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A Connectionist Approach to Airliner Safety

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***Abstract*— The present paper introduces the system SINCO-Flightsim, an intelligent hybrid symbolic connectionist approach for the treatment of emergency situations on commercial airliners, currently available as a computer simulation. The system's main focus is on human failure, which accounts for a major part of accidents and incidents in airline traffic. The underlying architecture, using the biologically more plausible learning algorithm GeneRec and contrasting it to learning via back-propagation is presented. System modules are described as well as the learned data sets. In its first version, the system provides a series of typical sensors and means of interaction for treating emergency situations successfully. The respective results are outlined in this paper. We trust that the approach has the potential to contribute to airliner safety as it takes major stress factors off the pilots' shoulders and helps treating emergency situations in a more objective manner.**

I. Introduction

On DECEMBER 20, 1995, American Airlines Flight 965, from Miami to Cali in Colombia had 155 passengers and 8 crew members on board. On the approach to Cali after an uneventful flight, suddenly the navigation system of the Boeing 757 presented a failure causing it to "forget" a way point, which had to be reprogrammed. The reprogramming was done in a hurry and it did not become clear that actually a wrong course was provided, moving the plane in the direction of Bogotá, whereas it should have gone via Rozo. The mistake was discovered, but as the pilots tried to solve the condition, they were not aware they had put the plane on a crash course, at 3000 meters, with a mountain of that height. Shortly before the impact, the Ground Proximity Warning System sounded. Meanwhile, pilot reaction was immediate (moving up the nose of the plane) but not adequate (as the speed brakes did not allow going up sufficiently). The plane crashed into the top of the mountain. Only 4 passengers survived. More details may be found in Aircraft Owners and Pilot Association [1].

On September 29, 2006, a Boeing 737-800 of the Brazilian company GOL was on its way from Manaus (Northern Brazil) to Brasilia (Central Brazil) with 154 passengers on board. It disappeared from radars 4.48pm that day. The plane had crashed with the tip of its wings with an Embraer Legacy jet, which was about to be delivered to a customer. The Legacy, which was at a wrong altitude, could execute an emergency landing and there were no injuries whereas the pilot of the GOL jet lost control. The plane flew in circles to the ground, causing gravitational forces much stronger than the planes project, which caused it to rip open yet airborne. On September 30, it was found destroyed in dense Amazon forest, inside a radius of 20 kilometers, at the Serra do Cachimbo. Nobody survived. For more information, refer to [20].

These and many other crashes have appeared instantly in the international press and shocked the world. And despite all efforts of the industry, every new year brings about new accidents, with one large focus on human error.

The present approach was developed to treat situations similar to these, preventing losses of human lives and of high amounts of investment. It is currently available as a simulation. With support of the industry, future versions could be implemented on real airliners.

II. Motivation

As said above, accidents are continuously happening. Analyzing accident databases the following main characteristics may be found [4][8][15]:

- System malfunction;
- Need for rapid (to very rapid) pilot response;
- Surprise/shock;
- High physical and emotional stress on the pilot;
- Result: Pilot is prone to take the wrong decision.

Clearly, there are accidents which cannot be avoided after an initial fatal setting. When KLM flight 4805 hit Pan Am flight 1736 on March, 27, 1977 in Tenerife [3], there was no way anymore to save the situation. In this case, anticipation is the only thing that could be done.

In many other cases, however, the emergency situation can be treated. And this treatment is the main focus of the approach we propose.

In the mentioned situations, an automated approach may react better and much more accurately than a human pilot, which is due to the fact that it is not subject to: Emotional stress, physical stress (the way it is experienced by the pilot), narrow limitations on parallel processing, arrow limitations on action speed, corporal needs (causing for instance fatigue) or negligence after training.

III. Related Work

Work related to airliner safety may be classified in approaches, which treat single aspects and systems, integrating a family of characteristics.

Single aspect approaches, by their very nature are merely an auxiliary means of detecting dangers. Though useful as a

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“standalone” object, in conjunction with a series of others they cause stress and an overload situation to the pilot (colloquially called a “horn concert” as by Stünkel [19]), which in most cases may result in sheer panic and loss of focus as shown by the Cali accident described above. As Stünkel also mentions, pilots are constantly trained to support multiple stimuli, but the conclusion that all this has a very narrow limit, is fairly trivial. Or, as aptly stressed by Hamilton [5]: “Our brains are set up to do two things, but not three (…)”. Thus, such systems are almost completely useless when an emergency with several focal points and necessity of in-depth analysis occurs and a solution seems a case of rather being lucky than interpreting things correctly. This is especially true in the dynamic environment of a modern jet airplane, where seconds of distraction can mean hundreds of deaths (due to jet speed and the need of the pilots to plan ahead).

Some examples of single aspect approaches (see also [2]):

- Landing gear warning systems, which advise the pilot that the landing gear has to be extended or retracted, de-pending on the altitude;
- Traffic Alert and Collision Avoidance Systems (TCAS), which sound warning signals before an imminent mid-air crash [14]. The development has been motivated by the crash of a TWA Super Constellation and a United DC-7 [16], just as many other improvements were only executed after huge accidents and massive negative press.
- Ground Proximity Warning Systems (GPWS), which alert the pilot of a possible collision with ground;
- Inertial Navigation System (INS), which is a navigational aid that determines position, orientation and velocity through motion and rotation sensors [7];
- Stall warning systems, which sound a few seconds before the real stall happens;
- Weather radars with their known problems. The detect precipitation, which is related, but which is not at all the exclusive factor of turbulence. Weather radars have only short range on aircrafts and are prone to suffering a lot of distortion from external factors [9];
- System failure alerts (standard to some extent in any airplane).

As useful as all of these systems may be on its own de-spite their common failures and malfunctions, the main issue remains that the pilot himself is the main and over-charged distribution node.

There is already a tendency of integrating systems, which, however, has not been fully achieved yet. This means that there is no specific approach for emergency situations, but rather grouped in families of characteristics.

Firstly, it should be mentioned that progress in modern jets’ cockpits has transformed the round “clock-like” instruments of more ancient aircraft into a series of computer screens, where information is displayed in a better, but yet mostly parallel and “indigested” manner (see [10][11][19]):

- Primary flight display (PFD), showing heading, height, velocity and glide path for landings;
- Navigation display (ND), which keeps track of the aircraft’s navigation with several ground elements dis-played as well as the weather radar;
- Control and display units (CDUs), which are little screens with keyboard for the interaction with the Flight Management Computer.

Finally, there are some systems being developed by NASA [12][13] which shall integrate some information and make the interpretation faster and more intelligent. As mentioned, they are grouped by characteristics [18]:

- Integrated Intelligent Flight Deck (IIFD): optimized access to controls and better establishment of awareness on aircraft condition. Possibility of detection of internal and external hazards;
- Integrated Resilient Aircraft Control (IRAC): objective is the maintenance of maneuverability in adverse conditions (structural damage, control surface failure, icing etc.), relying on multidisciplinary design tools.
- Integrated Vehicle Health Management Project (IVHM) has its focus on the treatment of adverse conditions related to the hardware and software situation of the aircraft. One of the main outputs is the remaining useful life of equipment with the possibility of posterior datamining.

IV. SYSTEM OVERVIEW

As said, the system SINCO-Flightsim is a simulation. It uses three main elements:

First simulation element: A simulated environment of width, height and depth of 300 spaces, which implement a series of real-life parameters such as: Terrain and weather (water, rocks, earth, sand, lawn, trees, ice, snow, hailstone, rain, cloud, fog, clear air, building, runway, animal/human being, airplane), intensity of the element to implement (if applicable, i.e., with weather and vegetation), humidity in percent, temperature in degrees Celsius, wind angles and speed in km/h, current pressure in kPa (kilopascal), light intensity in kLx (kilolux) and V.O.R. (very high frequency omnidirectional range) signal intensity and corresponding radio station.

Second simulation element: A simulated airplane (oriented at the Cessna® 172 Seahawk®), which uses typical aircraft sensors as well as additionally implemented ones for the treatment of emergency situations.

Implemented sensors are the following:

- Airspeed Indicator providing the airplane’s speed over ground in knots;
- Vertical Speed Indicator indicating climb or descend in feet;
- Bank Indicator for the coordination of rudder and aileron;
- Heading Indicator showing the heading of the air-plane in relation to the compass;
- Tachometer to show motor rotations per minute;
- Altimeter providing the altitude in feet;

• Attitude Indicator showing the angle of attack and turn angles of the aircraft;
• V.O.R. Indicator providing proximity to a V.O.R. signal;
• Fuel Indicator showing fuel level;
• Temperature Sensor analyzing outside air temperature;
• Current Time as by the clock;
• Positions of flaps, throttle, landing lights, rudder and trim wheel are also mapped.

Additionally implemented sensors are:
• Damage at wings, rudder, elevator, ailerons, landing gear, flaps, windows, doors, fuselage, motor, trim tabs;
• Water below (pilot informs this value);
• Weather information in front of the plane and at the sides;
• Instrument Landing System sensor ("out", "middle", "in");
• Anti-collision sensor.

The following actuators are provided:
• Accelerator, which may accelerate or slow down the propeller;
• Ailerons, moving surface on the wings used to fly curves (together with the rudder);
• Rudder, vertical moving surface at the tail to fly curves (together with aileron);
• Elevator, horizontal moving surfaces at the tail used to climb or descend;
• Trim wheel to stabilize climb or descend;
• Motor (on/off);
• Landing lights used near airports for better visibility (on/off).

Third simulation element: Simulated flight, which may be executed in a continuous manner (providing a sequence of steps) or positioning the airplane freely and defining overall conditions.

System processing happens as follows:

1. From raw sensor data the system uses production rules to interpret the input for the use with the Artificial Neural Network (ANN), which expects standard binary inputs. Continuous data is translated into binary classes given. Table 1 below describes all symbolic interpreter binary output mapped to the binary input layer of the network.
2. Recognition (or not) of the emergency situation is determined by the ANN.
3. After recognition the system generates an alert to the pilot, who may himself take action, let the system decide or preauthorize the system to act (which is configurable).
4. If the system is set to act, the recommended action will be executed (using a symbolic routine) until its break condition is given or until the pilot interrupts it. Recommended actions vary from elimination of the problem, restrictions to ensure maneuverability to emergency settings (depending on the problem detected).

The training set used in the SINCO-Flightsim comprises 48 accident or incident setups, including: open door, aileron on one side damaged, collision from below, bird strike, collision with traffic on runway, air collision, freezing of aileron, freezing of rudder, freezing of elevator, motor damage because of excessive rotations, take-off with excessive weight, takeoff in thin air, late takeoff, malfunction of trim tabs, low descent to airport, steep descent to airport, flight through thunderstorms, navigational instruments malfunction, structural damage by hailstone, excessive altitude, missing upper fuselage, lack of fuel, flap on one side damaged, flap on both sides damaged, flaps extended during cruise, motor on fire, rudder damaged, dangerous maneuvers during turbulences, involuntary maneuvers in altitude, incorrect air speed measures, flaps fully extended during takeoff, stall because of steep bank angle, stall because of steep angle of attack, stall because of low speed, landing with wake turbulence, landing on water, landing in bad weather, landing out, elevator on one side damaged, elevator on both sides damaged, landing gear damaged, mountain shear, over controlling rudder, high landing speed and crosswinds on landing. The following list shows outputs of the symbolic interpreters (which mostly map continuous data to classes). Each interpreter provides a Boolean value. Thus, the results may be then passed on to the ANN's inputs (table I). Note that some sensors are read directly (marked with "*"). Yet, it should be noted that the system determines the phase of the flight (takeoff, climb, cruise, descent, landing, taxi etc.) and provides it in a binary manner to the network (three bits).

TABLE I.
SYMBOLIC INTERPRETERS

Left wing damaged (*)	Day time
Right wing damaged (*)	Night time
Rudder damaged (*)	No ILS signal (*)
Elevator damaged (*)	ILS "out" (*)
Left aileron damaged (*)	ILS "middle" (*)
Right aileron damaged (*)	ILS "in" (*)
Landing gear damaged (*)	Flaps retracted
Left flap damaged (*)	Flaps extended
Right flap damaged (*)	Flaps completely extended
Window(s) broken(*)	Throttle used
Door damaged (*)	Lights on
Fuselage damaged (*)	Lights off
Motor damaged (*)	Rudder straight
Trim tab damaged (*)	Rudder left/right
Water below (*)	Excessive rudder
Anti-collision alert	Trim tab used
Normal air speed	Trim tab straight
Excessive air speed	Excessive trim
Slow air speed	Elevator straight
Stall	Elevator up/down
Normal vertical velocity	Excessive elevator
Excessive vertical velocity	Weather in front normal
Normal bank angle	Weather in front turbulent
Excessive bank angle	Weather to the left normal
Normal rotations	Weather to the left turbulent
Lack of rotations	Weather to the right normal
Excessive rotations	Weather to the right turbulent
Altitude normal	Currently light or no turbulence
Excessive altitude	Currently extreme turbulence
Altitude very low	Excessive distance travelled on runway
Excessive angle of attack	Distance travelled on runway normal
Normal angle of attack	Flight phase (Bit 1)
Fuel normal	Flight phase (Bit 2)
Imminent lack of fuel	Flight phase (Bit 3)
Lack of fuel	Normal aileron
Temperature above 0 degrees Celsius	Excessive aileron
Temperature below 0 degrees Celsius	

Every emergency case (including combined emergency cases) is codified by its characteristics in the following way: For every characteristic a relation is given, meaning the chance by which in a real setting the output of the related production rule would be positive. Values may be: Imperative (for values, which will always be present), strongly related, related, weakly related and no relation. Depending on the definition, training cases are presented to the network: 100% of the imperative characteristics are marked as "1" in the training sets' inputs, 75% of the strongly related cases, 40% of the related cases and 10% of the weakly related cases. Training sets are generated by random and every case may be trained over and over again – generating a different set every time according to the rules above.

There are 48 binary outputs, one for every problem case and if a case is identified, processing is handed over to a specific (rule based) treatment procedure, which should handle the case applying a series of measures until its condition of completion.

Depending on the number of problems, alerts and other conditions, levels of attention can be configured (green, yellow, orange, red) and it may be decided when the system should act and when it should merely alert the pilot.

V. Connectionist Core

SINCO-Flighsim uses a neural network topology as the data from the real world environment is noisy and needs a fault tolerant treatment. This is the main justification of its use along with good performance values needed in a real-life emergency situation. Quality guarantee of the system is provided through extensive tests, which were executed at the beginning of the development and shall be maintained throughout all subsequent phases (see future steps in section 7 below).

The neural network topology employed in SINCO-Flightsim is that of a bidirectional network (see Fig. 1), using the sigmoid activation function and presenting three layers with inputs ($x_1..x_A$), hidden layer ($h_1..h_B$) and output layer ($o_1..o_C$). Synaptic weights are between inputs and hidden layer ($w_{11}..w_{AB}$) and between hidden layer and outputs ($q_{11}..q_{BC}$).

Supervised learning is used and the desired output ($y_1..y_C$) is provided during the learning phase, where correct behavior in several cases of disaster situations is being trained.

The Generalized Recirculation algorithm (GeneRec) [14] is a supervised learning algorithm based on back-propagation. It has its origins, as the name says, in a generalization of the recirculation algorithm created by Hinton and McClelland [6]. Its purpose is to offer a means considered biologically more plausible of learning in ANNs by the propagation of two signals ("plus" and "minus") through the network, local calculations of errors and the respective adjustments [17].

This way, it differs from the back-propagation algorithm which propagates the error "back" from the outputs (directed to the inputs).

A successful implementation of GeneRec needs an architecture with bidirectional connection as is the case in the present approach (see Fig. 1). More specifically, signals from the output layer shall be propagated back to the hidden layer. The necessity of this backward propagation is given for the creation of memory, which is imperative for the treatment of sequences. Thus, the network's answer does not depend merely on the current situation, but also on the steps executed until then.

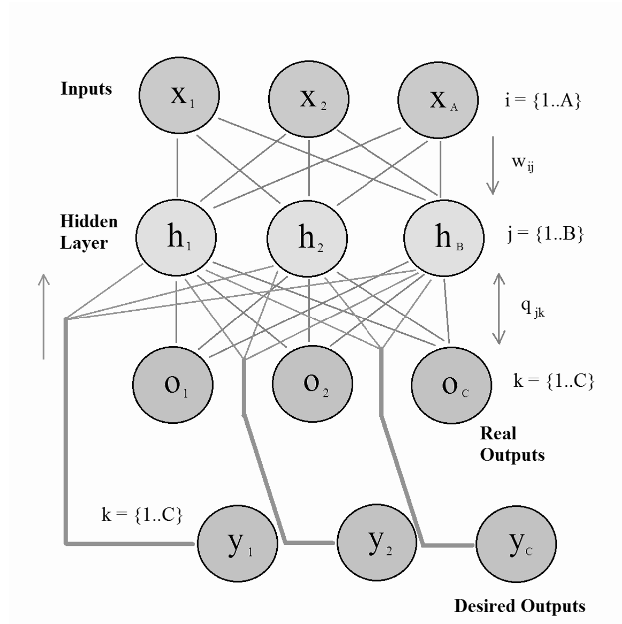

Fig. 1. SINCO-Flightsim artificial neural network layout

Still, network activations shall be calculated by the standard sigmoid function.

For the following calculation steps it should be assumed that the network has A inputs, B hidden neurons and C outputs. x_i are the binary values at the network's input layer (i={1..A}). h_j denote the activations at the hidden layer (j={1..B}), o_k symbolizes the calculated output values and y_k the desired output values (k={1..C}). w_{ij} are the weights between the inputs (x_i) and the hidden layer (h_j) whereas q_{jk} are the weights of the synapses between the hidden layer and the outputs (o_k). N denotes the learning rate (in analogy with the back-propagation algorithm, values should be between 1 and 0) and σ refers to the activation function via sigmoid ($\sigma = \frac{1}{(1+e^{-x})}$).

The GeneRec algorithm follows these processing steps:

Step 1: In the beginning real network outputs o_k are set to 0.

$$o_k \leftarrow 0 \tag{1}$$

Step 2: Inputs are attributed to the input layer x_i and desired outputs are attributed to the desired output layer y_k.

$$x_i \leftarrow \{0,1\}, y_k \leftarrow \{0,1\} \tag{2}$$

Step 3: Inputs are attributed to the input layer x_i and desired outputs are attributed to the desired output layer y_k.

$$h_j^+ = \sigma(\sum_{i=1}^{A} w_{ij}.x_i + \sum_{k=1}^{C} q_{jk}.y_k) \quad (3)$$

Step 4: Phase "minus" or "-": activations of the hidden layer at neurons h_j^- are calculated defining the network's "expectation" considering inputs x_i, previous outputs $o_k(t-1)$ as well as synapses (w_{ij} and q_{jk}).

$$h_j^- = \sigma(\sum_{i=1}^{A} w_{ij}.x_i + \sum_{k=1}^{C} q_{jk}.o_k(t-1)) \quad (4)$$

Step 5: Phase "minus" or "-": Next activations $o_k(t)$ are calculated from the activations at the hidden layer h_j^- and synapses q_{jk}.

$$o_{k(t)} = \sigma(\sum_{j=1}^{B} q_{jk}.h_j^-) \quad (5)$$

Step 6: Adjustments at synapses are calculated (Δq_{jk} and Δw_{ij}) considering activations of phase "plus" h_j^+, phase "minus" h_j^-, desired outputs (y_k), real outputs $o_k(t)$ and learning rate η.

$$\Delta q_{jk} = \eta.\left(y_k - o_k(t)\right).h_j^-, \Delta w_{ij} = \eta.\left(h_j^+ - h_j^-\right).x_i \quad (6)$$

VI. Results

Firstly, in the following part the learning of the training set was analyzed. During learning the training set is presented considering imperative characteristics to always map to "1" on the inputs and all other related to map to "1" or "0" depending on the probability of relation, thus generating different inputs with the same case and same training set. This also happens during later recognition of the real-life situation and is done to pre-model the noisy data, which is normally received in a real world setting.

As first analysis, the mean square error at the outputs was calculated after 1000 training iterations leading to the diagram in Fig. 2 with low errors being displayed and showing an opposite behavior of back-propagation and GeneRec (both performing well at different rates with a slight advantage of GeneRec). Backpropagation performs better at higher learning rates, GeneRec at lower learning rates.

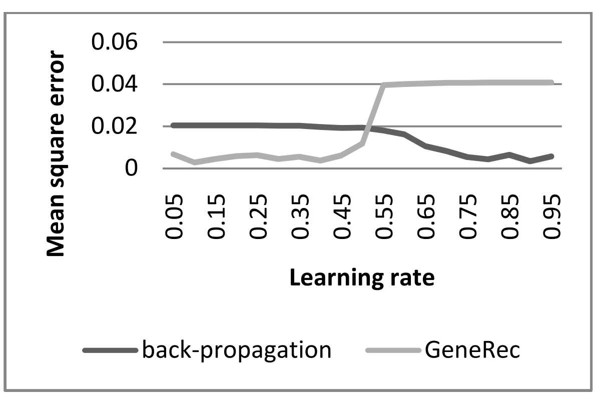

Fig. 2. Learning success and learning rate

In the following figures (figures 4-6) 30 neurons were used in the hidden layer. The best learning rates for each algorithm was chosen from figure 2, i.e. 0,1 for GeneRec and 0,9 for Backpropagation. As a second topic to look at, we are varying the configuration of the hidden layer. Values become relatively stable after the use of 18 neurons. GeneRec showed slightly better learning characteristics than back-propagation (Fig. 3).

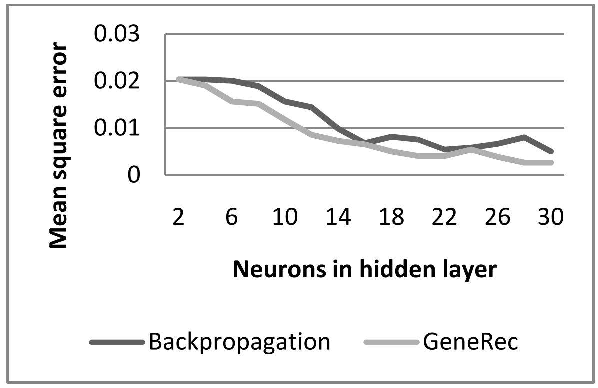

Fig. 3. Learning success and number of neurons in the hidden layer

In order to determine which number of training iterations would be best, training was continued up to 9500 iterations testing at every 250 iterations the network's training success. Firstly, it should be said that GeneRec has a much lower level of errors already at 500 iterations. Secondly, tendencies are relatively stable after 2500 iterations, whereas GeneRec still performs a little better showing an absolute minimum 8750 iterations (Fig. 4). In this example the practical side is analyzed, i.e., not the mean square error, but the incorrect outcome (meaning that any value below 0,5 is considered as 0 and any value 0,5 or above is considered as 1,0).

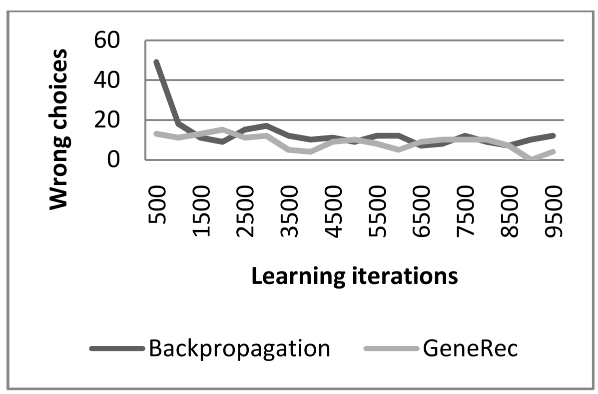

Fig. 4. Evaluation of wrong choices and learning iterations

Finally noise was introduced, meaning randomly inverting elements in the input layer (up to 15). Growth of error is relatively low and back-propagation shows very slightly more robust than GeneRec (Fig. 5).

During 200 test flights with potentially unknown situations (i.e., unmapped directly in the training set) "false positive" and correct recognition of problem cases were evaluated. "False positive" did not happen in a single case (of 100), which is important because of the fact that the system must by all means remain silent during normal operation in order not to cause damage and injuries instead of avoiding them. On the other hand, problem cases received plausible treatment indications.

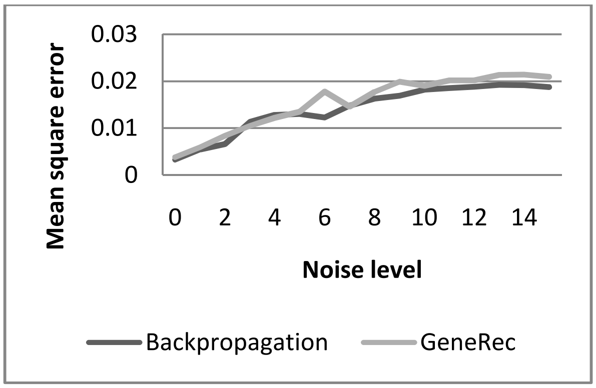

Fig. 5. Evaluation of robustness.

Considering the 100 problem flights, in all of the flights the problem condition was recognized and plausibly pointed at according to training. It should be noted that the network maps the problem condition itself (green, yellow, orange, red) and the diagnostic of the problem cause separately. Thus, even though some cases provided values below 0,5 for the chosen diagnostic, yet, it was always correctly mapped by the fact that it was the highest valued one of the given outputs.

VII. FUTURE DEVELOPMENTS

Logical next steps for the development of the present approach are firstly extension of the training set and its validation by aviation experts, next implementation on a physical model, implementation of additional aircraft characteristics modelling more complex settings and validation by additional physical models, test phase as parallel system on airplanes and finally productive rollout on airliners.

VIII. CONCLUSION

This paper presented SINCO-Flightsim, a simulator of emergency settings during flight, their detection by a connectionist core involving learning through GeneRec and treatment by symbolic routines. Detection through an Artificial Neural Network was implemented because of fault tolerance characteristics, which show advantages over classical approaches.

The architecture of the system and its processing steps were discussed and learning as well as test flight results were commented. The use of GeneRec as learning method seems indicated as it provides better performance in most cases.

The results obtained indicate that the approach success-fully detects and treats emergency setting in a simulation environment. This represents a proof of concept for the overall idea and opens the doors for further development. The authors trust that further development using physical models might in the end lead to a significant contribution to tomorrow's aviation industry.

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