ISTANBUL UNIVERSITY –
JOURNAL OF ELECTRICAL & ELECTRONICS ENGINEERING

YEAR : 2006 (27 - 33)
VOLUME : 6
NUMBER : 1

# DETERMINATION OF THE NEXT STOPPING FLOOR IN ELEVATOR TRAFFIC CONTROL BY MEANS OF NEURAL NETWORKS

**C.Erdem İMRAK[1]** **Mustafa ÖZKIRIM[2]**

[1,2] Istanbul Technical University, Department of Mechanical Engineering
Gumussuyu, 34439 Istanbul, Turkey.

[1] E-mail: imrak@itu.edu.tr [2] E-mail: ozkirimmu@itu.edu.tr

## *ABSTRACT*

*When a group of lifts serve together it is important coordinate the movements of the individual lifts in such a way that the lift group should operate efficiently. This is dealt with elevator control systems, which have become more and more complicated due to their nature of intelligence. Neural networks, which have been proved to be successful in many fields, can also be applied to the next stopping floor problem in elevator traffic control algorithms. In particular, neural networks can offer better solutions to the next stopping floor problem when compared to the classical traffic control methods. Elevator control algorithms based on neural networks can dynamically learn the behavior of an elevator system and predict the next floors to stop by considering what has been learnt by processing the changes in passenger service demand pattern. Neural networks have been used to build a one step ahead predictor for elevator traffic pattern. In this paper a neural network algorithm is apllied to obtain a better solution to the next stopping floor problem in elevator group control and its learning capability is assessed by means of simulation software developed.*

***Keywords:*** *backpropagation, elevator control, group control, next stopping floor, neural networks.*

## 1. INTRODUCTION

Elevators nowadays are neccessary in modern buildings. and have to transport a group of passengers in a building with a given number of floors above the main terminal. The cars are attending to a call from any floor or at rest or attending to a car call. When a new hall call exists, the control system has to chose which car will attend to the new call. To do this, it has to consider the path the car that would have to follow before answering the new call. Thus, the system has to consider the suitability of each car for attending to the call and then select the most feasible one.

Control systems for groups of elevators try to manage the joint operation of several cars for assigning one of the elevators to a new hall call. To make this assignment, several variables are considered such as the mean response time of the elevator system, the mean waiting time for passengers and mean time of travel, the maximum waiting and travel times, the number of passengers waiting on every floor. Different

*Received Date :06.02.2004*
*Accepted Date: 10.12.2005*

traffic patterns can exist at different periods of the day.

In offering a solution to elevator traffic problems, the traditional methods often yield unsatisfactory results because they lack in considering number of technical characteristics and possibilities to be taken in to account. Conventional algorithms also possess limitations and their flexibility is still restricted even if they are adapted to utilize computers.

Computer based traffic control systems can assign cars more effectively than the classical traffic control systems, there exists, however, a limit to what can be achieved. The main limit is the finite capacity of the underlying equipment to handle the traffic demands. Hall and car calls are often allocated to suitable cars by taking into account of the minimum cost concept that operates by performing a trial allocation to all avaliable cars and allocationg the call to the car giving the lowest cost [1].

Artificial intelligence has been used in elevator control systems, although this has been later than other fields. Three potential application areas for an elevator expert system, elevator group control and system managements are propesed by Wareing [2]. An expert system for the design of elevator systems is used by Alexandiris et al. [3]. A rule based expert system for elevator control are employed by Prowse et al. [4]. To find the number of passengers in a given visual pattern captured by a camera fuzzy logic has been used by So et al. [5]. Al-Sharif employes neural network technique to predict elevator traffic pattern [6]. The fields of artificial intelligence applications in lifts may include: fuzzy logic [7], knowledge based systems [4], expert systems [8], dynamic programming [9], genetic algorithms [10], optimal control [11] and neural networks [12].

Artificial neural networks are computer algorithms that simulate the way that human neural networks operate and learn [13]. They consist of several units – artificial neurons – that carry out a simple task and are fully interconnected. This layout allows reproducing some features of the brain that are not usual on computers [14].

In this work, a neural network is used to predict the number of hall calls likely to be made and the cars' likely destination for the time of service in order to optimise the car allocation efficiency. The prediction is made by combining predictions from historic data learnt during corresponding periods of previous days and real time data learnt during a short interval. To do this a neural network algorithm inserted into an elevator traffic control system is developed to model the behaviour of the building population and also to automatically adapt the algorithm to changes in traffic behaviour without any further redefinition [15]. The selection and distribution of the most suitable cars in the building is a function of the assignment of calls. Neural networks have been applied to tackle this problem in the elevator control algorithm [16].

For training the neural networks, the backpropagation method was used in the program. The work presented has been carried out using the software written in Turbo Pascal 7.0 [15].

## 2. FEEDFORWARD NEURAL NETWORK

The feedforward neural network is a very popular model in neural networks as it provides predictive information, backpropagates the least mean squared errors during training and does not have feedback connections. The backpropagation algorithm always converges to a local error minimum [17, 18].

The neural network composes of a layer of input neurons at the beginning, any number of hidden layers and a layer of output neurons at the end as shown Figure 1. The hidden layer size is somewhere between the input layer size and the output layer size. In general, connections among neurons within any layer and the connections among neurons in non-adjacent layers are allowed [19]. Each neuron of the neural network creates an output when an activation function is applied to the weighted sum of the inputs. The Sigmoid function is generally used as an activation function because of simulating biological neuron activities. The Sigmoid function also defines the nonlinearities [20].

The backpropagation training algorithm is an iterative gradient descent algorithm that attempts to minimize the mean square error between the actual network output and the desired output [21].

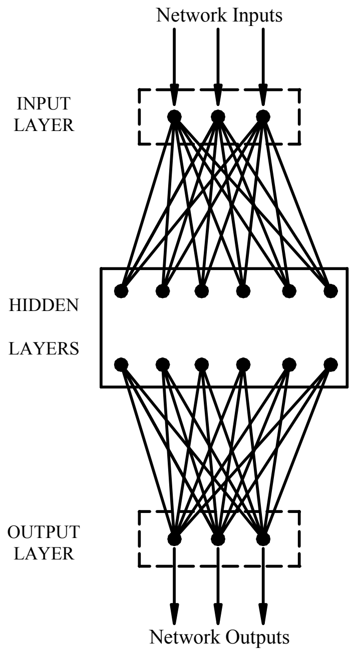



***Figure 1. A feedforward network***

In the process of training in backpropagation algorithm, firstly, the training set is presented to the network and secondly the error at the output nodes is reduced along the steepest descent direction. The initial weights and the thresholds are randomly generated at the beginning. The training set is presented to the network, until it learns the internal representation of training pairs [22]. Errors in the output determine measures of hidden layer output errors, which are used as a basis for the adjustment of the connection weights between the input and hidden layers. Adjusting the weights and re-calculating the outputs is an iterative process that is carried out until the errors fall below a tolerance level. Increasing the number of hidden layers may improve the generalization capacity. Two hidden layers are usually preferred to achieve a good convergence to the global minimum error. After training when presented with an arbitrary input pattern the units in the hidden layers of the network will respond with an active output, if the new input contains a pattern that resembles the feature the individual units learnt to recognize during training.

## 3. NEURAL NETWORK BASED ELEVATOR GROUP CONTROL SYSTEMS

The goal of elevator group control is to provide operational management of a group of elevators, by selecting cars to meet landing calls and achive passengers' destinations pleasently and promptly. The process of elevator selection is called assignment control of landing calls. This selection is often made with a large number of control indices taken into consideration, including the average elevator system reponse time and the average passenger waiting. Due to the random nature of the time and landing at which passengers arrive and request service an elevator control algorithm must be able to follow the change in passenger demand at all times. Elevator group control algorithms therefore become more complicated as they become more intelligent [23]. To solve this problem, neural networks were applied to the elevator control algorithm and optimization of the system was carried out considering many parameters such as waiting time and performance figure [15].

The primary task of an elevator group control algorithm is to enable the cars to answer the car and landing calls in the most appropriate way. An efficient elevator traffic control system has four properties [24]: to provide even service to every floor in a building, to minimize the passengers' journay time in the car, to minimze the passengers' waiting time, and to serve as many passengers as possible within a given time.

Neural network based elevator group control models continuously learn passenger arrival rate patterns throughout the day of the lift system. As this model has been implemented with neural network techniques this process is referred to as neural network training. The model can predict the passenger arrival rates for each floor and destination in the building in the future [1, 23].

## 4. NEURAL NETWORK APPLICATION IN ELEVATOR TRAFFIC MODELLING

The design of intelligent systems that model human behaviour, using neural networks, has captured the attention of the world for years. However, in view of the rapidly changing the traffic demands made on elevator systems, neural networks can respond in time to be effective. In an elevator systems, when a landing call is registered at a given floor, the information the traffic control system receives is the floor identification and desired direction of travel. The destination (next stopping) floor is not known. The information could be used by the traffic control algorithm to send the best car to answer the landing call. Neural network application in identification of vertical traffic pattern uses a neural network to perform this task [5].

Using neural networks these models can be placed in a variety of buildings and left to learn the actucal traffic pattern automatically. There is no need to predifine traffic events; output from these models simply predicts the level of traffic expected based on previos observations. Conservative approaches can not provide such flexibility and autonomous behaviour. As a preffered embodiment of this technique, population behaviour is modelled using a backpropagation neural network approach as described by Rumelhart and McClelland [19].

## 5. NEURAL NETWORKS APPLIED TO THE NEXT STOPPING FLOOR PROBLEM

The explicit problem which has been tackled is the next stopping floor problem. The next stopping floor is found as a function of the car position, landing up and down calls, and direction commitment as shown in Figure 2. In this work, to find the next stopping floor, a neural network algorithm is developed.

The flow chart of the simulation program developed, which employs both conventional control and the neural network algorithm, is shown in Figure 3.

In this work, the neural network is embedded in the car control and distribution module as shown in Figure 4. In the network, input and output layers are configured by number of floors, and two hidden layers are used. The Sigmoid non-linear function is used as threshold function. To improve the generalization of the backpropagation algorithm, the number of hidden layers are double that of the number of input layer nodes. In addition the normalizing factor and the learning rate are set at 0.5 [16].

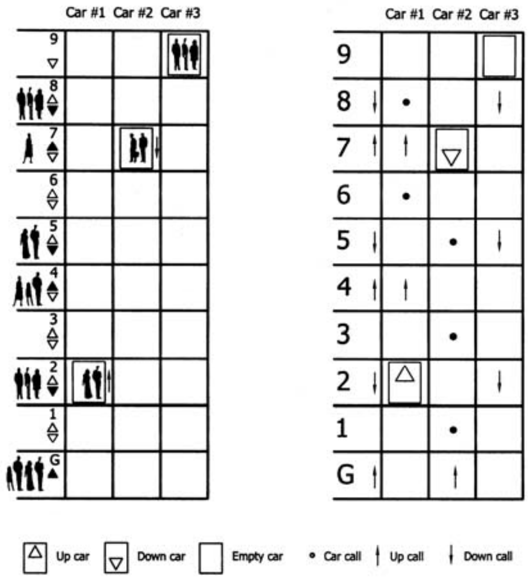



*Figure 2. Example of the next stopping floors*

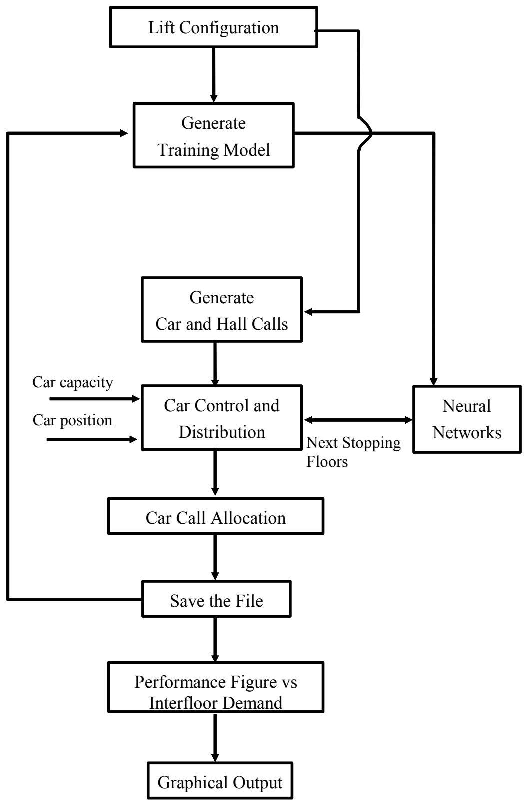



*Figure 3. General flow chart of simulation program*

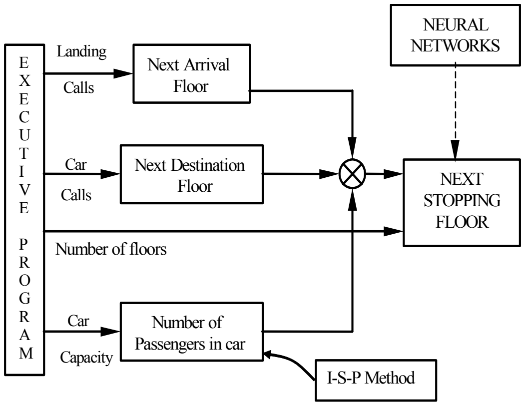



***Figure 4. Car control and distribution module***

The program uses the multi-layer backpropagation method for determining the NSF and calculates the outputs by multiplying the input matrix by the weight matrix to produce the outputs vector. Then it sets the heighest output to “1”, while setting all other ouputs to “0”. It compares this output with the desired output, and then adjusts the weights.

The program uses training patterns for training the network. All the input patterns were introduced for several epochs. The next step is to calculate the number of inputs and outputs as a function of the number of stops *n*. In order to train the neural network to be able to determine the NSF, the set of possible patterns has to be evaluated in advance, and stored in a file to be used later by the training program. The training program stops if the sum of the squares of the errors is less than 0.01 or after 1000 epochs.

The main executive program generates landing and car calls as shown in Figure 4. The car capacity is a variable input as required. The goal of the module is to obtain the NSF in order to allocate the calls to the cars. In the first step by considering the landing calls and car calls, the next arrival floors and next destination floors are determined respectively. The number of passengers, which is another component of next stopping floor, is determined using Inverse-Stop-Passenger (I-S-P) method [6].

The simulation program is executed for a test building whose technical specifications are given as follows:

| | |
|---|---|
| Building type | : Office |
| Building population | : 1000 |
| Arrival rate | : % 15 |
| Interval | : % 30 |
| Number of floors | : 9 |
| Number of cars | : 3 |
| Car capacities | : 6 |
| Contract speed | : 1.0 m/s |
| Door type | : Side open |
| Door with | : 800 mm |
| Door opening time | : 2 s |
| Door clossing time | : 2.6 s |
| Interfloor distance | : 3.3 m |
| Single flight time | : 5 s |
| Acceleration | : 0.5 m/s$^2$ |
| Passenger transfer time | : 1.2 s |

Simulations are run for several levels of interfloor traffic demand for the improved control system (ICS). At the end of each simulation, the average waiting time is recorded and the performance figure calculated by dividing the average waiting time by the interval to normalise it. Table 1 gives the comparison of the performance figures of the traffic control algorithms in a normalised form [24]. The ICS shows an improvement over the fixed sectoring priority timed system (FSPTS) and the fixed sectoring common sector system (FSCSS) control algorithm, when the interfloor demand exceeds 55%.

***Table 1. Comparison of the system performance***

| Interfloor demand | FSPTS | FSCSS | ICS |
|---|---|---|---|
| 0.1 | 25.7 | 28.5 | 42.5 |
| 0.2 | 31.4 | 37.1 | 51.3 |
| 0.3 | 45.6 | 51.3 | 64.1 |
| 0.4 | 64.6 | 66.9 | 78.8 |
| 0.5 | 86.6 | 82.8 | 93.1 |
| 0.6 | 114.0 | 106.8 | 112.4 |
| 0.7 | 143.9 | 133.4 | 134.1 |
| 0.8 | 174.9 | 163.8 | 151.6 |
| 0.9 | 209.5 | 195.2 | 168.2 |
| 1.0 | 238.8 | 226.6 | 190.8 |

## 5. CONCLUSION

When applied to elevator installations, neural network based ICS is able to dynamically learn the behavior of the building traffic characteristics and predict future events based on what has been learnt. The application of ICS in elevator installations may shorten the waiting time by forecasting the positions of the cars and using call distribution laws. This system can recognize the changes in traffic patterns during the daytime and automatically adapt the control system to the changes. Artificial neural networks improve the performance of an elevator control system.

## REFERENCES

[1] Barney, G.C., “Elevator Traffic Handbook”, Spon Press, London, 2003.

[2] Waering, M., “A Network For Lift Status Monitoring”, MSc. Dissertation, UMIST, UK, 1983.

[3] Alexandris, N., Chrissikopoulos, V. and Vassilacopoulos, G., “Lifts- An Expert System For Lift System Design”, Elevator Technology 2, IAEE Publ., pp. 1-9, 1988.

[4] Prowse, R.W., Thomson, T. and Howells, D., “Design and Control of Lift Systems Using Expert Systems and Traffic Sensing”, Elevator Technology 4, IAEE Publ., pp.219-226, 1992.

[6] Al-Sharif, L.R., “Predictive Methods in Lift Traffic Analysis”, PhD thesis, UMIST, UK, 1992.

[7] Ho, M. and Robertson, B., “Elevator Group Supervisory Control Using Fuzzy Logic”, Canadian Conference on Elevator and Computer Engineering, **2**, 11.4.4, 1994.

[8] Qun, Z., Ding, S., Yu, C. and Xiaofeng, L., “Elevator Group Control System Modeling Based on Object Oriented Petri Net”, Elevator World Magazine, 2001.

[9] Chan W.L. and So, A.T.P., “Dynamic Zoning for Intelligent Supervisory Control”, Int. to Elevator Engineering, Vol.1, pp. 1-10, 1996.

[10] Siikonen, M-L., “On Traffic Planning Methodology”, Elevator Technology 10, IAEE Publ., pp.267-274, 2000.

[11] Closs, G.D., “The Computer Control of Passenger Traffic in Large Lift Systems”, PhD Thesis, UMIST, UK, 1970.

[12] Imrak, C.E., “Elevator Control Systems and Traffic Analysis”, Proceedings of 7th International Machine Design and Manufacturing Congress, Ankara, pp. 351-360, 1996.

[13] Rooney, M.F. and Smith, S.E., “Artificial Intelligence in Engineering Design”, Comput. Struct., Vol.16, pp. 279-288, 1983.

[14] Miravete, A.,”New Materials and New Technologies Applied to Elevators”, Elevator World Inc., 2002.

[15] Imrak, C.E., “Traffic Analysis, Design and Simulation of Elevator Systems”, PhD. Thesis, ITU, Istanbul, 1996.

[16] Imrak, C.E. and Ozkırım, M., “The Modeling And Simulation Of Elevator Group Control Systems For Public Service Buildings, Preprints the 3rd IFAC Workshop DECOM-TT 2003, Istanbul, pp. 159-164, 2003.

[17] Korn, A.G., “Neural Networks and Fuzzy-Logic Control on Personal Computers and Workstations”, MIT Press, London, 1995.

[18] Lisboa, R.G., “Neural Network Current Application”, Chapman and Hall Pub., New York, 1992.

[19] Rumelhart, D.E. and McClelland, J.L., “Parallel Distributed Processing, Vols 1 and 2”, MIT Press, Cambridge, 1986.

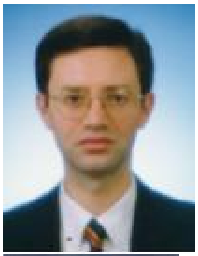
[20] Lippmann, R.P., “An Introduction to Computing with Neural Nets”, IEEE ASSP Magazine, Vol.4, pp. 4-22, 1987.

[21] Rumelhart,D.E., Hinton, G.E. and Williams, R.J., “Learning Representations by Backpropagation Errors”, Nature, Vol.323, pp. 533-536, 1986.

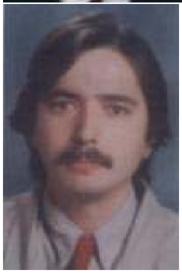
[22] Mukherjee, A. and Deshpande, J.M., “Application of Artificial Neural Networks In Structural Design Expert Systems, Computer & Structures, Vol.54, No.3, pp. 367-375, 1995.

[23] Barney, G.C. and Dos Santos, S.M., “Elevator Traffic Analysis, Design and Control”, Peter Peregrinus Ltd., London, 1985.

[24] Imrak, C.E. and Barney, G.C., “Application of Neural Networks on Traffic Control”, Elevator Technology 9, IAEE Publ., pp. 140-148, 1998.



**C.Erdem İMRAK** has been employed as a Lecturer in Istanbul Technical University (ITU). Dr İmrak received the B.Sc., M.Sc. and Ph.D. degrees in Mechanical Engineering from ITU in 1990, 1992 and 1996 respectively. He has carried out research into materials handling and especially lift systems. Currently his activities include: Vice-dean of Faculty of Mechanical Engineering, ITU; a Member of ASME; a Member of the IAEE; a Member of Chamber of Mechanical Engineers in Turkey; a Member of Steering & Consulting Committee of Asansor Dunyasi Magazine and a Member of International Committee of Elevatori and Rapporteur from Turkey.



**Mustafa ÖZKIRIM** has been employed as a research assistant in Istanbul Technical University (ITU). Mr Özkırım received the B.Sc., M.Sc. in Mechanical Engineering from ITU in 1980 and 1984 respectively. He has carried out research into materials handling and production systems. Currently his activities include: a Research Assistant and a Member of Chamber of Mechanical Engineers in Turkey.