APPLICATION OF NEURAL NETWORKS ON TRAFFIC CONTROL

Dr.Ing.C.Erdem Imrak* and Dr.Eur.Ing.G.C. Barney+:
*Istanbul Technical University, Inonu Caddesi No.85, Istanbul 80191, Turkey;
+Lerch, Bates & Associates Ltd, Kendal, Cumbria, LA8 8AP, England.

ABSTRACT
Digital computer parallel processing and the learning ability of neural networks techniques are widely used in solving engineering problems. In lift traffic control, neural networks can be used to distribute the most suitable cars to answer calls in the building. In this paper neural networks are used in a Duplex/Triplex traffic control for improving passenger waiting time. Lift traffic analysis and simulation results were obtained by running computer software programs for different building types and parameters and then compared to other control algorithms.

1. INTRODUCTION

Passenger traffic flows increase proportionally, as the number of floors increase in high rise buildings. Thus it becomes essential to use the lift installation in these buildings more effectively. High rise buildings, which have a large vertical transportation capacity obviously require more than one lift. Therefore the need for more effective lift control systems has become important.

Digital computers can be used to make decisions on how the cars should be distributed around the building in the long term. The advent of time sharing digital computers and graphical terminals have made it possible for designers to obtain an extremely close contact with the design by means of conversational software techniques.

The need for more intelligent lift control systems has been recognized. Artificial intelligence based lift control systems known as knowledge based systems, expert systems, fuzzy logic and neural networks have evolved. The use of neural networks, which models human behaviour, has captured the attention of the world for years. Their application to lift traffic control is not surprising.

The work described here arose, when the second author (Barney) challenged the first author (Imrak) to prove or disprove whether neural networks could improve lift traffic performance. As neural networks had not been able to make millionaires on the stock markets, why should they be able to react to the rapidly changing traffic conditions in a building ?

AN INTERLUDE: ***To explain the theory.***

2. NEURAL NETWORKS AND LEARNING ALGORITHMS

Neural networks are composed of elements, that are designed to model some of the more elementary functions of their biological counterparts, the neurons. Neural networks model the human brain's cognitive process. An artificial neuron is a very approximately simulated mathematical model of a biological neuron.

Each neuron has one output, which is generally related to the state of the neurons, and receives several inputs. The inputs are the activation of the incoming neurons multiplied by the weights as seen in Figure 1. The activation of the neuron is computed by applying a threshold function to this product. The Sigmoidal function is generally used as a threshold function because of simulating biological neurons activities (Lisboa, 1992).

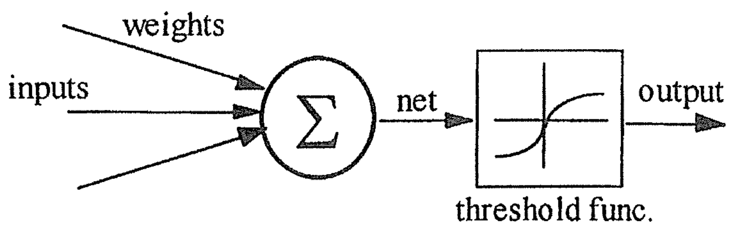

Figure 1: a model of an artificial neuron

The technique of backpropagation is a systematic method for training multilayer neural networks. A multilayer backpropagation algorithm, which is the most well known learning algorithm has three layers of neurons:

- an input layer
- hidden layers
- an output layer.

The input layer configuration depends on the possible parameters, that effects the network outputs. The careful selection of the input parameters may improve the network performance and reduce the learning time. The use of a binary type of input is also recommended instead of a normalized continuous valued input. The selection of a threshold function depends on the network and method of learning. Using the backpropagation learning algorithm the Sigmoidal function is used as a threshold function.

It is possible to derive the backpropagation algorithm with a few iterated applications of differential calculus and embed them in the stochastic (random) approximation frame work. In the backpropagation algorithm first: the training set is presented to the network and then second: 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 (Mukherjee & Despande, 1995).

Increasing the number of hidden layers may improve the generalization capacity. Two hidden layers are preferred, because a network with one hidden layer can not achieve good convergence.

The number of output parameters depends on the number of desired output parameters. The use of the higher number is not desired as the networks are generally simulated on the computer and this can create floating point overflow problems. It is essential to normalize the input/output values to suit the network function. The backpropagation algorithm as a feed forward network is as seen in Figure 2.

The training set is presented to the network, until it learns the interval representation of training pairs. Normally, it takes a long time for the successful training of a network using the backpropagation algorithm. The organization of training set is not important, but it is found that if the weights are not updated for each epoch, the positioning of the training set does affect the learning speed.

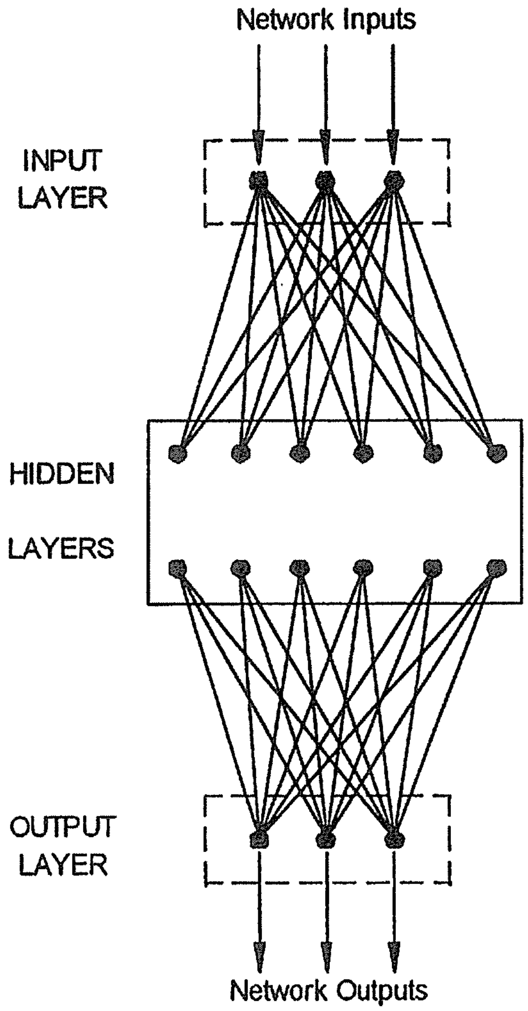

Figure 2: Multilayer backpropagation

3. LIFT CONTROL ALGORITHM

Once larger and taller buildings were built, more than one lift car in a building was needed, in order to meet the traffic demand for the higher handling capacity of vertical transportation installation, owing to the growing size of the building's population. A lift traffic control system is necessary to organize traffic and minimize the passenger waiting times according to the building characteristics.

The primary task of a lift control algorithm is to enable the lifts to answer the car and landing calls in the most appropriate way. An efficient lift traffic control system has four properties:

1. To provide even service to every floor in a building.
2. To minimize the passengers' journey time in the car.
3. To minimize the passengers' waiting time.
4. To serve as many passengers as possible in a given time.

The above requirements result from the random nature of the time and landing at which passengers arrive and request service. This means that the lift traffic control algorithm must be able to follow the changes in passenger demand at all times (Barney & Dos Santos, 1985).

The goal of lift traffic group control is to provide the operational management of a group of lifts by selecting cars to meet hall calls originating from the landings. The process of lift car selection is called hall call assignment. This selection is made with a large number of control indices taken into consideration, including the average passenger waiting time and maximum passenger waiting time.

Lift traffic control has become more complicated as it becomes more intelligent. The aim of the lift traffic control system is to control the cars as a group and passengers' destinations pleasantly and promptly. Its unique function is to select and distribute the most suitable cars as an assignment of landing and car calls. To solve this problem, neural networks were applied to the lift traffic control algorithm and optimization was performed against many parameters such as passenger average waiting time and performance figure (Imrak, 1996a).

4. NEURAL NETWORKS IN LIFT CONTROL

The backpropagation algorithm is used as an exploration into the possibilities of the various fields in which neural networks can be applied in lift control. Neural networks are usually applied to problems, where no set of clear and decisive rules exist, and where the nature of the problem requires intuitive reasoning, such as pattern recognition problems.

The need for more intelligent lift traffic group control systems has been recognized. Consequently, the artificial intelligent traffic processor has been designed as a number of modules or objects which interact with each other, resulting in a more flexible and intelligent system. Modelling and prediction of traffic patterns has already been identified as a possible means of improving passenger service.

In particular, these neural network techniques provide systems for traffic modelling, which automatically adapt to changes in traffic behaviour without the redefinition of events; produces the traffic generation as well as the traffic patterns; and provides predictive information.

Applied to lift installations, neural networks potentially provide the mechanism for dynamically learning the behaviour of a building and predicting future events based on what has been learnt. To do this neural networks are inserted into an lift traffic control algorithm and are made to model the behaviour of building population and to automatically adapt the algorithm to changes in traffic behaviour without any further redefinition. Neural networks applied lift traffic control systems can shorten the waiting time by forecasting car position and using call distribution laws. This system recognizes the change of traffic during the day time and adapts the control system (Imrak, 1996a).

Neural networks as applied lift control system is illustrated in Figure 3. Landing and car calls with car positions are the input data of control system, and also building configuration effects directly the control unit and neural networks unit. The outputs of the control system are the distribution of calls to the most suitable cars and car direction. The artificial intelligence traffic modelling and prediction system uses several neural networks for the lift traffic control. It optimizes a suitable allocation of landing calls to cars in order to the serve the calls.

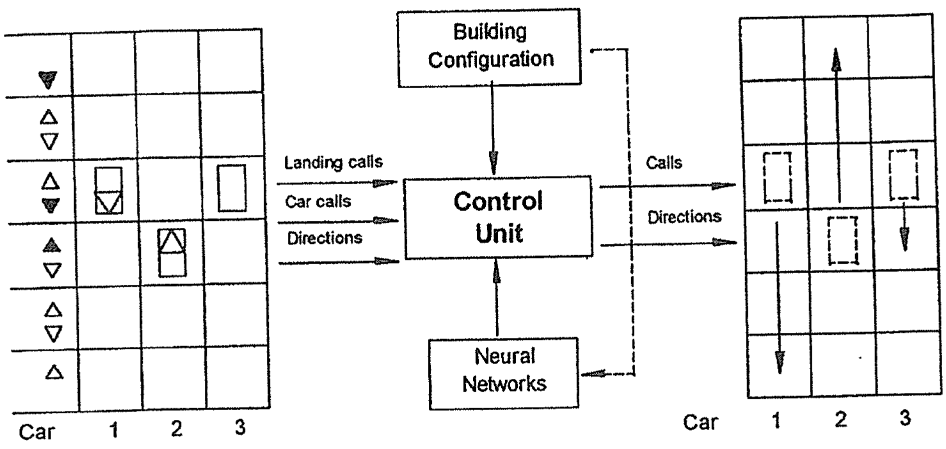

Figure 3: Flow chart of lift control

These neural network models can be placed in a variety of buildings and left to learn the actual traffic patterns automatically. There is no need to predefine traffic events; output from these models simply predicts the level of traffic expected based on previous observations. This is especially important where behaviour which previously was defined as heavy is now average when compared to other floors. Current approaches cannot provide such flexible and autonomous population behaviour is modeled using a backpropagation neural networks approach.

5. STRUCTURE OF SIMULATION PROGRAM

A backpropagation algorithm was used in the neural networks lift traffic modelling and simulation program. Input and output layers were configured by the number of floors, and two hidden layers were used. The Sigmoidal non-linear function was used as the threshold function. To improve the generalization, the two hidden layers' nodes have twice the number of the input layer's node each. In addition, the normalizing factor and the learning rate were set at 0.5 (Imrak, 1996b).

The traffic modelling and control module is shown in Figure 4 and is part of the simulation program. It allocates the calls to suitable cars according to the duplex/triplex control algorithm as improved by the neural networks.

The main executive program generates the landing and car calls. The car capacity is selected by users. The goal of the module is to obtain the next stopping floor, which is important in the allocation of the cars. In the first step, the landing calls and car calls, next arrival floors and next destination floors are determined using the neural networks. The number of passengers which is another component of next arrival floor decision is determined using Inverse-Stop-Passenger (ISP) method (Al-Sharif, 1992). After two steps the next stopping floors can be determined using neural networks.

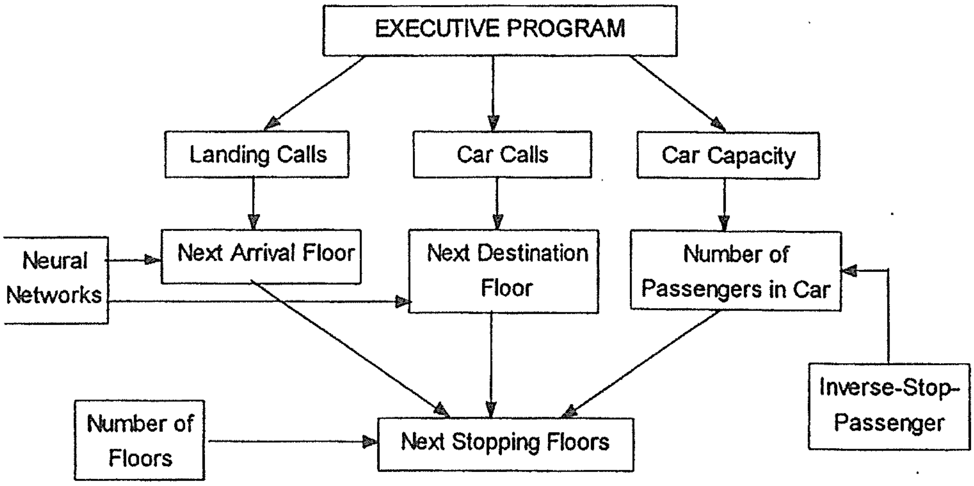

Figure 4: Traffic modelling and the control module

The general flow chart of the improved duplex/triplex (IDT) control algorithm, which has the advantages of both the conventional duplex/triplex control algorithm and neural network is shown as Figure 5. In this control system the neural networks are used to allocate the calls to the best cars during the day period by means of weighted matrix. This system also learns the passengers' demand through out the daytime and sets the car movements into the building with parking function.

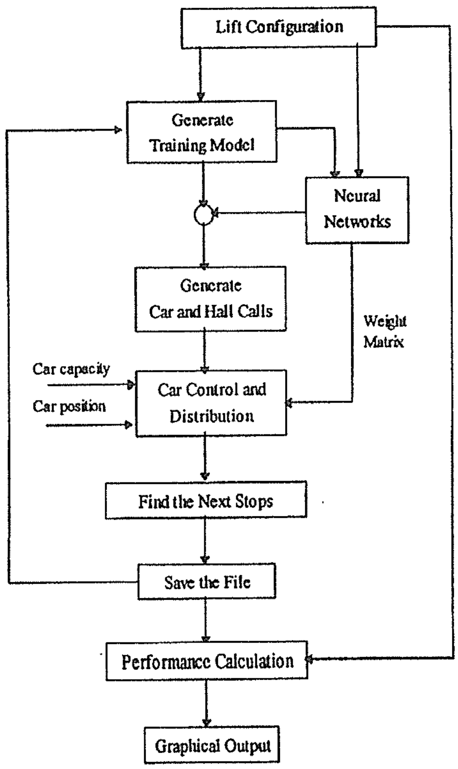

Figure 5: General flow chart of IDT control

6. TEST SYSTEM

To investigate the improvement in this control algorithm, neural networks were introduced into an lift control algorithm and optimization was carried out with many parameters such as passenger waiting time and various performance criteria (Imrak & Barney, 1997). The chosen system was a duplex/triplex control system, which is suitable for groups of two or three cars in low rise buildings and distributed the cars on the registration of landing calls according to the directional distributive control principles. The car answers its landing and car calls in floor sequence from its current position and in the direction of travel to which it is committed. The allocation procedure has some similarities with dynamic sectoring (Barney & Dos Santos, 1985), however it does not take significant advantage of the direction of landing call. This algorithm provides reasonable interfloor traffic performance, which is the pattern to be considered.

The simulation program is executed on a pseudo building with nine (9) floors, excluding the main terminal. Three cars with various rated capacities are used to service the whole building. In this program: interfloor distance, rated speed, door operating times, passenger transfer times are chosen by the user.

Simulations were run for several levels of interfloor traffic demand level (β) for the improved duplex/triplex (IDT) control system. At the end of each simulation, the average passenger waiting time was noted and the performance figure calculated by dividing it by the interval to normalize it. The results are plotted in Figure 6 as a comparison with other traffic control algorithms (Imrak, 1996a; 1996b). The IDT algorithm shows an improvement over the FS4 (fixed sectoring, priority timed) and the FSO (fixed sectoring, bidirectional sectors) control algorithms over 55% of interfloor demand. It also shows that the improved duplex/triplex control system is less effective for balanced interfloor traffic compared to the DS (dynamic sectoring), CGC (computer group control) and ACA (adaptive call allocation) control algorithms. Table 1 shows the tabulated results of simulations for all the control algorithms which were compared. (Imrak & Barney, 1997).

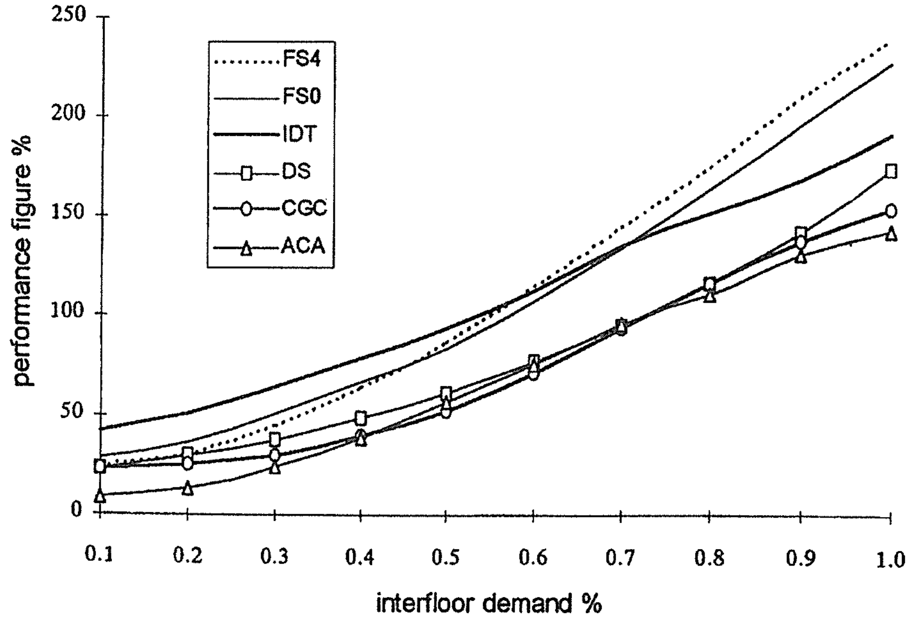

Figure 6: Interfloor performance of the control algorithms

Table 1: Comparison of interfloor performance for different traffic control algorithms

β	FS4	FSO	IDT	DS	CGC	ACA
0.1	25.7	28.5	42.5	23.2	23.8	8.8
0.2	31.4	37.1	51.3	29.5	25.1	12.8
0.3	45.6	51.3	64.1	37.7	29.5	24.2
0.4	64.6	66.9	78.8	49.0	39.9	38.5
0.5	86.8	82.8	93.1	61.5	52.1	57.0
0.6	114.0	106.8	112.4	77.2	70.9	75.5
0.7	143.9	133.4	134.1	94.8	92.9	95.5
0.8	174.9	163.8	151.6	115.5	115.5	109.7
0.9	209.5	195.2	168.2	140.6	136.8	129.7
1.0	238.8	226.6	190.8	173.2	153.1	142.4

7. CONCLUSION

A neural network aided traffic control algorithm, was included in the conventional duplex/triplex control system to improve its performance. Under a heavy interfloor demand it shows better performance than the fixed sectoring systems such as FS4 and FSO, but it is still has a poorer performance against the other traffic control systems. In low rise buildings it gives a better performance against the conventional traffic control systems. To improve the IDT interfloor performance further, the neural network learning algorithm must be improved or the backpropagation algorithm changed.

No firm conclusion can be drawn from this work as to whether neural networks improve traffic performance as only a very simple traffic control system (duplex/triplex) applied to a small lift installation (3 lifts x 9 floors) has been analysed. The limitations were due to the digital computing power employed for the work (PC-386 machines), not being sufficient powerful to carry out the computations in real time. Further work needs to be carried out with more powerful digital computers (PC-300 MHz Pentiums) with up to eight lifts serving at least 16 floors.

The jury is still out.

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ABOUT THE AUTHORS

C.Erdem Imrak, received the B.Sc., M.Sc. and Ph.D. degrees in Mechanical Engineering from Istanbul Technical University (ITU) in 1990, 1992 and 1996 respectively. He was a visitor researcher in UMIST from 1994 for a period of one year. Dr. Imrak has carried out research into materials handling and especially lift systems. Currently his activities include: Lecturer in ITU, a Member of International Committee of Elevatori and Rapporteur from Turkey; a Member of Steering & Consulting Committee of Asansor Dunyasi Magazine; a Member of the International Association of Elevator Engineers and a Member of Chamber of Mechanical Engineers in Turkey.

G.C.Barney, has the degrees of B.Sc. and M.Sc. from Durham University and a Ph.D. from Birmingham University, the latter for work on four quadrant thyristor power supplies. Joining UMIST in 1967, Dr. Barney has carried out research into many aspects of lift systems. An energetic writer, he has authored, co-authored or edit some 15 books and 80 papers on a variety of topics. Currently his activities include: Chairman of Lerch, Bates & Associates Ltd.; Visiting Senior Lecturer, UMIST; English Editor, Elevatori; Chairman of the Board of Executives of the International Association of Elevator Engineers; a Member of the British Standards lift committee MHE/4 and Principal of OutReach Collage.