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Neural network with single hidden layer for air traffic volume prediction in uncontrolled airspace

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Abstract

This article presents a model enabling more effcient air traffic management achieved by better data use. Appropriate resource allocation is possible if it is based on a high quality air traffic volume fo recast. The proposed approach is inspired by procedures used in flow management in air traffic con trol. Staff planning in controlled airspace is easier because almost all operations are communicated in the submitted flight p lan. Short-term prediction of the number of operations in uncontrolled airspace is a much more challenging task. It is correlated with weather parameters and moreover, it naturally fluctuates throughout the day and the season. The relationship between General Aviation (GA) traffic volume and meteorological conditions were modeled using neural network. The obtained results confirm that it is possible to use the decision support system to plan the number of operational sectors. The described results open a scientific discussion about designing tools predicting air traffic volume in uncontrolled air space. The accuracy of the model can be improved by processing data from additional sources, but it is associated with a significant increase in the complexity of the solution.

Keywords:

general aviation; uncontrolled airspace; neural networks

1. Introduction

Aviation is a technically advanced industry. Many scientific studies and analysis have been carried out to improve the functioning of civil aviation. This article deals with a specific branch of aviation - General Aviation (GA). The aim of the article is to present a model that predicts air traffic intensity depending on meteorological conditions. This issue has not been described in the scientific literature and concerns an important topic - safety in the air. Forecasting GA air traffic volume will enable effective management of the number of available sectors in uncontrolled airspace. Very precise management of sectorization in controlled airspace is already a European standard. In section 2 air traffic management was described along with relevant details about uncontrolled airspace. Sections 3 and 4 discuss the theory of modeling, the data used and the details of the neural network used for classification. Finally sections 5 and 6 present the results of the conducted research and discuss the conclusions of the analysis.

2. Air traffic management

According to Eurostat in 2020 even 93,5% of the reported air accident fatalities were related to General Aviation and more than 97% occurred in uncontrolled airspace [1]. That is one of the reasons why providing flight information and alerting services are common worldwide standards [2]. Flight Information Service (FIS) in most European countries is divided into operational sectors. The rapid growth of GA traffic in recent years led to situations of almost 100% frequency occupancy. In these extreme situations, pilots may have problems contacting ground operational staff immediately when they need information or advice. It forced institutions providing air traffic services to increase the number of operational sectors available to keep the highest safety standards. On the other hand, an important key performance indicator in air traffic management is cost efficiency. The amount of GA traffic varies with the daily and seasonal cycles. It is also significantly correlated with meteorological conditions. Taking inspiration from flow management in air traffic control, uncontrolled airspace also began to implement dynamic sector management. The purpose of this publication is to present a model allowing forecasting the volume of General Aviation. The model will work if fed with a high-quality meteorological forecast.

General Aviation is defined as aircraft's operations other than commercial air transport operations or aerial work operations [3]. In practice, GA is mostly the operations of small aircraft owners or is carried out as part of flight training. Most GA flights take place in the airspace class G - uncontrolled airspace. The main feature of uncontrolled airspace is the lack of air traffic control (ATC). This implies the pilot's responsibility to ensure a safe distance from other aircraft. In practice in Poland, class G airspace is from ground to Flight Level 95 (about 3 kilometers above the mean sea level) without areas around and above controlled aerodromes, airways, and flexible airspaces classified as controlled. In uncontrolled airspace, pilots may take off and land without ATC clearance. In most cases, it is not obligatory to inform air traffic services about the flight when it takes place during the day. Usually, aircraft don't have to be equipped with a transponder and there is no radio communication capability requirement [4]. The above-mentioned circumstances cause forecasting traffic volume in uncontrolled airspace difficult.

Most of the air traffic forecasting literature focuses on commercial traffic. This publication describes General Aviation. In recent years, there have been only a few publications on GA traffic volume forecasting, with the majority focusing on economic-driven long-term forecasts. Part of it concerns the airport level GA demand forecast [5] or predictions on the entire GA industry development [6]. Some researchers identify determinants of GA development at commercial airports [7]. There is an article focusing on very short-term forecasts and analysis. Almathami and Ammar are predicting an aircraft's trajectory in the context of a controlled airspace violation [8]. The topic of collision avoidance was explored by research being a part of SESAR innovation [9]. According to the author, the following publication is the first about forecasting GA traffic volume in the short-term. It presents air traffic services operational perspective. The forecast range is limited only by meteorological forecast quality.

Each Air Traffic Services division in Poland has an operational supervisor called "Senior Informant" or "Senior Controller". This person is responsible for changing the number of active sectors. In practice, it means adjusting the number of operational positions active in a time unit - usually one hour. Senior Informant is also responsible for staff planning for the following days. If the traffic volume could be forecasted it would be also possible to improve the management of available operational staff to ensure reduced crew on calm days in order to be able to open all sectors during busy shifts.

3. Neural network model based machine learning

3.1. Machine learning

Machine learning is a subfield of artificial intelligence, which allows to make predictions based on the known data. There are several methods of making predictions about new observations, some of which are regression and classification. Numerical value of a parameter can be predicted based on the values of other parameters in regression model. The model described in the article uses classification. Having a set of values of several dozen attributes, the model tries to predict if air traffic volume will be small in analysed period. The first group includes days with less than 60 operations. The second group includes days with moderate and heavy air traffic. Days with 60 or more GA operations will be included into this group.

3.2. Differences between knowledge and data based models

While creating a model of physical processes one of two approaches may be used. The knowledge-driven model relies on knowledge of underlying laws of physics that govern the process. The main advantage of this approach is its high explainability and reliability as every parameter of the model corresponds with some specific physical property. However, this model has a very significant downside, it requires detailed knowledge of physical phenomena. This means that for complex processes it might be very difficult or even impossible to create a model. Another drawback is that as complexity of the process grows the computational cost is rising. Other possible approach is data-driven modeling in which model is selected arbitrarily with little or no relation to underlying physics. Then its parameters are adjusted until they fit experimental data. The main advantage of a data-driven approach is the lack of required knowledge of the process. This allows for prediction of events which are not known in detail [10]. In a data-driven approach, the complexity of the model is independent of the complexity of the underlying process. The main disadvantage is its lower reliability and explainability. This is the main reason why the data-driven approach is usually avoided in critical implementations. Another significant downside is a requirement of a large amount of experimental data for model adjustment which means that in many cases this approach simply cannot be used. The last thing that must be said about the data-driven approach is that it still requires some knowledge to work efficiently as for model selection some assumptions must be made. For example, the use of linear regression assumes that the model is linear. The variable selection used in the presented model was made based on domain knowledge. Hiperparameters adjustment was made with data-driven approach.

Term machine learning describes a subset of algorithms that adjust the parameters of other algorithms according to data [11]. To provide a more formal definition an algorithm can be described as a transformation function $\mathscr{Y}_a$ such that [12]:

$$\mathscr{Y}_a = \phi_a(\mathscr{X}, \Theta_a), \tag{1}$$

where $\mathscr{Y}_a$ is set of algorithm responses, $\mathscr{X}$ is set of inputs and Θ_a is algorithm parameter set. Input space $\mathscr{U}_x$ and response space $\mathscr{U}_y$ can be simply a numerical space, but can also represent more abstract concepts. For example in the case of database software input space will consist of queries while response space will contain information stored in a database as well as error status in case the query was written incorrectly. Machine learning algorithm, denoted as ϕ_m can also be described in that general form however, what is special in this case is that input space $\mathscr{U}_m$ consists of either:

$$\mathscr{X}_m = \{\phi_a, \mathscr{X}_a, \mathscr{Y}_a, \Theta_a\}, \tag{2}$$

in case of supervised learning or just :

$$\mathscr{X}_m = \{\phi_a, \mathscr{X}_a, \Theta_a\}, \tag{3}$$

in case of unsupervised learning.
In both cases response of machine learning algorithm is described as a:

$$\mathscr{Y}_m = \{\hat{\Theta}_a, E_a\}, \tag{4}$$

where $\hat{\Theta}_a$ is adjusted set of parameters and E_a is value prediction error for this new set of parameters. The machine learning algorithm aims to adjust parameters Θ_a of given algorithm ϕ_a in such a way to minimize error E_a for given data. In case of supervised learning a correct response $\mathscr{Y}_a$ for inputs is known whereas, in the case of unsupervised learning, only input set $\mathscr{X}_a$ is known. In order to avoid confusion parameters of machine learning algorithm Θ_m will be referred to as a *metaparameters*. The exact set of metaparameters varies between specific algorithms, however, there is one crucial metaparameter that will appear in every machine-learning algorithm. Error function is required for error value calculation and minimization of that value is the goal of machine learning.

4. Architecture

In this section an architecture of neural network used in paper will be described. Additionally overwiew of data model will be provided.

4.1. Overview and preprocessing of data

The model is based on two data sources: a database of historical air operations and historical meteorological observations. The first of the datasets cover almost six years: from January 2016 to September 2021. It contains the number of flights splitted per the airship type (aircraft, helicopter, and other) and the time of the day (day/night). In this publication, only data concerning aircraft flying during the day were analyzed. The presented model uses historical data containing information about the number of flights that contacted the Flight Information Service. It has been assumed that in the near future the percentage of aircraft flying and reporting this fact by radio communication will not change significantly. The analysis concerns the uncontrolled airspace managed by the Polish Air Navigation Services Agency which is currently divided into 9 FIS sectors. Drones, paragliders, and helicopters were not taken into account. Military aircraft flights were also analyzed. The data was collected by FIS Poland - the PANSA department responsible for managing uncontrolled space. The model tries to predict if the number of flights during any given day will be larger than a predefined value. If a pilot is switching frequency to another sector and returns after some time it counts as two operations. There is no difference between air operations lasting 5 minutes or several hours. They are both treated as a single unique unit. The dataset consists of about 2000 records. The number of operations varies from 0 to 360. This model was built for one sector named: "Warsaw Information".

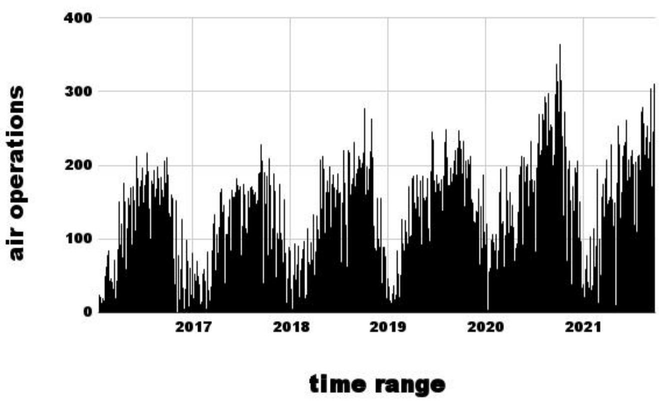

Figure 1: Number of air operations in "Warsaw Information" sector from Jan. 2016 to Sep. 2021

Meteorological data is more complex. It is provided by the Institute of Meteorology and Water Management - National Research Institute. The data was processed for the purposes of building the model. It covers the same period. Hourly data is available from about 50 observation stations evenly distributed across Poland. Each station generates up to a hundred variables, but there are gaps in available data. For the presented models one station located in the center of the sector has been chosen. Variables have been selected based on operational knowledge. The number of daily operations is a dependent variable. Data was pre-processed for classification with a threshold of 60 operations. The model detects calm days. A decision about the threshold value was made based on the operational knowledge and the goal were to maximize the value of recommendations provided to a decision maker.

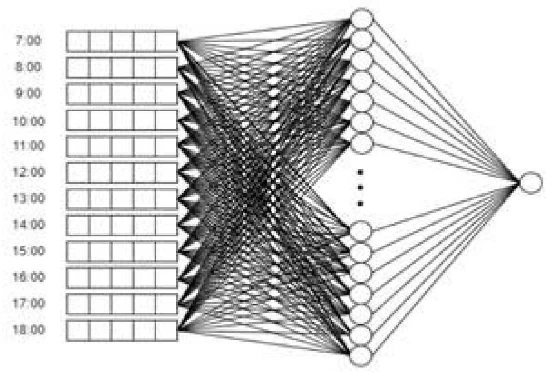

Figure 2: Visualization of meteorological data input to neural network (70 neurons)

Each input to the neural network is a vector of 64 features. 5 meteorological variables for each hour between 7 am and 7 pm.: cloud base, percentage of the sky covered with clouds, temperature, visibility, and wind speed. Additionally, there is information about the current: day, month, year, and day of the week. Daily weather changes have different impacts on operations depending on the season, the time when they occur, and their duration. In this context, it is challenging when data point density is inconsistent. Aircraft operations applies to the whole day, but meteorological observations were recorded for each hour. Data visualization provided an initial understanding of the impact of weather conditions on the number of flights during a given day. **Fig. 3** to **Fig. 9** present a relationship between the daily number of operations (different colors) and the value of two meteorological variables (location of dots). Yellow dots represent days with 60 or more operations, and dark blue - less than 60 operations. The figures were generated using the matplotlib library. Opacity was set at 80%. To prevent overfitting or underfitting learning rate was analysed for training and validation sets. Results presented in **Fig. 10**.

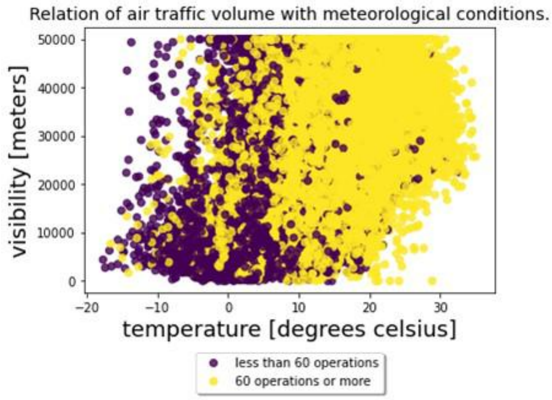

Figure 3: Visualization of relationship between number of air traffic operations and meteorological conditions (Visibility and Temperature)

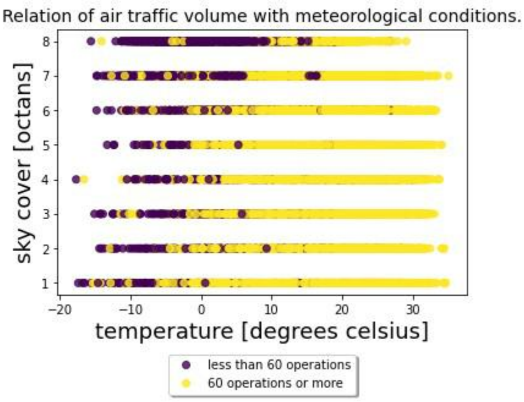

Figure 4: Visualization of relationship between number of air traffic operations and meteorological conditions (Sky Cover and Temperature)

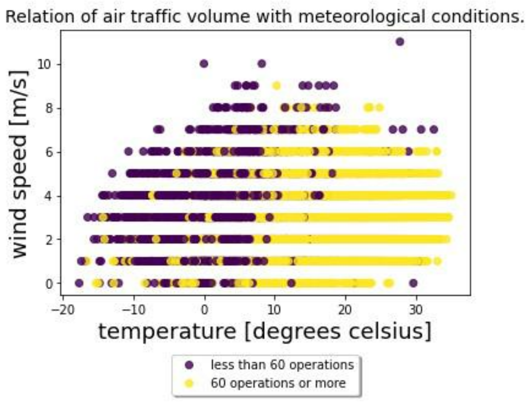

Figure 5: Visualization of relationship between number of air traffic operations and meteorological conditions (Wind Speed and Temperature)

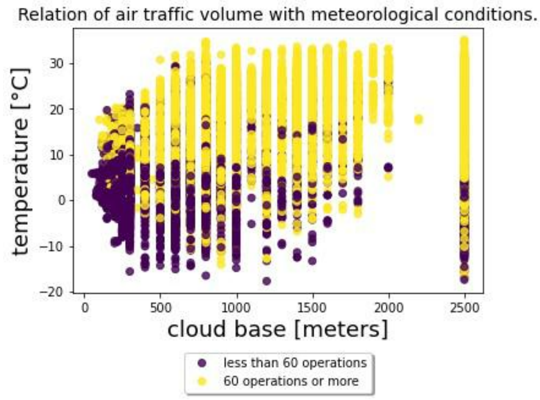

Figure 6: Visualization of relationship between number of air traffic operations and meteorological conditions (Temperature and Cloud Base)

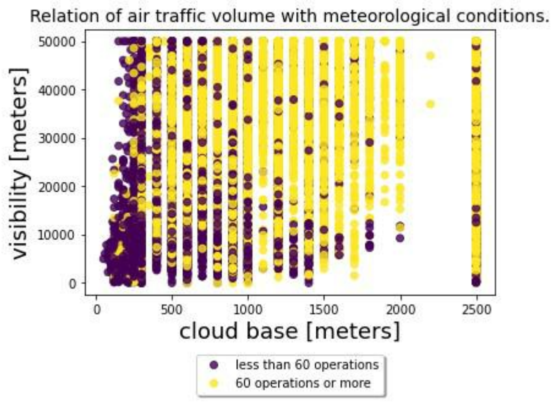

Figure 7: Visualization of relationship between number of air traffic operations and meteorological conditions (Visibility and Cloud Base)

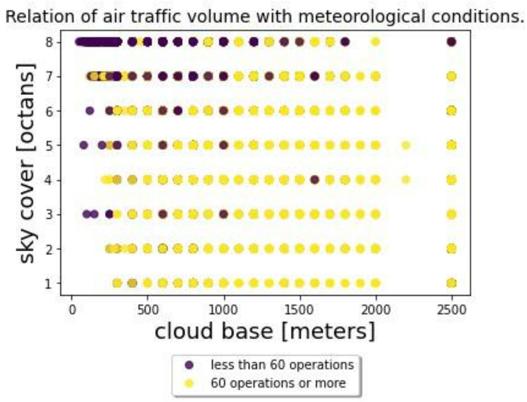

Figure 8: Visualization of relationship between number of air traffic operations and meteorological conditions (Sky Cover and Cloud Base)

4.2. Neural network architecture and learning metaparameters

The model was prepared with the use of the MLPClassiffier Python library[13]. Data were divided into training (70%) and testing sets (30%). Data was standardized with the use of the StandardScaler function. The best set of network parameters was found with the use of GridSearchCV, and a 10-fold cross-validation was performed. Multilayer network architecture was also tested but better results were not achieved. Detailed information about network parameters is presented in the **Tab. 1**.

Output of neural network is a binary variable classifying object to one group above or below a threshold of 60 operations.

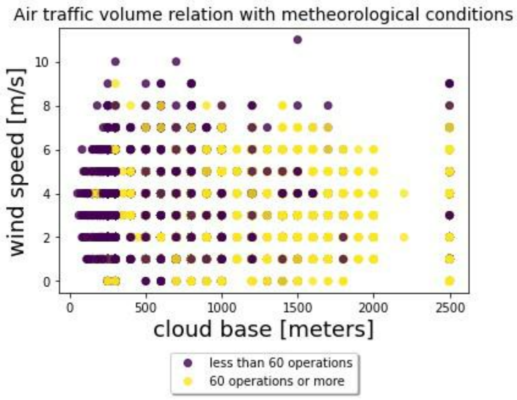

Figure 9: Visualization of relationship between number of air traffic operations and meteorological conditions (Wind Speed and Cloud Base)

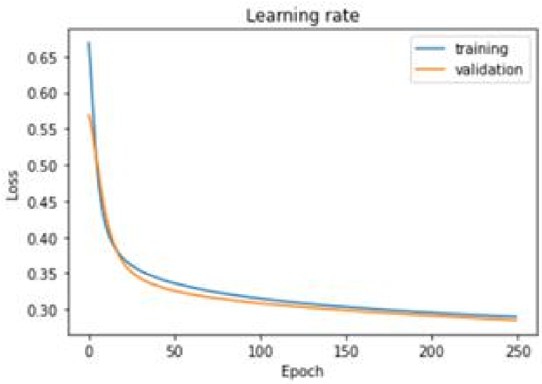

Figure 10: Learning rate

Table 1: Network parameters

Parameter	Value
Hidden layers	1
Neurons per layer	70
Activation	hyperbolic tangens
Solver	stochastic gradient descent
α	0.001
Learning rate	0.001

5. Results

5.1. Model quality measures

The quality of the model was assessed on the basis of the measures related to confusion matrix. Precision is calculated by dividing the true positives by number of observations classified as positive by model:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \quad (5)$$

Recall is calculated by dividing the true positives by number of positive observations.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \quad (6)$$

5.2. Model results

Tab. 2 presents confusion matrix summary statistics regarding the dataset with a threshold of 60 operations. 90% of forecasts defined as "calm" were correct. 85% days was properly classified as "moderate or heavy air traffic". Model found 92% of days with "higher" air traffic volume and 80% of calm periods.

Table 2: Classification metrics

Air traffic	Precision	Recall
$60 > x$	0.90	0.80
$59 < x$	0.85	0.92

Above mentioned means that in 10% to 15% of cases the system gives the wrong recommendation. It can lead to dangerous situations, because it may result in a decision to reduce operational staff on a particular day which in fact can turn out to be a moderate or heavy traffic period. This model should be used with a deep understanding of safety procedures when used to reduce a number of operational sectors. On the other hand, very good classification results show that modeling of air traffic volume in uncontrolled airspace is possible. Model detecting days with heavy air traffic may be used with fewer safety concerns. It is important to remember that model prediction highly depends on meteorological forecast quality. That is a reason why recommended forecast range is up to 72 hours.

6. Conclusions

Results described above show that there is a significant relationship between the weather conditions and the volume of General Aviation operations. Accurate forecasting of air traffic volume allows to increase aviation safety and simultaneously keep costs at the same level. It can be achieved by better staff management.

Similar solutions can be built for other parts of the European airspace. Another way to improve model is incorporating more detailed data about weather conditions. In the presented model, only one meteorological data source is used. In Poland a few dozens of additional data sources are available. The development of the air traffic management systems infrastructure should result in a piece of much more detailed information about the number of GA operations. In a few years, there will be enough data to prepare forecasts with hourly resolution. Another direction of research may cover forecasting helicopter operations. It is much more difficult because rotorcraft pilots are more resistant to bad weather conditions. The reason is simple - in an emergency, they can land almost anywhere.

Acknowledgements

Data source for described research is the Institute of Meteorology and Water Management - National Research Institute (IMGW-PIB)[14].

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