Journal of Research and Innovation in Engineering
Volume 9, Number 1, 2024 ISSN: 2659-1790

THERMAL ANALYSIS OF A COMBINED CYCLE LOW-EMISSION POWER PLANT USING EVOLUTIONARY PROGRAMMING TECHNIQUES

Prince Okorefe Agbainor[1] and Aniekan A. Okon[2]
Department of Mechanical and Aerospace Engineering,
Faculty of Engineering, University Uyo, Nigeria.
Corresponding Author's E-mail Address: princeoagbainor@gmail.com

ABSTRACT

In this research, the use of evolutionary programming (EP) and continual learning neural network (EP-CLNN) technique is used which employed using the generative artificial intelligence (GAI) approach. The approach was applied to a case study dataset acquired from Afam gas turbine combined cycle power plant. The turbine generated power and destroyed energies response was simulated for a hundred data points which indicates a reduced power output with an increase in inlet temperatures. Exergies destroyed exhibited a random fluctuation with several peaks at around 20th, 30th and 90th points indicating a tendency for increase. The EP-CLNN gave a good solution with RMSE estimates of 4.76 MW over the linear regressors – Poly-1, Poly-2, Poly-3 and Poly-4 with RMSE estimates of 5.14 MW, 5.00 MW, 5.01 MW and 5.00 MW respectively. These findings hold promises in the development of predictor schemes to uncover hidden and novel model patterns describing power plant operational conditions.

***Keywords**: Evolutionary Programming – Continuous Learning Neural Network, Gas Turbine combined cycle.*

INTRODUCTION

Nigeria is blessed with abundant oil and gas reserves. However, her electricity generation capacity is among the lowest in Africa with an average of about 4,000 megawatts. One of the promising energy generation areas for meeting this very important requirement is in the gas-turbine industry where the source of power is served by the highly abundant resource – natural gas. Natural Gas Turbines or simply Gas Turbines (GTs) are widely used in several industries such as in the aviation sector – in operating jet turbo-engines or air-craft propulsion systems and in power systems network as power generators (Çengel *et al.*, 2023) and for industrial applications such as in petrochemical refineries and plants (Oyedepo and Kilanko, 2014). GTs may be operated in a combined solution in which the hot exhaust flue gases generated are further converted into steam which is in turn used to operate a steam turbine in a Combined Cycle Power Plant (CCPP) system (Tufekci, 2014).

GTs are primarily affected by ambient conditions such as temperature, pressure and relative humidity in which their power output might deviate slightly or greatly depending on the value state of the aforementioned parameters. This makes it particularly challenging to monitor and perform precise control and notification operations, particularly as it concerns the very important task of GT power output estimation. Indeed, the task of modeling effectively the Power-Ambient relations in a GT is becoming a core priority for proper energy accounting and systems planning.

As the cost of operations around the world is becoming an issue due to economic problems, the deployment of hardware metering and control solutions is gradually becoming less attractive. To minimize overall system costs and assure sustainable economic policies, it is important to adopt more cost-friendly solutions such that the impact of system operations does not adversely affect the plant operation. In this regard, software-oriented systems are gradually becoming mainstream in new types of GT systems in which models that describe effectively the Power-Ambient relationships among various power plant systems and considering the ambient variables or parameters are programmed into computing systems. In such systems, metering units by way of adaptive sensors are employed to capture real time ambient data in order to predict the GT power output state. To make power output predictions, statistical models including standard Linear Regressors (LR), to statistical Machine Learning (ML) approaches such as Artificial Neural Networks (ANNs) are very popular and widely applied both in research and in industry operations (Tufeckci, 2014; Saleel *et al.,* 2021).

However, the conventional LR and ANN-ML techniques may suffer from sub-optimal conditions and get stuck in local optimal; the LR approach may offer faster speeds of processing, but they are indeed greatly limited in the available options to get out from local optimal due to their lack of learning. In particular, existing (conventional) ANN structures that use back-propagation learning rules are lacking in scalability as they may not do well with highly limited data samples and/or limited input feature data parameters (variables).

Fortunately, current research has shown that it is possible to develop more effective model based approaches and considering limited data and feature parameters for modeling Power-Ambient (PA) conditions (see for instance the recent research in Osegi *et al.*, 2023).

In this research, an emerging approach inspired by more progressive, proactive and less data hungry Generative Artificial Intelligence (GAI) based on the merger of a more bio-inspired artificial neural processing technique and Symbolic Regression (SR) computing model capabilities that learn to evolve the solution space while avoiding local optimal states is proposed. These approaches are described as a combined Neural and Generative (Neuro-Generative) solution incorporating recent ideas and discoveries in the rapidly evolving field of AI in the energy industry.

MATERIALS AND METHODS

Operational data was obtained from the Afam Gas Plant, which is located in the Oyigbo region of Rivers State, Southern Nigeria. The data obtained consists of a total of 12 system operating variables and 24 samples of data corresponding to the number of hours in the day. This data was obtained from field measurements using the relevant sensors and remote data capture devices on an hourly basis and the data checked for consistency with conventional analytic models. Matlab / Simulink and hybridized Neural and Generative software were used for model development.

Gas Turbine Model

The gas turbine model allows the computation of the ideal and actual turbine powers, turbine isentropic efficiency and the rate of exergy destroyed.

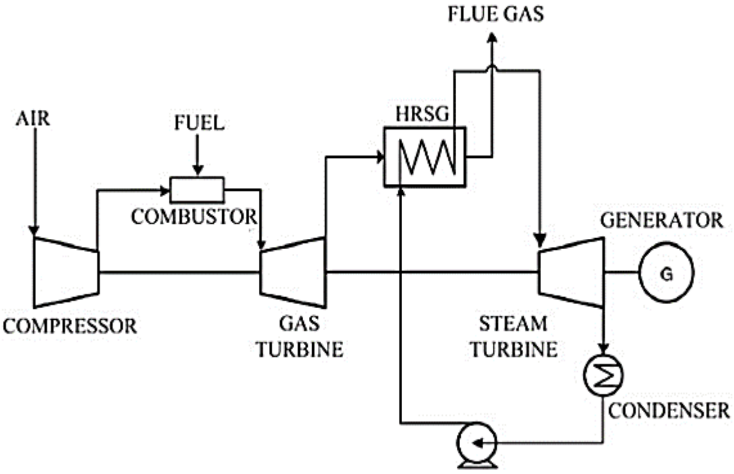

Figure 1: Combined Cycle Gas Turbine

Following the research in (Oko and Njoku, 2017), the ideal and real power of the gas turbine are given as:

$$W_{s,\,GT} = m_g c_{pg}(T_i - T_o) \quad (1)$$

$$W_{a,\,GT} = W_{S,GT}\eta_{S,GT} \quad (2)$$

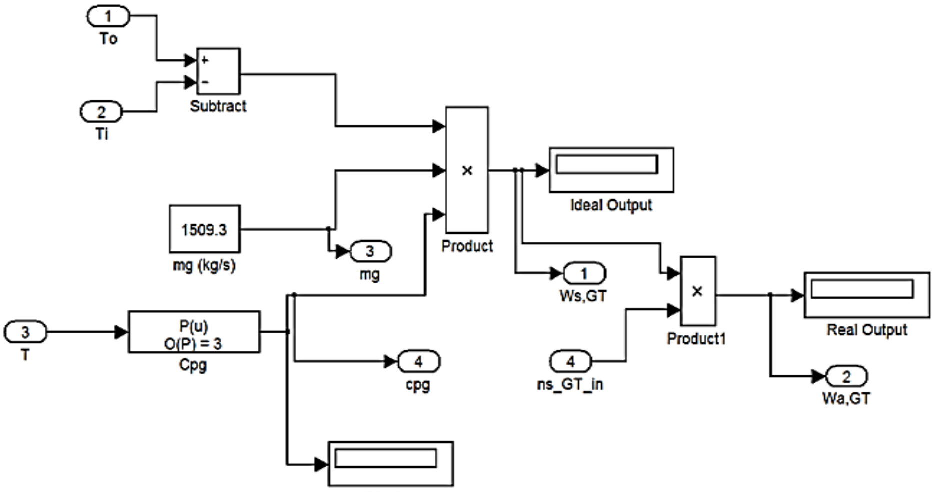

Figure 2: The Conceptual Model of Gas turbine ideal and real powers implemented as a sub-system in SIMULINK

Since gas turbines are not 100% efficient devices, the real or actual power must be computed from an isentropic efficiency.

The gas turbine isentropic efficiency is expressed as:

$$\eta_{S,GT} = 1 - \left[0.03 + \frac{\left[\frac{P_2}{P_1}\right] - 1}{180}\right] \quad (3)$$

The rate of exergy destroyed is also computed as:

$$E_{d,GT} = m_g T\left[C_{pg} ln\frac{T_0}{T_i} - R_g ln\frac{P_0}{P_i}\right] \qquad (4)$$

The efficiency and exergy rate are also implemented as subsystems as shown in Figures 3 and 4 respectively

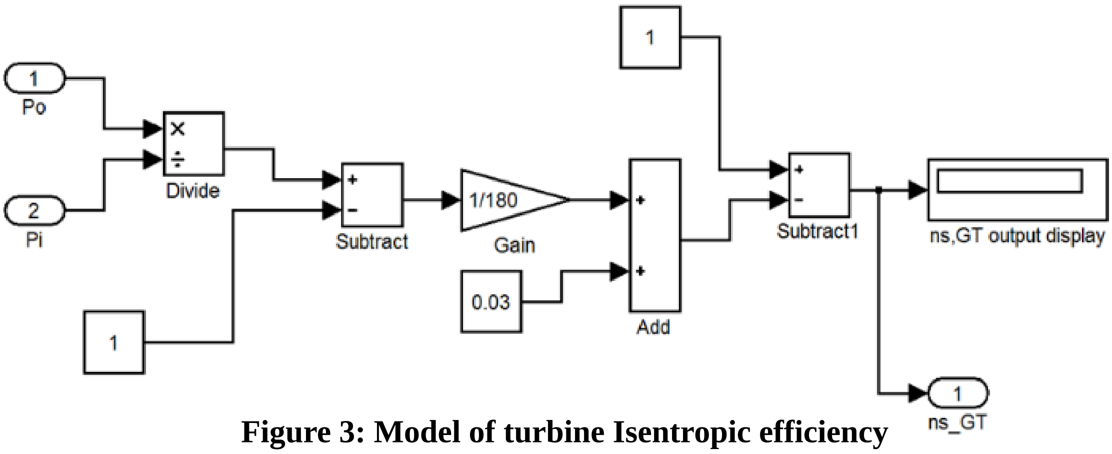

Figure 3: Model of turbine Isentropic efficiency

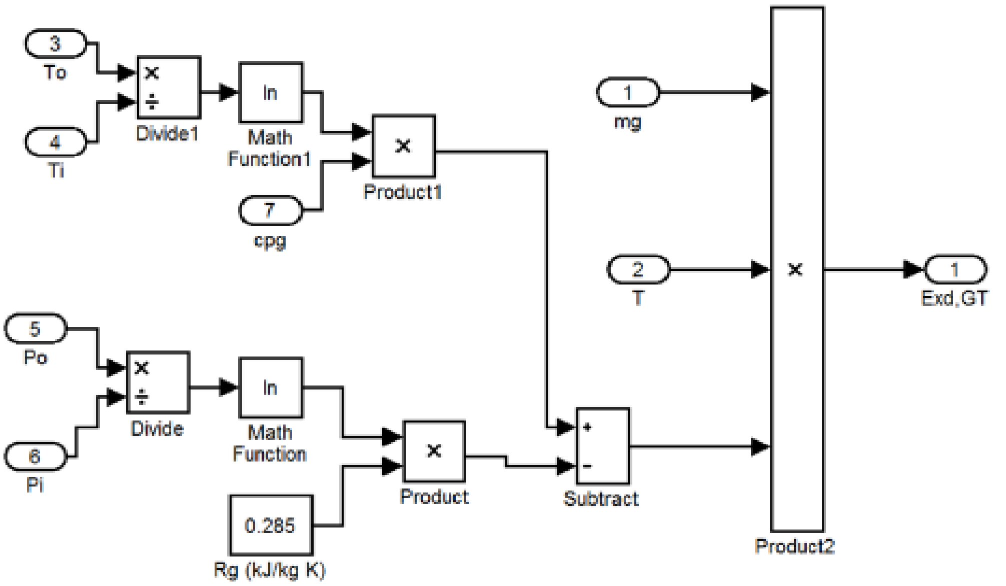

Figure 4: Model of exergy destruction rate

Steam Turbine Model

The total output power of a steam turbine is computed. The steam turbine model consists of low- and high-pressure turbines, as shown in figure 5; the total power is given as:

$$W_{st} = \eta_{S,GT}\lfloor(1 - \alpha)rh\left(h_{exit} - h_{entry}\right) + m_f\left(h_{exit} - h_{entry}\right)\rfloor \qquad (5)$$

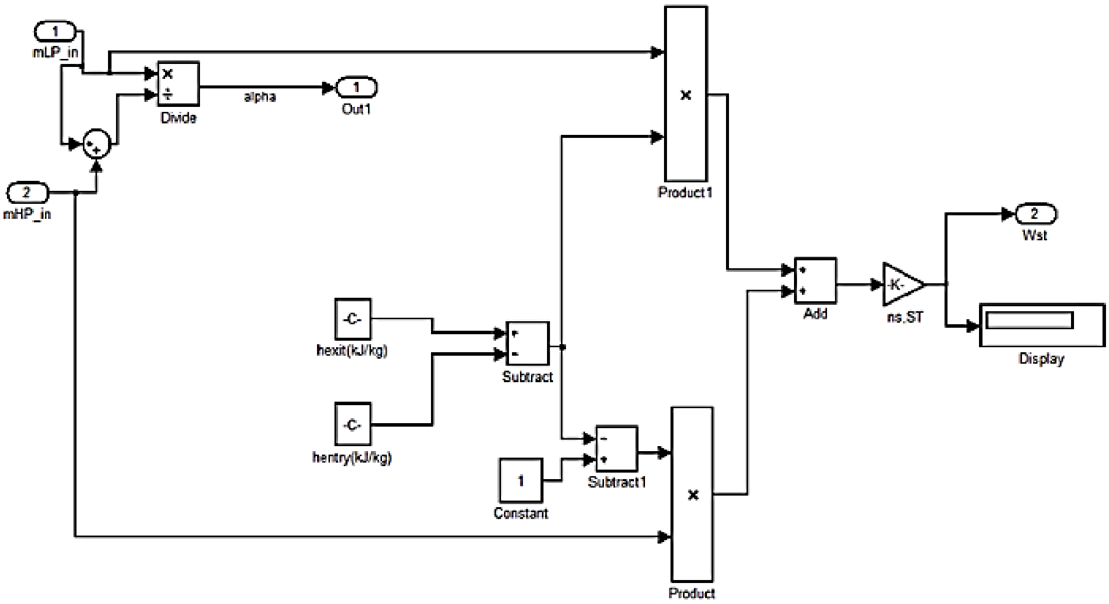

Figure 5: Computing the total output power of a Steam-Turbine power; implemented as a sub-system in SIMULINK

Combined steam-gas system model

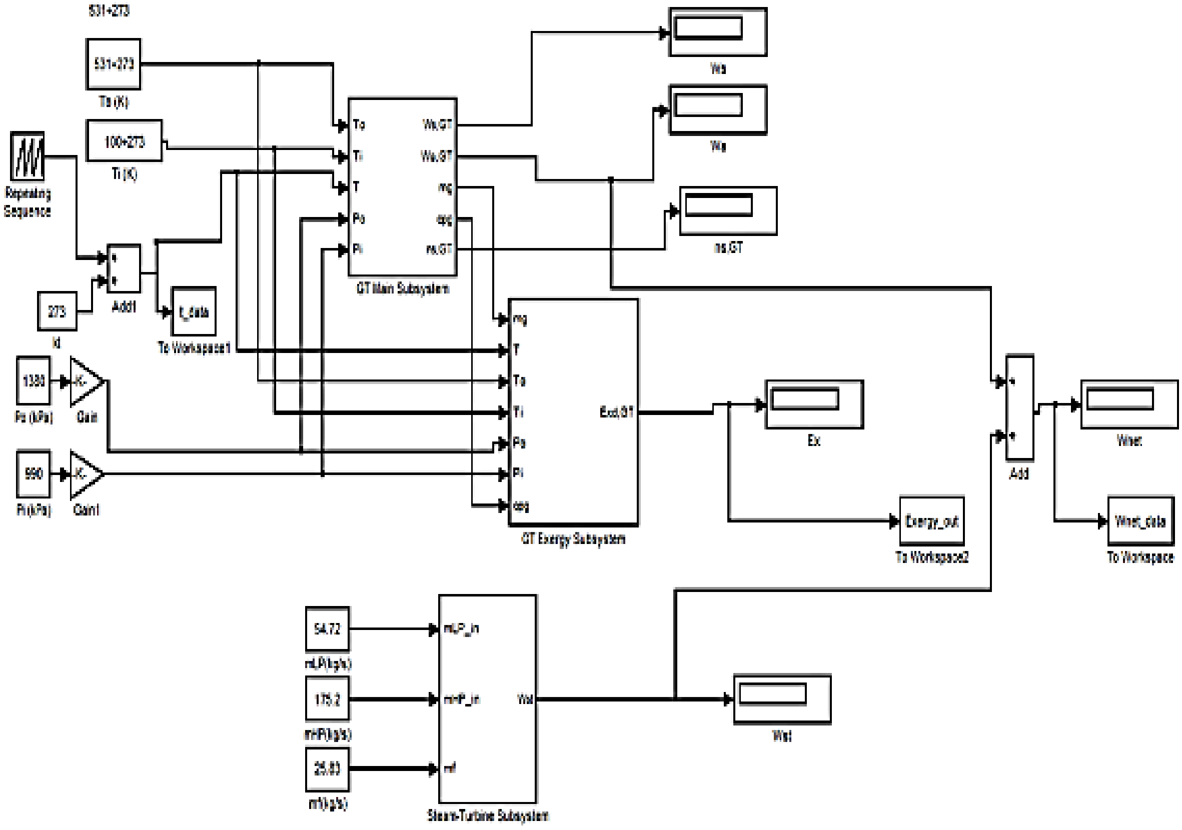

Figure 6: Combined steam gas turbine plant model

Simulations (performance and sensitivity analysis) are performed to determine the effect of ambient temperature and gas turbine inlet temperatures on the combined cycle turbine output power generated and the exergies destroyed. Ambient temperature conditions and gas inlet temperatures are modeled as repeating sequence source blocks as shown in figure 6.

RESULTS AND DISCUSSION

Presented next is the performance analysis with varying ambient temperature using a fixed inlet temperature, the sensitivity Analysis of varying Turbine Inlet Temperature and a prediction of the Afam CCGT Net Power Generated Using AI.

Performance analysis with varying ambient temperature for a fixed inlet temperature

For this analysis the ambient conditions were set to a range of 20^0C (293K) and 40^0C (313K) spaced at 5^0C interval while the gas turbine inlet temperature was fixed at 100^0C (373K). Figure 7 shows a line plot of varying values of ambient temperatures with respect to turbine power generated and at a specified gas turbine inlet temperature of 100^0C (373K); this indicates a linear response of the model i.e. there is a graded increase in MW output power of turbine for a corresponding increase in ambient temperature.

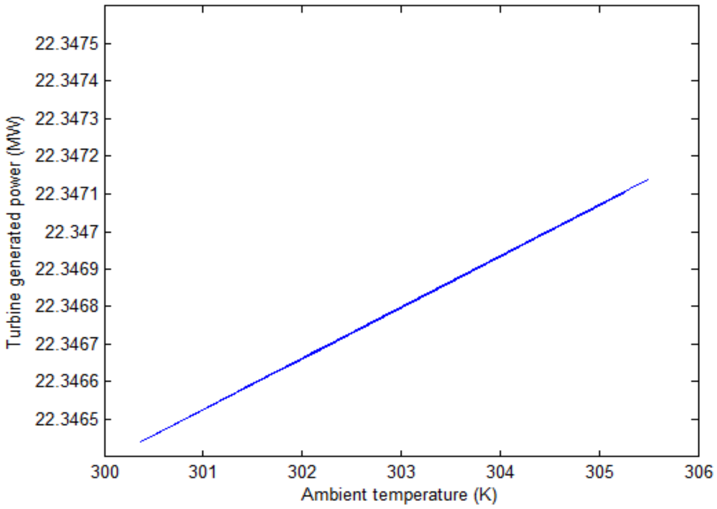

Figure 7: Graphical presentation of generated power from gas-turbine plant for a range of ambient temperature

The exergy destroyed due to ambient temperature rise and at the specified base inlet temperature of 100^0C (373K) is as shown in Fig 8. The graph shows that exergy destroyed will decrease for every increase in ambient temperature.

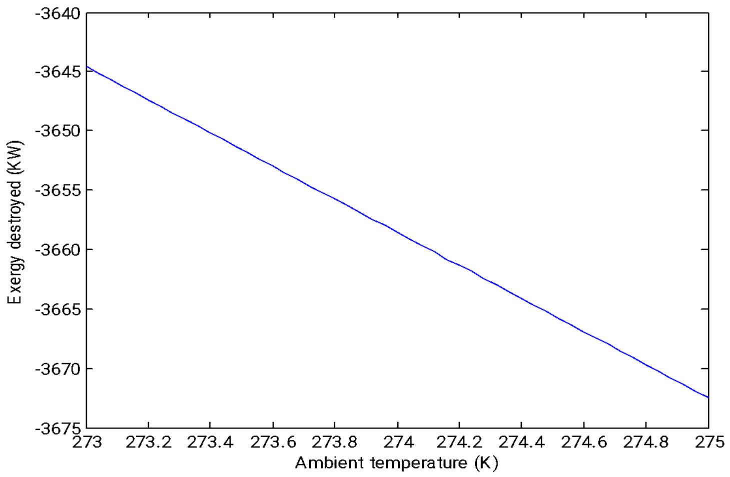

Figure 8: Graphical presentation of destroyed exergy for a range of ambient temperature.

Sensitivity Analysis by Varying Turbine Inlet Temperature

The gas turbine inlet temperature was adjusted slightly in steps of 20ºC from 100ºC (373K) to 160ºC (433K) and the model simulated. The same ambient conditions were used but with the ambient temperature modeled as a random source block with a mean of 30C and unit variance. The turbine generated power and destroyed exergies response were simulated for a hundred data points and are as shown in Figures 9 and 10 respectively. The plot in Figure 9 indicates a reduced power output with increase in inlet temperatures. The exergies destroyed on the other hand exhibited a random fluctuation with several peaks at around 20th, 30th and 90th points indicating a tendency to increase (see Figure 10).

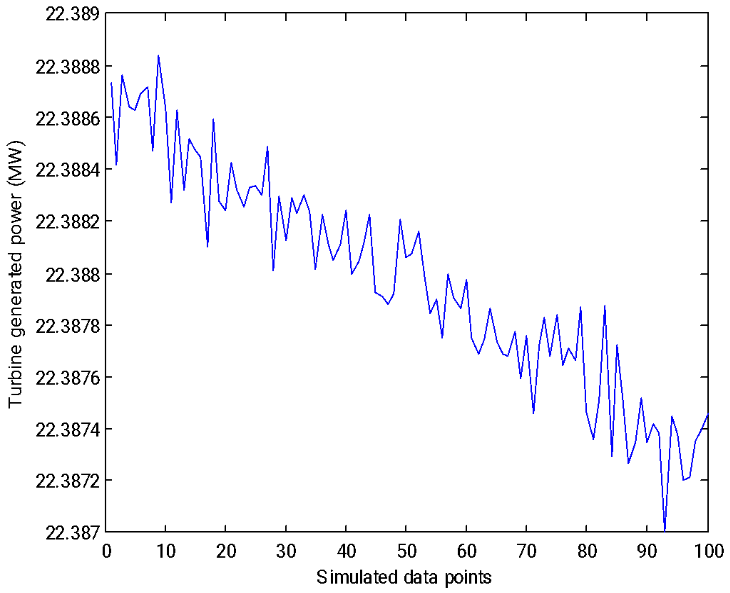

Figure 9: Graphical presentation of generated power of gas- turbine plant for varying amounts of inlet temperatures for 100 100 data point.

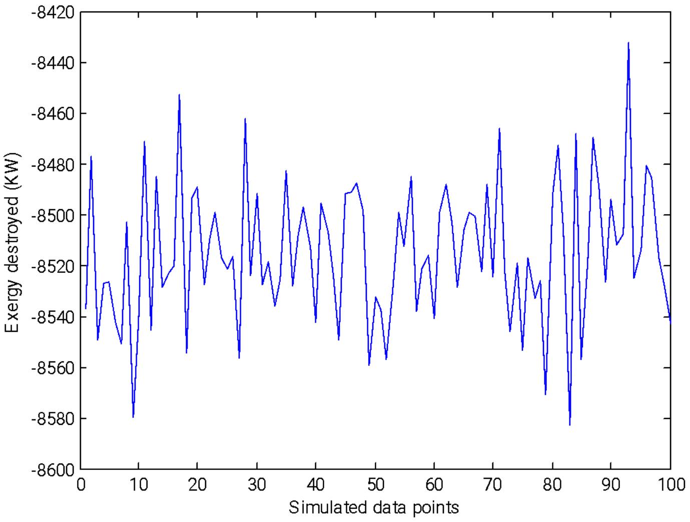

Figure 10: Graphical presentation of destroyed exergies of gas-turbine plant for varying amounts of inlet temperatures for 100 data

Sensitivity Analysis on Specific CO_2 Emission by Varying Mass Flow Rate

The changes in recuperative mass flow rate through the steam turbines in a CCGT have been shown to have a considerable impact on the net generated power output (Li *et al.*, 2020). In particular, reducing the compression ratio increases the air mass flow rate which in turn leads to an increasing Specific CO_2 Emission (SEC) level but at the price of reducing power output (Rigo-Mariani *et al.*, 2018). Care must also be taken with the increase in the rate of mass flow so as not to impact negatively (in a reducing sense) the TET.

In the presented simulation, the effect of varying the mass flow rate from 50kg/s to 100kg/s and at intervals of 10kg/s units is as shown in Figure 11.

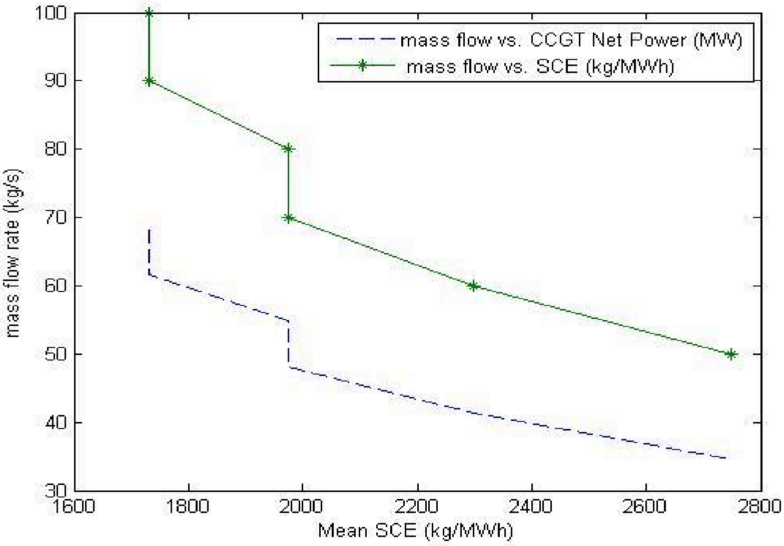

Figure 11: Effect of varying mass flow rate on turbine power and emission level

As can be inferred, the mean SCE is increased at lower mass flow rates. Closer inspection reveal two SCE break even points at mass flow of about 60kg/s and 50kg/s after which a steady increase in SCE levels is noticed till around the cut of flow rate of 30kg/s.

Predicting the Afam CCGT Net Power Generated Using AI

The considerations of the ambient temperature, permissible emissions level and air mass flow rate of the CCGT are accounted for.

Table 1: Test RMSE estimates of EP and other methods using field data

Method	Order	$\text{RMSE}_{\text{TEST}}$ (MW)
Basic Linear	1	5.14
Quadratic	2	5.00
Cubic	3	5.01
Quartic	4	5.00
EP		4.76

As shown in Table 1, similar results are obtained when compared to that reported in (Osegi *et al.*, 2023). Furthermore, the discovered model expressions using a Multi-Gene Genetic Programming (MGGP) technique is as shown in Table 2.

Table 2: Discovered expressions using linear regressor and EP methods

Method	Expression
Basic Linear	Pnet = -2.11*T + 490
Quadratic	Pnet = 0.027*T^2 - 3.1*T + 501.4
Cubic	Pnet = 0.0025*T^3 - 0.125*T^2 - 0.57*T + 476.5
Quartic	Pnet = -1.345e - 0.05*T^4 + 0.00309*T^3 - 0.151*T^2 - 0.3011*T + 451.5
EP	Pnet = 0.00025*T^3 - 0.1202*T^2 - 0.4640*T + 444

IMPLICATIONS OF STUDY

The results obtained are in line with the findings of Oko and Njoku, (2017) and Ibrahim *et al.*, (2017), that the ambient temperature and the inlet turbine temperature have considerable influence over the power deliverable by the Gas-Turbine in addition to the useful energy destroyed. Thus, considerable attention is needed concerning these core parameters in establishing the Combined Steam/Gas Cycle plant at site. Also, important considerations should be paid to the mass flow rates to check its impact on power shortages while compromising the SEC levels. The use of MGGP technique holds promises as a predictor of turbine power output and therefore requires careful consideration in power model formulation.

CONCLUSION

In conclusion, power plant mass flow rates must be enhanced in hybridized power plant in order to boost power plant capacity and reliability for sustained operations while reducing intake fluid demand for power generation. The use of regenerative Gas Turbine for generation of Electricity – the Combined Cycle Gas Turbine (CCGT) is most economical and technically viable; this is because it is operator friendly as far as cost generation is concerned hence more reliable.

The use of Evolutionary Artificial Intelligence (EAI) based on the MGGP technique also holds useful promises in the development of predictor schemes to uncover hidden and novel model patterns describing power plant operational conditions.

REFERENCES

Çengel, Y. A., Boles, M. A. & Kanoglu M. (2023) Thermodynamics: An Engineering Approach, 10th ed., McGraw-Hill, NY.

Ibrahim, T. K., Basrawi, F., Awad, O., Abdullah, A. N., Najafi, G., Manmat, R. & Hagos, F. Y. (2017). Thermal Performance of Gas Turbine Power Plant Based on Exergy Analysis. *Applied Thermal Engineering*, 115, 977-985.

Oko, C. O. C. & Njoku, I. H. (2017). Performance Analysis of an Integrated Gas-, Steam- And Organic Fluid-Cycle Thermal Power Plant. *Energy*, 122, 431-443.

Osegi, E. N., Jagun, Z. O., Chujor, C. C., Anireh, V. I., Wokoma, B. A., & Ojuka, O. (2023). An evolutionary programming technique for evaluating the effect of ambient conditions on the power output of open cycle gas turbine plants-A case study of Afam GT13E2 gas turbine. *Applied Energy*, *349*, 121661.

Oyedepo, S. O., Kilanko, O. (2014). Thermodynamic analysis of a gas turbine power plant modeled with an evaporative cooler. *International Journal of Thermodynamics*. *17(1)*, 14–20.

Rigo-Mariani, R., Ling, K. V., & Maciejowski, J. M. (2018). A Generic Method to Model CO2 Emission Performances of Combined-Cycle Power Plants for Environmental Unit Commitment. Energy Technology, 6(1), 72-83.

Saleel, C.A. (2021). Forecasting the energy output from a combined cycle thermal power plant using deep learning models. *Case Studies in Thermal Engineering*. https://doi.org/10.1016/j.csite.2021.101693

Tüfekci, P. (2014). Prediction of full load electrical power output of a base load operated combined cycle power plant using machine learning methods. *Int J Electr Power Energy Syst*. *60*, 126–140. https://doi.org/10.1016/j.ijepes.2014.02.027.