AN ARTIFICIAL NEURAL NETWORK BASED SENSOR SYSTEMS FOR GAS LEAKAGE MONITORING

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ABSTRACT

The purpose of this paper is to predict the situation of leak in closed space using an Artificial Neural Network (ANN). The existing system can't monitor the whole the situations with on/off signals. Especially the first stage of data determines the leak spot and intensity is disregarded in gas accidents. To complement these faults, a new prototype of monitoring system is proposed. The system is composed of sensing system, data acquisition system, computer, and ANN implemented in software and is capable of identifying the leak spot and intensity in closed space.

The concentration of gas is measured at the 4 different places. The network has 3 layers that are composed of 4 input Processing Elements (PE), 24 hidden PEs, and 4 output PEs. The ANN has optimum condiuon through several experiments and as a consequence the recognition rate of 93.75% is achieved finally.

INTRODUCTION

In the case of gas accidents, the accidents mainly occur as a type of leakage, explosion, and fire in gas facilities. According to the annual report of the Korea Gas Safety Co. Ltd. in 1995, gas accidents occurred by Liquefied Petroleum Gas (LPG) and Liquefied Natural Gas (LNG) in a kind of gas occupied 57.3%, gas leak in the type of accidents occupied 48.3% of the whole [1]. Nowadays, the accident caused by gas leak has been increasing rapidly.

The existing systems have faults in expressing sensor signal to qualitative data, because the system used numerical and symbolic method to find the cause of accident [2]. To complement the faults, a new system with ANN is proposed in this paper. The prototyped system has the initial data of leak spot and intensity help engineer to rapidly establish the counterplan. The collection of initial leak information can be useful to mitigate accidental gas leak.

On the other hand, Paul E. Keller and F. Winqüist have been study in this field. The former proposed the Chemical Vapor Sensing System to extract quantity of gas components, the latter measured quantity of each component by ANN respectively [3,4]. The prototyped ANN was constructed as a multi-layer feedforward network and was trained with the backpropagation of error algorithm by using training set from the data acquisition system.

ARTIFICIAL NEURAL NETWORK

MULTI-LAYER BACKPROPAGATION NETWORKS

A typical multi-layered backpropagation neural network is shown in Fig 1. It is widely used in monitoring and automation. It consists of a certain number of PEs(Processing Element), arranged in 3 layers one behind the other (k=0,1,2). Every PE in a layer of the network is cross connected to the outputs of PE in front layer by a group of adjustable factors called weights. The output of the PE is the output of a so-called activation function.

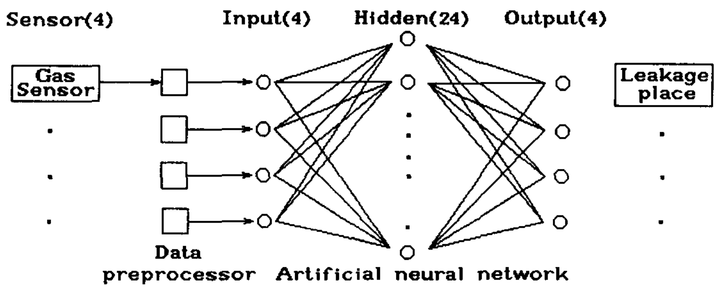

Fig. 1 The structure of 3 layer's neural network

Assuming u_i^k is the output of the i-th PE of layer k, w_{ij}^k is the weight that connects the i-th PE of the k-th layer and the j-th PE of the k+1-th layer. t_i^k is the threshold of units, $f(x_i^k)$ is the activation function [5]. So output of a PE could be expressed as

$$u_i^k = f(\Sigma_j w_{ij}^{k-1} u_I^{k-1} + t_i^k) . \tag{1}$$

Generally the activation functions are sigmoid function or tangent hyperbolic function which can be express as

$$f(x) = 1 / 1+e^{-x} . \tag{2}$$

Where x is input vector. An input vector, $x_i = (x_{i1}, x_{i2}, x_{i3}, \ldots, x_{iN})^t$, is applied to input layer of the network. The input PEs distributed the values to the hidden layer PEs.

By training the network with prepared samples, the weights of network can be adjusted gradually so that the networks outputs can be matched the actual outputs when corresponding inputs are given to the network. This kind of process is called the learning. Generalized Delta Rule (GDR), namely error backpropagation learning among the supervised learning is used in this study [6].

TRAINING AND TESTING THE NEURAL NETWORK

The ANN has 3 layers, which are composed of 4 input PEs, 24 hidden PEs, and 4 output PEs. The prototyped ANN was constructed as a multilayer network. The ANN was trained with the backpropagation algorithm by using training set from the data acquisition system. The sigmoid function is selected as the PE's activation function. The parameters used for the ANN training is shown in Table 1. The learning of ANN is trained for reducing the error. The learning's degree by the repeat of the training data is shown in Fig 2. The learning rates are changed from 0.1 to 0.9 at the constant momentum value to 0.70. According to the results of training, learning rate don't have an influence in training convergence. In the Fig 2, the Y axis shows the r.m.s(root mean square) of error value, it use for comparing the efficiency of ANN.

$$E = \Sigma_p E_{rms,t} \;\; ; \quad p = 1, 2, 3, \cdots, P \qquad (3)$$

In Eq. (3), P is the total number of training pattern and a sign $E_{rms,t}$ is a r.m.s error about pattern p.

Table. 1 ANN training parameters

Type	Backpropagation in batch mode
Architecture	4 – 24 – 4 feedforward
Activation	Linear / sigmoid
Learning Rate	0.3
Momentum	0.7
No. of Iterations	10000

EXPERIMENT

A generic system is shown in Fig 3. The system is composed of sensing elements, data acquisition system, computer, and ANN implemented in software and is capable of identifying leak spot and intensity. To reflect various situations in training data, the sampling time of data acquisition system was completely allocated for data collection where each of 4 leak detectors was set in closed space. Then the concentrations of leaking gases were measured at 40 spots. To consider various leak situations, leak spots was dispersed at the all directions of closed space and the concentrations was changed within the Lower Flammable Limit (LFL).

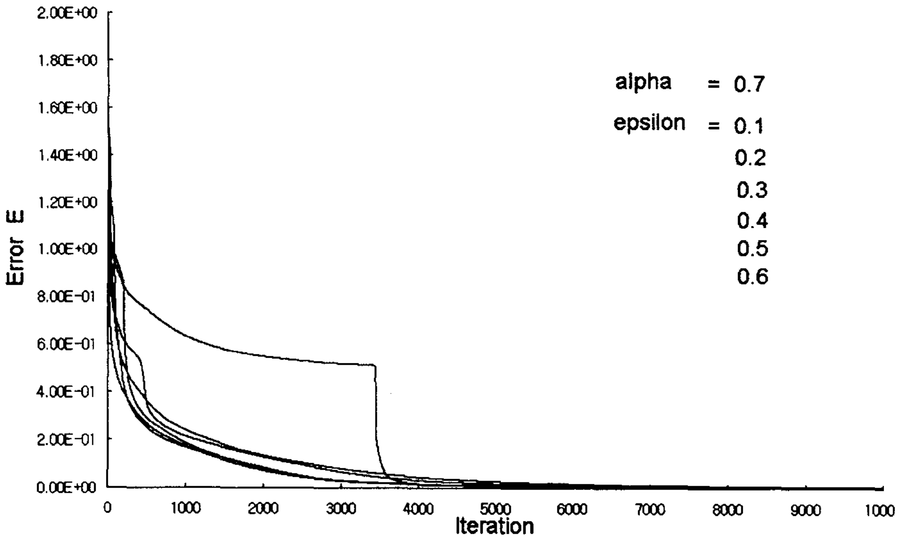

Fig. 2 Convergence of the training

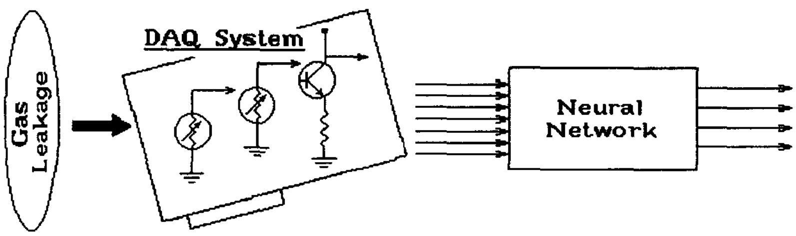

Fig. 3 Monitoring system combined with an ANN

LEAKAGE INTENSITY

The leakage intensity of each leak spot was determined by the slope of concentration. Fig.4 shows the measured signal at each detector under one fourth of LFL. The leakage velocities were 0.20[l/sec] and 0.50[l/sec] respectively. The line A and B in Fig.4 show the different slopes. To calculate the slope, the data after 5 seconds from the beginning of leakage was used.

EXTRACTION OF INPUT VECTOR FOR ANN

Fig.5 shows an example of leaking pattern at one spot and the straight line having –1/100 slope give 4 distinctive points for ANN input vector. The intersecting points get the formulated value from 0 to 1. They represent 4 gas detectors in closed space and their patterns make the input vectors, which are shown in Table 2.

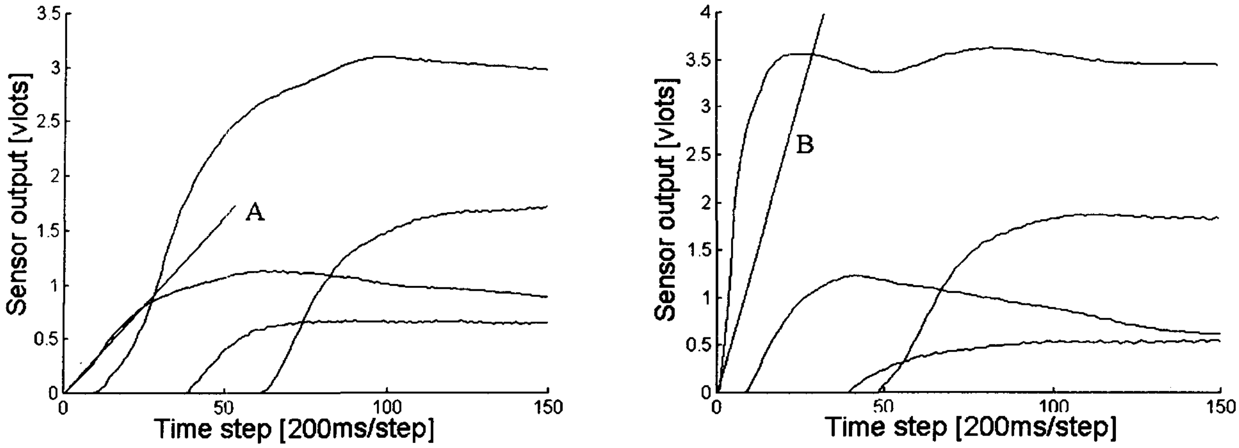

Fig. 4 Leakage pattern at leak spot

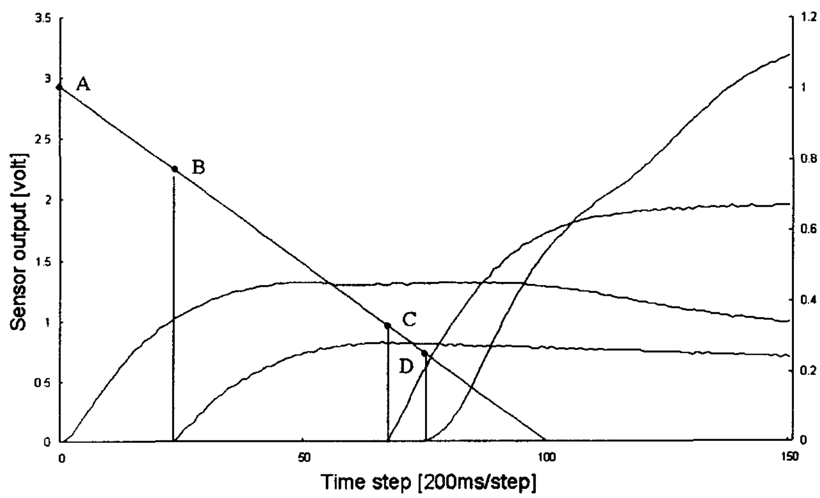

Fig. 5 Distinctive points for input vector

RESULTS

(1) Perceptron test results

Convergence of the training is shown in Fig 3. When the network has gone through 10,000 training iterations, the error of an ANN go down 0.02 for all PEs in the output layer. Then the ANN training parameters are set 0.70 and 3.00 for momentum and weight value respectively. The error of ANN is influenced by initial weights on the recall. It is reached 0.02 under less than 5000 iterations in case of adjusting the weights.

(2) Comparison with a numerical approach

The outputs of a constructed ANN simulator are shown in Table 2. Each row shows output for each input vector. The first 4 numbers in each row are an input vectors, and the rest 4 numbers appear as the outputs from the 4 PE in the output layer. We use a value of 0.6 for evaluating the outputs. If the output is more than, or equal to, 0.6, such as 0.67, 0.60, The evaluation of ANN is considered to be correct. For this case, the ANN correctly extracts 15 of the 16 leakage spots. Hence, the recognition rate is 93.75%.

Table. 2 Output of a constructed ANN simulator

Input				Output			
0.90	0.36	0.11	0	0.0000	0.9994	0.3881	0.0000
0.70	0.51	0.85	0	0.0109	0.1302	0.0059	0.9648
0.38	0.61	0	0.90	0.0265	0.0298	0.9838	0.0080
0.32	0.76	0	0.25	0.0179	0.0605	0.9541	0.9998
0	0.22	0.41	0.85	0.0010	0.9059	0.0418	0.0263
0.51	0.6	0	0.90	0.0378	0.9094	0.0018	0.9993
0.70	0.63	0	0.90	0.0297	0.9804	0.9999	0.0483
0.47	0.81	0	0.67	0.0067	0.9857	0.9987	0.9225
0	0.22	0.41	0.85	0.9957	0.0549	0.0311	0.0000
0	0.88	0.38	0.69	0.9696	0.0599	0.0298	0.9645
0.87	0	0.70	0.46	0.9979	0.1139	0.9953	0.0498
0.45	0	0.77	0.25	0.9879	0.0713	0.9524	0.9982
0	0.69	0.43	0.88	0.9935	0.9401	0.0023	0.0469
0	0.89	0.42	0.14	0.9707	0.9590	0.0179	0.9752
0.91	0	0.37	0.54	0.9544	0.9498	0.9991	0.0000
0.65	0	0.79	0.49	0.9994	0.8699	0.9913	0.9500

(3) Output of monitoring system

To test the proposed system, the trained input vector and non-trained input vector were given in the system. Fig.6 shows an example of monitoring program. The test was performed with 20 times at 16 spots. Then the system correctly extracted 320 of the 320 leak patterns. Hence, the proposed system has a good reproduction.

CONCLUSION

In this paper, the proposed systems that employ ANN for the prediction leak spot and intensity. To perform this, the initial leak patterns were collected for input vectors. And they play an important role in the recognition capabilities of the ANN. The optimal ANN having 24 hidden PE and 5000 iterations number is constructed through several experiments and recognition rate of 93.75% is achieved.

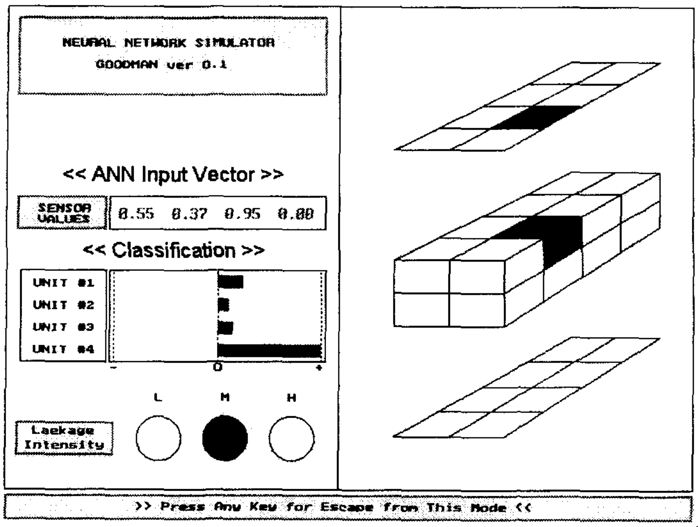

Fig. 6 The example of monitoring system

REFERENCES

1. KGS, The Handbook of Gas Accidents, KGS97-017, March, 1997, Korea

2. S.Y. Lee, S.W. Park, Fault of a Distillation Column Using an Artificial Neural Network, Journal of the Korea Institute of Chemical Engineering, vol 29, no. 5, pp.545-556, Oct 1991.

3. P.E. Keller, R.T. Kouzes, L.J. Kangas, Neural Network Based Sensor Systems for Manufacturing Applications, the Advanced Information Systems and Technology Conference in Williamsburg, VA, USA during 28-30 March 1994.

4. H. Sundgren, F. Winqüist, I. Lukkari, I. Lundström, Artificial Neural Network Network and Gas Sensor Arrays: Quantification of Indidual Components in a Gas Mixture, Measurement Science and Technology, vol.2, no.5, pp.446-469, May 1991.

5. Tarun Khanna, Foundation of neural networks, Addison-Wesley, Reading, MA, 1990.

6. D.E. Eumelhart, G.E. Hinton and R.J. William, Learning internal representation by error propagation, in Parallel Distributed Processing: Exploation in the Microstructure of Cognition. vol. 1: Foundation, D.E. Rumelhart and J.L. McClelland, Eds. Cambridge, MA, MIT Press, pp. 318-362, 1986.