Aircraft Fault Diagnosis and Decision System based on Improved Artificial Neural Networks

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Abstract— **The goal of this work is to build an aircraft fault diagnosis and decision system, which uses data-driven methods to automatically detect and isolate faults in the aircraft, while keeping its reliability and safety. As a fundamental specification, this fault diagnosis system should not be a black box, the condition monitoring and the results of comprehensive diagnosis shall be illuminated to engineering consulting services, and it can help engineers to accumulate the knowledge for re-engineering purposes (including diagnosis operational rules) and improve the design of new aircraft. In comparison with some methods, Artificial Neural Networks (ANN) has been shown to be more advantageous and is currently used in fault diagnosis system. For example, it hasn't any problem of conflict of new rules, which is a big problem in Expert System while adding new fault. In this work, ANN is improved. Its speed of learning and the iteration times can be self-corrected or mutated. Moreover, neural network can be combined with other optimization methods, like genetic methods, to achieve a better performance. Furthermore, according to the different types of sensors, certain sub-networks are built to assist the principal network or replace it in some anomaly condition. A decision system treats the results of all the networks and comes to a conclusion, which will be sent to pilot, airport command center (ACC), or fault tolerant system.**

I. INTRODUCTION

With the development of aerotechnics, aircraft's mechanical system and electronic system become more and more complex [1]. Such a fact requires the increase of sub-component systems monitoring and maintenance. Traditionally, the diagnosis and the troubleshooting are performed by expertise, by observing how the system works (generally through unit tests on each component of the complex system) [2]. But for aircraft, this "planned maintenance" becomes more and more impossible, in terms of complexity and economical cost. Consequently, aircraft needs to embed intelligent systems dedicated to their self-diagnosis [3].

In an aircraft system, inner sensors are important to fault diagnosis. Their information (temperature (T), pressure (P), debit (D), system variables (S) - for example to indicate the position of the valve, etc.) are defined as the inputs of the diagnostic system [4], while the outputs (preliminary results) are delivered to the decision system which can come to a conclusion (see Fig.1). Their role is to show the final result of diagnosis to the pilot and to ACC, and to propose some suggestions or decisions like "emergency landing", "return to base", or "continue the mission" if the fault tolerant system is able to resolve the problem(s). In accordance with the results of the decision system, pilots or ACC can decide the next action.

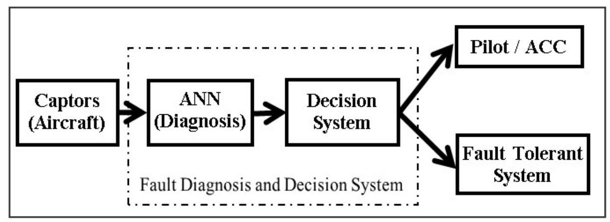

Fig. 1. Schema of Overall Diagnosis System

Actually, many aircrafts generally use an artificial expert system mainly based on knowledge base and inference engine [5] at the present. It is a practical system, which only needs human experts to stock their knowledge and the rules of finding faults in a database. Then, logic rules are built to link the sensor's information to the diagnosis. But such an approach has to face an intractable problem: the conflict between rules, especially when the system has to add a new fault and its rules into the knowledge database [6]. Because of these new failures, the resulting system becomes too difficult for the inference engine to make a convincing diagnosis result. But ANN doesn't have these problems [7], as they only require a relearning step to update the system [8].

In this work, ANN is used to build the diagnostic system and it is improved in some areas to avoid the over-fitting and augment correct rate of the system. For example, the speed of learning can be automatically amended to avoid local optimization, and the number of iteration can also be automatically increased with an agreement of cross validation; apart from this, a genetic method is also used to help ANN to find the global optimal value in the whole feature space.In real condition of flight missions, especially for aircraft fighters, there is a risk to lose some sensors information, but the system of aircraft (for example the engine) which is monitored by fault diagnosis

*This work was supported by Institute for Intelligent Systems and Robotics (ISIR) - University Pierre and Marie Curie (UPMC), Dassault Aviation, DGCIS, Conseil régional d'Ile de France, Conseils généraux 77 et 78.

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system actually continues to work. In order to face this condition, the whole fault diagnosis and decision system contains six different neural networks according to the different arrangements of sensors. Even though one group of sensors are lost, the fault diagnosis system can be updated immediately and then continue to work.

The rest of this paper is organized as follows. The organization of six neural networks are depicted in Section II. The robustness of the system, when some sensors are lost, is also addressed. Section III demonstrates the improvement of the approach in comparison with classical Net - Back Propagation Neural Network; Section IV shows a test of the fault diagnosis system on the anti-icing system of an aircraft X from Dassault Aviation, and demonstrates how the decision system works. Finally, the last section is devoted to conclusions and future work.

II. DIAGNOSTIC SYSTEM WITH SIX NEURAL NETWORKS ACCORDING TO THE DIFFERENT ARRANGEMENT OF SENSORS

A. Selecting a Template (Heading 2)

In this paper, the inputs of the fault diagnosis system are divided into four groups, according to the four types of inner sensors of anti-icing system in the aircraft X: T (temperature), P (pressure), D (debit), S (system variables). As shown in Fig. 2, for each group of sensors, a neural network is built to diagnose the faults (these are called NET 1-4). In addition to this, two additional neural networks (NET 5 and NET 6), are also exploited, with all sensors being linked to their inputs.

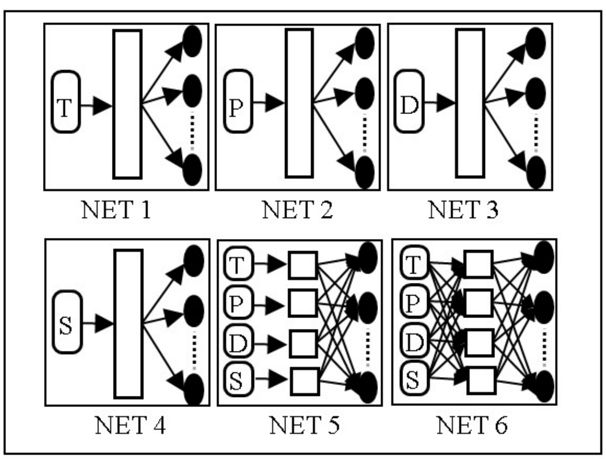

Fig. 2. Six neural networks according to different arrangements of sensors

There are two reasons to build six different nets:

- Data Mining: Generally, a very large numbers of sensors are used on an aircraft. So, it is necessary to know exactly which sensors or which classes of sensors are more sensitive to faults [9]. In other words, aim at each fault, the system will find which type of sensors are more important to diagnose it. This information is very useful for engineers and maintenance personnel to analysis faults and improve the design of new aircraft. Moreover, if the system has to deal with the information originating from all the sensors, then the machine-learning task would become extremely laborious. Hence, as shown in the Fig. 2the relevance of each type of sensors is evaluated by NET 1-4. Note that NET 5 is a partial connection neural network, while NET 6 is fully connected. Indeed, the results of both nets will then be compared to decide whether NET 5 is more effective than NET 6.
- In some real condition of flight mission, there is a risk to lose some sensors or sensors' information during the mission. Obviously, this is a catastrophe for the diagnosis system, it will lead to an incorrect response if some inputs are muted. In this case, there is no time to perform the relearning with the existing sensors. So, we propose in this paper to build a vote system with the 4 sub nets NET 1-4. Even if one group of sensors is lost, the system is able to continue the work

In order to face the different situations of combat aircraft X during its missions, according to different situations of sensors, the decision system has different ways to treat the results of networks and draw a conclusion. In view of possibility of losing sensors or sensors' information, any method of compression of data, as Principal component analysis, hasn't been used in this paper. If the initial dimension of data is changed, the rules of compression (covariance matrix) cannot be used any more [10].

III. FAULT DIAGNOSIS SYSTEM WITH IMPROVED ARTIFICIAL NEURAL NETWORK

In order to improve performances and accuracy of the fault diagnosis system, ANN is improved in three areas in this paper.

A. Self-correcting and mutation of speed of learning

In this work, an improved method of the Gradient descent with momentum back propagation is used to train the weights (W) and thresholds (B) [11].

$$W(t) = W(t-1) + \lambda \Delta W(t) + \alpha(W(t-1) - W(t-2)) \quad (1)$$

$$B(t) = B(t-1) + \lambda \Delta B(t) + \alpha(B(t-1) - B(t-2)) \quad (2)$$

At first, in order to do a full search of minimum of error (E) - global optimization, the speed of learning (λ) is self-corrected by three rules during the process of learning. In other words, the speed of learning is not fixed at any time. It is a dynamic parameter which can be auto-corrected, so as to improve the speed of learning in different cases.

As shown in Fig.3, if E becomes smaller during successive iterations (Case 1 in Fig.3 and Fig.4), then the gradient of E is descending. So λ can be multiplied with a factor β which is greater than 1 (for example $\beta = 1.2$), in order to accelerate the learning. On the contrary, if E becomes bigger (Case 2), it means that the learning step is too large to stride over the

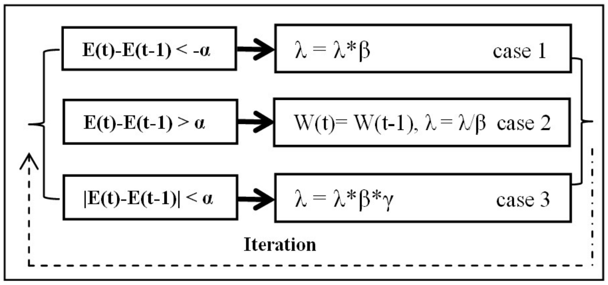

Fig. 3. Schema of logic plan of self-correcting and mutation of the speed of learning; α : performance goal; β : a positive multiplicator > 1; γ : a great positive multiplicator for mutation; three cases to choose during each time of iteration to auto-correct λ .

local minimum (see ① in the Fig.4). So, the system needs reloading the weights and thresholds of the last iteration (see ② in Fig.4) and lowers λ with the factor β $(\lambda = \lambda/\beta)$ to continue search the local minimum (see ③ in Fig.4). After an iteration period, the difference of E(t) and the E(t-1) will be close to zero: it means that one local minimum of E is found. In order to 'jump' out of this local and continue to research the true global minimum of E, λ must be 'mutated', through a multiplication by a great positive number γ and 'jump' to other local (Case 3). Finally, after the whole iterations, the system has found certain local minimums of E. The weights and thresholds, which corresponding to the smallest quadratic error, are selected as the solution.

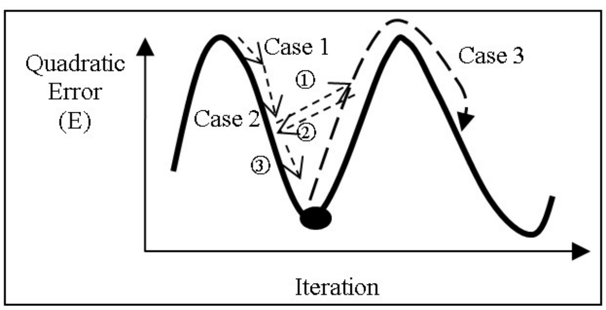

Fig. 4. Self-correcting and mutation of Speed of learning

B. Self-correcting of iteration times and Cross validation

In general, owe learning and over learning are two common problems of machine learning. The second point of improvement of ANN in this paper is that the iteration times can be self-corrected to avoid the lack of learning and Cross Validation (CV) [12] is used to avoid the over-fitting. At first, as the classical theory of CV, the data of learning are divided into n parts, one part for the test and the others parts for the training. Then, an initial iteration number is proposed. If the quadratic error (E) of training and of testing is descending together until the initial iteration times, the iteration times can be auto-augmented to continue the iteration until finding the final minimum of E of test. As show in Fig.5, the original setting of iteration times is 1000, but the quadratic error (E) of training and testing are still descending at the 1000th iteration (at Point A), so the system increases the number of iteration in this case; but if the testing error raises, over fitting is present. So the iteration according the minimum of E of testing is held, and the weights and thresholds according this point (B) are tare taken as the best result of the learning.

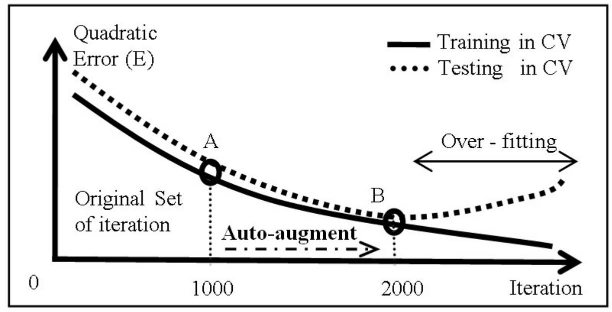

Fig. 5. Schema of CV and Self-correcting of times of iteration

C. Genetic Algorithm

In order to perform the global optimization of E, the 'jump' of is sometimes not sufficient. Because it is a large-scale search, many local minimums are found in a local space not covering all the feature space. For purpose of solving this problem, genetic algorithm (GA) can be used to reach another part of the feature space so as to help ANN to find the global minimum [13]. In fact, neural network is sensitive to the initial values of weights and thresholds. So GA in this paper is used to find the best initial values of these parameters for ANN. These parameters constitute a chromosome as show in the Fig.6, and the quadratic of each individual is considered as fitness. After a certain generations, the best individual is chosen as the best initial values of the weights and thresholds.

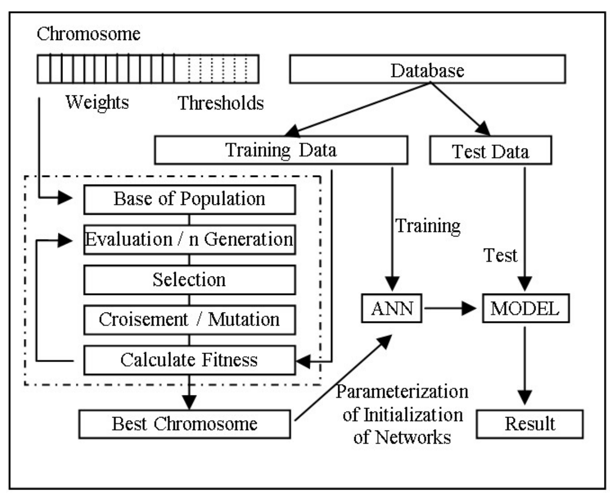

Fig. 6. Schema of Genetic Algorithm in the training of ANN

IV. RESULTS OF EXPERIMENTS AND DECISION SYSTEM

A. Experiment Drawing

In this work, the ANN diagnostic system is built for the anti-icing system of an aircraft X from Dassault Aviation. This anti-icing system consists of three engines and a complex tubes system. which uses the hot air from engines to warm wings and fuselage. As Fig.7 shown, it mainly consists of engine bleed systems, bleed air system and valves system. The database of the anti-icing system consists of 120000 samples (120000 records, with 1 sample per second) of 21 sensors (6T, 4P, 3D, and 8S). In others words, the size of the database is 120000 multiplying by 21. Among these data, 75% of data are chosen randomly for machine learning and the remaining is used to test the system. It costs 36.8 minuets to complete the machine learning with a computer - Intel Pentium Dual-Core T4400 and 2G memory.

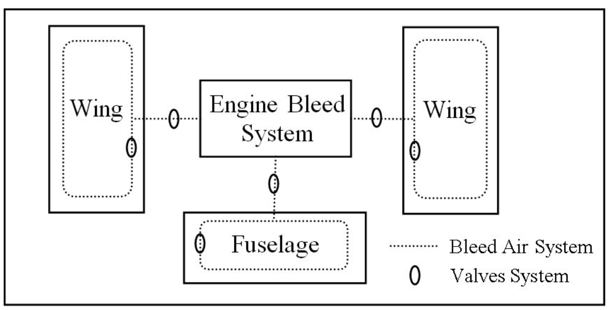

Fig. 7. Schema of Anti-icing System's Structure

In fact, there are 13 types of faults* about this anti-icing system. Among these faults, there are two terrible faults that the aircraft needs to make an emergency loading, and the others can be temporarily resolved by fault tolerant system. Therefore, in this experiment, all the faults are divided into 3 types of faults - two terrible faults (Fault 1 and Fault 2) and one class of others conditions (Fault X). Including the normal situation, the system is built to diagnose four different conditions of the anti-icing system. This fault diagnosis system is not only useful for maintenance (off-line), but also important to show the conditions of aircraft to pilot and ACC (on-line). (*Because of confidentiality, the detail of the faults can not be presented in the paper).

B. Cross Validation and 'jump' of λ

Fig.8 shows an example of the cross validation and 'jump' of λ within NET-1. It demonstrates 4 'jump' of λ during the machine learning: two times nearby the 100th iteration, one time close to 300th iteration and the last around 620th iteration. It means that the system does four global researches during 1000 iteration. Obviously, the best weights and thresholds are achieved from the 389th iteration, they are considered as the best result of this learning.

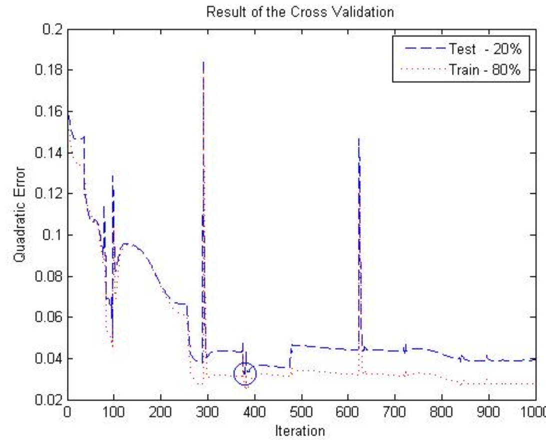

Fig. 8. Result of CV and 'jump' of λ in the real test

C. Results of the tests of six nets

In order to get results more scientific and convincing, all the results in Table I and Table II are tested and verified for 100 times. As shown in Fig.9, the database is randomly divided into 2 parties for 100 times, one part for machine learning and another part for test; 100 different models are built by the 100 different datasets of machine learning. The mean of the 100 different test results are show in the tables. Indeed, among these 100 models, the best model is chosen to use for the aircraft.

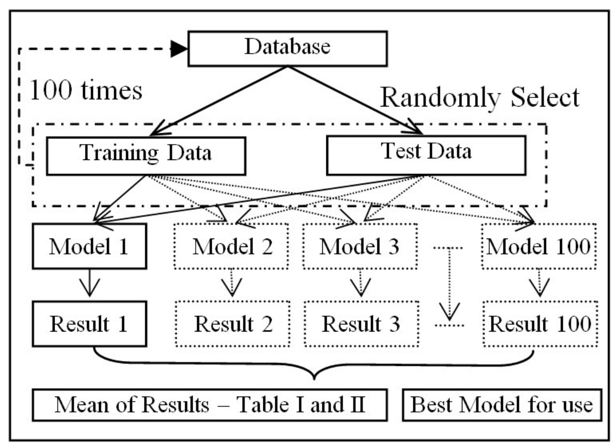

Fig. 9. Schema of the Test

The confusion matrix in Table I and Table II are calculated by the outputs of the system and the targets of the test. It is clearly that the results of improved ANN (in Table II) are much better than the results with classical ANN without the aforementioned improvements (in Table I). The score of Net (6) in Table I is only 69.92%, but in Table II is 93.28%. It is very clearly that these improvements included genetic algorithm can effectively improve noise immunity and correct rate of system.

TABLE I
RESULT OF STANDARD ANN WITHOUT IMPROVEMENTS (NET 6); O: OUTPUTS OF SYSTEM; T: TARGETS OF OUTPUT

Net(6)T\O	Normal	Fault 1	Fault 2	Fault X
Normal	75.24%	8.57%	6.09%	10.10%
Fault 1	4.12%	83.74%	7.03%	5.11%
Fault 2	6.13%	21.04%	68.79%	4.04%
Fault 3	12.05%	8.93%	27.13%	51.89%

As show in the Table II, the test results of six different networks reveal five important points:

- The temperature sensors (see Net(1)) are more important to diagnose the faults than others sensors (see Net(2), Net(3), Net(4)). Compared with the results of Net (6), Net(1) is less good. But if any others sensors are mute or broken during flight mission - Net (6) can't work anymore, Net (1) is able to replace it and keep a good status of the fault diagnosis systems.

- Net (1) can distinguish two groups of conditions without any mistake: one group consists of Normal and Fault1, another group consists of Fault 2 and Fault X. Therefore, if the diagnosis results of Net (1) show that there is Fault 2 or Fault X, it means that there is an indeed fault; and there is quite impossible of Normal Condition or Fault 1. So does Net (6).

- The results of Net (2) are less good than Net (1), but it is much better than Net (3) and Net (4). It means that Net (2) can also replace Net (5) (6) or Net (1) in some dangerous and necessary conditions. According to the results, Net (3) and Net (4) are not proposed to work independently.

- Although the results of Net(3) are less good than Net(1), it is very useful to diagnose the Fault X. If there is a true Fault X in the aircraft, the diagnosis result of Net(3) is that there are 85.92% possibilities of Fault X and 14.08% possibilities of Fault 1, not any other possibility. Combined with Net(1), the system of Net (3) can improve the detection ratio of Fault 2 and Fault X. Therefore, a decision tree can be built by Net(1) and Net(3) as Fig.10 left. Indeed, so does Net(6), which can be combined with Net(3) and make a same decision tree.

- Among these results, Net (5) has the best ratio correct detection of Fault X, through its other results are less good than Net(6). Thus, the diagnosis results of Net(5) can assist Net(6).

According to the confusion matrixes, some rules of decision system can be concluded. For example: if the diagnosis result of Net(6) is Fault X, then it is 100% Fault X. Based on these rules, a voting system can be built, as shown in Fig.10 right. At last, if the decision system draws a conclusion as

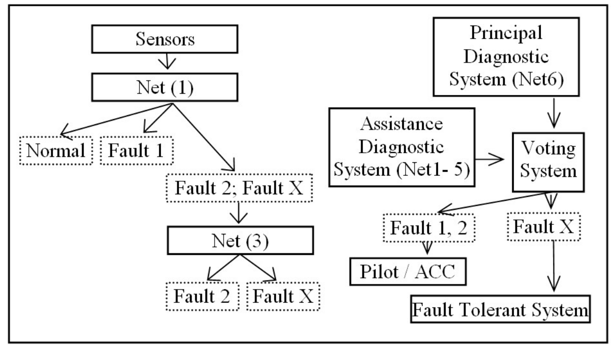

Fig. 10. Example of Decision Tree and Voting System

TABLE II
CONFUSION MATRIX OF THE RESULTS OF THE TESTES OF SIX NETS WITH IMPROVED ANN; O: OUTPUTS OF SYSTEM; T: TARGETS OF OUTPUT

Net(1)T\O	Normal	Fault 1	Fault 2	Fault X
Normal	91.96%	8.04%	0.00%	0.00%
Fault 1	2.65%	97.35%	0.00%	0.00%
Fault 2	0.00%	0.00%	94.37%	5.63%
Fault 3	0.00%	0.00%	17.39%	82.61%
Net(2)T\O	**Normal**	**Fault 1**	**Fault 2**	**Fault X**
Normal	90.95%	8.04%	1.01%	0.00%
Fault 1	4.91%	95.09%	0.00%	0.00%
Fault 2	4.23%	0.00%	94.37%	1.41%
Fault 3	0.00%	0.00%	47.83%	52.17%
Net(3)T\O	**Normal**	**Fault 1**	**Fault 2**	**Fault X**
Normal	82.41%	2.01%	13.07%	2.51%
Fault 1	0.00%	56.52%	0.00%	43.48%
Fault 2	17.18%	0.00%	82.21%	0.61%
Fault 3	0.00%	14.08%	0.00%	85.92%
Net(4)T\O	**Normal**	**Fault 1**	**Fault 2**	**Fault X**
Normal	85.93%	12.56%	1.51%	0.00%
Fault 1	3.07%	96.32%	0.61%	0.00%
Fault 2	59.15%	0.00%	40.85%	0.00%
Fault 3	34.78%	0.00%	4.35%	60.87%
Net(5)T\O	**Normal**	**Fault 1**	**Fault 2**	**Fault X**
Normal	90.95%	9.05%	0.00%	0.00%
Fault 1	5.52%	93.87%	0.61%	0.00%
Fault 2	0.00%	0.00%	86.96%	13.04%
Fault 3	0.00%	0.00%	5.63%	94.37%
Net(6)T\O	**Normal**	**Fault 1**	**Fault 2**	**Fault X**
Normal	92.96%	7.04%	0.00%	0.00%
Fault 1	2.45%	97.55%	0.00%	0.00%
Fault 2	0.00%	0.00%	100.00%	0.00%
Fault 3	0.00%	0.00%	17.39%	82.61%

Fault 1 or 2, it will give an alarm to pilot and ACC, show this terrible condition to them; and if it is considered as Fault X, Fault Tolerant System will be started to resolve the fault(s).

V. CONCLUSIONS

In this paper, a fault diagnosis and decision system of aircraft is built by ANN. Some methods as auto-correcting / mutation of the speed of learning and genetic algorithm are used to help ANN to find the true global minimum of E (global optimization) during machine learning. In addition to this, in order to avoid the over fitting or lack of training, Cross Validation and Self-correcting of iteration times are active during all the iterations. In the experiment, 21 sensors are used to build a fault diagnosis system of anti-icing system of aircraft X. On basis of the arrangement of different types of sensors, six networks are designed. According to the diagnosis results of these networks, a decision system is projected to combine all the results and make a final conclusion of diagnosis. Furthermore, if fighting aircrafts lose some sensors or sensors' information, the assistant fault diagnosis system can replace the principal system in order to ensure the normal operation of fault diagnosis. Some words about future work, not only for the anti-icing system, a global fault diagnosis and decision system of aircraft X is being scheduled. It consists of all the subsystem of fault diagnosis, such as engine system, military system, etc. Moreover, this fault diagnosis system will be practiced in others transport systems, for example train and ship.

ACKNOWLEDGMENT

All the data are supplied by Project MODIPRO "MOdelisation, DIagnosis and PROnostic".
Partners: DASSAULT AVIATION, ISIR/UPMC, IT4 CONTROL, INRIA, SupElec, SNECMA, BAYESIA, KBS.

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