Elevator Group Control System
with a Fuzzy Neural Network Model

S. Kubo*, S. Nakai*, N. Imasaki**, T. Yoshitsugu***
* Toshiba Corp., Fuchu Works , Tokyo, Japan
** Toshiba Corp., Systems & Software Engineering Lab., Kawasaki, Japan
*** Toshiba Corp., Elevator & Escalator Div., Tokyo, Japan

Abstract

With the increase in construction of tall buildings and skyscrapers, elevators have become even more important to transport passengers to and from the higher floors.

We have developed a high-performance system that has a fuzzy neural network model. This model reduces the passengers' waiting time in various traffic situations. The fuzzy neural network consists of neural networks that perform the fuzzy rule-based approximate reasoning.

We also improved the control system by making it more efficient and reliable by adopting a decentralized control technology and 32-bit microcomputers.

1. PREFACE

Large high-rise buildings, dependent on elevators for their principal means of transportation, require streamlined control of the elevators to handle the complex demand for traffic efficiently. With the onset of the present era of intensified information flow, intelligent buildings have come into existence in big cities to make better use of telecommunication facilities, thereby calling for more sophisticated functionality from elevators than ever. The demand for elevators has been evolving shorter and more uniform waiting times to include increased convenience and comfort for the tenants, quick responses to the needs of the building administrator, and added system reliability.

To address these needs, we have renewed the existing artificial intelligence (AI) based elevator group control system, called Command-AI [1], and developed it into the EJ-1000FN. The EJ-1000FN takes advantage of the learning facilities of neural networks to adapt to changing traffic conditions in buildings of various kinds. At the same time, two similar systems tailored to smaller buildings have been developed as the EJ-100F and EJ-10F to complete the EJ-1000 series (Figure 1).

This paper presents a summarized description of the elevator group control system, EJ-1000FN, that tops the EJ-1000 series.

<table>
<tr><th>Model</th><th>EJ-1000FN</th><th>EJ-100F</th><th>EJ-10F</th></tr>
<tr><td>Number of Elevators</td><td>3～8</td><td>3～6</td><td>3～4</td></tr>
<tr><td rowspan="8">Basic Specifications</td><td colspan="3">Sensitivity Assignment Control (Control Applied Fuzzy Theory)</td></tr>
<tr><td colspan="3">Expert System</td></tr>
<tr><td colspan="3">Program Editing Function</td></tr>
<tr><td colspan="2">Function with Peak Operation</td><td rowspan="5"></td></tr>
<tr><td>Control Applied Neural Networks</td><td rowspan="4"></td></tr>
<tr><td>Learning Function</td></tr>
<tr><td>Traffic Harmonizer</td></tr>
<tr><td>Forecasting Assignment Function</td></tr>
</table>

Figure 1 Principal Functions by Model

2. Scheme of Elevator Group Control Based on Fuzzy Neural Network Concepts

2.1 Background

The goal of elevator group control is to provide operational management of a fleet of elevators, selecting elevators to meet calls originating from the halls (hereafter called hall calls), and lighting the hall lantern to guide the passengers waiting on the hall into the elevator as it comes around.

The process of elevator selection is called assignment control of hall calls. This selection is made with a large number of control indices taken into consideration, including the average waiting time, maximum waiting time, and hit ratio. Assignment control can be thought of as a decision problem, in which the most suitable plan is selected from a choice of N substitute plans (N: number of elevators available).

The environments in which elevator group control systems are used to manage fleets of elevators are characterized by:

(1) A large number of uncertainties prevailing, such as the occurrence of passengers on the halls and their destinations
(2) Changing traffic conditions in the buildings associated with environmental factors, such as time zones and the structure and use of the building.

A key to optimal operational management is the ability to predict uncertainties to meet the status of the system. What is equally important is to set appropriate control variables to keep track of various traffic scenes.

The previous control method would approach the problem (1) by using a fuzzy predict and control method[2] to formulate factors that could add to the ambiguity of the predictions developed by an elevator group control system and give a fuzzy representation to the knowledge needed to render decisions on the basis of these predictions. As for problem (2), however, the previous method would occasionally fail to come up with optimal control variables to keep track of changing traffic conditions following the opening of the buildings because its idea was to select control variables that had been calculated and preset by way of simulation to fit into specific traffic conditions.

In rule-based approaches to reasoning, an example of which is an implementation of the theory of fuzzy control, optimal tuning of control variables is important, which involves modeling the system to provide insight into the relationship between control variables and controlled responses. Systems that are intricately affected by uncertainties, such as elevator group control systems having building uses and time zones as variable factors, have been impractical to model with precision because of the unavailability of system solutions.

With the method developed this time, system modeling was accomplished by having the correlations between control variables and waiting times, or controlled responses, stored in memory for each set of traffic conditions on the halls by taking advantage of the learning facilities of a neural network. Consequently, a mix of control variables that yields an optimal waiting time for specific traffic conditions could be extracted, thereby allowing optimal control variables to be set to keep trace of a broad set of traffic conditions.

2.2 Fuzzy Neural Network Application System

As an evaluation function for the assignment control of hall calls, the linear sum of the evaluation result of multiple control indices with the addition of a weighting coefficient is used, so choice is made of the elevator having the least of such linear sums. These control indices are closely related to one another, requiring optimal tuning of the weighting coefficient in various traffic conditions associated with the use and time zone of the building.

Figure 2 shows the configuration of the fuzzy neural network application system. The control variable tuning unit, which optimizes the value of the weighting coefficient of each control index to serve as a control variable, is made up of a forecasting model and a control variable choosing unit.

On reading traffic conditions from the elevator group and candidate control variables from the control variable choosing unit, the forecasting model forecasts and generates a waiting time distribution of controlled responses associated with each control variable on the basis of the current traffic conditions.

The control variable choosing unit generates a candidate control variable to the forecasting model upon lapse of a predetermined time zone and gives a quantitative evaluation to the forecasted waiting time distribution received from the forecasting model according to the use of the building and traffic conditions to optimize the distribution. The candidate variable that yields the forecasted waiting time distribution thus extracted is issued to the elevator group control unit as an optimal control variable.

A fuzzy neural network is implemented in this forecasting model. It is a technique of representing fuzzy rules in a neural network for reasoning[3]. A neural network is an engineering model representation of the functions of human or animal brains. The nonlinearity and learning facilities of the neural network make it possible to build an adaptable model capable of high-speed reasoning and forecasting to meet short- and long-term changes in the traffic conditions. Short-term changes are the changing traffic conditions from one time zone within a day to another; long-term changes are the changing traffic conditions over months or even years. The forecasting model can deal with short-term changes by defining the entire set of traffic conditions as an input space and long-term changes by implementing a learning ability in the fuzzy neural network.

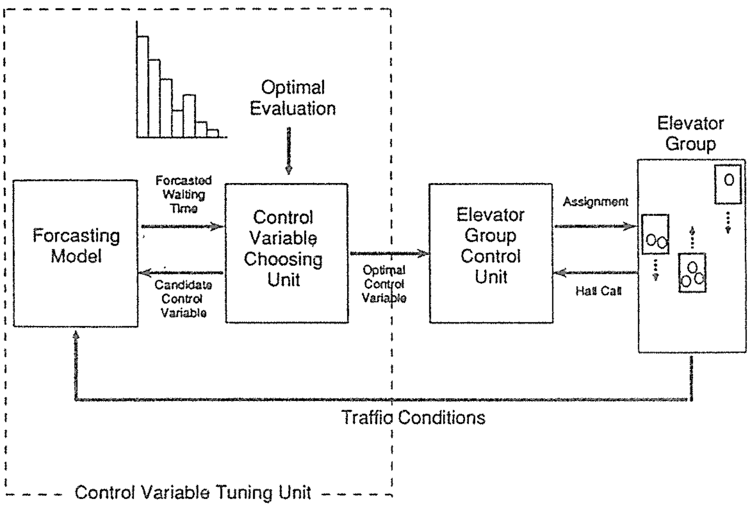


Figure 2 Fuzzy Neural Network Application System

2.3 Modeling an Elevator Group Control

Figure 3 shows the configuration of the forecasting model based on fuzzy neural networks. Traffic conditions are represented in three elements: the overall average interval of passenger birth D1, the average interval of passenger birth from the hall floor D2, and the average interval of passenger birth to the hall floor D3. D1 to D3 and the candidate control variable α from the control variable choosing unit are used as input. The controlled response of the elevator group control system, or the output of the forecasting model, is a distribution of waiting times on the hall. The waiting time distribution gives a seven-dimensional chart of the percentage ratios of the hall calls for waiting times of 0 to 10 seconds, 10 to 20 seconds, 20 to 30 seconds, 30 to 40 seconds, 40 to 50 seconds, 50 to 60 seconds, and longer.

The relationship between the input and output is represented in fuzzy rules, which are formed into a forecasting model by using neural networks. Specifically, the input traffic conditions (D1, D2, and D3) are divided into three fuzzy rules, that is, high demand (H), medium demand (M), and low demand (L), about each of the three axes, or into a total of 27 input subspaces (H-H-H, ..., L-L-M, L-L-L), with which submodels having the I/O relationship between the control variable and the waiting time distribution y ($f_{HHH}(\alpha)$, ..., $f_{LLM}(\alpha)$, $f_{LLL}(\alpha)$) for fuzzy representation in the following rules:

IF (decision based on traffic conditions) THEN (submodel selection)

For example, when the demand towards the hall floor, as during attendance or departure hours, is dominant, the following rule has a higher degree of fitness:

IF (D1 = H) & (D2 = L) & (D3 = H) THEN $y = f_{HLH}(\alpha)$

This rule means that the model $f_{HLH}(\alpha)$ is used when the demand for traffic in the building as a whole is high, with low demand for traffic from the hall floor and high demand for traffic to the hall floor.

In the traffic condition that completely belongs to one input subspace, the submodel associated with the input subspace generates a forecasted waiting time distribution. For a traffic condition locating on the boundary between two input subspaces, the forecasted waiting time distribution is the synthetic value of the output of the multiple submodels around the boundary.

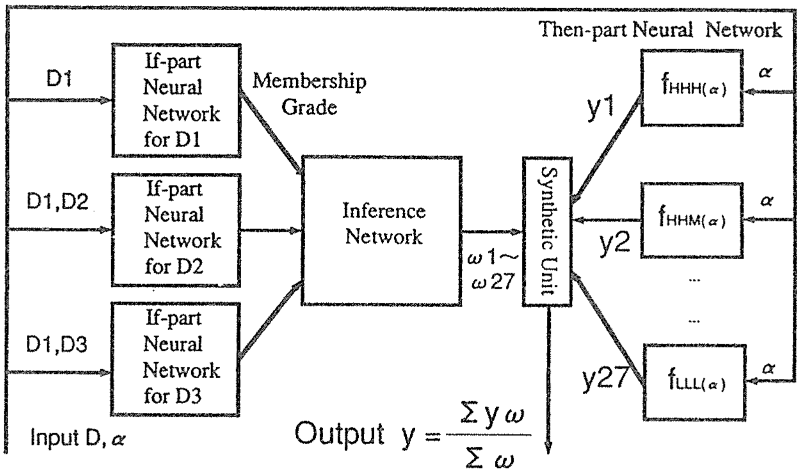
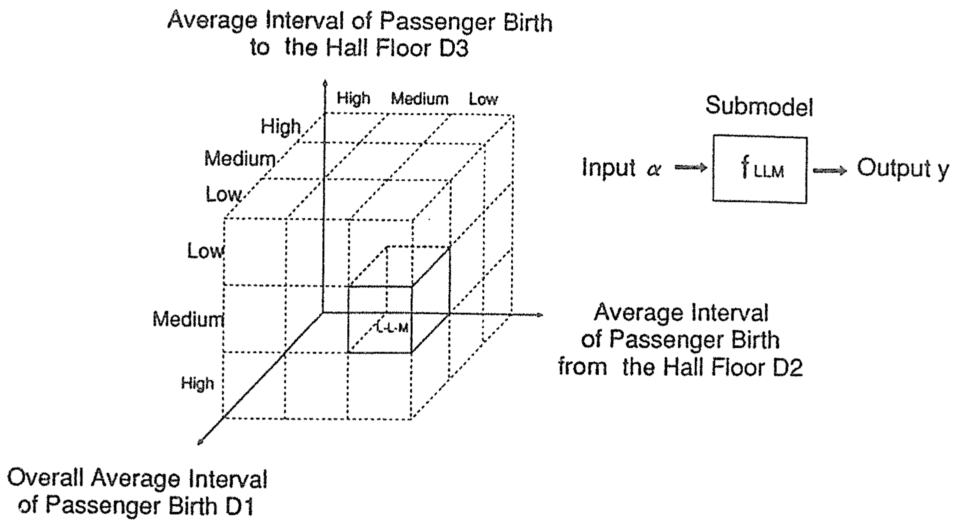


Figure 3 Forecasting Model Configuration

Fuzzy division of the input space is accomplished by creating a if-part neural network for each input variable D as a feedforward network in which membership functions are learned by back propagation (BP)[4]. Then-part networks are formed as feedforward networks in



(1) Fuzzy Division of Input Space (2) Submodel Associated with a Subspace

Figure 4 Fuzzy-divided Input Space

which the relationships at the control variables at representatives in the input subspaces and waiting time distributions are learned by BP. An inference network, composed of two bidirectional associative memories (BAMs)[5], stores the logical relationships between the traffic conditions, or the if-parts of fuzzy rules, and the waiting time distributions, or output of the then parts to form a forecasting model with overall I/O characteristics. The operational sequence of the forecasting model is described below.

(1) Traffic conditions are entered into the if-part networks to determine their degree of fitness to the traffic conditions.
(2) The degree of fitness is entered into the inference network to obtain the weights w1 to w27 to the then parts.
(3) Control variables are assigned to the then-part networks to obtain the waiting time distributions y1 to y27, or output of the then parts.
(4) The waiting time distributions y1 to y27 are weighted with the weights w1 to w27 for output of the overall waiting time distribution y.

The forecasted waiting time distribution y is given by solving the equation:

$$y = \sum_{i=1}^{27} \frac{yi \cdot wi}{wi}$$

The fuzzy neural network thus operates on the basis of an integration of multiple neural networks. The control variable selecting unit quantitatively determines the waiting time distributions generated by the forecasting model according to such elements as the ratio of longer waiting times, average, and standard deviation, so that the elements weighted with weighting coefficients set by the building use or time zone are added together. In office buildings, for example, more weights are given to the average to allow faster responses when the demand for traffic is low; as the demand for traffic increases, more weights are given to the ratio of longer waiting times to allow fewer passengers left waiting for long. Control variables can thus be set to meet the use of a particular building or time zones.

2.4 Fuzzy Neural Network Simulator

Prior to implementing an automatic control variable tuning facility based on fuzzy neural networks in the elevator group control system, a fuzzy neural network simulator was developed to verify the facility and support the design of a forecasting model composed of fuzzy neural networks[6]. Written in the C language, the simulator allows a software implementation of the automatic control variable tuning facility or data on a forecasting model that has undergone initial learning of neural networks to be directly assembled into a production system.

Figure 5 shows an example of the working screen of the simulator running on the workstations AS4000.

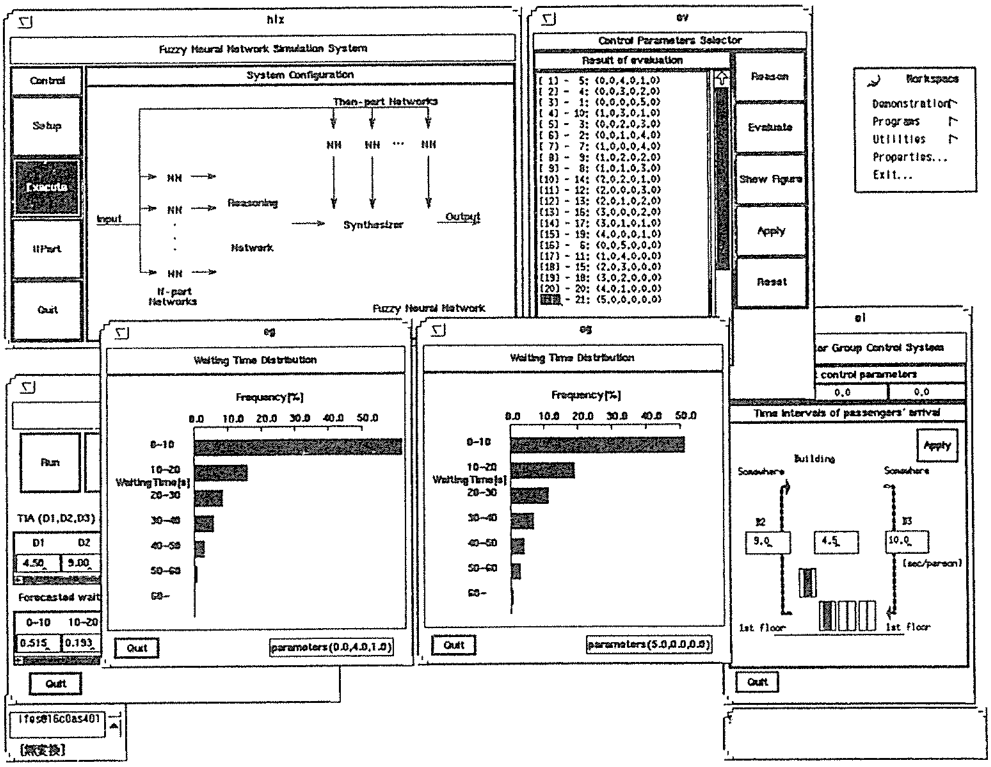
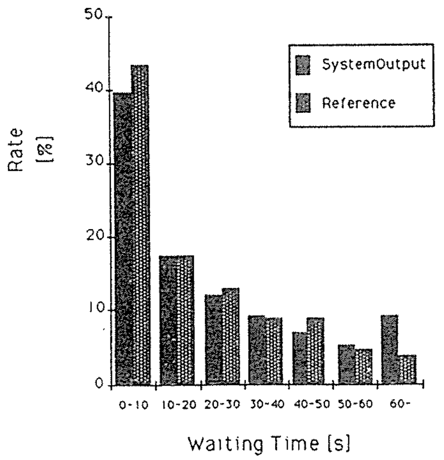


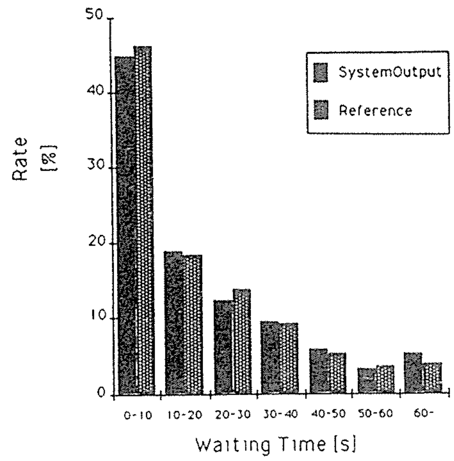
Figure 5 Typical Simulator Working Screen

The forecasting model was verified by using this simulator. For added adaptability of the forecasting model, the interval of passenger birth was set up across the whole set of traffic conditions beforehand, then combined with possible candidate control variables to produce several hundreds of waiting time distributions, which were collected by elevator group control simulation as teaching data for learning by the forecasting model. Verification was effected by comparing the forecast with regard to the intermediate value of the average interval of passenger birth that has been set in creating the forecasting model and the result of elevator group control simulation. Figure 6 gives typical forecasts with regard to the two intermediate values, one for high traffic demand and one for low traffic demand.

A comparison of the forecasts and simulation results reveals differences on the order of several tens of percent in the ratio of 60 second or longer waiting times, but generally, the differences are held to only several percent, thus supporting the exceptional high precision of the forecasts. This finding demonstrates the predictability of waiting time distributions similar to the actual response results even if various patterns of traffic demand different from teaching data are input the proof of usefulness of our forecasting model as a means to predicting waiting time distributions.



(1) Hall Call Birth Frequency
for The Intermediate Value
of High Demand



(2) Hall Call Birth Frequency
for The Intermediate Value
of Medium Demand

Figure 6 Typical Forecasts by the Forecasting Model

2.5 Verifying Performance by Elevator Group Control Simulation

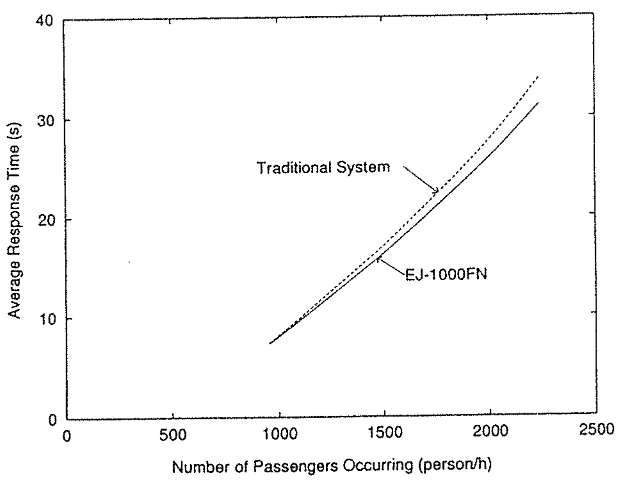
The new system based on the fuzzy neural network concept and the traditional system were compared in terms of their performance by means of elevator group control simulation.

The simulation model under discussion consisted of the following conditions:

-Number of elevators: 8
-Elevator speed: 420 m/min.
-Passenger capacity: 24 passengers
-Service floors: 15 (B1, 1 to 3, 22, and 30 to 39)
-Floor-to-floor traffic ratio: 50%

The conditions set above assumed floor-to-floor traffic in the single-office occupancy mode and an upper service bank in normal operation.

As can be seen from the simulations given in Figure 7, our system excelled the traditional system in both categories of the average response time and the long waiting rate. As a whole, our system was found to offer about a 10% decrease in the long waiting rate.



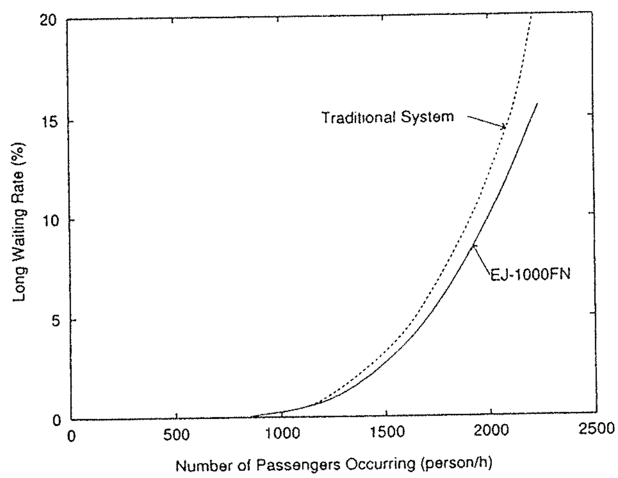


Figure 7 Simulation Results

3. Elevator Group Control System

3.1 System Features

System specifications unique to the use of a particular building are predefined and factored into the system when the building is planned. A need may arise to make modifications to the specifications when construction of the building is completed and it is commissioned into service. To allow for this situation, facilities are available to set interfaces with the elevator system and make modifications to the specifications without shutting down the system.

These facilities may well accommodate modifications to the system specifications within certain predefined limits, but would entail updates to the system software to effect any modifications specific to the building, requiring the elevator group control system be shut down during the software upgrade period. Such system shutdowns can be impractical depending on the use of the building or specific times of the day. The elevator group control system developed this time encompasses the concepts of decentralized control technology to allow software to be upgraded without having to shutting down the elevator group control facilities and also to make modifications to the system specifications within predefined limits.

3.2 Decentralized Control System

The facilities of the elevator group control system can be broadly classified into two groups: elevator group control facilities, which exercise traffic control of each individual control from short-term perspectives of the current traffic conditions, and elevator group control tuning facilities, which collect long-term perspectives of the traffic conditions depending on the use of each individual building and time zones to generate optimal control variables.

Figure 8 shows the configuration of the elevator group control system. The elevator group control facilities are organized into an elevator group main control unit with a 32-bit microprocessor and elevator group subcontrol units each with a 16-bit microprocessor. A coprocessor dedicated to transmission is installed in each control unit to form a decentralized control system based on a high-speed LAN. Figure 9 shows a surface-mounted elevator group subcontrol board.

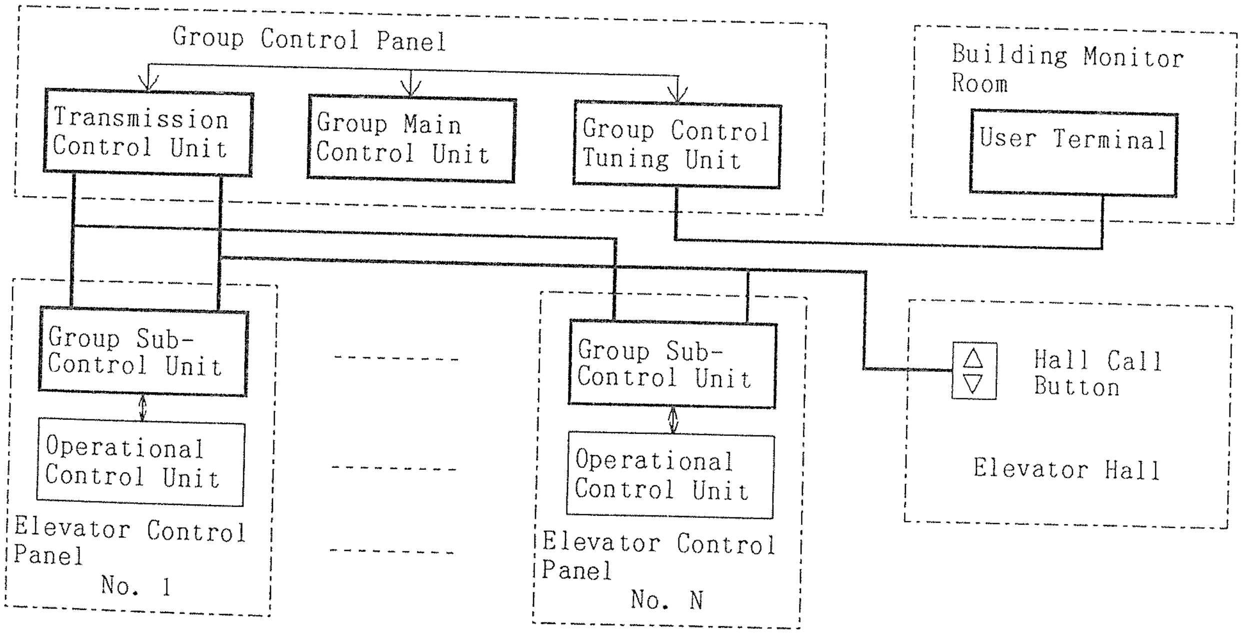


Figure 8 Elevator Group Control System Configuration

In operation, the main control unit manages common information flow to and from each subcontrol unit in synchronous control via a high-speed LAN. Each subcontrol unit, in turn, transfers data to and from an elevator via an operational control unit and a system bus, and also executes calculations relevant to the group control of the elevator as instructed by the main control unit. Each subcontrol unit also houses main control unit functions in the standby system to take over the functions of the CPU immediately when it fails.

This setup makes it possible to upgrade software with (N - 1) elevators in operation. The availability of one subcontrol unit for each elevator eliminates concern over changes in the operating load of the CPU associated with changes in the fleet of the elevators, thus ensuring added system reliability and efficiency. The elevator group control tuning facilities use a 32-bit microprocessor to execute optimal control variable calculations, including fuzzy neural network calculations.

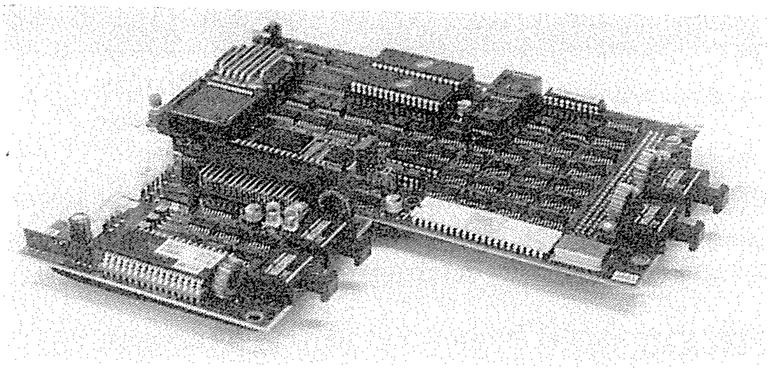
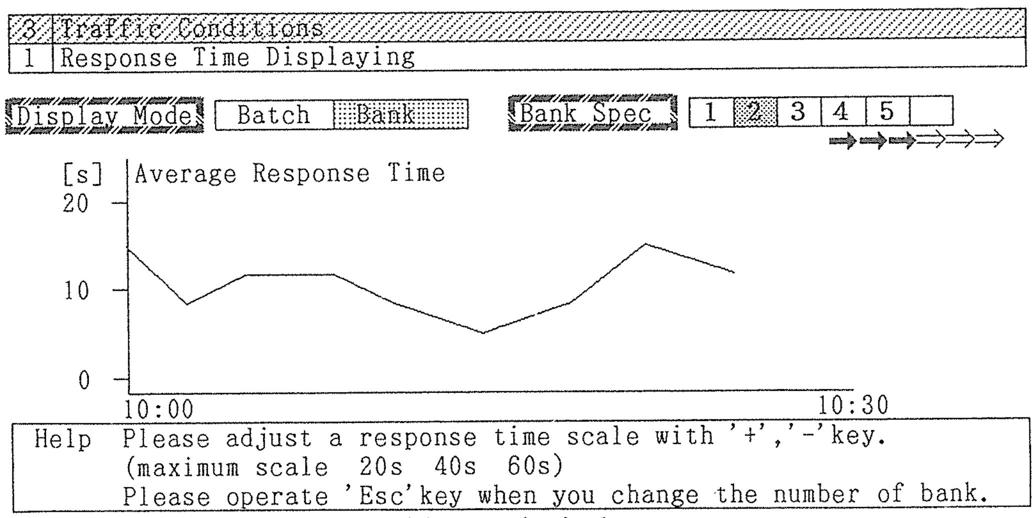


Figure 9 Elevator Group Subcontrol Board

3.3 User Interface

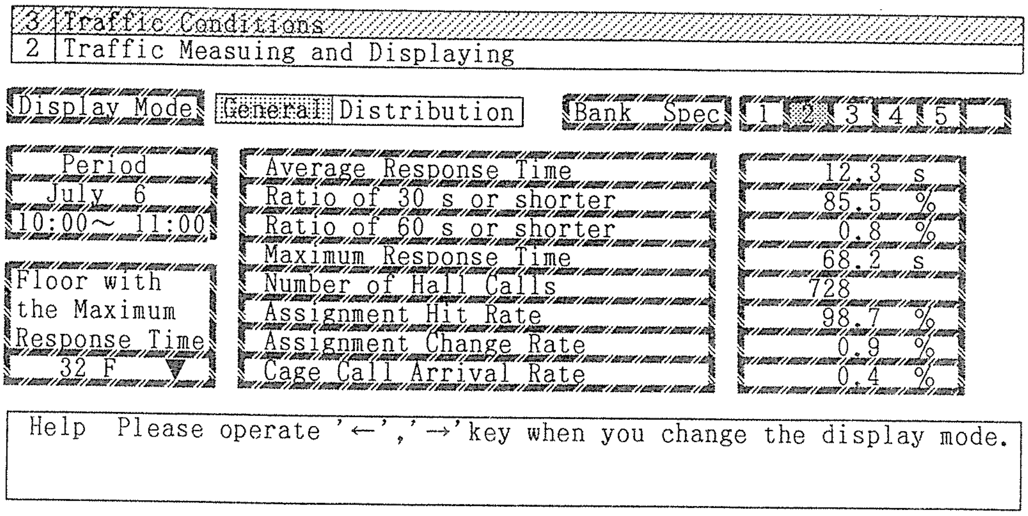
A traffic harmonizer has been developed to enable building administrators to directly manipulate the conditions on which the elevator group control system is based to provide quick responses to the usage status or user needs arising after the building is commissioned into service.

This system connects from a laptop personal computer as a terminal to the elevator group control system. The system features simple, display-guided operational workflow for building administrators. A traffic measuring and displaying function allows the building administrator the verify the status of elevator traffic following changes in the setup condi-



(1) Trend Display

Figure 10 Typical Working Screen



(2) Waiting Time Data Display
Figure 10 Typical Working Screen

tions. As shown in Figure 10, this function provides a real-time trend view of the current service status or a measurement of the waiting time for a specified period of time, so that the administrator can quantitatively determine the validity of his operations.

4. Conclusions

A summarized description of the elevator group control system, EJ-1000FN, based on the fuzzy neural network concept has been given. Further surveys and analyses of the field operation of the system are planned to define the validity of the system and to help develop a system better tailored to user needs.

References

(1) Y. Harada, etc.: Elevator Group Supervisory Control System with Artificial Intelligence Functions, Toshiba Review, Vol. 44, No. 9 (1988)

(2) T. Yamaguchi, etc.: Fuzzy Predict and Control Method and Its Applications, IEEE Int. Conf. CONTROL 88 c.p. No. 285 (1988)

(3) T. Yamaguchi, etc.: Method of Fuzzy Rule Inference and Learning Using Associative Memory, Institute of Electrical Engineers Collection of Papers C, Vol.110, No.3 (1990)

(4) Rumelhard, D.E., etc.: Learning Internal Representations by Error Propagation, Parallel Distributed Processing, MIT Press (1986)

(5) Kosho, B.: Bidirectional Associative Memories, IEEE Trans. on Systems, Ma, and Cybernetics Vol. 18, No. 1 (1988)

(6) N. Imamura: Fuzzy Neural Network Simulator and Its Applications, Institute of Electrical Engineers National Conference on Industrial Applications (1990)

Biography

S. Kubo joined Toshiba Corp. in 1980. He is engaged in elevator & escalator development & designing department in Fuchu Works.

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N. Imasaki joined Toshiba Corp. in 1988. He is engaged in systems & software engineering laboratory in the R & D center.

T. Yoshitsugu joined Toshiba Corp. in 1980. He is engaged in elevator & escalator engineering department in Principal Office.