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Real-Time Optimal Scheduling of a Group of Elevators in a Multi-Story Robotic Fully-Automated Parking Structure

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Abstract

This study presents a simulation-based feasibility study for development of a real-time scheduling algorithm for a multi-story and fully-automated parking structure with a group of elevators. Each elevator is conceived to carry one vehicle (car, small truck, SUV or minivan) between floors. Elevator count for a specific parking structure with number of floors in the range of 4 to 20, and 400 parking spaces on each floor is derived under an assumed customer arrival rate and mean service rate using the waiting line model of the queuing theory. A scheduling algorithm based on nested partitions and genetic algorithm is evaluated through the simulation study. The simulation environment models the mean arrival time of customers and elevator dynamics during morning rush hours for busy urban commercial multi-storied parking structures. Performance evaluation of the implemented elevator scheduling system was realized using the MATLAB environment. Performance metrics of mean customer waiting and elevator service times, and maximum customer waiting time were monitored. Simulation results demonstrate that the proposed design facilitates acceptable customer waiting and service times with good utilization rates for the elevators.

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Keywords: fully-automated robotic parking, elevator scheduling, real-time, optimal, genetic algorithm, queuing theory, nested partition

1. Introduction

Highly populous metro cities around the globe lack real estate space for many purposes among which parking is the most prominent. Multi-story parking structures are a promising venue for exploration to address the acute need for parking spaces. Efficient use of space in a parking structure further requires driving lanes to be eliminated so

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that they can be used as parking spaces as well. A fully-automated robotic parking structure then becomes a de facto option to pursue. Transporting vehicles in elevators among the floors is one engineering challenge that needs to be addressed to make such parking structures a reality.

Extensive research has been conducted for conventional passenger elevator systems in residential structures particularly for scheduling algorithms. Many heuristic-based scheduling algorithms have been developed [11]-[14]. These methods perform well for specific traffic patterns while being computationally efficient. Another approach is "zoning" where each elevator is assigned a number of floors grouped together as a zone [15-17]. The zoning approach makes it possible to deal with a variety of traffic patterns while also being robust in heavy traffic. Context-aware elevator scheduling takes advantage of ubiquitous computing and sensor technologies to dynamically chose and adjust scheduling algorithms based on current and near-future predicted passenger traffic scenarios [18,19]. Optimization of the scheduling process was attempted with genetic algorithms [20-24]. Queue models were applied in elevator scheduling problems and dynamic programming was used to derive the optimal policy [25]-[26]. In a destination entry system, passengers can enter their destinations through keyboards before they get into the elevator cars [10]. For these systems, passenger arrival times, origins, and destinations are known before the systems make scheduling decisions. For a destination entry system, an exact optimization algorithm was developed in [27] while dynamic programming and so-called hybrid nested partition and genetic algorithm based methods were developed in [5,28].

The research reported in this paper considers the elevator scheduling problem in a multi-story, and fully-automated robotic parking structure [4]. The elevators in such a structure are part of a destination entry system. Each elevator of this fully automated multi-story parking structure is conceived to carry one vehicle (car, small truck, SUV or minivan) between floors. This restriction on the carrying capacity of elevators makes it more challenging to minimize the customer waiting times. We use ideas from the queuing theory, linear programming and Genetic algorithms to first formulate bounds on the minimum number of elevators and develop an optimal schedule for elevators during the morning rush-hour period.

2. Methodology

2.1. Elevator scheduling as an optimization problem

The problem domain for the scheduling algorithm is a multi-story parking structure. The parking process is completely automated. For parking a vehicle, customers drive their≤ vehicles into the parking structure at the entry or ground floor and leave them at the elevator loading bays. For retrieving a parked vehicle, customers enter the structure at the ground or entry floor and request their vehicles to be delivered to them at the unloading bays. For parking, vehicles are loaded onto robotic carts and transported from the entry floor to upper floors using elevators, where they are moved again by the robotic carts to their designated parking locations. Each elevator can carry only one robotic cart without or with a vehicle loaded onto it. For retrieval, the requested vehicle, which is already loaded onto a robotic cart, is brought to the elevator on the same floor and transported by the elevator to the ground or entry floor. Next, the robotic cart moves the vehicle to the unloading bay for the customer to take delivery and drive away. We will consider only the parking of vehicles during the morning rush hour within the scope of this paper for reasons of space.

Consider a parking structure with N_F floors and N_E elevators. Let N_V represents the number of those vehicles, which are already inside the parking structure awaiting storage. Those vehicles are queued as first-come-first-served: they are sorted in the ascending order of their arrival times. For each vehicle i, $1 \le i \le N_V$, the arrival time t_i^a, the arrival floor f_i^a, and the destination floor f_i^d are tracked at the time of parking or storage requests made by customers. A two-level integer programming formulation is adapted for elevator scheduling problem in [6], where each elevator must transport multiple passengers to their destination floors. In our case, the problem is simplified in that each elevator carries only one vehicle (passenger). Therefore, there is only one assignment consideration, which is the vehicle-to-elevator assignment. The decision variable is the vehicle-to-elevator assignment, defined as an $N_V \times N_E$ matrix of binary variables, where the $(i,j)_{th}$ element $\delta_{i,j}$ equals 1 if the i-th vehicle is assigned to the j-th elevator and 0, otherwise. To guarantee that the decision variable is feasible, the following constraint should be satisfied: each vehicle must be assigned to one and only one elevator, i.e.

$$\sum_{j=1}^{N_E} \delta_{i,j} = 1, \forall i, i = 1,2,..., N_V. \tag{1}$$

For vehicles that are already inside the elevators prior to each scheduling iteration, their $\{\delta_{i,j}\}$ values are fixed. Assignment decisions are only made on those vehicles, which are waiting to be loaded into an elevator.

The objective is to measure the customer satisfaction through the average customer waiting time for delivery or pickup. Delivery of a vehicle for parking is relatively faster while the wait time for picking up a parked vehicle can be rather long especially during the rush hours. For a customer who has arrived at the parking structure ground floor to park his car, the waiting time in the queue until he delivers his car to one of the elevator loading bays forms the basis for his level of satisfaction. This time period is measured by t_i^d - t_i^a, where t_i^d is the delivery time and t_i^a is the arrival time. For a customer who is in the queue to pick up a parked vehicle, the waiting time is the time interval between the arrival time t_i^a and the pickup time t_i^p. This time period, t_i^p - t_i^a, is composed of the retrieval time (t_i^r) of the vehicle from its currently parked location to the elevator loading area and the transport time (t_i^t) by the elevator to the ground or entry floor. This ignores two other times: the elevator arrival time at the floor where the vehicle is currently parked, which may overlap with the retrieval time of the vehicle and therefore may well be zero, and the waiting time to unload from the elevator and move the vehicle to the pickup bay on the ground floor. In this study, since we only consider storage requests, the objective function is average customer waiting time for being able to deliver her vehicle to the queue for the elevator loading bay. The objective function is given by

$$J = \frac{1}{N_V} \sum_{i=1}^{N_V} \left(t_i^d - t_i^a \right) \tag{2}$$

The overall objective of scheduling is to find a solution for the problem as to minimize the *J* function in Equation 2 subject to the constraint given in Equation 1. For optimization, we use a hybrid technique based on nested partitions and Genetic algorithms as discussed next.

2.2. Hybrid Nested Partition and Genetic Algorithm for Elevator Scheduling

We adopt the so-called Hybrid Nested Partitioning and Genetic Algorithm (HNPGA) method to compute a solution that minimizes the *J* function in Equation 2 subject to the constraint in Equation 1 [5]. The Nested Partitioning (NP) method steadily partitions the feasible decision space into subregions, while trying to identify the most promising subregion. The optimal solution is taught to reside in the most promising subregion, which is located through sampling. Once the most promising subregion is identified, the NP concentrates on this subregion. Through iterations, the most promising subregion is gradually reduced by further partitioning and with backtracking. The promise of the NP method is to compute the optimal solution with probability one, while being a simple and robust[9]. For the application of NP method, the vehicle-to-elevator scheduling problem can be represented using a vector of length N_V where *i*-th element of this vector equals j ($1 \le j \le N_E$) where $N_E(k)$ represents the set of available elevators during the *k*-th scheduling iteration. Initial feasible space entails all those vectors of length N_V where any j (a specific available elevator) value can be assumed by no more than one *i*-th element of the vector (representing the *i*-th vehicle).

Similar to its application in [5], the Genetic algorithm (GA) is used twice in each iteration of the NP method, one for selecting the best subregion, and the other for the comparison of the best subregion with the surrounding region. For both cases, it is used to optimize the assignment of a group of vehicles N_V for minimizing objective function defined in Equation 2. The chromosome is defined as a vector of length N_V, where element i ($1 \le i \le N_V$) equals to element j ($1 \le j \le N_E$) if the *i*-th vehicle is assigned to the *j*-th elevator. Two types of mutation operators are employed: (1) random change of the elevator assignment of one vehicle, and (2) random swap of the elevator assignments of two vehicles. The GA as implemented employs the standard single point crossover operator, which combines two assignments with good assignment segments for different subgroups of vehicles to generate better assignments. The fitness of each chromosome is defined as the performance of the corresponding assignment per Equation 2. The pseudocode for the GA is as follows:

- Initialize population with randomly-generated feasible vehicle-to-elevator assignments.
- Expand population through crossover and mutation.
- Evaluate the fitness of individual assignments.
- Select subset of assignments for the next-generation population based on fitness values.
- Repeat previous steps until either a predetermined time period expires or an acceptable quality assignment is found.

2.3. M/M/S queue model

We employ the M/M/S queue model, which is a system of a single queue (of vehicles in line waiting to be transported by elevators for parking) with multiple servers (elevators), for our design. According to Kendall [7], it describes a system where arrivals form a single queue and are governed by a Poisson process; there are N_E servers (elevators) and job service times are exponentially distributed.

An M/M/S queue operation maps to a stochastic process whose state space is the set {0, 1, 2, 3, ...}, where the value corresponds to the number of customers in the system, including any currently in service. Arrivals occur at a rate of λ according to a Poisson process and move the process from one state to its next. Service times have an exponential distribution with mean service rate of μ in the M/M/S queue. All N_E servers (elevators) serve from the front of the queue. If there is less than N_E jobs (vehicles), some of the servers will be idle. If there are more than N_S jobs, the jobs queue in a buffer. The buffer is of infinite size (which is akin to extending the queue of waiting vehicles to outside of the parking structure along the side of streets around the city block), so there is no limit on the number of customers (vehicles) it can contain. The M/M/S queue model can be described as a continuous time Markov chain and is a type of birth–death process. Let $\rho = \lambda/(\mu\times N_E)$ denote the server utilization and require the following for the queue to be stable (see reference [8] for a proof):

$$\rho < 1 \xrightarrow{yields} \left(\frac{\lambda}{\mu \times N_E}\right) \xrightarrow{yields} \{\lambda < (\mu \times N_E)\} \tag{3}$$

2.4. Elevator dynamics model

We assume that elevators will reach maximum velocity of V_E starting from zero initial velocity with constant acceleration, a_E , after they travel a distance of $V_{E,\max}^2 / 2a_E$. Similarly, an elevator needs to travel the same distance to make a complete stop starting with the maximum velocity and down to zero velocity with constant deceleration of $-a_E$. There might be two probable scenarios for elevator travel, depending on the travel distance between the starting and the destination floors.

If the distance between starting and the destination floors is greater than $V_{E,\max}^2 / 2a_E$, an elevator travels with constant acceleration until reaching its maximum velocity permitted by its design. After that, it travels with constant velocity and starts decreasing its velocity at the point where the distance from the destination is $V_{E,\max}^2 / 2a_E$. Hence, there are three states of motion and they are speeding up, traveling at constant velocity and slowing down as illustrated in Figure 1 (a). On the other hand, if the distance between the starting and the destination floors is less than $V_{E,\max}^2 / 2a_E$, an elevator goes halfway with constant acceleration and after that (before reaching its maximum speed) slows down with constant deceleration to a complete stop at the destination floor. There are two travel modes as speedup, and slowdown as shown in Figure 1 (b).

2.5. M/M/S queuing model and elevator dynamics for scheduling

Customer arrivals are described by a Poisson distribution with a mean arrival rate of λ (lambda) i.e. average number of customers arriving per unit of time [2]. This means that the time between successive customer arrivals follows an exponential distribution with an average of 1/λ seconds. The customer service rate is described by a Poisson distribution with a mean service rate of μ (number of customers) i.e. average number of customers that can be served per unit of time. This means that the service time for one customer follows an exponential distribution with an average of 1/μ. The model assumes that there are N_E identical elevators, the service time distribution for each elevator is exponential, and the mean service time is 1/μ seconds.

The total service rate must be greater than the arrival rate, that is $\mu\times N_E>\lambda$ as given by Equation 3. Otherwise, the waiting line would eventually grow infinitely large. Through this bound, we will formulate the minimum required number of elevators with respect to number of floors for a given multi-storied parking structure.

The total number of parking spaces on each floor of multi storied parking lot [4] is $N_C\times N_R$. Assuming that each elevator occupies two spaces, N_E elevators will occupy a total of $2N_E$ spaces on each floor. As each elevator has a loading area, the number of loading areas is N_E which will cost an additional N_E spaces. The number of available parking spots at each floor is then calculated as $(N_C\times N_R)$-$2N_E$-N_E = $N_C\times N_R$-$3N_E$. Out of these ($N_C\times N_R$-$3N_E$) parking spots, at least 0.05($N_C\times N_R$-$3N_E$) parking spots (which is 5% of $N_C\times N_R$-$3N_E$) must always be open or empty [4]. So the total capacity of each parking floor is ($N_C\times N_R$-$3N_E$)-0.05($N_C\times N_R$-$3N_E$)=0.95N_CN_R-2.85N_E parking spots. Consequently, the capacity (C) of entire multi-storied parking structure in terms of the total number of usable parking spaces can be defined as $N_F\times$(0.95N_CN_R-2.85N_E).

Assuming that a morning rush hour period lasts two clock hours for filling the entire parking structure, mean arrival rate (λ) of vehicles (average number of vehicles arriving per sec interval) is of interest which can be calculated as the ratio of "total number of vehicles arriving per hour" to "the number of seconds per hour." Total number of vehicles arriving per hour is equal to the product of "average number of vehicles arriving per parking space per hour" ($N_{V,ave}$) with "total number of parking spaces in the parking structure (C)." The formula for the mean arrival rate is then given by $\lambda= (N_{V,ave}\times C)/3600$. Mean service rate (average number of customers that can be served per second) of elevators is calculated as

$$\mu = \frac{1}{EMSTR} = \frac{1}{ETT + T_L + T_U + 2\left(T_{EDO} + T_{EDC}\right)}, \tag{5}$$

where $EMSTR$ is the elevator mean service time per request; ETT is the elevator travel time for a distance that is equal to the halfway height of the parking structure; T_L is vehicle loading or embarkation time; T_U is vehicle unloading or dis-embarkation time; T_{EDO} is elevator door opening time, and T_{EDC} is elevator door closing time. We assume that an elevator needs to travel, on the average, halfway for the multi-storied parking structure to serve a customer request. The halfway height of a multistoried parking structure is simply the number of floors multiplied by the height of a floor, where the latter is represented by D_F, and is given by $D_{HH}=(D_F\times N_F)/2$.

The time it takes for an elevator to travel a distance of D_{HH} is of interest next. Given the value of D_{HH} and the maximum velocity of the elevators, $V_{E,max}$, where the latter is design and technology driven, it is likely that one of two scenarios as discussed under the "Elevator Dynamics" will be applicable. Therefore, we will derive the bounds for both scenarios and use the bound that gives the larger count of elevators for the design and simulation study.

First scenario assumes that, $D_{HH} \le V_{E,\max}^2 / a_E$ holds for which the elevator travel time is given by $ETT=SUT+SDT$, where SUT and SDT represent the "speed up" time and "slow down" time for the elevator. Let v_f, v_i, a, d and t represent final velocity, initial velocity, acceleration, distance traveled, and the time duration of travel, respectively, then the "speed up" time can be calculated as follows:

$$v_f^2 = v_i^2 + 2ad \xrightarrow{yields} v_f = \sqrt{D_F N_F a_E / 2}$$

given that initial velocity is zero: $v_i = 0$; the acceleration is given by a=a_E; and the travel distance is given as $d = D_{HH} = D_F N_F / 2$. The travel time can be calculated using

$$v_f = v_i + at \xrightarrow{yields} t = SUT = \sqrt{D_F N_F / 2a_E},$$

where $v_f = \sqrt{D_F N_F a_E / 2}$. Similarly time to "slow down" can be derived which is same as the time to "speed up", *SDT*=*SUT*. Therefore, the total time to move the elevator by the half distance of parking structure height is given by

$$ETT = 2\sqrt{D_F N_F / 2a_E} \ .$$

Mean service rate (average number of customers that can be served per second) for this first scenario is given by

$$\mu = \frac{1}{EMSTR} = \frac{1}{ETT + T_L + T_U + 2(T_{EDO} + T_{EDC})} = \frac{1}{2\left(\sqrt{D_F N_F / 2a_E} + T_{EDO} + T_{EDC}\right) + T_L + T_U}$$

The second scenario assumes that, $D_{HH} > \left(V_{E,\max}^2 / a_E\right)$ holds for which the elevator travel time is given by *ETT*=*SUT* + *CST* + *SDT*, where *SUT*, *CST* and *SDT* represent the "speed up" time, "constant speed" time, and "slow down" time for the elevator, respectively. Following a similar derivation as the first scenario, the mean service rate (average number of customers that can be served per second) for the second scenario is given by

$$\mu = 1 \Bigg/ \left[\sqrt{\left(\frac{V_{E,\max}}{a_E} + \frac{D_F N_F}{2V_{E,\max}} \right)} + 2(T_{EDO} + T_{EDC}) + T_L + T_U \right]$$

Now, substituting the values of the mean arrival rate (λ) and the mean service rate (μ) in $\mu \times N_E > \lambda$ from the waiting line model, bounds on the minimum number of elevators for a specific floor count can be derived. It is further relevant to note that these bounds have been derived by applying the steady-state condition of the M/M/S queuing model on the fully-automated parking structure.

3. Simulation Study

We have implemented a simulation study for a parking structure with story counts from 4 to 20. Each floor had the exact same rectangular layout of 20×20 with 400 parking spaces. We only considered the morning rush hour when almost all of the customer requests are for parking their vehicles. Poisson distributed customer arrivals were simulated according to the arrival scenario in [3]. The simulation was implemented in MATLAB, version 7.11.0 (R2010b), on a desktop PC with the following specifications: the processor is Intel(R) Core(TM) i7 CPU 950 @ 3.07 GHz, main memory has 20 GB RAM, and the operating system is Windows 7 Ultimate (64-bit).

Parameters and values used in the simulation study are as follows: D_F= 3.5 m, a_E=0.7 m/s^2, $V_{E,max}$ = 2.5 m/s, $T_{EDO} + T_{EDC} + T_L + T_U = 10$ seconds, $N_{V,ave}$= 0.6175 vehicle per parking space per hour [1], and N_C = N_R = 20. Applying values of these parameters on bounds derived in Equation (6) yields the minimum number of elevators for different floor counts in a parking structure as presented in Table 1. The genetic algorithm (GA) employed the following values for its parameters [5]: number of generations: N_g=10; population size: N_p= 6; crossover probability = 0.6; and mutation probability = 0.7. Additionally, the nested partition parameters N and N_t are related and defined as follows to facilitate the assignment of the next 3 vehicles based on the optimization of next 6 vehicles: N=3, and N_t=6.

We define several performance metrics that will appear in the following figures as follows:

- Waiting Time: The time between a customer vehicle's arrival and its pickup by an elevator
- Service Time = Elevator travel time between starting floor and destination floor + 2 × (elevator door open time + elevator door close time) + Vehicle load time + Vehicle unload time
- Scheduling Time: the time required for the HNPGA to schedule $N_V(k)$ vehicles to $N_E(k)$ available elevators at iteration k: N_V represents only those vehicles which are already in the queue inside the parking structure awaiting storage.

The most important performance metric is the waiting time for customers. Table 1 presents customer waiting and elevator service times for floors counts of 4 to 20 along with the required minimum number of elevators. For the range of floor counts simulated, the worst-case customer waiting time occurs for the 20-story parking structure with an average of approximately half a minute and a maximum value of 4.5 minutes. The scheduling times presented in Table * suggests that the system is feasible for real-time operation and there is room to even further speed up the computations needed for scheduling since MATLAB implementations are comparatively slower than those in compiled executables. In general, waiting time values are likely to be considered very reasonable by most customers.

Table 1. Customer waiting and elevator scheduling times.

Number of Floors	4	6	8	10	12	14	16	18	20
Minimum Number of Elevators	17	25	32	39	45	50	56	60	65
Average Waiting Time (sec)	10.8	11.9	14.7	14.1	15.8	19	20.8	21.6	28.8
Maximum Waiting Time (sec)	65.9	68.4	111.5	49.4	50.0	131.4	204.3	143.1	269.0
Average Scheduling Time (sec)	0.1	0.1	0.2	0.2	0.2	0.4	0.4	0.4	0.9
Maximum Scheduling Time (sec)	1.5	2.1	6.1	1.7	5.078	15.7	12.8	14.4	22.8

For a more detailed look at the individual customer waiting and elevator service times for a specific story and elevator count, Figure 1 is presented. Customer waiting times are mostly small with less than 15 seconds for 4 floors. Waiting times for most customers increase to 20 seconds, 30 seconds and 35 seconds for floor counts of 10, 14 and 20, respectively. Elevator service times are in the neighborhood of 50, 60, 65, and 75 for the same floor counts. In general, other than a few spikes in customer waiting times, most customers experience a consistently small wait in all cases. The increase in the elevator scheduling times as the floor count increases appears to be minimal and does not preclude real-time operation.

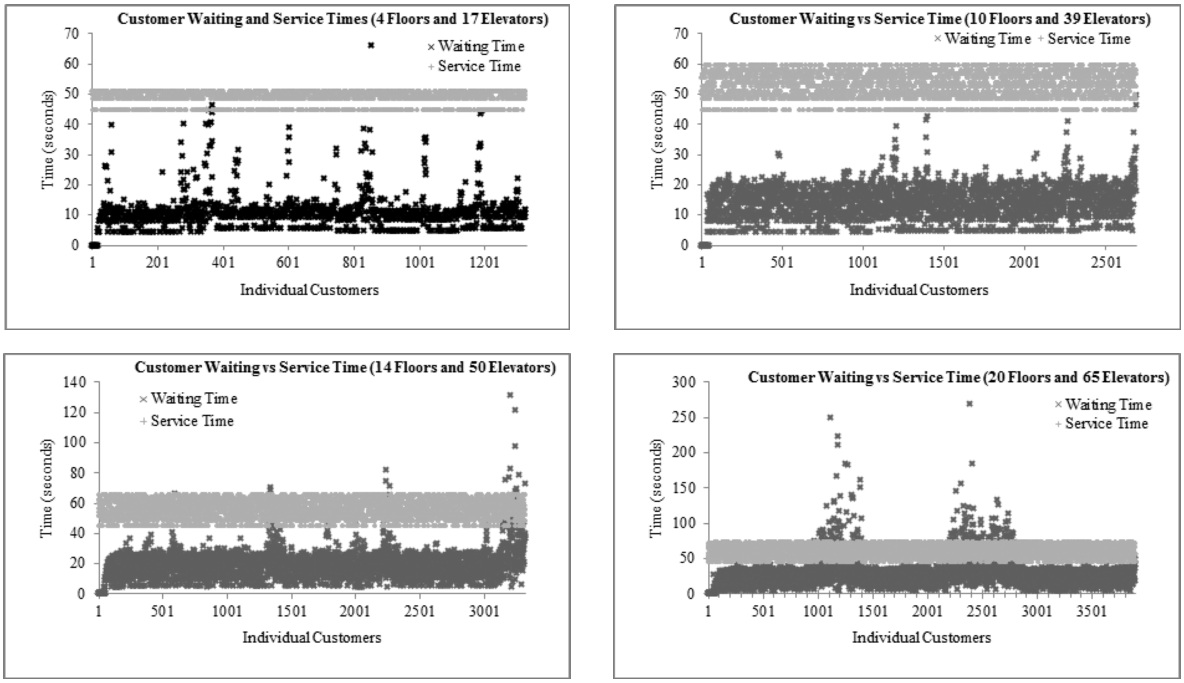

Figure 1.. Customer waiting and elevator service times for various floor and elevator counts

4. Conclusions

This paper presented a simulation study for an elevator scheduling system for a fully-automated robotic and multistorey parking structure which is intended for large metro areas where real estate is at premium. The presented study considered the morning rush hour period with nearly all customer requesting to park their cars. Queuing theory was employed to derive bounds on the minimum number of elevators for a given floor count in the parking structure. Schedule optimization was accomplished using the nested partitions and genetic algorithms. Simulation was conducted for floor counts of 4 to 20. Simulation results suggest that the proposed elevator counts will facilitate real time scheduling with reasonable customer wait times.

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