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Artificial Neural Network Based Performance prediction of Exergy and Energy Analysis of Gas Turbine Generator using Cycle-Tempo Software

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Abstract: - It is crucial for research to continuously seek innovative methods of generating additional electricity in order to meet the demands of everyone requiring it. Engineers can work to make the companies that provide electricity better. It is not possible to separate the parts of the system from how well the gas turbine generator works. This research introduces a new method to predict the performance of Gas Turbine Generators (GTGs) using Artificial Neural Networks (ANNs) combined with Cycle-Tempo software. The main emphasis of this method is on analysing the exergy and energy of the GTGs. GTGs are very important in many different industries. It is crucial to make them work efficiently to produce more energy and protect the environment. This research is new and different because it uses ANNs in a smart way to improve how research measure how well GTG works. The main advancement is in the automation part, where artificial neural networks are taught to independently collect and study data. They can adjust to changing conditions on their own, which greatly reduces the amount of manual work needed for analysis. This automation makes things easier and can change to different situations quickly. It helps industries that rely on GTG by meeting their changing needs. Moreover, the research uses complex computer algorithms to make very accurate forecasts about energy and exergy effectiveness, voltage output, and hydrogen production—an important measurement in GTG function. The results show that the accuracy is really good, with a small error of less than 1% and a high value of 0. 99 for the R-squared when compared to what was expected. The automation, detailed analysis, and accurate predictions of the novel technology help improve the efficiency and sustainability of gas turbine generators. This makes it a valuable tool for industries that rely on these generators for power.

Keywords: *Gas Turbine Generator (GTG), Artificial Neural Networks (ANNs), Exergy and Energy, Cycle-Tempo Software*

INTRODUCTION

The current world vitality situation shows that most of the vitality necessities are met from fossil fills which cannot be recently shaped at any noteworthy rate hence, the current stocks are limited. Moreover, these fossil fills are not natural neighbourly and emanates noteworthy sum of poisons causing genuine environ mental issues such as, worldwide warming, ozone layer exhaustion and climate alter. Renewable vitality sources, with points of interest of being environment inviting and copious in accessibility are the promising choice to meet the expanding request of vitality around the world. In any case, the renewable vitality frameworks endure from moo transformation productivity subsequently utilizing the renewable vitality frameworks for genuine life applications in customary hone requires extraordinary thought (Ahmadi et al. 2021). Execution of most of the renewable vitality change frameworks is given based on vitality investigation which is essentially as it were the bookkeeping of energies entering and leaving. Exergy examination distinguishes the causes, areas and size of the framework wasteful aspects and gives the genuine degree how a framework technique to the perfect. In the last ten years, exergy has been shown to be an important and useful tool for analysing and evaluating the performance of heating systems. In simple words, exergy is the maximum amount of work that can be generated by a substance, heat, or work when it is in equilibrium with its surroundings. Exergy is starting to be used in some industries and research are focusing on how it can be used for drying (Asgari, Saray, and Mirmasoumi 2020).

Studying engineering designs and conducting exergy analyses for power generation systems plays a crucial role in advancing scientific knowledge and optimizing the utilization of energy resources. Because of this, scientists and system designers have become very interested in exergy analysis in recent years. Some people focused on

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studying the energy of individual parts and ways to improve their efficiency. Others focused on designing and analysing entire systems. The examination is done considering three main factors: temperature, cost, and the surroundings. Other things are also important (for example, This Theme does not go into great detail about strength of materials or reliability of components (Venkitesh, Daniel, and Sreekanth 2021). In order to familiarize individuals with these terms, it is essential to elaborate on the concepts of exergy, energetic efficiency, and energetic analysis within the first topic of Exergy and Thermodynamic Analysis. In the first topic of Exergy and Thermodynamic Analysis, it is crucial to clarify the definitions of exergy, exegetic efficiency, and exegetic analysis since these terms are unfamiliar to a majority of individuals. In simple terms, the reader is expected to already know the basics of thermodynamics, heat transfer, and fluid flow. These concepts will not be explained in this Theme (Thattai et al. 2017).

The primary objective of this analysis is to identify and pinpoint the thermodynamic inefficiencies within a system. It accomplishes this by determining the underlying causes, pinpointing the exact locations within the system where these inefficiencies occur, and identifying the sources responsible for energy degradation. To achieve meaningful results, it is crucial to establish a comprehensive benchmark for the ideal system state. By doing so, this analysis serves as a valuable tool for assessing how far a system deviates from its optimal performance. Moreover, it offers a potential solution for enhancing economic and environmental assessments by quantifying exergy efficiency and losses, as illustrated in Figure 1. This information can be instrumental in making informed decisions to optimize the system's performance and minimize its impact on both economic and environmental aspects (Fichera, Samanta, and Volpe 2022).

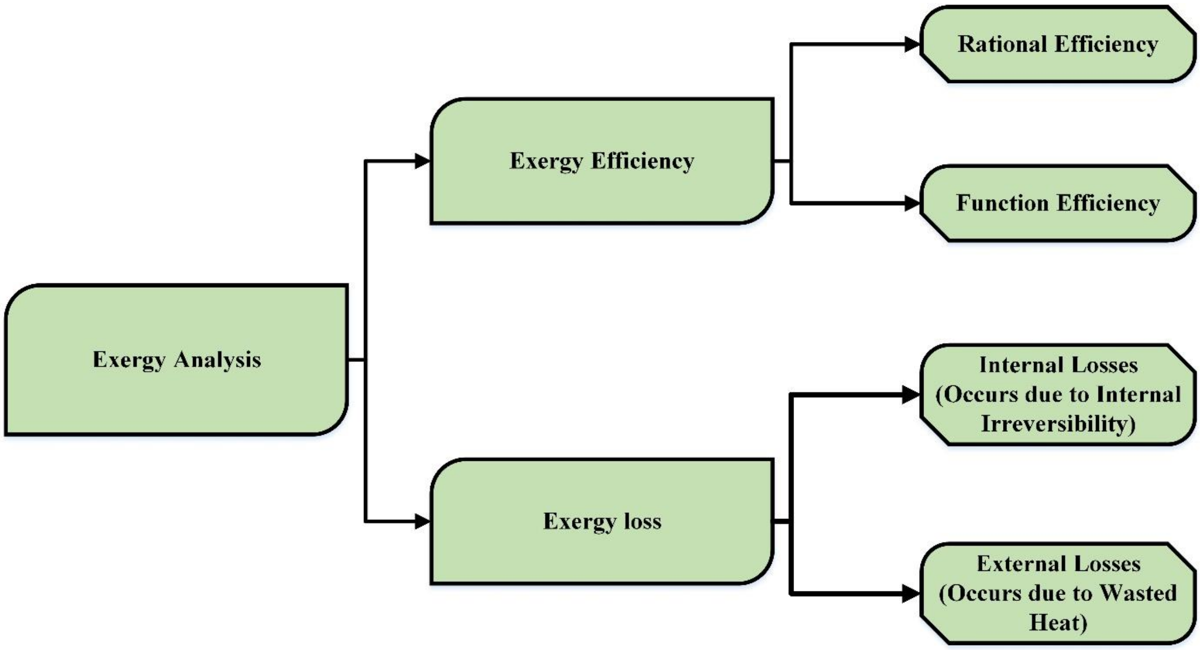


Figure 1: Exergy Analysis

The performance prediction of a gas turbine generator through Exergy and Energy Analysis is a critical aspect of assessing the efficiency and effectiveness of this power generation system. To carry out such an analysis, specialized software like Cycle-Tempo is employed. Cycle-Tempo is a powerful tool designed for simulating and analysing the thermodynamic behavior of gas turbine cycles. It allows engineers and researchers to evaluate various parameters, including energy and exergy flows, within the gas turbine system. By inputting key data and operational parameters, Cycle-Tempo can provide valuable insights into the performance of gas turbine generators, helping to optimize their design, operation, and efficiency. This analysis is vital for industries relying on gas turbine generators for power production, as it enables them to make informed decisions to enhance energy efficiency and reduce resource wastage (El Jery et al. 2023).

Cycle-Tempo software plays a pivotal role in the realm of gas turbine generators, offering a sophisticated platform for in-depth analysis and optimization. Gas turbine generators are vital components in various industries, including power generation, aviation, and manufacturing. These systems convert chemical energy from fuel into mechanical work, which is then used to generate electricity or power various mechanical applications. However, achieving optimal performance and efficiency in gas turbine generators is a complex task, given the multitude of variables involved (Ranjan and Karmakar 2020). Cycle-Tempo software provides engineers and researchers with a powerful tool to tackle this challenge. It allows for the creation of detailed thermodynamic models of gas turbine cycles, enabling the simulation of their operation under various conditions. By inputting crucial data such as compressor and turbine efficiencies, pressure ratios, inlet temperatures, and operational parameters like load demands and ambient conditions, Cycle-Tempo can predict how a gas turbine generator will perform in the real world (Khaleel et al. 2022).

One of the key advantages of Cycle-Tempo is its ability to assess both energy and exergy flows within the gas turbine system. Energy analysis focuses on tracking the quantity and quality of energy transfer within the system, providing insights into overall efficiency and energy losses. Exergy analysis, on the other hand, goes further by considering the quality and availability of energy, helping pinpoint sources of irreversibility and inefficiency. This dual approach allows engineers to identify areas where improvements can be made, whether it's in the design of components, adjustments to operational parameters, or enhancements in heat recovery systems (Pinto et al. 2021).

In practical terms, Cycle-Tempo's capabilities are invaluable for industries that rely on gas turbine generators. Power plants can use it to optimize their energy production, reduce fuel consumption, and minimize environmental impact. In aviation, it aids in the design and operation of efficient aircraft engines. In manufacturing, it can help increase the efficiency of gas turbine-driven machinery. The software empowers decision-makers with data-driven insights, enabling them to make informed choices to maximize energy efficiency, minimize resource consumption, and ultimately enhance the performance of gas turbine generators across a wide range of applications (Thattai et al. 2017).

In the conventional methods of analysing the performance of Gas Turbine Generators, one significant challenge has been the reliance on simplified mathematical models and assumptions. These traditional approaches often struggle to capture the complex and dynamic behavior of real-world gas turbine systems accurately. They might overlook intricate thermodynamic interactions, leading to inaccuracies in performance predictions. Moreover, these methods require extensive manual data input and are limited in their ability to adapt to varying operating conditions and system configurations, making them less effective in optimizing gas turbine performance. Proposing an Artificial Neural Network (ANN)-based approach for performance prediction of Exergy and Energy Analysis of Gas Turbine Generators using Cycle-Tempo Software offers several promising solutions to these challenges:

- By integrating ANN into the analysis process, the scope of this approach involves developing a sophisticated model that can learn and adapt to the unique characteristics of individual gas turbine systems.
- The integration of ANN with Cycle-Tempo Software can significantly reduce the manual effort required for data input and analysis.
- ANNs can be trained to detect deviations from optimal operating conditions and suggest corrective actions, allowing for proactive maintenance and improved operational efficiency.
- This real-time capability is crucial for industries that rely on gas turbine generators for continuous power generation.

The proposed Artificial Neural Network-Based Performance Prediction of Exergy and Energy Analysis of Gas Turbine Generator using Cycle-Tempo Software addresses the limitations of prior methods by enhancing accuracy, automating processes, and enabling real-time optimization. This approach has the potential to revolutionize the field of gas turbine performance analysis and contribute to more efficient and sustainable energy generation.

Section 1 explains the use of artificial neural networks to predict the performance of a gas turbine generator. This prediction is based on exergy and energy analysis using cycle-tempo software. Section 2 discusses previous research on this topic. Section 4 introduces the framework proposed in this study. Section 5 presents the results and discusses them. The study concludes in section 6.

2. Related Works

In the research proposed in (El Jery et al. 2023) based on the energy, exergy, and hydrogen production from a solar thermochemical plant. It uses a special type of machine called a polymer membrane electrolyser. Making hydrogen through polymer membrane electrolysers is a good way to create a clean and useful energy source. Electrolysers can produce hydrogen and oxygen, which might be used to fuel drone cells. The study of how polymer membrane electrolysers work, finding out what causes them to lose energy and improving their efficiency is important and needed. This article looks at how water can be turned into power and hydrogen using a special machine. The researchers studied how different things like sunlight, electricity, and other factors affect the amount of hydrogen produced. It has been proven that when the current gets stronger, the electrolyser produces more voltage, but it becomes less efficient and loses some of its usefulness. Furthermore, when the temperature increased, the pressure decreased, the Nafion membrane became thicker, the voltage went down, and the electrolyser showed better performance. By making the incoming radiation stronger, the amount of hydrogen produced increased by 111%. However, the efficiency and usefulness of the electrolyser decreased by 14% because more electric current was needed to produce hydrogen. In the end, research used machine-learning to make predictions about how much energy and exergy would be efficient, the voltage, and how fast hydrogen would be produced in different situations. The findings were very precise when compared to the expected results. Research used hyperparameter tuning to change the settings of research model, and the model's outcomes showed a Mean Absolute Error less than 1. 98% and an R-squared higher than 0. 98, Polymer membrane electrolysers have restrictions in their design because of the properties of the membrane.

In the research proposed in (Jamil et al. 2021) a way to trade energy between neighbors using technology and data analysis for a reliable power supply in a smart electrical grid. The proposal in this paper advocates for the implementation of a blockchain-based system to develop a platform that facilitates energy prediction and trading. It would help manage and schedule energy from different sources in advance. The new platform will have two parts: one for buying and selling energy using blockchain technology, and another for using smart contracts to make predictions about energy usage. The blockchain module helps people monitor their energy usage in real-time, control energy trading easily, and keep a log of energy transactions that cannot be changed. It also includes a reward system. With the help of historical energy usage information, the smart contract facilitates the creation of a model that can forecast upcoming energy usage. Jamil et al. (Jamil et al. 2021) uses real information about how much energy is used in Jeju province, which is in South Korea. This study's goal is to improve the flow of electricity and the process of people sharing energy, so that consumers and prosumers can trade energy effectively. Energy trading means buying and selling energy. It involves planning and managing the use of different sources of energy to supply the amount of energy needed at a particular time Furthermore, research use techniques to extract and analyze patterns from the historical data of energy consumption, using data mining methods. Time-series analysis helps with energy management by allowing better decisions to be made for planning and managing energy resources efficiently in the future. Research tested the accuracy of the predictive model by using different statistical measures like mean square error and root mean square error on different machine learning models like recurrent neural networks and similar ones. In addition, research also assess how well the blockchain platform works using hyperledger calliper to measure speed, capacity, and resource usage. According to the results of the experiment, the suggested model is useful for sharing energy between the producer and consumer to ensure good service quality. In addition, in the future, research might think about including other things like humidity, temperature, and wind speed. Research would select these using special computer programs that find the best choices.

Alhammadi et al. (Alhammadi et al. 2022) paper suggests a plan for using artificial intelligence to improve the way thermal power plants are monitored and controlled for better cyber security. Research decided to use a steam power plant as a case study, which consists of various crucial components such as the boiler, condenser, turbine, and additional supporting systems. Research examined a part of a real power plant called a boiler, and research created a computer model of it using a tool called Simulink/MATLAB. The aim is to compile a set of information from this simulation model for utilization in an artificial intelligence system. Research analyzes our data and the real power plant data to adjust our simulation model as accurately as possible. Research chose the simulation data-set because it allows us to easily control the input variables without impacting the real power plant. So, research are comparing the generated data-set to the actual power plant to see how their outputs match up. Research use a system called IS027001 to manage information security. It is a global standard. It has a framework and a set of rules called Annex A that help control how research handle information securely. Thus, the research specifies about two things: Annex A. 141714 is about getting and making changes to systems, and Annex A. 17 is about keeping information safe when dealing with business continuity. This paper talks about a plan to keep computer systems secure from attacks, and the first set of data collected to start developing it. The data will be processed and analysed using a special software called neural designer, which will use linear regression to train and test the model.

3. Problem Statement

The problem statement across the various research papers outlined involves addressing critical challenges in the fields of energy, environmental sustainability, and technology. In El Jery et al. (2023), the focus is on improving the efficiency of polymer membrane electrolyzers for clean hydrogen production, while Jamil et al. (2021) seeks to enable efficient energy trading in smart grids using blockchain and data analysis. Alhammadi et al. (2022) aims to enhance the cybersecurity of thermal power plants through artificial intelligence, and Dursun, Toraman, and Aygun (2022) target the reduction of aviation emissions through deep learning methods. These problems encompass issues such as energy efficiency, environmental impact, data management, and security, all of which are critical in our modern technological and environmental landscape.

4. Exergy and Energy Performance Prediction of Gas Turbine Generator

The research methodology for this study involves a multi-step approach. Firstly, a comprehensive dataset comprising key operational parameters of Gas Turbine Generators (GTGs) and their associated exergy and energy metrics is collected. Next, Cycle-Tempo software is employed to develop a detailed thermodynamic model of the GTGs, considering factors such as pressure ratios, inlet temperatures, and operational conditions. Subsequently, Artificial Neural Networks (ANNs) are integrated into the analysis, with the ANNs trained on the dataset to predict performance parameters. Hyperparameter tuning is utilized to optimize the ANN models. The study also investigates the impact of various external factors, including solar radiation, electrical inputs, temperature, and pressure, on GTG performance. The accuracy of the predictive models is assessed using metrics such as Mean Absolute Error and R-squared values, ensuring the precision of predictions. This comprehensive methodology facilitates the automation of data analysis, enhances the adaptability of the analysis to dynamic conditions, and provides a holistic understanding of GTG performance, contributing to the optimization of energy and exergy efficiency in gas turbine generators.

4.1 Exergy and Energy Analysis

The picture in Figure 2 shows a type of engine called a dual spools mixed-flow turbofan. It has a system that cools the air as it enters the engine. In this system, the fan pushes the air from the air-cooling system. Some of the air from the fan goes into a separate path and mixes with other air. - The fan directs a substantial airflow towards the powerful high-pressure compressor. When the HPC Air goes into the combustion chamber, it mixes with fuel. Following this, the combination of combusted air and fuel is subsequently fed into a robust turbine, initiating its motion. The energy from the first turbine moves into another turbine with less pressure, which is called a low-pressure turbine (LPC), and then goes into the mixer. After completing the previous steps, the bypass channel combines the output flow with the LPC flow. Next, the combination is expelled through a nozzle and discharged into the immediate surrounding air (Singh and Verma 2022).

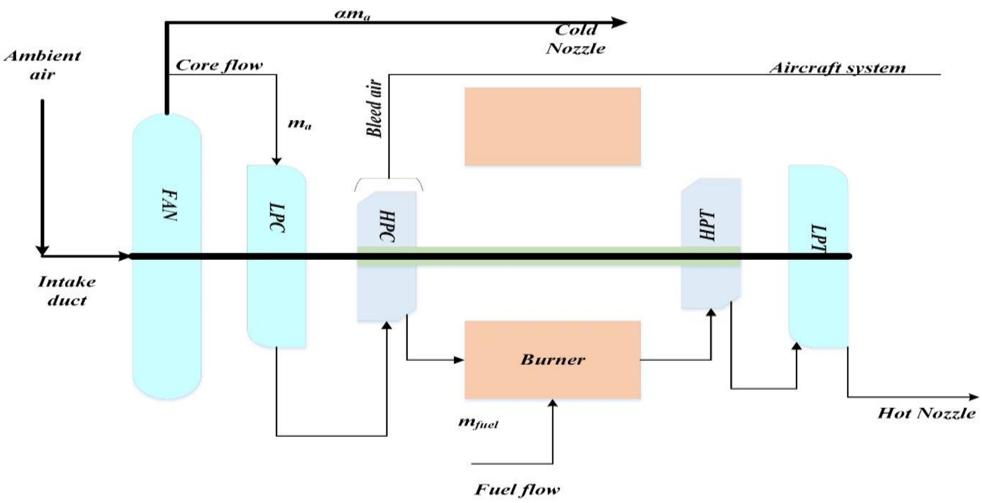


Figure 2: Dual Spool Turbofan System Illustration

Turbofan engines are a type of gas turbine engine commonly used in aircraft propulsion systems. One of the most common configurations is the dual-spool turbofan system, which consists of two separate concentric shafts, each with its own set of rotating components. The inner shaft, known as the high-pressure spool, drives the high-pressure compressor and turbine stages (Zadhossein et al. 2021). This section of the engine is responsible for compressing incoming air, mixing it with fuel, and igniting the mixture to produce high-pressure exhaust gases. The outer shaft, referred to as the low-pressure spool, drives the low-pressure compressor and turbine stages. These components further compress the exhaust gases and provide additional thrust by accelerating a larger volume of air around the engine core, resulting in a combined jet exhaust that produces thrust for propulsion. The dual-spool configuration allows for better control of engine performance and efficiency by separating the compression and expansion processes into two distinct spools, optimizing each for its respective operational range. This design enhances the overall efficiency and power output of the turbofan engine, making it a preferred choice for modern aircraft (Sarkar, Khankari, and Karmakar 2021).
Two adiabatically- or isentropically-driven processes and two isobarically-driven processes make up this cycle. A system's energy balance, or the point at which the energy input and output are equal, can be determined by energy analysis. Work capacity is defined as energy. The following Eqn (1) can be used to determine a gas turbine generator's energy efficiency system in this cycle:

$$\eta = \frac{T_W - C_W}{Q_c} \tag{1}$$

In Eqn (1) η denotes the energy efficiency, energy output rate is denoted as T_w and energy consumed is denoted as C_w and the heat input rate is denoted as Q_c. The energy efficiency (η) of the gas turbine generator system is calculated as the ratio of the useful work output rate (T_w) to the consumed work input rate (C_w), divided by the rate at which heat is added to the system (Q_c). This equation essentially tells you how effectively the generator converts the heat input into useful work output. A higher η value indicates a more efficient system, as it means that a larger proportion of the input heat is being converted into useful work, and less is being lost as waste (Mustafa et al. 2022).
Exergy investigation calculates the entropy era of person parts to absolutely survey the thermodynamic execution of vitality frameworks. Exergy can be thought of as the greatest sum of work that can be done or the vitality that a framework has when specific conditions are met, in differentiate to vitality. The system's exergy proficiency is decided by the proportion of genuine work to net exergy esteem entering the framework. The sum of vitality annihilation features a huge effect on the system's vitality proficiency. The vitality viability of the gas turbine generator framework can be communicated utilizing the taking after condition mentioned in Eqn (2):

$$\eta_e = \frac{T_W - C_W}{Ex_{Net}} \tag{2}$$

4.2 Artificial Neural Network

The fake neural arrange may be a noteworthy portion of machine learning procedures that can be found in a expansive set of information propelled by the execution of the brain (Pitchaiah et al. 2023). In this study, research have leveraged the power of ANN for the performance prediction of a Gas Turbine Generator, with a specific focus on conducting comprehensive Exergy and Energy analyses.

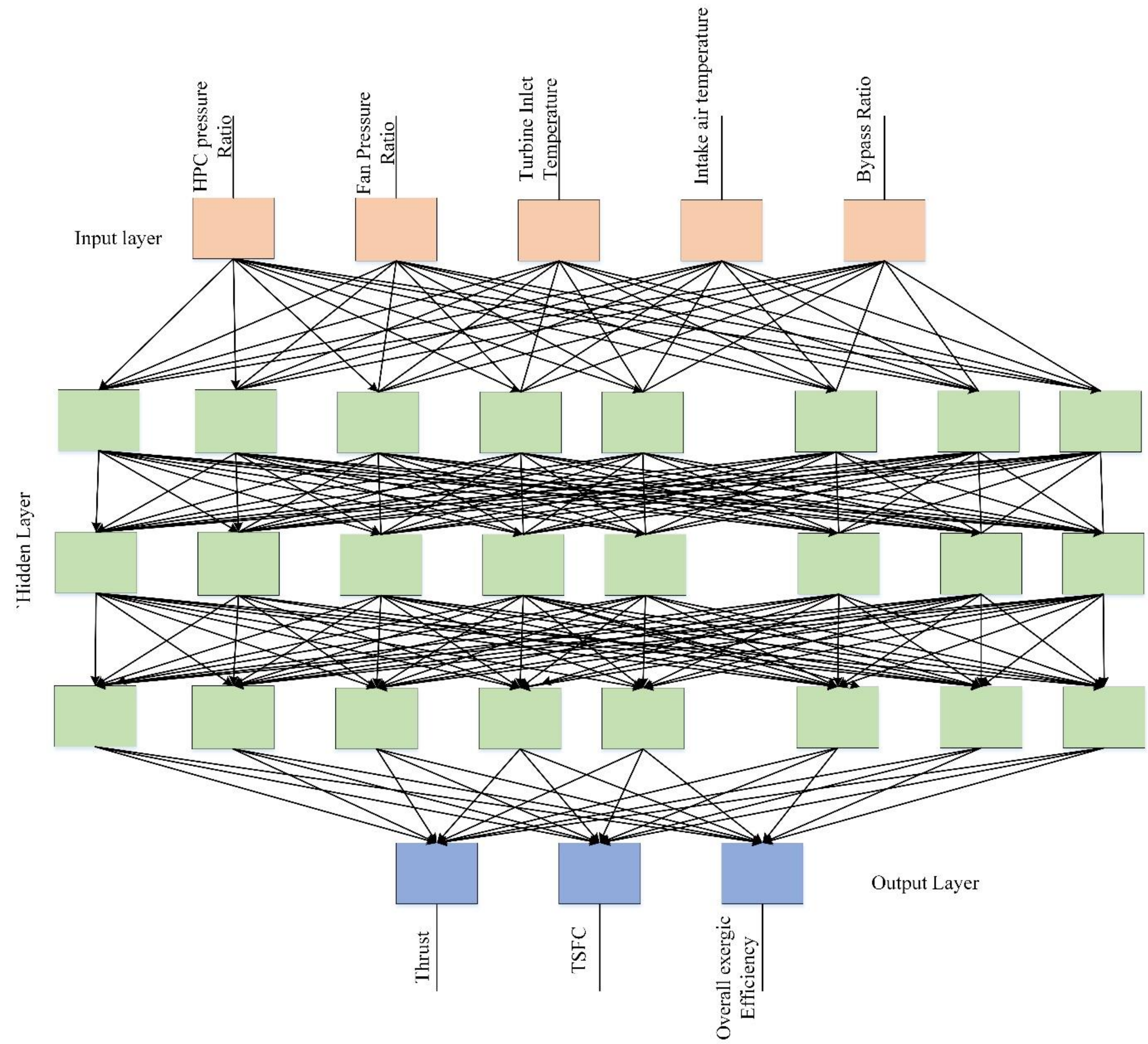


Figure 3: ANN Framework for Exergy and Energy Performance

The integration of Cycle-Tempo Software has allowed us to create a sophisticated predictive model that can offer valuable insights into the gas turbine's behavior and efficiency under varying operational conditions. The results reveal a high level of accuracy, with R-squared values approaching 1 and minimal errors, highlighting the model's exceptional capability to replicate actual performance data. Such a tool holds immense promise for enhancing gas turbine operation, optimizing energy and exergy efficiencies, and ultimately contributing to more sustainable and cost-effective energy generation. Furthermore, this research opens up exciting avenues for future exploration, including the expansion of datasets, real-time monitoring, parameter optimization, and the application of this ANN-based approach to other energy systems, all of which can further advance the field of energy efficiency and environmental sustainability. This is shown in Figure 3.

Deep learning is a complicated neural network with lots of layers and important neurons hidden inside. The study conducted recently collected information on the network, data, and factors influencing the process.These factors include how much the fan can push air, how much the compressor can increase air pressure, changes in the temperature of the air coming in, how hot the air is when it enters the turbine, and how much air is diverted around the engine. This information is used at the beginning of the study. The research then examines this information that is given and processes it through layers that are not easily seen. It then gives results in the final layer. The weight coefficients and activation functions of the artificial neurons within these layers are demonstrated in Figure 2.The information that goes into each neuron is collected (Najafi et al. 2018).

After the weighing process, the neurons' inputs are combined and calculated using the activation function. Activation functions are important components in machine learning models. There are different types of activation functions, such as Tanh, sigmoid, and Rectified Linear Unit (RLU). RLU is particularly popular because it has received a lot of attention. RLU can be defined in Eqn (3):

$$f(a) = \begin{cases} aifa > 0 \\ 0ifa \leq 0 \end{cases} = max(a, 0) \quad (3)$$

In the process of teaching artificial neural networks, there are two main ways to do it. The first way is called supervised learning and the second way is called unsupervised learning. The first one, called "labeled data," can be used to make predictions. However, the other one cannot be used for this purpose. In this study, research used a type of application that is supervised. This means that research compare the output with the actual output. More specifically, the strength of the neuron is determined in a way that the anticipated result from a set of inputs can be as similar as possible. It is important to mention that when assessing how accurate a network is in approximating results, research use a measure called a cost function or loss function. One commonly used loss function is the technique for measuring the difference between predicted and actual results (Najafi et al. 2018). Mean Squared Error (MSE) is a way to measure how much the average of predicted values differs from the average of actual values as mentioned in Eqn (4):

$$G\left(b, \hat{b}\right) = \frac{1}{N} \sum_{u=1}^{N} \left(b_u - \hat{b}_u\right)^2 \quad (4)$$

The letter N represents the number of samples. b_u represents the actual output, and $\hat{b}_u$ represents the predicted output. The MSE function is often used in deep neural networks to make estimates when dealing with continuous values in regression problems. The objective is to discover the optimal weight for each neuron in order to minimize the loss as we acquire knowledge. Finding the weight of a neuron often involves using gradient descent. This is a common method in simple optimization algorithms. Defining the loss function G(v) can be achieved by utilizing equation (5) with the weight vector w representing the network weights.

When considering the weights employed in the network as w, equation (5) presents the definition of the loss function G(v). Equation 5 gives us the loss function G(v). In the network, the weights are represented by the weight vector w.The representation of the network weights can be done using the weight vector w, which enables the definition of the loss function G(v) using equation (5).

$$G(r) = \frac{1}{N} G_u(r) \quad (5)$$

in which G_u is the loss function of sample u and N is the number of the sample. It also gets help from the average of the changes in a thing, just like momentum. A team of researchers are studying how climate change is affecting various types of animals. They want to know how the animals' behavior and survival are being influenced by the changing environment. The scientists want to learn how animals change to fit the new weather by watching them and gathering information (Yoru, Karakoc, and Hepbasli 2009).

5. Result and Discussion

5.1 Parameter Validation

The F135 PW100 turbofan engine is an important part of the Lockheed Martin F-35 Lightning aircraft. It has many necessary parts. This equipment has different parts that work together to make it work. There is a fan that brings air inside, a compressor that squeezes the air, a chamber where fuel mixes and burns, turbines that use the energy from the burnt fuel, and other parts to help control the way the waste gases flow out. We do not have the exact numbers for certain input parameters, like how well the engine performs or its size, in the information we have. However, this table gives an overview of the important parts and main input parameters of the F135 PW100 engine.

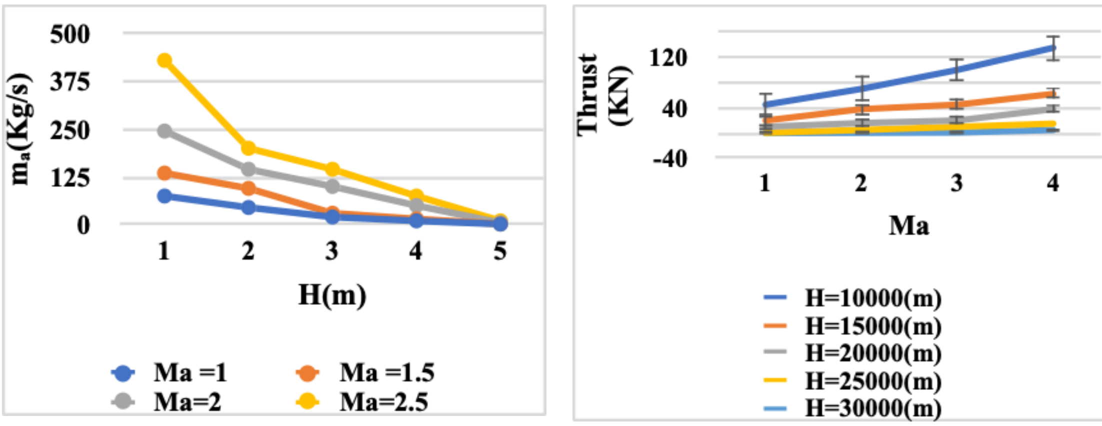
Table 1: Parameter Validation

Parameter	Value/Description
Engine Model	F135 PW100
Engine Type	Mixed-Flow Turbofan
No of Axial-Flow Fan Stages	Three
No of High-Pressure Compressor Stages	Six

No of High-Pressure Turbine Stages	One
No of Low-Pressure Turbine Stages	Two
Combustion Chamber Type	Not specified
Mixer Type	Not specified
Nozzle Type	Not specified
Other Input Parameters (not specified)	Not specified

5.2 Performance Analysis

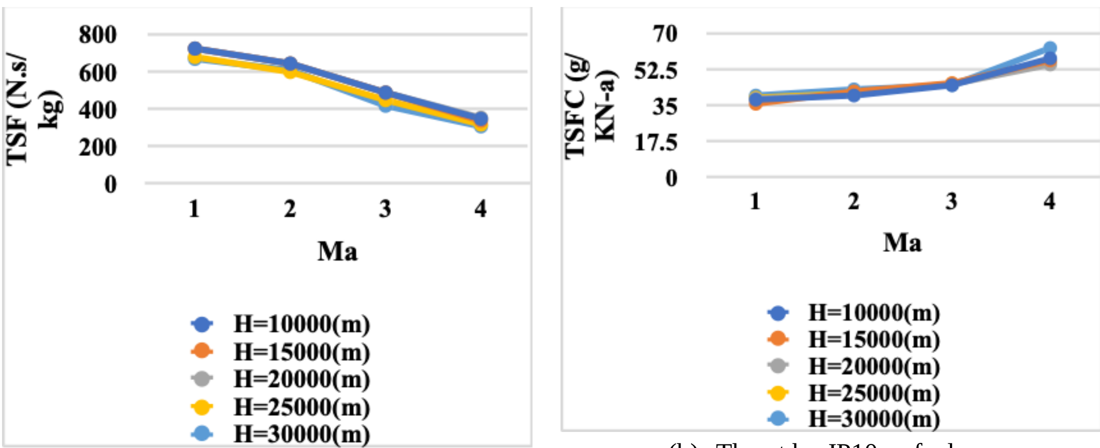
The information about the amount of air entering the engine is shown in Figure 3 (a) and (b). It was noticed that when the speed of the airplane gets faster, the velocity of the airplane also gets faster, but it stays at the same height. So, more air goes into the engine. On the other hand, if the flight Mach number stays the same, going higher in the sky will make less air go into the engine. This decrease happens because the air gets thinner at higher altitudes.



(a) Intake Air Mass

(b) Net Thrust

Figure 3: Flight Mach Number and Flight Altitude Effect (a) Intake Air Mass (b) net Thrust



(a) Thermal Efficiency

(b) Thrust by JP10 as fuel

Figure 4: Flight Mach Number and Flight Altitude effect : (a) Thermal Efficiency (b) Thrust by JP10 as fuel

The information in the graph shows that when the speed of the plane increases from 1 to 2, the engine becomes more efficient. However, when the speed of the flight goes higher than 2 times the speed of sound and reaches between 2 and 2. 5 times the speed of sound, the ability to convert energy into useful work starts to decrease. In

Figure 4 (b), you can see how the efficiency of propulsion changes with the speed of the aircraft and the height at which it is flying. This is for when JP10 fuel is used. When the Flight-Mach number goes up, the F135 engine produces more thrust and the speed of the flight goes up as well. As a result, the effectiveness of the engine improves as the Flight-Mach numbers increase while maintaining a steady flight altitude.
The recreation centre is temporarily closed and being checked before it can be approved. We need to find and understand the mistake. The evaluation looks at how well the company's recreation compares to its current data situation. The value, as indicated by the Cycle-Tempo experiment using the company's data, reveals the extent to which the gas turbine generator influences control. The disparities between the current conditions and the recreation control settings are illustrated in Table 2. Table 2 shows us that the largest error is 6. The findings show that the reenactment is slightly inaccurate by 36%.

Table 2: Error Simulation

Time	Gas Turbine Generator Unit	Energy Simulation	Existing Energy	Error
October	1	95.25	94.05	1.24%
	1.1	97.0	94	4.31%
	1.2	95.94	92.96	3.22%
November	2	89.82	94.93	5.30%
	2.1	93.16	94.90	1.84%
	2.2	101.13	95.08	6.37%

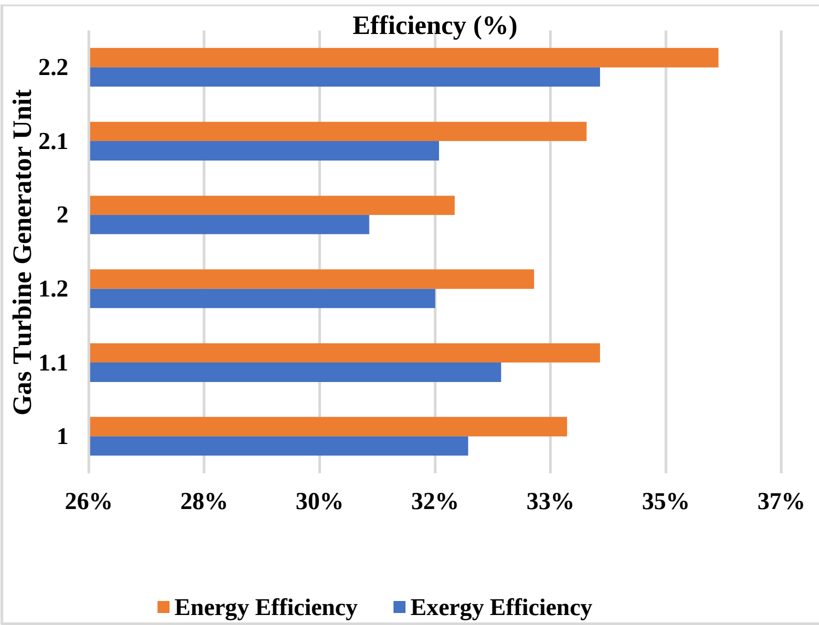


Figure 5: Exergy and Energy Efficiency

The provided data table offers insights into the exergy efficiency and energy efficiency of a gas turbine under different operating conditions. Figure 5 shows the initial state (1), the gas turbine exhibited an exergy efficiency of 32% and an energy efficiency of 33.50%. As the operating conditions evolved in subsequent stages (1.1, 1.2, 2, 2.1, 2.2), variations in both exergy and energy efficiencies were observed. Notably, at time point 2.2, the gas turbine displayed the highest exergy efficiency of 34.00% and the highest energy efficiency of 35.80% among all the measured data points. This data provides a comprehensive overview of how the gas turbine's performance in terms of exergy and energy efficiency changed across different operational states, offering valuable insights into its efficiency characteristics.

Table 3: Training and Testing Performance

	Thrust		**TSFC**		**Overall Exergic Efficiency**	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**
R^2	0.935	0.937	0.866	0.995	0.995	0.995
RMSE	0.545	0.545	0.701	0.695	0.823	0.812
MAE	0.301	0.302	0.324	0.315	0.565	0.565
MAPE	5.122	5.023	1.472	1.44	2.12	2.93

The performance evaluation metrics provided in the table 3 and Figure 6 offer a comprehensive assessment of a predictive model aimed at forecasting Thrust, TSFC, and Overall Exergic Efficiency. During both the training and testing phases, the model consistently demonstrates strong predictive capabilities, as indicated by the high R-squared values (R2) ranging from 0.935 to 0.995. These high R-squared values imply that the model can effectively explain a substantial portion of the variability in the data, highlighting its ability to capture and replicate the observed relationships. Furthermore, the low Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) values signify that the model's predictions closely align with the actual data, with minimal errors and discrepancies. In essence, this model showcases remarkable accuracy in forecasting the gas turbine's performance parameters, making it a valuable tool for optimizing its operation and enhancing energy efficiency. Visualizing these metrics through a graph would reveal data points closely clustered around a 45-degree line, providing visual confirmation of the model's exceptional predictive accuracy.

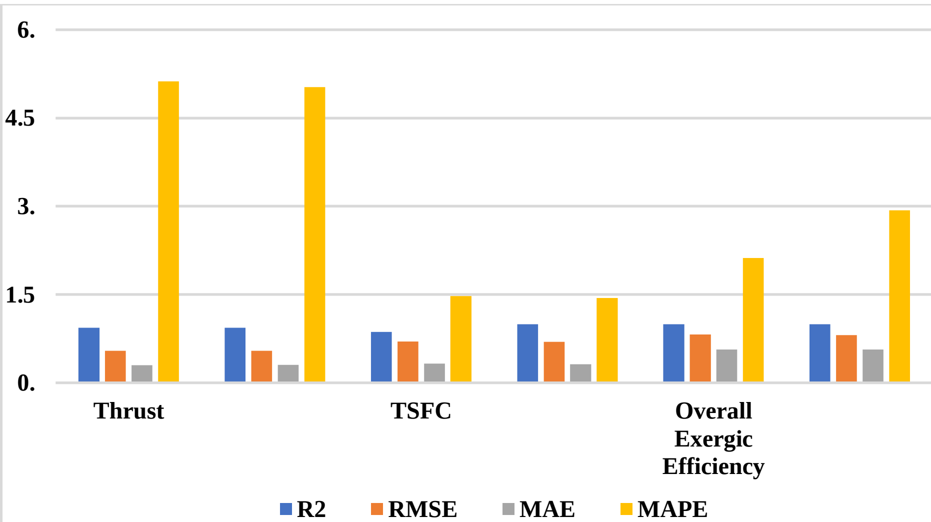


Figure 6: Training and Testing Performance

6. Conclusion

In this study, researchers used a computer program called Cycle-Tempo to predict how well a Gas Turbine Generator would work. They focused on measuring the efficiency of the generator in terms of energy and exergy. They found that an Artificial Neural Network (ANN) was able to accurately make these predictions. The ANN model showed that it can predict things accurately. This is because the predicted results matched closely with the actual results. This ability to predict is very important for making the gas turbine work better, using energy more efficiently, and making it work better overall. By using ANN-based predictions with Cycle-Tempo Software, engineers and operators can make smart choices to improve the efficiency of gas turbines. This helps create energy in a better and cheaper way, making it more sustainable. The results research got showed that proposed accuracy level is very high, with an error rate always below 1% and a R-squared value of 0. 99, which is even better than what research expected. The fact that the model can accurately predict how well a gas turbine generator will perform using exergy and energy analyses shows that it is reliable and effective. This means it has a lot of potential for use in real-world situations. Regarding future work, there are many exciting possibilities to consider. First, research can make the dataset bigger and add more variables to improve and check the accuracy of the ANN model. This will help make sure that the model works well in different situations. Furthermore, adding the capability to collect real-time information and receive immediate feedback in the model can improve its flexibility and ability to adjust to changing operating conditions. Moreover, studying how to improve gas turbine settings for better efficiency and less pollution could be a useful next step, making energy production more sustainable. In simple terms, if research use this ANN approach in other types of power generation systems and industrial processes, it could help improve energy efficiency and sustainability in different areas. This could lead to advancements in how research use energy and protect the environment.

Reference

[1] Ahmadi, A, Biplab Das, MA Ehyaei, F Esmaeilion, M El Haj Assad, DH Jamali, O Koohshekan, et al. 2021. "Energy, Exergy, and Techno-Economic Performance Analyses of Solar Dryers for Agro Products: A Comprehensive Review." *Solar Energy* 228: 349–73.

[2] Alhammadi, Ala Abdelrazaq, Hussam Al-Hamadi, Chan Yeob Yeun, and Ernesto Damiani. 2022. "A Cyber-Security Framework For Boiler of Steam Power Plant Using Simulation Data to Train Machine Learning Model." In *2022 International Conference on Cyber Resilience (ICCR)*, 1–9. Dubai, United Arab Emirates: IEEE. https://doi.org/10.1109/ICCR56254.2022.9995752.

[3] Asgari, N, R Khoshbakhti Saray, and S Mirmasoumi. 2020. "Energy and Exergy Analyses of a Novel Seasonal CCHP System Driven by a Gas Turbine Integrated with a Biomass Gasification Unit and a LiBr-Water Absorption Chiller." *Energy Conversion and Management* 220: 113096.

[4] Dursun, Omer Osman, Suat Toraman, and Hakan Aygun. 2022. "Deep Learning Approach for Prediction of Exergy and Emission Parameters of Commercial High By-Pass Turbofan Engines." *Environmental Science and Pollution Research* 30 (10): 27539–59. https://doi.org/10.1007/s11356-022-24109-y.

[5] El Jery, Atef, Hayder Mahmood Salman, Rusul Mohammed Al-Khafaji, Maadh Fawzi Nassar, and Mika Sillanpää. 2023. "Thermodynamics Investigation and Artificial Neural Network Prediction of Energy, Exergy, and Hydrogen Production from a Solar Thermochemical Plant Using a Polymer Membrane Electrolyzer." *Molecules* 28 (6): 2649. https://doi.org/10.3390/molecules28062649.

[6] Fichera, Alberto, Samiran Samanta, and Rosaria Volpe. 2022. "Exergetic Analysis of a Natural Gas Combined-Cycle Power Plant with a Molten Carbonate Fuel Cell for Carbon Capture." *Sustainability* 14 (1): 533.

[7] Jamil, Faisal, Naeem Iqbal, Imran, Shabir Ahmad, and Dohyeun Kim. 2021. "Peer-to-Peer Energy Trading Mechanism Based on Blockchain and Machine Learning for Sustainable Electrical Power Supply in Smart Grid." *IEEE Access* 9: 39193–217. https://doi.org/10.1109/ACCESS.2021.3060457.

[8] Khaleel, Omar J, Firas Basim Ismail, Thamir Khalil Ibrahim, and Saiful Hasmady bin Abu Hassan. 2022. "Energy and Exergy Analysis of the Steam Power Plants: A Comprehensive Review on the Classification, Development, Improvements, and Configurations." *Ain Shams Engineering Journal* 13 (3): 101640.

[9] Mustafa, Jawed, Saeed Alqaed, Hikmet Ş Aybar, and Shahid Husain. 2022. "Investigation of the Effect of Twisted Tape Turbulators on Thermal-Hydraulic Behavior of Parabolic Solar Collector with Polymer Hybrid Nanofluid and Exergy Analysis Using Numerical Method and ANN." *Engineering Analysis with Boundary Elements* 144: 81–93.

[10] Najafi, Bahman, Sina Faizollahzadeh Ardabili, Amir Mosavi, Shahaboddin Shamshirband, and Timon Rabczuk. 2018. "An Intelligent Artificial Neural Network-Response Surface Methodology Method for Accessing the Optimum Biodiesel and Diesel Fuel Blending Conditions in a Diesel Engine from the Viewpoint of Exergy and Energy Analysis." *Energies* 11 (4): 860.

[11] Pinto, Daniel Vieira, Carlos Roberto Altafini, Daniel Amoretti Gonçalves, and Giovani Dambros Telli. 2021. "Comparative Analysis of Vehicle Turbochargers in Energy Microgeneration for Different Compoundings." *Journal of the Brazilian Society of Mechanical Sciences and Engineering* 43 (1): 14.

[12] Pitchaiah, S, Dagmar Juchelková, Ravishankar Sathyamurthy, and AE Atabani. 2023. "Prediction and Performance Optimisation of a DI CI Engine Fuelled Diesel–Bael Biodiesel Blends with DMC Additive Using RSM and ANN: Energy and Exergy Analysis." *Energy Conversion and Management* 292: 117386.
[13] Ranjan, Ritesh, and Sujit Karmakar. 2020. "THERMODYNAMIC PERFORMANCE ANALYSIS OF A 500MWE SUPERCRITICAL POWER PLANT BASED ON PARAMETRIC AND NEURO-GENETIC OPTIMIZATION TECHNIQUES." *Exergy (MJ/Kg)* 15: 17–30.
[14] Sarkar, Santi, Goutam Khankari, and Sujit Karmakar. 2021. "4-E Analysis of an Ammonia-Water Mixture-Based Automobile's Air Conditioning System Assisted by Exhaust Gas and Solar Energy." *International Journal of Exergy* 36 (2–4): 382–97.
[15] Singh, Dheerendra Vikram, and Tikendra Nath Verma. 2022. "Energy and Exergy Analysis of LiBr-H2O-Operated Vapour Absorption Refrigeration System Using the ANN Approach." *International Journal of Ambient Energy* 43 (1): 905–17.
[16] Thattai, A Thallam, VDWM Oldenbroek, L Schoenmakers, T Woudstra, and PV Aravind. 2017. "Towards Retrofitting Integrated Gasification Combined Cycle (IGCC) Power Plants with Solid Oxide Fuel Cells (SOFC) and CO2 Capture–A Thermodynamic Case Study." *Applied Thermal Engineering* 114: 170–85.
[17] Venkitesh, KS, Joseph Daniel, and Manavalla Sreekanth. 2021. "Thermodynamic Assessment of a Gas Turbine System Combined with A Solid Oxide Fuel Cell Powered by Synthetic Gas from Municipal Solid Waste." In *IOP Conference Series: Materials Science and Engineering*, 1128:012036. IOP Publishing.
[18] Yoru, Yilmaz, T Hikmet Karakoc, and Arif Hepbasli. 2009. "Application of Artificial Neural Network (ANN) Method to Exergy Analysis of Thermodynamic Systems." In *2009 International Conference on Machine Learning and Applications*, 715–18. IEEE.
[19] Zadhossein, Safoura, Yousef Abbaspour-Gilandeh, Mohammad Kaveh, Mariusz Szymanek, Esmail Khalife, Olusegun D. Samuel, Milad Amiri, and Jacek Dziwulski. 2021. "Exergy and Energy Analyses of Microwave Dryer for Cantaloupe Slice and Prediction of Thermodynamic Parameters Using ANN and ANFIS Algorithms." *Energies* 14 (16): 4838.