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APPLICATION OF ARTIFICIAL NEURAL NETWORK FOR PREDICTION OF SPRINKLER ACTUATION TIME IN FIRE

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Abstract Fire phenomena are complex and involve non-linear interactions between environmental and fire parameters. Computer based methods (Field model and Zone models), by use of numerical methods applyied on mathematical models in the form of differential equations have been widely used for predicting the results of fire phenomena. In the present work an Artificial neural network (ANN) model has been used to predict the time for sprinkler actuation as a function of heat release rate, vertical distance from the ceiling and horizontal distance from the fire source. A set of input data has been generated from numerical studies where the code BRANZFIRE for a typical geometry of Emergency Switch Gear Room (ESGR) of a Pressurised Water Reactor (PWR) for different heat release rate, vertical distance from the ceiling and horizontal distance from the fire source for training the ANN model. The trained ANN model was used for the predictions of the time to sprinkler actuation. The ANN predictions were in good agreement with the predictions from the numerical analysis results. This paper also discusses briefly the ANN back propagation model used in this study.

Keywords: Fire modelling, Artificial Neural Network, Sprinkler Actuation, Backpropagation, BRANZFIRE

INTRODUCTION

Fire physics involves highly non-linear interactions between interacting and growth parameters. In place of using conventional analytical expression or numerical methods, this paper depicts the use of artificial neural network (ANN) to simulate the behaviour of the fire phenomena. The ANN is based on the human judgment mechanism and has been considered effective in understanding data regression and functional interpolation. Presently, fire modelling based on numerical simulations using high-speed computers (e.g. CFD, zone models, etc.) is very popular. Earlier some preliminary studies on the use of ANN along with other methods have been reported to model the time to sprinkler actuation, time to flashover, possibility of flashover [Beard et al., 1998], [Lee Wai Ming, WEB], [Ghojel, 1998], [Ingason, 1998], [Cheng] in compartment fires. Efforts are underway to predict temperature, possibility of flashover, time of occurrence of flashover, equipment survivability in the event of fire and time of sprinkler actuation at the Bhabha Atomic Research Centre (BARC). The present paper depicts the application of neural networks to the problem of predicting sprinkler actuation time.

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ARTIFICIAL NEURAL NETWORK

Full description of ANN structures and backpropagation training algorithm is beyond the scope of this paper. However, a brief description is given below. The interest in artificial neural network has considerably increased in recent years. World wide web contains a lot of information about the neural networks and its applications [NN FAQ, WEB], [Korotky, WEB], [Lampinen Jouko and Selonen Arto, WEB]. ANN is a mathematical simulation of human brain neuron. It consists of numbers of interconnected artificial neurons. Each link between neurons is capable to scale the signal transmitting from one neuron to another. The scaling factor is called weight of the link. In addition to weights, bias is introduced for offsetting input signals to a neuron. Bias is one of the inputs to a neuron with unity input. The weight of the bias input controls the degree of offsetting. The inputs, upon scaling and offsetting, will be processed by an activation function, which is continuously differentiable. Equations (1) and (2) describe the mathematical model of an artificial neuron [Lee Wai Ming, WEB].

$$S = f\left[W_b + \sum_{i=1}^{n}\left(w_i I_i\right)\right] \qquad (1)$$

$$f(x) = \frac{1}{1+e^{-\beta x}} \qquad (2)$$

Where I_i are the inputs, w_i the weights, S the output and f is the activation function of the neuron which is an important part of the neural network. This activation function is a continuous differentiable function which changes its state from 0 to 1 within a range close to x=0.

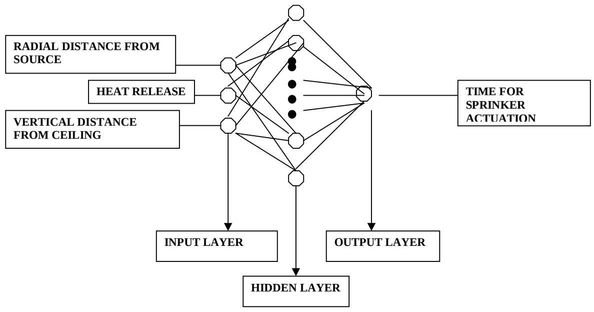

Fig. 1 The ANN architecture

There are various network architectures for linking the neurons. In the present case, the networks chosen are the most commonly used architecture feed forward, three-layered networks, trained using a backpropagation algorithm The first layer receiving input signals from outside of the network is called the input layer and the layer that outputs results to ouside is called output layer. Layers in between these two are called hidden layers. Feed-Forward architecture is explained in various references including [Yu-Lin et al., 1998]. Currently, for deciding upon the number of hidden layer and hidden neurons, it is required to carry out trials to obtain a desirable arrangement in form of Feed-Forward architecture. The three layers in this case are the *input* layer, which distributes the inputs heat release rate, vertical distance from the ceiling, horizontal distance from the fire source to the *hidden* layer, and an *output* layer which provides the time of sprinkler actuation. Networks as shown on Fig. 1 are used to determine the time of sprinkler actuation.

TRAINING ALGORITHM

Upon the availability of input data for a problem, which is called training data set, the network for simulating the problem is required to be trained by learning the training data as its knowledge for future prediction. The most commonly used training method is backpropagation algorithm. It uses the errors of output to adjust the weights linking to the output layer. These errors and adjustments propagate back to the weights linking the input layers and complete the weight adjustment. This algorithm is executed for every learning pattern and iterated under a minimum error achieved in the network prediction to the training patterns. Equation (3) describes the basic mathematical mechanism of backpropagation [Yu-Lin et. al., 1998], [McAuley Devin, WEB].

$$\Delta w_{ij}^{new} = \eta \delta_j S_i + \varphi \Delta w_{ij}^{old} \qquad (3)$$

PBACKPROP [Sharma et. al., 2001] is a training algorithm based on backpropagation. Error obtained from each training pattern is accumulated until the whole batch of training data is processed. The accumulated error is then used to update the weights. This will iterate until the prediction of the network is acceptable. PBACKPROP which needs learning factor and momentum factor, has been proven to be an efficient and speedy algorithm for network training which has been earlier used successfully for thermal analysis of a quarantined pressure tube of a Pressurised Heavy Water Reactor (PHWR) [Verma et al., 2002]. In order to avoid overtraining of the network, some of the learning data set will be separated as test data set, which will particularly be used to test the network for over-training. By summation of errors of network prediction on test data, the degree of over-training can be observed. This technique can effectively avoid the network overtraining. Along with the development of any ANN model, one is always limited by the quantity and quality of data that are available. In this case, the quality of data depended on the accuracy of the code , on the expert experience and the requirement of the user. The quantity of experimental data available was very less and they are very costly to generate. However, sufficient data has been generated for this preliminary study using the zone based model code BRANZFIRE. The data consisted of a set of values of time of sprinkler actuation based on three drivers viz. fire heat release rate vertical distance from the ceiling, horizontal distance from the fire source.

FIRE MODEL

For obtaining learning patterns for training artificial neural network, instead of experimental data which is considered costly besides being limited, data generated from well-recognized computer software (i.e. BRANZFIRE) is considered sufficient enough to be used for studying the applicability of ANN in fire phenomena. The code BRANZFIRE [BRANZFIRE, 1999] has been developed by the Building Research Association of New Zealand. The code models fire in multiple rooms (based on the zone model concept) with multiple vents and multiple burning objects. The code BRANZFIRE is reported to have been validated earlier against experimental data from the EUREFIC research project [Wade et al., 1997].

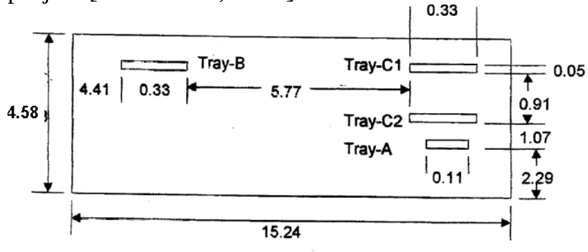

Fig. 2 Schematic of ESGR room (Not to scale)

Further validation of the code BRANZFIRE was carried out at BARC against the earlier reported studies on fire postulated in the Emergency Switch Gear Room (ESGR) of a PWR, and against the data from experiments conducted at Lawrence Livermore National Laboratory, Livermore [Sharma et al., 2000].

SPRINKLER ACTUATION TIME

The problem chosen for analysis is taken from one of the widely reported earlier case studies [Day, 1996] related to postulated fire in the Emergency Switch Gear Room (ESGR) in a PWR. Schematic of the ESGR of size 15.2mX9.1mX4.6m (length X width X height) along with the cable trays locations is shown in Fig. 2. The trays A, C1 and C2 contain power and instrumentation cables and the tray B contains safe shutdown related instrumentation cables. A cable fire in the tray A is postulated (by some fault) which spreads to the upper cable trays C1 and C2. The hot gas mixture moves up and forms a hot layer below the ceiling. The possibility of damage to the cable (which has a damage temperature of 640 K) in tray B, was required to be evaluated to assess resulting impairment of safe shutdown instrumentation scheme. But in the present work we have directed effort on analysis of sprinkler actuation time in different locations in the enclosure. The room model developed for the investigation of sprinkler actuation problem is shown in Fig. 3. For simplifying the problem, only fire size, height of sprinkler and horizontal distance from sprinkler to axis of fire are varied, with the other parameters being kept constant to obtain the sprinkler actuation time by use of computer simulation software BRANZFIRE. Equation (4) given below is the basic equation to be used for determination of sprinkler actuation time.

$$\frac{d\Delta T_g}{dt} = \frac{\sqrt{u}}{RTI}\left(\Delta T_g - \Delta T_e\right) \qquad (4)$$

The time to sprinkler actuation can be obtained by using BRANZFIRE for the numerical integration of Equation (4) where the sprinkler response time index (RTI=$\tau\sqrt{u}$) is fixed to be $140 m^{1/2}s^{1/2}$ (for a commercial sprinkler) and actuation temperature of 68^oC. It should be kept in mind that the right side of the equation needs the solution of mass, momentum and energy conservation in an enclosure simultaneously with this equation. More details about the mathematical details of BRANZFIRE is described in the reference [BRANZFIRE, 1990]. Also, a constant fire source of assumed intensities (Q) of 1 MW, 2 MW, 3MW, 4MW and 5 MW are used in the simulation . The results from these case studies are used for network training. Table -1 depicts the typical compilation from aforesaid case studies.

NETWORK DESIGN

For the fire phenomena under study, a general pattern of output (i.e. time to sprinkler actuation) with respect to fire size, it was observed that there is a minimum fire size under which there is non occurance of sprinkler actuation. Also, there is a maximum fire size at and above which the time to sprinkler actuation is constant. Data for network training is only available within the range bounded by the minimum and maximum fire sizes. Since the network only carries out regression on the data sets, it is unable to predict non-happening of sprinkler actuation. So from the data set from the BRANZFIRE studies corresponding data point of non-happening of sprinkler actuation have been removed, although a different approach can be utilised to find out even the non-happening of sprinkler actuation [Lee Wai Ming, WEB].

NETWORK ARCHITECTURE

A three layers feed-forward neural network, which has been proved to be applicable for most problems, is to be designed for the fire problems under study. However, the number of neurons in hidden layers should be determined by trial to obtain acceptable predictions. Error generated by the PBACKPROP is a useful index for showing the goodness of regression with multiple independent variables. The error is a measure of the proportion of variation that is explained by the independent variable in the regression model. An error approach to a smaller value implies the prediction is well fitted to the actual. Different values of number of hidden neurons, number of layer of neurons, momentum parameter and activation coefficient have been tried to obtain a low value of error.

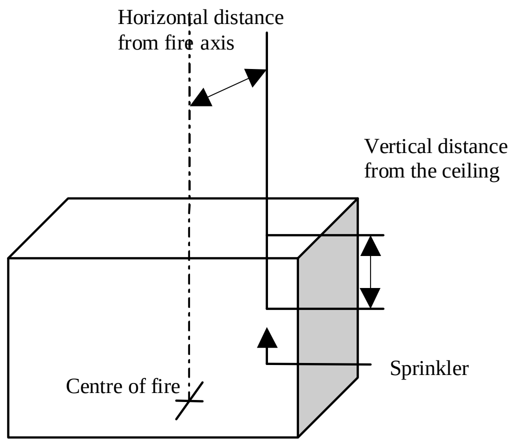

Fig. 3 Room model for investigation of sprinkler actuation time

NETWORK TRAINING

There are a number of different parameters one can manipulate when constructing ANNs. These parameters include variations in the number of hidden nodes, variations in the 'speed' of the training algorithm employed (by adjusting a *learning parameter*), and variations in the length of time one chooses to train a network for (the number of training cycles, iteration or *epochs*). In this particular study a number of different network configurations were investigated (different numbers of hidden nodes) along with various epochs. In the present effort the two rows of five hidden nodes with φ=0.5,η=0.5 were found to be acceptable after various trials. The stop criterion of training is that no further decrease in prediction errors on test data for 50,000 iterations, then the training processes would be stopped.

RESULTS AND DISCUSSION

Upon the completion of training, the weights of all links of all networks has been determined. It is necessary to compare the results predicted by the neural network to the results obtained using fire simulation computer software. Table 2 compares the predicted results of ANN and BRANZFIRE for the fire phenomenon of sprinkler actuation. It can be observed that the ANN prediction results are very close to the results of computer software BRANZFIRE. It may be concluded that the prediction is successful. ANN method reduces the computer time considerably where repetitive time consuming calculations are involved. The efficiency of ANN model over the direct solution (after obtaining the direct solution) is evident for a more complex problem.

CONCLUSION

The fire phenomena is reasonably well simulated by ANN. The accuracy of prediction is highly dependent on the accuracy of training data sets. Also, different network architectures should be designed for different kinds of problems. This paper has investigated the application of the ANN in modelling fires in enclosure. Upon completion of the training, the trained ANN was used to test the value for three data points. The predicted values were in good agreement with the experimental values of upper layer temperatures.

NOMENCLATURE

I_i :ith Input of neuron
w_i :ith weight of neuron
w_{ij} :weight between ith neuron and jth neuron
S_i :output of ith neuron
T_i :target value of output of ith neuron
b_i :bias of ith neuron
Δw_{ij} :change of weight linking ith and jth neuron
η :learning rate of the network training
φ: momentum coefficient of the network training
β: constant
e: error of network prediction to training patterns
τ : time constant [s]
T_o: initial temperature [K]
t : time [s]
Q : heat release rate from fire [kW]
T_e : temperature of the sensing element [K]
T_g : temperature of the hot gas around the sensing element [K]
$\Delta T_e = T_e - T_o$
$\Delta T_g = T_g - T_o$
u : hot gas velocity around sensing element [ms^{-1}]

Table-1: Training data set generated using code BRANZFIRE

Fire Size (MW)	Distance from ceiling(m)	Horizontal Distance from fire(m)	Time of sprinkler actuation (sec)
1	0.2	4.5	20
2	0.4	3.5	12
4	0.6	2.5	26.0
3	0.6	2.5	35
4	0.8	2	38
5	1.0	1.5	34
1	0.4	3.5	50
2	0.6	2.5	55
3	0.8	2	50
4	1.0	1.5	42.0
5	0.2	4.5	1.0
1	0.6	2.5	109.0
2	0.8	2	75.0
3	1.0	1.5	58.0
4	0.2	4.5	1.0
5	0.4	3.5	2.0
1	0.8	2	145.0
2	1.0	1.5	248.0
3	0.2	4.5	2.0
4	0.4	3.5	3.0
5	0.6	2.5	20.0
1	1.0	1.5	282.0
2	0.2	4.5	3.0
3	0.4	3.5	5.0
4	0.6	2.5	26.0
5	0.8	2	31.0
2	0.8	1.25	208.0
3	0.6	4.25	14.0
4	0.4	3.25	4.0
1	0.8	1.75	160
2	0.6	2	64
3	0.4	3.9	4.0
5	1.0	1.75	33.0
1	1.0	2.5	149.0
2	2.0	4	94.0
4	0.1	1.4	1.0
5	0.25	4	1.0
2	0.3	1.5	35.0
3	1.0	2	54.0
4	1.1	3	38.0
5	1.25	4.15	28.0
2	0.35	3.25	9.0
3	0.45	3.75	7.0
4	0.55	1.25	38.0
5	0.5	2.75	10.0
2	0.15	3.2	3.0
2	0.15	4.5	3.0
2	0.15	1.0	8.0
2	0.5	1.5	67.0
2	0.5	3.0	33.0

Contd.

2	0.5	4.0	19.0
2	0.5	4.5	15.0
3	0.15	3.2	2.0
3	0.15	4.5	2.0
3	0.15	1.0	3.0
3	0.5	1.5	45.0
3	0.5	3.0	18.0
3	0.5	4.0	8.0
3	0.5	4.5	6.0
4	0.15	3.2	1.0
4	0.15	4.5	1.0
4	0.15	1.0	2.0
4	0.5	1.5	33.0
4	0.5	3.0	11.0
4	0.5	4.0	5.0
4	0.5	4.5	4.0
5	0.15	3.2	1.0
5	0.15	4.5	1.0
5	0.15	1.0	2.0
5	0.5	1.5	27.0
5	0.5	3.0	8.0
5	0.5	4.0	3.0
5	0.5	4.5	3.0

Table-2: Comparison of PBACKPROP ANN predictions against the BRANZFIRE numerical predictions

Fire size (Mw)	Distance from ceiling (m)	Radial distance from fire source (m)	Sprinkler actuation time(sec)	
			ANN	BRAN ZFIRE
4.0	0.20	4.50	0.56129	1.0
5.0	0.40	3.50	1.89715	2.0
4.0	0.55	1.25	37.73915	38.0
5.0	0.50	2.75	11.46131	10.0
4.0	0.50	1.50	32.10176	33.0
4.0	0.50	3.00	12.36275	11.0
55.0	1.00	1.75	28.87376	33.0
1.0	1.00	2.50	130.5032	149.0
5.0	0.50	1.50	28.32191	27.0
5.0	0.50	3.00	9.66382	8.0

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