

The Effect of Meteorological Data on Energy Efficiency and Flight Performance in Sustainable Aviation

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Corresponding Author: *Fatih Koçyiğit***RESEARCH ARTICLE**<https://doi.org/10.30518/jav.1656416>**Abstract**

The aviation industry is closely associated with the effects of weather conditions on flight safety, but energy efficiency and sustainability issues have also gained importance in recent years. Meteorological data plays a critical role in determining flight routes, increasing fuel efficiency and ensuring flight safety. More efficient flight routes can be planned by considering the impact of meteorological events on the energy consumption of aircraft, in particular factors such as wind, temperature changes, humidity and turbulence during flight. This reduces fuel consumption and minimizes environmental impact. Particular attention should be paid to the use of renewable energy, the energy efficiency of aircraft and the impact of weather conditions on energy production. In addition, the integration of meteorological data with energy efficiency in future aircraft systems should be assessed. In this study, net thrust, fuel consumption, fuel flow and core efficiency factors of a turboshaft engine were predicted by artificial neural networks based on meteorological data such as ambient temperature. The best predicted output parameter, which varies depending on the ambient temperature input, is the core efficiency with 0.9 MAPE. It also investigated the role of aviation meteorology in predicting weather conditions and improving flight safety, and the interface between energy management and sustainable aviation.

1. Introduction

The aviation industry is an important part of the world's energy consumption and is also an area directly affected by weather conditions. Accurate use of meteorological data is required to ensure flight safety, but energy efficiency and efforts to reduce carbon emissions are also becoming increasingly important.

The aviation sector not only constitutes an important transport network worldwide, but also draws attention with its energy consumption and environmental impacts. Globally, aviation accounts for approximately 2% of total energy consumption and 3% of carbon dioxide (CO₂) emissions (IATA, 2020). In the report titled Carbon Offsetting and Reduction Scheme for International Aviation published in 2022, ICAO aims to reduce global aviation emissions by 50% by 2050. These data reveal that the aviation sector has a critical importance in terms of energy efficiency and carbon emissions. In particular, a large portion of aviation's energy consumption is provided by fossil fuels used in flight, which threatens environmental sustainability (Lee et al., 2020). In this regard, the examination of aviation meteorology and energy management is of great importance for both flight safety and environmental sustainability.

Aviation meteorology is a science that monitors weather conditions and uses this data in flight planning and operations

to ensure flight safety. The impact of weather conditions on flight is particularly dependent on the accuracy and speed of weather data. These meteorological data play a fundamental role in the landing and take-off of aircraft at airports, the flow of traffic at the airport and the determination of flight routes. For example, wind direction and speed can directly affect the take-off and landing performance of a flight. In addition, weather conditions causing low visibility, such as fog, can jeopardize the timing and safety of flights (Moser, 2017).

The effects of meteorological phenomena on flight safety becomes even more critical especially since aircraft fly at high altitudes. Aircraft flying at such altitudes are more susceptible to harsh weather conditions such as turbulence, thunderstorms and high wind speeds. Such weather events can have a direct impact on the energy efficiency of aircraft as they can alter the speed, fuel consumption, and route of aircraft (Fraser, 2019). In addition, events such as low visibility and thunderstorms pose a threat to flight safety, while also challenging the aviation industry's energy efficiency targets. The impact of aviation meteorology on flight safety and energy efficiency is therefore important throughout the industry.

Energy management in the aviation sector is a process that aims to mitigate the environmental effects of flights and lower operating costs. In this sense, sustainable aviation includes practices aimed at increasing energy efficiency and reducing carbon emissions. Several strategies are implemented to

achieve sustainable aviation. The most remarkable of these are the use of renewable energy sources and the development of electric aircraft. By replacing fossil fuels with alternative energy sources, electric aircraft can significantly mitigate the environmental impact of aviation (Bortolotti et al., 2021).

However, many technologies have been developed to use renewable energy sources in aviation. In particular, solar and wind energy have significant potential to meet the energy needs of the aviation sector. Weather conditions have a direct impact on the efficiency of these renewable energy sources. For example, high wind speeds and solar radiation can increase or decrease the efficiency of energy systems used at airports (Khatib, 2019). This requires the integration of aviation meteorology with energy management.

The relationship between aviation meteorology and energy management has become increasingly important in recent years. Meteorological data has a significant impact on flight safety and energy efficiency. For example, wind direction and speed in flight can directly affect aircraft fuel consumption. Similarly, aircraft flying at high altitudes can be affected by jet streams and other weather conditions in the atmosphere. Therefore, accurate analysis of aviation meteorology and its use in a manner compatible with energy efficiency can reduce the environmental impacts of flights (Kandil, 2018).

Another important development in energy management is that aircraft reduce energy consumption by flying more efficient routes. Meteorological data plays a crucial role in route planning. Forecasting weather conditions allows aircraft to fly shorter and more energy-efficient routes. In this context, technologies such as artificial intelligence and machine learning can be used to optimize flight routes by analyzing meteorological data. By continuously analyzing data of aviation meteorology, AI-based systems can determine the most energy-efficient routes for flights (Xie et al., 2020).

Aviation meteorology and energy management are two critical complementary factors for sustainable aviation. Accurate analysis of weather conditions not only improves flight safety, but also optimizes energy efficiency. In a world where the use of renewable energy is increasing and electric aircraft are being developed, reducing the environmental impacts of the aviation sector depend on accurate weather forecasting and the integration of this data with energy management. Therefore, developments in aviation meteorology and energy management will form the basis for future sustainable aviation systems. The aim of this study is to investigate the interaction between aviation meteorology and energy management and to provide a new perspective for sustainable aviation practices.

2. Impacts of Aviation Meteorology on Energy

Aviation meteorology analyzes weather conditions to ensure flight safety and optimize operations. In addition, meteorological factors are crucial not only for flight safety, but also for energy efficiency and sustainability. In particular, it is important to use accurate meteorological data to ensure energy efficiency. Factors such as wind, temperature and humidity encountered during flight can have a direct impact on an aircraft's energy consumption. For example, wind direction and speed play an important role in determining flight routes and speeds. Takeoff and landing speeds, as well as tire braking distances, are mostly calculated based on meteorological conditions. While airplanes are in cruise conditions, tailwinds reduce fuel consumption, whereas headwinds can increase it.

With accurate weather forecasts, aircraft can choose more efficient routes, reducing energy consumption. While low temperatures can improve engine efficiency, extreme temperatures can adversely affect aircraft performance. Accurate wind data is needed for wind turbines to operate effectively. Using high-altitude wind data from flights, aviation meteorology can predict when turbines will operate more efficiently. This helps optimize energy production (Wiser and Bolinger, 2022). Data from aircraft provides information about wind speeds and currents at higher altitudes, not near the ground. This data can be used to generate more energy by increasing the efficiency of turbines. In particular, high-altitude wind currents can be tracked more accurately with airborne meteorology (Gueymard, 2018). Figure 1 shows the energy consumption in kWh for the three phases of the flight (taxi, take-off and flight) for different weather categories (sunny, rainy, windy, cloudy and snowy days). Figure 1 shows that energy consumption for takeoff and flight increases, especially on windy and snowy days, while taxiing generally consumes less energy. This type of analysis highlights the importance of considering weather for operational efficiency.

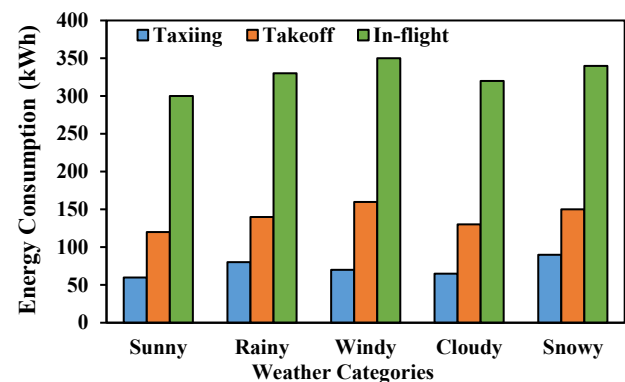


Figure 1. Effect of weather conditions on aircraft energy consumption.

Weather conditions can affect not only aircraft energy consumption, but also aviation-related power generation systems. In particular, renewable energy sources such as wind and solar can increase or decrease their efficiency based on weather conditions. Aviation meteorology analyzes atmospheric cloud structure and radiation data to provide accurate estimates of solar power generation capacity. As cloud cover increases, the amount of sunlight reaching the ground surface is reduced. Meteorological data from aircrafts can predict when solar power generation will decrease by determining cloud rates. This provides critical data to ensure the efficient operation of solar power plants (Hughes and Henshaw, 2021). Aviation meteorology can analyze how particles in the atmosphere (such as dust, steam, and pollution) affect sunlight. This data can help energy producers adjust production capacity based on weather conditions (Gueymard, 2018).

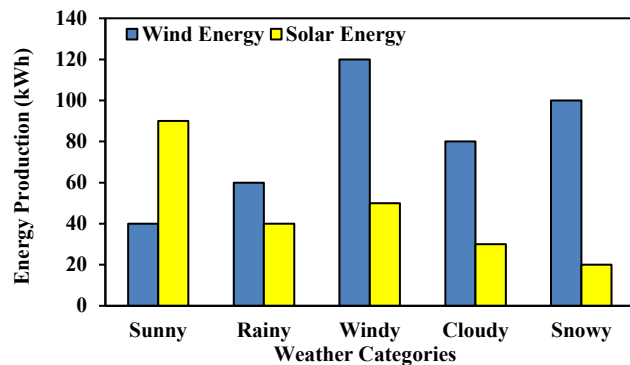


Figure 2. Effect of weather conditions on wind and solar energy production.

Figure 2 shows that solar power generation is highest on sunny days and decreases significantly on cloudy and snowy days, while wind power generation peaks on windy and snowy days but remains relatively low on sunny days.

3. Sustainable Aviation and Energy Efficiency

Sustainable aviation aims to increase energy efficiency to reduce carbon footprint and realize more efficient flights. Thus, more efficient and environmentally friendly flights can be possible when energy-efficient aviation technologies are supported by meteorological data. The use of renewable energy has a great potential for aircraft in the future. Electric aircraft and hybrid energy systems are important developments to reduce the energy consumption of aviation. For these aircraft to operate efficiently, continuous monitoring with meteorological data is required. As can be seen in Figure 3, a head wind increases energy consumption while the tail wind decreases it. High humidity leads to higher energy consumption than low humidity. Rainy and snowy weather increases energy consumption. High altitude reduces energy consumption as air density decreases, while low altitude consumes more energy. Cold weather leads to the highest power consumption because it reduces battery efficiency and increases the need for anti-icing procedures on aircraft.

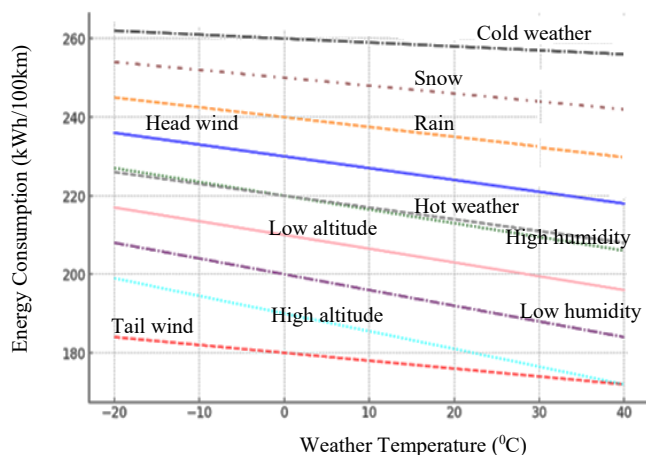


Figure 3. The Relationship Between Weather Conditions and Energy Efficiency of Electric Aircraft.

Accurate weather forecasting can optimize both the energy efficiency of aircraft and the energy management of airports. In particular, meteorological forecasts can be used to reduce energy consumption at airports by planning aircraft landing

and takeoff times more efficiently. Meteorological data is critical to the safety and efficiency of flights. This data must be accurately collected, transmitted, and interpreted. Pre-flight weather reports (METAR and TAF) and advanced meteorological analysis provide great guidance for aircraft operators and pilots. METAR shows instantaneous weather conditions, while TAF reports provide longer-term forecasts. Critical to flights, these reports are used to monitor and predict the effects of weather conditions on flight. Figure 4 shows the energy consumption in kWh regarding lighting, heating/cooling and operational needs for different weather categories (sunny, rainy, windy, cloudy and snowy days). It is emphasized that energy consumption is lower on sunny days, while energy consumption increases on snowy and rainy days.

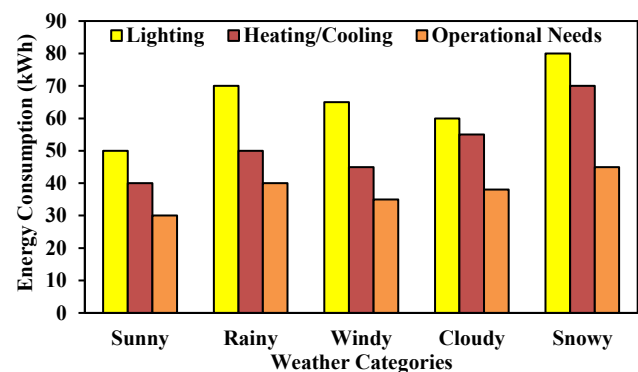


Figure 4. Effect of weather forecasts on airport management

3.1. METAR (Meteorological Aerodrome Report)

METAR is a standardized report that provides weather conditions every hour at international airports and every half hour at domestic airports. A METAR report includes the following components:

- ✓ **Location and Time:** For example, LTBA 301350Z (Istanbul Airport, day 30 at 13:50 UTC).
- ✓ **Wind Data:** Wind direction (degrees) and speed (knots). For example, 09010KT (10 knots at 090 degrees).
- ✓ **Ground visibility:** Visibility on the runway (meters or kilometers). For example, 5000m.
- ✓ **Weather Events:** They are expressed by abbreviations such as rain (RA), snow (SN), fog (FG).
- ✓ **Cloud cover:** Type and height of cloud layers (feet). For example, FEW030 (low cloud at 3,000 feet).
- ✓ **Temperature/Dew Point:** 15/12 (15°C temperature, 12°C dew point).
- ✓ **Pressure:** Q1013 (1013 hPa).

METAR's application areas can be listed as follows.

- ✓ **Flight Operations:** Take-off and landing performance calculations (e.g. runway selection if the wind is in the opposite direction).
- ✓ **Ground Services:** Runway and apron maintenance planning in case of fog or snow.
- ✓ **Fuel Optimization:** Recalculation of fuel consumption depending on wind direction.

3.2. TAF (Terminal Aerodrome Forecast)

TAF are reports containing 24–30-hour weather forecasts and used in operational planning. They are structurally similar to METAR but focused on forecasting:

- ✓ **Location and Validity Period:** LTBA 301200Z 3012/3112 (from day 30 at 12:00 UTC to day 31 at 12:00 UTC).
- ✓ **Wind Forecast:** VRB05KT (Variable direction 5 knots).
- ✓ **Weather Forecasting:** TEMPO 3018/3022 4000 RA (Temporarily rainy between 18:00-22:00 and 4,000m visibility).
- ✓ **Cloud Forecast:** BKN015 (Partly cloudy at 1,500 feet).

The application areas of TAF can be listed as follows.

- ✓ **Long Distance Flight Planning:** Saving fuel by utilizing jet streams.
- ✓ **Airport Energy Management:** Adjustment of solar/wind power generation capacity according to forecasts.
- ✓ **Critical Operations:** Revising flight schedules according to storm forecasts.

This data provides aircraft operators with critical information for flight planning and routing.

4. Future Applications and Technological Advances

The intersection of aviation meteorology and energy management is becoming more efficient and sustainable as technology developments. Advancing technologies have improved the accuracy of aviation meteorology and strengthened the link between flight safety and energy management. Satellite systems, radars, and artificial intelligence-based analytical tools are used to improve flight safety. Satellite imageries and radars monitor instantaneous changes in the atmosphere and provide critical data to ensure flight safety. Energy management in aviation begins not only during flight, but also in-flight planning and real-time flight management. AI-aided flight management systems optimize flight path and speed based on weather conditions, thus saving fuel. Dynamic route adjustments can improve fuel efficiency by reshaping flight paths based on current weather changes. Systematic monitoring and optimization of fuel consumption can improve efficiency during flight by controlling the energy consumption of various systems. In particular, technologies such as artificial intelligence, machine learning, and data analytics are used to integrate meteorological data with flight and energy efficiency.

Radars and satellites used to monitor and analyze weather phenomena are critical, especially for detecting storms, turbulence and other meteorological events. These systems provide real-time information to flight crews to ensure safe flight operations. In addition, high-resolution weather sensors and satellite systems can monitor changes in different layers of the atmosphere in real time. Technologies such as synthetic aperture radar (SAR) and infrared sensors can be particularly useful for low-altitude flights. These sensors can more quickly and accurately detect weather conditions such as turbulence, rain, icing, etc. during flight, which is critical for aircraft. Machine learning and artificial intelligence are used to optimize flight routes and aircraft energy consumption by analyzing information from meteorological data. These systems help determine the most efficient routes by analyzing weather conditions during flight. Aircraft can continuously collect weather data during flights. This data can be collected by using on-board weather sensors and analyzed in real time. Using this data, AI-based systems can develop the best strategies for optimal fuel consumption and safety during flight.

By continuously monitoring weather conditions, autonomous flight technologies can optimize flights to increase energy efficiency. Autonomous flight systems have the potential to automatically optimize flight routes, speeds, and fuel consumption. By integrating weather data, these systems can make more efficient decisions during flight. Autonomous systems can instantly change flight paths based on weather conditions and maximize energy efficiency. Such flights can use meteorological data to provide more efficient flight routes and takeoff and landing times. In addition, artificial intelligence-based forecasting algorithms predict future weather conditions, allowing autonomous flight systems to perform efficient flight planning.

5. Flight Performance Analysis of a Turboshaft Engine with Artificial Neural Networks According to Ambient Temperature

5.1. Dataset and Preprocessing

In this study, the input turboshaft engine dataset is obtained from Gasturb. Ambient temperature of 19 °C variable data as input were used to change the turboshaft engine parameters net thrust, fuel consumption, fuel flow, core efficiency as output. Raw data is shown in Figure 5.

Table 1. Statistical features of the raw data

| Features | Min | Max | Mean | Median | Standard Deviation | Variance |
|-----------------------------|--------|--------|-------|--------|--------------------|----------|
| Input data | | | | | | |
| Ambient Temperature (°C) | -15 | 39 | 12 | 12 | 16.88 | 285 |
| Output data | | | | | | |
| Net Thrust (kN) | 81.84 | 111.68 | 99.53 | 100.66 | 8.69 | 75.65 |
| Fuel Consumption (g/(kN.s)) | 10.27 | 11.03 | 10.43 | 10.38 | 0.188 | 0.035 |
| Fuel Flow (kg/s) | 0.9034 | 1.1831 | 1.038 | 1.035 | 0.087 | 0.007 |
| Core Efficiency | 0.3720 | 0.4335 | 0.404 | 0.405 | 0.019 | 0.0003 |

Minimum, maximum, mean, median, standard deviation, variance statistical features of the raw data are given in Table 1. When ambient temperature is considered as the input data

its minimum, maximum, mean, median, standard deviation, variance value is respectively -15, 39, 12, 12, 16.88 and 285.

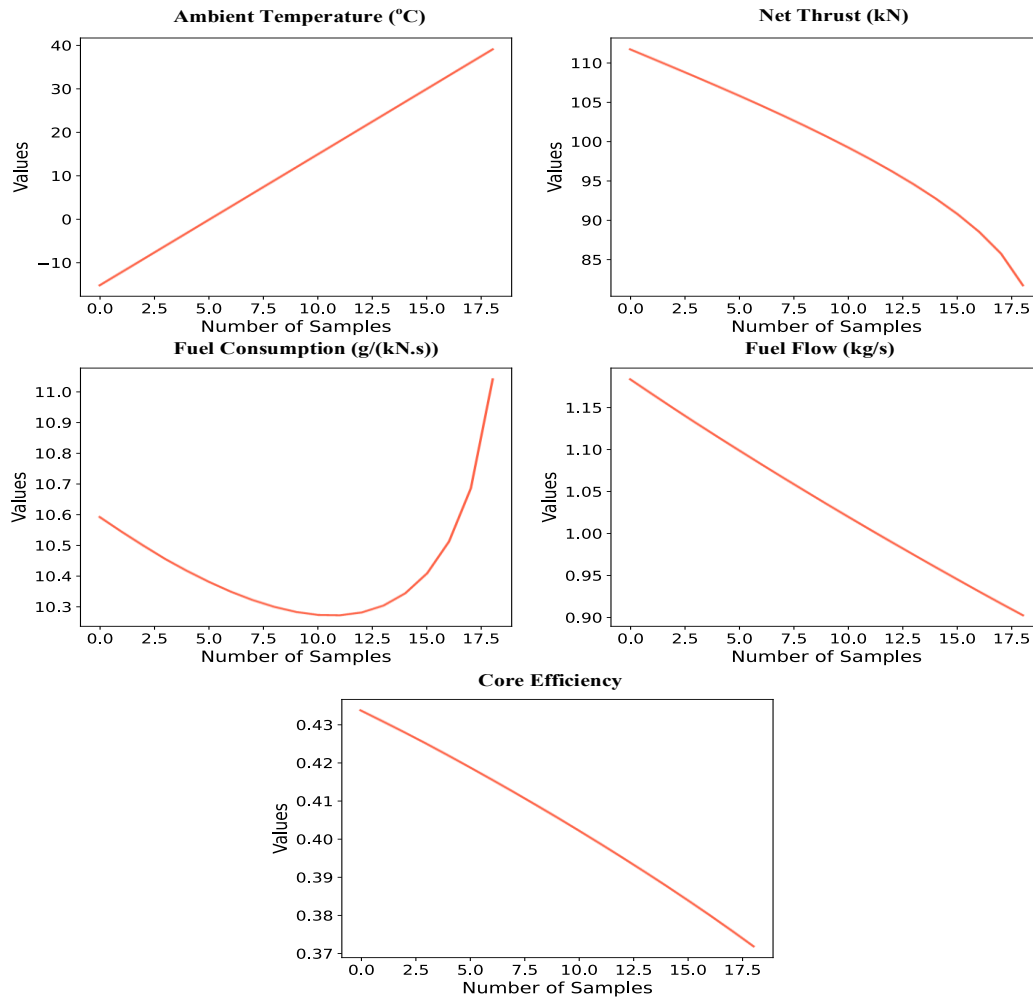


Figure 5. Raw data

The data is normalized to [0-1] range so that the ANN model are converge faster. The normalization process is shown in Equation 1.

$$\bar{x} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (1)$$

While 80% of the normalized data was used for training the ANN model, the remaining 20% was used for testing. Test and predicted data were converted to actual values.

5.2. ANN

The model known as artificial neural networks have been developed by taking inspiration from the biological structure of the human brain. Artificial neural networks are built on reproducing the neurons in the brain and the connections and relationships that exist between them. ANNs are created by connecting neurons. This network structure, created by connecting neurons, reveals the relationship between the data. Signal processing, image processing and time series prediction have all benefited from the effective application of ANNs. Figure 6. reveals the basic architecture of ANN (Dursun et al., 2022; Yousif and Kazem, 2021).

The turboshaft engine data obtained from Gasturb (Ambient temperature) was given as input to the ANN and the engine output data (Net thrust, Fuel consumption, Fuel flow, and Core efficiency) were predicted.

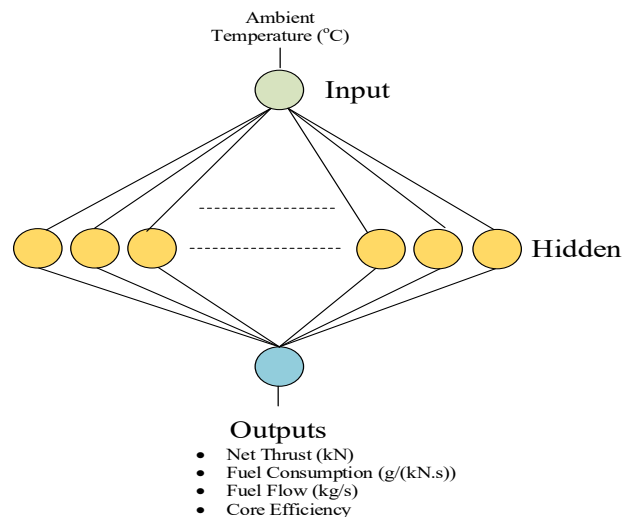


Figure 6. ANN architecture

In the study, the effect of the ambient temperature, which varies with altitude, on the engine parameters was investigated. The use of a single input parameter can be considered as a limitation of the study.

Multilayer neural networks, which are the most popular among ANN models, were used in this study to predict the turboshaft engine data. The grid search algorithm was used in the determination of parameters such as the number of neurons and the batch size used in the hidden layer of the ANN. The batch size and the number of neurons was found with grid search respectively as 2 and 16. Tanh function was used as the activation function. The parameters of the proposed ANN model are shown in Table 2.

Table 2. Parameters of the ANN

| Activation function | Loss function | Optimizer | Epoch | Neuron | Batch size | lr |
|---------------------|---------------|-----------|-------|--------|------------|-------|
| Tanh | MSE | Adam | 100 | 16 | 2 | 0.001 |

Abbreviation: *lr*, learning rate

5.3. Performance Metrics

Evaluation of the performance of the proposed model with artificial neural network is very important in terms of determining the reliability and validity of the model. Therefore, MSE, RMSE, MAE and MAPE metrics are used in the evaluation of the proposed model. The mathematical expressions of the metrics are given in Equations 2-5 (Aygun and Turan, 2022). Where, y_r represents the actual values and y_p represents the predicted values.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_r - y_p)^2 \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_r - y_p)^2} \quad (2)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_r - y_p| \quad (3)$$

$$MAPE = 100 \left(\frac{1}{n} \sum_{i=1}^n |y_r - y_p| \right) \quad (4)$$

6. Results and Discussion

Machine learning models making predictions, the extent to which the model has made a good prediction is understood from the loss graph. The closer the loss graph is to zero, the better the model is at making a good prediction. At the same time, looking at the prediction graph, it is desired that the test and predicted values are closer to each other. Figure 7 shows the loss function and prediction graphs of the output parameters of the ANN model. When the loss graph of the net thrust parameter is examined, it is seen that the loss function value approaches zero from approximately 0.45. At the same time, when the prediction graph is examined, it is seen that the test and prediction values approach each other. The loss graph of the fuel consumption parameter is observed, it decreases from the value of 0.7 to around 0.1. When the prediction graph is looked, the test and prediction values are obtained a little more apart from each other. It is seen that the loss graph of the fuel flow parameter decreases from the value of approximately 0.20 to the value of zero. In the prediction graph, it is seen that the test and prediction values are close to each other. Finally,

it is seen that in the loss function graph of the core efficiency parameter, the loss value decreases from approximately 0.30 to zero, and in the prediction graph, the test and prediction values are close to each other.

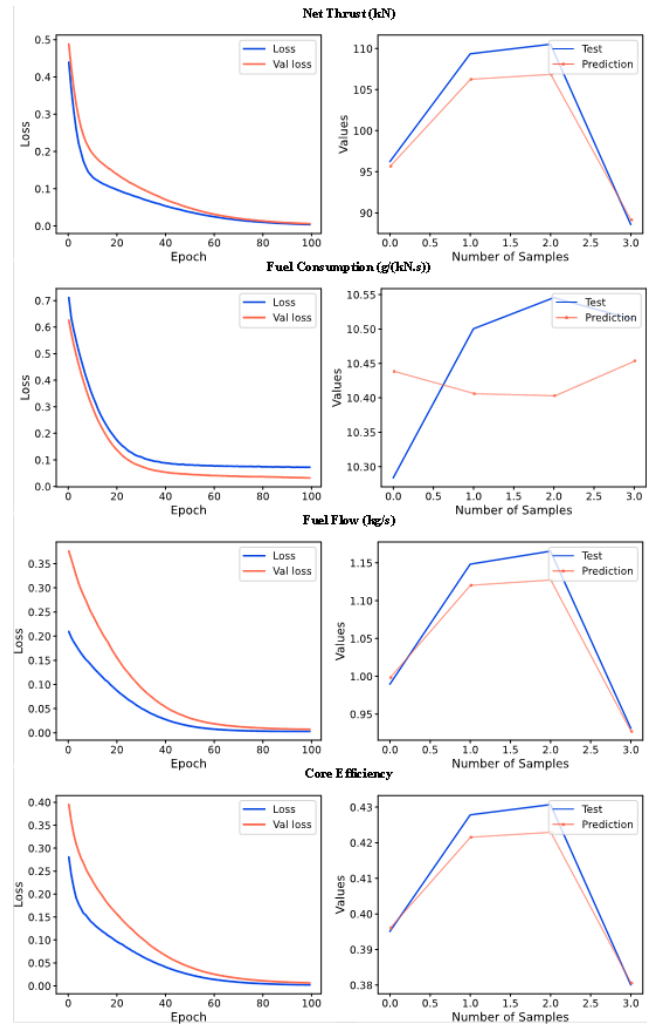


Figure 7. Loss function (left) and prediction (right) graphs of the ANN

Depending on the ambient temperature which was input feature of ANN, net thrust, fuel consumption, fuel flow, core efficiency output features of the turboshaft engine were estimated. As a result of the estimation, the test and predicted values of the outputs are shown in Table 3. When Table 3. is examined, the test data of the net thrust parameter's real value was 96.26, was found a predicted value of 95.69. The real value of the fuel consumption output feature, which was 10.28, was obtained as 10.43 after prediction. The real value of the fuel flow parameter, which was 0.98, was predicted as 0.99. The real value of the core efficiency output, which was 0.3951, was estimated as 0.3960. The proposed ANN model predicted values are compared with real values, it is observed that ANN model makes efficient prediction.

Table 3. Test and predicted values of outputs

| Net Thrust (kN) | | Fuel Consumption (g/(kN.s)) | | Fuel Flow (kg/s) | | Core Efficiency | |
|-----------------|------------|-----------------------------|------------|------------------|------------|-----------------|------------|
| Test | Prediction | Test | Prediction | Test | Prediction | Test | Prediction |
| 96.26 | 95.69 | 10.28 | 10.43 | 0.98 | 0.99 | 0.3951 | 0.3960 |
| 109.37 | 106.27 | 10.50 | 10.40 | 1.14 | 1.12 | 0.4278 | 0.4215 |
| 110.53 | 106.87 | 10.54 | 10.40 | 1.16 | 1.12 | 0.4307 | 0.4229 |
| 88.60 | 89.16 | 10.51 | 10.45 | 0.93 | 0.92 | 0.3801 | 0.3806 |

MSE, RMSE, MAE, MAPE metrics were used for the performance evaluation of the ANN model. The analysis results of the test data metrics are shown in Table 4. According to the results of the metrics, the MSE value of the net thrust parameter was found to be 5.924, RMSE 2.434, MAE 1.975 and finally MAPE 1.8%. The MSE of the fuel consumption parameter was 0.014, RMSE 0.119, MAE 0.112, and MAPE around 1%. The MSE of the fuel flow output was 0.0005, RMSE 0.024, MAE 0.019 and MAPE 1.7%. The MSE, RMSE, MAE and MAPE values of the core efficiency output were found to be 2.529, 0.005, 0.003 and 0.9%, respectively. When the results are examined, it is seen that the MSE values of all outputs are low and the MAPE value varies between approximately 0.9-1.8%. The low MAPE value shows that the model has obtained an effective estimate.

As a result, an ANN model is proposed to predict the net thrust, fuel consumption, fuel flow, core efficiency output parameters of a turboshaft engine according to the change in ambient temperature. Considering the MAPE metric, the best predicted turboshaft engine output parameter according to the ambient temperature inlet characteristic that varies with altitude is core efficiency, followed by fuel consumption, fuel flow and net thrust, respectively. When the metrics of the output parameters are examined, it is shown that the proposed ANN model makes an efficient prediction.

Table 4. Analysis results of test data

| Outputs | MSE | RMSE | MAE | MAPE |
|-----------------------------|--------|-------|-------|------|
| Net Thrust (kN) | 5.924 | 2.434 | 1.975 | 1.8 |
| Fuel Consumption (g/(kN.s)) | 0.014 | 0.119 | 0.112 | 1.0 |
| Fuel Flow (kg/s) | 0.0005 | 0.024 | 0.019 | 1.7 |
| Core Efficiency | 2.529 | 0.005 | 0.003 | 0.9 |

7. Conclusion

Aviation meteorology is a critical area for flight safety and requires accurate analysis and use of meteorological data. Technological advancements are improving the accuracy in this field and enabling more precise prediction of for effects of weather conditions on flights. In the future, the integration of autonomous flight systems with aviation meteorology and the development of artificial intelligence-based forecasting models will further improve flight safety. In order to improve flight safety and efficiency:

- ✓ Improving weather monitoring and reporting processes,
- ✓ Rapid integration of new technologies,
- ✓ Improved training and support systems are needed for pilots and air traffic controllers to access meteorological data more effectively.

In particular, the study is limited in terms of data acquisition by using turboshaft engine data in the aviation field. It is very difficult to obtain data in the aviation field. At

the same time, the use of the single input parameter ambient temperature limits the study. In future studies, the use of the pressure parameter, which varies according to altitude from meteorological data, is also considered.

The interaction between aviation meteorology and energy management plays a critical role in creating sustainable aviation systems. Accurately forecasting weather conditions and using these data for energy efficiency will make flights more environmentally friendly and efficient. Advanced weather forecasting technologies allow flight routes to be optimized, both increasing safety and reducing energy consumption. In the future, innovative solutions such as artificial intelligence, sensor technologies and autonomous systems will further strengthen the integration between flight safety and energy management and will contribute greatly to aviation sustainability. Furthermore, further integration of renewable energy sources and the use of advanced technologies will create a significant transformation in the aviation industry. For this transformation to be successful, further research is required on the integration of meteorological data with energy efficiency and sustainable aviation solutions.

The study will provide convenience to turboshaft engine manufacturers in engine production in a computer environment without real experimental data.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper

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