



HAL
open science

Combined optimization methodology for operational planning and service policies: a case study of urban ropeway transport

Ronald Martinod, Olivier Bistorin, Leonel F Castañeda, Nidhal Rezg

► To cite this version:

Ronald Martinod, Olivier Bistorin, Leonel F Castañeda, Nidhal Rezg. Combined optimization methodology for operational planning and service policies: a case study of urban ropeway transport. International Journal of Transport Economics, 2020, 47 (3), pp.337-363. 10.19272/202006703006 . hal-03110193

HAL Id: hal-03110193

<https://hal.science/hal-03110193>

Submitted on 8 Feb 2021

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Copyright

Title:

Combined optimisation methodology for operation planning and service policies: a case study of urban ropeway transport

Authors:

Ronald M. MARTINOD^{1,3}

Olivier BISTORIN²

Leonel F. CASTAÑEDA¹

Nidhal REZG³

Address for Correspondence

Universidad EAFIT. Dpt. of Mechanical Engineering. Engineering School. Carrera 49 Nr. 7 Sur-50, Medellín (Colombia). rmartino@eafit.edu.co

Affiliations of additional authors

¹ Universidad EAFIT. Dpt. of Mechanical Engineering. Engineering School. Carrera 49 Nr. 7 Sur-50, Medellín (Colombia). lcasta@eafit.edu.co

² ICN Business School Nancy Metz. Dpt. Management de la Supply Chain et des Systèmes d'information. 3, place Edouard Branly, 57070 Metz Technopôle, Metz (France). olivier.bistorin@icn-groupe.fr

³ Université de Lorraine. Laboratoire de Génie Industriel de Production et de Maintenance (LGIPM). College of Mathematics, Information, Mechanics and Automatics. Ile du Saulcy, 57045 Metz Cedex, Metz (France). nidhal.rezg@univ-lorraine.fr

Acknowledgement

This work was supported by an international agreement of cooperation between l'Université de Lorraine and Universidad EAFIT by means of the laboratories *Laboratoire de Génie Informatique, de Production et de Maintenance* (LGIPM) and *Grupo de Estudios en Mantenimiento Industrial* (GEMI). We owe our deepest gratitude to the engineers of the metropolitan transport company of Medellín city who provided us with valuable information and data to carry out this study.

Abstract

The long-term efficiency of transport operator profit and the benefits for passengers conduce to opposite results. Actually, intervention by previous decision-makers to pursue one of the two goals generate opposite results on the other, forcing decision-makers to a difficult trade-off. The aim of this work is to provide a model that analyses, in an integrated perspective, operation and Service Policies (SPs), making an appropriate synthesis on both policies. This work proposes a cost-model formulation to optimize the merged operation and SPs to improve the current exploitation strategies according the service and maintenance activities. The proposed work is based on the following approaches: (i) a numerical model for the operation policy to determine the profit value of different working periods; (ii) a stochastic process for the passenger flow that considers the uncertainty of passenger travel to compute the benefits according to their travel time; and (iii) a cost-based optimization to bring together the operation and SPs. Finally, the proposed optimization model is applied to a massive urban ropeway operation of a public transportation system, in which the current SPs has been evaluated, considering the established transportation operation.

Date of final version

12 November 2020

keywords

Aerial cableway system; cost-model optimization; operation policy; public transport; service policy; urban ropeway transport

1. Introduction

Urban Public Transport Systems (UPTSs) influence the infrastructure of cities and the lives of their residents while directly stimulating the economy. High levels of urban development (densification) and increasing mobility requirements of residents tend to degrade urban environments. Smart UPTSs contribute to improve the quality of life and the environment in cities, thus, increasing upright habits among the citizens (Belli et al., 2020). In general, UPTSs reduce the environmental burden resulting from traffic congestion and gas emissions. However, the inefficient operation of UPTSs do not necessarily reduce the environmental burden, and Urban Transport Operators (UTOs) may not be able to manage it sustainably (Campbell and Van Woensel, 2019; Tamaki, 2019).

Long-standing problems for UPTSs (e.g., low operational efficiency, a lack of punctuality of transport service, etc.) have negative consequences such as passengers are not attracted (Tang et al., 2018; Steiner and Irnich, 2018). Poor performance of UPTSs, downtime and inefficient planning lead to a loss of service, increase costs and reduce profits for UTOs, and passengers as well (Cholasuke et al., 2004). On the other hand, UPTS companies that can effectively implement their operation will save time, money and other resources in dealing with reliability, availability, maintainability and performance issues (Fraser et al., 2015). The rational planning of UPTS operations improves the overall operational efficiency and service level management. Optimizing UPTS operations is fundamental to achieving intelligent mobility. Smart UPTSs improve their sustainability level, reducing transport costs and waste of resources as well as helps UTOs to manage the transport network (Bibri, 2018). Smart urban mobility managements are aiming at reconsidering the public transport network to cope with actual user expectations in terms of efficiency, quality and fast access to information (Ivaldi and Ciacci, 2020).

Rational operation planning has a significant effect on reducing the cost of transport operations, enhancing the operational efficiency and improving the service capacity. The

motivation for the research is caused by a lack of studies concerning: (i) the assessment of operation performance (as impacted by the cost of in-service periods, dead-time, stop periods and maintenance) combined with the management of the service level (as impacted by the travel time) and (ii) the assessment of operator efficiency and passenger benefits considering the deterioration of the system. In particular, the authors found few studies dealing with the simultaneous optimization of transport operation and Service Policies (SPs) in urban ropeway systems. An efficient SP (i.e., parameters which affect the passenger perception such as vehicles frequency, speed, capacity, waiting time) transport should consider the total travel time of the users, but on the operation side, decreasing the travel time increases the operational cost in terms of the intensity of the operation periods, system wear, faults, and maintenance (i.e., the progressive deterioration of the system).

This work develops an optimization model for the operation plan and SPs for a UPTS over its working life applied to a typical urban ropeway system (called aerial cable-car or cableway as well). The research question is formulated as how maximize the long-term efficiency of the combined transport operation profit and the benefits for passengers concurrently; thus, the research question is addressed to a stochastic simulation model of ropeway transport was developed in a virtual environment (where the typical passenger demand is defined as a set of variables with a stochastic Poisson distribution) for investigating the effects of a wide range of possible conditions and parameter variations associated to operation and SPs.

The main novelty of the work can be summarized as follows:

- (i) a cost-based optimization model for transport operation and SPs is developed to solve the problem of long-term sustainability considering the progressive deterioration of the system;

- (ii) a stochastic optimization model is developed to support efficient operation planning to reach the maximum profit for the UTO and the minimum cost to the passengers for delayed service;
- (iii) this work presents a decision-making tool for operation planning centered on UPTS services. The approach has been developed specifically for considering the UTOs in urban ropeway systems.

The remainder of this work is organized as follows. Section 2 introduces the literature review. Section 3 describes the problem. The cost-based models for the operation plan and service level management are developed in Section 4 and Section 5, respectively. The mathematical expression of the optimization process is presented in Section 6. The model is applied in Section 7 using an example focused on an urban ropeway system. Section 8 presents an analysis and discussion of the results and the research work. Finally, Section 9 concludes the work and discusses future research. Table 1 presents the coefficients, parameters and variables that will be used throughout this article.

Table 1. Abbreviations, Indices and parameters used throughout the article.

Abbreviations:

CM	Corrective maintenance;
MP	Maintenance Policy;
PD	Passengers' Demand;
PM	Preventive maintenance;
PWT	Passenger Waiting Time;
SP	Service policy;
UPTS	Urban Public Transport System;
UTO	Urban Transport Operator.

Indices:

$i = \{0, 1, \dots, I\}$	Indices for the platforms in the system
$j = \{1, 2, \dots, J\}$	indices for the passengers;
$k = \{1, 2, \dots, K\}$	indices for the PM over a long-time horizon;
t	working day time [hours];
η	long-time horizon [years].

Operation parameters:

A_k	k th working cycle range between two age-based PM actions [cycles/maint.];
$f(\eta), F(\eta)$	fault distribution and cumulative probability function [faults/maint.], respectively;
N_k	k th PM action for a periodic block-type [maint./year];
$R(\eta), R_{TS}$	reliability probability function and reliability threshold level, respectively;
S^*	total long-term operation of the system [hours/year];
TS_1, TS_2	working-time periods of system operation and stop-time periods of the system over a long-time horizon [hours/year], respectively;

TS_3, TS_4	downtime periods for maintenance actions over a long-time horizon and failure-time by faults [hours/year], respectively;
w_c, w_s	system operation profit for the in-service periods system operation costs for stop-time periods over a long-time horizon [mu/hour], respectively; which are quantified in terms of a monetary unit (mu);
w_f, w_m	system operation costs per maintenance action for CM [mu/maint.] and PM [mu/hour], respectively;
α_k	working rate of the system [cycles/year];
δ_k	spent to carry out the k th PM action [hours/maint.];
ϕ_η, ϕ_k	current working-life and mean working-time from the current working-life to the k th PM action, respectively;
φ_k	average probability of a fault occurring from the current working life to the k th PM action [faults/maint.];
τ_k	time spent repairing faults for the k th PM action [hours/fault.];
$\Gamma S_1, \Gamma S_2$	financial profit to the UTO for the in-service periods, and cost covered by the UTO for the stop-time periods [mu/year], respectively;
$\Gamma S_3, \Gamma S_4$	cost covered by the UTO over a long-time horizon [mu/year], for downtime and failure periods, respectively.

SP parameters:

le_i	Equivalent distance for a vehicle which would travel if the vehicle were to travel at a constant speed [m];
v_i	speed of vehicles during the in-service periods [km/h];
$p_{i,j}$	j th passenger travelling from the $(i-1)$ th platform to the i th station;
P^*	total time spent by the passengers receiving service [hours/year];
c	number of vehicles on a transport line [veh/line];
ts_i	required time for a vehicle to travel from the $(i-1)$ th station to the i th station [hours];
TP_1, TP_2	time spent by passengers on the journey and global PWT mean in a queue over a long-time horizon [hours/year], respectively;
w_p, w_t	PWT cost and time benefit for passengers during the journey [mu/hour], respectively;
Lq_i	quantity of users in the queue on the i th platform, over a long-time horizon [pax];
μ_i	number of passengers boarding a vehicle from the i th platform [pax];
$\psi_{i,t}$	instantaneous PWT average at the i th platform;
f_i	frequency of the arriving vehicles at the i th platform [hour ⁻¹];
Tv_i	the demanded time to travel to the i th station from the $(i-1)$ th station [hours];
$\Gamma p_1, \Gamma p_2$	financial benefit for the passengers and PWT cost for passengers during the journeys [mu/year], respectively.

Optimization parameters:

α, β	Significance coefficients which are defined by the operation and SPs;
Δp	outcome obtained by the passengers over a long-time horizon [mu/year];
Δs	outcome for the UTO over a long-term operation period [mu/year];
Y_1	operation efficiency ratio over a long-time horizon [--];
Y_2	long-term service efficiency ratio experienced by the passengers [--];
$\chi_{i,j}^*$	combined (operation-service) optimization function.

2. Literature review

There are studies that have considered the time schedule planning to improve the level of service management; thus, we present works focused on UPTS sector. Previous studies (Niu and Zhou, 2013; Barrena et al., 2014-b) minimized the Passenger Waiting Time (PWT) based on the arrival process at stations, which were modelled as uniform and Poisson process. Lee and Vuchic (2005) proposed an optimal transit system as a compromise between the minimal

travel time and UTO profits, and the minimization of social costs. Parbo et al. (2014) dealt with timetable optimization from the perspective of minimizing the PWT, and they obtained a minimization formulation through a nonconvex nonlinear mixed integer problem. Barrena et al. (2014-a) and Sun et al. (2014) have focused on a non-periodic timetable that explicitly considers the time-dependent Passenger Demand (PD) to reduce the PWT and traveling times. A detailed review of these approaches is provided by Caris et al. (2013) and Yin et al. (2017).

Significant researches have been carried out on the efficient management of UTOs and on increasing the level of service as well. Hadas and Shnaiderman (2012) presented optimal frequency settings based on supply chain models that integrate costs, stochastic demand, and travel time. Herbon and Hadas (2015) attempted to determine the departure frequency and vehicle capacity using the newsvendor model, in which both the passenger and operator costs were considered in the objective function for a given fixed route and under stochastic demand. Afterward, Yin et al. (2017) proposed a dynamic scheduling of metro trains oriented to PD through an integrated approach to the train the scheduling problem to minimize the operational costs and PWT, obtaining a mixed-integer linear programming problem. Later, Tang et al. (2018) proposed an algorithm to optimize the transit schedules of bus lines, with the aim of improving the customer satisfaction in terms of reducing the PWT and the operating costs of buses.

There are some works that have focused on the interaction between maintenance and transport schedules using different levels of integration. Souheil et al. (2012) proposed an optimal plan for a Preventive Maintenance (PM) policy aimed at reducing the machine deterioration while minimizing the total cost (production, inventory and maintenance costs). Giacco et al. (2014) and Lai et al. (2015) worked to improve the integration between railway traffic and maintenance planning. Dollevoet et al. (2014) and Corman et al. (2017) integrated railways and passenger schedules. Recently, D'Ariano et al. (2019) dealt with the integration

of railway scheduling and maintenance activities using optimization techniques for some tactical operation issues, and Martinod et al. (2019) studied the combined optimization of operation and Maintenance Policies (MPs) in urban ropeway systems.

All the previous work is addressed to solve to improve just the level of service management or just the operator profit. Our work proposes an integrated solution, which merges the optimization of operation and the service policy applied to urban ropeway systems.

3. Problem formulation

An efficient service should consider the PWT cost, but from the operational point of view, decreasing the PWT cost increases the operating cost over a long-time horizon. UTOs try to maximize their profits, by attempting to increase their revenues and decrease their operation cost, leading to conflicts of interest between the UTO and passengers. These two types of costs are in conflict, any increase to one automatically affects the other. The proposed methodology for addressing the problem is a cost-based model that attempts to balance: the UTO profit and the PWT cost.

We focus on the time criterion to quantify the cost-model, as reducing the travel time can result in other improvements (e.g., widened access to the job market, health care, and education, increased opportunities for leisure activities and political, and civic participation) (Garsous and et al., 2019). The approach recognizes that higher service levels reduce the PWT in the system, and the methodology strikes a balance between the profit from transport operation and the PWT. Our work focuses on the cause-effect relationship between the service level and operational policies, which is developed in the context of the time cost for the combined efficiency of: (i) the operation of the system by UTOs and (ii) the service from the point of view of the passengers.

Section 4 and section 5 describe the problem by analysing the characteristics of each policy separately: the operation plan of the UPTS and quality level of the service, as follows.

4. Operation plan for UPTSs

The operation of the system can be quantified by the classification of the different working periods (Ortega et al., 2018): (i) a period of time in which the system is in-service to the passengers, it is defined as the working-time, TS_1 , and produces the UTO profit; and (ii) the dead time periods of system operation in which the system is out-of-service to the passengers and costs are being generated for the UTO: (a) stop-time, when the system is closed because the time is outside of the service period, TS_2 ; (b) downtime due to maintenance actions, TS_3 ; and, (c) downtime due to faults in the system, TS_4 ; and, (d) the total long-term operation of the system can be expressed as $S^* = \sum_n TS_n - \sum_{n,m}(TS_n \cap TS_m)$, $\forall n \in \{1, \dots, 4\}$ and $\forall m \in \{(n + 1), \dots, 4\}$ (see Fig. 1.a). In this section, the operation plan of a UPTS is developed by analysing the working periods separately as follows.

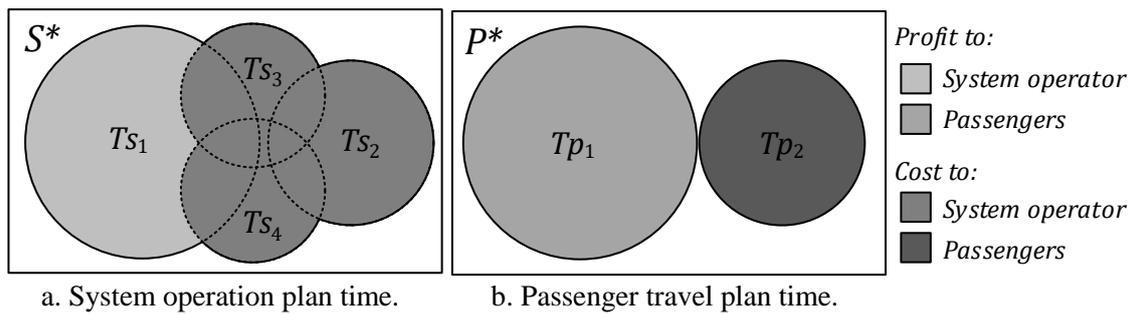


Figure 1. Time relationship for UTOs and passengers.

4.1. Working-time periods

The real time periods that the transport service is available to the passengers, TS_1 , indicates the periods in which the system produces a profit for the UTO and provides a social benefit for the community as well. TS_1 is defined by the authorities and specified by formal contracts that commit the UTOs. These contracts define the operational, financial and technical requirements to be fulfilled by the UTOs and sanctions in case of noncompliance. The UTO profit, w_c , is also specified in these contracts, which is expressed as a cost value in the monetary unit (mu) over a working time [mu/hour].

The w_c value can be defined using different payment mechanisms to the UTO (Canitez et al., 2019): (i) the gross-cost is used in contracts that specify the payment of a lump sum amount to the UTO, where the payments are made in terms of passengers per kilometre, occupied places per vehicle, service hour per transport line or a combination of these; (ii) net-cost contracts require the payment of a flat-rate sum subsidy plus the receipts from ticket revenues, and (iii) performance-based contracts require the calculation of the payments to UTOs according to quality incentives, such as punctuality, customer satisfaction or patronage. The cost-based model to quantify the financial outcome for the in-service periods is expressed as follows:

$$\Gamma S_1 = T S_1 w_c . \quad (1)$$

4.2. Stop-time periods

The period of time in which the system is closed because it is out-hour of service is denoted by $T S_2$. The cost-based model to quantify the stop-time cost is expressed as

$$\Gamma S_2 = T S_2 w_s \quad (2)$$

where w_s [mu/hour] represents the cost covered for the UTO per time unit during the stop-time.

4.3. Downtime periods due to PM

PM has been introduced to minimize the effect of unscheduled breakdown time and is implemented in a planned manner to improve the reliability level, R . Imperfect PM is widely applied in the engineering field and has been adopted mainly by UTOs (Liu et al., 2017; Qiu et al., 2017). Our work focuses on imperfect PM because is because is the most worldwide used by UTOs. After each PM action, the system is restored to a lower level than the nominal state of its components, i.e., over a long-time horizon, η , the components will wear out.

UTOs can adopt different MPs regarding the repair actions, but considering a long-time horizon, a series of repair actions does not avoid the effects of the wearing out of the components in the system (Martinod et al., 2018). This work considers two PM policies:

- (i) Periodic block-type maintenance is carried out periodically using maintenance actions over the long-term for the life of the system (e.g., maintenance/year). This policy accounts for a long-time horizon with a piecewise linear time distribution and an even frequency of maintenance actions, N_k (Khatab, et al., 2013; Martinod et al., 2018), see Fig. 2.a.
- (ii) Age-based maintenance is carried out as the reliability indices of the components reach a predetermined level, i.e., the system undergoes PM whenever the $R(\eta)$ value reaches a given threshold level, R_{Ts} , and the period of time between the PM actions are defined by the working cycle range, A_k (Alaswad et al., 2017; Martinod et al., 2019); see Fig. 2.b.

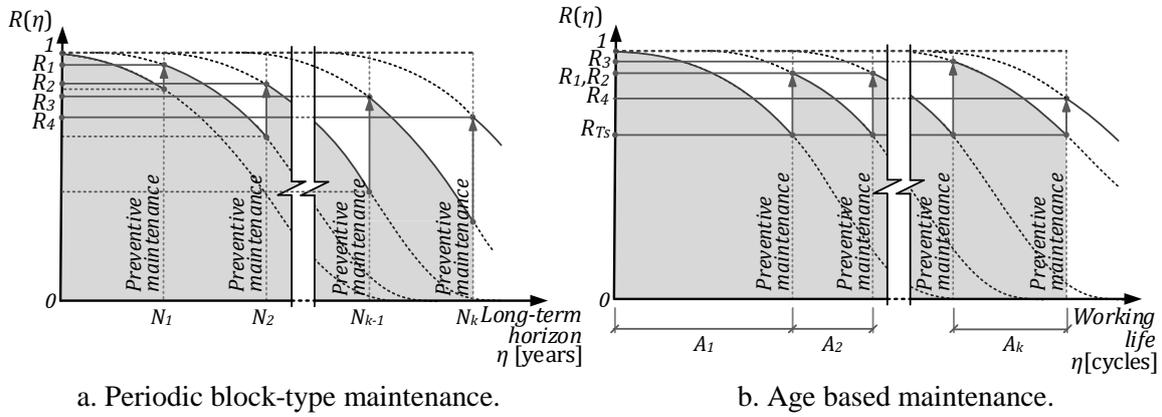


Figure 2. Preventive MP.

Proposition 1. The cost-based model to quantify the downtime cost is expressed as

$$\Gamma s_3 = T s_3 w_m \quad (3)$$

where w_m [mu/hour] represents the cost covered by the UTO per time unit during the downtime.

Proof 1. Consider a periodic block-type MP, the downtime periods for maintenance actions over a long-time horizon are

$$\sum_k N_k \delta_k \quad (4)$$

where δ_k [hour/maint.] quantifies the spent time to carry out the k th PM. Again, if the age-based MP is considered, the downtime periods are

$$\sum_k A_k^{-1} \alpha_k \delta_k. \quad (5)$$

where α_k [cycles/year] is the working rate of the system. Taking Eqs. (4) and (5), it is possible to express

$$Ts_3 = \begin{cases} \sum_k N_k \delta_k & ; \text{ for periodic block type MP} \\ \sum_k A_k^{-1} \alpha_k \delta_k & ; \text{ for age based MP} \end{cases} \quad (6)$$

thus, the cost covered by the UTO over a long-time horizon, η , for the downtime due to PM actions has been proved. ■

Assertion 1. The type-block MP is most suitable for UPTSs in the early stages of life for urban aerial ropeway systems (Martinod et al., 2019); thus, our work uses this maintenance type for next analyses.

4.4. Breakdown time due to faults

The repair actions for a failed component are carried out between the scheduled PM actions (Yang et al., 2017); i.e., within the working cycle range, A_k (see Fig. 3). In addition, the repair actions have a cost associated with the system failure, w_f [mu/hour]. The breakdown cost for Corrective Maintenance (CM) is covered by the UTO.

Proposition 2. *The cost-based model to quantify the breakdown time is expressed as*

$$\Gamma s_4 = Ts_4 w_f . \quad (7)$$

Proof 2. By definition, the fault probability in the working life range A_k is $P(\phi_\eta \leq \eta \leq N_k)$, which is quantified from the area of the fault distribution, $\int_{\phi_\eta}^{N_k} f(\eta)$; thus, the cumulative probability function is defined as

$$P(\phi_\eta \leq \eta \leq N_n) = \int_{\phi_\eta}^{N_k} f(\eta) = F(\eta) ; \quad (8)$$

moreover, the mean value of the cumulative fault function, $F(\phi_k)$, can be expressed by the average probability value of fault within PM actions, φ_k [faults/maint.] (Martinod et al., 2019)

$$F(\phi_k) = \varphi_k , \quad (9)$$

with $\phi_k = (\phi_\eta + N_n)/2$. In addition, the probability of breakdown time caused by faults, TS_4 , over a long-time horizon relies on the sum of the PM actions and its average probability of fault, as following

$$TS_4 = \sum_k N_k \phi_k \tau_k, \quad (10)$$

where τ_k [hours/fault.] represents the time spent repairing faults; thus, the formulation for TS_4 , the breakdown time, has been proven. ■

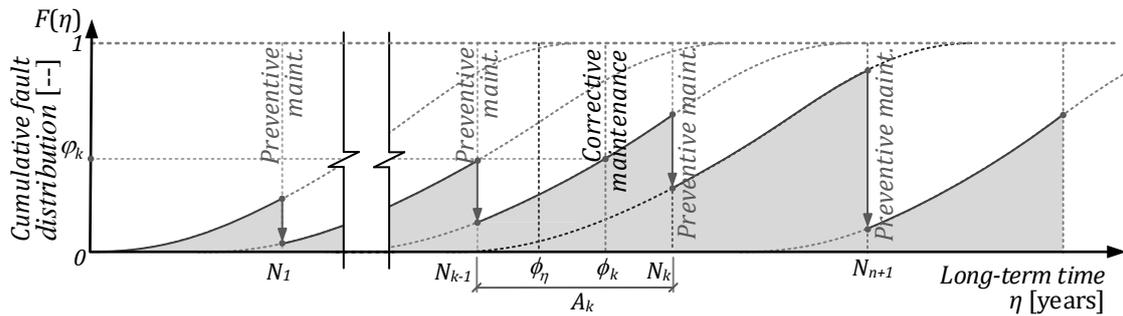


Figure 3. Corrective MP.

5. Service level management

The travel time of passengers is an effective factor for measuring transport performance in terms of the efficiency of the service quality management. The travel time varies according to the operating conditions and is influenced by a number of factors that contribute to congestion (Song and Wei, 2018). The service quality can be assessed by classifying the time spent by the passengers during the travel time, i.e., Tp_1 and Tp_2 . The total time spent by the passengers over a long-time horizon can be expressed as $P^* = \sum_i Tp_i$ (see Fig. 1.b). In this section, we develop the formulation for the service management quality as follows.

5.1. Passenger travel time model

The travel time is defined as the real time in displacement and has been increasingly recognized as an important measure for assessing the operational efficiency of transport facilities (Rojo et al., 2012). Accordingly, when the travel time is affected, travellers spend more time on their trips to reduce the possibility of arriving late at their destination. An adequate

travel time means that this extra time could be reduced or avoided altogether, which is a clear benefit for the passengers (Torrise et al., 2017).

Proposition 3. *The cost-based model to quantify the travel time is*

$$\Gamma p_1 = T p_1 w_t, \quad (11)$$

where w_t [mu/hour] represents the time benefit for the displacement of passengers.

Proof 3. Consider an equivalent distance, le_i , that the vehicle would travel if the vehicle was traveling at a constant speed, v_i , through the i th station; and consider the required time for a vehicle, ts_i , to travel from the $(i-1)$ th station to the i th station. Therefore, the total required time to travel between the i th station and the $(i-1)$ th station is expressed as

$$Tv_i = le_i v_i^{-1} + ts_i. \quad (12)$$

The time spent by the passengers during the travel can be expressed as

$$Tp_1 = \sum_{i,j} p_{i,j} Tv_i, \quad (13)$$

with $p_{i,j} = \{0,1\}$, where $p_{i,j} = 1$ with $j \in i$, i.e., if the j th passenger travels from the $(i-1)$ th station to the i th station; but, if that is not the case, $p_{i,j} = 0$ with $j \notin i$. The value Tp_1 equals to the total time of the passengers who travel between the i th and $(i-1)$ th stations to arrive at their destination; thus, the proposition is proved. ■

Assertion 3. The w_t value constitutes a penalty cost to the UTO. The methodologies to quantify the penalty costs are directly defined by the operation managers of the UPTS. Each operation manager uses different criteria to quantify the penalty cost according to their SP.

5.2. PWT model

A characteristic of transportation mainlines (e.g., long-distance trains, high-speed railways, airlines) is that passengers make their trip plans according to the given transport timetable, and the passenger is attentive to the vehicle schedule (Yin et al., 2017). However, the assessment of the PWT in an urban transport mode (e.g., bus, metro, ropeway systems) is directly subject to the complex passenger flow characteristics over a day-long planning horizon. Passengers in

an UPTS do not usually consider the transport timetable before their trips, leading to the evident dynamic (or time-variant) features of PD (Freys et al., 2013; Yang et al., 2015; Gu et al. 2015). The SP for urban transport must correspond to the PD of the system, which must naturally take account of the variations for PD (Amirgholy and Gonzales, 2016).

The theory of the compound Poisson process is introduced as the principal model to address the targeted queueing problem in UPTSs (Niu and Zhou, 2013; Barrena et al., 2014-b; Xu et al., 2014; Wang et al., 2014; Nesheli et al., 2015). In this work, the theory of the compound Poisson process is used to establish the stochastic process of the PD on platforms. To formulate the mathematical models for the cost of an urban transport service, this work is supported by the following context and assumptions:

Assumption 1. The UPTS is characterized by nondeterministic batch arrivals and bulk service patterns.

Assumption 2. If the capacity of an urban transport mode is less than the number of passengers queuing, the UTO will leave behind some passengers (Kahraman and Gosavi, 2011). The system has a limited capacity to serve users, and the PD rate may exceed the capacity of an urban transport mode in some time periods, which leads to the undesirable consequences of a PD rate that is higher than the capacity of the system.

Proposition 4. *The cost-based model to quantify the penalty cost for the PWT global is*

$$\Gamma p_2 = T p_2 w_p , \quad (14)$$

where w_p [mu/hour] represents the PWT cost.

Proof 4. Given an instantaneous PWT mean at the i th platform, $\psi_{i,t}$, which is defined by the boarding rate, and it is described as the ratio of the number of users in the queue, Lq_i , with the number of passengers boarding the vehicle, $\mu_{i,t}$, and are both affected by the frequency of the vehicles in service over time t (Martinod et al., 2019); i.e.,

$$\psi_{i,t} = \frac{1}{f_i} \frac{Lq_{i,t}}{\mu_{i,t}}. \quad (15)$$

By definition, the frequency of vehicles, f_i , relies on the speed of vehicles, v_i , and the number of vehicles in service, q , i.e.,

$$f_i = v_i q, \quad (16)$$

then, taking Eqs. (15) and (16) and summing the instantaneous PWT mean (sum the values at every instant time for every platform), we obtain the general formulation for the mean PWT, which is expressed as

$$Tp_2 = q^{-1} \sum_i (v_i^{-1} \sum_t \psi_{i,t}). \quad (17)$$

The value Tp_2 equals to the global PWT ; thus, the proposition is proved. ■

Assertion 5. The w_p value represents another penalty cost for the UTO, and the methodology to quantify it is defined by the transport operation manager.

6. Optimization process

The outcome obtained by the UTO over a long time period of system operation is expressed as $\Delta s = \Gamma s_1 - \sum_m \Gamma s_m, \forall m \in \{2,3,4\}$. It is possible to define the ratio value to assess the operation efficiency over a long-term horizon as

$$\gamma_1 = \Gamma s_1 (\sum_m \Gamma s_m)^{-1}, \forall m \in \{2,3,4\}. \quad (18)$$

Likewise, the outcome obtained by the passengers over a long time period of travel is expressed as $\Delta p = \Gamma p_1 - \Gamma p_2$, and the ratio to assess the long-term efficiency of the level of service quality is expressed as

$$\gamma_2 = \Gamma p_1 \Gamma p_2^{-1}, \quad (19)$$

This work introduces a stochastic optimization model to simultaneously develop a cost-efficient service and operation plan. The decision variables are: (i) the service rate expressed in terms of the vehicle speeds v_i ; and (ii) the periodicity of the PM actions, N_k and A_k , for periodic block-type and age-based MP, respectively. The optimal operation plan is obtained by minimizing the expected penalty cost for the PWT and the cost of maintenance activities. From

that point, the proposed model merges the operation and SPs. The maintenance cost increases as the service level increases (i.e., decreasing the PWT cost). Formally, the problem of long-term sustainability (i.e., considering the progressive deterioration of the UPTS) is solved through a cost-based optimization, $\chi_{i,j}^*$, which is based on a merged model for transport operation and service management. $\chi_{i,j}^*$ is made up of the maintenance cost ratio, $Y_1 = f(\Gamma s_m)$, and the PWT cost ratio, $Y_2 = f(\Gamma p_m)$, as follows:

$$\chi_{i,j}^* = \max_{\omega} (\alpha Y_1 + \beta Y_2), \quad (20)$$

where $\alpha, \beta \in [0, \dots, 1]$ represent the significance coefficients that are defined by the operation and SPs, with $\alpha = 1 - \beta$. The optimization model is subject to the following constraints

$$0 \leq \psi_{i,t}, \quad \forall i, t \quad (20.a)$$

$$0 \leq \mu_{i,t} \leq Lq_i, \quad \forall i, t \quad (20.b)$$

$$s_{inf} \leq v_i \leq s_{sup}, \quad (20.c)$$

$$q_{inf} \leq q_i \leq q_{sup}, \quad (20.d)$$

$$R_{Ts} \leq R(\eta) \leq 1, \quad (20.e)$$

$$0 < \tau, N_k, A_k; \quad (20.f)$$

where:

- Eq. (20.a) is related to the SP, where $\psi_{i,t}$ is the upper limit of the PWT global in the queue;
- Eq. (20.b) indicates that the number of passengers boarding the vehicle, $\mu_{i,t}$, which must be less than or equal to the number of passengers queuing, Lq_i .
- Eq. (20.c) is related to an operating condition; namely, the speed of the vehicles, v_i , is limited by a range $[s_{inf}, s_{sup}]$;
- Eq. (20.d) refers to other operating condition, namely, that the system must have a range of vehicles in active service (density of vehicles) $[q_{inf}, q_{sup}]$;
- Eq. (20.e) is related to MPs, where R_{Ts} is the lower limit of the global reliability of the system;
- Eq. (20.f) expresses that a period of time must exist between PM actions.

Remark 1. If the values of the significance coefficients are $\alpha = 1$ and $\beta = 0$, then the operation policy has all of the focus, and the SP is not considered; thus, all the benefit will be directed to the UTO. Otherwise, if $\alpha = 0$ and $\beta = 1$, the SP is extremely relevant and the operation policy is not considered; thus, the all the benefit will be in favor of the passengers.

7. Study Object: an urban aerial ropeway system

To respond to the challenges of growth and mobility, UTOs have considered alternatives to conventional modes of urban transport, including aerial ropeway systems, which led to improvements in (Heinrichs and Bernet, 2014; Bocarejo et al., 2014): (i) urban integration and neighbourhood upgrading; (ii) accessibility and safety, (iii) quality of life; (iv) employment opportunities, and (v) perceived pollution. Garsous (2019) estimates that travel by ropeway systems cuts commuting times over other transport modes, which translates into a daily reduction in travel time and an average net benefit per commute. The effect holds across the commuting time distribution.

Currently, ropeway systems are becoming a popular transport mode and a logical choice for their ability to efficiently move passengers from the tops of hilly metropolitan areas to lower-lying areas. A significant number of urban ropeway installations worldwide have been used as parts of the UPTS in larger cities (Bocarejo et al., 2014; Heinrichs and Bernet, 2014; Težak et al., 2016), including, for example: in North America, New York (USA), Portland (USA), Roosevelt Island (USA) and Mexico D.F. (Mx); in South America, Rio de Janeiro (Br), Medellín (Co), Cali (Co), Manizales (Co), Caracas (Ve) and La Paz (Bo); in Europe, Nizhny Novgorod Bor (Ru); in Asia, Taipei Maokong (Tw), Hong Kong and Ankara (Tr); and in Africa, Constantine (Dz).

The study object comprises a fleet of aerial ropeway vehicles guided by gondola-type aerial cable on a continuous cycle (Estepa et al., 2014), operating in the city of Medellín (Co) since 2004 as a UPTS facility, see Fig. 4. The ropeway operates for 20 hours a day, 7 days a week

and 360 days a year (Martinod et al. 2015); therefore, the system has extremely high operation levels and requires a highly elevated SP (Hoffmann, 2006; Martinod et al., 2018). Appendix A (Table A.1) shows the overall technical characteristics of the study object.

A set of field measurements were taken to establish the flow of passengers using the system during a typical working day. The set of measures was supported by the UTO, which were a part of an analysis to quantify the PD for the system transport. The analysis covered a wide range of different days from 4a.m. to 11p.m. to define the PD behaviour. Therefore, the typical PD for the system transport service was characterized in terms of passengers per hour. Over a typical working day, the PD has large fluctuations, and it is possible to distinguish that the morning rush hour is from 5 a.m. to 9 a.m., while the evening rush hour is from 5 p.m. to 8 p.m. (see Appendix, Fig. B.1).

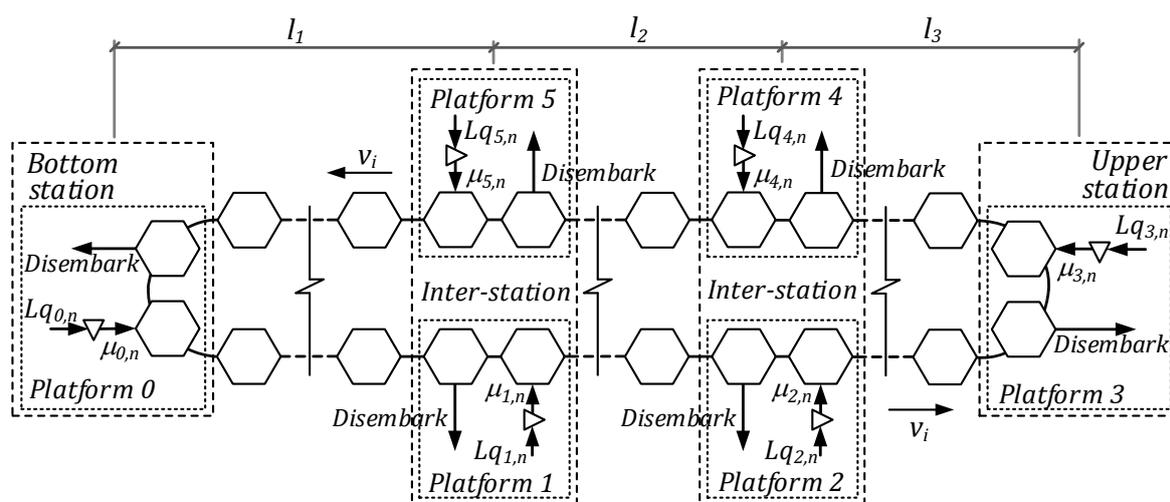


Figure 4. General diagram of an urban ropeway (*télécabine*) system.

Remark 2. This field measurements are regularly performed by the UTO to quantify the PD of the system, since the urban ropeway provides commercial service; thus, UTOs have identified a stable PD profile because of the population of this zone in the city is quite constant, and moreover, there is not a direct UPTS competition in the influence area with respect to others transport modes.

The stochastic simulation was developed in a virtual environment using a programming language. The PD values are the input data for the simulation, which are defined as a set of variables with a stochastic Poisson distribution (see the Appendix, Fig. B.1). The simulation outputs the number of disembarking passengers from the vehicles, which is compared to the measured number of disembarking passengers (see Appendix, Fig. B.2); then, the stochastic simulations are validated according to two criteria: (i) the data correlation values, R_i^2 , between the measured data from the UPTS and the output data from the simulations, the values of which are $R_i^2 = \{0.991, 0.969, 0.966, 0.981, 0.970, 0.991\}$, where each value corresponds to the i th platform; and (ii) the deviation error, E_i , which has values of $E_i = \{3.614, 5.755, 5.065, 4.955, 4.740, 2.551\}\%$, where each value also corresponds to the i th platform.

In addition, the stochastic simulations are subjected to a convergence analysis to achieve more precise and stable results. A minimal correlation threshold is defined ($R_i^2 \geq 0.995$) as an acceptable level of accuracy for this study, and a set of correlation calculations is performed based on the increasing iterations over the stochastic simulations; thus, we find that at least 5 iterations are required to reach the correlation threshold (see Fig. 5). Using the same approach, a maximal error threshold is defined ($E_i \leq 1\%$) as an acceptable level of deviation, and we find that at least 31 iterations are required to reach the error threshold. Therefore, to fulfil the convergence requirement, a total of 31 simulation iterations are required for each analysis.

Remark 3. Note that the $R_i^2 \geq 0.995$ and $E_i \leq 1.0\%$ results represent an acceptable level for the scope of this work.

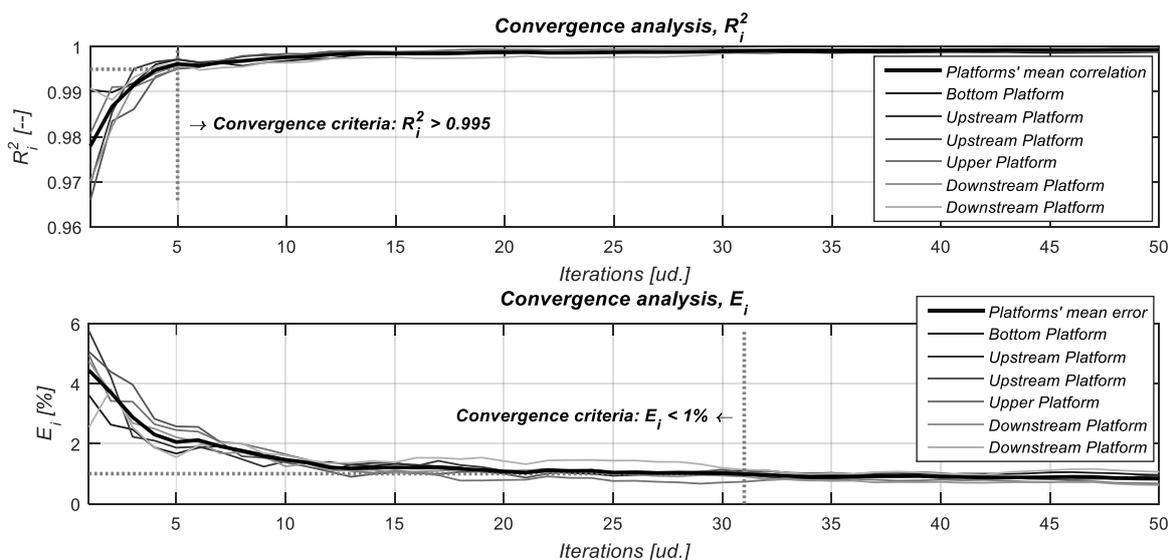


Figure 5. Convergence test results.

8. Results and discussion

We show the results and analysis by discussing each stage of the optimization process:

8.1. Operation time costs

The maintenance actions is computed in three steps: (i) the functions $f(\eta)$, $F(\eta)$, and $R(\eta)$, are calculated to obtain the progressive deterioration of the components when working under the operation conditions, which considers just the CM actions, which means that a reactive MP is applied, without PM actions; (ii) the effect of the imperfect maintenance action is calculated, varying N_k ; and (iii) the deterioration of each component is found by the superposition principle, to get the merged maintenance cost due to CM and PM actions. Ropeway transport operators use to carry out a fixed schedule following the linearly spaced periods (i.e., a periodic block-type MP), then, we are focused on the results of this maintenance policy.

Fig. 6 shows the performance of $F(\eta)$ and $R(\eta)$, based on analysing the periodic block-type maintenance over a long time period that is equivalent to $\eta = [0, \dots, 5]$ [years]. If increases the frequency of the PM action, the reliability function of the ropeway system increases and the corrective actions decrease; but the PM cost increase as well.

The cost-based model for the operation policy was estimated considering the CM and PM actions (see Fig. 7.a). The CM cost increases substantially as the number of PM actions

decreases. Fig. 7.b shows the non-linear behaviour of the operation efficiency ratio, Υ_1 , which is clearly non-linear, but has a creased tendency regarding the frequency of maintenance actions.

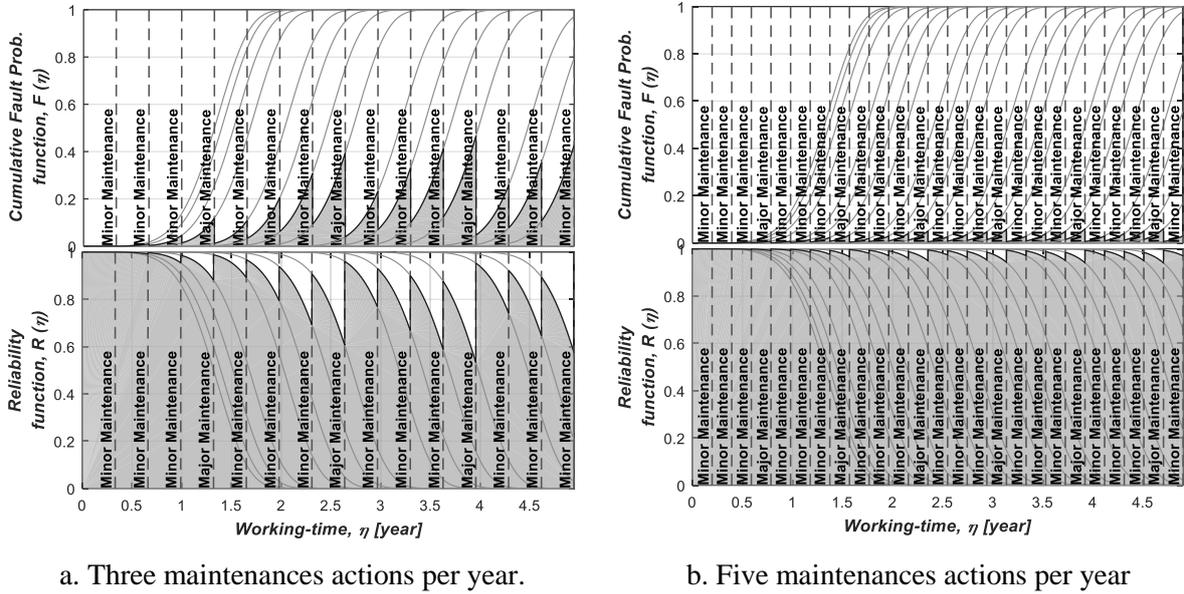


Figure 6. Reliability functions for periodic block-type MP.

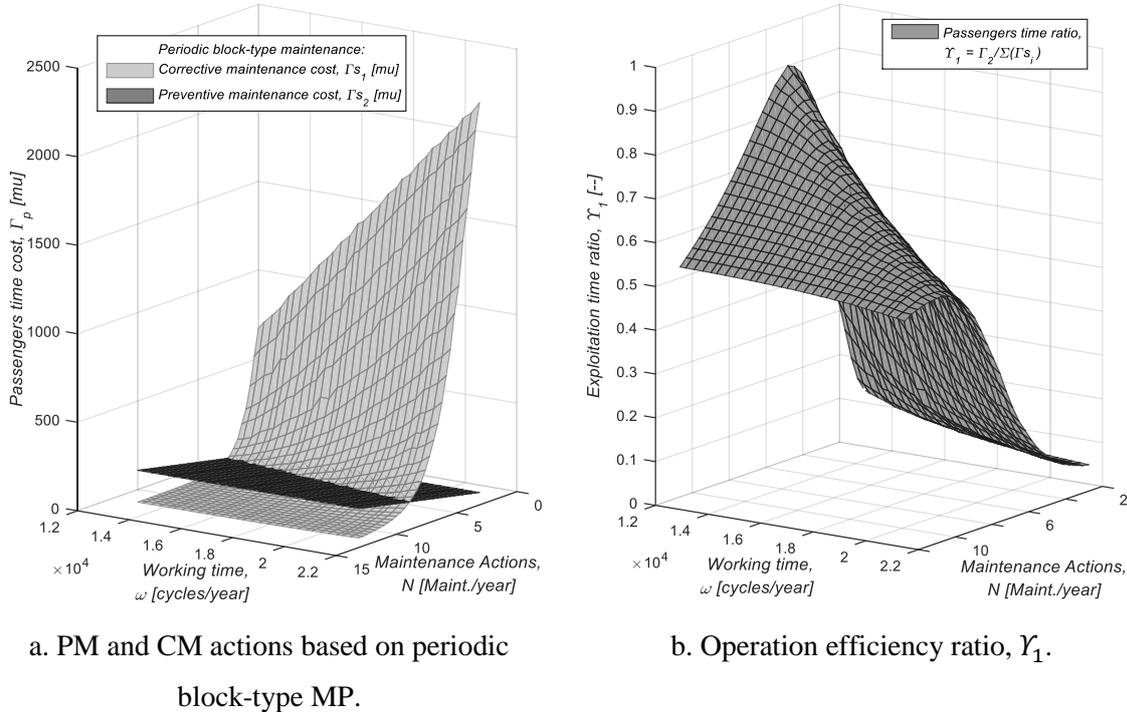
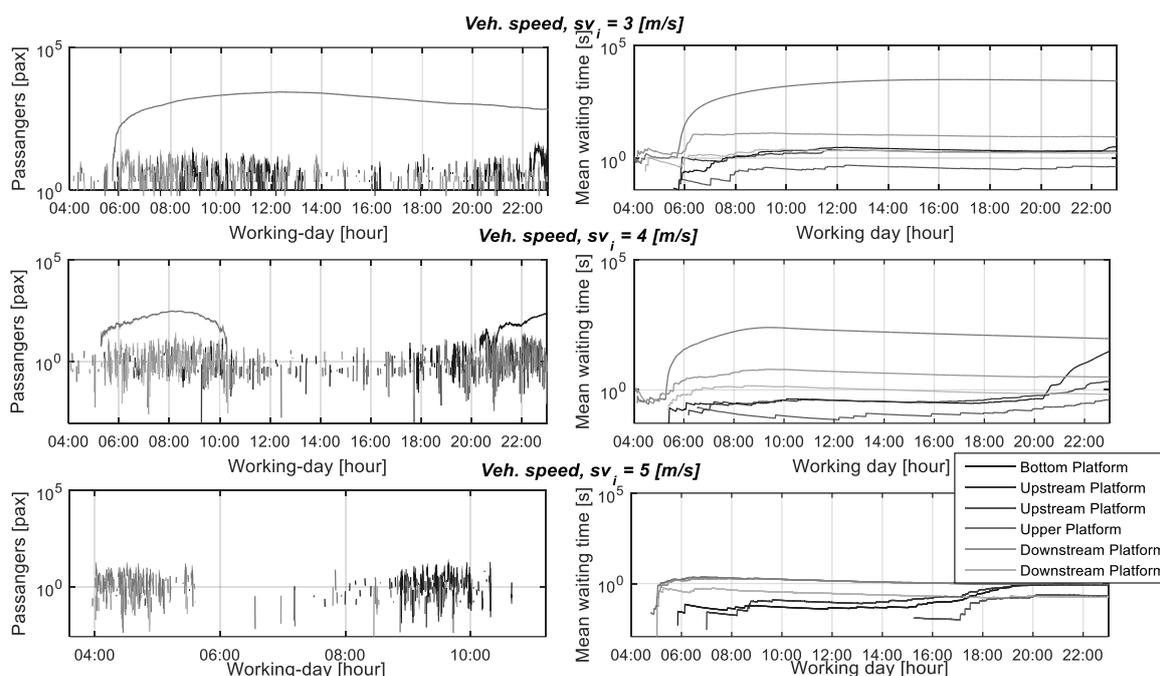


Figure 7. Cost-based model for the operation policy.

8.2. Passenger time costs

UTOs periodically perform a set of measurements for the PD behaviour to assess the passenger flow through the UPTS. Based on a set of metrics (see Appendix, Fig. B2), it is possible to estimate the typical service demand during a working day. Fig. 8.a shows the queuing behaviour of passengers on the platforms for three different operational vehicles speeds, $v_i = \{3,4,5\}$ [m/s], which represents the lowest, average and highest permissible speeds for the operation of the ropeway system. Fig. 8.b shows the global PWT mean. The PWT value substantially increases if the operational vehicle speed decreases, e.g., when the vehicle speed decreases by a factor equivalent to 0.4, the PWT value increases by an incremental factor of 140. Therefore, the PWT variation is highly dependent on the vehicle speed parameter.



a. Queue of passengers on platforms. b. PWT mean on platforms.

Figure 8. Queuing behaviour on the platforms at different transport service speeds.

Fig. 9 shows the typical PWT mean for different operational vehicle speeds and shows that when the vehicle speed is lower than 4[m/s], PWT tends to be zero, but when the speed of the vehicles is greater than 4[m/s], PWT tends to increase considerably. Fig. 10a shows the passenger time costs, which depend on the working waiting time. In this case study, the passenger travel

time is not affected by the maintenance actions since the travel time between stations is a fixed parameter set by the ropeway operator because it is the stabilized value given by its SP. Fig. 10.b shows the non-linear behaviour of γ_2 , which indicates that if the working life of the system is lower than $\omega = 1.8E4$ [cycles/year], the service level ratio increases dramatically.

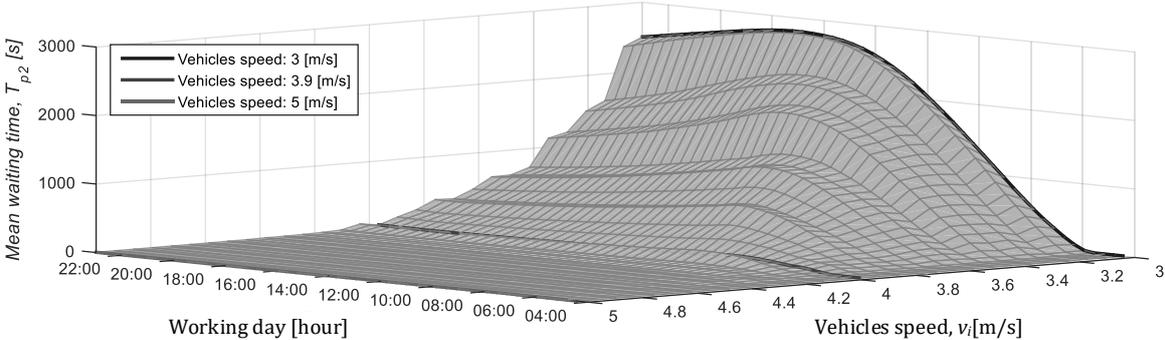
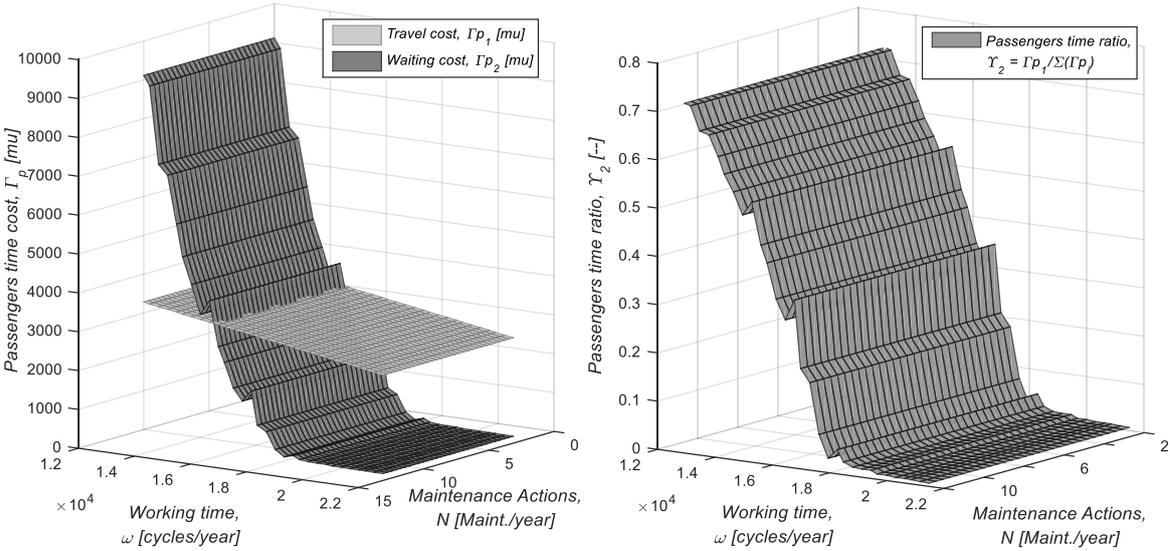


Figure 9. PWT global mean, T_{p2} , at different transport service speeds.



a. Passenger cost, Γ_p . b. Service efficiency ratio, γ_2 .

Figure 10. Cost-based model for the SP.

8.3. Optimization results

The objective function value, $\chi_{i,n}$, is evaluated with a set of combinatorial values for the significance coefficients, i.e., $(\alpha, \beta) = \{(0, 1), (0.2, 0.8), (0.4, 0.6), (0.6, 0.4), (0.8, 0.2), (1, 0)\}$ (see Fig. 11) to assess the different possible configurations between the operation and SPs. Each

surface is a combinatorial value for the significance coefficients in function of the lifetime of the ropeway system and the frequency of maintenance actions.

Fig. 12 shows the functions for $\chi_{i,j}^*$, i.e., the optimum values over the working cycles during a long time period (5 years) indicate an increase in the maintenance frequency according to the deterioration of the system. Moreover, Fig. 12 shows that the proposed study object has a particular behaviour because the $\chi_{i,j}^*$ functions are strongly stable relative to the α and β values, which means that the periodic block-type maintenance is not affected by the different focuses for UTOs to establish the operation and SPs. UTOs may consider implementing a service-oriented operation for the benefits of passengers ($\alpha < \beta$) or a financial/profit-oriented operation ($\alpha > \beta$), but the maintenance policy must be established as a function of the system deterioration. Only in the event that the UTO establishes an operation policy in which only the economic profit is considered and the service issue is disregarded ($\alpha = 1, \beta = 0$) will the MP vary.

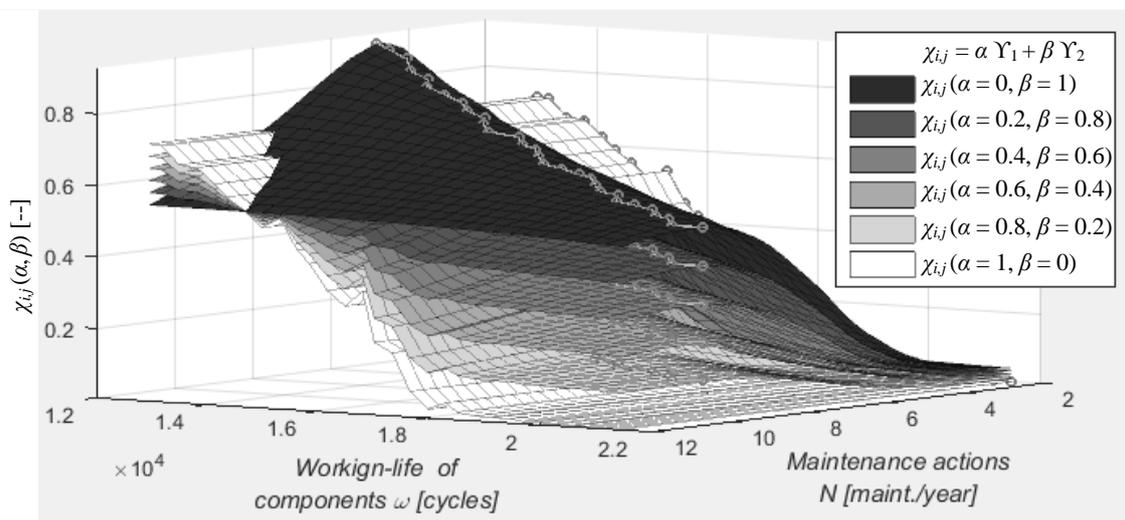


Figure 11. Behaviour of $\chi_{i,j}$ for different significance coefficients, α and β .

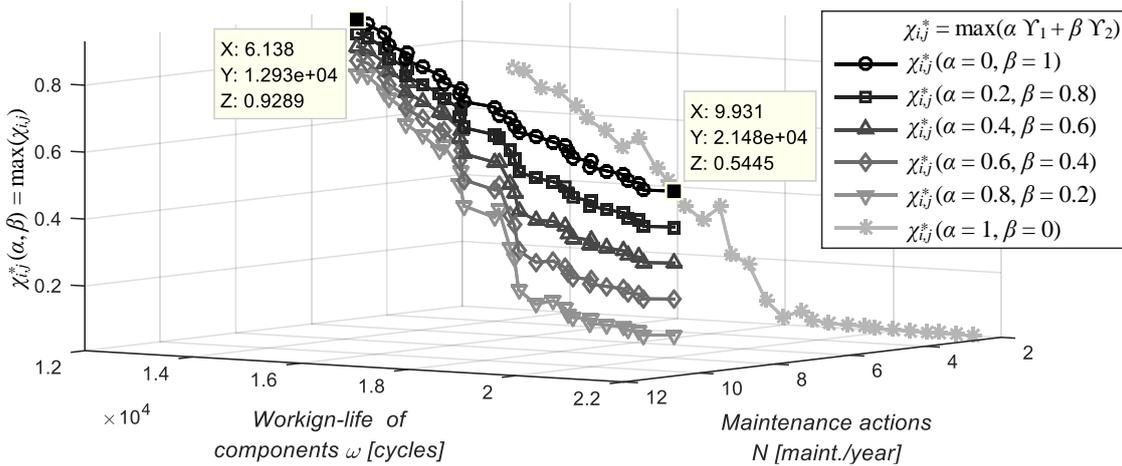


Figure 12. Behaviour of $\max(\chi_{i,j})$ for different significance coefficients, α and β .

9. Conclusions and perspectives

This work optimizes the operations and service policies, applied to urban ropeway systems by means a stochastic model that synthesises in an integrated perspective to improve the operation management cost for UPTSs.

This work provides strong support to the concept that the long-term sustainability for operation of UPTSs must be a combined optimization methodology for the operation planning and SPs. Therefore, the current operation strategies should be reconsidered to improve the service and maintenance activities.

This work developed a mathematical framework for cost-model formulation to rise the exploitation strategy levels according the service and maintenance activities. In the first stage of our work, a mathematical cost-model of the operation policy was proposed to determine the profit values from the different working periods: (i) working-time, TS_1 ; (ii) stop-time, TS_2 (iii) downtime, TS_3 , and (iv) breakdown time, TS_4 . Furthermore, in our research, the operation efficiency ratio over the long-term horizon, Y_1 , was considered as a term in the optimization model for cost, $\chi_{i,j}$. In a later stage of our research, this work developed stochastic processes that consider the uncertainty of the passenger arrival times at platforms to assess the time spent according to the passengers' travel plans, Tp_1 and Tp_2 . Through our analysis, the SP model completes the cost-based optimization function, $\chi_{i,j}$, to bring together the operation and SPs,

thus making it possible to determine the optimal cost function, $\chi_{i,j}^*$, which maximizes the outcome over the working-life of the system.

The work shows that considering the early stages of the study object (a fleet of aerial ropeway vehicles operating in Medellin city), the appropriated maintenance action frequency is $N_k = 6$ [maint./year], and this frequency gradually increases to $N_k = 10$ [maint./year] over working 5 years, obtaining a win-win compromise between the UTO income and the passenger benefit.

Future research will focus on two major aspects. The first aspect is related to the perspective of urban mobility. Changes in mobility using different transport modes increase the requirements of transport integration because in many urban contexts, the geographical and topographical barriers, such as mountains, valleys and bodies of water, and the very large infrastructure costs associated with overcoming these barriers may not allow for the implementation of a single transport mode for such areas. In such cases, transport managers may offer different modes of travel to serve the needs of residents in geographically constrained areas. Further analysis of the intermodal urban transport can be undertaken to tackle the requirements of transport network integration. This calls for a stochastic process to consider the interdependencies of the PD in intermodal UPTSs. The second aspect is focused on a study which would broaden different SPs according to the annual seasons. The present work has only considered a single SP because the study object is a fleet of aerial ropeway vehicles operating in the city of Medellin (Co); therefore, the seasonal impacts on the operation of this UPTS is not significant because this region has only two non-intense seasons (rainy season and dry season).

This work has been focused on a fleet of aerial ropeway vehicles operating in Medellin city, which has fitted with Poisson distribution, further research can enhance the model for other distributions for others urban transport modes.

UPTSs have strong PD asymmetries (e.g., on morning, people go from residential areas to working and educative areas, generating congestion at one transport line direction while the other one is almost empty), this work optimize the PWT, i.e., reduces the undesirable consequence. But, this work does not tackle the causes. Such a case is relevant for solving queues.

References

- Alaswad, S., Cassady, R., Pohl, E., Li, X. (2017), A model of system limiting availability under imperfect maintenance. *Int. J. of Quality & Reliab. Manag.*, 23(4), pp. 415–436.
- Amirgholy, M., Gonzales, E.J. (2016) Demand responsive transit systems with time-dependent demand: User equilibrium, system optimum, and management strategy. *Transp. Res. Part B*, 92, pp. 234–252.
- Barrena, E., Canca, D., Coelho, L.C., Laporte, G. (2014-a) Single-line rail transit timetabling under dynamic passenger demand. *Transp. Res. Part B*, 70, pp. 134–150.
- Barrena, E., Canca, D., Coelho, L.C., Laporte, G. (2014-b) Exact formulations and algorithm for the train scheduling problem with dynamic demand. *Comp. Oper. Res.*, pp. 44, 66–74.
- Belli, L., Cilfone, A., Davoli, L., Ferrari, G., Adorni, P., Di Nocera, F., Dall’Olio, A., Pellegrini, C., Mordacci, M. and Bertolotti, E. (2020) IoT-Enabled Smart Sustainable Cities: Challenges and Approaches. *Smart Cities*, 3, pp. 1039-1071.
- Bibri, S.E. (2018) The IoT for smart sustainable cities of the future: An analytical framework for sensor-based big data applications for environmental sustainability. *Sustainable Cities and Society*, 38, pp. 230-253.
- Bocarejo, J.P., Portilla, I.J., Velásquez, J.M., Cruz, M.N., Peña, A., Oviedo, D.R. (2014) An innovative transit system and its impact on low-income users: the case of the Metrocable in Medellín. *J. Transp. Geogr.*, 39, pp. 49–61.
- Campbell, A.M., Van Woensel, T. (2019) Special Issue on Recent Advances in Urban Transport and Logistics Through Optimization and Analytics. *Transp. Sc.*, 53(1), pp. 1–5.
- Caris, A., Macharis, C., Janssens, G.K. (2013) Decision support in intermodal transport: a new research agenda. *Comp. in Ind.*, 64, pp. 105–112.
- Canitez, F., Alpkokin, P., Blackc J.A. (2019) Agency costs in UPTSs: Net-cost contracting between the transport authority and private operators - impact on passengers. *Cities*, 86, pp. 154-166.

- Cholasuke, C., Bhardwa, R., Antong, J. (2004) The status of maintenance management in UK manufacturing organisations: results from a pilot survey, *J. of Quality in Maint. Eng.*, 10 (1), pp. 5–15.
- Corman, F., D’Ariano, A., Pacciarelli, D., Pranzo, M. (2012). Bi-objective conflict detection and resolution in railway traffic management. *Transp. Res. Part C*, 20(1), pp. 79–94.
- D’Ariano, A., Meng, L., Centulio, G., Corman, F. (2019) Integrated stochastic optimisation approaches for tactical scheduling of trains and railway infrastructure maintenance. *Comp. & Ind. Eng.*, 127, pp. 1315–1335.
- Dollevoet, T., Corman, F., D’Ariano, A., Huisman, D. (2014). An iterative optimisation framework for delay management and train scheduling. *J. of Flexible Serv. and Manuf.*, 26(4), pp. 490–515.
- Estepa, D., Martinod, R.M., Paris, C.E., Pineda, F.A., Restrepo, J.L., Castañeda, L.F., Mejía, G.A., 2014. Operating conditions effect over the coupling strength for urban aerial ropeways. *Transp. Problems*, 9 (3), pp. 5–14.
- Fraser, K., Hvolby, H.H., Tseng, B. (2015) Maintenance management models: a study of the published literature to identify empirical evidence. A greater practical focus is needed”, *International J. of Quality & Reliab. Manag.*, 32 (6), pp. 635-664.
- Freyss, M., Giesen, R., Munoz, J. (2013) Continuous approximation for skip-stop operation in rail transit. *Transp. Res. Part C*, 36, pp. 419–433.
- Giacco, G. L., D’Ariano, A., Pacciarelli, D. (2014). Rolling stock rostering optimisation under maintenance constraints. *J. of Intell. Transp. Syst.: Tech., Plann., and Oper.*, 18(1), pp. 95–105.
- Garsous, G., Suárez-Alemán, A., Serebrisky, T. (2019) Cable cars in urban transport: Travel time savings from La Paz-El Alto (Bolivia). *Transp. Policy*, 75, pp. 171–182.
- Gu, W., Cassidy, M.J., Li, Y. (2015) Models of bus queueing at curbside stops. *Transp. Science*, 49(2), pp. 204–212.
- Hadas, Y., Shnaiderman, M. (2012) Public-transit frequency setting using minimum-cost approach with stochastic demand and travel time. *Transp. Res. Part B*, 46(8), pp. 1068–1084.
- Heinrichs, D., Bernet, J.S. (2014) Public transport and accessibility in informal settlements: aerial cable cars in Medellín, Colombia. *Transp. Res. Procedia*, 4, pp. 55–67.
- Herbon, A., Hadas, Y. (2015) Determining optimal frequency and vehicle capacity for public transit routes: A generalized newsvendor model. *Trans. Res. Part B*, pp. 71, pp. 85–99.

- Hoffmann, K., 2006. Recent developments in cable-drawn urban transport systems. *FME Transactions*, 34 (4), pp. 205–212.
- Ivaldi E., Ciacci A. (2020) Measuring Level of Technological Infrastructure in Smart Cities: A Non-compensatory Approach. In: Dincer H., Yüksel S. (eds) *Strategic Outlook for Innovative Work Behaviours*. Springer.
- Kahraman, A., Gosavi, A. (2011) On the distribution of the number stranded in bulk-arrival, bulk-service queues of the $M/G/1$ Form. *Eur. J. Oper. Res.*, 212 (2), pp. 352–360.
- Khatab, A., Ait-Kadi, D., Rezg, N. (2013) Availability optimisation for stochastic degrading systems under imperfect preventive maintenance. *Int. J. of Prod. Res.*, 52 (4), pp. 4132–4141.
- Lai, Y.C., Fan, D.C., Huang, K.L. (2015). Optimizing rolling stock assignment and maintenance plan for passenger railway operations. *Comp. and Ind. Eng.*, 85, pp. 284–295.
- Lee, Y.J., Vuchic, V.R. (2005) Transit network design with variable demand. *J. Transp. Eng.*, 131 (1), pp. 1–10.
- Liu, H., Yeh, R.H., Cai, B. (2017). Reliability modeling for dependent competing failure processes of damage self-healing systems. *Comp. & Ind. Eng.*, 105, pp. 55–62.
- Martinod, R.M., Bistorin, O., Castañeda L.F., Rezg, N. (2018) Maintenance policy optimisation for multi-component systems considering degradation of components and imperfect maintenance actions. *Comp. & Ind. Eng.*, 124, pp. 100–112.
- Martinod, R.M., Bistorin, O., Castañeda L., Rezg, N. (2019) Joint optimisation of operation and maintenance policies in an urban ropeway transport systems context. *Int. J. of Quality & Reliab. Manag.*, 36, pp. 1106–1136.
- Martinod, R.M., Estepa, D., Paris, C.E., Trujillo, A., Pineda, F.A., Castañeda, L.F., Restrepo, J.L., 2015. Journey safety assessment to urban aerial ropeways transport systems based on continuous inspection during operation. *J. Transp. Safety & Security*, 7, pp. 279–290.
- Nesheli, M.M., Ceder, A., Liu, T. (2015) A Robust, Tactic-Based, Real-Time Framework for Public-Transport Transfer Synchronization. *Transp. Res. Procedia*, 9, pp. 246–268.
- Niu, H., Zhou, X. (2013) Optimizing urban rail timetable under time-dependent demand and oversaturated conditions. *Transp. Res. Part C*, 36, pp. 212–230.
- Ortega, F.A., Pozo, M.A., Puerto, J. On-Line Timetable Rescheduling in a Transit Line. *Transport Science*, 52(5), pp. 1106–1121.
- Parbo, J., Nielsen, O.A., Prato, C.G. (2014) User perspectives in public transport timetable optimisation. *Transp. Res. Part C*, 48, pp. 269–284.

- Qiu, Q., Cui, L., Shen, J., Yang, L. (2017). Optimal maintenance policy considering maintenance errors for systems operating under performance-based contracts. *Comp. & Ind. Eng.*, 112, pp. 147–155.
- Rojo, M, Gonzalo-Orden, M., Dell’Olio, L., Ibeas, A. (2012) Relationship between service quality and demand for inter-urban buses. *Transp. Res. Part A*, 46, pp. 1716–1729.
- Song, C., Wei, C. (2018) Travel time use over five decades. *Transp. Res. Part A*, 116, 73–96.
- Steiner, K., Irnich, S. (2018) Schedule-based integrated intercity bus line planning via branch-and-cut. *Transport Science*, 52(4), pp. 882–897.
- Sun, L., Jin, J., Lee, D., Axhausen, K.W., Erath, A. (2014) Demand-driven timetable design for metro services. *Transp. Res. Part C*, 46, pp. 284–299.
- Tamaki, T., Nakamura, H., Fujii, H., Managi, S. (2019) Efficiency and emissions from urban transport: Application to world city-level public transportation. *Economic Analysis and Policy*, pp. 61, 55–63.
- Tang, J., Yang, Y., Qi, Y. (2018) A hybrid algorithm for Urban transit schedule optimisation. *Physica A: Statistical Mechanics and its Applications*, 512, pp. 745–755.
- Težak, S., Sever, D., Lep, M. (2016) Increasing the capacities of cable cars for use in public transport, *J. of Public Transp.*, 19 (1), pp. 1–16.
- Torrise, V., Ignaccolo, M., Inturri, G. (2017) Estimating travel time reliability in urban areas through a dynamic simulation model. *Transp. Res Procedia*, 27, pp. 857–864.
- Trujillo, A. (2013) Impacto esperado en indicadores de desempeño con la implementación del SPD-Cable en la Línea J del Metro de Medellín. MSc thesis. Universidad EAFIT. Medellín, pp. 261.
- Wang, Y., Tang, T., Ning, B., Van den Boom, T.J.J., De Schutter, B. (2015) Passenger-demands-oriented train scheduling for an urban rail transit network. *Transp. Res. Part C*, 60, pp. 1–23.
- Xu, X.Y., Liu, J., Li H.Y., Hu, J.Q. (2014) Analysis of subway station capacity with the use of queueing theory, *Transp. Res. Part C*, 38, pp. 28–43.
- Yang, L., Li, S., Gao, Y., Gao, Z. (2015) A coordinated routing model with optimized velocity for train scheduling on a single-track railway line. *Int. J. Intell. Syst.*, 30, pp. 3–22.
- Yin, J., Yang, L., Tang T., Gao, Z., Ran, B. (2017) Dynamic passenger demand oriented metro train scheduling with energy-efficiency and waiting time minimisation: mixed-integer linear programming approaches. *Transp. Res. Part B*, 97, pp. 182–213.

APPENDIX A

Table A.1. General features of the ropeway transport system.

Service parameters		Value
Number of service days [day/year]		360
Time for rush hour service [hour/day]		7
Time for valley rush hour service [hour/day]		13
Commercial speed during rush hours, v_i [m/s]		5
Commercial speed during valley hours, v_i [m/s]		3
Nominal number of vehicles in service, q_i [veh]		64
Vehicle (gondola) capacity [pax]		10
Frequency of the SP, f_i [min]		12,33
Length of trip (round trip) [km]		6,00
Operation parameters		Value
Capacity [pax/h]		3000
Length of the plot [m]		2072
Height difference [m]		399
Medium slope [%]		20
Maximum slope [%]		49
Distance between vehicles [m]		61,67
Lower threshold of the reliability function, R_{TS} [cycles]		0,98
Number of PM actions per year, $N[-]$		{2, ...,12}
Number of platforms [ud.]		{0, ...,5}
Number of stations [ud.]		{1, ...,4}
Travel between stations {start – end}	{1 – 2} {2 – 3} {3 – 4} {4 – 3} {3 – 2} {2 – 1}	
Interstation length [m]	840,67 443,41 768,98 768,98 443,41 840,67	
Interstation time travel [s]	219,38 137,06 215,17 215,17 137,06 219,38	
Interstation vehicles [veh]	17 11 17 17 11 17	

APPENDIX B

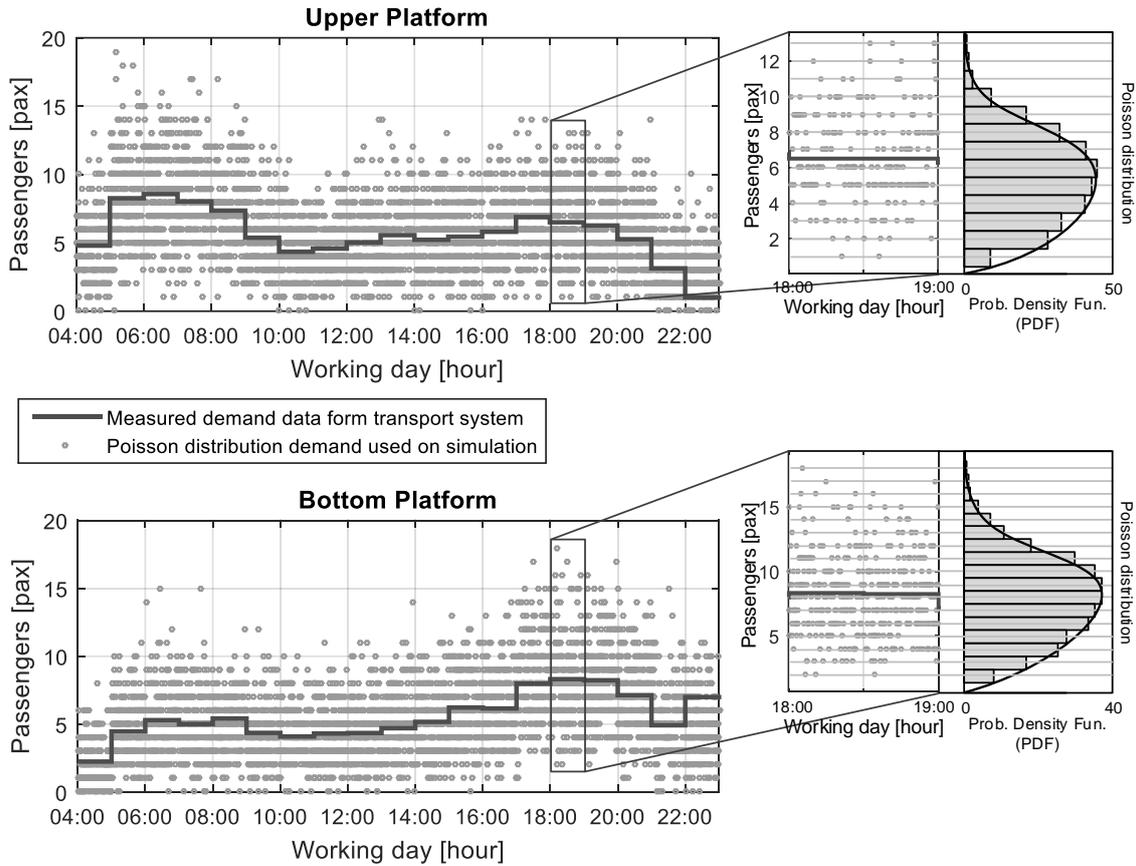


Figure B.1. Typical input of passengers to the system, i.e., distribution of arriving passengers at platforms during a working day.

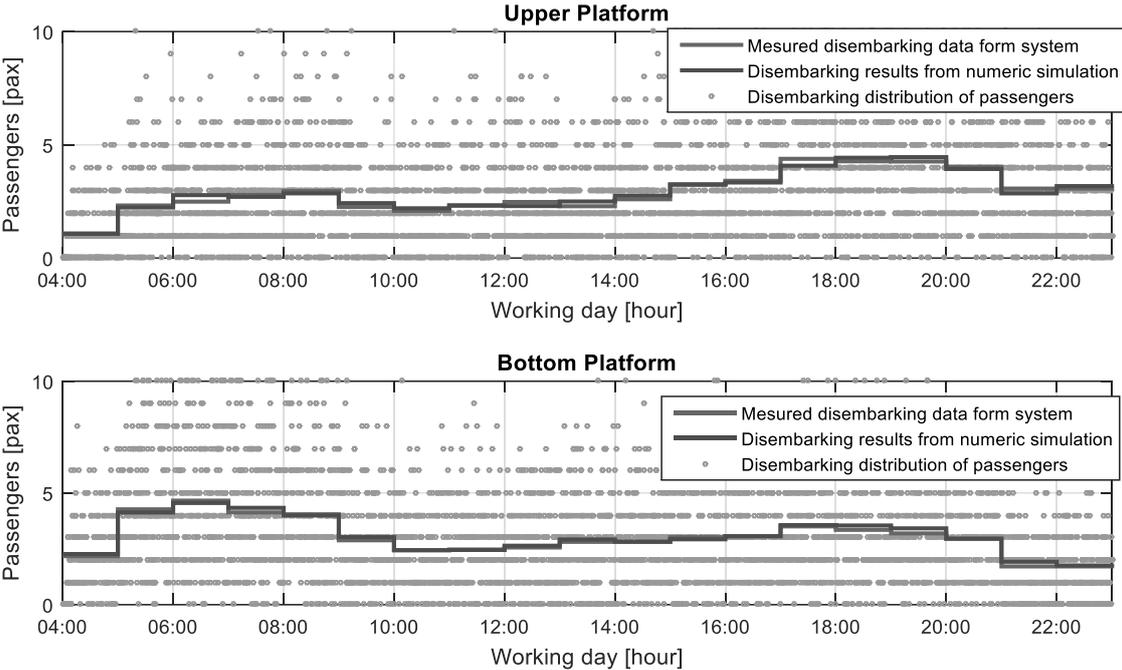


Figure B.2. Output of passengers from the system, i.e., distribution of passengers disembarking during a working day.