

Behaviorally Driven Train Timetable Design

THÈSE N° 7411 (2016)

PRÉSENTÉE LE 9 DÉCEMBRE 2016

À LA FACULTÉ DE L'ENVIRONNEMENT NATUREL, ARCHITECTURAL ET CONSTRUIT
LABORATOIRE TRANSPORT ET MOBILITÉ
PROGRAMME DOCTORAL EN GÉNIE CIVIL ET ENVIRONNEMENT

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

POUR L'OBTENTION DU GRADE DE DOCTEUR ÈS SCIENCES

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ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

Suisse
2016

“Creativity is intelligence having fun.”

— Albert Einstein

To my family. . .

Acknowledgements

Four years ago, I set on the journey of research and exploration. When I look back, at what I have experienced during those four years, there is no doubt that taking this journey was one of the best decisions I have made. Indeed, it is not a simple journey, but what would be a life without challenges?

Firstly, I would like to express my sincere gratitude to my advisor Prof. Michel Bierlaire. His support and leadership made this thesis possible. From day one, he was always there and not only as a professor, but as a mentor and a best friend as well. He is one of a kind and his management of the lab makes it one of the best places to work at, both professionally and personally. I can already tell, that when I will face challenges in the future, I will ask myself: “What would Michel do?”.

Besides my advisor, I would like to thank the rest of my thesis committee: Prof. Katrin Beyer, Dr. Tal Raviv, Prof. Anita Schöbel and Prof. Ulrich Alois Weidmann, for their insightful comments that have improved the quality of this thesis.

A special thanks goes to all the members of Transport and Mobility Laboratory, who have made it a great place to work. I am taking with me many memories of things that we have done together and I am grateful for having met you. Thank you: Anna Fernández Antolín for being my flatmate and for always being the first person to join me in mischief; Mila Bender for the ability of bringing a joy in the lab; Stefan Binder for the car lifts, badminton games and discussions; Anne Curchod for helping me fight computers, Matthieu de Lapparent for trying to make me understand discrete choice models, Eva Kazagli for undertaking the research journey with me from the beginning, Virginie Lurkin for her unique personality, Yousef Maknoon for his honest opinions and celebration spirit, Iliya Markov for educating us in french language, Nicholas Molyneaux for his awesome British accent, Marija Nikolić for being the kindest person on Earth and awesome officemate, Meritxell Pacheco Panneque for being the main star in my short movie, Riccardo Scarinci for his life style coaching (I promise not to drink cappuccino in the afternoon) and Shadi Sharif Azadeh for taking care of us and supplying us with chocolate.

I would like to also extend my gratitude towards the former members of the lab, namely: Bilge Atasoy, Jianghang Chen, Jingmin Chen, Antonin Danalet, Bernard Gendron, Aurélie Glerum, Flurin Hänseler, Hainan Hu, Riccardo Hurtubia, Sofia Kalakou, Prem Kumar, Xinjun Lai, Marianne Ruegg, Aisté Ruseckaitė, Amanda Stathopoulos, Heather Twaddle and Nitish Umang. I also thank my fellow colleagues in the Urban Transport Systems Laboratory at EPFL with whom we shared many stimulating seminars. My

Acknowledgements

gratitude goes as well towards the members of the Transportation Center at EPFL. Special thanks to Emma Sorrentino for overseeing the administration of my doctoral studies.

My sincere gratitude goes also towards the people who have made my life in Switzerland easier, namely: Virginia and Luma Pillet for taking care of me, Sofia Samoili and Stefanos Giannakis for being awesome neighbors, Anastasia Founta for the coffee afternoons all over Lausanne, Bilal Farooq for the evenings out, Dimitrios Efthymiou for turning Starbucks into office space, Sophia Anna Wallerand for organizing the best party ever, Aitor Pérez for his cooking skills and Darko Bardić for the Rakija supplies and his humour.

Last but not the least, I would like to thank my family: my parents Lubica Kowalová and Miroslav Robenek and my two sisters Miroslava Robenková and Kateřina Kowalová, who have supported me during my entire life.

Lausanne, 18 November 2016

Tomáš Robenek

Abstract

The focus of this thesis is to include the passengers and their behavior inside the train timetable design. This is done through three main objectives: timetable design based on passenger satisfaction, exploitation of hybrid cyclicity and choice based revenue optimization.

At first, a new Passenger Centric Train Timetabling Problem is introduced into the planning horizon of the passenger railway service. This problem is inter-disciplinary. It combines the discrete choice theory, that models the passengers' behavior, and operations research, that decides on the departure times of the trains (*i.e.* the timetable). The attributes affecting the passengers' choices with respect to the operated timetable are quantified into a single variable of passenger satisfaction. The objective of the proposed model is the trade-off between the profit of the train operating company and the overall satisfaction of the passengers. The problem is tested on the case study of the morning peak hours in S-train network of Canton Vaud in Switzerland. The results not only confirm that the passenger centric timetables outperform the operational timetable of Swiss Federal Railways (SBB), but they also demonstrate that there is a considerable gap between the performance of the cyclic and the non-cyclic timetable.

The cause of this gap are the cyclicity constraints and therefore, new types of hybrid cyclicity are proposed and tested. The aim of the hybrid cyclic timetables is to provide similar level of flexibility (passenger satisfaction) as the non-cyclic timetables while keeping a certain level of regularity (cyclicity). The regularity is taken care of by the design and the flexibility is evaluated upon solving of the previously defined Passenger Centric Train Timetabling Problem. The new types of timetables are tested against the existing types on the case study of one day in the whole network of Israeli Railways. It is shown that the hybrid cyclic timetable can achieve both benefits (regularity and flexibility) at the same time.

In the last part of this thesis, the passengers' actual choices are obtained through a discrete choice model. The model takes into account fundamental principles in economics such as demand elasticity, ticket price and opt-out option for passengers. Therefore, the probabilistic Elastic Passenger Centric Train Timetabling Problem provides more realistic solutions. Moreover, since the choice is explicitly modeled, the new problem is integrated with a ticket pricing, in order to improve the level of service. In other words, to prevent overcrowding or to secure the service for passengers who need it the most, *etc.*

To summarize, this thesis makes significant contributions in the conceptual design of

Abstract

timetables by taking into account the passengers and their wishes. Indeed, the planning from the operator's point-of-view is in the state-of-the-art, whereas the passengers have been neglected or have been considered only as an abstract concept.

Keywords: passenger behavior, passenger satisfaction, cyclicity, timetabling, hybrid cyclicity, ticket pricing

Résumé

Le but de cette thèse est d'inclure les passagers, ainsi que leur comportement, dans la conception des horaires ferroviaires. Trois objectifs principaux sont poursuivis: la conception d'horaires basée sur la satisfaction des passagers, l'exploitation de la cyclicité hybride et l'optimisation du revenu incluant des modèles de choix.

Dans un premier temps, le "Passenger Centric Train Timetabling Problem" est introduit dans l'horizon de planification du service ferroviaire. Ce problème est interdisciplinaire. Il combine les modèles de choix discrets, qui représentent le comportement des passagers, et la recherche opérationnelle, qui décide des heures de départ des trains (l'horaire, en d'autres termes). Les choix des passagers en fonction de l'horaire opéré sont quantifiés par une seule variable, la satisfaction des passagers. L'objectif du modèle qui est proposé est de trouver un compromis entre le bénéfice de l'opérateur ferroviaire et la satisfaction générale des passagers. Un cas d'étude à l'heure de pointe du matin sur le réseau régional du Canton de Vaud (Suisse) est utilisé pour valider le modèle. Non seulement, les résultats confirment que les horaires de train ajustés à la demande surpassent l'horaire opéré par les Chemins de Fer Fédéraux (CFF), mais ils démontrent aussi qu'il existe un écart considérable entre la performance des horaires cycliques et acycliques.

Les contraintes de cyclicité sont la raison pour cet écart. Par conséquent, des nouveaux types de cyclicité hybride sont proposés et validés. Le but des horaires cycliques hybrides est de maintenir un niveau de flexibilité similaire (satisfaction des passagers) aux horaires acycliques, tout en gardant un certain niveau de régularité (cyclicité). La régularité est considérée lors de la conception et la flexibilité est évaluée en résolvant le "Passenger Centric Train Timetabling Problem" défini plus haut. Ces nouveaux types d'horaires sont comparés aux horaires existants pour le cas d'étude d'un jour sur l'ensemble du réseau ferroviaire israélien. Il est montré qu'un horaire cyclique hybride peut atteindre les deux objectifs (régularité et flexibilité) en même temps.

Dans la dernière partie de cette thèse, les choix réels des passagers sont obtenus à l'aide d'un modèle de choix discret. Le modèle considère des principes économiques fondamentaux, tels que l'élasticité de la demande, le prix du billet ou la possibilité de voyager par un autre moyen. Ainsi, le "Elastic Passenger Centric Train Timetabling Problem", qui est un modèle probabiliste, fournit des solutions plus réalistes. De plus, comme le choix des passagers est modélisé explicitement, le nouveau problème est intégré avec la tarification des billets, afin d'améliorer le niveau de service. En d'autres termes, pour éviter l'encombrement des trains ou pour assurer un service aux passagers qui en ont le plus besoin.

En conclusion, cette thèse apporte des contributions significatives au domaine de la conception des horaires ferroviaires, en prenant en compte les passagers ainsi que leurs choix. En effet, l'état de l'art est la planification du point de vue de l'opérateur, alors que les passagers sont négligés ou considérés seulement de manière abstraite.

Mots clefs: le comportement des passagers, la satisfaction des passagers, la cyclicité, les horaires, la cyclicité hybride, la tarification des billets

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List of Acronyms

AG	Abonnement General
CHF	Swiss Franc
EPCTTP	Elastic Passenger Centric Train Timetabling Problem
FCFS	First Come First Serve
ILP	Integer Linear Programming
IM	Infrastructure Manager
IR	Israeli Railways
LPP	Line Planning Problem
MILP	Mixed Integer Linear Programming
NIS	New Israeli Shekel
OD	Origin-Destination
PCTTP	Passenger Centric Train Timetabling Problem
PESP	Periodic Event Scheduling Problem
RM	Revenue Management
SA	Simulated Annealing
SBB	Swiss Federal Railways
TOC	Train Operating Company
TTP	Train Timetabling Problem
VOT	Value-Of-Time

List of Symbols

Sets and Indices

$i \in I$	–	set of origin-destination pairs	[–]
(i, t)	–	group of passengers traveling between OD pair i wishing to arrive at their destination at time t	[–]
$j \in J^p$	–	set of trains in path p	[–]
$k \in K$	–	set of cycles within the planning horizon	[–]
$\ell \in L$	–	set of operated train lines given by the LPP	[–]
$\ell \in L^p$	–	set of (ordered) lines in path p	[–]
(ℓ, v)	–	train v serving line ℓ	[–]
$p \in P_i$	–	set of available paths between OD pair i	[–]
$p \in P_{it}$	–	set of available paths between for passenger group (i, t)	[–]
$s \in S$	–	set of segments in the network	[–]
$s \in S^\ell$	–	set of segments crossed by the line ℓ to get from its origin station to its destination station in order of appearance	[–]
$t \in T_i$	–	set of desired arrival times to the destination of OD pair i	[–]
$v \in V^\ell$	–	set of trains available for line ℓ (frequency)	[–]
$ set $	–	number of elements in the set	[–]

Parameters

a_{it}	–	desired arrival time of passenger group (i, t) to its destination	[min]
b_i^{pj}	–	time to get from the origin station of train j in path p to a boarding station of passengers traveling between OD pair i	[min]

List of Symbols

$b_i^{p\ell}$	–	time to get from the origin station of a train on line ℓ in path p to a boarding station of passengers traveling between OD pair i	[min]
c	–	size of the cycle	[min]
ξ	–	percentage of cyclic trains within a timetable	[%]
η	–	number of cyclic trains per line	[–]
g	–	train driver salary	$[\frac{\text{monetary}}{\text{km}}]$
G	–	maximum length of a train as a number of units	[units]
H	–	planning horizon	[min]
k_ℓ	–	length of line ℓ in kilometers	[km]
$ L^p - 1 $	–	number of transfers in path p	[–]
$ L^0 - 1 _i$	–	number of transfers in the shortest path between OD pair i	[–]
m	–	minimum transfer time from one train to another	[min]
n_{it}	–	number of passengers in group (i, t)	[–]
r_i^{pj}	–	in-vehicle-time on train j in path p between OD pair i	[min]
$r_i^{p\ell}$	–	in-vehicle-time on a train on line ℓ in path p between OD pair i	[min]
r_i^0	–	in-vehicle-time of the shortest path between OD pair i	[min]
θ	–	maximum allowed deviation from a cyclic departure time	[min]
u	–	operating cost of a train unit per kilometer	$[\frac{\text{monetary}}{\text{km}}]$
W	–	capacity of a train unit	[–]
$x_{\ell v}^{ps}$	–	1 – if path p uses train (ℓ, v) on segment s , 0 – otherwise	[binary]

Variables

\bar{a}_{it}^p	–	actual arrival time of passenger group (i, t) to its destination using path p	[min]
$\alpha_{\ell v}$	–	1 – if train (ℓ, v) is being operated; 0 – otherwise	[binary]
$d_{\ell v}$	–	departure time of train v on line ℓ (from its first station)	[min]
δ_{it}^p	–	early schedule passenger delay of passenger group (i, t) , when traveling on path p	[min]
$\Delta_{\ell v}$	–	deviation of train (ℓ, v) from its cyclic departure time	[min]
f^p	–	fare to be payed for using path p	[monetary]

γ_{it}^p	–	late schedule passenger delay of passenger group (i, t) , when traveling on path p	[min]
λ_k^ℓ	–	1 – if there is a cyclic train scheduled in cycle k on line ℓ , 0 – otherwise	[binary]
$o_{\ell v}^s$	–	occupation of train (ℓ, v) on segment s	[–]
$q_{\ell v}$	–	1 – if train (ℓ, v) is cyclic; 0 – otherwise	[binary]
τ_{it}^p	–	1 – if path p is included in the choice set of passenger group (i, t) ; 0 – otherwise	[binary]
$v_{\ell v}$	–	length of train (ℓ, v) expressed as the number of train units	[–]
w_{it}^p	–	total waiting time of a passenger group (i, t) using path p	[min]
w_{it}^{pj}	–	waiting time of passenger group (i, t) using path p while transferring from train j to train $j + 1$	[min]
$w_{it}^{p\ell}$	–	waiting time of passenger group (i, t) using path p while transferring from train on line $\ell - 1$ to train on line ℓ	[min]
x_{it}^p	–	1 – if passenger group (i, t) is traveling on path p ; 0 – otherwise	[binary]
$y_{it\ell v}^p$	–	1 – if passenger group (i, t) is using train (ℓ, v) in path p ; 0 – otherwise	[binary]
$z_{\ell v}$	–	dummy variable to help modeling the cyclicity, its value expresses the number of cycles between the departure time of (ℓ, v) and $(\ell, v - 1)$	$[\mathbb{N} \setminus \{0\}]$
$z_{\ell v}^1$	–	dummy variable to help modeling the cyclicity, 1 – if the difference between the departure times of two consecutive trains is 60 minutes; 0 – otherwise	[binary]
$z_{\ell v}^2$	–	dummy variable to help modeling the cyclicity, 1 – if the difference between the departure times of two consecutive trains is 120 minutes; 0 – otherwise	[binary]
$z_{\ell v}^{v'}$	–	dummy variable to help modeling the cyclicity, its value expresses the number of cycles between the departure time of (ℓ, v) and (ℓ, v')	$[\mathbb{N} \setminus \{0\}]$

Special Cases

f^s	–	fare to be payed for using segment s ; parameter in Chapter 3 and decision variable in Chapter 5	[monetary]
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Operations Research Convention

ε	–	controlled value of the secondary objective	[monetary]
M	–	sufficiently large number	[–]

Discrete Choice Analysis Convention

\mathcal{C}_{it}^p	–	generalized cost of a path p associated to the passenger group (i, t)	[monetary]
β_E	–	substitution rate between early schedule passenger delay and in-vehicle-time (<i>i.e.</i> willingness to arrive early)	[1/min]
β_L	–	substitution rate between late schedule passenger delay and in-vehicle-time (<i>i.e.</i> willingness to arrive late)	[1/min]
β_T	–	penalty for having a transfer	$[\frac{\text{min}}{\text{transfer}}]$
β_W	–	substitution rate between waiting time and in-vehicle-time	[1/min]
β'_E	–	weight of being early in the utility of passengers	[–]
β'_L	–	weight of being late in the utility of passengers	[–]
β'_T	–	weight of number of transfers in the utility of passengers	[–]
β'_V	–	weight of in-vehicle-time in the utility of passengers	[–]
β'_W	–	weight of waiting time in the utility of passengers	[–]
E	–	aggregate direct point elasticity of passenger demand	[–]
ϵ_{it}^p	–	stochastic residual/unobservable part of utility	[–]
μ	–	scale parameter of a discrete choice model	[–]
Pr_{it}^p	–	probability of passenger group (i, t) choosing path p	[–]
\mathcal{S}_{it}^p	–	satisfaction of a path p associated to the passenger group (i, t)	[monetary]
\mathcal{T}_{it}	–	generalized time of the path used by the passenger group (i, t)	[min]
$\bar{\mathcal{T}}_{it}$	–	generalized time of the penalty path (first shortest path after the end of the planning horizon)	[min]
\mathcal{T}_{it}^p	–	generalized time of a path p associated to the passenger group (i, t)	[min]
\mathcal{U}_{it}	–	utility of the path used by the passenger group (i, t) ; originally unit less, but it can be transformed	[–]

\mathcal{U}_{it}^p	–	utility of a path p associated to the passenger group (i, t) ; originally unit less, but it can be transformed	[–]
\mathcal{V}_{it}^p	–	systematic/observable part of utility	[–]
VOT	–	Value-Of-Time	$[\frac{\text{monetary}}{\text{time}}]$

Heuristic Notation

d_c	–	current solution/timetable	[–]
d'_c	–	potential new solution/timetable	[–]
d_0	–	initial solution/timetable	[–]
d^*	–	optimal solution/timetable	[–]
$f(d)$	–	value function	[–]
$j \in J$	–	set of neighborhood moves	[–]
N	–	number of iterations per temperature level	[–]
ρ_j	–	weight of neighborhood move j	[–]
T_c	–	current temperature	[–]
T_f	–	final temperature	[–]
T_0	–	initial temperature	[–]

1

Introduction

With the spread of smartphones and the functions that they provide, the transportation market(s) started to change in the recent years. The availability of instant information changed the passengers' behavior: they have switched from the planned behavior into a on-demand behavior. Moreover, this new behavior combined with the immediate access to information allowed for market penetration by peer-to-peer services that are more flexible in addressing the demand. This transition is naturally causing a decrease in passengers of the traditional mobility providers, but on the other hand, it opens the door to new possibilities. The market is no longer rigid and follows more closely the demand/supply relationship from the free economy. Therefore, the supply can be calibrated to the demand and lead to an increase in provider's revenue/profit. In revenue management, this approach is described by the saying: "sell the right product to the right customer at the right time for the right price".

This sentence basically means that each customer is having a different behavior and is willing to pay a different price at a different time. However, due to the lack of data, that would help model and to predict the behavior of passengers, this task was near impossible. Especially in the markets such as railways, where the ticket is often "open", *i.e.* the passengers are allowed to take any train during the day for their journey, hence the difficulty to track their behavior.

Given the rich data sets (mainly from the smartphones), this is less of an issue. The providers have the access to the information of the realized trips: origin, destination,

time of purchase, time of travel, *etc.* In some cases, when users sign in with their social network accounts, they provide their socio-economic data as well. Other information can be further obtained through techniques such as machine learning, in order to understand the trip purpose, for instance.

Once this data is assessed into a meaningful information, the passengers' behavior can be analyzed and modeled through discrete choice analysis. This methodology allows to build a behavioral model that can predict the choices of the passengers and to forecast the future demand. Such a behavioral model can then be used in an optimization problem and thus close the loop between the supply/demand interaction. The integrated supply/demand framework is sometimes referred to as "choice-based optimization". A pioneering work, establishing a generic choice-based optimization framework, has been done by Bierlaire and Azadeh (2016). This framework has the potential to sell the right product to the right customer for the right price at the right time.

The benefits of this approach are two-fold. Apart from the obvious profit/revenue maximization of the providers, the passengers receive higher level of service. This is due to the fact, that the service is now matching their wishes, since it was designed based on their behavior. Moreover, the passengers will pay for what they really need and save on what they don't need.

This new framework is suitable even for such traditional services as railways. The railways also need to take into account the passengers' behavior. In the passenger railway service, the main product of a Train Operating Company (TOC) are the seats on the trains. The value of such a seat should be given by the number of similar seats (supply) and the number of passengers willing to buy those seats (demand). The overall strategy of a TOC should then be to offer such seats that the revenue generated by the transported passengers is maximized. As discussed above, this is not possible without the knowledge of the passengers' behavior. But how do the operators plan their offer to the passengers in reality?

Typically, TOCs decompose their planning into several steps. At first, they decide on the composition of their train lines. In other words, what will be the exact paths of the trains. Given the estimate on the number of passengers, this stage also proposes the capacity and the frequency of the service to be. In the next stage, a decision on the exact arrival and departure times of the trains is made, *i.e.* the timetable design. Two types of timetables exist: cyclic and non-cyclic. In the cyclic one, the arrival and the departure times have to follow a repeating pattern. The reasoning behind it is the easier memorability of the patterns by the passengers. The non-cyclic timetables, on the other hand, have no restrictions. In the last stage, the assignment of the fleet and the crew is created. A more detailed overview of the planning process of the railways is presented further on in Chapter 2.

Since the first stage of the planning is based on the rough passenger flows, it is more or less matching the wishes of passengers. Also the last stage of the planning matches the problem at hand: the fleet and the crews are subject to the operated timetable. The timetable design, on the other hand, is suffering from several misconceptions.

In the non-cyclic timetable design, the goal is to resolve any potential conflicts among the trains by shifting their arrival/departure times in the original ideal timetables. Even though the ideal timetable is defined as the most profitable one, the adjustments themselves are expressed in time units (see Section 2.1.1). The cause of this misconception is the lack of methodology to create the ideal timetables in the first place. On the other hand, the misconception of the cyclic timetable design comes from its definition. Even though the repeating patterns are passenger friendly, they do not account for the variation of the demand. The passenger demand does not exert a repeating pattern (see Figure 4.6).

Therefore, both types of timetable design should take explicitly into account the behavior of passengers. Such a design would by definition maximize the profit (attracts more passengers) and it would be passenger friendly (fulfills their wishes) at the same time. But how can we quantify passengers' behavior?

At first, we need to consider the attributes of a timetable that play a role in the decision of a passenger, namely: the in-vehicle-time, the waiting time, the number of transfers and the arrival time to the passengers' destinations. Each of these is having a different weight on the decision itself. This is where the discrete choice analysis comes in: the discrete choice models take as an input the information about the passengers and their potential choices. Based on their previously made choices (also known as a revealed preference survey), the discrete choice model assesses the importance of the attributes that played a key role in this decision. Since none of the concerned attributes is a new concept, their weights have been already estimated and can be transferred from the existing literature. The sum of the weighted attributes forms the so called passenger satisfaction, which should be maximized during the timetable design. Indeed, the more satisfied the passenger is, the more likely it is that (s)he will actually take the train.

Using the above described passenger satisfaction, any type of a timetable can be created. But is it really necessary to create cyclic timetables? As shown above, the passenger demand does not follow a repeating pattern. Moreover, such timetables might induce further operational costs. However, some passengers might find the cyclicity attractive (Wardman et al. (2004), Johnson et al. (2006)). One way to solve this issue, would be to offer both: cyclic and non-cyclic trains. Given that there is always a minimum demand throughout the day, it might be worth to have some part of the trains to operate in a cyclic fashion to provide the base service and the rest of the trains in a non-cyclic manner to strengthen the service during the high demand periods of the day. It would then be up to the passengers, if they prefer a cyclic or a non-cyclic train. Again, the decision on

which train should be cyclic or not, should come from the passengers' wishes/behavior. Since the behavior is incorporated in the passenger satisfaction, it can be used to make this decision.

However, there is one lack of the passenger satisfaction: it does not provide the information, if the passenger is actually going to take the train or not. It only increases the attractiveness of a timetable and therefore, it is more likely that the passenger would take the train. But the operator needs to know what will be his expected train occupation, in order to sell the seat for the right price. Moreover, the operators are now facing intra-modal competition. The cause of it is the liberalization of the railway market that allows for the competition to exist. Hence, selecting the right price is even more important. Last but not least, planning the service for a passenger that would not use it is counter-productive.

The prediction, if a passenger would actually take the train, can be made by a discrete choice model. Indeed, these models can not only find out what played an important role in the passenger's decision, but to predict her future choices as well. In this case, the observable part of the decision is the passenger's satisfaction combined with the fare to be payed. The model also needs to take into account the elasticity of the demand, *i.e.* how does the demand change with the change in the cost. To make the correct prediction, it should consider the competitor's offer as well. Integrated in an optimization framework, it can design a timetable as well as decide on the pricing of each seat on each train. Therefore, it can sell the right seat on the right train to the right passenger for the right price. The only left out attribute in this framework is the right time. Given that it is independent of the timetable design itself, it is not in the scope of this research.

Overall, the aim of this thesis is to modify the train timetable design, in a way that the passengers and their behavior are properly taken into account during the process. Based on the above motivation(s), the thesis is having **three main objectives**:

- 1. Timetable design based on passenger satisfaction (Chapter 3)** – To characterize the passenger behavior in a quantitative way as the passenger satisfaction, so that a new mathematical optimization model of the timetable design can be defined and to assess the performance of the passenger oriented design as compared to the operation oriented one.
- 2. Exploitation of hybrid cyclicity (Chapter 4)** – To design such a combination of a cyclic and a non-cyclic timetable, that the impacts of the cyclicity constraints with respect to the passenger satisfaction are diminished.
- 3. Choice based revenue optimization (Chapter 5)** – To integrate a discrete choice model, predicting the passengers' choices based on their satisfaction and ticket fare, inside the train timetable design, so that the revenue of the operator can

be estimated. The model needs to take into account the elasticity of the demand and the market settings with respect to the competition. And to integrate the timetable design with pricing problem, in order to further increase the revenue.

The immediate practical advantage, of the above described passenger centric timetabling, is the ability to create a new timetable from scratch. The traditional operating companies evolved their timetables historically based on their previous performance during the operation. Therefore, the newly established operators do not have any quantitative means other than trial and error to create theirs.

However, the main advantage is the knowledge of the passenger flows and the underlying train occupation(s). By having this information the TOCs can evaluate the performance of different timetable types and to create new ones. They can also use the information to improve their revenue management or to make more informed strategic decisions about their future. For instance, they can analyze what would be the impact, if a new operator enters the market or what would be the investment return of their fleet extensions (*i.e.* what would be the revenue of a timetable that contains more trains).

Last but not least, a passenger centric timetable can increase the ridership of the passengers, which could indirectly decrease the CO₂ emissions, if the new comers were changing from a car to a train.

Aside of the above practical implications, the thesis provides the **scientific contributions** categorized per objective as follows:

1. Timetable design based on passenger satisfaction

- A new passenger centric train timetabling problem is presented.
- The proposed concept is inter-disciplinary, *i.e.* it combines operations research (supply) with discrete choice theory (demand).
- The attributes affecting the passengers' decision(s) with respect to the timetable are quantified into a single variable: passenger satisfaction.
- The mathematical model is flexible in two dimensions:
 - Objective function-wise: maximization of TOC's profit and maximization of passengers' satisfaction.
 - Timetable type-wise: it can design both cyclic and non-cyclic timetables.
- The proposed problem is tested on the case study of the morning peak hours in S-train network of Canton Vaud in Switzerland using commercial solver (CPLEX).
- The results not only confirm that the passenger centric timetables outperform the operational timetable of Swiss Federal Railways (SBB), but they also

demonstrate that there is a considerable gap between the performance of the cyclic and the non-cyclic timetable.

2. Exploitation of hybrid cyclicity

- An in-depth analysis on the effects of the timetable types on the passengers is presented.
- New types of timetables, that combine the benefits (namely the flexibility and the regularity) of the existing timetables are proposed and tested.
- Various types of timetables are tested on the case study of a whole day in the complete network of Israeli Railways using a simulated annealing heuristic.
- It is shown that the proposed hybrid cyclic timetable can achieve the goal of having the benefits of both cyclic and non-cyclic timetables.

3. Choice based revenue optimization

- The deterministic concept of passenger satisfaction is further replaced by a probabilistic prediction.
- The market is extended by a competing operator.
- The passengers' choices are now affected by the ticket fare as well.
- The ticket fare is further relaxed to be a decision variable and therefore, the train timetabling problem is now integrated with a pricing problem.
- The new types are tested on the case study of a whole day in the complete network of Israeli Railways using a simulated annealing heuristic.
- The results show that the integrated passenger centric train timetabling with pricing can increase the operator's revenue up to additional 15%.
- The revenue maximization design is compared to the passenger satisfaction design. The comparison confirms that the goal of revenue maximization is in line with the goal of the passengers (satisfaction maximization).

The structure of the thesis is as follows: in Chapter 2, the state-of-the-art in train timetable design is presented. In Chapter 3, a passenger centric train timetabling problem building on the behavioral aspect of the passengers through their satisfaction is introduced. This new problem is then used in Chapter 4 to evaluate the difference between the two known timetables and to design new hybrid timetables, that diminish these differences. The deterministic behavior of the passengers is replaced with a probabilistic one in Chapter 5. In Chapter 6, the conclusions are drawn along with the discussion on possible future extensions.

2

State of the Art

The aim of this chapter is to describe the planning process in railway operation and to address the literature related to the objectives of this thesis. To put matter into its context, the railway market settings is described first.

As mentioned in the Introduction, the railway market is going through changes – the so called liberalization of railways. In the previous market settings, the TOCs were government owned and they controlled the railway infrastructure. Being a state property with no direct private competition (*i.e.* other non-governmental TOCs), their aim was to provide accessibility and mobility to the general public. Thus, during their timetable design, they were more focused on its operational aspect(s) rather than on its generated demand in the form of the revenue/profit or the number of transported passengers.

However, with the liberal market that allows for competition to exist, this approach is no longer sustainable. In order to create the liberal market, the national carriers had to split into two entities: the operator and the Infrastructure Manager (IM). In other words, the aim of the separation is to take the control over the infrastructure away from the national TOCs. The infrastructure is now to be managed by an independent entity, that collects the desired timetables of all the TOCs and gives them right(s) to use the infrastructure for a certain fee(s) at a specific time(s). In Europe, the liberalization of the railways is enforced by the Directive 91/440/EEC¹).

¹Council Directive 91/440/EEC of 29 July 1991 on the development of the Community's railways

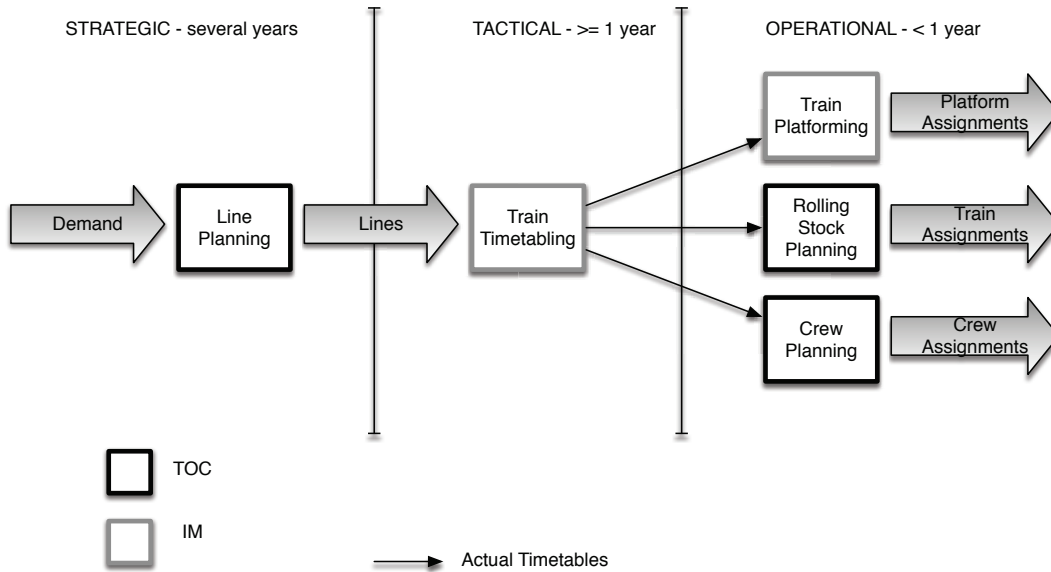


Figure 2.1: *Planning process of the passenger railway service*

In the liberalized market, it is the IM whom is responsible for the resolution of all potential conflicts among the trains commissioned by the TOCs to operate on the infrastructure. In case of such a conflict, it is entirely up to the IM to decide on which train gets the priority. As this issue is fairly new, no general recommendation on the priority rule(s) yet exists. Although, it is expected that an economic instrument such as a bid auction will be used.

The opening of the market to the competition is naturally having an impact on the purpose of the railway service. The governments are no longer allowed to subsidize the (national) careers on those parts of the infrastructure, where several operators compete. Since the goal of the private sector is to generate profit, they typically execute their operation between popular origins and destinations. Therefore, the accessibility/mobility concept is still kept for the less popular parts of the network (and remains subsidized).

The graphical representation of the planning process in the new market settings as described by Caprara et al. (2007) is shown in Figure 2.1. Due to the complexity of the planning task, it is decomposed into several problems that are solved sequentially. The various problems are solved by the different stakeholders. In the previous market settings, they were all solved by a single TOC.

The natural first step, in the planning process of the passenger railway service, should be the railway network design. However, since most of the railway infrastructure has been already built (starting in the early 19th century) and only small parts of the network are being build nowadays, it is often omitted from the planning process as such. Moreover, the decision, on what new parts to add to the network, is often political and handled by

the local authorities. The planning horizon then starts with the line design followed by the timetable design, rolling stock and crew scheduling and train platforming problems.

Line Planning Problem (LPP) is the first official step of the planning process, where each TOC solves its own LPP based on a pre-processed pool of potential lines and the estimated aggregated demand between every Origin-Destination (OD) pair. The LPP selects the most suitable combination of the lines and their frequencies with an objective of maximizing the number of direct travelers and/or minimizing the operating cost. This problem is strategic, *i.e.* it is solved every few years. Indeed, the railway infrastructure and the aggregated demand do not change rapidly. For more information about the LPP, refer to the latest survey by Schöbel (2012).

Train Timetabling Problem (TTP) In the next stage, the IM collects the timetable requests of each TOC and removes any potential conflicts by solving of the TTP. A conflict-free timetable is denoted as an actual timetable. Two versions of the problem exist: non-cyclic and cyclic.

In the **non-cyclic model**, the IM receives the so called ideal timetables as an input. These are defined as ones that bring the most profit to the company. The objective of the problem is to maximize the profit of the adjusted conflict-free timetables (Caprara et al. (2002)). The model does not take into account connections between the trains and thus, the timetable adjustments might disconnect the trains and cause discomfort to the passengers.

In the **cyclic model**, the focus is on the cyclicity (*i.e.* finding of a feasible cyclic solution) of the proposed timetable rather than on a specific objective function (Caprara et al. (2007)). Although, some user-defined objective functions exist (Peeters (2003)). In the cyclic TTP, the connections between the trains are always secured. However, it is not known, if these connections are actually used by the passengers. By the definition of cyclicity, *i.e.* repeating pattern that is easy to remember, the approach is considered passenger oriented.

Note that the TTP models in the current literature often deal with the old market settings. Although, the non-cyclic TTP could be suitable for the IM (as described by Caprara et al. (2007)), if all of the submitted timetables were to be non-cyclic. This problem is considered tactical: the change of a working timetable is effectuated once per year. In Europe, this change has been unified to take place at midnight of every second Saturday in December (Directive 2012/34/EU²).

²Directive 2012/34/EU of the European Parliament and of the Council of 21 November 2012 establishing a single European railway area

Train Platforming Problem The TTP in general is not able to solve all the conflicts, specifically within the train stations, where a microscopic approach is needed. To handle these conflicts, the Train Platforming Problem needs to be solved (Caprara et al. (2007)). This problem takes as input the actual timetables and creates conflict-free routings of the trains through the stations. This problem is considered operational (routings can be changed throughout the operation of the actual timetable) and it is handled by the IM.

Rolling Stock Planning Problem decides on the physical train composition, in the terms of seats and classes (1st and 2nd) offered to the passengers. Its goal is to satisfy the demand and to fulfill the published timetable without exceeding the available rolling stock (Caprara et al. (2007)). This problem is as well operational and in the jurisdiction of the TOC.

Crew Planning Problem assigns crew to the scheduled trains, subject to union rules and other working restrictions. The goal is to minimize the size of the crew needed for a global daily operation of the service (Caprara et al. (2007)). This problem is operational and handled by a TOC.

All the problems in the above planning horizon are offline, *i.e.* they are solved before the planned operation. For a more detailed description of the complete railway planning process, refer to Caprara et al. (2007) or to Huisman et al. (2005).

The above described planning process contains several gaps. One of them being the lack of methodology to create the ideal timetables, that are the input of the non-cyclic TTP. Since they are defined as the most profitable ones, knowledge of the expected passenger demand is needed.

Another gap is the inconsistency among the objectives of the LPP, that focuses on passengers (minimize travel time) and operator (minimize cost), and the TTP, that focuses on profit or cyclicity. This inconsistency may be counter productive. The operator's goal is to maximize his profits and the passengers' goal is to receive the best possible service from their origin(s) to their destination(s). The two goals are in conflict: the best possible service for passengers may also be the most costly alternative for the operator.

Therefore, this thesis addresses the problem of designing the timetable, taking into account both passengers and operators. However, the passengers' objective requires further modeling. A passenger's decision, to select an itinerary in a given timetable, is more complex than the travel time minimization. In order to fully understand passenger's decision process, the behavioral aspect needs to be analyzed. In this thesis, a discrete choice theory is used to quantify the decision process and it is further integrated into the timetable design. Such an approach allows for an estimate of the expected passenger de-

mand and thus, it provides the necessary information for the underlying revenue/profit estimation.

In the following sections, a more detailed literature survey is presented in relation to the specific issues addressed by this thesis.

2.1 Literature Review of the Objective Functions Used in Train Timetabling Models

The focus of the first part of the thesis is to analyze and to define the passengers' objective function and to understand its relation to the operator's objective function. Therefore, the literature review reports on different objective functions that have been used in the operations research literature on timetabling. The literature is organized based on the point-of-view: operator, passenger or integrating both.

2.1.1 Operator

In the literature, operator oriented objective functions can be found only for the non-cyclic version of the TTP. Two formulations of this model exist: Mixed Integer Linear Programming (MILP) or Integer Linear Programming (ILP). The MILP model uses continuous time, whereas the ILP model discretizes the time. The ILP models use the same objective function, whereas MILP models consider different objectives.

ILP Formulations of the non-cyclic TTP

In this formulation, it is assumed that the ideal timetables with the maximum profit are known a priori. Even though there is no available formal definition or methodology of creating such timetables in the literature, Caprara et al. (2002, 2006, 2007) mention that these timetables are defined as being the most profitable for the train operators. The objective is then to look for a conflict free (also called the actual) timetable for a whole railway network by minimizing the profit loss induced by changes made to the ideal timetables.

The model allows for two modifications of the ideal timetables: shifting of the departure time and shifting of the arrival time. Since a train can be kept waiting at a train station, the shift in the departure time is done by adding an extra waiting time at a station. On the other hand, the arrival time is dependent on the departure time from the previous station (already covered by the departure time change) and the running time between the stations. Thus, the arrival time adjustment is done by stretching the running time, *i.e.*

by lowering the speed of a train. Since the problem does not have access to the original profit function, the adjustments are actually addition of an extra waiting time/delay to the ideal timetable instead of adjustments of the real profit. However, there is a need for a more sophisticated method that would be used by the IM in the future.

One of the first TTP papers is by Brannlund et al. (1998). The authors discretize the time and solve the problem using Lagrangian relaxation of the track capacity constraints. The Lagrangian relaxation of the same constraints is used as well by Caprara et al. (2002, 2006), Fischer et al. (2008) and by Cacchiani et al. (2012). On the other hand, Cacchiani et al. (2008) apply the column generation. This approach tends to find better bounds than the Lagrangian relaxation. Subsequently, several ILP re-formulations are introduced and compared by Cacchiani et al. (2010a). Cacchiani et al. (2010b) adjust the ILP formulation, in order to be able to schedule extra freight trains, whilst keeping the timetables of the passengers' trains fixed. A dynamic programming approach, to solve the clique constraints, is used by Cacchiani et al. (2013).

MILP Formulations of the non-cyclic TTP

The MILP model has received less attention in the literature. A common assumption is the knowledge of the originally planned timetable constructed by the operator without stating its properties (unlike for the ILP models). Due to the complexity of the model, different heuristics are a common solution method.

Carey and Lockwood (1995) minimize the overall cost associated with allocating a train path consisting of a trip time, waiting time, dwell time, and arrival and departure time. A heuristic, that considers one train at a time and solves the MILP, based on the already scheduled trains, is introduced. Several more heuristics to solve the MILP model are presented by Higgins et al. (1997). They use minimization of a total weighted travel time as the objective. Another MILP formulation, minimizing the delays on arrivals and departures, is given by Harrod (2012).

Subsequently, Oliveira and Smith (2000) and Burdett and Kozan (2010) use a job-shop scheduling reformulation. Oliveira and Smith (2000) minimize the deviation from the originally planned timetable that is expressed as a delay. On the other hand, Burdett and Kozan (2010) minimize the feasibility violations through their penalization instead.

2.1.2 Passenger

As mentioned before, the cyclic version of the TTP is considered passenger oriented. The reasoning behind it is that, if a train line leaves from a station at the same time in every cycle, it is then easy for the passengers to remember the timetable and thus use

the railways more often.

All the cyclic models are based on the Periodic Event Scheduling Problem (PESP). It was first defined by Serafini and Ukovich (1989). The aim of the PESP is to schedule events in evenly spaced intervals/periods. In the early years of the PESP models, the focus was mainly on finding a feasible solution and these problems did not have an objective function per se (Odijk (1996)). Instead, an arbitrary feasible solution was selected. When the problem is too complex or when no feasible solution exists, a minimization of a constraint violation can be used as an objective (Peeters (2003)). Subsequently, the assumption that passengers' paths are known beforehand (*e.g.* as shortest paths) allows to formulate the objective function in the PESP model, namely to minimize the sum of traveling times which is equivalent to minimizing the sum of slack times. This assumption reduces the objective of minimizing the total travel time into minimizing the waiting time only (Nachtigall (1996), Peeters (2003), Liebchen (2008), Großmann et al. (2012)). This approach can be further extended by exploiting different waiting times and their values (Vansteenwegen and Oudheusden (2006, 2007)). Recently, the shortest path assumption has been relaxed and thus the passenger routing and train timetabling is an integrated decision based on the travel time minimization, see Schmidt and Schöbel (2015) for a non-cyclic version, and Kaspi and Raviv (2013), Hoppmann et al. (2015) and Gattermann et al. (2016) for a cyclic version. For a complete review of the PESP model's properties, refer to Liebchen and Möhring (2007). An example of a PESP timetable development is shown by Kroon et al. (2009).

Another way, of securing a higher comfort to the passengers, is to maximize the robustness of a timetable by pulling the trains apart of each other. Several techniques exist: maximize the departure time difference (Peeters (2003)), minimize the average weighted delay using simulation (Kroon et al. (2008)) or design of robust transfers (Vansteenwegen and Oudheusden (2007)). A different approach would be to minimize the maximum travel time Hoppmann et al. (2015).

All of the above examples take as input deterministic demand. However, the demand depends on the supply. A way to account for this phenomenon is to use discrete choice model to estimate the number of passengers for different versions of a timetable. This allows for a selection of a timetable that attracts the most passengers including other modes of transport (Cordone and Redaelli (2011)).

A "simple" approach to account for the passengers is to weight the delay of the trains by the amount of passengers on board (Espinosa-Aranda and García-Ródenas (2013)). However, a more sophisticated approach is to model the passenger satisfaction which constitutes in several elements that affect the passengers' choices (namely waiting time, running time and number of transfers) and to minimize it (Sato et al. (2013)). This approach can be further improved by taking into account passenger congestion on board of the trains (Kanai et al. (2011)). The framework of passenger inconvenience is a popular

measure in re-scheduling models (see Toletti and Weidmann (2016) for instance).

2.1.3 Integrated

Since the cyclicity constraints reduce the solution space significantly, the cyclic model has become more suitable for exploring of advanced objectives that can combine both operator's and passengers' point-of-view. One such example is a minimization of a weighted combination of the following objectives: required number of train compositions, passenger connection times, sum of running times and dwell times as shown by Kroon et al. (2014).

In order to further increase the potential gains in the objectives, an integration with the LPP could be suitable. Such an approach, consisting in an objective of minimization of weighted sum of the total engine time and the total passenger journey time, has been tested by Kaspi and Raviv (2013).

2.1.4 Summary

From the above literature review, it can be concluded that the main part of the publications in non-cyclic timetabling is rather focused on the operational aspect of the problem (network safety) than the search of the most suitable departure times for the passengers. However, it can be noticed that a new direction of passenger point-of-view problems is emerging. This class of problems aims at using passenger satisfaction as a quantitative measure. This attribute is based upon human behaviour, mathematically represented by discrete choice (utility) theory. This thesis is going to further extend this concept.

2.2 Literature Review of the Train Timetable Design

Since the aim of the second part of the thesis is to propose a new type of timetable, the literature review focuses on the timetable design, which is typically done by solving the Train Timetabling Problem (TTP). The main goal of the TTP is to resolve any potential track occupation conflicts among the trains, so as to construct an operational timetable. Two versions of this problem exist in the literature: cyclic and non-cyclic. The difference between the two versions is that the cyclic TTP imposes additional rules on the departure times.

2.2.1 Non-Cyclic TTP

This version of the problem is either formulated as an Integer Linear Programming (ILP) or as a Mixed Integer Linear Programming (MILP). The ILP model uses discretized time, whereas the MILP model uses continuous time.

Model

One of the main differences, between the two formulations, is the way how they handle the conflicts among the trains. The ILP model discretizes the time and splits the lines into blocks (Brannlund et al. (1998)). One train at a time can occupy a block. Clique constraints are then imposed to secure the safety (Caprara et al. (2002, 2006), *etc.*). They are growing exponentially in number with the size of the problem. Several other ILP re-formulations exist (Cacchiani et al. (2010a)). The ILP formulation can also allow for the scheduling of extra freight trains within the planning of the passenger service (Cacchiani et al. (2010b)).

The MILP model, on the other hand, is considering the departure times as continuous variables. The minimum headway between two trains is secured by using binary variables that indicate the order of the trains in which they leave from a given station (Carey and Lockwood (1995), Higgins et al. (1997), *etc.*).

Objective Function

The objective functions of the non-cyclic TTP are as described in Section 2.1.1.

Solution Approach

A common methodology to solve the ILP formulation is the Lagrangian relaxation of the track capacity constraints (Brannlund et al. (1998); Caprara et al. (2002, 2006); Cacchiani et al. (2012)). However, the column generation framework seems to find better bounds than the afore-mentioned relaxation (Cacchiani et al. (2008)). One may also use dynamic programming to solve the clique constraints (Cacchiani et al. (2013)).

For the MILP formulation, the literature agrees on using a heuristic as a common solution approach: a heuristic that considers one train at a time to solve the MILP based on the already scheduled trains (Carey and Lockwood (1995)), as well as local search, tabu search, genetic and hybrid heuristics (all presented in Higgins et al. (1997)), among others.

2.2.2 Cyclic TTP

The aim of the cyclic TTP is to resolve any potential track occupation conflicts and to make the departure times of all trains cyclic, *i.e.* the departure time of each train on each line is equally spaced with an interval of a cycle. This class of problems is referred to as Periodic Event Scheduling Problem (PESP). The PESP were first defined by Serafini and Ukovich (1989). Due to the nature of the problem (repeating pattern), it is sufficient to solve the cyclic TTP for one cycle only (typically the peak hour as it is the most dense part of the day) and repeat the solution in every other cycle. A special case of a cyclic timetable is the clock-faced timetable, where the cycle is equal to one hour (typical for railways).

Model

The majority of the cyclic TTP formulations are based on the PESP. In some cases, the PESP is extended with additional constraints such as train synchronization (Peeters (2003)) or symmetry (Liebchen (2004)). The symmetry can be described as follows: two trains of the same line traveling in opposite directions meet at time 0, *i.e.* if a train leaves at 14th minute of the cycle in one direction, then the train in the opposite direction leaves from the same station at time 46 for a cycle of one hour. The sum of the departure times at any station is equal to the cycle. The symmetry is a popular measure in Switzerland and Germany.

The basic PESP formulation considers one universal cycle, known a priori, for the whole railway network. However, one may consider to allow for varying sizes of the cycle over the planning horizon (Zhong et al. (2013)) or to make the size of the cycle a decision variable (Heydar et al. (2013)). The proposed measures have the intention of securing better transfers or to maximize the utilization of the infrastructure respectively.

Objective Function

The objective functions of the cyclic TTP are as described in Section 2.1.2.

Solution Approach

Similarly to the objective function, one superior methodology for solving the problem does not exist. The applied techniques span from the semi/exact methods, such as branch and bound (Nachtigall (1996)), constraint generation (Odijk (1996)), modulo simplex (Nachtigall and Opitz (2008)), cycle periodicity reformulation (Peeters (2003));

Liebchen and Peeters (2009)), satisfiability reformulation (Großmann et al. (2012)), decomposition using priority train classes Herrigel et al. (2013), *etc.*, to heuristic methods, such as genetic algorithm (Nachtigall and Voget (1996)), and simulated annealing with particle swarm optimization (Jamili et al. (2012)).

Remark Due to the restrictive (cyclicity) constraints, a feasible solution might not always be obtained. Two options for correction exist: the adjustment of the underlying assumptions (to keep the cyclicity intact) or allowing for some degrees of irregularity in the timetable. One of the assumptions that can be changed is the running time of a train in between two stations. Typically, the cyclic TTP treats it as a fixed input, but it can be turned into a decision on an interval of a minimal and a maximal value and possibly result into having a feasible solution (Kroon and Peeters (2003)). The other option is to affect the cyclicity itself. When a railway network is highly dense (such as in China), one can decide to have some lines cyclic and the others non-cyclic. This framework was proposed by Yang et al. (2010), where the cyclicity is primarily given to the most busy lines in terms of the transported passengers. This approach would make a whole train line non-cyclic, but sometimes it might be sufficient to allow only for a small deviation from the cyclic departure time of only a few trains. Such a framework is proposed by Caimi et al. (2011), where the problem has a periodic service as an intention and not as a hard constraint.

2.2.3 Summary

From the above survey, it can be seen that the most often goal is to provide either a fully non-cyclic or a fully cyclic timetable. A partially cyclic timetable is considered, only when no feasible solution can be obtained. However, a new direction of relaxing the cyclicity to achieve the benefits of the non-cyclic timetables is emerging. This thesis is going to further exploit this concept.

2.3 Literature Review of the Forms of Passenger Demand Used in Train Timetable Design

Since the aim of the third part of the thesis is to introduce the demand and its elasticity into the train timetabling, the focus of its literature review is on the passenger demand representation in the railway planning literature. At first, the demand representations used in the train timetabling problems are discussed in Section 2.3.1, followed by the presentation of various demand forecasting techniques used in the railway context in Section 2.3.2. Lastly, Section 2.3.3 shows how some of the forecasting techniques are used in the revenue management and ticket pricing within the railways.

2.3.1 Demand Representations

The most basic representation of the railway demand is an Origin-Destination (OD) matrix. Such a matrix is typically used in the Line Planning Problem (LPP) to determine the frequency of a train line (Schöbel (2012)).

Once the lines are designed, the Train Timetabling Problem (TTP) assigns a departure time to each train subject to the operational constraints. Two versions of this problem exist: cyclic and non-cyclic. In the cyclic TTP (Peeters (2003)), the main focus is on the cyclicity constraints, whereas in the non-cyclic TTP (Caprara et al. (2002)) the departure times do not have to follow any specific pattern. Traditionally, both problems assume that the passengers follow the shortest path. Therefore, there is no need to include the route choice dimension explicitly and the optimization is performed on the attributes of the shortest paths between the ODs.

Recently, this assumption has been relaxed and the passengers can choose from several paths while minimizing their total travel time: refer to Kaspi and Raviv (2013), Hoppmann et al. (2015) and Gattermann et al. (2016) for the cyclic TTP and Schmidt and Schöbel (2015) for the non-cyclic TTP. However, this approach can be further improved by maximizing the passenger satisfaction instead. The passenger satisfaction better reflects the human behavior. It combines the in-vehicle-time, the waiting time, the number of transfers and the desired arrival time to the destination of a given path, each weighted by the respective human perception. Such approach is called the Passenger Centric Train Timetabling Problem and it can design both: cyclic and non-cyclic timetables (Robenek, Maknoon, Azadeh, Chen and Bierlaire (2016)) or a recently proposed hybrid cyclic timetable by Robenek, Azadeh, Maknoon and Bierlaire (2016) (for a further description of this timetable refer to Section 5.2).

A different approach is to use the passenger arrival rates to their origin stations, in order to design a timetable (Luethi et al. (2007), Barrena et al. (2014a,b), Sun et al. (2014), Wang et al. (2015)). However, this method is only suitable for high frequency services such as the public transit.

2.3.2 Demand Forecasting

In order to forecast the demand, its behavior in form of the decisions needs to be modeled. The main decisions are: mode choice, route choice, operator choice, service choice and departure time choice. One of the first forecasting models has been introduced by Wardman (1997). He shows a direct demand model taking into account the mode competition (between rail and car) and the service offer (cost and service quality). He further extends this model with additional attributes such as car ownership, car travel time and fuel cost in Wardman (2006). Other models are investigated by Wardman

et al. (2007). The main focus is on the generalized cost, *i.e.* service choice. All of these models are in the settings of the British railway market.

Another group of demand forecasting models focuses on high speed rail. The case studies involve Italy (integrated demand model combining demand growth, mode choice and induced demand by Ben-Akiva et al. (2010)), China (hybrid approach combining empirical mode decomposition and gray support vector machine by Jiang et al. (2014)) and Sweden (nested logit model for mode choice by Börjesson (2014)), among others. A recent survey on a high speed railway demand forecasting models is presented by Börjesson (2014).

Remark However, all the above models only forecast the demand and do not combine it with a timetabling problem. The supply-demand interaction is a fairly new topic in the timetabling context. Two applications of a train timetabling problem incorporating a mode choice forecast exist: Cordone and Redaelli (2011) and Espinosa-Aranda et al. (2015). Cordone and Redaelli (2011) maximize the demand captured by a cyclic timetable using a logit model as a mode choice and Espinosa-Aranda et al. (2015) maximize the profit of a non-cyclic timetable using a constrained nested multinomial logit model as a mode choice combined with a departure time choice.

2.3.3 Revenue Management and Pricing

Typically, the demand forecasting models are used in a combination with the Revenue Management (RM) and pricing problems. The aim of these problems is to maximize the revenue while optimizing the prices based on the demand forecasts.

In the pricing problems, the strategy is to adjust the ticket prices based on a given timetable. The key attributes justifying the price variation are space (busy parts of the network vs. under-used parts of the network) and time of the day (peak hours vs. off-peak hours). One of the first frameworks to analyze different pricing policies was introduced by Nuzzolo et al. (2000). They present a nested logit model that takes into account elementary trains, instead of the frequencies. The model combines route choice, departure time choice and service choice. However, an empirical study of the effects of pricing policies and demand elasticities on a service choice in the context of Dutch Railways (van Vuuren (2002)) suggests that the peak hour demand is rather inelastic. This makes the strategy of higher prices during peak hours more effective than a price reduction during the off-peaks (Whelan and Johnson (2004)). This conclusion was found in the context of avoiding train overcrowding using an incremental logit model to do the forecasts. The model is predicting route choice, departure time choice and service choice. A similar goal, of flattening the demand throughout the service, is pursued by Li et al. (2006). They propose several pricing schemes combining spatial and time attributes.

The passenger behavior is mimicked through activity-based microsimulation that takes into account mode choice, route choice and service choice.

The RM models, on the other hand, focus more on the price adjustments related to the demographics of the population. The key attributes justifying the price variation are the time of the purchase, which is related to the trip purpose (leisure travelers buy their tickets early vs. business travelers, who buy last minute tickets), class (1st class vs. 2nd class), and others. For a more detailed overview discussing the principal differences in RM of airlines and railways refer to Armstrong and Meissner (2010).

Overall, the literature on RM in railways is sparse and focuses solely on the price variation over the time of the purchase. A quantitative analysis on the pricing suggestions for Indian Railways is presented by Bharill and Rangaraj (2008) and in Hetrakul and Cirillo (2014), a multinomial logit and latent class models are tested within the pricing optimization framework. Both focus on service choice.

2.3.4 Summary

From the above literature review, it can be seen that several railway passenger demand forecasting techniques exist, but that they are mainly used within the revenue management and the ticket pricing over a fixed timetable. Only a few models combine timetable design and demand forecasts and no model combining the demand forecasting, timetable design and ticket pricing exists.

3

Passenger Centric Train Timetabling Problem

This chapter is based on the article:

Robenek, T., Maknoon, Y., Azadeh, S. S., Chen, J. and Bierlaire, M. (2016). Passenger centric train timetabling problem, *Transportation Research Part B: Methodological* 89: 107 - 126.

The work has been performed by the candidate under the supervision of Yousef Maknoon PhD., Shadi Sharif Azadeh PhD., Jianghang Chen PhD. and prof. Michel Bierlaire.

The objective of this chapter is to provide a new train timetabling method, that would take into account the behavior of the passengers and that would, at the same time, consider the operator's objective of maximizing his profit.

The operator's profit as such is usually well defined (revenue minus the operating cost). The behavioral aspect of the passengers, on the other hand, needs specific modeling based on utility theory. The (dis)utility of traveling for an individual is a function of various features of the trip: the time spent in the train, the time spent waiting, the number of transfers from one train to another and the timeliness at the destination.

In the literature, the attribute of so called passenger satisfaction, based on the first three elements, already exists and is assessed together using the results of discrete choice

models (*i.e.* the passenger perception): the waiting time has a larger relative weight than the in-vehicle-time and the transfer from one train to another is penalized by adding extra in-vehicle-time (Kanai et al. (2011), Sato et al. (2013)). The presented applications are from the delay management, where the passengers are already in the network and the goal is to minimize their additional dissatisfaction as compared to the original timetable.

However, in the offline version of the train timetabling, the time dependency of the demand needs to be taken into account as well. Since passengers plan their arrival to the destination rather than to the origin, the schedule passenger delay at the destination can be used as a good measure (Small (1982)) to quantify this aspect. This approach is becoming more and more used in the railway applications: ticket pricing (Whelan and Johnson (2004)) and timetabling (Espinosa-Aranda et al. (2015)).

Further on, to achieve the full impact of the passenger satisfaction method, the model has to take into account all possible paths between an origin and a destination. In the literature, it is often assumed that the passengers take only their shortest path, which in the end might not be the case as it is dependent on the exact timetable as shown in Schmidt and Schöbel (2015) and in Hoppmann et al. (2015).

Therefore, this chapter further extends the concept of the passenger satisfaction by including the schedule passenger delay that accounts for the preferred arrival time at a passenger's destination. The overall passenger satisfaction may be expressed in monetary units. Apart from that, the passengers are allowed to select their most desirable path from the set of all possible paths between their OD pairs.

This chapter proposes to introduce an additional step in the railway planning process called the Passenger Centric Train Timetabling Problem (PCTTP). The PCTTP is formulated as a MILP and it is using the output of the LPP and serves as an input to the traditional TTP. Hence, it is placed between the two respective problems (Figure 3.1). The PCTTP is capable of designing both cyclic and non-cyclic timetables. Since the problem does not contain the track safety constraints, it only creates a preliminary timetable. The IM operated TTP is now considered as a one universal problem that should take the base of the non-cyclic TTP and add extra constraints that would secure cyclicity for the operators that wish to run the cyclic timetables (not in the scope of this research).

The structure of this chapter is as follows: in Section 3.1, the problem definition, different objectives, mathematical model and the procedure of how to construct the approximated Pareto frontier between the objectives is given. The case study, on which the model is tested, is shown in Section 4.3.5. The chapter is finalized by drawing some conclusions in Section 3.3.

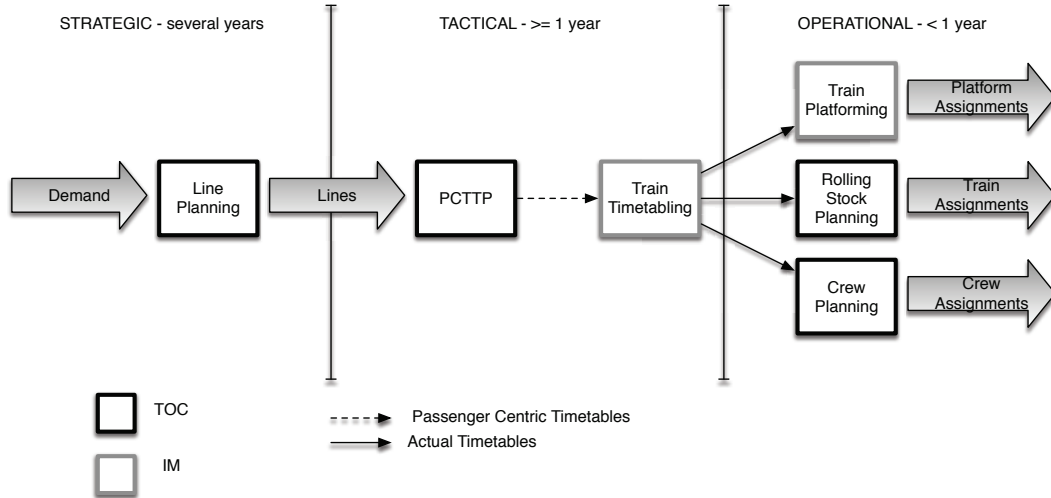


Figure 3.1: *Modified planning process of the passenger railway service*

3.1 Model

In this section, a mixed integer programming formulation for the Passenger Centric Train Timetabling Problem (PCTTP) is presented. It is a bi-objective optimization problem. The operator's objective function is treated as the main objective and the passenger satisfaction is included as an ε -constraint. In other words, the value of passenger satisfaction is limited by the value of ε . The model is solved for various values of ε , in order to exploit the Pareto frontier. For an introduction into ε -constraint optimization, refer to Ngatchou et al. (2005) as an example. For a detailed description, of the selected values for ε , refer to Section 3.1.4.

3.1.1 Data and variables

The input of the PCTTP is the demand that takes form of the number of passengers n_{it} that want to travel between OD pair $i \in I$ and that want to arrive to their destination at their desired arrival time $t \in T_i$. The actual value of their desired arrival time is stored in the parameter a_{it} and the set T_i is only used for indexing purposes. In other words, each OD pair i is having several passenger groups with different desired arrival times (indexed by $t \in T_i = \{t : n_{it} > 0\}$). Therefore, the combination of indices (i, t) forms a unique group of passengers. Note, that the time is discretized into minutes.

In PCTTP, a train is defined by its line $\ell \in L$, *i.e.* the sequence of stations that it serves. Each line ℓ has a train frequency that is expressed as the number of available trains $v \in V^\ell$, *e.g.* if a line has a frequency of 18 trains a day $v \in \{1, \dots, 18\} = V^\ell$. Both lines and frequencies are provided by the result of LPP. Each line ℓ can be further

decomposed into an ordered set of segments S^ℓ . A segment is a part of the line between two stations, where the train does not stop. Therefore, the purpose of the segments is to verify the train capacity constraints. The segments are unique part of an infrastructure irrespective of the lines.

A timetable is defined as a set of arrival and departure times of each train $v \in V^\ell$ of each line $\ell \in L$. The combination of indices (ℓ, v) forms a unique train. The model assumes the dwell times to be fixed at the time of solving. However, they can be adjusted further on upon solving of the traditional TTP. Since the travel times of $r_i^{p\ell}$ consisting of dwell times and running times in between stations are deterministic, it is sufficient to decide only on the departure time $d_{\ell v}$ of each train (ℓ, v) from its origin station. The model can design two types of a timetable: non-cyclic (by default) and cyclic (imposing cyclicity constraints). The size of the cycle is given by parameter c . The model does not take care of the conflicts among trains, in order to exploit the maximum impact of the passenger centric timetabling approach. In reality, the impact of such timetables might be smaller, due to the timetable shifts needed to secure the safety in the network. The safety of the network remains the task of the traditional train timetabling problems and can be removed upon solving of the model presented by Caprara et al. (2002) for the non-cyclic timetable and upon solving of the model presented by Peeters (2003) for the cyclic timetable.

Based on the set of trains, the set of paths P_i for each OD pair i is given. Each path p between an origin and a destination consists in several attributes: a sequence of lines L^p in order that they are being traversed, travel time $b_i^{p\ell}$ from the origin of the line to the origin of the OD pair (where $\ell = 1$), the travel time $r_i^{p\ell}$ from an origin of the OD pair to a transferring point between two lines (where $\ell = 1$), the travel time $b_i^{p\ell}$ from the origin of the line to the transferring point in the path (where $\ell > 1$ and $\ell < |L^p|$), the travel time $r_i^{p\ell}$ from one transferring point to another (where $\ell > 1$ and $\ell < |L^p|$) and the travel time $r_i^{p\ell}$ from the last transferring point to a destination of the OD pair (where $\ell = |L^p|$). Note that different lines using the same track might have different travel times (due to the different stopping patterns outside of the stations considered by the model). For more explanations of what a path is, refer to the Appendix A.3. The set of all paths is pre-processed and can be created with an algorithm described in Appendix A.

When making a transfer from one train to another, a minimum transfer time m is always secured. Any additional time spent in the transferring stations is counted as a waiting time ($w_{it}^{p\ell}$, where $\ell = 2$ is the waiting time for a transfer between the first and the second train and $\ell = 3$ is the waiting time for a transfer between the second and the third train). Given the actual departure times, the paths where a transfer is not possible are rendered infeasible.

Part of the PCTTP is the routing of the passengers through the railway network. Using

a decision variable x_{it}^p , we secure that each passenger group can use at most one path. All passengers, in the same passenger group, always follow exactly the same path and cannot be split. If there is no path assigned to a given passenger group (due to the limited capacity of trains given by parameter W), it is assumed that the passenger group would follow its shortest path after the end of the planning horizon H . In such a case, the revenue this passenger group would generate, is not accounted for in the objective function and different passenger satisfaction function will be applied (detailed explanation further on in Section 3.1.3).

Within the path itself, passenger group is taking exactly one train per each line in the path (decision variable y_{itlv}^p). These decision variables, among others, allow us to backtrace the exact itinerary of each passenger group. Since we know the exact itinerary of each passenger group, we can measure the train occupation o_{lv}^s of each train v on each line ℓ on each of its segment s . Derived from the occupation, number of train units v_{lv} is assigned to each train. This value can be equal to zero, which means that the train is not running and the frequency of the line can be reduced. The length of a train cannot exceed the maximum allowed length G . The variable length of the trains is used, in order to exploit the maximum impact of the new passenger centric approach. However, the feasibility of such a solution should be verified upon solving of the Rolling Stock Planning Problem. The model also keeps track of the number of train drivers α_{lv} needed to realize the timetable. The model assembles the revenues generated by the passengers and the costs inflicted by the operation. The two together allow for calculation of the profit.

3.1.2 Objective Functions

The aim of this section is to define the objective function for the PCTTP. Since the operator and the passengers have different goals, two objectives are defined: profit maximization for the operator and satisfaction maximization for the passengers. In both cases, it is assumed that a forecasted demand consisting of the location of the origin, the location of the destination, and the desired arrival time at the destination is known for each trip.

Operator

Given the free market settings, the goal of the operator is to maximize the profit. The profit itself is a well defined function: revenue minus the operating cost. In this formulation, a basic fare structure is assumed: the price of a ticket f^s on a segment s is irrespective of a line. The decision on train occupation is denoted as o_{lv}^s for each line ℓ , train v and segment s . By multiplying this value with the respective fares, we can

estimate the revenue (first term of the Equation 3.1).

$$\max \sum_{\ell \in L} \sum_{v \in V^\ell} \sum_{s \in S^\ell} o_{\ell v}^s \cdot f^s - \sum_{\ell \in L} \sum_{v \in V^\ell} \left(\alpha_{\ell v} \cdot g \cdot k_\ell + v_{\ell v} \cdot u \cdot k^\ell \right) \quad (3.1)$$

The operating cost (second term of the Equation 3.1) can be split into two parts: the cost of a driver and the cost of the rolling stock operations. The train driver salary g is given in monetary units per kilometer (standardized to the case study, different formulations for different countries might apply), k_ℓ is the length of line ℓ in kilometers. $\alpha_{\ell v}$ is a binary decision that is equal to one, if the train is being operated or to zero, where the train is being dropped from the timetable.

As for the rolling stock itself, a homogenous fleet of train units is assumed. Each train can consist of several units. The operating cost for a single train unit u is in monetary units per kilometer. The decision on number of units used per train v on a line ℓ is given by the integer variable $v_{\ell v}$. The overall profit maximization objective function is given by the Equation 3.1. Since each TOC has a different fare system, the profit function is subject to the respective fare scheme and can be adjusted with further modeling.

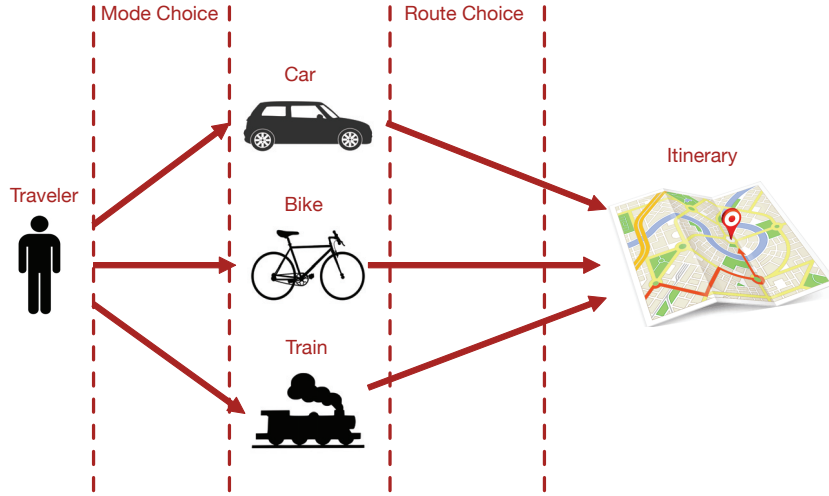
Passenger

In order to model the passenger behavior, it is assumed that a mode choice model has been already used to predict the railway mode users and that these users now face a route choice decision within their selected mode of transport (as shown in Figure 3.2). The route choice decision is further combined with the departure time choice.

In the route choice model, the passengers are presented with a set of paths/itineraries to get from their origin to their destination subject to the current timetable. When faced with a set of discrete path alternatives, it is assumed that a passenger chooses the one that yields her maximum level of utility (Ben-Akiva and Lerman (1985)). For a traveler in group (i, t) , utility \mathcal{U} for a path $p \in P_i$ is defined as:

$$\mathcal{U}_{it}^p = \mathcal{V}_{it}^p + \epsilon_{it}^p \quad (3.2)$$

The deterministic component \mathcal{V} of the utility function is a function of observable attributes, *i.e.* relevant variables that describe a choice alternative and which levels cause the expected level of utility. Note that no source of individual heterogeneity is considered outside of the error term ϵ . Moreover, as the discrete choice model itself is not being

Figure 3.2: *Decision process of a traveler*

estimated, the error term can be excluded from the utility function. Only attributes of alternatives enter the utility function. For a group (i, t) , all passengers face the same levels of these attributes. It is further assumed that \mathcal{V}_{it}^p is defined as a linear combination of the following travel attributes:

- **in-vehicle-time** $\sum_{\ell \in L^p} r_i^{p\ell}$ – is the time spent on board of each line ℓ in path p .
- **waiting time** w_{it}^p – is the total time passengers spend waiting in transferring stations.
- **number of transfers** $|L^p| - 1$
- **schedule passenger delay** – indicates the time dependency of passenger demand and drives the departure time choice. Given the desired arrival time a_{it} to the destination of passenger group it , it can either be on time (equal to zero), early or late (\bar{a}_{it} being the actual arrival time).

$$- \text{early} - \delta_{(i,t)}^p = \max(a_{it} - \bar{a}_{it}^p, 0)$$

$$- \text{late} - \gamma_{it}^p = \max(0, \bar{a}_{it}^p - a_{it})$$

Note that the schedule passenger delay is a term from transport economics (Arnott et al. (1990)). It is not a delay of a train during the operation of a timetable. The schedule passenger delay represents the difference between the desired arrival time of a passenger and her actual arrival time realized under the given timetable. As each passenger is having a different desired arrival time, one cannot secure a schedule passenger delay of value zero for all passengers as it would require extensive resources such as unlimited number of trains, unlimited infrastructure, unlimited staff, *etc.* The price of a ticket

is omitted from the utility function, as in the used case study the prices among the paths for same OD pairs do not differ and thus, no difference among alternatives in the utility function can be achieved. Note that the utility theory deals only with marginal differences among alternatives.

Since it is assumed that the passengers are homogenous, each attribute is having only one β estimate. The systematic part of the utility is unit-less and given as:

$$\mathcal{V}_{it}^p = -\beta'_V \cdot \sum_{\ell \in L^p} r_i^{p\ell} + \beta'_W \cdot w_{it}^p + \beta'_T \cdot (|L^p| - 1) + \beta'_E \cdot \delta_{it}^p + \beta'_L \cdot \gamma_{it}^p \quad [-] \quad (3.3)$$

The parameters β weigh the different attributes. They model sensitivity of the passengers to the change in the related attributes. Note that they are considered to be the same across individuals (homogeneity assumptions). The values of β s have to be estimated from data and have the following signs: $\beta'_V > 0$, $\beta'_W < 0$, $\beta'_T < 0$, $\beta'_E < 0$, and $\beta'_L < 0$. In this research, values of β s from the literature are used. To do so, the utility function is divided by $-\beta'_V$ in order to convert the utility into travel time units. Indeed, parameters themselves are not directly transferable, since they include the scale parameter of the error term. The scale parameter cancels out when ratios of parameters are considered, so the values of these ratios are comparable from one model to the next. The values of the parameters are as follows:

- $\beta_{\mathbf{W}} = \beta'_W / \beta'_V$ is the substitution rate between waiting time and in-vehicle-time per minute. Its value is equal to -2.5 (Wardman (2004)).
- $\beta_{\mathbf{T}} = \beta'_T / \beta'_V$ is the penalty for having to change a train, expressed as an additional in-vehicle-time per transfer. Its value is equal to -10 minutes (as used by Dutch Railways (de Keizer et al. (2012))).
- $\beta_{\mathbf{E}} = \beta'_E / \beta'_V$ is the willingness to arrive to the destination earlier then the desired arrival time, in order to reduce the in-vehicle-time. As shown in Small (1982), the travelers are willing to shift their arrival time by 1 to 2 minutes earlier, if it would save them 1 minute of the in-vehicle-time. Here the highest value is considered and β_E is set to -0.5.
- $\beta_{\mathbf{L}} = \beta'_L / \beta'_V$ is the willingness to arrive to the destination later then the desired arrival time, in order to reduce the in-vehicle-time. As shown in Small (1982), the travelers are willing to shift their arrival time by 1/3 to 1 minute later, if it would save them 1 minute of in-vehicle-time. Here the highest value is considered and β_L is set to -1.

By replacing the original β s in Equation 3.3 with the estimated ones (*i.e.* division by

$-\beta'_V$), a function that is expressed in minutes is obtained. This concept is also known as the generalized time \mathcal{T} , that is supposed to be minimized by the travelers:

$$\mathcal{T}_{it}^p = \sum_{\ell \in L^p} r_i^{p\ell} - \beta_W \cdot w_{it}^p - \beta_T \cdot (|L^p| - 1) - \beta_E \cdot \delta_{it}^p - \beta_L \cdot \gamma_{it}^p \quad [min] \quad (3.4)$$

The generalized time can be further monetarized by multiplication with the Value-Of-Time (VOT). The VOT is the willingness-to-pay for travel time savings. The average VOT for commuters using public transport in Switzerland is 27.81 Swiss Franc (CHF) per hour (Axhausen et al. (2008)). It basically means that the Swiss travelers are willing to pay in average 27.81 CHF to save one hour of travel time. Converted into the minutes, we get 0.4635 CHF/min. Using the VOT, we can obtain the generalized cost:

$$\mathcal{C}_{it}^p = VOT \cdot \mathcal{T}_{it}^p \quad [monetary] \quad (3.5)$$

Since in the utility theory, the travelers are maximizing their expected utility and all attributes in the generalized cost are making the alternatives less attractive, we need to multiply the Equation 3.5 by minus one. Indeed the higher the generalized cost is, the lower the value of the utility is. This concept is also known as the passenger satisfaction \mathcal{S} :

$$\mathcal{S}_{it}^p = (-1) \cdot \mathcal{C}_{it}^p \quad [monetary] \quad (3.6)$$

The passenger satisfaction is now the observable part of the utility function ($\mathcal{V} = \mathcal{S}$). Given that the unobservable part of the utility ϵ serves for the correction of the model's prediction error, it can be omitted from the utility function (therefore $\mathcal{U} = \mathcal{V}$). Indeed, the utility is not used for prediction or estimation of the β s, but rather for a quantification of a path's value associated to a specific passenger. By calculating it for all passengers, we get the following objective function:

$$\max \sum_{i \in I} \sum_{t \in T_i} n_{it} \cdot \mathcal{U}_{it} \quad (3.7)$$

Since a passenger group uses only one path (one with the highest utility – constraints

(**3.9**)), the path index is omitted from the objective function. In order to solve the multi-objective problem (profit maximization and passenger satisfaction maximization), the passengers' objective is transformed into an ε -constraint (**3.8**)).

3.1.3 Constraints

Feasibility Constraints The PCTTP model can be decomposed into 2 parts: Feasibility Constraints and Satisfaction Estimation. The first take care of the feasibility of the solution, whereas satisfaction estimation takes care of the passenger satisfaction related attributes. At first, the Feasibility Constraints are introduced:

$$(-1) \cdot VOT \cdot \sum_{i \in I} \sum_{t \in T_i} n_{it} \cdot \mathcal{T}_{it} \geq \varepsilon, \quad (3.8)$$

$$\mathcal{T}_{it} \geq \mathcal{T}_{it}^p - M \cdot (1 - x_{it}^p), \quad \forall i \in I, \forall t \in T_i, \forall p \in P_i, \quad (3.9)$$

$$\mathcal{T}_{it} \geq \bar{\mathcal{T}}_{it} \cdot \left(1 - \sum_{p \in P_i} x_{it}^p \right), \quad \forall i \in I, \forall t \in T_i, \quad (3.10)$$

$$\sum_{p \in P_i} x_{it}^p \leq 1, \quad \forall i \in I, \forall t \in T_i, \quad (3.11)$$

$$\sum_{v \in V^\ell} y_{itlv}^p = x_{it}^p, \quad \forall i \in I, \forall t \in T_i,$$

$$\forall p \in P_i, \forall \ell \in L^p, \quad (3.12)$$

$$o_{\ell v}^s = \sum_{i \in I} \sum_{t \in T_i} \sum_{p \in P_i} y_{itlv}^p \cdot x_{\ell v}^{ps} \cdot n_{it}, \quad \forall \ell \in L, \forall v \in V^\ell,$$

$$\forall s \in S^\ell, \quad (3.13)$$

$$o_{\ell v}^s \leq v_{\ell v} \cdot W, \quad \forall \ell \in L, \forall v \in V^\ell,$$

$$\forall s \in S^\ell, \quad (3.14)$$

$$\alpha_{\ell v} \cdot G \geq v_{\ell v}, \quad \forall \ell \in L, \forall v \in V^\ell, \quad (3.15)$$

$$d_{\ell v} \leq d_{\ell v+1} - 1, \quad \forall \ell \in L, \forall v \in V^\ell :$$

$$v < |V^\ell|, \quad (3.16)$$

$$d_{\ell v} - d_{\ell v-1} = c \cdot z_{\ell v}, \quad \forall \ell \in L, \forall v \in V^\ell : v > 1, \quad (3.17)$$

$$\mathcal{T}_{it} \geq 0, \quad \forall i \in I, \forall t \in T_i, \quad (3.18)$$

$$x_{it}^p \in (0, 1), \quad \forall i \in I, \forall t \in T_i, \forall p \in P_i, \quad (3.19)$$

$$y_{itlv}^p \in (0, 1), \quad \forall i \in I, \forall t \in T_i, \forall \ell \in L,$$

$$\forall v \in V^\ell, \forall p \in P_i, \quad (3.20)$$

$$o_{\ell v}^s \in \mathbb{N}, \quad \forall \ell \in L, \forall v \in V^\ell,$$

$$\forall s \in S^\ell, \quad (3.21)$$

$$v_{\ell v} \in \mathbb{N}, \quad \forall \ell \in L, \forall v \in V^\ell \quad (3.22)$$

$$\alpha_{\ell v} \in (0, 1), \quad \forall \ell \in L, \forall v \in V^\ell, \quad (3.23)$$

$$d_{\ell v} \in \mathbb{N}, \quad \forall \ell \in L, \forall v \in V^\ell \quad (3.24)$$

$$z_{\ell v} \in \mathbb{N} \setminus \{0\}, \quad \forall \ell \in L, \forall v \in V^\ell \quad (3.25)$$

Constraints **(3.8)** assure that a certain level of total passenger satisfaction will be maintained (for details refer to Section 3.1.4). The model is using generalized time rather than utility/passenger satisfaction. This approach allows for easier modeling of further constraints. Constraints **(3.9)** select the path with the best value of the generalized time for passenger group (i, t) from its set of potential paths. These are the so called big- M constraints, where the value of M can be equal to $\max(\mathcal{T}_{it}^p)$. Due to the capacity constraints **(3.14)**, some passengers might not be served within the planning horizon H . If such a case happens, first possible shortest path outside of the planning horizon is being offered (constraints **(3.10)**). Since a passenger will have to wait for a period of one cycle, the trains in the shortest path are assumed to be perfectly connected as the prospective waiting time would be in any case marginal to the waiting of one cycle and there might be earlier path offered as lines in the railway networks often overlap (constraints **(3.37)**). Constraints **(3.11)** secure that each passenger group is using at most one path to get from its origin to its destination. Similarly constraints **(3.12)** make sure that each group takes exactly one train on each of the lines in its path, if this path is being used. Constraints **(3.13)** translate the paths that the passengers have selected into the respective train occupation. The linking itself is through a binary parameter $x_{\ell v}^p$ that equals to one, if a train (ℓ, v) is being used in path p on segment s , zero otherwise. Naturally, when a passenger group selects the penalty path, the values of $y = 0$ and $x = 0$ secure that these passengers do not occupy any seat within the planning horizon H of the problem. Constraints **(3.14)** verify that the train capacity is not exceeded on any segment of any train. Constraints **(3.15)** assign train drivers, *i.e.* if a train v on the line ℓ is being operated or not. Constraints **(3.16)** aim at reducing the solution space in terms of the departure time combinations, *i.e.* the departures of the trains are in ascending order with a difference of at least one minute. Constraints **(3.17)** model the cyclicity using integer division through dummy variable $z_{\ell v}$, that expresses the number of cycles in between the departures of two consecutive trains on the same line ℓ . When solving the non-cyclic version of the problem, these constraints have to be removed. Constraints **(3.18)**-**(3.25)** are the domain constraints.

Satisfaction Estimation To make the PCTTP formulation complete, it needs to contain the Satisfaction Estimation. The constraints, related to the passenger satisfaction, are introduced in blocks of attributes that constitute it.

$$\begin{aligned} \delta_{it}^p \geq & \left(a_{it} - \left(d_{|L^p|v} + b_i^{p|L^p|} + r_i^{p|L^p|} \right) \right) \\ & - M \cdot \left(1 - y_{it|L^p|v}^p \right), \quad \forall i \in I, \forall t \in T_i, \forall p \in P_i, \end{aligned} \quad (3.26)$$

$$\begin{aligned} \gamma_{it}^p \geq & \left(\left(d_{|L^p|v} + b_i^{p|L^p|} + r_i^{p|L^p|} \right) - a_{it} \right) \\ & - M \cdot \left(1 - y_{it|L^p|v}^p \right), \quad \forall i \in I, \forall t \in T_i, \forall p \in P_i, \end{aligned} \quad (3.27)$$

$$\delta_{it}^p \geq 0, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_i \quad (3.28)$$

$$\gamma_{it}^p \geq 0, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_i, \quad (3.29)$$

$$\bar{a}_{it}^p \geq 0, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_i, \quad (3.30)$$

The first block of constraints takes care of the **schedule passenger delay**. Constraints (3.26) model the earliness of the passengers and constraints (3.27) model the lateness. If a passenger arrives early to her destination then the earliness has a positive value and the lateness has a negative value (and thus forced to be zero by the positivity domain constraints – (3.29)), and vice versa in case the passenger arrives late (positivity domain constraints (3.28)). The exact value of the schedule passenger delay is derived from passenger group's desired arrival time a_{it} and its actual arrival time into its destination. The actual arrival time is obtained from the departure time $d_{|L^p|v}$ from the origin station of all potential trains in the last line $|L^p|$ in the group's path and the time $b_i^{p|L^p|}$, these trains need to reach the group's boarding station and the time $r_i^{p|L^p|}$, they need to get from its boarding station to its alighting station.

$$w_{it}^p = \sum_{\ell \in L^p: \ell > 1} w_{it}^{p\ell}, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_i, \quad (3.31)$$

$$\begin{aligned} w_{it}^{p\ell_1} \geq & \left(\left(d_{\ell_1 v_1} + b_i^{p\ell_1} \right) - \left(d_{\ell_2 v_2} + b_i^{p\ell_2} + r_i^{p\ell_2} + m \right) \right) \\ & - M \cdot \left(1 - y_{it\ell_2 v_2}^p \right) - M \cdot \left(1 - y_{it\ell_1 v_1}^p \right), \quad \forall \ell_1 \in L^p: \ell_1 > 1, \\ & \ell_2 = \ell_1 - 1, \forall v_1 \in V^{\ell_1}, \\ & \forall v_2 \in V^{\ell_2}, \end{aligned} \quad (3.32)$$

$$\begin{aligned} w_{it}^{p\ell_1} \leq & \left(\left(d_{\ell_1 v_1} + b_i^{p\ell_1} \right) - \left(d_{\ell_2 v_2} + b_i^{p\ell_2} + r_i^{p\ell_2} + m \right) \right) \\ & + M \cdot \left(1 - y_{it\ell_2 v_2}^p \right) + M \cdot \left(1 - y_{it\ell_1 v_1}^p \right), \quad \forall \ell_1 \in L^p: \ell_1 > 1, \\ & \ell_2 = \ell_1 - 1, \forall v \in V^{\ell_1}, \\ & \forall v_2 \in V^{\ell_2}, \end{aligned} \quad (3.33)$$

$$w_{it}^p \geq 0, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_i, \quad (3.34)$$

$$w_{it}^{p\ell} \geq 0, \quad \forall i \in I, \forall t \in T_i, \\ \forall p \in P_i, \forall \ell \in L^p : \ell > 1, \quad (3.35)$$

The second block of constraints is modeling the **waiting time**. There are 2 types of waiting time: the total waiting time w_{it}^p each passenger group (i, t) experiences on each of its paths p (constraints **(3.34)**) and its decomposition into waiting times $w_{it}^{p\ell}$ at each of the transferring stations (constraints **(3.35)**). Constraints **(3.31)** add up the waiting times in all the transfer stations in path p . Subsequently, constraints **(3.32)** and **(3.33)** are complementary and they define the value of the waiting time in the transferring stations. These constraints subtract the arrival time (departure time from its origin station plus the time to get to the boarding station of the passenger group plus the time to get to the transfer station) of the origin train at the transferring station plus the necessary minimum transfer time m , from the departure time of the destination train at the transferring station (departure time from its origin station plus the time to get to the transfer station). These two constraints find the two best connected trains in the two train lines in the passengers' path. Therefore, the connections between the trains will be passenger imposed.

$$\mathcal{T}_{it}^p = \sum_{\ell \in L^p} r_i^{p\ell} - \beta_W \cdot w_{it}^p \\ -\beta_T \cdot (|L^p| - 1) - \beta_E \cdot \delta_{it}^t - \beta_L \cdot \gamma_{it}^p, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_i, \quad (3.36)$$

$$\bar{\mathcal{T}}_{it} = r_i^0 - \beta_W \cdot c - \beta_T \cdot |L^0 - 1|_i \\ -\beta_L \cdot (H + c + r_i^0 + m \cdot |L^0 - 1|_i - a_{it}), \quad \forall i \in I, \forall t \in T_i. \quad (3.37)$$

At last, constraints **(3.36)** combine all the attributes together into a generalized time of a passenger group (i, t) for a path p . Constraints **(3.37)** do not involve any decision variable and are included in the model only to show, how the generalized time of a passenger group that can not be served within the planned horizon is obtained. It consists in the shortest path between OD pair i realized in one cycle c after the end of the planning horizon H .

Note that in this optimization model, the amount of available trains is given by the LPP and it is used only as an upper bound. The model is allowed to reduce the number of trains as needed (mostly due to the low occupation). Since the goal of the PCTTP is to look for the best timetables from both point-of-views, it leaves the safety issues to the IM operated TTP. The main complexity of the model comes from the integration

of the routing of the passengers through the network, while considering all the possible paths (source of the big- M constraints). The PCTTP formulation is an original work with only cyclicity constraints taken from the existing literature.

Remark Note that the above model is not flawless. The number of big- M constraints could be reduced: including the penalty path as a part of the set P_i , would remove constraints (3.10). The proposed change has not been carried out as the results of the case study would no longer match the complexity of the model. Moreover, some notation has been changed as compared to the initial formulation in the published article, in order to simplify the orientation within the model.

3.1.4 Pareto Frontier

In order to construct the approximated Pareto Frontier of the two objectives, the model needs to be solved for several levels of ε under the objective of maximizing the TOC's profit (Equation 3.1). At first, two extreme points are being solved: $\varepsilon = 0$, where constraints (3.8) are removed from the model (thus pure profit maximization, *i.e.* objective (3.1) and constraints (3.9)-(3.37)), and $\varepsilon = 100$, where the passenger satisfaction level is set to the best possible value minus one (as the satisfaction is a real number and it would have been difficult to set it to the exact value, when using warm starts of CPLEX; objective (3.1) and constraints (3.8)-(3.37)) upon solving the model with objective of pure passenger satisfaction maximization (objective (3.7) and constraints (3.9)-(3.37)) noted as $\varepsilon = *$. All other ε s (20, 40, 60, 80) are equally spaced intervals with passenger satisfaction expressed as a percentage of the difference between the best and the worst passenger satisfaction possible (objective (3.1) and constraints (3.8)-(3.37)), *i.e.* $\varepsilon = 20$ meaning that passenger satisfaction is being set to the worst possible value plus 20% of the gap between the worst and the best satisfaction level.

3.2 Case study

In order to test the PCTTP model, the network of S-trains in canton Vaud, Switzerland during the morning peak hours has been selected as a case study. The aim is at comparing the currently operated cyclic timetable of Swiss Federal Railways (SBB) with the PCTTP designed cyclic and non-cyclic timetables. The results represent the highest possible impact of the passenger centric timetable as compared to the SBB timetable that is actually conflict-free. The exact procedures, assumptions and further information about the data can be found in Appendix A.

The reduced network of S-trains is represented in Figure 3.3 (as of timetable 2014, note

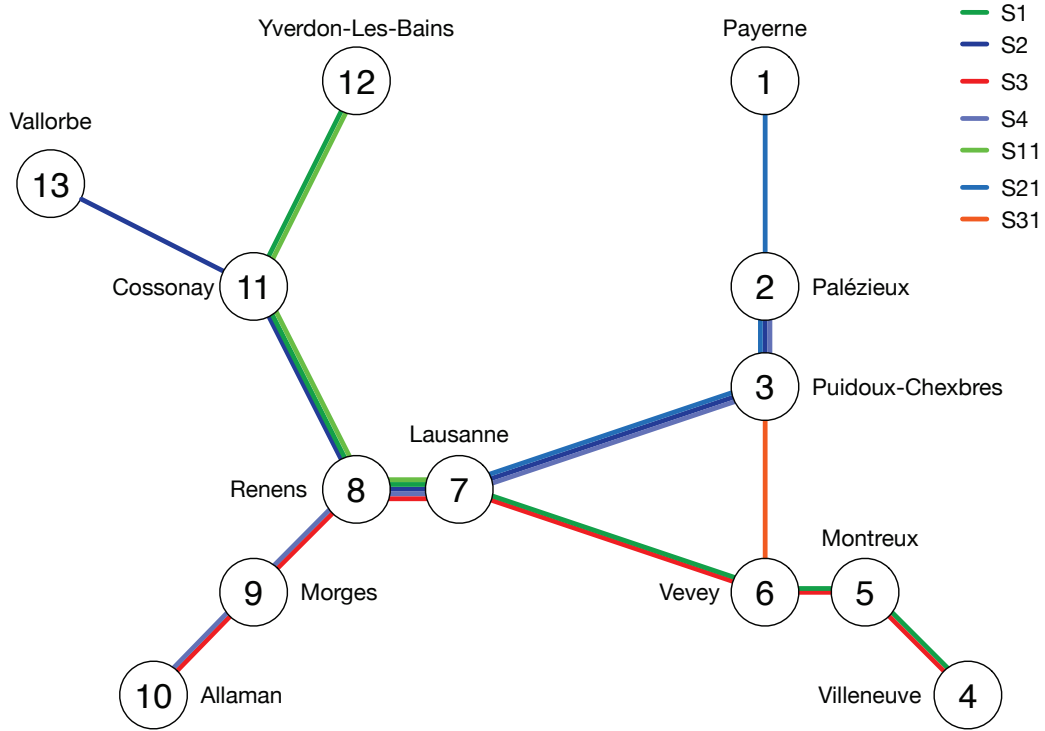


Figure 3.3: *S-train Network of canton Vaud, Switzerland*

that the line design has been changed in 2015). Only the main stations in the network are considered (in total 13 stations). The network consists of 14 bidirectional lines ($S1$, $S2$, $S3$, $S4$, $S11$, $S21$ and $S31$). The SBB operated timetable of the lines can be seen in Table 3.1. The Table presents the 7 lines that run in both directions. Each combination of a line and its direction has its unique ID number. Column “from” marks the origin station of the line and column “to” marks its destination. The columns “departures” report the currently operated timetable (*i.e.* departures from the origin of the line) in the morning peak hours (5 a.m. to 9 a.m.), which is the time horizon used in this study. Trains that did not follow the cycle (marked with a star *) were set to the closest cyclic value, in order to enforce the cyclicity constraints (the timetables in Switzerland are cyclic with a cycle of one hour). Overall, there are 49 trains in the network between 5 a.m. and 9 a.m.

Overall, there are three instances of the model. The instance labeled “SBB 2014” is designed to mimic an existing timetable. The decision variables d_{ℓ_v} are set to the values presented in Table 3.1. The instance labeled “cyclic” considers the departure time d_{ℓ_v} as decision variables, and includes the cyclicity constraints (3.16). Finally, the instance labeled “non cyclic” is the same as the cyclic one, without the constraints (3.16). Furthermore, in this specific case study, we can reformulate the cyclicity constraints (3.16) in the following manner:

Line	ID	From	To	Departures			
S1	1	Yverdon-les-Bains	Villeneuve	–	6:19	7:19	8:19
	2	Villeneuve	Yverdon-les-Bains	5:24	6:24	7:24	8:24
S2	3	Vallorbe	Palézieux	5:43	6:43	7:43	8:43
	4	Palézieux	Vallorbe	–	6:08	7:08	8:08
S3	5	Allaman	Villeneuve	–	6:08	7:08	8:08
	6	Villeneuve	Allaman	–	6:53	7:53	8:53
S4	7	Allaman	Palézieux	5:41	6:41	7:41	8:41
	8	Palézieux	Allaman	–	6:35	7:35	8:35
S11	9	Yverdon-les-Bains	Lausanne	5:26*	6:34	7:34	8:34
	10	Lausanne	Yverdon-les-Bains	5:55	6:55	7:55	8:55
S21	11	Payerne	Lausanne	5:39	6:39	7:38*	8:39
	12	Lausanne	Payerne	5:24	6:24	7:24	8:24
S31	13	Vevey	Puidoux-Chexbres	–	6:09	7:09	8:09
	14	Puidoux-Chexbres	Vevey	–	6:31*	7:36	8:36

 Table 3.1: *Timetable of S-train Network of Canton Vaud, Switzerland in 2014*

$$d_{\ell v} - d_{\ell v-1} = 60 \cdot z_{\ell v}^1 + 120 \cdot z_{\ell v}^2, \quad \forall \ell \in L, \forall v \in V^\ell : v > 1, \quad (3.38)$$

$$z_{\ell v}^1 + z_{\ell v}^2 = 1, \quad \forall \ell \in L, \forall v \in V^\ell : v > 1. \quad (3.39)$$

As we can notice in Table 3.1, we either have 4 trains over 4 hours horizon (60 minutes difference between all consecutive trains) per line or 3 trains over 4 hours horizon (one train will have 120 minutes time distance from the next train, whereas the other trains will keep the 60 minutes difference) per line. This attribute is modeled by adding an extra index to the cyclicity variable z , stating if the difference between two consecutive trains is 60 or 120 minutes. The decision z is now binary.

All of the tested instances have been run in CPLEX Interactive Optimizer (CPLEX version 12.5.1) on a Unix server with 8 cores of 3.33 GHz and 62 GiB RAM. The CPLEX time limit has been set to 2 hours as most of the gap improvement is covered in this horizon (several models were tested over a period of 6 hours, however the gap improvement in the additional 4 hours was less than 1 percent). In order to speed up CPLEX, the SBB 2014 timetable is solved first and its solution is given as a warm start to the cyclic model. Further along, the solution of the cyclic model is given as a warm start to the non-cyclic model.

ε [%]	0	20	40	60	80	100	*
profit [CHF]	53 067	52 926	50 730	49 564	13 826	4 211	-27 168
satisfaction [CHF]	-588 934	-505 899	-422 864	-339 828	-256 793	-173 759	-173 758
cs [CHF]	-	589	71	71	8	8	-
ub [CHF]	54 046	54 598	54 776	54 394	54 600	51 195	-168 016
gap [%]	1.84	3.16	7.98	9.74	294.91	1 115.74	3.30
gap [CHF]	979	1 672	4 046	4 830	40 774	46 984	5 742
drivers [-]	17	17	22	22	46	48	49
rolling stock [-]	32	32	32	32	46	55	98
covered [%]	99.35	99.34	100.00	100.00	100.00	100.00	100.00

Table 3.2: *Computational results of the SBB 2014 timetable*

ε [%]	0	20	40	60	80	100	*
profit [CHF]	53 145	41 565	15 543	13 833	4 917	-27 200	-27,200
satisfaction [CHF]	-523 367	-452 808	-382 249	-311 691	-241 132	-170 574	-170,573
cs [CHF]	-	6	4	5	6	4	-
ub [CHF]	54 805	55 026	54 513	54 759	54 555	54 470	-129 258
gap [%]	3.12	32.39	250.72	295.86	1009.52	300.26	24.22
gap [CHF]	1 660	13 461	38 970	40 926	49 638	81 670	41 315
drivers [-]	17	25	47	47	48	49	49
rolling stock [-]	32	36	47	47	54	98	98
covered [%]	99.35	97.42	99.91	100.00	100.00	100.00	100.00

Table 3.3: *Computational results of the cyclic timetable*

ε [%]	0	20	40	60	80	100	*
profit [CHF]	53 159	17 791	12 573	11 871	6 584	4 479	-27 257
satisfaction [CHF]	-516 011	-462 005	-376 000	-305 994	-235 989	-165 984	-165 983
cs [CHF]	-	2	3	5	6	7	-
ub [CHF]	54 465	54 955	54 927	54 862	54 824	54 682	-124 693
gap [%]	2.46	208.89	336.86	362.15	732.69	1120.85	24.88
gap [CHF]	1 306	37 164	42 354	42 991	48 240	50 203	41 290
drivers [-]	17	46	48	48	48	48	49
rolling stock [-]	32	48	49	49	52	54	98
covered [%]	99.35	100.00	100.00	100.00	100.00	100.00	100.00

Table 3.4: *Computational results of the non-cyclic timetable*

3.2.1 Results

In this section, the results of the case study are introduced. The detailed numerical results can be found in Tables 3.2, 3.3 and 3.4. The first row of the tables represents the level of the passenger satisfaction in percentage with respect to the gap between the best and the worst level of the satisfaction. The row *cs* provides the consumer surplus, *i.e.* how many Swiss Francs can be gained in passenger satisfaction per one franc of profit loss as compared to the ε at level 0. The row *ub* provides upper bound on satisfaction for the case $\varepsilon = *$ and upper bound on profit for all other cases. The final gap obtained by CPLEX between the lower bound and the upper bound is reported in percentages and in Swiss Franc (CHF). Note that the value and the sign of the satisfaction has no meaning as such and should be used only for comparison across instances. Following rows state number of needed drivers, rolling stock and the percentage of served passengers (*i.e.* passengers that do not take penalty path).

From the tables, the cyclic and the non-cyclic timetables yield lesser profit than the SBB 2014 timetable for ε between 20 and 100. Indeed, in the SBB 2014 case, the departure times are fixed. Therefore CPLEX can converge faster to the solutions with better objective values. For $\varepsilon = 0$, the passenger satisfaction does not matter, *i.e.* the departure times do not matter and CPLEX can find a solution with an equivalent objective value within the set time frame. However, since the SBB 2014 timetable is cyclic, its result can be a feasible solution for the other two cases as well (cyclic timetable is a feasible solution for the non-cyclic timetable) and thus, if CPLEX is given infinite time, it would find at least as good solution for the cyclic and non-cyclic timetable. At the $\varepsilon = 0$, the timetables give similar profit. Indeed, almost all of the passengers get served while using the same number of trains. In case of the $\varepsilon = *$, we can see a difference for the passenger satisfaction between the models: the cyclic model achieves 3 185 CHF of savings and the non-cyclic timetable improves this value further by 4 590 CHF. Moreover, if we consider the maximum profit while securing the minimum passenger satisfaction ($\varepsilon = 100$), the non-cyclic timetable needs one driver and 43 train units less for operation.

Lastly, the trade-off between the profit and the satisfaction as an approximated Pareto frontier is plotted in Figure 3.4 for the SBB 2014 timetable. In this Figure, we can spot an almost vertical line consisting of four points ($\varepsilon = 0, 20, 40, 60$). This means that large increase in passenger satisfaction can be achieved without having a significant change in the TOC profit. However, the TOC might choose even the points with lower profit as the passenger satisfaction difference between points 60 and 100 is 166 069 CHF. Since the difference is quite large, it can justify running of the $\varepsilon = 100$ percent solution for public operators or to give an incentive on how to increase the ticket prices to private operators. Running of the whole fleet ($\varepsilon = *$), on the other hand, would not make sense as the current demand can be operated efficiently with less resources and achieve

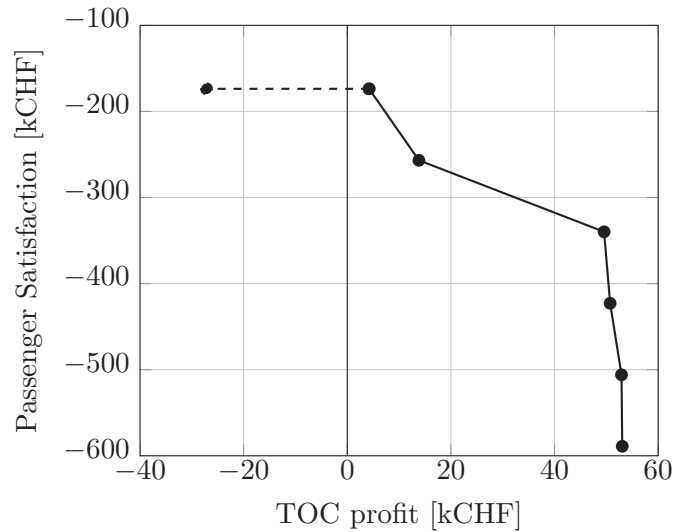


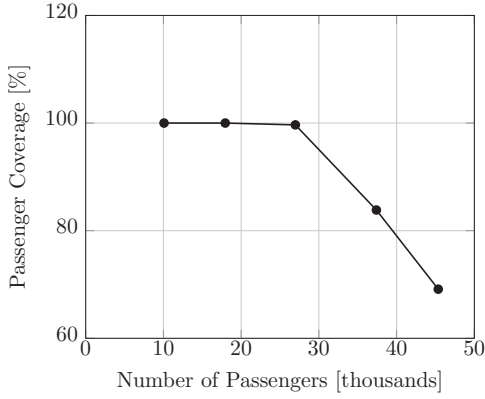
Figure 3.4: *Approximated Pareto frontier of the SBB 2014 timetable*

at least a small profit. It is worth mentioning that the consumer surplus has the highest value at $\varepsilon = 20$. It can be seen in Figure 3.4 that there is almost vertical line between the points $\varepsilon = 0$ and $\varepsilon = 20$, *i.e.* almost no profit loss and large satisfaction gain.

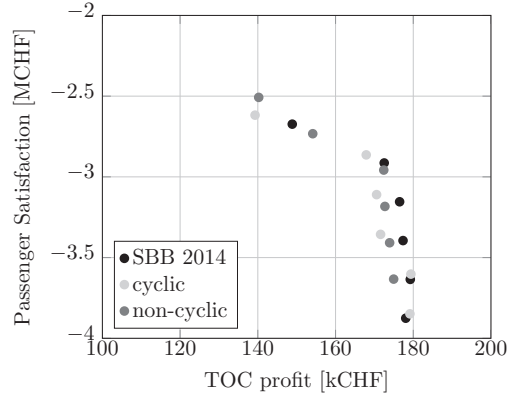
Overall, the insignificant difference among the three instances has two causes: low level of passenger demand and historical evolution of timetables. By the historical evolution, it is meant that the operators have been offering their service for decades and thus, they have learned how to match their supply with demand by trial and error.

3.2.2 Impacts of Passenger Congestion

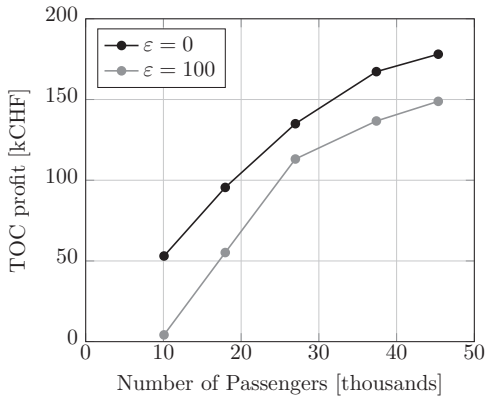
In this section, it is further investigated what would be the effect of a passenger congestion on the results from both points-of-view: operator's and passengers'. In order to do so, the demand is gradually increased (by multiplying the arrival rates by the same factor (Appendix A)) up until the point where the coverage decreases to a level of 70%. The passenger coverage as a function of the demand for the SBB 2014 timetable (the coverage is more or less the same for the other two timetables) can be found in Figure 3.5(a). As it can be seen, the congestion starts at the amount of approx. 27 000 passengers and that the coverage goes down almost linearly. All of the discussed sensitivity analysis results can be found in Figure 3.5.



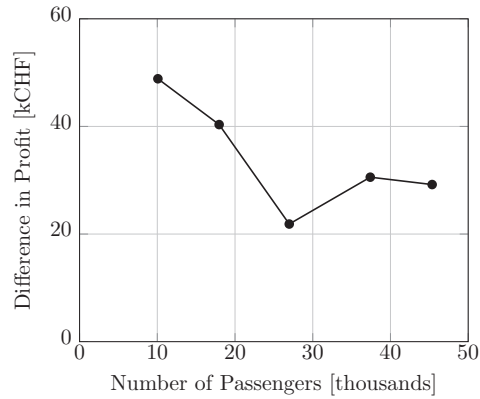
(a) Passenger coverage as a function of the demand for the SBB 2014 timetable



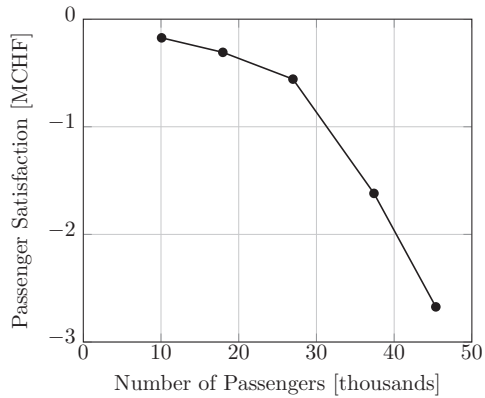
(b) Approximated Pareto frontiers of the most congested case



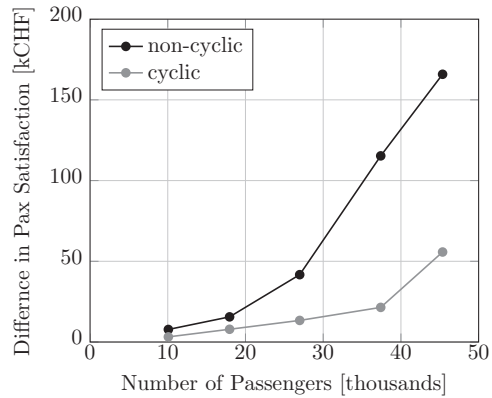
(c) Profit as a function of the demand for the SBB 2014 timetable



(d) Difference in profit as a function of the demand for the SBB 2014 timetable



(e) Passenger satisfaction as a function of the demand for the SBB 2014 timetable at $\varepsilon = *$



(f) The difference in passenger satisfaction of the cyclic and non-cyclic timetable as compared to the SBB 2014 timetable at $\varepsilon = *$

Figure 3.5: Impacts of passenger congestion

Impacts on Operator(s)

At first, let's consider the operator's point-of-view, *i.e.* how increase in demand affects the profit. The profit as a function of demand can be seen in Figure 3.5(c). The plot shows the results of the SBB 2014 timetable only (as from the previous section this timetable gave the smallest gap given its restrictions on the decision variables). Both minimum ($\varepsilon = 100$) and maximum ($\varepsilon = 0$) profit tend to grow (as expected). The difference between the two respective profit functions tends to decrease with the size of the demand (Figures 3.5(c) and 3.5(d)). The function becomes less steep when the network is experiencing the congestion. This seems logical accounted to the fact that when the trains become completely full (*i.e.* equally occupied), the profit should stabilize on the same values for both cases of ε . Note that, if a passenger cannot realize her complete journey due to the capacity limits, she would abandon the whole trip, thus when the congestion starts, some trains are not yet at a full capacity. Moreover, the model changes its behavior under the congestion: in the profit maximization, passengers who travel longer distances and thus pay more are given advantage, whereas in the satisfaction maximization, large groups of passengers are given advantage. This fact allows for increase in the profit difference at the beginning of the congestion (Figure 3.5(d)). A more realistic model for the selection of passengers during congestion would reduce this bias.

Impacts on Passengers

Subsequently, the effects of congestion on the passenger satisfaction are considered. In all plots, only the satisfaction at the $\varepsilon = *$ is shown, as these are the best possible values. The satisfaction of the passengers, in the SBB 2014 timetable, as a function of the demand can be found in Figure 3.5(e). This function, for the other two timetables, yields similar result. In opposition to the profit, the passenger satisfaction decreases rather exponentially and its function can be split into two linear parts: non-congested (gradual slope) and congested (steep slope). This might be useful for practitioners, as it would allow them to predict the passenger satisfaction.

Subsequently, the relative difference of cyclic and non-cyclic timetables as opposed to the SBB 2014 timetable is shown in Figure 3.5(f). In general, the cyclic timetable tends to find slightly better timetables than the SBB 2014 model (in the congested cases the benefit even dramatically increases). The non-cyclic timetable, on the other hand, is more flexible and achieves significantly higher satisfaction. This is due to the fact that the trains do not have to follow the cyclic pattern and thus, are more densely scheduled. For instance, in the most congested case (approx. 45 000 passengers), the average headway between two consecutive trains on the same lines is 22.6 minutes, with minimum value of 1 minute and maximum value of 238 minutes.

It could be objected that the relative difference is rather marginal compared to the total satisfaction level (in the best case 165 000 CHF against 2.5 million CHF). However, it is still considered to be a significant value, especially since the network is quite dense (the demand goes towards *Lausanne* area and most of the trains pass through *Lausanne* and overlap in the network). In a less dense network, the difference between the cyclic and the non-cyclic timetable is expected to be much larger.

Analysis of Trade-off(s)

The final step of the sensitivity analysis, is the exploitation of the approximated Pareto frontiers in the most congested case (Figure 3.5(b)). The three frontiers are horizontally spaced as they yield different levels of satisfaction (previous paragraphs). Shape-wise, the SBB 2014 timetable, as compared to the base demand scenario, has a frontier with one base point ($\varepsilon = 100$) and direct transition to an almost vertical line of solutions, which now contains one more point ($\varepsilon = 80$). The approximated Pareto frontier for the cyclic timetable exhibits a transition phase (between the solution with the best satisfaction and the (vertical) set of solutions with the best profit) consisting of $\varepsilon = 80 - 60 - 40$, before moving to the same solutions as the SBB 2014 timetable. This means that ε other than 100, 20 or 0 is not a good trade-off solution as it would lead to a worse profit than the SBB 2014 solutions. Lastly, frontier of the non-cyclic timetable has a longer transition period than the other two frontiers and it stops at a higher level of passenger satisfaction ($\varepsilon = 0$ of the non-cyclic timetable is at the same level as $\varepsilon = 20$ of the other two timetables). However, with a slightly worse profit.

The best trade-off between the two objectives lies within the region of cyclic timetable at $\varepsilon = 20$, SBB 2014 timetable at $\varepsilon = 20$ and non-cyclic timetable at $\varepsilon = 40$. Solutions in this area lead to approx. 1 million CHF of passenger satisfaction increase with a profit loss of approx. 15 000 CHF (thus, having the largest consumer surplus).

3.3 Summary

In this chapter, the passenger centric train timetabling problem is introduced. In this problem, both the TOC(s) and the passengers are taken into account. The passengers' interests are modeled as a passenger satisfaction using utility theory. The model considers all possible paths between passenger's origin and destination. The connections between two trains are then passenger induced. The model does not take into account conflicts among the trains. The resulted timetables are trade-offs between the two stakeholders. The model is fit for a design of a new timetable or for a validation of an existing one. The operator can select, if the designed timetables are to be cyclic or non-cyclic. The model has been tested through an experiment on a realistic railway network. The

model is able to handle 1 000 passenger groups (combination of OD pairs and desired arrival times to the destinations).

The results show that it is possible to achieve large improvements in passenger satisfaction, while keeping a low profit loss for the operator. It has been shown that in a dense railway network with low volume of passengers, running cyclic or non-cyclic timetable has marginal impacts on the passengers. However, when the volume of passengers is high, the non-cyclic timetable outperforms the cyclic one. In less dense networks, the impacts are expected to be larger.

4

Hybrid Cyclicality

This chapter is based on the technical report:

Robenek, T., Maknoon, Y., Azadeh, S. S., and Bierlaire, M. (2016). Hybrid cyclicality: Combining the benefits of cyclic and non-cyclic timetables. Technical report TRANSP-OR 160510.

The work has been performed by the candidate under the supervision of Yousef Maknoon PhD., Shadi Sharif Azadeh PhD., and prof. Michel Bierlaire.

The objective of this chapter is to analyze the existing types of timetables with respect to the passengers and to find a new type of a timetable that would merge the benefits of the existing ones.

Two types of timetables in passenger railway service exist: cyclic and non-cyclic. The cyclicality originates from the Periodic Event Scheduling Problem (PESP), where a given set of events is scheduled in equally spaced intervals (first defined by Serafini and Ukovich (1989)). In the case of passenger railway service, a special type of cyclic timetables is the clock-faced timetable, where the cycle is one hour. This is especially popular within railways, following the assumption that such timetables are easy to remember and thus, preferred by the passengers. Some studies confirm that indeed a regularity of a timetable leads to an increase in the passenger demand (Wardman et al. (2004), Johnson et al. (2006)). However, such a timetable design provides an inefficient operation mode as

there is a mismatch between the supply (determined by the timetables) and the demand (characterized by the time dependent passengers arrival rate).

In the non-cyclic timetable, on the other hand, no special rule is imposed on the departure time of the trains (see Caprara et al. (2002) for instance). This makes the non-cyclic timetable more flexible in accounting for the passenger demand. The previous chapter shows that this is especially true for high volumes of passengers. The flexibility was compared based on the passenger satisfaction. But given the structure of a non-cyclic timetable (no repeating pattern), it might discourage some passengers from choosing the train as their mode of transport.

Given the above, one cannot make a statement about the superiority of one timetable over the other. A combination of the two is needed. Therefore, this chapter investigates concept of hybrid timetables that combine the benefits of both - the regularity of the cyclic timetable and the flexibility of the non-cyclic one. The approach consists in imposing various levels of cyclicity and evaluating their corresponding flexibility.

The timetables are obtained by solving the previously defined Passenger Centric Train Timetabling Problem (PCTTP) through using a large neighborhood search heuristic combined with simulated annealing. The performance, of each of the newly proposed timetables, is assessed and compared to the cyclic and non-cyclic timetables on the real network of Israeli Railways (IR).

The chapter is structured as follows: Section 4.1 shows the definitions of the existing types of the timetables and the constraints that they impose on the PCTTP model. Similarly, in Section 4.2, the hybrid timetables and their impacts on the PCTTP are discussed. Section 4.3 provides the insights about the solution methodology that is used to obtain the results for the case study in Section 4.4. The chapter is finalized by drawing some conclusions in Section 4.5.

4.1 Existing Timetables

As mentioned in the previous chapter, a timetable is defined as a set of departure times $d_{\ell v}$ of each train $v \in V^\ell$ from its origin station on each line $\ell \in L$. Even though the lines consist of several stopping stations, in the PCTTP it is sufficient to decide only the departure time of each train from the origin station of its line, as the arrival times to the subsequent stations are derived from the deterministic travel times and dwell times. By imposing rules on train departure times, one can obtain two types of timetables: cyclic and non-cyclic.

4.1.1 Cyclic

The cycle c represents the difference between the departure times of two consecutive trains on each line. It is given in minutes and its value holds for the entire timetable. When varying size of the cycle is needed, one can either solve a TTP model of variable cycles (Zhong et al. (2013)) or (more often) to conceptually split a line into several ones. However, the split of a line is viable only when the various sizes of the cycle are its divisors. In railways, the typical value of the cycle c is 60 minutes. The regularity is enforced by including the cyclicity constraints in the model. They can take the following form:

$$d_{\ell v} - d_{\ell v-1} = c, \quad \forall \ell \in L, \forall v \in V^\ell : v > 1. \quad (4.1)$$

Adding cyclicity constraints to the model creates a *strictly cyclic* timetable, *i.e.* once the operation of a line ℓ has started, there would be a train departing in each cycle. An example of such a timetable is shown in Table C.2 (in Appendix C). This type of timetable is not always desirable. The passenger demand is time dependent and is lower in between the peak hours. Therefore, operators might choose to interrupt their operation for the duration of the off-peak hours. In this case, constraints (4.1) can be modified to a version where the departures of two consecutive trains are spaced in multiples of cycles $z_{\ell v}$. In other words, the difference between two consecutive trains can now have values of 60, 120, 180, *etc.* minutes. The values of these variables are integers with the lowest value being 1. Constraints (4.1) are reformulated as:

$$d_{\ell v} - d_{\ell v-1} = c \cdot z_{\ell v}, \quad \forall \ell \in L, \forall v \in V^\ell : v > 1. \quad (4.2)$$

In this thesis, a PCTTP containing constraints (4.2) is named as *cyclic*. An example of such a timetable is presented in Table C.1 (in Appendix C).

4.1.2 Non-Cyclic

In the non-cyclic timetable, no rule is enforced on the departure times of trains. However, one can add the below constraints, in order to avoid the symmetry in the model.

$$d_{\ell v} \leq d_{\ell v+1} - 1, \quad \forall \ell \in L, \forall v \in V^\ell : v < |V^\ell|. \quad (4.3)$$

No other buffer time between two consecutive trains, than the above one minute, is needed. The decision, if two trains are being scheduled close to each other, is driven by the objective function. Note that the PCTTP model does not handle potential conflicts among trains. Since no rule on the departure times is enforced, the non-cyclic timetables are better in accordance with the time dependency of the demand. Therefore, the non-cyclic timetable is more flexible than the cyclic one. An example of such timetable is shown in Table C.4 (in Appendix C).

4.2 Hybrid Timetables

In this section, the concept of hybrid timetables is introduced. These timetables are combinations of the timetables described in the previous Section. Each type of hybrid timetable is given in the form of the additional constraints that are imposed on the original PCTTP formulation. All proposed hybrid timetables can contain the symmetry breaking constraints (4.3), in order to improve the formulation. Since the regularity of a timetable cannot be quantified, it is taken care of by design and the flexibility is evaluated using the passenger satisfaction upon solving the respective PCTTP formulation. In other words, the additional constraints take care of the regularity while the objective function (passenger satisfaction maximization) takes care of the flexibility evaluation. Later on (in Section 4.4), the hybrid timetables are tested and compared against each other, and against the existing ones, using real case data.

4.2.1 θ Shifted Cyclic

The first hybrid timetable is inspired by Caimi et al. (2011). They allow small deviations from the cyclic departure times, in order to obtain a feasible solution. To do something similar, a variable $\Delta_{\ell v}$, capturing the deviation from the cyclic departure time of a train v on line ℓ (in minutes), is introduced. This deviation is restricted within the bounds $[-\theta, \theta]$ in minutes, in order to control it.

For illustration, consider the example of a $\theta (= 15 \text{ min})$ shifted timetable for a single line in Figure 4.1. The cyclic departures of this line are scheduled every $xx:30$. For each of them a deviation of $[-15, 15]$ minutes is allowed. Hence, a train at 13:30 might depart at 13:34 and a train originally scheduled at 22:30 is now departing at 22:20 instead. This framework applies to all trains. Note that other lines might have different cyclic times, but their actual departure times follow the same rule of $[-15, 15]$ minutes within its cyclic departure time. To obtain such a timetable for a given θ , constraints (4.4) and (4.5) need to be included in the model of the PCTTP.

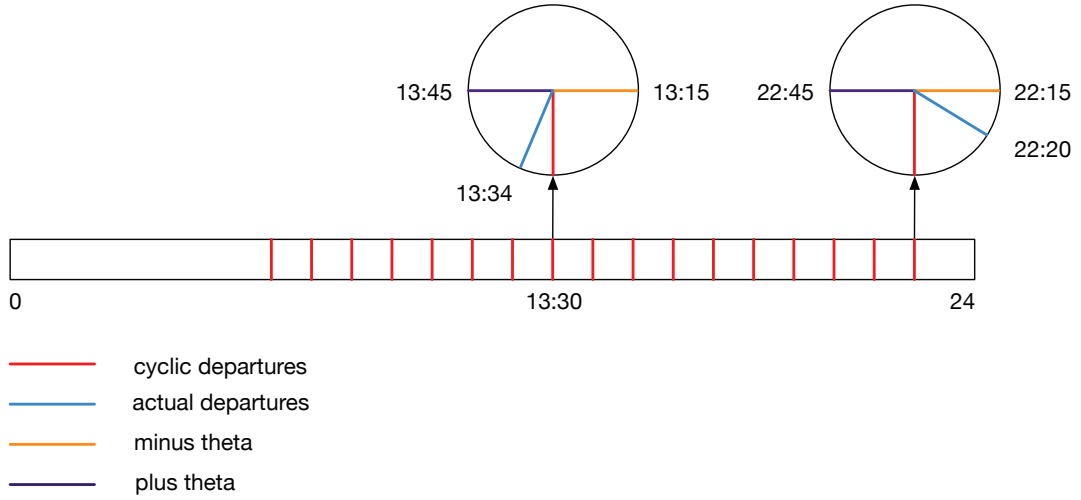


Figure 4.1: Example of a $\theta(= 15 \text{ min})$ shifted cyclic timetable for a single line

$$(d_{\ell v} - \Delta_{\ell v}) - (d_{\ell v-1} - \Delta_{\ell v-1}) = c \cdot z_{\ell v}, \quad \forall \ell \in L, \forall v \in V^\ell : v > 1, \quad (4.4)$$

$$-\theta \leq \Delta_{\ell v} \leq \theta, \quad \forall \ell \in L, \forall v \in V^\ell. \quad (4.5)$$

Constraints (4.4) impose that the original cyclic departure times must respect the cycle. Constraints (4.5) set the maximum shift from the cyclic departure times. 0 min shifted cyclic timetable is equivalent to the cyclic one. For a cycle of one hour, 30 min shifted cyclic timetable denotes the highest possible deviation, otherwise the trains would overlap. Due to the case, where two consecutive trains might have +30 minutes and -30 minutes deviations, the constraints (4.5) have to be adjusted to the form:

$$-\theta \leq \Delta_{\ell v} \leq \theta - 1, \quad \forall \ell \in L, \forall v \in V^\ell. \quad (4.6)$$

Therefore, this type of timetable is tested for all values of θ between 3 and 30 in 30 minute intervals.

4.2.2 ξ Partially Cyclic

This hybrid timetable is constructed by allowing a percentage of trains on a given line to be non-cyclic. The degree of the regularity is then expressed as $\xi\%$, where ξ is a parameter decided a priori. Since different lines are served by a different amount of trains, applying the same ξ to each line separately might significantly disrupt the

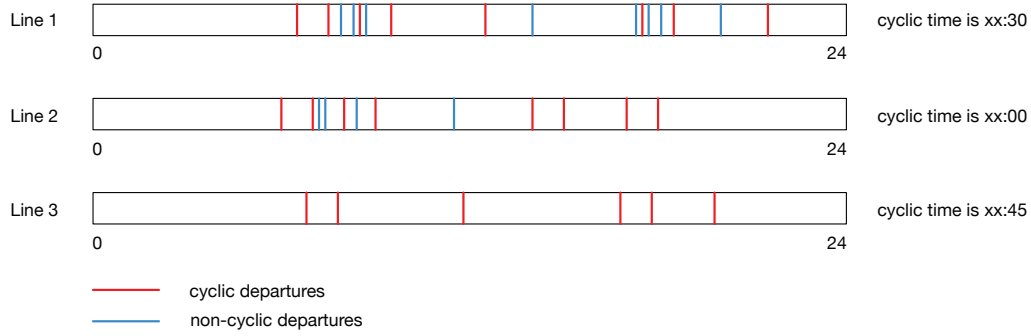


Figure 4.2: *Example of a $\xi (= 50\%)$ partially cyclic timetable*

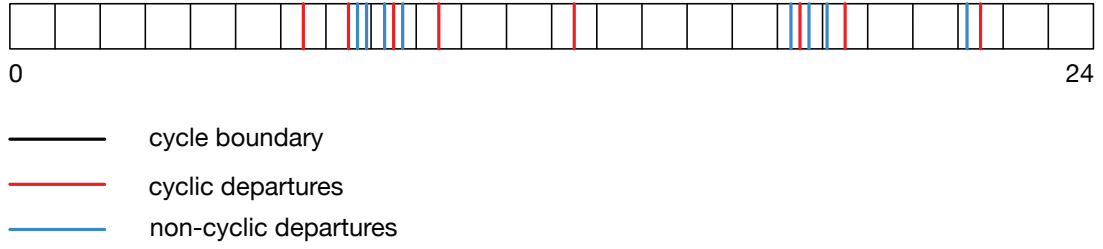
regularity of the service. Instead, it is proposed to treat the ξ as a percentage of the number of trains of the most frequent line ($\max(|V^\ell|)$) denoted as η . The η number of trains of each line are having a cyclic departure time and the rest of the trains is having a non-cyclic departure time. The decision on which trains are to be cyclic and non-cyclic is arbitrary. Indeed, the order of appearance within the set V^ℓ does not have any impact. The optimal solution will consist in the same values of the departure times no matter the internal order of the trains. For a notation convenience, the first η trains are assigned to be cyclic.

For illustration, consider the example of a $\xi (= 50\%)$ partially cyclic timetable in Figure 4.2. The number of trains per line ($|V^\ell|$) is 16, 12 and 6, respectively. The most frequent line being line 1, *i.e.* $\eta = 16 \cdot 0.5 = 8$. Therefore, each line has to have at least 8 trains with a cyclic departure or to have all trains with cyclic departure, if $|V^\ell|$ is smaller than 9. The rest of the trains can be scheduled at any time throughout the horizon (1 day in this case). To obtain such a timetable for a given ξ , constraints (4.7) need to be included in the model of the PCTTP.

$$d_{\ell v} - d_{\ell v-1} = c \cdot z_{\ell v}, \quad \forall \ell \in L, \forall v \in V^\ell : 1 < v \leq \eta = \max(|V^\ell|) \cdot \frac{\xi}{100}. \quad (4.7)$$

This type of timetable is tested for all values of ξ between 10% and 90% in 10% intervals. The 100% partially cyclic timetable is equivalent to the cyclic one and the 0% partially cyclic timetable is equivalent to the non-cyclic one. Note that the ξ of 0% is a special case. Since zero divided by any number is equal to zero, the above constraint does not hold. However, since the 0% partially cyclic timetable is equivalent to the non-cyclic one, it is sufficient to solve the non-cyclic version of the PCTTP. The non-cyclic trains are most likely to be scheduled within the high demand density periods of the day.

This hybrid timetable is inspired by Yang et al. (2010). They allow a certain number of lines to be non-cyclic. The motivation is again the infeasibility of the problem due to


 Figure 4.3: *Example of a hybrid cyclic timetable*

the high density of the trains.

4.2.3 Hybrid Cyclic

Even though both, θ shifted cyclicity and $\xi\%$ partial cyclicity, keep some degree of regularity, the newly created patterns might be too disorganized for the passengers to see. Therefore, one additional type of a hybrid timetable is proposed. The hybrid cyclic timetable schedules non-cyclic trains only in the hours/cycles where there is already a cyclic train being scheduled. Note that according to constraints (4.2), not every cycle is required to have a cyclic train scheduled. With such pattern, all passengers would obtain the same level of service as a cyclic timetable, with more flexibility. Within a given cycle, the passenger can decide to use the cyclic train or the non-cyclic one (if there is any). The ratio, between the amount of cyclic and non-cyclic trains, is a decision of the model.

For illustration, consider the example of a hybrid cyclic timetable in Figure 4.3. In this Figure, each box represents a cycle. Each cycle can either have no train, one cyclic train or one cyclic train and one or more non-cyclic trains within. The cyclic departure times, in this case, follow the pattern of xx:30. To obtain such a timetable, the constraints (4.8)-(4.13) need to be included in the PCTTP model.

$$\begin{aligned}
 q_{lv} \cdot q_{lv'} \cdot d_{lv} - q_{lv} \cdot q_{lv'} \cdot d_{lv'} & \quad \forall \ell \in L, \\
 & = q_{lv} \cdot q_{lv'} \cdot \left(c \cdot z_{lv'}^{v'} \right), \quad \forall v, v' \in V^\ell : v > 1, v \neq v', \quad (4.8)
 \end{aligned}$$

$$\lambda_k^\ell \leq \sum_{v \in V^\ell : d_{lv}/c=k} q_{lv}, \quad \forall k \in K, \forall \ell \in L, \quad (4.9)$$

$$(1 - q_{lv}) \cdot d_{lv} \leq \lambda_{d_{lv}/c}^\ell \cdot H, \quad \forall \ell \in L, \forall v \in V^\ell, \quad (4.10)$$

$$q_{lv} \in (0, 1), \quad \forall \ell \in L, \forall v \in V^\ell, \quad (4.11)$$

$$z_{lv'}^{v'} \in \mathbb{N} \setminus \{0\}, \quad \forall \ell \in L, \forall v, v' \in V^\ell : v > 1, v \neq v', \quad (4.12)$$

$$\lambda_k^\ell \in (0, 1), \quad \forall k \in K, \forall \ell \in L. \quad (4.13)$$

The cyclicity of a train is modeled through the binary decision $q_{\ell v}$. Value 1 indicates that the train is a cyclic one, 0 otherwise. The cyclicity pattern only among the departure times of the cyclic trains is enforced by constraints (4.8). The planning horizon consists of $k \in K = H/c$ cycles. For a planning horizon of one day, the value of k is on the interval from 1 to 24. Since the non-cyclic trains can be scheduled only in the cycles, where there is a cyclic train running, the binary decision λ_k^ℓ indicates whether there is such a train in the cycle k (equals to 1) or not (equals to 0). Since there is at most one cyclic train per cycle, the right hand side of constraints (4.9) is either equal to 1 (when there is a cyclic train scheduled in cycle k) or equal to 0 (otherwise). Lastly, constraints (4.10) allow for non-cyclic trains to exist only in the cycles, where there is a cyclic train scheduled. Constraints (4.11)-(4.13) are the domain constraints. Note that constraints (4.8)-(4.13) introduce non-linearity in the model.

4.3 Solution Methodology

In order to solve the problem for large networks (and to deal with the non-linearity), Simulated Annealing (SA) heuristic is used to solve the PCTTP. Since the SA is a well known heuristic (defined by Kirkpatrick et al. (1983)), the focus is mainly on the description of the specifics of the heuristic with respect to the PCTTP. The general pseudocode of the heuristic is shown in Algorithm 1.

Algorithm 1: Simulated Annealing

Data: d_c, N, ρ, T_c, T_f **Result:** Best timetable d^*

```
1 begin
2   Initialize
3   repeat
4     reset operators
5     for  $n \in N$  do
6       select a neighborhood move
7       impose this move on  $d_c$  and obtain  $d'_c$ 
8       perform passenger assignment on  $d'_c$ 
9       apply acceptance criterion on  $d'_c$ 
10      update weights  $\rho$ 
11    cooling of the  $T_c$ 
12  until  $T_c \leq T_f$ 
```

4.3.1 Solution Representation

A solution of the PCTTP problem consists in the departure times d for each train (ℓ, v) , that constitute the timetable, and its underlying flexibility. We distinguish among four types of a solution: the initial solution, the current solution d_c , the potential new solution d'_c and the best found solution d^* . Any cyclic timetable can be used as an initial solution. Indeed, the other types of timetable have less constraints, so that a cyclic timetable satisfies their constraints as well. A cyclic timetable can be constructed for instance by randomly generating the departure time of the first train of each line and setting the departure times of each subsequent train on each line by adding the value of the cycle to the departure time of the previous train. The other three types of a solution follow the standard SA logic.

The flexibility of a solution is its passenger satisfaction that is estimated using the value function (see Section 4.3.2).

4.3.2 Value Function and Its Estimation

The value function of the problem is the overall passenger satisfaction that is to be maximized. In order to estimate its value, the passenger assignment to the trains is carried out on the associated timetable. Five different ways of passenger assignment were considered. The typical assignment in the literature was excluded as it is not suitable for the value function of the PCTTP. The classical assignment approach is based on the First Come First Serve (FCFS) policy. Such an assignment provides user optimum whereas the goal of the PCTTP is the global optimum. Moreover, since the demand elasticity is not modeled, the FCFS might give priority to a passenger that might not realize her journey and another passenger that would realize her journey, is either left out or re-routed on a worse path due to the capacity issues. Whereas in the PCTTP, the goal is to take care of the demand elasticity implicitly by maximizing the overall passenger satisfaction.

The tested assignment procedures can be categorized into two groups: train based and passenger based. Each passenger has its own *path ordering*, *i.e.* set of available paths ordered by their respective level of passenger satisfaction in the descending fashion.

Train Based

Two different methods for the train based approach are considered: *Train 1* and *Train 2*. In these two assignment techniques, all passengers are loaded onto the network using their best path irrespective of the capacity issues. In the second stage of the approach,

the passengers are being re-assigned from the overloaded trains onto less occupied trains. Two rules on how to select a train to be processed exist:

- *Train 1* – trains are processed according to their natural order, *i.e.* the first train on the first line is processed as first and the last train on the last line is processed as last.
- *Train 2* – trains are processed according to their occupation in descending manner, *i.e.* the most occupied train above capacity is processed as first and the least occupied train above capacity as last.

For each selected train, the algorithms iterate through the passengers on-board and re-assign them to their next path in their *path ordering* irrespective of the capacity issues. The algorithms terminate once all capacity issues have been resolved. The passengers that cannot be served are using their penalty path.

Passenger Based

Three different methods for the passenger based approach are considered: *Pax 1*, *Pax 2* and *Pax 3*. In these three assignment techniques, the passengers themselves have a *passenger ordering*. For each method, the algorithm iterates through the *passenger ordering* and assigns the first realizable (capacities of the trains are respected) path in the *path ordering*. The three methods are:

- *Pax 1* – passenger ordering follows ascending worst satisfaction, *i.e.* a passenger with her worst path being the worst path of the whole problem is processed first.
- *Pax 2* – passenger ordering follows ascending difference between their best and worst satisfaction.
- *Pax 3* – passenger ordering follows ascending average satisfaction.

Performance

The five different methods have been tested on the case study of S-train Network of Canton Vaud, Switzerland (Appendix A) using the SBB 2014 timetable and the five different demand scenarios (Figure 3.5(a)).

The performance of the various algorithms can be seen in Table 4.1. The performance is shown as gaps in percentages between the solutions given by CPLEX (shown in Section

Algorithm	Instance					Sum
	1	2	3	4	5	
Train 1	00	04	33	25	24	86
Train 2	00	04	31	17	14	65
Pax 1	00	03	25	10	07	45
Pax 2	00	03	26	09	07	46
Pax 3	00	03	25	10	11	49

Table 4.1: Performance of different passenger assignments with passengers as groups

Algorithm	Instance					Sum
	1	2	3	4	5	
Train 1	00	06	38	52	39	135
Train 2	00	06	38	51	45	139
Pax 1	00	01	17	05	02	25
Pax 2	00	01	20	07	01	29
Pax 3	00	02	34	05	06	47

Table 4.2: Performance of different passenger assignments with passengers as individuals

4.3.5) and the solutions given by the algorithms. All values have been rounded. The sum is the addition of the performances over all instances for each algorithm. The addition was done with the original gaps and then rounded (*i.e.* the inconsistency in summing). Instances 1 and 2 allow transportation of all passengers. The volume of passengers in Instance 3 reaches the maximum number of passengers that can be transported, thus being the toughest instance as an improper assignment of passengers on trains will affect the number of passengers that can be transported. Instances 4 and 5 experience passenger congestion.

The performance of the algorithms is very similar for the two first instances. Subsequently, the Instance 3 indeed proves to be difficult to solve for all algorithms. On top of that, the train based algorithms perform much worse than the passenger based algorithms for instances 3, 4 and 5. On the other hand, the passenger based algorithms yield better (and similar) performance with the *Pax 1* method being slightly better than the rest.

In order to improve the performance of the algorithms, the groups of passengers are split into individuals. The results of the updated algorithms can be seen in Table 4.2. The split leads to a much worse performance of the train based algorithms and at the same time to a better performance of the passenger based algorithms. The *Pax 1* method has become distinctly the best algorithm and thus, the SA heuristic is implemented with the passenger assignment *Pax 1*.

Algorithm**Algorithm 2:** Passenger Assignment**Data:** I, n_{it}, P_i, T_i **Result:** \mathcal{S}

```

1 begin
2    $\mathcal{S} = 0$ 
3   for  $i \in I$  do
4     for  $t \in T_i$  do
5       for  $p \in P_i$  do
6         calculate  $\mathcal{S}_{it}^p$ 
7       sort paths  $P_i$  according to  $\mathcal{S}_{it}^p$  descending
8   sort  $(i, t)$  according to  $\mathcal{S}_{it}^{|P_i|}$  ascending
9   for  $i \in I$  do
10    for  $t \in T_i$  do
11     for  $j = 1 .. n_{it}$  do
12      for  $p \in P_i$  do
13       if path  $p$  does not violate capacity of any of its trains then
14        assign passenger  $j$  of the group  $(i, t)$  to path  $p$ 
15         $\mathcal{S} = \mathcal{S} + \mathcal{S}_{it}^p$ 
16        break

```

The general pseudocode of the proposed passenger assignment is shown in Algorithm 3. In the first stage of the algorithm, the satisfaction of each path of each passenger group is calculated and sorted in the descending order. This part of the algorithm is parallelized. In the second stage of the algorithm, the passenger groups are sorted according to their last (worst) path (index $|P_i|$) in the ascending order. This means that, in the next stage, the first processed passenger is having the worst possible satisfaction of the whole problem within her choice set. However, since the paths are sorted in the descending fashion, she will be first offered her best possible path. The algorithm splits the passenger groups into individuals, in order to achieve better values of the overall satisfaction. For each passenger, the algorithm iterates through the respective set of possible paths and assigns the first realizable path. Such a path does not violate the capacity constraints of the trains. No passenger remains unassigned as each set P_i contains the respective penalty path. The algorithm terminates once all passengers are assigned to the paths.

		N.	Cyclic	θ Shifted C.	ξ Partially C.	Hybrid Cyclic	Distribution
Select	(ℓ, v)	■	■	■	■	■	$\mathcal{U}(1, L), \mathcal{U}(1, V^\ell)$
	ℓ		■		■		$\mathcal{U}(1, L)$
	$q_{\ell v} = 0$				■	■	
	$q_{\ell v} = 1$					■	
Modify	$d_{\ell v}$	■			■	■	$\mathcal{U}(0, h - 1)$
	$d_{\ell v} \bmod c$		■	■	■	■	$\mathcal{U}(0, c - 1)$
	k		■	■	■	■	$\mathcal{U}(0, h/c - 1)$
	$\Delta_{\ell v}$			■			$\mathcal{U}(-\theta, \theta)$
Apply	$\forall q_{\ell v} = 1$				■	■	
	$\lambda_{k/c}^\ell = 0$		■	■	■	■	
	$\lambda_{d_{\ell v}/c}^\ell = 1$					■	

Table 4.3: Overview of the neighborhood moves by the type of a timetable

4.3.3 Neighborhood Structure

Each type of a timetable is having a different neighborhood structure. A neighborhood is defined as a set of candidate solutions that can be reached by a modification of the current solution d_c using a single neighborhood move. A timetable type can have more than one neighborhood that is characterized by its move. An overview of all the moves per type of a timetable is shown in Table 4.3.

Columns represent the moves and rows represent a stage of a move. The moves are categorized by the type of a timetable they belong to. The first column denoted N. stands for the non-cyclic timetable. The last column shows the distributions from which to draw randomly, in order to obtain the respective attribute's value. Only the cells with a grey background constitute a move. Each move is decomposed into 3 parts: selection, modification and application. Two entities can be selected: a specific train (ℓ, v) or the entire line ℓ . The selection of a specific train might be conditioned by its type ($q_{\ell v}$). If no condition is specified, any train can be selected.

The aim of the modification is to replace the value of one of the 4 attributes with a new one. The only not yet defined attribute is $d_{\ell v} \bmod c$. This attribute represents the modulo time within any cycle. For instance, when the cycle c is equal to one hour and the departure time of a train is 5:45, then the modulo time is 45 minutes. This time is the same among all cyclic trains of the same line.

The application of the modification is always performed on the pre-selected entity. However, its application might be conditioned. Some applications are made only to the cyclic trains of the given line ($\forall q_{\ell v} = 1$). Other applications are conditioned that the new cycle k does not already contain a cyclic train ($\lambda_{k/c}^\ell = 0$) or that the new departure time $d_{\ell v}$ is in a cycle that does already contain a cyclic train ($\lambda_{d_{\ell v}/c}^\ell = 1$). If the newly generated values of attributes fail to fulfill the last two conditions (when they are required), the

modification is repeated (until they do).

For illustration, consider the first move of the hybrid cyclic timetable: at first a train is selected by drawing the line ℓ from $\mathcal{U}(1, |L|)$ and subsequently drawing the v from $\mathcal{U}(1, |V^\ell|)$. The drawing from the distribution(s) is repeated until the condition $q_{(\ell,v)} = 0$ is satisfied. Hence, a non-cyclic train is selected. In the second phase, a new departure time $d_{\ell v}$ of this train is drawn from $\mathcal{U}(0, h - 1)$. In the third phase, this new departure time is applied given that it is in the cycle where there is a cyclic train scheduled ($\lambda_{d_{\ell v}/c}^\ell = 1$). Otherwise the modification phase is repeated until this condition is complied.

When a timetable type has more than one neighborhood move j , each move is associated with a weight ρ_j . Each ρ_j is initialized to 1 at the beginning of every new temperature T_c . Based on the performance of the move, its weight is being updated according to the below scheme ($f(d)$ is the value function):

- If $f(d_{c'}) \geq f(d^*) \rightarrow \rho_j = \rho_j + 3$
- If $f(d_{c'}) \geq f(d_c) \rightarrow \rho_j = \rho_j + 2$
- If $f(d_{c'}) < f(d_c)$ and the new solution is accepted with a probability $r < \exp(-(d_c - d_{c'})/T_c)$, where r is drawn from $\mathcal{U}(0, 1)$, then $\rho_j = \rho_j + 1$

In each iteration of the SA heuristic, a move is selected using the roulette wheel mechanism based on the weights ρ of the currently solved type of a timetable.

4.3.4 Values of the Parameters

The final temperature T_f is set to be zero and the initial temperature T_0 to be a function of the passenger satisfaction value of the initial timetable $f(d_0)$ where $T_0 = 10^{-5} \cdot f(d_0)$. The other two parameters, which values need to be tested, are the cooling scheme and the total number of iterations N per temperature T_c . The cooling scheme provides the information on how to decrease the temperature T_c . The tested values are: the cooling scheme of 5, 10 and 20% of the initial temperature T_0 and 100, 500 and 1 000 iterations of N .

The tests were performed on the case study of S-train Network of Canton Vaud, Switzerland (Appendix A) and the five different demand scenarios (Figure 3.5(a)) for the cyclic and non-cyclic timetable. As the rest of the timetables use a combination of the neighborhood moves contained in the two timetables, there is no need for an explicit testing of the other types. Each test comprised in 10 runs of each combination of the parameter settings for both types of the timetables. The cooling scheme of 5% and the number

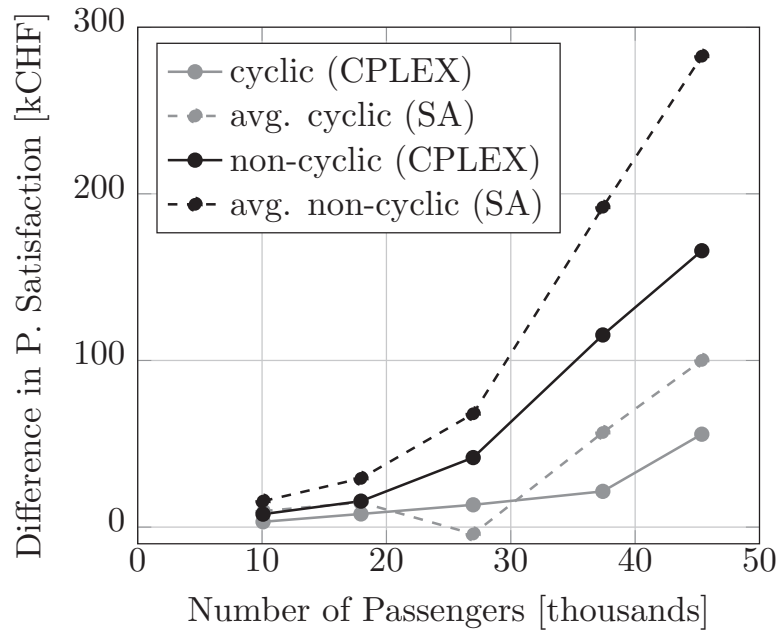


Figure 4.4: *SA performance as compared to CPLEX*

of iterations $N = 1000$ provided on average the best values of the passenger satisfaction. Given that the solution time was fast (on average 5 minutes for both cyclic and non-cyclic timetables), it has been selected it as the final parameter setting.

Figure 4.4 shows the average values of achieved solutions under this parameter setting as compared to the original results obtained by CPLEX (Figure 3.5(f)). The reasons, for such large improvements, are two-fold: CPLEX only reported the best solution found after the 2 hours time limit and it was not allowed to split the passenger groups, as opposed to the SA heuristic. The SA heuristic performs worse only in the third instance of the cyclic timetable. This is due to the fact that the number of passengers almost matches the offered capacity and at the same time, the cyclic trains are scheduled in even intervals. Therefore, there are only small differences among the offered paths and even marginal differences in their values of passenger satisfaction can have a large impact on the sorting within the passenger assignment. Nonetheless, the large gap between the cyclic and the non-cyclic timetable shows that there is indeed need for a hybrid (compromise) solution.

4.3.5 Validation

This section presents validation of the SA heuristic as compared to CPLEX (solved to optimality) on a small artificial network. The considered instances vary in the distribution and the number of passengers, and the capacity of the trains. The size of the

Instance	Cyclic Timetable					Non-Cyclic Timetable				
	Optimal	Time [s]	SA	Time[s]	Gap [%]	Optimal	Time [s]	SA	Time[s]	Gap [%]
0-d35-c1	-3 269	4	-3 358	11	2.72	-3 208	2	-3 272	12	1.98
0-d41-c2	-2 504	59	-2 624	13	4.80	-2 482	127	-2 589	12	4.29
0-d40-c2	-2 515	385	-2 570	14	2.20	-2 479	152	-2 507	10	1.15
1-d37-c2	-2 184	18	-2 236	11	2.37	-2 165	40	-2 215	11	2.30
0-d53-c3	-3 729	6 177	-3 887	13	4.25	-3 698	716	-3 826	13	3.45
1-d36-c3	-3 020	4	-3 066	11	1.50	-2 989	3	-3 019	11	0.99
0-d52-c4	-5 686	20	-5 761	12	1.32	-5 641	7	-5 720	13	1.41
1-d63-c4	-6 568	2 686	-6 656	14	1.34	-6 531	2 905	-6 613	14	1.26
1-d63-c4	-6 854	6 853	-6 966	12	1.63	-6 803	1 854	-6 904	14	1.49
1-d80-c4	-11 204	1 457	-12 021	15	7.29	-11 133	32	-11 866	15	6.58
Avg.	-4 753	1 766	-4 914	13	2.94	-4713	584	-4853	13	2.49

Table 4.4: *Validation of SA heuristic as compared to the optimal solutions*

groups is one passenger, therefore CPLEX now provides equivalent solution as the SA heuristic. The precise information of each instance is incorporated in their names: 0 - if the demand is evenly distributed across the planned horizon (the horizon is 3 hours), 1 - otherwise; d - provides the total number of passengers in the network; c - is the capacity of a single train (in total there are 16 trains).

The detailed numerical results can be found in Table 4.4. They have been categorized by the type of the solved timetable: cyclic or non-cyclic. The first column provides the information about the solved instance. The optimal solution is the passenger satisfaction obtained by CPLEX and SA is the passenger satisfaction obtained by the SA heuristic. Both values are in Swiss Franc (CHF). All methods have solution time reported in seconds. The gap between the optimal solution and the solution found by the SA heuristic is reported in percentages.

The SA heuristic can find solutions with a reasonable gap from the optimal solution. The worst performance is for the instances *0-d41-c2*, *0-d53-c3* and *1-d80-c4*. The first two instances are hard to solve as the demand is almost matching the supply. Therefore the order, in which the passengers are being processed in the assignment procedure, plays a crucial role. The FCFS policy would obtain worse values. The instance *1-d80-c4*, on the other hand, has the most extreme passenger distribution: 90% of the passengers in the first hour and 5% in each of the two subsequent hours. The average gap for the cyclic timetable is 2.94% and for the non-cyclic timetable 2.49%. In terms of the time, the SA heuristic performs better than CPLEX.

4.4 Case Study

In order to evaluate the performance of the various timetables, the proposed methodology is applied to the network of Israeli Railways (IR) shown in Figure 4.5. The aim

is to compare the level of passenger satisfaction for different timetables. The exact procedures, assumptions and information about the data can be found in Appendix B.

Two instances are considered in the study: the *2008* situation and the *2014* situation. The 2008 situation is built from the ticket selling machines' data of an average working day (from 6 a.m. to 1 a.m.) in 2008 in Israel. This data was kindly provided by Mor Kaspi and Tal Raviv, who have used it in their study Kaspi and Raviv (2013). The 2008 situation constitutes in 126 036 passengers. The 2014 scenarios assume that the structure of the demand is the same as in 2008, with a uniform growth rate of 60% (the flow between each OD pair is multiplied by a constant factor of 1.6), resulting in a total number of 193 886 passengers (based on the newspaper article in Globes (2015)).

The network layout of 2008 is used: there were 47 stations and the red line in Figure 4.5 was operated only between *Hod HaSharon* and *Tel Aviv - HaHagana*. The night line (blue with black bordering) is not in consideration as it runs mainly in the period for which there is no demand data (*i.e.* between 1 a.m. and 6 a.m.). Even though there are only 18 unidirectional lines visualized in Figure 4.5, in reality there are 34 unidirectional lines in the timetable (some lines are operated with higher frequency of 2 or more cyclic times, *e.g.* every xx:15 and xx:45). Since some of the trains follow different stopping patterns within a line, a union of stopping stations for each line is used (but same colored lines with different cyclic times may operate different stopping patterns). Since the OD matrix is given for an average working day, the trains that operate only during the holidays have been removed.

The timetable operated in Israel is cyclic with a cycle of 60 minutes. The timetable of 2013/14³ is used (it was the latest published timetable at the time of the implementation). In this timetable, 6 out of the total number of 388 trains have non-cyclic departure times. The planning horizon H of this case study is one day. Even though the demand is between 6 a.m. and 1 a.m., the PCTTP model is allowed to schedule trains during any time of the day. The PCTTP is solved using the SA heuristic (defined in the previous Section) for the following timetables:

- **Non-Cyclic** – no specific rule on the departure times is enforced.
- **Cyclic** – the departure times have to be cyclic according to constraints (4.2).
- **θ Shifted Cyclic** – the departure times are subject to constraints (4.4) and (4.5). The values of θ vary between 3 and 30 minutes in 3 minute intervals. Since θ of 0 is equivalent to the cyclic timetable, it does not need to be solved.
- **ξ Partially Cyclic** – the departure times are subject to constraints (4.7). The values of ξ vary between 10 and 90% in 10% intervals. Since ξ of 0 and 100 is

³Unlike Europe, the timetable change in Israel happens during the summer period, *i.e.* the naming 13/14.

CHAPTER 4. HYBRID CYCLICITY

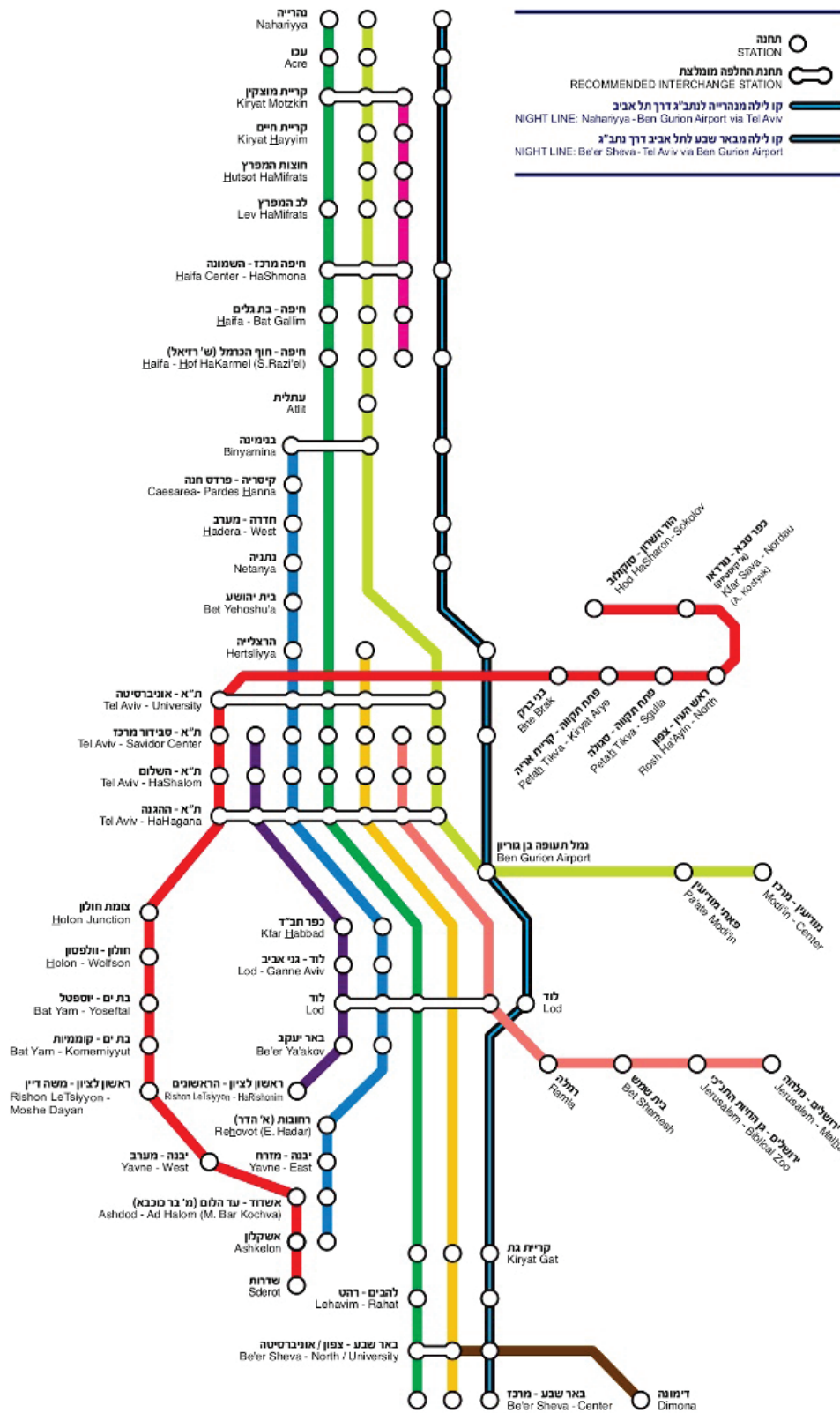


Figure 4.5: Network of Israeli Railways (www.rail.co.il)

equivalent to the cyclic and the non-cyclic timetables respectively, they do not need to be solved.

- **Hybrid Cyclic** – the departure times have to comply with constraints (4.8) - (4.13).

For the sake of the comparison, the performances of the two timetables below are shown as well:

- **IR 13/14** – the departure times are fixed to the ones of IR timetable of 13/14. The IR timetable is cyclic as using constraints (4.2), with an exception of having the aforementioned 6 non-cyclic trains.
- **IR 13/14 as Strictly Cyclic** – is the same as IR 13/14, where the 6 non-cyclic trains are fixed to their closest cyclic departure time, and the gaps, between the first and the last scheduled train on each line, are filled with cyclic trains (in total 82 trains more). This is equivalent to having constraints (4.1). The exact difference between the two timetables can be observed on the train distributions in Table C.1 and Table C.2 in Appendix C.

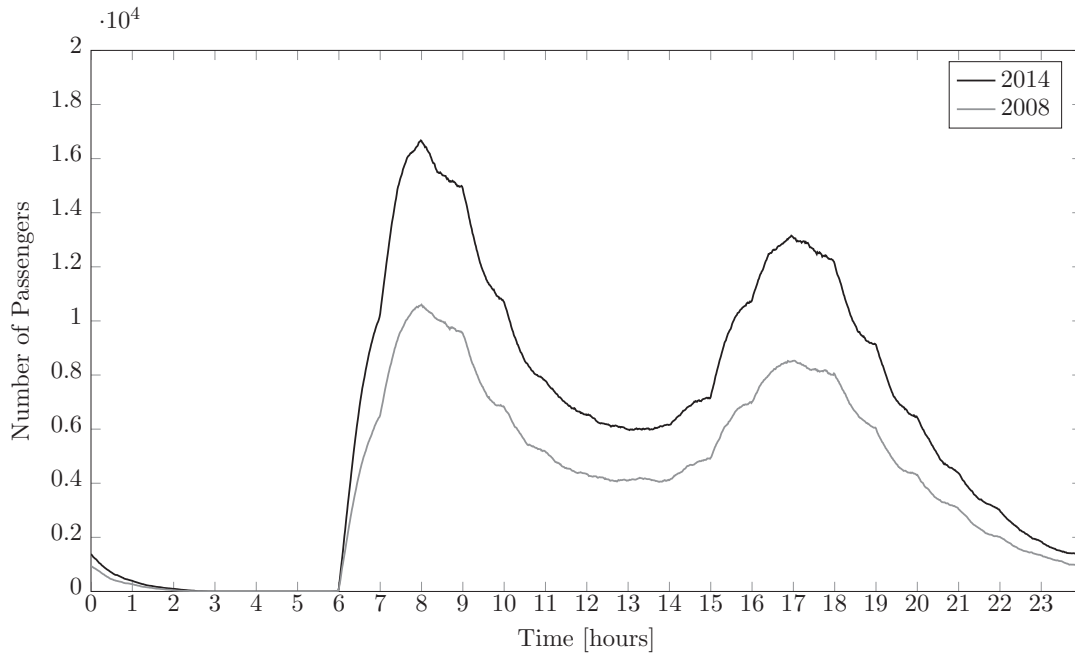
The passenger satisfaction of each type of timetable is given in New Israeli Shekel (NIS). All tested instances have been run in Java on a Unix server with up to 24 cores of 3.33 GHz and 62 GiB RAM. Since 3 instances were typically ran at the same time, the average core usage would be then 8.

4.4.1 Results

In this section, the results of the case study are presented. They are categorized into two groups: existing and hybrid timetables. The existing ones are: strictly cyclic, cyclic and non-cyclic timetables. The hybrid ones are: θ shifted cyclic, ξ partially cyclic and hybrid cyclic timetables.

At first, the demand distributions over the day are constructed (Figure 4.6). Each distribution is in fact a network load, where the passengers take their shortest path between their origin and destination with just a minimum transfer time (*i.e.* no waiting time in transfers) and arriving to their destinations exactly on time, thus their schedule passenger delay being zero. Note that this network load does not involve any actual timetable and it is only used as a benchmark. It is denoted it as the *perfect service*.

The passenger satisfaction of the 2008 situation under the *perfect service* is -2 089 049 NIS and of the 2014 situation -3 171 721 NIS. These two values are upper bounds of the

Figure 4.6: *Demand distributions over the day*

two instances for all the types of the timetables (no better solution exists). The aim of the timetable design should be a network load as close as possible to the perfect service.

Existing Timetables

The performance of each timetable can be found in Table 4.5 for the 2008 situation and in Table 4.6 for the 2014 situation. For each timetable, the underlying passenger satisfaction in New Israeli Shekel (NIS) is reported. The perfect service reports the satisfaction as it is and the different timetables report the passenger satisfaction as a relative difference to the perfect service. Apart from the satisfaction, the tables provide information on the number of train drivers needed to realize the operation, as well as the needed number of train units, the percentages of passengers that were able to realize their journeys and the solution time in seconds.

It is interesting to see (from the tables) that even though the IR 13/14 as strictly cyclic timetable offers more trains, its passenger satisfaction is lower than of the IR 13/14 timetable for both situations. The reason behind this, is the fact that there are 6 non-cyclic trains in the IR 13/14 timetable that need to have a cyclic departure time in the strictly cyclic one. The decrease is then caused by the additional waiting time between the original non-cyclic departure and the new (strictly) cyclic one. Overall, running a strictly cyclic timetable is not desirable as the operating cost is higher and the additional benefit is either low or non-existent.

	IR 13/14 as Strictly Cyclic	IR 13/14	cyclic	non-cyclic	perfect service
satisfaction [NIS]	-704 904	-537 503	-476 774	-424 529	-2 089 049
drivers [-]	470	388	388	388	48 960
rolling stock [-]	940	776	776	776	48 960
covered [%]	100	100	100	100	100
time [sec]	12	6	24 997	25 613	1

Table 4.5: *Computational results of the existing timetables for the 2008 situation*

	IR 13/14 as Strictly Cyclic	IR 13/14	cyclic	non-cyclic	perfect service
satisfaction [NIS]	-3 792 733	-3 379 596	-2 392 909	-1 365 779	-3 171 721
drivers [-]	470	388	388	388	48 960
rolling stock [-]	940	776	776	776	48 960
covered [%]	99.17	99.32	99.32	99.23	100
time [sec]	11	8	86 627	88 342	2

Table 4.6: *Computational results of the existing timetables for the 2014 situation*

When we compare the IR 13/14 timetable with the cyclic timetable, we can see that proportionally large increase in passenger satisfaction can be achieved: approx. 60 000 NIS for the 2008 situation and approx. 1 million NIS for the 2014 situation. As the passenger coverage is 100% and 99.32% respectively, we can assume that the 2014 situation is just about the maximum capacity of the network, whereas the 2008 situation is over supplied.

A similar situation happens for the difference between the cyclic and the non-cyclic timetable. The differences in the passenger satisfaction are approx. 50 000 NIS and approx. 1 million NIS for the two situations respectively. The solution time of the SA heuristic is on average 7 hours for the 2008 situation and one day for the 2014 situation. As the differences among the timetables in the 2008 situation are marginal, the focus from now on will be only on the 2014 situation.

When we plot the network load for the 2014 case of the IR 13/14 timetable and of the cyclic timetable (Figure 4.7), we can see that both timetables are fairly good in addressing the evening peak hours, but fail at addressing the morning ones. The failure propagates into surrounding time periods: early start of the morning peak (*i.e.* some passengers arriving early at their destinations) and a heightened level of passengers in the network during the off peak hours (*i.e.* late arrivals from the morning peak and early arrivals for the evening peak). Both timetables exhibit the nature of the repeating pattern inside the plot.

The improvement of the cyclic timetable over the IR 13/14 timetable is approx. 1 million NIS. According to the breakdown of the passenger satisfaction (in Figure 4.9), the improvement is mainly in the passenger schedule delay. This is due to the fact, that the cyclic timetable is having more passengers arriving earlier into their destinations

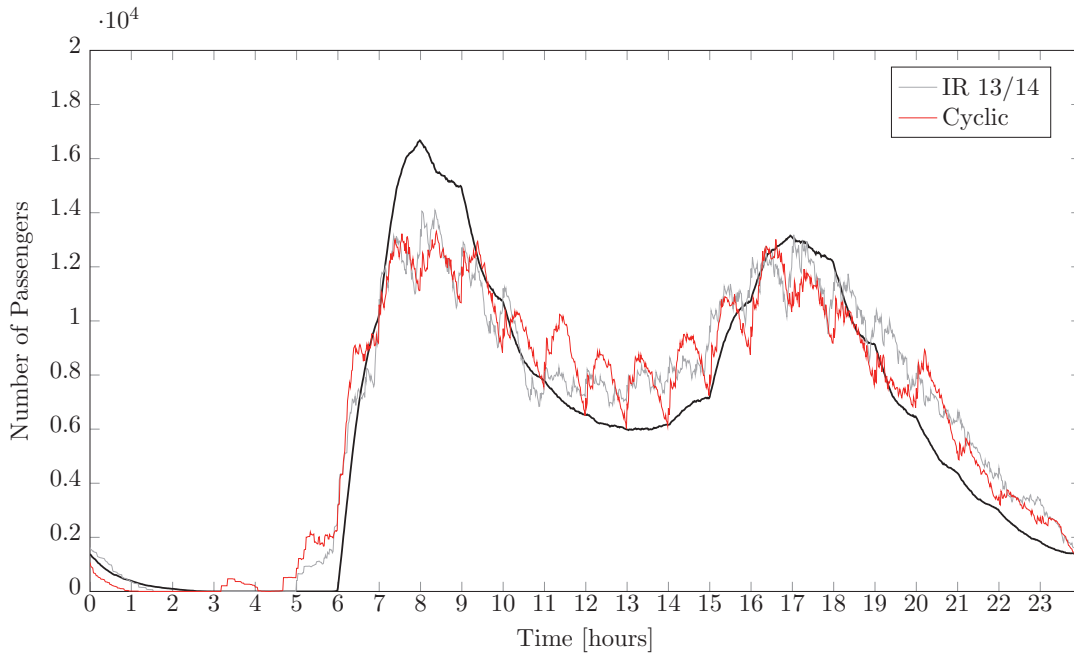


Figure 4.7: *Network load of the IR 13/14 and of the cyclic timetable for the 2014 situation*

than the IR 13/14 timetable. Indeed, the β parameter of being early has higher value ($= -0.5$) than the β parameter of being late ($= -1$).

When we compare the network load of the cyclic and the non-cyclic timetable (Figure 4.8), we can see that the non-cyclic one is indeed more flexible in accounting for the passenger demand. Especially within the peak hours, where there is often more than one train being scheduled (in some cases even 4 trains per hour, Table C.4 in Appendix C). This brings about one more million NIS of improvement in the schedule passenger delay (Figure 4.9).

When we look at the breakdown of the passenger satisfaction (Figure 4.9), we can see that the most important is the attribute of schedule passenger delay representing the fact that the passenger demand is time dependent. Thus, when designing a railway timetable, one should always take into account the passengers and their desired arrival time preferences.

θ Shifted Cyclic Timetable

As mentioned before, this type of timetable is solved for various values of θ within the interval between 3 and 30 in 3 minute step size (0 being the solution of the cyclic timetable). The plot of the passenger satisfaction as a function of θ can be found in

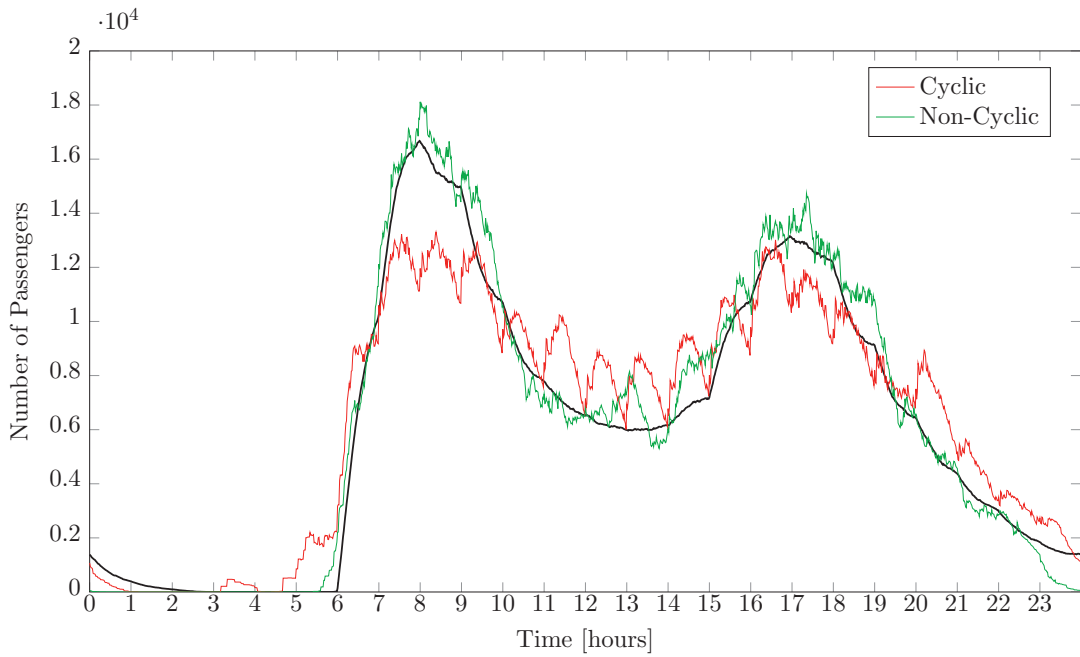


Figure 4.8: *Network load of the cyclic and of the non-cyclic timetable for the 2014 situation*



Figure 4.9: *Breakdown of the passenger satisfaction for various timetables under the 2014 situation*

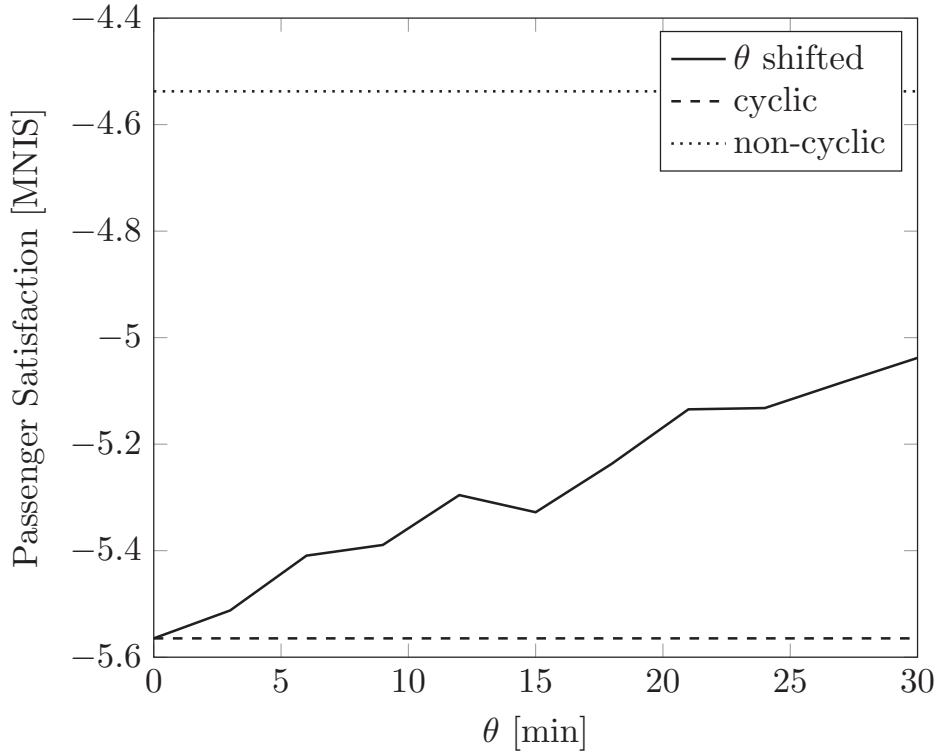


Figure 4.10: *Passenger satisfaction of the θ shifted cyclic timetable for the 2014 situation*

Figure 4.10.

The 0 min shifted cyclic timetable is equivalent to the cyclic one, which is represented by the dashed line. The 30 min shifted cyclic timetable, on the other hand, is not equivalent to the non-cyclic one (the dotted line), as the maximum number of trains that are scheduled within one hour is 2 (Table C.5 in Appendix C) and 4 (Table C.4 in Appendix C) respectively. Thus, the θ shifted cyclic timetable can achieve at most half of the flexibility of the non-cyclic one (around half a million NIS). The trend of the function is rather linear.

Overall, the improvement in flexibility of the newly proposed timetable is promising. It is a sign that new alternative timetables exist and should be taken into account. As this was the more restrictive configuration, even larger impacts are expected from the other two hybrid timetables.

ξ Partially Cyclic Timetable

In this section, the computational results, of the ξ partially cyclic timetable for different levels of partiality under the 2014 situation (Table 4.7), are presented. The first column

ξ [%]	P. Satisfaction [NIS]	η	Cyclic	Non-Cyclic	Time [sec]
0	+1 027 131	0	0	388	–
10	+996 108	2	64	324	48 698
20	+998 444	4	124	264	59 889
30	+1 059 768	5	152	236	64 320
40	+991 634	7	207	181	69 351
50	+1 002 523	9	254	134	66 584
60	+973 353	11	296	92	72 352
70	+842 934	13	331	57	77 017
80	+811 925	14	346	42	69 147
90	+629 754	16	372	16	76 766
100	-5 564 631	18	388	0	–

Table 4.7: *Computational results of partially cyclic timetables for different levels of partiality under the 2014 situation*

represents the level of the partiality as a percentage. The second column shows the passenger satisfaction in NIS. The satisfaction for $\xi = 100\%$ is given as it is and all other satisfactions are given as relative to this one. Next columns give information on the η (which is the number of trains per line that have to follow the cyclic pattern, Equation 4.7), the total number of trains that follow cyclic pattern, the total number of trains that are non-cyclic and the solution time of the SA heuristic.

The passenger satisfaction as a function of ξ is plotted in Figure 4.11. The function is rather exponential. At the partiality of 30%, it outperforms the non-cyclic timetable. This is caused due to the heuristical solution approach, *i.e.* the non-cyclic timetable might have gotten trapped in a local optimum.

More importantly, the 90% partially cyclic timetable can achieve slightly better values of the passenger satisfaction than the 30 min shifted cyclic timetable by having only 16 trains non-cyclic. Overall, the partially cyclic timetable achieves the passenger satisfaction values close to the ones of the non-cyclic timetable already around 60% partiality. The ratio, of the cyclic and the non-cyclic trains at this level of the partiality, is approximately 3:1. This means that a large improvement can be achieved by having only small adjustments made to the cyclic timetable. This conclusion is further supported by the results of the hybrid cyclic timetable (in the next Section).

Hybrid Cyclic Timetable

The hybrid cyclic timetable as compared to the partially cyclic one, controls the ratio between the number of the cyclic and the non-cyclic trains by itself. The resulting ratio is approximately 3:1, which is the same case as for the 60% partially cyclic timetable.

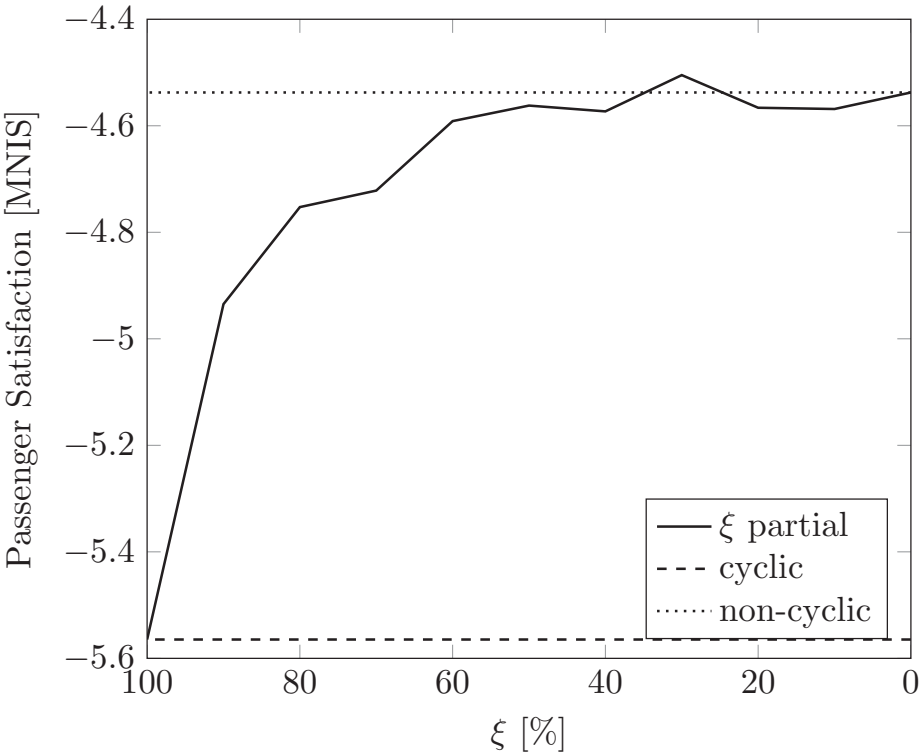


Figure 4.11: *Passenger satisfaction of the ξ partially cyclic timetable for the 2014 situation*

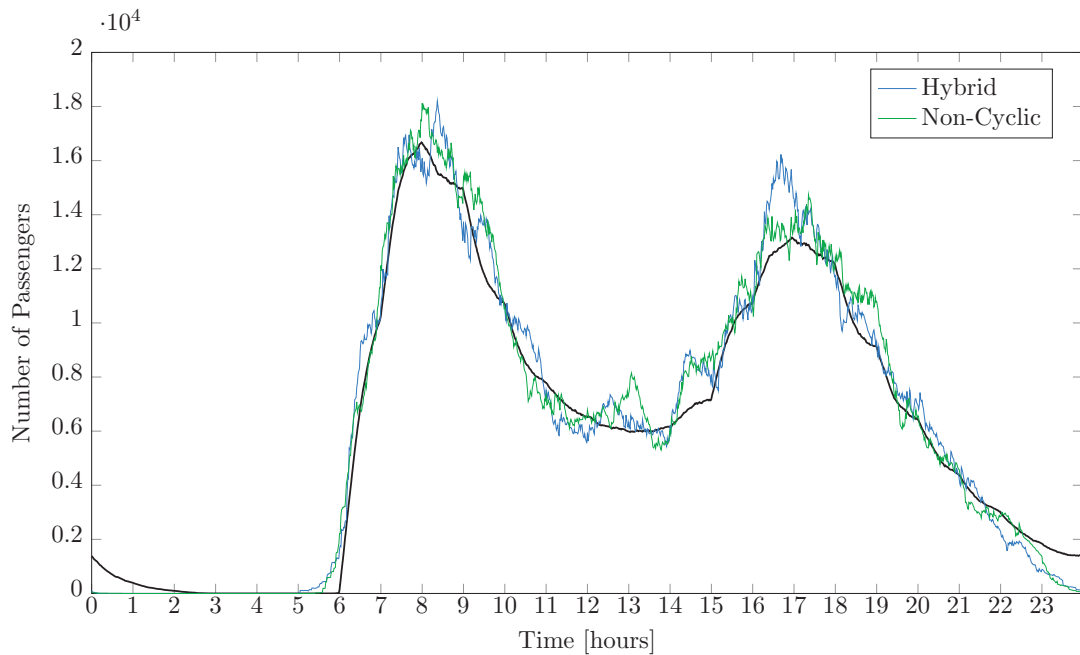


Figure 4.12: *Network load of the non-cyclic and of the hybrid cyclic timetable for the 2014 situation*

The passenger satisfaction is close to the one of the non-cyclic timetable (it is worse by only 13 405 NIS) and of the aforementioned 60% partially cyclic timetable (it is better by 40 373 NIS).

When we consider the network load (Figure 4.12), it is having a similar shape as the one of the non-cyclic timetable. In terms of the train distribution (Table C.6 in Appendix C), we can see the trend of the non-cyclic trains being mainly scheduled during the morning and evening peak hours. The actual departure times of all trains can be found in Table C.7 in Appendix C. The solution time of the SA heuristic is 60 113 seconds. Overall, the hybrid cyclic timetable has proven to be the most suitable configuration as it achieves the flexibility of the non-cyclic one, while keeping a good level of regularity.

4.4.2 Remark

Overall for this case study, the proposed hybrid timetables tend to reduce or to completely diminish the quantitative impact of the regularity (cyclic constraints). The original gap between the flexibility of the cyclic and the non-cyclic timetable is 18.5%. The θ shifted cyclic timetable is able to reduce this gap to a half (for $\theta = 30$). The ξ partially cyclic timetable can further reduce this gap to zero already at a level of $\xi = 60$. The ratio of the cyclic and the non-cyclic trains under this ξ is 75% and 25% respectively. This ratio of trains is further supported by the hybrid cyclic timetable,

that aims at providing more even offer of the regularity to the passengers than the other hybrid timetables. Cycles can have either only a cyclic train or both cyclic and several non-cyclic ones. The cyclic trains are used to secure the regularity and the non-cyclic trains are used to improve the service level during high demand periods.

4.5 Summary

In this chapter, the quantitative and the qualitative aspects of different passenger railway timetables were considered. The quantitative attributes (the passenger satisfaction) show that the non-cyclic timetable is more flexible to account for the passenger demand than the cyclic one. On the other hand, the cyclic timetable has some qualitative aspects that are favored by the passengers. Namely the regularity of the service, which makes the timetable easy to be memorized by the passengers. Thus, a superiority of one over the other is difficult to estimate.

In the light of these findings, several combinations of the two, that would implement the qualitative aspects and that allow to explore and to reduce the quantitative impacts of the regularity, were proposed. Three types of hybrid timetables were considered. The first two are generalizations of existing methods, where the relaxations of the cyclicity are explicitly modeled. The last one is an extension of the cyclic timetable imposing the non-cyclic trains to be coordinated with cyclic ones. The basic idea is that the passengers can choose between the flexibility and the regularity. The Passenger Centric Train Timetabling Problem has been used to design the different timetables and it was solved using the simulated annealing heuristic, which has proven to be an effective instrument. The findings were illustrated on the network of Israeli Railways using the ticket selling machines' data to construct the passenger demand data. The results of the case study suggest that the hybrid cyclic timetable is the most promising approach.

The above findings have important impacts for TOCs. Indeed, cyclicity is desired in order to encourage the passengers to use train as a mode of transportation. Still, its lack of flexibility does not generate a supply configuration that is satisfying for the travelers in terms of level of service. The concept of hybrid timetables that has been proposed in this chapter allows to maintain the perception of regularity of the cyclic timetable, and to introduce the necessary flexibility for a high level of service. Although, it has not been explicitly analyzed in this chapter, this added flexibility is expected to generate significant cost reductions. Also, the actual impact of the hybrid timetables is context dependent, and other case studies should be analyzed.

5

Train Timetable Design Under Elastic Demand

This chapter is based on the technical report:

Robenek, T., Azadeh, S. S., Maknoon, Y., Lapparent, M. and Bierlaire, M. (2016). Train timetable design under elastic demand. Technical report TRANSP-OR 160923.

The work has been performed by the candidate under the supervision of Shadi Sharif Azadeh PhD., Yousef Maknoon PhD., Matthieu Lapparent PhD. and prof. Michel Bierlaire.

The objective of this chapter is to extend the original PCTTP model with a probabilistic behavior of the passengers and to include a competing operator into the passengers' choice sets. The passengers' behavior is further calibrated to follow known demand elasticities and therefore, it allows for a realistic demand forecasts. Knowing the forecasts, one can calculate the operator's revenue and further integrate the train timetable design with ticket pricing.

From economic theory, it is well known that the demand is influenced by the supply. In the railway context: different timetables would attract different passengers, as they provide different levels of services. Therefore, it is important to include the passenger demand and its elasticity in the timetable design. This is particularly crucial nowadays, when the railway market is open for competition. This has lead to a release of the gov-

ernment's subsidies and the operators thus face a pressure to be profitable by increasing their revenues.

The passenger demand itself can be predicted through the choices that the passengers face: mode choice, route choice, operator choice, service choice and departure time choice. At first, the passengers decide on their mode of transport, *i.e.* car, bus, train, *etc.* Subsequently, they decide on their exact path within the selected mode, *e.g.* the exact trains and interchanges. As transportation is offered by several providers, the passengers can select which one to take and in what kind of service, *e.g.* first class with a private operator, having a club card of a specific operator, *etc.* Lastly, the departure time choice of the passengers is affected by the trip purpose (commuting to be on time at work, leisure to be on time for cinema for instance, *etc.*). This choice is the so called time dependency of the demand. The mode choice and the operator choice are especially important when optimizing a service. If not included, the passengers are captive in the system and such optimization would lead to unrealistic performance (*i.e.* departure times leading to a lower ridership than anticipated).

Typically, the train timetabling models use the simplifying assumption that the passengers always take their shortest paths (see Caprara et al. (2002) for instance) and omit the demand from the problem. Recent models relax this assumption and include the demand in the optimization (see Schmidt and Schöbel (2015) for instance). However, these models only increase the attractiveness of a timetable and cannot estimate the realized demand and the underlying revenue. In order to do so, a demand forecasting model is needed. One of such models, integrating the train timetabling and the demand forecast, is presented by Cordone and Redaelli (2011). However, they only consider the mode choice and omit the other choices. Moreover, they consider the timetable only as a frequency of the service rather than the actual departure times. In the model of Espinosa-Aranda et al. (2015), the mode choice is combined with a departure time choice. But their application involves a single high speed railway line and lacks the network dimension (*i.e.* the route choice).

In this chapter, the Passenger Centric Train Timetabling Problem (PCTTP) model from Chapter 3, that can design a timetable for a whole railway network, is extended with a demand forecasting model. The new model is denoted as the Elastic Passenger Centric Train Timetabling Problem (EPCTTP). The objective of the new optimization framework is to maximize the TOC's revenue. The framework is using a discrete choice model to predict the demand throughout the timetable design process. Prior solving of the mode choice model is assumed and the framework deals with the route choice model along with the departure time choice and the operator choice. The following attributes have influence on the passengers' choices: the travel time, the desired arrival time to their destinations (the time dependency), the ticket fare and the capacity of the trains. An universal option of opting out is included into the passengers' choice set(s), in order to avoid their captivity. The demand elasticity and other parameters of the discrete

choice model are calibrated to known values from the literature and provide a “ready to use” framework. It can design cyclic, non-cyclic and hybrid cyclic timetables. The resulted timetables increase the ridership through accounting for the passengers’ wishes and therefore, they increase the operator’s revenue as well. The new approach is tested on a case study of Israeli Railways.

The chapter is structured as follows: Section 5.1 further extends the utility function of passenger satisfaction with the fare attribute and shows how to obtain the choice probabilities and how to calibrate the demand elasticity. The prediction model is further incorporated into the PCTTP model in Section 5.2. The insight, about the methodology of how to solve such integrated demand-supply optimization framework, is given in Section 5.3. The benefits and the impacts of the framework are shown on a case study of Israeli Railways in Section 5.4. The chapter is finalized by drawing some conclusions in Section 5.5.

5.1 Demand Model

Here, the concept of the passenger satisfaction (defined in Section 3.1.2) is further extended with the fare attribute and it is used to predict the passengers’ choices with a certain probability. To make the total demand elastic, an opt-out option is included in the set of paths P_{it} . Otherwise the passengers are captive in the system, *i.e.* the total demand would not change whatever changes in the timetable and levels of fares. Note, that the set of available paths is extended by the index of the passenger group (i, t) (detailed explanation is provided in the next Section 5.2). Since a prior solving of the mode choice model is assumed, a passenger can exit the system only by usage of another TOC. If a competing operator exists, it is sufficient to add his itineraries inside of the set $p \in P_{it}$. However, since the existence of a competition is not yet wide spread, the following assumption is proposed: given the nature of the railway competition (fighting for the same finite demand), the OD pairs served, the departure times and the prices of the competing operators are typically very similar, *i.e.* the opt-out option for every passenger group is the current shortest path (that has the lowest value of the in-vehicle time and has zero waiting time in the transfers and arrives to the passengers’ destination exactly at their desired arrival time) and its underlying ticket fare. Such an assumption is realistic and allows to explore the “worst” case scenario.

The fare f^p can be directly added into the generalized cost:

$$C_{it}^p = VOT \cdot \mathcal{T}_{it}^p + f^p \quad [monetary] \quad (5.1)$$

We can now further assume that the unobservable part of the utility function ϵ_{it}^p , is independently and identically distributed according to the Extreme Value distribution. The utility is then equal to the passenger satisfaction only ($\mathcal{U} = \mathcal{V} = \mathcal{S} = -\mathcal{C}$). The probability Pr_{it}^p of a passenger group (i, t) selecting a path p can be reformulated as:

$$Pr_{it}^p(w_{it}^p, \delta_{it}^p, \gamma_{it}^p, f^p | d_{\ell v}) = \frac{e^{\mu S_{it}^p}}{\sum_{p' \in P_{it}} e^{\mu S_{it}^{p'}}} \quad (5.2)$$

The probability Pr is a function of endogenous and exogenous variables. The endogenous ones being the waiting time, the schedule passenger delay and the fare, and the exogenous variable being the timetable (modeled through decisions on departure times $d_{\ell v}$). μ is a scale parameter. This parameter is related to the variance of ϵ in Equation 3.2 and it indirectly controls the elasticity of the passenger demand. A last step in calibrating the parameters of the choice probabilities is to find appropriate value of the scale parameter μ . It can be done by computing the elasticity of the total demand. The aggregate direct point elasticity related to the changes in the generalized cost is given as:

$$E = \frac{\sum_{it} \sum_{p \in P_{it}} \left(\frac{\partial Pr_{it}^p}{\partial S_{it}^p} \cdot \frac{S_{it}^p}{Pr_{it}^p} \cdot Pr_{it}^p \cdot n_{it} \right)}{\sum_{it} \sum_{p' \in P_{it}} Pr_{it}^{p'} \cdot n_{it}} \quad (5.3)$$

Upon solving of the derivatives, this transforms into:

$$E = \frac{\sum_{it} \sum_{p \in P_{it}} (1 - Pr_{it}^p) \cdot \mu \cdot Pr_{it}^p \cdot n_{it}}{\sum_{it} \sum_{p' \in P_{it}} Pr_{it}^{p'} \cdot n_{it}} \quad (5.4)$$

According to Whelan and Johnson (2004), the value of the elasticity for the railway passenger demand with respect to the fare and the generalized cost is $E = -0.58$. Therefore, the value of μ can be calibrated by solving Equation 5.4 for any case study. In this case, μ has been calibrated to the value of 0.06.

Remark In this application, a simple operational demand model, that is designed to illustrate the framework, is used. More advanced models, such as path-size logit or nested logit models, could be used instead if available.

5.2 Mathematical Formulation of EPCTTP

In this section, the Elastic Passenger Centric Train Timetabling Problem (EPCTTP) is presented. The aim of the EPCTTP is to design timetable maximizing the TOC's revenue accounting for the passenger forecasts. Whereas the aim of the original PCTTP was to design timetable maximizing the overall passenger satisfaction (without the fare) and thus, securing the social optimum (the actual choices of the passengers were unknown). The performance of the two models is compared in Section 5.4.3.

The extended model differs from the original one in the following areas:

- **Objective Function** – revenue maximization instead of profit maximization or passenger satisfaction maximization. It seems that the tickets in the used case study are subsidized, hence the resulting profit being negative. Therefore, the optimal solution under the objective of profit maximization would be no operation. That is why the current objective is the revenue maximization. The passengers' objective of satisfaction maximization is captured within the probability prediction.
- **Probabilistic Demand** – the model now includes the previously defined demand forecasting model. The predictions are based on the passengers' satisfaction.
- **Path Representation** – instead of using a general path p and to look for suitable trains in this path, the model is using paths that already have assigned specific trains $j \in J^p$. For a notation convenience, the additional index j is added to a train. It expresses its position within a given path, *i.e.* (ℓ_j, v_j) . To prevent infeasibility of the model through inclusion of infeasible paths (due to the train capacity or infeasible connection), the decision variable τ_{it}^p is in charge of controlling the set of available paths to the passengers (equals to one if the path is included, zero otherwise). This being said, passengers traveling between the same OD pairs might have different paths, *i.e.* the set of paths is now having the group index (i, t) .
- **Ticket Fare** – is now a decision variable.

The EPCTTP model is formulated as follows:

$$\begin{aligned} \max \quad & \sum_{\ell \in L} \sum_{v \in V^\ell} \sum_{s \in S^\ell} o_{\ell v}^s \cdot f_{\ell v}^s, \\ o_{\ell v}^s = & \sum_{i \in I} \sum_{t \in T_i} \sum_{p \in P_{it}} x_{\ell v}^{ps} \cdot n_{it} \end{aligned} \tag{5.5}$$

$$\cdot Pr_{it}^p(w_{it}^p, \delta_{it}^p, \gamma_{it}^p, f^p | d_{\ell v}), \quad \forall \ell \in L, \forall v \in V^\ell, \forall s \in S^\ell, \quad (5.6)$$

$$o_{\ell v}^s \leq W, \quad \forall \ell \in L, \forall v \in V^\ell, \forall s \in S^\ell, \quad (5.7)$$

$$P_{it} = \bigcup_{p=1}^{|P_i|} p \cdot \tau_{it}^p, \quad \forall i \in I, \forall t \in T_i, \quad (5.8)$$

$$f^p = \sum_{j \in J^p} \sum_{s \in S^{\ell_j}} f_{\ell_j v_j}^s, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_{it}, \quad (5.9)$$

$$d_{\ell v} \leq d_{\ell v+1} - 1, \quad \forall \ell \in L, \forall v \in V^\ell : v < |V^\ell|, \quad (5.10)$$

$$d_{\ell v} \in \mathbb{N}, \quad \forall \ell \in L, \forall v \in V^\ell, \quad (5.11)$$

$$f_{\ell v}^s \geq 0, \quad \forall \ell \in L, \forall v \in V^\ell, \forall s \in S^\ell, \quad (5.12)$$

$$f^p \geq 0, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_{it}, \quad (5.13)$$

$$o_{\ell v}^s \geq 0, \quad \forall \ell \in L, \forall v \in V^\ell, \forall s \in S^\ell, \quad (5.14)$$

$$\tau_{it}^p \in (0, 1), \quad \forall i \in I, \forall t \in T_i, \forall p \in P_{it}, \quad (5.15)$$

$$Pr_{it}^p \geq 0, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_{it}, \quad (5.16)$$

Objective function **(5.5)** is maximizing the TOC's revenue that is given as the train occupation $o_{\ell v}^s$ of each train (ℓ, v) on each of its segments multiplied by the fare cost $f_{\ell v}^s$ of train (ℓ, v) on segment s . Constraints **(5.6)** use the logit model to estimate the train occupation. The parameter $x_{\ell v}^{ps}$ indicates whether path p is using train (ℓ, v) on segment s (equals to 1) or not (equals to 0). Constraints **(5.7)** secure that the capacity of a train is not exceeded at any point of its travel. If a train is full at some of the segments, all the paths of any additional passengers using that train at that segment are removed from their choice sets inside of the logit model. Note, that a simple multiplication by the decision variable τ_{it}^p would create a proper behavior within the optimization model, but would lead to wrong predictions of the probabilities. Therefore, constraints **(5.8)** explicitly define those paths that are to be included in the set P_{it} . The decision itself, on which passenger should be restricted, is driven by the objective function. Constraints **(5.9)** calculate the fare to be paid for usage of each path p . Constraints **(5.10)** remove the symmetrical solutions, *i.e.* trains are ordered according to their departure times (ascending). The constraints **(5.11)-(5.16)** are the domain constraints.

Additional constraints, modeling some of the attributes used in the observable part of the utility function, are needed:

$$w_{it}^p = \sum_{j \in J^p: j < |J^p|} w_{it}^{pj}, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_{it}, \quad (5.17)$$

$$\begin{aligned} w_{it}^{pj} &= \left(d_{\ell_{j+1} v_{j+1}} + b_i^{pj+1} \right) & \forall i \in I, \forall t \in T_i, \forall p \in P_{it}, \\ &- \left(d_{\ell_j v_j} + b_i^{pj} + r_i^{pj} + m \right), & \forall j \in J^p : j < |J^p|, \end{aligned} \quad (5.18)$$

$$\delta_{it}^p \geq a_{it} - \bar{a}_{it}^p, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_{it}, \quad (5.19)$$

$$\gamma_{it}^p \geq \bar{a}_{it}^p - a_{it}, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_{it}, \quad (5.20)$$

$$\bar{a}_{it}^p = \left(d_{\ell_{|J^p|} v_{|J^p|}} + b_i^{p|J^p|} + r_i^{p|J^p|} \right), \quad \forall i \in I, \forall t \in T_i, \forall p \in P_{it}, \quad (5.21)$$

$$w_{it}^p \geq 0, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_{it}, \quad (5.22)$$

$$w_{it}^{pj} \geq 0, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_{it}, \\ \forall j \in J^p : j < |J^p|, \quad (5.23)$$

$$\delta_{it}^p \geq 0, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_{it} \quad (5.24)$$

$$\gamma_{it}^p \geq 0, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_{it}, \quad (5.25)$$

$$\bar{a}_{it}^p \geq 0, \quad \forall i \in I, \forall t \in T_i, \forall p \in P_{it}. \quad (5.26)$$

Constraints (5.17) add up the waiting times in all of the transfer stations in path p . Subsequently, constraints (5.18) define the value of the waiting time in the transferring stations. These constraints subtract the arrival time (departure time from its origin station plus the time to get to the boarding station of the passenger plus the time to get to the transfer station) of the origin train at the transferring station plus the necessary minimum transfer time m , from the departure time of the destination train at the transferring station (departure time from its origin station plus the time to get to the transfer station). Note, that the paths where a transfer is not possible will be removed by constraints (5.8). Constraints (5.19) calculate the early schedule passenger delay and the constraints (5.20) calculate the late schedule passenger delay. The actual arrival time of a passenger group to its destination is given by constraints (5.21). Constraints (5.22)-(5.26) are the domain constraints.

The above model would produce a non-cyclic timetable. However, by adding some additional constraints, the model can produce any type of a timetable. In this chapter, two additional timetable types are considered: cyclic and hybrid cyclic. The constraints the additional timetables impose are as shown in Chapter 4.

5.3 Extension of the Heuristic Method

Similarly as in Chapter 4, the EPCTTP formulation is non-linear. Therefore, the same algorithm, with some changes to reflect the novelty of the extended formulation, is used. The changes are related to the value function (revenue maximization based on probabilities instead of deterministic passenger satisfaction maximization), the passenger assignment (user optimum to reflect better passenger behavior instead of system optimum) and new neighborhood moves (for the pricing of the tickets). Since the heuristic is well defined and has been calibrated and validated in Section 4.3, only the differences are discussed in this Section.

The general procedure of the heuristic is the same as in Algorithm 1. The set of the neighborhood moves (Table 4.3) has been extended with one additional move of the pricing scheme. This move selects any train randomly (according to the distributions in the first part of Table 4.3) and subsequently, it selects a random segment s traversed by the selected train from a uniform distribution $\mathcal{U}(1, |S^\ell|)$. In the modification stage, it first decides if the price has to be increased or decreased (with a uniform probability of 50:50%) and subsequently, by how much it will be changed ($\mathcal{U}(1, 5)$ in monetary units). As this move is valid for any train, it is not further conditioned in the application stage. At the beginning of the algorithm, the prices are set to the values used by Israeli Railways.

Algorithm 3: Passenger Assignment

Data: $C, I, L, n_{it}, P_{it}, S^\ell, T_i, V^\ell$
Result: revenue

```

1 begin
2   for  $i \in I$  do
3     for  $t \in T_i$  do
4       for  $p \in P_{it}$  do
5         calculate  $Pr_{it}^p(w_{it}^p, \delta_{it}^p, \gamma_{it}^p, f^p | d_{c'})$ 
6         assign  $n_{it} \cdot Pr_{it}^p$  passengers to the trains in the path  $p$ 
7   run  $\leftarrow true$ 
8   while run do
9     run  $\leftarrow false$ 
10    sort overflowing trains  $(\ell, v)$  according to their occupation descending
11    for  $\ell \in L$  do
12      for  $v \in V^\ell$  do
13        for  $s \in S^\ell$  do
14          if  $o_{\ell v}^s > C$  then
15            sort passengers entering the train on the segment  $s$  by revenue
16              ascending
17            for these passengers do
18              remove  $(i, t)$  from the current path
19              update its probabilities
20              run  $\leftarrow true$ 
21              if  $o_{\ell v}^s \leq C$  then
22                break
23    if run then
24      re-assign passengers
25  calculate revenue
    
```

Since the objective function has changed to revenue maximization and the goal is to

model the passenger behavior as realistically as possible, also the passenger assignment has changed as shown in Algorithm 3. The assignment is now using a First Come First Serve (FCFS) policy. At the beginning, the probabilities of all paths of all passengers are predicted. The passengers are then assigned to the trains in their paths with their probabilities in a non-capacitated fashion. Afterwards, the algorithm enters a while loop that serves to resolve any capacity issues. It iterates through all overflowing trains (*i.e.* those exceeding their capacity) that have been sorted according to their descending occupation. If a train exceeds its capacity on any of its segments, the passengers that have entered this train on this specific segment are sorted ascending according to the overall revenue that they bring to the company (the FCFS policy). Even though the passengers do not behave this way (they would sort themselves randomly), this policy is in line with the objective of revenue maximization. Afterwards, the algorithm removes these passengers one by one until the occupation of this train on this segment does not exceed its capacity. For each of the removed passengers, the path that they were using to travel on the segment of the concerned train is removed from their choice set and the probabilities of their remaining paths are recalculated. Once all the conflicts (of this iteration of the while loop) are resolved, the algorithm again re-assigns all the passengers to the trains in a non-capacitated fashion from scratch (the new probabilities of the removed passengers affect other passengers and trains). The algorithm terminates when there are no capacity issues found in a one single iteration of the while loop. Lastly, it provides as a result the overall revenue calculated according to Equation 5.5.

5.4 Case Study

The same case study (of Israeli Railways), as in the previous Chapter, is used to show the performance of the EPCTTP model. The aim is to evaluate the effect of different timetables on the revenue and what is the potential increase in the revenue, when the timetable design is integrated with ticket pricing. The exact procedures, assumptions and information about the data can be found in Appendix B.

The EPCTTP is solved using the extended SA heuristic for the following timetables:

- **IR 13/14** – the departure times are fixed to the ones of IR timetable of 13/14. Since the departure times are fixed, its solution serves as the benchmark for comparison of the performance of the other timetables.
- **Non-Cyclic** – no specific rule on the departure times is enforced.
- **Cyclic** – the departure times have to be cyclic according to constraints (4.2).
- **Hybrid Cyclic** – the departure times have to comply with constraints (4.8) - (4.13).

	IR 13/14	cyclic	hybrid cyclic	non-cyclic
revenue [NIS]	4 865 777	5 083 828	5 299 618	5 269 661
revenue gain [NIS]	–	+218 051	+433 841	+ 403 884
market share [%]	73.61	75.47	77.96	–
# transported passengers	92 779	95 127	98 267	–
avg. train occupation	116	121	126	–
median train occupation	84	90	98	–
solution time [sec]	7	174 897	164 828	167 939

Table 5.1: *Computational results of the various timetables for 2008 situation without pricing*

	IR 13/14	cyclic	hybrid cyclic	non-cyclic
revenue [NIS]	7 150 254	7 490 054	7 896 806	7 905 615
revenue gain [NIS]	–	+339 800	+746 552	+755 361
market share [%]	70.63	72.78	75.56	75.59
# transported passengers	136 981	141 143	146 535	146 606
avg. train occupation	172	180	189	189
median train occupation	130	141	159	157
solution time [sec]	11	287 531	295 501	298 114

Table 5.2: *Computational results of the various timetables for 2014 situation without pricing*

The revenues of each type of timetable are given in New Israeli Shekel (NIS). At first, the problem is solved without pricing and subsequently, it is solved with pricing. Each time, the heuristic is given as an initial solution the previously found timetables. All of the tested instances have been run in Java on a Unix server with up to 24 cores of 3.33 GHz and 62 GiB RAM.

5.4.1 Results without pricing

The results of the extended EPCTTP model without pricing can be found in Tables 5.1 and 5.2. Therefore, the prices in the model are fixed to those used by Israeli Railways (obtained from IR’s website *www.rail.co.il*). The columns represent the different types of timetables (as described above) and the rows show the values of various attributes. The concerned attributes are: the revenue, the revenue gain as compared to the initial IR 13/14 timetable, the market share (percentage of passengers transported by IR), the number of passengers transported by IR, the average and the median train occupation and the solution time of the heuristic.

Both tables show that taking into account passenger behavior leads to a better perform-

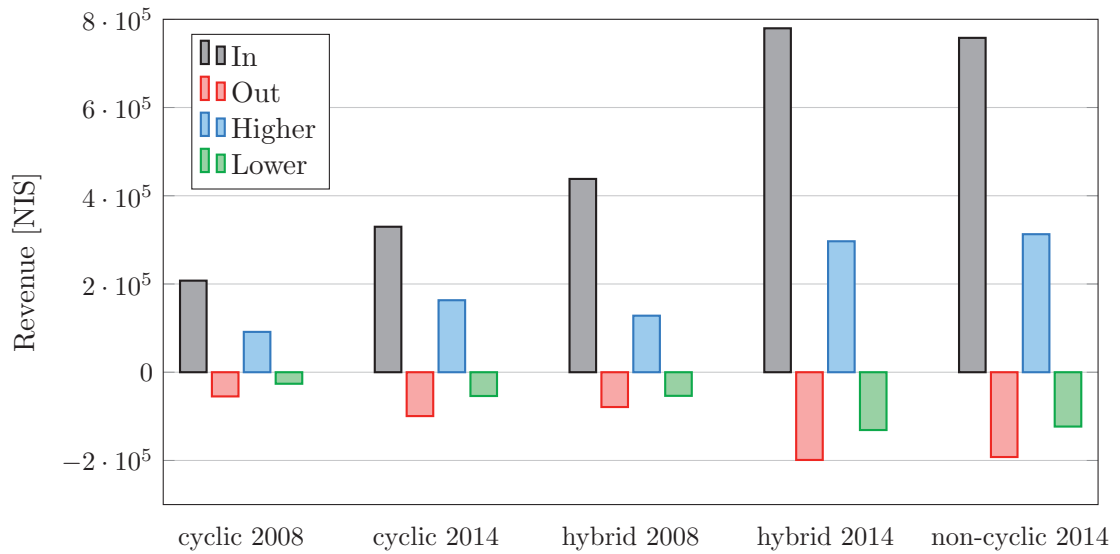


Figure 5.1: *Difference in composition of passengers for the various timetables*

ing timetables (in all of the relevant attributes). The EPCTTP based timetables were able to attract back some passengers from the competition and thus, increase the IR's market share. The average revenue increase is 5% and 10% for the cyclic and hybrid cyclic timetable respectively.

The hybrid cyclic timetable was used as the initial solution for the non-cyclic one in the 2008 situation. However, it has failed to find a better solution than the hybrid cyclic one. In the 2014 situation, it was able to improve the solution only marginally. The marginal differences are caused by the randomness of the heuristic approach. The similarity, in the solutions of the two types of timetables, shows that the concept of the hybrid cyclic timetable can diminish any impact of the cyclicity constraints on the performance of the timetable (the impact being the differences between a cyclic and a non-cyclic solution).

The average ratio between the cyclic and the non-cyclic trains, in the hybrid cyclic timetable, is around 50:50%. The solution time of the heuristics was on average 2 (for 2008) and 3 (for 2014) days.

In order to better understand, what is the cause of the additional revenue, the difference in composition of passengers per timetable as compared to the IR 13/14 timetable is plotted in Figure 5.1. This Figure shows the revenues generated by 4 different groups of passengers: *in* – the ones who were not using IR in the original timetable, *out* – the ones who were using IR in the original timetable and left, *higher* – the passengers who stay and pay more, *lower* – the passengers who stay and pay less. The sum of these groups per timetable provides the value of revenue gain. It can be seen that the main source of the additional revenue across timetables is the new coming passengers. However, we can see that in the hybrid cyclic and non-cyclic timetables for the situation in 2014, the

	cyclic		hybrid cyclic		non-cyclic	
	2008	2014	2008	2014	2008	2014
revenue [NIS]	5 256 959	7 767 140	5 461 559	8 229 227	–	8 259 557
revenue gain [NIS]	+173 132	+277 087	+161 942	+332 421	–	+353 942
market share [%]	76.31	74.05	76.87	75.99	–	76.32
# transported passengers	93 848	139 451	96 886	147 373	–	148 017
avg. train occupation	127	188	128	194	–	196
median train occupation	95	148	99	156	–	157
solution time [sec]	97 105	185 560	89 044	197 695	–	182 810
overall revenue gain [NIS]	+391 183	+616 887	+595 783	+1 078 973	–	+1 109 303

Table 5.3: *Computational results of the various timetables with pricing*

strategy also includes preference to the more paying passengers.

5.4.2 Results with pricing

The results of the EPCTTP model with pricing can be found in Table 5.3. The prices are now decision variables with their initial values set to those of IR. The revenue gain is now the additional revenue as compared to the solution of the same timetable without pricing. The overall revenue shows the additional profit as compared to the original IR 13/14 timetable.

The pricing was able to further improve the revenue of the timetables. All timetables increased the ridership with an exception of the hybrid cyclic one for the 2008 situation. However, it has still managed to achieve a higher profit. This is due to the fact, that the passengers who left were generating lesser profit than the ones who came in (Figure 5.2(e)). The additional increase in the revenues by pricing is up to 5%. The hybrid cyclic timetable was used as the initial solution for the non-cyclic one in the 2008 situation. However, it has failed to find a better solution than the hybrid cyclic one.

In order to analyze the pricing scheme, various graphs are plotted in Figure 5.2. At first, we look at the pricing variations by location – Figures 5.2(a) and 5.2(b). Both plots show the overall increase/decrease in price per segment of the network as compared to the original prices set by Israeli Railways. The x -axis represents the segments by volumes of passengers traveling on them. For low demand segments the pricing can go either way, whereas for the high demand segments the prices go strictly up. The boundary between the two pricing strategies is around 20 000 passengers per segment.

Subsequently, we look at the price variations based on the time of the day – Figures 5.2(c) and 5.2(d). Both plots show the overall increase/decrease in price per hour in the network as compared to the original prices set by Israeli Railways. The figures exhibit clear patterns on how to adjust the pricing: increase the price for high demand density

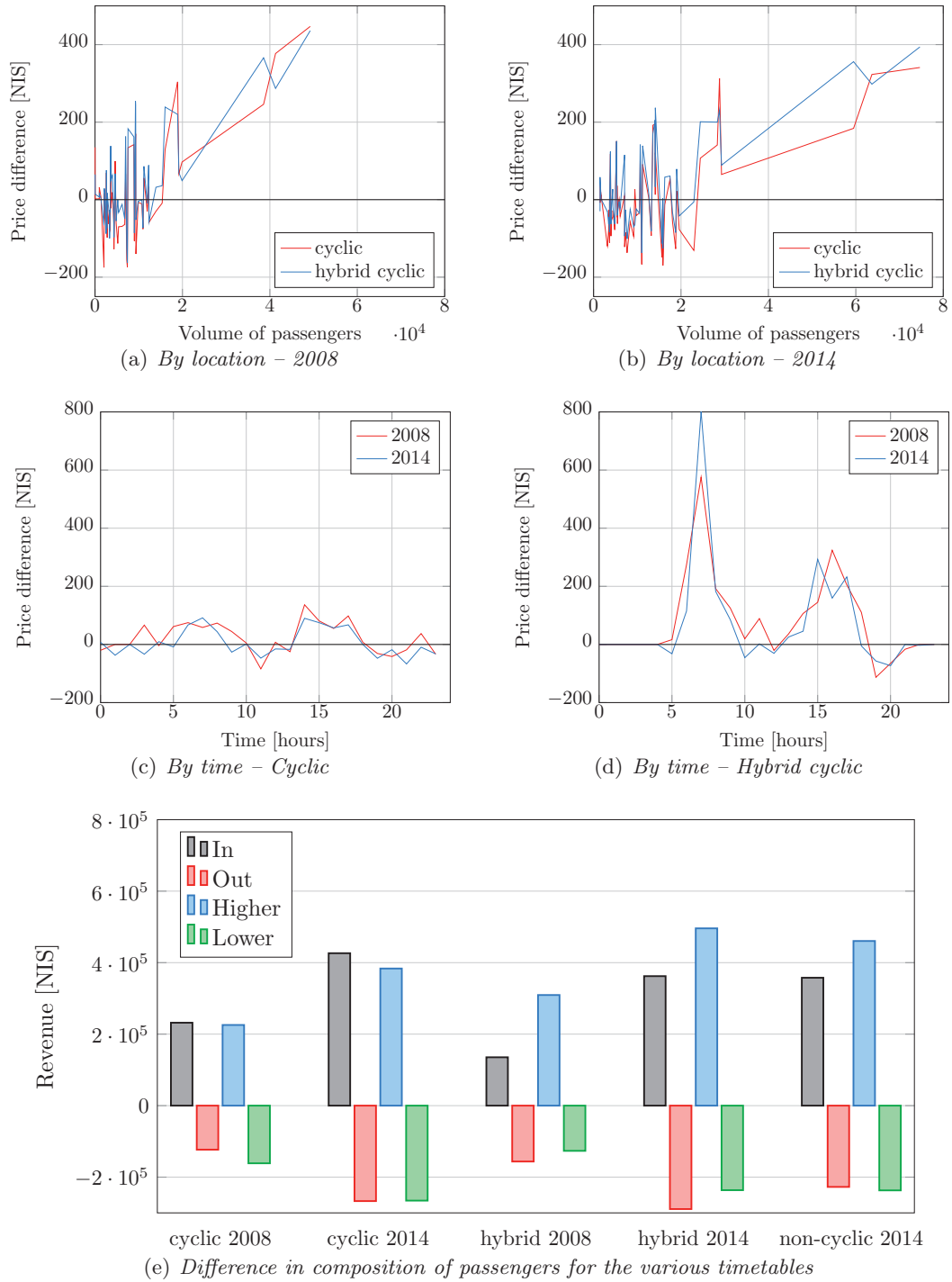


Figure 5.2: Pricing analysis

periods and decrease the price for low demand density periods. Since the morning peak is more dense, its prices are higher than of the evening peak (the evening demand is more spread). The price decrease, as compared to the increase in peak hours, is lower. This might be due to the fact that during the off-peak hours also the supply is more scarce, *i.e.* the prices can be higher. The cyclic timetable is having less extreme changes than the hybrid cyclic one. This is due to the fact that the cyclicity makes the trains more spread. Therefore, the results in Figure 5.2(c) are somewhat more aggregate (the hours contain a larger mix of trains with increased and decreased prices).

Finally, to understand the changes in the served passengers, the differences in the composition of the passengers for various timetables as compared to their previous versions without pricing are plotted in Figure 5.2(e). The legend is the same as in Figure 5.1. It can be seen, that as compared to the timetabling without pricing, the higher paying passengers are now having a larger contribution to the revenue gain. In the hybrid and non-cyclic timetables, the share is even larger than of the new coming passengers. The revenue loss of leaving and less paying passengers is now larger. These passengers are most likely left out or less paying, in order to free the space in the trains desired by the higher paying passengers. This behavior is in line with the objective of maximizing revenue, but might not be desired by public owned operators. Therefore in the next Section, it is further investigated what is the impact of this approach on the passengers' satisfaction.

5.4.3 Maximize satisfaction or maximize revenue?

Maximizing revenues is a natural objective in a competitive environment. However, in many countries, particularly in Europe, there is little or no competition. Moreover, many railway operators are subsidized by public money, and must focus on public services as well. Therefore, the revenue maximization might be considered controversial. In order to analyze the situation, two approaches are evaluated against each other: one timetable designed to maximize the satisfaction of the passengers (Chapter 4), and one timetable designed to maximize revenues, as described in this Chapter. In order to do so, the timetables (*i.e.* the decision variables $d_{\ell v}$) created in Chapter 4 (through the passenger satisfaction maximization) are given as a fixed input to the probabilistic model of EPCTTP. The comparison consists in the resulting revenue, satisfaction and number of transported passengers per timetable in Table 5.4.

In this Table, (*s*) denotes satisfaction maximization approach, (*r*) denotes the revenue maximization approach and (*p*) denotes the presence of prices generated by the pricing problem. If (*p*) is missing, the original prices given by IR are used. Note that in the 2008 situation, the hybrid cyclic timetable was not designed using the satisfaction approach (due to the insignificant differences in satisfaction among the cyclic and non-cyclic timetables in 2008 (Section 4.4.1)). The non-cyclic timetable in 2008 with pricing

	revenue [NIS]	satisfaction [NIS]	# transported passengers
cyclic 2008 (s)	4 950 614	-10 264 108	93 580
cyclic 2008 (r)	5 083 827	-10 314 244	95 127
hybrid 2008 (r)	5 299 618	-10 396 741	98 267
non-cyclic 2008 (s)	5 043 234	-10 281 466	95 438
cyclic 2014 (s)	7 287 127	-15 630 858	138 778
cyclic 2014 (r)	7 490 054	-15 680 300	141 143
hybrid 2014 (s)	7 526 215	-15 647 618	142 228
hybrid 2014 (r)	7 896 806	-15 920 860	146 535
non-cyclic 2014 (s)	7 452 564	-15 627 362	141 918
non-cyclic 2014 (r)	7 905 615	-15 952 986	146 606
cyclic 2008 (p)(s)	5 142 573	-10 311 044	95 396
cyclic 2008 (p)(r)	5 256 959	-10 399 474	96 196
hybrid 2008 (p)(r)	5 461 560	-10 564 349	96 886
cyclic 2014 (p)(s)	7 596 212	-15 686 365	143 135
cyclic 2014 (p)(r)	7 767 140	-15 955 037	143 612
hybrid 2014 (p)(s)	7 821 338	-15 855 025	143 345
hybrid 2014 (p)(r)	8 229 227	-16 174 935	147 373
non-cyclic 2014 (p)(s)	7 749 755	-15 803 502	143 227
non-cyclic 2014 (p)(r)	8 259 557	-16 166 223	148 017

Table 5.4: *Differences between passenger satisfaction (s) and revenue (r) oriented timetable designs*

is not included as it did not improve the revenue and its fares were never reported.

The main observation from the results is that even though the objectives were different, the resulting passenger satisfaction is more or less similar. Indeed, when maximizing the revenue, the passengers need to be satisfied, in order to take the train. The main difference, between the two approaches, is the generated revenue. This is again in line with the objectives: the objective of revenue maximization takes care of both revenue and satisfaction, whereas the other approach only cares about the satisfaction. Notable to mention, that the presence of pricing did not distort the average values of the satisfaction. Its values are similar with and without pricing. The cause of it is most likely the reduced fare for some of the passengers.

It could be observed that the satisfaction is now similar across conceptually different timetables and that it is caused by the opt-out option of the competitor. However, given that the number of passengers is more or less the same between the two concepts of the design, it proves that the somehow “capitalist” concept of revenue maximization is not anti-passenger and that it is suitable for the public operators as well. This should encourage operators to consider the new approach proposed in this research to design their timetable.

5.5 Summary

In this Chapter, the passenger centric train timetabling approach has been further extended with the concept of the competitive market by accounting for elasticity of the passenger demand. A competing operator has been included into the market, so that the passengers are not a captive in the system. This framework allows for a prediction of the realized demand, which subsequently allows to calculate the revenue of the operator. In the second phase, the proposed timetabling problem has been integrated with the ticket pricing problem.

The results of the case study show that accounting for the behavioral dimension of the problem has a significant impact on the generated revenue. It has been shown on the case study that the passenger oriented timetabling can be combined with the ticket pricing. The resulting pricing strategies suggest higher prices for large volumes of demand by location and time. The two together can further increase the revenue up to an additional 15%. Given that the best possible competitor has been used in the case study, the gain is expected to be even larger, when this is not the case. Lastly, the empirical evidence, that the concept of revenue maximization is in line with passengers’ objective of their satisfaction maximization, has been provided. Therefore, this concept is suitable for public operators as well.

6

Conclusion

In this thesis, the impact of the passenger behavior on the performance and on the design of various timetables has been studied. The empirical evidence presented in this thesis, indeed shows that it is important to take into account the passengers and their wishes.

In Chapter 3, the passenger's behavior has been quantified into a single variable of passenger satisfaction. Using this concept, a new planning phase of the passenger railway service has been proposed: the Passenger Centric Train Timetabling Problem. The aim of this problem is to maximize the Train Operating Company's profit while maintaining a certain level of the passenger satisfaction. Therefore, it is up to the company itself to select the trade-off ratio. From the results of the case study of S-train network of Canton Vaud in Switzerland, it has been concluded that the passenger centric approach is somewhat more important for larger volumes of demand and less important in situations, where supply is much larger than the demand. The case study has uncovered as well the quantitative difference between the two well-known timetables. It shows that the cyclic timetable is indeed less flexible than the non-cyclic one. This conclusion served as a motivation for the subsequent Chapter.

In Chapter 4, different timetable designs were proposed and evaluated. The goal was to remove the gap between the value of passenger satisfaction of the cyclic timetable and the non-cyclic one. In other words, the goal was to diminish the impact of the cyclicity constraints. The new designs were based on two attributes: regularity (cyclic)

and flexibility (non-cyclic). The regularity has been taken care of by the design and the flexibility was evaluated in the form of the passenger satisfaction. It has been shown, on the case study of Israeli Railways, that a hybrid cyclic timetable is able to diminish the impact of the cyclic constraints. This type of timetable schedules part of the trains in the cyclic fashion and the other trains in a non-cyclic manner. The purpose of the cyclic trains is to offer the base service and the non-cyclic trains are used to strengthen the service in high demand periods. The combination also allows for passengers to select by themselves, which type of service they prefer.

In Chapter 5, the concept of the passenger centric timetable design has been extended with the actual choices of the passengers and the railway market structure. This approach allows for a realistic forecast of the train occupation and therefore, it allows for the estimation of the revenue. It also allows for the integration of the pricing problem with the timetable design itself and thus, it leads to a further increase in the revenue of the operator. The analysis of the results, on the case study of Israeli Railways, further confirms that the passenger centric timetable attracts more passengers and that the pricing scheme can further control the composition of the passengers. In other words, the pricing scheme increases the prices of high demand periods or locations and therefore, the passengers that have higher need (either travel longer distance or their satisfaction is already very low) get the priority. The revenue based optimization has been compared to the satisfaction based optimization. The comparison shows that the two goals are in agreement and that the pricing scheme can improve the level of service.

One aspect needs to be emphasized: the results are over estimating the input. The passenger centric timetabling introduces the simplifying assumption of not looking at the potential conflicts among the trains and leaves them to the traditional train timetabling models. Therefore, the results are showing the maximum impact of the passenger centric approach, which is clearly not the case in practice. Especially in the Israeli case, where several trains may meet at Tel Aviv station. This could cause a bottleneck in the network. Beside this, the fare structure used throughout this thesis, is more suitable for commuting services such as the S-train network in Canton Vaud. A more sophisticated fare structure is recommended for networks similar to the one of Israeli Railways. The last assumption, that might be considered controversial, is the decision of which passenger gets priority within the passenger assignment in the case of a tie. In the elastic model (which is the one that is the closest to the real behavior), the passenger who was paying higher fare got the priority over the other conflicting passengers. A more realistic assignment, in the case of passenger congestion, is suggested as a future extension.

Overall, the main contribution of this thesis is the inclusion of the passenger behavior in the timetable design. This new design improves the level of service which has been long needed. The railways and their operation have been neglected since the car-boom in the 60's, which projected into the continuously decreasing shares of this mode. Even though that the competition in the transportation market has since increased and evolved into

more sophisticated services, the evidence from the liberalized railway markets shows that the railways can become attractive mode of transport and be preferred by the passengers. Its cause being the increased level of service offered by the competing train operators.

The level of service can be further improved by taking into account the specifics of each passenger. In this research, the passengers were considered to be homogeneous. However, in the real world, this is not the case. Each person has a different behavior. This behavior is incorporated in the discrete choice model through the taste parameters β . These parameters may vary across the population. The heterogeneity can be treated as a possible future extension. Subsequently, this would allow for an introduction of different class fares and to further improve the revenue of the operator.

However, not only the passengers can benefit from the passenger centric approach. Since now the operators know the expected train occupation, they can better plan their fleet assignment and composition. The proposed passenger centric approach can be integrated into the rolling stock planning problem and achieve better fleet utilization and planning. Moreover, the operators can estimate the value of each scheduled train in the planned timetable and hence assess the correct price to offer to the infrastructure manager for its utilization. Last but not least, the passenger centric approach can go back to the line design and change it. Instead of designing the lines based on the Origin-Destination flows, the passenger satisfaction can be used as a better measure. It can also provide an insight on the general network guidelines, *i.e.* it can be used to categorize the various network layouts (hub-and-spoke, star, main/feeder lines, *etc.*) in a similar way, it has been used in Chapter 4 to generalize the timetable type. Last but not least, the passenger centric approach is transferrable to the bus operation. The passengers are facing the same decisions and given that the buses do not experience infrastructure conflicts, it can be directly transferred without any changes. Moreover, this framework can be applied to any scheduling system containing a human factor: airline scheduling, university course scheduling, worker shift scheduling, *etc.*

Overall, the basic operation based planning of railways is in the state-of-the-art and the future lies in the modeling of the consumer and its behavior. It is expected that not only behavioral models from the discrete choice theory will be used, but that also the booming methodologies, such as advanced analytics comprising in the machine learning, will be used. Indeed, as the mobility and standards of living increase, the pressure on level of service increases as well. Moreover, many insights on the consumers' behavior can be already found in the big data that will be used throughout the future planning.



Data Description of S-train Network of Canton Vaud, Switzerland

The data used in this case study were taken directly from the SBB's website (www.sbb.ch) and from the SBB's annual report for 2013 (Swiss Federal Railways (2013)). However, not all of the data required to solve the PCTTP were available and thus, some assumptions and approximation techniques have been used. The synthetic data consists in the passenger demand (OD flows estimated based on demographic data and observation, desired arrival times estimated based on the SBB's report and statistical theory, volume of the passengers estimated on demographics and statistical theory), the ticket fare distribution (several fare reduction schemes exist in Switzerland, distributed using simple assumption), maximum number of train units per train (based on observation) and the operator's cost structure (based on the aggregated value from the SBB's report and broken down by external knowledge).

An algorithm in Java has been coded, in order to find a set of possible paths between each OD pair. The algorithm allowed maximum of 3 consecutive lines to get from an origin to a destination. The algorithm enumerates all possible paths (using at most 3 trains) between each origin and destination. The algorithm implicitly removes the paths that do not make sense, *e.g.* when going from *Payerne* to *Yverdon-Les-Bains*, it would not make sense to have a transfer in *Allaman etc.* In total there are 660 paths in the network among the 156 OD pairs.

The travel times have been extracted from the SBB's website and they include stopping

times at the stations that are not part of the case study, thus the distinction between the slow and fast services remains part of the problem. The minimum transfer time between two trains has been set to 4 minutes. The values of used β parameters are as described in Section 3.1.2.

A.1 Operator

SBB is operating the Stadler Flirt train units on the lines $S1$, $S2$, $S3$ and $S4$. In this case study, the fleet has been homogenized and thus, this type of train is also used for the rest of the lines. The capacity of this unit is 160 seats and 220 standing people. The operating cost has been taken from the SBB's annual report for 2013 (Swiss Federal Railways (2013)), where a regional service has a cost of 30 CHF of a train per kilometer. Since no further details have been provided, the cost has been broken down using the external knowledge. From a project for a Swiss public transport operator, it was known that the driver's salary makes up more than a half of the cost, *i.e.* in the "worst" case, it is equal to a half (the higher the cost of the driver the cheaper the operating cost of additional train units thus, the worst case). This leads to an operating cost of 15 CHF per train unit per km. The length of the lines in kilometers has been estimated using Google Maps. The maximum amount of train units per train is 2 (as SBB never uses more units). The amount of train units per train remains the same along the line, but it might change at the end stations (the rolling stock management is not in the scope of this research and is left to be dealt with by the Rolling Stock Problem).

The ticket prices have been taken directly from the SBB's website. In Switzerland, many people have the so called Abonnement General (AG) or the half-fare card. With AG, a passenger pays yearly fee and gets a free access to almost all public transportation in Switzerland. The half-fare card also involves a yearly fee (significantly smaller than AG) and gives access to a half price tickets for public transportation. In this case study, the half-fare prices were applied to all passengers. This approach balances the prices between AG users and normal users (normal user does not possess the AG or the half-fare card and thus, pays the full price).

A.2 Passengers

The total amount of passengers in the network has been estimated in the following manner: the population of Switzerland is 8 211 700 habitants and the population of Canton Vaud is 755 369 habitants, which leads to a rough ratio of 1:10. Applying this ratio to a reported amount of passenger journeys per day by Swiss Federal Railways (2013) (in total one million for the whole SBB network), we arrive to a demand volume

of 100 000 passenger journeys per day in canton Vaud. However, not all of these journeys are being realized using S-trains. Since almost all trains in Canton Vaud have to pass through its capital city *Lausanne*, we can derive the ratio, between the S-trains and other class trains passing through *Lausanne*, of 40:60 percent, which leaves us with a 40 000 passenger journeys per day using S-trains in Canton Vaud. Furthermore, the report of SBB provides hourly distribution of passengers on regional services from Monday to Friday. According to this report, 25 percent of the journeys are being realized in the morning peak hours, which gives us approx. 10 000 passenger journeys in the morning peak hours in the S-train network of Canton Vaud.

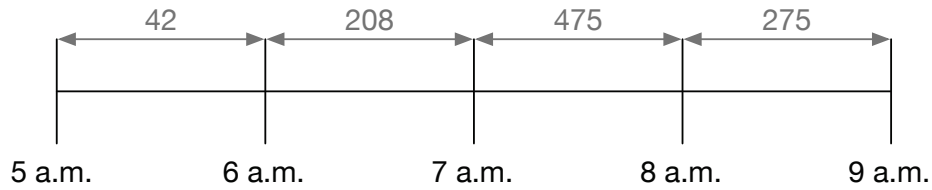


Figure A.1: *The hourly distribution of passenger groups*

In order to ease the size of the generated lp file(s), the passengers have been split into 1 000 passenger groups (indices (i, t)) of varying sizes. These groups have been divided into hourly rates (Figure A.1) according to the report of SBB and smoothed into minutes using non-homogenous Poisson process. Since a concept of a desired arrival time to the destination is being used, the generated arrival time at the origin station has been shifted by adding up the shortest path travel time between the OD pair to the destination of the passengers.

In order to generate realistic OD flows (index i), we consider the following probabilities:

- $p(D = 7) = 0.5$ – probability of a destination being *Lausanne*
- $p(D = 8) = 0.2$ – probability of a destination being *Renens*
- $p(D = other) = 0.3$ – probability of a destination being other than *Lausanne* or *Renens*
- $p(O = any) = 1/12$ – probability of an origin being any station (except the already selected destination)

Since *Lausanne* is the biggest city in the Canton with all lines, except the lines *13* and *14*, passing through it, it has the largest probability of being a destination (many people also use *Lausanne* as a transfer point to higher class trains). The city with the second highest probability is *Renens*, because it is the closest station to one of the biggest universities in Switzerland and from the network diagram (Figure 3.3), we can see that most of the lines stop there, which suggests high demand. The rest of the stations have equal probability of being a destination ($0.3/11$), which is rather small as in the morning

peak hours people travel towards their work/school in big cities. On the other hand, the probability of being an origin is uniformly distributed and dependent on its destination (origin cannot be the same as a destination). The final probability $p(O = o, D = d)$ for every OD pair can be seen in Table A.1.

In order to reach the total demand, the average size of a group should be $\rho =$ the total demand divided by the number of groups. In the current scenario $\rho = 10000/1000 = 10$. In this study, 3 different classes of groups are used: small, medium and large. The size of the small group is drawn from the uniform distribution $\mathcal{U}(1, 0.6\rho)$ and applied to OD pairs with a probability $p(O = o, D = d) \in [0, 1.5)\%$. The size of the medium group follows $\mathcal{U}(0.6\rho + 1, \rho)$ and is applied to OD pairs with a probability $p(O = o, D = d) \in [1.5, 3)\%$. The largest group size follows a distribution $\mathcal{U}(\rho + 1, 2\rho)$ and is applied to a probability $p(O = o, D = d) \in [3, 4.5)\%$. In total there are 10 077 passengers in the network for the current situation (the deviation from the estimated value of 10 000 is due to the randomness).

A.3 Path Representation

In order to better understand what a path is, consider the following example of going from *Allaman* (Station 10) to *Villeneuve* (Station 4) in the network of the case study (Figure 3.3). The set P_i (where i is the index of the given OD pair, in this case $i=134$) consists of 4 paths p . Each path p consists of the lines (L^p) ordered as they are traversed. The sets are as follows (numbered as in Table 3.1):

$$\begin{aligned} L^1 &= \{ 5 \} \\ L^2 &= \{ 7, 1 \} \\ L^3 &= \{ 7, 1 \} \\ L^4 &= \{ 7, 14, 1 \} \end{aligned}$$

There are two ways of transferring between lines 7 and 1: either the transfer is made in *Renens* or in *Lausanne*. The information of where the transfer is made can be extracted either from parameter $r_i^{p\ell}$ or parameter $b_i^{p\ell}$. The parameter $r_i^{p\ell}$ is the in-vehicle time of each line in the path. Note that the line ID is now value in the set and that the indexing is within a set, thus $\ell \in L$ is different from $\ell \in L^p$.

$$\begin{aligned} r_{134}^1 &= \{ 58 \} \\ r_{134}^2 &= \{ 14, 49 \} \\ r_{134}^3 &= \{ 21, 42 \} \\ r_{134}^4 &= \{ 37, 12, 17 \} \end{aligned}$$

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	0	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.041666667	0.016666667	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727
2	0.002272727	0	0.002272727	0.002272727	0.002272727	0.002272727	0.041666667	0.016666667	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727
3	0.002272727	0.002272727	0	0.002272727	0.002272727	0.002272727	0.041666667	0.016666667	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727
4	0.002272727	0.002272727	0.002272727	0	0.002272727	0.002272727	0.041666667	0.016666667	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727
5	0.002272727	0.002272727	0.002272727	0.002272727	0	0.002272727	0.041666667	0.016666667	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727
6	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0	0.041666667	0.016666667	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727
7	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0	0.016666667	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727
8	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.041666667	0	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727
9	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.041666667	0.016666667	0	0.002272727	0.002272727	0.002272727	0.002272727
10	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.041666667	0.016666667	0.002272727	0	0.002272727	0.002272727	0.002272727
11	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.041666667	0.016666667	0.002272727	0.002272727	0	0.002272727	0.002272727
12	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.041666667	0.016666667	0.002272727	0.002272727	0.002272727	0	0.002272727
13	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.002272727	0.041666667	0.016666667	0.002272727	0.002272727	0.002272727	0.002272727	0

Table A.1: *Origin – Destination probabilities*

APPENDIX A. DATA DESCRIPTION OF S-TRAIN NETWORK OF CANTON VAUD,
SWITZERLAND

Segment	Origin	Destination
1	Payerne (1)	Palézieux (2)
2	Palézieux (2)	Puidoux-Chexbres (3)
3	Puidoux-Chexbres (3)	Vevey (6)
4	Villeneuve (4)	Montreux (5)
5	Montreux (5)	Vevey (6)
6	Vevey (6)	Lausanne (7)
7	Puidoux-Chexbres (3)	Lausanne (7)
8	Lausanne (7)	Renens (8)
9	Renens (8)	Morges (9)
10	Morges (9)	Allaman (10)
11	Renens (8)	Cossonay (11)
12	Cossonay (11)	Yverdon-les-Bains (12)
13	Cossonay (11)	Vallorbe (13)

Table A.2: *List of segments used in the case study*

Since the decision of departure times of each train $d_{\ell v}$ is related to the starting station of each line, we also need to know the traveling time from the origin of the line to the embarking station of a passenger $b_i^{p\ell}$.

Each path p can be realized with different trains that have different departure times. The decision $y_{it\ell v}^p$ relates the exact trains a passenger is taking in her path.

In order to verify that the capacity of a train is not exceeded, we need to measure train occupancy between any two stopping stations. This is done by using segments. Table A.2 shows all the segments in the case study. Each line consists of a set of segments S^ℓ (visible in Figure 3.3). For instance line 1 (from *Yverdon-les-Bains* to *Villeneuve*) has the following segments $S^1 = \{12, 11, 8, 6, 5, 4\}$.

B

Data Description of Israeli Railways

The data used in this study were obtained from the IR's website (www.rail.co.il/EN) and from other studies concerning the IR's network (Kaspi and Raviv (2013)). An algorithm in Java was coded, in order to find a set of all possible paths between each OD pair. The algorithm allows for a maximum of 3 consecutive lines to get from an origin to a destination. The algorithm iterates through all OD pairs, where at first it considers the paths that consist of a single line and then the paths that would transfer from the currently selected line up to two other lines. The transfer from one line to another can be made only at one of the designated transfer points (there are 7 recommended interchange stations in the network of Israel – Figure 4.5). Note that the fact, that a transfer is actually possible depends on the operated timetable. Therefore, some paths might be eliminated later on by the PCTTP model itself. When all possible paths are generated, the algorithm removes those paths that a passenger would not consider (note that these rules are related to the network layout of Israel and might differ for other case studies):

- paths that consist of several lines including a direct line between the given OD pair, where both options travel on the same infrastructure (*i.e.* the passenger would rather stay on the direct line instead of transferring to another line).
- paths that consist of several lines, where two of them can reach the given destination. Changing one train to another, when both of them are going to the same destination would not make sense (the same does not happen for the origin).

- paths that take 25% longer generalized time (sum of in-vehicle-times and transfer penalties) than the shortest possible path.
- paths that consist of redundant transfers, *i.e.* transferring from one line to another line that covers the same stations.

Each passenger is having one extra path that represents their shortest path between an origin and their destination, when using the first scheduled train after the planning horizon. This path represents a penalty of not being served. The largest number of paths between an origin and a destination is 73 and the total amount of paths in the network is 21 469.

The traveling times have been extracted from the IR’s website along with the dwell times at stations that remain fixed (as of the timetable 2013/14). The minimum transfer time is set to 4 minutes as in Kaspi and Raviv (2013). The VOT of commuters in Israel as of the year 2012 is 21.12 New Israeli Shekel (NIS)/hour (the updated value was given to us by the author of Shiftan et al. (2008)). The β parameters and their values are as follows: $\beta_W = -2.5$ (Wardman (2004)), $\beta_T = -10$ (de Keizer et al. (2012)), $\beta_E = -0.5$ and $\beta_L = -1$ (Small (1982)).

B.1 Passenger

The OD flows were kindly provided by Mor Kaspi and Tal Raviv, who have cleaned the ticket selling machines’ data for the year 2008 and produced the flows of an average working day in Israel. They have used this data in their study Kaspi and Raviv (2013). The OD matrix consists in hourly passenger rates between 6 a.m. and 1 a.m. The flows were smoothed into minutes by using non-homogenous Poisson process, where the hourly flows per OD pair were used as the arrival rate variable. Since the schedule passenger delay is related to the destination, the time that it takes to get from an origin to a destination using the shortest path has been added to the generated time of the flow (if the path consisted of transfers, the perfect connection was assumed, *i.e.* only the minimum transfer time without any additional waiting time at the transferring stations). In total there are 1 505 out of 2 162 OD pairs with 126 036 passengers.

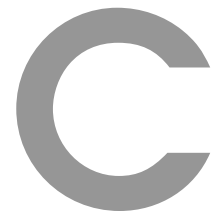
B.2 Operator

As no information about the rolling stock fleet of IR is available, the following assumptions were introduced:

- The fleet is homogenous.

- A train unit has a passenger capacity of 250.
- Each train can consist in up to 2 train units.
- The number of train units remains the same between the start and the end station of a train.

In order to verify that the assumed train capacity is reasonable, the un-capacitated PCTTP model has been solved for the IR 13/14 timetable for the 2008 situation. Its average train occupation was 172 passengers per train per segment (ppts), minimum occupation was 0 ppts, maximum occupation 1188 ppts and median was 124 ppts. Thus, the capacity of 250 passengers per train unit offers a good level of service.



Additional Results

This appendix presents several additional results for Chapter 4.

C.1 Train Distributions

In the tables of this section, the train distributions of various types of timetables are shown. The first row of each table, represents the hour of the day. Each subsequent row, represents each of the lines in the network (in total 34 lines). The number in each cell gives the information about the number of trains scheduled in that given hour on that given line. The minimum value found is 0 and the maximum value found is 4.

APPENDIX C. ADDITIONAL RESULTS

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	0	0	0	0
0	0	0	0	0	0	1	1	1	1	1	0	0	0	1	1	1	1	1	1	0	0	0	0
0	0	0	0	0	0	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	0	0
0	0	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	1	1	1	0	0	0	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0
0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0
0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0
0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0
0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0
0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	1	1	1	1	1	0	0	0	0
0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	1	1	1	1	0	0	0	0	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	0	1	1	1	1	0	1	0	0	1	0	1	1	1	0	0	0	0	0
0	0	0	0	0	0	1	1	1	1	1	0	1	0	1	1	1	1	1	0	0	0	0	0
0	0	0	0	0	0	1	1	1	1	1	0	1	0	1	1	1	1	1	0	0	0	0	0

Table C.1: Train distribution of the IR 13/14 timetable

APPENDIX C. ADDITIONAL RESULTS

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	0	0	0	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	0	1	1	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
0	0	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0	0	0	0	0	0	1	1	1	1	0	1	0	0	1	1	1	1	1	1	0	0	0	0
0	0	0	0	0	0	1	1	1	1	1	1	0	1	0	0	1	1	1	1	0	0	0	0
0	0	0	0	0	0	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	0	0	0	0
0	0	0	0	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	0
0	0	0	0	0	1	1	1	1	0	0	1	0	1	1	1	1	1	1	1	1	1	1	1
0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	1	1	1	1	0	1	0	0	0	0	1	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	1	0	1	0	1	0	0	1	1	0	0	1	0	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
1	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0
0	0	0	0	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	1
0	0	0	0	0	0	1	0	1	0	0	0	0	1	0	1	1	1	1	1	1	1	0	0
0	0	0	0	0	1	1	1	1	1	0	0	0	0	1	0	1	1	0	0	0	0	0	0
0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	0	0	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	1	0	0	0	1	1	0	0	1	0	0	1	0	0	0	0
0	0	0	0	0	0	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0
0	0	0	0	0	0	1	1	1	1	0	1	0	1	0	1	1	1	1	0	0	0	0	1

Table C.3: Train distribution of the cyclic timetable under the 2014 situation

C.1. TRAIN DISTRIBUTIONS

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	0	0	0	0	2	2	2	1	1	1	1	0	1	1	1	1	1	1	1	0	1	0	0
0	0	0	0	0	0	1	1	1	1	1	0	1	0	1	2	2	2	2	0	2	0	0	1
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	2	4	1	1	0	1	0	1	1	1	0	2	0	1	0	1	0	0
0	0	0	0	0	0	2	1	2	1	1	1	1	0	2	2	1	1	1	1	0	0	0	0
0	0	0	0	0	1	1	1	0	1	1	0	0	0	1	0	3	1	1	0	0	0	0	0
0	0	0	0	0	0	1	2	2	2	0	0	0	0	0	1	2	0	0	0	0	1	0	0
0	0	0	0	0	0	0	1	2	0	0	0	1	0	1	2	2	1	1	1	0	1	0	0
0	0	0	0	0	0	2	2	1	1	0	0	0	0	1	1	1	1	1	0	1	0	0	0
0	0	0	0	0	1	1	2	1	1	1	0	1	1	1	1	1	1	0	1	0	1	0	0
0	0	0	0	0	0	1	1	1	0	1	0	1	1	1	2	2	2	1	0	1	0	1	0
0	0	0	0	0	1	1	2	1	1	1	1	1	0	2	1	3	1	1	1	0	0	0	0
0	0	0	0	0	2	2	2	2	0	1	0	1	2	0	1	1	0	2	0	1	0	0	0
0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0
0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0
0	0	0	0	0	0	1	1	1	1	0	1	0	0	1	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	1	1	0	1	1	0	1	0	0	0	1	0	1	0	1	0	0	0
0	0	0	0	0	0	0	2	3	2	0	1	1	0	0	1	3	2	1	2	0	0	0	0
0	0	0	0	0	1	1	2	2	1	0	1	0	1	2	1	1	1	2	0	1	0	1	0
0	0	0	0	0	0	1	2	1	1	1	0	0	0	0	2	1	1	3	0	0	1	1	0
0	0	0	0	0	0	2	1	2	3	1	0	1	0	0	1	0	2	0	1	1	0	1	0
0	0	0	0	0	0	1	0	0	0	1	1	1	2	1	0	0	0	0	0	1	0	0	1
0	0	0	0	0	0	0	3	0	0	1	0	0	0	1	0	2	0	1	0	0	0	0	0
0	0	0	0	0	1	2	1	1	1	1	0	2	0	1	4	0	1	1	1	1	0	0	0
0	0	0	0	0	0	1	1	3	2	0	1	2	0	2	0	1	2	1	0	1	1	0	0
0	0	0	0	0	0	1	1	1	1	0	1	1	0	1	1	2	2	1	0	0	0	0	0
0	0	0	0	0	0	1	3	1	0	2	1	1	0	1	1	1	1	0	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0
0	0	0	0	0	1	1	0	1	0	1	1	0	0	0	2	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	1	1	1	0	1	1	0	1	1	0	1	0	0	0	0
0	0	0	0	0	0	1	3	1	1	1	0	0	0	0	1	0	1	0	1	0	0	0	1

Table C.4: Train distribution of the non-cyclic timetable under the 2014 situation

APPENDIX C. ADDITIONAL RESULTS

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	0	0	0	0	1	2	1	1	1	1	1	1	1	0	2	1	1	1	0	1	1	0	1
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	2	0	1	2	0
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	1	1	1	1	1	2	0	2	0	1	1	1	1	1	1	0	1	0	0	0
0	0	0	0	0	0	1	2	1	1	1	0	1	1	1	1	2	1	1	1	1	0	1	0
0	0	0	0	0	0	1	1	2	0	0	1	0	0	1	1	1	2	0	1	0	0	0	0
0	0	0	0	0	0	2	1	1	1	1	1	0	0	0	1	1	0	2	0	0	0	0	0
0	0	0	0	0	0	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	1	0	0
0	0	0	0	0	0	1	2	1	1	1	1	1	0	1	1	1	1	0	0	0	0	0	0
0	0	0	0	0	0	1	2	1	1	1	0	1	1	0	2	0	2	0	1	1	1	0	0
0	0	0	0	0	0	1	1	1	1	0	1	0	1	0	2	1	1	1	1	1	1	0	1
0	0	0	0	0	1	1	2	1	1	0	1	1	1	1	2	1	1	1	1	1	1	1	0
0	0	0	0	1	1	2	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0
0	0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0
0	0	0	0	0	0	1	1	0	1	1	0	0	0	0	1	1	0	1	0	0	0	0	0
0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	1	1	1	0	1	0	0	0	0
0	0	0	0	0	0	2	1	1	1	1	1	0	1	0	2	1	1	1	1	1	1	1	1
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1
0	0	0	0	0	0	0	1	2	1	1	0	1	1	1	0	2	0	1	1	2	0	0	1
0	0	0	0	0	0	1	2	1	1	1	1	1	0	1	1	1	1	1	1	1	0	1	0
0	0	0	0	0	0	1	0	0	1	0	1	1	0	0	1	0	2	1	1	0	0	0	0
0	0	0	0	0	1	1	2	1	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0
0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	1	1	2	0	2	1	1	0	2	1	1	1	1	1	1	1	1	1	0
0	0	0	0	0	0	1	2	1	0	1	1	1	2	0	2	1	1	0	0	0	0	0	0
0	0	0	0	0	0	2	1	0	2	1	1	1	1	1	0	1	1	1	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	2	1	0	0	0	0	0	0
0	0	0	0	0	0	1	1	1	0	0	1	0	1	0	1	0	0	0	0	0	0	0	1
0	0	0	0	0	0	1	1	1	0	0	1	1	0	1	1	0	1	1	0	0	0	0	0
0	0	0	0	0	0	1	2	0	2	0	1	1	0	0	0	1	1	0	0	0	0	1	0

Table C.5: Train distribution of the 30 min shifted cyclic timetable under the 2014 situation

C.1. TRAIN DISTRIBUTIONS

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	0	0	0	0	1	2	2	1	2	1	1	0	1	1	1	1	0	2	0	1	1	0	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	0	1
0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	3	2	2	1	0	0	2	0	1	1	2	1	0	0	0	1	0	0
0	0	0	0	0	0	1	1	2	0	1	1	0	1	1	3	1	2	0	1	1	0	1	0
0	0	0	0	0	0	1	0	1	1	0	1	1	0	1	1	1	1	0	1	1	0	0	0
0	0	0	0	0	0	1	1	3	2	0	0	0	0	0	0	1	1	2	0	0	0	0	0
0	0	0	0	0	0	1	3	0	2	0	0	0	0	0	2	2	1	0	2	0	0	0	0
0	0	0	0	0	0	2	1	3	0	2	0	0	0	2	0	1	1	0	0	0	0	0	0
0	0	0	0	0	0	2	2	2	1	1	1	0	0	1	1	1	1	1	1	0	0	0	0
0	0	0	0	0	0	0	2	1	0	0	0	2	1	2	1	2	1	2	1	0	0	1	0
0	0	0	0	0	1	1	3	1	1	0	2	1	1	1	2	1	3	0	0	0	0	0	0
0	0	0	0	0	1	1	1	2	1	1	1	1	1	1	1	2	1	1	1	0	0	0	0
0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
0	0	0	0	0	0	1	1	0	1	0	0	0	0	0	1	0	0	2	1	0	0	0	0
0	0	0	0	0	0	1	2	0	0	1	1	0	0	0	0	1	0	0	0	1	0	0	0
0	0	0	0	0	0	2	1	1	1	0	1	0	1	2	1	3	1	1	1	1	0	1	0
0	0	0	0	0	0	2	3	1	1	1	0	2	0	0	1	1	1	2	2	0	1	0	0
0	0	0	0	0	0	1	1	2	0	0	1	3	1	0	3	1	1	1	0	0	0	0	0
0	0	0	0	0	1	2	1	1	1	1	1	1	0	1	1	1	1	2	0	1	0	0	0
0	0	0	0	0	0	0	0	1	2	1	1	0	0	0	0	0	1	1	1	0	1	0	0
0	0	0	0	0	0	0	0	1	3	0	0	0	2	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	1	1	1	1	0	1	1	0	1	2	2	1	2	2	1	1	0	0	0
0	0	0	0	0	1	3	1	2	2	1	0	0	1	0	2	1	1	0	1	1	1	0	0
0	0	0	0	0	0	1	0	2	2	0	1	0	1	1	1	2	0	0	2	0	0	0	0
0	0	0	0	0	0	0	3	1	1	2	0	2	0	1	1	1	0	2	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	3	0	0	0	0	0
0	0	0	0	0	0	0	2	1	1	1	0	2	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0	1	0	1	1	1	1	1	0	0	0	1	1	0
0	0	0	0	0	0	2	2	0	0	0	1	0	1	1	1	0	0	1	0	0	0	0	1

Table C.6: Train distribution of the hybrid cyclic timetable under the 2014 situation

C.2 Resulting Hybrid Cyclic Timetable

ct																		
43	343	388	403	436	463	523	544	583	643	703	823	883	943	1003	1082	1123	1243	1303
17	377	437	497	557	617	677	737	797	857	917	977	1000	1037	1097	1157	1217	1277	1397
38	398																	
9	969																	
11	371	401	417	431	461	488	491	551	731	776	851	911	971	1015	1031	1271		
17	377	437	497	498	617	677	797	857	917	949	956	977	1034	1037	1157	1217	1337	
22	382	502	562	682	742	862	922	982	1042	1162	1222							
11	371	431	482	487	491	551	557	971	1031	1091	1116							
11	371	431	444	472	551	597	911	948	961	971	1031	1151	1155					
14	374	408	434	493	494	522	614	649	849	854	974	1034						
25	385	418	445	476	505	536	565	625	685	865	925	985	1045	1105	1165			
54	427	474	534	725	774	834	876	894	954	976	1014	1074	1119	1134	1194	1374		
0	300	360	420	455	477	480	540	660	711	720	780	840	900	909	960	1020	1026	1063
20	320	380	440	488	500	560	620	680	740	800	860	920	972	980	1040	1100	1160	
35	431	445	455	995														
9	429	489	1089	1149														
54	414	474	594	954	1109	1134	1194											
6	366	426	479	606	666	966	1206											
56	385	416	476	536	596	716	836	856	896	956	984	995	1016	1076	1136	1196	1256	1376
9	369	382	423	429	452	489	549	609	729	742	909	969	1029	1089	1137	1149	1197	1269
12	372	432	492	522	672	732	748	775	792	912	940	947	972	1032	1092			
41	341	389	401	461	521	581	641	701	761	881	941	1001	1061	1108	1121	1241		
29	509	569	586	629	689	1049	1109	1169	1289									
49	469	498	510	529	829	836	1069	1369										
31	331	391	451	511	631	691	811	871	892	902	931	991	1051	1070	1081	1111	1171	1231
3	303	363	387	390	423	483	515	543	599	603	783	903	941	963	1023	1143	1203	1263
30	390	487	510	564	570	690	810	870	930	990	997	1163	1170					
0	420	442	453	480	540	600	629	720	747	840	900	960	1080	1117				
17	1337																	
32	932																	
38	398	818	998	1095	1104	1118												
39	421	459	519	579	639	726	759											
13	493	673	793	853	913	973	1033	1273	1333									
40	374	400	460	479	700	820	880	940	1120	1300	1420							

Table C.7: Resulting hybrid cyclic timetable under the 2014 situation

Each line of the above table represents a single line. The first column of the table provides the value of the cyclic time ($d_{lv} \bmod c$). The following columns show the value of the departure times in minutes. The cyclic trains have a clear background, whereas the non-cyclic trains have a grey background. If a cell is empty, it means that its line is having less trains available than the most frequent line.

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