Strain predictions using Artificial Neural Networks for a full-scale fatigue monitoring system

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Abstract

The Military Transport Aircraft Division (MTAD) of EADS is carrying out a number of tests on several ANNs used to predict accurately strains from flight parameters. This process is part of the development of the Structural Health Monitoring System (SHMS), a parametric full-scale fatigue monitoring system that is going to be incorporated in the A330 Multirole Tanker Transport (MRTT), which will first enter into service in the Royal Australian Air Force (RAAF) with the denomination KC-30A. All the tests are based on real flight data collected from the flight tests performed by the A310 Boom Demonstrator. This aircraft is used by EADS MTAD as a testbed for aerial refuelling technologies, and carries a prototype of the SHMS. Results of these tests are provided for different structural components of the aircraft (wing, fuselage, horizontal and vertical tailplanes, engine pylon). A discussion of the involved technologies, strategies and solutions adopted to build and train the ANNs is included as well.

Keywords: Artificial Neural Network, Structural Health Monitoring System, ANN training.

Introduction

Artificial Neural Networks (ANN) are data-driven statistical models capable of capturing the underlying nonlinear relationships between variables. Recently, several authors have tested the capability of ANNs to reproduce the strain history of real structural elements from flight parameters [1-4], yielding good results for complex non-linear scenarios, such as those appearing in empennages.

In 2004 EADS-CASA started the development of a fatigue monitoring system –named Structural Health Monitoring System (SHMS)– for the A330 Multirole Tanker Transport (MRTT) [5]. The SHMS was conceived as a full-scale system with capability to monitor the main structural elements of the aircraft (wing, fuselage, horizontal and vertical tailplanes, engine pylon, backup structure of landing gears, etc.). Using the experience acquired from previous programs, two well-known architectures were considered initially: an indirect measurement system (based on a classical parametric system involving the loads model used for certification to derive strains from the flight parameters), or a direct measurement approach based on the installation of strain gauges.

The preliminary analyses showed that both types of systems have advantages (low cost in the case of the parametric approach, good accuracy for strain gauges-based concept) but also important drawbacks (moderate accuracy for some elements or locations in parametric systems, high installation and maintenance costs in strain gauge-based architectures). In this context, it was considered that a system based on ANNs to calculate stresses from the flight parameters had the potential to merge a high accuracy (the ANNs would be based on real measurements rather than theoretical formulae) with a moderate cost (as the installation of strain gauges on all the aircraft would be avoided), thus combining the advantages of both approaches and minimizing their drawbacks, so it was decided to incorporate this promising methodology to the SHMS [5].

One of the milestones of the development process was the installation of a prototype of the system in order to achieve the Technology Readiness Level (TRL) 7 [6]. Part of the development effort involved in this milestone was based on extensive testing of the ANNs using real flight data (i.e., flight parameters and strains) from the A310 Boom Demonstrator, an aircraft used by EADS as testbed for aerial refuelling technologies. Within this process, several neural networks were used to predict the strains in the main structural components. The inputs to the networks were provided by signals collected in flight from the computers of the aircraft (airspeed, pressure altitude, angle of attack, etc). Strain gauges were installed in order to obtain the expected outputs to train the ANNs with.

The aim of the present work is to describe the procedures followed during those tests, and the results obtained. This paper is organized as follows. First, main concepts about ANNs are provided. In particular, the several criteria to be taken into account when defining their architecture are discussed. The experimental setup used to collect flight data is then described. The paper concludes with a presentation of the predictions for wing, fuselage, horizontal and vertical tailplanes, and engine pylon.

Artificial Neural Networks

Artificial Neural Networks (or simply neural networks) are information processing systems inspired by the way biological nervous system process information [7]. Much like the human brain, an Artificial Neural Network (ANN) consists of a large number of highly interconnected simple processing elements. This organization gives the neural network a high parallel processing and learning capability.

ANNs have two main components: the processing elements and the connections between them. The processing elements, usually called neurons, work as information processors, and the connections are used for information storage. Figure 1 shows a diagram of a neuron with connections going in and out of it. Each neuron *k* first calculates the 'activation state', consisting of a weighted sum of the input signals and the addition of a threshold or bias $\left(\sum_j w_{jk} y_j + \theta_k\right)$, then applies a transfer function *f* –named 'activation function'– to this sum and outputs the result (y_k), which can be used by other neurons of the network or directly as the network output. Activation functions *f* must be nonlinear if the problem to be solved is nonlinear.

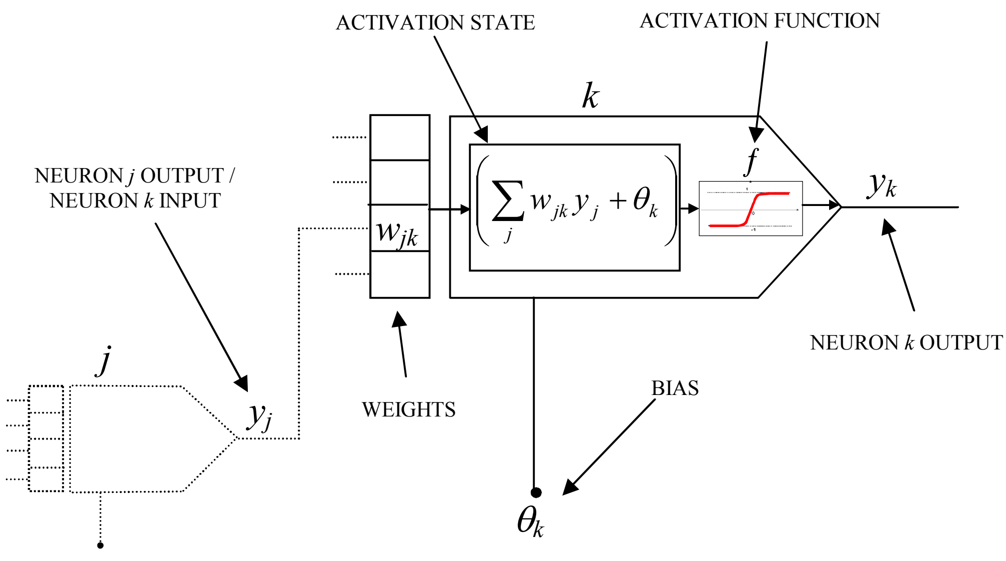


Fig. 1: Neuron

Neurons within a network are arranged in groups called layers. Each layer processes its inputs and provides the corresponding outputs to the next layer (and/or the previous layer if the network contains feedbacks). Figure 2 shows a neural network that consists of an input layer, two hidden layers, and an output layer. The data enters the network through the input layer. Most of the processing takes place in the hidden layers, so more or less of these layers may be required depending on the complexity of the problem. Finally, the output layer yields the desired information.

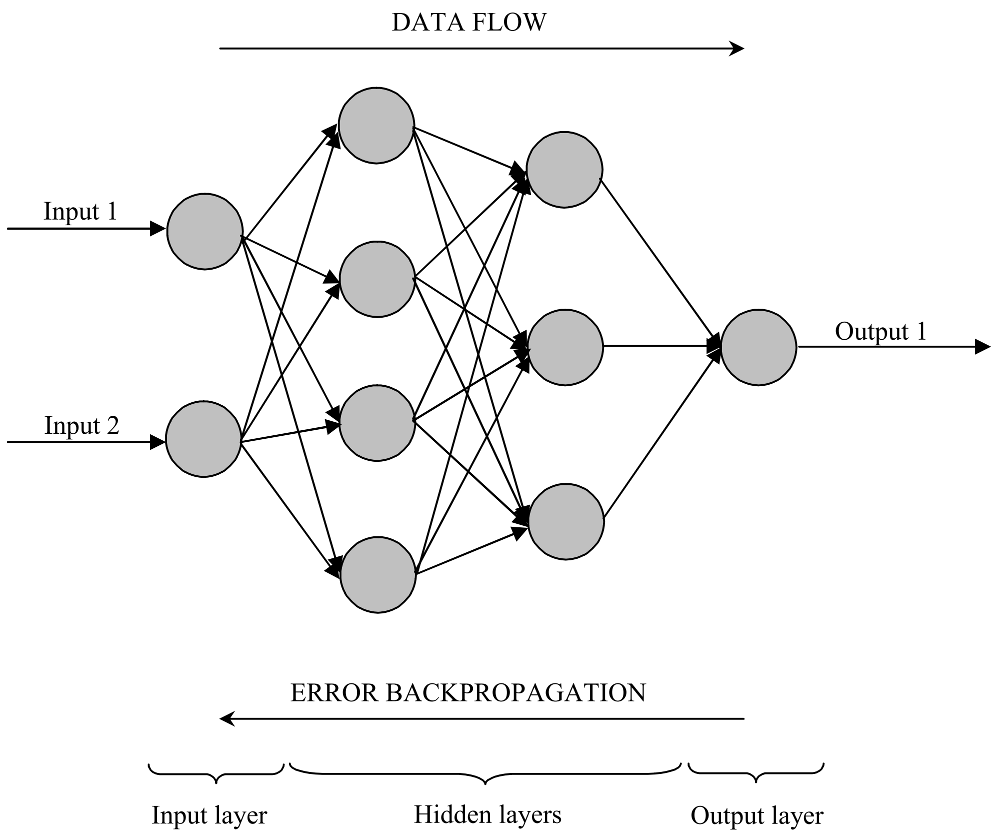


Fig. 2: Neural network

Although there are numerous types of ANNs, one of the most common is the 'feed-forward backpropagation' neural network. In this class of networks there are two information flows (Figure 2). On one side, the forward propagation of network input values to the output that gives the processed values. On the other side, the backpropagation of the difference between the desired output and the processed one (error backpropagation). The process by which the error is backpropagated in order to adjust the weights and biases is called 'training' or 'network learning'. From a mathematical point of view, the training is based on a gradient descent method that minimizes the total squared error of the output computed by the net. Once trained, the ANNs allow signals to travel one way only, from input to output (feed-forward). The backpropagation training method gives to this class of networks a great capacity to solve multivariate regression problems.

Neural network definition

Selection of the proper network for a given problem is a complex task that involves aspects such as selection of the number of neurons and layers, selection of training data set, determination of the length of the training cycle and correct use of the domain knowledge available. Actually, this process is not specific of neural networks, as similar decisions have to be taken to determine the initial parameters and configuration of most numerical methods. Here only some general ideas about this subject are provided. Further information can be found in the specialized literature [8, 9].

Layers and neurons

The total number of connections of the ANN (determined by the number neurons and the organization in layers) must be carefully assessed. A network that is not complex enough can fail to detect fully the signal in a complicated data set, leading to underfitting. A network that is too complex may not recognize the underlying dynamics hidden in the data, but learn the data by heart (overfitting). Overfitting is especially dangerous because it can easily lead to predictions that are far beyond the range of the training data. But underfitting can also produce erroneous predictions.

General rule for the input layer indicates that it must have a number of neurons equal to the number of the input variables. Similarly, the number of neurons in the output layer must be equal to the number of predicted variables. The number of hidden layers and the number of neurons included in each layer is more difficult to establish, and an iterative process is usually needed.

Training data set

Feed-forward backpropagation networks are trained using a 'supervised learning' technique, in which the network is trained by providing it with input and matching output patterns, so weights and biases can be adjusted by successive backpropagation of the error until the computed output get close enough to the desired output. The training set must be a representative sample of the data that a given network is expected to process after the training cycle has finished. This means that the training data set must have a sufficiently large number of training pairs (input, output) and it must cover the full range of the expected inputs and outputs.

Some trial and error is required for the determination of the proper number of training pairs. This process is not completely blind, however, as some general ratios must be observed. For example, it is usually recommended to have at least 30 times as many training cases as there are weights in the network to make unlikely to suffer from overfitting.

The problem of covering the full range of expected inputs and outputs depends in most of the cases on a proper procedure for the management of data. If certain ranges of inputs and outputs are not sufficiently represented in the training set, they will not be predicted correctly by the ANN, because neural networks –as any other data-driven mathematical method– cannot extrapolate accurately far from the known values.

Length of training cycle

The purpose of training a network by backpropagation is to achieve a balance between correct responses to training values (memorization) and good responses to new input patterns (generalization). During the training process, the training pairs are presented several times to the network. If the number of times is not high enough, it will not be able to predict any values correctly. If it is excessive, it will begin to memorize the training data (over-approximation).

The problem of the length of the training cycle cannot be successfully addressed before the training begins. Performance of the net must be periodically evaluated during the training using a validation set that is completely separate from the training data.

Domain knowledge

Domain knowledge is defined as 'the specialist or a priori knowledge about the system' [10]. A complete physical analysis is needed in order to determine, for example, what inputs have a significant impact on the desired outputs. This analysis should prevent the use of inputs into the network without physical correlation with the expected output, thus shortening the training and speeding up the convergence. At the same time, a good analysis must ensure that all the parameters with physical relationship with the output are included as inputs.

The knowledge available can be used also to simplify the problem or reduce the number of inputs of the network. For example, in some cases is advantageous to introduce the dynamic pressure as a flight parameter rather than using the altitude and the airspeed separately.

Experimental setup and testing procedure

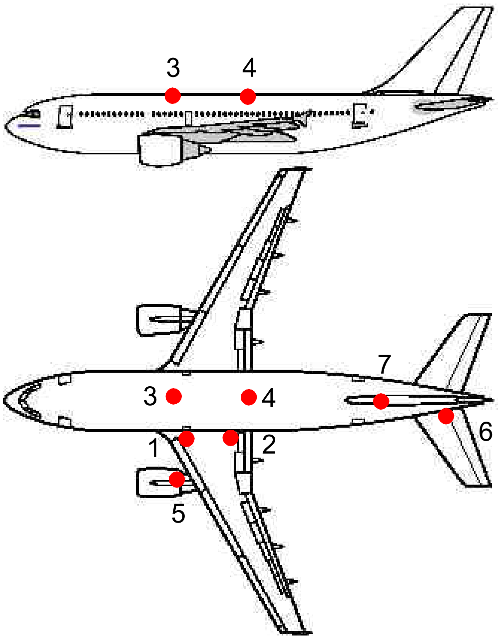
The A310 Boom Demonstrator aircraft (Figure 3) was used to collect the information needed for this research. This aircraft has been used by EADS during a 40-month flight test phase in Getafe (Spain) to test aerial refuelling technologies to be included also in the A330 MRTT.

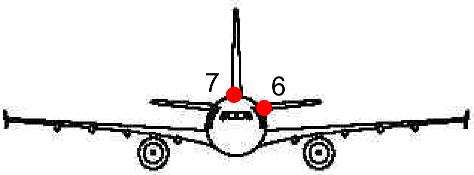
Fig. 3: A310 Boom Demonstrator

The variety of flight conditions scheduled for the A310 Boom Demonstrator was considered ideal to test the Artificial Neural Networks and develop the technologies to be used later in the SHMS. Therefore, several strain sensors were installed in the main components (wing, fuselage, horizontal and vertical tailplanes, landing gear), following the load monitoring philosophy [11], i.e., locating of the gauge so that its response is predominantly influenced by the principal loading, and avoiding 'hot spots' or elements with high strain gradients. Figure 4 shows the locations of the sensors.

The strain sensors were temperature compensated to account for the changes in temperature expected with altitude, and had a special coating to provide environmental and mechanical protection. A special bonding procedure for long-term monitoring purposes was also developed.

Strain gauges were sampled at rate considered enough to capture every possible relevant vibration mode, taking into account the stiffness of the different components of the A310.





Strain gauge nr.	Location
1	Wing root, forward spar (lower cap)
2	Wing root, rear spar (lower cap)

Fig. 4: Location of the sensors

In parallel to the installation of the strain gauges, several connections were made to extract flight data from the ARINC429 data buses of the aircraft. Flight parameters such as acceleration on the centre of gravity, airspeed, pressure altitude, air temperature or deflection of control surfaces were extracted from these ARINC data streams. The signals were sampled at higher rate than that used by the onboard systems to refresh the parameters onto the data buses. The information was stored using data acquisition units already installed for flight test instrumentation purposes.

Aside from the onboard infrastructure, some other ground elements were also prepared. Thus, EADS MTAD flight test hardware was used to download the flight parameters and strain data (Figure 5). Besides, an in-house software application was developed, using MATLAB®, to manage the data, clean the information received, select the training set, train the ANN and provide the outputs. Figure 6 shows the basic flowchart of this application. Once the recordings were checked (and errors corrected, if necessary), they were analysed looking for representative data (e.g., take offs or landings with new weights, cruises at different altitudes, etc.). If this information was found, it was included in the training data set and stored in a database. In parallel, a validation data set was constructed using information not selected for the training data set and, therefore, completely new for the ANN. Training of the ANN was based on the Neural Network Toolbox of MATLAB®. Data selected for training represent less than 5% of the total information collected.

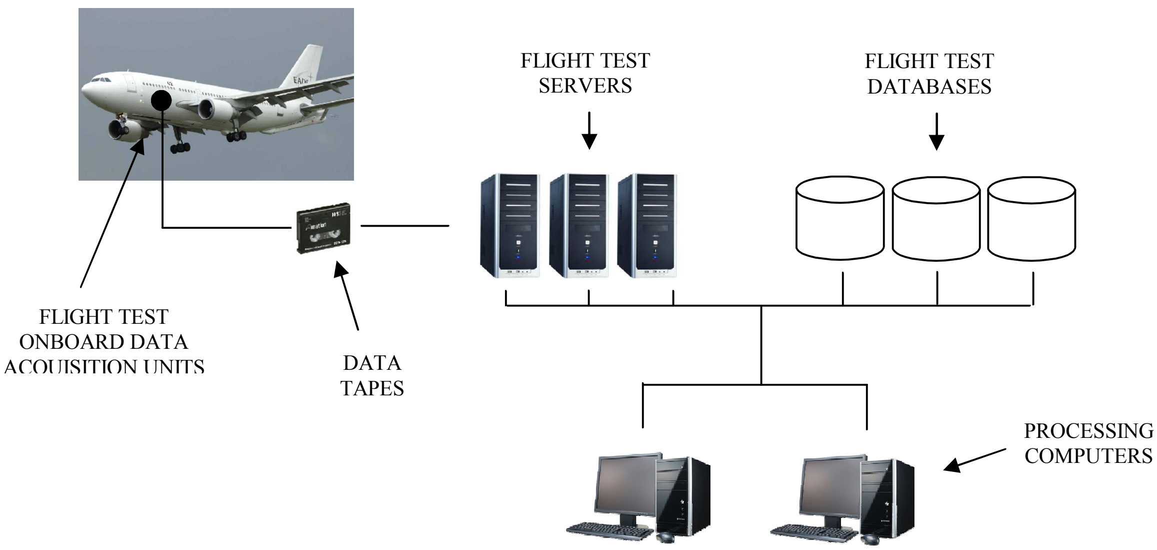


Fig. 5: General arrangement

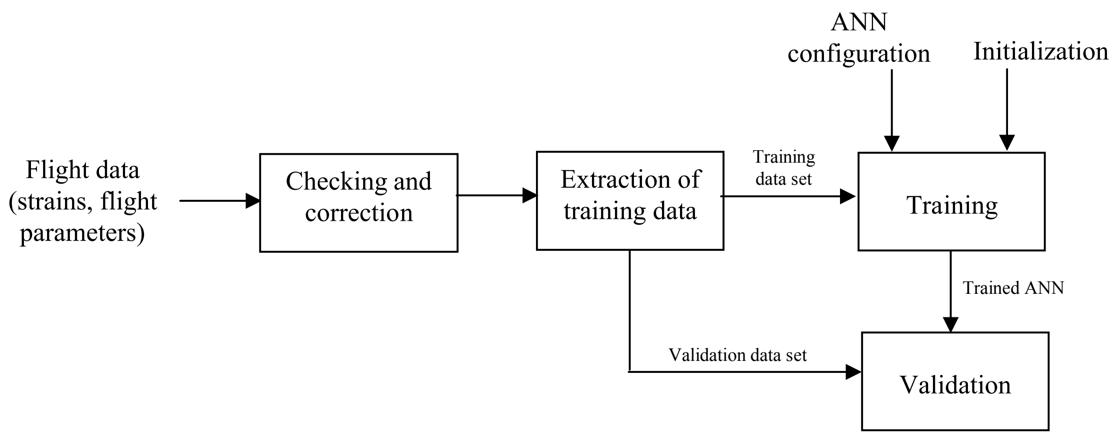


Fig. 6: Ground software analysis

Implementation

An extensive number of tests using the flight data collected were designed in order to give insight into the performance of the neural networks for the given problem under real conditions. These tests were divided into two groups. The first one consisted of applying the same ANN architecture to all the structural locations analysed in order to make comparisons using the same basis. The second group of tests was oriented to find the optimum ANN architecture for each case. This paper deals with the first group, as the activities under the second group have not been finished yet.

Domain knowledge analysis

Domain knowledge was obtained from a loads analysis of the different locations being predicted. Thus, the loading on each component was studied in order to determine the flight parameters involved.

The results of the domain knowledge analysis yielded –as could be expected– a large list of parameters having an impact on the strains of the different locations. In the end, the list included 40 parameters describing:

- Accelerations on centre of gravity
- Attitude of the aircraft
- Trimmed conditions of the aircraft
- Engine performance
- Fuel contents and distribution
- High lift and control surfaces evolution

Another outcome of the domain knowledge analysis was that most of the locations were subjected to different loading depending upon the aircraft was on ground or in flight conditions. For example, the strains on the wing on ground depend on the accelerations on the centre of gravity, fuel weight, total weight and wheel speed, while in flight several other parameters have to be included, such as angle of attack, airspeed or deflection of control surfaces. Even in those cases in which the parameters are the same in both conditions, the underlying mathematical relationship is different.

Therefore, and taking into account the results of previous theoretical tests, it was decided to use two different neural networks for each location: one for ground and another for flight. Training of both would be independent, and the activation of each ANN would be triggered by the Weight on Wheels (WOW) parameter, provided by a mechanical switch already included in the landing gear, and available from one of the ARINC429 data buses connected to the onboard acquisition units.

ANN selection and architecture

After a trade-off analysis, it was considered that feed-forward backpropagation was the best network type for a problem such as the one addressed in this research. Sigmoid function was also selected as activation function for neurons, because in all the cases the relationship between strains and flight parameters was deemed nonlinear.

One of the design basis established for the SHMS was the use of a modular arrangement of ANNs, so each network would only fit one single location (Figure 7). This concept simplifies the customization of the characteristics of the ANN (input parameters, number layers and neurons, training technique, etc.), taking into account the specific structural response of each element of the airframe. Besides, it was considered that this architecture allows the addition of new ANNs if more strain gauges are installed without modifying the existing ones. This arrangement has also disadvantages, however, as is more demanding in terms of data processing and management.

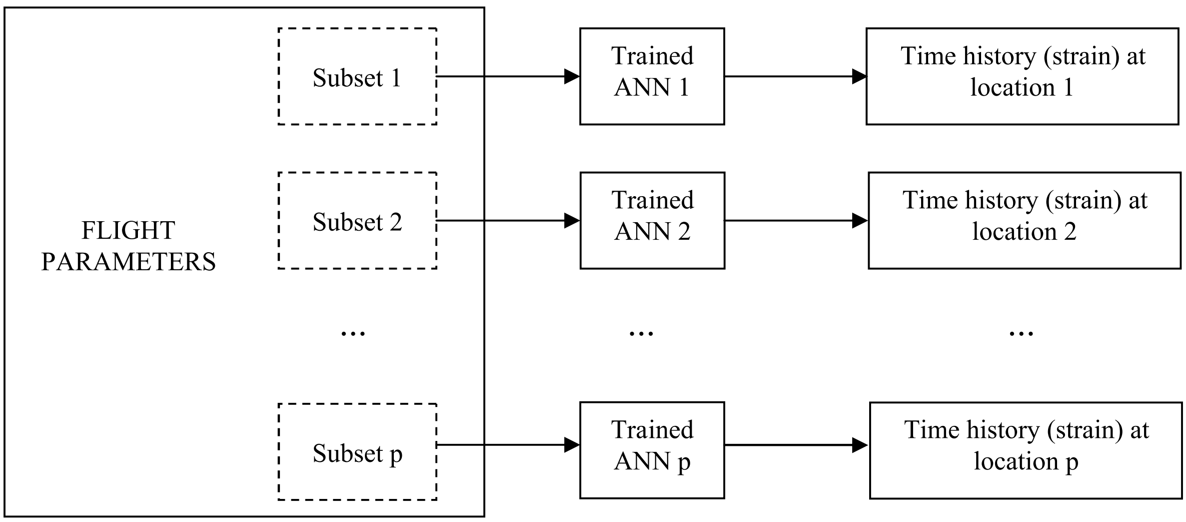


Fig. 7: Modular architecture

Therefore, the output layers of all neural networks used in this research had a single neuron, dictated by the fact that each of these networks was expected to predict a single value (the strain in the corresponding element). Bearing in mind that an input layer with 40 neurons (same number as input parameters) could lead to overfitting due to a high number of weights, it was decided to reduce the input layer in order to have a good ratio of neurons in the input and hidden layers. During the trade-off analyses performed, the number of input layer neurons varied from 10 to 40. At the same time, various combinations of neurons in the hidden layers were also tried out, varying from 10 to 15.

In the end, the configuration of Figure 8 was considered for all the structural locations. As can be seen, the number of neurons in the input and hidden layers was set to 10 and 15, respectively.

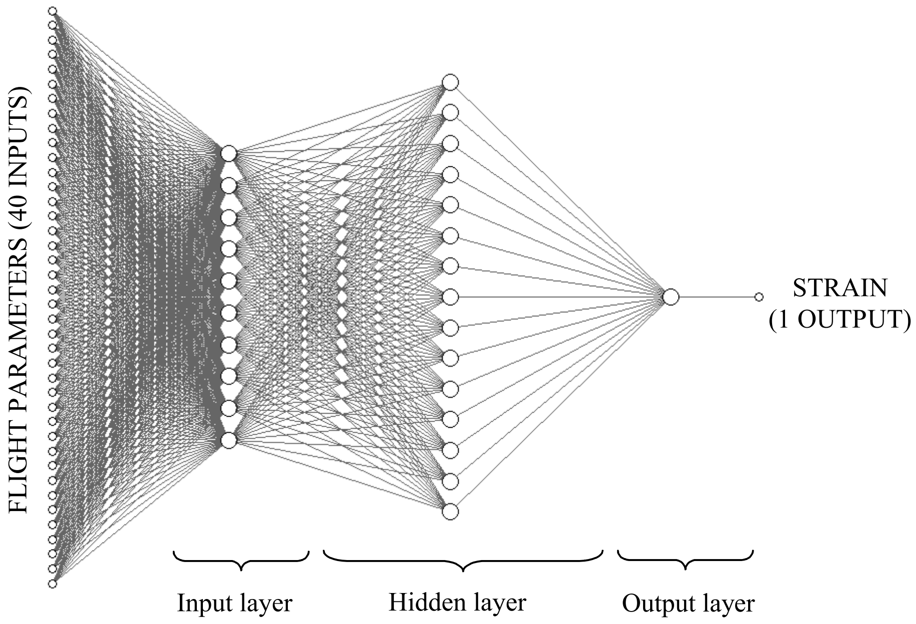


Fig. 8: ANN reference configuration

Aside from the selection of layers and neurons, the initial values of the weights had to be determined before the training commenced. The values for the initial weights had not to be too large, or the signals received by the neurons would be likely to fall in the saturation region of the transfer function. On the contrary, if the initial weights were too small, the signal received by the neurons would be close to zero. In both cases the learning rate would be extremely slow. To avoid these problems, a pseudo-random method that produced a value between the suitable interval of the sigmoid function was used.

Results

In total, the A310 Boom Demonstrator had logged more than 150 flight hours during around 120 sorties when the analysis was initiated. Numerous wet and dry contacts were accomplished with small and large receivers such as F-16 fighter aircraft or NATO Airborne Warning and Control System aircraft, respectively, at various altitudes and airspeeds, in order to explore and validate the Boom in-flight refuelling envelope, so a great variety of flight conditions were collected.

Source data for the analysis presented here consisted of 100 hours of recordings, from which approximately 92 hours corresponding to flight conditions were extracted. The different flight parameter and strain data channels were all identified as recording high quality data. Total information stored was 2.3 Gb, from which were extracted around $3{\cdot}10^6$ valid records.

This paper presents results for the wing, fuselage, horizontal tailplane, vertical tailplane and engine pylon. Flight ANNs have been considered here only. Root Mean Squared Error (RMSE) between the real and the predicted strain has been used as a measurement of the neural networks performance. As part of the validation process, charts showing the comparison of the simulations performed with real data were produced, some of which have been also included. In these charts, both the theoretical and the experimental strains have been normalized with respect to the maximum and minimum real strains measured during the flight.

Wing

The domain knowledge analysis determined that virtually all the 40 flight parameters selected as inputs for the neural network had an influence on the strains of the wing. This meant that the mathematical complexity of the problem was high. Despite this fact, the results were good, with a RMSE of only 1.1%. Figure 9 shows a detail of one of the simulations. As can be seen, the real (measured using strain gauge #2 of Figure 4) and the predicted signals are almost identical.

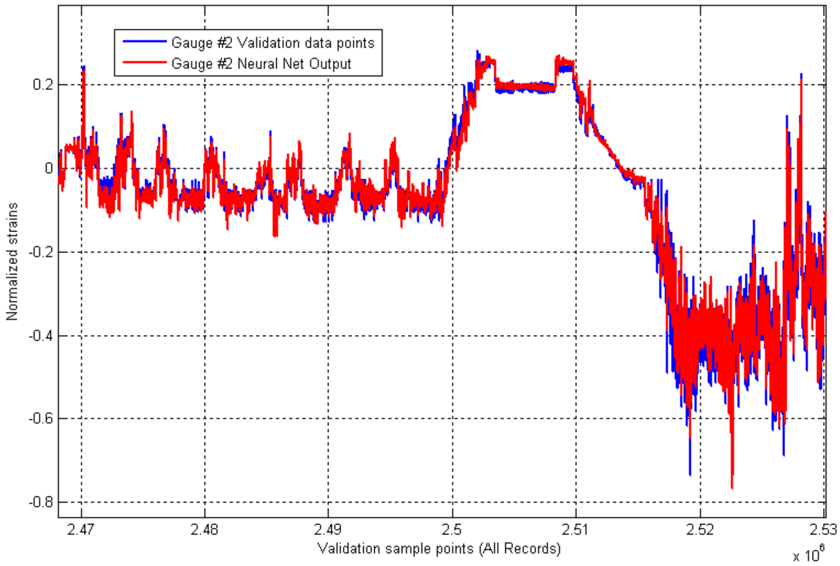


Fig. 9: Wing strain measurements vs predictions

(Rear) fuselage

The strains of the rear fuselage (measured using strain gauge #4 of Figure 4) are influenced by either intrinsic factors, such as pressurization or aircraft accelerations, or extrinsic actions due to the empennage. Both aspects were captured correctly by the neural network, as the RMSE obtained was of 1.4 %, with a fairly good correlation between real and predicted strains (Figure 10).

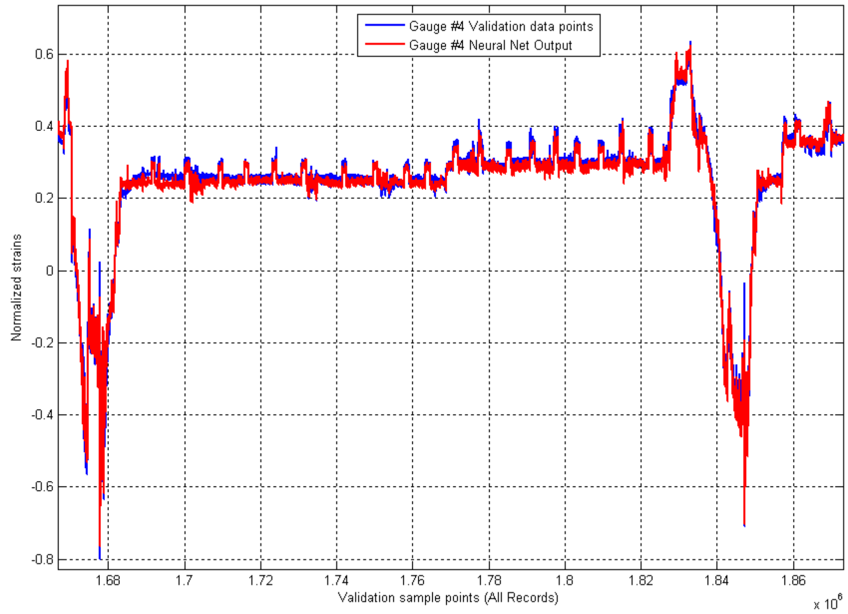


Fig. 10: Fuselage strain measurements vs predictions

Horizontal and vertical tailplanes

At some extent, the scenario of the empennage is similar to that of the wing, as in both cases the number of parameters related to the corresponding strains is high. However, error was expected to be higher, as accelerations on the centre of gravity are seldom correlated with the real accelerations experienced by the horizontal and vertical tailplanes.

The results confirm this assumption, as the RMSE obtained (2.1% for HTP, 3.4% for VTP) double and triple the error of the wing. Nevertheless, Figures 11 and 12 show that these predictions still represent a good approximation to the real measurements (obtained from strain gauges #6 and #7 of Figure 4).

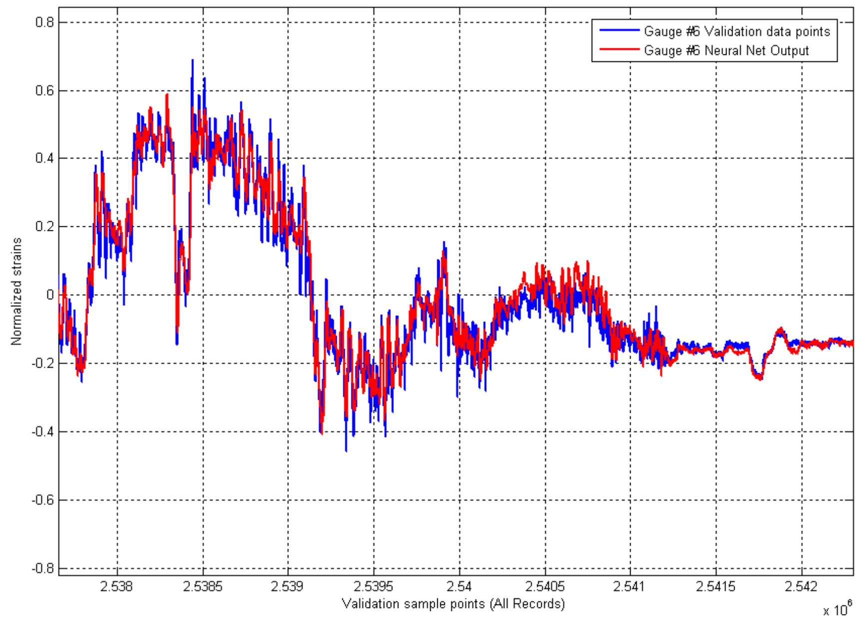


Fig. 11: HTP strain measurements vs predictions

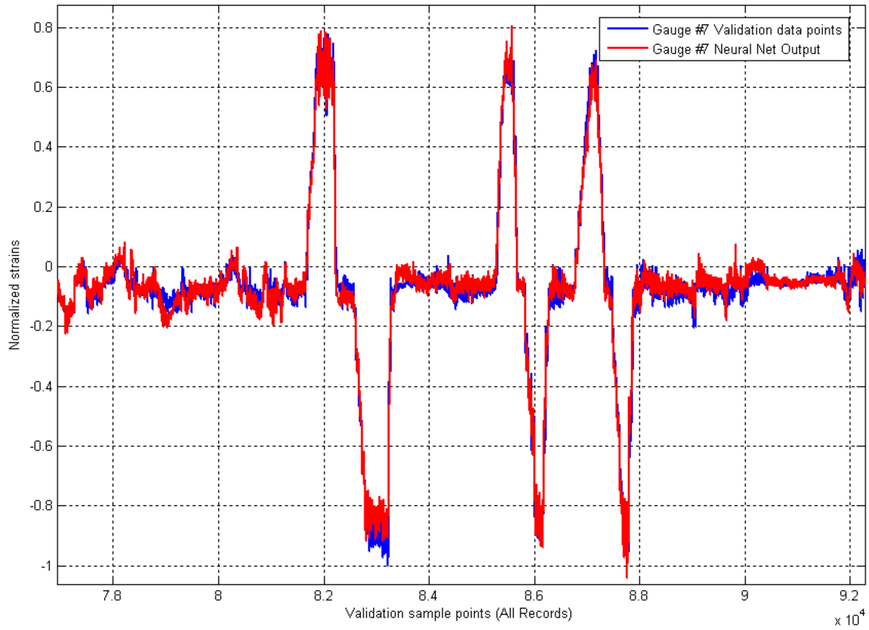


Fig. 12: VTP strain measurements vs predictions

Engine pylon

The high correlation between real and predicted strains at the engine pylon of Figure 13, indicates that the loading of the engine pylon has been correctly generalized by the neural network. Actually, the strain RMSE obtained was of 1.5%, in line with the results of wing and fuselage. Real strains of the engine pylon were measured using strain gauge #5 of Figure 4.

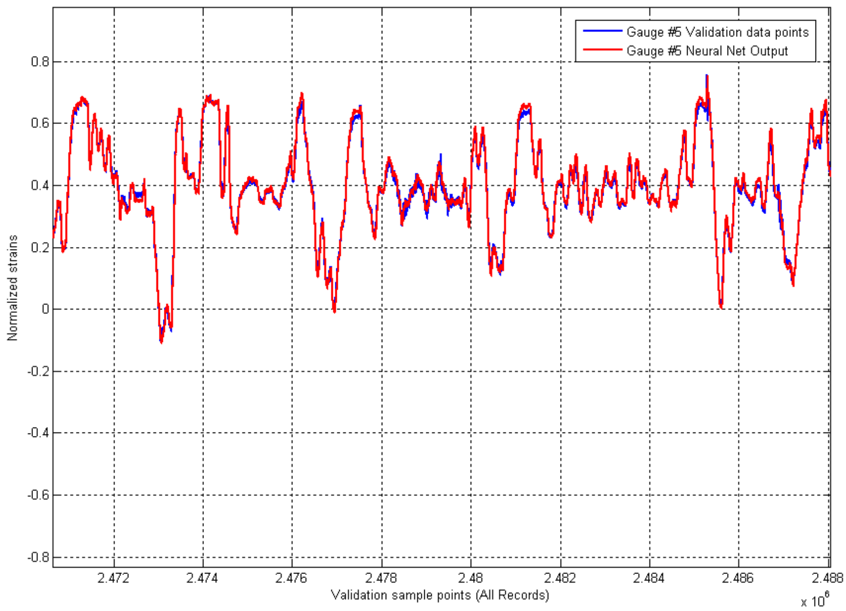


Fig. 13: Engine pylon strain measurements vs predictions

Conclusions

Five ANN-based predictions of strains for the main structural components of an A310 (wing, fuselage, horizontal tailplane, vertical tailplane, engine pylon) using a common architecture have been shown. The errors obtained are lower than 3.5%, which indicates that even without using highly optimized ANN for each location, the capability of the networks to learn the underlying mathematical relationship is outstanding. As could be expected, horizontal and vertical tailplanes had the higher errors, due to their specific difficulties.

The process followed to develop the neural networks used in this work has been also discussed. Aside from a deep knowledge of the mathematical concepts behind the construction and training of neural networks, it has been shown that a complete physical assessment is needed in order to ensure that all the physical information has been correctly captured and provided to the network. A successful result cannot be obtained without the combination of both factors.

Acknowledgments

The authors wish to thank the members of the Military Transport Aircraft Division of EADS involved in the installation of the strain sensors, the preparation of ARINC429 data buses connections and the flight tests of the A310 Boom Demonstrator, who all contributed to the success of this programme. Special thanks go to the colleagues of the Fatigue and Fracture Mechanics Dpt for their support and advice during this work.

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