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Neural Model of the Aircraft Landing Phase

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Abstract

The article deals with mathematical modeling of the aircraft landing phase using artificial neural networks. The network was determined based on the data recorded by an aircraft's quick access recorder. Networks were developed for each flight under review, which resulted from the different durations of this flight phase. It presents the accuracy results of representation across a flight simulation network. It was analyzed how the structure of the neural network affects the quantitative and qualitative accuracy of the actual flight representation.

The determined networks will provide a basis for working out a model, among others, for simulation tests of air traffic and flight evaluation. General conclusions about neural networks and basic ones regarding their practical use were formulated.

1. Introduction

In the recent years, an extremely strong growth can be observed in all fields of aviation [1], [2]. The growing number of flights, flying personnel, and new types of aircraft imposes the use of new technologies to meet safety and transportation economics requirements [7], [13]-[16]. Simulation test models based on mathematical models with a high accuracy of the reality representation are employed in these fields [3], [7]. The high representation accuracy enables to use the results of tests (experiments) conducted on real objects, and subsequently include them in modeling. For aviation, this can be, among other things, flight data recording. In this context, it should be stressed that this approach was used by aircraft flight dynamics models developed for use in training simulators [8]-[9]. One of such techniques which has been adapted for aviation purposes is the use of artificial neuronal networks (NNs) [10]. This technique uses simultaneous data processing algorithms which are structured and operate similar to the neural structures of hu-

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man cells, especially the brain. Although due to many simplifications they cannot replace it, these structures are used in many fields, such as diagnostics, forecasting, optimization, and control. Provided with appropriate mechanisms, they are able to analyze the presented mathematical models on their own. The efficiency of NNs will be evaluated through experiments assessing the network's ability to simulate the aircraft flight speed during the landing phase. The landing phase is subject to certain procedures; it also depends on various weather conditions and assumed aircraft performance.

If the thesis that neural networks are useful should prove to be true, then a package of efficient tools could be created for designing, economic analysis or as a part of task completion checks, both at the training stage and thereafter, during the routine work of flying personnel.

In addition to many advantages, artificial neural networks also show certain drawbacks, among which an important one is the high specialization of the network. This means that every network structure and learning model match only one type of task for which solutions have been designed. The essence of the article is to define a mathematical model consisting of an artificial neural network to be used, among other things, for simulation tests of the aircraft landing phase.

2. Neural Model

In [17] presents mathematical and computer modeling of aircraft landing phases. Flight recording data (quick access recorder) of aircraft landing performance and computer identification methods were used for this purpose [8], [11], and [19]. Of particular interest was an aircraft flight speed model in the function of time t, segment s, flight speed in previous instants, and values t^2 and ts called pseudo-signals. A segment is understood to be the flight stage at which a specific aircraft configuration exists (extended/retracted landing gear, flap position, flight speed range, etc.).

In this article, the input signals of the artificial neural network are t, s, v_{i-2}, v_{i-1}, represented in the form of vector $\underline{x}_i$(1) – Figure 1, index i – means ith time instant

$$\underline{x}_i^T = [t_i,\ s_i,\ v_{i-2},\ v_{i-1}] \tag{1}$$

The output signal is the flight speed in instant v_i. Unlike in model [17], there are no pseudo-signals t^2 and ts in the input signals. In this article, nonlinearities representing these signals are included in the model of artificial neural networks using hidden layers. The block model of aircraft landing [4] is shown in Figure 1.

The (Norm.) block shown in Figure 1 normalizes inputs x_i and outputs v_i. The normalization applies to N data from flight data recording. Then, a neural network is determined for the normalized signals. Once the neural network is defined, dimensional values are calculated for the normalized signals (Dimens. value transl. block). The neural network applied is shown in Figure 2 [6].

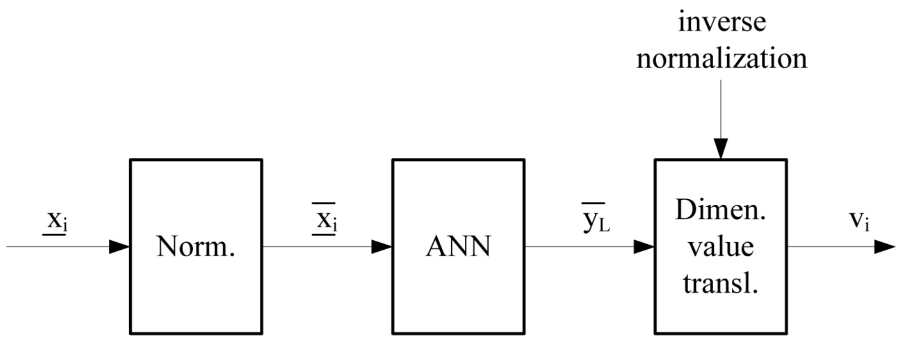

Fig. 1. Block diagram of the aircraft landing model

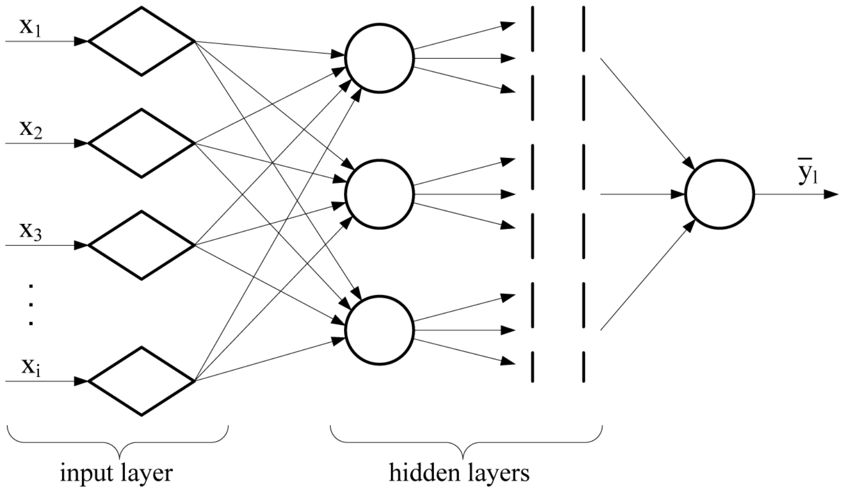

Fig. 2. Artificial neural network of the aircraft landing phase

In the neural network discussed, the neuron was used as shown in Figure 3, i.e. for the lth neuron.

In the neuron applied, the output signal from the lth neuron is the total of constant s_l and scalar of vector $\underline{x}_l\,(l, I)$ and $\underline{w}\,(I, 1)$.

The output signal from neuron y_L in question is defined as follows:

$$y_L = \underline{x}_l\,(l, I)\ \underline{w}\,(I, 1) + s_1 \qquad (2)$$

where:

– vector of input signals;

– vector of weights;

$$\begin{gathered} \underline{x}_l = [x_{11}, x_{21}, ..., x_{I1}] \\ \underline{w}^T(I, 1) = [w_{1l}, w_{2l}, ..., w_{Il}] \end{gathered} \qquad (3)$$

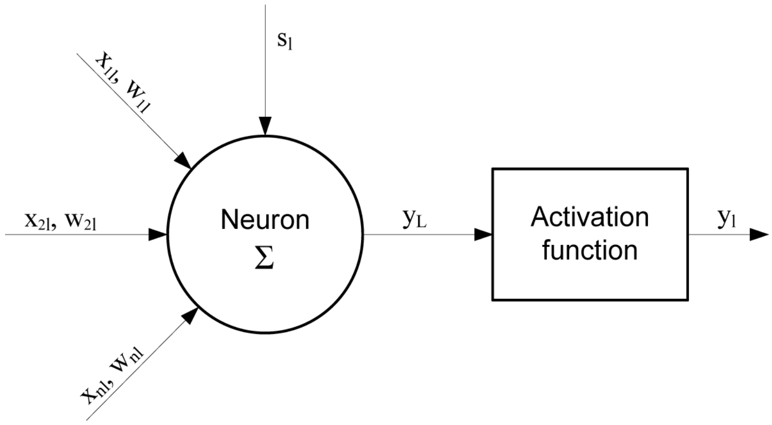

Fig. 3. lth neuron of the network in Figure 2

The development of the network consists in determining the weights w_{il} and constants s_l that are described above using flight recording data. The criterion defining the said weights and constants is the minimization of the sum of the differential squares of output signals form the network and experiment.

JETNET 2.0 software was used to develop the artificial neural network (i.e. determine the constants and weights described above). The network learning software uses the algorithm of instantaneous reverse error propagation method [5], [6], [20]. The control variables of the above algorithm are learning constant α (allowable error increase) and momentum η (parameter to prevent the local minimum of the purpose function from being assumed as a global minimum).

The program enables to select various forms of activation function F (Figure 3). To develop the landing phase model, the following activation function was used:

$$y_l = \frac{1}{1 + \exp(-2\ y_L)} \tag{4}$$

The representation accuracy is evaluated using:

– the sum of the differential squares between the values from the model (Y_{iNN}) and actual object (y_{iREAL}) for the ith measurement (experiment)

$$\chi^2_{AVG} = \frac{1}{N}\sum_{i=1}^{N}\chi_i^2 \qquad \chi_i = (Y_{iNN} - y_{iREAL}) \tag{5}$$

– number *l*p of positive events, i.e. which fulfill the condition:

$$(Y_{iNN} - y_{iREAL})^2 \le \varepsilon \tag{6}$$

where ε is an arbitrarily determined value.

Another step in evaluating the representation accuracy of the actual performance data is to test the network. The testing involves the comparison of the input and output network signals that have not been used for network learning. One-fifth to one-third of the whole set of experimental data is used for this purpose.

3. Modeling Results

This section presents the results of mathematical modeling that uses an artificial neural network of the Embryer 170 aircraft's landing phase [4], [12]. According to the technical specifications of this aircraft, the landing phase consists of six segments, which are described in [17]. The further steps to compile data needed to determine an artificial neural network (teach a neural network) are similar to those in the mathematical modeling using computer identification methods [19].

Table 1 shows the results of the mathematical modeling of the aircraft landing phase using an artificial neural network. The table provides an assessment of how accurately the artificial neural network model represents the actual flight speed data during landing. These results were presented for the inputs represented by vector (1) and various structures of the neuronal structure, i.e. the number of hidden layers and that of neurons in such layers. The neuronal network's output is the normalized flight speed described above.

Table 1

Evaluation of how accurately the ANN with various structures represents the actual landing phase

ANN No.	Input	Neurons in Hidden Layers 1	2	Output	Number of Positive Events l_p [%]	χ^2_{AVG}
1	4	2	0	1	96.8	0.85490 10^{-3}
2	4	3	0	1	98.8	0.48343 10^{-3}
3	4	4	0	1	100	0.65367 10^{-3}
4	4	5	0	1	100	0.38917 10^{-3}
5	4	6	0	1	100	0.47192 10^{-3}
6	4	2	2	1	96	0.99844 10^{-3}
7	4	3	2	1	96	0.10610 10^{-2}
8	4	4	2	1	96.8	0.84687 10^{-3}
9	4	5	2	1	96.4	0.93394 10^{-3}
10	4	2	4	1	96.4	0.92893 10^{-3}
11	4	3	4	1	97.6	0.64125 10^{-3}
12	4	4	4	1	97.2	0.68621 10^{-3}
13	4	5	4	1	97.2	0.70582 10^{-3}

The results presented for the network structures numbered 3, 4, and 5 show 100% of positive events. Network structure 451 (4 inputs, 1 hidden layer with 5 neurons, 1 output) returns the lowest value of χ^2_{AVG}. Using more than one layer does not make sense. This is visible for network structure 4321, where the lowest numbers of positive events and χ^2_{AVG} are obtained.

Figure 4 presents values χ^2_{AVG} obtained for various network structures. It is a graphic representation of the results shown in Table 1.

Table 2

Effect of the momentum η and learning constant α on how accurately the model represents the actual landing

α	η	**Input**	**Neurons in Hidden Layers**	**Output**	**Number of Positive Events l_p [%]**	χ^2_{AVG}
0.04	0.2	4	5	1	100	$0.39799\ 10^{-3}$
0.04	0.3	4	5	1	100	$0.39504\ 10^{-3}$
0.04	0.4	4	5	1	100	$0.39198\ 10^{-3}$
0.04	0.5	4	5	1	100	$0.38855\ 10^{-3}$
0.04	0.6	4	5	1	100	$0.38419\ 10^{-3}$
0.04	0.7	4	5	1	100	$0.37901\ 10^{-3}$
0.04	0.8	4	5	1	100	$0.37101\ 10^{-3}$
0.04	0.9	4	5	1	100	$0.43866\ 10^{-3}$
0.05	0.2	4	5	1	100	$0.39852\ 10^{-3}$
0.05	0.3	4	5	1	100	$0.39789\ 10^{-3}$
0.05	0.4	4	5	1	100	$0.39535\ 10^{-3}$
0.05	0.5	4	5	1	100	$0.38917\ 10^{-3}$
0.05	0.6	4	5	1	100	$0.38005\ 10^{-3}$
0.05	0.7	4	5	1	100	$0.37175\ 10^{-3}$
0.05	0.8	4	5	1	100	$0.36702\ 10^{-3}$
0.05	0.9	4	5	1	98.4	$0.49942\ 10^{-3}$
0.06	0.2	4	5	1	100	$0.40712\ 10^{-3}$
0.06	0.3	4	5	1	100	$0.40738\ 10^{-3}$
0.06	0.4	4	5	1	100	$0.39935\ 10^{-3}$
0.06	0.5	4	5	1	100	$0.38642\ 10^{-3}$
0.06	0.6	4	5	1	100	$0.37357\ 10^{-3}$
0.06	0.7	4	5	1	100	$0.36901\ 10^{-3}$
0.06	0.8	4	5	1	100	$0.36999\ 10^{-3}$
0.06	0.9	4	5	1	100	$0.49900\ 10^{-3}$

The tests determined the effect of momentum η and learning constant α on the accuracy of the network's representation of the actual speed during landing. It appears from the results presented as a percentage of positive events and values χ^2_{AVG} that the most favorable values of the said parameters are obtained when α = approx. 0.05 and momentum η = approx. 0.05.

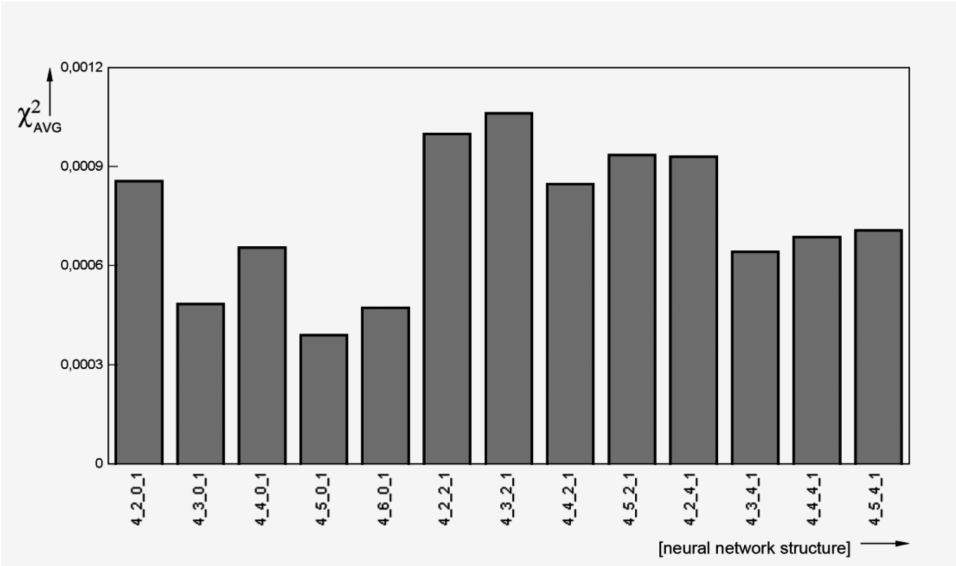

Fig. 4. Effect of the network structure on χ^2_{AVG}

Figure 5 shows values χ^2_{AVG} (5) in individual time instants. The landing time is 250 sec., and from 144 sec. the aircraft moves along the runway with intensive braking. The χ_i^2 performance indicates that the artificial neural network reflects the actual flight very well until approx. 150 sec., i.e. until the touchdown. For the movement along the runway, the representation is worse. Nevertheless, this cannot be deemed to be a misrepresentation of the actual flight because average deviation $|\chi|$ between the speeds recorded during flight and those derived from the network is approx. 0.03.

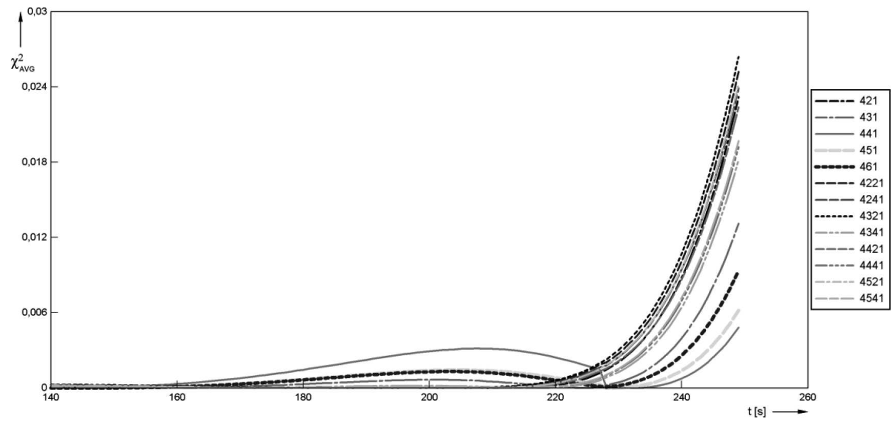

Fig. 5. Values χ_i^2 (5) in the function of landing phase duration

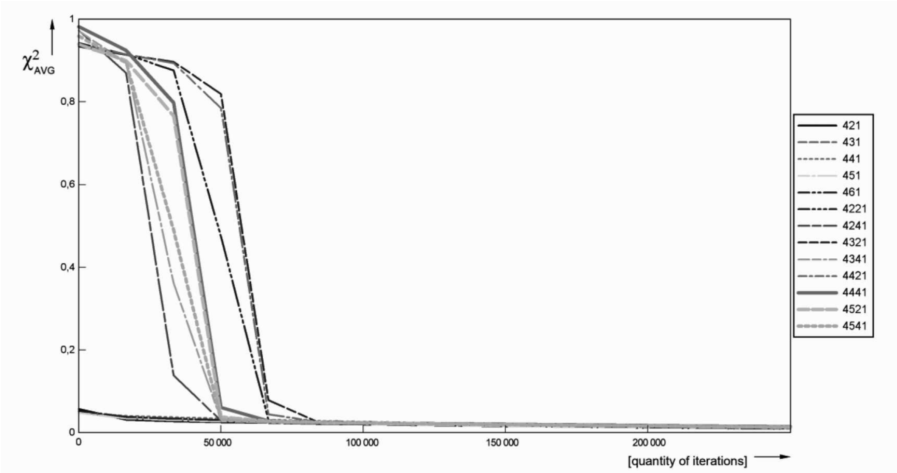

Fig. 6. Learning process in various ANN structures

The learning process in various network structures is shown in Figure 6.

It appears from the figure that the network is learnt from 4 10^5 iterations. You can see here that the assumed network structure hardly affects the network learning process. The descriptions given in the figure, e.g. 451, mean a network with four inputs, one hidden layer with five neurons, and one output.

In tests of how accurately the network represents the actual processes, it is interesting to compare the speed data recorded during the experiment with that derived from the neural network. Such results are shown in Figure 7.

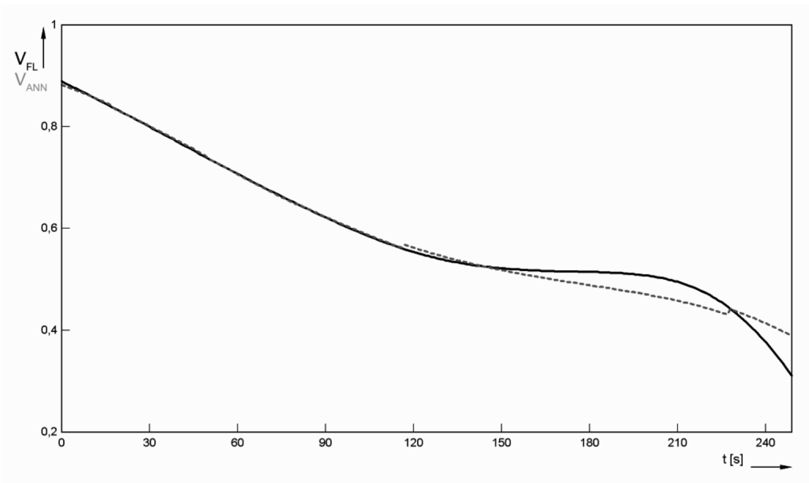

Fig. 7. Comparison of the aircraft landing speed recorded during flight and that derived from the neural network

You can see here that until 150 sec. there is barely any difference between the speed data discussed above. After 150 sec., the representation accuracy deteriorates. This is the flight stage with intensive braking on the runway. As already noted before, the differences between such data do not disqualify the assumed model.

4. Summary

The results obtained for the quality of the neural mode's representation of the actual landing can be considered satisfactory. Hence, the neural network can be used for aircraft flight modeling. The resultant model can be used, therefore, to develop a simulation model for air traffic tests and training simulators. This modeling method can be found to be inconvenient, as much effort is required to compile data needed to develop a network, which results from the peculiarity of flight data recording.

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