APPLICATION OF NEURAL NETWORKS IN FIRE DETECTION SYSTEMS

***Svetlin Antonov*[1], *Iglika Andonova*[2]**

Department of Theoretical Electrical Engineering, Technical University Sofia,
Kliment Ohridski boulevard No. 8, 1000 Sofia, Bulgaria,
*1- e-mail: svantonov@yahoo.com *2- e-mail: iglikaa@yahoo.com

Abstract. *Different people have different criteria for detecting a fire. In general the human recognize it correctly. Some of the criteria are: location of the flame, size of the flame, the amount of the generated smoke etc. Neural networks based systems use output of different sensors to obtain data about the parameters of the fire. This paper present a principle fire detection algorithms based on a neural network.*

Keywords: *fire detection, algorithm, neural network*

1. INTRODUCTION

In this study, the applications of neural networks in fire detection systems were reviewed for identifying smoke and flames from fires. Artificial neural networks (NN) are developed for years. The artificial neural networks are applicable even in these cases. Based on artificial neural networks there are some different algorithms applied in fire detection. These algorithms are applicable especially when fire can't be detected using the classical fire detection approach using thermal channels.

Fire usually goes through three distinct stages, namely, the ignition phase, propagation phase, and extinction phase [1]. The prediction of fire danger is a desirable goal as regards the prevention of fire occurrence. Fire detection in the ignition stage or early in the propagation stage will be of great help regarding fire suppression.

Fire detection systems should have the ability to discriminate signatures between fire and non-fire sources. Data from 1980's shows that 95% of smoke alarm signals were for non-hazardous conditions [2].

In high value installations such as semiconductor clean rooms and telephone central offices, it is obvious that reliable fire detection systems are needed, since usually these detection systems are used to activate fixed fire suppression systems, and false discharges are certainly undesirable. False alarms can cause unnecessary down time and undermine the operator's confidence in the monitoring systems. In light of these, a new fire detection system using infrared diagnostics (FT-IR spectroscopy) together with advanced signal processing technique (artificial neural networks) has been developed [3,4].

2. HISTORY OF ARTIFICIAL NEURAL MODELS IN FIRE DETECTING SYSTEMS

McCulloch and Pitts (1943) developed models of neural networks based on their understanding of neurology. These models made several assumptions about how neurons worked.

Rosenblatt stirred considerable interest and activity in the field when he designed and developed the Perceptron. Another system was the Adaptive Linear Element which was developed in 1960 by Widrow and Hoff. The method used for learning was different to that of the Perceptron, it employed the Least-Mean-Squares (LMS) learning rule. In 1969 Minsky and Papert wrote a book in which they generalised the limitations of single layer Perceptrons to multilayered systems. Some view of the history os shown on Table 1 [2,3,5]

Table 1. A breaf history of neural networks and fire detection

year	***action***
1943	*McCulloch and Pitts developed models of neural networks.*
1954	*Farley and Clark (IBM reserchers) maintained closed contact with neuroscientists at McGill University.*
1956	*Rochester, Holland, Haibit and Duda*
1958	*Rosenblatt designed and developed the Perceptron.*
1960	*Widrow and Hoff (of Stanford University) ADALINE (ADAptive LInear Element) was developed .*
1969	*Minsky and Papert wrote a book in which they generalised the limitations of single layer Perceptrons to multilayered systems. The significant result of their book was to eliminate funding for research with neural network simulations.*
1988	*Steve Grossberg and Gail Carpenter developed the ART (Adaptive Resonance Theory) networks based on biologically plausible models.*
1972	*A. Henry Klopf developed a basis for learning in artificial neurons based on a biological principle for neuronal learning called heterostasis.*
1974	*Paul Werbos developed and used the back-propagation learning method.*
1975	*Fukushima Kunihiko developed a step wise trained multilayered neural network for interpretation of handwritten characters called the Cognitron.*
1992	*First attempts to incorporate a neural network into fire detection system*

During this period several paradigms were generated which modern work continues to enhance.Grossberg's (1988) influence founded a school of thought which explores resonating algorithms. They developed the ART (Adaptive Resonance Theory) networks based on biologically plausible models. Anderson and Kohonen developed associative techniques independent of each other. Klopf in 1972, developed a basis for learning in artificial neurons based on a biological principle for neuronal learning called heterostasis.

Werbos 1974 developed and used the back-propagation learning method, however several years passed before this approach was popularized. Fukushima (F. Kunihiko) developed a step wise trained multilayered neural network for interpretation of handwritten characters Neurally based chips are emerging and applications to complex problems developing. Clearly, today is a period of transition for neural network technology. Neural networks are in progress of developing in fire detection systems for better fire recognition.

3. A GENERAL VIEW OF A FIRE DETECTION SYSTEM CONTAINING AN ARTIFICIAL NEURAL NETWORK

Fig. 1 shows a block diagram of a fire detection system containing an artificial neural network [2]. As it shows, the neural network can't be the only element in the system which plays a role of importance for the properly fire detection.

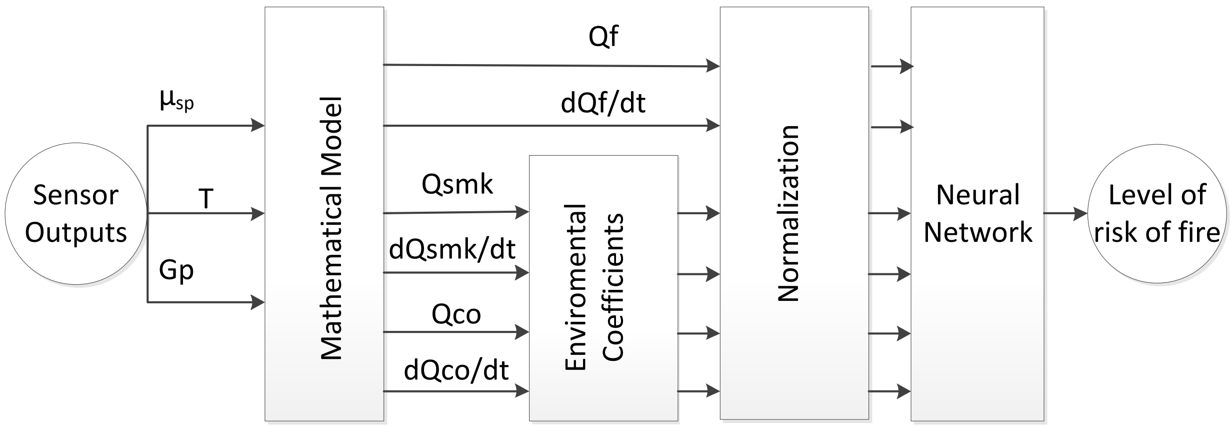

Fig. 1. Block diagram of fire detection system containing an artificial neural network

The sensor outputs deliver information about the temperature T, extinction coefficient μ_{sp} and gas concentration G_p. To receive the source information (data from the sensor), a mathematical fire model is used, which may be a simple zone model to calculate the average values for temperature, smoke concentration and gas concentration near the ceiling using as input the fire source conditions such as the heat release rate, smoke generation rate and gas generation rate. The presented model can be used as a "reverse" to obtain the source information of heat release rate Qf, smoke generation rate Q_{smk}, and gas generation rate Q_{CO} from the corresponding sensor outputs. The temporal differentials dQf / dt, dQ_{smk} / dt and dQ_{CO} / dt are also calculated. These quantities are then normalized with the relevant predetermined normalization coefficients. These normalized quantities are then applied to the neural network. On the final stage the neural network outputs the danger level of the fire.

4. THE PROBABILISTIC NEURAL NETWORK

The presented schema can be built by 3 layers of neurons. The first layer is the input layer with 6xn units. The second layer is a hidden layer with m units. The last layer (output) is with 1 unit.

The described neural network can consist of 6 different inputs corresponding to the actual quantities and their time differentials. On other side, the input layer shows the time of the delay circuit, which is a product of a delay units- delay time and delay count.

Assuming this group of input signals are applied at a certain point in time. The k-th unit has an internal condition u_k in the hidden layer and outputs as $f\left(u_k\right)$ [2]:

$$u_k = \sum_{i=1}^{6} \sum_{j=1}^{n} S_{i(n-j)} \omega_{i(n-j),k} \tag{1}$$

$$f(u_k) = \frac{1}{1 + \exp(-u_k + \theta_k)} \tag{2}$$

Where:

$\omega_{i(n-j),k}$ is the weight coefficient of the path between the input and the hidden layer,

θ_k is the threshold of the hidden layer.

The internal conditions are [2,5]:

$$u^* = \sum_{k=1}^{m} f(u_k) \omega^*_k \tag{3}$$

$$f(u^*) = \frac{1}{1 + \exp(-u^* + \theta^*)} \tag{4}$$

Where

ω^*_k is the weight coefficient of the paths between the hidden layer and the output layer,

θ^* is the threshold for the output layer.

The weight coefficients can be optimized by back- propagation method [3].

5. CONCLUSIONS

The neural network with a delay circuit, which handles the previously collected data as well as the actual data obtained from different sensors, can reduce false alarms caused by transient variation of output of a single sensor. Neural networks are able to learn representative examples by back propagating errors.

This paper leads to the next steps of exploring, simulating and producing fire detection systems based on neural networks.

References

[1] K. Clarke, J. Brass, P. Riggan, A cellular automation Model of wildfire propagation and extinction, Photogrammetic Engineering and Remote Sensing, 60, pp. 1355-1367, 1994

[2] H. Ishi, T. Ono. Fire detection system by multy-layered neural network with delay circuit, Fire safety science – Proceedings of the fourth international symposium, pp. 761-772, 1995

[3] Ishii H., T. Ono, An algorithm for improving the reliability of detection with processing of multiple sensors signal, Fire safety journal, vol. 17, pp. 469-484, 1991

[4] M. Bahrepour, P. Havinga, Automatic fire detection: a survey from wireless sensor network perspective, White Paper, University of Twente, 2010

[5] R. Lipmann, An Introduction to Computing with Neural Nets, IEEE ASSP Magazine, 1987

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