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Data-driven Maintenance Analysis of Tramway Network

Towards Digital Transformation of Gothenburg Tramways

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Abstract

One of the proven applications of digitalization in public transport in recent times is the improvement of maintenance strategies using data-driven methods. A robust maintenance strategy ensures the availability of assets to perform its designated operations maximizing the owner's revenue at minimum costs. This thesis carries out a data-driven analysis of the tram system in Gothenburg with an objective to generate insights on the current maintenance procedures and asset performance which would aid the tram operator in their journey towards digital transformation. The analysis focuses on critical fixed infrastructure assets such as track, switches and catenary and was carried out following CRISP-DM, one of the most common frameworks for data mining. The project analyzed three different data sets – monthly track switching operations, operating restrictions resulting from faulty infrastructure assets and unscheduled maintenance events and historical maintenance records of the fixed assets. Few performance indicators were measured from the switching data such as vehicle passage error rates and rate of manual switching operations. The analysis on operating restrictions focused on identifying the reasons for restriction, its duration, the occurrence of restrictions over time and the associated cost impacts. The most significant part of the analysis was carried out on the past maintenance records available as inspections and work orders. Maintenance performance indicators based on the time incurred to perform such activities were measured. The primary causes of a failure for each asset category were identified. Further, a comparative analysis of inspections done against the standard requirements was also carried out. The analysis found satisfactory performance of switching operations. Regarding track restrictions, a pattern on the number of restrictions over time was observed. The analysis of inspections and work orders pointed out underperformance by maintenance teams and evident shortcomings in data collection. The performance indicators of maintenance teams measured may be used as a benchmark for better monitoring and control. However, they should be subject to scrutiny owing to questionable data quality. Future research should explore the feasibility of employing real-time predictive analytics for maintenance in tram systems based on machine learning.

Keywords tram, maintenance, track, switch, contact line, inspection, work order

Contents

Preface

This master thesis project was carried out in the spring of 2022 at the Department of Built Environment at Aalto University and in cooperation with Trivector Traffic, Gothenburg, Sweden.

I would like to thank my supervisor and professor Dr. Miloš N Mladenović and my advisor Dr. Murat Bayrak for their great guidance and support throughout the course of this thesis project.

I want to thank Mr. Lennart Persson from Trivector Traffic for giving me the opportunity to be a part of their project, Ms. Olivera Puljić for helping me get the data access from the client and Mr. Leif Linse for always clarifying my doubts on tram operations. A big thanks to Mr. Michael Thulin from Alstom for spending his valuable time discussing the advancements of digitalization in light rail transport.

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Otaniemi, 14 July 2022
Bilal Baiju

1 Introduction

Trams are one of the rail transit modes operated primarily on streets in mixed traffic but can also include off-street running on segregated paths with an exclusive right of way [1]. Nowadays, there are tram systems with predominantly exclusive right of way and is called Light Rail Transit (LRT). LRT systems uses smaller vehicles with relatively lower capacity and operating speeds compared to conventional railway systems [2]. Modern trams are electrically powered, high capacity, environmentally friendly and quiet [1]. They use a pantograph to draw electricity for its propulsion from overhead contact wires called catenary or from a third rail. Trams offer superior riding comfort, provides accessible mobility for people with reduced mobility and integrates more into the urban environment than other rail transit modes driving a strong urban identity [3].

Despite losing its popularity following the rise of the automobile, trams are being reintroduced in North America and Europe as a high-performance transport mode since the 1980s [4]. Currently, half of the world's tram systems and a significant proportion of the yearly passenger journeys are in Europe [3].

Figure 1: A modern tram in Dijion, France [5]

The Nordic region have some of the most advanced public transportation systems in the world [6]. In Scandinavia, the public transport systems have high usage levels, offers higher levels of service even in off-peak times and features innovative on-vehicle technologies [7]. In recent times, the three main goals identified by the Nordic public transport industry are increasing ridership, reducing costs, and meeting up to the high sustainability standards set by the industry, hence realizing its full potential [6]. Public transport authorities have already identified digitalization as having a great potential in helping to achieve these goals. Digitalization comes with multiple benefits for the transport operators and the customers. Digital solutions such as smart ticketing, real-time fleet management, eco-driving which reduces fuel costs and emissions, crowd movement analysis that optimize route planning, predictive maintenance etc. are some proven examples.

The city of Gothenburg in Sweden has the largest and one of the oldest tram networks in the Nordics [8] and forms the core of the city's public transport system. It has undergone multiple modernizing efforts in the recent years towards providing safe, reliable, efficient, and sustainable tram traffic and digitalization is one of them. Gothenburg Tramways continue to work with the development of digitalization and identified it as a necessity to stay competitive in the market.

This master thesis was carried out as part of a bigger project on the digital transformation of Gothenburg's tram system awarded to Trivector Traffic by the traffic office of the City of Gothenburg. The traffic office wanted to investigate how they should move forward with digital transformation and develop an action plan for the areas in which a more data-driven approach can improve the quality of the light rail network. The project was divided into three stages as market analysis, strategy development and proposals for implementation and governance.

The thesis rather deals with a fast-track phase of the project which aims to identify how the existing collected data can be used and what insights can be generated out of it. However, only a few data sets were made available for the study during the course of the thesis project, and they were primarily on the infrastructure maintenance processes of the tram network. Even though, the data sets had maintenance information on many types of assets under the tram network like bridges, tunnels, stops, lighting etc., the study focuses on the more critical assets such as tracks, track switches and the catenary system.

The section 2 of thesis provides a case background on the Gothenburg's tram network and literature background in digital technology and maintenance, section 3 explains the research methodology followed and the data sets which were available for the analysis, section 4 presents the results of the data analysis with various figures and explanations and section 5 discusses the findings and concludes the thesis.

2 Background

2.1 Gothenburg

2.1.1 The city

Located in the west coast of Sweden, Gothenburg is the second largest city in Sweden, the capital of Västra Götaland county and the largest port in Scandinavia [9]. Gothenburg, with a population of around 600,000 is growing fast and has a series of major infrastructure projects planned [10]. The city's population is projected to increase by 150,000 and create 80,000 more jobs by the year 2035. A sustainable and efficient transport system also needs to be in place to accommodate this growth which reduces the climate impact of the transport sector and provide better travel possibilities for people at the same time. According to the Comprehensive Plan for Gothenburg in 2009, the total number of journeys are estimated to increase by 27% as the city grows [11]. It is also predicted that the number of private car journeys will increase by 35% to 2030 contributing to congestion and poor air quality which is not favourable for the city's climate objectives. Hence, large volumes of traffic need to be shifted to public transport. As outlined in the Gothenburg 2035 Transport Strategy, the city targets to achieve a 55% share of all motorized journeys performed by public transport and 35% of all journeys by foot or bicycle [10]. The changing transport demands is one of the thirteen strategic questions in the Comprehensive Plan for the Gothenburg. In 2020, 66.5 million bus journeys and 95 million tram journeys were performed using Gothenburg's public transport [12].

2.1.2 Public transportation

2.1.2.1 Efforts towards sustainability

Gothenburg is at the forefront of sustainable and innovative public transport solutions. It started testing electric buses in 2011 and in 2015 [16], Gothenburg launched its first electric bus route, Route 55, which is run by three fully electric and seven electric hybrid buses from Volvo powered by 100% renewable electricity [17]. The route was a result of ElectriCity, a collaborative project with partners from industry, academia, and society to develop sustainable transport systems for the future. Currently, the city operates the largest electric bus fleet in the Nordic region [18]. In 2020, 145 articulated electric buses were added to the city's fleet and there was a significant reduction in the nitrogen dioxide and carbon dioxide emissions from bus traffic during the first year of its operations. The users also enjoy silent bus rides with noise levels reduced by 7dB [16]. Currently, around 220 electric buses are operating in the Gothenburg area and is expected that all of Västtrafik's buses will be electric by 2030 [18].

Figure 2: Volvo electric buses in Gothenburg [16]

2.2 Gothenburg's Tram System

Trams are one of the primary modes of public transport in the city. The city boasts a historic tram network that has been in existence for more than 140 years and has been a natural part of Gothenburg's development [19]. The first trams pulled by horses started operating in the year 1879 and the first electric tram in 1902. Today, the blue-white trams in Gothenburg are something which makes the city unique, is part of the city's brand and almost 400,000 trips are made aboard Gothenburg's trams every day [20]. Since the last major line restructuring in 2003, the tram ridership in the city has increased by 80% until 2019 [21]. Figure 2 shows the city's public transport network map [22].

2.2.1 Ownership and operation

The City of Gothenburg owns the trams and tramways but the operations, maintenance and traffic management in Gothenburg and Mölndal are exclusively handled by Göteborgs Spårvägar (in Swedish but hereinafter referred as Gothenburg Tramways), which is a municipally owned company through

Västtrafik [14]. The company is 85% owned by the City of Gothenburg and remaining 15% shares are owned by Västtrafik [21]. Gothenburg Tramways is the largest operator of public transport in the city and accounts for 40% of the public transport in Västra Götaland. They are also the largest tramway company in the Nordic region and one of the largest players in Europe. There are other private actors as well in Gothenburg public transport which operates buses and ferries, which are partner companies of Västtrafik [7].

2.2.2 Sustainability targets and efforts

Gothenburg Tramways calculates and reports its climate footprint according to the GHG protocol every year [21]. The direct climate impact from the operation of vehicles, indirect impact from energy consumption, procurement of goods and services and waste management is reported. The company has its own set of environmental policies and goals apart from other regulatory laws and requirements to reduce the negative environmental impact of their business [23]. The company aims to carry out its operations and maintenance in an environmentally friendly manner by following a systematic approach based on continuous improvements. They only use electricity from renewable sources for running their trams and they are run by 100% eco-labelled electricity from wind power. Their long-term energy efficiency goal is to reduce the total energy consumption of its entire operations and targets to reduce the energy consumption per trip by 13% by 2030 [24].

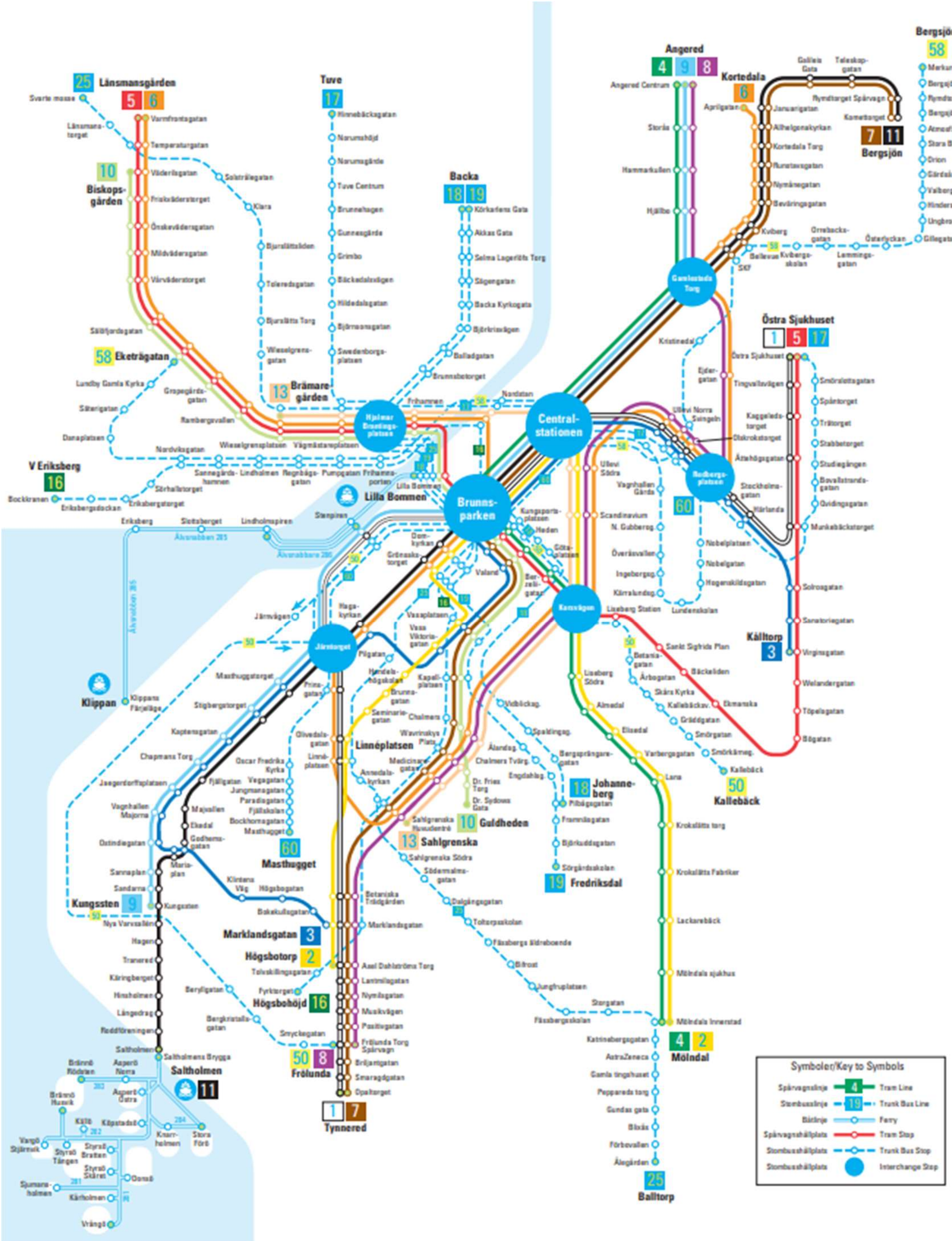


Figure 3: Public transport network map – Gothenburg [22]

An environmental study was carried out in 2021 which shows that the largest climate footprint of the company comes from the purchase of goods and services which includes rails, tram components and other investments [21]. The company aims to integrate purchasing and procurement with the environmental requirements to make sustainable material choices. Maintenance plans have been developed to improve energy efficiency at their properties, depots, and major technical installations. They are also working towards making improvements in waste disposal, chemical usage and increasing the proportion of fossil-free vehicles in their fleet. The company works actively to reduce the noise that arises from tram operation primarily through revised maintenance routine, better lubrication as well as new methods [21]. For instance, the M32 tram models are equipped with noise reduction films on the rail head to dampen the squeaks.

2.2.3 Recent trends and future goals

In 2021, a new long-term product strategy was introduced by Gothenburg Tramways towards their quality development journey [21]. Together with Västtrafik and City of Gothenburg, they want to develop and increase tram travel in Gothenburg by 2035. New tracks are planned to be constructed. It is forecasted that, by 2035 everyone living in Gothenburg would make an average of 1.13 tram trips per day. Towards achieving this target, the importance of digitalization should also be stressed. It has been a common challenge for traffic operators, and it is necessary to carry out digital transformation due to the competent market situation. This involves upgrading the operator's IT architecture contributing to improved operations and cost reduction.

In 2021, the production was strained due to the pandemic situation, primarily due to sick employees and secondly due to the changed travel patterns in the Central Gothenburg with more users with bicycles, electric scooters, or cars. This has caused an increase in road accidents and falls aboard tram due to heavy braking. Along with this, the delivery delay of new generation trams and the sudden phasing out of some older ones added to the recent difficulties. However, the situation is expected to improve when the new tram models get deployed.

2.2.3.1 Organization of public transport

The public transport network in Gothenburg currently has a radial structure [10] and it includes trams, buses, commuter trains and ferries [13]. It is managed by Västtrafik AB, the agency responsible for the planning and procurement of public transportation in the Västra Götaland region of Sweden [14]. Västtrafik is owned by Västra Götaland region, which is the regional public transport authority. However, the City of Gothenburg through their traffic office is also involved in influencing the traffic in the city and they communicate the public transport needs of the local population to the transport authority.

Västtrafik has agreements with many public and private partner companies to operate traffic and provide associated services in different municipalities in the region. The drivers, ticket inspectors and train hosts are also employed by these partner companies. Gothenburg has multiple such partners running the public transport system [15].

2.2.4 Vehicle fleet and infrastructure

This section covers the details about the existing fleet, infrastructure, and some upcoming development plans. A product strategy was released by Gothenburg Tramways in 2021 which details their development plans to accommodate the increased travel demand in the coming years [24].

Gothenburg's tram network has a track length of more than 160 kilometres, 132 stops and 12 routes of operation. The trams are propelled by 750V DC electric lines, and the track gauge is 1435mm [25]. Currently, the Gothenburg tram network has a fleet of more than 200 trams in four different models. The information about the existing fleet is detailed in Table 1 [26].

Table 1: Fleet - Gothenburg Trams [26]

Model	Manufacturer	Country of Origin	Low floor	Length (m)	No. of passengers		No. of convoys
					Seated	Standing	
M33	Bombardier Sweden AB/Kiepe Electric	Germany/ Austria	Yes	33	75	155	14
M32	Ansaldobreda	Italy	Yes	29,5	87	104	64
M31	ASEA/ABB	Sweden	Middle section	30,6	81	109	80
M29	Hägglund & Söner	Sweden	No	14,2	36	82	55

The oldest generation of trams, M28 was taken out of service permanently on 28 October 2021 due to rust damage, after 56 years of operation [27]. The tram type in question did undergo inspection rounds but were rejected for traffic safety reasons and all 48 carriages from the series were withdrawn from service. These trams will be demolished and scrapped.

The older trams (M28 and M29) will be replaced by newer generations of trams with higher passenger capacity. M29 will also be eventually phased out following the delivery of new trams. Västtrafik has ordered 40 M33 trams which are currently being delivered and 40 M34 trams, which is a longer version of the M33 with a length of 45 meters and a capacity of 319 passengers which is 50% more than its predecessor [28] [29]. Of the ordered M33 trams, ten are two-way wagons, having driver seats at both the ends and doors at both the sides [28]. This helps in easy change of direction without performing a reversing loop. The M33 trams consumes 30% less energy per passenger than the previous generation M32 trams [21]. The new trams will be manufactured by Alstom (Bombardier Transportation was acquired by Alstom in 2021 [30]) with electrical parts coming from Kiepe-Electric [29]. Figures 4–7 shows the trams currently under operation.

Figure 4: M29 Tram [31]

Figure 5: M31 Tram [31]

Figure 6: M32 Tram [31]

Figure 7: M33 Tram [32]

Gothenburg Tramways aims to have a modern, robust, and reliable fleet of trams. The current fleet consists of many older trams which has even undergone life-extensions and major redesigns [24]. The older trams have a difficult time living up to passenger's expectations of a modern tram journey. The trams have operated for a longer period than technical service life specified by the manufacturer. An outdated fleet contributes to many issues since the old trams has less electronics and are not computerized like the newer generation of wagons resulting in a complex depot strategy and difficulties in accessing spare parts. The company faces a risk regarding the supply of spare parts and to reduce these risks, they are continuously working to improve the planning of maintenance [21]. It is difficult to get a reliable supply of spare parts for the maintenance of M29 and M32 types of trams.

Fleet modernization requires proper planning in scrapping and purchasing, and effective transitioning to ensure the availability of carriages required to operate the network according to the growing demands [24]. However, according to Gothenburg Tramways there has been lack of planning with a long-term perspective and passenger demands in consideration in the past. For instance, the procured M32 trams from AnsaldoBreda did not meet the quality expectations which resulted in the older trams to compensate for it by continuing in the service. The procurement of new M33 trams has been done taking into account the lessons learned from the past procurement projects.

It is forecasted that around 172 trams will be put into operation to meet the traffic needs during the period 2021-2025 [24]. During 2018-2020, 66% of M28/M29, 82% of M31 and 64% of M32 were available for service and the rest of the fleet were under reserve, maintenance, audit, and training tasks. The reserve fleet mainly has M28/M29 trams and M32 trams has the highest proportion under maintenance. However, with the fleet modernization, an 85-90% traffic availability is targeted.

There are currently four depots for Gothenburg Tramways located at Majorna, Slottsskogen, Ringön and Rantorget where maintenance activities are carried out [24]. There is a direct link between the depots and the vehicle fleet and tram network. The depots should be able to meet the maintenance requirements of the tram system and the development of the tram network is constrained by the depot capacity. Hence, necessary adjustments should be made at the depots towards it so that it does not hinder the further development of the tram system. Proper maintenance of the infrastructure and rolling stock is of utmost importance to provide travelers a reliable, safe, and comfortable travel experience.

The depot at Majorna which opened in 1921 is already 100 years old [21]. This depot requires substantial refurbishment, and the renovation needs are being investigated. However, in 2020 the first phase of a new depot Ringödepån was inaugurated. Following the completion of the new depot, it will be able to maintain the new 45-meter long M34 trams.

2.2.5 Traffic safety

Safety remains at the core of the Gothenburg Tramway's operations. For ensuring safe and sustainable tram service, the infrastructure and operational security department of the company carries out planned annual inspections, maintenance and repair of tram tracks and overhead power lines in collaboration with the traffic office of the City of Gothenburg [21]. All incidents and accidents are reported and investigated to implement measures so that similar occurrences are not repeated.

The tram traffic in Gothenburg run on segregated tracks and on street tracks where the space is shared with other road users such as pedestrians, cyclists and motorists which increases the risk of accidents [21]. Accidents often occur at sites where several types of traffic converge. Gothenburg Tramways is actively working with the City of Gothenburg's traffic office to improve the traffic safety at the most vulnerable locations. In 2017, Gothenburg Tramways defined six safety goals for tram traffic and the actions need to be taken to achieve it.

2.2.6 Administration plan for the tramway facility

This section summarizes the administration plan (abbreviated as BUSKK in Swedish) for the tramway facility in the municipalities of Gothenburg and Mölndal [33]. The plan provides the basis for planning the operations and maintenance of the facility.

The operation and maintenance of the tramway network needs to be well-planned ensure the highest levels of safety, reliability, accessibility, security, and comfort. The traffic office of the City of Gothenburg, the facility owner is responsible to maintain the permit to operate the tramway facility by carrying out safety and regulatory measures that meets the requirements of several public authorities such as Swedish Transport Agency, Swedish Electrical Safety Authority, Swedish Environmental Protection Agency, Swedish Rescue Services Agency etc. The traffic office is required to maintain state of readiness to intervene in case of an accident or incident at the tramway facility and is also responsible for the traffic management of the tramway system maintaining safe and reliable tram traffic.

The traffic office describes the operation and maintenance plan for the tram system to ensure its technical function and economic value throughout its lifetime. The measures are specified to maintain the system at a normal level of standard (Level 0). Level 0 is the level of operation and maintenance measures that provides satisfactory levels of safety, availability, and reliability of the system. The funds availability for operations and maintenance were to fall below Level 0, it would adversely affect the life cycle cost and reliability and availability of the tram system. Reduced O&M measures would lead to increased wear and tear on system components before action can be taken, affecting the standard levels of the system and will have consequences for the stakeholders like increased waiting and travel times, poor levels of comfort and noise, and reduced service life of equipment. However, a fundamental requirement by law is that the operation and maintenance measures should maintain the system at a level that the there are no safety threats.

Apart from Level 0, the background study of the O&M plan by the traffic office presented two lower default levels of standard (Level -1 and Level -2) and one higher level (Level +1). The impact on the stakeholders from reduced O&M measures in few areas were analyzed in the background study by the traffic office and significant direct cost savings could be achieved by carrying out the maintenance activities as planned. Maintaining the system at Level +1 showed even higher cost savings compared to Level 0 and the traffic office found that it is economically more advantageous to keep the standard level of the tramway facility at Level +1.

If the facility has a reduced standard level than the planned standard level as per the O&M plan, the difference is labeled as backlogged maintenance. It is possible to monitor this by measuring the difference over time in available funds and the funds necessary for keeping the facility at the planned level. A negative value build up would represent a backlogged maintenance and is referred to as maintenance debt.

$$\text{Maintenance Debt} = \text{Available Funds} - \text{Required Funds}$$

The traffic office also allocates funds for measures that are outside the direct O&M measures to act proactively that reduce disruptions in the tram system which may include incident analysis, operational monitoring of the installations, preventive protection measures etc. The tramway facility needs to be closed when carrying out maintenance activities that may disrupt the tram traffic. When increased traffic is present, the slots for O&M activities needs to be shortened and more slots should be planned for nights and weekends to minimize the impact on tram traffic. However, certain O&M activities that requires closure of the tramway facility for longer periods of time causes regular traffic to be suspended and replacement to be provided. To reduce the impact from traffic closures, maintenance activities are planned for summer months, holidays, or weekends, when the traffic intensity is low.

The railway system of the tram network consists of tracks, signalling systems, overhead contact lines, electrical supply systems, stops and stations and support systems such as tunnels and bridges. The geographical area that accommodates the railway system is labeled as the railway area. The railway area is delimited based on whether the area only has tram traffic or is mixed with other modes of transport. Based on this classification, the railway area would consist of pavements, green areas, kerbs, fences etc.

The total track length is 169 kms which includes 74 km of street tracks and 95 kms of tracks on dedicated embankments for tram traffic. The street tracks are integrated with the municipality's street network and has mixed traffic whereas tracks in embankments only have tram traffic. The tracks include normal track sections, switches, and track crossings. The switches may be interlocking or non-interlocking types. The overhead contact line installations include the contact lines, feeder lines, feeder point cabinets, return to negative cabinet and protective earthing system for conductive components which are in the vicinity of tracks and the ones which might be exposed to a fallen contact line, rectifier stations etc. The railway system as summarized in BUSKK is shown in table 2.

Table 2: Railway system - Gothenburg Tramways [33]

Installation	Street Tracks	Special Embankments	Total	Unit
Tracks				
Standard Sections	74 289	94950	169239	m
Interlocked Switches	149	68	217	nos
Non-interlocked Switches	29	3	32	nos
Track Crossings	-	-	135	nos
Signaling Systems				
Safety Signaling	-	-	23	nos
Point Signaling	-	-	4	nos
Gear Drive	-	-	115	nos
Gear Heating	-	-	149	nos
Overhead Contact Line System				
Contact Line	74289	94950	169239	m
Masts for Contact Wires/Lighting	-	-	3678	nos
Rectifier Stations	-	-	71	nos
Tunnels and Bridges				
Tunnels	-	-	8	nos
Bridges (Tramway Only)	-	-	29	nos
Bridges (Combined)	-	-	16	nos
Stops and Stations				
Tram Stops	156	187	343	nos
Stations	-	-	5	nos

The track facility of the Gothenburg tram network has been divided into four traffic classes 1–4 (See table 3) based on the number of wagons crossing the section per year and the relative increase in wear and tear the passage of each additional wagon would cause [33]. Figure 8 shows a map of the track network divided into the four traffic classes and color coded. The traffic load varies across the tramway network. In the case of street tracks, the traffic load also includes the intermodal traffic load apart from the tram traffic load since the area is shared with mixed traffic (See table 4). Similarly, the stops in the tram network are also classified into four based on the traffic load measured by the number of boardings and alighting each stop (See table 5)

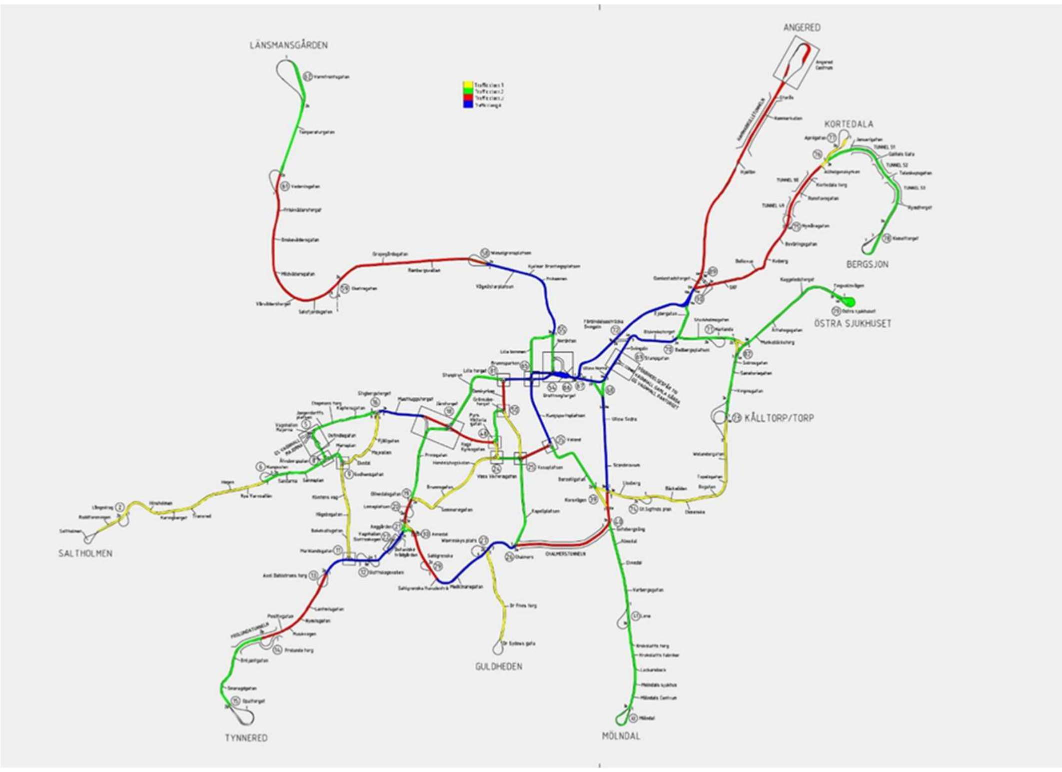


Figure 8: Track network - traffic classes [33]

Table 3: Traffic classes based on number of wagon crossings [33]

Traffic Class	Number of Wagons	Track Length (m)
1	< 55,000	32,065
2	55,000 - 90,000	57,799
3	90,001 - 155,000	48,847
4	155,000 <	26,193

Table 4:Traffic classes according to track type and proportion of intermodal traffic [33]

Traffic Class →	1	2	3	4	**Total**
Tracks Special Embankments (m)	16903	27379	38070	8351	90703
Street Tracks (m)	15162	30420	10777	17841	74200
Intermodal Traffic in Street Tracks (m)	8386	17838	5101	10672	41977
Percentage of Intermodal Traffic	55 %	59 %	47 %	60 %	57 %

Table 5: Stop classes based on number of travelers boarding or alighting [33]

Stop Class	**Number of Travelers**	**Percentage of Stops**	**No. of Stops**
1	< 5000	72 %	98
2	5000 - 10,000	16 %	22
3	10,001 - 20,000	7,50 %	10
4	20,000 <	4,50 %	6

2.3 Digital Technology

2.3.1 Digitization, Digitalization and Digital Transformation

Digital technology comprises of electronic devices and applications that stores, transmits, and forwards information in the form of a binary code, which is the digital format [34]. The use of digital technology facilitates digitization. The backbone of digitalization is digitization, which is the process of converting analogue data into digital discrete data in the form of ones and zeros and digitalization is the exploitation of these technological advancements that opens unprecedented business possibilities [34] [35]. According to the American consulting firm Gartner, Inc., "Digitalization is the use of digital technologies to change a business model and provide new revenue and value-producing opportunities; it is the process of moving to a digital business" [36].

However, Digital Transformation is a much broader term and might include multiple and wide variety of digitalization projects in a company not limited to using digital technologies but also to bring about an organizational change, shifts in corporate culture and achieving a customer-driven strategic business transformation [37]. Digitalization is the use of technology, but digital transformation is employing digitalization in making the business customer driven end-to-end [34] [37]. Also, digital transformation is not delimited to organizations but embraces changes on all societal levels [35].

Digital transformation is expected to become the new standard [34]. Digitalization has led to new product and service offerings and caused changes or modifications in company relationships with their customers and employees, and cooperation with other companies [35]. It has put pressure on organizations to evaluate their current strategies, find new business opportunities digitalization can bring and what it means to them in terms of economic impact. Hence, Digitalization can be considered as a new indicator of competitiveness of companies in various sectors.

A qualitative empirical study conducted among respondents from the media and automotive industries revealed that the companies identify the challenges and opportunities in digitalization, however the actual implementation and exploitation of these technological opportunities remains challenging [35]. An organization's capacity to accommodate such a change and employee competences were identified as future challenges in this respect. There was a positive effect at these firms on the value proposition due to digitalization which resulted in more revenues and the degree of digitalization carried out at these firms were dependent on the customer demand.

According to World Economic Forum, the combined value of digital transformation to society and industry could exceed $100 trillion by 2025 [38]. The potential of digital transformation is enormous and if Europe misses out on it, it could lose 605 billion euros in value added, according to the German management consultant Roland Berger [39]. This transformation takes place via four levels – digital data, automation, connectivity, and digital customer access.

Recent trends in digitalization includes the use of mobile devices, various analytics tools, and platforms [34]. These analytics tools analyze large, diverse volumes of data and generate useful insights that create value for the business. It is important for companies to find ways to make use of the technological progress, not lagging and stay competitive in the market.

Digitalization is a priority for the European Union and have been taking initiatives towards capturing the full potential of digitalization such as the digital single market strategy that proposes the removal of technical and legislative obstacles to tap fully the benefits from big data, IoT and cloud computing, regulations to promote free circulation and availability of non-personal data across the EU to competent authorities and ICT standardization to mention a few [40].

2.3.2 Digitalization in transport sector

The transport industry is highly competitive and has a large market size. According to Borisova and Pyataeva (2020), the transport sector has already recognized the importance of digitalization in the market and has been adopting measures to tap the possibilities the development of digital technologies has brought in [41]. The advantages include improved decision making, more revenue, simplified business processes and better quality of service to the customers. Hence, digitalization helps firms in gaining a competitive position in the market.

For example, the impacts of digitalization in the Slovak transport industry were measured by Chinoracky, Kuratova and Janoskova (2021) from a macro-economic perspective in different sectors within the transport industry based on its digital intensity [34]. The classification of digital intensiveness was done based on shares of ICT related investments and e-sales turnovers. It was found that the value added in the Slovak transport industry is growing. Regarding employment, the impacts were dependent on the sector's digital intensity. There was a growth in employment in some sectors whereas it reduced in others. The study didn't show a strong link between digitalization and employment since the total employment can be affected by other factors too. Nevertheless, the productivity levels increased significantly during the period under study which can be attributed to digital transformation. However, this study was mainly based on estimates and accurate measurements on the digitalization impact could be carried out on a microeconomic level.

2.3.3 Digitalization in public transportation

Digitalization helps increase the capacity and efficiency of public transportation systems in the most affordable way, making collective transport more attractive to potential users [42]. The adoption of digitalization is not homogenous across sectors and regions in Europe [40]. The transport sector has a low index of digital intensity. This section further discusses how far digitalization has progressed when it comes to urban public transportation, with an emphasis on rail transport. Rail transport is the most efficient mode of public transport in terms of energy efficiency per passenger kilometer [42]. It is not just a green solution but also tackles the congestion issues which many world cities are facing now. It accommodates a greater number of people per unit area than a private vehicle.

Rail transport is still in the early stages of digitalization [40]. Digitalization can improve manufacturing, operations and maintenance in this sector and will lead to better efficiency, low operating costs and competitivity among other modes of transport. The advent of ICT technologies and its influence on the business environment requires rail transport operators to review and update their existing business models and strategies [43]. Digitalization is about creating cyber-physical systems.

The digital technologies have already been put into use in the railway sector and related products and services are offered such as travel information, onboard leisure services, automation, and remote monitoring of assets. The changes brought by digital transformation comes with a lot of opportunities but challenges at the same time. In the case of rail transportation, financial investment and better cyber security measures are required [41]. According to the Road Map for Digital Railways published in collaboration with various international associations in rail transport, the key areas of digitalization in rail transport are provision of reliable connectivity, enhanced customer experience, increased capacity and boosting the rail sector's competitiveness making the best of transport data [44].

Another important factor when it comes to collective transport if safety, as the lives of hundreds or thousands of passengers are at stake [42]. As the transport networks becomes more digitalized, the risk of cyber-attacks increases as well. Cybersecurity must be prioritized to effectively manage the safety threats to the rail infrastructure, operator, and passengers. Operators need to stay ahead of the hackers to tackle these challenges. The key to cybersecurity is anticipation and it is facilitated by collaborative partnerships with other players in the transport sector, identifying shared threats and performing a comprehensive risk analysis to develop a detailed cybersecurity framework. It is important to design for cybersecurity at every stage of the product development, to make the whole system resilient against cyber-attacks.

2.3.3.1 Key enabling technologies

The key technologies driving digital transformation in the transportation sector are discussed below. New products and services are being offered and new concepts of mobility are emerging creating added value for the stakeholders.

A. Internet

The main driver of digitalization since the 1990s was the Internet [40]. As of January 2022, 4.95 billion people in the world uses internet which accounts to 62.5% of the total world population and 92.1% of them uses their mobile device to access the internet at least some time [45]. Internet-based technologies has disrupted the way communication is being carried out between organizations, communities, and individuals. Nowadays, social media has become a key tool for information sharing. There are 4.62 billion social media users as of January 2022 [46].

When it comes to recent advancements in telecommunications, the 5G technology having very high data rates and low latency will offer new opportunities when it comes to public transport [6]. 5G enables higher device density up to a million devices per square kilometer leading to everything in a city that generates data to be connected like sensors, traffic lights etc. With the full speed capabilities of 5G, millions of data sources can be combined producing real-time big data analytics and a traffic management system eliminating grid locks, traffic jams and prioritizing public transport. The ultra-low latency capabilities of 5G will help autonomous vehicles to better interact with the real-world traffic, making them safer, efficient, and reliable.

B. Internet of Things (IoT)

The Internet of Things (IoT) is a network of physical devices that are connected over the internet and exchanges data [47]. It is the convergence of digital and physical worlds and is one of the most fundamental trends in digital transformation [48]. IoT devices are embedded with sensors, software, and other digital technologies to enable this [47]. It is expected that the number of connected IoT devices would grow to 22 billion by 2025. IoT has evolved as one of the most important technologies of the 21st century.

According to a 2021 report by the management consultant McKinsey and Company, by 2030 \$5.5-\$12.6 trillion economic value could be captured globally by IoT with the largest potential concentrated in the production sector in areas such as operations optimization, human productivity, and condition-based maintenance [48]. When it comes to mobility technologies, autonomous vehicles are the fastest growing cluster. There has been a steady increase in the use of sensors in vehicles enabling enhanced safety and security features.

The concept of IoT employed in rail transport is called Internet of Trains in which various subsystems in rolling stock transmits data via cloud to a central platform, creating value for multiple stakeholders [43]. A reliable communication network is necessary for this and is facilitated by the implementation of GSM-R, a radio communication system dedicated for railway operations and is the data communication bearer for European Train Control System (ETCS) [49].

C. Cloud Computing

Cloud computing is a model that enables the usage of ICT services over a network at any moment of time [40]. With this model, the customers don't need to invest in massive IT infrastructure and only pay for what they use according to their demand, hence offering a lot of flexibility. The cloud services can include servers, operating systems, storage, software, and applications. It's an alternative to own data centers [43].

The range of cloud computing models include Software as a Service (SaaS), Platform as a Service (PaaS), Infrastructure as a Service (IaaS) and Anything as a Service (XaaS) in which different cloud computing models are combined [50]. Big Data as a Service (BDaaS) integrates the functionalities of these models and deals with the advanced analysis and management of large volumes of data. Examples include Big Data on AWS, Microsoft Azure, and Google BigQuery.

D. Big Data Analytics

Big data analytics is use of advanced analytics methods to process and analyze very large amounts of diverse structured, semi-structured or unstructured data produced from a variety of sources such as sensors, devices, applications, log files, web, satellites etc. to gain useful insights to make better decisions, create new products and services and do business more efficiently [51]. The potential of data in improving transport has been evident from several projects across the world which will be explained in the coming sections.

2.3.3.2 Recent developments in digitalization in the transport sector

This section presents some of the recent developments when it comes to digitalization in the transport sector in various categories along with some examples.

A. Infrastructure Planning

Big data is used for proper demand estimation and hence make better decisions in public transport investments and optimize costs [52]. Data collected from existing transport services such as validation cards, mobile phone, social media, sensors etc. and ticketing data [40] can be used to model passenger flows with higher levels of accuracy and hence plan infrastructure and routes based on actual passenger needs. Crowd movement data can be measured by the movement of mobile phones when they connect to different base stations in a cellular network [6]. This type of data provides greater accuracy on the people's movement pattern as it is based on actual data and capture's the entire door-to-door journey of a person. It can be used to identify unmet demand, and open new routes based on high passenger flows, or increase the service frequency based on demand during different times of the day, hence reducing the passenger waiting times and increasing the operator's revenue [52].

Some examples are as follows:

a. London uses data from smart tickets to deploy alternate bus routes during planned service disruptions [52].
b. In Seattle and Utrecht, big data was used in the cost-benefit analysis on their monorail and LRT projects respectively [52].
c. In Seoul, the night bus routes were planned based on the data gathered from mobile phones and taxi usage [52].
d. Digital Twins: When a new technology is under development or any changes in the transport system are going to be made, it's digital replica can be made to test in a simulated environment to analyze its potential impacts on the system, saving time and money [42].

B. Passenger Services

There has been a significant improvement in the number and quality of services offered to the customers in the recent times such as user-friendly informative websites, mobile applications with functionalities such as ticketing, real-time information like live location of vehicles in motion, journey planning, dynamic information screens at railway stations and infotainment services on-board [40]. Online ticketing services has benefits such as cost reduction in providing physical tickets and passengers find it easier to carry them in their mobile devices. The on-board security and safety of the passengers can be improved by using remote video surveillance systems [40]. CCTV AIs can detect any incidents compromising safety of passengers and automatically reports it to the relevant authorities [42].

Another service which resulted from the development of ICT technologies is multimodal transport solutions like Mobility as a Service (MaaS) which enables purchase of tickets for multimodal journeys through a single integrated platform according to the passenger's preferences on cost, time, and carbon footprint [40] [42]. It is important to connect conventional collective transport modes such as trains, metros, and trams with first and last-mile solutions such as bikes and taxi-shares to enable door-to-door connectivity [42]. Effective consolidation and sharing of data across transport operators is necessary towards its fulfilment, allowing easy access of reliable travel information and options for passengers [42].

Some examples are:

a. The Spanish infrastructure manager ADIF's app has station maps and shopping information apart from the standard functionalities [43].

b. The just go ticketing scheme by the Swiss railway company SBB which records the boarding and alighting of a passenger using their mobile device and low energy Bluetooth transmitters. Thus, it is not required to purchase a ticket in advance, but passengers can simply board the train and will be charged upon disembarking based on the travel data sent to the backend through the mobile device [40] [43]. This type of ticketing makes the boarding faster by enabling simultaneous validation and reduces the extensive infrastructure costs at railway stations [43].

c. ÖBB, Trenitalia, Deutsche Bundesbahn (DB) and SNCF - the Austrian, Italian, German, French national rail provides infotainment services on their trains [40].

d. German railway operator's DB Navigator application is an example of MaaS deployment in the railway sector which provides a multitude of functions to the users [40].

C. Daily Operations

There are several developments made in the public transport operations owing to digitalization [53]. Driver assistance systems are used in buses, metro and light rail improving the safety and energy efficient driving. This includes intelligent speed adaption which prevents over-speeding and uses advanced braking for accurate stopping, obstacle detection, collision avoidance, blind spot, and lane departure alerts. Another safety feature is the ignition system interlocked with a breathalyzer ensuring the driver is not under the influence of alcohol.

Digital control systems are used in metros and buses which communicates vehicle position by GPS or cameras which enables the control center to interference in case of any delays or incidents [53]. Another example is the adaptive traffic control system (ATCS) which employs automatic adaptation of traffic light timings helping public transport buses to follow their schedule and reduce traffic congestion.

D. Asset Monitoring & Management

Maintenance is one of the main aspects when it comes to asset management. Big data analytics and machine learning have contributed to the way in which maintenance of vehicles and infrastructure is carried out [53]. Predictive maintenance is considered as one of the key applications of artificial intelligence in public transport. The traditional reactive approaches in maintenance are changing to maintenance based on actual health condition of a component and predictions of failure, facilitating maximum usage of a component [52] [53]. Hence, operators get the best out of expensive components before they are replaced, lowering expenditure on spare parts and associated labor costs [52].

With transport systems becoming increasingly complex with a large degree of interdependency, a service outage can cause disruptions in the entire network resulting in loss of productive hours and revenue [52]. Minimization of unplanned maintenance using predictive maintenance improves reliability and solves this problem to a greater extent. However, urban public transport providers operate fleets comprised of vehicles from different generations and use different technologies [52] [53]. Transition towards predictive maintenance in such cases is challenging.

In rail transport, sensors installed in the rolling stock and infrastructure parts captures and sent data, which is then used in the detection of upcoming faults and monitoring of current condition [40]. The enormous volume of data points captured by these sensors in critical train components can detect imminent defects and maintenance is only done when required but before a failure occurs [43]. These data points can also be used to carry out root cause analysis when a failure occurs and make reliable predictions of failures in the future. This can ensure very high availability of the rolling stock avoiding any breakdowns since the vehicles will be repaired during the non-operating periods, improving the reliability. The proportion of reserves in the fleet can be reduced now which increases the overall capacity. By consolidation of maintenance data, the rolling stock manufacturers are now able to offer services like fault detection and predictive maintenance. However, digitalized maintenance comes with high investment costs due to infrastructure, legal and regulatory requirements but less operational costs [53].

Some examples when it comes to remote monitoring and management of rail assets are as follows:

a. Siemens Mobility offers a range of predictive maintenance related services such as real-time remote condition monitoring of vehicles, remote diagnostics, root cause investigation and data visualizations, hence improving the performance of rail assets [43]. DB Cargo in Germany uses these services, improving their availability and optimizing life cycle costs covering around 300 Siemens locomotives of different series [54].

b. DB Netz, the infrastructure manager of the German railway network uses its diagnosis and analysis platform, DIANA, which evaluates real time data enabling predictive maintenance [55].

c. The German rail company DB opened its first digital interlocking system in 2018 in Saxony that authorizes train movement based on network traffic in which the control commands are digitally transmitted to the field devices such as signals, switches, and track contacts [56]. This eliminates the requirement of physical connections via long cable bundles to the interlocking elements on field.

d. The Spanish rail operator Renfe uses digital predictive maintenance to improve the train availability in their Barcelona-Madrid route [40] [43] [52]. The employment of predictive maintenance reduced mechanical failures and helped them capture 60% of the market share in this route offering passengers a reliable and punctual service. This route now has a service reliability of around 99.9% and the costs savings alone returned the investment costs in eight years.

e. Digital technology can also be used to provide warnings in case of abnormal observations [40]. UK's Network rail uses drones to monitor trespassing and damage to the assets.

f. The public transport operators in Spain, Metro de Madrid and TMB Barcelona uses digitalized maintenance [53].

g. ABB, a leading Swiss-Swedish technology company provides a wide range of top-notch digital solutions when it comes to rail and urban transportation with their ABB Ability platform, helping transport agencies keep their operations safe, reliable, and efficient and ensuring peak performance of the assets [57].

E. Automated Operations

Autonomous vehicles can be seen in automated metros, light rail systems and self-driving minibuses [53]. As of December 2018, there was 1026km of fully automated GOA4 (See table 5) metro lines worldwide and is projected to reach 4000kms by 2030 [58]. Automatic train operations (ATO) shift driver responsibilities to the train control system. In this way, driving is optimized, and more vehicles can be operated at faster speeds and shorter headways, increasing the system capacity and contributes to a better passenger experience, reduces their waiting times, less delays, and reliable journeys [42]. It also improves safety, reduces energy consumption, and provides high levels of passenger comfort due to smooth braking and acceleration and precise driving [59].

There are four grades of automation and the highest grade GOA4 is unattended train operation [58]. The grades of automation according to the International Electrotechnical Commission is shown in table 6 [60]. The right amount of automation needs to be applied to suit the needs of operators based on budget, type of network and status of the rolling stock [42]. For example, some old rolling stock cannot operate fully autonomous, but a semi-autonomous degree can be applied.

Table 6: Grades of Automation – Automated urban guided transport [60]

Basic functions of train operation		On-sight train operation TOS	Non-automated train operation NTO	Semi-automated train operation STO	Driverless train operation DTO	Unattended train operation UTO
		GOA0	GOA1	GOA2	GOA3	GOA4
Ensuring safe movement of trains	Ensure safe route	X (points command/ control in system)	S	S	S	S
	Ensure safe separation of trains	X	S	S	S	S
	Ensure safe speed	X	X (partly supervised by system)	S	S	S
Driving	Control acceleration and braking	X	X	S	S	S
Supervising guideway	Prevent collision with obstacles	X	X	X	S	S
	Prevent collision with persons	X	X	X	S	S
Supervising passenger transfer	Control passengers doors	X	X	X	X or S	S
	Prevent injuries to persons between cars or between platform and train	X	X	X	X or S	S
	Ensure safe starting conditions	X	X	X	X or S	S
Operating a train	Put in or take out of operation	X	X	X	X	S
	Supervise the status of the train	X	X	X	X	S
Ensuring detection and management of emergency situations	Perform train diagnostic, detect fire/smoke and detect derailment, handle emergency situations (call/evacuation, supervision)	X	X	X	X	S and/or staff in OCC

NOTE

X = responsibility of operations staff (may be realised by technical system).

S = realised by technical system.

A few examples of recent advancements when it comes automated operations are discussed below:

a. The Swiss railway company SBB tested their first automatic operations in 2017 [61]. Currently they have technologies that calculates the maximum safe speed based on current traffic conditions, enables automatic braking [62], automatic door control helping to determine which side the doors should open [59] , stop skipping [59] and an adaptive steering system which helps drivers to avoid unscheduled halts [63].

b. The first automatic train in the world that operates by itself in rail traffic developed by DB and Siemens Mobility was presented at the ITS World Congress in Hamburg in 2021 [64]. The train's operations are based on the combination of ATO and ETCS.

c. London Thameslink, now there are on-board systems which adjusts the air-conditioning according to passenger volume inside the wagon and there is vehicle loading system which measures the level of crowdedness in wagons and directs passengers at stations using live information systems to less crowded wagons during boarding [52].

F. Open Data

Digitalization enables the capture and analysis of large volumes of transport related data [65]. Transport operators have a very large variety and quantity of data which is collected in a common data pool [52]. This data is openly made available to third parties to develop services for travelers, encouraging innovation reaping huge benefits for all stakeholders. However, only non-personal and non-critical data is considered as open data and made available. Open data increases the transparency of available and best transport options to the public and enables its efficient use. According to the Swiss railway operator SBB which also shares open data, "Open Data is data that a company makes available to third parties for secondary use free of charge and in machine-readable form" [66].

Some examples are as follows:

a. Trafiklab in Sweden, an open traffic platform developed on the behalf of Swedish public transport authorities where developers can access data and APIs to develop travel related smart services [65].

b. The authorities in San Francisco shares travel data sets through a cloud- based data sharing site. The data is published in Google's General Transit Feed Specification (GTFS), a general format which can be used world-wide [52].

G. Intelligent Transport Systems (ITS)

This involves the use of data driven solutions to coordinate, control and effectively manage urban traffic flow, reducing congestion [52]. ITS prioritizes the flow of public transit vehicles driving modal shift and helps users in making better travel decisions since they get upfront and accurate information on the travel options and travel time. Another application of ITS is when it comes to high occupancy toll lanes which charges single occupancy private vehicles, that encourages car-pooling [52].

Some examples are as follows:

a. Tel Aviv dynamic pricing based on real time traffic state on a 13-km stretch to the city from the airport. The dynamic pricing scheme used guarantees an average speed of at least 70km/h and a capacity of 1600 vehicles per hour, ensuring travel times of 10-15 minutes and maximum revenue for the operator [52].

b. A similar strategy is employed in Singapore when it comes to congestion pricing, called the electronic road pricing system which applies congestion charges when road capacity gets limited [52].

c. Berlin tackled its congestion problem using ITS technologies by establishing a control center that uses data from various roadside sources [52].

H. HR Management

Digitalization has also impacted human resources management in transport companies leading to emergence of new jobs and job profile changes [53]. Possibilities include process optimization, rostering, developing shift schedules, teleworking, new recruitment channels, training through e-learning and virtual reality etc.

Some examples are as follows:

a. A bus driver training company TTS in Finland uses simulators equipped with virtual reality in training drivers along with actual buses [53].

b. The heavy digitalization in Metro de Madrid especially in ticket sales and information services made the service personnel became redundant leading to a job profile change [53].

2.4 Maintenance

This section describes maintenance and different maintenance strategies followed in various industries.

2.4.1 Definition

Maintenance is a collective term including all planned and unplanned activities and procedures carried out to ensure constant accessibility to operation equipment [67]. According to the Swedish Standard SS-EN 13306:2017, maintenance is defined as "the combination of all technical, administrative, and managerial tasks during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function" [68].

A primary objective of maintenance is to reduce decrease total costs and maximize revenue by eliminating breakdowns and all undesirable events [67]. Poorly maintained assets would cause unexpected breakdowns creating service unavailability [69]. Maintenance aims at total asset lifecycle optimization which implies the maximization of asset availability and reliability to achieve business objectives.

In large plant-based industries, maintenance costs can account up to 40% of the total operational costs which implies that improved maintenance operations can bring in financial savings [70]. The competitive nature of the industry demands minimizing capital costs and maximizing the output making use of its full capability. Hence the system uptime should be maximized through proper and effective maintenance. The evolution of maintenance practices results from the advancement of technologies which drives companies to adapt to the changes to remain competitive in the market [71]. As detailed in 2.3.3.2 digitalization has an influence in the development of maintenance practices.

2.4.2 Maintenance Strategies

Proper maintenance strategy is required to lower maintenance costs [67]. Maintenance strategies are management methods employed to achieve maintenance objectives [68]. Several maintenance strategies and procedures has evolved over the years due to industry transformations, changing market expectations and customer needs and the need for companies to adapt to this change [67].

The selection of appropriate maintenance strategy is based on the strategic needs of the organization and is quite a challenge with some organizations employing a mix of different strategies [67]. The classification of maintenance strategies is presented in different ways in different sources. The Swedish Standard SS-EN 13306:2017 classifies the maintenance strategies in two broad categories [68] as shown below in figure 9.

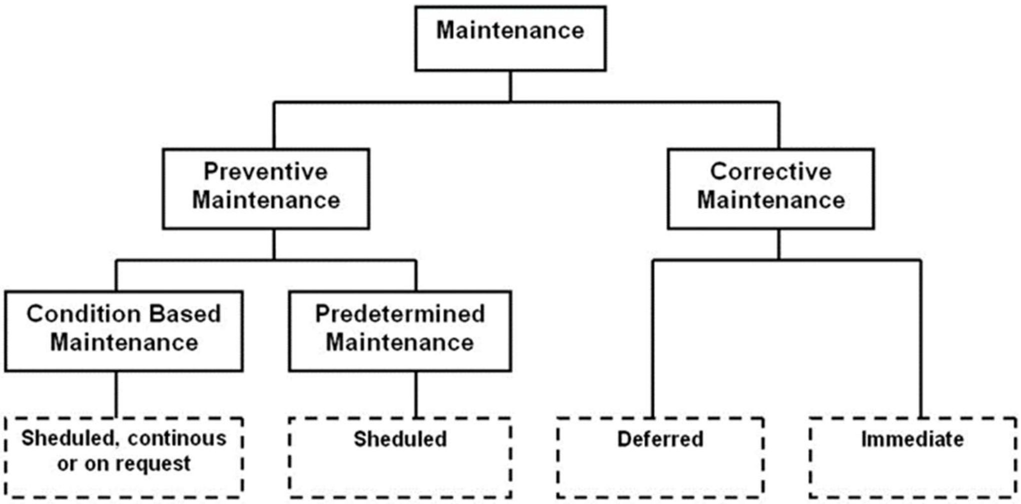


Figure 9: Classification of maintenance strategies [68]

2.4.2.1 Corrective Maintenance

Corrective maintenance is the simplest maintenance strategy, and it is carried out after the breakdown and its related consequences [67]. The repair is performed immediately or at a later point of time [72]. It is also called unplanned maintenance [67], reactive maintenance , run-to-failure [73] or curative maintenance [74]. This is a costly maintenance strategy and creates availability issues [72]. It is a reasonable approach when maintenance costs are greater than the cost of replacement.

The Swedish Standard Institute (SS-EN 13306, 2001) defines corrective maintenance as “Maintenance carried out after fault recognition and intended to put an item into a state in which it can perform a required function” [68]. Corrective maintenance is not an efficient maintenance approach for businesses [75]. However, they are viable in certain situations where the components are of low criticality and does not affect the normal operations of the system.

Corrective maintenance of certain items can be deferred to a later point of time if the faulty item does not affect the overall functioning of the system [76]. Such maintenance actions can be scheduled to be carried out at an appropriate time with least impact on the output. However, breakdowns which affect the system functioning and poses a safety hazard must be fixed immediately without any delay. Hence, this type of maintenance is most suited for non-critical components whose failure consequences are not significant, does not create a safety risk and can be repaired easily.

2.4.2.2 Preventive Maintenance

Preventive maintenance also called proactive maintenance policies, is a maintenance strategy in which the maintenance is attempted to be carried out before a fatal failure occurs [72]. It aims to reduce the probability of future failures and need for corrective maintenance [74]. This is a relatively expensive and time-consuming maintenance method [73]. When a preventive maintenance strategy is employed, the costs are incurred from both corrective and preventive maintenance. Figure 10 shows the cost performance of corrective and preventive maintenance with respect to the frequency of maintenance [70]. When the maintenance frequency is low, the preventive maintenance costs are low but there is a higher probability of failure which increases the corrective maintenance costs and vice-versa.

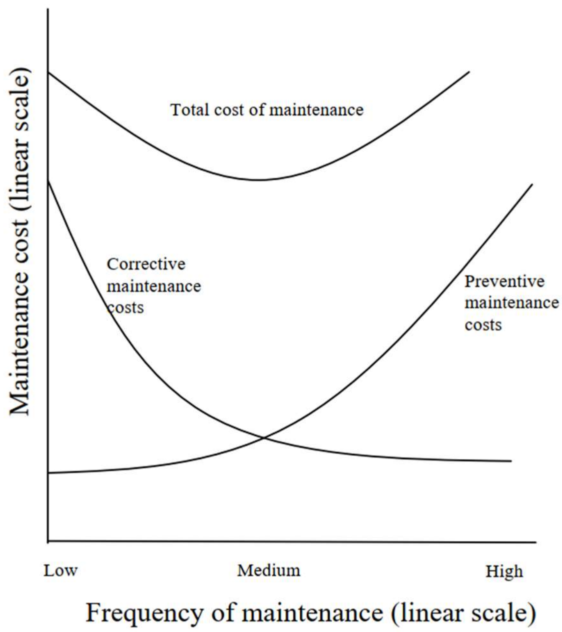


Figure 10: Cost performance of corrective and preventive maintenance

The Swedish Standard Institute (SS-EN 13306, 2001) defines preventive maintenance as "Maintenance carried out at predetermined intervals or according to prescribed criteria and intended to reduce the probability of failure or the degradation of the functioning of an item" [68]. Preventive maintenance can be further classified into predetermined maintenance [68] or condition-based maintenance [77].

a. Predetermined maintenance

This is a traditional preventive maintenance method [75]. Preventive maintenance is also called time-based maintenance, cyclic maintenance, or planned maintenance [67] which is the same as predetermined maintenance. However, preventive maintenance is not just predetermined maintenance, and this type of maintenance should be rather treated as a subset of preventive maintenance.

In this strategy, parts replacement or treatment are carried out at fixed intervals to protect against unforeseen failures [73]. It is carried out after the component or equipment is in service for a specified period. This strategy uses historical documented information regarding equipment or components to carry out maintenance activities at the specified intervals. The maintenance schedules are based on experience [78]. The historical operations and maintenance data is not only useful for the selection of the right maintenance type but also for the optimization of time interval between preventive maintenance activities [77].

The current state of an asset does not influence its maintenance schedule which is a drawback to this strategy [78] . The actual condition of the equipment, whether it is functioning normally or deteriorating, is disregarded [75]. Hence, this strategy is insufficient to deal with random failures and is only beneficial when the patterns of failure are predictable. This method is also criticized as a wasteful maintenance philosophy due to 'over-maintaining'.

b. Condition-based maintenance (CBM)

The Swedish Standard Institute (SS-EN 13306, 2001) defines condition-based maintenance as "Preventive maintenance based on performance and/or parameter monitoring and the subsequent actions" [68]. In CBM, the equipment condition is the driver of its maintenance. Condition can be monitored either by physical inspections or by advanced technologies like sensors and devices which continuously monitor the equipment status [75] and maintenance is scheduled based on that [72]. Sensors are a costly method, and its use is prioritized in critical assets. However, continuous condition monitoring gets more accessible with reduction in prices of sensors and other devices. Figure 11 shows a visual representation of condition-based maintenance [75].

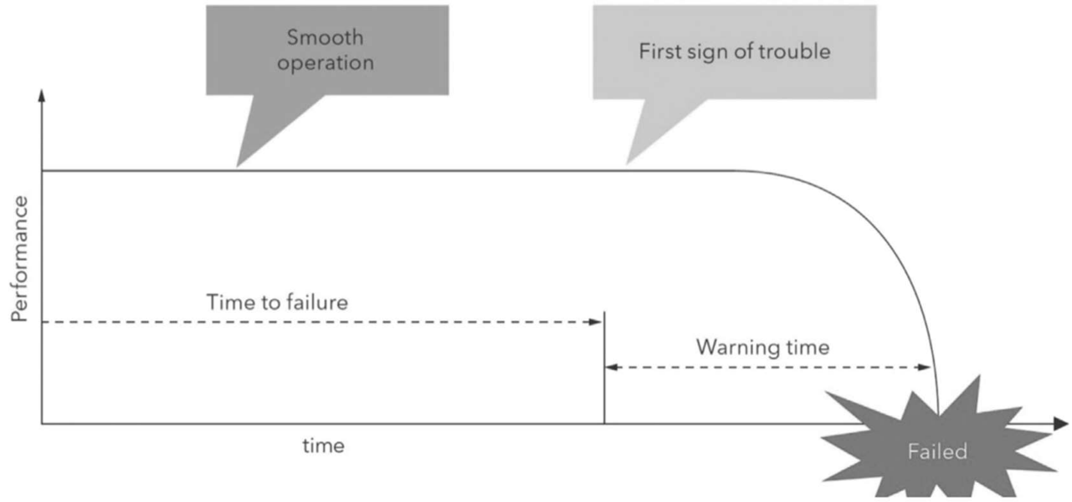


Figure 11:Condition-based maintenance [75]

Condition-based maintenance can be further classified based on the method by which the equipment condition is monitored.

- **Condition-based maintenance by inspection (iCBM)**

In this method, the condition monitoring is carried out by physical inspection of the asset by the maintenance personnel. Inspections can be performed based on a request or predetermined time schedules [72]. In this type of maintenance, inspection related costs can be the most critical component of the total maintenance cost [77].

- **Predictive maintenance (PdM)**

Predictive maintenance involves continuous monitoring of certain characteristics of an equipment using sensors. However, continuous monitoring only gives information on an equipment's current state but not its future state and does not alone facilitate predictive maintenance [72]. The Swedish Standard Institute (SS-EN 13306, 2001) defines predictive maintenance as "Condition based maintenance carried out following a forecast derived from the analysis and evaluation of significant parameters of the degradation of the item" [68]. Predictive maintenance is an enhancement of condition-based maintenance which involves the continuous collection of large amounts of monitoring data and employment of reliable prognostic methods to estimate the residual or remaining useful life (RUL) of a component. The approach uses historical data to identify trends in equipment behaviour to predict failures and plan maintenance activities, since the equipment generally shows signs of failure before actual breakdown [75]. These signs may include abnormal temperatures, vibrations, increase noise levels etc. indicating asset degradation and are also called precursors of failure [79]. The degradation signal of an asset which indicates its current health is an important element in the prediction of remaining useful life [78]. Figure 12 illustrates the degradation signal of a bearing from the time of its installation to the point of failure [80]. The Phase I denotes satisfactory operation and Phase II indicates the defective stage of operation.

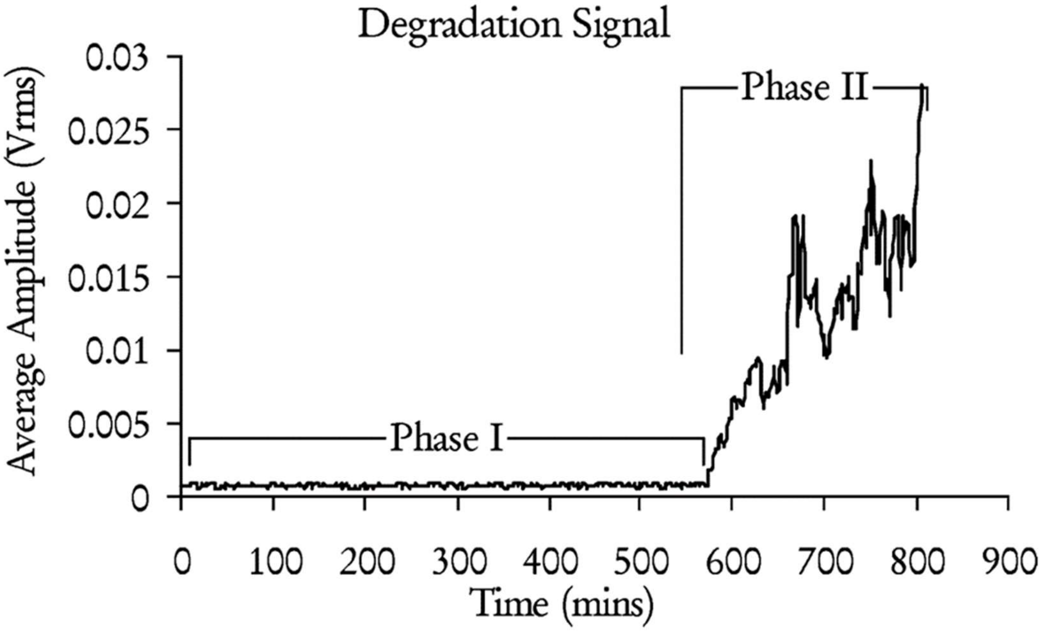


Figure 12: Degradation signal of a bearing [80]

The sensors installed on critical components monitors such parameters and detects any anomalies [75]. Accuracy and quality of historical and captured data is crucial for condition based or predictive maintenance [78] [79]. Good and correct understanding of failure modes is necessary to determine and monitor precursors of failure. Sensors should be calibrated, and routine recalibration should also be ensured to maintain data accuracy. The steps involved in predictive maintenance are data acquisition, data processing and maintenance decision making which includes diagnosis and prognosis [81]. A visual representation of the steps involved are shown in Figure 13 [79].

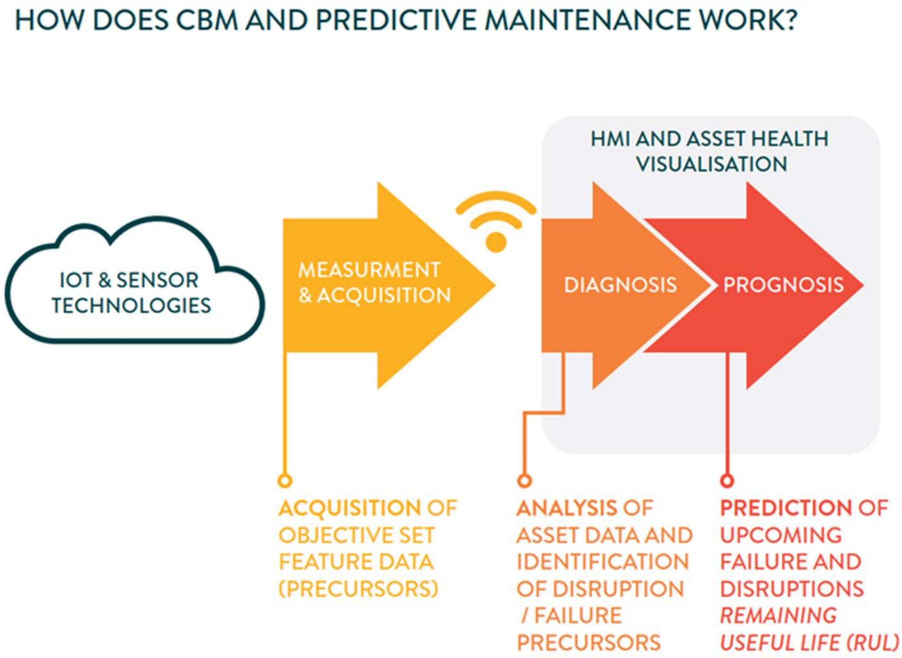


Figure 13: Steps involved in predictive maintenance [79]

Data acquisition technologies converts physical factors into analogue or digital signals [71]. The data acquisition system is comprised of data acquisition technologies and ICT. The data acquisition technologies comprise of sensors and devices responsible for actual capturing of data and ICT deals with the transmission, storage, data processing and analytics. Data transmission happens in a wired or wireless manner from the acquisition devices to a cloud server where real-time analysis and data processing happens. Figure 14 shows the blueprint of a data acquisition system.

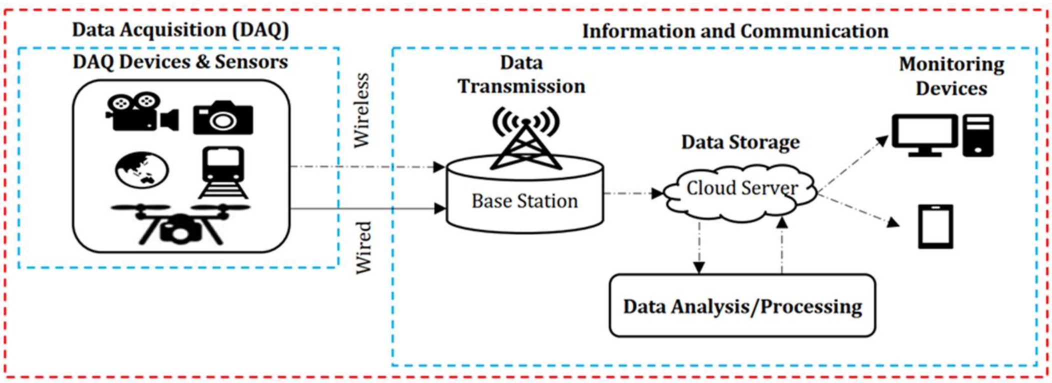


Figure 14: Data acquisiton system

Data processing interprets acquired data and would also involve noise reduction [78]. The continuous monitoring by increasing number of sensors results in a large amount of data to be handled and techniques like data fusion and data filtering are important for efficient data processing [72]. Data fusion integrates data from multiple sensors together to make it more reliable compared to a single sensor alone. Data filtering reduces the amount of data by filtering out non-useful data and only considers the informative parts of data making the analysis more efficient.

Failures are recorded and singled out in diagnosis. It involves data from multiple sources being analyzed to identify abnormal behavior exceeding a threshold or precursors of failure [79]. Prognostics attempt to predict the probability of a machine failure [72]. There are three approaches to prognostics: mathematical model-based approach, expert system approach and data-driven approach [82]. Model based approach is difficult to implement for complex systems and both model-based and expert system approaches are equipment and domain specific. However, the data-driven approach doesn't have this drawback and works well with complex systems and is not equipment and domain specific.

Data driven approaches use historical data inputs to make reliable predictions [72]. It involves the comparison of current asset condition with historical data sets [79]to estimate the time remaining until it fails, called the remaining useful life [78]. The data availability of past asset behavior is essential to interpret anomalies [79]. Many of the data driven approaches employ regression and a good regression model needs a large amount of training data for model definition [72]. Similarly, other data-driven AI based approaches like artificial neural networks (ANN) also needs a large amount of training data to build a reliable ANN. There is a trend in the advent of automated and real-time decision-making algorithms, due to recent technological advancements in sensors and big data which supports in efficient decision making. The basic elements of diagnostics and prognostics according to Chinnam and Baruah (2004) is shown in Figure 15 [83]. Figure 16 illustrates a framework for achieving predictive maintenance adapted by Jimenez, Bouhmala and Gausdal (2020) [75].

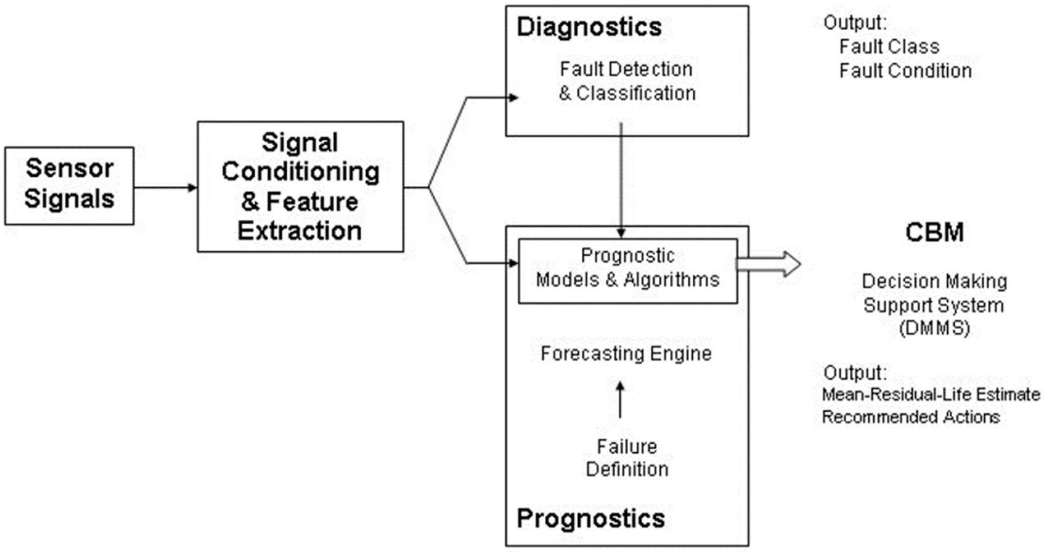


Figure 15: Basic elements of diagnostics and prognostics [83]

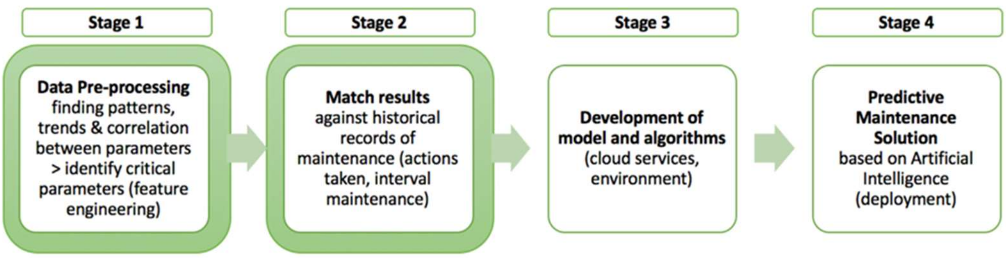


Figure 16: A framework for achieving predictive maintenance [75]

Predictive maintenance strategies are applied differently to single component systems and multicomponent systems [72]. Single component systems may be single machines which are made of multiple components but is considered single system. Whereas multicomponent systems are formed by multiple components or machines which forms a larger system with interdependencies. Dependencies are important when designing an effective predictive maintenance system.

The dependencies can be classified as economic, stochastic, and structural [72]. Economic dependencies help in cost reduction by combining maintenance process of multiple components at the same time since some of the components can’t operate when another one is being serviced. Hence, combining the maintenance activities of these components reduces the downtime from separate maintenance activities. Stochastic dependency means that the deterioration of one component may have an effect on one or more other components and a structural dependency means replacement of one component implies the replacement of another component since it functions as a whole. The approaches employed in single component systems cannot be applied directly to multicomponent systems due to these interdependencies. Horenbeek and Pintelon (2013) proposes a dynamic predictive maintenance strategy which updates the maintenance plan according to new information on component deterioration and remaining useful life, minimizing the mean maintenance cost per unit time over a long period resulting in significant cost savings [84].

Advantages of predictive maintenance

According to McKinsey and Company, predictive maintenance would reduce downtimes by 30-50% and increase life span by 20-40% [78]. According to Krupitzer et al. (2020), predictive maintenance is an efficient maintenance strategy and comes with multiple benefits. This type of maintenance strategy improves the efficiency since it reduces the number of unnecessary maintenance activities which are based on periodic maintenance intervals established by average values [72]. The reliance on these intervals might not only lead to early maintenance but can also cause maintenance activities to take place too late since these intervals are based on average lifetime of the component. Predictive maintenance policies would reduce unnecessary maintenance and equipment breakdowns hence reducing the equipment downtime.

It is having the potential to reduce spare sparts in stock since a reliable predictive maintenance system would only require the necessary parts needed soon to be in stock instead of storing all components, which means less inventory and cost reduction [72]. It can also enhance the overall lifetime of an equipment since continuous health monitoring and RUL prediction reduce the risk of fatal failures which affects the equipment longevity even proper corrective actions are carried out. The equipment structure is intervened every time a maintenance action is carried out and avoidance of unnecessary maintenance by predictive maintenance would improve the life span.

Predicitve maintenance allows for the preparation of maintenance activities ahead of time and grouping of maintenance activities reducing the number of times the equipment needs to be put in maintenance [72]. It also improves the safety parameter by the avoidance of fatal breakdowns continuous health monitoring. The implementation of predictive maintenance is costly but comes with long term benefits [72]. The high upfront costs are affordable for larger firms due to economies of scale, but it may not be the case for small companies. The other barriers in the implementation of PdM strategies are budgetary constraints, employee expertise, resistance to change, organizational maturity and complexity of application [78].

2.4.3 Maintenance in Transport Sector

Traditionally, public transport assets maintenance is carried out by a corrective and preventive strategy [79]. When it comes to time-based maintenance, the maintenance intervals are set by manufacturer or later adapted by the operator based on experience. The interval is set for all items of a given asset type. There have been advancements in maintenance when it comes to the transport sector too where digital technologies are used in asset monitoring and management as detailed in Section 2.3. According to the International Association of Public Transport (UITP), digitalization in public transport asset maintenance can lead to a zero-failure system [79]. Continuous condition monitoring ensures maintenance is done at the right time with the right method. Apart from the rolling stock, fixed assets like infrastructure are also equipped with measurement devices. Public transport assets where predictive models can be applied include but not limited to doors, brakes, traction equipment, air-conditioning systems, switches, rails, power supply, pantograph etc. According to McKinsey and Company (2017), it will be difficult for transport operators with a large heterogenous fleet and legacy assets to implement condition based and predictive maintenance [85]. Public transport authorities can procure new assets having sensors or retrofit the old ones if the remaining life span of the asset in question and costs for modification gives a positive return on investment [79]. Also, remote monitoring reduces asset possession times.

Maintenance strategy should be decided based on the type of asset and the severity of the consequences of its failure [79]. Assets can be grouped based on the impact type its failure would bring such as safety, availability, and comfort. Some challenges when it comes to the application of condition-based predictive maintenance strategy as listed by UITP is shown in Table 6 [79].

Table 6: Challenges in applying predictive maintenance in public transport

Technical	**Commercial**	**Economic**	**Organizational**	**Regulatory**
Transmisson/communication bandwidth, data accuracy, cybersecurity, lack of standards	Fragmented supply chain, data governance, warranty, propriety vs open software	High investment costs	Company culture, new skills, IT requirements	Reluctance from safety authorities, transit operators and insurance companies

Few research studies have been conducted in recent times with the theme of data-driven maintenance strategies in the transport sector. Predictive maintenance increases customer satisfaction by reducing delays due to breakdowns and improves safety [86]. COSMO is a predictive maintenance approach for public transport buses diagnosing faulty buses that deviates from the rest of the fleet [87]. Killeen et. Al (2019) proposed a new IoT architecture for public transport bus fleet management and fleet wide data analytics and proposes a semi supervised machine learning algorithm to improve the sensor selection in COSMO. Massaro, Selicato and Galiano (2020) focuses on the design and development of an electronic control unit (ECU) that extracts bus fleet data for employing predictive analytics for maintenance [88]. The acquired data is transferred to the cloud featuring a data mining engine employing artificial intelligence (AI) algorithms which provides driver performance indicators (k-means clustering algorithm) and prediction of engine stress (MLP-ANN algorithm). The drivers were categorized into three clusters by analyzing parameters like GPS speed, engine RPM, engine load and throttle position. The engine stress is a function of driver behavior, and it allows to establish predictive maintenance criteria. Results are visualized in graphical dashboards indicating KPIs such as vehicle health status, driver efficiency, fuel consumption etc. The data mining models employed have been tested against a stable dataset and has low MSE error indicating the great prediction capabilities.

Fleurent (2018) describes a system implemented in Angers, France for the maintenance optimization of its public transport bus fleet [74]. According to Fluerent, several factors need to be considered for the successful implementation of an effective preventive maintenance plan. The ideal frequency of a maintenance activity should be defined in such a way that the maintenance frequency is sufficient to reduce the number of failures or curative maintenance but not so frequent as it leads to unnecessary costs. The human resources and material availability needed for maintenance is limited and it varies throughout the year. If the same maintenance resources are requested at the same time for activities, that would create an availability issue and the maintenance would be delayed increasing the risk of failure. Even with a tolerance on these target values, several vehicles may be taken out of service at the same time affecting fleet availability. Also, the timely completion of inspections required by law is necessary otherwise the vehicle needs to be taken out of service. A good preventive maintenance plan should smoothen out the usage of maintenance resources without compromising on the maintenance frequencies and vehicle availability.

When it comes to trams, Wolf, Hofbauer and Rudolph (2016) attempts to estimate the wear in tram bearings via wireless sensors at Leipzig Transport Authority (LVB) trams [73]. The bearings are only replaced after an elaborate inspection which makes the tram out of service for several days. The data is automatically recorded, preprocessed, and transmitted to a central control unit where it is evaluated using fault analysis methods and maintenance recommendations are produced. This leads to reduced maintenance times, effective utilization of maintenance resources and reduced financial risks because of the possibility to reduce unforeseen failures.

According to Rosin and Möller (2006), telematics and remote-control systems can reduce maintenance costs and perform remote diagnostics among other benefits in traffic management [89]. They analyzed the then existing maintenance systems in the light rail network in Tallinn, Estonia and found that 75% of the service downtime resulted from technical failures and accidents and the remaining 25% from the power department and other factors. The old maintenance system (2006) had disadvantages like longer maintenance times, poor fault localization and notification, interval and failure-based maintenance rather than ones based actual condition or historical data. They developed a control and supervision system for the trams in Tallinn and reduced the maintenance costs by 20%.

Schalkwyk, Jooste and Lucke (2021) developed a framework support the railway operators in the identification and acquisition of appropriate data acquisition technologies [71]. The condition monitoring technologies are only effective if the selected technology can capture and report relevant indicators which shows the asset performance. Pater, Reijns and Mitici (2022) presents a predictive maintenance framework for aircraft engines that considers imperfect remaining useful life prognostics, triggering an alarm to schedule maintenance based on the evolution of RUL prognostics over time [90]. In automotive sector, manufacturers rely on on-board sensors in the vehicle which transmits the data to the cloud to deploy predictive maintenance [91]. Hence, vehicles are called to service before the customer experiences a component malfunction.

According to Gbadamosi et al (2021), the current maintenance approaches in the rail sector such as routine inspection by workers and corrective maintenance are inefficient [92]. This approach is not cost effective as it involves manual inspection in which areas with no faults are checked and some assets would have already failed or close to failure at the time of inspection. They proposed an IoT based asset management strategy for the rail industry in UK.

Jimenez, Bouhmala and Gausdal (2020) initiates the development of predictive maintenance solutions for the shipping industry using real-time monitoring data [75]. Yun, Han, and Kim (2011) dealt with time-based maintenance of rolling stock to determine the optimal interval for its preventive maintenance minimizing the system life cycle costs [93]. The system life cycle cost for maintenance consists of two parts – maintenance costs for corrective or preventive maintenance and logistics costs for spare parts and labor.

Patalay (2021) discusses a maintenance approach based on remote monitoring of railway switches to predict maintenance activities [94]. Railway switches are the main components in railway interlocking systems. It consists of geared DC electrical motors to actuate stretcher bars moving the switch rails to allow the movement of rolling stock to another set of rails. Faults in the switching mechanism could lead to fatal accidents.

Falamarzi, Moridpour and Nazem (2019) proposes a model for prediction of tram track degradation using datasets from Melbourne's tram system [95]. The model was based on historical geometry deviation which defines the track degradation index and the vehicle acceleration rate whose abrupt changes indicate track irregularities. The track degradation index can be predicted using the acceleration data instead of various geometry parameters saving time and money when it comes track geometry data collection. The acceleration data collection using condition monitoring systems in service vehicles is cost effective and does not cause any disruption to the regular transport services. According to Wang et al. (2021), measurement frequency using track geometry vehicles is low (usually twice a year) due to high costs and track closure disrupting normal traffic [96].

Some other examples of the application of digital data-driven technologies in asset management in the transport sector are as follows. Swedish railway uses E365 Analytics®, an analytics platform to acquire and manage a wide variety of maintenance, business, and condition data [97]. The infrastructure owner offers some degree of condition monitoring to the rail operators as they have equipped the entire rail network with several detectors and measurement devices which monitors and detects certain parameters of the passing trains. The operators can acquire this data from the Swedish Transport Administration since the trains have RFID tags with European Vehicle Number. CAF, the Spanish rolling stock manufacturer's Lead Mind, a highly adaptable digital platform uses advanced analytics to visualize the real time fleet status by monitoring the rail asset condition [98]. This helps customers get the best fleet performance and optimize maintenance, hence reducing the life cycle costs and increasing the availability and reliability of the vehicles. The data is captured from various on-board and wayside sensors. For example, tram systems in Zaragoza, Spain and Oslo, Norway uses Lead Mind to optimize their operations and maintenance. Singapore metro implemented predictive maintenance on its high value asserts and proved greater benefits such as increased life span of wheel sets, reduced hot bearings, reduced risk of suspension issues etc [99].

3 Research Methodology

Methodology forms a strategic structure guiding how the research project should be carried out [100]. It is not a synonym for 'methods' which describes the procedure or means of calculation to yield a particular result but rather a design process for carrying out research.

This section describes the primary research methodology followed and the different data sets available to perform the quantitative analysis. It was decided to carry out quantitative research due to the availability of historical data logged from multiple sources which will be explained in subsection 3.1. The quantitative research methodology will be explained in subsection 3.2.

The software and tools used in the quantitative analysis are:

1. Google BigQuery, R-Studio, Google Sheets and Microsoft Excel for data analysis
2. Python for geocoding
3. Kepler GL for GIS visualization

However, apart from quantitative analysis, an interview was also conducted with a subject matter expert from Alstom, the supplier for the new generation trams for the Gothenburg Tramways, on the latest technology trends in light rail rolling stock maintenance which helped the author to get further grasp on the influence of digitalization in this sector (See appendix A).

3.1 Data

Four data sets were available during the entire course of the project. They are listed below in the chronological order the sources were made available.

3.1.1 Switching Operations

This data source was made available by the client at the initial stages of the project. SoftPrio is a solution developed by the Swedish Transport Administration that keeps track of vehicle locations, gives priority at traffic signals, and performs the tram direction switching [101]. This system is RFID-based and does not require cabling in streets and tracks and hence makes it easier to implement and maintain.

The tram is equipped with an RFID reader, a radio modem and an 868 MHz antenna which transmits radio messages to the equipment room which controls the switching. The RFID tag is programmed with a defined code called tag ID that contains information about its function. RFID tags passed by the tram would determine which equipment room the message must be addressed to. The direction request is given by the tram driver. No request is given if the tram wants to go straight. Figure 17 shows a diagram of the RFID based track switching system.

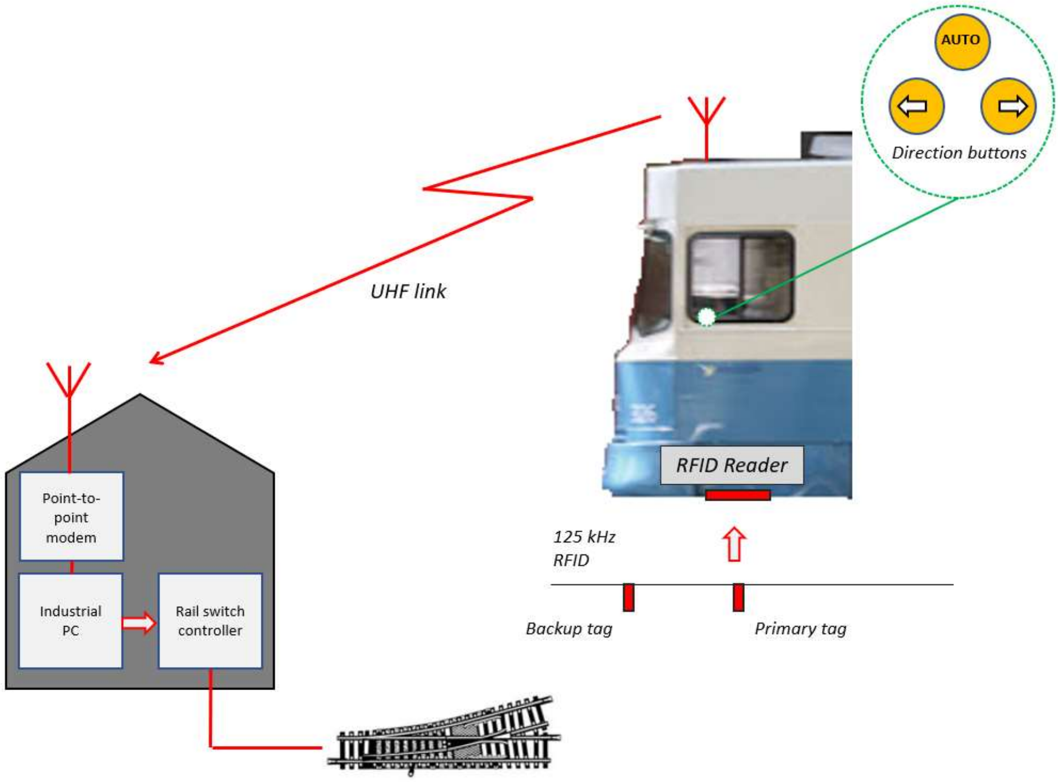


Figure 17: RFID based switch control

The tram network is equipped with a large number of switches. There are over 100 of them and majority of them are controlled by SoftPrio. The switches are interlocked which means that a tram cannot give direction request when another tram is already in the blocking zone. There are two layers of blocking in Gothenburg's tram network (See figure 18). The first layer is activated as soon as the tram passes the RFID tag which registers the presence of the tram in the blocking zone. The second layer is the track circuit which is completed when tram is in the blocking zone.

The log server of the system collects log messages from the gear control computers on switching operations. Hence, the summary statistics of events in the switches were available on a daily and monthly basis. The switching operations data for the month of March 2022 was extracted from the web application of SoftPrio as an excel file and was combined into a single spreadsheet. There were 107 data points (records) in the data set each representing one switch. The columns were renamed for easier coding in R Studio. An example of how the data table looks like is shown in figure 19 and the schema and field descriptions of switching operations table are shown in table 7.

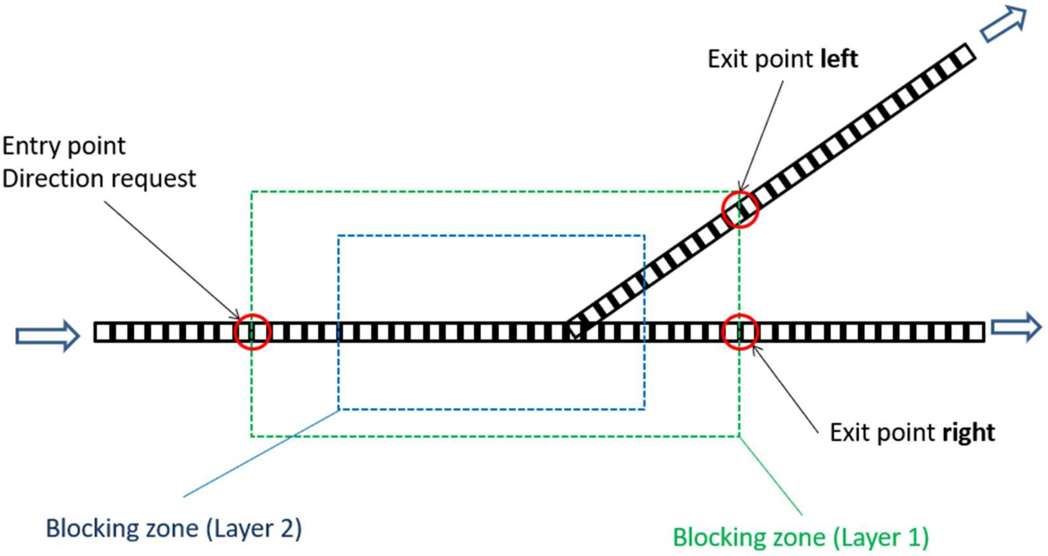


Figure 18: Blocking zones

Switch	cpass	icpass	avail	eo	feo	pfeo	skew	pskew
GS Allhelgonakyrkan 762 AH	10775	8	100	5928	0	0	14	0.00236
GS Angered C 30 SR	9045	1	100	5469	0	0	8	0.00146
GS Angered C 32 SR	8964	34	100	5444	0	0	15	0.00276
GS Annedalskyrkan 302 SHE	9773	15	100	12358	87	0.00704	71	0.00575
GS Aprilgatan 772 AH	3723	9	100	316	1	0.00316	9	0.02848

Figure 19: Switching operations data

Table 7: Switching operations table schema

Column Name	Type	Description
switch	STRING	Name of the switch
cpass	INTEGER	Number of correct vehicle passages - Number of vehicle passages where both entry and exit registrations of the blocking zone worked
icpass	INTEGER	Number of incorrect vehicle passages
avail	INTEGER	Availability of electrical control (%) - Percentage of the time the facility has been in OPERATION mode, i.e. able to execute the direction switching request
eo	INTEGER	Number of electrical operations - Number of times a switching request has initiated an electrical operation
feo	INTEGER	Number of failed electrical manoeuvres - Number of times a switching request has initiated an electrical operation but failed to get the switch in control.
pfeo	FLOAT	Proportion of failed electrical manoeuvres
skew	INTEGER	Number of manual switching by the tram driver with a rod (The number of times the switching rod is detected by the system)
pskew	FLOAT	Proportion of manual switching by the tram driver with a rod relative to electrical manoeuvres

3.1.2 Inspections

Cityworks is a GIS-centric infrastructure maintenance management platform used by the traffic office of the City of Gothenburg. The map interface of the platform is shown in figure 17. The platform enables the owner to manage service requests, work orders, inspections, permits and view asset history.

Figure 20: Cityworks Maintenance Management Tool

A service request is a request for service initiated through a contact to the organization, generally a citizen's call, describing some type of problem (usually at a specific location) and action is taken to remedy the situation. An inspection is carried out on an asset resulting from a service request or at predetermined time intervals to ensure the acceptable condition of the assets. A work order is designed for tracking maintenance activities performed by individuals or crews and detailing the tasks to be done and the costs incurred. Work orders can be associated to service requests and inspections, as well as other work orders through cyclical or parent-child relationships.

This data source was made available at a later stage of the project. The author extracted two data sets from this platform, one on inspections and the other on work orders. Since the author couldn't obtain the server access for easy extraction of data, all available data was downloaded as spreadsheets from the plaform. Along with this, smaller tables with information on inspection routes, depots and traffic intensive areas in the tramway network were extracted to link them with the unique identifiers of assets in the inspection and work order tables. The track network is divided into several lines which are further divided into smaller sections called inspection routes on which track related and overhead contact line inspections are carried out. Each of these sections are given a unique identifer.

The inspection data set had 59076 data points representing past data on the inspections performed on various categories of assets. The data was structured with multiple columns, however many of these columns which were not relevant for the analysis was excluded. Table 8 shows the schema and descriptions in the inspections table used for analysis.

Table 8. Inspections table schema

Field Name	Type	Description
iid	INTEGER	Inspection ID
fname	STRING	Name of the facility/asset
owner	STRING	Owner of the facility
ass_to	STRING	The group to which the inspection task is assigned
init_date	DATE	Initialization date of the inspection or the date on which the inspection request is entered on the Cityworks platform
ass_date	DATE	The date on which the inspection task is assigned to the group
insp_date	DATE	The date on which the inspection is carried out
clos_date	DATE	The date on which the inspection task is considered closed
act_fin_date	DATE	Actual finish date of the inspection
p_start	DATE	Planned starting date of the inspection
p_finish	DATE	Planned finishing date of the inspection
insp_type	STRING	Type of inspection
status	STRING	Status of the inspection (open/closed)
location	STRING	Location of the inspection
wid	INTEGER	Work order ID if the inspection results in a work order
rid	INTEGER	Service request ID if the inspection is associated with a service request
ftype	STRING	Type of the facility/asset inspected

outcome	STRING	Outcome of the inspection (passed/not passed/has remark)
obs	STRING	Observations in the inspection
fid	STRING	Unique ID of the facility/asset inspected

3.1.3 Work Orders

As mentioned in 3.1.2, the work orders data was also extracted from the City-works platform. The work order data set had 13247 data points representing previous data on the work orders carried out on various categories of assets. The data was structured with multiple columns, however many of these columns which were not relevant for the analysis was excluded. Table 9 shows the schema and field descriptions in the work orders table used for analysis.

Table 9: Work orders table schema

Field Name	**Type**	**Description**
wid	INTEGER	Work order ID
ftype	STRING	Type of facility/asset
fname	STRING	Name of facility/asset
dscr	STRING	Description of the work order
status	STRING	Status of the work order
pstart	DATE	Planned start date of the work order
pfinish	DATE	Planned finish date of the work order
astart	DATE	Actual start date of the work order
afinish	DATE	Actual finish date of the work order
address	STRING	Address of the facility/asset
location	STRING	Location of the facility/asset
category	STRING	Category of the work order
created_on	DATE	Date on which the work order is created
ass_to	STRING	The group to which the work order is assigned

ass_on	DATE	Date on which the work order is assigned to the group
work_dscr	STRING	Detailed work description
iid	INTEGER	Inspection ID to which the work order is associated
rid	INTEGER	Service request ID to which the work order is associated
fac_id	STRING	Unique ID of the facility/asset

3.1.4 Track Restrictions

This was the last data source the author got hold of during the project. The traffic office had a web application called 'Spårvägskartan' (in Swedish) which translates to tramway map, where any restrictions in the tramway network such as speed limit reductions and reversal bans could be monitored. The data on historical track restrictions was extracted from this application and had 144 data points each representing one restriction. Figure 21 shows a map from the application with track restrictions. Table 10 shows the schema and field descriptions in the track restrictions table used for analysis.

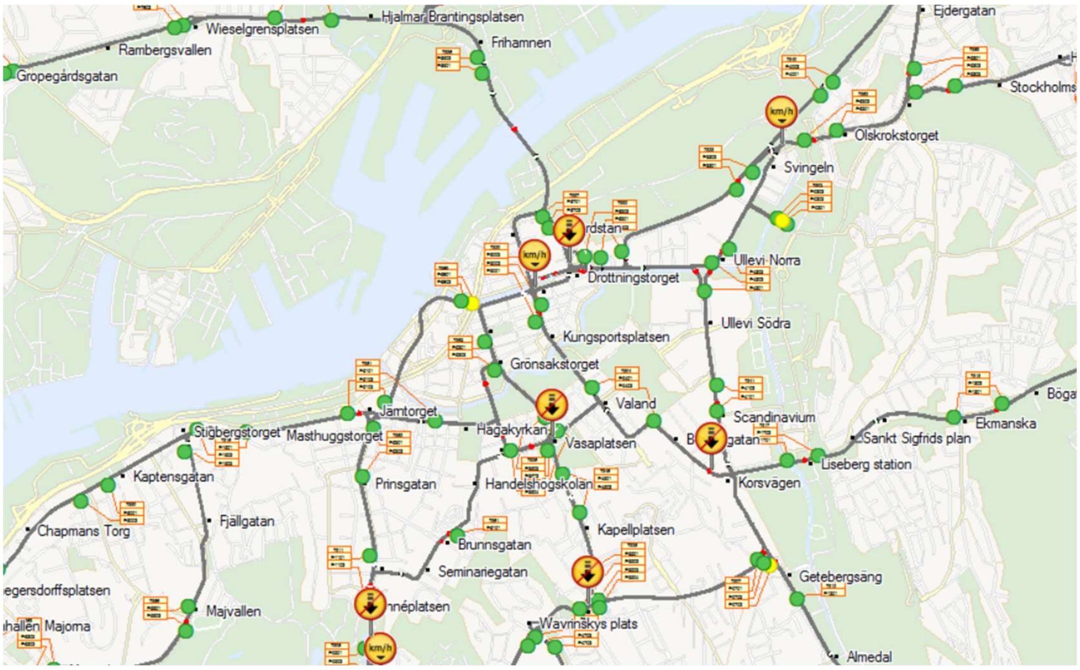


Figure 21: Track restrictions

Table 10: Restrictions table schema

Field Name	Type	Description
id	INTEGER	Event ID
start	STRING	Starting location of the restriction
stop	STRING	Ending location of the restriction
maxspeed	INTEGER	Maximum speed limit (restricted)
reason	STRING	Reason for restriction
tstart	TIMESTAMP	Starting date and time of the restriction
tstop	TIMESTAMP	Ending date and time of the restriction

3.2 Data Mining

Industries collect enormous amount of data, and this accumulated data does not create knowledge until it is studied and analyzed [102]. Due to large volume of data, it is necessary to use computational techniques to handle and extract beneficial information. Data mining is the process of extracting useful hidden information from large and complex data sets [103]. According to SAS, the American analytics software developer "Data mining is the process of finding anomalies, patterns and correlations within large data sets to predict outcomes" [104].

Data mining tasks can be classified as [105]:

- Exploratory data analysis – It involves simply exploring the available data without any clear idea of the intended result.

- Descriptive modeling – It describes data in terms of probability distributions and models indicating relationships between variables. Descriptive analytics deals with what has happened [93].

- Predictive modeling – It involves the prediction of an unknown variable value based on the know values of other variables.

- Discovering patterns and rules – It involves pattern recognition and classifies data points based on how they differ from the rest of the data points.

- Retrieval by content – It involves finding patterns which are similar to pattern of interest in the given data set.

Data mining models can be descriptive and predictive [105]. Predictive models provide estimation of unknown values of a variable based on the known values of other variables. Classification, regression, and time series analysis are examples of predictive models. Classification involves the examination and mapping of data points to predefined groups. Regression is learning of a function based on the historical data to estimate values of the prediction variable. Time-series analysis examines the variability of an attribute over time. Descriptive models deal with pattern recognition, relationships and properties of data being analyzed. Clustering and summarization are examples of such models. In clustering the groups are not predefined like classification, but it is rather segmented into groups based on the data alone. Data mining is a complex process involving various tools and personnel and its success depends on a good combination of both [106]. A process model helps to understand and manage this complex process and gives it a structure.

3.2.1 CRISP-DM Model

CRISP-DM, the acronym for Cross Industry Standard Process for Data Mining is a most common and industry-proven data mining process model [107]. It describes a data science project life cycle in six phases to help plan, implement and organize the project [108]. The six phases are:

- Business Understanding
- Data Understanding
- Data Preparation
- Modeling
- Evaluation
- Deployment

CRISP-DM is a de-facto standard in data mining projects. However, there are challenges since most studies in CRISP-DM application does not foresee a deployment phase [109]. The CRISP-DM framework will be used to carry out data mining in this project. However, the evaluation and deployment phases will not come under the scope of this project.

CRISP-DM is a generic, adaptable, and comprehensive data mining methodology and process model which can be used across different industries and applications [110]. It was developed by four industry leaders with inputs from various stakeholders. The model breaks down a data mining project into six phases that helps organizations understand the data mining process. The concept of CRISP-DM was not conceived until 1996. Prior to that a common approach to data mining process didn’t exist and it was necessary to develop a cross-industry standard. The model was presented in 2000 and now it is a widely accepted data mining methodology. Figure 14 shows different phases of the CRISP-DM model [107]. The arrows indicated the phase dependencies, and the outer circle shows the cyclical nature of the whole data mining process. This means that lessons learned from a project can trigger further iterations of the process to improve and cater to new business needs.

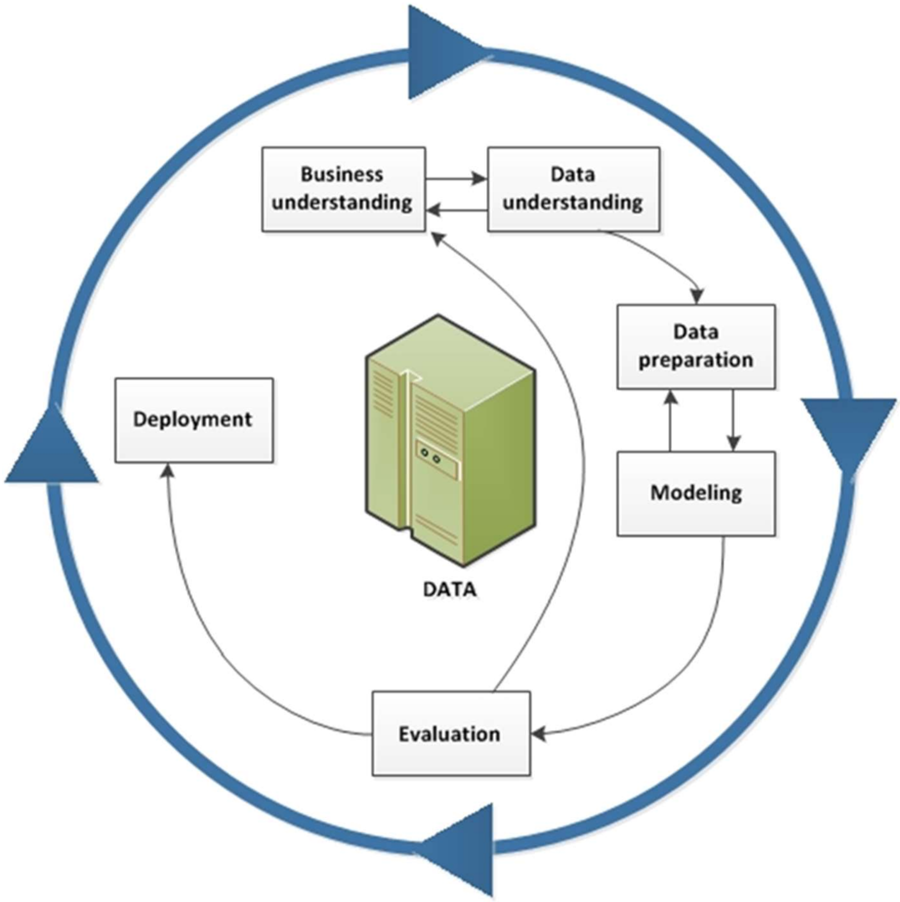


Figure 22: Phases of CRISP-DM model

The different phases of the CRISP-DM model and how this framework was followed in the project is explained in the following parts [110].

3.2.1.1 Business Understanding

It is considered as the most important and vital phase of any data mining project. This phase involves understanding the business objectives and translating them to into a data mining problem definition. A preliminary plan is designed to achieve these objectives by understanding the current scenario and decisions on what data to be analyzed is also made. In this project, the traffic office of the City of Gothenburg wanted to understand what insights can be derived from the data they already have, which is the fast-track phase of the bigger project on 'Digital Transformation of Gothenburg Tramways' assigned to Trivector Traffic. However, a clear definition of what the client wanted to achieve was not specified. Hence, the analysis was rather conducted by the author keeping in mind the administration plan for the tramway facility provided by the traffic office and background study in digitalization and maintenance, to generate whatever possible insights from the available data sources. Different data sets were available at different phases of the project and hence it was not able to produce a data mining project plan in the beginning. However, a few data sets which were made available at the later stages could be linked to each other and a plan for achieving the data mining goals was defined.

3.2.1.2 Data Understanding

This phase usually involves data collection, familiarization with the data and identify any quality issues related to data. The initial insights from data and hypothesis are derived in this stage. It involves four phases – data collection, data description, data exploration and verification of data quality.

Data collection involves acquiring data from relevant sources. The data can be from multiple different sources. Any problems faced in data collection should be recorded to avoid such problems in the future. In this project, the data was acquired from four different sources as described in 3.1. In data description, the surface properties of the acquired data are examined like date format, field descriptions in tables, number of records etc. Any shortcomings in the acquired data with respect to the requirements are also identified. This step is followed by data exploration where exploratory tools and techniques can be used to prepare a data exploration report with initial findings. Data quality verification involves checking the completeness of the data such as missing values, ambiguity and information that conflicts common sense. The data related to switching operations and track restrictions didn't had any evident quality issues, but the inspections and work orders data sets came with a lot of shortcomings which will be explained in the coming subsections.

3.2.1.3 Data Preparation

It involves activities that constructs the final data set to be used for modeling purposes. Data is cleaned, transformed and relevant attributes and records are chosen to be fed into modeling tools. The five steps are selection, cleansing, construction, integration, and formatting of data. Data selection can depend upon multiple factors like its relevance to the goals, data quality and technical constraints on the type and amount of data that can be handled. The data quality problems are addressed in the data cleaning phase. The clean subsets of data are selected and techniques to estimate the missing values may be employed. The inspections and work order data sets had a lot of records with missing values, especially for date variables. However, they were excluded only for modeling purposes involving time but were kept in other tasks. These will be explained in detail in the coming subsections. Data construction involves the insertion of new records or derived attributes from existing ones that would help in the modeling. Several derived attributes were used in modeling for this project. Data integration involves combining information from multiple tables or records, such as joining different tables with information about the same object. Integration would also include aggregations that summarize multiple records. The final step in this stage is data formatting and is done if required. In the work order and inspection data sets, a lot of redundancy was present in many categorical variables, due to improper formatting and it was corrected during the analysis.

3.2.1.4 Modeling

In this stage, various modeling techniques suitable for the data mining goal are selected. For this project, it was unable to build any predictive model due to unavailability of relevant data and hence it was decided to carry out descriptive modeling.

3.2.1.5 Evaluation

In-depth evaluation of the model is carried out before its final deployment to ensure it meets the business objectives. Apart from the results evaluation to check if the model sufficiently meets the business needs, a thorough review of the data mining process is conducted to check if any important factors have been overlooked. At the end of this process, decisions on proceeding with deployment are made or if necessary, to iterate the data mining process.

3.2.1.6 Deployment

The process doesn't end with model evaluation. The knowledge generated from the successful data mining process must be delivered to the customers in a way so that they can easily use it. The deployment is often carried out by the client; hence it is necessary for them to know the steps need to be taken to make use of the developed models. Generally, a deployment strategy is developed based on the results evaluation. However, deployment does not come under the scope of this project.

3.2.2 Analysis of Switching Operations Data

The switching operations data table for the month of March 2022 had 107 observations representing 107 switches and 9 columns. The data didn't have any evident quality issues and no missing values. The exploratory data analysis and descriptive modeling for this data set was carried out entirely in R-Studio. Graphical tools such as histogram and boxplot were used. The correlation between variables were checked using scatter plots and Pearson's correlation coefficients.

Correlation is a statistical term which denotes the linear association between two numerical variables [111]. The correlation can be either positive or negative. An increase in the value of one variable with respect to increase in the other denotes a positive correlation and decrease in the value of one variable with respect to increase in the other denotes a negative correlation. The degree of linear correlation is often measured by Pearson's correlation coefficient. The value of the correlation coefficient varies from -1 to +1, with -1 denoting an extreme negative correlation and +1 denoting an extreme positive correlation between the variables. A correlation coefficient of zero represents no correlation. R-Studio has the **cor ()** function to compute the correlation coefficient. A linear correlation can also be checked graphically using scatter plots.

Apart from the available variables, passage error rates were defined as a derived attribute (Equation 1).

$$Passage\ Error\ Rate\ (\%) = \frac{No.of\ incorrect\ vehic\quad passages}{Total\ number\ of\ vehicle\ passages} \times 100\% \qquad (1)$$

Histograms were plotted and summary statistics were obtained for the passage error rates, availability of switches, rate of failed electrical operations and rate of manual operations. Linear correlation was checked between the number of correct and incorrect passages and between the rate of failed electrical operations and rate of manual switching operations.

3.2.3 Analysis of Inspections Data

Prior to performing various analyses and estimations from the data, the following tasks were carried out:

- Checking for redundancy and missing values

A redundancy check was done to verify if all the data points (records) in this data set were unique to an inspection. Any missing values were also checked especially for inspection dates. There were 59076 data points in this table related to 56217 inspections which means that the data points were not unique for each inspection and 1.4% of records had missing values for inspection dates.

- Checking for date inconsistencies

Seven date fields were present in the table, of which five represent the actual workflow. They are initiation date, assigned date, inspection date, actual finish date and closing date. For the estimation of time related parameters, it is important to clean the data from inconsistencies in date values. An inspection record should follow the below logical condition for dates:

initiation date ≤ assigned date ≤ inspection date ≤ actual finishing date ≤ closing date

- Distribution of data points over time

It is necessary to check the distribution of data points over time to choose the subsets of data suitable for certain analyses. For example, when estimating average values of certain variables over time (day, month, or year), a non-uniform distribution of data over time can lead to biased estimates.

- Perform any necessary data formatting

Based on an initial look at the dataset, the author aimed to perform following analyses and estimations.

- Estimation of overall average inspection cycle time and average inspection cycle times for each type of inspection activity. Based on the available data, the average time between initiation and assignment of an inspection is 0.2 days which implies there is very little delay between these two stages. Moreover, 99% of the inspections have the same initiation and assignment dates. Also, 99% of the inspections have the same actual finish date and assignment date. It is decided not to consider the initiation and actual finish date fields since they are redundant. The dates associated with the actual workflow will be narrowed down to assigned date inspection date and closing date. Hence, the time incurred between the assignment and closure of an inspection will be defined as the Inspection Cycle Time (Equation 2). The inspection is composed of two parts, the time between the assignment date and inspection date (T_{ai}) and the time between the inspection date and closing date (T_{ic}) (Equation 3).

$$T_{ins} = Closing\ Date - Assigned\ Date \quad (2)$$

$$T_{ins} = T_{ai} + T_{ic} \quad (3)$$

- Estimation of planned inspection durations for each type of inspection activity. These estimates can be used to carry out a comparative analysis with the actual inspection cycle times.

- Comparison of average inspection cycle times and planned inspection durations for each type of inspection activity

- Proportion of inspections with inspection cycle times greater than planned durations.

- Average number of inspections performed on each asset type and compare it with the minimum requirements as per the maintenance management plans of the traffic office.

- Distribution of different inspection types over months.

- Analyze the relationship between inspections and work orders. Inspections sometimes result in a work order when the asset condition is not found satisfactory.

3.2.4 Analysis of Work Orders Data

Prior to performing various analyses and estimations from the data, the following tasks were carried out:

- Checking for redundancy and missing values

A redundancy check was done to verify if all the data points (records) in this data set were unique to work order. It was found that all the records were unique to each work order. The missing values especially in the date fields were checked. The date fields of interest in this data set were planned start date, planned finish date, actual start date, actual finish date, and assignment date. However, the planned start and finish dates were missing for 70% of the work orders and actual start dates were missing for 85% of the work orders. The assignment date is available for 99% of the work orders, actual finish date for 88% of the work orders and both assignment and actual finish date is available for 87% of the work orders. The missing values of facility ID which is the unique identifier of an asset is also checked and it was missing in 81% of the records. 64% of the work order records had a missing inspection ID, which might also mean that those work orders were not associated with an inspection.

- Checking for date inconsistencies

Five date fields were present in the table, of which three represent the actual workflow. They are actual start date, assignment date and actual finish date. However actual start dates are missing for 85% of the work orders. For the estimation of time related parameters, it is important to clean the data from inconsistencies in date values. A work order record should follow the below logical condition for dates:

assignment date <= actual finish date

Approximately 82% of the data points satisfy this logical condition for date.

- Distribution of data points over time

It is necessary to check the distribution of data points over time to choose the subsets of data suitable for certain analyses. For example, when estimating average values of certain variables over time (day, month, or year), a non-uniform distribution of data over time can lead to biased estimates.

- Perform any necessary data formatting

Based an initial look at the dataset, the author aimed to perform following analyses and estimations.

- Estimation of overall average work order cycle time and average work order cycle time for each category of asset. Based on the available date fields, The work order cycle time is defined as the duration between the assignment date of a work order and finish date of a work order (Equation 4).

$$T_{work} = Finish\ Date - Assignment\ Date \qquad (4)$$

- Comparison of actual work order cycle times and average work order cycle times.

- Proportion of work orders assigned to different categories.

- Estimation of mean time between maintenance (MTBM) [112]. It is a measure of reliability calculated by dividing the total uptime of an asset which is the sum of the time between two successive maintenance events for that asset divided by the number of maintenance activities for the asset during that period of observation (See figure 23). An algorithm was written in SQL to sort the associated maintenance events (work orders) in succession for each asset and then calculates the MTBM for that asset.

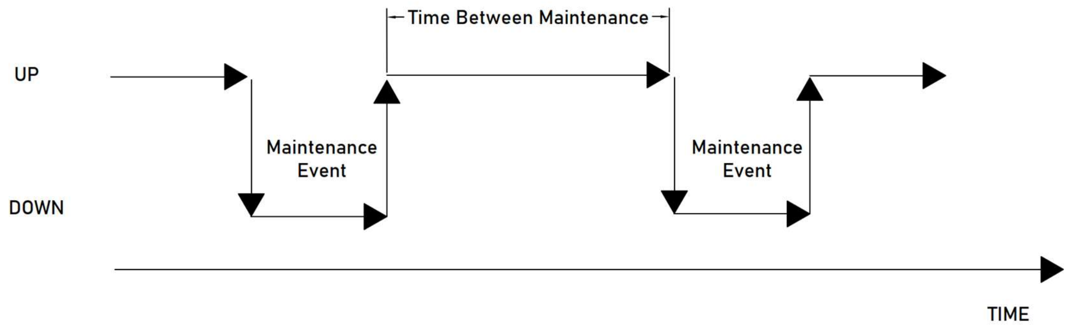


Figure 23: Time between maintenance. Adapted from [113]

The MTBM for an item k is expressed as:

$$MTBM_k = \frac{T_{up}^k}{n} \quad (5)$$

$$T_{up}^k = \sum_{i=1}^{n-1} D_{finish}^i - D_{assign}^{i+1} \quad (6)$$

T_{up}^k = Total uptime for asset k

n = No. of maintenance events during that period

D_{finis}^i = Finishing date of maintenance event i

D_{assign}^{i+1} = Assignment date of maintenance event i+1

In this case, the MTBM will be calculated on an aggregate level, according to the asset category rather than each asset.

$$MTBM_{ASSET\ CATEGORY} = \frac{\sum MTBM_k}{No.of\ items\ of\ that\ asset\ category} \quad (7)$$

3.2.5 Analysis of Track Restrictions Data

The records on operating restrictions on the track infrastructure during the period Jan 2020 to May 2022 was available and a total of 144 restrictions occurred during this period. The data didn't have any evident quality issues and no missing values.

Based an initial look at the dataset, the author aimed to perform following analyses and estimations.

- Proportions of restrictions by the type of restriction
- Proportions of restrictions by the reason for restrictions
- Proportions of restrictions by various speed limits
- The distribution of restrictions every month over the period under analysis
- Average duration of a restriction and average duration of a restriction by the type of restriction and reason for restriction
- Estimation of the total operating cost consequences of these restrictions based on the example calculation in the administrative plan for the tramway facility in Gothenburg.

4 Results

4.1 Digital Solutions in Light Rail Maintenance

The interview with a subject matter expert from Alstom provided the author with further understanding of the challenges and trends in digitalization in light rail transport, especially when it comes to predictive maintenance and is summarized in this subsection.

According to the interviewee, one of the key challenges of digitalization is the acquisition of information from the vehicles which requires very good connectivity. However, in case of trams the connectivity challenges do not pose a big problem since it is being operated in a smaller environment. The employment of digital solutions is even challenging when the transit operator owns and operates a fleet with different types and generations of vehicles. There are differences in digitalization in different countries and transit operators primarily due to budgetary constraints, organizational traditions and differences in construction of the vehicle. The interviewee considers trams to be simple vehicles, with shorter life span than conventional railway rolling stock and their maintenance schemes are not so advanced. However, low floor trams have complex wheel bogie design compared to the ones on traditional wagons. Wolf, Hofbauer and Rudolph (2016) also discusses about the challenges related to space constraints in low floor trams when using wireless sensors for condition monitoring [73].

There are several predictive maintenance platforms offered by leading rolling stock manufacturers that uses advanced data analytics and is also available for light rail vehicles. The data acquired from the vehicles sensors is transmitted to the cloud-based servers. Manufacturers like Alstom provides a complete package when it comes to predictive maintenance. All sensors and equipment required are provided and the data transmission and storage is also handled by them. However, if the customer prefers to store the data locally, there is a possibility to do that as well. The presence of different sensors depends on the contract with the customer and their requirements. However, there are pre-installed sensors in vehicles as part of the standard offering, like certain sensors in propulsion and door operations.

Predictive maintenance is costly to deploy. From a technical perspective, it is possible to equip the predictive maintenance solutions offered by a specific manufacturer to older rolling stock if contractual obligations with the supplier of those vehicles does not prohibit doing so. However, it is difficult to employ a condition monitoring and predictive maintenance solution to a fleet comprised of different types of rolling stock and the development of a generic platform is necessary to do this. It would be rather easy to do predictive maintenance on a homogenous fleet of rolling stock. The interviewee stressed the importance of fleet homogeneity when it comes to maintenance and pointed out the case of AnsaldoBreda trams in Gothenburg's tram fleet which are individual units without a homogenous design and situations like this can skyrocket the maintenance costs.

4.2 Results of Analysis of Switching Operations Data

4.2.1 Passage errors

The passage error rates (see equation 1, subsection 3.2.2) at the switches was analyzed and it was found that the error rates are very low with the mean error rate being 0.32% and the maximum error rate as 0.99%. Figure 24 shows a histogram with passage error rates on the horizontal axis and number of switches on the vertical axis. However, there were some outliers and has been excluded from the estimations. These outliers with high error rates were the switches at the depots in Ringön and Majorna (see figure 25).

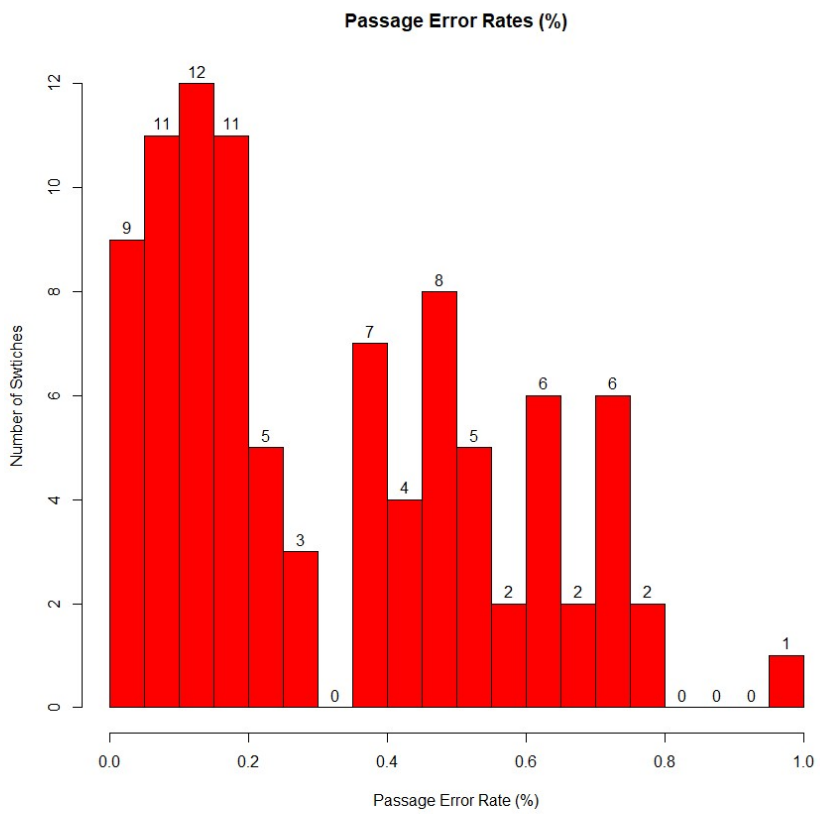


Figure 24: Passage error rates at switches

	Switch	Correct.passages	Incorrect.passages	error_rate
100	RX Ringön K05	26	62	70.454545
105	RX Ringön K72a	509	1136	69.057751
101	RX Ringön K06	33	63	65.625000
99	RX Ringön K04	64	102	61.445783
104	RX Ringön K71	77	45	36.885246
97	Majorna utfart F4	3322	436	11.601916
106	RX Ringön K74	523	55	9.515571
81	GS Vasa Viktoria 242 HAND	2873	266	8.474036
107	RX Ringön K76	926	63	6.370071
103	RX Ringön K61	767	37	4.601990
66	GS Stampgatan 6910 RTX	2521	82	3.150211
74	GS Ullevi Södra 686 ULS	9935	167	1.653138
29	GS Järntorget 1804 PRIN-H	6908	103	1.469120

Figure 25: Outliers - passage error rates

4.2.2 Availability of switches

The availability of switches denotes the amount of time in percentage the switches were available for normal operations mode. Figure 26 shows a histogram with availability on the horizontal axis and number of switches on the vertical axis. The availability was always high with the mean availability being 99.7%.

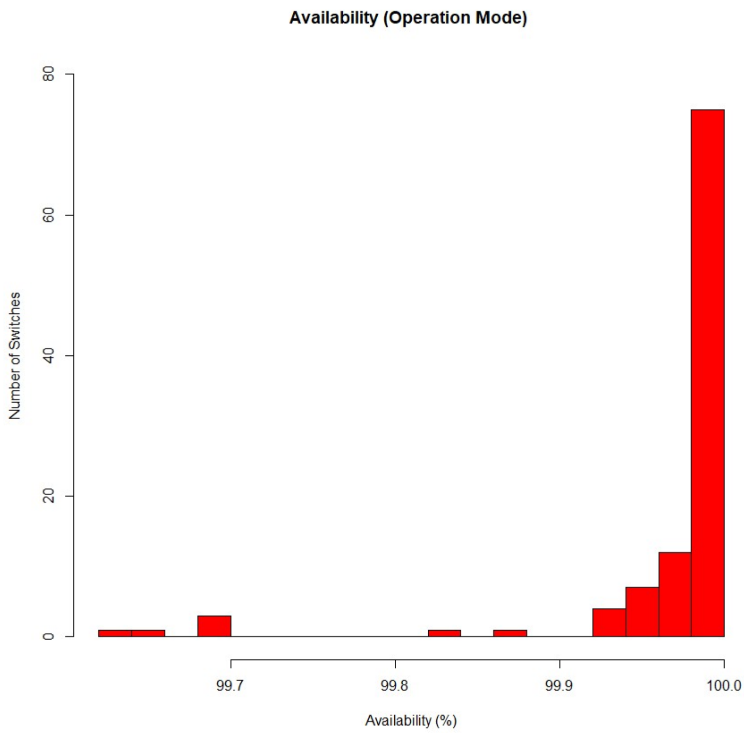


Figure 26: Availability of switches

4.2.3 Rate of failed electrical operations

The rate of failed electrical operations denotes the number of times an initiated electrical operation did not get the switch in control. Figure 27 shows a histogram with the rate of failed electrical operations (%) on the horizontal axis and number of switches on the vertical axis. It is evident that the probability of such events occurring is quite low with the mean rate of failed electrical operations at just 0.04%.

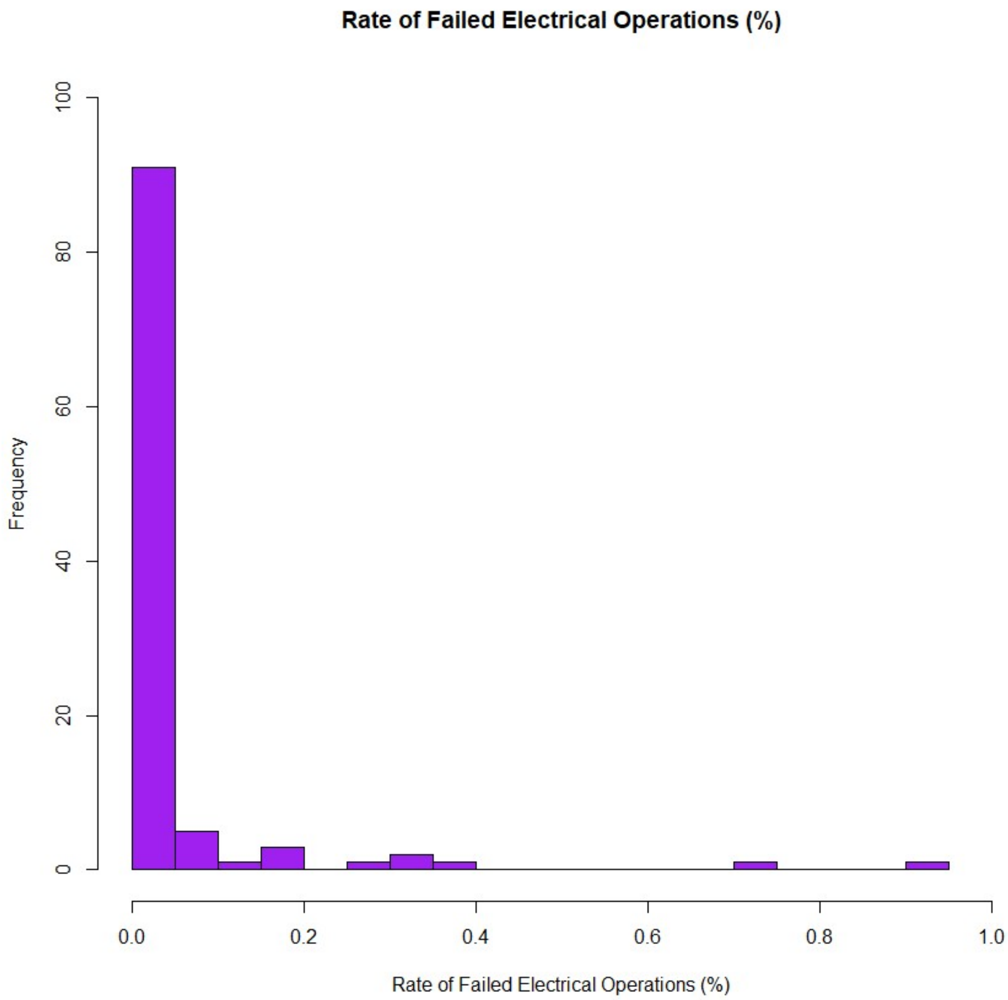


Figure 27: Rate of failed electrical operations

4.2.4 Rate of manual switching operations

The rate of manual operations denotes the number of times the switching operation was done manually by the tram driver with a rod relative to the number of electrical operations initiated. Figure 28 shows a histogram with the rate of manual operations (%) on the horizontal axis and number of switches on the vertical axis. This measure was low for most of the switches with the mean value being 1.6%. However, some outliers were found and have been excluded from this estimate. As shown in figure 29, the switches at Grönsakstorget and Stigbergstorget has a greater number of manual operations than the electrical operations. However, it is noticed that these switches had a small number of switching operations which is much smaller than 3836, the mean number of switching operations (electrical and manual) at Gothenburg's switches.

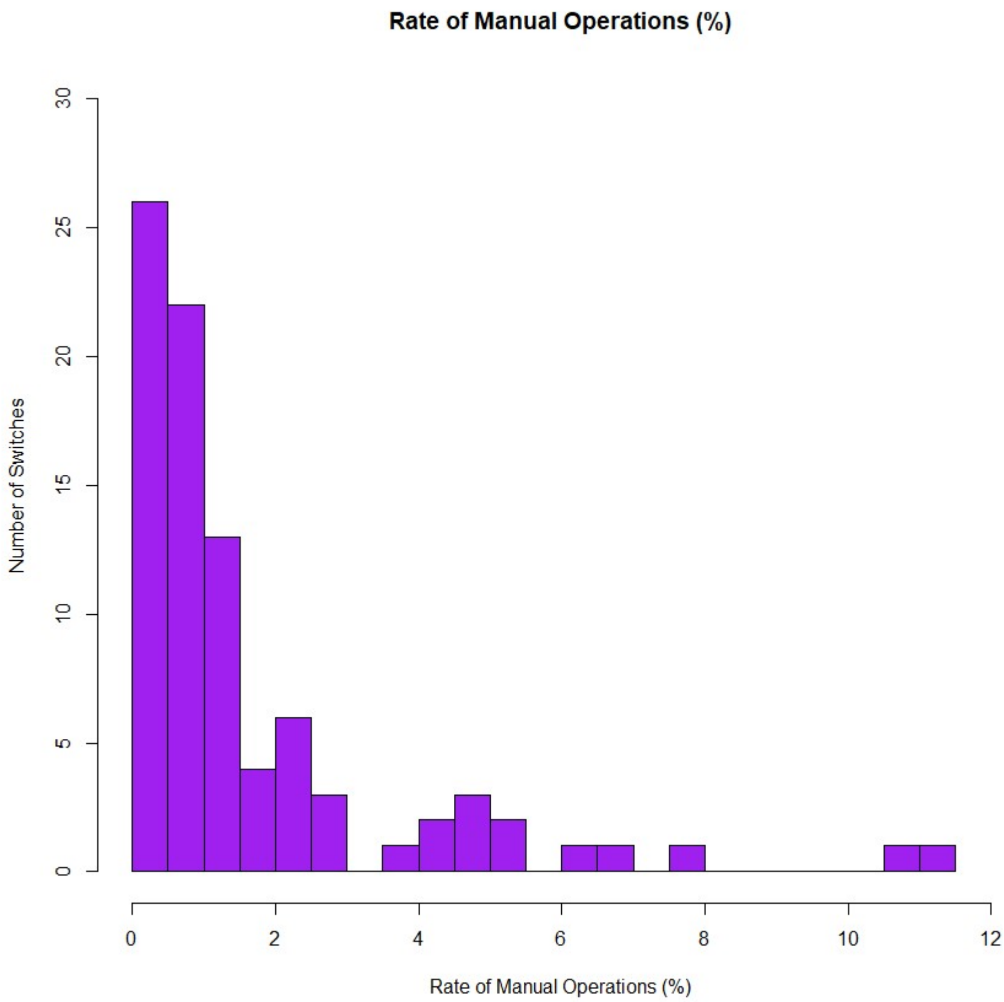


Figure 28: Rate of manual operations

	Switch	eo	skew	pskew
24	GS Grönsakstorget 504 PV	18	28	1.5555556
25	GS Grönsakstorget 506 VP	38	43	1.1315789
68	GS Stigbergstorget 164 FG	32	35	1.0937500
69	GS Stigbergstorget 166 KG	49	41	0.8367347
81	GS Vasa Viktoria 242 HAND	62	36	0.5806452
63	GS St Sigfrids plan 742 LI	79	39	0.4936709
43	GS Lilla Torget 814 DOM	36	17	0.4722222
31	GS Järntorget 1808 ST	116	53	0.4568966
21	GS Godhemsgatan 94 EKE	72	31	0.4305556
83	GS Vasa Viktoria 246 HK	71	28	0.3943662
77	GS Valand 352 VP	74	29	0.3918919
22	GS Godhemsgatan 96 MG	80	31	0.3875000
42	GS Lilla Torget 812 STPI	34	12	0.3529412
57	GS Park Viktoria 484 GT	134	29	0.2164179
85	GS Vasaplatsen 252 GT	152	32	0.2105263
46	GS Långedrag 22 LD	338	70	0.2071006
79	GS Valand 358 KV	105	20	0.1904762
70	GS Svingeln 724 OM	186	34	0.1827957
32	GS Järntorget 1810 PRIN	252	35	0.1388889
14	GS Drottningtorget 5402	375	52	0.1386667

Figure 29: Outliers - rate of manual operations

4.2.5 Correlation analysis

The existence of a linear correlation between the failed electrical operations and manual operations was checked. There is no linear trend between these two as evident from the scatterplot in figure 22. The horizontal axis represents the number of failed electrical operations and vertical axis represents the number of manual operations. Further, the Pearson's correlation coefficient which denotes the degree of association between two numeric variables is 0.085 in this case which is close to zero. A correlation coefficient very close to zero denotes extremely weak or no correlation. Hence, the manual switching operations are happening due to reasons other than failed electrical operations. Also, three of the switches had a greater number of failed electrical operations than the number of manual operations, which may imply that despite a failed electrical operation, it works in subsequent requests by the same vehicle.

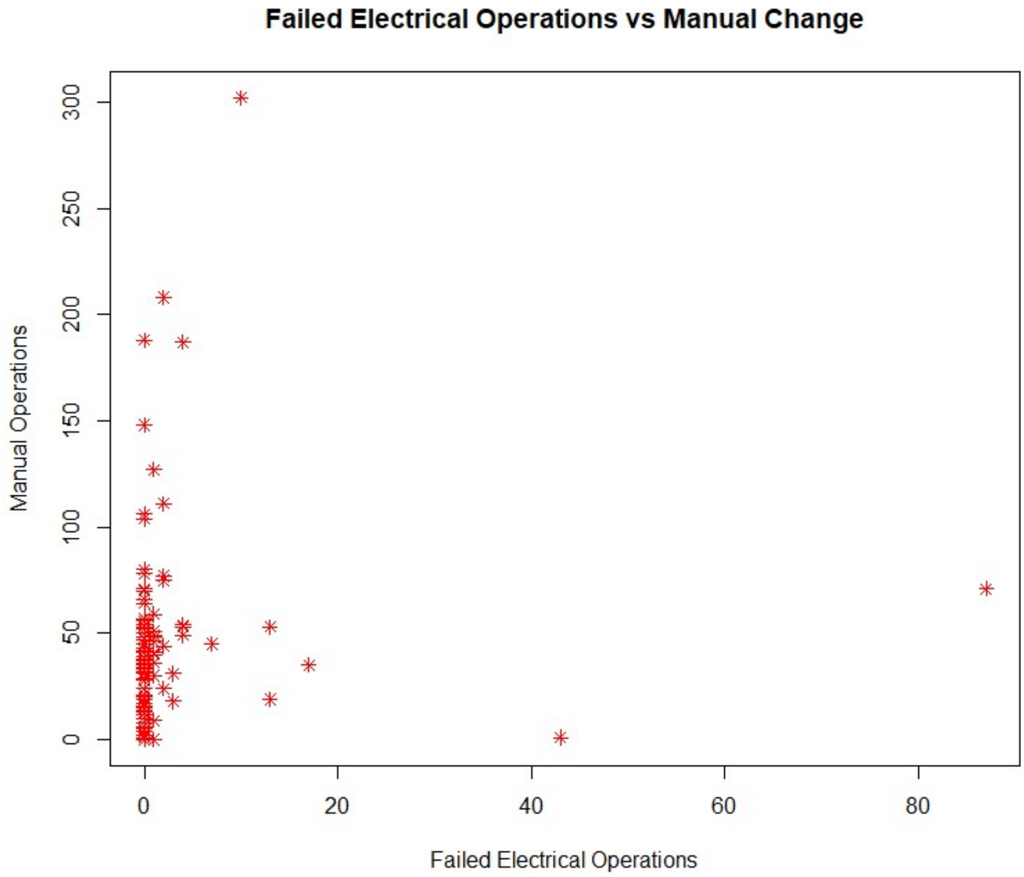


Figure 30: Correlation between failed electrical operations and manual operations

4.3 Results of Analysis of Inspections Data

4.3.1 Date inconsistencies

Several date inconsistencies were present in the data set and were counter intuitive. Logically, the dates in the data set should follow the below condition:

initiation date ≤ assigned date ≤ inspection date ≤ actual finishing date ≤ closing date

Around 48% of the inspection records, didn't obey the condition need to be excluded from the data set when doing time related estimations.

4.3.2 Distribution of data over time

The distribution of the inspection data over time is shown in figure 31 and is non-uniformly distributed over the years. The horizontal axis represents the years in which the data was available, and the vertical axis represents the percentage of data points. A large proportion of data points are during the years 2021 and 2022.

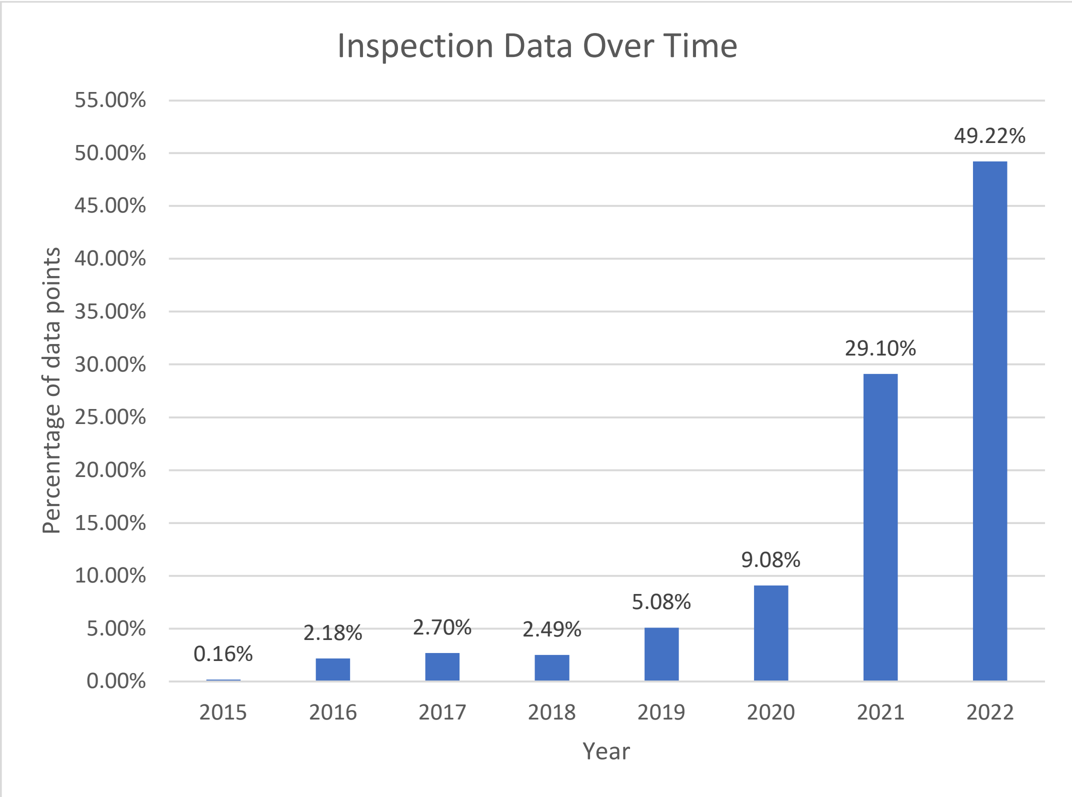


Figure 31: Inspection data over years

Figure 32 shows the distribution of inspection data over time excluding the records with date inconsistencies as mentioned in 4.2.1. Around 90% of the records available are for the years 2021 and 2022.

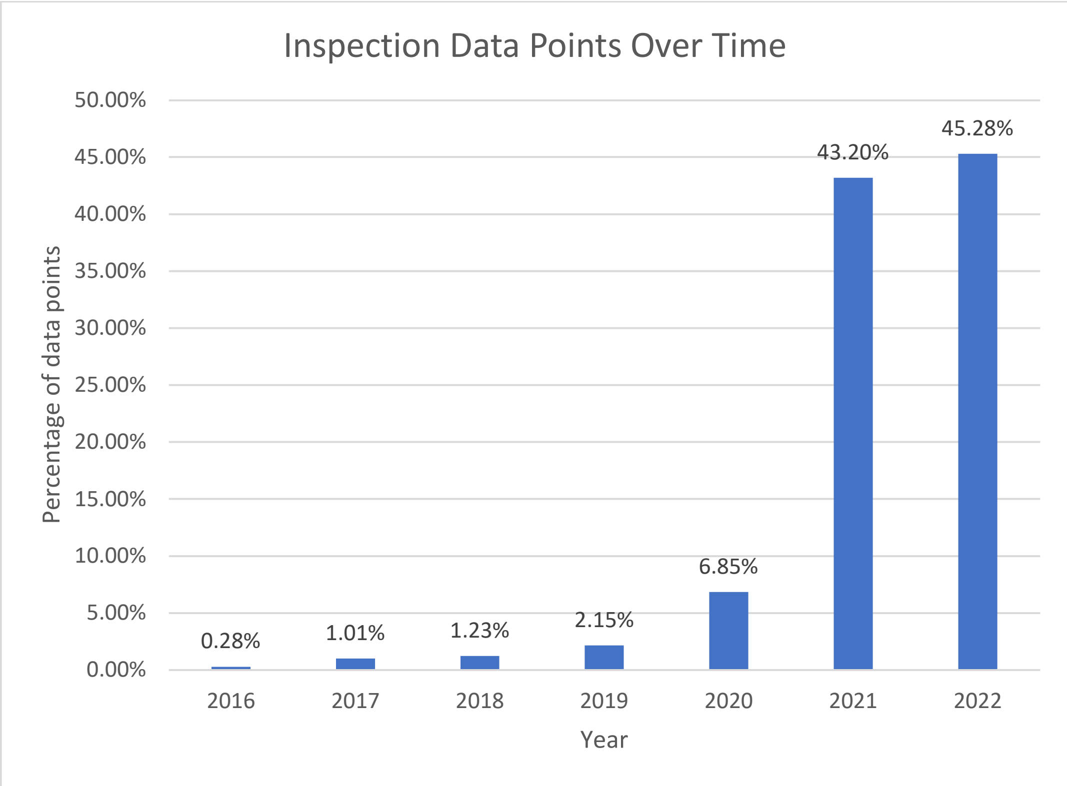


Figure 32: Inspection data over years (without date inconsistencies)

4.3.3 Inspection cycle time

The average inspection cycle time considering all types of inspection activities was estimated as approx. 23 days. The histogram in figure 33 shows the number of inspections against cycle times in days. Outliers with very large cycle times can be observed.

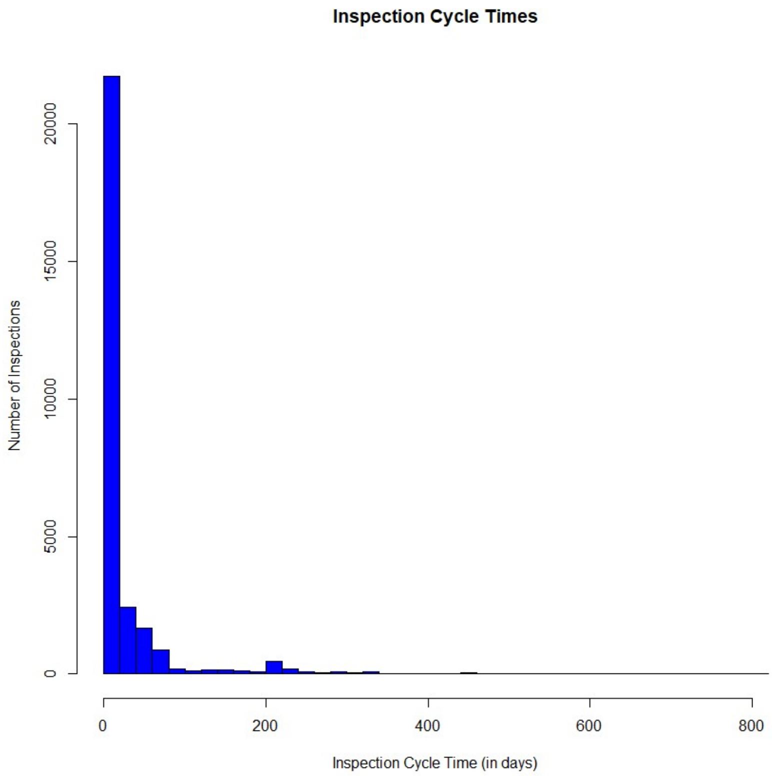


Figure 33: Inspection cycle times

Observations with cycle times beyond the criteria as mentioned in equation 8 will be treated as outliers. Hence the outlier fence will be 46 days and there are 3662 outliers (13%).

$$Upper\ Fence\ for\ Outliers = 3rd\ Quartile + 1.5 * Interquartile\ Range \quad (8)$$

Hence, the new estimates are as follows:

Average Inspection Cycle Time = 7 days ($T_{ai} + T_{ic}$)

Average time between assignment and inspection = 5 days (T_{ai})

Average time between inspection and closure = 2 days (T_{ic})

75% of the inspections had a cycle time less than or equal to the average time cycle time of 12 days. In a similar way, the average inspection cycle times for each type of inspection activity was estimated and is shown in table 11 and figure 26.

Table 11: Average inspection cycle times (by inspection type)

Category	Facility Type	Inspection Type	Inspection Cycle Time (days)	T_ai	T_ic
CONTACT LINE	INSPECTION FACILITY	Directed Inspection - Contact Line	11	10	0
CONTACT LINE	INSPECTION ROUTE	Contact Line Inspection	14	10	4
CONTACT LINE	INSPECTION ROUTE	Insulation Measurement	34	34	0
CONTACT LINE	FEEDING POINT	Feeding Point	0	0	0
CONTACT LINE	MINUS CABINET	Minus Cabinet	0	0	0
TRACK	INSPECTION FACILITY	Directed Inspection - Tracks	7	7	0
TRACK	INSPECTION ROUTE	Safety/Maintenance Inspection	37	32	4
TRACK	CROSSING	Track Geometry - Crossing	22	18	4
TRACK	SWITCH	Track Geometry - Switch	34	29	5
SWITCH	SWITCH	Periodic Maintenance - Switches	59	55	4

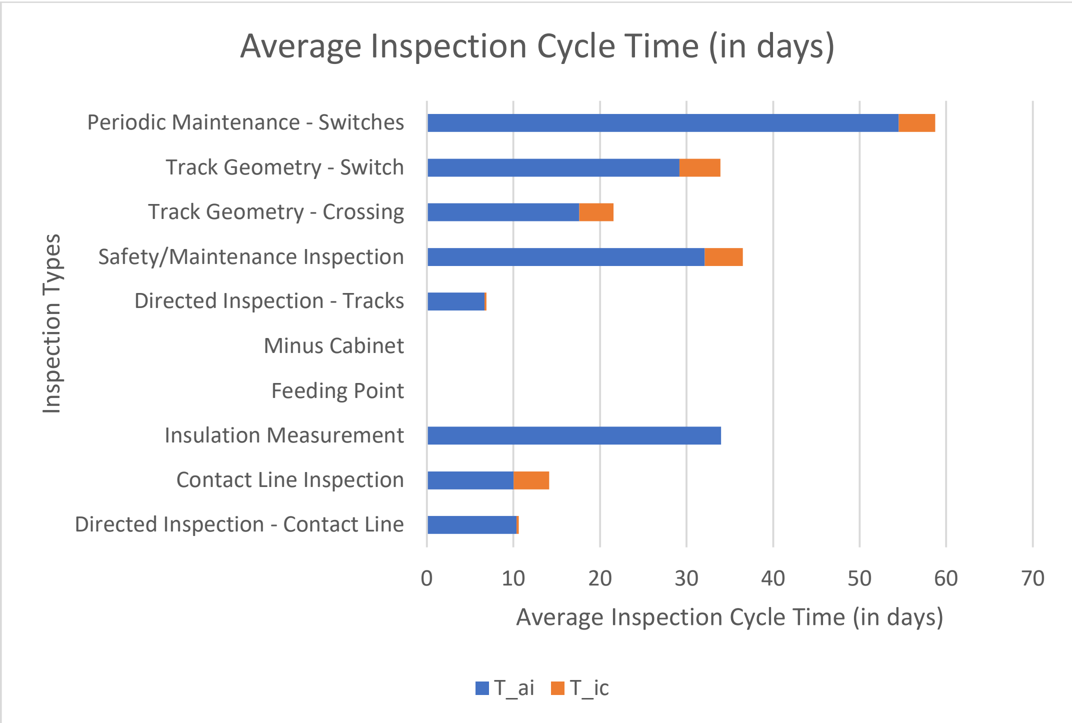


Figure 34: Average inspection cycle times (by inspection type)

It can be noticed that some activities have high average inspection cycle times and indicates a significant delay in performing and closing an inspection once assigned. However, these estimates are not an indicator of the actual required time to perform this inspection but rather the time between assignment and closure of an inspection and essentially a performance indicator of the maintenance teams.

4.3.4 Planned inspection durations

Planned start and planned end dates were missing in 73% of the inspection records. The remaining records obey the logical condition (planned start ≤ planned finish) was used to estimate the planned duration of each type of inspection activity. Surprisingly, it was found that the same inspection types had more than one planned duration associated with it and for the same asset. For example, as shown in figure 35, the track safety and maintenance inspection at this particular asset and location had planned inspection durations of 11 and 74 days.

itype	fid	location	p_dur	iid
Safety/Maintenance Inspection	99113040001	Linnéplatsen 202 - Änggården vxl 211	11	25663
Safety/Maintenance Inspection	99113040001	Linnéplatsen 202 - Änggården vxl 211	74	60824

Figure 35: Same inspection activity having different planned durations

The weighted average of the planned durations was not considered as an estimate since many of the inspection types had a large difference between the minimum and maximum values of the planned durations. It is assumed that some inspections of the same type had a higher time buffer allocated due to some reason which cannot be deciphered from the available data. Hence, it was decided to consider the minimum value as an estimate of the planned duration. This estimate will be used as the planned duration of inspection activities of each type, irrespective of whether the date values are missing or not. The planned durations of each inspection type are shown in figure 36.

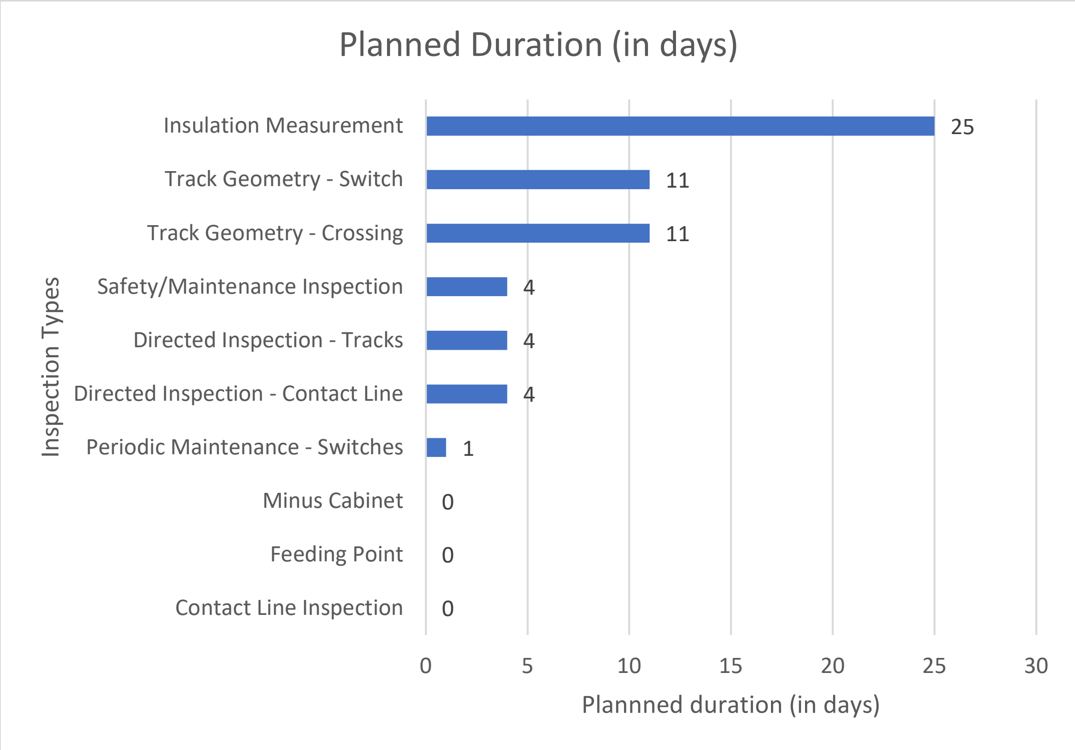


Figure 36: Planned inspection durations

4.3.5 Comparing average inspection cycle times and planned durations

Since the planned inspection durations are estimated from the dataset, it can be compared with the available average inspection cycle times. Most of the inspection activities are having the average inspection cycle time greater than the planned inspection duration (see figure 37). Especially, the periodic maintenance inspection of switches has the highest absolute error from the planned duration.

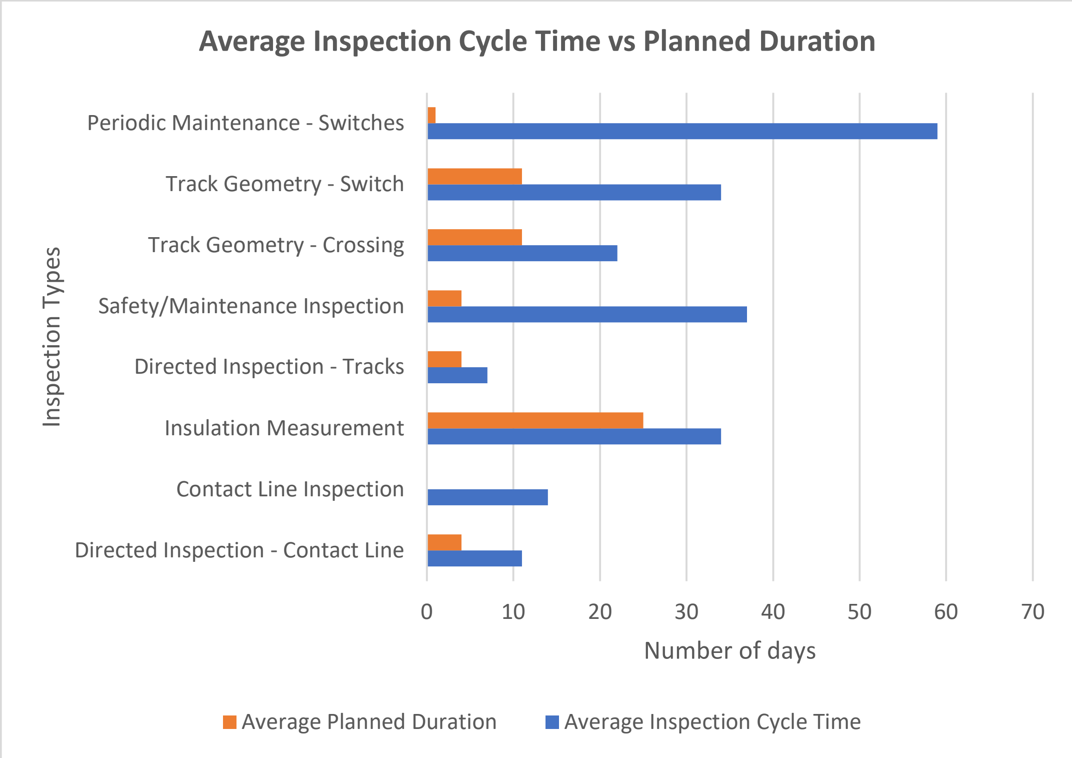


Figure 37: Average inspection cycle time vs planned duration

4.2.6 Analyzing the trends for a period of one year

According to the traffic office's maintenance strategy document adopted in 2019, inspections happen at least once a year for majority of the installations at a normal level. As mentioned earlier, the distribution of data points over time is non-uniform and most of the data points are during the period 2021-2022. Hence, the data during the period May 2021 to May 2022 will be considered for this analysis. During this period, it is observed that a large proportion of the inspections of each type are having higher actual inspection cycle times than its planned durations and on an average 97% of all the inspections had a higher inspection cycle times than the planned durations. Figure 38 shows the percentage of inspections of each type with actual cycle times greater than planned durations.

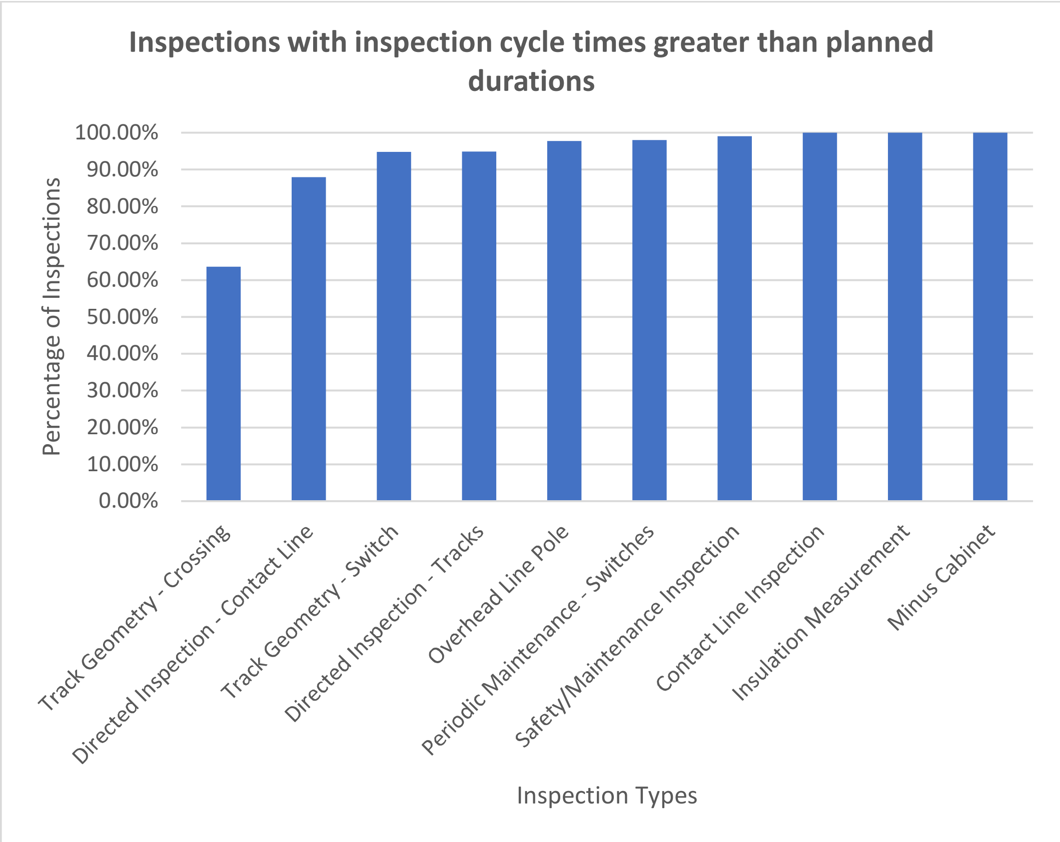


Figure 38: Percentage of inspections with cycle times greater than planned durations

4.3.7 Yearly average of the number of inspections on each asset type

The average number of inspections of each type performed on each facility during the period May 2021-May 2022 are shown in Table 12. It is estimated by dividing the total number of inspections of each type during the period over the total number of assets these inspections were performed on. These values can be compared with the recommended annual inspection frequencies to maintain the facility at a normal level of standard as detailed in the traffic office's management plan (BUSKK) for the tramway facility in Gothenburg and Mölndal. However, the required frequencies for all inspection types were not defined in BUSKK. For example, inspection frequencies were not explicitly mentioned in BUSKK for track inspections at depots, track geometry inspections at crossings and switches and contact line inspections for inspections routes that didn't belong to any traffic class.

Table 12: Yearly average of the number of inspections on each asset type

Category	Asset Type	Inspection Type	Number of Inspections	Number of Assets	Yearly Average	Required at Normal Standard Level
CONTACT LINE	INSPECTION ROUTE	Contact Line Inspection (Traffic Class 1)	100	64	1.56	2
CONTACT LINE	INSPECTION ROUTE	Contact Line Inspection (Traffic Class 2)	244	140	1.74	4
CONTACT LINE	INSPECTION ROUTE	Contact Line Inspection (Traffic Class 3)	288	91	3.16	6
CONTACT LINE	INSPECTION ROUTE	Contact Line Inspection (Traffic Class 4)	362	73	4.96	12
CONTACT LINE	INSPECTION ROUTE	Contact Line Inspection	71	22	3.23	-
CONTACT LINE	INSPECTION ROUTE	Insulation Measurement	74	74	1.00	1
CONTACT LINE	FEEDING POINT	Feeding Point	157	156	1.01	1
CONTACT LINE	MINUS CABINET	Minus Cabinet	84	84	1.00	1
TRACK	INSPECTION ROUTE	Track Safety/Maintenance Inspection (Traffic Class 1)	72	70	1.03	1
TRACK	INSPECTION ROUTE	Track Safety/Maintenance Inspection (Traffic Class 2)	144	142	1.01	1
TRACK	INSPECTION ROUTE	Track Safety/Maintenance Inspection (Traffic Class 3)	91	91	1.00	1
TRACK	INSPECTION ROUTE	Track Safety/Maintenance Inspection (Traffic Class 4)	79	73	1.08	1
TRACK	INSPECTION ROUTE	Track Safety/Maintenance Inspection	33	33	1.00	1
TRACK	FACILITY	Tracks - Depot	8	4	2.00	-
TRACK	CROSSING	Track Geometry - Crossing	11	7	1.57	-
TRACK	SWITCH	Track Geometry - Switch	685	418	1.63	-
SWITCH	SWITCH	Periodic Maintenance - Switches	943	244	3.86	4,4,6,12

The inspection frequencies for certain inspection types like contact line inspections, track safety and maintenance inspections and periodic inspections of switches were different for each traffic class and is mentioned in the table. The inspection frequencies for switches were defined only for the interlocking types based on the traffic class. However, from the available data it was not possible to decipher which traffic class a switch belongs to and hence the author was not able to properly compare the inspection frequencies of the switches with the actual required frequencies which range from 4 – 12 based on the traffic class. The estimate of the average number of inspections performed on a switch (both interlocking and non-interlocking) during the year was 3.86. Also, of the 244 switches, 111 were interlocked and its average inspection frequency was 3.88 is less than the minimum of 4 inspections (quarterly) required for traffic class 1. Hence it can be concluded that the inspection frequencies of interlocking switches during the period considered were not sufficient as per the management plan. It is also noticed that the periodic inspections of the contact line system are not carried according to the required frequency as mentioned in management plan, which is 2-12 times in a year according to the traffic class.

Directed inspections are performed at locations which are traffic intensive or for other reasons sensitive from an operational point of view. The required frequencies of such inspections are only mentioned for the contact line system in certain locations in the management plan and not for the tracks. Table 14 shows the number of directed inspections performed at such locations and the recommended number of inspections as per the management plan for contact line inspections and table 15 shows the number of directed inspections performed for tracks. Contact line inspections are performed at Brunnsparken, Marklandsgatan, Valand & Vasa Viktoriagatan at much lesser frequency than the ones recommended in the management plan. The Göta älv Bridge, one of the locations for directed inspection has been closed for decommissioning since June 2021 which explains why there was only inspection performed after May 2021.

Table 13: Directed Inspections - Contact Line

DIRECTED INSPECTION - CONTACT LINE		
Facility	**Number of Inspections Performed/Year**	**Required at Normal Level**
Brunnsparken	19	52
Axel Dahlströms torg	11	12
Marklandsgatan	11	27
Wieselgrensplatsen	11	12
Valand	18	27
Vasaplatsen	19	52
Vasa Viktoriagatan	21	27
Göta Älvbron	1	52
Nymånegatan	11	-
Drottningtorget	17	-
Järntorget	17	-
Korsvägen	18	-
Hisingsbron	12	-

Table 14: Directed Inspection – Tracks

DIRECTED INSPECTION - TRACKS	
Facility	**Number of Inspections Performed/Year**
Gårdahallen	12
Brunnsparken	49
Drottningtorget	15
Järntorget	49
Korsvägen	49
Grönsakstorget	49
Mölndal	35
Mölndal	35
Svingeln	17

4.3.8 Contact line and track inspections distributed over the period under analysis

Figure 39 shows the distribution of contact line and track inspections over the period under analysis. Contact line inspections were happening in all the months except November and July. However, almost all the track inspections which had an inspection frequency requirement of once in a year were performed during the period February to April. There were directed inspections for tracks and contact lines happening every month, which can be attributed to the higher inspection frequencies required at traffic intensive locations.

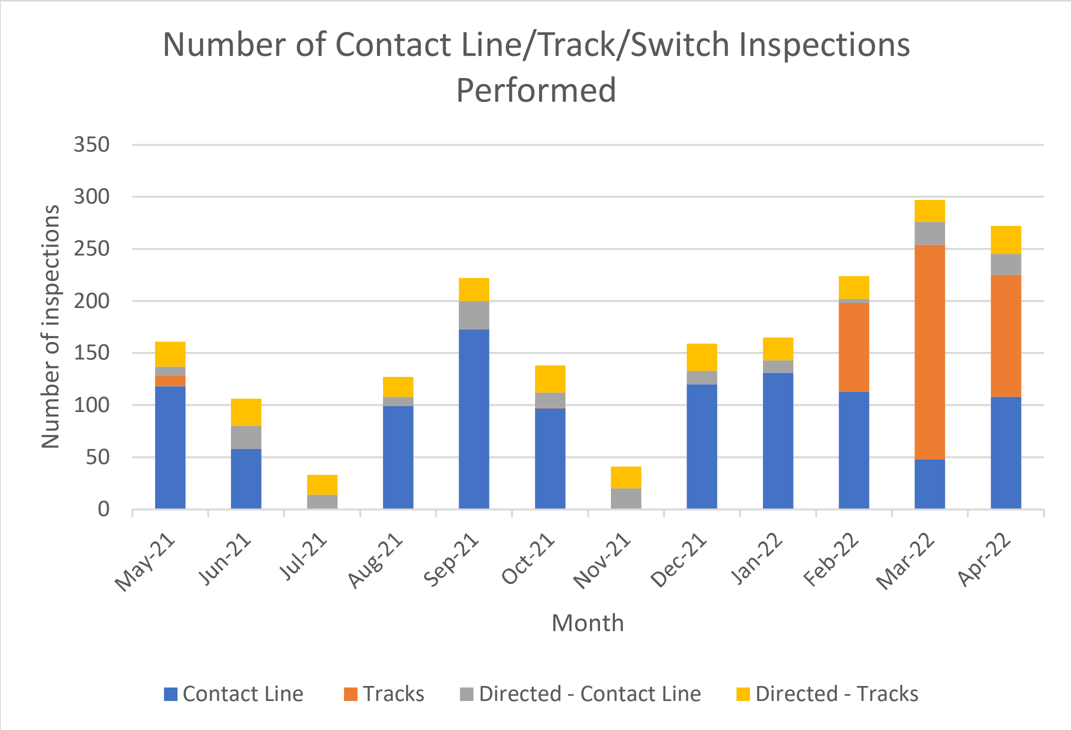


Figure 39: Number of contact line, track and switch inspections performed during May 2021 - April 2022

4.2.9 Linking inspection to work orders

As stated before, 59076 data points were associated with 56217 inspections and redundant records were expected. 1796 inspections (3.2%) had two or more records associated with it. With further analysis of the table, it was found that these multiple records were associated with more than one work order for an inspection. Similarly, there are many cases where a work order is associated with multiple inspections. The inspections resulted in 4606 work orders and 19% of them were associated with multiple inspections. 17% of the inspections resulted in only one work order and 3% of the inspections resulted in more than one work order.

A separatable table with approx. 13000 data points were available with work order data. The inspections have been linked to the work orders using the unique work order ID associated with inspections. However, in the work order table the administrative tasks were also described as work orders apart from the actual maintenance tasks. Such work orders were linked with multiple inspections. For example, an instruction to the team leaders or working foreman to fill out some fields in the asset management platform after an inspection is carried out is listed as a work order with a unique ID in the database. Such administrative tasks were filtered out to analyze the relationship between inspections and actual work orders.

Figure 40 shows the proportion of inspections of each type which results in a work order. It can be noticed that more than 50% of the all the track related inspections result in a work order whereas the rates are low for the ones related to the catenary system (contact lines). On an average, approximately 60% of the track related inspections resulted in a work order and only around 10% in the case of contact line related inspections. Figure 41 shows the percentage of directed inspections which resulted in a work order for tracks.

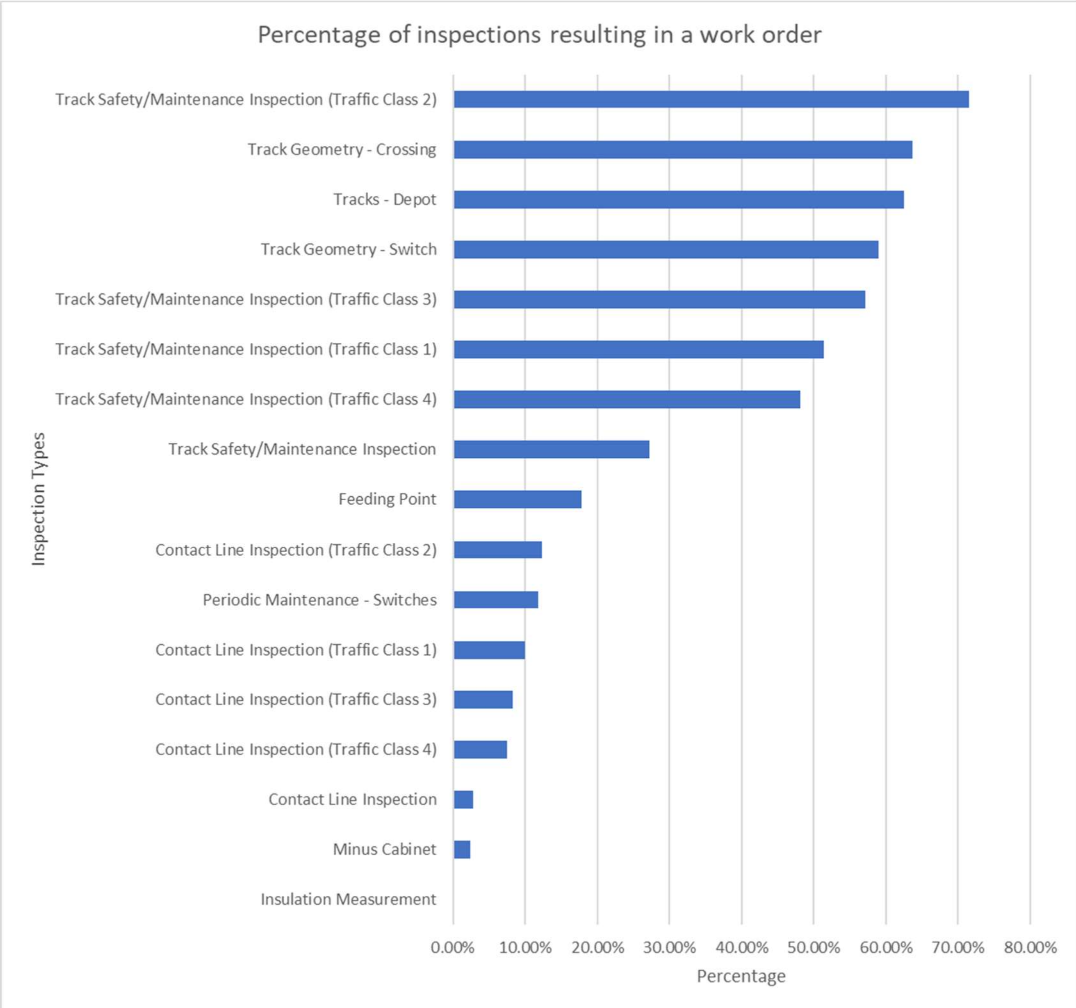


Figure 40: Percentage of inspections resulting in a work order

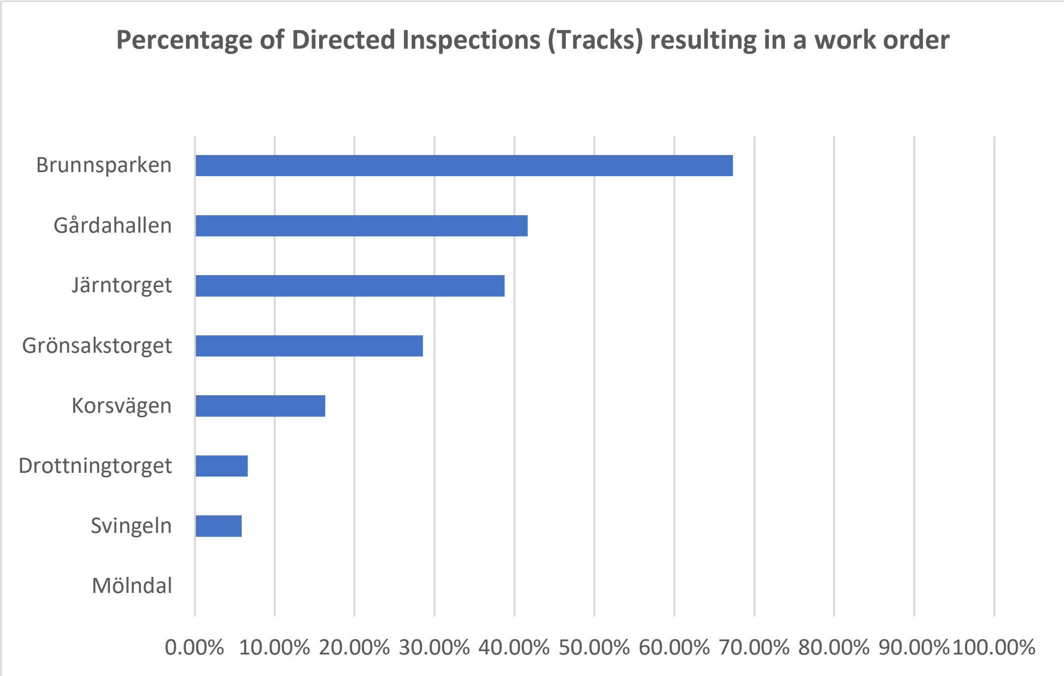


Figure 41: Percentage of track directed inspections resulting in a work order

The trend is similar in case of directed inspections. Only one among all the directed inspections (at Vasa Viktoriagatan) carried out for the catenary system resulted in a work order, unlike the directed inspections for tracks where 30% of the inspections on an average resulted in a work order. Also, almost 70% of the directed track inspections at Brunnsparken resulted in a work order.

4.2.10 Distribution of work orders resulting from inspections

The number of work orders resulting from different inspection types are shown in figure 42. The highest number of work orders issued arised from track geometry inspections performed at switches and safety/maintenance inspection of tracks. Figure 43 shows the proportion of work orders resulting from inspections on a category level and the largest proportion of the work orders were track related (1168 work orders) and almost half of them were welding/grinding work orders as shown in figure 44. Figure 44 represents the distribution of work orders to different maintenance groups.

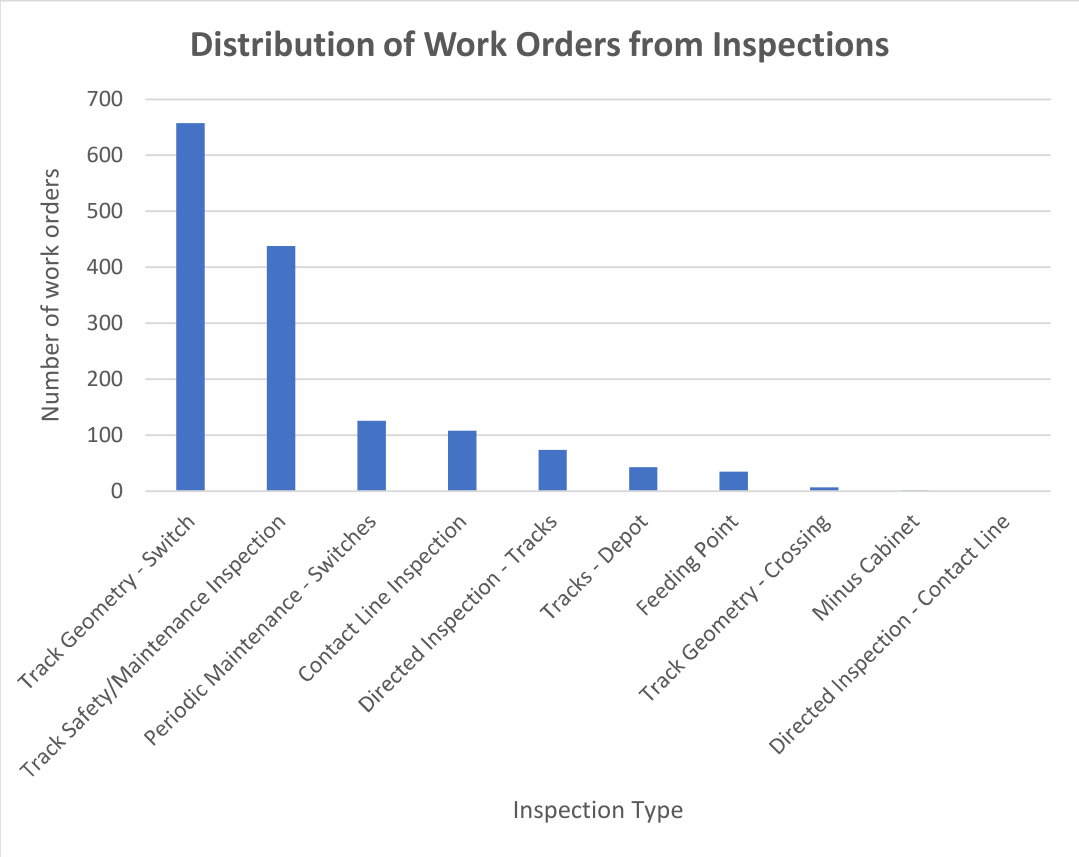


Figure 42: Distribution of work orders from different inspection types

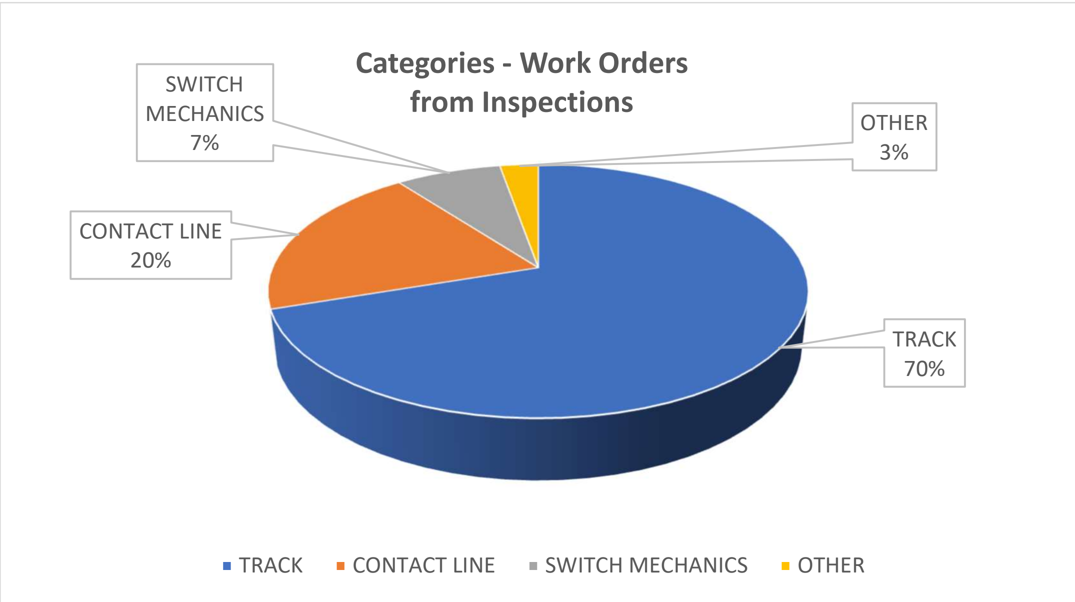


Figure 43: Work orders from different inspection categories

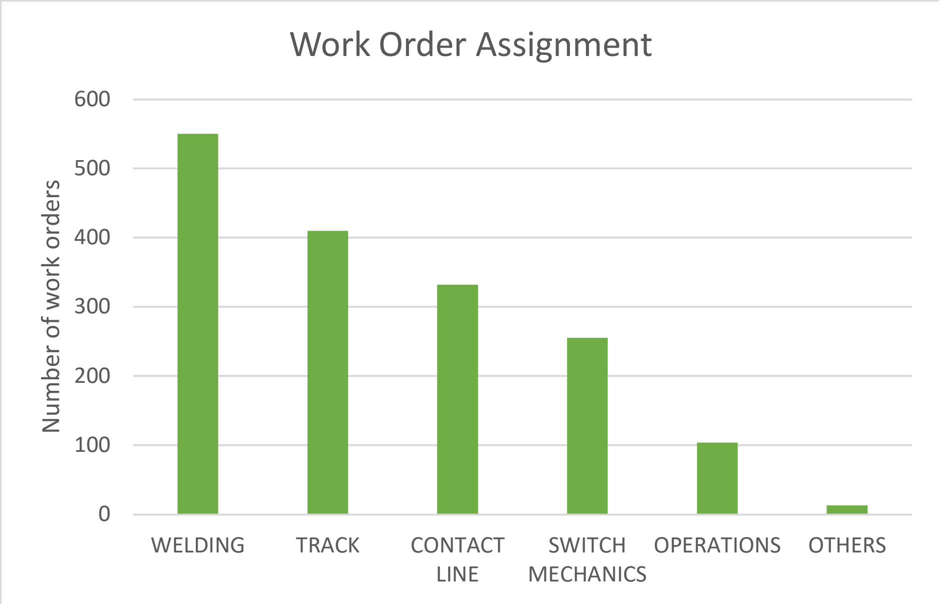


Figure 44: Work order assignment to different maintenance groups

4.2.11 Contact line inspections to work orders

A total of 1065 inspections were carried out for the contact line, of which 96 resulted in 108 work orders. The type of work orders resulting from contact line inspections are shown in figure 45 and the maximum number of work orders were related to point wear in the contact line and the second highest number of work orders relates to the suspension of the catenary system.

Figure 45: Reasons for contact line work orders

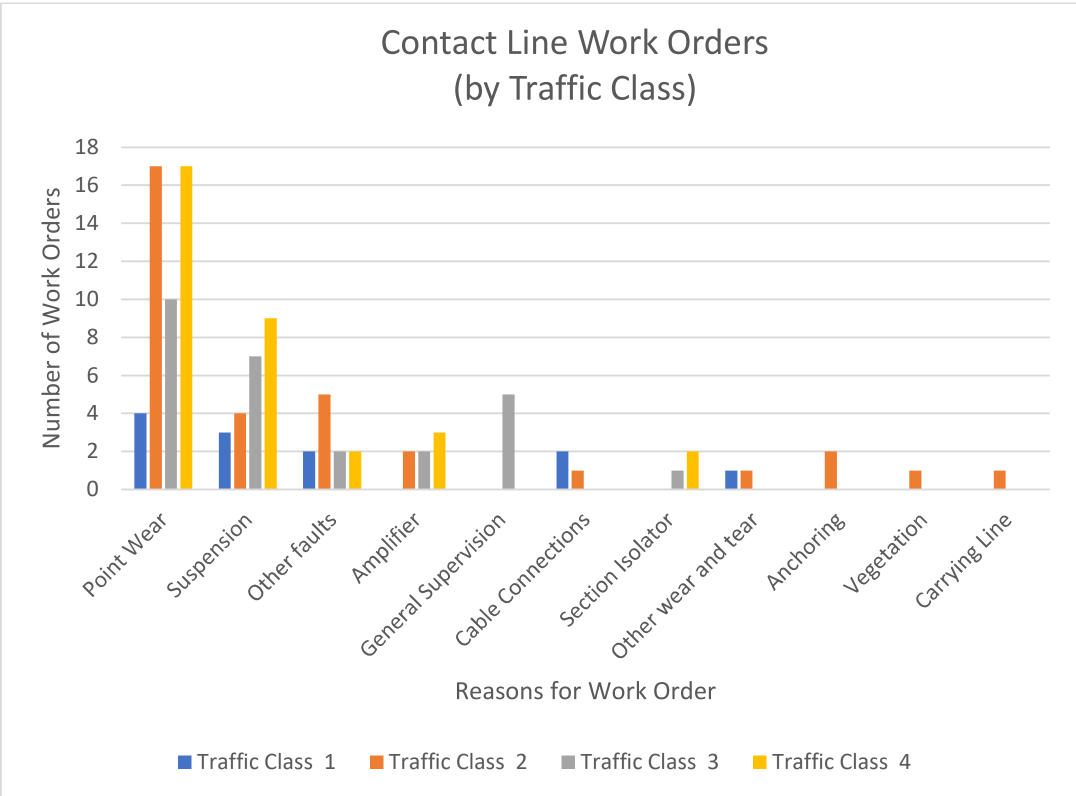


Figure 46: Contact line work orders by traffic class

Figure 46 shows the reasons for contact line work orders by traffic classes 1 – 4. The point wear work orders were highest for traffic classes 2 and 4 and lowest for 1. An increasing trend was expected in the number of point wear work orders from traffic class 1 to 4, but that was not the case. The traffic class 3 had less number of point wear work orders than traffic class 2. But this also depends on the time since last contact wire replacement and only one year of inspection data points were considered and available. In the case of suspension related work orders, there was an increasing trend in the number of such work orders from traffic class 1 to 4.

4.2.12 Feeding point inspections to work orders

Figure 40 shows the distribution of work orders arising from feeding point inspections among the reasons for work order. Most of the feeding point work orders was associated with signs and markings, and bar maneuver associated with the contact line section isolator. In case of minus cabinets only two work orders were there, one was related to fixing a lock and other one was regarding cable damage inside the cabinet.

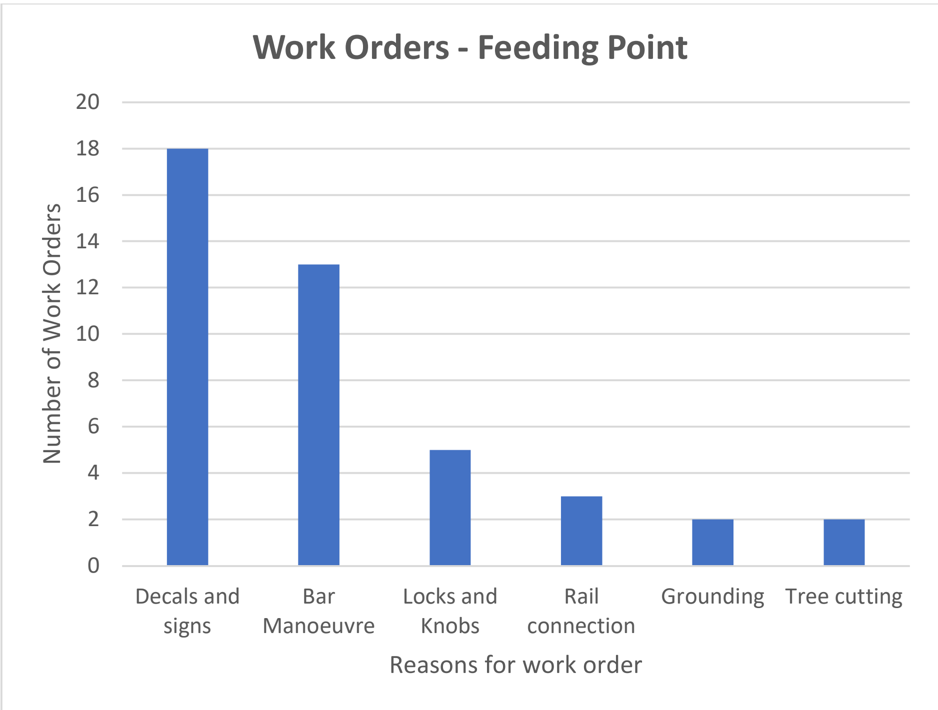


Figure 47: Reasons for work order - feeding point

4.2.13 Depot track inspections to work orders

Figure 48 shows the distribution of work orders arising from depot track inspections among the reasons for work order. Two track related inspections each were carried out at the four depots of the facility during the period under analysis resulting in 43 work orders. The most common fault identified during these inspections were related to the tongue rail occurring at the depots in Rantorget and Majorna. There were only a few asphalt damage work orders in Slottsskogen depot and none at Ringön.

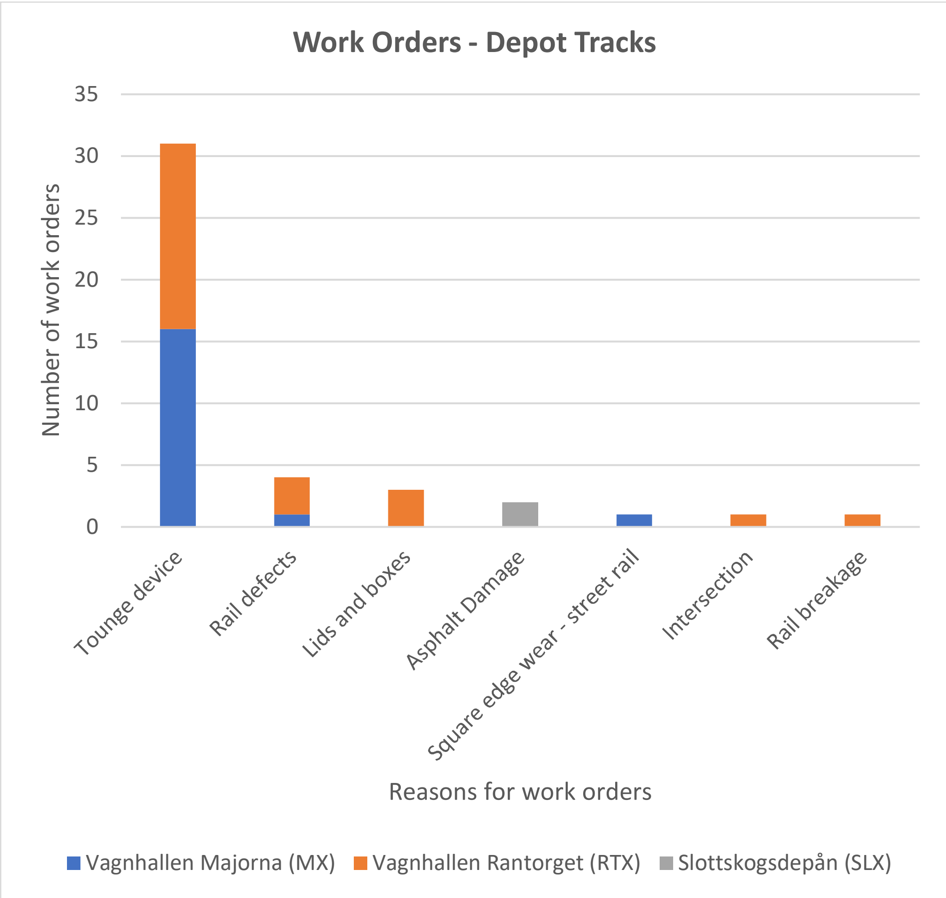


Figure 48: Reasons for work order - tracks at depot

4.2.14 Inspections to work orders: track geometry - switches

Figure 49 shows the distribution of work orders arising from track geometry inspections at switches among the reasons for work order. Of the 685 inspections carried out during the period of analysis, 404 inspections resulted in 657 work orders. Most of these work orders were related to the tongue rail and other rail defects. It is also observed that a large majority of all these work orders were assigned to the track welding team indicating many welding related work orders (see figure 50).

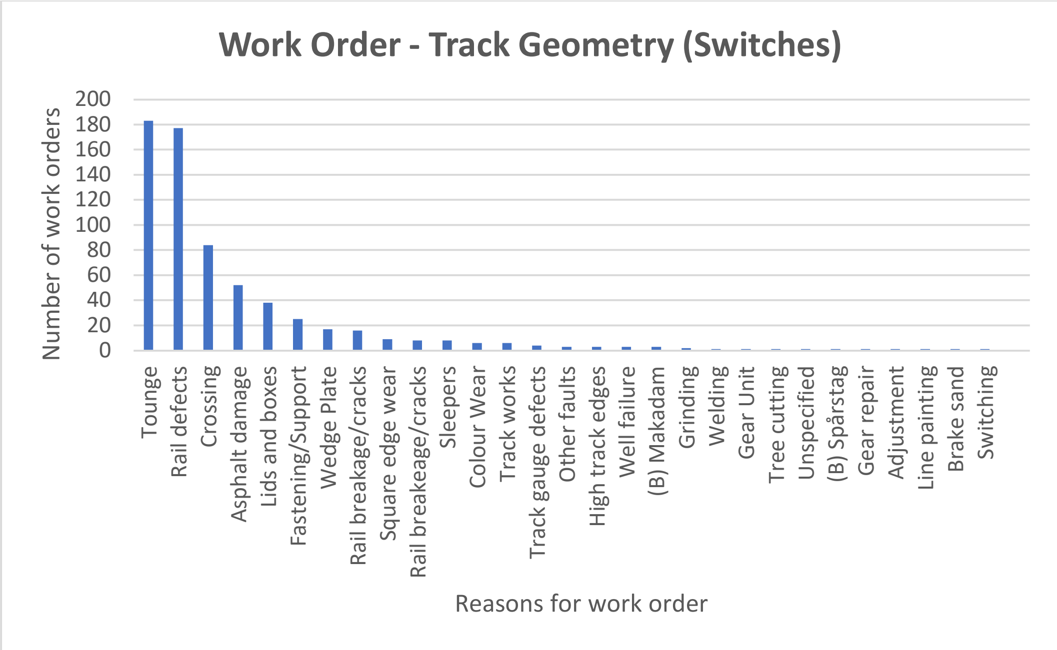


Figure 49: Reasons for work order - track geometry (switches)

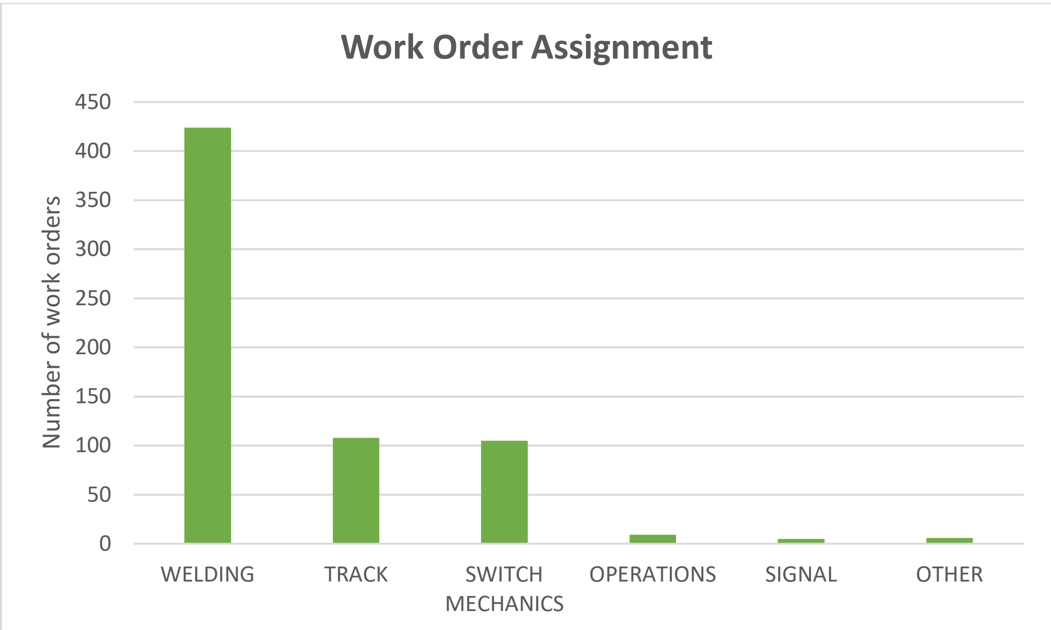


Figure 50: Work order assignment to different maintenance groups

4.2.15 Inspections to work orders: tracks

Of the 419 track inspections carried out, 239 inspections resulted in 438 work orders. Most of these work orders resulted from asphalt and settlement damages followed by rail defects and sleepers (See figure 51). Figure 52 shows the top five reasons of work order in each traffic class (1 – 4). The horizonal axis represents the top five reasons of work order along with the traffic class and the vertical axis represents the number of work orders. It is observed that asphalt and settlement damages were the most common reason for work orders in traffic class 3 and 4, and most of the work orders related to rail defects and sleepers were arising from traffic class 2. Most of the work order tasks were assigned to the track maintenance group. The welding work orders are much less in work orders arising from track safety and maintenance inspections (see figure 53).

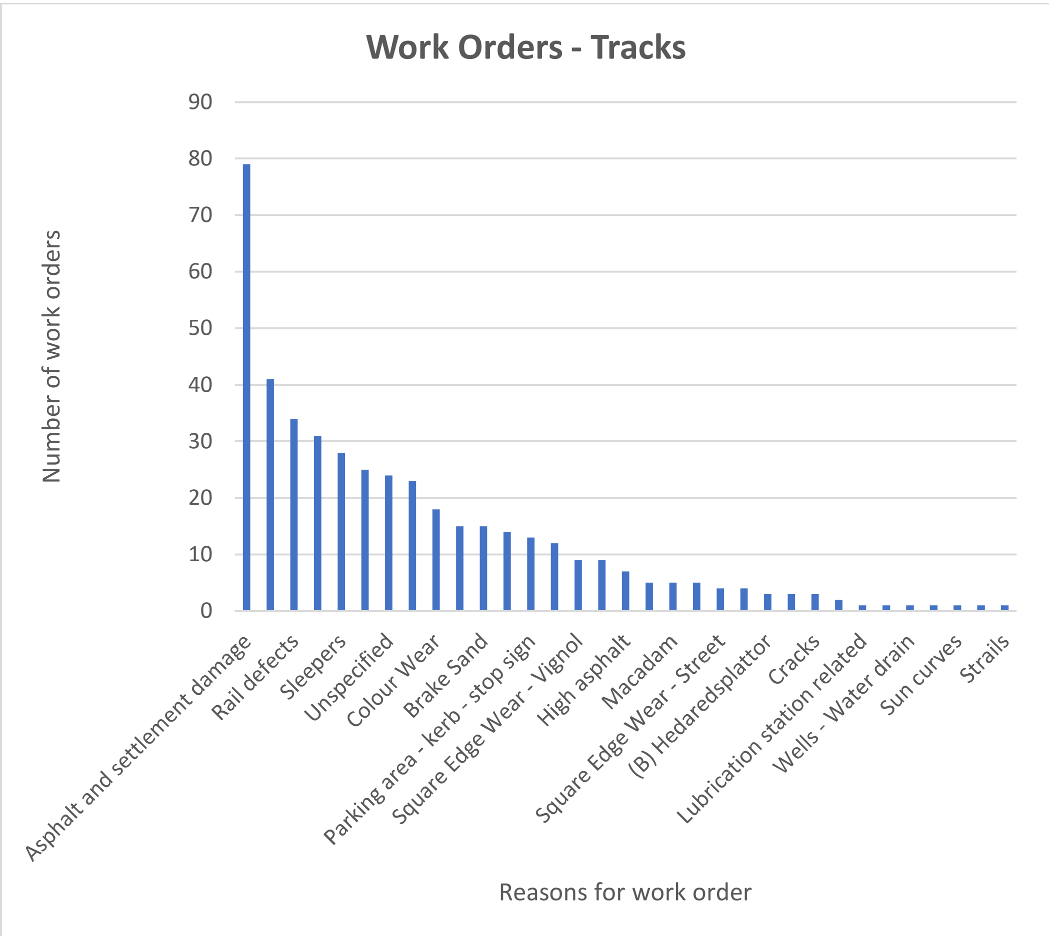


Figure 51: Reasons for work order - tracks

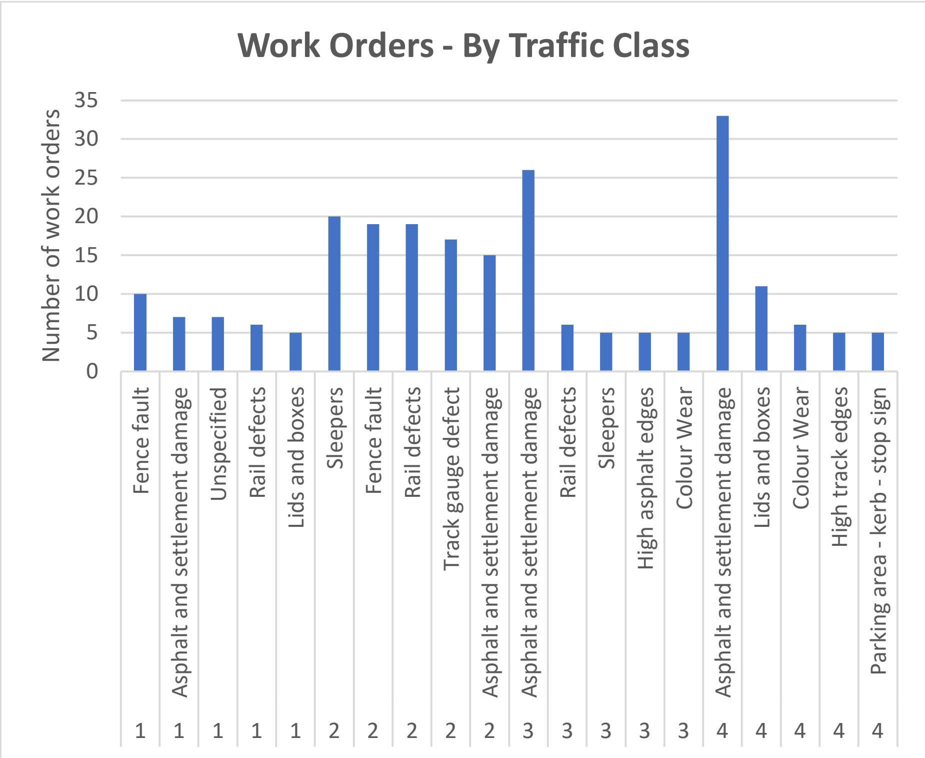


Figure 52: Top five reasons for track work orders by traffic class

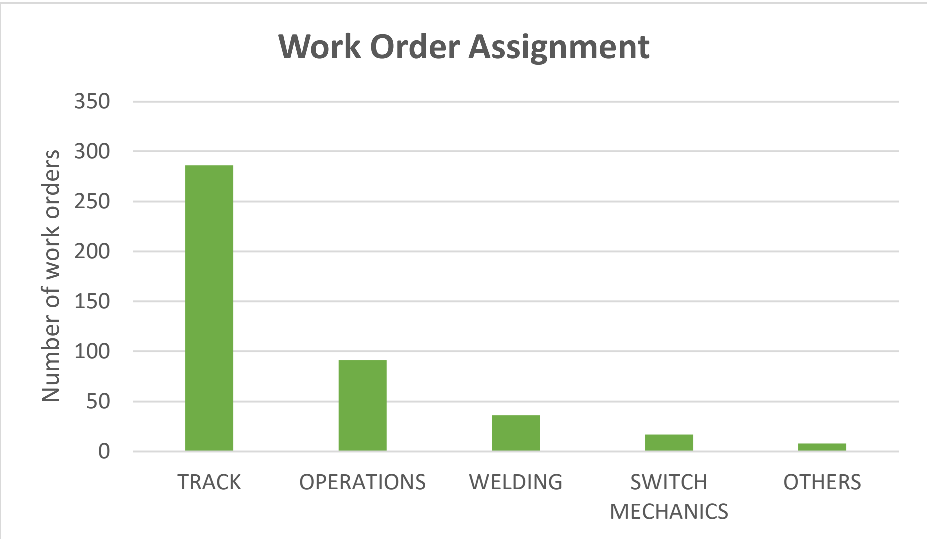


Figure 53: Work order assignment to different maintenance groups

4.2.16 Inspections to work orders: Switches

As shown in figure 47, the highest proportion of switch related work orders are handled by the switch mechanics maintenance group.

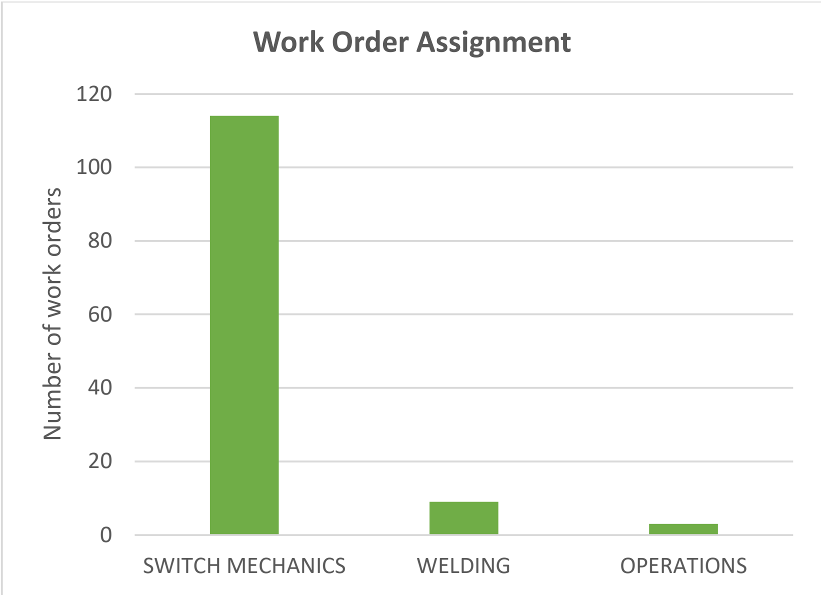


Figure 54: Work order assignment to different maintenance groups

4.4 Results of Analysis of Work Orders Data

4.4.1 Distribution of data over time

The work order data set represents 13247 work orders (data points). As shown in figure 55, the work order data is not uniformly distributed over the years. 82% of the work order data points available are between 2019-2022, which implies there is a lot of missing work order data for the earlier years.

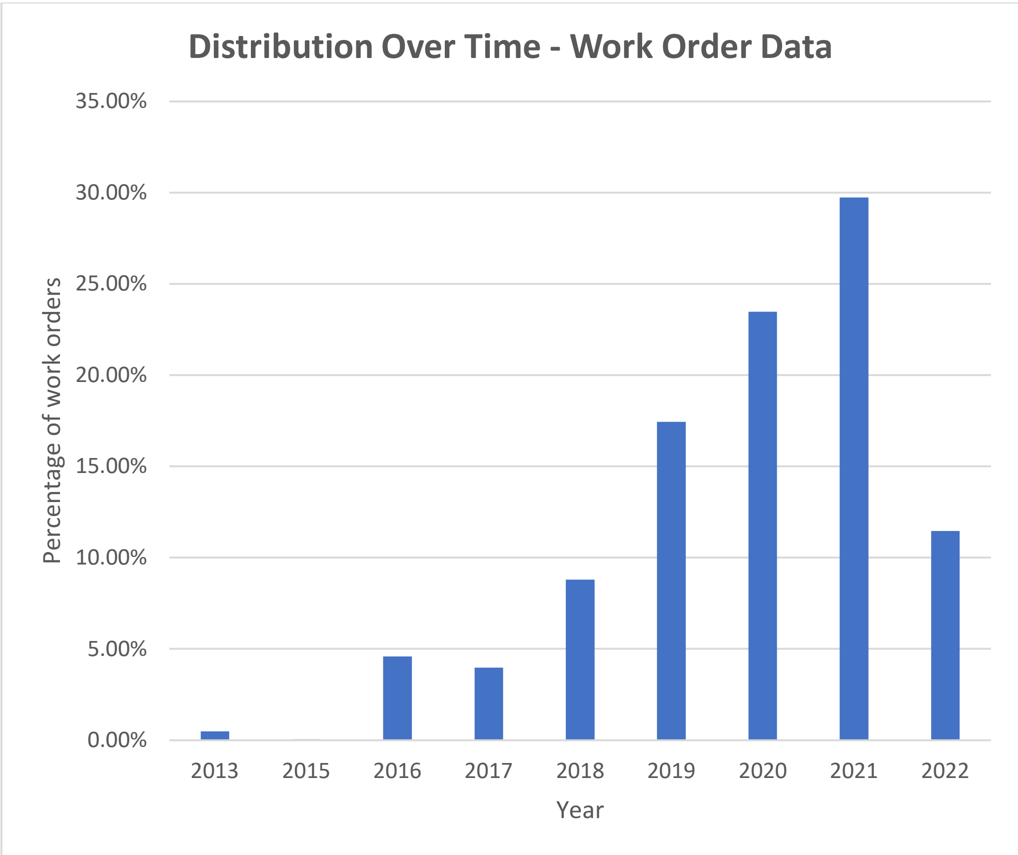


Figure 55: Distribution of work order data over time

4.4.1 Work Order Cycle Times

The cycle times of all available work orders in the dataset was measured and plotted on a boxplot (see figure 56). It is observed that the dataset contains so many outliers based on cycle times.

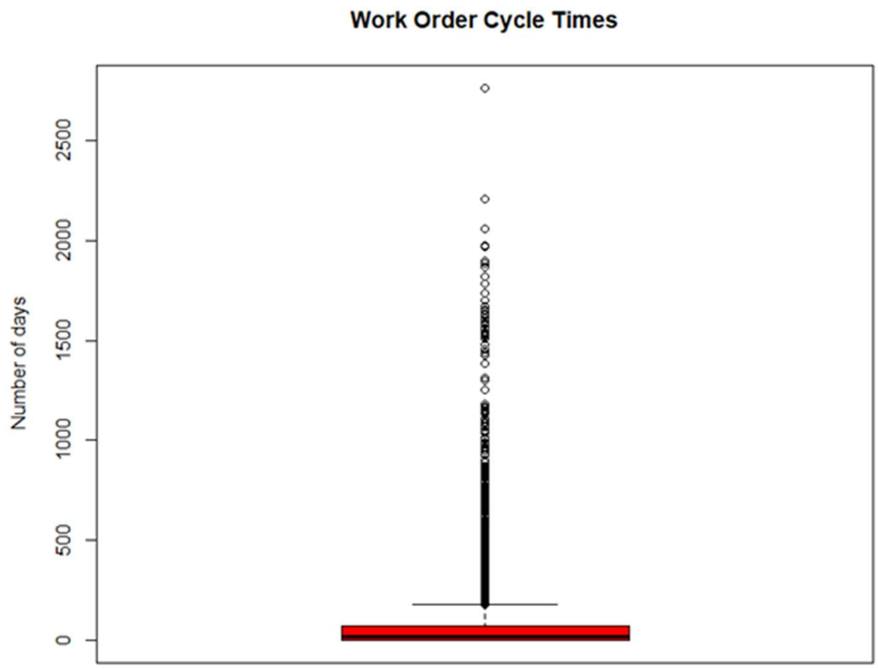


Figure 56: Boxplot - work order cycle times

The outlier limit was calculated using the criteria in Equation 8 in 4.2.3.

$$\text{Limit} = 73 + 1.5\,(73 - 2) = \text{Approx. } 180 \text{ days}$$

There are 1424 work orders with cycle time above this limit (13%). The average work order cycle time excluding these outliers is 29 days. However, this value is an average considering all types of work orders. The average work order cycle times for each type of work order was estimated following the same method. Outliers were removed before calculating the average cycle time. It was cumbersome to estimate the average work order cycle times to resolve each type of fault (failure mode) due to redundant labeling of the failure modes in the data set available. However, estimates at an aggregate level based on a broader categorization of work orders were calculated as shown in table 15. The average cycle time was estimated for the overhead contact line only based on the work orders directly related to the contact line and not the associated equipment like feeding points, minus cabinets, masts etc. The average work order cycle times for work orders only associated with the inspections performed during May 2021 – May 2022 are shown in table 16.

Table 15: Average work order cycle times

Category	**Average WO Cycle Time**
Overhead Contact Line	31 days
Track	50 days
Welding	26 days
Switch Mechanics	19 days

Table 16: Average work order cycle times (2021 - 2022)

Category	**Average WO Cycle Time**
Overhead Contact Line	31 days
Track	55 days
Welding	47 days
Switch Mechanics	25 days

4.4.2 Proportion of work orders among different categories

Figure 57 shows the distribution of work orders among different categories. Work orders were almost uniformly distributed among the categories of track, welding, contact line and switch mechanics, with the highest proportion of work orders being assigned to track.

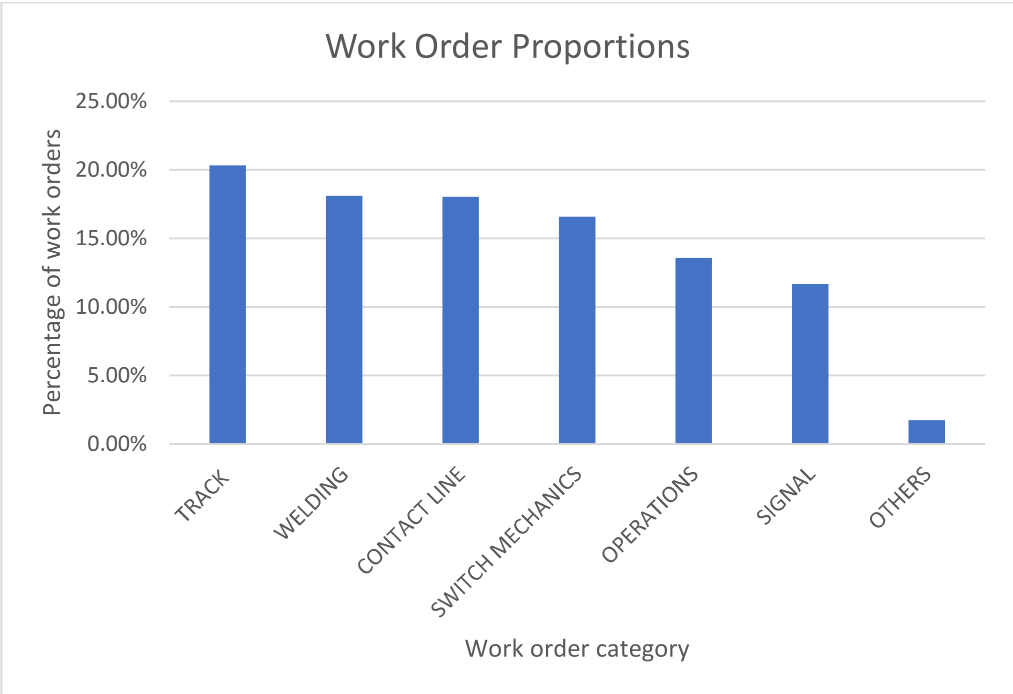


Figure 57: Distribution of work orders in different categories

4.4.1 Actual Work Order Cycle Times vs Average Work Order Cycle Times

Since the average work order cycle times for contact line, track, welding, and switch mechanics categories are estimated, this can be compared with the actual cycle times of each work order. Figures 58, 59, 60 and 61 represents the cumulative distribution functions of work order cycle times of contact line, track, welding, and switch categories. The horizontal axis represents the work order cycle times in days and the vertical axis represents the probability of a work order having a cycle time less than the corresponding cycle time on the horizontal axis. The blue vertical line in all these figures represent the average work order cycle time of that category of work order. In the case of contact lines, 77% of all the contact line work orders have a cycle time less than the average work order cycle time and 66% of work orders have a cycle time less than average cycle times in the case of tracks, welding, and switches. Hence, historically, majority of the work orders had a cycle time within the average and this metric can be used to monitor the performance of maintenance teams.

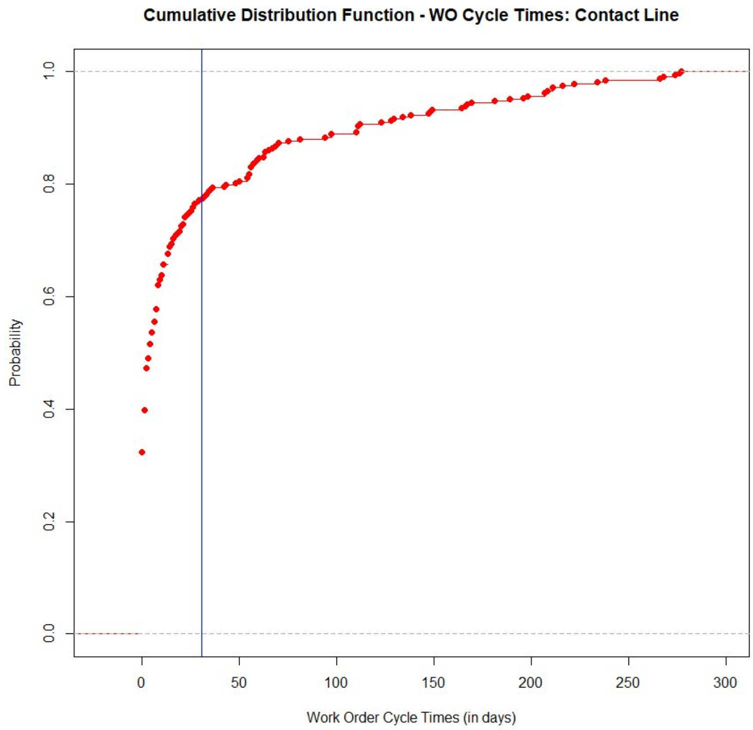


Figure 58: Cumulative distribution function – contact line work order cycle times

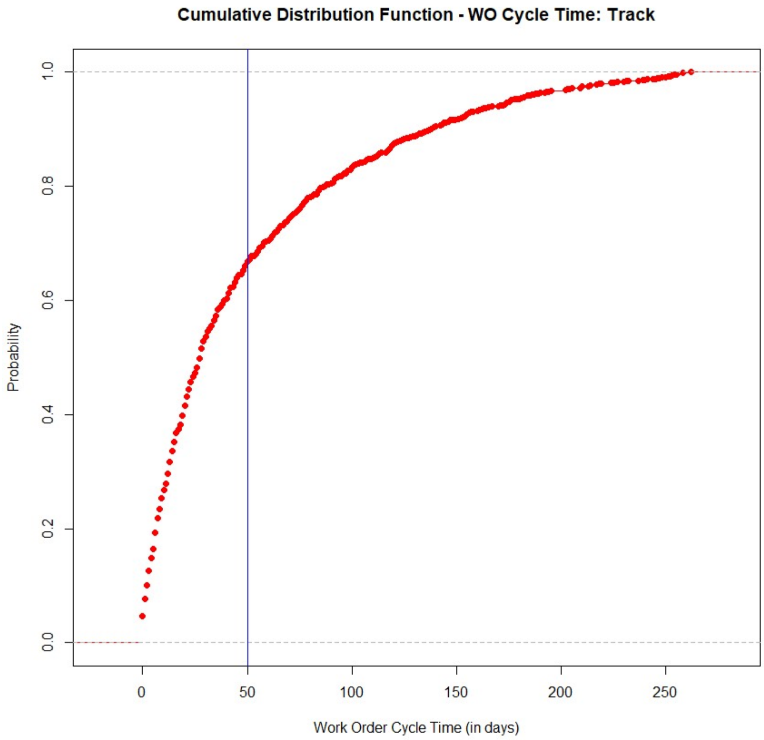


Figure 59: Cumulative distribution function – contact line work order cycle times

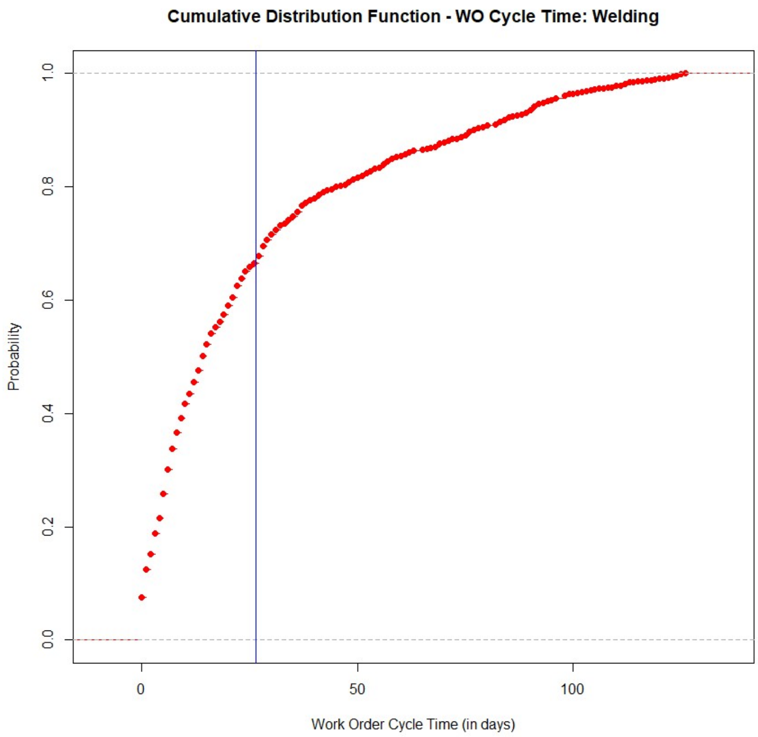


Figure 60: Cumulative distribution function – welding work order cycle times

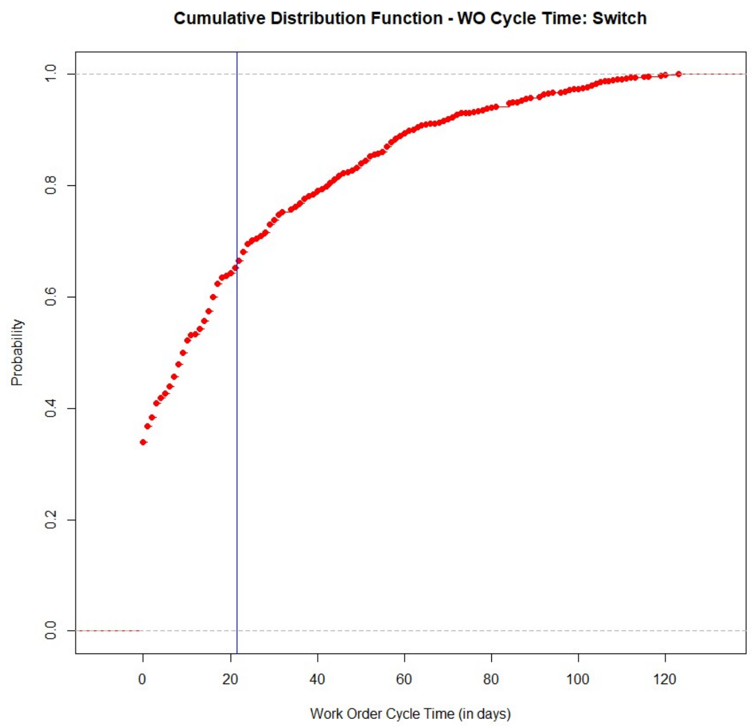


Figure 61: Cumulative distribution function – switch work order cycle times

4.4.1 Mean Time Between Maintenance (MTBM)

The estimation of this value requires the data about two or more maintenance events for the same asset. The available data set had very few records like that. The greatest number of such records were available for switches, track, and contact line as shown in table 17. The rest of the asset types like feeding points or minus cabinets were not considered since they had too few data points to do such estimations.

Table 17: Assets with two or more associated work orders

Facility Type	Items	Work Orders
SWITCH	212	918
TRACK	37	81
CONTACT LINE	26	65

Hence, the estimations of MTBM for contact line, track and switches are as follows:

$$MTBM_{CONTACT\ LINE} = 167\ days$$

$$MTBM_{TRACK} = 146\ days$$

$$MTBM_{SWITCH} = 142\ days$$

The mean time between maintenance for switches at different locations except depots in the tram network were also estimated based on the available data and is shown in table 17. Figure 62 also represents the MTBM for switches at various locations. A few locations like Angered Centrum, Stigbergstorget and Majorna has high mean time between maintenance events. However, these estimates are based on a very few numbers of past maintenance events.

Table 18: MTBM for switches at various locations

Location	Number of Switches Considered for Estimation	Number of Past Work Orders Considered for Estimation	Number of Work Orders Per Switch (Approx.)	Total Number of Switches at this Location	% of Total Switches Available for Estimation	MTBM (days)
ALLHELGONAKYRKAN	2	6	3	2	100%	186
ANGERED CENTRUM	1	3	3	2	50%	472
ANNEDAL	2	15	8	2	100%	97
APRILGATAN	2	8	4	2	100%	170
AXEL DAHLSTRÖMS TORG	2	14	7	2	100%	106
BRUNNSPARKEN	11	56	5	14	79%	126
CHALMERS	2	7	4	2	100%	245
DROTTNINGTORGET	11	38	3	18	61%	191
EKETRÄGATAN	3	14	5	3	100%	113
FRIHAMNEN	4	10	3	4	100%	186
FRÖLUNDA TORG	1	4	4	1	100%	95
GETEBERGSÄNG	2	18	9	4	50%	83
GODHEMSGATAN	5	20	4	6	83%	99
GRÖNSAKSTORGET	5	28	6	6	83%	113
GÅRDA	5	12	2	13	38%	257
HÄRLANDA	1	10	10	2	50%	134
JÄRNTORGET	10	48	5	12	83%	131
KOMETTORGET	2	6	3	3	67%	115
KORSVÄGEN	1	2	2	6	17%	161
KUNGSTEN	3	12	4	3	100%	158
KÅLLTORP	2	10	5	4	50%	131
LANA	2	10	5	2	100%	128
LINNÉPLATSEN	2	8	4	2	100%	155
LILLA TORGET	6	26	4	6	100%	121
LÅNGEDRAG	2	14	7	2	100%	97
MAJORNA	6	10	2	7	86%	341
MARKLANDSGATAN	6	23	4	6	100%	154
MUNKEBÄCK	6	20	3	6	100%	146
MÖLNDAL	2	6	3	2	100%	131
NYMÅNEGATAN	1	5	5	2	50%	112
OLIVEDALSGATAN	2	16	8	2	100%	82
OPALTORGET	2	10	5	2	100%	128
PARK VIKTORIAGATAN	5	20	4	6	83%	116
REDBERGSPLATSEN	2	15	8	2	100%	145
SAHLGRENSKA	2	13	7	2	100%	120
SANKT SIGFRIDSPLAN	2	4	2	2	100%	195
SLOTTSSKOGSVALLEN	3	15	5	4	75%	98
STAMPGATAN	11	40	4	15	73%	164
STIGBERGSTORGET	4	8	2	6	67%	461
SVINGELN	2	9	5	2	100%	194
ULLEVI	6	36	6	6	100%	104
VALAND	5	25	5	6	83%	120
VARMFRONTSGATAN	2	12	6	2	100%	160
VASA VIKTORIAGATAN	4	13	3	6	67%	221
VASAPLATSEN	8	44	6	10	80%	112
VÄDERILSGATAN	2	12	6	2	100%	147
WAVRINSKYS PLATS	4	21	5	4	100%	120
WIESELGRENSPLATSEN	2	12	6	2	100%	113
ÄLVSBORGSPLAN	4	17	4	6	67%	136
ÅKAREPLATSEN	3	12	4	4	75%	164
ÖSTRA SJUKHUSET	3	9	3	4	75%	276

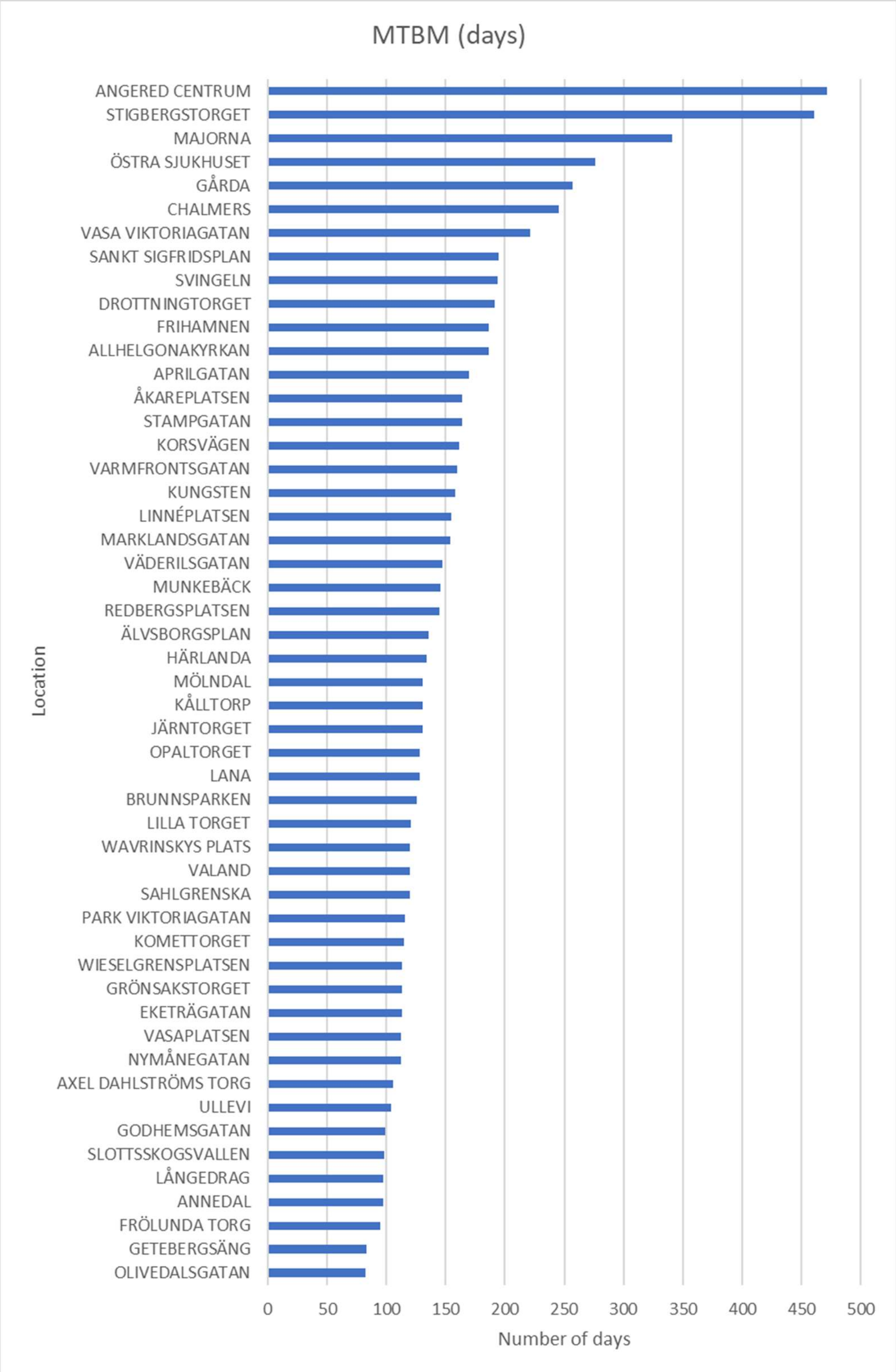


Figure 62: MTBM for switches at various locations

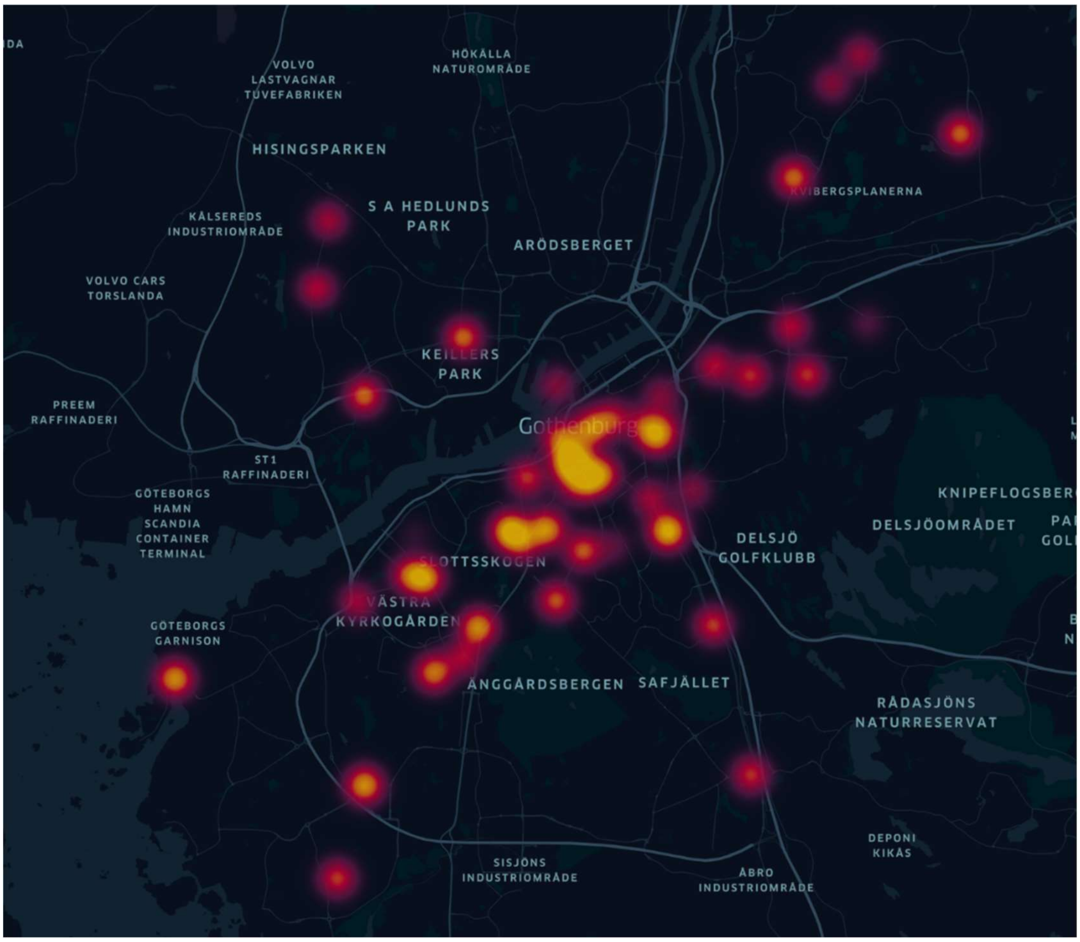


Figure 63: Heat Map – Maintenance Frequency of Switches

Figure 63 shows a heatmap based on the average frequency of maintenance events (inverse of MTBM) of switches at different locations in the track network. Figure 64 represents a point map showing the locations with switches and the mean time between maintenance for switches at these locations. It can be noticed that switches at locations near the center has a relatively higher maintenance frequency. The colors are coded according to the percentage of the total switches at a particular location considered for estimation (based on the data availability) and the radius represents the magnitude of the mean time between maintenance. It can be notice from figure 62 and 64 that there are few locations with a high time interval between maintenance events. However, caution should be exercised with these values since they are estimated based on a small number of work orders per switch.

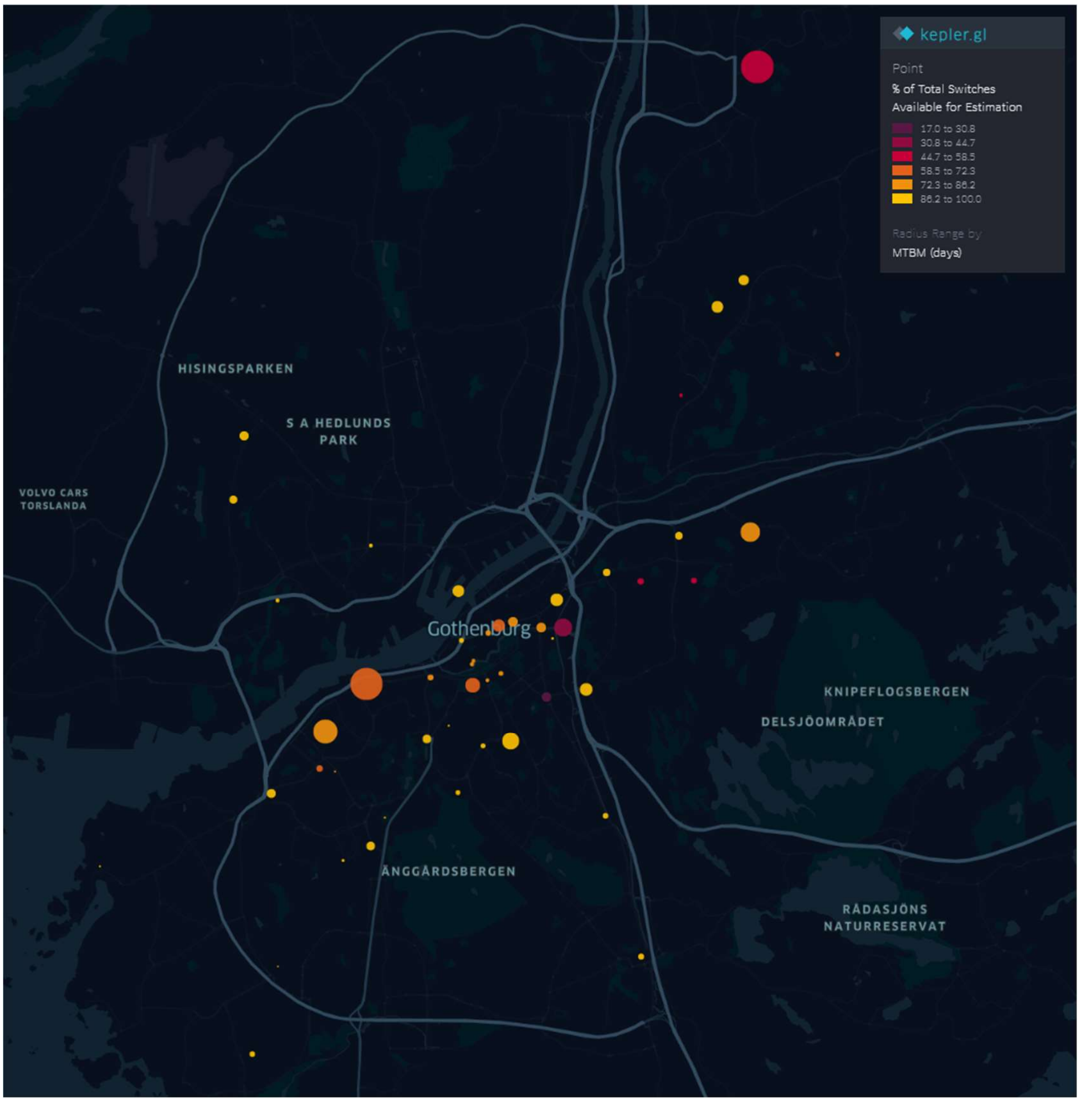
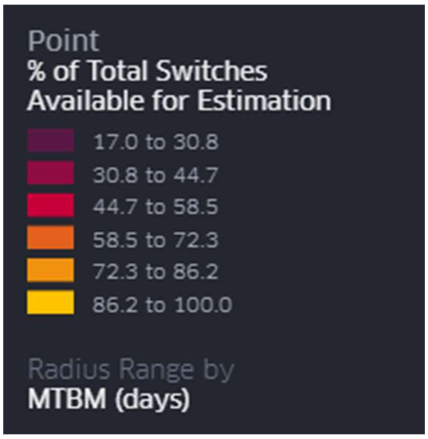


Figure 64: Point Map – Mean Time Between Maintenance Events



4.5 Results of Analysis of Track Restrictions Data

4.5.1 Reasons for restriction

A total of 144 restrictions occurred during the period under analysis (Jan 2020 – May 2022). There were primarily two types of operating restrictions – 99 speed limit restrictions and 45 non-speed limit restrictions like reversal ban. Approx. 90% of the non-speed limit restrictions were caused by faulty track switches. As shown figure 65, the most common reason for operating restrictions in the infrastructure were also faulty switches. There were speed restrictions of 5, 10, 15, 20, 30 and 40 km/h. However, as shown in figure 66, the majority were of 15 km/h. 86 speed restrictions had the speed limit set as 15 km/h.

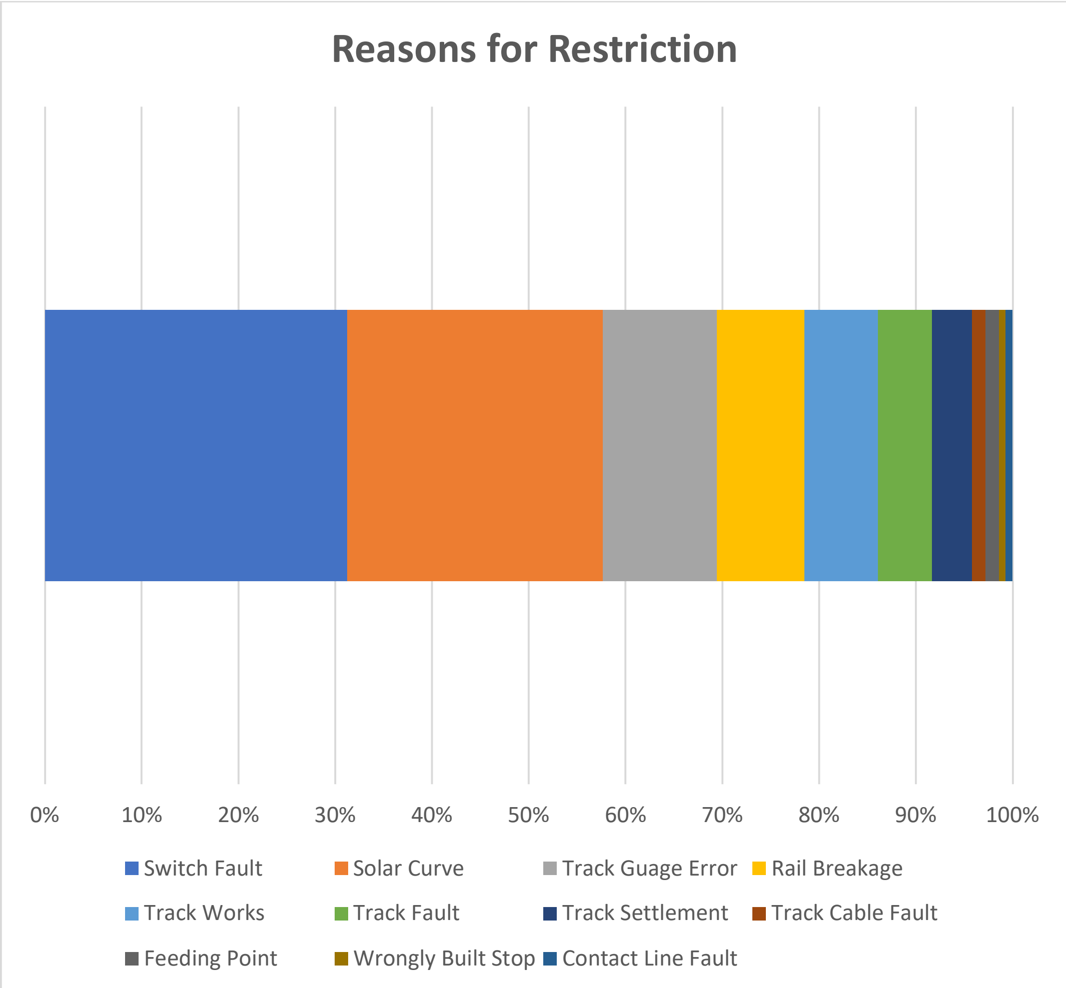


Figure 65: Reasons for track restrictions

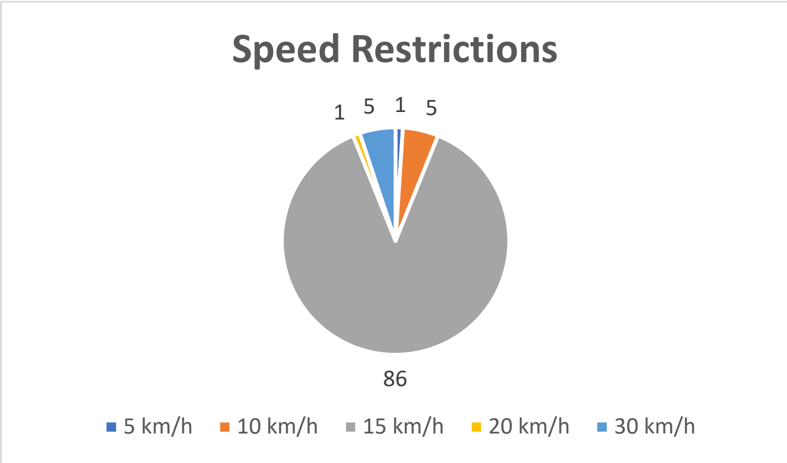


Figure 66: Proportion of different speed limit restrictions

4.5.2 Distribution of restrictions over time

The distribution of restrictions every month over the period under analysis was plotted and a pattern was noticed (see figure 67). The restrictions peaked during the months of June & July caused mainly by speed restrictions and trend remained the same in both 2021 and 2022. The reasons for restrictions were also plotted in a similar way and it was found that these peaks were caused by solar curves in the track (see figure 68).

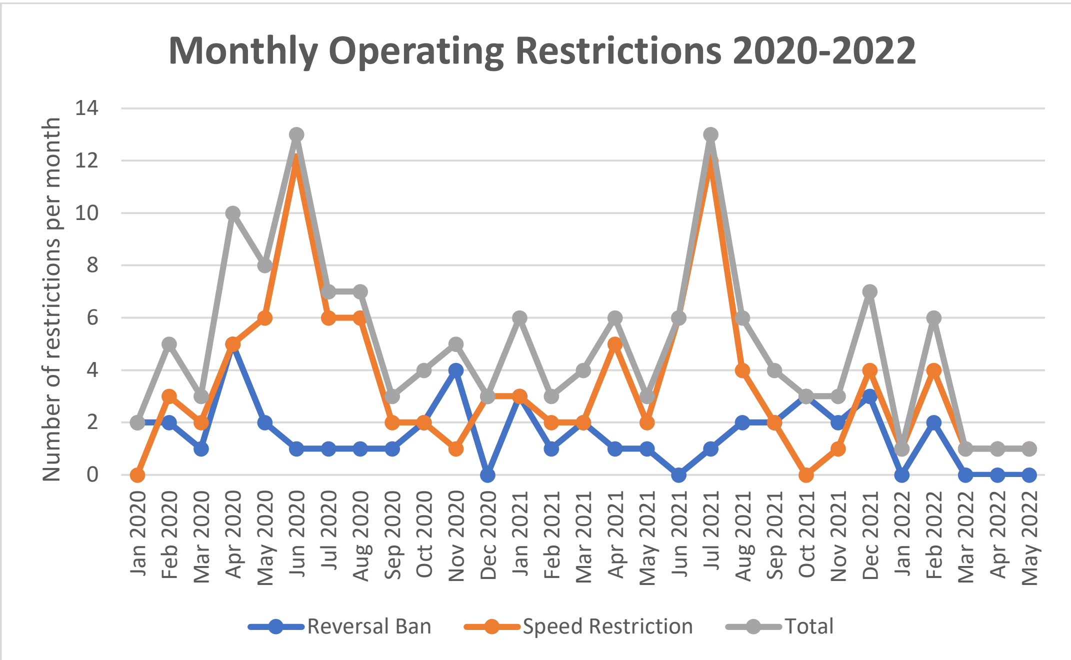


Figure 67: Operating restrictions over time

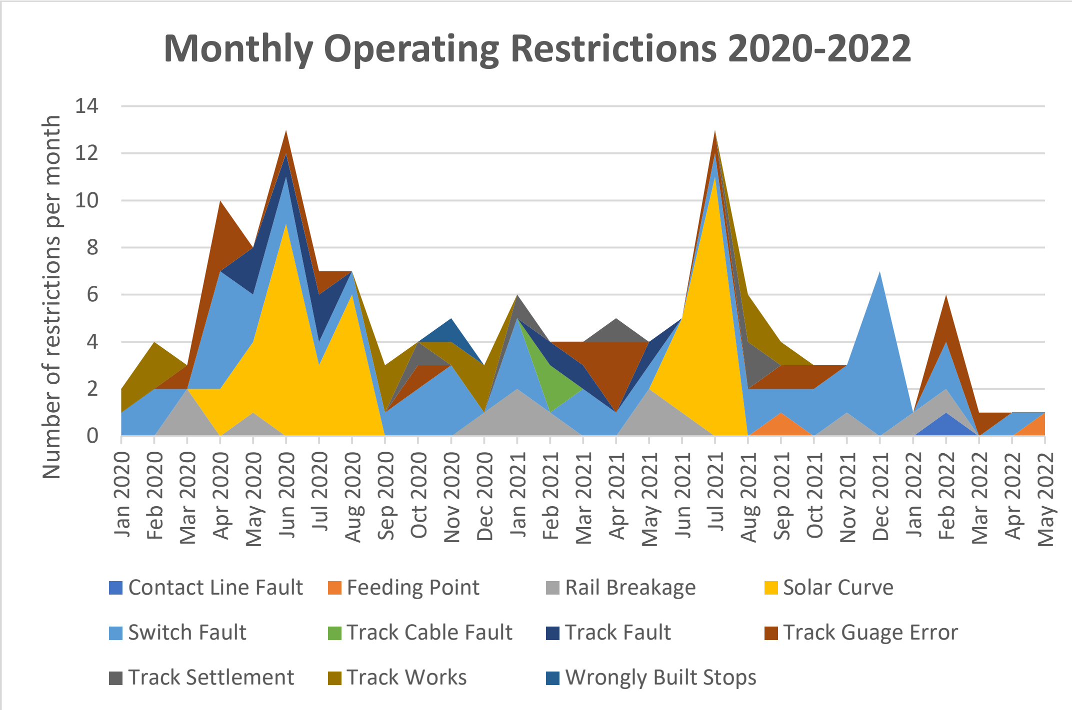


Figure 68: Operating restrictions over time (by reasons for restriction)

4.5.3 Restriction durations

The average duration of a restriction was around 47 days (70th percentile). When it comes to speed limit restrictions, the average was 38 days and for non-speed limit restrictions like reversal ban, it was 68 days. Generally, speed limit restrictions were having a relatively shorter duration compared to non-speed limit restrictions. There were few unusual observations with very high restriction durations and were treated as outliers. The outlier limit was set as sum of the third quartile and 1.5 times the interquartile range, which is 130 days. There were 13 such having a duration more than 130 days and the maximum duration was 396 days for a speed limit restriction related to a track fault. Excluding these outliers, the average duration of a restriction was 30 days, 26 days for a speed limit restriction and 40 days for a non-speed limit restriction. The average durations of restrictions which arouse from different reasons are shown in figure 69.

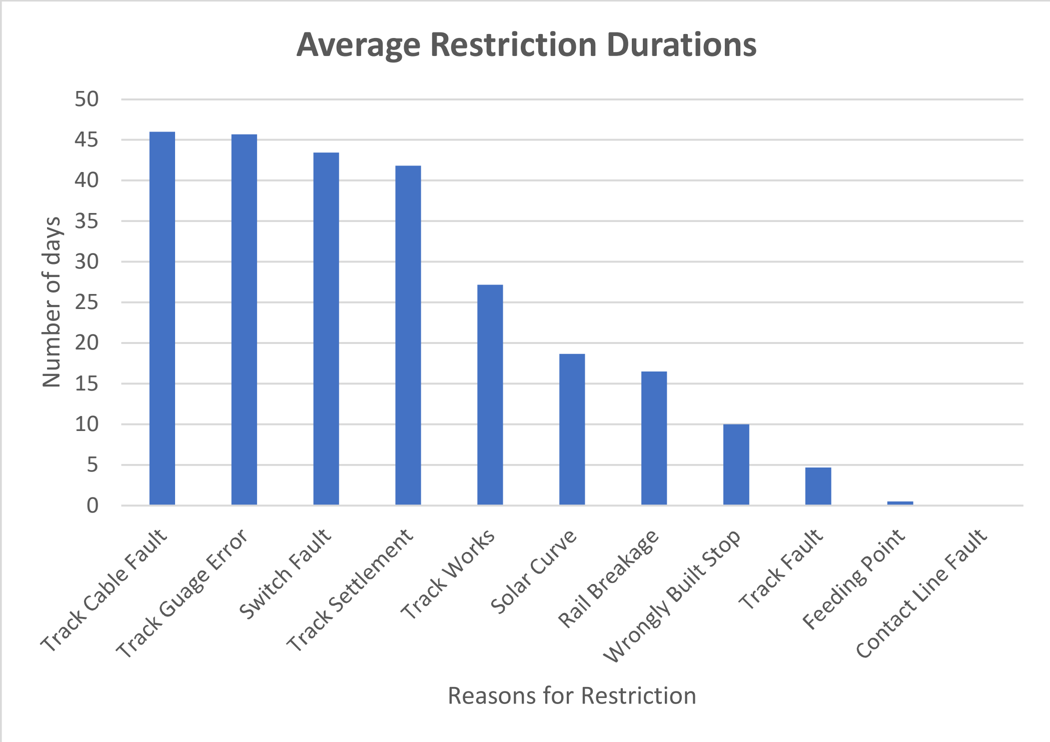


Figure 69: Average restriction durations by reasons for restriction

The most common reasons for restriction – faulty switches and solar curves, has an average restriction duration of 44 days and 19 days respectively. A restriction involving contact line which only occurred once since 2020 was just for a period of 2 hours, implying it was fixed almost immediately. Similarly, restrictions involving feeding point occurred only twice and was fixed in less than 2 days in both cases.

4.5.4 Impact of speed limit restrictions

Speed reductions in the tram network would have an impact on its accessibility, that is the extent to which it can be used [25]. Reduced speeds would increase the user's waiting times and travel times and disrupts the operating timetables. The delays incurred would result in additional operating costs and socio-economic costs. The background material of the administration plan for tramway facilities in Gothenburg and Mölndal shows an example of estimating the cost consequences of a 15km/h speed limit restriction applied to track sections intended to operate at 30 km/h and 60 km/h respectively.

According to the traffic office, a speed restriction affects 15 trips per hour (3 trips crossing a section every 12 minutes) and during a whole day of operation (20 hours), it affects 300 trips/day. When a speed restriction of 15km/h is applied on a 50m section intended to operate at speed of 60 km/h, results in a delay of 14.5 seconds per trip. Hence the total delay of such a restriction per day would be:

Average number of trips per hour * Number of hours of operation in a day * Delay per trip
=15 * 20 * 14.5 = 4350 seconds/day

During the period under analysis (June 2020 – May 2022), there were 86 speed limit restrictions of 15 km/h for an average duration of 40 days. Assuming that the reductions were on 60km/h sections for a length of at least 50m and it affects 300 trips in a day, the total delay would be:

Number of 15km/h speed restrictions * Average duration of the speed restriction * Delay per day = 4157 hours

According to the traffic office, the tram traffic operational cost is 1500 SEK/hour, and this delay translates to a cost impact of approximately 6.24 million in operating costs alone.

5 Discussion & Conclusion

5.1 Switching Operations

The proper functioning of track switching operations in any rail-based transport mode is necessary as failures in switching can lead to fatal accidents [94]. Based on analyzing the switching operations in Gothenburg's tram network, it was found that the system works quite well. The passage error rates denote the proportion of vehicle passages through a direction switching point where the registration or deregistration of vehicle presence in the blocking zones based on RFID tags didn't function as intended. When a vehicle is in the blocking zone, another vehicle cannot send a direction switching request until the vehicle in the blocking zone moves out and is deregistered by the RFID tags present at the exit of the blocking zone. The average vehicle passage error rates were quite low at 0.32% and the maximum being 0.99%. This indicates that such instances seldom happen except few outliers at the depots in Ringön and Majorna. The availability of switches for electrical operations were also very high at 99.7% and the rate of failed electrical operations was averaged at 0.04% which is very low.

The manual switching operations, which means instances where the tram driver uses a rod to manually change the track direction do happen but again at a low rate averaged at 1.6% compared with the number of electrical operations. The outliers with higher rate of manual operations were switches which are much less used. It would be beneficial for the operator to reduce the number of instances which require manual switching since it can cause operational delays which comes with cost consequences for both the operator and the user. There wasn't any information available on the data set regarding the time taken to perform a manual switching operation. It would be beneficial to estimate the total delay from manual switching and its cost consequences over a large period of time to determine whether any interference is required based on how significant the impact is or whether it is tolerable. It was also found there is no association between the number of failed electrical operations and manual switching which means the switches with greater number of failed electrical operations doesn't have more instances of manual switching or vice versa. Any further studies regarding this should focus on reducing the number of manual switching operations. Nevertheless, it can be concluded that the switching operations using the RFID-based SoftPrio system works satisfactorily.

5.2 Inspections and Work Orders

It was found that around half of the inspection data available had inconsistent date values which were counter intuitive and doesn't obey the logical conditions. This indicates that data is not entered correctly by the maintenance staff. For example, as per the Cityworks manual, the initiation date is automatically filled with the date when the data is entered into the system, whereas it is also possible to insert a custom date. There is a chance that some inspection records are being entered into the system later and the initiation date field gets automatically filled with the current date. The data quality is of great importance when it comes to making data-driven decisions. Wrong measurements would lead to incorrect insights. The tramway network owner may need to retrain the staff on properly using this platform or take necessary measures to ensure that data is being entered correctly keeping in mind that they can generate valuable business insights. The distribution of data was non-uniform and the rising trend in the distribution of data over years implies that the Cityworks platform is more used in the later years after its introduction and the employees might have taken some time to adapt to using this platform.

When measuring indicators like average inspection cycle times, very large outliers could be found (13% of the dataset) which might imply inspections getting delayed or data being incorrectly recorded. However, such observations were excluded from the data set to avoid bias. It was noticed that some activities such as periodic inspection of switches and track related inspection activities have high average inspection cycle times and indicates a significant delay in performing and closing an inspection once assigned. However, the average inspection cycle time is not an indicator of the actual required time to perform this inspection but rather the time between assignment and closure of an inspection and essentially a performance indicator of the maintenance teams. It was found that 75% of all the inspections performed had an inspection cycle time less than this average.

It is also noticed that the T_{ai} component in inspection cycle time (time between assignment and inspection) contributes the significant part of the inspection cycle time, which means there is a larger delay in performing the inspection after it has been assigned. T_{ic} is assumed as the time to perform an inspection. The operator should target to reduce the T_{ai} times or keep this metric within the acceptable limits according to the time buffer associated with the inspections. There was no information available in the dataset regarding any time buffer for each type of inspection. It is assumed that the data after the removal of date inconsistencies is correct. The importance of data accuracy needs to be stressed, otherwise these estimates would be wrong. Hence, it is concluded that average inspection cycle time can be a performance indicator for the maintenance teams measuring their responsiveness to an inspection request and time efficiency to perform an inspection activity.

The planned durations for an inspection activity were established simply based on the planned start and finish date values available for previous inspections. Despite, the same inspection for the same asset type having different durations, the minimum duration was considered as the planned duration assuming it was possible to perform that inspection within this time. However, it was not clear whether this duration is equivalent to the inspection cycle time, or the actual time required to perform an inspection. It was assumed that are synonymous to the inspection cycle times and the average inspection cycle times for inspections performed were compared against the established planned durations. It was found that all the inspection types had an a much higher actual average inspection cycle time than the planned durations. Also, the proportion of inspections performed during 2021-2022 having inspection cycle times greater than the planned durations were very high averaging at 97%. This clearly states an underperformance by the maintenance teams. However, the concerned authority should reassess whether the planned durations are realistic, if not, modify it to realistic values based on experience and expertise and use it as a benchmark to monitor the performance of maintenance teams or even use average inspection cycle time as a benchmark to monitor the proportion of inspections deviating from this value.

When the actual frequency of different inspection types was compared against the recommended inspection frequencies as mentioned in the administration plan, it was found that the contact line and switch inspections are performed at a much lesser frequency than the recommendation, even in the case of directed inspections at traffic intensive areas. This also shows an underperformance of the maintenance teams.

Asset condition if not found satisfactory results in a work order to bring the asset condition to acceptable levels. More than half of the track related inspections resulted in a work order whereas relatively smaller number of inspections related to the catenary system resulted in a work order. Most of track related work orders resulted from track geometry issues at switches rather than general safety and maintenance inspection of tram tracks. The highest proportion of track work orders arising from inspections were primarily handled by the welding group. The primary cause of work orders in contact lines were point wear and issues related to suspension of contact lines. When it comes to track geometry at switches, the defects were primarily with the tongue rail of at the switch followed by other rail defects and regarding safety and maintenance inspections at tracks, the most common defect was related to track settlement, followed by other rail defects and issues with track sleepers. Asphalt and track settlement issues were most common in traffic classes 3 and 4 and may be attributed to higher wagon passages rates in these classes. It is important to monitor the proportion of total work orders arising from each asset type and the type of defect to better plan the maintenance activities, prioritize the allocation of resources and ensure adequate inventory levels.

Similar data quality issues were found in the work order data set as well like date inconsistencies, non-uniform distribution of data indicating more usage of the maintenance management platform in the recent years and several outliers based on work order cycle times. Apart from this, in the work order data set, it was unable to link a work order to an inspection or a service request as there were many records with missing inspection or service request IDs. The work order cycle time was defined as the total time incurred between assignment of a work order to the maintenance team and its completion. Like inspection cycle times, it is also a performance indicator of the maintenance teams. However, the time incurred between the assignment of a work order and the actual start of a work order was not available which could have been an indicator of responsiveness by the maintenance teams. The average work order cycle time was estimated on a categorical level rather than on a fault level since it was difficult to do so due to redundant labeling of the failure modes in the data set available. Based on the average values, it was found that work orders assigned to the track maintenance group takes the most time to finish whereas the work orders assigned to switch mechanics maintenance group are carried in at a much shorter duration. This can be due to track related work orders are more time consuming than switch mechanics work orders and doesn't mean than one group is performing better over the other.

The average work order cycle times and the actual work order cycle times were compared, and a cumulative distribution curve of work order cycle times was plotted. More than three-fourth of the contact work line orders had a cycle time less than or equal to the average work order cycle time for contact lines and 66% of the work orders in track, welding and switches category had a work order cycle time less than the average. As a data-driven approach, the concerned authority can use this average as a benchmark to monitor the proportion of work orders deviating from this value and intervene in case of unsatisfactory performance. However, these benchmarks should be evaluated by subject matter experts and if not found realistic or having a high time buffer than required, the optimal work order cycle times should be established based on experience and expertise, since the reliability of these values are very dependent on the data quality.

The mean time between maintenance is an indicator of the frequency of occurrence of a defect in an asset or the frequency of a maintenance activity being carried out on an asset. This value is a data-driven benchmark to anticipate a defective asset followed by maintenance downtime. This measure can be used to better plan maintenance events and avoid any unplanned disruptions. However, the estimates in this project were carried out on a broader asset category level rather than on an asset type level due to the unavailability of enough data points on defects and past maintenance events. Hence, caution should be exercise when using these values as a benchmark.

Owing to questionable data quality, the author would recommend using the results from this thesis as a guide to identify the shortcomings in data collection to properly estimate the maintenance performance indicators mentioned and take adequate measures to resolve such issues rather than directly utilizing these estimates without further evaluation and scrutiny. As stated in a report by McKinsey in 2017, the operators need to combine the expert knowledge in railway engineering and advanced analytics to develop robust and promising analytics models for maintenance rather than pure analytical approach. The author recommends future data mining projects in Gothenburg Tramways should be done with effective collaboration between the data scientists, concerned staff and subject matter experts. Further studies should focus on how the advancements in digital technologies can be utilized to improve the data collection and perform real time analytics estimating various performance indicators but not limited to ones mentioned in this thesis, to better monitor and control the maintenance operations. A few other maintenance related performance indicators which could be measured are unscheduled downtime, maintenance costs per vehicle kilometer traversed, availability, schedule adherence and mean time to acknowledge, respond or repair a fault with better granularity on date data collection [93] [114] [115]. Studies should also be conducted on organizational acceptance of digital solutions and what measures should be taken to improve its penetration in the organization.

As detailed in the previous sections, there are many advancements in digitalization in the transport sector especially in maintenance and asset management. Several leading companies like ABB, Siemens, Alstom, and CAF offers remote conditioning monitoring of assets and predictive maintenance solutions through their cloud-based big data analytics platforms. There are several cases where modern predictive maintenance solutions have been successfully implemented in large rail networks across Europe, especially with rolling stock and similar approaches in public transport bus fleet management. But there are not enough examples when it comes to trams. Currently the rolling stock fleet of Gothenburg Tramways comprises of vehicles of different generations. However, the economic feasibility of employing such real time condition monitoring systems in Gothenburg's tram network should be studied as the rolling stock fleet is getting upgraded with modern trams from Alstom. When it comes to tram track infrastructure, few studies have been conducted on it, and the author would like to point out the tram track degradation model presented by Falamarzi, Moridpour and Nazem (2019) which made accurate predictions of track degradation in Melbourne's tram system [95]. The model predicts the degradation indices of different track segments enabling the facility manager to better plan maintenance work. A similar approach could be carried out and tested in Gothenburg using the past track geometry deviations and recording vehicle acceleration data. Had the associated costs with maintenance activities been available, an approach similar to De Carlo and Arleo (2013) could be attempted to find the best maintenance strategy for each asset type that minimizes the average cost of maintenance per unit time [77].

5.3 Track Restrictions

Track restrictions are caused by unscheduled maintenance activities. Faulty switches were identified as the most common reason for operating restrictions in the tram network, majority of them resulting in non-speed limit restrictions. Speed limit restrictions which formed the majority of all restrictions, resulted from other track defects. When analyzing the restrictions over the last two years, it peaked in the relatively hot summer months on June and July and the primary cause of this was solar curves. It was the most common cause of a restriction after faulty switches. Solar curves occur in tracks when the heat of the sun rises the rail temperature resulting in its deformation [116]. This can cause derailments and poses an important safety concern. Around 40% of all the speed restrictions during the period under analysis was due to solar curves. As discussed, there is a trend of solar curves occurring during the summer months and the readiness of the maintenance teams should be ensured ahead of time to handle them. This might be already the case since the average duration of restrictions resulting from solar curves is 19 days and is relatively low. However, the tram network owner should always try to reduce this duration or unscheduled downtime since any track restriction leads to operational delays translating into economic consequences. A rough estimate of operating cost impacts alone due to 15 km/h speed restrictions during the period under analysis was big in monetary terms. Hence, it is very important to fix the faults that cause track restrictions in the shortest time possible which would require better maintenance planning and readiness in terms of labor, material, and equipment.

5.4 Delimitations

The delimitations of this master thesis project are listed below:

- There was a delay in gaining access to the data.
- There was no clarity on the type of data that would be made available from the client in the beginning, and access to different data sources were obtained at different phases of the thesis project timeline.
- The data quality was questionable especially on the maintenance related data sets. There was considerable amount of missing data, uneven distribution of data over the years, redundant classification, other discrepancies and too less data points for certain estimations. Hence, estimations made in this analysis should be took with caution.
- The maintenance data was made available only for the tram network infrastructure and not for the rolling stock, the most important subsystem of a rail-based transport system.
- The maintenance data on tracks didn't have any information on the track geometry measurements with which the author could have attempted to build a prediction model on track degradation based on [91].
- The maintenance data sets didn't had any information on the costs associated with each activity with which an approach similar to [74] could have been done.
- Also, there were no relevant fields in these data sets with which any kind of prediction model could have been built. Hence, the thesis focuses on a descriptive approach.
- The author could spot a yearly seasonality in the number of restrictions in the track network every month over a period of two years. However, there was not enough data points to build a robust time-series model.

5.5 Thesis Placement

This master's thesis was carried out in collaboration with Trivector Traffic AB, Gothenburg, Sweden. They are a leading firm providing consulting and research and development services in the transport sector, for over 20 years across Europe. The company is headquartered in Lund, with other offices in Stockholm, Gothenburg and Luleå.

The thesis was part of a bigger project on the digital transformation of Gothenburg's tram system awarded to Trivector by the City of Gothenburg which kicked off in February 2022. The project was divided into three phases and the author was part of the five-member project team at Trivector. The three phases were background analysis, development of strategy and plan for digitalization and proposals for implementation and governance respectively. It included a fast-track phase which analyses the existing available data sets with its results to be fed back to the primary investigation. The project team met twice every month where project progress is presented and discussed, and action plan for the coming two weeks are established. The author was primarily involved in the background analysis on digitalization in the transport sector and the in-depth analysis of the existing data sets. The author also participated in meetings with representatives from the traffic office of the City of Gothenburg as part of the project.

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A. Interview Questions with Alstom Representative

Date	27-04-2022
Interviewer	Bilal Baiju, Aalto University, Finland
Interviewee	Michael Thulin, Alstom, Sweden

1. What are the big challenges in digitalization when it comes to trains and trams?

2. Does the level of automation and digitalization differ in different countries? If yes, why is that? Only because of the cost or are there some more factors (e.g., tram's lifespan)?

3. The data coming in from the system, how do you handle that information? What do you do with it?

4. What are the main differences with digitalization between buses and trams?

5. What digital solutions does Alstom offer in their LRT vehicles improving passenger experience?

6. What digital solutions does Alstom offer in their LRT vehicles to facilitate energy efficiency and eco-driving?

7. What kind of driver assistance and safety systems are available on Alstom LRT vehicles?

8. What is the level of automation is offered in Alstom's latest generation LRT vehicles?

9. What are the signaling solutions Alstom offers when it comes to LRT? Do the vehicles have onboard technology enabling vehicle to vehicle communication? Is there a particular signaling standard in case of trams like ERTMS in rail transport?

10. Do the trams come preinstalled with necessary sensors onboard collecting data to enable condition monitoring and predictive maintenance?

11. Is it possible to retrofit older generations of rolling stock with Alstom's condition monitoring technology and integrate it to the analytics platform?

12. Does Alstom LRT vehicles have smart solutions when it comes to passenger movement tracking? How does it measure the vehicle occupancy?

13. What are the potential cybersecurity threats that digitalization in light rail would bring and what solutions does Alstom have in tackling this?

14. What degree of infrastructure does the public transport operator need to have to benefit the full potential of Alstom LRT's digital solutions or does it offer a complete cloud-based service? Any additional investment in wayside equipment is needed?

15. Do the trams have vehicle-to-vehicle communication systems or wayside equipment to improve the operations by running at optimal headways and speed?

16. How does Alstom use geofencing with trams, say when placing driving restrictions in areas with complex and high traffic density?