Application of Artificial Neural Networks for Fog Forecast

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ABSTRACT: This study examines the development of a system that assists in planning flight activities of the Academia da Força Aérea (AFA) so that meteorological data can be used to predict the occurrence of fog. This system was developed in MATLAB 8.0 by applying multilayer perceptron-type artificial neural networks and using an error correction algorithm called backpropagation. The methodology used to implement the network comprises eight input variables, five neurons in the intermediary layer, and one neuron in the output layer, which corresponds to the presence or absence of fog. The fog phenomenon is very important for the study and definition of flight strategic planning. Data taken from 1989 to 2008 and related to the input variables were used for the training and validation of the proposed network. Consequently, the multilayer perceptron network has a 95% reliability compared with the data collected. This high level of reliability is an exceptional result for the management, planning, and decision making team of the AFA strategic group. Thus, it can be concluded that the proposed system is efficient and will subsidize, with good safety margin, AFA's flight activity planning and could also be applied to other air activities in Brazil.

KEYWORDS: Strategic planning, Operational management, Intelligent systems, Decision support systems.

INTRODUCTION

One of the concerns of the scientific community and certain sectors of society in recent years with respect to meteorological factors and their consequences in relation to all the social, environmental and economic implications. This leads companies and institutions to develop strategies in order to predict future situations to mitigate possible adverse situations.

Low visibility in bad weather conditions (even in fog) may adversely affect society. Fog affects air, sea, railway, and road transport systems, requiring specific safety measures to prevent accidents, delays, and even cancellation in transport operations (Gultepe *et al.*, 2007).

Fog is formed due to condensation of water vapor into liquid droplets or ice crystals as a result of air cooling, humidification, and/or by mixing contrasting air portions. A most common form of fog occurs when its formation on land involves nocturnal radiative cooling under low wind conditions (Roach, 1995) when dissipation usually occurs a few hours after sunrise because of the heat flux on a surface heated by solar radiation.

Fog has significant importance in the airport sector, taking into account the considerable restriction of landing and takeoff, affecting aircraft and passengers' safety. The forecast of weather events is becoming increasingly vital in various sectors of society, such as in agriculture, construction, economics, public health, transportation, especially in aviation, as it is susceptible to weather conditions, which may cause delays and flight cancellations or even air accidents or incidents due to the adverse conditions, indicating the need for confronting possible problems. Although the occurrence of fog is inevitable, airport and road authorities specifically require a more reliable

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forecast. The interest in studying the meteorological variables in airfields, especially the fog phenomenon, is in the need to obtain, in advance, information on weather conditions at the local scale, for changes in the planning of flight activities if necessary.

The concepts of the meteorological variables presented herein can be found in the Manual of Surface Weather Station (MCA 105-2; Brasil, 2013). For the Departamento de Controle do Espaço Aéreo, fog formation is characterized when the prevailing visibility is reduced to below 1,000 m.

The restriction of visibility due to fog formation occurs sharply at Academia da Força Aérea (AFA) aerodrome, in the municipality of Pirassununga, São Paulo State, as shown in Fig. 1. The occurrence of fog causes cancellations of flights, leading to delays and changes in the training schedule.

Several studies have been conducted to establish a pattern of the phenomena occurrence, with the objective of short-term forecasting, which, theoretically, will allow the reduction of operating costs and time (Rezende, 2005). Tarmeňo and Altamirano (2004) performed a climate study of fog events in Jorge Chavez Callao International Airport



Photos: Rosângela de Oliveira Colabone.

Figure 1. Illustrative photos of reduction visibility due to fog occurrence on the AFA airfield - Pirassununga/SP.

in Lima, Peru. The analysis of a time series of 30 years of climatological data (1968 - 1997) recorded 329 events, with the highest monthly frequency of fog between March and June, and the lowest frequency in November, which allows managers to optimize and perform, in short and medium terms, contingency plans that will enable restructuring and, consequently, a significant reduction of budget funds, as well as a greater respect to target audience or users of services offered by institutions.

Tardif and Rasmussen (2007) investigated fog events in New York City, United States of America, using a 20-year time series data. Surface hourly data were used to identify fog events in 17 locations under the influence of various physiographic characteristics such as the type of land cover (urban, suburban, and rural) and contrasts between water and land.

The events in each site were ranked according to an algorithm based on the fog formation process. The results showed that the probability of fog occurrence is negatively influenced by the presence of New York City urban heat islands, reinforced in places on direct influence of sea air.

In Brazil, França (2008), using the numerical weather forecast model Eta in 4-km resolution, evaluated the fog forecasting methodology and horizontal visibility from the National Centers for Environmental Prediction analysis and Centro de Previsão de Tempo e Estudos Climáticos/Eta model predictions of 40 km. Two methods for estimating horizontal profile were evaluated: Kunkel (1984) and Gultepe et al. (2006) methods. Test cases were chosen for the evaluation depending on the season when fog occurs.

Integrated experiments on Afonso Pena airport, in Curitiba, Paraná State; Guarulhos International airport, in Guarulhos, São Paulo State; and Salgado Filho airport, in Porto Alegre, Rio Grande do Sul State, suggested that the 4-km Eta model may be used as a tool in predicting fog occurrences and horizontal visibility or even in regions with probability of fog within 36 to 48 h in advance.

Currently, artificial neural networks (ANNs) have increasing applications as a tool for prediction of events owing to its competence to simulate the human brain's ability to recognize, associate, and generalize patterns (Russel and Norvig, 2013). A neural network can approximate functional relationships, particularly when relationships are not well-defined and/or are not linear, which makes it difficult to use conventional methods to predict future variations of these relationships (Tafner et al., 1996).

The ANNs have, as a main point, the interaction and manipulation of input data in order to find a satisfactory response within a reliability limit for an expected result. The ANNs are networks trained through entries obtained from external or internal scenarios in the system, and these entries are multiplied by randomly assigned weights. The process takes place throughout the network until an expected error within the proposed limit is reached; otherwise, the process continues to perform new calculations through an error correction of input data called backpropagation (Fig. 2) (Tafner *et al.*, 1996).

After the required value is obtained, it is tested with known data; it is common to use 2/3 of data for training and 1/3 for network validation, with reliability verification, which may provide parameters for managers so they are able to make decisions about future information (Tafner *et al.*, 1996). This allows executives and their teams to analyze future data and propose actions to minimize errors and increase the chances of success, as input data are based on historical data, which served as network training so that one can even perform simulations of future events (Rezende, 2005).

Time series are nothing more than a sequence of measurements for a given event, chronologically organized, which, apparently, does not follow any law or trend. However, in time series related to natural phenomena, one may note certain characteristics that are repeated after a certain period of time (seasonality) and others that maintain itself during the considered range (trends), even without obeying linear patterns. According to Fabbian *et al.* (2007), the occurrence of fog in aerodromes may negatively impact the air transport operations, thus influencing significantly the overhead activities during this period, with respect to flight safety.

The authors also used ANNs to provide predictions about future events that could occur in Canberra International Airport (YSCB) and observed that, contrary to conventional statistical techniques, ANNs are better suited to solve problems that involve nonlinear complex interactions and thus have a great potential for the fog forecast, which characterizes the importance of developing models that can help those responsible for planning the flight instruction activities to be undertaken by learners in the learning phase and training.

According to Chaudhuri *et al.* (2015), the reduced visibility during fog significantly influences the surface and air transport operations. The fog forecast at aerodromes is a complex and difficult task, despite constant improvements in numerical weather prediction models and, to improve the model, the authors used the neural networks of the type Multilayer Perceptron (MLP) and observed that the forecasting error decreases, thereby improving the learning model in predicting possible fog, which corroborates the use of RNAs for future prediction airfields.

This study proposes a method to forecast fog occurrence through ANNs, and temporal series of meteorological variables related to 19 years of data is used for training a multilayer perceptron neural network with a backpropagation error correction method, focusing on fog forecast in the Brazilian AFA.

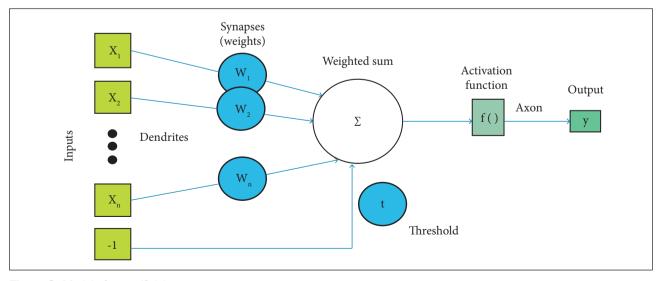


Figure 2. Model of an artificial neuron.

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In the AFA, the students of the airmen official board receive, in addition to academic training, flight instruction in two aircrafts, T-25 "Universal", in the basic flight education phase, and T-27 "Tucano", a turboprop type, during the advanced phase to improve and prepare the future official airmen in their end mission. AFA has an airfield called Campo Fontenelle (SBYS encoding) for the operation of its mission. This airfield has two lane sectors, with an average of 160 landings and takeoffs each day.

The process of training or flight instruction, as it is called in AFA, depends on the weather conditions. Thus, severe weather conditions, such as heavy rainfall and incidence of winds and fog formation, are limiting factors, since they may cause human and material risks to the institution.

MATERIAL AND METHODS

The AFA located in the town of Pirassununga, São Paulo State, within the coordinates 21°56'04" to 22°00'29" south latitude and 47°17'16" to 47°22'07" west longitude, is a higher education institution subordinated to the Departamento de Ensino da Aeronáutica, whose mission is to train air force officers.

AFA has a surface weather station on its premises that is responsible for monitoring the (local) weather condition. It is classified as Centro Meteorológico Militar to provide specific meteorological support to military aviation according to the Instituto de Controle do Espaço Aéreo (ICEA 105-2; Brasil, 2013).

The military flight instructions take place, preferably, during the day, starting at 5 a.m. and ending at 11 p.m. By the fact that flight activities are carried out in this period, weather data, including cloud cover, fog, and wind direction, are important variables for the strategic management of the missions (planning).

The data for training and testing of the ANNs were provided by the ICEA, located in São José dos Campos, São Paulo State. Regarding precipitation, there was a need for data collection directly through the forms available at ICEA, in São José dos Campos.

A total of 7,305 forms were assessed to obtain the cumulative sum (24 h) of rainfall, corresponding to what was verified in the AFA airfield. Fog data were similarly evaluated, as records contained only codes that had to be decoded using a table reference. The fog records were obtained by visual estimates through meteorological observations made by the military, executed at fixed intervals (every hour) and complemented with intermediate observations. In case of significant changes to aviation, depending on the activity, the collection of other variables is considered, such as wind, visibility, visual range, cloud cover, air and dew point temperature, sea level pressure, and weather in the flight track.

Data related to fog, encoded in the range 40 – 49, provided information on fog conditions. The data or codes, as provided in Table 4655 of MCA 105-10 (Brasil, 2011), provided information regarding the fog. The data were also provided by the ICEA and had to be decoded for interpretation.

MATLAB 8.0 was used to develop the system, where the data were processed and the network was built for training, validation, and testing of the proposed model.

The following control variables were chosen as inputs for network training: year, month, day, time, temperature, relative humidity, pressure, and wind speed. These inputs are identified as X_i , and the network output was stipulated as 0 or 1 for fog, where 0 means absence and 1 means presence of fog.

In the network training, the sigmoid function was used, with five neurons in the intermediary layer and one neuron in the output layer, indicating the presence or absence of fog at the AFA airfield. To correct the network error as a function of X_i input and Y_i output, the backpropagation algorithm was used.

According to Russel and Norvig (2013), Eq. 1 represents the input characteristics that will be processed by the network for its training, where ω is the synaptic weights and X_i represents the network entries.

$$\sigma = \omega_0 X_0 + \omega_1 X_1 + \omega_2 X_2 + \omega_3 X_3 + \dots + \omega_i X_i$$
(1)

The sigmoid function is represented by Eq. 2:

$$Y = 1 \frac{1}{(1 + e^{-\sigma})}$$
(2)

Equation 2 is used as a neuron activation function that will generate an activation value (σ) on the basis of the sum of the inputs X_i multiplied by synaptic weights ω_i (Eq. 1); according to the generated response, this will be used in Eq. 2, where it is possible to obtain the output (Y) that, given by the network, will be compared with the expected response (historical data). If the results are not the same, it will be reprocessed by error backpropagation depending on Eqs. 3 to 9.

$$O_j = X_j \tag{3}$$

where *O* and *X* represent the network entries. Equation 4 represents the calculation of *X*:

$$X_{j} = \sum_{i} w_{ij} O_{i} + \theta_{j}$$
(4)

where *w* denotes the synaptic weights and θ represents the bias.

Equation 5 represents the sigmoid function:

$$O_j = f(X_j) = \frac{1}{1 + e^{-X_j}}$$
 (5)

where *e* represents the natural logarithm.

Equation 6 corresponds to error correction of the last or output layer:

$$e_{i} = O_{i} (1 - O_{i})(Y - O_{i})$$
(6)

where Y denotes the network output.

Equation 7 corresponds to correction of the hidden or intermediate layers:

$$e_j = O_j \left(1 - O_j\right) \sum_k w_{jk} e_k \tag{7}$$

Equations 8 and 9, respectively, denote adjustments of synaptic weights and bias:

$$w_{ij}^{(k)} = w_{ij}^{(k-1)} + ne_j^{(k)} O_j^{(k)}$$
(8)

$$\theta_{j}^{(k)} = \theta_{j}^{(k-1)} + ne_{j}^{(k)}$$
(9)

where *n* denotes the neural network learning coefficient.

For the beginning of the training, random synaptic weights were generated and 2/3 of the acquired data were used. After obtaining the smallest or acceptable error, the network was subjected to tests with the remaining 1/3 of the data, corresponding to the period 1989 – 2008, *i.e.* a relatively significant amount of data was used for training and validation of the model.

RESULTS AND DISCUSSION

After the training and the determination of the results, the proposed network achieved a reliability of 95.949% with 2/3 of the data. In other words, the network with input data X_i and output Y_i achieved a satisfactory result by undergoing the network validation test. Using the remaining 1/3 of the data, the network achieved a reliability of 98.107%.

These results demonstrate that the network was capable of learning and the test results were satisfactory, which provides for the executive managers, in this case, the military responsible for the planning of flight activities, an effective tool, enabling them to develop a strategic plan for the following years, with significant and reliable projections on the basis of historical data of approximately 95% reliability. It significantly decreases future changes in plans related to operational cost and time as well as human resources.

Nevertheless, the information provided by the network has the greater purpose of improving planning and designing of campaign activities of cadet airmen, since they also conduct educational activities with other areas of expertise. So there is no loss to the learning process but an advantage to flight and other academic activities.

The result of training can be seen in Fig. 3. The dotted line represents the expected outcome Y_i and the blue line, the results obtained by the network in training, indicating an equation in relation to the obtained results.

Figure 4 shows the network validation after the training was conducted and finalized, with error matrices and synaptic

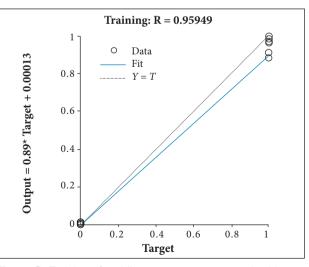


Figure 3. Training of multilayer perceptron network with error correction backpropagation algorithm.

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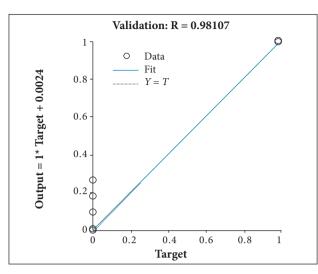


Figure 4. Network validation with 1/3 of the remaining data for the 1989 - 2008 period.

weights adjusted and ready to infer possible future projections. This will help managers (senior military) to develop a more structured and proper planning. Adjustments could be possible if based on recent data, *i.e.* from the last two or three years.

The data obtained by the network were compared with the statistical data of the same period for comparison and analysis of network performance. The tests performed with the network show values very close to the statistical ones, with the great advantage of agility and speed of the network, since it had already been trained and prepared for this analysis.

The statistical data can be seen in Fig. 5, which are similar to the values obtained by the proposed network. The figure shows the relative and absolute frequencies with respect to fog occurrence at the AFA airfield in the period 1989 – 2008.

From a total of 821 cases of fog occurrence in the whole period, 67% occurred from April to July, with a predominance in May and June. The lower frequencies were observed from October to January, with a total occurrence of 9.5%; and in February, March, August, and September, the occurrence was around 23.4%.

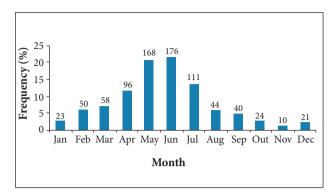


Figure 5. Relative and absolute frequencies of fog occurrence at the AFA airfield in the 1989 – 2008 period.

CONCLUSION

The results showed that the use of multilayer perceptrontype ANNs with error correction using the backpropagation algorithm was efficient and fast, providing data to executive managers for better planning, with a reduced error margin, considering that the system was fed with data of 20 years. This favored the network learning process with a 95% percentage of success, which is considered suitable for the use of ANNs.

Thus, the system proposed for the planning and assistance to military officers tends to enhance planning, allowing a more efficient decision-making process, which will greatly benefit the Academia da Força Aérea, in regard to reduction of operational work, reduction of costs in terms of time dedicated to the personnel and possible flight adjustments as well as academic activities related to cadet airmen.

The model was based on past meteorological data. If the data continues in the same pattern, the degree of reliability will remain the same. If there are sharp changes in the input variables, the network provides a new level of reliability, since the previous state has changed.

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