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DESIGN AND ANALYSIS OF AN INTELLIGENT FIRE DETECTION SYSTEM FOR AIRCRAFT

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Abstract:
Fire detection system and fire warning are design features of an aircraft. Fire detection system protects the aircraft and passengers both in case of actual fire during flight. But spurious fire warning during flight creates a panic situation in flight crews and passengers. The conventional fire alarm system of an aircraft is triggered by false signal. ANN based fire detection system provides real observation of deployed zones. An intelligent fire detection system is developed based on artificial neural network using three detection information such as heat (temperature), smoke density and CO gas. This Information helps in determining the probability of three representative of Fire condition which is Fire, smoke and no fire. The simulated MATLAB results Show that the errors in identification are very less. The neural network based fire detection system integrates different types of sensor data and improves the ability of system to correct prediction of fires. It gives early alarm when any kind of fire broke out and helps to decrease in spurious warning.

Keywords: *Fire Detection; Artificial Neural Network; Simulation; Back Propagation; Intelligent Fire Alarm.*

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1. Introduction

In different part of aircraft where a fire protection is required the cargo compartment are important. Because cargo's area is dynamic in terms of dimensions and topologies as well as environmental conditions. As we know fire causes and there ingredients are different in nature. Due to that a single physical value may not allow the detection of the broad fire in a correct manner. In recent era many types of automatic fire alarm systems are used in aircraft, which bear with some types of shortcomings. For example detection methods using thermal detectors are affected by transient current. Smoke detectors can be affected by different gases developed in cargo compartment. Due to which we often get spurious (false) fire signal. Thus fire detection systems based on single sensor input are not able to meet the needs of real fire alarm. In view of the above Artificial Neural Network (ANN) based fire alarm system is more compatible than traditional fire alarm system because it can intelligently handles the multi sensor information theory.

The project presents a fire protection system designed on neural networks which uses the fire heat, smoke density and CO gas in the primary fire stage as a input. The software used for the project is MATLAB.

1.1. Statement of the Problem

In recent years despite development of advanced fire detection technology in aircraft, spurious fire warnings are still a serious problem. Spurious fire warning can occur at any mode of flight. Whether the aircraft is on ground or in flight. If spurious fire warning comes in air it lead to an emergency landing of the aircraft. After the study it is acquainted that the fire detection system in aircraft Cargo compartment is more responsible for spurious fire warning. Proper identification of fire signature in the cargo compartment of the aircraft is a complex task to understand.

1.2. Background and History

- During 10 years of study between March 1998 to April 2008, the International Air Transport Association found 2,596 reports of fire/sparks/smoke/fume occurrences on transport aircraft.
- Out of the 2,596 reports, 525 (20%) were false warnings due to which many flight were diverted for emergency landing.
- Further study acquainted that 40% of cargo compartment fire warnings were false.
- The Federal Aviation Administration research Cell analysed the ratio of false warnings in cargo compartments to actual smoke or fire and recommended the installation of advanced fire detection and suppression systems for cargo compartments in commercial air transport aeroplanes.
- However this requirement helped in reduction of false cargo compartment fire warnings to some limit but problem of false fire warning still persist.
- Latter the FAA/CAA/DGCA proposed that an improvement in the fire protection system is required and system must provide accurate fire warning to the flight crew.

2. Why Ann Required for Aircraft Fire Detection System

The technology to provide rapid fire warning with reduced no of false fire warning can be achieved by three types of sensors (*e.g.* thermal, smoke and co gas) with an algorithm to calculate inputs to determine a spurious input from all inputs. Most of the cargo compartments of airplanes have only single source fire detectors. Recently many aircraft manufacturers have proposed for using multi-source sensors in new airplanes. Since ANN is a best classifier and pattern recognition once trained properly on multi sensors input data. So it can be utilized in fire detection system of aircraft. We have a clear data of ignition point of each material used in the aircraft. In addition to this we also have idea about the different zone temperature of the aircraft. The ANN can be trained on the selected input with targeted output variables, which is more useful to understand the input signal. It helps in reducing the nuisance fire warning.

2.1. The Principle of Fire, Smoke and Co Detection Methods Used in Aircraft

2.1.1. Unit /Spot Fire Detection

In aircraft two types of unit fire detectors are used that is thermocouple and a bi-metallic switch. For thermocouple two dissimilar materials are connected to each other. These are deployed in aircraft engines internal and external area.

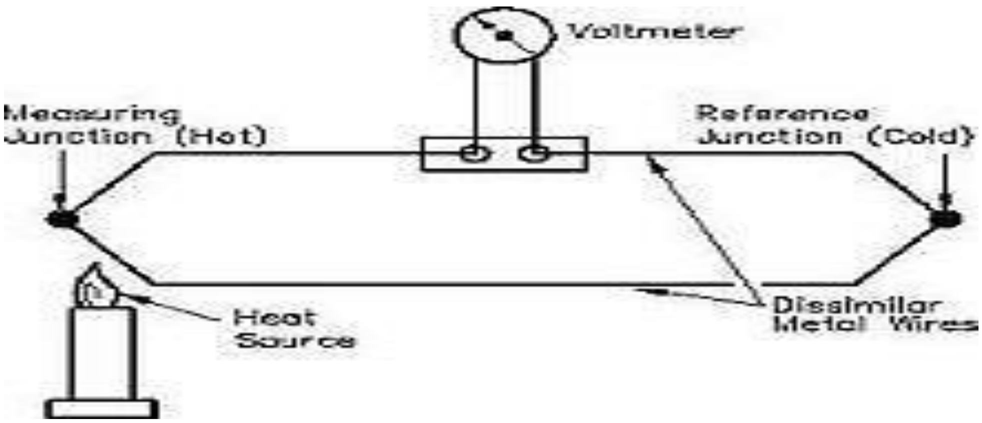

Figure 1: Thermocouple

In Bimetallic switch two dissimilar materials have a different expansion coefficient on certain temperature. Due to which it closes its contacts and give the fire signal.

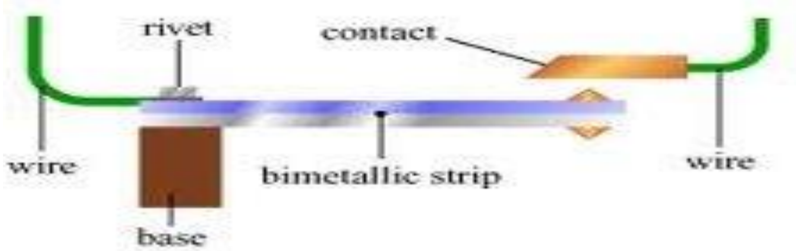

Figure 2: Bimetallic switch

2.1.2. Continuous-Loop Fire Detectors

Fire detection by loop method has advantage over spot/unit fire detection system. They are deployed for multi-tasking activity like it gives overheat signal and fire signal both. It also covers more area compare to unit fire detector. ***Two mostly installed continuous loop systems on the aircraft are the Kidde and the Fenwal systems***.

Kidde continuous loop system, have two wires imbedded in a separate ceramic core inside an Inconel tube.

Fenwal system uses a single wire surrounded by a continuous chain of ceramic beads in an Inconel tube.

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2.1.3. Smoke Detector

2.1.3.1.Photoelectric Smoke Detector

In aircraft many numbers of smoke detectors are deployed in cargo compartment. As we know smoke signal is prior information of a fire. So smoke detection system is used where the type of fire is expected to generate a huge amount of smoke before temperature changes and is sufficient to actuate a heat detection system.

A photoelectric smoke detector is mostly used in aircraft application. It detects smoke by using either the principle of light scattering. Its capability to detect smoke initialized from fire. it is best utilized for fires that produce large particles during combustion.

Figure 3: Smoke sensor

2.1.3.2.Ionization Type

Some aircraft have ionization type smoke detector. The system generates an alarm signal (both horn and indicator) by detecting a change in ion density due to smoke in the cabin. The system is connected to the 28 volt DC electrical power supplied from the aircraft. Alarm output and sensor sensitive checks are performed simply with the test switch on the control panel.

2.1.4. Carbon Monoxide Detector

C O gas is always present with smoke hence carbon monoxide detector is required for prediction of actual fire and smoke. As we know CO gas odourless and colourless, so it is not visible to crews of the aircraft. For riskless flying and actual fire detection with smoke detectors CO detectors are required.

3. Fire Detection based on Artificial Neural Network

For process information and recognition an Artificial Neural Network has upper hand over the other application. We are opting ANN based fire detection for the project due to its simple understanding to a complicated input. Artificial neural networks are intelligent information processing systems which mimic human brain functions. In the project three inputs are taken with forty neurons in each input. These neurons are manipulated by Artificial Neural Network in a software program. If an ANN is trained on proper input then it remembers the law in the form of weights. This is a great advantage of ANN for fire detection of aircraft. We adopt Back Propagation algorithm to train the network. After training the fire system is tested on particular input for its max error, min error and root mean square error. The aim of training the neural network is to minimise the error so that false fire warning is minimised.

4. Assumption of Fire Detection ANN Model

The ANN fire detection model is shown in Fig 4.

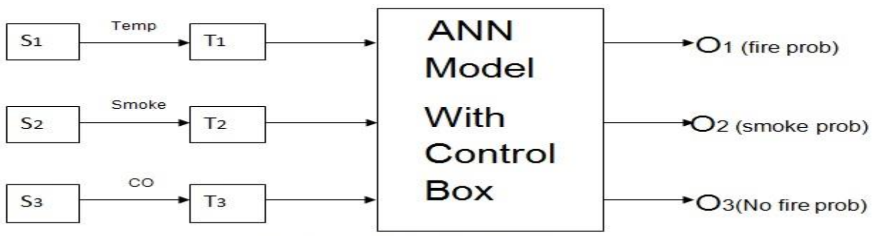

Fig 4: ANN model for fire detection

The sensor 1, sensor 2, sensor 3 are three types of sensors that detect smoke/fire in the deployed zone. Temperature 1, Temperature 2, Temperature 3 are three input variables to the ANN model. The Artificial Neural Network is being trained by the selected data. After training ANN find law between fire sample input data and detected input data. The outputs are O1 (Fire Probability), O2 (Smoke Probability) and O3 (No Fire Probability). The application of Back propagation (BP) has been taken in this project. Back Propagation forms an error minimizing mapping between two related spaces on the basis of training data. It consists of several hidden layers of neurons that are capable of performing complex nonlinear mapping between the input and output layer. In general all neurons in a layer are fully interconnected to neurons in adjacent layers. Data information is recorded into the hidden layers and the output is generated by combination operations on the input layer, hidden layer and output layer.

5. Network Structure

5.1. Back propagation Neural Network (BPNN)

The fire protections using neural network technology are trained to improve reliability and reduce false alarms. The function of system depends on the network structure, connection strength and unit approach. Neural networks can be self adaptive and self organizing with strong learning ability. The ANN has been successfully used to resolve many complex practical problems in pattern recognition, system identification, signal processing and forecasting. Most existing fire detection artificial neural networks use the Back Propagation network structure.

The input variables and the corresponding target output are used to train a neural network till it approximate a function associate input variables with specified output variables. Back propagation arranged to the manner in which the slope is computed for nonlinear multilayer networks. The properly trained back propagation neural network tends to give reasonable answers when presented with inputs that they have never tested. Typically a new input leads to an output similar to the correct output for input variables used in training.

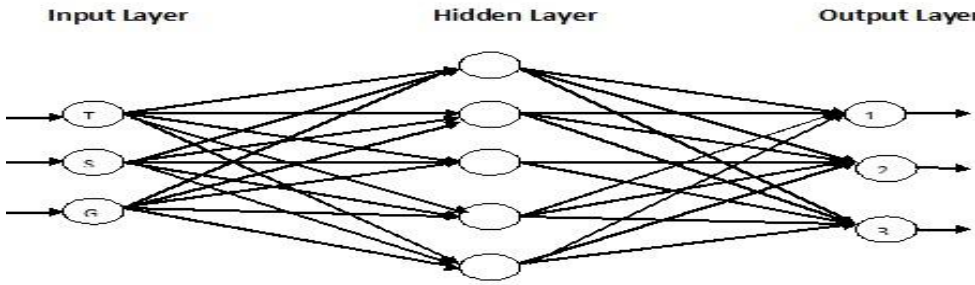

Fig 5: BP Network structure

5.2. Learning Algorithm

A learning algorithm for the project is based on a learning rule of MATLAB. This technique can also be referred to as a training algorithm. The learning rule is implemented to train the network to perform some specified task. In supervised learning, the learning rule is based on selected sample input data, which is also known as training sets. The programming pattern selected for the project is as follows.

{X1, Y1}, {X2, Y2}.................. {Xq, Yq}

Where Xq is selected input to the network and Yq is the corresponding target output. The inputs are applied to the network, the simulated network outputs are compared with the target output. The learning rule is used to adjust the weights and biases of the network in MATLAB ANN software in order to move the network outputs closer to the targets**.** In this study the learning rule falls in the supervised learning category.

The weights and biases are modified in unsupervised learning to network inputs only. In this rule no target output is given. They categorize the input patterns into a finite number of classes. This is especially useful in such applications as vector quantization.

6. Simulation

6.1. Simulation Model

The model uses the Back Propagation neural network structure. It has been given three input signals i.e. temperature, smoke density and CO concentration. The output of the model gives the probabilities of the three fire states such as fire, smoke and no fire. For the project 40 sample inputs are taken and listed in Table 1 for the BP network training. The sample inputs are selected after deep study the parameters of different types of sensors data used on various transport aircraft. The expected values corresponding to selected inputs are choosen as per the requirement of fire alarm of the aircraft. The collected data is trained in Artificial Neural Network model of MATLAB to meet the real time situation of fire. In the MATLAB program two hidden layers are taken with five and three neurons. The two nonlinear transfer functions selected for the program are tangent sigmoid and logarithm sigmoid. These two transfer functions give better output for the data taken as input samples of the fire detection of the aircraft.

6.2. Simulation Results Analysis

MATLAB PROGRAM FOR THE SELECTED INPUT SAMPLES

```
clear all;
clc;
X=[20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100 105 108 110 113 115 118 120 123 125
128 130 133 135 138 140 142 145 148 150 152 153 154 155 %Temp (degree centigrade)
  0.1 0.2 0.3 0.5 1.0 1.4 1.6 1.9 2.1 2.3 3.0 4.5 4.2 4.0 3.8 3.7 3.5 3.2 3.1 3.0 2.8 2.6 2.4 2.2 2.1
2.0 1.9 1.8 1.7 1.6 1.5 1.4 1.3 1.2 1.1 1.0 0.9 0.8 0.7 0.6  % Smoke density (mg/cubic meter)
  0.5 0.6 0.7 1.0 1.5 2.1 2.5 3.9 4.2 4.6 4.9 5.3 5.2 5.2 4.8 4.6 4.2 4.0 3.9 3.8 3.6 3.4 3.2 3.0 2.9
2.8 2.7 2.6 2.5 2.3 2.0 1.8 1.5 1.0 0.8 0.5 0.4 0.3 0.2 0.1 ];    % co concentration (mg/cubic meter)
Y=[0.01 0.02 0.03 0.05 0.08 0.10 0.15 0.20 0.30 0.35 0.40 0.55 0.60 0.65 0.68 0.70 0.72 0.73
0.74 0.75 0.76 0.77 0.78 0.79 0.80 0.81 0.82 0.83 0.84 0.85 0.86 0.87 0.88 0.89 0.90 0.91 0.92
0.93 0.94 0.95 % Fire Warning prob
  0.03 0.04 0.05 0.10 0.15 0.20 0.35 0.36 0.38 0.40 0.45 0.47 0.50 0.52 0.55 0.57 0.60 0.62 0.65
0.55 0.51 0.48 0.45 0.40 0.38 0.35 0.33 0.30 0.28 0.27 0.26 0.25 0.24 0.21 0.20 0.18 0.15 0.10
0.05 0.03    %Smoke prob
  0.94 0.93 0.91 0.90 0.85 0.80 0.75 0.70 0.65 0.55 0.50 0.45 0.40 0.30 0.26 0.25 0.24 0.23 0.22
0.21 0.20 0.19 0.18 0.17 0.16 0.15 0.14 0.13 0.12 0.11 0.10 0.09 0.08 0.07 0.06 0.05 0.04 0.03
0.02 0.01 ];  % No   fire prob
net=newff(X,Y,[5 3],{'tansig', 'logsig'});
net=init(net);
net=train(net,X,Y);
X1=[100 50 20 % Temp( degree centigrade)
   3.8 5.5 3.0 % smoke ( mg/cubic meter)
   4.6 6.5 5.8 ]  % co concentration (mg/cubic meter)
Ysim=sim(net,X)
subplot(2,2,1)
plot(Y(1,:),'-'); hold; plot(Ysim(1,:),'r-o')
title('Fire Warning Prob')
subplot(2,2,2)
plot(Y(2,:),'-'); hold; plot(Ysim(2,:),'r-o')
title('Smoke prob')
subplot(2,2,3)
plot(Y(3,:),'-'); hold; plot(Ysim(3,:),'r-o')
title('No Fire Prob')
```

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Table 1 Training samples for ANN Model

	Input Samples			Expected Value		
Sample Number	Temperature (℃)	Smoke density (mg/m3)	CO Concentration (mg/m3)	Fire Probability	Smoke Prob.	No Fire Prob.
1	20	0.1	0.5	0.01	0.03	0.94
2	25	0.2	0.6	0.02	0.04	0.93
3	30	0.3	0.7	0.03	0.05	0.91
4	35	0.5	1.0	0.05	0.10	0.90
5	40	1.0	1.4	0.08	0.15	0.85
6	45	1.4	1.6	0.10	0.20	0.80
7	50	1.9	2.1	0.15	0.25	0.75
8	55	2.1	2.5	0.20	0.30	0.70
9	60	2.1	3.9	0.30	0.35	0.65
10	65	2.3	4.2	0.35	0.40	0.60
11	70	3.0	4.6	0.40	0.45	0.55
12	75	4.5	4.9	0.45	0.47	0.50
13	80	4.2	5.3	0.55	0.50	0.45
14	85	4.0	5.2	0.60	0.52	0.40
15	90	3.8	4.8	0.65	0.55	0.35
16	95	3.7	4.6	0.68	0.57	0.30
17	100	3.5	4.2	0.70	0.60	0.25
18	105	3.2	4.0	0.72	0.62	0.25
19	108	3.1	3.9	0.73	0.65	0.23
20	110	3.0	3.8	0.75	0.55	0.21
21	113	2.8	3.6	0.76	0.51	0.20
22	115	2.6	3.4	0.77	0.46	0.19
23	118	2.4	3.2	0.78	0.45	0.18
24	120	2.2	3.0	0.79	0.40	0.17
25	123	2.1	2.9	0.80	0.38	0.16
26	125	2.0	2.8	0.81	0.35	0.15
27	128	1.9	2.7	0.82	0.33	0.14
28	130	1.8	2.6	0.83	0.30	0.13
29	133	1.7	2.5	0.84	0.28	0.12
30	135	1.6	2.3	0.85	0.27	0.11
31	138	1.5	2.0	0.86	0.26	0.10
32	140	1.4	1.8	0.87	0.25	0.09
33	142	1.3	1.5	0.88	0.24	0.08
34	145	1.2	1.0	0.89	0.21	0.07
35	148	1.1	0.8	0.90	0.20	0.06
36	150	1.0	0.5	0.91	0.18	0.05
37	152	0.9	0.4	0.92	0.15	0.04
38	153	0.8	0.3	0.93	0.10	0.03
39	154	0.7	0.2	0.94	0.05	0.02
40	155	0.6	0.1	0.95	0.03	0.01

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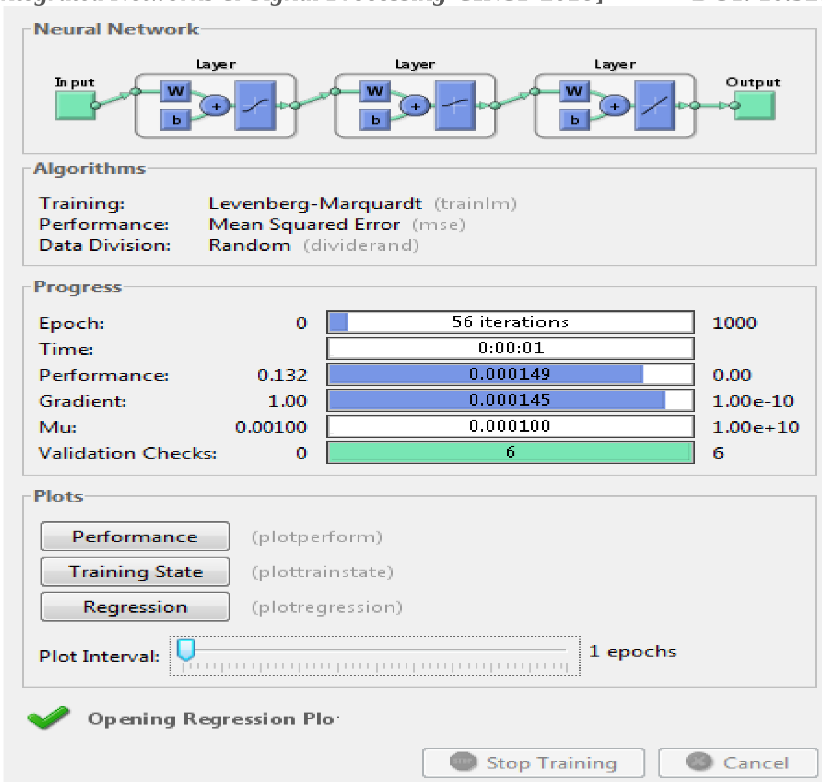

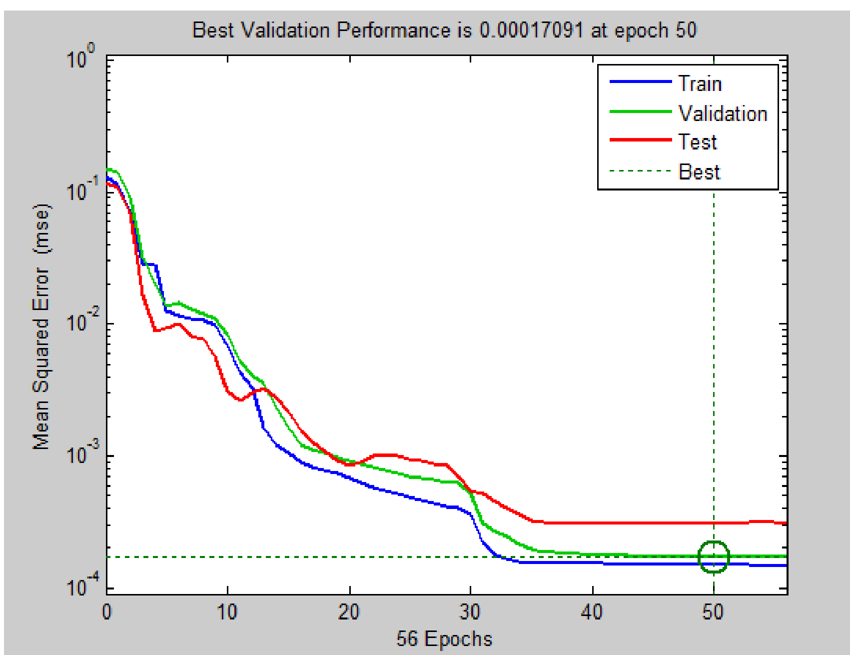

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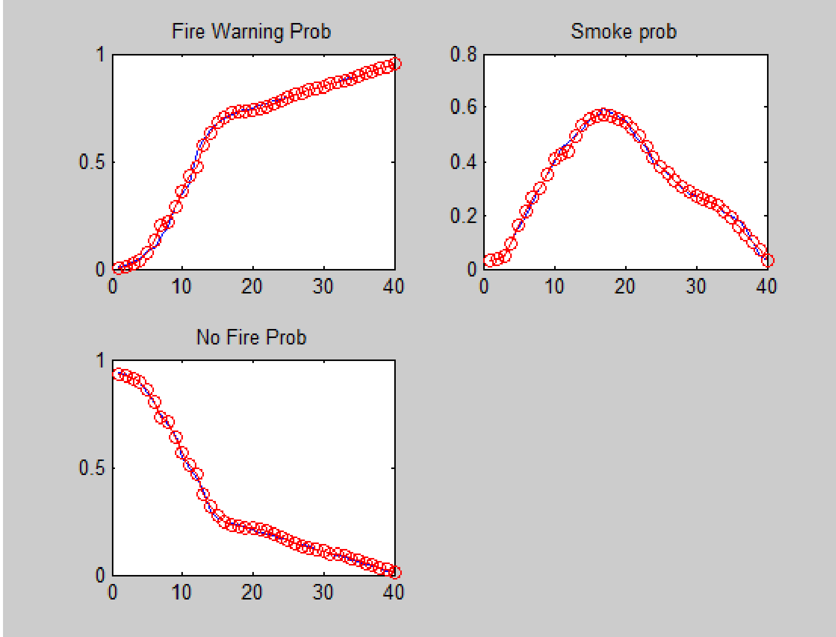

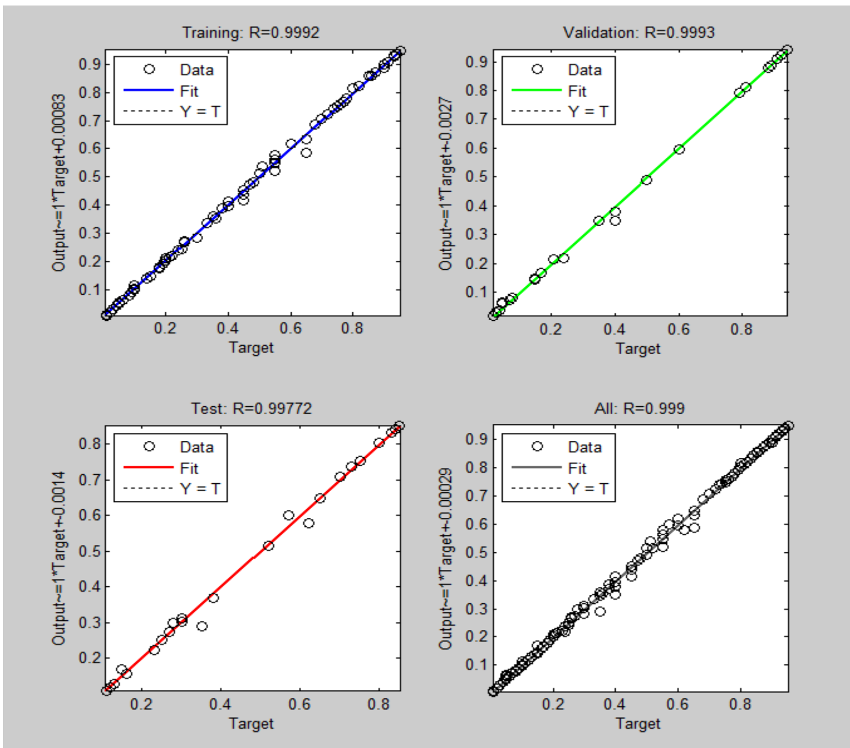

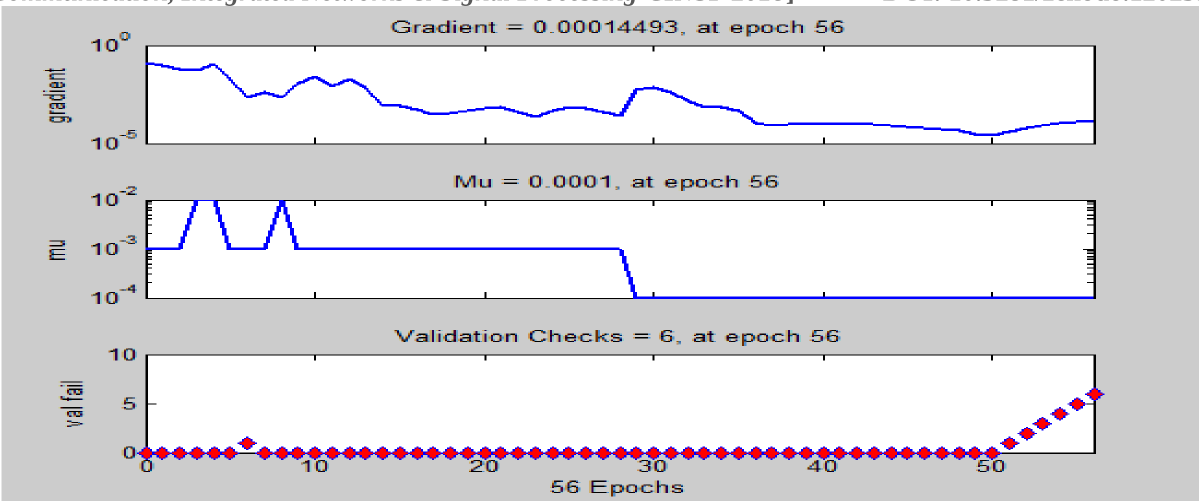

6.3. Comparison of Simulated Results with Expected Values

The comparison of simulated results and expected values are shown in the Table 3.

From the table the obtained results are satisfactory. The simulated results are very close to the expected values. It shows that artificial neural networks have quality of acceptation with strong recognition. This technique has excellent prospects in fire detection and recognition. It can be best technique to reduce the number of false alarms and determine the status of fire quickly and accurately.

The full detail of the error chart is shown in table 4. The value of simulation results are very close to expected value. Comparison of the simulation results and the expected values shows that the maximum error for fire is 2.3%. The maximum error for smoke is 2.8% and the maximum error for no fire is 3.6%. Thus the fire detection neural network after training has a high accuracy recognition rate for fire. The ANN based fire protection system reduces false fire alarms with improvement in the reliability and credibility of automatic fire alarm systems of aircraft.

6.4. 9.4- Calculation of RMS Error of the Model

The Root Mean Square Error (**RMSE**) is a prediction of the difference between values predicted by selected inputs and the values actually observed from the environment that is being modelled. The individual differences are known as residuals. The RMSE serves to aggregate them into a single predictive power.

The RMSE of a model prediction with respect to the estimated variable is defined as the square root of the mean squared error:

$$\text{Error (e)} = Ep - Ea$$

Where Ep = Predicted value and Ea = Actual value

RMSE = SQRT($\sum_{n=1}^{40} e^2 / 40$)

	Simulation Results (Ea)			Expected Value (Ep)		
Sample No	Fire prob.	Smoke prob.	No Fire Prob.	Fire prob.	Smoke prob.	No Fire Prob.
1	0.0131	0.0290	0.9384	0.01	0.03	0.94
2	0.0191	0.0369	0.9287	0.02	0.04	0.93
3	0.0275	0.0509	0.9134	0.03	0.05	0.91
4	0.0463	0.0960	0.8946	0.05	0.10	0.90
5	0.0792	0.1581	0.8502	0.08	0.15	0.85
6	0.1078	0.2014	0.7966	0.10	0.20	0.80
7	0.1550	0.3356	0.7475	0.15	0.25	0.75
8	0.2007	0.3618	0.7050	0.20	0.30	0.70
9	0.3037	0.3761	0.6487	0.30	0.35	0.65
10	0.3462	0.3935	0.5917	0.35	0.40	0.60
11	0.4004	0.4404	0.5504	0.40	0.45	0.55
12	0.4705	0.4667	0.5014	0.45	0.47	0.50
13	0.5583	0.5095	0.4511	0.55	0.50	0.45
14	0.6290	0.4977	0.4026	0.60	0.52	0.40
15	0.6696	0.5449	0.3477	0.65	0.55	0.35
16	0.6839	0.5835	0.2999	0.68	0.57	0.30
17	0.7107	0.6194	0.2357	0.70	0.60	0.25
18	0.7211	0.6223	0.2670	0.72	0.62	0.25
19	0.7359	0.6224	0.2242	0.73	0.65	0.23
20	0.7520	0.5787	0.1805	0.75	0.55	0.21
21	0.7641	0.5311	0.1925	0.76	0.51	0.20
22	0.7760	0.4667	0.1926	0.77	0.46	0.19
23	0.7983	0.4478	0.1735	0.78	0.45	0.18
24	0.8040	0.3919	0.1703	0.79	0.40	0.17
25	0.8161	0.3707	0.1581	0.80	0.38	0.16
26	0.8115	0.3552	0.1330	0.81	0.35	0.15
27	0.8234	0.3527	0.1306	0.82	0.33	0.14
28	0.8491	0.3058	0.1250	0.83	0.30	0.13
29	0.8432	0.2921	0.1311	0.84	0.28	0.12
30	0.8515	0.2682	0.1025	0.85	0.27	0.11
31	0.8677	0.2517	0.0953	0.86	0.26	0.10
32	0.8815	0.2463	0.0860	0.87	0.25	0.09
33	0.8976	0.2345	0.0741	0.88	0.24	0.08
34	0.9086	0.2040	0.0617	0.89	0.21	0.07
35	0.8989	0.1946	0.0780	0.90	0.20	0.06
36	0.9104	0.1614	0.0585	0.91	0.18	0.05
37	0.9177	0.1403	0.0405	0.92	0.15	0.04
38	0.9298	0.1051	0.0377	0.93	0.10	0.03
39	0.9417	0.0461	0.0249	0.94	0.05	0.02
40	0.9533	0.0369	0.0124	0.95	0.03	0.01

Table 3: Testing Results

Table 4: (Error Chart of ANN model)

	Fire Prob.	**Smoke Prob.**	**No Fire Prob.**
Error (max)	2.3%	2.8%	3.6%
Error (min)	1.4%	1.7%	1.3%
Error (RMS)	0.6%	1.0%	0.9%

7. Conclusions

In this project the artificial neural networks have been applied for fire detection in aircraft. The study describes a neural network based fire detection using temperature, smoke density and CO gas to detect and forecast fire and smoke warning. The following outcome has been concluded

1) The neural network based fire protection system has very less error as shown in table 4. The good decision making rate of the neural network reduces the risk of false alarms.

2) Also the neural network based fire alarm can analyze various types of sensor data and can improve the ability of systems to adapt in the environment. It accurately predicts fire warning with the very least chance of false fire alarm.
3) The project also describes how neural networks can integrate different sensors data in an intelligent manner to effectively identify fires, which has great significance for safety.
4) The simulation results are satisfying and show that RMS error for fire prob. is 0.6%, for smoke prob. 1.0% and for no fire prob. is 0.9%. Hence it shows that the Artificial Neural Network based fire alarm sensitivity is high and it will definitely reduce the spurious fire warning in the aircraft.

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