Model-Based Multiobjective Optimization of Elevator Group Control

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ABSTRACT

Finding a suitable control strategy for the elevator group controller (EGC) is a complex optimization problem with several objectives. We utilize the sequential-ring (S-Ring) model of EGC systems and propose a biobjective formulation of the EGC optimization problem. Unlike the previous work, we use true multiobjective optimizers in solving this problem. Their results on three real-world elevator systems reveal the possible trade-offs between the objectives and offer a valuable insight into the problem.

Keywords

elevator group control, S-Ring, perceptron, multiobjective optimization, NSGA-II, DEMO

1. INTRODUCTION

With larger number of people living in urban areas and modern barrier-free building design, elevator systems are becoming more and more important. Modern multi-car elevator systems are controlled by elevator group controllers (EGC) that assign elevator cars to their destinations based on the customer service calls. The control strategy strongly affects the desired service quality, customer satisfaction, energy consumption, and material attrition. Thus, finding an adequate control strategy depicts a complex optimization problem with several objectives, which is further dependent on the building structure and the passenger traffic situation. Optimization of EGC imposes challenges, such as being nonlinear and multimodal, as well as highly dynamic and stochastic due to the stochasticity of customer arrivals. This renders classic gradient-based optimizers as not applicable to these problems [1]. Moreover, EGC simulators are computationally expensive and limit the number of control strategy evaluations.

While EGC optimization problems are widely discussed and known for involving conflicting objectives, they are seldom solved with true multiobjective optimization. Hakonen et al. [3] utilize a set of objectives, such as the customer waiting time, the ride time, and the total number of elevator stops, but combine them linearly into a single objective. Tyni and Ylinen [7] use a weighted aggregation method to optimize the landing call waiting time and energy consumption with an evolutionary algorithm in a real-time environment. In Sahin et al. [6], a real-time monitoring system is installed to reduce the number of redundant stops, and improve passenger comfort and energy consumption. In [1], an approximation model for EGC systems, the so-called *sequential ring* (S-Ring) [4], is used to benchmark single-objective heuristics. Using the S-Ring model, it is possible to retain a high level of complexity and optimize an EGC control strategy using modern heuristics with a high number of strategy evaluations, while keeping a feasible computational load.

In this paper, we utilize the S-Ring model of EGC systems and propose a biobjective formulation of the EGC optimization problem. In this formulation, the objectives are normalized to allow for comparison of results for elevator systems of various configurations. As opposed to previous work, we apply true multiobjective optimizers capable of finding approximations for Pareto-optimal solutions that represent trade-offs between the objectives. Specifically, we use two multiobjective evolutionary algorithms (MOEAs) and demonstrate their performance in optimizing EGC for three real-world elevator systems.

The paper is further organized as follows. Section 2 introduces the S-Ring model, explains its elements and illustrates it with an example. Section 3 provides the optimization problem formulation. In Section 4, numerical experiments on the three test elevator systems and the results are presented. Section 5 concludes the paper by summarizing the study and planning future work.

2. S-RING MODEL OF ELEVATOR GROUP CONTROL

The S-Ring is a discrete, nontrivial event system to optimize and benchmark control strategies without the need to use expensive EGC simulators [4]. It focuses on modeling the operation of an elevator system, i.e., handling the passenger traffic and serving passengers in the fastest and most comfortable way. We adapted the S-Ring model to feature two service quality related objectives as described in Section 3.

In general, the S-Ring consists of three key elements:

- The deterministic state-space representation of the elevator control inputs for the customers c_i and elevator cars s_i, $i = \{1, ..., N_s\}$, where $N_s = 2n - 2$ is the number of states, while n is the number of floors. Figure 1 shows an example of this state-space representation. The size of the S-Ring depends on the number of floors n, and the number of active elevator states is equal to the number of elevator cars m. The number of currently active customer states is influenced by the probability of a new arriving customer, p.

- The state transition table, which is explained in detail by Markon [4], defines fixed and dynamic rules for a transition in the current position of the S-Ring. If no fixed rule is triggered, the dynamic rules decide how the state transition is performed. They are established by a control policy.
- The control policy π can be realized by a lookup table, but as its size grows exponentially with n, it is maintained by a perceptron with a weight vector of length $|\mathbf{w}| = 2N_s$. The perceptron represents the most elementary implementation of neural network (NN). For a given setup of n, m and p the objectives are only influenced by the weight vector $\mathbf{w}$ of the NN controller and the number of state transition steps, N_t. At each state, it is first checked whether a new customer arrived. Next, if the current state is an active elevator state, the controller determines whether the elevator car stops or continues to the next state. Finally, the indication of the customer active state is updated depending on whether or not the customers were served.

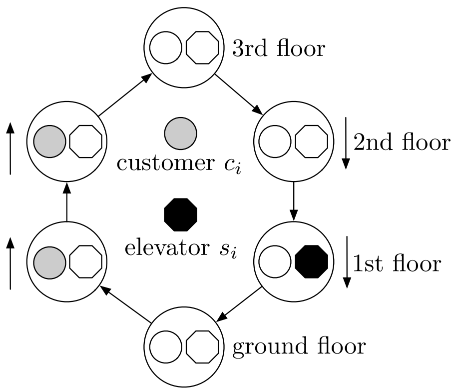

Figure 1: S-Ring: No waiting customer at the ground and floor ("0"), two customers who want to go up on the first and second floor ("1,1"), and no customers who want to go down on the third, second and first floor ("0,0,0"). By combining these information we obtain the following state vector for waiting customers: (0,1,1,0,0,0). The state vector for the elevator is obtained in a similar manner.

Due to its low computational costs, the S-Ring can quickly evaluate a broad variety of EGC instances as benchmarks for the proposed multiobjective optimization approach.

3. OPTIMIZATION PROBLEM FORMULATION

In this work, we deal with two EGC objectives that are often studied in the literature and both need to be minimized: i) the average number of states with waiting customers, and ii) the total number of elevator stops [3, 6, 7]. In contrast to previous publications, we do not combine the objectives into a single function, but adopt the multiobjective perspective. Moreover, to make it possible to compare the performance of elevator systems of various configurations (determined by the number of floors n and the number of elevator cars m), we consider normalized objective function values.

The first objective (h_1) is the proportion of states with waiting customers. It is expressed as the average number of states with waiting customers, M_w, divided by the number of all states, N_s:

$$h_1 = \frac{M_w}{N_s}. \tag{1}$$

The second objective (h_2) is the proportion of elevator stops. It is equal to the total number of elevator stops, M_t, divided by the maximum possible number of elevator stops. The latter can be calculated as the number of elevator cars m multiplied by the number of EGC simulation cycles, which is in turn equal to the number of state transition steps, N_t, divided by the number of states, N_s, therefore

$$h_2 = \frac{M_t}{mN_t/N_s}. \tag{2}$$

Intuitively, the customers' discomfort with long waiting times and long riding times due to many elevator stops does not increase linearly with time, but more drastically. To model this effect, we have additionally modified the original objectives as

$$f_1 = h_1^\alpha \quad \text{and} \quad f_2 = h_2^\beta, \tag{3}$$

where $\alpha, \beta \in [1, 2]$ are the objective function coefficients. The choice of their values is subjective, but the idea is to reflect the elevator system characteristics and the custumer preferences.

The control policy π is represented by a perceptron as $\pi(\mathbf{x}) = \theta(\mathbf{w}^{\mathrm{T}}\mathbf{x})$, where $\mathbf{x}$ is a binary input vector, i.e., a concatenation of the waiting customer and the elevator car state vectors of total length equal to $2(2n-2) = 4(n-1)$, θ is the Heaviside function, and $\mathbf{w}$ a vector of perceptron weights from $W = [-1, 1]^{4(n-1)}$. In this framework, the policy π is defined by the weight vector w only. Therefore, the decision space of the EGC optimization problem as defined here is equal to W.

4. EXPERIMENTS AND RESULTS

The multiobjective optimization of EGC was experimentally evaluated on three test problems reflecting the characteristics of real-world elevator systems operating in various buildings in Ljubljana, Slovenia. They are as follows.

- S1: This system operates in a parking building ("Parking garage Šentpeter") situated in the city center. Intensive passenger traffic can be observed in the building on workdays.
- S2: This is an elevator system installed in a typical residential building in the densely populated neighborhood ("Nove Fužine") in the eastern part of Ljubljana. Here the traffic intensity alternates between high (e.g., early in the morning) and low (e.g., at midday).

- S3: This is the elevator system in the "Crystal Palace", a skyscraper situated in the north-western area of the city. With its 89 meters it is currently the tallest building in Slovenia. As an office building it has low passenger traffic.

The characteristics of these elevator systems are summarized in Table 1.

Table 1: Characteristics of the test elevator systems: number of floors n, number of elevator cars m, probability of new arriving customer p, objective function coefficients α and β, number of states in the S-Ring representation N_s.

System	n	m	p	α	β	N_s
S1	7	2	0.6	1.0	1.5	12
S2	13	2	0.3	1.4	1.8	24
S3	21	4	0.2	1.5	1.5	40

Based on the multiobjective formulation of the EGC optimization problem, the experimental evaluation aimed at finding sets of trade-off solutions representing approximations for Pareto fronts. For this purpose we used two well-known MOEAs: Nondominated Sorting Genetic Algorithm II (NSGA-II) [2] and Differential Evolution for Multiobjective Optimization (DEMO) [5]. The algorithms were assessed from the point of view of both effectiveness (quality of results) and efficiency (spent computational resources).

The experimental setup was defined in the following way. Both algorithms were run with populations of 100 solutions for 100 generations. Specifically, in NSGA-II, the crossover probability was set to 0.7 and the mutation probability to 0.2, while DEMO was run using the SPEA selection procedure, the crossover probability of 0.3 and the scaling factor of 0.5. On each test problem every MOEA was run 30 times, each time with a new randomly initialized population.

Population members were the perceptron weight vectors of length $2N_s = 4(n-1)$. Each solution was evaluated through a computer simulation of the perceptron EGC during which the values of objectives f_1 and f_2 were calculated. The simulation was performed for a predefined number of simulation cycles which was 100.000 for all test problems. As a consequence, the number of state transition steps was equal to $N_t = 100.000N_s$.

The quality of results of an algorithm run was measured with the hypervolume of the Pareto front approximation found in that run. Given $f_1, f_2 \in [0, 1]$, the reference point for hypervolume calculations was set to $(1.1, 1.1)^{\mathrm{T}}$. As the computational efficiency measure the execution time of algorithm runs was recorded. The experiments were run on a 3.50 GHz Intel(R) Xeon(R) E5-2637V4 CPU with 64 GB RAM.

The hypervolume and execution time results are shown in Table 2, both averaged over 30 runs of every MOEA on each test problem. From these results it is evident that regardless of the elevator system, the hypervolumes obtained with NSGA-II and DEMO are very similar. Standard deviations for both optimizers are small (less than 10^{-3}), indicating robust and repeatable algorithm behavior on all three elevator systems. Similarly, small deviations are present for execution times no matter which MOEA is used to produce approximations for Pareto fronts.

Figures 2 and 3 show Pareto front approximations for the test elevator systems resulting from typical runs of NSGA-II and DEMO, respectively (there were negligible differences between the results of different runs). As we can see, both MOEAs obtain well-distributed and very similar sets of solutions. The best solutions with respect to both objectives were found for system S3. This was expected since S3 has more elevator cars and a lower probability of new customer arrivals than S1 and S2.

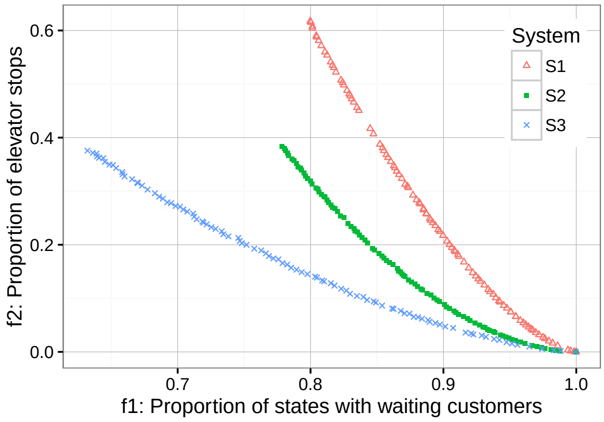

Figure 2: Pareto front approximations for the test elevator systems produced by NSGA-II.

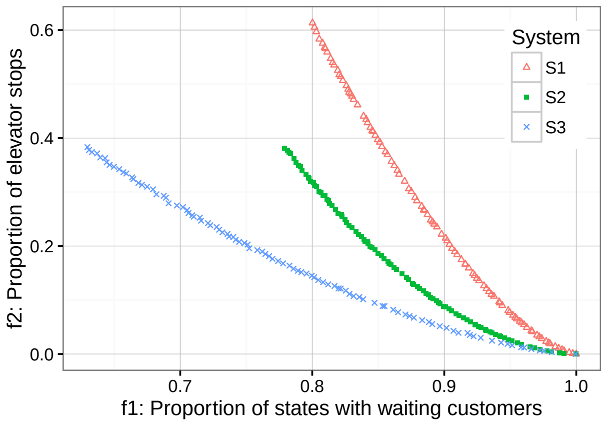

Figure 3: Pareto front approximations for the test elevator systems produced by DEMO.

An additional experiment was devoted to the analysis of hypothetical variants of system S3 with various numbers of elevator cars. While S3 has its fixed configuration, such a study is relevant for designing elevator systems for new buildings and assessing potential configurations.

Pareto front approximations obtained with NSGA-II for variants of S3 with 2, 3, 4, 5 and 6 elevator cars are presented in Figure 4. The figure clearly shows how the number of

Table 2: **Average hypervolume and average execution time for both optimizers on the test elevator systems.**

Elevator system	NSGA-II		DEMO	
	Hypervolume	Time [min]	Hypervolume	Time [min]
S1	0.28066 ± 0.00005	38 ± 1	0.28069 ± 0.00005	28 ± 1
S2	0.32455 ± 0.00016	147 ± 1	0.32450 ± 0.00014	128 ± 1
S3	0.46506 ± 0.00081	398 ± 2	0.46543 ± 0.00037	401 ± 2

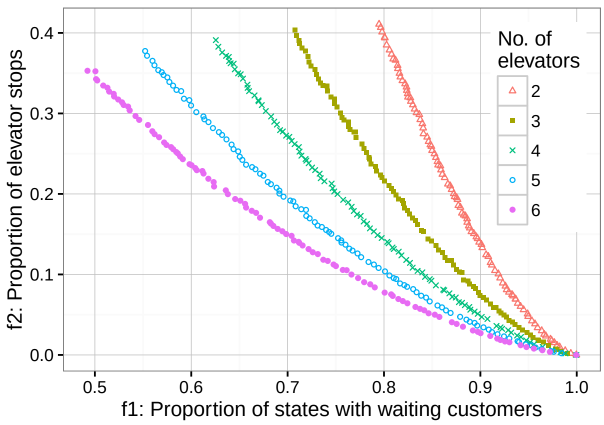

Figure 4: Pareto front approximations for variants of S3 with different numbers of elevator cars (2, 3, 4, 5, 6) found by NSGA-II.

cars affects the trade-off EGC policies. Higher number of cars implies policies that can reduce the proportion of states with waiting customers and the proportion of elevator stops simultaneously. For example, in the case of only 2 elevator cars the lowest value of objective f_1 is about 0.8, while with 6 elevator cars it can be reduced to 0.5. However, one should be careful in comparing the results with respect to f_2, since the maximum possible number of elevator stops increases with the number of elevator cars. Nevertheless, these results allow for better problem understanding and are insightful to various stakeholders involved in deciding on elevator system configurations, ranging from EGC designers to investors.

5. CONCLUSIONS

We studied the optimization of EGC needed in the design and operation of multi-car elevator systems. Utilizing the S-Ring model of EGC systems, we proposed a biobjective formulation of the EGC optimization problem that takes into account the proportion of states with waiting customers and the proportion of elevator stops, both subject to minimization. In this formulation, the objectives are normalized to support comparative empirical studies on elevator systems with various numbers of floors and elevator cars.

As opposed to previous work, we applied true multiobjective optimizers capable of finding approximations of Pareto-optimal solutions. The results of two MOEAs for three real-world elevator systems were comparable regarding both the quality and execution time. They revealed the nondominated sets of trade-off control policies for the considered elevator systems. Moreover, we demonstrated how the approach can be used to support the elevator system configuring at the design stage.

In the future we plan to further assess the resulting elevator control policies through a comparisson with the results of single-objective optimization and investigate the scalability of the applied optimization methodology. We will also analyze the produced trade-off solutions in the design space, and deal with alternative, potentially more transparent policy implementations.

6. ACKNOWLEDGMENTS

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