Robustness simulation of bus crew schedules

Case Study Frihamnen Depot (Stockholm)

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ACKNOWLEDGEMENT

My passion for transports systems came since I was a child, when I used to travel with my parents. I remember to be curious about any aspect of those systems (railways, highways, bus, airplanes, maritime, …). I dreamed to be a part of those working environments, as planner, designer or manager. That is why I chose to study Civil Engineering and after specialized in Transport, it was what I always wanted and finally I accomplish it.

The topic of this master thesis, *Robustness Simulation in Bus Crew Schedules* are based on my willingness to work at the Public Transport sector after finishing this master. It has been developed with Keolis Sverige AB, the main bus operator at the Stockholm's city center. I would like to thank the good treatment I got there by all the office, but especially to Astrid, my supervisor. She was always available for my questions and very supportive in the whole process. Also, I would like to thank all teachers of my master at KTH and TU Delft, I have learned a huge amount of information and techniques to face properly the problems we have to face as engineers. A special mention to Erik (my thesis supervisor) and Bibbi who were the ones who explained and gave me more opportunities related to our master.

Finally, I would like to thank all my family and friends who supported me all these years, all that people whom I have spent wonderful time living in Sweden and The Netherlands. Furthermore, in Spanish, I would like to thank to my parents. *Gracias Mamá, gracias Papá. Sin vosotros todos estos logros no habrían sido posibles. Vuestra conexión terrenal y espiritual me han hecho llegar aquí.*

ABSTRACT

This thesis develops a model aimed at predicting the performance of bus crew schedules and study their operational capacity to face disruptions, that is, its robustness. It is based on the relation among schedule deviation, passengers and slack times, considered as non-productive times before trips.

Optimization of Public Transport is a challenge that main cities are facing since this type of transport is the backbone of mobility. New powerful versions of transport planning software are providing more optimal schedules to operators, therefore decreasing their costs, but increasing the risk of delays due to more gathered schedules that can cause fines and passengers' dissatisfaction.

A trade-off between production and fines costs is needed to find the optimal slack times. To reach that goal, the Frihamnen bus depot in Stockholm (Sweden) was selected as case study, having historical data of all their lines for last year. A regression model for schedule deviation was calculated which served to create a computer tool in Microsoft Excel, giving the possibility to checking the performance of new schedules based on that historical data.

The results showed an inverse relation between schedule deviation and slack times. Moreover, short non-productive times before trips also mean high delays on departures. A positive output is that adding a stop of at least 10% of the total trip time, the first departure would be on time or 2 minutes late as maximum. Several software developers are applying similar studies to their products to keep optimizing bus schedules while taking an economic and social approach.

ABSTRAKT

Denna avhandling utvecklar en modell som syftar till att förutsäga prestandan hos bussbesättningsplanerna och studera deras operativa kapacitet för att möta störningar, det vill säga dess robusthet. Det är baserat på förhållandet mellan schemalagd avvikelse, passagerare och slacktiderna, som anses vara icke-produktiva tider före resor.

Optimering av kollektivtrafik är en utmaning som stora städer står inför eftersom denna typ av transport är ryggraden i rörlighet. Nya kraftfulla versioner av programvaran för transportplanering tillhandahåller mer optimala scheman till operatörerna, vilket minskar deras kostnader, men ökar risken för förseningar på grund av mer samlade scheman som kan orsaka böter och passagerares missnöje.

En avvägning mellan produktionskostnader och böter krävs för att hitta de optimala slacktiderna. För att nå detta mål valdes Frihamnen-bussdepot i Stockholm (Sverige) som fallstudie med tidigare uppgifter om alla dessa linjer för förra året. En regressionsmodell för schemats avvikelse beräknades som tjänade till att skapa ett datorverktyg i Microsoft Excel, vilket gav möjligheten att kontrollera prestanda för nya scheman baserat på den tidigare data.

Resultaten visade ett omvänt samband mellan schemaläggsavvikelse och slacktiderna. Dessutom innebär korta, icke-produktiva tider före resor också stora förseningar vid avgångar. En positiv utgång är att lägga till ett stopp på minst 10% av den totala resetiden, den första avgången skulle vara i tid, eller maximalt 2 minuter för sent. Flera mjukvaruutvecklare tillämpar liknande studier på sina produkter för att hålla optimerade busscheman medan de tar en ekonomisk och social strategi.

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1. INTRODUCTION

What this work discusses is the actual trend of planning and optimization software which are applying more efficient algorithms to reach lower operator costs but as a counterpoint the resulting schedules do not have large margins to recover, which can finally result in extra costs due for operator to fines. These margins, which are non-productive time of vehicle and driver, are also called buffer times or **slack times**. This last term is the one used among this thesis and it would be the main dependent variable to predict future average schedule deviations. It is a value that depend from the planning department and at the same time is a key to have a robust schedule, considering *robustness* as "operational capacity of the system to face disruptions".

1.1.   Background

Cities have been growing exponentially last decades, urban agglomerations represent more than 50% of population worldwide, besides the expectations for 2050 are 70%, reaching 85% on high income countries [UN, 2018]. This situation creates several challenges that public administrations have to deal with, as mobility. Larger cities mean longer travel times, more vehicles, pollution from fuels and road accidents. To face these undesired effects, a good service of public transport is completely needed, connecting all areas of the cities with competitive times and prices. Several types of transport are considered public transport, the most important at EU are *bus* (56% share, more than 30 billion passengers), *metro* (16%, 9 billion), *tram-light rail and suburban rail* (14%, 8 billion each one) [UITP,2014].

Public transport is handled on different ways depending on the countries and regions. Some of them have a public transport authority who is also the operator, being in charge of the whole process, from planning to maintenance. Others let the market to regulate itself, usually creating a chaos without any public control on the planning and operations. Sometimes creating traffic accidents on buses that are competing for passengers and only the profitable routes are served, causing that some areas end to be disconnected [Gomez-Lobo, 2011]. And the latest current which are adopting more cities in the world, public tendering. A big public transport authority is in charge of network planning and pricing, but the operations and maintenance are delegated to private operators. This is the case of Stockholm bus network, where *SL* (Storstockholms Lokaltrafik) is the public transport authority and *Keolis, Nobina, Transdev and Arriva* are the private operators.

Development of new technologies is helping to reach a better service level of public transport. Currently, it is possible to know where and when is exactly each vehicle, to count how many passengers board and get off, to predict how demand will spread, etc. These technologies, as *APC* (Automated Passenger Counter), *AVL* (Automated Vehicle Location), *GPS* (Global Positioning System) and *AFC* (Automated Fare Collection), plus the latest software (PT and big data) are expanding the possibilities of planning and operating public transport.

The city of Stockholm has forecasted a growth of 25% on its population by 2030 with a consequent increasing on the mobility. To face properly this challenge, several measures are being studied and applied, mainly related to public transport network. Trunk lines are in the focus of that research, with an expected goal of reaching an average speed of 20 km/h, from 14-15 km/h of nowadays [City of Stockholm, 2012]. Besides the rest of the bus lines that complement trunk lines and other types of transport by providing an attractive and effective service of public transportation.

To apply these future measures, an optimal planning and operational control is needed. Public Transport bus operators are in charge for these challenges, they try to provide the best possible service and at the same time keeping the company's best interest in mind. This is why Keolis is interested to study its robustness looking for some recommendations, as an operator wants to perform better and trying to optimize as much as possible its bus operations, which move more than 800,000 passengers every day in Sweden.

To have a background of the topic, these are the main terms related to this work:

- **Crew Scheduling Problem (CSP):** Main problem of crew scheduling resides in their high crew costs, which are the dominant among total costs of a public transport operator. An optimization of their duties is always necessary but also taking care about future issues during operations.

- **Robust schedules:** Robust crew schedules need a trade-off between minimizing *operational costs*, crew and vehicle schedules calculated with potent optimization software, and *slack times*, the non-productive time that is placed to absorb possible delays without affecting future operations.

- **Slack time:** As this term is essential for the understanding of the whole thesis, Figure 1 shows more in detail what is considered *slack time*. It is the non-productive time between trips at the same stop, which can coordinate timetables to make departures leaving at the same minutes every hour, or can absorb extra times created by incidents at the previous trip.
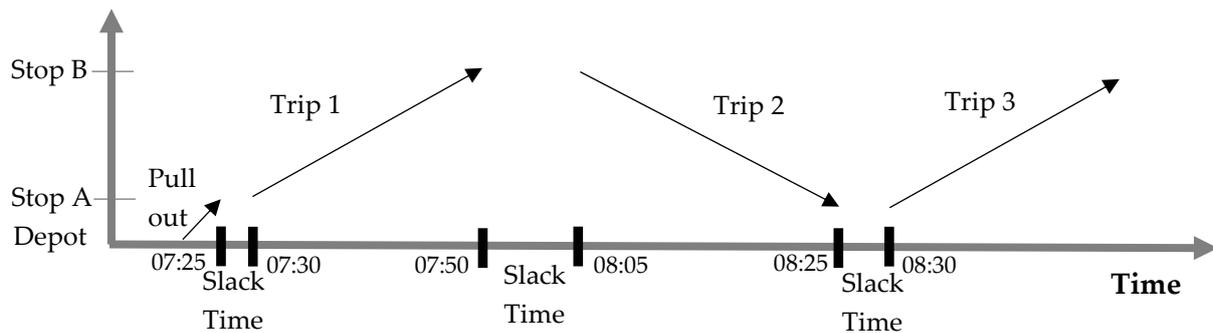
Figure 1. Slack time diagram.

1.2. Objective & Scope

There are 3 main objectives on this thesis, explained more in detail below:

1. To study how *robustness* ("capacity of the system to face disruptions") behaves among Stockholm bus network.
2. To analyse historical and planned data from Frihamnen depot.
3. To develop a tool that can predict the performance of crew and vehicle schedules to help Keolis in its planning process.

The first objective of this thesis is to study if there is a correlation between robustness and planning parameters. It is important to know how service performance can be improved with values that can be changed by the operator. In this study, the slack time (explained before) is that variable value, being comparing with the actual departure times at the first stop and its deviation. Another important factor in this project is the influence of crew schedules on actual delays. Drivers have pauses every 2 hours and a longer meal break at the middle of the duty. These stops are mandatory by regulation to ensure good working conditions and to avoid risky situations when the drivers are tired that could finish into unsecure scenario. Pauses and breaks have a minimum length time, which can maintain a delay in case the previous trip was late and there is no enough time to absorb it. Also can be affected by late or absent arrivals, sometimes there is not a fast communication between center control and drivers which can make more complex to reschedule a trip.

After this initial analysis among the variables that can determine the robustness, it is developed an economic analysis which shows the correlation between cost of production and delays. A reduction of production's costs can lead to an increasing of delays, and vice versa, but it is not always relevant. Depending where and how

operator's costs are reduced, it is also possible to keep the same level of delays, reaching even a better costs situation than actual.

Based on the whole development of this thesis, finally some recommendations are presented for a more robust vehicle and crew planning, taking into consideration the results of this case study and trends that are being researched nowadays. Besides this final objective, it is created a robustness tool (developed in MS Excel software) that can predict a model of average schedule deviations, operator and fines costs, and a comparison between two new vehicle and crew plans, which could be use by Keolis planning department.

As this thesis' topic can be very extensive, the adapted scope is to implement these analyses and recommendations for a specific case study, which is the Frihamnen bus depot in Stockholm. Having the opportunity to access an immense quantity of data of all their lines for the long period from Dec'17 to Mar´19.

1.3.   Thesis outline

This thesis is structured as follows: Section 2 goes across the literature review about related topics, from bus planning process to technical definitions, considering first studies in the 60's to nowadays. Section 3 presents the case study, Frihamnen depot in the city of Stockholm (Sweden). Section 4 explains the methodology followed during this thesis, the procedure of data collection and analysis, ending with the way of facing the robustness tool and economic analysis for the operator. Section 5 shows the results after creating these models and analysis, as the relation among average schedule deviation-slack%-passengers, its regression models, and how there are applied at the final simulation tool. Finally, Section 6 presents some conclusions and recommendations based on the whole thesis, as well as previous works and author's point of view.

2. LITERATURE REVIEW

2.1. Introduction

This section reviews all relevant topics related to the objectives of the thesis, starting by the whole bus planning process but focusing on vehicle and crew scheduling as well as its relation. A detailed definition of the terms *reliability* and *robustness*, to finally difference bus planning with other means of transport (railways and airplanes). Following the book of Ceder [2007], a compilation book for public transport operations, transit planning can be decomposed in 4 main activities: Network route design, Timetable development, Vehicle scheduling and Crew scheduling.
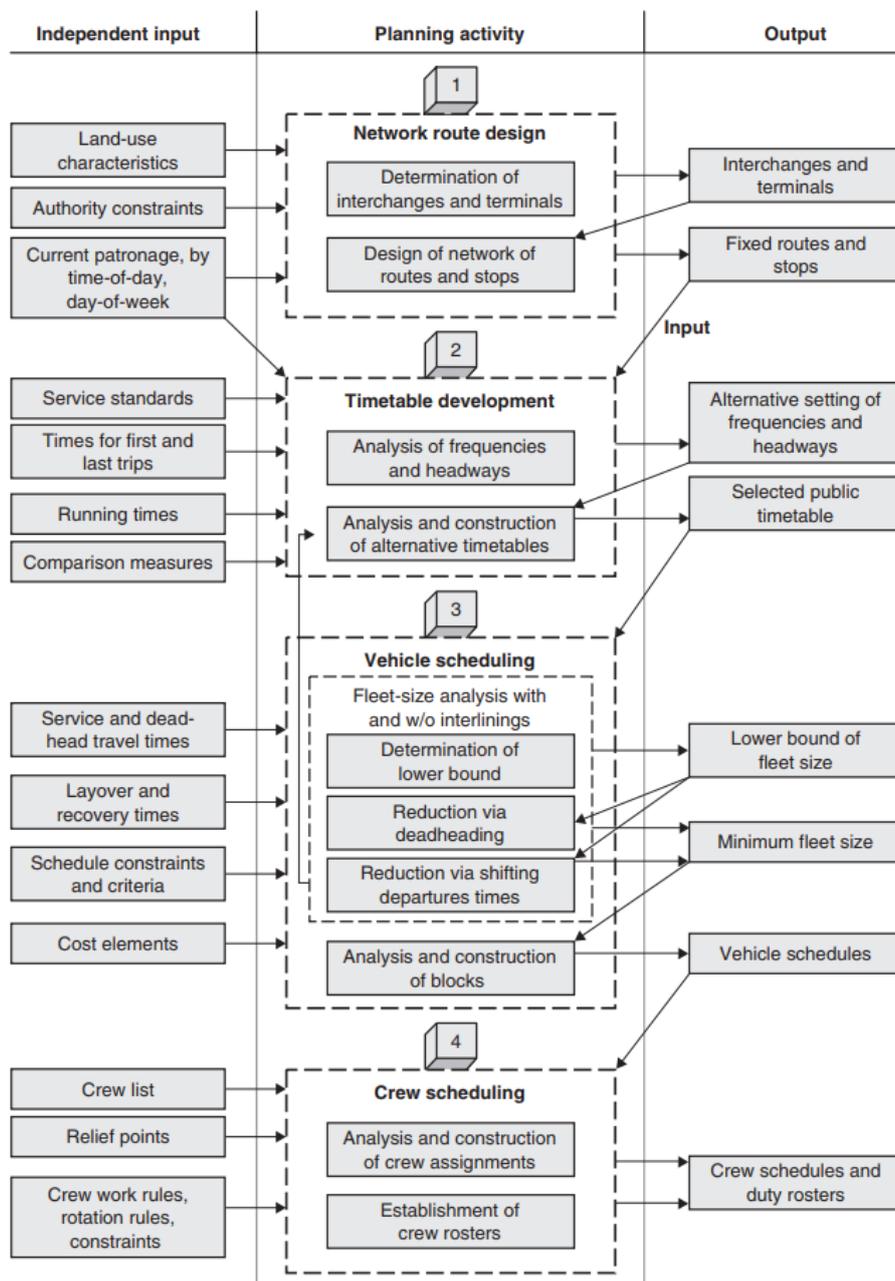
Figure 2. Transit operation planning process. Source: Ceder, 2007

2.2.   Planning process

The planning process for transit also can be classified according its *strategical* (network planning), *tactical* (frequencies and timetables) and *operational stage* (vehicle and crew schedules). Lately, a new stage is added at the end, the disruption recovery plan based on the real-time control for dynamic operations. In detail, the sub-problems can be classified like this according to Desaulniers & Hickman [2007]:

- **Transit Network Design (TND):** First step is to develop a network, their respective lines and spacing between stops and lines. Usually the objective function is to optimize costs for operators and passengers, in order to perform that, some initial frequencies are used being changed on the next sub-problem. This step is mainly performed by the transport authority to assure good connections for their citizens.

- **Frequency Setting (FS):** In this step, frequencies are calculated based on passengers' demand and time during the day. This frequency shows how many times a trip should be served during one hour, or what is the same, dividing 60 by this value gives the headway of the line, the space time between two trips. As the previous sub-problem, it is calculated by the transport authority to have minimum standards at peak hours and minimum service at other times.

- **Transit Network Timetabling (TNT):** After defining frequency and headways, an exact timetable is developed giving departure and arrival times at stops. This timetable is based on standards fixed by the PTA and it is calculated by them or by the operator. Besides frequency and headways, some parameters as: demand, coordination between buses, temporary known disruptions, waiting times and crowed stations are taken in account on this sub-problem.

- **Vehicle Scheduling Problem (VSP):** A fix timetable allows operators to know how many buses they need and how to use them. An objective function for minimizing operator cost is used, assigning *blocks* for vehicles to all planned trips in the most efficient way. As this sub-problem is developed by the operator, a larger optimization of costs is done, i.e. using deadhead trips, high utilization of buses and short slack times. In this step it can be also considered which type of vehicle is needed based on demand and costs.

- **Crew Scheduling Problem (CSP):** Related to the previous sub-problem, CSP is based on the VSP. All trips need drivers to perform them and they are the main cost for operators, therefore its optimization is crucial for profitable transit operations. There are some working constrains as: total driving time per day, continuous driving time, pauses and break meals; which have to be considered in this optimization process.

- **Driver Rostering Problem (DRP):** Finally, the last sub-problem is relating a specific driver to each duty of CSP, following the same philosophy of maximum costs optimization. This process is done for a period of time, usually weekly or monthly, when each driver knows its future working schedule (*rosters*).

In this work, Vehicle and Crew Scheduling Problems are the most important ones, where operator costs can be optimized on a larger level. For that, the following part is a more detailed literature review of both sub-problems, including when they are integrated on the same optimization problem.

2.3.   Vehicle and Crew Scheduling Problems

Since the 60´s, based on the concept of *column generation* for linear programming developed by Dantzing & Wolfe [1960], manual calculations were changing to computer ones due to the difficulty of handling the huge amount of solutions that each problem has. This technique decomposes the whole problem on short periods (columns) and solves them sequentially finding the optimal solution among these columns. Other optimization technique used in this field is *Lagrangian relaxation*, sometimes used together with CG. As Huisman [2004] explains, this method obtains lower bounds on the optimal solution, relaxing some hard constraints and penalizing their violations in the objective function.

These methods giving the best approach of optimal solution are called *heuristics*, and their use is the foundation of several optimization problems, e.g. *CrewOpt* tool of Hastus (the main tool for CSP in that software) is calculated by column generation [Fores, 1996]. Going beyond, new methods for public transport planning based on *metaheuristics*, as *HACO* (Hybrid Ant Colony Optimization) and *GRASP* (Greedy Randomized Adaptive Search Procedure), are been discussed [Ma et al., 2017; Lourenço et al., 1998].

Vehicle Scheduling Problem

The main objective of VSP is to minimize the costs of vehicle usage for all planned trips, composed by: commercial services trips (passengers on board), deadhead trips (bus running empty), standing time (between trips), pull-in and pull-out (trips from/to depot). To develop this problem, it must to be considered some determinant elements like number of depots, different fleets with costs and resting points [Ibarra-Rojas et al., 2015].

The simplest formulation of this problem is the *SDVSP* (Single Depot Vehicle Scheduling Problem), which can solve this process for small and medium size networks with just one depot. Although, its mathematical formulation was developed on the 50´s, new studies have increased its performance. Baita et al. [2000] presented a multicriteria optimization formulation with 3 different algorithms on a real case, ending with a modified genetic algorithm to get Pareto optimal solutions. And Zhoucong et al. [2013] tested on the city of Shanghai a clustering model based on real GPS and passengers' data, giving more accurate information to minimize costs.

For bigger cities that usually have more than one depot, a *MDVSP* (Multi Depot Vehicle Scheduling Problem) should be used. This problem is taking in consideration all network possibilities of assigning a bus to each trip, giving a better output when a line can be served by more than one depot. It handles huge amount of possible solutions and has a complex mathematical formulation, being classified as NP-hard (what means its solutions grow exponentially with larger inputs). First, it was introduced by Bertossi [1987], using a heuristic algorithm based on Lagrangean relaxation. Kliewer et al. [2006] developed a MDVSP considering time-space based networks instead of connection ones, reducing mathematical complexity. Several heuristics methods were compared after by Pepin et al. [2009] and Milovanovic [2015], resulting the truncated CG a good solution for this problem. Also a MDVSP can be developed with an optimal timetable as an output, that is the case Hassold & Ceder [2014] studied, reducing 15% fleet costs.

Two new variants of this problem were introduced, *DVSP* (Dynamic Vehicle Scheduling Problem) and *VRSP* (Vehicle Re-Scheduling Problem). The first variant was presented by Huisman et al. [2004], they clustered each trip to a depot and scheduled it based on the dynamics of travel times. VRSP consists on re-schedule the vehicle blocks when a disruption occurs, minimizing the resulting costs. It has been studied mainly by Lin et al. [2007 & 2009].

Crew Scheduling Problem

Also called *DSP* (Driver Scheduling Problem) or duty scheduling, defines the drivers' duties for all vehicle blocks minimizing its costs and considering all labor regulations. Its output is the starting and final working times for drivers, taking into account their pauses and meal breaks. Due to the number of trips and drivers, this problem deals with a large amount of possible solutions, finding these ones with different heuristic methods.

The first approximation to the problem using mathematical programming was developed by Smith & When [1988] for the London bus network, minimizing the number of duties and therefore, the total crew costs. After this, methods using Column Generation or different algorithms were created. Fores et al. [2003] mixed integer lineal programming with heuristics in their method for public transport systems, selecting at the beginning possible duties according constraints and applying CG after to the best options. This process was improved (especially reducing computational times) by Chen & Shen [2013], developing a new CG algorithm that studies just the duties from a shift pool, being these ones the most optimal based on networks constrains.

Other ways to face this problem are doing some bigger assumptions, e.g. Zhao [2006] split CSP in two sub-problems, one for morning period and other one for afternoon. This simplification reduced computational time but gave a less optimal solution. Chen et al. [2013] studied this problem fixing the meal breaks to a window time, reducing the total feasible options and getting a good result in their case study applied to a Chinese city with 10.000 trips.

Beyond the simple crew scheduling problem, a multi-objective CSP has been studied with metaheuristics. Lourenço et al [2001] compared *GRASP* (Greedy Randomized Adaptive Search Procedure), *TS* and *Genetic Algorithm* optimizing several criteria at the same time. And Li & Kwan [2003] presented a hybrid GA for a bi-objective CSP, minimizing number of shifts and total costs, applying a fuzzy set theory. However, these approaches (multi-criteria and re-scheduling) could be more developed in the future.

Integrated Vehicle-Crew Scheduling Problem

In order to reach even a better optimization, both problems can be integrated in one. In fact, at the initial phase of bus planning research both problems were treated together, considering the constraints of CSP on VSP but sequentially calculated [Scott,

1985]. However, new exact and heuristic approaches have been studied in the last years considering both problems for the objective function.

Huisman [2004] wrote his PhD thesis about *IVCSP* (Integrated Vehicle Crew Scheduling Problem) for single and multi-depot situations. The aim for this research, focus in extra-urban area, was that an optimal VSP could not proportionate an optimal CSP because relief points are less common on this situation. Therefore, calculating both at the same problem will provide the optimal solution, but the large amount of feasible options complicates this problem having to split them in smaller groups of options.

Freling et al. [2003] developed an integrated mathematical model for vehicle and crew problems considering just single depot, but taking all constrains of both into account using column generation method. Borndörfer et al. [2008] proposed a Lagrangean relaxation based on a bundle method using a branch & bound algorithm, resulting a good output reducing costs and improving drivers' satisfaction but with long computational times.

Lately, due to more computational capacity, some levels of flexibility were added creating more optimal algorithms however large computational times that still can be considered acceptable. Kliewer et al. [2012] developed a model with variable trip departure and arrival times using time windows, so scheduled trips can be shift which would lead to savings. Furthermore, new integrations with more problems (Driver Rostering Problem) were studied by Mesquita et al. [2011 & 2013], it was denoted as VDRP (Vehicle, Driver and Rostering Problem). In this multi-objective formulation were taken into account drivers' preferences for duties, creating satisfactory results for all involved parts but in some cases with extremely long computational times.

2.4.   Service Reliability

Reliability in Public Transport is determinant to make attractive this mode of mobility. First of all, for assuring a good level of service reliability is totally needed an optimal planning, but in some cases, it is not enough because there are more variables significant to the performance of that service, known as disruptions (traffic congestion, boarding problems, driver late or sick, vehicle malfunctions, etc.). These events create delays (*primary* or *secondary*) that could produce fines to the operator, besides are unpleasant for passengers making losing that service reliability.

The two types of delays are well described in literature [i.e. Carey 1999], the *primary* delays are directly caused by disruptions, these ones are unpredictable and therefore, difficult to avoid them. The resulting effect is a late arrival of that specific trip. The

secondary delays are the ones occurring after a primary delay if there is not enough time to recover. This type of delays can be reduced adding some *slack time* (non-productive time before trip), which would do a more robust schedule, but at the same time it would increase the total operator costs.

Punctuality & Regularity

Reliability can be measured by punctuality or regularity indicators, the type of this indicator should be choose depending on the own characteristics of each line. Passengers tend to check the timetables when headways are larger than 12 minutes [Jolliffe & Hutchinson, 1975], therefore punctuality indicators are more relevant. However, city center lines usually have smaller headways and people just appear at bus stops without checking departure times, in this case regularity indicators are the ones decisive. This thesis considers both indicators due that studied lines have low and high headways. Punctuality indicators are based on adherence of schedules and its deviation [Barabinoa et al., 2015], regularity indicators are based on its relation with headways, these ones are [Cats, 2014]: *Headway coefficient of variation* ("ratio between the standard deviation and the mean actual headway"), *headway adherence* ("the share of buses that arrives with a headway that does not deviate from the planned headway") and *average excess waiting time* ("the additional waiting time that passengers experience due to irregular bus arrival").

2.5.   Robustness

Robustness has been always a difficult goal to reach in public transport operations due to an unexpected behavior of drivers and traffic, but it was not until last decade that several studies have been produced looking into more detail about this topic. Kramkowski et al. [2009] related buffer times and average delay deviation from schedule for SDVSP (a similar relation is used later on this thesis), getting the output that larger buffer times resulted in lower propagation of delays.

Naumann et al. [2011] and Yap & Van Oort [2018] presented new optimization models based on minimize the sum of planned and delays costs. In both cases there was a Pareto optimal solution because delays costs grow at the same time planned costs decrease. The results showed that a stochastic programming with a parameter depending on overtime fines was the best solution.

Another approach to the problem was done with Monte Carlo simulations, Wei et al. [2012] and Yan et al. [2012] created some robust models considering parameters as mileage expenses or minimizing the schedule deviation at control points avoiding

fines there. To reach this objective, drivers could adjust their speeds (to increase or decrease) among that stops.

An important term that describes one of the main goals of this thesis is *delay tolerant*, which means that a schedule can absorb the secondary delays (as the primary are unexpected and difficult to predict) in a better way than other schedule. When more delay tolerant is a schedule, more robust is, having the inconvenient of higher operator costs. Therefore, the optimal result is a trade-off between planned and additional costs.

2.6.   Differences with railway and airlines scheduling

Literature about railway and airplane planning is very extended, in some cases even more than for bus planning, especially for the *robustness* topic [i.e. Jamili, 2016 and Amberg et al., 2017]. The planning process for the 3 main means of transport (bus, railway and aircraft) are similar on the essence but different on the application, especially the railway can have more limitations. These differences can be summarized [Huisman, 2004] as:

- Timetables are more complex in railway planning, due to a rigid infrastructure which do not allow minimal headways between vehicles, besides having these ones different speeds make more complicated to optimize them. Airplane planning has the inconvenient of adapting its timetables to specific hours when there are limited slots (time windows to operate on the runways at the airports).

- Railway vehicle scheduling problem differs from bus planning on the possibility of combine different vehicles just in one, being more flexible at peak hours. Also empty train trips are more restricted because there are not as many options as on the bus networks. Regards differences with airplanes, these ones are planned for longer time horizon, meanwhile for buses usually is just one day. Essentially, trip times are longer in airplanes, which can mean that not all planes will come back to the same hub.

- Crew scheduling has its main difference on the number of workers needed among these systems. Buses only need one driver per vehicle, but trains usually need guards as well and airplanes are operated with a larger team composed of pilots, copilots and cabin crew. Although, these groups can be scheduled separately and the total trips number per duty is smaller than for buses, which can reduce computational time.

3. Case study: Frihamnen depot

The case study of this thesis is explained first to have a better understanding of the following collection data. As it has been mentioned before, this work is focus on one bus depot of Stockholm, *Frihamnen*.

Stockholm's Bus network

The capital of Sweden, Stockholm, is also considered the capital of Scandinavia based on its economic and demographic importance on the region, 2.1 million inhabitants. It is one of the European capitals with higher expectation of growing, in fact it is the fastest with a 11% increase up to 2020 [Stockholm Chamber of Commerce, 2015]. New population also means new challenges on mobility, for that reason the City of Stockholm developed a strategy in 2013 to provide sustainable and robust transport modes, focusing on three areas: City, infrastructure and transport planning [City of Stockholm, 2013]. In summary, that mobility strategy promotes greener transport modes as cycling and public transport, in contrast of private use of vehicle continuing the policy of congestion charge and increasing parking prices at city centre. Although nowadays, the use of public transport in peak hour is already high (80% of travellers), operational challenges would appear in the future as the need of transport routes to new neighbourhoods.

One main part of that public transport system is the huge bus network, composed by 544 bus routes, 5299 stops and 10,032 km length [SL, 2019]. It covers the whole Greater Stockholm area, from Norrtälje (North) to Nynäshamn (South), and Värmdö (East) to Nykvarn (West), a region extended more than 6,000 km². Region Stockholm, with its trademark SL, is the public transport authority in charge of that network, having 4 contractors for operating and providing maintenance to busses: *Keolis, Arriva, Transdev and Nobina*. As environment is another main concern for SL, Stockholm was pioneer using eco-friendly fuels since 1990s, and it has the goal of fossil-fuel free by 2025 [City of Stockholm, 2013]. Bus lines are classified in 3 groups:

- **Trunk lines (city and suburban – blue buses):** 5 inner-city lines with high frequency and priority bus lanes at some parts. Other trunk lines connect suburbs with important transport terminals close to city centre, usually using large capacity vehicles.
- **Local lines (Red buses):** the majority of lines belong to this group, normal bus lines connecting different neighbourhoods, in some cases they also have high frequency at peak hours and they circulate through bus lanes. And

- **Local service buses:** smaller buses intended for passengers with higher service requirements (i.e. elders), sometimes without fixed stops and timetables.

SL use a single zone ticket, what means you can travel everywhere among the network paying the same. Besides, all transport systems are joined in the ticket, having the possibility of using bus, metro, commuter train, trams and boats to reach any destination. The funding of PT is covered more than 50% by operations, the rest is financed by the Region Stockholm [EMTA, 2011].

Frihamnen depot

This thesis was done in collaboration with Keolis Sverige AB, the main bus operator in the city of Stockholm, providing service to 4 main areas: City centre, Lidingö, Nacka & Värmdö and Stockholm Sydväst (South-West). To handle these heavy operations, they possess 9 depots in different parts of those areas (3 of them in the city), being the one in Frihamnen an excellent option for a case study because of its location. It serves the whole bus network in Lidingö besides city lines, some of them very important as lines 1 and 6. This relation between networks has its node at Ropsten, a bus-metro-tram terminal, providing service to 16 bus lines, the metro red line 13, and Lidingöbanan tram.
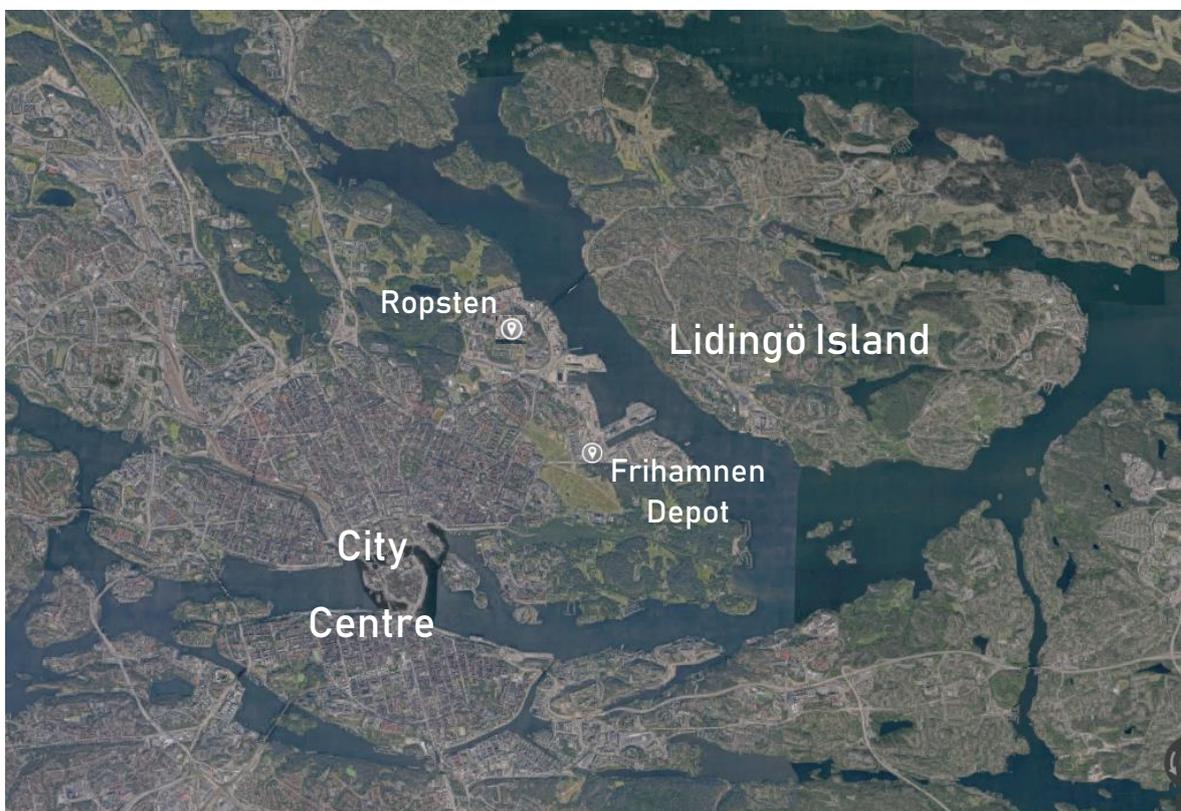
Figure 3. Location of Frihamnen Depot and Ropsten Terminal

As Figure 3 shows, Frihamnen depot is located at the Easter part of Stockholm's city centre, next to an industrial area that belongs to Frihamnen port (Frihamnen means "*Free Port*" in Swedish). This port is mainly used for ferry passengers' operations, having regular services to St. Petersburg, Helsinki and Tallinn operated by Moby Line SPL. Besides, carrying the half of seasonal cruise's passengers arriving to Stockholm (Port of Stockholm, 2018).

Ropsten terminal (*Appendix I. Detail map Ropsten*) is situated at North-East of city centre, next to the only bridge connecting the island of Lidingö with the rest of Stockholm and 2 Km North from Frihamnen, having just a 5-10 minutes' bus ride (depending on traffic). This closeness makes this depot the most ideal for Lidingö network. Although the land extension of Lidingö is almost as big as the whole Stockholm's city centre, difference in population is notorious, having the first one 47,000 inhabitants and almost 1 million the city of Stockholm [SCB, 2018]. Thus, demand is higher at city centre lines, and Lidingö lines are characterizes by a peak hour patterns, at morning peak passengers travel from Lidingö to Ropsten and opposite direction at evening peak. Some services just operate during these hours and directions.

City centre lines

City lines represent 40% of operations at Frihamnen depot operating 7 lines, but move more than 60% of daily passengers on buses depending of this depot. Besides, some of that lines are also depending of more depots, bigger ones as Hornsberg and Fredriksdal. However, two lines (1 & 6) are especially determinant in this high demand phenomenon running with high frequency, large capacity buses and connecting key places of city centre. They are cataloged as *trunk lines*, having regularity as a main goal instead of fixing to schedule.

Line 1 crosses city centre from East to West, departs next to Frihamnen depot and runs until the island of Stora Essingen, passing by important spots as Östermalm, Central Station and Fridhemsplan. And line 6 is connecting two developing areas, Hjorthagen (close to Ropsten) and Karolinska institutet (main medical and health sciences university), stopping at other large university (KTH) and a key multi-modal terminal (Odenplan). More detailed information of each city line is represented in Table 1 and Figure 4.

Table 1. City bus lines based on Frihamnen.

Line	Route	Frequency MO-FR	Frequency SA-SU
1	**Frihamnen – Stora Essingen** (Trunk Line). 13% Depot operations.	4-8 min [*7-19*] 8-10 min *rest*	7-10 min [*10-17*] 10-15 min *rest*
6	**Ropsten – Karolinska institutet** (Trunk Line). 12% Depot operations.	10 min [*6-10,14-20*] 15 min *rest*	15 min [*10-00*] 20 min *rest*
69	**Centralen – Kaknästornet/Blockhusudden** 5% Depot operations.	5-10 min [*7-19*] 20 min *rest*	6-10 min [*9-18*] 20 min *rest*
72	**Frihamnen – Odenplan** 2% Depot operations.	10 min [*7-10, 15-18*] 15 min *rest, stops 19*	No service
75	**Ropsten – Centralen** 5% Depot operations.	10 min [*7-10*] 15 min [*15-18*] 20 min *rest, stops 18*	20 min [*10-17*]
76	**Ropsten – Norra Hammarbyhamnen** 5% Depot operations.	10 min [*7-11,14-18*] 15 min *rest*	20 min [*9-18*] 30 min [*18-22*]
91	**Frihamnen – Stora Essingen (Night line)** <1% Depot operations.	5 services all night	20-30 min [*01-05*]
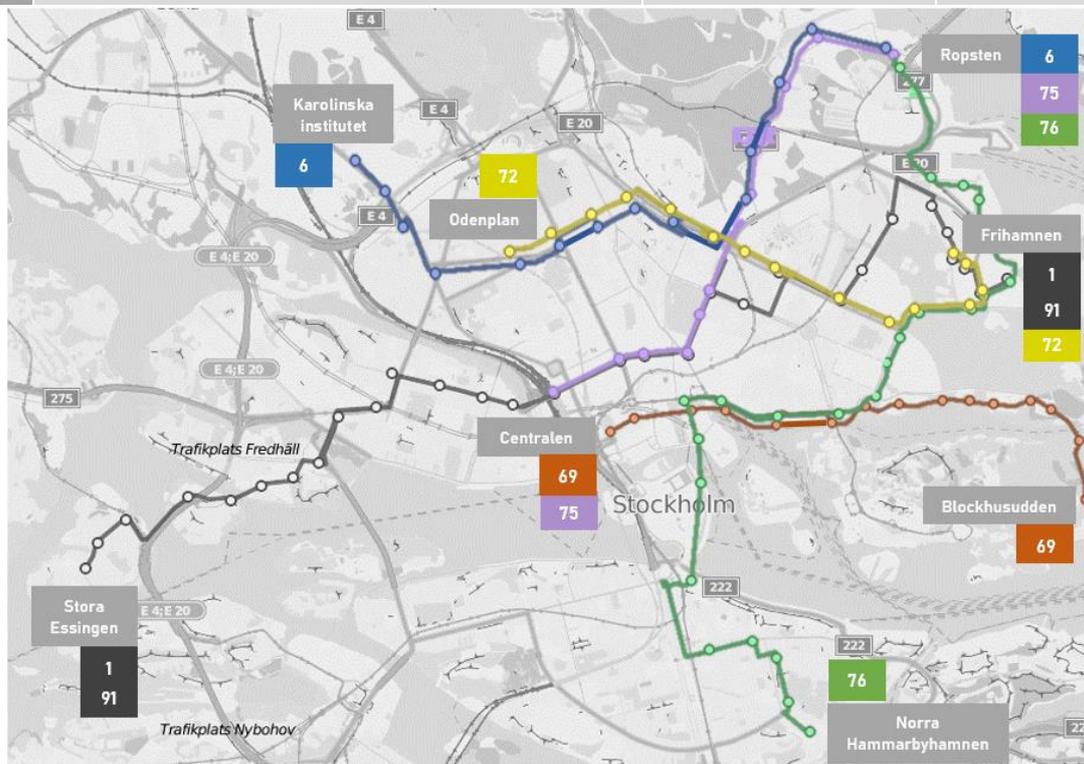
Figure 4. City centre bus lines.

Lidingö lines

Lidingö network has some particular characteristics which make it unique, as an island with just one bridge, where public transport has an important role on the mobility of its citizens. The majority of them live close to that bridge, having a traveller tendency of going to Stockholm, that's why almost all lines are based on connecting the multi-modal terminal of Ropsten (in Stockholm) with different neighbourhoods of Lidingö, passing by Lidingö centrum where is the main terminal. Only 2 lines run exclusively inside Lidingö without crossing to Stockholm. All Lidingö lines are depending of Frihamnen depot, more detailed information of these lines on Table 2 and Figure 5.

Table 2. Lidingö bus lines

Line	Route	Frequency MO-FR	Frequency SA-SU
201	**Ropsten – Kottla** 8% Depot operations.	10 min [*7-9, 15-19*] 20 min *rest*	20 min [*9-20*] 30 min *rest*
203	**Ropsten – Näset** 5% Depot operations.	20 min [*6-21*]	20 min [*6-21*]
204	**Ropsten – Elfvik** 5% Depot operations.	30 min [*6-9, 15-18*] 40 min *rest*	40 min [*10-18*] 60 min *rest*
205	**Ropsten – Sticklinge** 6% Depot operations.	15 min [*6-9*] 20 min *rest*	30 min [*9-00*]
206	**Ropsten – Gångsätra gård** 4% Depot operations.	30 min [*6-21*]	30 min [*6-21*]
211	**Ropsten – Böson** 1% Depot operations.	60 min [8-*16,19*]	60 min [8-*17*]
212	**Ropsten – Björnbo** 5% Depot operations.	30 min [*6-9, 15-18*] 40 min *rest*	40 min [*10-18*] 60 min *rest*
221	**Ropsten – Högsätra** 8% Depot operations.	10-15 min [*7-9, 15-18*] 20 min *rest*	20 min [*10-20*] 30 min rest
222	**Ropsten – Rudboda** <1% Depot operations.	20 min [*7-9, 16-18*] Rud-Rop morning Rop-Rud evening	No service

225	**Ropsten – Sticklinge** Express version of line 205. <1% Depot operations.	20 min [7-*9*, *15-18*] Sti-Rop morning Rop-Sti evening	No service
233	**Larsberg – Rudboda** <1% Depot operations.	3 morning services 3 evening services	No service
238	**Näset – Högsätra** 5% Depot operations.	30 min [*6-21*]	30 min [*9-21*]
291	**Gåshaga – Centralen (Night line)** 1% Depot operations.	30-60 min [*01-05*]	30 min [*01-05*]
293	**Ropsten – Rudboda (Night line)** <1% Depot operations.	3 services all night	30 min [*01-05*]
921	**Käppala – Servicehuset Tor** <1% Depot operations.	5 services all day	No service
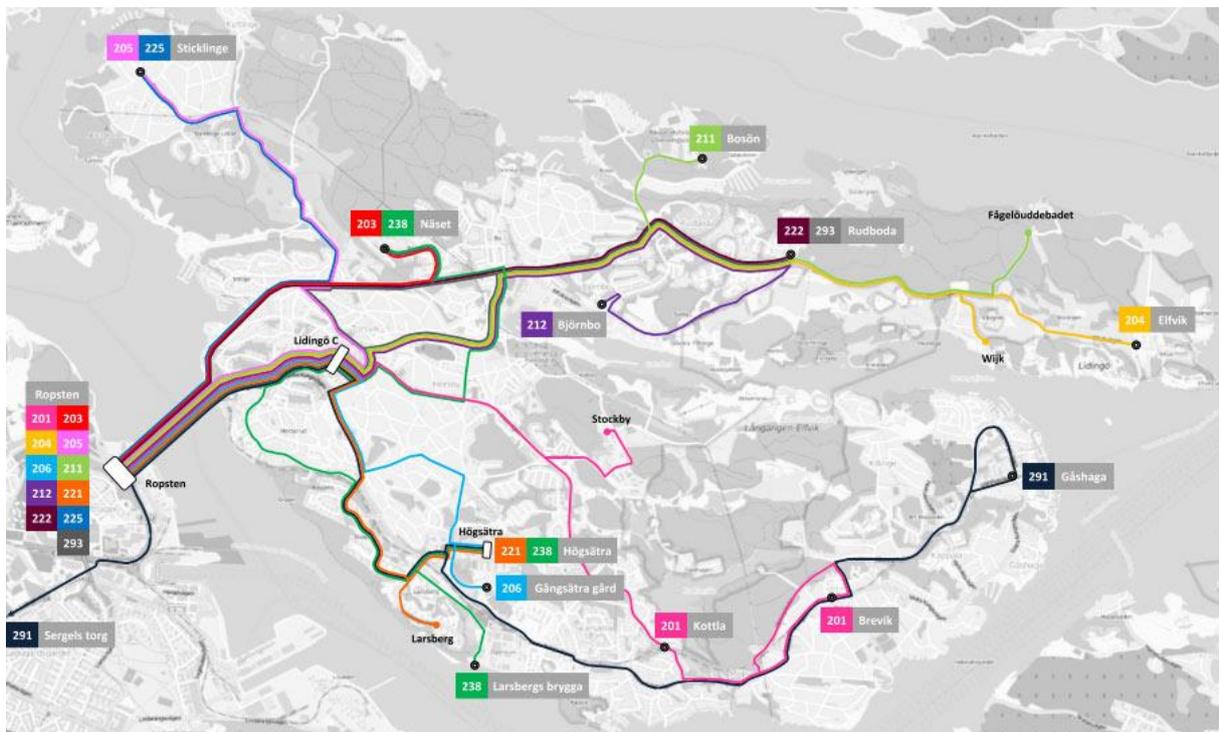
Figure 5. Lidingö bus lines. Source: Lidingösidan

4. METHODOLOGY

To develop a proper robustness model based on slack times, several options could be studied due to the extension of the term *robustness*, but in this study the relationship among that non-productive times before and after trips (*slack times*) and the average schedule deviation in seconds were the essential for analysing the actual situation and to performance future calculations and assumptions. After an extensive literature research and review about this topic, a process of data collection was done. Two main sources were used to collect planned and historical data of these variables, *Hastus* and *MOBILEstatistics*, both software accessible thanks to Keolis Sverige AB. That data was analysed focusing on one depot of Stockholm's bus network, Frihamnen, calculating its average (without outliers) of schedule deviation, slack%, passengers & probability of fines for last year. A regression model was performed based on those variables. To finally develop a robustness tool that can predict the performance of vehicle and crew schedules plus expected production and fines costs.

4.1. Data collection

A good data source is determinant to analyse a case, as important as amount of relevant data. Fortunately, both situations occurred in this thesis. On the one hand, all operational plans of last seasons were accessible by Hastus software and Keolis permission. On the other hand, SL provided all daily performance data of last and present year with MOBILEstatistics.

Hastus: Operational plans

This software developed by GIRO, a Canadian company, is positioned as one of main public transport software for scheduling and operations of bus, metro, light rail and tram. It is used by more than 300 worldwide clients and it has the possibility to manage up to 6,500 vehicles. It is a powerful tool that can based its optimization on preferences provide by the operator for work duties and schedules limitations, giving operational costs savings of 2-5% on average. [GIRO, 2019]

Due to these useful characteristics, the planning department of Keolis creates their new operational plans with this software, which also saves the previous plans. On an ordinary week there are 4 different operational plans: Monday to Thursday (MO-TH), Friday (FR), Saturday (SAT) and Sunday (SU). Besides these basic plans, there are

specific ones for special days as: Holidays, events, Summer, etc. Usually, a basic plan is the same for winter-spring (January to May) and autumn (September to December). Based on that, 12 different operational plans were collected, the 4 basic ones (MO-TH, FR, SA and SU) of 3 different periods: **winter-spring 2018**, **autumn 2018** and **winter-spring 2019**.

For each operational plan it was possible to collect a huge amount of data, but having in mind the important information needed for the consequent analysis, just the vehicle activity and crew breaks plans were taken in account (*OmlAkt* and *Uppehåll* plans), with some common values to related them. Each plan listed all bus trips depending on Frihamnen depot, considering only the first departure information of each trip. The vehicle activity and crew breaks plans were composed of:

- Crew ID: Common for both plans. Hastus gives a number for each necessary duty, after a specific driver will be assigned every day for that plan based on crew scheduling.
- Vehicle ID: Common for both plans. Same situation than drivers, each vehicle has a related number that will be assigned with vehicle scheduling.
- Line: Common for both plans. Line number of that trip.
- Activity: Common for both plans. In case of vehicle activity can be *regular* (productive trip service), *deadhead* (non-productive trip), *stand-by* (non-productive time), *pull-in* and *pull-out* (first and last trip from/to depot). Only regular activities were considered. For breaks plan, activity can be *paus* (10-30 min) or *meal break* (30-90 min).
- From: Common for both plans. Departure trip stop or crew break place.
- Start time before boarding: Only for vehicle activity. Indicates when boarding time should start, sometimes is the same than start time but on peak hours or high demand it can be 1 or 2 minutes before.
- Start time: Only for vehicle activity. Scheduled starting time of the trip.
- Final time: Only for vehicle activity. Scheduled final time of the trip.
- To: Common for both plans. Final trip stop or crew break place.
- Time Activity: Only for vehicle activity. Total scheduled trip time.
- Slack time: Only for vehicle activity. This value was the main one for the analysis coming from operational plans. It represents the non-productive time before a trip, it is a buffer time to absorb possible delays of previous trips.
- Minimum slack time: Only for vehicle activity. Minimum slack time to consider before a trip due to stop, traffic and/or demand conditions.
- Start time break: Only for break plans. Scheduled starting time of the break.

- <u>Final time break:</u> Only for break plans. Scheduled final time of the break.
- <u>Start time next productive trip:</u> Only for break plans. Scheduled starting time of the next productive trip, same as starting time of vehicle activity for those specific trips, it was used to related vehicle activity and break plans.
- <u>Break duration:</u> Only for break plans. Total break duration, always higher or equal than 10 minutes.

MOBILEstatistics: performance data

This software is used as an analysis tool to look on detail how is the performance working, and studying trends of actual operations. It can provide huge amount of data based on different parameters and situations, also can merge that data on clean reports to help planning department to base some decisions on historical data. It is developed by INIT, a German company with extensive experience in public transport software. [INIT, 2014]

Storstockholms Lokaltrafik (SL) recollects real time data from the buses with AVL (*Automatic Vehicle Location*). This system uses Global Positioning System (GPS) on the vehicles, besides a computer software to calculate different performance measurements, and communication platforms between driver, control centre and passengers. That data is updated to MOBILEstatistics every day and saved it for more than one year on the system. From that empirical datasets, historical data was collected for the 12 operational plans selected previously, on the same 3 different seasons: Winter-spring 2018 (**10/January-01/June**), Autumn 2018 (**20/August-08/December**) and Winter 2019 (**09/December-15/March**). Some exceptions were applied to avoid different operational plans on special days. Last period, Winter 2019, studied less days due to the starting date of data collection for this thesis, 18/March.

As previously with Hastus datasets, MOBILEstatistics also provides different type of data on large amounts. Meanwhile the most important value from operational plans was slack time, from performance data was the average deviation from schedule at departures to represent actual delays of each trip. This software offers a query called *Average Deviation On Time*, with a sub-class *Average trip*. This query was composed by:

- <u>Line:</u> Line number of that trip. Same as Hastus datasets.
- <u>Pattern:</u> Initial and final stops of that trip. Same of Hastus datasets.
- <u>Scheduled time:</u> Schedule departure time of that trip. Same of Hastus datasets.

- <u>Stop:</u> Address of stop. AVL records the exact location, in some terminals depending on that can mean different departure or arrival stops.
- <u>Avg.departure:</u> Average deviation from schedule departure of that specific trip during the whole studied period. Represented in seconds, it shows in detail how late (or early, rarely) is each trip.
- <u>Sample size:</u> In some cases, MOBILEstatistics did not provide total average of all trips on the studied period, probably due to different events. Giving the sample size of how many days were considered for that value. This problem was solved applying a total weighted average based on this value.

Furthermore, following the final recommendations of Amberg et al. (2018), passengers' data could be determinant for robustness. For that reason, also some information about demand per trip was collected by MOBILEstatistics. Another query provided those numbers as an average of passengers during the studied period for each specific trip, that could be related to the same trips of Hastus.

4.2.   Data analysis

After data collection, the amount of data was enormous, more than 502,000 data trips from MOBILEstatistics had to be related to the 12 operational plans, each one composed with 700 to 1300 daily trips. To performance that data analysis it was used the software MS Excel. Its function of Query Editor gave the option to merge in one table the vehicle activity plan, crew breaks plan, the average schedule deviation and passengers for each initial trip departure, due to the existence of common values at their tables.

In order to consider both slack times from vehicle and crew breaks, a new parameter was created on that merged table, *slack%*. It showed on percentage the restricting slack time in relation to the total trip time (with boarding and slack times). That restriction came from the minimum value among vehicle and break slack time, having at least 10-minutes break. Creating this value, it was also taking into account how long is the trip, it is not the same a 2-minutes slack time on a 15-minutes trip than a 50-minutes trip. Probably the second one will be more delayed, needing a longer slack time. In addition, using this value instead of minutes of slack time gave a better distribution of points (avoiding just columns of points at 1, 2, 3 minutes, …), real important aspect to find some correlations among that big amount of data.

Several transformations (logarithm, exponential, squares, inverse value, …) of the parameter *slack%* were analysed trying to find out which would be the best fitted option.

The formulation of *slack%* is:

$$
Slack\% = \begin{cases} \dfrac{Ts}{Ts + Tt + Tb} & if\ \ Td = 0\ \ \ or\ \ \ Ts < (Td - 10) \\[4mm] \dfrac{Td - 10}{(Td - 10) + Tt + Tb} & if\ Ts \geq (Td - 10) \end{cases} \qquad (1)
$$

Where:

Ts = Vehicle Slack time

Tt = Trip time

Tb = Boarding time

Td = Driver Paus/Break time

All the following analyses were done relating that new value, *slack%*, and the average schedule deviation (in seconds) for each single trip of the 12 operational plans. The goal was to demonstrate the fact that lower slack times before the beginning of each trip can mean higher schedule deviation, which could seem very logical but it had to be proved, also to calculate the parameters of that relationship. The reason of choosing the slack time before trip and not after was mainly due to data of first stop is more accurate than last stop, therefore considering the previous non-productive time (minutes that can be taken without altering following operations) and the actual deviation of schedule was possible to know when that factor was determinant for the future delays.

These analyses where conducted in Excel following the format of Figure 6 (Appendix II for more detail), showing all relevant data collected together. The column of average schedule deviation was classified by colour to highlight the most delayed trips. Also it was studied the most restrictive slack time among vehicle or crew for trips with a deviation higher than 180 seconds (3 minutes).

CrewID	VehID	Line	Activity	From	Start_befb	Start	Final	To	TimeA	Slack	MinS	Stop	AVG dev	Board	Paus	Slack%	Passeng	Perception
2002	801	1	Regular	FRI	05:22:00	05:23:00	05:55:00	EST	32	0	2	Frihamnen,3	20	1	0	0.00	21	0
2002	801	1	Regular	EST	06:09:00	06:10:00	06:50:00	FRI	40	14	2	Essingetorget,	20	1	0	25.45	76	0
2606	808	1	Regular	FRI	06:17:00	06:18:00	06:55:00	EST	37	0	2	Frihamnen,3	75	1	0	0.00	41	10
2704	801	1	Regular	FRI	06:53:00	06:54:00	07:38:00	EST	44	3	2	Frihamnen,3	32	1	0	6.25	71	0
2606	808	1	Regular	EST	06:59:00	07:00:00	07:45:00	FRI	45	4	0	Essingetorget,	40	1	0	8.00	130	0
2705	810	1	Regular	FRI	06:59:00	07:00:00	07:45:00	EST	45	0	2	Frihamnen,3	51	1	0	0.00	98	0
2605	813	1	Regular	FRI	07:21:00	07:22:00	08:09:00	EST	47	0	2	Frihamnen,3	77	1	26	0.00	79	22
2704	801	1	Regular	EST	07:41:00	07:43:00	08:34:00	FRI	51	3	2	Essingetorget,	35	2	0	5.36	162	0
2705	810	1	Regular	EST	07:47:00	07:49:00	08:41:00	FRI	52	2	2	Essingetorget,	61	2	0	3.57	210	4
2109	814	1	Regular	FRI	07:51:00	07:52:00	08:42:00	EST	50	0	2	Frihamnen,3	74	1	0	0.00	130	31
2606	808	1	Regular	FRI	08:01:00	08:02:00	08:52:00	EST	50	0	3	Frihamnen,3	48	1	12	0.00	165	0
2605	813	1	Regular	EST	08:11:00	08:13:00	09:05:00	FRI	52	2	2	Essingetorget,	117	2	0	3.57	218	206
2202	801	1	Regular	FRI	08:37:00	08:38:00	09:26:00	EST	48	3	2	Frihamnen,3	132	1	0	5.77	104	124
2701	810	1	Regular	FRI	08:43:00	08:44:00	09:30:00	EST	46	2	3	Frihamnen,3	124	1	13	4.08	97	104
2109	814	1	Regular	EST	08:47:00	08:49:00	09:39:00	FRI	50	5	2	Essingetorget,	71	2	0	8.77	91	16
2606	808	1	Regular	EST	09:05:00	09:07:00	09:55:00	FRI	48	13	2	Essingetorget,	29	2	0	20.63	110	0
502	813	1	Regular	FRI	09:07:00	09:08:00	09:53:00	EST	45	2	3	Frihamnen,3	253	1	12	4.17	65	207
2202	801	1	Regular	EST	09:31:00	09:32:00	10:20:00	FRI	48	5	0	Essingetorget,	61	1	0	9.26	103	2
2701	810	1	Regular	EST	09:38:00	09:39:00	10:26:00	FRI	47	8	2	Essingetorget,	27	1	0	14.29	92	0
2703	814	1	Regular	FRI	09:41:00	09:42:00	10:27:00	EST	45	2	2	Frihamnen,3	157	1	17	4.17	77	124

Figure 6. Extract Robustness analysis

The last column of perception passengers was created to quantify the perception of lost time for them, which can produce future costs by a decreasing of demand if travellers do not think that service is respecting timetables. This value was calculated by multiplying the number of passengers per seconds of deviation (for trips of more than 60 seconds deviation, otherwise it is one time).

To study the slack%-average schedule deviation relation, some regression models were performed using the same software, Excel. In order to find some parameters to predict an average schedule deviation (dependent variable) with new slack times (primary independent variable), which are selected during the planning process. Same analyses were done considering passengers' parameter as a secondary independent variable.

4.3.   Robustness economic analysis

To find out the trade-off needed among lower production costs (lower slack%) and lower fines costs (usually higher slack%) some formulas were applied to obtain different costs for: operator (production and fines) and passengers (perception lost time). This mathematical formulation was a simplified version of the one exposed by Yap & Van Oort [2018] where takes more into account passengers costs. In this case it only took consideration of overtime passengers perception per value of time (equation 2). Production costs (equation 3) were based on the extra costs due to non-productive times (*slack*), of having a driver and a vehicle on circulation or stopped without any passengers. Finally, the fines costs (equation 4) were the sum of early, late, partial cancelled or total cancelled trips, which could change depending on the contract with the PTA.

$$Cpass = VoT * \sum_{i}^{K} \left((AVGdev_i - 60) \big/ 3600 \right) * Pass_i \qquad i{\neq}0 \ if \ AVGdev > 60 \ sec \quad (2)$$

$$Cprod = \beta extra * \sum_{i}^{K} Slack_i \tag{3}$$

$$Cfine = \beta 1 * (Early + Late + Partial\ cancelled) + \beta 2 * Cancelled \tag{4}$$

Where:

Cpass = Passengers costs (SEK)

Cprod = Slack production costs (SEK)

Cfine = Fines costs (SEK)

AVGdev = Average schedule deviation (seconds)

Pass = Passengers per trip

VoT = Value of time urban bus (SEK/h)

K = Total number of trips

i = Trip i

βextra = Operator cost extra time (SEK/h)

β1 = Half-fine cost for early, late or partial cancelled (SEK)

β2 = Fine cost for total cancelled (SEK)

Early = Number of fined early departures trips

Late = Number of fined late departures trips

Partial cancelled = Number of fined partial cancelled trips

Cancelled = Number of fined total cancelled trips

The optimal solution would be the one with lower total sum of costs, especially considering production and fines costs (the passenger costs are more informative than determinant for the operator). This formulation can be modified in order to consider a larger limit time for passengers' lost time perception. All these methodology lead to a robustness tool, a simulation model made with the software MS Excel which is the final goal of this thesis.

5. RESULTS

5.1.   Slack% - Average Schedule Deviation

As it has been discussed on the Methodology part, the two main variables in this study are the *average schedule deviation* and a new parameter called s*lack%*, which takes in account the slack time (before each trip according to vehicle and crew limitations) as a percentage of the total trip time. This relation has been studied in the 4 different week plans (Monday-Thursday, Friday, Saturday & Sunday) for the whole period of data collection, January '18 to March '19. Figure 7 shows a comparison between these plans and their variables' distribution for each trip. Subsequently, each plan is treated in detail.
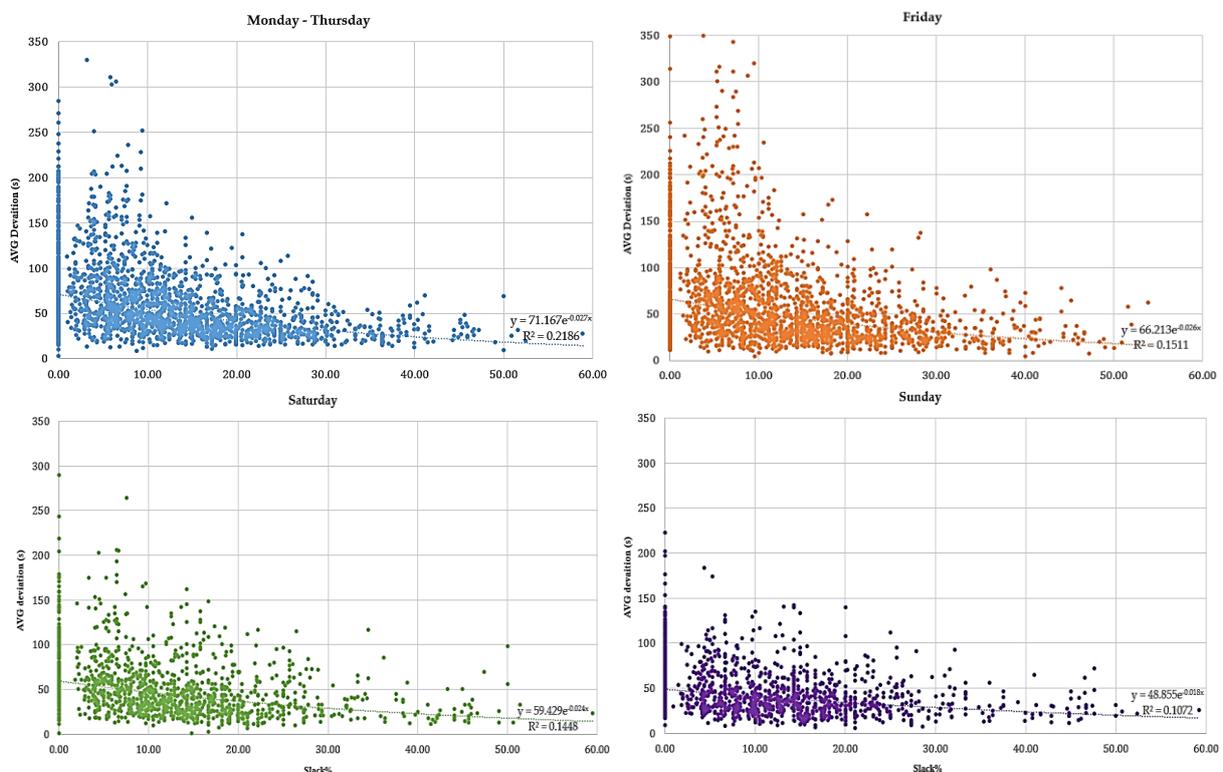
Figure 7. Comparison 4 different weekly plans (MOTH, FR, SAT & SU)

Monday-Thursday and Friday plans have more trips clearly, more than 2,000. Meanwhile the weekends plans are limited to almost the half, above 1,000. Therefore, a higher distribution of late trips (up to 350 seconds late) can be found on the weekdays plans, especially on Friday, introducing the idea of higher issues due to larger number of passengers and heavy traffic conditions. Also, a slightly exponential trend can be noticed but with low R^2 due to the variance of the large amount of points. To check this assumption, the whole same data is aggregated into intervals of 10% of *slack%* (plus considering the situation of 0%, Figure 8), giving as a result more clarifying trends that have higher variance due to *slack%* on weekdays, especially below 20%.
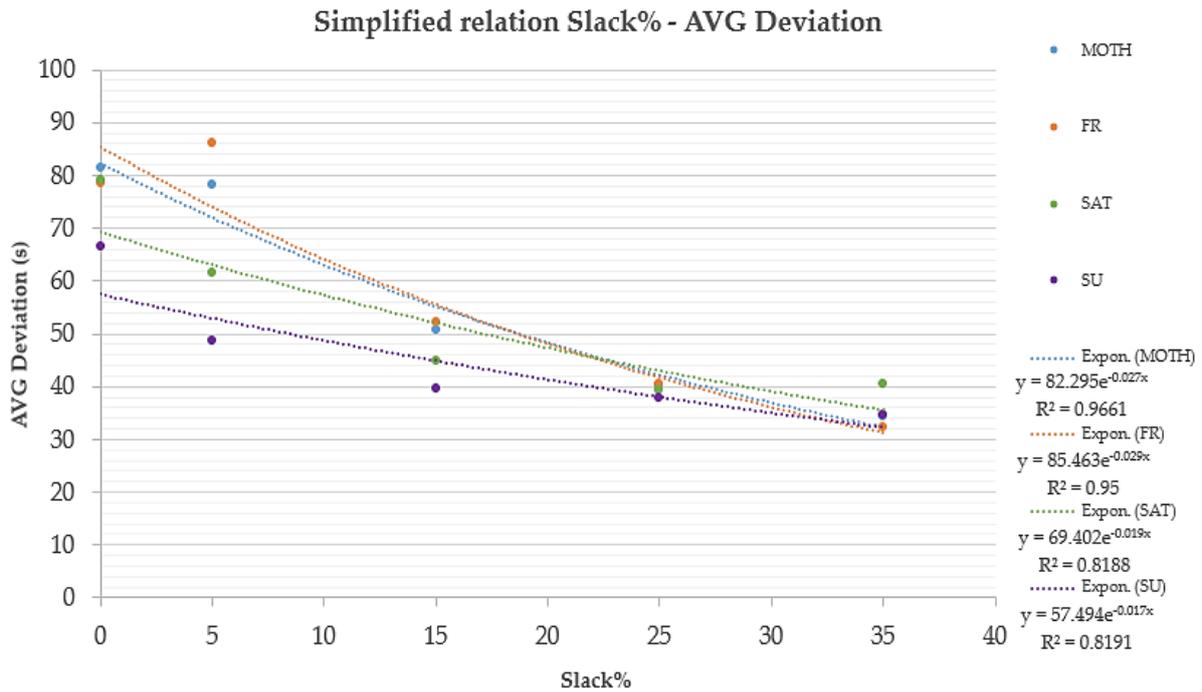
Figure 8. Simplified relation Slack% - AVG Deviation

After this value, all trends tend to have similar schedule deviation, what means *slack%* is not a determinant factor on the delays anymore when its value is larger than 20-25%. Therefore, it is possible to affirm (as it was set out at the beginning of this study) that a variance of slack time before each trip can determine future delays, avoiding its spreading when this time is enough long to absorb previous delays, or increasing them more due to a "*snowfall*" effect when it is too short.

Monday-Thursday

The first plan recollects all trips during weekdays (Monday to Thursday) which have the same timetables. As the amount of raw data was huge (more than 200 days), the average values that are shown in Figure 9 are quite accurate. There, a noteworthy fact is that a higher value above 10 of *slack%* also means that no trips have a first departure more delayed than 3 minutes on average, which can avoid fines in some cases. Only few trips have a delay larger than 200 seconds. The exponential trend is almost linear because majority of the points are located on the same region, between 0-20 *slack%* and less than 75 s *average deviation*. Focusing in sub-groups (Table 3), all trips in that region represents almost the 80% of the total. Another aspect that clearly shows this variance is the difference of the averages deviation values when *slack%* is 0 or 1-10 (81 and 78 seconds, respectively) and the rest of situations, decreasing to 50, 40 and 30 seconds.
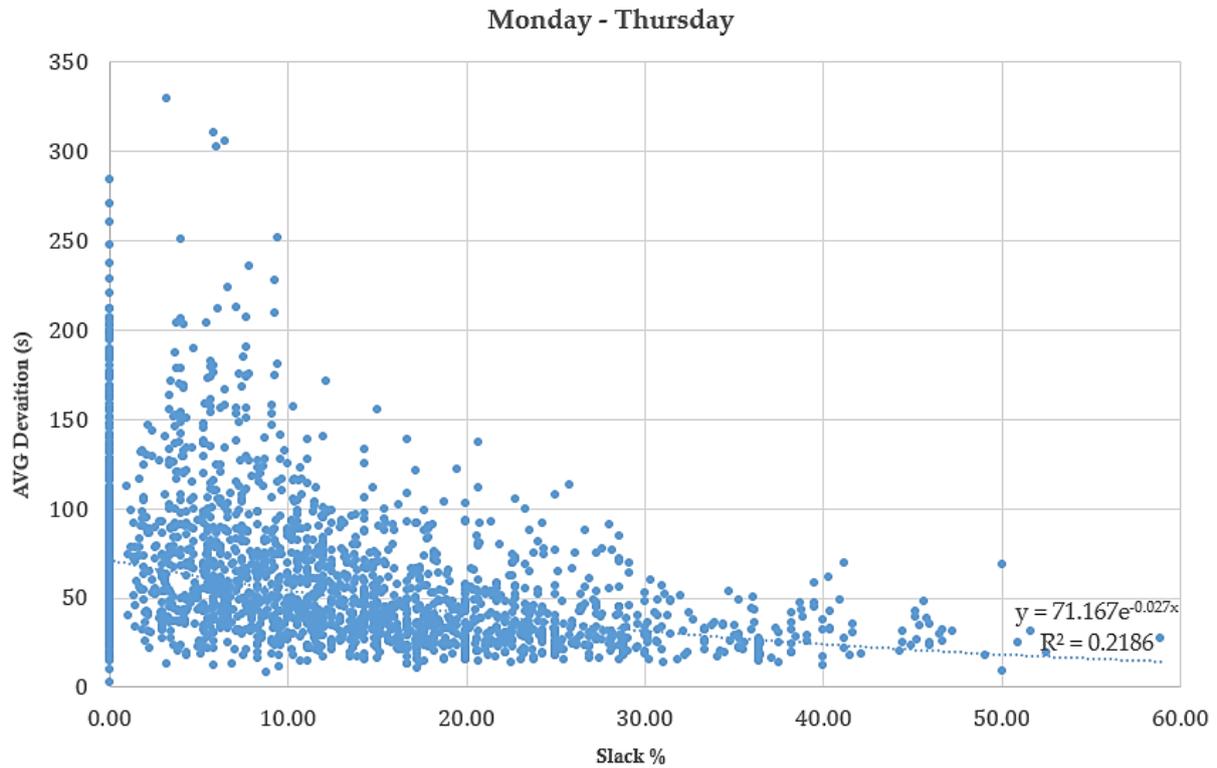
Figure 9. Slack% - AVG Deviation (Monday – Thursday)

Concentrating on the most delayed trips (AVG dev > 180 s), they just represent the 2% of the total, usually happening on evening peak and crowded lines, the biggest problems occur on line **1** (half of these delayed trips, in this case also on the morning peak) and line **238**. Besides, some large delays on lines **6, 201 and 221**, which are a *trunk line* and the most transited lines in Lidingö.

Table 3. Aggregated data in sub-groups (Monday - Thursday)

MONDAY-THURSDAY	Dev (sec)	Trips	%Total
AVG TOTAL	62.12	2243	100
Slack% 0	81.50	407	18.15
Slack% 1-10	78.33	675	30.09
Slack% 11-20	50.76	712	31.74
Slack% 21-30	40.08	312	13.91
Slack% 30-40	34.38	101	4.50

	Slack%	Trips	%Total
AVG dev > 180s	3.53	51	2.27
120s < AVG dev < 180s	4.89	161	7.18
60s < AVG dev < 120s	8.17	663	29.56
AVG dev < 60s	15.26	1368	60.99

Friday

Friday is the most problematic day of the week, especially on the evening, probably a higher anxiety of arriving home and starting the weekend generates this small chaos. Although the trend is quite similar to the situation of Monday-Thursday (Figure 10), both plans share the same timetables but there is a higher production on Friday (more buses and drivers) based on these recurrent problems, the total number of delayed trips increase considerably, doubling the previous situation and reaching a 5% of total trips, more than 100 trips are departing later than 180 seconds and more departures have a null slack time creating more critical situations without any margin to recover (Table 4). The number of late departures with large *slack%* also increase, which can mean that in some trips with presence of chaos the system cannot absorb all delays with just the slack time. However, as it happens on the Monday-Thursday plan, on average the deviation drops drastically having a *slack%* higher than 10.

Once again, line **1** has the worst performance, more than 50 late departures during the day. Remarkable is the situation at the evening peak, when almost all trips are delayed, but it is necessary to mention again that this line is based on regularity and not on fixed-schedule. It could happen that these trips are late according to the planning but they respect their headways, however the raw data shows that bunching is quite usual in these conditions. In addition to this line, all other lines have at least some late departure in Friday evening peak.
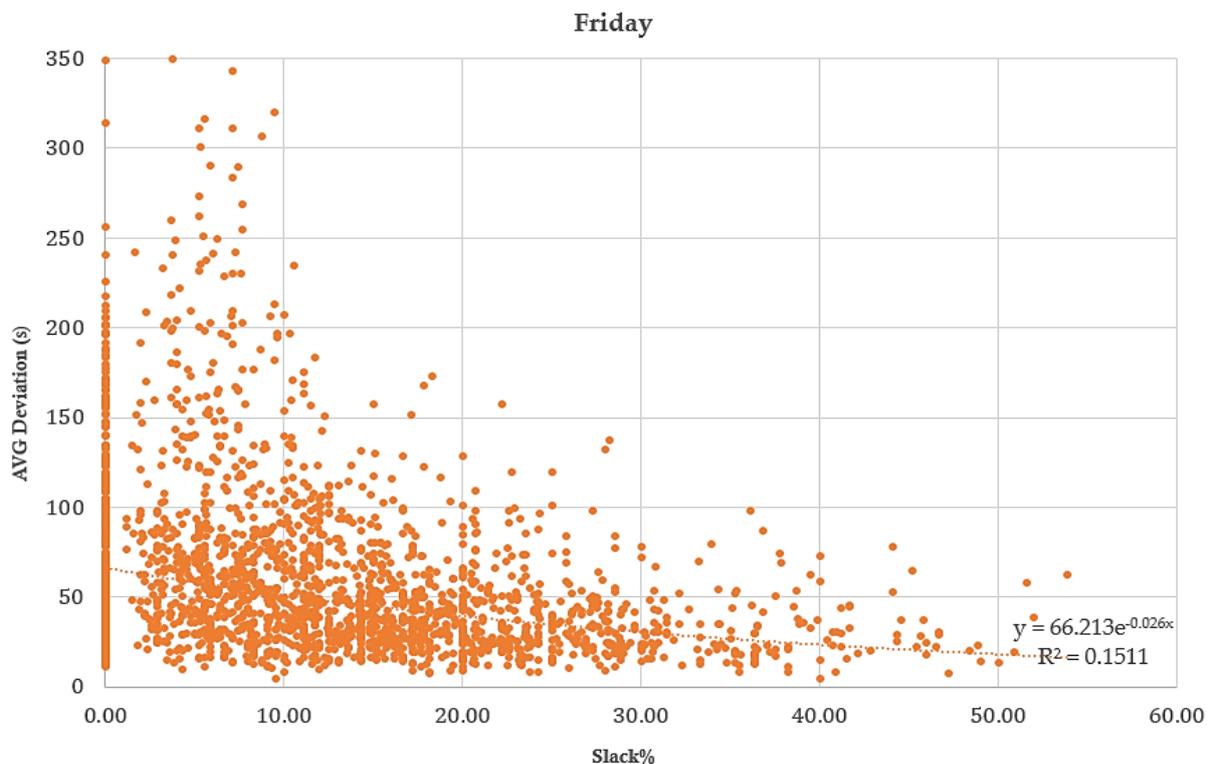
Figure 10. Slack% - AVG Deviation (Friday)

The trendline equation shown in the figure:

$$y = 66.213e^{-0.026x}$$
$$R^2 = 0.1511$$

Table 4. Aggregated data in sub-groups (Friday)

FRIDAY	Dev (sec)	Trips	%Total
AVG TOTAL	64.58	2229	100
Slack% 0	78.56	436	19.56
Slack% 1-10	86.08	665	29.83
Slack% 11-20	52.15	686	30.78
Slack% 21-30	40.38	305	13.68
Slack% 30-40	32.16	100	4.49

	Slack%	Trips	%Total
AVG dev > 180s	5.06	111	4.98
120s < AVG dev < 180s	5.67	147	6.59
60s < AVG dev < 120s	8.60	596	26.74
AVG dev < 60s	14.79	1375	61.69

Saturday

On weekends the situation changes to better, there are less delayed departures (just 12 trips on Saturdays, less than 1%, Table 5). Even delays between 120 and 180 seconds go down, resulting that almost 95% of the trips have an acceptable departure time. Its trend is quite horizontal because there are not big changes among schedule deviation based on *slack%* (Figure 11).
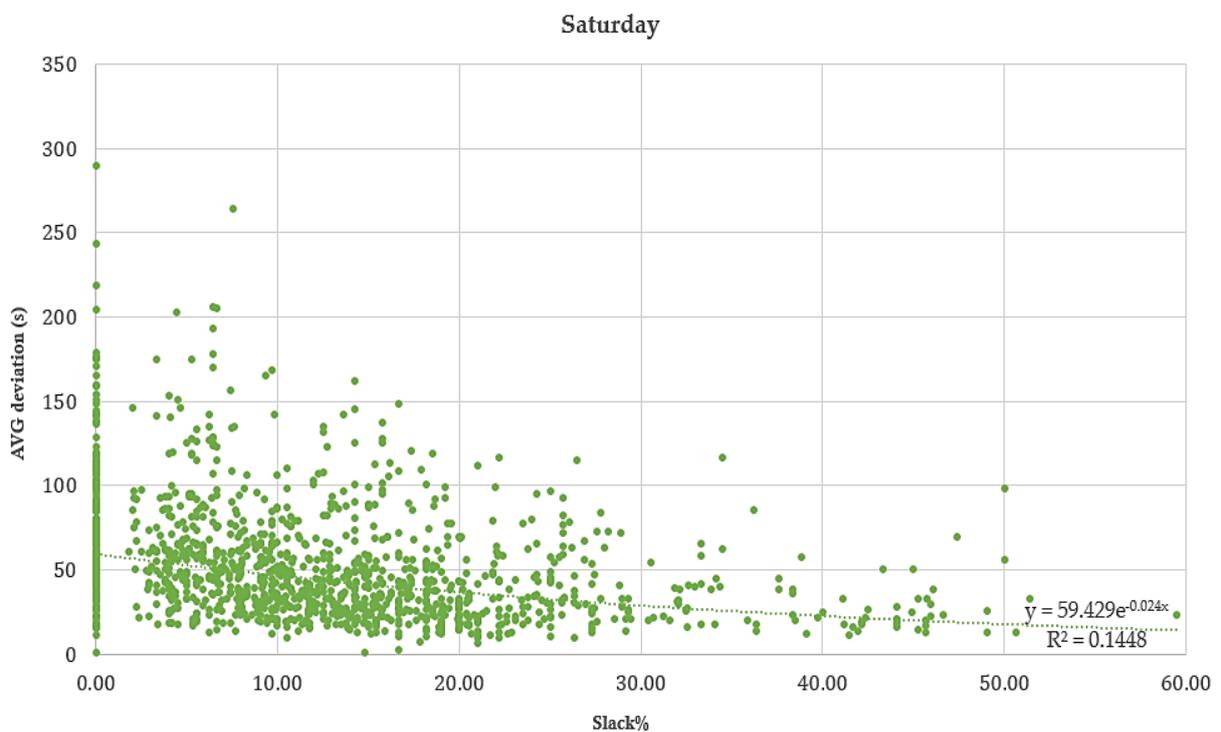
Figure 11. Slack% - AVG Deviation (Saturday)

Table 5. Aggregated data in sub-groups (Saturday)

SATURDAY	Dev (sec)	Trips	%Total
AVG TOTAL	54.09	1279	100
Slack% 0	79.18	191	14.93
Slack% 1-10	61.63	405	31.67
Slack% 11-20	44.80	455	35.57
Slack% 21-30	39.33	153	11.96
Slack% 30-40	40.57	40	3.13

	Slack%	Trips	%Total
AVG dev > 180s	6.76	12	0.94
120s < AVG dev < 180s	5.55	62	4.85
60s < AVG dev < 120s	8.70	331	25.88
AVG dev < 60s	14.58	874	68.33

The average deviation is just high when there is not slack time (79 seconds), otherwise the values are considered admissible (less than 60 seconds). The number of departures in the first case have dropped to 15% of the total, there are less strict limits on the planning these days. Besides, there is not a delay patron as weekdays on peak hours. Usually late departures happen when more passengers are but demand distribution changes depending on lines and times.

Sunday

The last plan is the quietest day, disturbances on Sunday are very limited being the day with less production and demand. Only 4 departures are considered very late, which represents 0.3% of total trips, practically nothing. On Figure 12 there are not trips with extreme delays as the previous cases, all departures are quite plain, that is why *slack%* is less determinant in this case as the trend shows and it has the lower R^2.

Table 6 also explains that a null slack time has less effect that other days, having an acceptable value in this case (66 seconds). Besides this situation, the average schedule deviation keeps a similar value independently of *slack%* (around 40 seconds), which can verify the assumption done for the Saturday plan, on weekends the slack time is not as determinant as during weekdays. As before, joining the departures between 0 and 120 seconds late, they represent more than 97%, which means that almost all trips start on time.
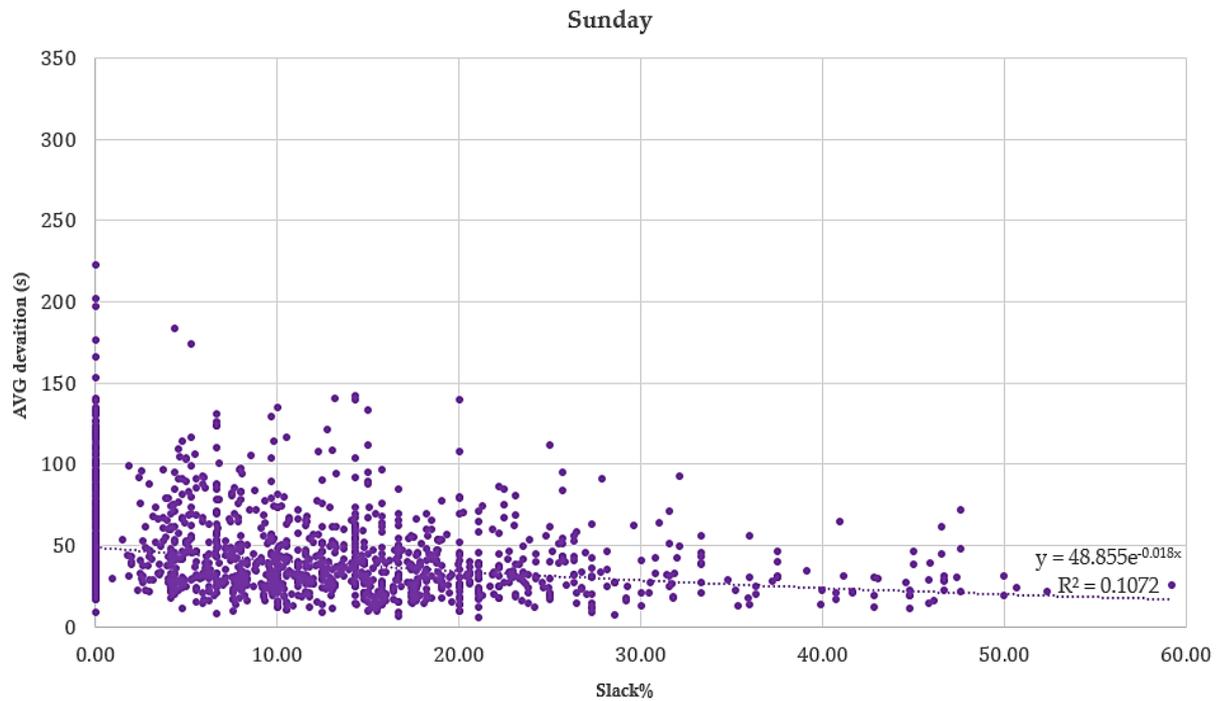
Figure 12. Slack% - AVG Deviation (Sunday)

Table 6. Aggregated data in sub-groups (Sunday)

SUNDAY	Dev (sec)	Trips	%Total
AVG TOTAL	46.18	1252	100
Slack% 0	66.58	202	16.13
Slack% 1-10	48.56	399	31.87
Slack% 11-20	39.64	420	33.55
Slack% 21-30	37.86	152	12.14
Slack% 30-40	34.59	42	3.35

	Slack%	Trips	%Total
AVG dev > 180s	1.09	4	0.32
120s < AVG dev < 180s	6.27	31	2.48
60s < AVG dev < 120s	8.39	258	20.61
AVG dev < 60s	13.93	959	76.60

5.2.   Regression models (Deviation - slack% - passengers)

To calculate the regression models, this study also considers other relevant parameter, *passengers flow*, following recommendations for future work of Amberg et al. [2018]. Effectively, this parameter affects in weekdays, especially during peak hours. As Figure 13 shows hourly (all Frihamnen data), there are two passenger peaks: *morning* (7-9) and *evening* (14-18). These peaks coincide with the largest values of *schedule deviation* and the smallest ones of *slack%*, having the evening peak worst results.
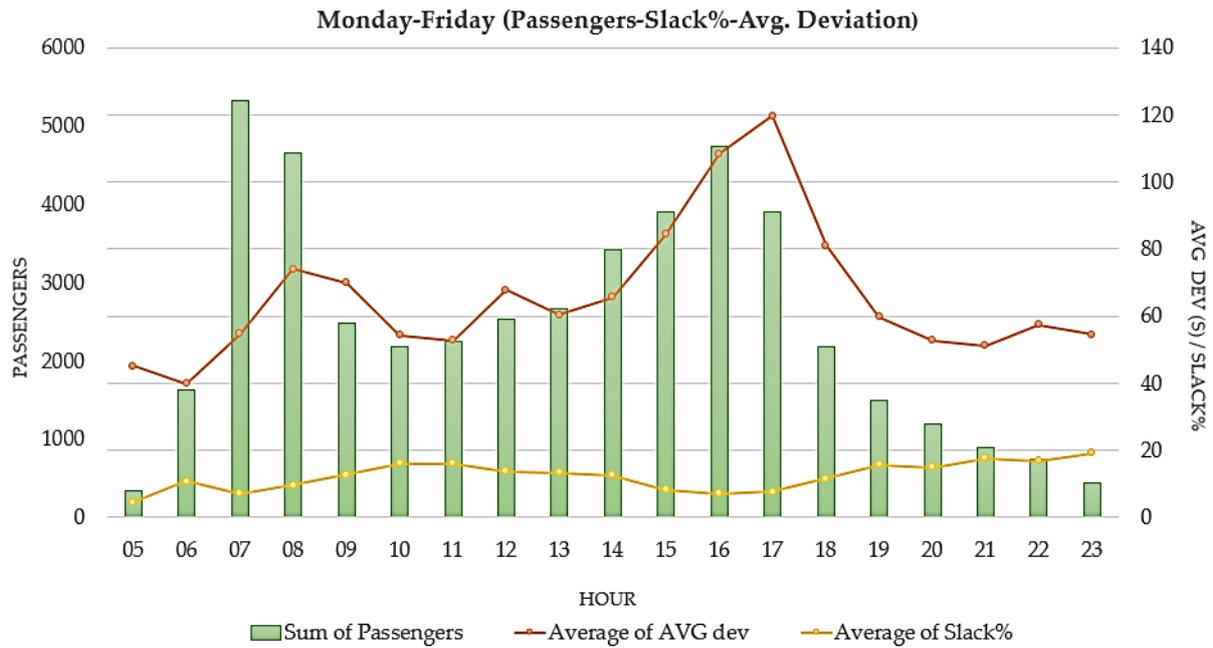
Figure 13. Relation Passengers - Slack% - AVG Deviation (Monday – Friday)

It makes sense because during that hours is when the network is more optimized, planning shorter slack times (several null) to have a higher use of vehicles, ending on larger delays when you consider all parameters (plus heavier traffic conditions). Another interesting output from this graph, is that the system has more problems with longer periods of demand (*evening peak*) and its worst moment is later than demand peak. This can happen due to a waterfall effect of some early delay that is not absorb until slack times and planned trip times are higher.
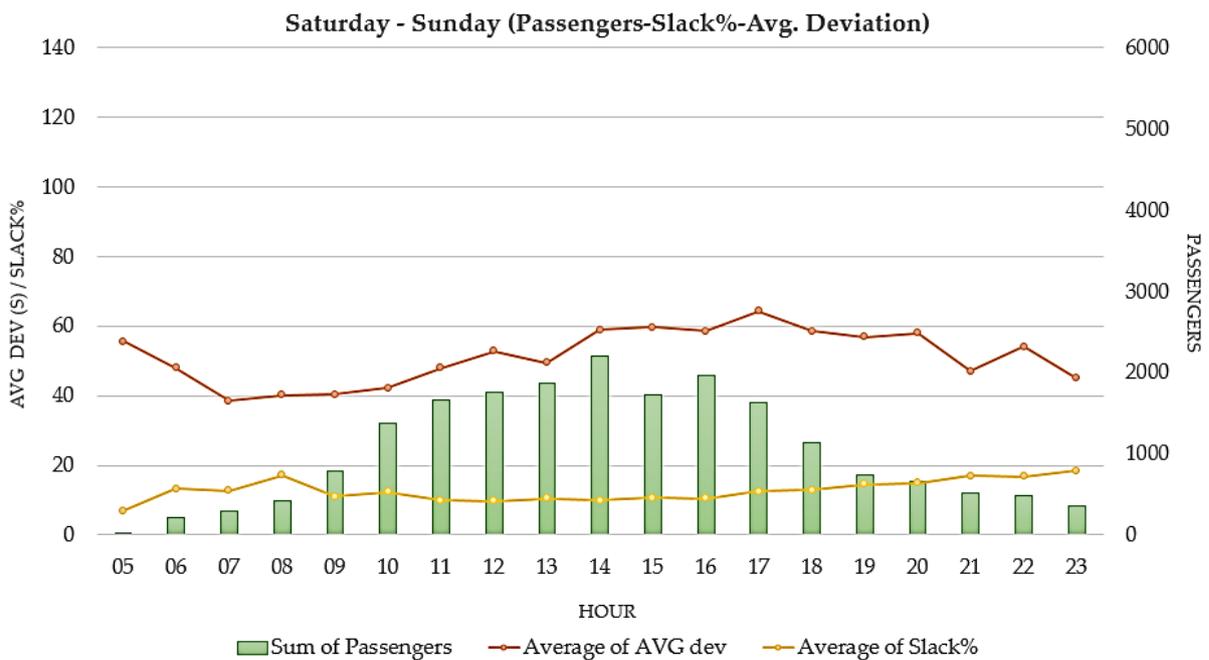
Figure 14. Relation Passengers - Slack% - AVG Deviation (Saturday - Sunday)

Figure 14 shows the situation for weekends, which is more plain the whole day, without any considerable peak. Passenger demand follows a normal distribution having the largest values at the middle of the day, but these ones are equivalent to the ones of non-peak hours in weekdays, so *passengers flow* is not a determinant parameter for schedule deviation during weekends.

As mentioned before, several transformations of slack% have been evaluated to know which one fits better the model. There were focus on the case of Monday-Thursday, giving as a result that the normal variable without any transformation would be the best choice having the best indicators of adjusted R square, T statistics and P value (Table 7).

Table 7. Transformations of slack%

TRANSFORMATIONS OF SLACK%	Adjusted R^2	T stat	P value
None (Slack%)	0,183589	-19,04036	4,89E-75
Inverse (1/Slack%)	0,077906	13,79633	1,28E-41
Squares (Slack%^2)	0,106709	-16,3921	4,03E-57
Logarithm (Log Slack%)	0,140073	-19,1321	1,08E-75
Exponential (Exp Slack%)	-0,00014	-0,83106	0,406031

Therefore, regression parameters are calculated studying the relations of the 4 different plans: Monday-Thursday, Friday, Saturday and Sunday (Table 8). During weekdays, the model is definitely more significant, being influenced by *slack%* and *passengers*. Monday-Thursday and Friday have a similar behavior with the difference of passengers' parameter on Friday, when is more determinant, as it has been said Friday evening presents the worst system situation. These parameters are less significant during weekends, and there is no passenger effect. All these values are used on the prediction schedule deviation at the robustness tool. To see all results of these regression models, go to *Appendix III*.

Table 8. Regression Parameters

REGRESSION PARAMETERS	Constant deviation	Slack%	Passengers
Monday-Thursday	73.17	-1.50	0.18
Friday	65.91	-1.49	0.38
Saturday	69.24	-1.20	0.00
Sunday	56.43	-0.80	0.00

5.3.   Fines of delays and cancelled trips

A main concern for transport operators are fines, these unexpected extra payments can determine the final economical balance. In order to see why, when and where happen, several analyses were made based on historical data.

<u>Cause of delay</u>

Focusing just on trips with an average schedule deviation higher than 3 minutes (Figure 15), it is clear than based on planned slack times, the most restrictive one usually (more than 90%) comes from vehicle schedule. Which means that crew breaks are planned with more extra time than vehicles. Expressed as a formula:

$$Veh.\, Slack\, time \ < \ (Crew\, Slack\, time \ - \ 10)$$
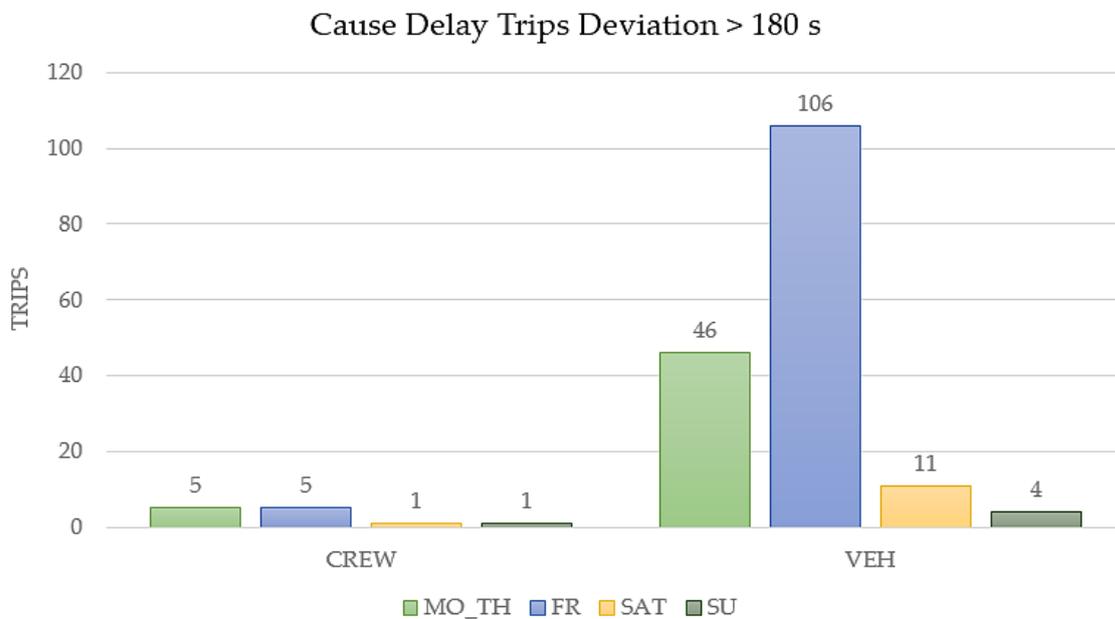
Figure 15. Cause of delay for trips later than 180 seconds

Special is the case of Friday, where there are a lot of late departures due to vehicle slack times, a consequence of trying to optimize as much as possible and when some problems start to appear (mainly truck lines at evening peak) it will affect hardly to the rest of network. Another factor which is no considered here, is when the driver arrives later than the most restrictive time of vehicle, however as this fact depends on driver behavior is difficult to estimate. Despite of this uncertainty, the percentage of late trips having a break before is between 20-30%, so independently of the most restrictive slack among vehicle and crew, short slack times of vehicles are the main cause of secondary delays.

Partial cancelled & Late departures / Total Cancelled

Based on the production information collected by Keolis for the last period (*Winter 19'*/ Dec'18 – Mar'19), it was possible to classify all fines by line and hour. Late departures & partial cancelled trip for one side, and total cancelled trips for other side. After taking into consideration the number of total trips during that period, it was possible to calculate which is the probability to get a fine. Winter usually is the worst season for fines due to the hard weather conditions, especially snow problems. However, considering this negative scenario, some fines will be overestimate which is better than being underestimate [Kliewer et al., 2012].

Table 9 indicates that probability per line and day. As the plan Monday-Thursday englobes 4 days is the one with higher probabilities and present in more lines. Continuing previous results, the trunk line 1 has the most problematic performance on the partial fines. Total cancelled probabilities are lower than the ones of partial cancelled and late departures, but this second group has just half fine (1500 SEK) meanwhile the fines for total cancelled are 3000 SEK. Noteworthy is the case of trunk lines 1 & 6 on Sunday, that have high values due to some lack of operating buses.

Table 9. Percentage of trips with partial or total fine

Line	Partial cancelled/Late departures				Total Cancelled			
	MOTH%	FR%	SAT%	SU%	MOTH%	FR%	SAT%	SU%
1	2.5	3.0	2.4	0.7	0.7	0.6	0.0	6.3
6	0.8	0.6	0.0	1.4	0.6	1.5	0.2	5.5
69	0.4	0.3	0.0	0.0	0.2	0.3	0.0	0.0
72	1.0	1.0	0.0	0.0	0.9	0.0	0.0	0.0
75	0.4	0.2	0.0	0.0	0.7	0.1	0.0	0.0
76	0.5	0.3	0.5	0.2	0.2	0.3	0.2	0.0
91	0.0	1.8	1.9	0.0	0.0	0.0	0.0	0.0
201	0.3	0.2	0.5	0.0	0.7	0.2	0.3	0.0
203	0.1	0.4	0.0	0.0	0.7	0.5	0.7	0.2
204	0.5	0.6	0.3	0.6	0.7	0.5	1.2	0.0
205	0.2	0.6	0.0	0.0	0.7	0.5	0.0	0.6
206	0.9	0.0	0.0	0.3	1.1	0.7	0.0	0.0
211	0.9	0.0	0.0	0.0	1.3	0.0	0.0	0.0
212	0.4	0.9	0.4	1.3	0.6	0.3	0.2	0.7
221	0.3	0.1	0.2	0.5	0.7	0.6	0.5	0.0
222	0.4	0.0	0.0	0.0	1.3	0.0	0.0	0.0
225	0.6	0.0	0.0	0.0	1.4	0.7	0.0	0.0
233	1.1	0.0	0.0	0.0	0.7	0.0	0.0	0.0
238	1.0	0.4	0.2	0.2	0.2	0.8	1.3	0.3
293	1.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0
921	2.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0
923	3.6	0.0	0.0	0.0	0.9	3.6	0.0	0.0

5.4.   Economic Analysis

Related to the previous table, an economic analysis has been performed summing the operator costs caused by the lack of robustness, inspired by the formulas already explained in the Methodology section. This economic analysis (Table 10) is totally related to the previous studies about fines costs (early & late departures, and total cancelled), which was considering only the last Winter, worst season for fines.

Passengers costs are quite high because all trips with a delay higher than one minute are been considered. Regards the PTA fines, cancellations costs are the largest ones, although are the less common they have the highest cost when it is fined. As previous cases, differences among weekdays and weekends are very significant in all sections. Early departure case is the only one that is not very different, due to drivers' behavior does not change during the week.

Table 10. Operator daily costs due to loss of robustness

Costs (SEK)	MOTH	FR	SAT	SU
Passengers costs	68408	87235	15288	11119
Overtime costs	1272	1190	368	257
Early departures costs	1473	2143	1962	1269
Late departures costs	9375	8357	3808	3346
Cancellation costs	19982	17571	6231	7000
OPERATOR COSTS	**32102**	**29261**	**12368**	**11872**

5.5.   Robustness tool

Finally, the last result and objective of this thesis has been developing a robustness tool, created in Excel. It allows to compare two different packages of vehicle and crew timetables to determine which could perform better service based on its robustness. To predict these schedule deviations, it has been used a regression model (section 5.2) considering historical data (data analysis of section 5.1). Also, the model calculates the possible production and fines costs based on sections 5.3 and 5.4.

This tool has several sheets: *Summary* (comparison between packages), *Classification* (an explanatory sheet for each package based on the mentioned methodology), *OmlAkt & Uppehåll* (where packages from Hastus software are introduced) and *Historical Data* (which can be changed in case different regions are being studied).

Summary

This sheet contains all relevant results from both packages. First table on the left compares operator and passengers' costs, having the following elements:

Lost time perception - Indicated in hours, it sums all lost times. Those times comes from multiplying the *average deviation of schedule* (minus 60 seconds, just to consider overtime after 1 minute) per the *number of passengers* of the trips above 1 minute which are considered not on time for passengers.

Passengers costs – Expressed in Swedish Krona and per period (N. days), multiplies the *lost time perception* by the *value of time* for urban buses recommend by Trafikverket.

Sum deviation – It sums all *average schedule deviation*, in hours. To have an overall of how late is the system with that package.

Sum slack – It sums all non-productive times (*slack*), in hours. Higher means more expensive for operator but also could mean better performance and less delays.

Production costs slack – Costs for operator of those slack times, in SEK. It multiplies the *sum slack* per *overtime operator costs*.

Average Slack% - Average of the parameter *slack%*, which expresses the most restrictive non-productive time (vehicle or crew) in relation with the total trip time.

Overtime – It sums the *schedule deviation* of trips above the overtime limit (which can be changed in the parameters), represented in hours.

Overtime costs – Multiplication of the *overtime* hours per *overtime cost* per hour, in SEK.

N. Late departures – *Average late departures* per day, based on historical data for specific lines and times, considering also *partial cancelled* trips.

Late departures costs – Multiplication of *late departures* per its respective *fine*, in SEK.

N. Cancellations – *Average cancellations* per day, based on historical data for specific lines and times.

Cancellations costs - Multiplication of *cancellations* per its respective *fine*, result in SEK.

Operator costs – Sum of *overtime, late departures and cancellations* costs, in SEK.

Next to this table there is another of parameters applied to both packages, which can be fixed or variable:

Overtime – Approximate total extra costs considered by the operator when overtime occurs, taking into consideration vehicle and crew costs. Expressed in SEK/h.

Late departure fine – Value of late departure fine determined at the contract with the PTA, in SEK.

Cancellation fine - Value of cancellation fine determined at the contract with the PTA, in SEK.

Value of time – Value of time for urban buses travelers recommend by Trafikverket, in SEK/h.

N. Days – Variable parameter chosen by tool´s user. Indicates the total amount of days will be considered for those packages. It is necessary to calculate the expected fined trips.

Overtime limit – Variable parameter chosen by tool´s user. The tool will consider trips for overtime above that limit. Indicated in seconds.

Day type – Variable parameter chosen by tool´s user. There are 4 different choices of plans (Monday-Thursday, Friday, Saturday and Sunday), which will determine historical data to consider.

Tables 11. Costs per day & parameters (Summary – Robustness tool)

Costs per day	Package 1	Package 2
Lost time perception (h)	211.34	205.61
Passengers perception costs	42057	40917
Sum Deviation (h)	19.69	21.89
Sum Slack (h)	89.53	77.63
Production slack costs (SEK)	**62673**	**54343**
Average Slack%	14.34	12.44
Overtime (h)	1.51	1.87
Overtime costs (SEK)	1056	1308
N. Late departures	4.45	3.64
Late departures costs (SEK)	6677	5462
N. Cancellations	2.08	1.77
Cancellation costs (SEK)	6252	5317
OPERATOR COSTS (SEK) (Overtime + Late + Cancel)	**13985**	**12086**

PARAMETERS	SEK/h
Overtime costs	700
Late departure fine	1500
Cancellation fine	3000
Value of Time	199
N. Days *(Variable)*	*40*
Overtime limit *(Variable)*	*120*
Day type *(Variable)*	*Monday*

N.days = Number of package's days
Overtime limit = Consider trips for overtime above that limit (Seconds)
Monday = Monday - Thursday Package
Friday = Friday Package
Saturday = Saturday package
Sunday = Sunday package

Below these tables (Tables 11), there is a graph (Figure 16) showing the most important costs to consider: Passengers perception (not essential for the operator, but it can mean future variation of ridership), production slack costs (operator cost of having that non-productive times), overtime costs (based on a variable parameter which determined the limit), late departures costs (fine costs for this issue) and cancellation costs (fine costs for cancelling a trip).
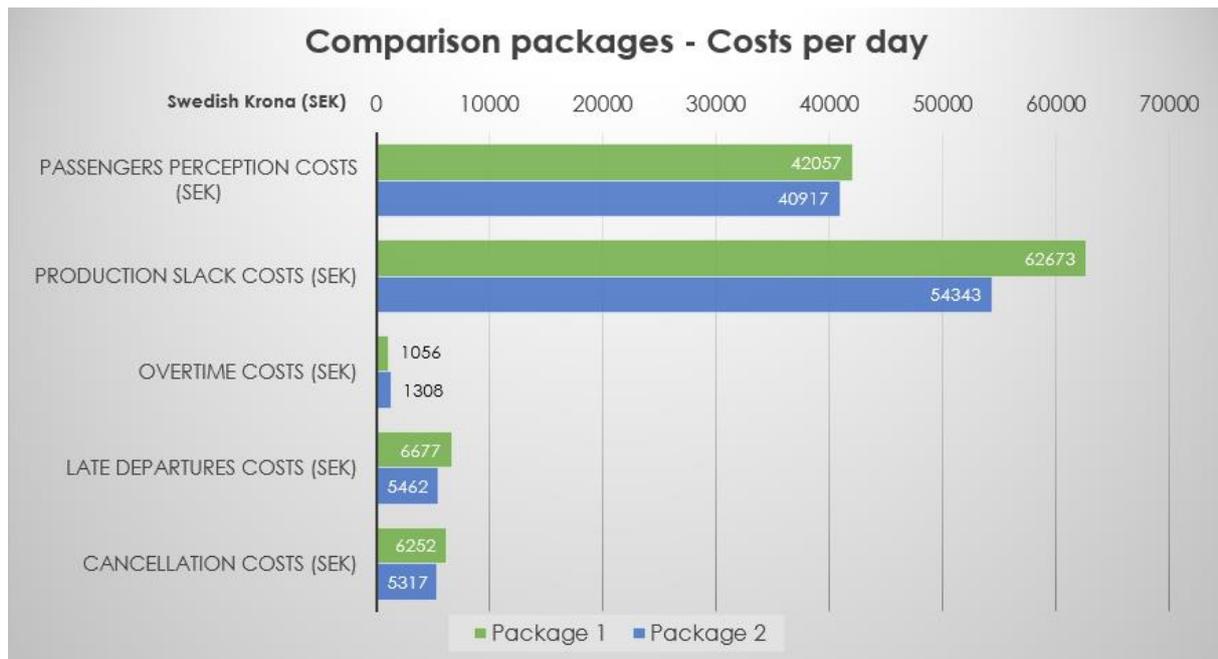
Figure 16. Comparison packages – Costs per day (Summary – Robustness tool)

On the middle right of Summary sheet, there are 4 tables comparing number of trips classified by *Slack%* and *Average Schedule deviation* of both packages (Tables 12). Tables on the top indicates average deviation in seconds of a determined group based on its value of slack% (0%, 1-10%, 10-20%, 20-30% & 30-40%), with their respective number of trips and percentage among total trips. Below these tables, others are classifying expected number of trips that would be on time besides the ones that would be 1, 2, or more than 3 minutes late. Relating also the average slack% among those trips.

Tables 12. Comparison packages Avg Deviation-Slack% (Summary – Robustness tool)

Package 1	Dev (sec)	Trips	%Total
AVG TOTAL	56.92	1245	100
Slack% 0	76.59	205	16.47
Slack% 1-10	75.79	330	26.51
Slack% 10-20	52.88	368	29.56
Slack% 20-30	36.97	219	17.59
Slack% 30-40	27.27	74	5.94

Package 2	Dev (sec)	Trips	%Total
AVG TOTAL	59.80	1318	100
Slack% 0	79.36	332	25.19
Slack% 1-10	71.29	306	23.22
Slack% 10-20	54.00	396	30.05
Slack% 20-30	40.30	182	13.81
Slack% 30-40	23.36	63	4.78

	Slack%	Trips	%Total
AVG dev > 180s	3.13	4	0.32
120s < AVG dev < 180s	6.11	32	2.57
60s < AVG dev < 120s	6.86	439	35.26
AVG dev < 60s	19.00	770	61.85

	Slack%	Trips	%Total
AVG dev > 180s	4.74	8	0.61
120s < AVG dev < 180s	4.25	38	2.88
60s < AVG dev < 120s	5.79	522	39.61
AVG dev < 60s	17.58	750	56.90

Classification

These 2 sheets join all data provided by OmlAkt and Uppehåll plans (Vehicle and crew schedules from planning software) to after developing new values. First 12 columns are a copy of OmlAkt plan, which has been explained on Methodology section and it

is composed of: Crew ID, Vehicle ID, Line, Activity ID, From, Start before boarding, Start, Final, To, Time Activity, Slack Time & Minimum slack.

Next column (Paus) relates the duration of a paus or break before that specific trip, taking that information from the Uppehåll plan. Boarding column shows how many minutes have been planned for boarding time at the first stop, calculated as the difference between *Start before boarding* and *Start.* To relate every trip with an entire hour, as it is the historical data, the Hour column just takes the entire hour of the departure time at *Start.*

The last 8 columns are values based on the previous ones besides historical data. The first is *slack%*, the percentage of non-production time among total trip time, which uses the most restrictive slack time from vehicle and crew schedules. The average schedule deviation of following column is a predicted value (equation 5) using the *historical average deviation, regression parameters, and the difference of historical and planned slack%* based on section 5.2.

(5)

$$AVG\ dev = HistDev + \beta slack * (Slack\% - HistSlack\%)$$

Where:

AVG dev = Predicted average schedule deviation (seconds)

HistDev = Historical average schedule deviation (seconds)

βslack = Regression parameter of slack%

Slack% = Planned slack%

HistSlack% = Historical slack%

Passengers data comes directly from the historical one classified per day type, line and hour. Lost time multiplies *passengers* of the trips above 1 minute which are considered not on time for passengers per *average deviation of schedule* (minus 60 seconds, just to consider overtime after 1 minute), the result is showed in minutes. The columns Part Cancel/late and Cancelled indicate the probability of that trip to get fine, either for partial cancelled, late or total cancelled trip based on historical data. Finally, expected late and cancelled columns are the result of multiplying that probability per total number of days (variable) that package is expected to be used. Figure 17 and Appendix IV (more detail) represent a classification sheet and the legend used to classify them.

| CrewID	VehID	Line	ActivityID	From	Start_bef	Start	Final	To	TimeAct	SlackTime	MinSlack	Paxs	Boarding t	Hour	Slack%	AVG dev	Passengers	Lost time	Part Cancel/Late	Cancelled	Expected late	Expected cancel
2001	801	1	Regular	FRI	05:22:00	05:23:00	05:55:00	EST	32	0	2	0	1	5	0.00	28	21	0	1.79	0.00	0.71	0.00
2001	801	1	Regular	EST	05:59:00	06:00:00	06:38:00	FRI	38	4	2	0	1	6	9.30	45	63	0	2.86	0.71	1.14	0.29
2603	807	1	Regular	FRI	06:17:00	06:18:00	06:55:00	EST	37	0	2	0	1	6	0.00	59	63	0	2.86	0.71	1.14	0.29
2605	809	1	Regular	FRI	06:27:00	06:28:00	07:06:00	EST	38	0	2	0	1	6	0.00	59	63	0	2.86	0.71	1.14	0.29
506	802	1	Regular	FRI	06:37:00	06:38:00	07:18:00	EST	40	2	2	0	1	6	4.65	52	63	0	2.86	0.71	1.14	0.29
2002	801	1	Regular	FRI	06:47:00	06:48:00	07:30:00	EST	42	9	2	27	1	6	17.31	33	63	0	2.86	0.71	1.14	0.29
2606	811	1	Regular	FRI	06:53:00	06:54:00	07:38:00	EST	44	0	2	0	1	6	0.00	59	63	0	2.86	0.71	1.14	0.29
2603	807	1	Regular	EST	06:59:00	07:00:00	07:45:00	FRI	45	4	2	0	1	7	8.00	37	130	0	0.45	1.79	0.18	0.71
2605	809	1	Regular	FRI	07:09:00	07:11:00	07:56:00	FRI	45	3	2	0	2	7	6.00	40	130	0	0.45	1.79	0.18	0.71
2704	901	1	Regular	FRI	07:11:00	07:12:00	07:57:00	FRI	45	0	2	0	1	7	0.00	49	130	0	0.45	1.79	0.18	0.71
2008	813	1	Regular	FRI	07:16:00	07:17:00	08:03:00	EST	46	0	2	14	1	7	0.00	49	130	0	0.45	1.79	0.18	0.71
506	802	1	Regular	EST	07:24:00	07:26:00	08:15:00	FRI	49	6	2	0	2	7	10.53	34	130	0	0.45	1.79	0.18	0.71
2002	801	1	Regular	EST	07:34:00	07:36:00	08:26:00	FRI	50	4	2	0	2	7	7.14	39	130	0	0.45	1.79	0.18	0.71
504	815	1	Regular	EST	07:41:00	07:42:00	08:31:00	EST	49	0	3	23	1	7	0.00	49	130	0	0.45	1.79	0.18	0.71
2606	811	1	Regular	EST	07:44:00	07:46:00	08:37:00	EST	51	6	2	0	2	7	10.17	34	130	0	0.45	1.79	0.18	0.71
2131	807	1	Regular	EST	07:51:00	07:52:00	08:42:00	EST	50	6	2	0	1	7	10.53	34	130	0	0.45	1.79	0.18	0.71
503	809	1	Regular	FRI	08:01:00	08:02:00	08:52:00	EST	50	5	3	12	1	8	3.77	100	131	88	2.50	0.71	1.00	0.29
2704	901	1	Regular	EST	08:04:00	08:06:00	08:58:00	FRI	52	7	0	0	2	8	11.48	89	131	62	2.50	0.71	1.00	0.29
2008	813	1	Regular	EST	08:08:00	08:10:00	09:02:00	FRI	52	5	2	0	2	8	8.47	93	131	72	2.50	0.71	1.00	0.29
2605	802	1	Regular	EST	08:18:00	08:19:00	09:08:00	EST	49	3	3	15	1	8	5.66	97	131	81	2.50	0.71	1.00	0.29
2705	801	1	Regular	EST	08:29:00	08:30:00	09:19:00	EST	49	3	3	21	1	8	5.66	97	131	81	2.50	0.71	1.00	0.29
504	815	1	Regular	EST	08:34:00	08:36:00	09:27:00	EST	51	3	2	0	2	8	5.36	98	131	82	2.50	0.71	1.00	0.29
506	811	1	Regular	EST	08:40:00	08:41:00	09:28:00	EST	47	3	3	18	1	8	5.88	97	131	81	2.50	0.71	1.00	0.29
2131	807	1	Regular	EST	08:45:00	08:47:00	09:37:00	EST	50	3	0	0	2	8	5.45	98	131	82	2.50	0.71	1.00	0.29
503	809	1	Regular	EST	08:55:00	08:57:00	09:45:00	EST	48	3	2	0	2	8	5.66	97	131	81	2.50	0.71	1.00	0.29
2606	813	1	Regular	FRI	09:05:00	09:06:00	09:51:00	EST	45	3	3	21	1	9	6.12	113	89	79	1.19	0.60	0.48	0.24
2605	802	1	Regular	FRI	09:11:00	09:13:00	10:01:00	FRI	48	3	2	0	2	9	5.66	114	89	80	1.19	0.60	0.48	0.24
2705	801	1	Regular	FRI	09:23:00	09:25:00	10:13:00	FRI	48	4	0	0	2	9	7.41	111	89	76	1.19	0.60	0.48	0.24
2703	815	1	Regular	FRI	09:29:00	09:30:00	10:15:00	EST	45	2	3	20	1	9	4.17	116	89	83	1.19	0.60	0.48	0.24
506	811	1	Regular	FRI	09:31:00	09:32:00	10:20:00	EST	48	3	2	0	1	9	5.77	114	89	79	1.19	0.60	0.48	0.24
502	809	1	Regular	FRI	09:50:00	09:51:00	10:36:00	EST	45	5	3	39	1	9	9.80	108	89	71	1.19	0.60	0.48	0.24
2606	813	1	Regular	FRI	09:59:00	10:00:00	10:47:00	EST	47	8	2	0	1	10	14.29	74	99	22	1.43	0.00	0.57	0.00
2131	802	1	Regular	FRI	10:11:00	10:12:00	10:57:00	FRI	45	10	3	18	1	10	14.81	73	99	21	1.43	0.00	0.57	0.00
2703	815	1	Regular	FRI	10:20:00	10:21:00	11:08:00	FRI	47	5	2	0	1	10	9.43	81	99	34	1.43	0.00	0.57	0.00
2004	811	1	Regular	FRI	10:25:00	10:26:00	11:12:00	EST	46	5	3	84	1	10	9.62	81	99	34	1.43	0.00	0.57	0.00
502	809	1	Regular	FRI	10:41:00	10:42:00	11:30:00	FRI	48	5	2	0	1	10	9.26	81	99	35	1.43	0.00	0.57	0.00
2010	813	1	Regular	FRI	10:52:00	10:53:00	11:39:00	EST	46	5	3	86	1	10	9.62	81	99	34	1.43	0.00	0.57	0.00

LEGEND	Slack%	AVG dev (sec)	Passengers (pax)	Lost time perception (min)	Part Cancel/Late dep %	Cancelled %
	> 20	< 60	0 - 33	0 - 33	0	0
	10 - 20	60 -120	33 - 66	33 - 66	0 - 2.5	0 - 2.5
	0 - 10	120 - 180	66 - 100	66 - 100	2.5 - 5	2.5 - 5
	0	>180	>100	>100	>5	>5

Figure 17. Extract Classification & Legend (Classification – Robustness tool)

OmlAkt & Uppehåll

These 4 sheets are organized to input vehicle and crew plans, which are the same ones described on the Data Collection section, from the planning software *Hastus*.

Historical Data

This sheet compiles all historical data that comes from the studied period, Dec'17 to Mar'19. The first table has average values per *day*, *line* and *hour* of: Schedule deviation (seconds), Slack% and Passengers per trip (Table 12). This historical data is used on classification sheets. And it is possible to be changed if this tool wants to be used for another depot.

At the middle of the sheet, there are some informative tables about distribution of *average schedule deviation* and *slack%* of the historical data, besides regression parameters (which can be recalculated if the raw data is changed) used for the predicted AVG deviation.

Tables at the right indicates de probability of partial cancelled trip/late departures fines and total cancelled trip fines. These values are based on an analysis of Keolis' production results. It is possible to calculate again for other lines based on the same raw information.

Table 12. Extract historical data table 1 (Historical data – Robustness tool)

Day	Line	Hour	Deviation	Slack%	Passengers
Monday	1	0	32.30	11.25	22
Monday	1	5	27.50	0.00	21
Monday	1	6	47.98	7.61	63
Monday	1	7	42.88	4.36	133
Monday	1	8	96.41	6.25	131
Monday	1	9	110.39	8.01	89
Monday	1	10	77.43	11.73	99
Monday	1	11	86.83	8.34	120
Monday	1	12	145.55	6.05	134
Monday	1	13	131.19	6.54	131
Monday	1	14	73.32	7.52	123
Monday	1	15	77.78	6.85	139
Monday	1	16	118.75	6.29	149
Monday	1	17	178.97	6.63	120
Monday	1	18	116.95	9.79	88
Monday	1	19	60.69	12.23	79
Monday	1	20	87.39	7.91	67
Monday	1	21	56.91	12.17	54
Monday	1	22	45.80	14.36	50
Monday	1	23	39.90	13.25	28

6. CONCLUSIONS & RECOMMENDATIONS

This thesis has gone through the relation among robustness and planning parameters (*slack%*, *average schedule deviation* and *passengers*) of crew bus schedules, taking as a case study one depot from Stockholm (*Frihamnen*) which gives service to two totally different areas. Besides, it has been studied its economic effects and finally has been created an Excel tool that can simulate how different crew and vehicle bus schedules will work based on historical data from the case study, reaching in that way all the initial objectives.

As results have showed, in effect there is a correlation between the non-productive time before each trip, what has been called *slack%*, and the deviation from schedule, especially during weekdays. Also those days, the *passengers'* parameter is significant. Large schedule deviations occur at peak hours, being the one of evening more critical. One of the reasons for this fact is a more prolonged high demand, from 15 to 18, which can create a delay propagation effect when some bus fails its schedule, because at the same time is when buses have shorter slack times in order to optimize as much as they can the whole network.

Another initial objective was to know the effect of crew schedules on delays, which can be decisive in some cases but usually have a lower effect than the ones created by vehicle schedules. These ones are the cause of 90% of secondary delays, considering trips with deviation larger than 3 minutes. Besides, just 20% of this type of trips have a driver break before starting.

When a schedule is not robust, probably will have fines costs. These costs are classified in two different types: *half fine* when a bus has an early or late departure from control points, or it is partial cancelled, and *total fine* when a bus is total cancelled. The probability of getting half fine usually is higher, but as the fine cost is larger when is total cancelled, the final output costs are more significant is this case. The lines more crowded are the ones with more probability to get fines, and is more common to have these extra costs during weekdays.

The final goal for Keolis as an operator, it was to have a tool which could help them to analyze better the robustness among their trips. This objective was implemented in Excel, having as a result a friendly interface tool that has some predetermined empty pages to insert packages (vehicle and crew schedules) directly from the software Hastus, giving back a comparison between two different packages. Considering their expected operator and fines costs, schedule deviation and classification of trips according those expected delays (1, 2, 3 and more than 3 minutes). This tool can help on future planned schedules, giving an overall of how they will perform based on historical data of the last year.

Recommendations

Based on these results and after analyzing a huge amount of raw data, some recommendations can be done. The relation *slack%-average schedule deviation* is especially critical with high delays, when the value of *slack%* is below 10%. This means that adding a slack time **higher than 10% of total trip time**, should be enough to absorb most of the secondary delays, mainly the ones during peak hours.

Another way of avoiding secondary delays is to do changes on **planned trip times**, in some trips are underestimated, producing delays at the last stops. Other situations are overestimated, sometimes planners include the non-productive time in this value which can cause a lack of adherence to schedule, that can reach to early departures fines.

In this specific case study, Frihamnen depot, some advices would be to change slack times or trip times for specific trips. Very noticeable are the cases of the trunk lines (1 & 6) during weekdays and peak hours, when almost all trips are delayed and for Lidingö lines the main problems are at the most crowded lines (201 & 221) besides line 238 at evening peak, that one due to a short planned trip time. A small consideration for weekends (especially Sunday), is the lack of trunk lines vehicles on the road which can create some fines for not using a vehicle with that specifications.

Besides recommendations that are applicable for planning department, several topics can be discussed to improve the robustness, and therefore the performance, of the whole bus system. One measure that could be implemented is a **faster boarding procedure**, more doors to access the bus. That would help to reduce non-productive times at main stations, being mostly useful in the trunk lines**.**

Other topic well studied to progress on bus performance is to **control the bunching effect**, the one that happens when several buses are next to each other due to an organic process, if the first bus gets delayed at some point later would be more delayed because it is taking more people at every stop, meanwhile the previous bus is going faster because less people is boarding on it. To avoid this effect can be challenged but there are actual investigations [i.e. Cats, 2011] which already proposed effective ways to control it.

Despite of these studies, schedules and planning decisions are created by transport planners, a crucial actor to be considered in all this process are **drivers**. At the end, they are in charge of the vehicle and each of them will have a specific behavior for different situations. In their hands, a disruption can be avoided it or made it worse. Some factors that should be controlled are: an efficient driver changing, a faster communication in case of being late (or sick) and to respect timetables to not getting early fines.

Future recommendation of this work, would be to introduce a more intense use of big data, programming algorithms which could take directly all raw data and analyze them in a simple way. Actually that is what is happening in all new versions of planning and optimization **software** (Hastus, Optibus, Goal, INIT, etc.), which are following the idea of this thesis, to incorporate historical data in order to calculate more precise timetables taking into consideration robustness as an important performance indicator, considering in their objective functions expected delays, fines and production costs, at the same time. It is possible to admit that this topic is trending right now among planning and optimization of public transport.

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APPENDIX I: ROPSTEN TERMINAL MAP (SL, 2018)

APPENDIX II: EXTRACT OF ROBUSTNESS ANALYSIS

CrewID	VehID	Line	Activity	From	Start_befb	Start	Final	To	TimeA	Slack	MinS	Stop	AVG dev	Board	Paus	Slack%	Passeng	Perception
2002	801	1	Regular	FRI	05:22:00	05:23:00	05:55:00	EST	32	0	2	Frihamnen,3	20	1	0	0.00	21	0
2002	801	1	Regular	EST	06:09:00	06:10:00	06:50:00	FRI	40	14	2	Essingetorget	20	1	0	25.45	76	0
2606	808	1	Regular	FRI	06:17:00	06:18:00	06:55:00	EST	37	0	2	Frihamnen,3	75	1	0	0.00	41	10
2704	801	1	Regular	FRI	06:53:00	06:54:00	07:38:00	EST	44	3	2	Frihamnen,3	32	1	0	6.25	71	0
2606	808	1	Regular	EST	06:59:00	07:00:00	07:45:00	FRI	45	4	0	Essingetorget	40	1	0	8.00	130	0
2705	810	1	Regular	FRI	06:59:00	07:00:00	07:45:00	EST	45	0	2	Frihamnen,3	51	1	0	0.00	98	0
2605	813	1	Regular	FRI	07:21:00	07:22:00	08:09:00	EST	47	0	2	Frihamnen,3	77	1	26	0.00	79	22
2704	801	1	Regular	EST	07:41:00	07:43:00	08:34:00	FRI	51	3	2	Essingetorget	35	2	0	5.36	162	0
2705	810	1	Regular	EST	07:47:00	07:49:00	08:41:00	FRI	52	2	2	Essingetorget	61	2	0	3.57	210	4
2109	814	1	Regular	FRI	07:51:00	07:52:00	08:42:00	EST	50	0	2	Frihamnen,3	74	1	0	0.00	130	31
2606	808	1	Regular	FRI	08:01:00	08:02:00	08:52:00	EST	50	0	3	Frihamnen,3	48	1	12	0.00	165	0
2605	813	1	Regular	EST	08:11:00	08:13:00	09:05:00	FRI	52	2	2	Essingetorget	117	2	0	3.57	218	206
2202	801	1	Regular	FRI	08:37:00	08:38:00	09:26:00	EST	48	3	2	Frihamnen,3	132	1	0	5.77	104	124
2701	810	1	Regular	FRI	08:43:00	08:44:00	09:30:00	EST	46	2	3	Frihamnen,3	124	1	13	4.08	97	104
2109	814	1	Regular	EST	08:47:00	08:49:00	09:39:00	FRI	50	5	2	Essingetorget	71	2	0	8.77	91	16
2606	808	1	Regular	EST	09:05:00	09:07:00	09:55:00	FRI	48	13	2	Essingetorget	29	2	0	20.63	110	0
502	813	1	Regular	FRI	09:07:00	09:08:00	09:53:00	EST	45	2	3	Frihamnen,3	253	1	12	4.17	65	207
2202	801	1	Regular	EST	09:31:00	09:32:00	10:20:00	FRI	48	5	0	Essingetorget	61	1	0	9.26	103	2
2701	810	1	Regular	EST	09:38:00	09:39:00	10:26:00	FRI	47	8	2	Essingetorget	27	1	0	14.29	92	0
2703	814	1	Regular	FRI	09:41:00	09:42:00	10:27:00	EST	45	2	2	Frihamnen,3	157	1	17	4.17	77	124

APPENDIX III: REGRESSION MODELS

Summary output Monday-Thursday

Regression Statistics	
Multiple R	0.4293228
R Square	0.1843181
Adjusted R Square	0.1835894
Standard Error	38.311157
Observations	2242

ANOVA

	df	SS	MS	F	Significance F
Regression	2	742594.4278	371297.21	252.97124	8.863E-100
Residual	2239	3286280.566	1467.7448		
Total	2241	4028874.993			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
AVG dev	73.174373	1.611452295	45.40896	0	70.0142767	76.33447
Slack%	-1.503289	0.078952741	-19.04036	4.892E-75	-1.65811691	-1.34846
Passengers	0.1823211	0.021577611	8.4495508	5.186E-17	0.14000691	0.2246353

Summary output Friday

Regression Statistics	
Multiple R	0.3914329
R Square	0.1532197
Adjusted R Square	0.1524585
Standard Error	50.696208
Observations	2228

ANOVA

	df	SS	MS	F	Significance F
Regression	2	1034724.58	517362.29	201.30002	4.4154E-81
Residual	2225	5718484.84	2570.1055		
Total	2227	6753209.42			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
AVG dev	65.913075	2.34667059	28.087911	7.72E-149	61.311182	70.514968
Slack%	-1.49001	0.10448621	-14.26035	3.228E-44	-1.69491045	-1.285109
Passengers	0.3820705	0.0334723	11.414526	2.283E-29	0.31643027	0.4477107

APPENDIX III: REGRESSION MODELS

Summary output Saturday

Regression Statistics	
Multiple R	0.330626691
R Square	0.109314009
Adjusted R Square	0.108615979
Standard Error	35.20348162
Observations	1278

ANOVA

	df	SS	MS	F	Significance F
Regression	1	194076.57	194076.57	156.60365	5.63864E-34
Residual	1276	1581327.81	1239.2851		
Total	1277	1775404.38			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
AVG dev	69.24222143	1.55919053	44.409083	3.67E-261	66.18336267	72.30108
Slack%	-1.20541759	0.09632446	-12.51414	5.639E-34	-1.39438931	-1.016446

Summary output Sunday

Regression Statistics	
Multiple R	0.299292039
R Square	0.089575725
Adjusted R Square	0.088846802
Standard Error	27.3829219
Observations	1251

ANOVA

	df	SS	MS	F	Significance F
Regression	1	92144.3086	92144.309	122.88785	2.6411E-27
Residual	1249	936530.69	749.82441		
Total	1250	1028675			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
AVG dev	56.43755559	1.20558416	46.813452	4.31E-277	54.0723621	58.802749
Slack%	-0.815500647	0.07356476	-11.08548	2.641E-27	-0.95982479	-0.671177

APPENDIX IV: EXTRACT OF ROBUSTNESS TOOL (CLASSIFICATION)

CrewID	VehID	Line	Activity	From	Start_bef	Start	Final	To	TimeAc	Slack	MinSlar	Paus	Board	Hour	Slack%	AVG dev	Passenge	Lost tin	Part Canc	Cancel	Cancel Expected	Expected
2001	801	1	Regular	FRI	05:22:00	05:23:00	05:55:00	EST	32	0	2	0	1	5	0.00	28	21	0	1.79	0.00	0.71	0.00
2001	801	1	Regular	EST	05:59:00	06:00:00	06:38:00	FRI	38	4	2	0	1	6	9.30	45	63	0	2.86	0.71	1.14	0.29
2603	807	1	Regular	FRI	06:17:00	06:18:00	06:55:00	EST	37	0	2	0	1	6	0.00	59	63	0	2.86	0.71	1.14	0.29
2605	809	1	Regular	FRI	06:27:00	06:28:00	07:06:00	EST	38	0	2	0	1	6	0.00	59	63	0	2.86	0.71	1.14	0.29
506	802	1	Regular	FRI	06:37:00	06:38:00	07:18:00	EST	40	2	2	0	1	6	4.65	52	63	0	2.86	0.71	1.14	0.29
2002	801	1	Regular	FRI	06:47:00	06:48:00	07:30:00	EST	42	9	2	27	1	6	17.31	33	63	0	2.86	0.71	1.14	0.29
2606	811	1	Regular	FRI	06:53:00	06:54:00	07:38:00	EST	44	0	2	0	1	6	0.00	59	63	0	2.86	0.71	1.14	0.29
2603	807	1	Regular	EST	06:59:00	07:00:00	07:45:00	FRI	45	4	2	0	2	7	8.00	37	133	0	0.45	1.79	0.18	0.71
2605	809	1	Regular	EST	07:09:00	07:11:00	07:56:00	FRI	45	3	2	0	1	7	6.00	40	133	0	0.45	1.79	0.18	0.71
2704	901	1	Regular	FRI	07:11:00	07:12:00	07:57:00	EST	45	0	2	0	1	7	0.00	49	133	0	0.45	1.79	0.18	0.71
2008	813	1	Regular	FRI	07:16:00	07:17:00	08:03:00	EST	46	0	2	14	1	7	0.00	49	133	0	0.45	1.79	0.18	0.71
506	802	1	Regular	EST	07:24:00	07:26:00	08:15:00	FRI	49	6	2	0	2	7	10.53	34	133	0	0.45	1.79	0.18	0.71
2002	801	1	Regular	EST	07:34:00	07:36:00	08:26:00	FRI	50	4	2	0	2	7	7.14	39	133	0	0.45	1.79	0.18	0.71
504	815	1	Regular	FRI	07:41:00	07:42:00	08:31:00	EST	49	0	3	23	1	7	0.00	49	133	0	0.45	1.79	0.18	0.71
2606	811	1	Regular	EST	07:44:00	07:46:00	08:37:00	FRI	51	6	2	0	2	7	10.17	34	133	0	0.45	1.79	0.18	0.71
2131	807	1	Regular	FRI	07:51:00	07:52:00	08:42:00	EST	50	6	2	0	1	7	10.53	34	133	0	0.45	1.79	0.18	0.71
503	809	1	Regular	FRI	08:01:00	08:02:00	08:52:00	EST	50	5	3	12	1	8	3.77	100	131	88	2.50	0.71	1.00	0.29
2704	901	1	Regular	EST	08:04:00	08:06:00	08:58:00	FRI	52	7	0	0	2	8	11.48	89	131	62	2.50	0.71	1.00	0.29
2008	813	1	Regular	EST	08:08:00	08:10:00	09:02:00	FRI	52	5	2	0	2	8	8.47	93	131	72	2.50	0.71	1.00	0.29
2605	802	1	Regular	FRI	08:18:00	08:19:00	09:08:00	EST	49	3	3	15	1	8	5.66	97	131	81	2.50	0.71	1.00	0.29
2705	801	1	Regular	FRI	08:29:00	08:30:00	09:19:00	EST	49	3	3	21	1	8	5.66	97	131	81	2.50	0.71	1.00	0.29
504	815	1	Regular	EST	08:34:00	08:36:00	09:27:00	FRI	51	3	2	0	2	8	5.36	98	131	82	2.50	0.71	1.00	0.29
506	811	1	Regular	FRI	08:40:00	08:41:00	09:28:00	EST	47	3	3	18	1	8	5.88	97	131	81	2.50	0.71	1.00	0.29
2131	807	1	Regular	EST	08:45:00	08:47:00	09:37:00	FRI	50	3	0	0	2	8	5.45	98	131	82	2.50	0.71	1.00	0.29
503	809	1	Regular	EST	08:55:00	08:57:00	09:45:00	FRI	48	3	2	0	2	8	5.66	97	131	81	2.50	0.71	1.00	0.29
2606	813	1	Regular	FRI	09:05:00	09:06:00	09:51:00	EST	45	3	3	21	1	9	6.12	113	89	79	1.19	0.60	0.48	0.24
2605	802	1	Regular	EST	09:11:00	09:13:00	10:01:00	FRI	48	3	2	0	2	9	5.66	114	89	80	1.19	0.60	0.48	0.24
2705	801	1	Regular	EST	09:23:00	09:25:00	10:13:00	FRI	48	4	0	0	2	9	7.41	111	89	76	1.19	0.60	0.48	0.24
2703	815	1	Regular	FRI	09:29:00	09:30:00	10:15:00	EST	45	2	3	20	1	9	4.17	116	89	83	1.19	0.60	0.48	0.24
506	811	1	Regular	EST	09:31:00	09:32:00	10:20:00	FRI	48	3	2	0	1	9	5.77	114	89	79	1.19	0.60	0.48	0.24
502	809	1	Regular	FRI	09:50:00	09:51:00	10:36:00	EST	45	5	3	39	1	9	9.80	108	89	71	1.19	0.60	0.48	0.24