Airplane Vortex Encounters Identification Using Multilayer Feed-Forward Neural Networks

Faouzi Bouslama and Aziz Al-Mahadin

***Abstract*—The encounter of vortices generated by a leading aircraft during takeoff or landing can be a source of hazard to a following aircraft. In spite of airport efforts to keep safe separation distances between aircrafts, a number of them encounter severe vortices each year. It has been challenging to accurately identify those encounters by manual approaches. To mitigate the impact of vortex encounters on an aircraft, it is important that more reliable identification techniques be developed. This research is a contribution towards the automatic identification of vortex encounters using artificial neural networks. Multilayer feedforward neural networks are trained using the back-propagation learning algorithm to classify flight events into either vortex encounters or other events. Using salient inputs such as aircraft roll angle, normal acceleration and lateral acceleration, the neural networks are able to achieve an overall average identification rate of about 88%. These results confirm the authors' earlier assumption on using a reduced set of critical inputs to properly classify aircraft vortex encounters.**

***Index Terms*—Vortex encounter, flight data recorder (FDR), neural networks (NN), multilayer feed-forward (MLFF) network.**

I. Introduction

Aircraft encounter various types of turbulences during a flight. One of the most hazardous turbulence is caused by the wing tip vortices. This type of turbulence is critical to flight safety as its decay is slow and can produce a significant rotational airflow that severely influence a following aircraft. In fact, aircraft safety is greatly affected by wake vortices generated by a leading aircraft.

An aircraft wake vortex [1] is naturally produced by all types of aircraft. The severity of vortex encounter can vary depending on parameters such as the type of leading and following aircraft, the flight phase, the aircraft weight, the wing size, the configuration, and the weather conditions. Encountering a vortex can be hazardous during flight, in particular, at landing and takeoff flight phases, where the aircraft are required to fly within confined flight paths, which makes vortex encounter avoidance and recovery more difficult.

In fact, the wake vortex hazard is one of the main factors defining safe separation minima between two aircrafts. The international wake vortex separation rules are based upon the aircraft weight categorization whether it is Heavy, Medium or Light. However, such categorization has become inappropriate which led some countries to introduce their local separation standards [2]. Moreover, the vortex separations sometime unnecessarily reduce airports capacity. In fact, for any vortex separation modifications, there is a need for comprehensive relevant investigations to ensure safety and appropriateness. For this reason, it is necessary to examine and accurately identify actual vortex encounters.

The identification of vortex encounters has been conducted manually in most cases. Very often, pilots are requested to report any vortex encounters, hence providing vital information to vortex analysis. The complete analysis report is supplemented by radar and meteorological information. Consequently, a flight data recording (FDR) analyst carries out a manual analysis of flight data to confirm the vortex encounters. Nevertheless, the manual analysis agreement with pilot reporting of vortex encounters is appoximately in the range of 55 to 70% [3].

In some studies, however, the focus has been on the automatic identification. Various modeling and classification approches were used to better capture uncertainties and complexities in data and also to reduce subjective human judgment errors. In [4], the authors reconstructed FDRs time histories using neural networks and established the concept of virtual flight data recorder. In [5], the authors evaluated the performance of neural networks and fuzzy logic re-constructors for the development of a virtual flight data recorder. They stated that the main drawback of their method was that specific flight data at each flight phase were needed for effective training of the neural network.

More recent studies have shown more potential in using soft-computing approaches in the identification of vortex encounters. In [6], the authors use fuzzy logic (FL) to model and identify vortex encounters. FL tolerates data imprecision and cope well with complexities in modeling the vortex encounters. Fuzzy linguistic variables were used to model FDR data. The fuzzy rules were derived from a collection of 54 pilot reports of vortex encounters and 210 records of flight events from FDRs. An average success rate of identification of 83.7% was obtained. In [7], a neuro-fuzzy identification system was used to classify vortex encounters. Artificial neural networks integrated with fuzzy systems have been used as a solution in the automatic tuning of the membership functions of fuzzy linguistic variables and applied to various problems. The authors used a hybrid Adaptive Neuro-Fuzzy Inference System (ANFIS) to automatically tune the parameters of the fuzzy membership functions. They investigated various neuro-fuzzy models having different

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sets of parameters and factors, and they achieved an average identification accuracy of 84.2%.

This paper builds on the previous results achieved in the automatic identification of aircraft vortex encounters with pure fuzzy logic (FL) and neuro-fuzzy ANFIS approaches, respectively. The authors continue to investigate machine learning by using in this case a supervised multilayer feedforward (MLFF) neural network. The MLFF is constructed based on a reduced set of parameters collected from flight data recorders and pilot reports, and which are related to vortex encounters. The same number of salient inputs has been identified and tested with classifiers based on pure FL and ANFIS approaches.

The remaining of the paper is structured as follows: Section II is an overview of neural networks with a focus on MLFF type of supervised networks. Section III describes the vortex encounters and the training data, including the data preprocessing and normalization, and the selection of the main parameters for the MLFF. Section IV presents the structure of the MLFF classifier and presents the simulation results obtained using the NN toolbox on MATLAB. Section V discusses the optimization of obtained results. Section VI contrasts the obtained results with those achieved with pure Fuzzy Logic and Neuro-Fuzzy approaches. Finally, Section VII presents the research conclusions.

II. Overview of Feedforward Neural Networks

Artificial Neural networks (ANNs) [8] are powerful computational models that have been inspired by the human brain and the biological neurons. The main objective of using an artificial neural network is to mimic human brain functioning in building systems that are capable of understanding the underlying behavior of complex systems. ANNs have found important applications in various domains and diverse areas including finance, medicine, and engineering. In the aerospace field, ANNs have been used in aircraft fault detection, control system, autopilot development and many other areas [9]-[11].

The basic element in any artificial neural network is the neuron which is often called node or unit. ANNs are made of a number of these simplified computational models, which are arranged in various layers. A node receives input from other nodes or from an external source and generates an output. The neuron associates a weight to the input assigned based on the input's relative importance to other inputs. The node then applies a transformation function (activation function) to the weighted sum of inputs. There are many types of activation functions and their proper choice depends on the particular problem under consideration.

The architecture of a network consists of a description of how many layers the network has, the number of neurons in each layer, the transfer functions in a node, and how the layers are connected to each other. The best architecture to consider depends on the type of problem under consideration [12], [13].

In most applications of ANNs, a commonly maximum number of three layers is used [14]. In the feedforward type of neural networks (FFNN), the information flows in one direction. Fig. 1 depicts a three-layer feedforward neural network.

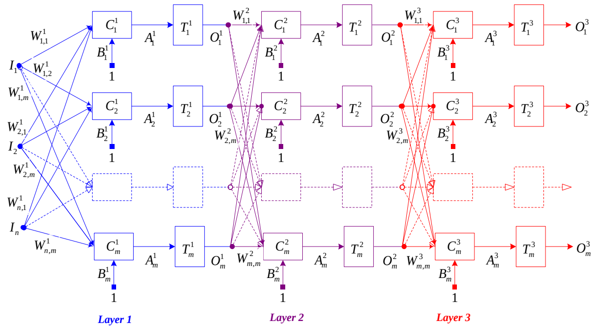

Fig. 1. Multiple layers feedforward neural network.

ANNs can be trained to perform a particular task through the adjustment of weights and biases, which can be carried out in a variety of ways. Supervised neural network carry out this adjustment based on a comparison of the output and the desired target. Hence, there are many kinds of ANNs design and learning techniques that can be used. However, the proper choice of an ANN type or learning algorithm is problem dependent and hard to verify without testing [12], [13]. The focus in this research is on FFNN. The back-propagation learning algorithm, which looks for the minimum in the error function in weight space using the method of the gradient descent, is applied in this case [15].

Properly trained backpropagation networks give acceptable accuracies when presented with unknown inputs. This generalization property makes it possible to get good results from an ANN by using only a representative set of training data. The following sections present the research results obtained when applying FFNN to the identification of aircraft vortex encounters.

III. Vortex Encounters and Data Collection

A. Aircraft Vortex Encounters

Aircraft safety is usually influenced by a number of flight events such as turbulences, wind shear, hard landing, and especially wake vortex. Aircraft wake vortex [1], which is the focus of this investigation, is produced by virtue of aircraft lift generation due to pressure difference between the upper and lower wing surfaces. A turbulent air layer is generated behind the wing that rolls up and forms two counter-rotating vortices, as shown in Fig. 2. Aircraft vortices may persist for several minutes depending on its strength and the atmospheric conditions. These vortices are able to impose significant forces on a following aircraft causing a considerable threat.

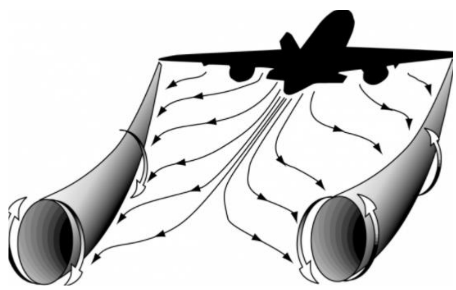
Fig. 2. Pressure difference causing wingtip vortices (source: http://controle-aerien.chakram.info/turbulence-de-sillage/).

Encountering vortex can be hazardous during flight, in particular at landing and takeoff flight phases. During these pahses, aircrafts are required to fly within confined flight paths and pilots are required to fly by a set of very restricted rules in a close proximity to the ground, which makes vortex encounter avoidance and recovery more difficult. The increase of encounter probability in ground vicinity is confirmed through analysis of collected pilots' vortex encounter reports [6], [7].

The separation minima required by the International Civil Aviation Organization sometimes unnecessarily limit airspace and airport capacity and, therefore, requires revision based on thorough investigations and flight data analysis to avoid negatively affecting flight safety and to ensure appropriateness. The investigation of the automatic identification of vortex encounters by artificial neural network techniques is conducted to help contribute reasonable solutions to this end.

B. Data Collection

Pilot reports and flight data recorders (FDRs) are the main source of data used in investigating any flight events. The FDRs are used in most aircraft to record data reflecting mainly aircraft operation and performance. This research is conducted using data obtained from an airline's FDRs. A total of 181 records of vortex encounters and other 29 records of flight events are analyzed as shown in Table I. The FDRs contain over one thousand parameters, but only eight are found to be relevant to the investigation of vortex encounters. Table II lists the salient parameters used as inputs in this investigation.

C. Data Normalization

TABLE I: COLLECTED FLIGHT DATA RECORDS

Reported Events	***Number of Records***
Wake Vortex	181
Wind Shear	5
Atmospheric Turbulence	12
Hard Landing	3
Go Around	1
Unknown	8
Total	210

TABLE II: INPUT PARAMETERS RELEVANT TO VORTEX ENCOUNTERS

#	*INPUTS*
1	Normal Acceleration
2	Lateral Acceleration
3	Derived Normal Acc. Rate
4	Roll Angle
5	Derived Roll Rate
6	Control Wheel
7	Derived G-Time
8	Derived Roll Time

Data normalization is performed on the inputs and outputs data before training is conducted. One of the normalization techniques used in this research is to scale the inputs to fall within the [-1, 1] range. Normalized vectors derived by using this technique are referred to as *Vn*. Another approach for scaling network inputs is to normalize the inputs and targets to have zero mean and unity standard deviation. Normalized vectors derived by using this technique are referred to as *Vs*.

The appropriateness of these normalization techniques depends greatly on the type of neural network and the data. However, it is noted that squeezing the data range between [-1, 1] or eliminating a high percentage of principal components sometimes reduces the variation between the input vectors.

IV. IDENTIFICATION OF VORTEX ENCOUNTERS USING MLFF NETWORK

In this research, three different model classes are considered: *Class 1* indicating a vortex encounter, *Class 2* pointing to a possible vortex encounter, and *Class 3* representing a non-vortex encounter with probability values of 1.0, 0.5 and 0, respectively. The evaluation of the classification capability is based on two values, which are deduced as follows:

$$\%ClassN = \frac{NumberOf\ RecordsCorrectlyClassifiedInClassN}{Total\ RecordsInClassN} \times 100\% \quad (1)$$

$$\%Overall = \frac{NumberOf\ RecordsCorrectlyClassifiedFromAllClasses}{TotalNumberOf\ Records} \times 100\% \quad (2)$$

where N=1, 2, 3.

A three-layer feedforward neural network (MLFF) is constructed and then trained to classify input-output data into one of the above specified classes. Various factors affecting the output of the MLFF network are investigated including the epoch number, the number of units in the middle layer, the type of activation function, and the learning rate. The simulation is conducted using the Mathworks MATLAB Neural Networks Toolbox [16].

Fig. 3 and 4 show the effect of epoch number on the classification accuracy. Here, it is clear that the two classes based model gives higher accuracy than the 3-class based model. The investigation reveals that the accuracy increases until a certain epoch and then it either degrades or remains the same. These findings can be clarified using Fig. 5, which shows that the highest overall training data accuracy is about 96% at 100,000 epochs and 84% at 150,000 epochs for the 2-class and 3-class models respectively.

The number of neurons in the first layer is also investigated. In fact, the classification accuracy increases for both classes (*Class 1*, *Class 3*) up to 32 neurons then it starts decreasing for *Class 3* of the testing set, hence, 32 neurons are taken to be the optimal number as shown in Fig. 6.

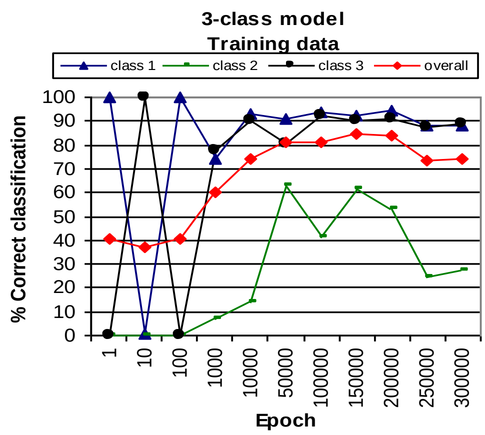

Fig. 3. Effect of epoch on modelling accuracy using MLFF: 3-class model.

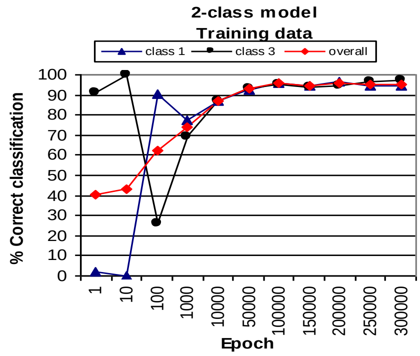

Fig. 4. Effect of epoch on modelling accuracy using MLFF: 2-class model.

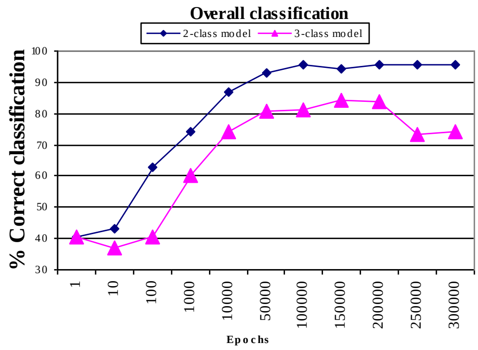

Fig. 5. Training set classification accuracy versus epochs.

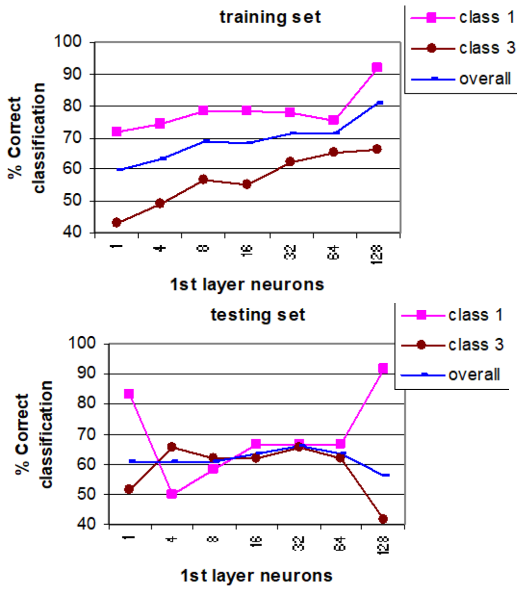

Fig. 6. Effect of number of neurons on classification of the 2-class model.

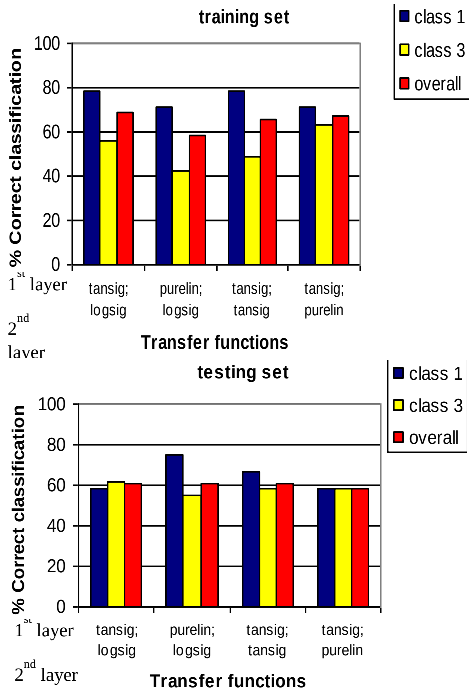

Fig. 7. Effect of activation functions on classification accuracy.

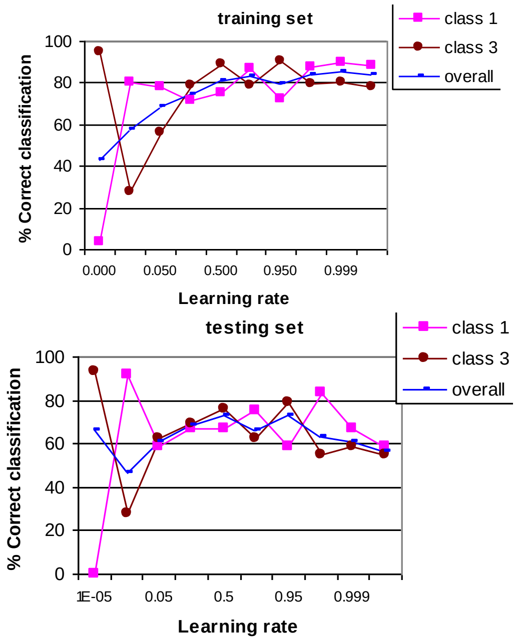

Fig. 8. Effect of learning rate on classification accuracy.

Neural networks depend greatly on the type of activation functions. Therefore, this factor is also investigated and the results of investigations are depicted in Fig. 7. According to these results, the tan-sigmoidal and log-sigmoidal activation functions are the most suitable for the first and second layers, respectively. Another factor which can influence the ANN is the he learning rate. Fig. 8 shows that a value of 0.5 best satisfied both the training and the testing data.

The impact of other factors on the identification accuracy is also studied. This includes a comparison of the various normalization approaches, an investigation on the type of learning algorithm where the testing of two optimization techniques are carried out inlcuding the the gradient-descent (learngd) vs. the gradient descent momentum (learngdm), and studying ways to address generalization i.e. regularization (msereg) vs. stopped training (mse).

V. Investigation of the Optimal MLFF Network

To optimize the outputs of the MLFF, the value of various network parameters such as the number of inputs, the type of inputs, and the number of trials are all investigated. It is found that the optimal neural network performance occurs at various combinations of parameters and not necessarily at the collection of individually optimized parameters.

A. *Various Investigation Trials Using Single Input*

The simulation results shown in the previous sections and hereafter relate to a network having a single input, which is the *roll angle*. From over 300 trials carried out, only 50 and 37 trials for the 2-class and 3-class models, respectively, are selected to represent the results of MLFF neural network investigation. Fig. 9 and Fig.10 depict a summary of the

MLFF networks investigation for the 2-class and the 3-class models, respectively.

With respect to the 2-class model shown in Fig. 9, trials 39 and 44 have the best results for the training data with accuracies of 98.1% and 92.2%, respectively. As for the testing data of the 2-class model, the best results are obtained from trial 23 and 42 with accuracy of 82.9%. However, trial 23 best satisfies both the training and the testing data with an overall average accuracy of 85.6%. The results of investigation of the 3-class model shows, on the other hand, that the only satisfying training data classification results are obtained at trial 25 with an overall training accuracy of 97.4%. The testing data accuracy is very low for all trials of this modeling class.

Tables III and Table IV show the selected parameters and the percentages of correct classification of the best four trials. These results confirm that the MLFF gives very good classification results when applied for the identification of aircraft vortex encounters.

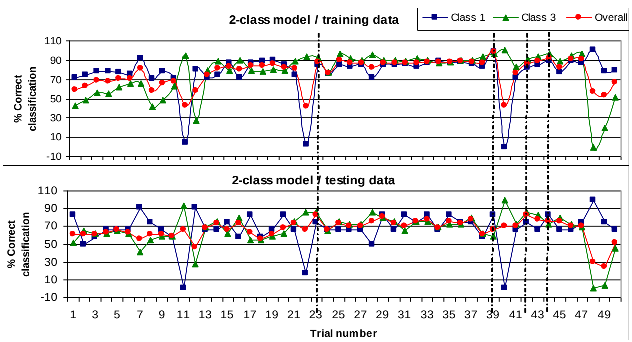

Fig. 9. Summary of the MLFF networks investigation for the 2-class model.

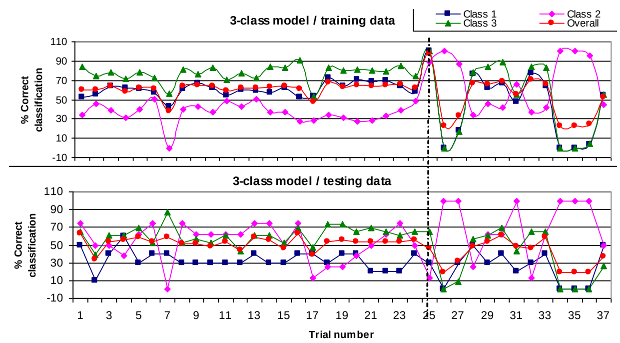

Fig. 10. Summary of the MLFF networks investigation for the 3-class model.

Furthermore, the 2-class model is more appropriate to use than the 3-class model. The MLFF technique is further investigated by using a multi-input (parameter) neural network, which includes three identification parameters as shown in the following section.

B. Multi-parameter (Input) MLFF Network

The training and testing is now conducted using three input parameters namely: the *roll angle*, the *normal acceleration*, and the *lateral acceleration*. This network is investigated by using the data corresponding to all five trials shown in Table III. Seven combinations of the three identification parameters are considered. The simulation results are depicted in Fig. 11.

These results show that the accuracy of 1-paramter model is the highest when using the *roll angle* followed by the results based on the *lateral acceleration*. This is in agreement with the fact that most of the vortex encounters are parallel since they happen in the vicinity of airports, hence the *roll angle* is more affected than the *normal acceleration*. As for the *lateral acceleration*, the results show consistent fluctuation pattern in the majority of FDR vortex records.

Fig. 10 also indicates that training data is less affected by the selection of parameters since the network is able to adjust its weights and biases to achieve high accuracies by comparison with the desired targets. The testing data accuracy, on the other hand, shows greater dependence on the selection of parameters. Using the *roll angle* and any of the other two parameters (points 4 and 5 along the x-axis) gave the best results. The relative low performance using all three parameters (point 7 compared to point 4 and 5) happened because sometimes the effect of increasing the number of parameters causes the network to track the training data rigidly and increase its accuracy while greatly decreasing the testing data accuracy.

TABLE III: SELECTED PARAMETERS OF THE BEST TRIALS OF THE MLFF NETWORK INVESTIGATION

Parameters	***2-Class model***				***3-Class model***
	Trial 23	**Trial 39**	**Trial 42**	**Trial 44**	**Trial 25**
Normalization	*Vs*	*Vs*	*Vs*	*Vs*	*Vs*
Layer 1 neurons	8	32	32	32	32
Layer 2 neurons	1	1	1	1	1
Learning rate	0.5	NA	NA	NA	NA
Layer1transfer function	tansig	tansig	tansig	tansig	tansig
Layer transfer function	logsig	logsig	logsig	logsig	logsig
Learning function	learngd m	learngd m	learngd m	learngd m	learngd m
Performance function	mse	mse	msereg	msereg	mse
Epoch	4000	1673	67	1859	2182
Goal	0.1	0	0.1	0.1	0
Momentum coefficient	NA	NA	NA	NA	NA
Performance ratio γ	NA	NA	1	0.85	NA

TABLE IV: RESULTS OF THE BEST TRIALS OF THE MLFF NETWORK

Results	***2-Class model***				***3-Class model***
	Tria l 23	**Trial 39**	**Trial 42**	**Trial 44**	**Trial 25**
Training time [s]	63.6 6	135.3 9	6.48	156.8 1	160.11
%Class1 accuracy/training	85.1	98.9	81.7	89.1	100
%Class1 accuracy/testing	75	83.3	75	83.3	30
% Class 2 accuracy/training	NA	NA	NA	NA	88.6
% Class 2 accuracy/testing	NA	NA	NA	NA	12.5
% Class 3 accuracy/training	92.5	97.0	91.0	96.2	100
% Class 3 accuracy/testing	86.2	58.6	86.2	72.4	65.2
% Overall accuracy/training	88.3	98.1	85.7	92.2	97.4
% Overall accuracy/testing	82.9	65.8	82.9	75.6	46.3
Overall average accuracy	85.6	81.9	84.3	83.9	71.9

The combination of the *roll angle* and the *normal acceleration* while using the parameters of trial 39 in Table

III gives the highest accuracy of about 88%. This finding confirms that *roll angle* and *normal acceleration* are the primary parameters that complement each other and are the most relevant inputs to the challenge of vortex encounters. Hence, any vortex encounter identification technique should be based on at least these two input parameters.

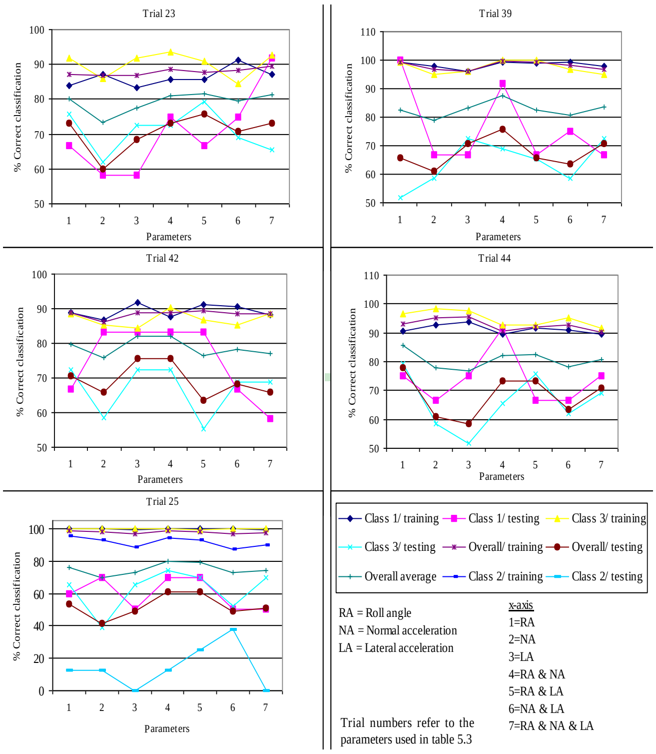

Fig. 11. Results of the multi-parameter neural network.

VI. Comparing Pure FFNN to Pure FL and ANFIS

In earlier research work, the authors conducted investigations of vortex encounter identification using other types of machine learning. Pure Fuzzy Logic (FL) [17] and ANFIS [18] type of classifiers were used in setting up models that can capture data imprecision and complexities of the problem.

In [6], the authors demonstrated that FL and fuzzy linguistic variables [19] are powerful tools to model certain FDR inputs that could not be easily represented by crisp sets. Initially the authors started with a large number of parameters affecting vortex encounters, then, this number was reduced to only seven critical inputs. These paramters are the same ones used in this research except for the *Lateral Acceleration*. These parameters were used in the fuzzy rule base and fuzzy inference. The modeling of these inputs by FL allowed to capture any imprecision and addressed ay inherent complexities in the system. The FL-based vortex encounters identifier achieved an average classification rate of 83.7%. The authors discovered that the tuning of the fuzzy membership functions (MFs) represented a challenge. It could only be achieved manually through an ad hoc tuning procedure that was not based on historical data and the system performance.

In [7], the authors proposed a hybrid Adaptive Neuro-Fuzzy Inference System (ANFIS) [18], [20], [21] to automatically tune the seven parameters of the fuzzy membership functions in the classification of aircraft vortex encounters (the same parameters used in this research except for the *Lateral Acceleration*). While the system dynamics are still captured through a set of fuzzy rules that are created based on data from pilot reports and flight recorders (FDR's), the tuning of the fuzzy membership functions was conducted thorough the use of artificial neural networks. The neuro-fuzzy system is then trained based on historical data while the parameters of the fuzzy membership functions are automatically tuned to obtain better identification results. The authors investigated various neuro-fuzzy models having different sets of parameters and factors, and the achieved average identification accuracy was around 84.2%.

The proposed pure MLFF approach in this paper is based on the same seven salient inputs in addition to the *Lateral Acceleration* parameter. The achieved average classification resulted are slightly higher. However, these results confirm the assumption that the 7+1 critical input variables (those depicted in Table II) are the ones to consider in an effective aircraft vortex encounter identification system.

VII. Conclusions

The main source of data in the study of aircraft vortex encounters is mainly based on subjective pilot reports highlighting any potential threats as well as flight data recorders (FDRs) which are data reflecting mainly the aircraft operation and performance. On one hand, there are an overwelmaingly large number of variables involved in these reports and FDR records. The investigation in this research, which was conducted using data obtained from an airline's FDRs, led to a focus on a reduced number of parameters found to be hihgly relevant to any vortex encounter's study. Using these critical parameters, such as an aircraft roll angle, its normal acceleration and its lateral acceleration as inputs in a classifier such as the proposed feedforward neural networks, led to the achievement of a high identification rate of about 88%. In fact, these results confirmed the outcomes of investigation obtained by the authors when using other types of soft-computing approaches also focused on almost the same type of critical inputs. On the other hand, researchers worldwide [22], [23] focusing on the study of vortex encounters by simulating their dynamics in order to define vortex encounter hazards, are urgently seeking answers to redefine safety measures, such as separation schemes. The expectation is to allow air traffic to increase airport capacities by revising the existing schemes while not compromising safety. The work presented in this paper can help these researchers create simplified models of the inherent complexities of vortex encounters while only focusing on the most important parameters that greatly impact them. The future research work of the authors will investigate this research problem while attempting to model and understand the vortex behavior during decay and their impact on a trailing aircraft.

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