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Model Identification Of Correlation Of Avionic Parameters With Magnetic Field Intensity Using Neutral Networks

***Abstract**. The article presents the identification of the magnetic field with the use of neural network model. The research on the value of the magnetic component of the electromagnetic field (EM) was determined with the NHT3DL broadband meter from Microrad with the 02H measuring probe during training flights. A convolutional autoencoder model of a neural network was developed to filter out outliers obtained during measurements.*

***Streszczenie.** W artykule przedstawiono identyfikacje składowej magnetycznej pola elektromagnetycznego przy użyciu modelu sieci neuronowych. Badania dotyczące wartości składowej magnetycznej (EM) wyznaczono miernikiem szerokopasmowym NHT3DL firmy Microrad z sondą pomiarową 02 H podczas lotów szkoleniowych statkami powietrznymi. Opracowano model konwolucyjnego autoencondera sieci neuronowej (ang. convolutional autoencoder model) stużący do odfiltrowania danych odstających uzyskanych podczas pomiarów. **(Modelowa identyfikacja korelacji parametrów awioniki z natężeniem pola magnetycznego z wykorzystaniem sieci neutralnych**)*

Keywords: magnetic field (EM), neural network, aircrafts, measurements
Słowa kluczowe: pole magnetyczne, sieci neuronowe, samoloty, pomiary

Introduction

Electromagnetic waves are associated with energy distribution phenomena. As a result, they can have a negative impact on both the human body and electronic devices. Monitoring and measuring of the electromagnetic field generated by devices are important from the point of view of the human body and environmental protection [1-3].

The use of deep learning methods automatically detects the required representation of features directly from the data. One of the important advantages of this approach is that the deep model does not require manual feature engineering. These methods are used in a wide variety of practical applications, such as estimating and recognizing human position and activity, vehicle motion detection, and manufacturing engineering applications [4-7].

A convolutional neural network selected in this study was used for recognizing avionic parameters. Distinctive features, compared to standard neural networks, is the presence of convolutional layers in addition to fully connected layers. Convolutional layers train filters that move along the input and apply to subregions of the input. Each neural network should be trained on the basis of as much data as possible to best describe the study process under [8-12].

Method and Materials

In order to determine the general impact of the magnetic field strength that affects humans and electronic devices while flying a given type of aircraft, experimental measurements were made, and then the obtained results were implemented to develop a neural network model to correlate avionics parameters with the occurring field phenomena. Measurements of the magnetic component H were carried out in various types of Aero AT-3, Tecnam P2006T aircraft using the NHT3DL broadband meter by Microrad with the 02H measuring probe [13-15]. Identification of flight parameters was performed using neural networks (convolutional autoencoder model). In order to filter the data, the convolutional autoencoder model was used. The task of the created neural network model is to reduce the dimension and reproduce the input data based on this information . The model learns a generalized representation of the data so that data such as outliers are corrected [16, 17] (Fig.1).

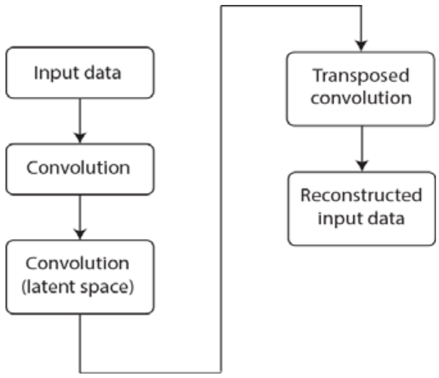
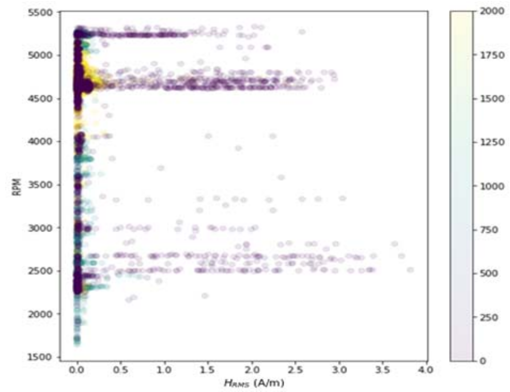


Fig 1. Convolutional autoencoder

a)



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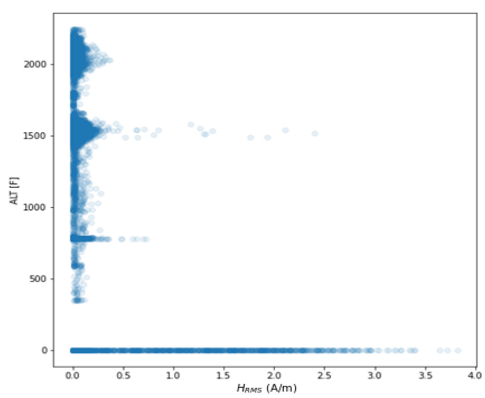


c)

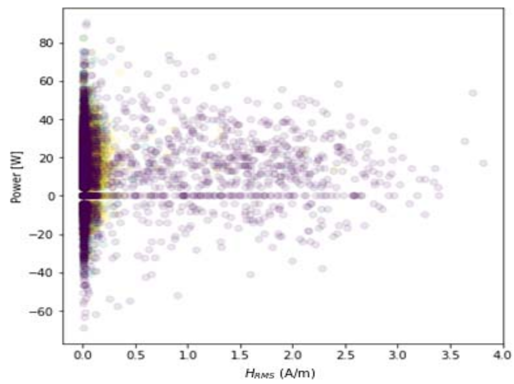


Fig.2. The dependence of the magnetic field on flight parameters in the Aero AT3 aircraft: a) rotational speed (RPM), b) altitude (ALT) and c) power.

The waveforms of the magnetic component of the electromagnetic field, rotational speed (RPM), altitude (ALT) and power (power) during flights carried out as part of the training flight test campaign were used to create and train a neural network.

Figure 2 shows the correlations between the magnetic field parameters and the instantaneous flight parameters.

Based on the analysis, it can be seen that the range of values for HRMS, which fall at the height of 0, i.e. the ground, can be seen. Due to the determination of the value of the magnetic component that occurs during the flight, the values of the magnetic component obtained during the measurements were filtered out. Figure 3 shows the filtered values of rotational speed (RPM) and magnetic field for altitudes above 100f.

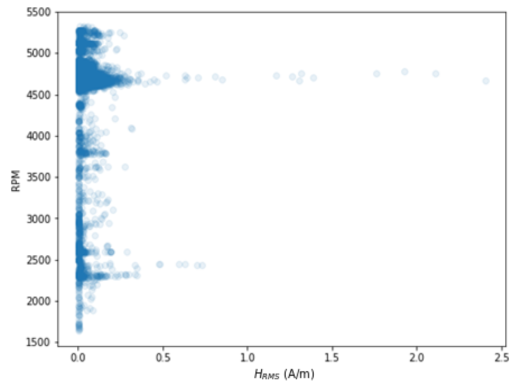


Fig.3. The dependence of the magnetic field on the rotational speed (RPM) of flight above 100f in the Aero AT3 aircraft

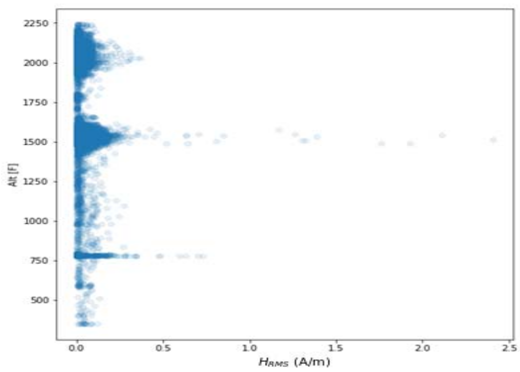


Fig.4. The dependence of the magnetic field on the altitude (ALT) of flight above 100f in the Aero AT3 aircraft

A high concentration of readings and the highest values of the magnetic component occur in the range of 4500-5000 rpm and 2000-2500 rpm. Fig. 4 shows the filtered values of the correlation of altitude (Alt) and the magnetic component for altitudes above 100f.

Based on the analysis carried out using the neural network model, it can be seen that after filtering, the values of the magnetic component above 2.5 A/m disappeared.

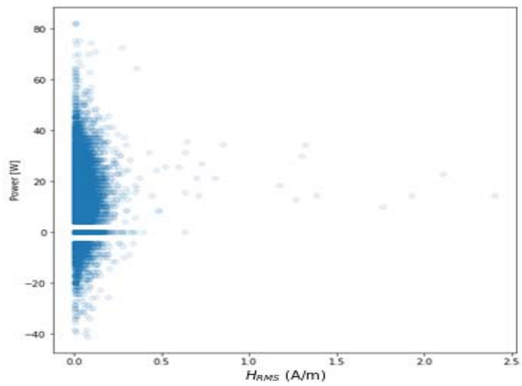


Fig.5. The dependence of the magnetic field on the altitude (Power) of flight above 100f in the Aero AT3 aircraft

Figure 5 shows the filtered values for power and magnetic field, and Figure 6 shows the same values in 10W increments.

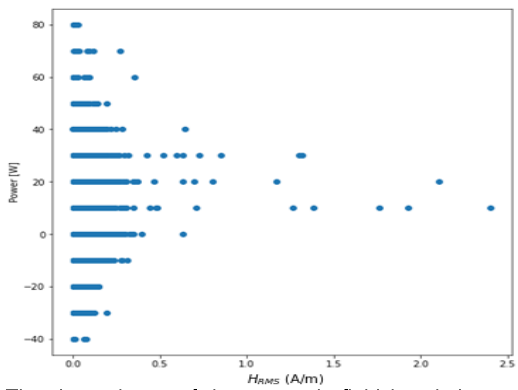
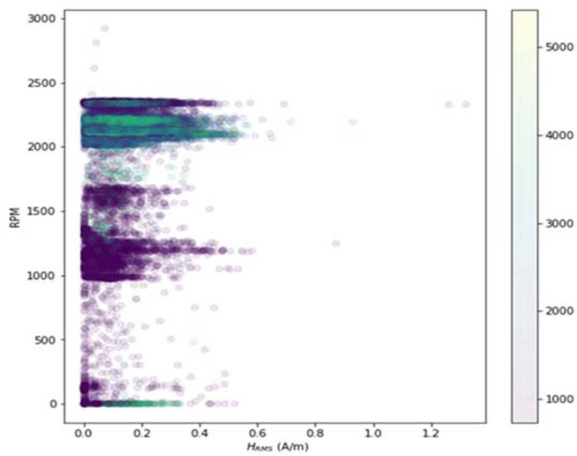


Fig.6. The dependence of the magnetic field in relation to power (power) in the range of 10W during flight at an altitude above 100f in the Aero AT3 aircraft

Based on the analysis, it can be seen that there is a relationship between power and the magnetic component of the electromagnetic field.

a)



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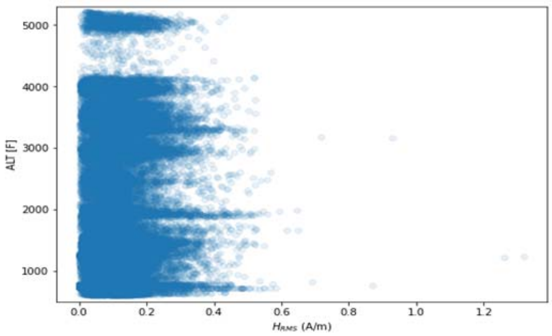
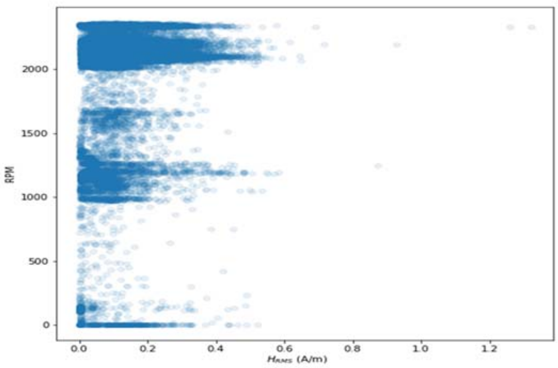


Fig.7. The dependence of the magnetic field on flight parameters in the Tecnam P2006 aircraft: a) rotational speed (RPM), b) altitude (ALT).

a)



b)

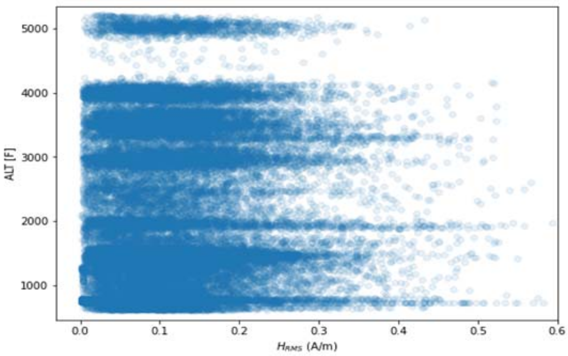


Fig.8. The dependence of the magnetic field of flight above 100f in the Tecnam P2006T aircraft: a) rotational speed (RPM), b) altitude (ALT)

In order to observe the regularities, an analysis was performed using a neural network model for the second type of Tecnam P2006T aircraft. Measurement values have been filtered out for altitudes above 100f. In the Tecnam P2006T aircraft, it is not possible to read the power data compared to the Aero AT3 aircraft. Figure 7 illustrates the correlations between the magnetic field parameters and the instantaneous flight parameters for the Tecnam P2006T.

Fig. 8 shows the filtered values of rotational speed (RPM) and magnetic component correlation for the altitude above 100f for the Tecnam P2006T aircraft.

In this case, filtering does not significantly change the value on the graph compared to the Aero AT3 aircraft.

Summary

A convolutional neural network model was developed in this study and recognizes characteristic avionics parameters. Based on the analysis for the selected type of Aero AT3 aircraft, it can be seen that the HRMS value of the magnetic component depends on the engine speed and altitude. A fairly large range of magnetic field values falls at the altitude of 0 - that is, the ground. These altitudes fall on the base of the airport, where there are many different devices, including radio navigation devices, which increase the magnetic component of the electromagnetic field. A large concentration of readings and the highest magnetic field values occur in the range of 4500-5000 rpm and 2000-2500 rpm. These altitudes are considered typical for training flights. The method was tested for two different types of aircraft, where a significant difference in the measurement results was observed only for the Aero AT3 aircraft

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