Elevator Group Control with Artificial Intelligence

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Abstract

In this report a novel control that optimizes passenger service in an elevator group is described. Fuzzy logic and artificial intelligence are applied in the control when allocating landing calls to the elevators. Fuzzy logic is used to recognize the traffic pattern and the traffic peaks from statistical forecasts. In order to form the statistical forecasts, the passenger traffic flow in the building is measured. In the statistics the passenger traffic flow is learned day by day, and the control adapts to the prevailing traffic situation. The validity of the forecast data is confirmed before applying it in the control. The measured passenger arrival rate at each floor is used in optimizing the passenger waiting times and the ride times inside a car. The methods developed in this work are utilized in real group controls. With these controls average waiting times and waiting time distribution floor by floor are decreased compared with conventional controls that optimize landing call times. An example of an office building where an old electronic control was modernized with the TMS9000 control shows a considerable improvement in the resulting landing call times.

Keywords: group control, call allocation, optimization, fuzzy logic, forecast

CONTENTS

NOMENCLATURE

a_t	smoothed observation value at the time t
b_t	estimate of a change due to a trend during a time
C	set of floors of existing car calls
cc_i	number of new car calls from floor i
f(k)	value of measured load signal k
F_t	forecast value at the time t
I_t	traffic intensity value at the time t
K	set of existing landing calls
L	number of elevators in group
M	car size in persons
n	number of measurements
N	number of floors in the building
p_{Ii}	number of entering passengers
p_{Oi}	number of exiting passengers
S, F	space definitions for fuzzy sets
S_t	moving average at the time t
S_{tt}	moving average of the moving averages at the time t
t_a	parking delay time
t_c	remaining standing time of a stopped car
t_{cc}	car call time
t_{ct}	landing call time
t_{eta}	estimated time of arrival to a landing call
t_{ride}	passenger ride time inside a car
t_s	average stop time
$t_{service}$	elevator service time
t_v	a single floor drive time at rated speed v
U	space definitions for traffic factors
v	rated elevator speed
x_l	elevator position in units of floors
X_{av}	forecast number of passengers during a typical day
X_{day}	measured number of passengers during the day
Y_i	observation value i
α,β	smoothing constants
γ	weight factor for the cost function
χ^2	Chi-squared test value
μ_i	membership function I
σ_i	weight factor for the landing call i
τ	average elevator round trip time
Indexes	
i, k	observation, floor and call indexes
l	elevator index
m,t	time indexes

1. INTRODUCTION

In modern elevators the control is distributed in the elevator components. Doors or call buttons can have their own microprocessor control. The three main tasks in an elevator group with their own controls are: the drive control, the elevator control and the group control. The controls communicate through serial transmission. The drive system moves elevators from one floor to another. The elevator control handles the peripheral devices in an elevator cabin, such as load weighing device, registers and cancels car calls given by passengers, and gives commands to the drive control. A single elevator handles also the landing calls that passengers give at the floors. In a building with heavy traffic, more than one elevator is needed. The effectiveness of an elevator group can be significantly increased by a group control. It delivers the landing call to the most appropriate elevator, or dispatches elevators to specific floors for parking or for another reason. This report describes the intelligent part of an elevator group, the group control, and the way elevators are dispatched to calls.

The car calls are always served collectively, i.e. the elevator serves the nearest car call in the travel direction. All the car calls must be served before an elevator can change its direction. The collective principle can also be used for the landing calls, but in a modern group control the landing call service is optimized by more sophisticated algorithms. A typical optimization target is to minimize the average and maximum call times. A landing call comes on when a passenger pushes the call button and is canceled when a car starts to decelerate to the call floor. Behind a landing call there is one or more passengers. Passenger waiting times differ from the landing call times especially during a high passenger arrival rate. Then all the passengers may not fit into a car and they have to wait for another car. Conventionally, the traffic peak periods are recognized on the basis of the car load data and the numbers of car and landing calls. As a result the control operations to serve the traffic peak begin after the peak traffic period has already continued for some time.

If the main process that keeps elevators running, the passenger traffic flow, was known, intelligent control actions could be taken. With the normal up and down call buttons the number of people behind the call, their arrival times and destination floors are not known at the moment of the call allocation. This information could be obtained with modern access control systems, or by providing destination call buttons already at the landing floors (Schröder 1990). Consequently, with these systems optimal call allocations for the existing static situation can be obtained. They are, however, mostly applied in office buildings with regular users only. Destination buttons are difficult to use and understand by occasional visitors, and access control systems are not very common even in office buildings. Because of these reasons, the normal up and down landing call buttons will be used. The lack of current traffic flow information in the control is substituted by statistical forecasts. When forming and utilizing statistical forecasts the passengers need not be aware of the control system requirements at all.

The development of the TMS9000 control started in 1989. Part of the control, i.e. forming of statistics, was earlier studied in a TEKES project (TEKES 1989). In the TMS9000, the static situation and the predicted future events are considered during the call allocation. The number of passengers using the car load weighing device and the photocell signals at the elevator door opening during a stop are measured. Short-term statistics of the last five minutes and long-term statistical forecasts of the passenger traffic flow in the building are formed. From the statistical forecasts, traffic patterns and the peak traffic hours during the day are forecast using fuzzy logic. The control adapts to the peak traffic service as soon as the peak hour is predicted to start. The number of waiting passengers behind the landing calls is estimated according to the measured short-term statistics. Passenger waiting and ride times are optimized during the landing call allocation to elevators instead of optimizing landing call times.

In this report the main principles of forming and utilizing passenger traffic forecasts in the group control are described. The related work in this area is briefly described first. The same methods are shared in the controls of several manufacturers, although the methods are applied in a different way. The main schema of utilization of the passenger traffic information in the group control is given in Section 3. Measurement of the passenger traffic and the method of forming the statistical forecasts are explained in Section 4. The recognition of traffic patterns is described in Section 5. In Section 6 the way the control utilizes the measured and forecast data is described. The control was tested with an elevator traffic simulator (Siikonen 1993). The results and measured data from an existing office building where the TMS9000 was installed are shown in Section 7. In the conclusion new approaches to utilize the statistical forecasts in the control are suggested.

2. RELATED DEVELOPMENT WORK

The main principles of the latest group controls are described first. The best features of the new controls are adapted by most of the manufacturers and the modern controls seem to have more or less the same features. Still the application of the modern methods and the basic call allocation differ greatly from each other.

There are two different approaches in delivering landing calls to the elevators. The landing calls can be allocated continuously or call allocation can be activated by a specific traffic event. In the continuous allocation the landing calls are reallocated to the last moment before stopping at a floor (Kameli et al. 1989). The last moment to reserve the landing call finally to an elevator is when the car has to start to decelerate for the call floor. The optimization becomes more and more accurate when the car approaches the landing call. This principle is applied in the present control. In the other method, a new landing call is instantly after registration reserved to a car. This kind of principle is applied in the Miconic 10 control (Schröder 1990) and in the *min-max* control (Hirasawa et al. 1978). Passengers are immediately after giving the landing call informed of the arriving car which shortens the psychological waiting time. At the instant of landing call allocation, the reservation of the call to a car is optimal. After a while the optimization result can be different if, for instance, car is delayed at some landing floor. The elevator stops, stop times, and loads have to be predicted as accurately as possible at the time of allocating the landing call. This is important especially when landing calls are reserved instantly to elevators.

In the late 1980's the group controls were transferred to microprocessors and it became possible to measure and make statistics of the traffic events and to predict future events. Statistical forecasts were also adapted to the continuously allocating group controls, although the prediction of future events is not as critical as for the controls with instant call reservation. Real-time detectors were developed to measure the number of passengers at the landing floors or inside the cars. With lobby detectors (Kulju 1987) or cameras at the landing floors the number of passengers in front of the elevators is detected. Cameras or special sensitive mats (Haraguchi 1990) can be used to detect the passengers inside the elevator. The number of passenger transfers during an elevator stop can be estimated from the differences of the car arrival load, minimum load and departure load information (Sakai 1984). The number of entering and exiting passengers is obtained by dividing the load differences by an average passenger weight. The traffic flow modes and the total volume of traffic during the day and during some specific hours of the day is learned in *daily and weekly* feature tables. Analogous learning features are used in other Japanese group controls (Hayase et al. 1984). In the control of this report the car load information is analyzed continuously during the elevator stop. The passenger traffic flow in the building is learned for the whole day.

In the early 1990's *artificial intelligence* in the form of *embedded expert systems* was adapted in the group controls (Aoki et al. 1990; TEKES 1989). Rules based on expert knowledge were applied in forming or utilizing the statistical forecasts, or in the call allocation. With fuzzy logic the uncertainties in estimating landing call times and future events could be described. The applications of fuzzy logic vary among different controls. In a multiobjective control the importance of the optimization targets, such average waiting times or transportation capacity, are defined interactively by the building manager. Fuzzy logic is used to change the importance factors to control parameters (Tobita et al. 1991). In an application the spacing of the elevators inside a served zone has been described in linguistic terms, such as the number of cars in a zone is *large* (Umeda et al. 1989). In a control with fuzzy neural networks the number of passengers arriving from and at the entrance floor is defined in linguistic terms, such as *high, medium* or *low* (Nakai et al. 1995). A control where fuzzy logic was applied for several purposes within the control, such as to estimate the car load, to select the traffic mode, or to estimate people behind the call, has been introduced (Powell et al. 1993). In the previous context the traffic mode shows the relative presence of up, down and mixed traffic. In this report the control recognizes traffic pattern from the portions of incoming, outgoing and inter-floor traffic, and from the relative traffic intensity.

3. GROUP CONTROL WITH ARTIFICIAL INTELLIGENCE

The embedded expert system of the TMS9000 group control is shown in Figure 1. The measurement, data storage and utilization of passenger traffic information is handled in four stages as shown in the figure. At the first stage the passenger traffic flow is measured and saved in the short-term statistics with other traffic events, such as registering and canceling of landing calls. The number of entering and exiting passengers per floor is gathered for the whole day in fifteen-minute periods. Once a day the current day statistics are saved in the long-term statistics. At this second stage, exponential smoothing is used when adapting the new data in the long-term statistical forecasts. Forecasts are made for a typical day or for a one-week period. The number of forecast days depends on the building type. At the third stage the statistical forecasts are utilized in the traffic pattern recognition. The uncertainties in the limits of the traffic patterns are modelled with fuzzy logic. At the fourth stage the measured passenger traffic and the prevailing traffic pattern information are used in the landing call allocation and in the dispatching of elevators to the floors. In the basic call allocation algorithm the landing calls with more waiting passengers are preferred to calls with only one or a few waiting passengers. During heavy traffic peaks extra cars can be dispatched to the busiest floors according to the forecast traffic pattern; during light traffic, cars can be parked at the floors with most probable traffic.

The TMS9000 group control computer contains several boards, such as the CPU board, boards for the serial communication, for the memory and matrix, for the floor modules, and for the power supply. The CPU (Central Processing Unit) board of the TMS9000 group control microcomputer was realized with the Intel 80286 microprocessor. It was considered effective enough for a sophisticated control code in 1989. The statistical forecasts are saved on a board with battery RAM (Random Access Memory) memory. This ensures that no data is lost during a power failure. The four stages of Figure 1 will be discussed in the following sections.

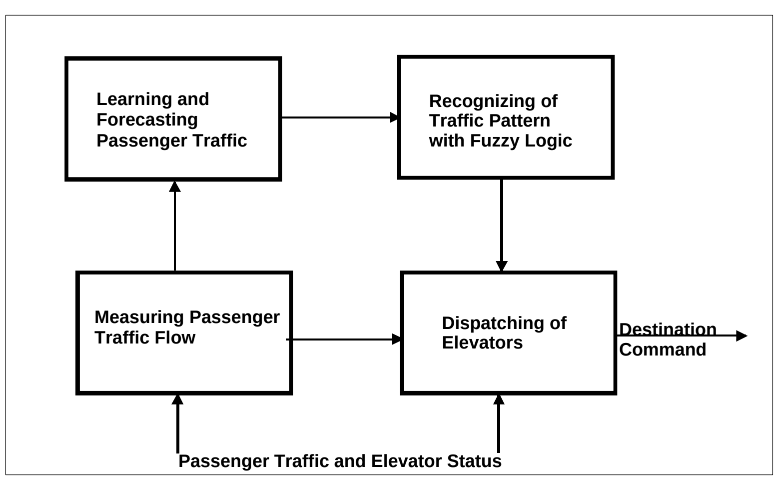

Figure 1. Group control with artificial intelligence.

4. MEASUREMENT AND FORECASTING OF THE PASSENGER TRAFFIC

4.1 Measurement of passenger traffic

The number of entering and exiting passengers per floor and per direction was chosen as a variable to be forecast. This data is based on a large number of detailed measurements. To find out the passenger traffic flow in a building, the car load and the photocell signal information are utilized. The benefit of these two detectors is that the passenger is not aware of the measurement at all. Two methods are used since sometimes the old inaccurate load weighing devices are left in elevators, or with wide doors the photocell signal information can be inaccurate. If either of the measurement methods fails, only the prevailing method is applicable. If the photocell signals and car load estimation are near to each other, the estimate with the smallest value is chosen. If the passenger arrival rate with either of the methods is 33 per cent less than with the other method, the lower value is rejected. These heuristic rules are based on practical reasoning and in practice they have proven to be accurate enough to distinguish the best estimate.

With an accurate digital car load weighing device the step-wise changes in the load values can be counted during an elevator stop. A step-wise increment in the car load information indicates that a passenger enters the car. A sudden decrease means that passenger exits the car, correspondingly. The threshold load value to recognize an increment of decrement step is scaled to a rated car load. The threshold value is 25 % of the average passenger weight. The threshold value varies between 17-20 kg, depending on the elevator car size. In Figure 2 an example of load variation during a stop is shown. With the step counting method three entering and two exiting passengers are recognized. If only arrival load, minimum load and departure load information were analyzed, one exiting and one entering passenger would be recognized. The information of the car load signal oscillates especially when stopping at a floor. Median type filters have been successfully applied to suppress noise (Ovaska 1989). In the median filter method, the median value is selected from a specified sequence of samples. The median value f(0) of a discrete time sequence, {f(.)}, is

$$f(0) = \{MED\{(f(-k),\ldots, f(-1), f(0), f(1),\ldots f(k))\} \qquad (1)$$

where $f(-k) < f(-k+1) < \ldots < f(-1) < f(0) < f(1) < \ldots < f(k)$. In the defined sequence the number of samples 2k+1 has to be odd.

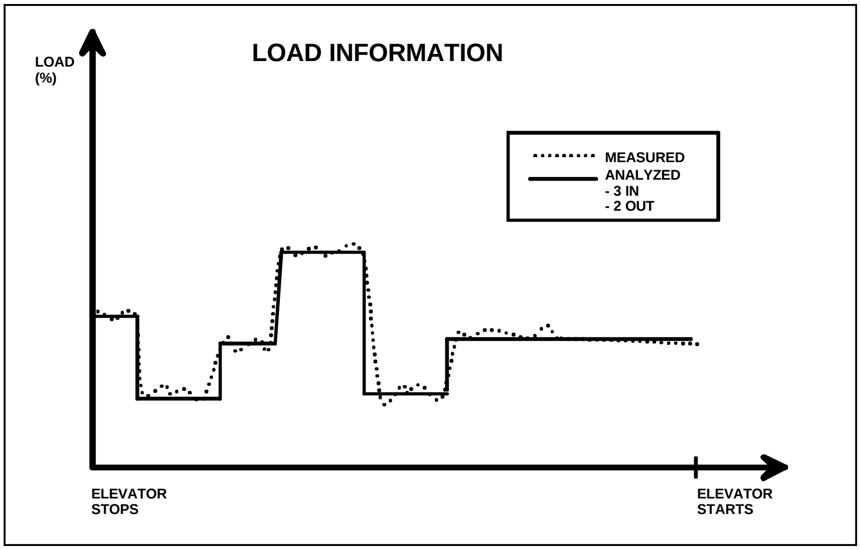

Figure 2. Step counting method to count the number of entering and exiting passengers during an elevator stop (Siikonen et al. 1994).

The other method to estimate the number of passenger transfers is an electronic safety beam, or a photocell signal device installed in the elevator door opening. An entering or exiting passenger breaks the safety beam or the photocell signal. An estimate to the total number of the transported passengers is obtained by dividing the number of photocell cuts by two since one passenger breaks the light ray twice during one journey. The direction of the transfer, in or out of the car, cannot be deduced without additional traffic data. From the landing call and elevator status data the individual passenger trips can be reconstructed by keeping a record of the number of passengers inside the car during the elevator up and the down trips. Rough rules are used when analyzing the event data. The number of passengers inside the car during an up or a down trip cannot momentarily exceed the nominal car size M. If N is the number of floors, the limits to the entering P_{ii} and exiting passengers P_{Oi} at floor i are

$$0 \le \sum_{i=1}^{k} P_{Ii} - \sum_{i=1}^{k} P_{Oi} \le M,\ if\ \ k = 1, \dots, N \tag{2}$$

At the reversal floors it is assumed that all the entered passengers during the trip have exited the elevator

$$\sum_{i=1}^{n} P_{Ii} - \sum_{i=1}^{n} P_{Oi} = 0 \tag{3}$$

It is assumed that the floors of existing up calls form a set K. If there is an up call at the floor i where the car stops during the up trip, at least one passenger enters the car

$$1 \le P_{Ii} \le M, \forall i \in K \tag{4}$$

An analogous equation is valid for the down calls. The rules of Eq. (2)-(4) can be used when the traffic is measured with external analyzers attached to the elevator control board (Roschier et al. 1991). An accuracy of 10 % for the passenger traffic intensity was obtained when reconstructing individual passenger trips from elevator traffic events (Väljä 1990). The accuracy of the photocell signal based method can still be improved.

Within a control system, more information on the elevator status is available than with external traffic analyzers. The passenger trips can be reconstructed more accurately as the car calls given inside each car are known. The number of entering passengers can be adjusted from the number of new car calls. The number of entering passengers from floor i is at least the number of new car calls cc_i from that floor, but always less than the nominal car size

$$cc_i \le P_{Ii} \le M, \ \ if \ \ i = 1, \ldots, N \tag{5}$$

The destinations of entering passengers are obtained from the new or existing car call floors. If the floors of existing car calls form a set C, it can be assumed that at least one passenger exits at the car call floor i

$$1 \le P_{Oi} \le M, \forall i \in C \tag{6}$$

By using the rules of Eq. (2)-(6) an error of 5 % was found for the passenger arrival and destination floors (Leppälä, 1991). No exceptional behavior, such as passengers remaining in the car at the reversal floor, or one passenger pressing landing call buttons in both directions, was taken into account. Any exceptional behavior will reduce the accuracy, and sometimes the method fails. That is why the test to find the more accurate method is always used.

4.2 Forecasting method

As mentioned in Section 3, long-term statistical forecasts of the passenger traffic are formed, and the forecasts are utilized in several control operations. The forecasting methods of economical and technical phenomena can roughly be classified into one of two categories: time series and causal regression (Makridakis et al. 1983). The causal regression forecasts deal with several variables and equations. The relationship between the causes and the consequences is described mathematically. These methods give the best results in long-term forecasting. In the time series methods the forecast is based on the earlier behavior. The time series methods are suitable for the forecasting of elevator traffic phenomena since the forecast periods are short. According to the traffic measurements of an elevator system, the traffic repeats quite similarly day by day. Exceptional days are known in advance from the calendar. Within a day 97 per cent of the changes in traffic intensity can be explained by periodical changes (Leppälä 1989). A fifteen-minute period was considered to be suitable for elevator traffic phenomena (Leppälä 1991). Half an hour is too long for the peak traffic periods and, on the other hand, five minutes is too short to analyze the elevator round trips. The statistics for the day contains a total of 96 time slots. In the group control, full-day statistical forecasts are formed once a day.

In a real time control system there is often shortage of the calculation time. The available memory size sets its limitations to the amount of data to be collected. In most situations a *Single Exponential Smoothing* method gives the best results

$$F_t = \alpha Y_t + (1-\alpha)F_{t-1}, \tag{7}$$

where the F is a smoothed value and α is a smoothing constant with a value between zero and one. In this method an exponentially decreasing weight is given for the old data. The old data is gradually ignored and the new data is adapted instead. For controls in real buildings the optimal smoothing parameter is not easy to define in advance. A method that continuously optimizes the smoothing parameter, the *Adaptive Response Rate Single Exponential Smoothing* (ARRSES) method, was found to be the most suitable for the present application (Makridakis et al. 1983)

$$F_t = \alpha_t Y_t + (1-\alpha_t)F_{t-1}, \tag{8}$$

where

$$\alpha_t = \left|\frac{E_t}{M_t}\right|,$$

$$E_t = \beta\, e_t + (1-\beta)E_{t-1},$$

$$M_t = \beta\, |e_t| + (1-\beta)\, M_{t-1},$$

$$e_t = Y_t - F_{t-1}$$

Variable F_{t-1} refers to the smoothed value of the previous period, and Y_t to the observed value of the same period. F_t is the new smoothed value, and α_t is the smoothing constant. A constant value between zero and one, e.g. 0.2, is set beforehand for the parameter β. In the group control the smoothing constants in Eq. (8) are updated per floor and per direction.

4.3 Elimination of seasonal variations

In the initialization phase of statistical forecasts single averages for the first five days are gathered. During that time the group control operates without the forecast data, which reduces the control efficiency. Then the landing call times are optimized in the basic call allocation algorithm. Statistics for a full day are collected before being used to modify the statistical forecasts. The seasonal variations in the measured traffic data are eliminated by the calendar, and by making two tests. With these tests the periodical changes, such as Christmas, are not included in the statistical forecasts. Exceptional days, or failures in recording the data, are eliminated. If there is a power failure for more than half an hour during a day, the observed data of that day is rejected.

The traffic intensity profile during the day is checked using a χ^2-test. The hours of the day are divided into six time slices between 7:00 and 19:00. Five degrees of freedom are used in testing. If the observed intensity is Y_i, and the forecast intensity is F_i, the test value is

$$c^2 = \sum_{i=1}^{6} \frac{(Y_i - F_i)^n}{F_i} \tag{9}$$

If the value χ^2 is greater than the critical value $\chi^2_{0.95}$, the observed intensity differs significantly from the forecast value and it is rejected. If the observed intensities are proportional to the intensities of the forecast day, the observed data is accepted.

Another test is made for the passenger arrival rate during the day. The observed arrival rate is compared with the forecast arrival rate of a typical day. The arrival rate is assumed to follow Poisson's distribution and the following test is applied (Laininen 1980)

$$X_{day} \langle \; X_{av} - 3 * \sqrt{X_{av}} \tag{10}$$

where X_{day} is the measured number of passengers during the day, and X_{av} is a forecast number of passengers during a typical day. The test is based on the normal distribution approximation for Poisson's distribution. If the number of arriving passengers has been too low, the day will not be accepted in the statistics. If there have been more than ten consecutive days that have been rejected, the control clears the old statistics and starts to collect a new set.

4.4 Forecast traffic profile in an office building

The main streams of traffic flows can be divided roughly into three traffic components. The incoming, outgoing and inter-floor passenger traffic components are shown in Figure 3. During the incoming traffic, passengers arrive at the building, and during the outgoing traffic they exit the building. In the inter-floor traffic the passengers travel from one populated floor to another inside the building.

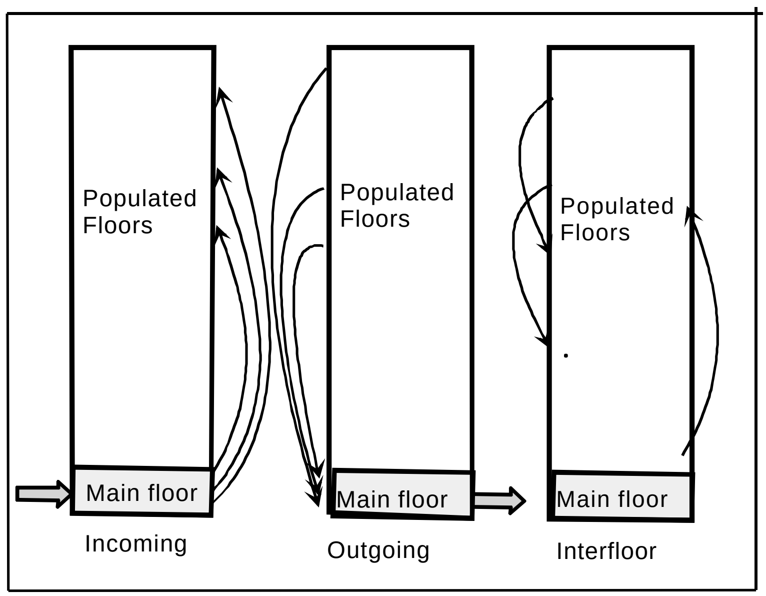

Figure 3. Three main passenger traffic components.

Real traffic patterns during a day are combinations of these three traffic components. A statistical forecast for a typical day in a single tenant office building with common working hours is shown in Figure 4. The three passenger traffic components were forecast by the TMS9000 control. According to the figure, traffic intensity is highest in the morning at 8:30 a.m. and during the lunch hour at 12:00 a.m. During the morning up-peak, people arrive at work and it is the most demanding time for the elevator handling capacity. A lot of inter-floor traffic in the morning has also been measured. During the lunch hour there is typically about 40 per cent incoming, 40 per cent outgoing, and 20 per cent inter-floor traffic. The lunch hour traffic is the most demanding for the group control capability since there are a lot of car and landing calls to be served. In the evening, people exit the building, and mostly outgoing traffic is forecast.

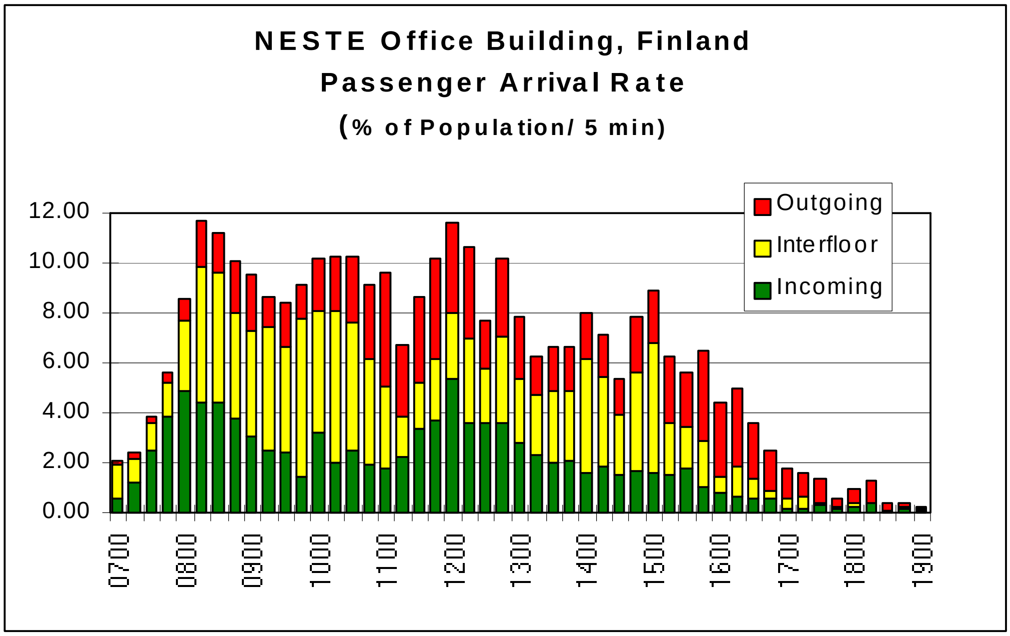

Figure 4. An example of the three passenger traffic components for a typical weekday. The statistical forecast was formed by the TMS9000 control system in Neste's office building in Espoo, Finland.

5. TRAFFIC PATTERN RECOGNITION WITH FUZZY LOGIC

5.1 Inputs and outputs

In the group control, to avoid abrupt changes of traffic pattern due to small changes in the passenger traffic, fuzzy logic is utilized (Zadeh 1975). The traffic patterns are recognized by using the forecast traffic component values and the relative traffic intensity as an input.

The *traffic type* is first determined from the relative portions of *incoming*, *outgoing*, and *inter-floor* traffic components. The traffic component values show the portions of the three components as percentages of the total traffic volume at the defined time. The incoming traffic component value, u_1, is

$$u_1 = 100 * \lambda_{inc} / (\lambda_{inc} + \lambda_{out} + \lambda_{inter-floor}) \qquad (11)$$

where λ_{inc}, λ_{out} and $\lambda_{inter\text{-}floor}$ are the passenger arrival rates for incoming, outgoing and inter-floor traffic, respectively. Analogous equations for the outgoing (u_2) and inter-floor (u_3) traffic component values exist. According to the definition of Eq. (11) the following equation is valid

$$u_1 + u_2 + u_3 = 100 \qquad (12)$$

In addition to the traffic type, the number of arriving passengers in a defined time affects the traffic pattern. Obviously, the same absolute passenger arrival rates cannot be used to recognize a traffic peak for every building. The relative intensity that takes into account the building and elevator group configuration is obtained by scaling the arrival rate to the up-peak handling capacity of the elevator group. The relative traffic intensity value is

$$u_4 = 100 * (\lambda_{inc} + \lambda_{out} + \lambda_{inter-floor}) / HC \qquad (13)$$

where HC is the up-peak handling capacity of the elevator group (Barney et al. 1985; Roschier et al. 1979). The input values of passenger arrival rates (λ_{inc}, λ_{out} and $\lambda_{inter-floor}$) and the relative traffic intensity (u_4) are obtained from statistical forecasts. The exact values are interpolated between the values of the two nearest 15 minutes time slots in the statistics. All four traffic factors u_1, u_2, u_3 and u_4 are expressed in integer values.

As an output, the prevailing traffic pattern is recognized. Altogether 25 different traffic patterns can be recognized. The control actions during rush hour are stronger compared to when the passenger arrival rate is small. Different control actions are applied during incoming, outgoing, inter-floor, two-way and mixed traffic.

5.2. Membership functions

How well the current traffic components and the current traffic intensity describe a certain traffic pattern is found by using membership functions. The traffic type can be determined from the traffic component values u_1, u_2 and u_3. Fuzzy sets *high, medium* or *low* are used. Each set covers about one third of the total traffic volume, as shown in Figure 5 (Siikonen et al. 1991).

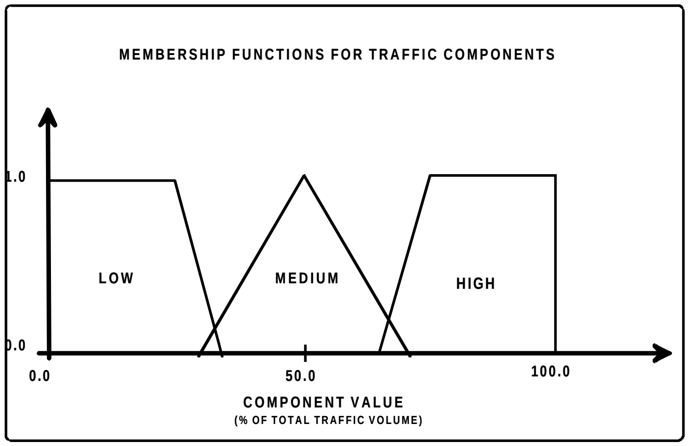

Figure 5. Membership functions μ for the incoming, outgoing and inter-floor traffic components.

Convex and linear membership functions are used for the traffic components. The membership functions for the traffic components $\mu_i : U_1 \rightarrow [0,1]$ where $u_i \in U_1$ are

$$\mu_{low}(u_1) = \begin{cases} 1, & if \;\; u_1 < 25 \\ \dfrac{35 - u_1}{10}, & if \;\; 25 \le u_1 < 35 \\ 0, & if \;\; u_1 \ge 35 \end{cases} \tag{14}$$

$$\mu_{medium}(u_1) = \begin{cases} 0, & if \;\; u_1 < 30 \\ \dfrac{u_1 - 30}{20}, & if \;\; 30 \le u_1 < 50 \\ \dfrac{70 - u_1}{20}, & if \;\; 50 \le u_1 < 70 \\ 0, & if \;\; u_1 \ge 70 \end{cases} \tag{15}$$

$$\mu_{high}(u_1) = \begin{cases} 0, & if \;\; u_1 < 65 \\ \dfrac{u_1 - 65}{10}, & if \;\; 65 \le u_1 < 75 \\ 1, & if \;\; u_1 \ge 75 \end{cases} \tag{16}$$

where the fuzzy sets *low*, *medium* and *high* $\in$ S. The same membership functions of Eq. (14)-(16) are used for all the three traffic components u_1, u_2 and u_3. The traffic type is recognized from the combination of the fuzzy sets of the three traffic components. As an example, if the values of incoming, outgoing and inter-floor traffic components are 20 %, 70 % and 10 % of the total traffic volume, then the grades of memberships to fuzzy sets (*high*, *medium* and *low*) for the incoming traffic (20 %) are (0.0, 0.0 and 1.0), for the outgoing traffic (0.5, 0.0 and 0.0), and for inter-floor traffic (0.0, 0.0 and 1.0), respectively.

The traffic intensity is scaled to the up-peak handling capacity to identify when the passenger arrival rate is critically high. During incoming traffic the intensity is critical when it is near to the handling capacity. During pure inter-floor and outgoing traffic, elevators can transport 1.1-1.8 times more passengers than during up-peak (Siikonen 1993), and the passenger arrival rates for the critical traffic intensity are higher. The same linguistic names are used for the fuzzy sets of traffic intensity, i.e. *intense, heavy, normal* and *light*, but their definitions for different traffic types are not similar. The traffic becomes *intense*, for example, in situations where one or more elevators are disconnected from the elevator group, and *heavy* when it is near to the handling capacity of that traffic type. The fuzzy sets for traffic intensity of incoming traffic are shown in Figure 6.

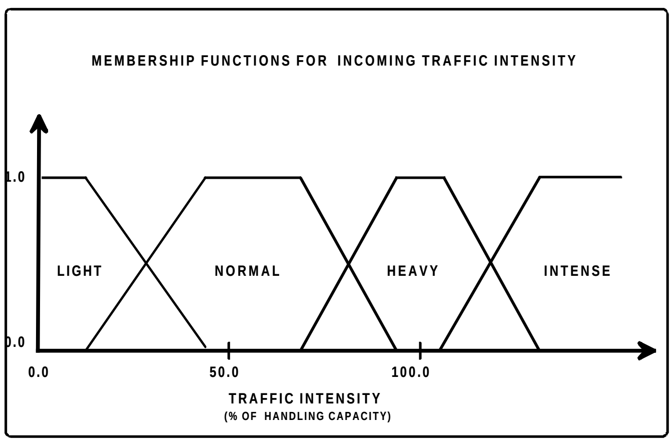

Figure 6. Membership functions σ for the traffic intensity of the incoming traffic type.

A general form of the membership functions for the traffic intensity is

$$m_i(u_4) = s\,i(u_{4,}\,u_{type}) = \begin{cases} 0, & if\;\; u_1 \langle\, a_i \\ \dfrac{u_4 - a_i}{b_i - a_i}, & if\;\; a_i \le u_4 \langle\, b_i \\ 1, & if\;\; b_i \le u_4 \langle\, c_i \\ \dfrac{d_i - u_4}{d_i - c_i}, & if\;\; c_i \le u_4 \langle\, d_i \\ 0, & if\;\; u_4 \ge d_i \end{cases} \tag{17}$$

where u_{type} refers to the traffic type, and $a_i \le b_i \le c_i \le d_i$ and $a_{i,}b_i,c_{i,}d_i,\ u_4 \in U_2$ and $I \in F$ refers to the fuzzy set. For fuzzy set i different limits a_i, b_i, c_i, d_i are used for different traffic types. For example, the limit a_i for the fuzzy set {*intense*} during incoming traffic is 105, during inter-floor 110, and during outgoing traffic 150 per cent of the up-peak handling capacity. The limits a_i, b_i, c_i, and d_i for the fuzzy set *heavy* during incoming traffic are (55, 85, 100, 130), during inter-floor traffic (60, 90, 110, 140), and during outgoing traffic (70, 100, 150, 180), respectively. The limits for the fuzzy set *normal* during incoming traffic are (10, 40, 55, 85), during inter-floor traffic (15, 45, 60, 90), and during outgoing traffic (20, 50, 70, 100), respectively. As an example, if the relative intensity for outgoing traffic is 90 %, the grade of membership to the fuzzy set *heavy* is 0.67, to the fuzzy set *normal,* 0.33, and to the fuzzy sets *light* and *intense* 0.0. The nearer the grade of membership is to one, the higher the relation to the defined fuzzy set. In this case the fuzzy set *heavy* best describes the given relative intensity value of outgoing traffic.

5.3 Fuzzy rules

The traffic pattern is reasoned from the three traffic components and the traffic intensity value according to the rules connected to these four traffic factors. Traffic type is recognized using the fuzzy sets of the three traffic components. The number of organized combinations of the three fuzzy sets *high*, *medium* and *low* for the three traffic components is $3^3 = 27$. The number of organized combinations can be reduced to nine by utilizing the information of Eq. (12) and the shape of the membership functions in Eq. (14)-(16). The defined traffic types are shown in Table 1.

Table 1. Rules to determine the traffic type from the three traffic component values.

Incoming	Outgoing	Inter-floor	Traffic Type
high	*low*	*low*	incoming
medium	*low*	*low*	incoming
low	*high*	*low*	outgoing
low	*medium*	*low*	outgoing
low	*low*	*high*	inter-floor
low	*low*	*medium*	inter-floor
medium	*medium*	*low*	two-way
medium	*low*	*medium*	mixed
low	*medium*	*medium*	mixed

Within the rules the grades of membership to the fuzzy sets are defined. The minimum value of the fuzzy sets within a rule is searched and that value is assigned as the value of the rule. The grades of membership for the traffic components and for the traffic intensity are compared using *and* -operator (Λ)

$$m_{i'}(u_1,\ldots,u_4) = m_i(u_1) \wedge m_i(u_2) \wedge m_i(u_3) \wedge m_f(u_4)$$
$$= Min\{m_i(u_1), m_i(u_2), m_i(u_3), m_f(u_4)\}$$
(18)

where I ∈ S, f ∈ F, i' ∈ Z, and Z is a space of all the traffic patterns.

In the group control, when taking into account the traffic intensity, altogether 36 rules are defined (Table 2). First, the minimum values for all the 36 rules are searched, and the found values are assigned to the rules. The rules are numbered from 1 to 36, where each index refers to a certain traffic pattern. Secondly, the rule with the highest grade of membership is searched, and that index is assigned to the prevailing traffic pattern. Inside the control the index of prevailing traffic pattern refers to a specified traffic pattern within the rule table, and the control actions are made according to the prevailing traffic pattern.

According to the example of the previous chapter the grades of membership, (*high*, *medium* and *low*), for the incoming, outgoing and inter-floor traffic components are (0.0, 0.0 and 1.0), (0.5, 0.0 and 0.0) and (0.0, 0.0 and 1.0), respectively. Thus the traffic type is outgoing. The grades of memberships, (*intense*, *heavy*, *normal* and *light*) for the traffic intensity value 90 % are (0.0, 0.67, 0.33 and 0.0). According to the eleventh rule in Table 2, the traffic pattern down-peak is assigned the value

$$\begin{aligned}
&m_{down-peak} = intensity \approx heavy \; and \; incoming \approx low \\
&and \; outgoing \approx high \; and \; inter-floor \approx low \\
&= Min\left\{ s_{heavy}(intensity, outgoing), m_{low}(incoming), m_{high}(outgoing), m_{low}(inter-floor) \right\} \\
&= Min\left\{ 0.67, 1.0, 0.5, 1.0 \right\} \\
&= 0.5
\end{aligned} \qquad (19)$$

the minimum value 0.5 is assigned to the eleventh rule in Table 2. The minimum grade of membership, for instance, for the tenth rule (up-peak*)* is 0.0. The eleventh rule has the highest grade of membership of all the rules in Table 2. The prevailing traffic pattern is assigned an index 11 and the traffic pattern down-peak is recognized.

5.4 Confirmation of the forecast traffic pattern

To prevent the group control from using the forecast traffic pattern during exceptional days, such as during Christmas, the forecast data is compared with the short-term statistics from the last five minutes. In the short term statistics, traffic events, such as the values of current traffic components, elevator starts from certain floors with heavy car loads, and the number of up and down calls from the entrance and populated floors, are gathered. The prevailing traffic pattern is determined from this data and it is compared to the forecast traffic pattern for the current time t. When obtaining the forecast traffic factor values for the current time t, linear interpolation between the two nearest fifteen-minute time slots is used. If the forecast traffic pattern is in conflict with the short-term statistics, the basic call allocation algorithm without statistical forecasts is applied.

Table 2. Rules to determine the traffic pattern (Siikonen et al. 1993).

Intensity	Incoming	Outgoing	Interfloor	Traffic Pattern (Index)
intense	*high*	*low*	*low*	intense up-peak (1)
intense	*low*	*high*	*low*	intense down-peak (2)
intense	*low*	*low*	*high*	intense inter-floor (3)
intense	*medium*	*low*	*low*	intense incoming (4)
intense	*low*	*medium*	*low*	intense outgoing (5)
intense	*low*	*low*	*medium*	intense inter-floor (6)
intense	*medium*	*medium*	*low*	intense two-way (7)
intense	*medium*	*low*	*medium*	intense mixed (8)
intense	*low*	*medium*	*medium*	intense mixed (9)
heavy	*high*	*low*	*low*	up-peak (10)
heavy	*low*	*high*	*low*	d own-peak (11)
heavy	*low*	*low*	*high*	heavy inter-floor (12)
heavy	*medium*	*low*	*low*	heavy incoming (13)
heavy	*low*	*medium*	*low*	heavy outgoing (14)
heavy	*low*	*low*	*medium*	heavy inter-floor (15)
heavy	*medium*	*medium*	*low*	two-way peak (16)
heavy	*medium*	*low*	*medium*	heavy mixed (17)
heavy	*low*	*medium*	*medium*	heavy mixed (18)
normal	*high*	*low*	*low*	incoming (19)
normal	*low*	*high*	*low*	outgoing (20)
normal	*low*	*low*	*high*	inter-floor (21)
normal	*medium*	*low*	*low*	incoming (22)
normal	*low*	*medium*	*low*	outgoing (23)
normal	*low*	*low*	*medium*	inter-floor (24)
normal	*medium*	*medium*	*low*	two-way (25)
normal	*medium*	*low*	*medium*	mixed (26)
normal	*low*	*medium*	*medium*	mixed (27)
light	*high*	*low*	*low*	light incoming (28)
light	*low*	*high*	*low*	light outgoing (29)
light	*low*	*low*	*high*	light inter-floor (30)
light	*medium*	*low*	*low*	light incoming (31)
light	*low*	*medium*	*low*	light outgoing (32)
light	*low*	*low*	*medium*	light inter-floor (33)
light	*medium*	*medium*	*low*	light two-way (34)
light	*medium*	*low*	*medium*	light mixed (35)
light	*low*	*medium*	*medium*	light mixed (36)

6. DISPATCHING OF ELEVATORS

6.1 Enhanced Spacing Principle for allocating landing calls

The basic call allocation algorithm of the TMS9000 control, the Enhanced Spacing Principle (ESP), will be described in this section. The group control utilizes normal up and down landing call buttons and reallocates the landing calls continuously. The same basic call allocation algorithm handles all the traffic situations by changing the weight factors of the landing call service times. Passenger arrival rates at each floor and in each direction are used to optimize the passenger waiting times and ride times inside a car. In the cost function the estimated landing call time, and the maximum passenger ride time inside the car, t_{rmax}, are minimized. The landing call time, t_{ct}, stays constant when the landing call k is allocated to the best car. Thus it is sufficient to optimize only the estimated car arrival time to the landing call, t_{eta} (see Figure 7). The car with the lowest cost J is chosen to serve the landing call k

$$
\begin{aligned}
J^*(k) &= \min_{l} J(l,k) \\
&= \min_{l} (g t_{r\,\max}(l,k) + (1-g) t_{eta}(l,k)), \quad l = 1,\ldots,L
\end{aligned}
\tag{20}
$$

where γ is an adjustable weight factor and L is the number of elevators in the group. Weight factor obtains values between zero and one, and it is defined separately for each building. The group control continuously estimates the maximum passenger ride times in each car. The maximum passenger ride time inside a car is obtained by calculating the estimated car arrival time to the car call floor, and by adding it to the current car call time (t_{cc}). If the existing car calls of car l form a set C, for Eq. (20), the maximum passenger ride time when car l serves the landing call k is

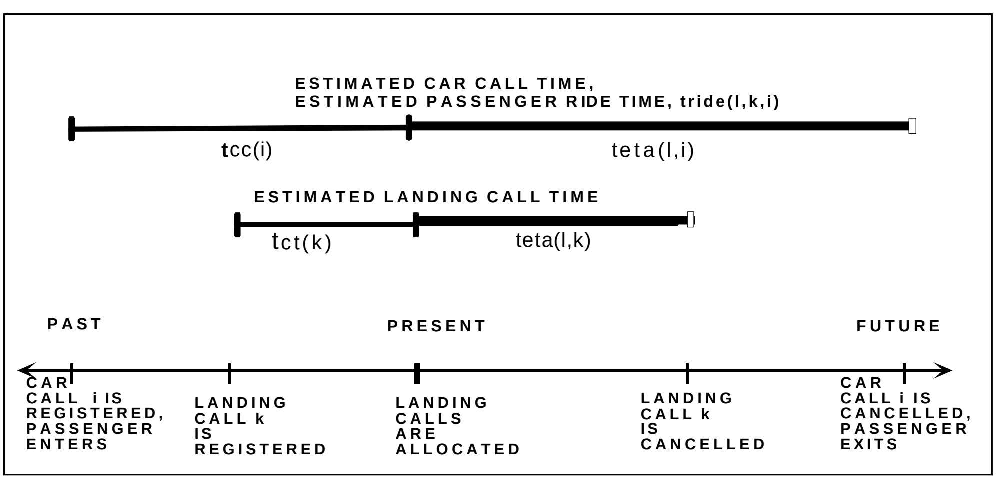

Figure 7. Definitions of the estimated landing and car call times of car l.

$$
\begin{aligned}
t_{r\,\max}(l,k) &= \max_{i} t_{ride}(l,k,i) \\
&= \max_{i} (t_{cc}(i) + t_{eta}(l,i)), \quad \forall i \in C
\end{aligned}
\tag{21}
$$

For the estimated car arrival time in equations (20) and (21), the drive time and the time spent during the probable stops before serving the landing call are calculated. The estimated arrival time of car l to the landing call k is

$$t_{eta}(l,k) = (\sum_{i=xl}^{xk} t_v + \sum_{j=xl}^{xk} t_s + t_c + t_a) \qquad (22)$$

where the first term on the right refers to the elevator drive time, and the second term to the stop times before serving the call. The elevator floor position is x_l and the call floor is x_k. The floor drive time at full speed is t_v. Parameter t_s is the average time spent during a stop. The remaining standing time of a stopped car, t_c, and additional time delays t_a, such as parking delay time, are added to the estimated time of arrival. Landing calls are allocated to cars until all the cars have a reserved call. The landing calls with long service times are thus guaranteed to get fast service and the maximum times are cut. If there are more landing calls than cars, the landing calls with a short service time forecasts are by-passed. Before by-passing a landing call it is always checked that another car will serve the call in a proper time. The allocation of landing calls starts from the landing call with the longest service time, $t_{service}$. An estimate of the call service time is obtained by adding the current landing call time to the estimated car arrival time given in Eq. (22). The time a landing call has been on, t_{ct}, is updated every second. The service time forecast of elevator l to the landing call floor k is

$$t_{service}(l,k) = s_k t_{ct}(k) + t_{eta}(l,k) \qquad (23)$$

The landing call weight factor, σ_k, is used in two different manners. Without statistical forecasts it can be used in landing call time optimization, or if statistical forecasts are available, in passenger waiting time optimization. When optimizing landing call times, σ_k correlates to the traffic pattern. The weight factors for the up calls above the entrance floor, for the down calls, and for the calls from the entrance floors are defined. These three weight factors are changed in different traffic situations. For example, during down peak all down calls get a higher weight than the up calls above the entrance floor. When optimizing passenger waiting times there are twice as many weight factors as there are floors served by the elevator group. Different weights are given for each landing and in both directions according to the estimated number of waiting passengers behind the landing call (Kontturi et al. 1995). The number of waiting passengers is estimated by multiplying the passenger arrival rate in given direction by the current landing call time. The passenger arrival rate is obtained from the short-term statistics. From two landing calls that are of the same age, the landing call with more waiting passengers gets a higher weight σ_k. Only the cars that are allowed to serve the call are included in the call allocation. The cars that are not capable of serving the call, for example, the cars that are disconnected from the group, are not included in the call allocation. A car whose load exceeds the full load limit is considered during the allocation only if it has a coincident car call at the landing call floor.

6.2 Service during forecast traffic patterns

As described in Section 5, fuzzy logic is utilized to recognize the prevailing traffic pattern from the statistical forecasts. With the basic call allocation algorithm an elevator is dispatched to serve an existing landing call. The forecast traffic pattern is used to recognize situations where more than one cars are needed to serve a floor, or if a car should be dispatched to a floor even if there is no call.

During peak traffic hours, several cars can be returned to the populated floors that need urgent service. For example, if an up-peak is forecast to begin, one or several vacant cars can be returned to the entrance floors. In the case of multiple entrance floors the group control returns cars at the entrance floors according to the forecast passenger arrival rates to the entrance floors. Special options, such as fixed or dynamic sectoring of the building (Ekholm et al. 1988), can be used to increase the handling capacity during up-peak. With these methods the building is divided into zones. The elevators accept car calls given from the entrance floors only to the floors within the zone. The round trip time, i.e. the average time it takes for an elevator to make an up and a down trip, is shortened because of the decreased number of stops during the trips. If an elevator with a certain load requires a shorter round trip time, the elevator group can transport more passengers and the handling capacity is increased. The limits between the zones are determined by choosing equal handling capacities in each zone. During down-peak, heavy inter-floor, two-way or mixed traffic, no special control operations in addition to the basic control are needed. Only the weight factors of landing call times are varied in the basic call allocation algorithm. During the call allocation, weight factors to the calls are given according the estimated number of passenger behind the calls, as was explained in Section 6.1. The cars reverse their direction and by-pass landing calls more easily than, for example, in collective control. This is due to the order
in which the landing calls are allocated.

During light traffic the statistical passenger traffic forecasts are used in parking the cars at the floors with probably arriving passengers. The statistical forecasts are searched as long as the number of arriving passengers exceeds a certain percentage of the up-peak handling capacity (Leppälä 1991). A building is divided into sectors with equal passenger arrival rates, and sectors are given priorities. Sectors are arranged in a priority order. The priority of a sector is found by dividing the passenger arrival rate in the sector by the number of floors inside the sector. The sector with highest arrival rate per floor is served first. After an elevator has been vacant for a defined time, it is returned to the busiest parking floor within a sector. The parking operation is cancelled if new landing calls are registered and a reason for car dispatching arises.

7. TEST RESULTS

7.1 Sample simulation

In the following, the effect of landing call time minimization is compared to the passenger waiting time minimization by the TMS9000 control system. The ALTS (Advanced Lift Traffic Simulator) (Siikonen 1993) was used in the tests. The building has one entrance floor and 16 populated floors. The population distribution is shown in Figure 8. There are six and ten times as many people on the two highest floors as there are on the lower floors. The test is made for an elevator group with five 16-person cars. The speed of the elevators is 2.0 m/s.

Outgoing traffic was simulated. The average passenger waiting times with both optimization methods are shown in Figures 9 and 10. Figure 9 shows the passenger waiting times as a function of the passenger arrival rate. Figure 10 shows the landing call times as a function of the passenger arrival rate. The average waiting times are considerably decreased during heavy traffic, but the average landing call times are slightly increased with waiting time optimization. The available handling capacity is better utilized as the passenger waiting times are optimized. Figures 11 and 12 show the passenger waiting time and the landing call time distribution floor by floor for a passenger arrival rate that is 1.2 times the handling capacity. By optimizing passenger waiting times the average waiting times floor by floor are balanced. Crowded floors with high passenger arrival rates have better service than by optimizing the landing call times. The maximum waiting times are cut at heavily populated floors and the average passenger waiting times become shorter. Waiting time optimization improves passenger waiting times especially in buildings with uneven population distributions.

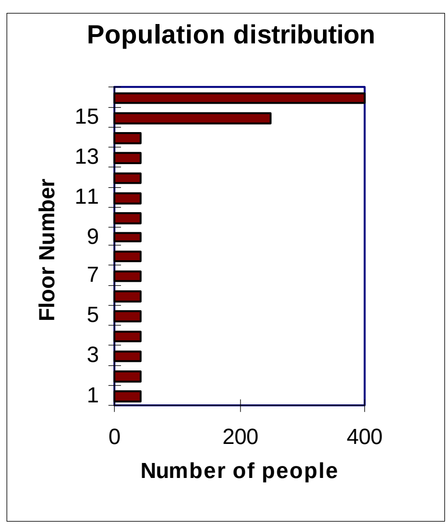

Figure 8. Population distribution in the test building.

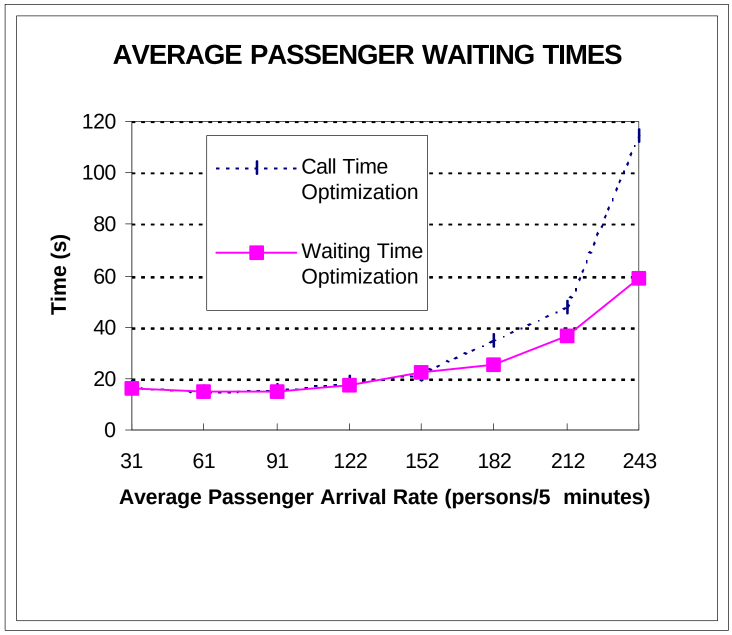

Figure 9. Average passenger waiting times as a function of the passenger arrival rate.

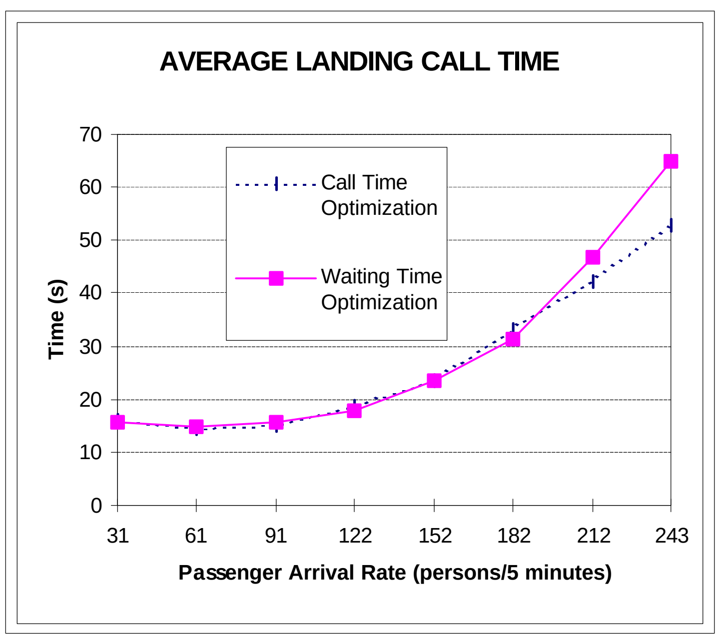

Figure 10. Average landing call times as a function of the passenger arrival rate.

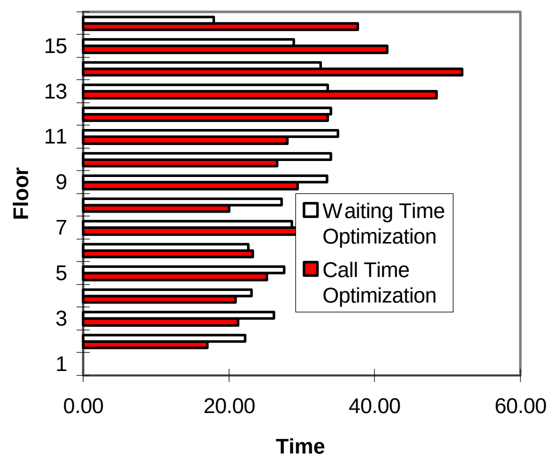

Figure 11. Average passenger waiting times floor by floor with the 120 per cent traffic intensity.

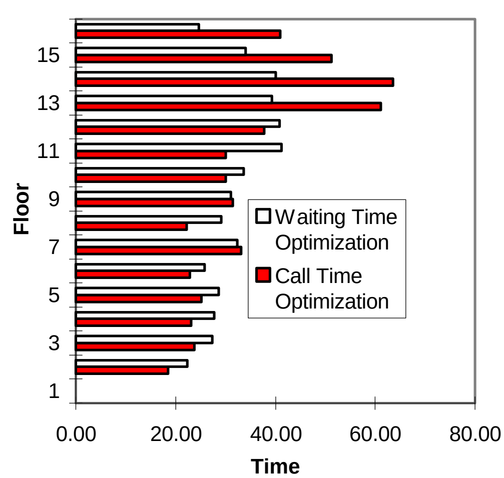

Figure 12. Average landing call times floor by floor with the 120 per cent traffic intensity.

7.2 Measurements before and after a modernization

In existing buildings the landing call times are often available, since they are easier to measure in elevator banks with up and down landing call buttons than the passenger waiting times. The passenger service level has to be judged from the landing call times. Figure 13 shows landing call time distributions before and after a modernization of an 18-floor office building in Helsinki, Finland. An old electronic control was replaced with the TMS9000 control. Call times were exponentially distributed with a mean of about 18 s before the modernization and about 11 s after the modernization. The improvement in the mean landing call time is $35-40 %. In this specific case, the elevator door-to-door time remained unchanged in the modernization of the doors and the drive system. The availability of the new elevators, however, was increased by the modernization. The passenger traffic in the building changed somewhat between the measurements because of the enlargement of the ground floor. The number of landing calls, however, has remained about the same. In this case almost all of the improvement in landing call times is caused by the change of the group and elevator controls.

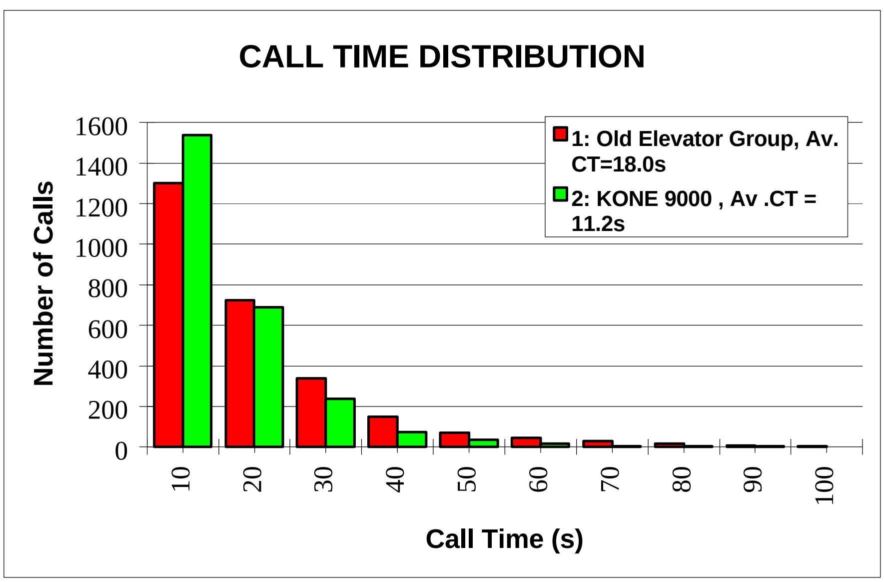

Figure 13. Landing call time distribution before and after modernization of Neste office building in Espoo, Finland.

8. CONCLUSIONS

The control methods and principles of different manufacturers have approached each other with microprocessor technology. The best features of the new controls have been adapted by the producers. Nowadays all advanced group controls utilize statistical forecasts, fuzzy logic, and artificial intelligence. The control principles described in this report were first applied in the TMS9000 control for high rise buildings, but later on they were apdapted also to the controls for mid rise buildings.

In TMS9000, passenger waiting times and ride times inside the car are optimized according to the observed passenger arrival rates at each floor and in each direction from the last five minutes. The number of waiting passengers behind each call is estimated. By optimizing passenger waiting times instead of landing call times, the average waiting times become more balanced floor by floor. Crowded floors with high passenger arrival rates have better service than by optimizing the landing call times. The maximum waiting times are cut at heavily populated floors and the average passenger waiting times become shorter. Optimization of waiting times improves the service especially in buildings with unequal passenger arrival rates at different floors and directions. The landing call times are slightly decreased but during heavy traffic they can be a little increased.

The group control adapts to the prevailing traffic pattern. Control actions, such as returning cars automatically to busy traffic floors, or parking cars during light traffic, follow from the forecast traffic pattern. Fuzzy logic is applied in recognizing the prevailing traffic patterns according to the forecast traffic component and passenger arrival rates. Passenger arrival rates at and exiting rates from each floor and in each direction are forecast for each time period. Statistical forecasts of the passenger traffic are made in 15-minute periods for a typical day, or separately for every weekday. Contrary to conventional controls, the peak traffic periods are predicted in advance. Before implementing a forecast traffic pattern, the validity of the forecast is confirmed. If the forecast is in conflict with the short-term statistics, the forecast is not applied in the control.

The group control decisions can be further improved by utilizing the statistical forecasts more. The reservations of landing calls to cars can be fixed at an earlier stage if the future events are simulated more accurately during the call allocation. Passengers can then be informed earlier about the arriving car, which shortens the psychological waiting time. The number of optimization targets can be increased. All the optimization targets cannot be reached simultaneously since they often are in conflict with each other. The optimization targets can be switched according to the forecast traffic pattern. For example, during the up-peak the optimization target could be to increase handling capacity and decrease journey time, and during the down peak to balance car load and to minimize passenger waiting times. The optimization targets should be selected so that they have the greatest positive influence on the defined cost and on the overall performance of the elevator group.

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