Performance improvement of cabin-based transport systems

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Abstract

Cabin-based transport systems such as cable cars are of increasing importance for urban infrastructures. Such systems consist of one line, connecting several stations in tandem. During rush hours, customers are served with full capacity at the first station and consequently, cabins arrive almost fully loaded to the subsequent stations. Customers at these stations experience longer waiting times and a stressful situation. The overall objective of this study is to propose and evaluate alternative access control policies to improve the customer experience in terms of waiting times and a defined "fairness" measure. The model integrates realistic features such as non-stationary arrivals and finite operation time. Therefore, we adopt a finite horizon simulation approach and define the appropriate performance measures. In particular, a service level measure is used to compare the proposed access control policies. The obtained results allow us to determine the policy with the most substantial improvement in the performance of the system compared to the actual situation.

Keywords: cabin-based transport systems, non-stationary arrivals, finite horizon simulation, waiting times, performance measures.

Introduction

Cabin-based transport systems (cable cars) are becoming important components of urban and recreational infrastructures. Typically, they consist of interconnected lines of stations in tandem. During rush hours, customers are served with full capacity at the first station and consequently, cabins arrive almost fully loaded to the subsequent stations. Therefore, customers at these stations experience longer waiting times with more uncertainty and move slowly in the queue. This situation creates stress and a feeling of unfairness among the customers of downstream stations. In order to improve the costumer experience in the whole system, it is necessary to take into account the psychological aspect of waiting (Maister, 1984) and to (re)balance the capacity at all stations consequently.

In a previous study (Oberegger et al., 2018), infinite horizon simulation has been used to derive the performance measures and to compare different configurations of this system under some quite restrictive conditions such as a stationary arrival process, infinite horizon and idealistic customer behaviour. In this case, the indicators of interest are the stationary measures (mean waiting time, mean queue length, etc.) under a certain stability condition. This approach is useful to study systems that run long enough to reach stationarity. However, the dynamics of the real system modelled here are different. Firstly, the system opens and shuts down at given hours, which result in the initialization of its state every day. Then, the arrival process of the customers might not be stationary and variations in the traffic intensity are observed during the same day. Hence, the system might not even have a permanent regime and therefore, infinite horizon simulation is not a suitable approach in this case. Furthermore, we show that basic performance measures such as utilization cannot be calculated by simple formulas of queueing theory as usual. The majority of queuing models does not take into consideration these dynamics (Islam et al., 2017).

The aim of this paper is to explore the foundations for designing smart public cabin-based transport systems, i.e., cable cars, underground railways, etc... The managerial implications will improve the current state of cabin-based transport systems in terms of customer experience.

The need for scientific research in the field of an efficient and effective access management for cabin-based transport systems is motivated by the following research questions:

- *RQ1: How can useful performance measures of the system be defined and calculated?*
- *RQ2: How can performance measures reflect equal treatment of customers (fairness) and provide overall measure of customer experience?*
- *RQ3: How can the attractiveness of the system be increased in order to achieve long-term profits by taking customer demand into account?*

Related work and methodology

Simulation techniques can be used to study, observe, and evaluate the behaviour of the real system under various realistic conditions and in situations where analytical models may not be manageable (Law, 2005; Maria, 1997). There are many simulation studies of transportation systems. Here, we focus on line systems, such as bus and metro lines, similar to our cabin transport systems. Several studies are using terminating simulation techniques to investigate the behaviour and the performance of transit systems. Especially, discrete-event simulation approaches find a broad field of applications for the evaluation of urban transport systems (Hassannayebi et al., 2014; Vázquez-Abad and Zubieta, 2005; Yalcınkaya and Mirac Bayhan, 2009). Hassannayebi et al. (2014) proposed a two-stage simulation-based optimization approach of an urban metro system, where variations of passenger demand, stochastic running time and capacity constraints are considered in order to minimize the average passenger waiting time. Vázquez-Abad and Zubieta (2005) proposed a simulation model of a subway network that includes operating and social costs based on passengers' waiting times. Yalcınkaya and Bayhan (2009) provide a modelling and solution approach based on discrete-event simulation and response surface methodology to optimize the average passenger travel time for an urban transport system. Observations on passenger arrivals were recorded and registered through turnstiles. In addition, a Poisson distribution was determined, which fits best to the collected data. Grube et al. (2011) presented a simulator for metro systems to analyse real-time control strategies by evaluating the system performance in terms of average passenger waiting time. Ding and Chien (2001) tested the efficiency of a real-time control by simulation modelling. The results indicate that the proposed real-time control model reduces the average passenger waiting time significantly.

Our model differs from the above ones because the cabin capacity is fixed and the time between two cabins is constant. With respect to the two previous parameters, there is a little room for manoeuvre in terms of control policies based on cabin speed and capacity. For example, it is not possible to change dynamically the capacity of the cabins. Compared to buses or subway lines, our model has fewer stations where passengers can board, but the majority of customers arrive to the first station, which causes the problem described above.

System description

Fig. 1 shows the basic structure of a gondola lift typically used in ski resorts as well as increasingly in urban areas. The underlying system consists of one transport line to which mobile cabins are attached. The cabins have a fixed capacity C (seats), they move with a constant speed and keep a constant distance to each other. The time between two consecutive cabins is T_c.

The transport line connects three stations (S_1, S_2, S_3) in tandem, in which passengers can enter and/or leave the system. All cabins arrive empty to the first station (S_1).

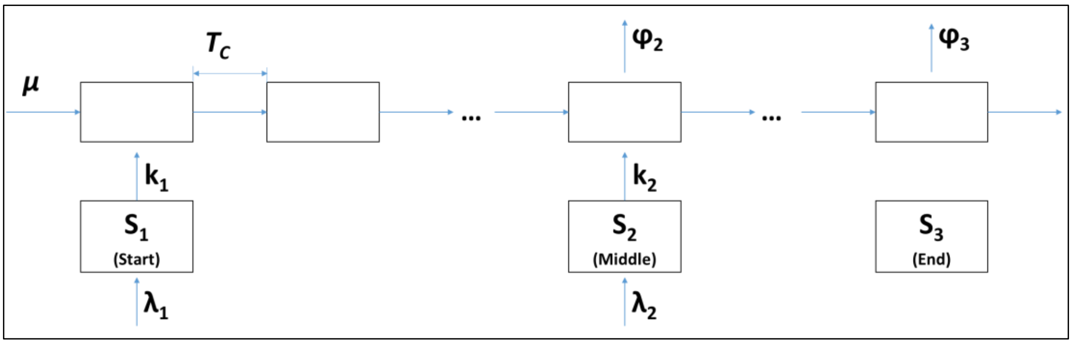

Figure 1 – Structure of the transport system (Oberegger et al., 2018)

Station S_1 is the launch station in which passengers enter the system at the rate λ_1. Depending on the access control policy, the maximum number of passengers allowed to board a cabin at this station is denoted k_1 (each cabin leaves station S_1 with at most k_1 passengers on board). The arrival rate of the passenger to station S_2 is denoted λ_2. In this station, passengers arriving from the previous station may leave the system with probability φ_2. k_2 defines the maximum number of passengers in the cabin when leaving station S_2 (k_2 is equal to C if no access restriction applies at this station). Station S_3 is the ending station where all passengers must leave the system ($\varphi_3 = 1$).

Data collection and preparation

This study is based on an empirical quantitative approach. Empirical data such as demand patterns, system characteristics and customer behaviour are collected. In urban transit systems, passenger demand usually varies significantly between peak and off-peak hours.

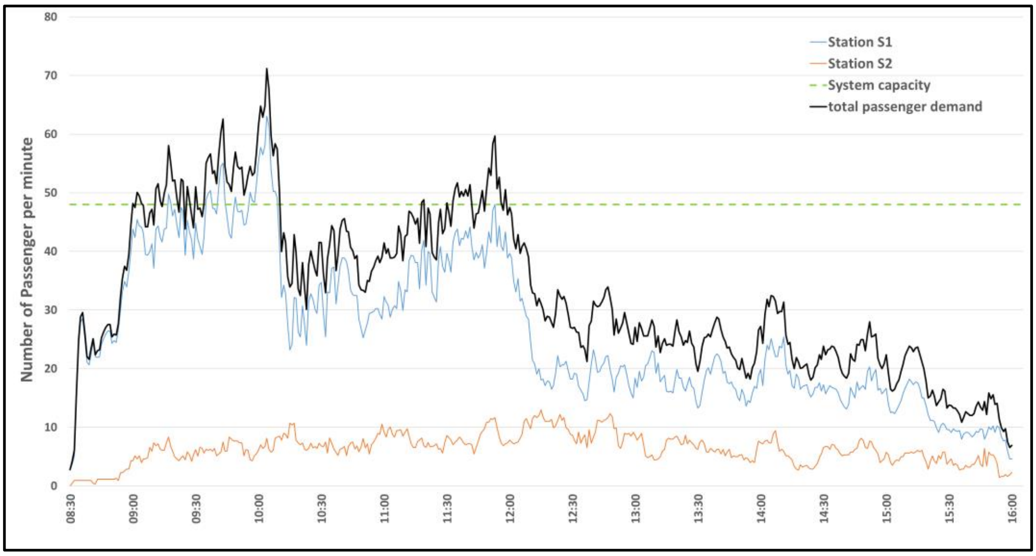

Figure 2 - Passenger arrivals per minute from 8:30 to 16:00

This can be observed in ski resorts as well, where especially in the morning hours increasing passenger flows are to be expected. The passenger demand associated with such a system is therefore a non-stationary process. Several studies consider that passengers arrive according to a Poisson process at time-dependent rates (e.g. Hassannayebi et al., 2014; Ding and Chien, 2001; Eberlein et al., 1998; Grube et al., 2011; Ahn et al., 2017).

Fig. 2 shows the passenger demand distribution and variation of passenger arrivals over a day from 08:30 to 16:00. We can observe that at Station S_1 the arrival rate in the morning hours is higher than the system capacity. During this period, the queue in Station S_1 builds up. Thus, only fully loaded cabins arrive at the next station (S_2) and passengers at this station experience even longer waiting times and uncertainty. Traffic intensity changes significantly during the day. Therefore, we divided the observation period (one day) into time intervals. The length of these time intervals are not constant. To account for the variability of passenger arrivals during such a time, we consider for each interval a Poisson distribution with the rate of occurrence $a(t)$ for Station S_1 and $b(t)$ for Station S_2, resulting in a time-dependent rate.

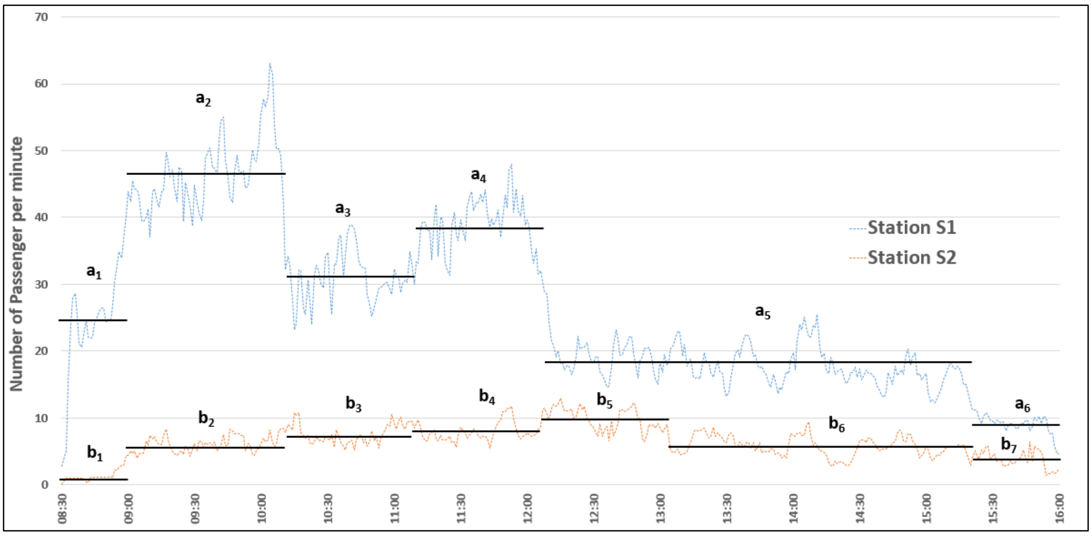

Figure 3 - Time dependent passenger arrivals

Simulation model

In order to model realistic conditions we use a finite horizon simulation approach. The system is simulated during the duration of its operation and the simulation is terminated at the end of this period (e.g. day).

A discrete event simulation model is built to analyse and to evaluate the behaviour of the transport system under different realistic conditions. Fig. 4 shows the basic elements of the simulation model.

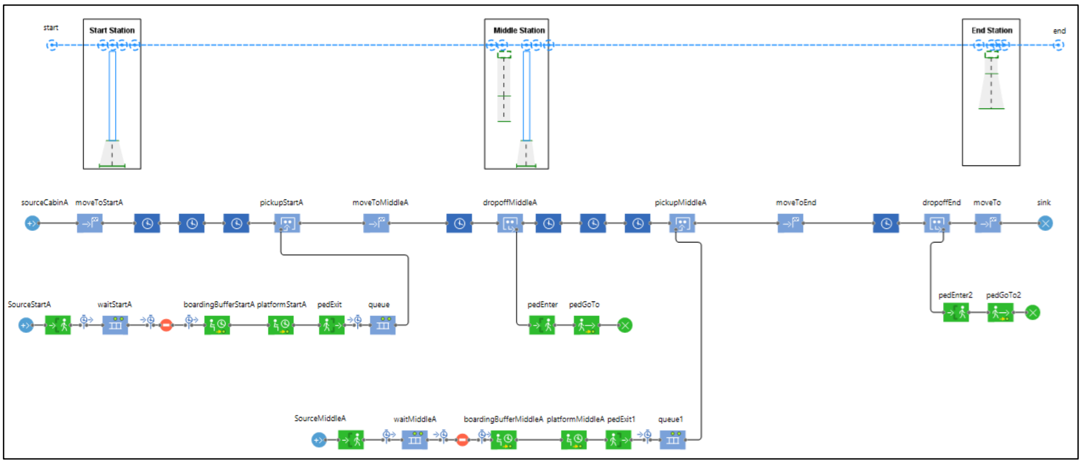

Figure 4 - Simulation model

Some basic assumptions that where applied in the simulation model are as follows:

- The system is a terminating system and the duration of its operation is approximately 7.5 hours per day. The system opens at 8:30 a.m. and closes at 16:00.
- We assume that passengers arrive to the system according to a stochastic process (Poisson) with time-dependent rates. Average arrivals are shown in Table 1 for each time interval.

Table 1 - Average number of arrivals per minute ($a(t), b(t)$)

Station S_1			Station S_2		
from	**to**	a(t)	**from**	**to**	b(t)
08:30	08:59	24.15	08:30	08:59	1.35
09:00	10:09	46.7	09:00	10:09	6.04
10:10	11:09	31.2	10:10	11:09	7.63
11:10	12:09	38.7	11:10	12:09	8.04
12:10	15:19	17.99	12:10	13:03	9.79
15:20	16:00	9.17	13:04	15:19	5.8
			15:20	16:00	3.7

- The system starts with an empty queue every day (initialization, regeneration).
- The capacity of the waiting areas in the stations is assumed to be unlimited.
- Passengers are served according to a first come, first served (FCFS) policy.

This approach allows us to study various arrival patterns (non-stationary) and to derive new performance measures. For instance, since the system runs for a finite duration before reinitializing, it is not necessary to impose the usual stability condition (utilization less than 1). The system can receive more customers than its nominal capacity but the number of customers remaining in the queue (non-served) at shutdown time is a useful indicator.

Performance measures
Compared to the infinite horizon simulation approach (Oberegger et al., 2018), finite horizon simulation provides a way to analyse and understand the considered system under realistic conditions such as, limited operation time, non-stationary arrival process, customer behaviour, etc. Additionally, different kind of performance measures can be derived. Note that, since the system is reinitialized every day with the same conditions, consecutive replications are independent.

Utilization : Usual stability condition (utilization less than one) is not necessary but extra measures (such as the number of non-served customers at the end of the day) could be of interest. Additionally, the utilization cannot be simply obtain from arrival and service rate. Instead, the dynamics of the system must be considered.

Waiting time and queue length : Waiting time and queue length processes are not stationary and their mean values are not informative. However, since the system is initialized every day, the waiting time (or queue length) at the same time every day (say, the queue length at midday) is a stationary process. The mean value of the latter is of interest.

Service level $\boldsymbol{\sigma_i}$: We define this performance measure as the proportion of customers waiting more than a given amount of time $\bar{w}_i$ (Customers experiencing long waiting times) at station i.

Service level $\boldsymbol{\mu_i}$: We define this performance measure as the proportion of non-served customers at the end of the day at station i. Indeed, since the operation time of the system is finite and it shuts down at fixed time of the day, the length of the residual queue might be of interest.

Fairness measure : As discussed before, the main issue here is the unequitable treatment of the customers at different stations. We combine the performance measures of individual stations to create a global performance measure that takes into account overall customer experience. Since long waiting times in station S_1 and S_2 are perceived differently, a different weight is given to each station. We may do so by fixing a different threshold $\bar{w}_i$ for each station, then balancing the corresponding service levels σ_i. This leads us to the following global performance measure (to be minimized)

$$\phi = \text{abs}(\sigma_1(\bar{w}_1) - \sigma_2(\bar{w}_2)) \qquad (1)$$

Simulation scenarios
We explore and evaluate three access management policies (along with their sub-policies, see Table 1):

P1: No access control (default policy).
P2: Reserve n seats in each cabin for the next station.
P3: Reserve every n^{th} cabin (fully) for the next station.

Table 2 - Access control policies Px-y: x…policy, y…sub-policy

Policy P(x)	Sub-policy (y)	Description	Avg. available seats per cabin S_1	S_2
P1	0	No control	8	8
P2	1	Reserve 1 seat in each cabin	7	8
	2	Reserve 2 seat in each cabin	6	8
P3	1	Reserve every 8th cabin	7	8
	2	Reserve every 7th cabin	6,86	8
	3	Reserve every 6th cabin	6,67	8
	4	Reserve every 5th cabin	6,4	8
	5	Reserve every 4th cabin	6	8

Based on the defined global measure, those access management policies are simulated and compared. Then, we select the best policy depending on traffic conditions and system configurations.

Results

Fig. 5 shows the waiting times of the customers in station S_1 and station S_2 under each of the defined access policies. The waiting times vary significantly from one period to another (peak and off-peak hours) and has therefore been defined as a function of time $w_i(t)$.

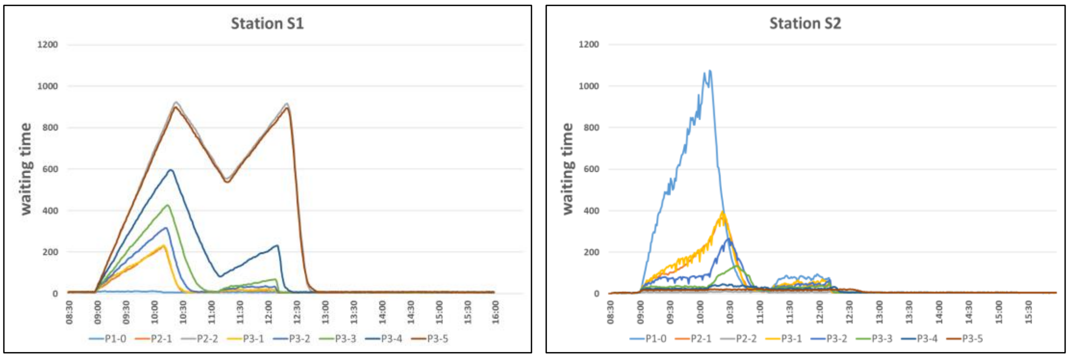

Figure 5 – Passenger waiting times in station S_1 and S_2 for the defined policies

Policy P1: No access control (default policy)

If no access control is applied, almost the whole cabin capacity is used at Station S_1 and therefore passengers at station S_2 experience long waiting times. Fig. 6 shows the results in this case. Low waiting times are observed at station S_1 whereas passengers in station S_2 wait longer (more than 10% of them wait more than 600 seconds). The maximum waiting time in station S_2 is about 1000 seconds.

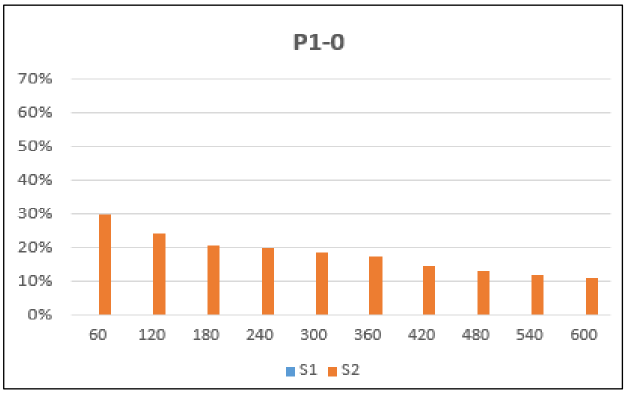

Figure 6 - No access control

Since we want to improve the customer experience throughout the system, it is necessary to balance the capacity at all stations (e.g., passengers at one station wait longer to reduce the waiting time at subsequent stations).

Policy P2: Reserve n seats in each cabin for the next station

A reduction of the capacity in the first station results in longer waiting times at this station but reduces the waiting time at the second station. Fig. 7 shows the results when a fixed number of seats is reserved in each cabin for station S_2. By reserving one seat per cabin in station S_1, a substantial reduction of the waiting time can be observed in station S_2 (compared to policy P1-0). The maximum waiting time of passengers in station S_2 is now 480 seconds. In station S_1, the waiting time has increased due to reduced available capacity. About 5 percent of all passengers wait more than 180 seconds (see P2-1).

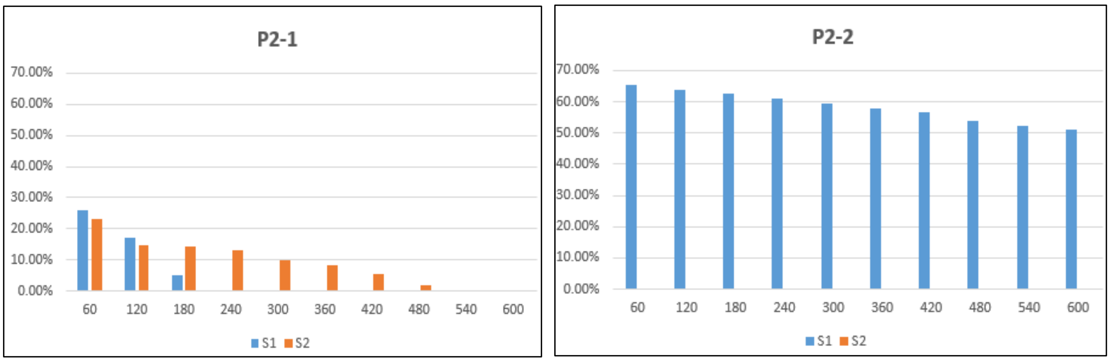

Figure 7 - Policy P2: -1 reserving one seat in each cabin; -2 reserving two seats in each cabin for Station S_2

Reserving two seats per cabin in station S_1 (policy P2-2) will shift the problem from station S_2 to station S_1. In this case, long waiting times could be observed in station S_1 (about 50% of all passengers have to wait longer than 600 seconds in station S_1) whereas barely any waiting times were observed in station S_2.

Policy P3: Reserve every n^{th} cabin (fully) for the next station

Reserving every 8^{th} cabin for station S_2 (policy P3-1), will result in the same average number of seats reserved as in P2-1. However, policy P3 creates more variability in the service than policy P2. For instance, P3-1 leads to longer waiting times in station S_2 compared to P2-1. However, P3 allows a more granulated control. For example, P3-2 reserves on average 1.14 seats per cabin. Hence, it is observed that 2.5% of all passengers are waiting more than 180 seconds in station S_2, while about 1% wait more than 300 seconds in station S_1.

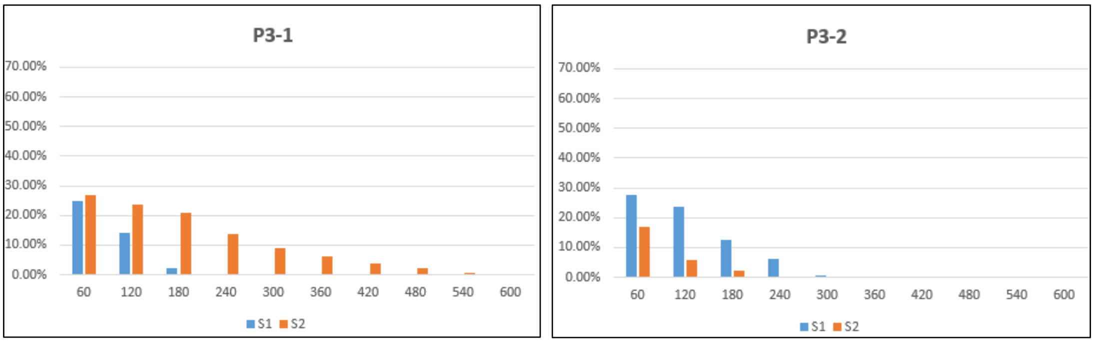

Figure 8 - Policy P3: -1 reserving every 8th cabin; -2 reserving every 7th cabin for station S_2

In this section, the threshold $\overline{w}_1$ is set to 300 seconds whereas $\overline{w}_2 = 180$.

By applying the global performance measure ϕ, the comparison of the proposed access control policies shows that the best results are achieved by reserving every 7th cabin for station S_2 (see Table 3: P3-2).

Table 3 - Summary of results

Station		**S1**	**S2**	**Φ**
Threshold	$\overline{w_i}$	300	180	
P1-0	σ_i	0.0%	20.3%	**20.3%**
P2-1	σ_i	0.0%	14.2%	**14.2%**
P2-2	σ_i	59.5%	0.0%	**59.5%**
P3-1	σ_i	0.0%	20.9%	**20.9%**
P3-2	σ_i	0.8%	2.3%	**1.5%**

Conclusion

The developed simulation model enables performance evaluation and improvement of cabin-based transport systems with respect to the overall customer experience under realistic conditions. Indeed, non-stationary arrivals and finite operation time are considered.

Since the arrival process is not stationary, we define a set of new measures, such as, the service level σ_i (proportion of customers waiting more than a given threshold $\overline{w_i}$ at station i) and the global performance measure ϕ that reflects the equitability in different stations (fairness).

The results show that it is not possible to reduce the waiting time in a given station without managing the passenger access of a previous station. With respect to the defined performance measure ϕ, policy P3-2 provides the best performance.

The findings provide guidance in the design and operation of such system taking into account the overall customer experience rather than only throughput and cycle time measures.

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