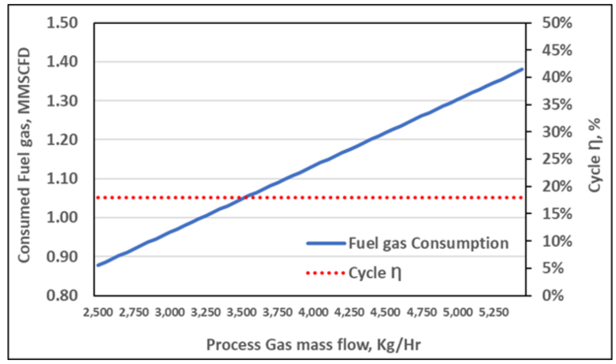

Figure 9. Effect of process gas mass flow rate on cycle performance.

2.2.9. Effect of the compressor differential pressure on the cycle performance

An extensive analysis was conducted by systematically manipulating the differential pressure across the compressor within the range of 20 to 50 bar while maintaining all other operating parameters consistent. The results consistently indicated that as the differential pressure across the compressor increased, there was a corresponding increase in fuel gas consumption. However, the performance of both the compressor and the overall cycle remained unaffected, as illustrated in Figure 16.

2.2.10. Effect of the process gas molecular weight on the system performance

A comprehensive analysis was conducted by systematically varying the process gas molecular weight within the range of 19 to 22 gm/mol while maintaining all other operating parameters constant. The results consistently indicated a slight effect of the process gas molecular weight on cycle performance, as shown in Figure 17.

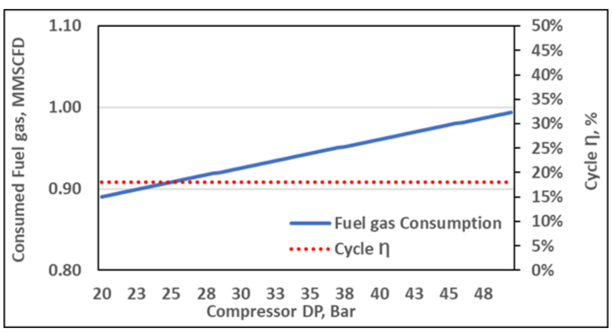

Figure 10. Effect of compressor differential pressure on cycle performance.

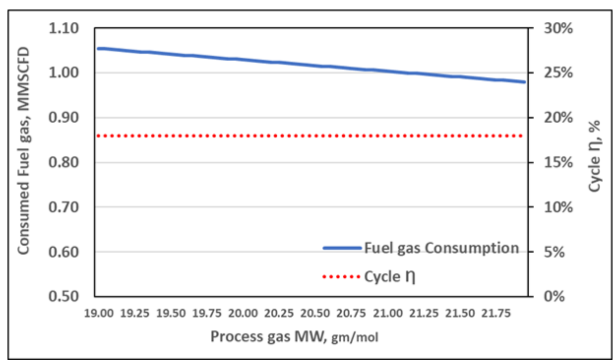

Figure 11. Effect of process gas molecular weight on cycle performance.

2.3. Developing a mathematical model for the gas compression packages

To gain a comprehensive understanding of the intricate behavior and performance of the gas compression system, a mathematical model was developed utilizing multi-regression analysis. This model was designed to encompass and consider a diverse array of factors that directly impact the operational dynamics of the system. The results of the sensitivity analysis were used to identify the key variables that affect the system's behavior. Subsequently, regression analysis was employed to establish the mathematical relationship between these variables and the consumed power of the system.

3. Results and discussion

3.1. Regression analysis output

Table 3 presents the regression statistics. The statistics reveal a remarkably strong association, demonstrating high explanatory power. The multiple R value of 0.999429 suggests an extremely close fit between the predictor variables and the response variable. The R-square value of 0.998859 indicates that approximately 99.89% of the variability in the response variable can be explained by the predictor variables. The adjusted R-square value of 0.998597, which takes into account the number of predictors, further confirms the robustness of the model. Additionally, the standard error of 0.005648 suggests relatively small prediction errors, indicating the accuracy and precision of the model's predictions. The analysis is based on 60 observations, providing a solid foundation for the findings.

Table 3. Compression package regression statistics.

Multiple R	0.999429	Adjusted R square	0.998597
R square	0.998859	Standard error	0.005648
Observations	60		

Table 4 presents the regression output, providing insights into the relationship between the predictor variables and the response variable. The coefficients indicate the estimated effect of each predictor variable on the response variable. The intercept, -4.97147, represents the estimated response when all predictor variables are zero.

Table 4. Compression package regression output.

	Coefficients	Standard error	P-value
Intercept	-4.97147	1.018241	1.2E-05
Ambient temp., °C	0.007088	0.000433	2.95E-21
Cycle operating years	0.017211	0.002463	7.66E-09
Turbine design η%	-8.58233	0.727073	8.46E-16
Turbine load %	-0.11468	0.052377	0.033447
Fuel gas HHV, BTU/SCF	-0.00073	8.29E-05	1.64E-11
Fuel gas temp., °C	-0.00047	0.000107	6.21E-05
Comp. design η%	11.11859	1.509591	2.03E-09
Compressor load %	0.080234	0.042337	0.064105
Process gas flow rate, MMSCFD	0.00017	1.52E-05	4.88E-15
Comp. delta P, bar	0.003506	0.000868	0.000192
Gas MW, g/mol	-0.02547	0.013935	0.073791

The ambient temperature (°C) variable shows a positive coefficient of 0.007088, indicating that an increase in ambient temperature is associated with an increase in the response variable. This relationship is statistically significant with a very small p-value of 2.95E-21.

Cycle operating years also have a positive coefficient of 0.017211, suggesting that as the operating years increase, the response variable tends to increase as well. This relationship is statistically significant with a p-value of 7.66E-09.

The turbine design efficiency (η%) variable has a negative coefficient of -8.58233, indicating that an increase in design efficiency is associated with a decrease in the response variable. This relationship is highly significant with a p-value of 8.46E-16.

The turbine load percentage and fuel gas higher heating value (HHV) variables have coefficients of -0.11468 and -0.00073, respectively. The negative coefficients suggest that higher load percentages and higher fuel gas HHV values are associated with a decrease in the response variable. The p-values for these variables are 0.033447 and 1.64E-11, respectively, indicating statistical significance.

Other predictor variables, such as fuel gas temperature, process gas flow rate, and compressor delta P (pressure difference) also exhibit significant relationships with the response variable, as evidenced by their low p-values.

The variables "Process gas MW" and "compressor load percentage" exhibit p-values slightly above the conventional threshold of 0.05, indicating a weaker level of statistical significance.

Based on the regression analysis, Equation 2 was derived to describe the performance of the gas compressor driven by a dual-shaft gas turbine in relation to the consumed fuel gas (MMSCFD).

Equation 2: Performance equation for gas compressor driven by dual-shaft gas turbine

Consumed fuel gas (MMSCFD) = (0.007088Ta) + (0.017211n) - (8.58233ηT) - (0.11468LT) - (0.00073h) - (0.00047TF) + (11.11859ηC) + (0.00017Q) + (0.003506dp) -(0.02547MW) - 4.97147

3.2. Constructing a steady state model for compression package

A steady-state module was developed for a gas compressor driven by the TB-5000 Ruston Gas Turbine, a commonly utilized and renowned dual-shaft gas turbine in gas processing plants. The gas turbine exhibits an efficiency of 23% and a total power capacity of 3.1 MW. The module's development was accomplished by employing Aspen HYSYS V11 software. The design parameters for both the chosen compressor and gas turbine are outlined in Table 5. Additionally, a detailed process flow diagram depicting the simulation model can be observed in Figure 18.

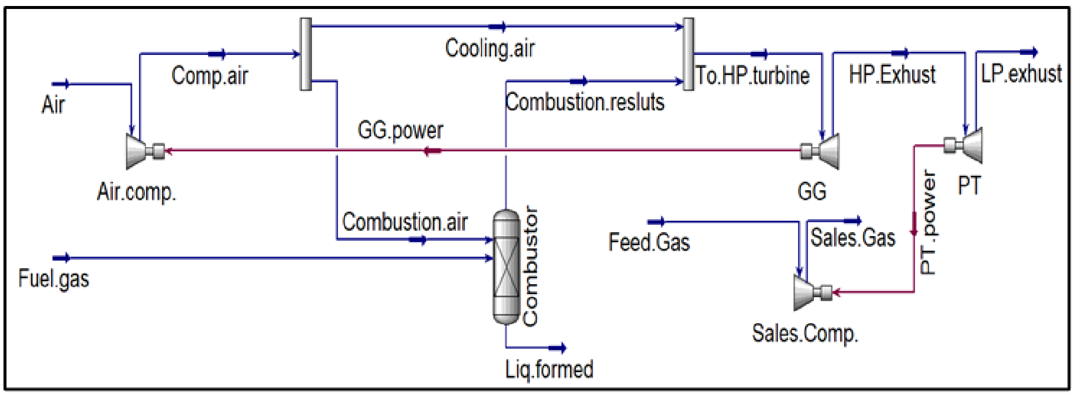

Figure 12. Gas compressor system simulation module.

Table 5. Design parameters for the gas compressor & turbine utilized in the simulation module.

Fuel used	Natural gas	Turbine efficiency (%)	25.7
Fuel flow rate (Nm^3/hr)	1119	Process gas inlet pressure (barg)	54
Fuel gas pressure (barg)	7	Process gas outlet pressure (barg)	101
Air flow rate (kg/s)	18.90	Process gas flow rate (MMSCFD)	100
Exhaust flow (kg/s)	19.10	Compressor efficiency (%)	72
Exhaust temperature (°C)	530	Overall set efficiency %	
Firing temperature (°C)	900	(Compressor +Turbine)	18.5

To ensure the reliability and accuracy of the simulation module, a thorough verification process was conducted using the parameters obtained from the gas turbine supplier's data sheets. The results obtained from the simulation were compared with the data provided in the supplier's manual, and the validation results are presented in Table 6. The close agreement between the simulation model and the supplier's data sheets demonstrates the module's robustness and its ability to generate precise and reliable results, establishing its credibility.

Table 6. Validation results of the gas turbine simulation model.

	Power (MW)	Exhaust mass flow (kg/s)	Exhaust temperature °C	Net η (%)
Design data	3.10	19.10	530	18.50
Simulation results	3.10	19.19	536	18.30
Error (%)	0.00	0.47	1.13	1.14

3.3 Equation validation

The validation of the regression equation involved a meticulous comparison of its results with both simulated data and actual measurements. To assess the equation's performance, identical input parameters derived from both the actual data and the simulation model were employed, enabling the calculation of predicted values for the consumed fuel gas. Figure 19 presents a visual comparison of the consumed fuel gas, measured in MMSCFD, among the actual data, regression results, and simulation results. Furthermore, Figure 20 illustrates the cumulative sum of differences between the consumed fuel gas results from the regression equation, simulation, and the actual data. This chart quantitatively measures the overall deviation between the three datasets. The figure clearly demonstrates a strong alignment between the regression equation and the actual data. Conversely, there is a notable misalignment between the simulation data and the actual data.

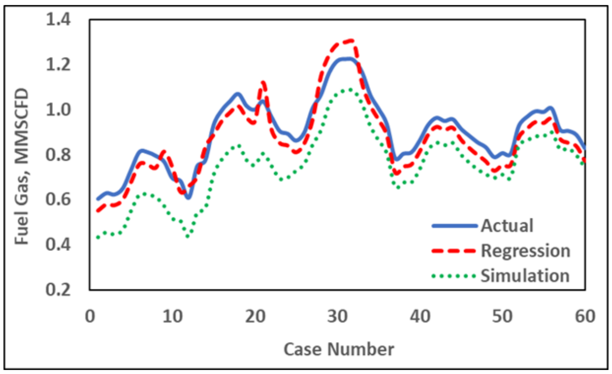

Figure 13. Actual, Regression, and Simulation results.

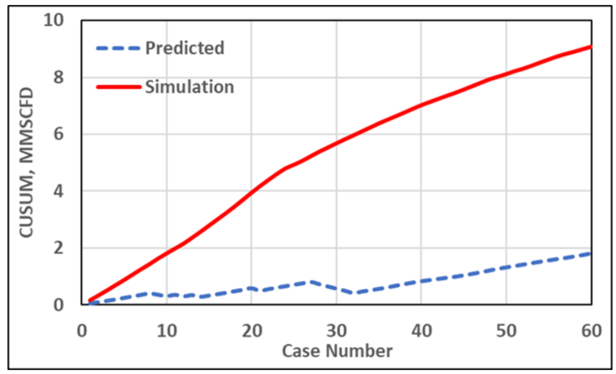

Figure 14. CUSUM between predicted, simulated, and actual fuel consumption.

Based on these figures, it is apparent that the regression equation provides a strong representation of the actual data and exhibits a close match with it. This alignment between the regression results and the actual data serves as a positive indication of the equation's reliability and accuracy. Additionally, comparing the cumulative sum of differences between the regression equation and the actual data with the CUSUM between the simulated and actual data further reinforces the effectiveness of the regression equation in capturing the true values of the consumed fuel gas.

4. Conclusions

In this study, a methodological framework for effectively monitoring the energy performance of the gas compressors driven by dual-shaft gas turbines in the gas processing plants was developed. The research methodology involved analyzing the performance of the gas compression package and identifying key process variables that significantly influence energy consumption. Statistical techniques, including CUSUM analysis, were employed, and a sensitivity analysis was conducted on the compression system. Additionally, a mathematical model using multiple regression analysis was constructed to overcome the limitations of the linear regression model, and the resulting regression equation accurately represents the performance of the gas compressor system in terms of consumed fuel gas (MMSCFD).

The findings of this research contribute to the existing knowledge in the field of energy performance monitoring of gas compressors driven by gas turbines and provide a practical framework that can be applied in the gas processing plants. It is hoped that this research will serve as a foundation for further investigations and improvements in the energy efficiency of gas compression packages, ultimately benefiting the sustainable development of the gas sector.

List of symbols

CUSUM	*Cumulative sum of difference*
T_a	*Ambient temp., °C,*
n	*Cycle operating years*
η_T	*Turbine design efficiency%*
L_T	*Turbine load %*
h	*Fuel gas HHV, BTU/SCF*
T_F	*Fuel gas temp., °C*
η_C	*Comp. design η%*
Q	*Process gas flow rate, MMSCFD*
dp	*Comp. delta Pressure, Bar*
MW	*Gas molecular weight, gm/mol*
MMSCFD	*Million standard cubic feet per day*

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