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MULTIOBJECTIVE OPTIMIZATION IN ELEVATOR GROUP CONTROL

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Abstract. *Modern elevator systems in high-rise buildings consist of groups of elevators with centralized control. The group control allocates hall calls to the most suitable elevators by optimizing a cost function. This problem can be viewed as a combination of online scheduling, resource allocation, and stochastic control. The usual performance criterion to be optimized when scheduling passenger pick-ups is the average waiting time of all passengers in the system, i.e., the time period from the moment when the passenger arrives until the moment when this passenger boards some elevator. Alternative criteria are sometimes used as well, such as the ride time, defined from the time of boarding until a passenger arrives at the desired floor, the percentage of waiting times exceeding a certain limit or the number of elevator stops, which is related to energy consumption. Considering two or more of these criteria simultaneously results into a multiobjective optimization problem, where the group control algorithm should be tuned in order to find a good compromise between the different criteria. We study the relations between the criteria and some tuning parameters of to our Estimated Time of Arrival (ETA) algorithm by simulating different traffic patterns. Then we define a linear utility function form combining the criteria. Based on reasonable weights for the criteria we determine find optimal values for the tuning parameters.*

1 INTRODUCTION

Elevator group control systems are widely used to operate multiple elevators in a building in order to efficiently transport the passengers. The group control system allocates the appropriate service car for each new passenger making a hall call. This problem can be viewed as a combination of online scheduling, resource allocation, and stochastic control. The stream of arriving passengers is a stochastic process. Each passenger introduces three random variables: arrival time, arrival floor and desired destination floor. In addition, the number of passengers behind each hall call is unknown. The system must respond quickly to new calls. Therefore the optimization time is limited to a few hundred milliseconds, which excludes computationally expensive methods.

The elevator group control algorithms span from ad hoc approximations and heuristics to AI planning, fuzzy logic [3, 9, 20], genetic algorithms [24] and decision-theoretic planning [15, 16]. Pure up-peak and down-peak traffic patterns can be analyzed from a theoretical viewpoint [5, 6, 7, 19]. Special-purpose group control algorithms based on such traffic patterns have provably optimal solutions. The threshold based dynamic programming method [17] provides an optimal solution during up-peak traffic. Dynamic zoning [1] can make the controller adapt to up-peak and down-peak traffic to obtain the optimal solution.

The performance of the elevator group control is measured by several criteria such as the average waiting time of passengers, the average ride time of the passengers, the percentage of passengers waiting more than 60 s and power consumption [9]. Considering two or more of these criteria simultaneously results in a multiobjective optimization problem [14], where the group control algorithm should find a good compromise between the different criteria. Some studies regarding the methods to deal with multicriteria optimization elevator group control problem have been reported. Fujino et al. [3] developed a floor-attribute control method in conjunction with an on-line parameter tuning method using genetic algorithm. Kim et al. [9] proposed a control strategy generation method based on fuzzy logic to generate the weights of the different performance criteria. Different decision makers have different preference for the performance criteria. e.g. some decision makers pay attention to the average waiting time while others think that the long waiting percentage is more important since it represents the fairness in service. The building owner may stress the power consumption. In addition, the requirements for different traffic patterns may vary. In the up-peak traffic pattern, average waiting time is important while long waiting percentage may be important in down-peak traffic pattern.

In this paper we consider the mentioned four performance criteria in the multi-criteria analysis and evaluate the effect of different traffic patterns. We present an offline tuning method for an Estimated Time of Arrival (ETA) elevator group control algorithm [18] based on extensive simulations. First, we study the effect of tuning parameters on the individual performance criteria. Then we define a linear utility function combining the different criteria based on the weight assigned to different criteria. After that we determine the optimal values for the tuning parameters in the algorithm.

The rest of paper is organized as follows. The multiobjective optimization method is explained in section 2. In Section 3, we briefly review the ETA algorithm and elevator systems. Section 4 gives the design of simulation experiment. Section 5 investigates the effect of parameters on the individual performance criterion. Section 6 combines the different performance criteria by assigning the importance weights so that the resulting utility function can be maximized.

2 MULTIOBJECTIVE OPTIMIZATION METHOD

The optimization is based on an elevator system simulator. The simulator inputs a vector of control parameters y ($y \in Y$), traffic pattern p ($p \in \{1, 2, \ldots, P\}$) and a seed for random traffic generation s ($s \in \{1, 2, \ldots, S\}$). The simulation result is a vector of performance criteria (x').

$$x' = f(y, p, s) \tag{1}$$

The true performance of the elevator system is stochastic since it depends on random traffic situations. Therefore the simulation is executed S times for each traffic pattern generated with different random seeds, and the results are averaged. It would be possible to optimize a separate parameter setting for each traffic pattern. Another way is to combine the studied traffic patterns using a weighted sum or simply an average as in (2).

$$x(y) = \frac{\sum_{p=1}^{P} \sum_{s=1}^{S} f(y, p, s)}{PS} \tag{2}$$

$x = (x_1, \ldots, x_n)$ are criteria measurements and n is the number of criteria. We form a linear utility function from the criteria measurements by applying the weighting method. The importance weights w_j represent the decision makers' preferences. The linear utility function has the shape

$$U(x) = \sum_{j=1}^{n} w_j \frac{x_j - x_j^{worst}}{x_j^{best} - x_j^{worst}}, \tag{3}$$

where x_j^{worst} and x_j^{best} define the worst and best values for criterion j. correspondingly. The result of multiobjective optimization problem is the maximum of utility function.

$$\max_{y \in Y} U(x(y)) \tag{4}$$

In this paper the parameters in set Y are discretized. The criteria measurements are uncertain, thus besides the optimum it is necessary to consider also the parameters values that are nearly optimal and their standard deviations.

3 REVIEW OF THE ETA ALGORITHMS AND ELEVATOR SIMULATION MODEL

3.1 ETA group control algorithms

ETA is a control principle which attempts to treat all hall calls (or passengers) equally by introducing the system degrade factor (SDF) to find the appropriate elevator to serve each new hall call [15, 16, 23]. Not only is the attending time of the new hall call considered, but also the delay it will cause to the successive unattended hall calls that have been allocated to the same elevator. Thus, the total cost of allocating the new hall call to elevator *i* is given below.

$$t_i^{total} = \sum_{j=1}^{n_i} t_{i,j}^{delay} + t_i^{attending} \tag{5}$$

Here n_i is the number of the passengers that have been allocated to elevator *i* and not been served yet, $t_{i,j}^{delay}$ (≥ 0) is the expected delay (in waiting time) that the new hall call will cause to passenger *j*, who has been allocated to elevator *i* and not been served, $t_i^{attending}$ (≥ 0) is the estimated attending time of the new hall call. To increase the accuracy of $t_{i,j}^{delay}$ and $t_i^{attending}$ estimation we try to consider the number of extra stops caused by the new hall call and apply the three-passage concept [2, 4] to determine the service order of the hall calls: passage one (P1) hall calls are those that can be served by the elevator along its current travel direction, passage two (P2) hall calls require reversing the direction once, and passage three (P3) hall calls require two reversals.

This paper considers a variant of the ETA algorithm having an additional *degrade coefficient* b^{SDF} (≥ 0), which is used to weight the previously allocated calls. The coefficient compensates the weakness that ETA does not explicitly consider future calls. The allocation cost is thus expressed as

$$t_i^{total} = b^{SDF} \sum_{j=1}^{n_i} t_{i,j}^{delay} + t_i^{attending} \tag{6}$$

The system will allocate the new hall call to the elevator with the lowest total cost. That is,

$$e_{\text{candidate}} = \underset{i \in [1, M]}{\arg\min}\, t_i^{total} \tag{7}$$

In the immediate allocation policy, the system tells the passenger immediately which elevator to use when the passenger makes a hall call, whereas in the continuous allocation policy the system does not inform passengers until an elevator is about to arrive. Some earlyallocated hall call may lose optimality as future events appear in the system. In our original ETA algorithm [18], we introduced a reallocation mechanism to compensate for the shortcomings of immediate allocations because continuous allocation is widely adopted in traditional UP-DOWN button elevator systems in Western countries. (Only Destination Control System (DCS) justifies the use of immediate allocation, but in Japan immediate allocation is used even in traditional elevator systems). Our reallocation variant of ETA selects heuristically a limited number of calls for reallocation. The selection includes several categories of hall calls, e.g. the oldest hall call in the systems and some other hall calls that could be severely affected. As a general principle, hall calls should be reallocated after they have stayed in the system for a sufficiently long time. This time is the *reallocation limit* parameter. In this paper, we only choose the oldest hall call in the system for reallocation because there is tradeoff between the reallocation of different categories of hall calls and that would make tuning the algorithm more difficult. The attending time of the oldest hall call will be most severely affected by the incoming events. Reallocating the oldest hall call should have significant effect on the performance of algorithm.

3.2 The simulation model

The group control algorithm was attached to a discrete-event simulator [12]. The simulation model consists of the elevator model and traffic generation [22]. The features of the model are

- The elevator must not pass a floor at which a passenger wishes to get off.
- The elevator must fulfill its current commitment and not reverse direction with passengers aboard.
- An empty elevator can stop, go up or go down. Some elevator systems have parking or returning algorithm, which sends elevator to a suitable floor for future calls. However this implementation does not have such an algorithm, so an elevator will not start unless there is a call.
- The flight times of elevators are determined by the distances between floors, constant acceleration and maximum speed.
- There are fixed delays for door openings, closings and passenger transfers.
- If there are enough queuing passengers, they fill the elevator up to the rated load. However the elevator will not stop for landing calls, if the load exceeds *bypass load* limit which is defined as a portion of the rated load (0,1].
- The passengers arrive to different floors according to the Poisson process. This means that the inter-arrival times follow the exponential distribution, $f(x) = \lambda e^{-\lambda x}$, where λ is the arrival rate.
- There are one or several *entrance floors* and the rest of floors are *populated floors*. Traffic consists of three components: incoming, outgoing and inter-floor components. Incoming passengers travel from an entrance floor to populated floors, outgoing passengers from populated floors to an entrance floor and inter-floor passenger travel between populated floors. Intensity of traffic and the percentages of incoming, outgoing

and inter-floor passengers are determined by traffic parameters.

Two first of the listed features are common to all elevator systems. The delays and the behavior of passengers are deterministic and the models are somewhat simplified compared to Building Traffic Simulator [13, 8]. The arrival of passengers is the only stochastic process. The passengers are generated as follows:

1. The inter-arrival time between the previous passenger and the next passenger is taken from an exponential distribution. The arrival intensity is the total population times traffic intensity, which is expressed as portion of population per time unit.
2. The type of passenger (incoming, outgoing or inter-floor) is chosen according to the percentages specific for the traffic pattern.
3. The type determines whether the arrival and destination floors are entrance or populated floors
    a. If the floor is populated floor, the probability of the floor is proportional to the floor population.
    b. If the floor is an entrance floor and there are more than one entrance floors, the probability of floor is proportional to the *entrance attraction*.
    c. If independently generated arrival and destination floors happen to be equal, the floor generation is repeated.

4 EXPERIMENTAL DESIGN

In the simulation, we will investigate how the concerned performance criteria will be affected by the chosen control parameters for the typical traffic patterns in the building so that we can find the best combination of the parameter settings to satisfy the decision maker's preferences.

4.1 Control parameter setting

Based on the review in section 2, we choose following three parameters as control parameters

- Degrade coefficient b^{SDF} (≥ 0) in the ETA algorithm (**19** levels)
- Reallocation limit (>0) for the oldest hall call in the system in the ETA algorithms (**6** levels)
- Bypass load ($\in(0,1]$) in the elevator systems (**6** levels)

The settings of control parameters are shown in Table 1.

Parameter	Values
Bypass load	0.5 0.6 0.7 0.8 0.9 1.0
Degrade coefficient b^{SDF}	0 0.25 0.5 0.75 1 1.25 1.5 1.75 2 2.25 2.5 2.75 3 3.5 4 4.5 5 5.5 6
Reallocation limit [s]	5 10 15 20 25 30

Table 1. Control parameter settings

4.2 Performance criteria

The following four performance criteria are chosen.

- waiting time; the time between passenger arrival and entering to elevator
- ride time; the time that the passenger is aboard the elevator
- P>60; the percentage of passengers that wait over 60 s
- total number of elevator stops

Waiting time is a psychologically important criterion to the passenger. The ride time has something to do with the utilization of the elevator capacity. Since the purpose of system is to transport passengers between floors, *journey time* is also an important measure. However, journey time need not be considered as a separate criterion, because it is the sum of the waiting time and ride time criteria. P>60 measures the porting of long waits. It is also related to the uncertainty of waiting time. The total number of stops is related to energy consumption and wear of mechanical parts; thus it is more meaningful to the building owner than to the passengers.

4.3 Traffic patterns in the building

Traffic pattern	Incoming (%)	Outgoing (%)	Inter-floor (%)
Incoming (I)	95	5	0
Outgoing (O)	0	100	0
Lunch (L)	40	40	20
Two-way (T)	50	50	0

Table 2. Traffic patterns.

The simulated building has 40 floors with floor height 3.6 m. The lowest floor 0 is an entrance floor. The elevator group serves an upper zone, which means that floors 1-24 are not served. The population of each of the floors 25-39 is 90. The group has 8 elevators with rated load 21, speed 4.0 m/s and acceleration 1.0 m/s^2. Door opening time is 1.6 s and closing time 2.6 s, passenger transfer time into elevator is 1.0 s and transfer time out from elevator is 1.0 s. The heavy intensity is 13 % of the population per 5 minutes. One hour of traffic was generated for each simulation.

Table 2 shows typical traffic patterns in the building [21]. The traffic patterns are defined by three basic traffic components: incoming traffic, outgoing traffic and inter-floor traffic. Incoming traffic represents passengers arriving only at the main lobby and traveling to their destination floors in the upper zone of the building; Outgoing traffic represents passengers traveling from the upper floors down to the main lobby; and inter-floor traffic is due to passengers moving randomly between the upper floors. Here, we investigate the four typical traffic patterns in the building: Incoming pattern (I), Outgoing pattern (O), Lunch pattern (L) and Two-way pattern (T). *Incoming* pattern includes small percentage of outgoing traffic to compensate for the lack of the returning algorithm. *Outgoing* pattern consists of 100%

outgoing passengers. *Lunch* pattern consists of all three basic traffic components and *two-way* traffic includes same proportion of incoming and outgoing traffic. In addition, two arrival intensities are chosen for each traffic pattern: heavy (H) and moderate (M). *Heavy* intensity is near the upper limit of the transportation capacity and *moderate* intensity is the half of the heavy intensity. This results in a total of **8** different traffic scenarios (HI, HO, HL, HT, MI, MO, ML, and MT).

Traditional elevator planning concentrates on the up-peak (HI) traffic situation. The main reason is that the up-peak situation in office buildings is intense and the most difficult one to handle. Another reason is that there are analytical formulas for that situation, because pure 100% up-peak in a building with one entrance floor is theoretically simple. The optimization has no effect in that case, so up-peak is not so interesting situation for call allocation. The authors did not find any reason to prefer any traffic pattern, therefore each of them is considered equally important. A good group control should handle all traffic situations well. Even the moderate intensity is higher than average intensity over a day in an office, so actually this data emphasizes the importance of higher intensities compared to the typical traffic in Western countries. These cases are however the most interesting ones, since optimization makes bigger difference for higher intensities. The used traffic patterns are recognizable in real daily traffic, but they do not appear in pure form like in this data.

For each traffic scenario, a random sample of **10** traffic files is generated. Based on the above experimental design, a total of 6×19×6×8×10 = 54720 test runs are conducted. Next we will study the effect of control parameter settings on the concerned performance criteria.

5 EFFECT OF THE CONTROL PARAMETERS

Figures 1 a & b show the overall effect of each control parameter on the four performance criteria. These are just rough trends, since each graph only involves the effect of one control parameter and the other two parameters are averaged over all combinations. That is, the plotted value y_i of control parameter i is

$$x^i(y_i) = \frac{\sum_{y \in Y_i} x(y)}{|Y_i|}, Y_i = \{(y_1', y_2', y_3') \in Y \mid y_i = y_i'\} \tag{8}$$

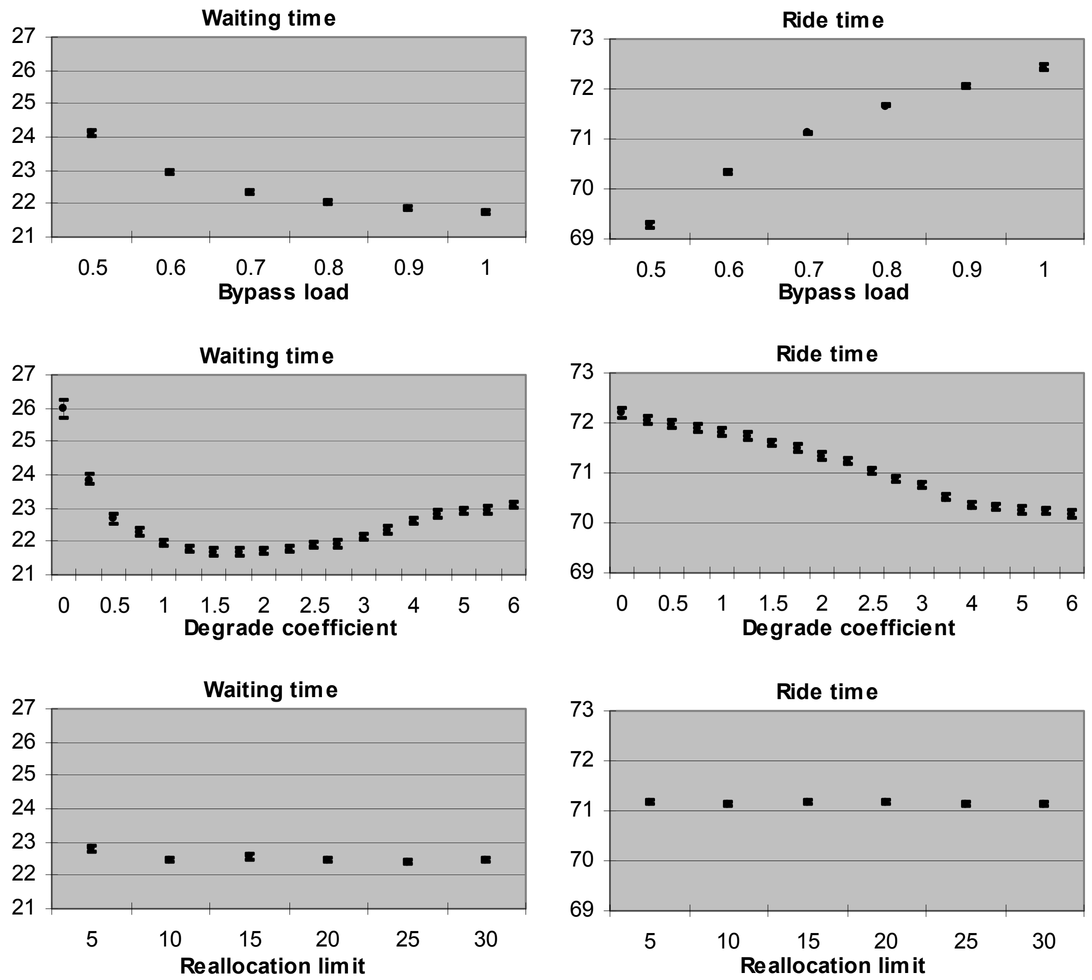


Figure 1a. Effect of three control parameters on waiting time and ride time.

According to Figures 1 a & b, both Waiting time and P>60 behave in a similar way, both decrease monotonically by increasing Bypass load and both have minimum with respect to Degrade coefficient. Ride time and the number of stops increase monotonically by increasing Bypass load. Ride time decreases monotonically respect to Degrade coefficient and the number of stops has maximum respect to Degrade coefficient. The effect of Reallocation limit is smaller and there are no clear trends.

Table 3 lists the full ranges for criteria $\left[\min_{y\in Y} x_j(y), \max_{y\in Y} x_j(y)\right]$. Smaller values of criteria are better, thus the minimum values are more interesting than the maximum values. The variation in Figures 1 a & b is smaller, because the plotted values are averages over the other dimensions.

Next we consider minimizing each criterion separately. Table 4 shows the parameter values $\arg\min_{y\in Y} x_j(y)$ and the corresponding criteria values that minimize each criterion j

separately. If the decision maker considered one criterion far more important than the others, he or she could choose a parameter combination from this table. A more general method is to consider the trade offs between criteria, which is done in section 6.

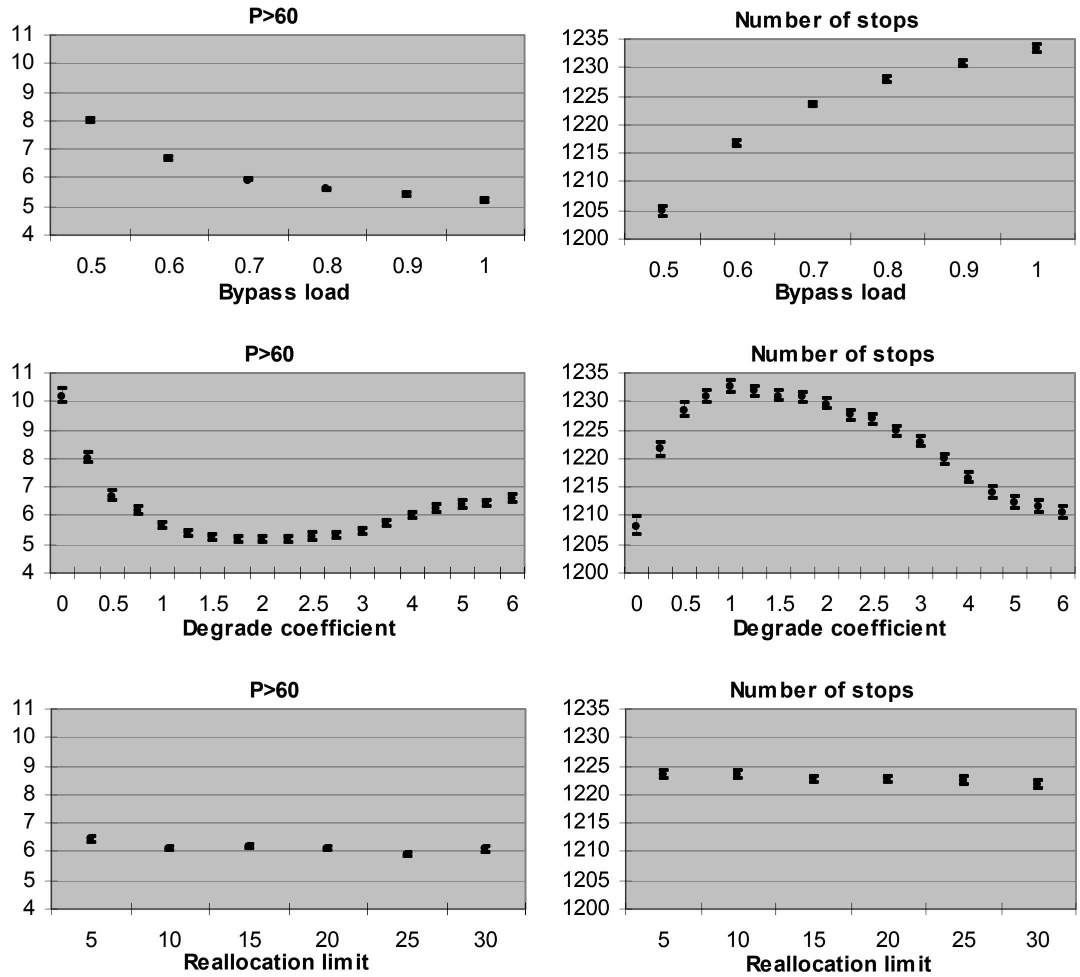


Figure 1b. Effect of three control parameters on P>60 and the number of stops.

Criterion	Minimum	Maximum
Waiting time [s]	20.6	28.4
Ride time [s]	68.4	73.9
P>60 [%]	3.8	12.7
Number of stops	1188	1245

Table 3. Ranges for criteria

	Parameters			Criteria values			
Criterion	**Bypass load**	**Degrade coefficient**	**Reallocation limit [s]**	**Waiting time [s]**	**Ride time [s]**	**P>60 [%]**	**Number of stops**
Waiting time	1	1.75	10	**20.6**	72.8	4.1	1244
Ride time	0.5	6	30	24.6	**68.4**	8.4	1192
P>60	1	2	25	20.7	72.7	**3.8**	1241
Number of stops	0.5	0	30	28.3	70.1	12.7	**1188**

Table 4. Parameter combinations minimizing each criterion separately.

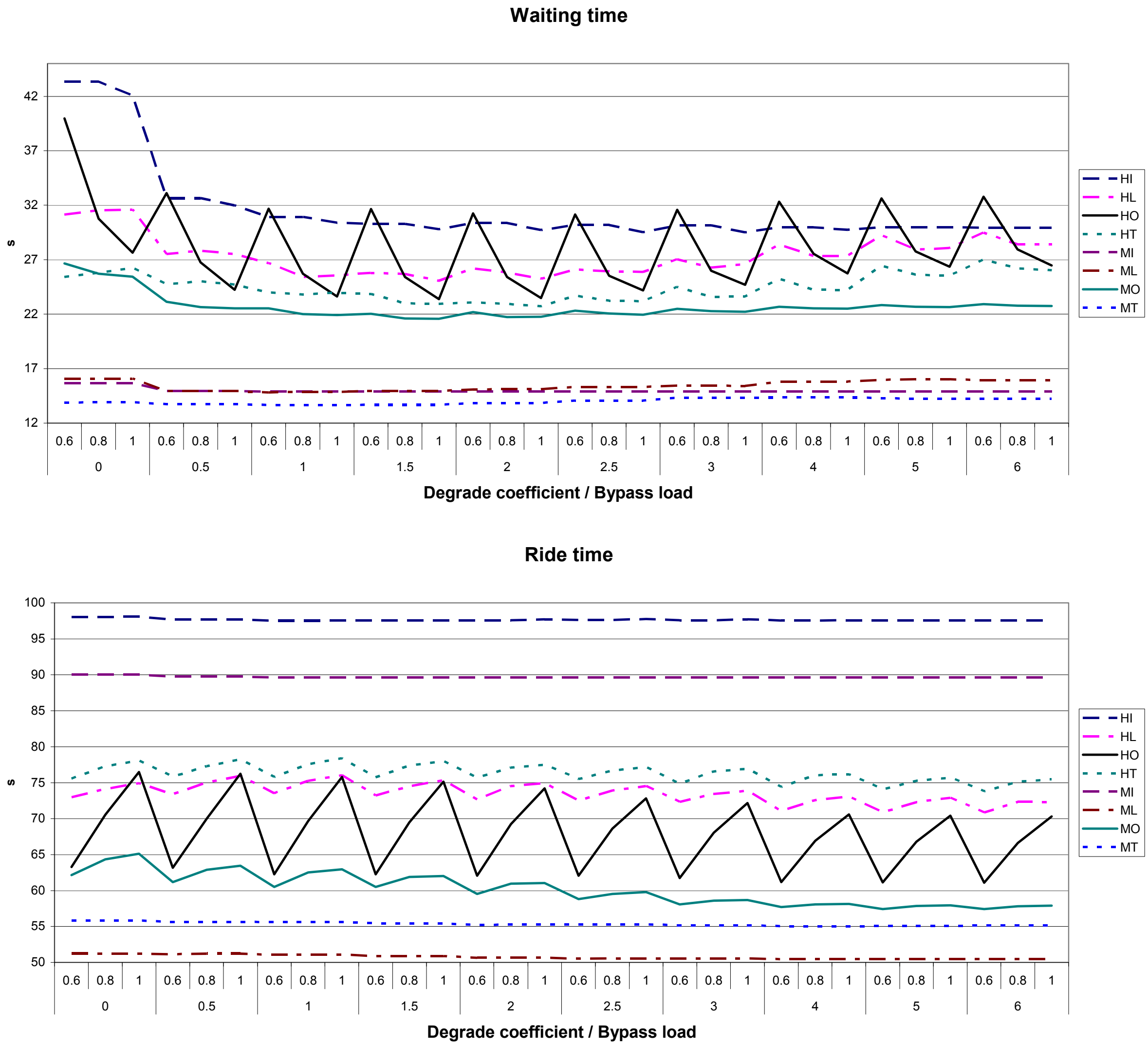
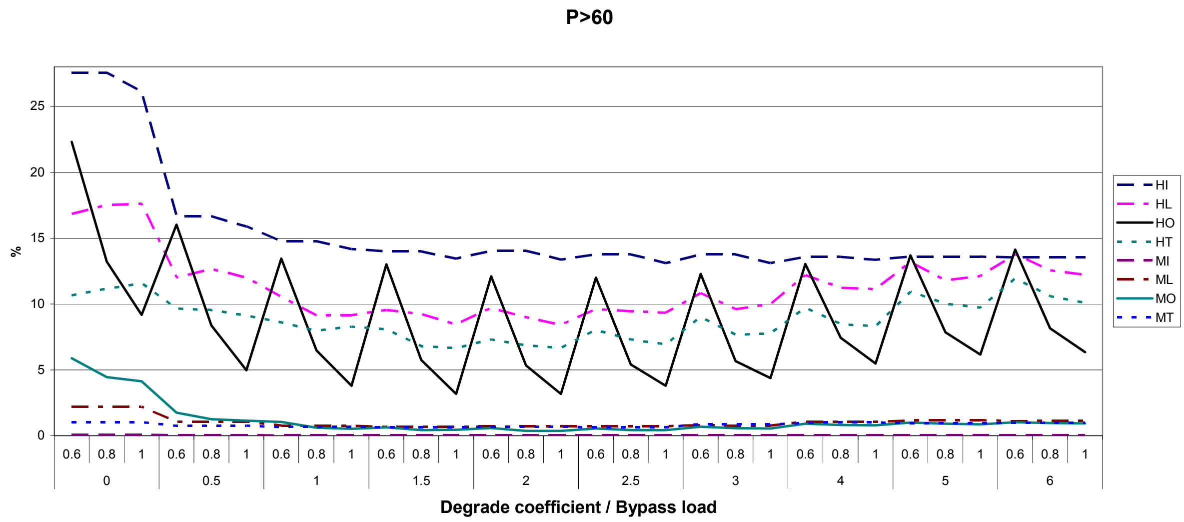


Figure 2a. Effect of Bypass load and Degrade coefficient in different traffic situations (HI, HL, HO, HT, MI, ML, MO, MT) on waiting time and ride time.



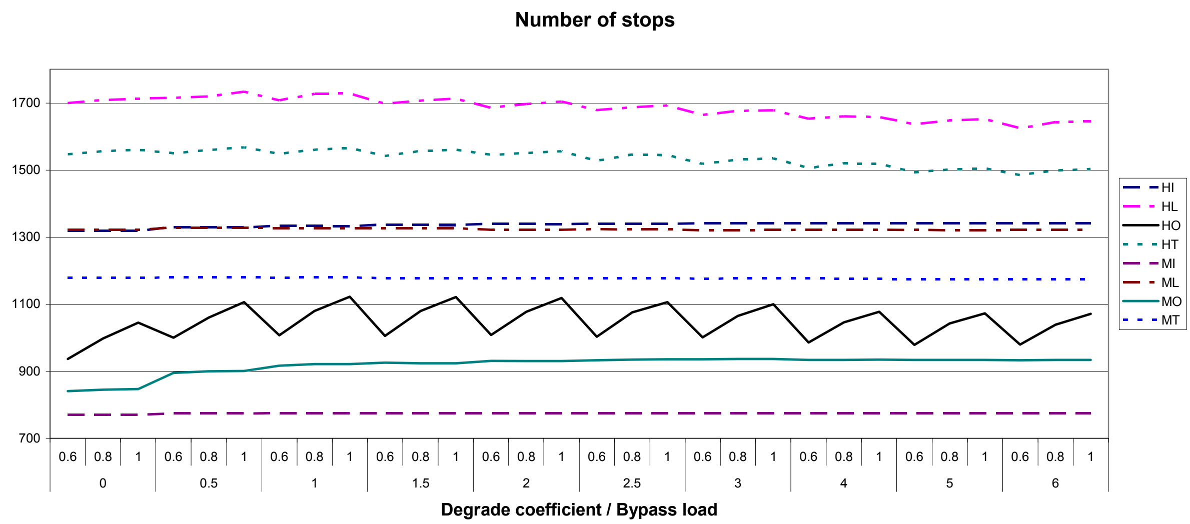


Figure 2b. Effect of Bypass load and Degrade coefficient in different traffic situations (HI, HL, HO, HT, MI, ML, MO, MT) on P>60 and the number of stops.

Figures 2 a & b show the effect of all combinations of Degrade coefficient and Bypass load on the criteria in different traffic patterns. We can see that the criteria behave roughly similarly in the different traffic patterns. Parameters have less effect in medium intensity patterns. As could be expected, Bypass load makes a difference only when loads are high. The Number of stops is an exception: degrade coefficient $b^{SDF} = 0$ is best in down traffic (HO, MO), but $b^{SDF} = 6$ is best in heavy lunch hour (HL) and two way traffic (HT, MT). Therefore it could be useful to study further, whether using different parameter values in different traffic situations could improve the criteria.

6 CONSIDERING TRADEOFFS BETWEEN CRITERIA

Next we consider the tradeoffs between the criteria by forming a linear utility function (3). It may be difficult to assess the importance weights precisely. It is much easier to decide a relative importance order among the criteria. When determining the relative importance of the criteria, the decision maker must consider how important he considers the intervals for the different criteria. Recall the ranges in Table 3. Waiting time is in general an important criterion and the 7.8 s difference between the best and worst case is very significant. Thus, waiting time it is the most important criterion. Ride time is also important, but the range of ride times is smaller, so it is the second important. A few percent change is energy consumption or maintenance costs is no very important, so the number of stops is least important and P>60 is the third criteria.

There are many different ways to derive weights from an importance order of the criteria. One approach is to consider all different weights that satisfy the importance order as in Stochastic Multicriteria Acceptability Analysis (SMAA) methods [11, 10]. However, such an analysis is out of the scope of this paper. Instead, we apply a simple and commonly used method of Centroid weights. The centroid weights are given by

$$w_i = \frac{1}{n}\sum_{j=i}^{n}\frac{1}{j}, \; i = 1, \ldots, n. \tag{9}$$

In a four-criterion problem (n = 4), the centroid weights are 0.521, 0.271, 0.146, 0.062. The rank, intervals in Table 3 and formulas (3) and (9) yield utility function

$$U = 6.16 - 0.0670\, x_1 - 0.0499\, x_2 - 0.0164\, x_3 - 0.0011\, x_4 \tag{10}$$

where x_1 is waiting time, x_2 is ride time, x_3 is P>60, x_4 is the number of stops.

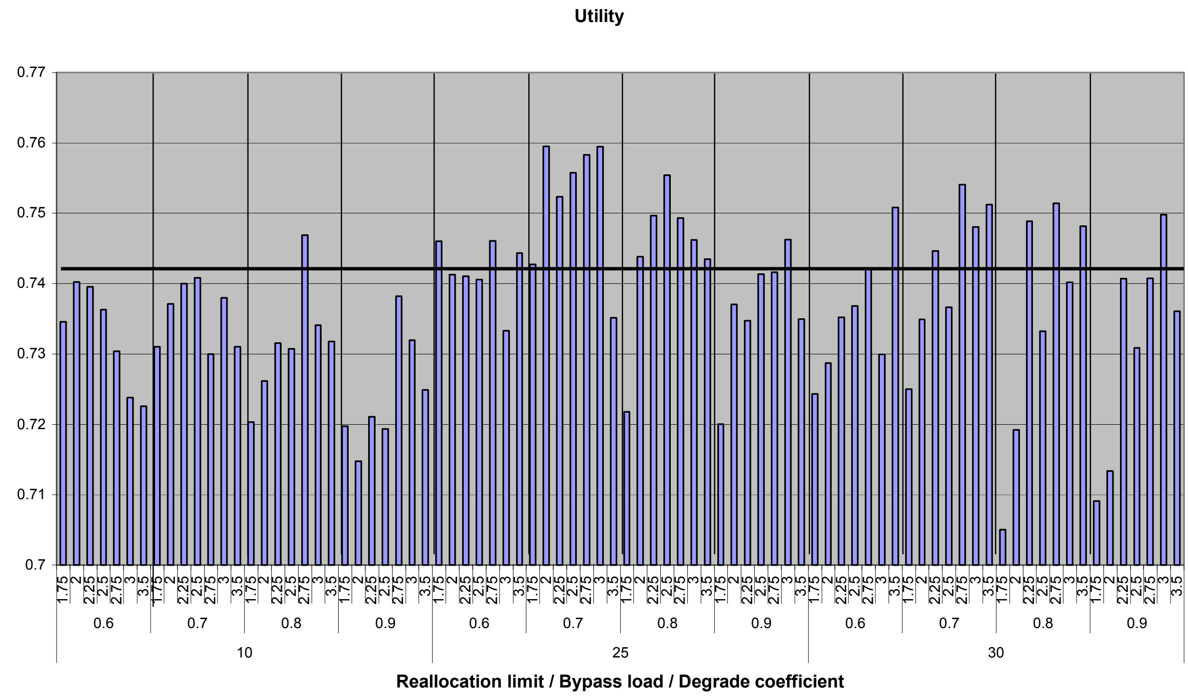


Figure 3. Utility function. Horizontal line marks standard deviation of optimum.

Figure 3 shows the utility function for best parameter values. The maximum utility $U = 0.760$ is at point Reallocation limit = 25, Bypass load = 0.7 and Degrade coefficient $b^{SDF} = 2$. There are random errors, since only 80 simulations were run for each data point. The horizontal line shows the highest point minus its standard deviation. Despite of randomness, Reallocation limit = 25 and Bypass load = 0.7 seem to be the best, but all b^{SDF} between 2 and 3 give high utility. Table 5 shows the values of criteria in the range.

If we smoothen the utility function by averaging over the two best Reallocation limits 25 and 30, Bypass loads 0.7 and 0.8 and over previous current and the next Degrade coefficient, then the best Degrade coefficient b^{SDF} will be 2.5 with utility 0.749 and the second best is $b^{SDF} = 2.75$ with utility 0.749. Point (0.7, 2.5, 25) is related to criteria values (21.5, 71.0, 4.7, 1227) and standard deviation of criteria (0.2, 0.1, 0.3, 1.6). The expected result when selecting one of the studied combinations without optimization is (22.5, 71.1, 6.1, 1223). The improvement is therefore (1.0, 0.1, 1.4, -4).

The results mean that waiting time has improved 1 s (4.4%), ride time is about the same, the number of long waits has dropped by 23% and the number of stops has risen by 0.3%.

Bypass load	Degrade coefficient	Reallocation limit [s]	Waiting time [s]	Ride time [s]	P>60 [%]	Number of stops	Utility
0.7	2	25	21.2	71.4	4.4	1231	0.760
0.7	2.25	25	21.4	71.2	4.6	1228	0.752
0.7	**2.5**	**25**	**21.5**	**71.0**	**4.7**	**1227**	**0.756**
0.7	2.75	25	21.6	70.8	4.8	1225	0.758
0.7	3	25	21.8	70.6	4.8	1224	0.759

Table 5. Criteria near the optimum. The best Degrade coefficient b^{SDF} = 2.5 was found after smoothening.

7 CONCLUSIONS

The purpose of group control is to allocate hall calls to the most suitable elevator to efficiently transport the passengers. The performance of the elevator group control is measured by several criteria such as the average waiting time of passengers, the ride time, the percentage of passengers waiting more than 60 s, and energy consumption. Different decision makers may attach different weight to different performance criteria. In addition, the control algorithms must consider many uncertain factors in the elevator systems such as the number of passengers at floors where hall calls and car calls are generated. In this paper, we developed an off-line tuning method by adjusting the Degrade coefficient and Reallocation limit control parameters of the ETA control algorithm [18] and the Bypass load of the elevator. The parameters define how the older calls are weighted, how old the calls must be to be considered for reallocation, and the load when elevator starts to bypass hall calls respectively. First we executed a series of simulations with different traffic patterns for 6 (relocation limit) × 19 (degrade coefficient) × 6 (bypass load) combinations of parameter values. Each simulation produced a measurement of four performance criteria; waiting time, ride time, P>60 and the number of stops. Then the performance criteria were ranked by importance and given different weights using the centroid method. Finally, the resulting utility function was maximized to find the optimal settings of the control parameters. There was substantial improvement in the most important criteria, waiting time and also in P>60. The offline tuning method provides a way to satisfy different decision maker's preferences by setting the level of control parameters.

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