Shared Mobility to Compensate for Public Transport Demand under the impacts of a pandemic crisis:

The Case of Bike Sharing System in Milan during COVID–19 pandemic

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The Case of Bike Sharing System in Milan during COVID–19 pandemic

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Abstract

The COVID-19 pandemic poses an unprecedented challenge for the public transport system. The capacity of the transport system has been significantly reduced due to the imposition of social distancing measures to reduce the spread of the coronavirus. People remain skeptical about the use of public transport and prefer alternatives for their transportation as the likelihood of the virus spreading through public transport is high. Therefore, new avenues to increase the resilience of public urban mobility need to be explored. This research proposes the integration of the bike sharing system into the existing public transport system to compensate for public transport demand under the disruptive impacts of the COVID-19 pandemic. To achieve this, a two-part methodology is developed. The first part concerns the development of a mathematical model for the demand integration of the two systems. The demand for the public transport system, which cannot be serviced by the system due to the distancing measures (distance of 1.5 meters between passengers), is considered as unsatisfied demand and is the new additional demand for the bike sharing system. The second part concerns the development of an optimization model for the design and operation of a bike sharing system with features that can cope with the mobility needs of the pandemic. These features of the bike sharing system are the mixed fleet, i.e., the system will provide the mode options of bike and e-bike, and the hybrid in its design, i.e., the bike system will be a free-floating system while the e-bike system will be docked. The developed methodology is applied in the case study of the Milan city in Italy. The two studied systems are the subway system and the public bike sharing system of Milan. For the implementation of the developed methodology, three demand scenarios and fifteen designs that reflect the needs of the bike sharing system are created. The parameters that differ in the designs are the number and location of the new (virtual) stations, the number of the maximum number of available bikes in the virtual stations of the bike system and the capacity specifications (number of docks) in the e-bikes stations. The selected locations of the new (virtual) stations in the designs are close to subway stations with unsatisfied demand. The obtained results show that 30% of the demand for the evening peak hour of the subway system in Milan cannot be satisfied due to distancing measures and that the current public bike sharing system can only compensate for 6% of the new demand (unsatisfied demand of public transport system and its own demand). However, the mobility capacity increases based on the system's features. The separation of the bike sharing system into a free-floating bike system and a docked e-bike system increases the covered demand at least twice (2.1-2.4 times). Moreover, an increase of the capacity specifications of the e-stations and the available bikes in virtual stations by 60% brings an additional increase of the covered demand by 6.5-7.5%. Despite the increased mobility capacity of the system with the incorporation of the mentioned features, to fully cover the bike system demand it is needed 30959 bikes, while 20445 e-bikes are needed for 70% coverage of e-bikes demand. In addition, there is no limit to the available bikes per station and the maximum number of docks per e-station is 200. It is concluded that the bike sharing system cannot fully counterbalance for limited capacity in the public transport system. These findings contribute worthwhile insights into the mobility capacity of the integrated public transport system during the pandemic and where the operators of both systems should give emphasis.

Keywords • Pandemic •COVID-19 •Public transport •Bike sharing •Resilience •Linear Programming Model •Milan

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1. Introduction

The global impact of coronavirus disease 2019 (COVID-19) has been established. The epidemic of COVID-19 was reported as pneumonia to the World Health Organization (WHO) on 31st December 2019 (WHO, 2020). Due to the high contagiousness of the virus, the WHO acclaimed the outbreak as a pandemic on 11th March 2020 (WHO, 2020). The main goal during a pandemic is to control and reduce the transmission of the virus. Measures and tactics such quarantine, lockdown, social distancing, travel restrictions, closing of restaurants and schools, and isolation help to reduce the spread of coronaviruses and were followed by many governments (de Haas, Faber, & Hamersma, 2020; De Vos, 2020; Qureshi, Suri, Chu, Suri, & Suri, 2021). Coronavirus measures, as well as people's prejudice against small and closed spaces, have greatly affected the public transport sector.

During the lockdown period of the first pandemic wave, public transport demand plummeted (ITF-OECD, 2020; Jenelius & Cebecauer, 2020). This drop in demand was due to the increased rates of e-learning and work from home as well as the closure of many stores and the annulment of numerous events. The result of the reduced demand was the reprogramming and the reduction in the frequencies of public transport services. Belgium, for example, reduced public transport services by about 75%, while Slovakia implemented a national transport program like that of weekends (ECDC, 2020). The New York transportation authority followed a similar tactic by reducing its services by at least 25% and modifying some subway lines (Goldbaum, 2020). Regarding Italy, the Ministry of Infrastructure and Transport has rationalized interregional services by changing and reducing non-scheduled services (Ministero delle Infrastrutture e dei Trasporti, 2020a). In addition, train services were rescheduled (Ministero delle Infrastrutture e dei Trasporti, 2020b) and there were no evening services (Ministero delle Infrastrutture e dei Trasporti, 2020c). However, a satisfactory level of service was sustained (Ministero delle Infrastrutture e dei Trasporti, 2020b). Transport for London (TfL) shut down the night overground service a few days a week and about 40 non-hub stations stopped operating, while in Valencia, Spain, public transport services operated at 65% of the usual services and there were no evening services on weekends (UITP, 2020).

The public transport sector is affected throughout the pandemic. The transmission of the COVID-19 virus on public transport modes is high. This is because the virus belongs to the category of respiratory viruses and is transmitted through the infectious aerosol which can accumulate over time in an enclosed place (Prather et al., (2020)). This fact affects the mobility capacity of public transport but also the transportation mode choice of commuters. Firstly, to reduce the transmission of the virus indoors, measures of social distancing (1-2 meters between people) are imposed, which greatly affect the mobility capacity of public transport. The capacity of a 48-passenger bus, for example, will be reduced to 11 passengers after the implementation of social distancing measures (ITF-OECD, 2020). Considering the metro (Washington DC metro), the implementation of the 1.5-meter distance will reduce the train's capacity by about 80%. While, if the measure of 1-meter or 2-meters distance is applied, the capacity reduction will be about 60% and 90%, respectively (Krishnakumari & Cats, 2020). In addition, people will be skeptical about the use of public transport and many of them would prefer an alternative for their transportation due to the high transmissibility of the virus in them. Specific group of people, like elderlies, are more prone and vulnerable to virus exposure (Yu et al., (2020)). Therefore, many people belonging to vulnerable health groups will look for an alternative for their transportation. The above reasons are challenges for the public transport sector.

1.1. Problem statement

The limited capacity of public transport due to the COVID-19 distancing measures (distance of 1.5 meters between passengers), the fear of people as well as the gradual return to normal rhythms and living conditions will lead the public transport system to an unprecedented state. The main feature of this state will be the excessive demand which will not be satisfied by the existing public transport system and will push for a transport alternative where people will be able to move in a safe and healthy way. There are several alternatives that can be integrated into public transport to create a system that can handle the new COVID-19 situation. However, traffic congestion in most cities and air pollution are prompting the choice of a green alternative that does not burden the network too much. In addition, Saberi et al. (2018) study concludes that integrating bike sharing system into the public transport system increase the system's resilience to disruptive events (e.g. strikes) and that there are already cities that plan to implement such systems. Taking into consideration the above, the alternative that is proposed to integrated in terms of mobility capacity, i.e., transport capacity supply and alternative way of transportation, with public transport system is the bike sharing system. With this mobility capacity integration and its efficient design and operation, a public transport system will be created that will be prepared to deal with excessive demand due to the COVID-19 measures.

The main challenge in implementing this integrated alternative is the way of designing and operating the bike sharing system to provide safe mobility for all unsatisfied demand. The unsatisfied demand will be the result of the assumption that demand exceeding the capacity implied by the 1.5 meters in public transport will not be allowed to board. This implies that the existing resources and the potential new resources of bike sharing system should be managed in such a way that the overall public transport system will operate efficiently under social distancing constraints. One of the main factors to be addressed is the bike fleet sizing that will be needed to meet the system's capacity needs after the effects of COVID-19 on the current public transport system. Increasing the number of bike fleet means that more parking slots and stations should be created. Therefore, the station location decision for the most efficient system design is added. In addition to the design of bike sharing system, we should also consider its operation. The main factor to consider is the relocation of the bike fleet to the bike stations according to the demand needs of each of them. The final step is to find the optimal features for the design and operation of the system including the conditions imposed by the COVID-19 measures. More specifically, the COVID-19 distancing measures will lead to unsatisfied demand since the demand exceeding the capacity implied by the 1.5 meters in public transport will not be allowed to board. The demand and mobility capacity integration of the bike sharing system into the public transport may solve the problem of unsatisfied demand which is caused by the distancing measures. Unsatisfied demand due to COVID-19 distancing measures is the input to the optimization model of the bike sharing system. Other factors related to the specific case of the COVID-19 situation that should be considered are the different categories of people (e.g., young, elderlies, vulnerable health people) and their needs (e.g., bike or e-bikes), the disinfection of the fleet, the additional costs of the system.

The literature presents several studies regarding the effective design and operation of bike sharing systems (Caggiani, Camporeale, Dimitrijević, & Vidović, 2020; Chen, Liu, & Liu, 2018; Frade & Ribeiro, 2015; Lu, 2016; Martinez, Caetano, Eiró, & Cruz, 2012; Saharidis, Fragkogios, & Zygouri, 2014; Sayarshad, Tavassoli, & Zhao, 2012; Sun, Li, & Zuo, 2019; Yan, Lin, Chen, & Xie, 2017). These methods vary in how they approach and optimize the design and operation of the bike sharing system. Most of these studies consider some of the various costs associated with a bike sharing system in their models' formulation.

Moreover, the only study that includes a mixed fleet ,i.e., bike and e-bike, in its formulation is the study of Martinez et al. (2012). All the above reported research study either free-floating or docked bike sharing systems. Therefore, they cannot cope with the features of the COVID-19 extreme situation. These methods do not consider the measures of social distancing and how they affect the capacity of public transport system, the mobility capacity integration of public transport and bike sharing system for solving the unpredictable increase of unsatisfied demand, and the required sanitation measures.

The present research will focus on the optimal design and operation of a hybrid mixed-fleet bike sharing system. The features of the mixed fleet-bike and e-bike-and the hybridity-free floating bike system and docked e-bike system-of the system are due to the needs arising from the pandemic situation. The main goal is to create an integrated in terms of demand and mobility capacity public transport system, i.e., public transport (i.e., subway, trams) and bike sharing system. That is, the study deals with the creation of a resilient public transport system that can provide mobility capacity in extreme and special situations. The prospect of approaching the problem will be supply-oriented.

1.2. Research objective and research questions

The main objective of this study is to create an integrated alternative solution of public transport system which will ensure a reduced exposure risk to the virus and be able to counterbalance the limited mobility capacity of the existing public transport system due to distancing measures. The aim of this research is to explore the impacts of social distancing measures during the pandemic period on the mobility capacity in public transport system. And then optimize the design and operation of the proposed alternative system based on aspects of the pandemic situation to maintain mobility capacity in public transport system.

Therefore, the research objectives have been formulated into the following main question:

"How can we maintain mobility capacity in public transport under the impacts of social distancing constraints, investigating the case of bike sharing mobility capacity for COVID-19 conditions?"

This question can be decomposed in the following sub questions:

1. How are social distancing measures limiting the mobility capacity in public transport system?
2. To what extent can a bike sharing system counterbalance for limited capacity in the public transport system?
3. How can the selected COVID-19 aspects be adapted to the developed optimization model of bike sharing systems?
4. To which extent these findings can be generalized?

1.3. Research scope

This section describes the scope of this research, i.e., defines the boundaries of the research. The options that define this research are:

- This research refers to two transport system which are the public transport system and the bike sharing system. However, no changes will be made to the public transport system due to time constraints. Public transport lines and their timetable will remain the same.

- In the case of the public transport system, the case study of this research will focus on the subway system. A subway network usually consists of few lines compared to other public transport systems whose line network is more extensive. Therefore, it is easier to understand its impact and study it. Regarding this research, the case study concerns the city of Milan. Milan's public transport system consists of a network of metro, buses, trams, and trolleys. In 2019 the passengers of the public transport system were 820.4 million. About 50% of passengers used the subway (ATM bilancio finanziario 2019, 2021). The metro in Milan is therefore the most common choice of passengers and can be considered the most important means of public transport.
- Users' movements are between public transport system stations. This means that the original origin and final destination of the commuters are not known. This may lead to the assignment of commuters to bike stations located close to public transport stations rather than to bike stations that may be closer to the origin and destination of their overall route. Therefore, there may be a shift in demand between stations.
- The choice of means of transport for users is between public transport and the bike sharing system. Other means of transport such as car or private bike will not be available as options for the users.

1.4. Societal and scientific relevance

The research conducted in this thesis has contributed to societal relevance. The result of this thesis provides an integrated public transport system that seeks to address the impacts of the pandemic in terms of mobility capacity on the existing public transport system. The demand and mobility capacity integration of the bike sharing system in the public transport system and the improved design and operation of the bike sharing system will offer a safe transport option to all the users and their movements will not be limited. The goal of this integration is to create a resilient public transport system that can meet the transport requirements during the pandemic. The integration of the public transport and bike sharing systems will also be beneficial in the post-pandemic period. A resilient public transport system will be able to cope with special transport situations such as a strike in the motorized public transport system and mass events. In addition, an improved system could attract users of other means of transport such as the private car. This might lead to a reduction in traffic congestion and thus a reduction in pollution and an increase in the sustainability of the city. The improved system might be an opportunity for elderlies to increase their mobility and not be isolated from society.

This research also has a scientific relevance. It contributes to the existing literature in the field of public transport during pandemics. This research aims to create a public transport system that can meet the transportation needs of people during the pandemic with reduced exposure to the virus. The research provides insight into how pandemic social distancing measures affect the mobility capacity of the public transport system and whether a mobility capacity integrated transport system-public transport and bike sharing systems-can maintain capacity under the pandemic circumstances. In addition, an optimization model is developed in this study aiming at the effective design and operation of a hybrid mixed-fleet bike sharing system. This optimization model will study whether a bike sharing system can compensate for the limited capacity in the motorized public transport system due to distancing constraints.

1.5. Research approach

This section provides the methodology for answering the sub questions of this thesis. A more detailed explanation of the developed modeling methodology is provided in Section 3.1.

The first sub question is related to the connection between the existing social distancing measures due to COVID-19 pandemic and the mobility capacity in public transport systems in different counties, states, or cities. This step applies literature research and desk research. The factors to consider during research are social distancing measures due to COVID-19 pandemic situation and the capacity restriction on public transport system. The collection and the deliberation of various cases will give a good overview of the general situation. Based on this collected information, the way in which social distancing measures affect capacity and disrupt the operation of public transport system can be understood.

It has already been mentioned that the bike sharing system will be operational integrated into the current public transport system. More specifically, this integration concerns the demand and mobility capacity provided by the public transport system. Thus, the next step is to determine the demand of the two systems, i.e., motorized public transport system and bike sharing system, considering the distancing measures that apply on the motorized public transport system and the new bike network. The basic assumption is that demand exceeding the capacity implied by the 1.5 meters in public transport will not be allowed to board. This unsatisfied demand will be the new demand for the bike sharing system. After the separation of demand in the two systems, the optimization model for the design and the operation of the hybrid mixed-fleet bike sharing system will be developed.

The next step corresponds to the analysis of the case study and the implementation of the developed approach in the case study. The case study is the city of Milan in Italy. The two systems under study are the subway system and the public bike sharing system. Based on the analysis of the given data for the bike sharing system, the needs that exist in the system will be more understood. The system's needs and the needs that will arise from the social distancing constraints will be the input information to create the various designs and demand scenarios. The main purpose is to understand the design and operation needs of the bike-sharing system in order to compensate for the limited capacity in the public transport system. There are different types of demand scenarios. The main distinction is between the demand scenarios for the normal state of the transport system and the demand scenario for the pandemic year. A bike sharing system is not in constant demand every day. Therefore, this fluctuation in demand will be studied by creating different demand scenarios. The characteristics of the bike sharing system will be reflected in the designs. The variables that will change in the designs are the number of stations in the system, the location of some stations and the values of the capacity parameters and available bikes in the stations. These scenarios and designs will be the input into the optimization model. Further analysis will find which features of the bike sharing system are more effective to compensate for the limited capacity in the public transport system.

The last step is to answer the 4th sub-question which is related to the possibility of generalizing the findings of the above approach. To answer this question, it should be kept in mind that case studies and public transport systems have similarities but also differences. The researcher will have to consider several things. Some of these are whether the development of the methodology is based on general principles or is relevant to the specific case study, whether the provision of additional mobility capacity with bike sharing systems can be applied to other cities and whether the alternative could be extended to the application of other shared mobility systems such as scooters or cars. By using critical mind, answers will be given to the above thoughts and the sub-question 4.

1.6. Report outline

The outline of the remaining thesis report is introduced in Figure 1-1. The literature review in Chapter 2 provides information about the public transport systems and the impacts of the pandemic, the bike sharing systems, the integration of bike sharing and public transport systems and approaches for the design and operation of bike sharing systems. In Chapter 3, the developed methodology is analyzed. On the one hand, the demand integration of the two systems is analyzed and on the other hand, the optimization model for the bike sharing system is described. Chapter 4 presents the case study which is the subway and public bike sharing systems in the city center of Milan, the implementation of the developed approach in the case study of Milan as well as the analysis and interpretation of the results. The last chapter, which is chapter 5, mentions the conclusions of the study and recommendations for further research.

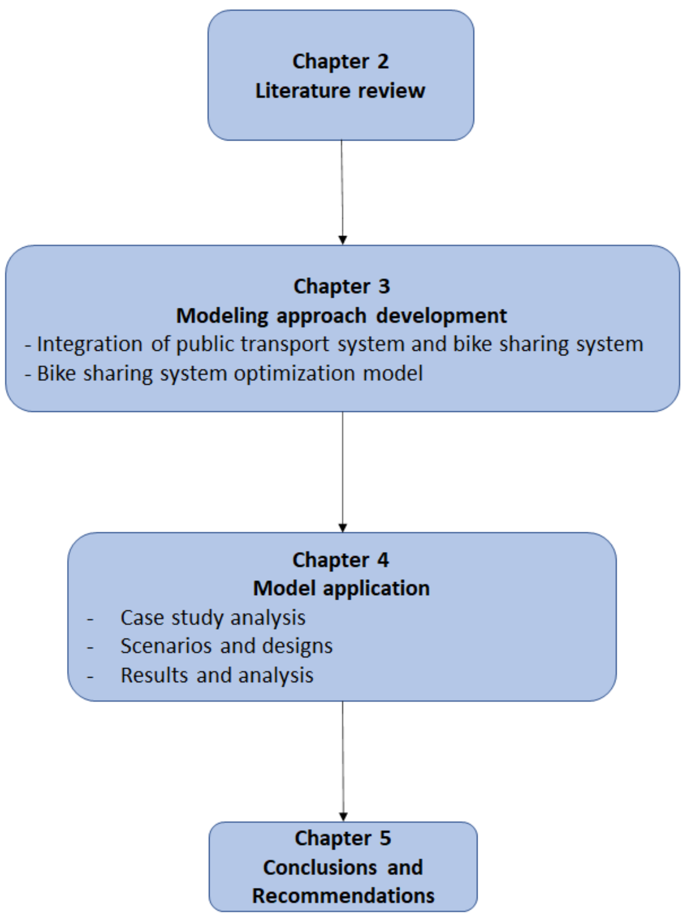

Figure 1-1: Thesis outline

2. Literature review

This section presents useful information and background work that has been on the field of this research. The aim is to understand how the social distancing measures affect the mobility capacity of public transport system and the relation that may exist between public transport and bike sharing systems. In addition, a broader insight into approaches to the design and operation of a bike sharing system is sought. Online libraries containing scientific research are used to prepare this literature review. These online libraries are Science Direct and Google Scholar. Some of the keywords used to find relevant literature are "bike sharing system design", "bike sharing system operation", "bike sharing system optimization model", "bike", "e-bike", "integration of public transport and bike sharing systems", "Covid-19", "Covid-19 and public transport capacity", "distancing measures". With searching these keywords, many interesting and related papers were found. Even more relevant research was found by checking and evaluating the references of these papers-known as snowballing method. It should be noted that the thesis topic is a dynamic topic since it is currently evolving. This means that new research is constantly being presented. Therefore, the literature can be updated.

The structure of the remaining chapter is as follows. Section 2.1 provide information and details for the public transport system and how it is affected by the Covid-19 pandemic. Section 2.2 and section 2.3 provide information on bike sharing systems and e-bikes introduction, while section 2.4 presents the relation between the public transport and bike sharing systems. Finally, optimization models and approaches for the design and operation of the bike sharing systems are presented in section 2.5.

2.1. COVID-19 safety measures and public transport system

The pandemic situation has forced many governments to take measures to reduce the spread of the coronavirus. Some of these measures, known as social distancing measures, are teleworking, closing schools, shops, and social places, banning public events, and keep at least 1 meter distance from others (De Vos, 2020; WHO, 2021). On the one hand, distancing measures as well as the personal choices of people to avoid transportation modes where social distancing cannot be easily applied led to the change of travel behavior and the fall of ridership in public transport (De Vos, 2020; Jenelius & Cebecauer, 2020). On the other hand, distancing measures affect the public transport system since transport agencies reduced or change their services and reduced the capacity of modes.

Several studies have reported a drop in public transport ridership and change in travel behavior during the first wave of the pandemic (Bucsky, 2020; de Haas, Faber, & Hamersma, 2020; Jenelius & Cebecauer, 2020; Teixeira & Lopes, 2020). In Sweden, there has been a 40-60% drop in public transport ridership. There was a decline in the road traffic, which was overcome, while the use of bikes showed stability compared to last year and in some areas showed an increase (Jenelius & Cebecauer, 2020). Bucsky (2020) stated that there was a decrease in demand in all means of transport in Budapest. Public transport showed the largest decrease, while cycling and the bike sharing showed the smallest. However, the car is the one that replaced the public transport share (Bucsky, 2020). In the case of New York, subway and bike sharing systems have seen a significant reduction in their ridership. However, research shows that the bike sharing system was more resilient to the pandemic situation (Teixeira & Lopes, 2020). A survey conducted in the Netherlands, de Haas et al. (2020), showed that the public tranport had the highest decline while cycling and walking become more attractive for use. Research has also shown that people are very positive about using a car and negative about using public transport during a pandemic de Haas et al. (2020).

Regarding the mobility capacity of public transport, it is also affected by the safety measures. One of the key suggestion for reducing the spread of the virus is to avoid small areas that are overcrowed such as public transport (Morawska, et al., 2020). This is consistent with the fact that viruses such as Covid-19 are trasmitted by breathing in large or small airborne particles, which accumulate over time in enclosed places, and by contact with already infected people or surfaces (Morawska, et al., 2020; Prather, Wang, & Schooley, 2020). This has led governments and local authorities to impose personal distance restrictions on public transport. A research was conducted to collect data, which are presented in Table 2-1, on how social distancing measures have affected public transport mobility capacity. Each country/state developed its own measures and applied them according to the periods of the outbreak of the virus. It is observed that a mask is mandatory in all cases while there is variation in the reduction of the mobility capacity per case. There are cases where the general measure of keeping 1-2 meters distance from others applies, such as in the Netherlands, Kansas or Austria (Bundesregierung, 2021; COVID-19 Updates, 2021a; Reis alleen als het nodig is , 2021). In these cases there are signs indicating which seats can be used (COVID-19 Updates, 2021a). There are also cases that have more specific personal distancing constraints for public transport such as capacity reduction rates (New measures here to suppress the pandemic spread, personal responsibility remains the key, 2020; Publiction: Level 5, 2021) or exact number of passengers on public transport (COVID-19 Updates, 2021b; Coronavirus government response tracker, 2021). In some cases there is a combinations of measures (Diouf, et al., 2020; Tobing, 2020) or different rates of mobility capacity reduction per transport system (Diouf, et al., 2020), while in other cases the rate of mobility capacity reduction depends on the pandemic level (Covid-19 updates: information for tourists, 2021; Government Gazette search, 2021). Finally, there are extreme cases, such as the case of Albania, where there was no public transport service during the first outbreak of pandemic (COVID-19 Information, 2021).

Table 2-1: Different cases and the way which safety measures limiting the mobility capacity in public transport system

Country/State	COVID-19 measures in public transport
Albania (COVID-19 Information, 2021)	• No public transport in Tirana for 4 months • Face masks are mandatory for any individual 11 years old and above
Australia: New South Wales (Public transport to double capacity, 2021; Transport, 2021)	• Till 30th June: Capacity on trains carriage was 32 passengers, while capacity for two-door buses was 12 passengers • From 1st July: Capacity on trains carriage is 68 passengers, while capacity for two-door buses is 23 passengers • Face mask is mandatory
Austria (Bundesregierung, 2021)	• Keep a distance of 1 meter on modes and stations • Face mask is mandatory
Croatia (New measures here to suppress the pandemic spread, personal responsibility remains the key, 2020)	• Public transport capacity is restricted to 40% • Face mask is mandatory
Greece (Government Gazette search, 2021)	• Public transport capacity is restricted to 50% or 65% (depends on the pandemic level of the province) • Face mask is mandatory

Country/State	COVID-19 measures in public transport
Indonesia (Tobing, 2020)	• Public transport capacity is restricted to 50% • Keep a distance of at least 1 meter from other passengers • Face mask is mandatory
Ireland (Publiction: Level 5, 2021)	• Public transport capacity is restricted to 25% • Face mask is mandatory
Israel (The Government Approved the Ministry of Health New Restrictions In Addition to the Ones in Force, 2021; Ministry of Health's Motion to Extend the Validity of the Activity Restriction Regulations and to Add Additional Relaxation Measures Approved, 2021)	• Public transport capacity is restricted to 50% or 75% (depends on the pandemic situation) • Face mask is mandatory
Italy (ATM and the COVID-19 emergency: the management of the different phases, 2021; Covid-19 updates: information for tourists, 2021)	• Public transport capacity is restricted to 50-80% (depends on the pandemic situation) • Face mask is mandatory
Kenya (in Nairobi) (Diouf, et al., 2020)	• Capacity of the formal public transport system is restricted to 50% • Paratransit (14, 25 or 30-seater matatus) capacity is restricted to 60% • Face mask is mandatory
Netherlands (Reis alleen als het nodig is , 2021; Verantwoord reizen tijdens corona, 2021)	• Keep a distance of 1.5 meters on vehicles and stations • Not all seats are used in public transport vehicles, and it is not allowed to stand • Face masks are mandatory for any individual 13 years old and above
Nigeria (in Lagos) (Covid 19: Lagos emphasises 60% loading capacity for public buses , 2020)	• Public buses capacity is restricted to 60% • Commercial buses: maximum 8 passengers (out of 14) • Face mask is mandatory
Sweden (Jenelius & Cebecauer, 2020; Domestic travel and public transport, 2021)	• Public transport capacity is limited to or close to nominal level (1st wave) • Mask is recommended during peak hours or throughout the trip in some regions (2nd wave) • Capacity of long-haul public transport is restricted to 50% (2nd wave)
Tanzania (in Dar es Salaam) (Diouf, et al., 2020)	• Capacity of the formal public transport system is restricted to 50% • Keep a distance of at least 1.5 meters on stations/stops • Face mask is mandatory
USA: Kansas (Coronavirus government response tracker, 2021; COVID-19 Updates, 2021a)	• Keep a distance of almost 2 meters (6 feet) on station and modes • Buses operate with social distancing measures • Face mask is mandatory
USA: Montana (in Helena capital) (2021; Governor's coronavirus task force, 2021)	• Public transport operates with social distancing measures • Fixed route buses capacity: maximum 4 passengers • ADA Paratransit Buses: maximum 2 passengers • Face mask is mandatory for any individual 5 years old and above

Country/State	COVID-19 measures in public transport
USA: New Hampshire (Coronavirus government response tracker, 2021)	• Bus capacity: 9 passengers per 10 meters (35 feet) bus • Face mask is mandatory
USA: Wisconsin (in Madison capital) (Coronavirus government response tracker, 2021; COVID-19 Updates, 2021b)	• Bus capacity: 20 people per bus • Face mask is mandatory

Public transport is a closed, overcrowded space that increases the chances of transmitting influenza viruses from infected to uninfected people (Goscé & Jahansson, 2018; Troko, et al., 2011). Goscé & Jahansson (2018) study on the London Underground showed that there is a link between undergroung use and the spread of influenza viruses. Research has shown that the transmission of the virus is related to the length of time a person stays on the mode (Goscé & Jahansson, 2018). Another study (Shen, et al., 2020) presents the evaluation of deferences between two buses that had the same origin and destination. There was an infected passanger on the one bus. The study claimed that 24 of the 68 passangers on this bus become infected. Also, the passengers of this bus had almost 40 times higher chance of being infected than the passengers of the other bus (Shen, et al., 2020). These studied conclude that public transport is a source of COVID-19 virus transmission.

The reduced public transport capacity due to social distancing constraints, the increased likelihood of the virus spreading into public transport modes, the need for people to keep moving, and the prejudice against public transport strengthen the need to find a safe alternative to satisfy people mobility. Based on the studies of (Bucsky, 2020; de Haas, Faber, & Hamersma, 2020; Jenelius & Cebecauer, 2020), it seems that this tends to become the car. However, global warming requires the use of a more sustainable alternative (Elvik, 2009). The alternative that could be integrated with the current public transport system in order to maintain mobility capacity in the public transport system is the bike sharing system. Beyond environmental reasons, there are two other reasons for choosing this alternative. Many cities around the world as they try to deal with social distances measures become more friendly to pedestrians and cyclists by providing them with more urban space (Broom, 2020; Mobycom, 2020). Moreover, this moment there is a surge of people turning to the use of bike shared systems (Naka, 2020; Schwedhelm, Li, Harms, & Adriazola-Steil, 2020).

2.2. Bike sharing systems

In recent years, bike sharing systems have become very popular around the world (DeMaio, 2009; Fishman, 2016; Nikitas, 2019). There are currently just under 2000 operating systems (Nikitas, 2019) spread across North and South America, Europe, Australia, and Asia (Parkes, Marsden, Shaheen, & Cohen, 2013; Shaheen, Guzman, & Zhang, 2010). Therefore, there is an increase in the design and operation studies of these systems. However, the existence of these systems is quite old.

There are four generations of bike sharing systems (Fishman, 2016). The first generation, namely the “White Bike”, was introduced in Amsterdam in 1965 (Fishman, 2016). Fifty bikes without a locking system were placed in Amsterdam and everyone could use them free of charge (Shaheen et al., (2010)). However, this program did not survive for a long time (DeMaio, 2009; Midgley, 2011). The second generation, known as ‘Coin Deposit System’, was launched in Denmark (Fishman, 2016). The bikes of this system had a locking system (Shaheen et al., (2010)). During the existence of the second generation, there was the first extensive program of shared bikes (DeMaio, 2009). These two generations of bike sharing systems have faced problems such as the theft of the fleet (DeMaio, 2009). To address these issues, the third generation of bike sharing systems has been established (Eren & Uz, 2020). This generation incorporates high-tech features such as smart cards or magnetic stripe cards for the locking system, phone access and telecommunication systems (Eren & Uz, 2020; Midgley, 2011; Shaheen, Guzman, & Zhang, 2010). Finally, the fourth generation of bike sharing system is demand-responsive and includes updated characteristics such as pricing policies for self-rebalancing and integration with the public transport or carsharing system (Shaheen et al., (2013)). The fourth-generation systems use GPS (Global Positioning Systems) for real time bikes' tracking (Shaheen et al., (2013)) and tries to increase the quality and effectiveness of the system by using smart systems (Eren & Uz, 2020).

Bike sharing systems can be divided into three categories considering the criterion of absence or existence of dock-based stations (Shaheen et al., (2020)). These three categories are the station-based or docked system, the free-floating system and the hybrid system which is a combination of both (Shaheen et al., (2020)). In the docked bike sharing system, the user can use a bike from one station and return it to any station in the system (Sayarshad et al., (2012)). This means that the users can make one-way trips, i.e., pick-up and drop-off stations are different, or retour trips, i.e., pick-up and drop-off station is the same. The disadvantages of the docked system are that its services are not door-to-door and the availability of bikes or parking slots at stations is not always adequate for the needs of the system (Ma, et al., 2020b). Another option is the free-floating bike sharing system which is dockless (Sun et al., (2019)). This system provides flexibility to the user as they do not need to pick up and return the bike to specific facilities (Sun et al., (2019)). The users do not need to worry about parking slot availability (Sun et al., (2019)) as they can leave the bike anywhere in the system's operating area. The third option is the hybrid bike sharing system. The user can use a bike from one station and return it to any station in the system or to a non-station area and vice versa (Shaheen et al., (2020)). In addition to its flexibility as a free-floating system, system stations provide additional benefits. In areas with high demand, the use of stations makes it easier to find a bike. In addition, the stations are charging points. Therefore, stations are useful for charging idle bikes (Albiński et al., (2018)).

2.3. Introduction of e-bikes

E-bikes have appeared and become a trend in parallel with the growing appearance of bike sharing systems (Ji et al., (2014)). Ownership of private e-bikes, despite their increased cost compared to conventional bikes (Ji, Cherry, Han, & Jordan, 2014; Paul & Bogenberger, 2014), is on the rise in regions such as Europe (Paul & Bogenberger, 2014), China (Campbell et al., (2016)) and Japan (Liu & Suzuki, 2019). The research of Ji et al. (2014) and Paul & Bogenberger (2014) indicate that e-bikes' high purchase cost as well as the risk of such a purchase can be solved by integrating e-bike in the bike sharing system. The integration of e-bikes will allow users to travel longer distances without much physical fatigue and the terrain of the area (hills or steep slopes) will no longer be a barrier for the system (Campbell, Cherry, Ryerson, & Yang, 2016; Liu & Suzuki, 2019; Shaheen, Guzman, & Zhang, 2010). A study conducted in Australia on the elderly (age >= 65) found that e-bikes are an option for their daily commuting (Johnson & Rose, 2015). Therefore, the integration of e-bikes in the bike sharing system will be a solution for the movement of elderly as well as people with physical limitations.

The integration of e-bikes in the bike sharing system will bring new challenges to the system. The first challenge to consider is costs. Ji et al. (2014) research states that the price of e-bikes fluctuates and is usually twice the price of a conventional bike of the same quality. In Galatoulas et al. (2018) research, information was collected on different models of e-bikes. The result of the research is that the price of an e-bike ranges between 690 and 1375 €. Other costs to consider are the operating costs and maintenance costs of e-bikes and stations. The other challenge of an e-bike system is the need to charge their battery. To achieve this, a dependable energy source is needed. There are two sources that can be used which are electricity and solar energy (Cherry, Worley, & Jordan, 2010; Ji, Cherry, Han, & Jordan, 2014). Both sources have their drawbacks. The use of the electricity source presupposes better design in the locations of the station which increases the installation costs, while the use of the solar energy presents the problem of not easy storage of energy in the battery (Cherry, Worley, & Jordan, 2010; Ji, Cherry, Han, & Jordan, 2014). Both studies report that the electrical source constitutes the most dependable energy source. An additional element to consider is the minimum charge rate of an e-bike which will allow its use.

2.4. Bike sharing and public transport systems

There are many elements that can influence users as to whether to use the integrated public transport and bike sharing system (van Mil et al., (2020)). Therefore, the bike sharing system can complement or substitute the existing public transport system (Martin & Shaheen, 2014). Leth et al. (2017) studied the spatial analysis of the bike sharing system in Vienna and the connection between the bike sharing system and public transport system, considering travel times. The result of the research was that the bike sharing system in Vienna was complementary to the public transport system (Leth et al., (2017)). Another research that used travel time to study the influence of a bike sharing system on the public transport system is that of (Jäppinen et al., (2013)). The research showed that travel time was reduced in integrated system compared to the public transport system. However, the difference in travel time was noticeable in remote areas of Greater Helsinki and not so much in areas with a dense public transport network. The final conclusion of the research is that a bike sharing system can be complimentary to public transport (Jäppinen et al., (2013)).

The research of Martin & Shaheen (2014), which was carried out in two U.S. cities -Washington DC and Minneapolis-, concluded that the bike sharing system was complementary to the public transport system in the suburbs, while it was a substitute for the public transport system in the densely populated city center. A recent research (Song & Huang, 2020) presented a structure based on temporal and spatial consideration to understand how the bike sharing system is connected to the public transport system. This research was tested in the Minnesota transport system. Research has shown that the two systems were more likely to be complementary. Another interesting thing was that even in some cases where the two systems were considered competitive, the first-/last-mile move to the public transport was done by the bike sharing system (Song & Huang, 2020). (Ma et al., (2020a)) research was conducted for the city of Delft in the Netherlands and aimed to understand the influence of bike sharing systems in modal shift. They found that bike sharing systems are competitive with bus and tram and are complementary to trains. Campbell & Brakewood (2017) studied the impacts of bike sharing system on bus ridership in various parts of New York. In their research, bus routes were separeted based on the existence or non-existence of the bikesharing system. The result of the research was that there was a reduction in bus ridership. The bike sharing system therefor operated competitively (Campbell & Brakewood, 2017).

A bike sharing system can also be a solution in the event of a long-term or short-term disruption of the public transport system (Fuller, Sahlqvist, Cummins, & Ogilvie, 2012; Saberi, Ghamami, Gu, Shojaei, & Fishman, 2018; Younes, Nasri, Baiocchi, & Zhang, 2019). Both researches (Fuller, Sahlqvist, Cummins, & Ogilvie, 2012; Saberi, Ghamami, Gu, Shojaei, & Fishman, 2018) explore the impacts of three London Underground strikes on bike sharing system. Fuller et al. (2012) used a discontinuous pattern of time series to study this. The research concluded that the disruptive events increased the number of trips per day in the bike sharing system. An increase in travels was also observed in the period before and after the strikes (Fuller et al. (2012)). In Saberi et al. (2018) research, two analyzes were combined to extract the results: spatial-temporal analysis and network-theoretical analysis. They found that public transport disruption caused a significant increase in the number of bike trips as well as an increase in travel time. In addition, public transport disruption has bought considerable connectivity to the bike network (Saberi et al. (2018)). Younes et al. (2019) research examined the impact that long-term disruptions to the Washington metro system have had on the bike sharing system. There has been an increase in the use of the bike sharing system at the topical level. However, the bike sharing system was complementary to the functional part of the metro system and after the ens of the disruptions, its use returned to its normal levels (Younes et al. (2019)).

2.5. Bike sharing systems design

An element to consider for the efficiency of a bike sharing system is its design and operation. These include the size of the system, the relocation of the bikes and the selection of the station locations with the goal of better system management. This type of problem can be addresses by optimization models. The main objective categories of these models are the maximization of demand coverage, the minimization of transportation costs and overall costs or the maximization of profit.

Many studies in the literature deal with the fleet sizing, the management of the bike sharing system and stations' location topic. The study of Saharidis et al. (2014) develops an integer linear program to satisfy the unmet demand having as limitation the available budget. The output of this model is the total number of bikes in the system, the location of the stations and their capacity as well as the allocation of the bike fleet in the system (Saharidis et al. (2014)). Frade & Ribeiro (2015) presents a model that maximizes demand coverage by having as restrictions the available budget and service level. The model, in addition to finding the size of the fleet and the number of relocated bikes, determines the location and capacity of the bike stations (Frade & Ribeiro, 2015). Çelebi et al. (2018) uses a combined approach to find the location and size of stations on a bike sharing system. The approach consists of a set covering problem for demand assignment and a queue model. The approach minimizes the total unsatisfied demand (Çelebi et al. (2018)). Another research that maximizes the demand covered by the installed stations is the research of Park & Sohn (2017). The researchers use the maximum coverage location problem to design the bike sharing system, i.e., bike station location and capacity of the station.

The study of Sayarshad et al. (2012) determines the planning and analysis of a bike sharing system by using a multi-periodic formulation. The model defines the fleet dimensioning and the number of relocated bikes with the aim of maximazing the profit of the system and reducing unsatisfied demand (Sayarshad et al. (2012)). Another study that introduces a model that maximizes revenue is that of Martinez et al. (2012). The study examines the optimal solution for the station location if mixed fleet (regular and electric bikes) bike sharing system having capacity limitations. In addition, the model defines the size of the fleet and the bike rebalancing operations in a day (Martinez et al. (2012)).

On the other hand, the approaches of Yan et al. (2017) minimize the overall costs of the system. They are proposing two time-space network models (deterministic and stochastic) to specify the size of the bike fleet and the allocation of the fleet of a leisure-oriented bike sharing system. The two models also determine the bike station location and the routing of bikes (Yan et al. (2017)). Caggiani et al. (2020) presents a model that minimizes costs (initial investement and operating) by trying to offer a balanced level of service in terms of spatial distribution. The model's outcomes are related to the fleet sizing, the number and capacity of the stations, and their location. Nevertheless, the application of the model is limited to small-scale networks (Caggiani et al. (2020)). The model created in Lin & Yang (2011) study aims to minimize the overal costs and takes into account the unmet demand by introducing penalty costs for it. The proposed approach intends at the design of the bike sharing system, i.e., the network structure, the station location problem and the users' routes, and proposes an intiger nonlinear program. The reseach does not apply in a real case (Lin & Yang, 2011). Yuan et al. (2019) uses a mixed integer linear program to design and operate a bike sharing system. The objective function minimizes daily costs. The model looks at the location and size of stations, the bike allocation and the location of system depots. The model is applied in a real case (Yuan et al. (2019)).

There are studies that use different approaches to designing and operating a bike sharing system. Jian et al. (2016) research aims to optimize the relocation of bikes and docks for each station, trying to reduce dissatisfied users. To achieve this, it is developed a discrete-event simulation model and four simulation optimization heuristics are created. The Citi Bike system in New York was used to apply the proposed methods (Jian et al., (2016)). Another study that uses simulation to operate a bike sharing system is that of (Soriguera et al., (2018)). The proposed approach is to better provide bikes and docks on the stations with the aim of reducing costs. This is achieved by developing an agent-based simulation model and evaluating different system designs. The Barcelona bike sharing system was used to implement the model (Soriguera et al., (2018)). Fernández et al. (2020) uses an agent-based simulation environment to evaluate different policies regarding the operation of the bike sharing system. The model implemented in the BiciMAD Madrid system. The main goal is to create the most efficient bike sharing system installation. The key elements that the simulation model plans are the location and capacity of the stations and the relocation (Fernández et al. (2020)).

Table 2-2 presents the above studies in summary. More specifically, reference is made to the problem studied by each research, the goal of the objective function of each research, the developed methodology and the case study of each research. The abbreviations that appear in the table are explained at the bottom part of the table.

The reported studies focus on the study of the design and operation of bike sharing systems. Their approaches simultaneously optimize various features of a bike sharing system such as station location, bike relocation, bike availability at stations or fleet size. Various programming and simulation methods are used to formulate the optimization models of the studies. However there is no programming method that is chosen more often than the rest for the formulation of the optimization models. In each study, the formulation of optimization models is based on different factors. All optimization models, apart from the models presented in the studies of Çelebi et al. (2018) and Park & Sohn (2017), take into account in their

Table 2-2: Analysis of research for Bike Sharing System Design

Reference	Problem	Objective				Method	Case
		MDC	MUD	MP	MC		
Caggiani et al. (2020)	Bike station				✓	ILP	AC
Çelebi et al. (2018)	Bike station		✓			MINLP	Istanbul
Fernández et al. (2020)	Bike location					ABS	Madrid
Frade et al. (2015)	Bike station, Bike relocation	✓				LP	Coimbra
Jian et al. (2016)	Bike allocation Dock allocation		✓			SO	New York
Lin et al. (2011)	Bike station, bikeways				✓	INLP	AC
Martinez et al. (2012)	(E)Bike station, (E)Bike relocation			✓		MILP	Lisbon
Park et al. (2017)	Bike station	✓				BILP	Seoul
Saharidis et al. (2014)	Bike station		✓			PILP	Athens
Sayarshad et al. (2012)	Bike station, Bike relocation			✓		ILP	Tehran
Soriguera et al. (2018)	Bike rebalancing Bike relocation				✓	ABS	Barcelona
Yan et al. (2017)	Bike station, Bike relocation				✓	MILP	New Taipei
Yuan et al. (2019)	Bike station, Bike relocation				✓	MILP	Beijing
This study	Bike virtual station, E-bike station, Bike relocation E-bike relocation	✓				LP	Milan

Objective: MDC (Maximization of demand coverage), MUD (Minimization of unmet demand), MP (Maximization of profit), MC (Minimization of costs)

Method: LP (Linear Program), ILP (Integer Linear Program), MILP (Mixed-Integer Linear Program), INLP (Integer Non-Linear Program), MINLP (Mixed-Integer Non-Linear Program), BILP (Binary Integer Linear Program), PILP (Pure Integer Linear Program), SO (Simulation – Optimization), ABS (Agent-Based Simulation)

AC: Artificial case

formulation various costs of a bike sharing system. Regarding the computational requirements, Çelebi et al. (2018) model may cannot cope with solving a large-scale problem due to non-linearity and dynamic programming. Also, Caggiani et al. (2020) model has not been tested on large-scale problems, so maybe this cannot cope with solving them. This of course can be solved by developing a heuristic technique. However, there are studies that have either used simple model for better computational effeciency (Park & Sohn, 2017) or have already developed a heuristic techinque (Martinez, Caetano, Eiró, & Cruz, 2012; Yan, Lin, Chen, & Xie, 2017). Frade & Ribeiro (2015) model places the bike stations in each demand zone, however, it does not provide their exact location. The only study that includes a mixed fleet, i.e., bike and e-bike, is the study of Martinez et al. (2012), while the model of Yan et al. (2017) is focuded on leisure bike sharing systems. Therefore each model has positive and negative features as well as interesting features but also limitations.

2.6. Scientific gap

There are many studies that research the design and operation of a bike sharing system. The optimization model developed in each study differs in the features, such as the level of service or the costs of the system, that it considers in its formulation. These features are expressed in the objective function and the type of constraints of the models. Most of the reported research include constraints regarding various costs of a bike sharing system or even their objective function refers to the cost or profit of the system. This means that the level of service offered by the bike sharing systems designed by these optimization models is limited by the available budget. It is also observed that the optimization models concern the design and operation of either free-floating systems or docked system whose characteristics differ. The main difference is that the design of the docked system requires the installation of stations, while in the free-floating system there may be no stations. Moreover, it is observed that only one study Martinez et al. (2012) approaches the design of a mixed-fleet-bike and e-bike-bike sharing system. Therefore, there is no study that simultaneously designs a bike sharing system consisting of a mixed-fleet and that the bike system is free-floating, while the e-bike system is docked. Finally, none of the research concern extreme situations and disturbances in public transport system such as a pandemic situation and the distancing constraints.

In the case that the system costs are not considered, it leads to the development of an optimization model that can provide the design and operation of a bike sharing system designed to provide increased mobility capacity. In addition, a mixed-fleet bike sharing system can serve different cases of people such as young people, the elderly, or people with a vulnerable health condition and different distances. A hybrid system can cope with the increased demand that will result from the distancing constraints-the reduction in the capacity of public transport systems-as it combines the positives of docked and free-floating systems. To the best of authors knowledge, this is the first study which considers a pandemic situation and mobility needs arising due to distancing constraints on public transport system and seeks to integrate the public transport system and the bike sharing system in terms of mobility capacity. In addition, it is the first research to develop an optimization model for a hybrid mixed-fleet bike sharing system. That is, the study deals with the creation of a resilient public transport system that can provide mobility capacity in extreme and special situations. In addition, it is the first research to develop a bike sharing system optimization model that incorporates the design and operation of a mixed-fleet system as well as the different design approach-free floating and docked-of the two modes system. All the above features create an advanced optimization model which optimizes the design and operation of bike and e-bike systems separately but simultaneously.

The following chapters present the developed methodology and its application in the chosen case study.

3. Modeling approach development

This section presents the developed framework of this study. The main goal of the framework is to present the methodology that will be developed in this study. More specifically, it refers to the steps of the methodology that will be taken as well as the order and the relation that exists between these steps. The framework is divided into two parts which are the integration of the public transport and bike sharing systems and the optimization in the design and operation of the bike sharing system. In the first part of the integration, the existing demand of the public transport system is separated in demand for the public transport and bike sharing systems. The effect of the social distancing measures on the capacity of the public transport system and the new bike network will be considered in carrying out this part. In the second part, the optimization model for the design and operation of the bike sharing system based on the needs arising from the pandemic will be developed. The optimization model will maximize the covered demand, i.e., the provision of mobility capacity, considering the level of services of the bike sharing system. Demand scenarios and system network designs for the implementation of the optimization model will be developed. The purpose of the developed methodology is to create an integrated public transport system that considers extreme situations and disturbances in the public transport system, such as the pandemic situation and social distancing measures, and the needs arising from this extreme situation.

Following the chapter, the modeling framework is described in section 3.1. The section 3.2 describes the assumptions made, while sections 3.3 and 3.4 present the mobility integration of the two systems and the optimization model of the bike sharing system, respectively.

3.1. The modeling framework

The pandemic is an unprecedented situation. Measures taken to reduce the spread of the virus have affected many sectors. The public transport sector is one of these sectors. The social distancing restrictions in force have greatly reduced public transport capacity (ITF-OECD, 2020; Krishnakumari & Cats, 2020). In addition, many people are suspicious of public transport because it is considered that the chances of transmitting the virus are increased in the closed and overcrowded public transport vehicles (Goscé & Jahansson, 2018; Troko, et al., 2011). The problem that arises from this situation is that the movement of people becomes more difficult as there is a reduced supply of mobility. The magnitude of this problem will be more pronounced when the normal rhythms of life return and therefore the demand for transportation reaches high levels. The purpose of this thesis is to create an integrated public transport system that can offer the required mobility capacity to public transport users during extreme situations and disturbance such as a pandemic situation. Therefore, a new public transport system should be set up to be able to counterbalance for limiting capacity in the current public transport system because of the distancing measures imposed. Given the global warming (Elvik, 2009), the tendency of cities to provide more urban space to cyclists and pedestrians due to the pandemic situation (Broom, 2020; Mobycom, 2020) and the increase in the use of bike sharing systems at this time (Naka, 2020; Schwedhelm, Li, Harms, & Adriazola-Steil, 2020), the bike sharing system is chosen to be integrated into the public transport system. This integration will provide the necessary mobility capacity to public transport users but also the alternative of a safer means of transport, i.e., the absence of contact with many people. Efficient design and proper operation of the bike sharing system based on the needs arising from the pandemic and the corresponding measures will try to counterbalance the needs for mobility. The modeling framework of the thesis which includes the demand and mobility integration of the public transport and bike sharing systems and the optimization model (design and operation) of the bike sharing system under the impacts of social distancing measures is shown in Figure 3-1. In essence, this framework is a flowchart. The flowchart shows the various steps of a process and their sequence. In this flowchart, the rectangles represent a process or a state, while parallelograms are used for input or output operation. The arrows connect the symbols and indicate the flow of process and information. The structure is described in more detail below.

The above part of the framework in Figure 3-1 shows the demand integration of the public transport and bike sharing systems. More specifically, the pandemic has created an extreme and unknown situation and the measures to reduce the spread of the virus are affecting the public transport sector. Distancing measures have reduced public transport capacity and governments are promoting bike use by creating new bike network or implementing policies. The available information, which is related to the pandemic situation, is the capacity limitation on public transport due to the social distancing measures. Additional information that will be used as input to the next step is system options (public transport or bike sharing systems), public transportation timetable and the origin and destination of public transport system users of a specific day. The reported data can be collected from internet sources such as the website of the public transport operator or case study analysis. In case some data is not available, this data can be generated. All this is the input data in the next step. The next step is to create a mathematical model that will calculate the load of each public transport vehicle per station and if exist, the demand per stop that cannot board the vehicle due to social distancing restrictions (system's unsatisfied demand). The formulation of the model considers boarding passengers per station and disembarking passengers per station. Moreover, it is considered the reduced capacity of the public transport system. This means that boarding the public transport vehicle is not allowed if the vehicle's available capacity due to the distancing measures has been exceeded. Moreover, the mathematical model will give priority to boarding people who have a more distant destination. This means that in the case that two passengers want to board but there is only one spot available based on the distancing constraints (vehicle free capacity = 1), the model will consider boarding the one whose destination is farthest away while the other passenger will be considered as unsatisfied demand. The result of implementing the mathematical model will be the distribution of public transport users in public transport demand and unsatisfied demand. Unsatisfied demand will be the demand of the bike sharing system as it has been assumed that there is only this transport alternative for users. Therefore, the demand will be divided into public transport system demand and bike sharing system demand which will be fixed. This means that the demand will be for a specific day. The bike sharing system consists of two modes, the bike and e-bike. The next step is the separation of public transport unsatisfied demand in these modes. The input data in this step will be the percentages of use of each mode for the realization of a certain travel distance and the travel distances based on the bike network between station with unsatisfied demand. The bike network consists of the existing network and the new network created due to the pandemic situation. After that step, the demand of the bike and e-bike will be known. The final output of this part will be the separation of demand into demand for public transport, bikes, and e-bikes systems. Demand for bikes and e-bikes is an input to the next part. Therefore, the demand for the bike sharing system is an exogenous factor in the next part of optimization.

The next part of the framework is the optimization part in which the demand of the integration part is the initial input. The first step is to develop an optimization model for the bike sharing system. This optimization model will focus on the design and operation of the bike sharing system to provide efficient mobility capacity in extreme situations and disturbances such as the pandemic situation. Based on this, the bike sharing system chosen to be studied is a hybrid mixed-fleet bike sharing system. The characteristics of the system-hybridity and mixed fleet-will target the needs of the pandemic. The provision of a mixed fleet will serve the needs of different types of users and the coverage of different distances, while the hybridity will serve the increased needs for the provision of mobility. These features are selected for the bike sharing system so that the best possible mobility capacity can be achieved. The main goal-objective to optimize-of the model will be the maximization of the total covered demand, i.e., the bike system's demand and e-bike system's demand, having as a criterion the level of services that the system will provide. The next parallel step is the creation of demand scenarios and designs. There are different types of demand scenarios in which the demand for the existing bike sharing system will vary while the demand for the bike sharing system resulting from the integration will be fixed in all scenarios to be used. A bike sharing system is not in constant demand every day. Therefore, this fluctuation in demand will be studied by creating different demand scenarios. The characteristics of the bike sharing system (model's parameters) and the current bike sharing system of the city will be reflected in the designs. The features that will change in the designs are the number of stations in the system, the location of new stations and the values of the capacity parameters or the available bikes in the stations. These demand scenarios and designs will be the input into the optimization model. In the next step, the model application will take place. This step is repeated. This repetition is symbolized as N in Figure 3-1. The outputs from each repetition will be the values for the model variables, i.e., the portion of covered demand, the number of stations, the number of available modes in each station and the number of relocated modes, and the total fleet size of the system. Once the data for all repetitions have been collected, the data will be interpreted and compared. After this process, the results for the integration of the two systems can be formed and whether this integration can maintain mobility capacity in public transport system in extreme situations and disturbances.

3.2. Assumptions

At this point a reference should be made to the research assumptions. The assumptions are defined below:

- It will be considered that there is no competition from other micromobility systems.
- Demand exceeding the capacity implied by the 1.5 meters in public transport will not be allowed to board.
- The optimization model satisfies the system's demand but also relocates bikes and e-bikes. The system is in demand throughout the day. However, the relocation takes place at specific times during the day. Hence, a common balanced approach should be found. This means that the day will be divided into equal time periods. The result of this approach is that demand will enter the system at specific times rather than continuously. Therefore, the needs for mobility provision will be overestimated.

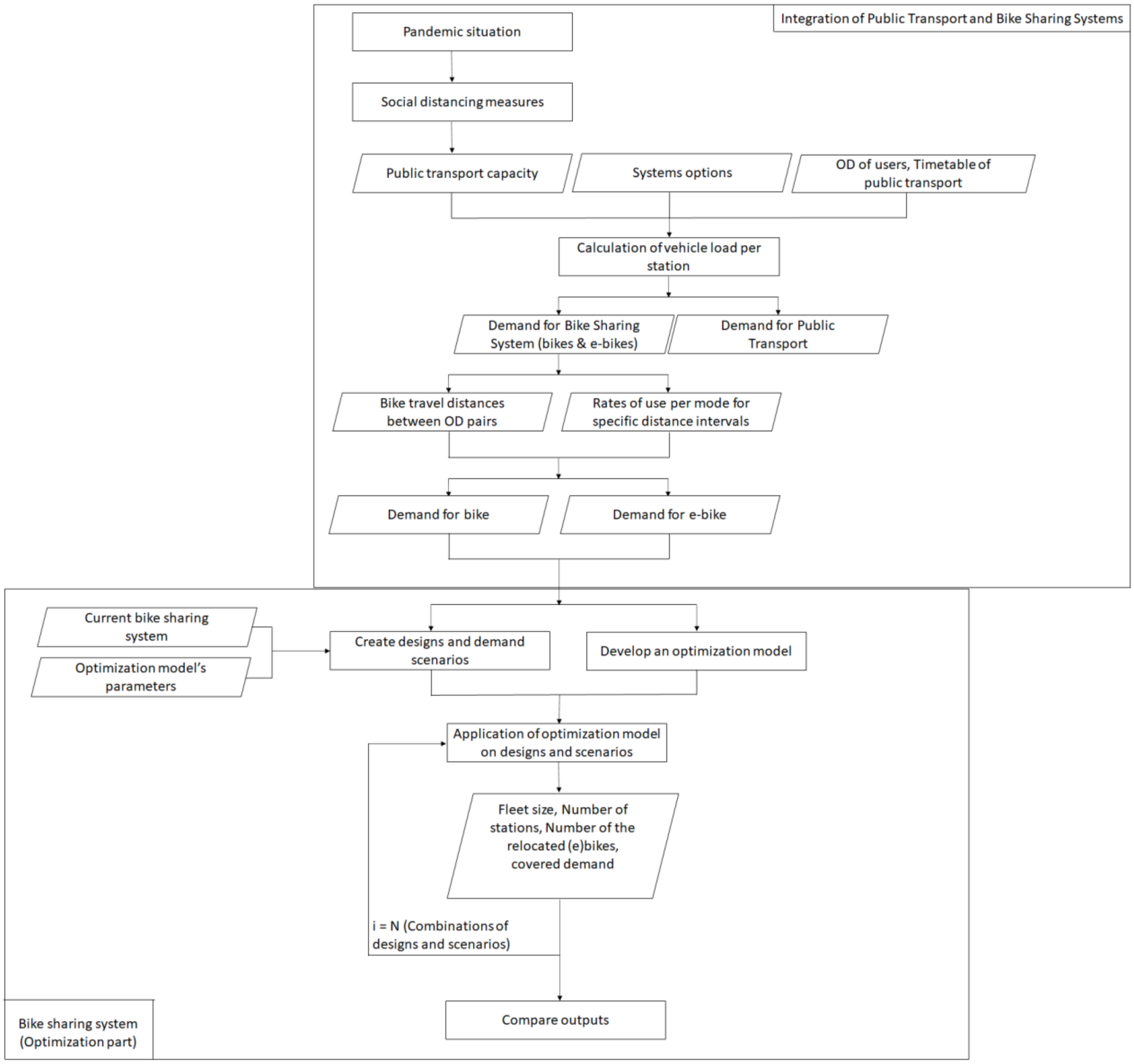

Figure 3-1: Modeling framework

3.3. Demand integration of public transport and bike sharing systems

The objective of the integration of the two systems is to find the demand per system. The approach to achieving this integration is based on the factors of the pandemic, namely the capacity constraints on public transport and the new bike system network. The first step is to create a mathematical model that calculates the permissible boarding of demand per station of each public transport vehicle and exports the unsatisfied demand per station. The mathematical model gives priority to boarding users with the farthest destination. The inputs of the model are the capacity of the public transport vehicle, the percentage of permissible occupancy due to the distancing constraints, the size of the network (i.e., the number of stations per line), the number of schedules and the existing demand of the public transport system. While the outputs of the model are the vehicle load per station, the demand boarded the vehicle per station as well as its destination station and the unsatisfied demand per station as well as its destination station. Therefore, the destination pairs of the unsatisfied demand are known. The result of this mathematical model is the distribution of demand in public transport and bike sharing systems.

The developed mathematical model and the notation of the model (Table 3-1) are presented below.

Table 3-1: Integration mathematical model notation

Sets and indices	
P	: set of stations with indices *i* and *j*
K	: index for schedule
Parameters	
ld_{ki}	: load of schedule *k* in station *i*
dem_{kij}	: demand from station *i* to station *j* for schedule *k*
$undem_{kij}$	: unsatisfied demand from station *i* to station *j* for schedule *k*
ac	: allowed capacity on the public transport vehicle
ub_{ki}	: disembarking passengers in station *i* for schedule *k*
b_{ki}	: boarding passengers at station *i* for schedule *k*

The developed integration approach is the following.

- For the first station of the line

The vehicle load is given by Equations (3-1) and (3-2). Equation (3-1) defines the vehicle load when it is lower than the available vehicle capacity, while Equation (3-2) defines the vehicle load when it is higher than the available vehicle capacity due to the distancing constraints. Equation (3-1) states that the load of the schedule *k* at the first station of the line is equal to the sum of the demand of the first station to all the other stations of the specific vehicle line. While the load of the schedule *k* at the first station of the line is equal to the allowed capacity of the vehicle due to the distancing constraints (Equation (3-2)).

$$ld_{k\,1} \begin{cases} = \sum_{j \epsilon P} dem_{k\,1\,j} & , \text{if } ld_{k\,1} < \text{ac} \quad (3\text{-}1) \\ = \text{ac} & , \text{if } ld_{k\,1} > \text{ac} \quad (3\text{-}2) \end{cases}$$

The unsatisfied demand of the schedule *k* from the first station to any other station is zero when the vehicle load is lower than the available vehicle capacity. (Equation (3-3)). In the case where the vehicle load is higher than the available vehicle capacity, the unsatisfied demand (Equation (3-4)) of the schedule *k* from the first station to a station *j* is equal to the sum of the demand from the first station to all other stations and the demand from the first station to the station *j* after subtracting the allowed capacity on the vehicle.

$$undem_{k\,1\,j} \begin{cases} = 0 \ \forall \text{j} \in \text{P} & , \text{if } ld_{k\,1} < \text{ac} \quad (3\text{-}3) \\ = \sum_{j \epsilon P} dem_{k\,1\,j} \text{ - ac + } dem_{k\,1\,j} \ \forall \text{j} \in \text{P} & , \text{if } ld_{k\,1} > \text{ac} \quad (3\text{-}4) \end{cases}$$

- For all other stations of the line

Equation (3-5) determines that the passengers who disembark from the schedule *k* in station *i* are equal to the total demand of all the previous stations that have as destination the station *i* if you exclude the unsatisfied demand of all the previous stations that have as destination the station *i*, while passengers boarding the schedule *k* at the station *i* are equal to the total demand from the station *i* to all subsequent stations on the line (Equation (3-6)).

$$ub_{k\ i} = \sum(dem_{k\ 1:i\ i} - undem_{k\ 1:i\ i}) \qquad (3\text{-}5)$$
$$b_{k\ i} = \sum dem_{k\ i\ i+1:P} \qquad (3\text{-}6)$$

In the case where the vehicle load is lower than the available vehicle capacity due to distancing constraints, the load of the schedule *k* at the station *i* is equal to the load of the schedule *k* at the previous station (*i*-1) and the passengers who want to board at station *i* minus the passengers who want to disembark at the station *i* (Equation (3-7)). Equation (3-8) specifies that the load of schedule *k* at station *i*, when the vehicle load is higher than the available vehicle capacity, is equal to the allowed capacity on the vehicle.

$$ld_{k\ i} \begin{cases} = ld_{k\ i-1} - ub_{k\ i} + b_{k\ i} & \text{, if } ld_{k\ i} < \text{ac} \qquad (3\text{-}7) \\ = \text{ac} & \text{, if } ld_{k\ i} > \text{ac} \qquad (3\text{-}8) \end{cases}$$

Equation (3-9) states that there is no unsatisfied demand for the schedule *k* from station *i* to any other station *j* when the vehicle load is lower than the available vehicle capacity. While the unsatisfied demand of schedule *k* from station *i* to station *j*, when the vehicle load is higher than the available vehicle capacity, is equal to the vehicle load at the previous station (*i*-1) and the demand of station *i* to the station *j* after subtracting the allowed capacity of the vehicle and passengers disembark at station *i* (Equation (3-10)).

$$undem_{k\ i\ j} \begin{cases} = 0\ \forall \text{j} \in \text{P} & \text{, if } ld_{k\ i} < \text{ac} \qquad (3\text{-}9) \\ = ld_{k\ i-1} - \text{ac} - ub_{k\ i} + dem_{k\ i\ j}\ \forall \text{j} \in \text{P} & \text{, if } ld_{k\ i} > \text{ac} \qquad (3\text{-}10) \end{cases}$$

The unsatisfied demand that is a result of the first step, is the demand of the bike sharing system. The second step of the integration approach is to separate bike sharing system demand into bike demand and e-bike demand. This can be achieved based on the travel distances. The input data for this step are the unsatisfied demand from the public transport system, the travel distances of the bike network, which has been extended due to the pandemic situation, between the stations of the public transport system with unsatisfied demand and the rates of use per mode-bike and e-bike-for specific distance intervals. Travel distances can be aggregated from internet sources, such as google maps, while the usage rates of each mode for different distance intervals can be derived from the case study analysis.

The result of this integration will be the separation of the existing demand of the public transport system into the demand of public transport, the demand of bike and the demand of e-bike of the bike sharing systems.

3.4. Bike sharing system model

This subchapter presents a detailed report on the changes (Section 3.4.1) that will be made to the reference model (Frade & Ribeiro, 2015), the notation and the optimization model (Section 3.4.2), and the sensitivity analysis of the optimization model (Section 3.4.3).

3.4.1. Model changes

The location decision or facility location is a strategic decision. Many problems/models have been developed that are used in the location decision. Some of these problems/models are the p-center and p-median problems, the maximum covering location problem, the uncapacitated facility location problem and the location covering problem (Contreras & Fernandez, 2012). Each of these models has its own mathematical model for example objective function and constraints. However, there are also similarities between the models i.e., common constraints. These models are considered basic models and are used in many applications after adapting to the needs of each situation.

In this study, the linear optimization model proposed by Frade & Ribeiro (2015) will be used as the reference. It is a maximum covering location problem. This model is chosen as the reference because it covers some of the features that were decided to be included in the model that will be developed in this study. The first of these features is the objective function of the model, which maximizes the demand covered by the bike sharing system. The main goal of this research is to find a way to maintain mobility capacity in public transport under the impacts of social distancing constraints. Public transport, i.e., subway, buses, trams, operate with reduced mobility capacity to prevent the transmission of the virus. The bike sharing system is therefore being integrated into the public transport system to compensate for the reduced mobility capacity. Choosing an objective function that maximizes the demand covered by the bike sharing system helps to design a bike sharing system that offers the best possible demand coverage and mobility capacity. The formation of the reference also determines the location of the stations, the size of the bike fleet and the relocation of the bikes at the stations. All these are features that lead to good design and operation of a bike sharing system.

In addition to the reference model's features that can be considered useful for developing the optimization model of this study, some changes need to be made to develop an optimization model suitable for this study. The main difference is the introduction of the e-bike mode in the bike sharing system. The introduction of the e-bike mode is related to the COVID-19 situation. The e-bike is more durable over longer distances and is suitable for elderly or people with an underlying disease because it requires less physical effort. Therefore, its introduction will provide mobility capacity for people who due to the COVID-19 situation are afraid or feel uncomfortable to be indoors with a lot of people as is the case with public transport. The main goal is to provide mobility capacity so that people can continue to move. With this in mind as well as the extreme demand that will arise for the bike sharing system due to the distancing constraints on public transport, it was decided that the bike system would be considered as a free-floating system. However, this will not apply to the e-bike system. The reason for this option is that in many cases the parking slots in a docked system are also the charging system of the e-bikes. As for the bike mode, it should be noted that there will be no parking spaces at a station. However, e-bikes mode stations will be virtual stations for the bike mode. More specifically, bikes will be moved between e-bikes stations but there will be no restrictions on parking availability. This serves to better organize the bike sharing system and facilitate the assignment of demand to stations.

Subsequently, the changes between the reference model (Frade & Ribeiro, 2015) and the model to be developed for this study are presented.

- Sets
  The study area in the reference model is divided into demand zones. There can be more than one station in each demand zone. The study area in the developed model is divided into stations and each station has its own demand. Therefore, in one case we have a set with demand zones, while in the other a set with stations.

- Objective function
  The objective function in the reference model maximizes the demand covered by the bike sharing system. In this study, the bike sharing system will also consist of an e-bike system. This means that the objective function should include one more term for the e-bike system.

- Constraints
  Reference has already been made to the introduction of e-bikes into the bike sharing system. The developed model should include new constraints for the e-bike system. The constrains for e-bike system are the constraint for the number of available e-bikes at a station, the constraint for the e-bikes fleet of the system that should remain the same between the first and the last period, the constraint for the number of docks at the stations, the constraint on the availability of free parking spaces and e-bikes at the stations, the constraint on the relocation of e-bikes, the constraint on the total e-bike fleet and the constraint on serving the demand only from existing stations.

  The bike system is designed as a free-floating system. Therefore, some of the constraints that exist in the reference model for the stations should be removed. These constraints concern the existence of docks at the stations and the existence of available parking space at the stations. An additional change that needs to be made is in the constraint associated with the portion of demand covered. In the reference model this constraint has this form $\sum_{j\epsilon J} x_{ijt} \leq 1$ ∀i∈J, t∈T, while in the developed model it will have this form $x_{ijt} \leq 1$ ∀i∈J, j∈J, t∈T. The constraint on the reference model states that the portion of covered demand by one zone to all the others should not exceed 1, while the constraint on the developed model states that the portion of covered demand from any virtual station to any virtual station should not exceed 1. This change is taking place because the demand of all pairs of virtual stations should be covered. This constraint should also be added for the e-bike system.

  The bike sharing system is trying to compensate for public transport demand under the impacts of a pandemic crisis. Consequently, the design and operation of the bike sharing system are considered key elements of the study, while system's costs are not a priority. So, the cost constraints of the reference model will not be used in the developed model. Also, the constraints that define the domain of decision variables of e-bike system and bike system should be formulated.

- Decision variables and parameters
  The decision variables and parameters differ between the reference model and the developed model. In the developed model, the features of the system with an important role in the design of the system having as a basic guide the provision of mobility capacity were defined as variables.

The decision variables of the reference model are five (5), while those of the developed model are eleven (11). The variables of the reference model are the portion of covered demand, the number of bikes in zone *i*, the number of bikes relocated, the number of docks in zone *i* and the binary variable for the existence or not of a station. The developed model has decision variables for bike system and for e-bike system. The decision variables of e-bike system do not differ from the decision variables of the reference model. There is only one additional decision variable which is the total e-bike fleet. The decision variables of the bike system in the developed model are the portion of covered demand, the number of bikes at virtual station *i*, the number of bikes relocated, and the binary variable for the existence or not of a virtual station. Also, the total bike fleet is a decision variable. This contrasts with what applies to the reference model because the total bike fleet is a parameter. In terms of parameters, the parameters associated with the cost constraints of the reference model do not exist in the developed model. The parameters for the capacity of the stations apply only to the e-bike system in the developed model, while parameters are added for maximum and minimum percentage of used capacity in e-bike system and the maximum available bikes at a virtual station.

3.4.2. Optimization model

This section presents the optimization model developed in this study. The optimization model determines the optimal design and operation of the bike sharing system, which consists of a bike and e-bike system, to counterbalance for limited capacity in public transport system in extreme situations and disturbances such as a pandemic situation and the distancing constraints. This is achieved by maximizing covered demand considering location and relocation constraints.

The model has some inputs and outputs. The inputs are a set of stations, the demand of the bike and e-bike systems, the values for the parameters of maximum and minimum capacity, maximum available bikes in a virtual station, and maximum and minimum percentage of used capacity of the e-bike system and the number of time periods. Time periods are essentially the number of the studied periods of a day. This number can be determined in each case study based on its data. The model satisfies the demand of the system but also relocate bikes and e-bikes, so there should be a balance between them when determining the number of time periods. In addition, the values of maximum and minimum capacity and percentage of used capacity can be determined based on the literature or there can be variation in their range of values. This depends on the requirements of each case study. The parameter for the maximum number of bikes in a virtual station depends on each case of study, i.e., the availability of public space. The outputs of the optimization model are the covered demand of the bike sharing system, the number of stations, the size of the bike and e-bike fleet, the number of bikes and e-bikes at stations in each period, the number of relocated bikes and e-bikes per stations pairs in each period, the portion of covered demand per stations pairs in each period, and the number of stations of the e-bike system.

The notation used to represent the elements of the optimization model is shown in

Table 3-2.

Table 3-2: Optimization model notation

Sets	
J	: set of stations, with indices *i* and *j*
T	: set of time period, with index *t*, T = {1,…,t)
P⊆T	: set of time period, with index *t*, P = {2,…,t}
Decision variables	
y_i	: is 1 if the bikes virtual station is opened and 0 otherwise
x_{ijt}	: proportion of covered bikes demand from station *i* to station *j* in period *t*
r_{ijt}	: relocated bikes from *i* to *j* at period *t*
v_{it}	: available bikes in station *i* at the onset of period *t*
Tu_t	: total bikes fleet size of the system
h_i	: is 1 if the e-bikes station is opened and 0 otherwise
v_i	: number of e-bikes docks in station *i*
w_{ijt}	: proportion of covered e-bikes demand from station *i* to station *j* in period *t*
s_{ijt}	: relocated e-bikes from *i* to *j* at period *t*
b_{it}	: available e-bikes in station *i* at the onset of period *t*
Te_t	: total e-bikes fleet size of the system
Parameters	
u_{ijt}	: demand of bikes from *i* to *j* in period *t*
e_{ijt}	: demand of e-bikes from *i* to *j* in period *t*
z_{max}	: maximum available bikes in a virtual station
v_{min}	: minimum capacity of e-bikes station
v_{max}	: maximum capacity of e-bikes station
p_{min}	: minimum percentage of used capacity in an e-bike station *i* at the onset of period *t*
p_{max}	: maximum percentage of used capacity in an e-bike station *i* at the onset of period *t*

The model is the following:

Max Z = $\sum_{i\epsilon J}\sum_{j\epsilon J}\sum_{t\epsilon T}(u_{ijt} \times x_{ijt}) + \sum_{i\epsilon J}\sum_{j\epsilon J}\sum_{t\epsilon T}(e_{ijt} \times w_{ijt})$ (1)

Subject to:

$v_{it} = v_{\iota(t-1)} - \sum_{j\epsilon J} u_{ij(t-1)}x_{ij(t-1)} + \sum_{j\epsilon J} u_{ji(t-1)}x_{ji(t-1)} + \sum_{j\epsilon J} r_{ji(t-1)} - \sum_{j\epsilon J} r_{ij(t-1)}$ (2)
$\forall$i∈J, j∈J, t∈P

$b_{it} = b_{\iota(t-1)} - \sum_{j\epsilon J} e_{ij(t-1)}w_{ij(t-1)} + \sum_{j\epsilon J} e_{ji(t-1)}w_{ji(t-1)} + \sum_{j\epsilon J} s_{ji(t-1)} - \sum_{j\epsilon J} s_{ij(t-1)}$ (3)
$\forall$i∈J, j∈J, t∈P

$v_{i,1} = v_{i,T}$ $\forall$i∈J (4)

$b_{i,1} = b_{i,T}$ $\forall$i∈J (5)

$v_i \le v_{max}\ h_i$ $\forall$i∈J (6)

$v_i \ge v_{min}\ h_i$ $\forall$i∈J (7)

$v_{it} \ge \sum_{j\epsilon J}(u_{ijt}x_{ijt})$ $\forall$i∈J, j∈J, t∈T (8)

$b_{it} \ge \sum_{j\epsilon J}(e_{ijt}w_{ijt})$ $\forall$i∈J, j∈J, t∈T (9)

$b_{it} \le p_{max}\, v_i$ $\forall$i∈J, t∈T (10)

$b_{it} \ge p_{min}\, v_i$ $\forall$i∈J, t∈T (11)

$v_{it} \le z_{max}\ y_i$ $\forall$i∈J, t∈T (12)

$\sum_{j\epsilon J} r_{ijt} \le v_{it}$ $\forall$i∈J, t∈T (13)

$\sum_{j\epsilon J} s_{ijt} \le b_{it}$ $\forall$i∈J, t∈T (14)

$Tu_t = \sum_{i\epsilon J} v_{it}$ $\forall$t∈T (15)

$Te_t = \sum_{i \epsilon J} b_{it}$ ∀t∈T (16)
x_{ijt} ≤ 1 ∀i∈J, j∈J, t∈T (17)
w_{ijt} ≤ 1 ∀i∈J, j∈J, t∈T (18)
$w_{ijt} \le h_i$ ∀i∈J, j∈J, t∈T (19)
$w_{ijt} \le h_j$ ∀i∈J, j∈J, t∈T (20)
$x_{ijt} \le y_i$ ∀i∈J, j∈J, t∈T (21)
$x_{ijt} \le y_j$ ∀i∈J, j∈J, t∈T (22)
r_{ijt} ≥ 0 ∀i∈J, j∈J, t∈T (23)
s_{ijt} ≥ 0 ∀i∈J, j∈J, t∈T (24)
x_{ijt} ≥ 0 ∀i∈J, j∈J, t∈T (25)
w_{ijt} ≥ 0 ∀i∈J, j∈J, t∈T (26)
$h_i \in \{0,1\}$ ∀i∈J (27)
v_{it} , b_{it}, v_i, r_{ijt}, s_{ijt}, Tu_t, Te_t ∈ N ∀i∈J, j∈J, t∈T (28)

The objective function (1) of this Linear programing consists of two terms. The first term is the system's bike covered demand, while the second term is the system's e-bike covered demand. The objective function maximizes the covered demand by the bike sharing system. Constraint (2) determines the available bikes at virtual station *i* at period *t*. The first term of the constraint refers to the available bikes at virtual station *i* in the previous period. The second and third terms refer to the number of bikes that left or arrived at the virtual station *i* respectively in the previous period, while the fourth and fifth terms refer to the bikes transported to or from the virtual station *i* respectively at the previous period. Constraint (3) determines the available e-bikes at station *i* at period *t*. Constraints (4) and (5) state that the bike and e-bike fleet of the system remains the same between the first and the last period. The capacity of an e-bike station is limited by the constraints (6) and (7). Constraint (6) specifies the upper capacity limit (maximum number of docks at the station), while constraint (7) specifies the lower capacity limit (minimum number of docks at the station). The available bikes at the virtual station *i* should meet the demand of the virtual station (constraint (8)), and the available e-bikes at the station *i* should meet the demand of the station (constraint (9)). Stations should always have available e-bikes as well as available docks for parking. This is achieved by constraints (10) and (11). Constraint (10) specifies that the number of available e-bikes at the station *i* at period *t* should not exceed a specific number, and there should be a minimum number of e-bikes at the station (constraint (11)). Constraints (12) sets a limit on the maximum number of available bikes at a virtual station. The relocated bikes from the virtual station *i* at the period *t* should not exceed the available bikes at the virtual station *i* at that period (constraint (13)). The corresponding constraint for e-bike system is constraint (14). Constraints (15) and (16) specify the total bike and e-bike fleet of the bike sharing system, respectively. The portion of covered demand from virtual station *i* to *j* at the period *t* cannot exceed the value 1 (constraint (17)). The corresponding constraint for the e-bike system is constraint (18). The demand for the bike and e-bike system can only be served by existing (virtual) stations (constraints (19) - (22)). Constraints (23) – (28) specify the domain of the decision variables.

3.4.3. Sensitivity analysis of optimization model

The solver that will be used to solve the problem is the Gurobi optimizer for python. The Gurobi optimizer is an optimization solver for linear programming (LP), quadratic programming (QP), mixed integer linear programming (MILP), mixed-integer quadratic programming (MIQP), and mixed-integer quadratically constrained programming (MIQCP) (Gurobi Optimization, 2020). The hardware of the used computer is Intel(R) Core(TM) i7-7500U CPU @ 2.70GHz 2.90 GHz, 8.00 GB RAM and the operating system is Windows 10 64-bit.

The Gurobi solver offers three different methods/algorithms for solving the optimization problems. These methods are primal simplex, dual simplex, and barrier. Each method solves an optimization model in a different approach. As a result, each method may provide a different solution for the same optimization model. In addition, each method can be more suitable and give better results in a specific type of programming-linear, quadradic, mixed integer linear. The Gurobi solver has, in addition to the three methods, other solution options. These options offer simultaneous solution of the model with different methods and the fastest method is selected.

The optimization model presented in section 3.4.2 is used to solve a small-scale problem and a large-scale problem with the three methods mentioned. This is to find the method that requires the least time to solve the model, and to identify the differences between the solutions. The data in small- and large-scale problems is random. Problems of different scales are used to determine whether the same conclusion apply in both cases.

The inputs of the two problems are shown in Table 3-3 and Table 3-4. Some additional data are listed here. The values for the parameters p_{max} and p_{min} are 0.75 and 0.25 and for the parameters v_{min} and v_{max} are 10 and 25, as mentioned in the study of Frade & Ribeiro (2015), for both models. The maximum number of available bikes (z_{max}) at a virtual bike station is 100 for the small-scale problem and 200 for the large-scale problem.

Table 3-3: Inputs and results of the three methods for small-scale problem

Inputs			
Number of stations	4		
Time periods	4		
Bike demand	1184		
E-bike demand	407		
Total demand	1591		
Outputs			
	Primal simplex	**Dual simplex**	**Barrier**
Time	0.18 sec	0.07 sec	0.38 sec
Number of selected stations	4	4	4
Number of virtual stations	4	4	4
Covered bike demand	1180	1180	1180
Covered e-bike demand	277	277	277
Covered demand	1457	1457	1457
Bike fleet	335	335	335
E-bike fleet	72	72	72
Relocated bikes	207	207	207
Relocated e-bikes	126	26	216

As shown in Table 3-3, the dual simplex method solves the small-scale problem faster and with a relatively considerable time difference from the other two methods. All methods give the same outputs, except for the number of relocated e-bikes. The dual simplex method gives the smallest number of relocated e-bikes, while the barrier method gives the largest number. The large-scale problem is solved faster with the dual simplex method, while the slowest method is the primal simplex method (Table 3-4). The three methods give different results for the size of the bike fleet and the number of relocated bikes. The dual simplex method gives the lowest values, while the barrier method gives extremely high values. From a computational point of view, the dual simplex method is the best choice for both problems-small/large-scale-since the time required for the solution of the model is the shortest. But also, in terms of design, the dual simplex method can be considered the best as it requires a lower fleet size and relocation of vehicles. Therefore, for the implementation of this linear programing optimization model for the design and operation of a hybrid mixed-fleet bike sharing system, the dual simplex method brings the most efficient application.

The three methods give the same optimal objective value to each problem. Also, there is no violation of the quality statistics-i.e., bound, constraints and integrality-of the model in any case. This means that the model has no numerical problems.

Table 3-4: Inputs and results of the three methods for large-scale problem

Inputs			
Number of stations	290		
Time periods	9		
Bike demand	36294		
E-bike demand	31184		
Total demand	5110		
Outputs			
	Primal simplex	**Dual simplex**	**Barrier**
Time	288.52 sec	74.97 sec	89.05 sec
Number of selected stations	279	279	279
Number of virtual stations	290	290	290
Covered bike demand	30852	30852	30852
Covered e-bike demand	5002	5002	5002
Covered demand	35854	35854	35854
Bike fleet	9886	9622	57854
E-bike fleet	3720	3720	3720
Relocated bikes	63640	54146	278160
Relocated e-bikes	3778	3778	3778

It should be noted that attempts were made to differentiate the formulation of the model. The first attempt is related to constraints $x_{ijt} \leq 1$ $\forall i \in J$, $j \in J$, $t \in T$ and $w_{ijt} \leq 1$ $\forall i \in J$, $j \in J$, $t \in T$. These two constraints originally had these forms x_{ijt} = 1 ∀i∈J, j∈J, t∈T , w_{ijt} = 1 ∀i∈J, j∈J, t∈T in the developed model. This form was chosen as the main purpose is to provide mobility capacity in the integrated system for those who want to move and do not want or cannot use public transport due to the distancing measures. In this way the mobility capacity of the integrated system would meet all the unsatisfied demand due to the existing distancing measures because of COVID-19. However, the problem was infeasible, i.e., no solution could be found that satisfies all the model's constraints. Therefore, inequality is used instead of equality, that is, they are more relaxed so that a solution can be found.

Another attempt did not involve constraint $v_{it} \leq z_{max} * y_i$ ∀i∈J, t∈T, which limits the number of bikes in a virtual station. The model of this form gave large number of available bikes at some stations. At several stations, this number exceeded the 2000 available bikes. This means that the bike sharing system would take up a lot of public space. However, this may not be possible in real life. In most cases public space is limited. Also, having so many bikes in the area would be annoying to most people.

3.5. Conclusion remarks

This chapter describes the methodology that is developed and applied in this study. This methodology consists of two main parts. The first part is the operational integration of public transport and bike sharing systems, i.e., the demand integration, and the second part is the development of an optimization model for the design and operation of a bike sharing system that considers the transportation impacts of extreme situations and disruptions on public transport such as a pandemic and social distancing measures. The city of Milan in Italy is chosen to apply the developed methodology. The studied systems are the subway and the public bike sharing systems of Milan. The next chapter refers to the analysis of the public transport and bike sharing systems, the application of the developed methodology and the analysis of the findings.

4. Model application

This chapter outlines and interprets the selection and analysis of the case study, the development of scenarios and designs, the results obtained from the implementation of the optimization model and their analysis. In this study, the geographical study area is the city center of Milan and the studied public transport systems are the subway system and the BikeMi bike sharing system. The choice is supported by the significant influence of the COVID-19 pandemic in Milan (Worldometer, 2021), the widespread use of the subway system and the availability of extensive data on the BikeMi system. The necessity to maintain mobility capacity in public transport under the impacts of social distancing constraints by offering a safe public transport system makes the choice of Milan and the integration of the two transport systems a promising case study.

The remaining of the chapter has the following structure: Section 4.1 provides general information on the geographical study area, while Section 4.2 deals with transport systems. Section 4.2.1 gives general information about the subway system and the generation of demand, while Section 4.2.2 presents general information about the BikeMi system and the analyzes for the users of the system but also for the system itself. Section 4.3 describes the scenarios and designs and Section 4.4 presents the results of the model application and their analysis.

4.1. Geographical study area

The city center of Milan was chosen to implement the developed model. The study focuses only on the city center of Milan in order to have a better insight of the area and its transport needs. In addition, most of the BikeMi bike sharing system extends to this area of the city. In Figure 4-1, the area enclosed in the red line is the city of Milan, while the area enclosed in the black line is the study area.

Milan is located in northern Italy and is the capital of the administrative region of Lombardy. The city is a leading financial center, a popular tourist destination and one of the main transport hubs of Italy. The population of Milan city is about 1.4 million and the density of the city is 7,684 inhabitants per km^2 (Maps, analysis and statistics about the resident population, 2021).

4.2. Public transport in Milan

Milan public transport is operated by the municipal public transport company Azienda Trasporti Milanesi (ATM). ATM company also manages the public transport of 46 surrounding municipalities. The company's transport service consists of 4 subway lines, 131 bus lines, 19 tram lines and 4 trolley bus lines (ATM in Figures, 2020). The subway network mainly covers the city of Milan while the surface transport network also covers part of the province of Milan. The number of passengers served by the company's network was 820.4 million in 2019, of which 386.8 million were served by the subway network (ATM bilancio finanziario 2019, 2021). The ATM company is constantly expanding its services in the sector of transport. The BikeMi bike sharing system is one such service. The BikeMi system is managed by the companies ATM and Clear Channel.

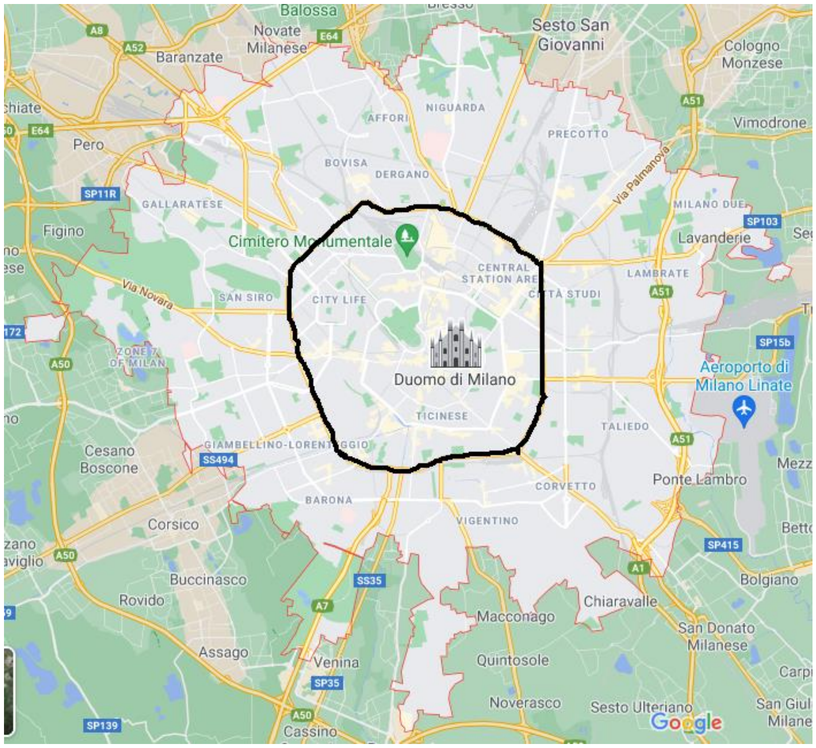

Figure 4-1: The city of Milan and the study area (Scale: 1:100000)

The two transport systems selected in this study are the BikeMi bike sharing system and the subway system. The BikeMi system is chosen because it is a safe choice in terms of hygiene as well as an environmentally friendly choice that does not burden the surface transport network compared to other means of transport. The choice of subway system is supported by its importance as it serves almost half of the passengers of motorized public transport and a large part of its network serves the same part of the city as the BikeMi system.

4.2.1. Subway system

4.2.1.1. Subway system general information

The Milan subway or Metropolitana di Milano opened in 1964. The red line or line 1 was the first line to operate and connect the stops from Sesto Marelli to Lotto station. At the moment the subway consists of four lines which have the names M1: Rho Fiera/Bisceglie – Sesto 1º Maggio, M2: Assago Milanofiori Forum/Abbiategrasso – Cologno Nord/Gessate, M3: Comasina – San Donato and M5: San Siro Stadio - Bignami and a fifth line is under construction. The system has 106 stations, and the length of its network is almost 100 kilometers. The subway is operated by Azienda Trasporti Milanesi (ATM) and is the largest subway system in Italy in terms of length and number of stations. Figure 4-2 illustrates a network map of Milan's subway.

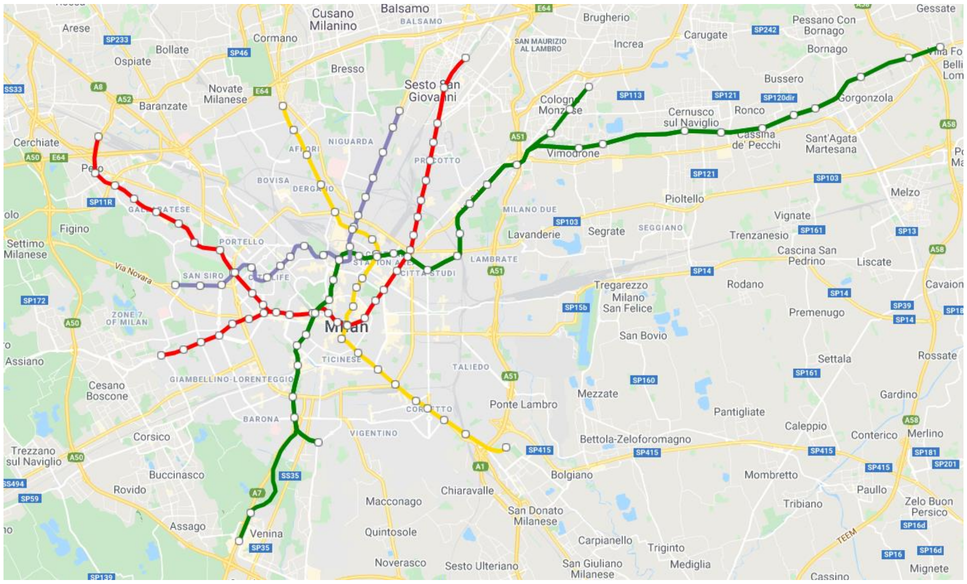

Figure 4-2: Map of Milan subway network (Scale: 1:100000) (Source: (Giromilano, 2021))

4.2.1.2. Subway system demand generation

Subway system demand data, i.e., origin-destination pairs data, are not available. Therefore, it is necessary to generate origin-destination data for the year 2019 for the needs of the case study. The generation of data means that the used data for the application of the developed methodology approximates reality but does not reflect the exact needs of the subway system. It should be noted that the generation of demand took place between stations of the same subway line. That is, the origin and destination of each passenger belongs to the same subway line. The first step in this process is to find information about the subway system and its demand. The available information is related to the daily passenger demand per line in 2018, the total daily system demand for 2019, the passenger use of each station (low, medium, or high) during the day at time intervals of half an hour for the first week of April 2021 and the system's peak hours. Based on this data, the generation of the origin-destination pairs will be performed.

The first information used is related to the daily passengers per line for the year 2018. In addition, the total daily demand of the subway system for the year 2019 is known. From the total daily demand of the two years, it results that the total daily demand of the system increased by 0.5% in 2019 compared to 2018. Based on this percentage and the available data for 2018, the daily demand per line for 2019 is calculated (Table 4-1).

Information related to the stations and their use during the day is then collected. This information was collected in the first week of April 2021. The selection of the specific period is made in order to be consistent with the data period of the BikeMi system. Based on this information, aggregate tables per subway line are created that show what hours of the day a station presents high, medium, or low passengers use. A small example of such a table is illustrated in

Table 4-2. The green color indicates that

Table 4-1: Daily demand of subway system for 2018 and 2019

Subway line	Daily passengers demand	
	2018	2019
M1	501480	504000
M2	473620	476000
M3	306460	308000
M5	1114400	112000
Total	1393000	1400000

the station is not in high demand at that time and trains have space available, the yellow color specifies that the station may be in high demand and there may be a wait for boarding on a train and the red color indicates that the station is in high demand and a change of travel time is suggested.

Table 4-2: Passenger use of M1 subway line (a small example)

Stations/Time	6:00-6:30	6:30-7:00	7:00-7:30	7:30-8:00	8:00-8:30
Bisceglie					
Inganni					
Primaticcio					
Bande Nere					
Gambara					

Based on the occurrence rate of low, medium, and high demand, stations are classified in terms of passengers use, i.e., which station has the highest and which the lowest demand. This analysis is performed per subway line, and it is assumed that each color (green, yellow, red) has the same importance in terms of demand regardless of the time of its appearance. The ranking of stations per line from lowest to highest demand can be found in Appendix B. Then the demand per station is found. In this process, each subway line is studied separately. For this process a Python code script is created which generates random numbers. The inputs to this code script are the number of stations per line and the total demand per line. Based on this data and the code script, 1000 different demand paradigms are created for each subway line. In each paradigm, the generated numbers are equal to the number of stations on the corresponding line, i.e., if the subway line has 25 stations, the paradigm will consist of 25 numbers, and the sum of stations demand is equal to the total demand of the line. The averages of these one thousand paradigms are the final demand per station considering the mentioned ranking of station. The output of this process is finding the demand per station shown in Figure 4-3.

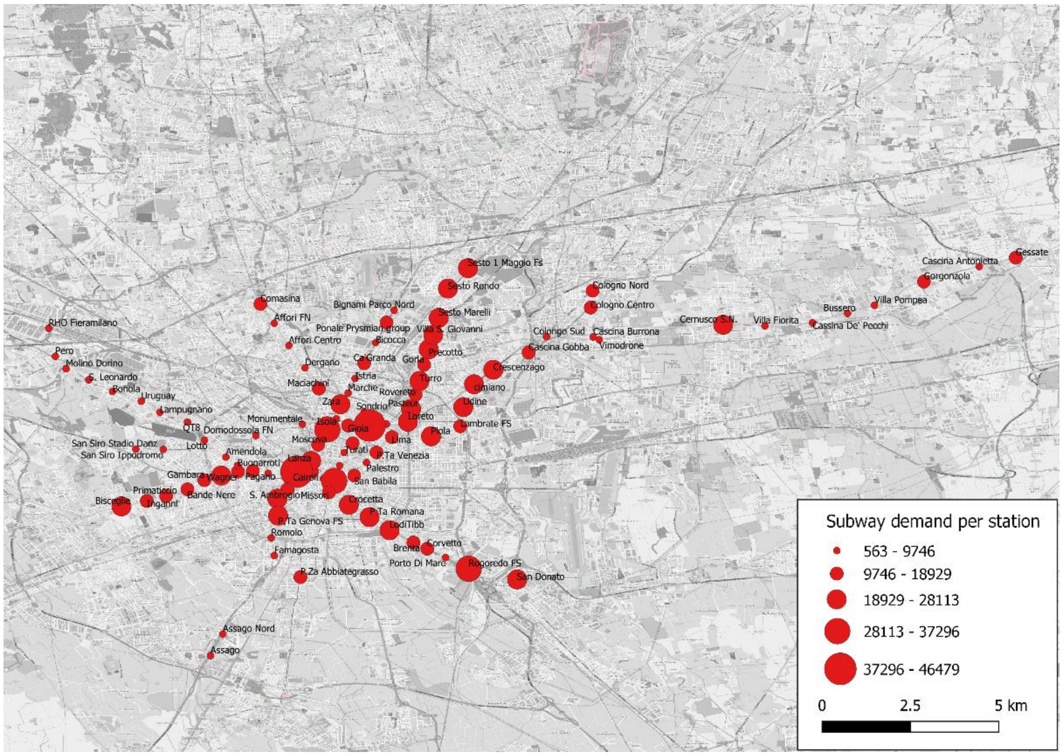

Figure 4-3: Subway station demand resulting from the computational process

Once the demand per station is known, the next step is to distribute the demand of each station by direction-two directions per stations. The first step is to divide the station demand evenly. This can be calculated by Equation (4-1). The station demand and the number of line stations are used for this calculation. Equation (4-1) states that the demand of each station is divided by the number of stations on the route minus one station. Demand is divided by the number of stations minus one because each station has demand for all other stations but not for itself. The output of equation (4-1) is denoted by T. The second step concerns the calculation of the station demand per direction. This is calculated from equation (4-2). Equation (4-2) shows that the station demand per direction is equal to the value of T (output of Equation (4-1)) multiplied by the number of stations further down the route, i.e., the number of subsequent stations on the line in one direction.

$$\text{T = demand of station / (Number of route station – 1)} \tag{4-1}$$

$$\text{Demand of station per direction = T * Number of stations further down the route} \tag{4-2}$$

At this point the stations demand per direction is known. The next step is related to the distribution of demand during the day (6 a.m. to midnight). The subway system has two peak periods during the day, the morning rush hour, 7:00 – 10:00, and the evening rush hour, 16:30 – 20:00. Based on the existence of these two peaks, the distribution used to disperse demand during the day is the binomial distribution, which is a mixture of two normal distributions with different average values and the same variance. The inputs to the distributions are the mean values, the variances, and the sample number. In this case, the first distribution has a mean value of 9, a variance of 3 and a sample number of half the station demand, while the second distribution have a mean value of 18, a variance of 3 and a sample number of half the station demand. The choice of values for average prices is related to the peak hours of the system. From this process arises the demand of the station per hour and direction.

The final step is to distribute the hourly demand to origin-destination pairs. This procedure takes place for 6 hours during the evening, 15:00 to 21:00. This period is selected because it includes the evening rush hour. The choice of the evening rush hour versus the morning rush hour is based on the bike sharing system. The bike sharing system is in greater demand during the evening rush hour in 2019, this is presented in Chapter 4.2.2.3, and that is why it is chosen. Note that lines M1 and M2 are treated as 4 routes, i.e., line M1 has 2 routes and line M2 has 2 routes, because they have branches in their network. As for the stations of each line that belong to both routes, their demand is divided in half. The distribution chosen to disperse demand in origin-destination pairs is the normal distribution. This distribution is chosen because most of the demand of a station will be aimed at the intermediate stations of the rest of the route and not the nearby or distant stations of the origin station. The mean value of the normal distribution will be the number of stations further down the route divided by two, the variance will take values from 4.4 - 1.8 (depends on the value of mean) and the sample will be equal to the demand of the station. The result of the process will be the hourly demand of the subway system in origin-destination pairs.

4.2.2. BikeMi system

4.2.2.1. BikeMi general information

The bike sharing system started operating at the end of 2008 and is a public bike sharing system. In 2015, e-bikes were introduced in the BikeMi system. At present the system has 4280 conventional bikes and 1150 e-bikes of which 150 are pedal-assisted bikes with child seat. The current number of operational stations is 320 and the system operates all year round from 6 am to midnight. The system's schedule can be extended on special occasions/days. During off-hours, users can only return a bike to a station. A bike can be used for a maximum period of two hours. If this time limit is exceeded, the user will be charged a fine.

Figure 4-4 shows the bike sharing system BikeMi in the city of Milan. The black dots represent the stations of the system. It is observed that most stations of the system are located in the city center of Milan which is the study area.

The analysis of the BikeMi system and its users is presented in the following subchapters. The data for the bike system, which were initially available, correspond to a two-week period of 2018. Therefore, the initial analysis was based on them. Then there were additional data available for 2018 as well as for the years 2019, 2020 and the analysis was expanded.

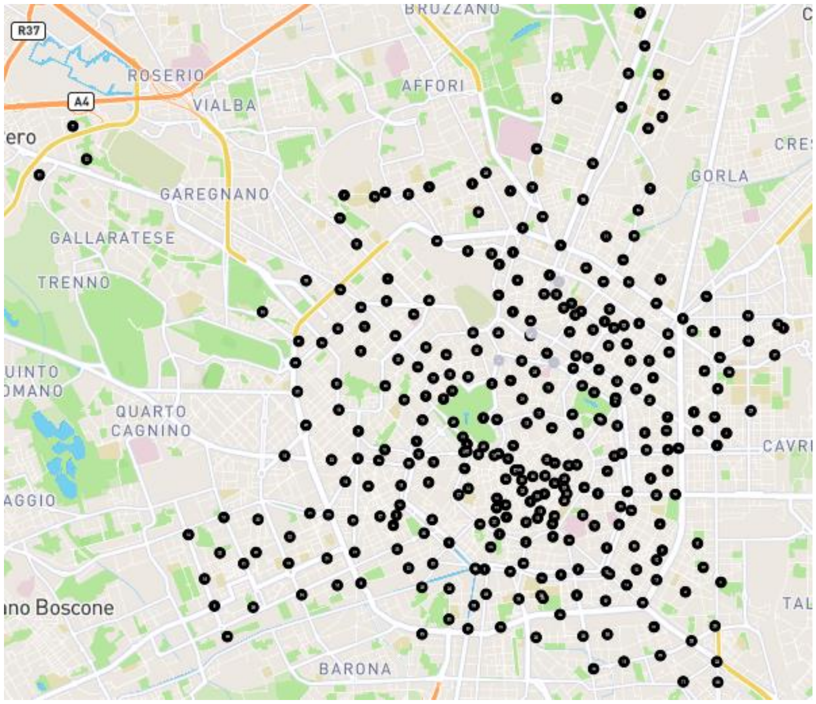

Figure 4-4: BikeMi system in the city of Milan (Source: (Station Map, 2021))

4.2.2.2. BikeMi users' analysis

The BikeMi system users' analysis is performed for the years 2018, 2019 and 2020. The available data provides information on the type of subscription of each user, the activation date, and personal details such as gender, age, and profession of users. In this section, the users' analysis of the years 2019 and 2020 is presented. The year 2019 is considered as a normal year without any particular disturbances, while the year 2020 is the pandemic year which is characterized by uncertainty. It should be noted that the analysis of 2020 does not include December due to lack of data. In addition, all the figures presented in this section are derived from the researcher's analysis of the available data. Further analysis of the year 2018 can be found in the Appendix C.

Based on the analysis, the annual subscriptions of the system range between 26 – 37 thousand. Figure 4-5 shows that the BikeMi system had the highest number of subscriptions in 2018. In 2019 there was a small drop of 3% compared to 2018, while the system subscription in 2020 decreased slightly more than 1/4 compared to the previous two years. During each year there is a variation in the number of subscriptions. This variation is shown in Figure 4-6. For all three years, the subscriptions are increased in spring and summer compared to autumn and winter months. The months of March and April 2020 are an exception. These two months, the system has a very low number of subscriptions. This is due to the strict lockdown implemented in Italy to curb the COVID-19 virus. The system presents the peaks of subscriptions in April 2018, September 2019, and May 2020, while the months with the lowest number of subscriptions are February, November, and April respectively.

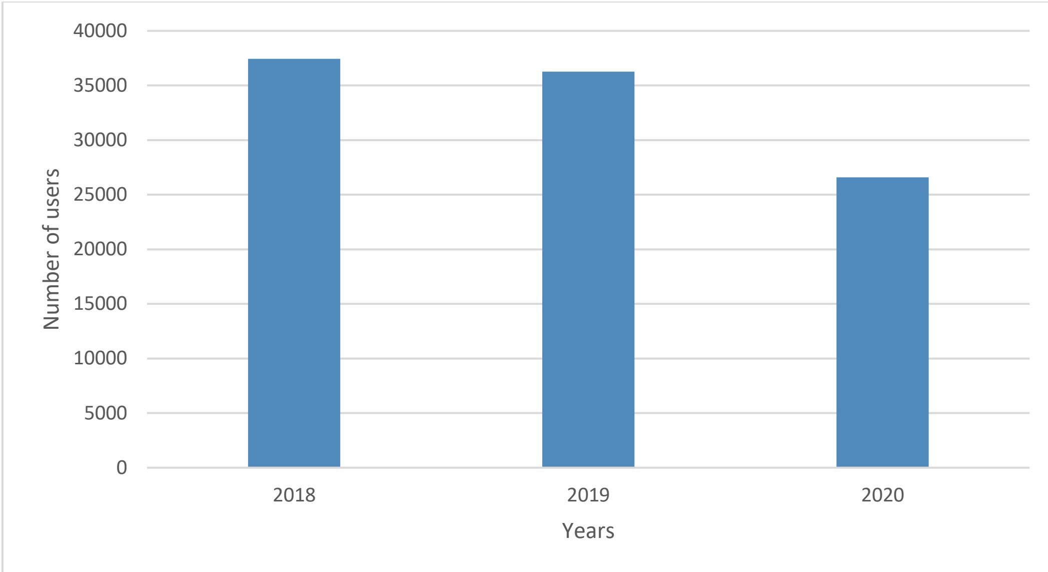

Figure 4-5: Annual subscriptions of BikeMi system for the years 2018 – 2020

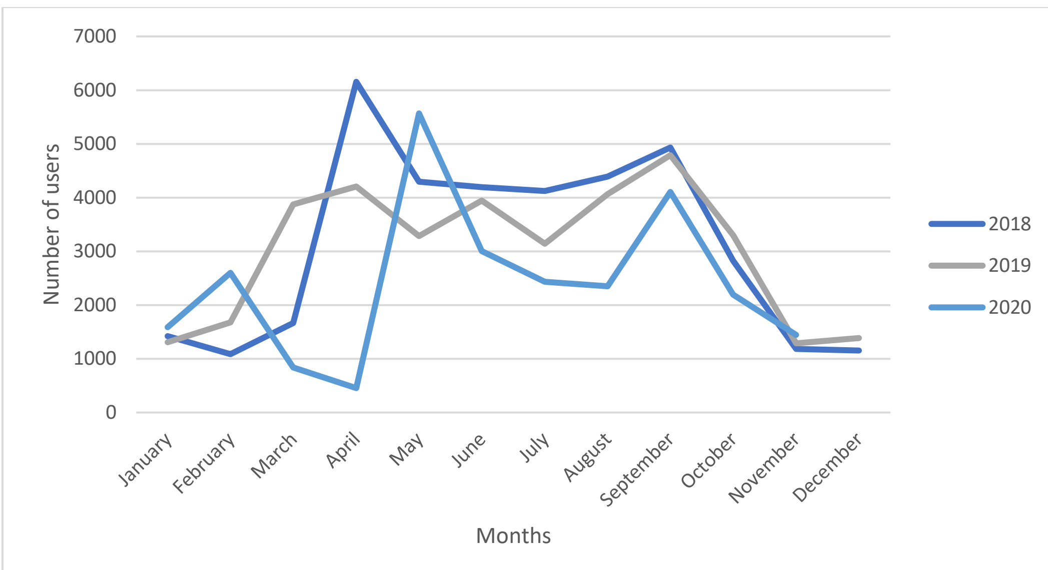

Figure 4-6: Monthly subscriptions of BikeMi system for the years 2018-2020

The basic subscriptions of the BikeMi system, which are available to the general public, are annual, weekly and daily. Their cost is 36€, 9€ and 4.5€ respectively. In basic subscriptions, in addition to the cost of purchasing the subscription, the user pays specific amounts depending on the time of use of a mode. There are also special subscriptions such as Freecard GOLD, Freecard Premium and Supervisor. In Freecard GOLD and Freecard Premium, the user uses the system's modes without paying extra based on the time of use. In 2019 the Corporate subscription was introduced in the system. Figure 4-7 and Figure 4-8 show that the monthly percentage of users who create one of the special subscriptions is low for all months of the two years. The monthly users' percentages of the weekly subscription range between 8-22% for 2019, while they range between 9-14% for 2020. It is observed that the highest percentages of users prefer the daily subscription. The months of March and April 2020 are an exception. During these two months, there is a drop in daily subscriptions and an increase in annual subscriptions. This differentiation is logically due to the strict lockdown that was implemented in those months. More specifically, during these months only essential movements were allowed. Therefore, daily subscription may not have been practical for the system's users. While the annual subscription offers a long-term use during an uncertain period of a transport system that is safe, i.e., there is no contact with other people, and has not been affected by the imposition of social distancing measures.

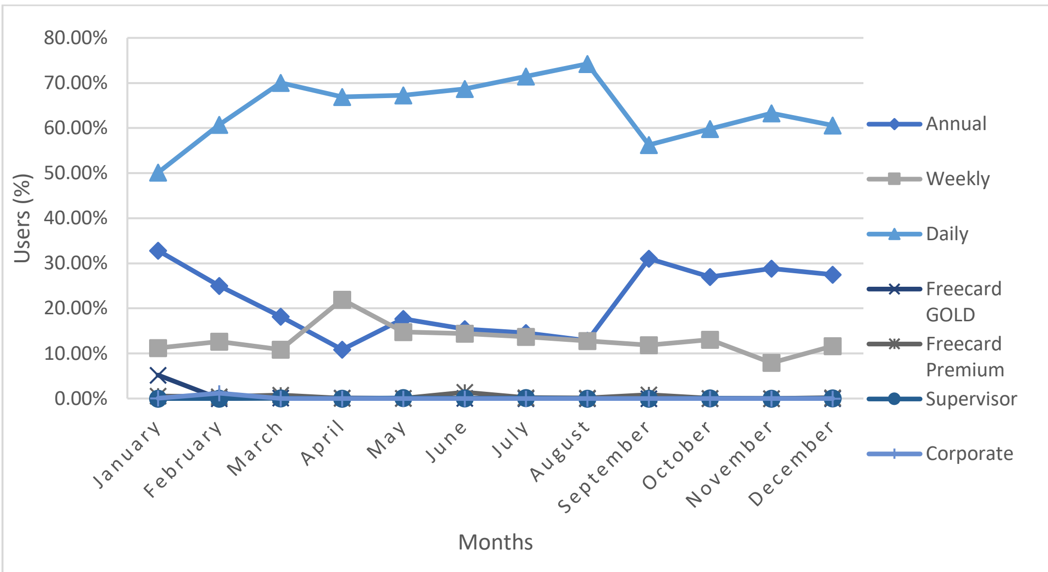

Figure 4-7: Subscription types of BikeMi users for the year 2019 (%)

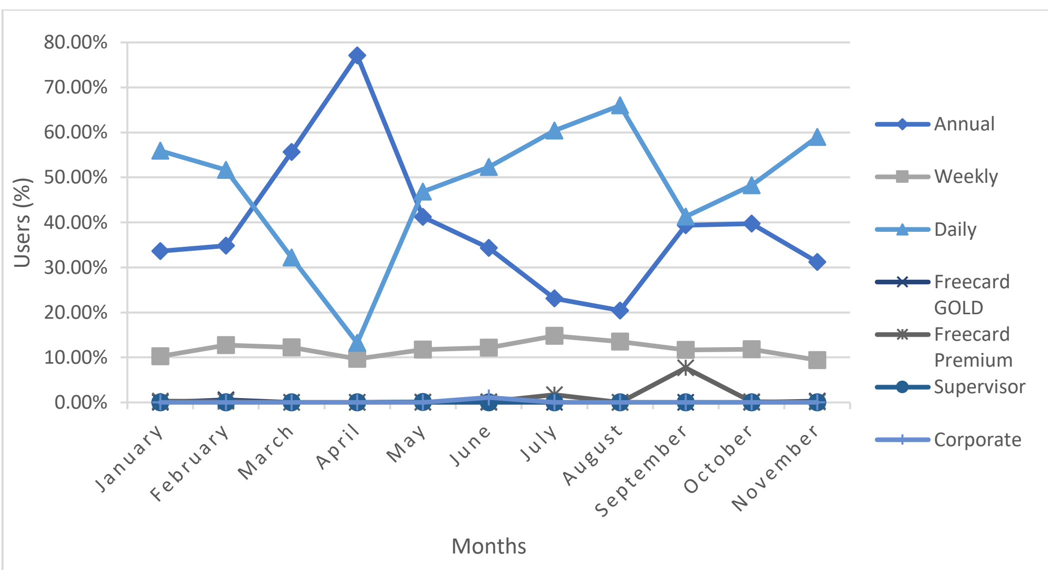

Figure 4-8: Subscription types of BikeMi users for the year 2020 (%)

An additional analysis performed based on the available data is related to the gender of the system users. It is observed that a significant percentage of users did not have this information available. This percentage exceeds 60% most months. However, it is not known if the data set is incomplete for this information or if it was the users' choice not to provide this information during the creation of the subscription. Figure 4-9 shows that for the whole 2019 the percentage of the male users is higher than women. The same trend prevails for the year 2020. However, this differs in the lockdown months (March and April) as well as for the next two.

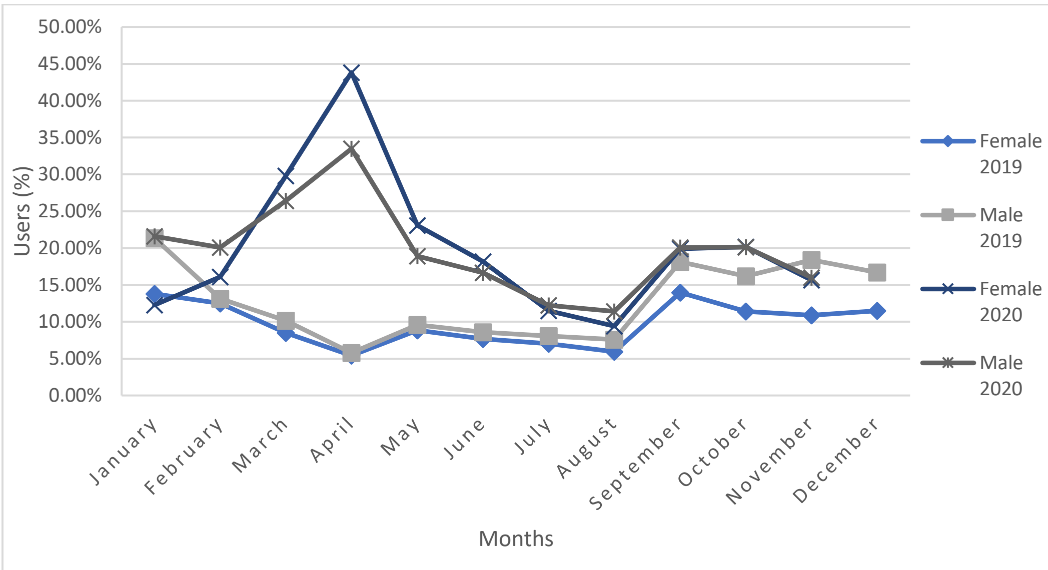

Figure 4-9: BikeMi users' gender for the years 2019 and 2020 (%)

The final analysis performed for the users of the system based on the available data is related to their profession. Unlike gender, information about the profession of users is available to almost all users. Figure 4-10 shows that most users of the BikeMi system in 2019 are either employees (29%) or students (25%). A large percentage of users have also chosen the option 'Other' (20%). A significant percentage of users are either Executive/Manager (10%) or Entrepreneur/Freelancer (11%). In contrast to the previous, the percentages of users, 3% and 1% respectively, who are in categories Worker/Craftsman and Retired are quite low. Regarding 2020 (Figure 4-11), the percentages of users per professional category present small differences compared to 2019. However, some categories show significant differences during the lockdown period. The percentages of Employee category, which is 34%, show a high increase during the lockdown period, while the percentages of the Student category (19%) show a particularly significant decrease. This drop in student users' rate is because educational institutions were closed at that time.

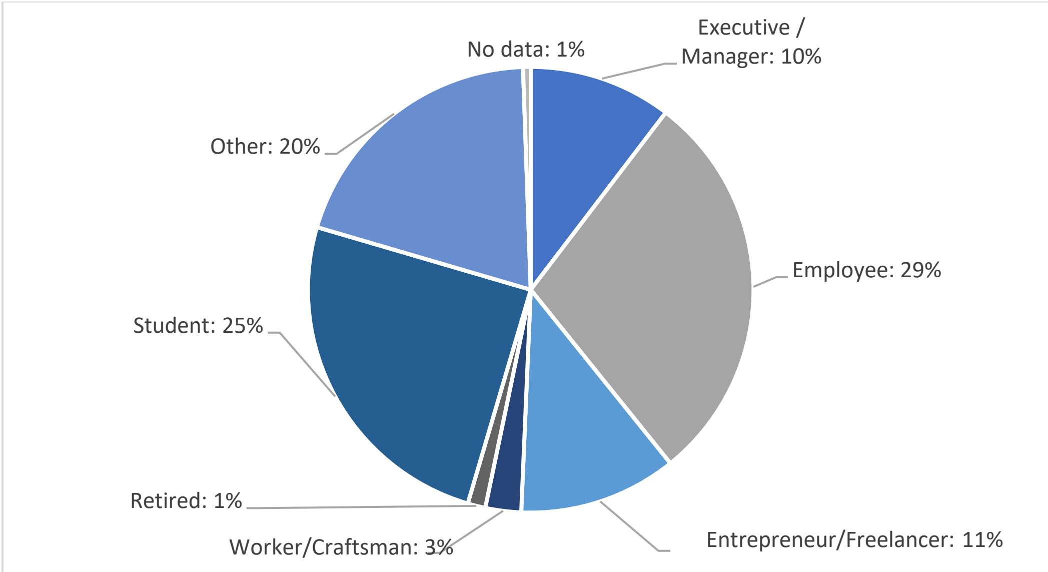

Figure 4-10: BikeMi users' profession for the year 2019 (%)

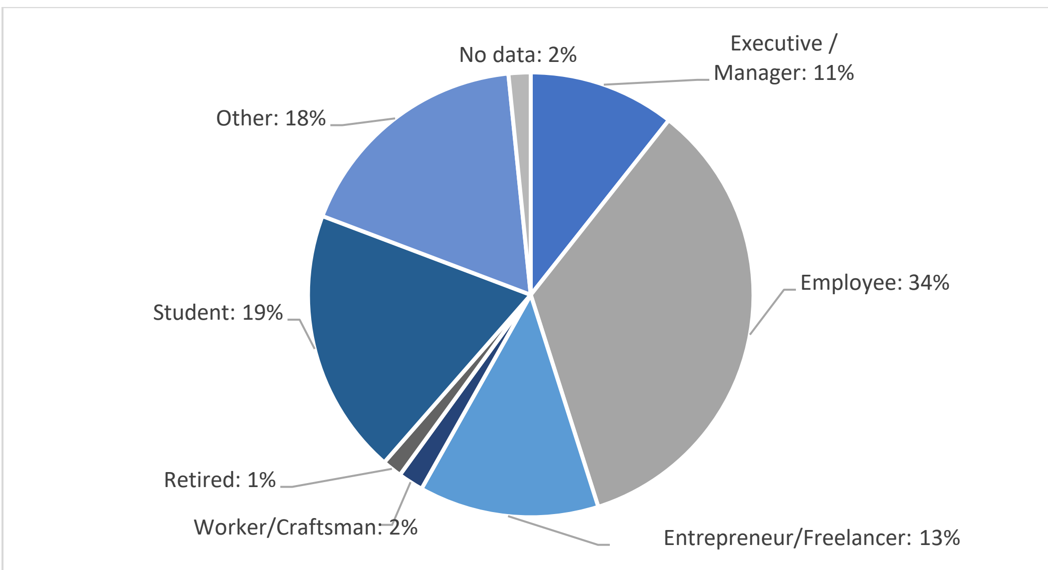

Figure 4-11: BikeMi users' profession for the year 2020 (%)

4.2.2.3. BikeMi analysis

The analysis of the BikeMi system was conducted for the years 2018, 2019 and 2020. More specifically, the first two weeks of April were selected. The choice of this period was due to the data that was initially available. The initial analysis of the BikeMi system was limited to the year 2018, while then it was conducted for the other two years. It was deemed necessary to process the data for the same period of each year and to compare the results between the same days. Therefore, the analysis of the system corresponds to the time periods 1-15 April 2018, 31 March-14 April 2019, and 29 March-12 April 2020. It would be good to note that the 1st of April 2018, 31st of March 2019 and 29th of March 2020 were Sundays. The available data provide information on the system demand, i.e., the origin-destination pairs and when they made, the identification number of the used bike, the type of used mode, the duration of the trip and the distance traveled, the calories consumed by the user and the carbon dioxide avoided by not using a car for this trip.

In this study, the day is set between midnight and 11:59 p.m. Based on the data, the system operates from 7 a.m. to 1 a.m. in the years 2018 and 2019, while it operates from 6 a.m. to midnight in 2020. It is observed that on some days the system operates at night (1 a.m. to 7 a.m.). Based on the information found, the system operates 24 hours a day in special cases. However, these days are an exception and therefor it is decided not to include night hours in the system's analysis.

Based on the available data, an attempt is made to understand the BikeMi system and its operation, as well as find information that can be used elsewhere in this study. The first analysis performed to understand the system is the daily use and daily usage rates of bikes, e-bikes, and e-bikes with a child seat. For the aggregate representation of daily use and daily usage rate per mode, the dates are reported as days, i.e., Day 1 represents 1/4/18, 31/3/19 and 29/3/20, while Day 15 represents the dates 15/4/19, 14/4/19 and 12/4/20. The same way of matching dates with days applies to intermediate cases. Regarding the daily use (Figure 4-12), there is no specific demand pattern between the years. The system demand increases towards the end of the week in 2018, while it increases at the beginning of the week in 2019. In 2020 the demand has decreased a lot due to the strict lockdown. However, the system demand shows a small range on working days per week. The daily usage rates of bikes and e-bikes, which are presented in Figure 4-13, show a uniformity in the years 2018 and 2019. The percentage of users who use an e-bike ranges between 13%-19%. This pattern, however, does not apply to 2020. In this year, about 1/3 of daily users choose to use an e-bike. The introduction of e-bikes with child seat took place in 2019. The percentage of use of these e-bikes is less than 1% most days.

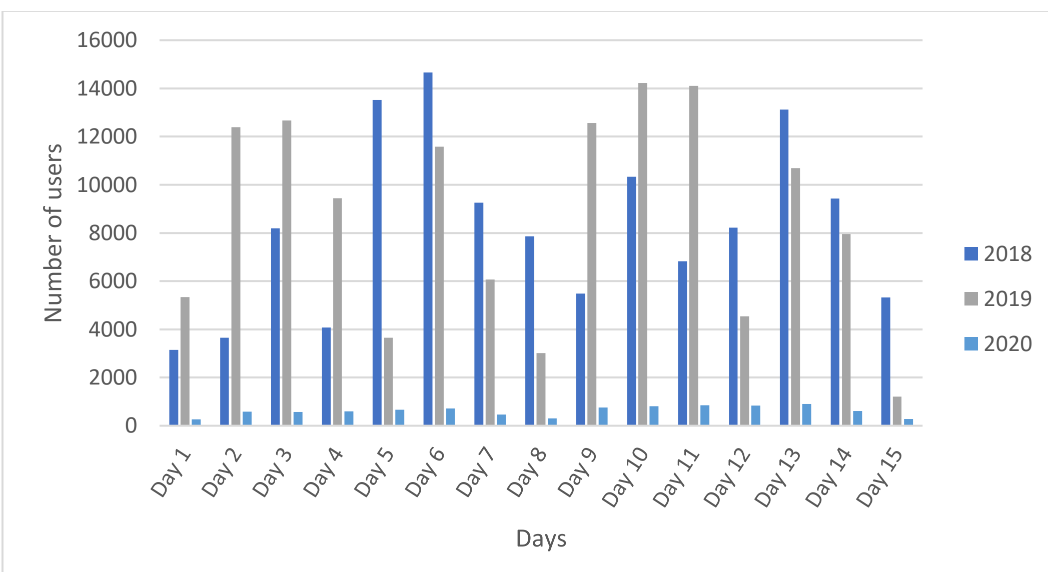

Figure 4-12: Daily use of the years 2018, 2019, and 2020

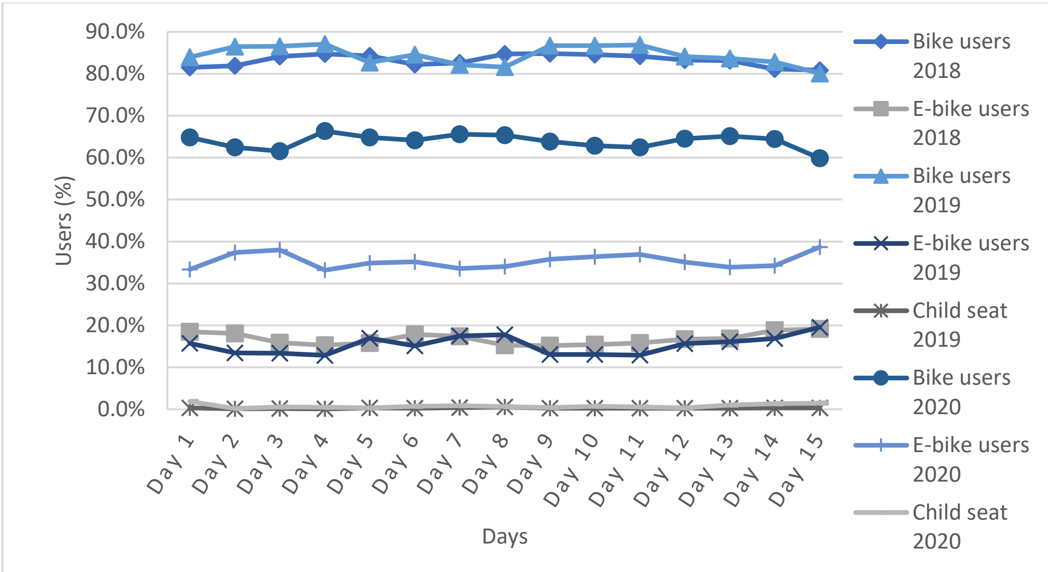

Figure 4-13: Daily usage rates of bikes, e-bikes, and e-bikes with child seat of the years 2018, 2019, and 2020

The network of system stations is growing over time. The system consists of 269, 290, and 302 stations in 2018, 2019, and 2020, respectively. The system currently has 320 stations. This indicates that the needs of the system have increased, and the result is the thickening of the network of stations or that the system is being developed in new areas. The extension of the station network for 2019 is illustrated in Figure 4-14a, while for 2020 in Figure 4-14b. The new stations are in the red circles. In both years there is a thickening and expansion of station network.

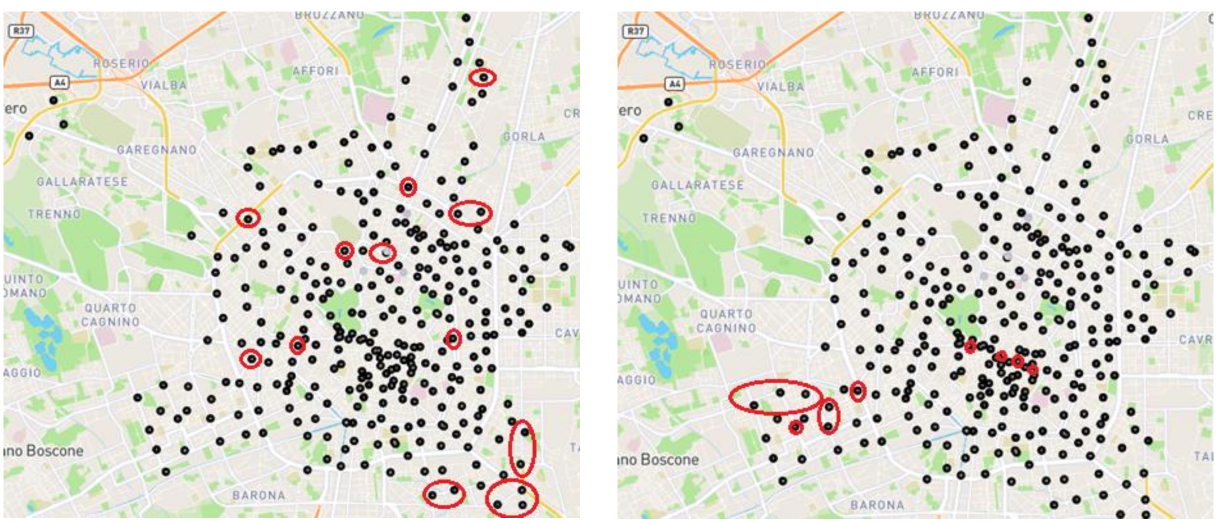

Figure 4-14: a) System extensions 2019 (left) and b) System extensions 2020 (right)

A further analysis is the daily use of the BikeMi system per hour. The purpose of this analysis is to find the peak hours of the system. The analysis is performed for the periods of 2018, 2019, and 2020 as already mentioned. The hours for which the analysis is performed differ for each year as the system seems to have small changes in its operating hours. Therefore, the period for 2018 and 2019 is 7 a.m.-1 a.m., while for 2020 it is 6 a.m.-midnight. In this section the way the analysis was performed will be explained, the results of the daily average demand analysis for 2019 is given as an example (Figure 4-15), and some general conclusions will be reported. For more details on this analysis one can refer to the Appendix C.

After separating the daily demand of the system per hour, the average daily demand and the overall average demand per annual period are calculated. Then the hours whose demand exceeds the corresponding daily average demand-the blue cells in Figure 4-15-and the hours whose demand exceeds the overall average demand per annual period are found. The general conclusions that can be drawn are that the BikeMi system is in relatively high demand on weekends as well. Therefore, the system is preferred by the users not only for their daily movements but also for their movements in their leisure time. It is observed that in the morning on weekdays, 7 a.m.-10 a.m., the demand exceeds the corresponding daily average. This also happens at noon and in the afternoon. On weekends, demand exceeds the corresponding average between 10 a.m. or 11 a.m. and 8 p.m. or 9 p.m. If one considers human activities such as work/school/university daily or leisure activities on the weekends, the above conclusions make sense. Regarding the analysis of the overall average demand per annual period, the conclusions differ slightly. It is observed that on days with low demand there is either no excess of the overall average demand or there is an excess in very few time periods. This is because the overall average demand is affected by the high demand values of some days. On the days with higher demand, the excess of the overall average demand presents a similar pattern to the analysis of the daily average demand. Through this information, there is better insight into the system. Also, some information can be used to determine the parameters of the research.

Hour	31-03-19	01-04-19	02-04-19	03-04-19	04-04-19	05-04-19	06-04-19	07-04-19	08-04-19	09-04-19	10-04-19	11-04-19	12-04-19	13-04-19	14-04-19
00:00- 00:59	155	48	62	66	69	50	152	187	35	86	144	144	28	227	83
7:00-7:59	31	577	633	653	41	498	117	37	533	658	693	244	343	125	22
8:00-8:59	60	1889	1954	2023	556	1593	193	105	1774	2071	2121	531	978	189	44
9:00-9:59	145	1147	1230	1173	458	1014	263	124	1078	1204	1243	389	651	360	79
10:00-10:59	232	418	454	388	223	412	378	201	413	527	548	133	193	461	57
11:00-11:59	334	369	398	111	108	336	437	230	342	433	443	133	242	543	50
12:00-12:59	430	536	606	124	257	641	502	306	503	638	612	253	475	583	52
13:00-13:59	366	719	767	137	276	729	402	225	698	822	805	309	658	554	19
14:00-14:59	341	618	707	160	157	636	397	201	709	749	752	235	674	498	42
15:00-15:59	495	510	543	202	121	543	466	187	538	590	588	107	586	587	65
16:00-16:59	496	633	633	422	180	620	471	212	728	684	625	223	755	602	92
17:00-17:59	491	1026	1013	807	396	1061	511	281	1029	1186	981	384	1136	638	88
18:00-18:59	472	1444	1322	1171	256	1205	468	298	1535	1566	1565	719	1269	633	154
19:00-19:59	513	1149	1070	973	189	912	408	166	1181	1201	1213	305	1089	580	119
20:00-20:59	288	668	617	513	117	594	358	100	694	764	815	246	651	467	49
21:00-21:59	185	279	308	222	132	288	183	36	358	413	349	84	418	234	49
22:00-22:59	162	230	198	157	56	242	181	67	213	345	295	45	275	234	48
23:00- 23:59	146	126	160	145	56	200	183	49	208	289	315	36	266	204	41

Figure 4-15: System daily demand per hour in 2019 and demand exceeds the corresponding daily average demand (blue cells)

Then the analysis of the stations and their use is given. The first step is to find the number of bikes rented and delivered to each station per day. The next step is to calculate the generator and attractor average per station for the study period per year. Therefore, two averages are obtained for each station per year.

The ratio of these two averages characterizes each station as “generator”, “attractor” or “neutral”. The ratio is calculated as:

$$Ratio = \frac{generator\ average}{attractor\ average} \tag{4-3}$$

If the ratio is less than 1 then the station is designated as “attractor”, if the ratio is greater than 1 then it is designated as “generator”, while if the ratio is equal to 1 then the station is considered “neutral”.

The results of this analysis are on two levels. The first level is the range of averages and therefore the use of stations, and the second level is the categorization-generator, attractor, or neutral-of stations. The main report presents only the analysis of 2019 and a typical reference to the years 2018 and 2020. Regarding the first level of analysis, the value interval of the generator and attractor averages used in the analysis are the same for all three years. On the one hand, the analysis needs to be as detailed as possible, on the other hand, the visualization of the analysis should be easily understood. Given this, the value intervals are six (0-29, 29-58, 58-88, 88-117, 117-146, 146-175) and are equal. Figure 4-16 and Figure 4-17 show the generator and attractor averages per station of 2019, respectively. It is observed that the busiest stations are in the city center of Milan, while as the distance from the city center increases, the low usage stations increase. The above remarks are also valid for 2018, while in 2020 the use of the system is very low throughout the network of the stations due to the strict lockdown.

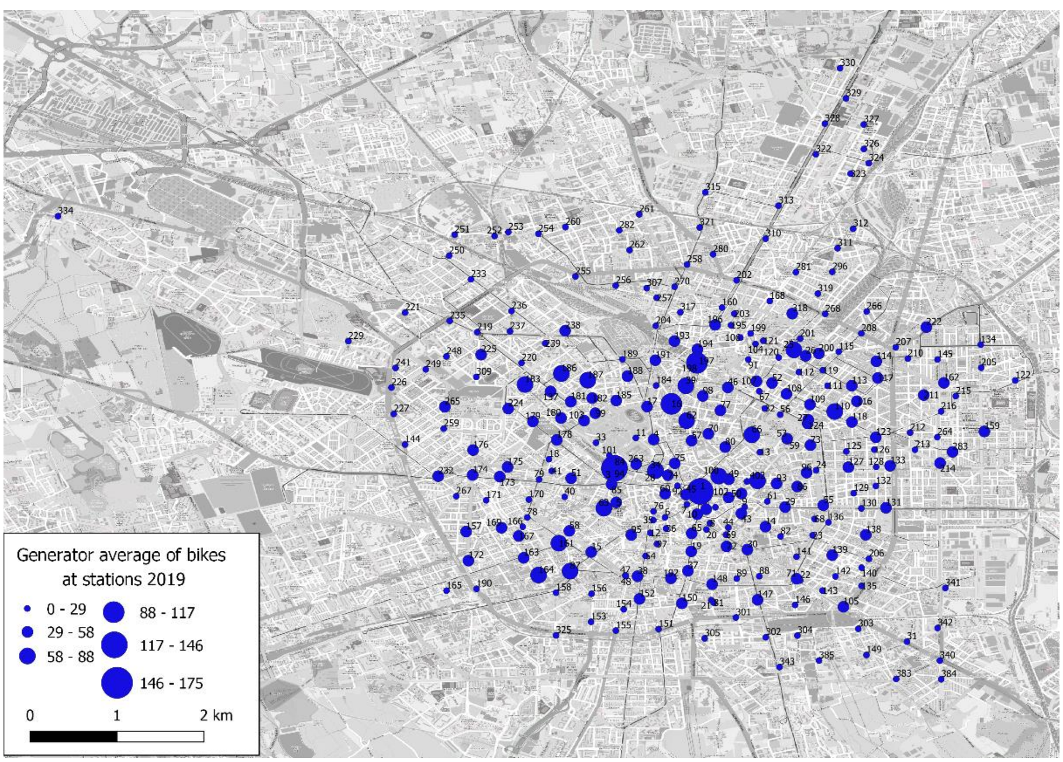

Figure 4-16: Generator averages of BikeMi stations 2019 (scale: 1:38000)

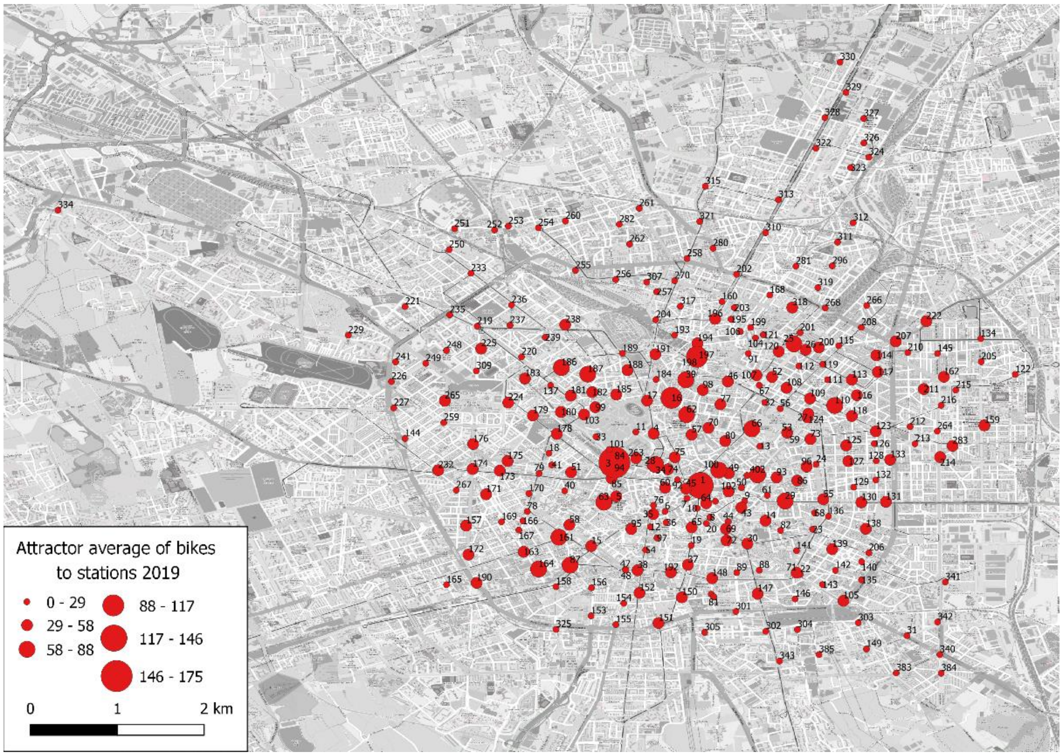

Figure 4-17: Attractor averages of BikeMi stations 2019 (scale: 1:38000)

In the second level of the analysis, stations are categorized according to the ratio value of the equation (4-3). It is concluded that 57% of the stations in 2018 are characterized as “attractor”, 42% as “generator”, while only 1% as “neutral”. The percentages of “attractor” stations show a decrease in 2019 and 2020. “Attractor” station in 2019 constitute 52%, while in 2020 they constitute 46%. The percentage of “neutral” stations remain stable for 2019, while it increases to 4% in 2020. Considering the narrow value range that the ratio receives, as well as the variations in the value range per year, it is decided that it is best to determine the values range of the ratio for each year separately. However, as in previous analysis, the value intervals are six and equal per station category- “generator” and “attractor”. The value range is 0.7-1.62, 0.66-1.46 and 0-3.83 for 2018, 2019, and 2020, respectively. Detailed reference is made to the year 2019, while the values of the ratios for the years 2018-2019 and the visualization of the analysis for the years 2018 and 2020 are presented in detail in Appendix C.

Figure 4-18 shows the ratio values (Equation (4-3)) of the stations. The generator stations are depicted in blue, while the attractor stations are depicted in red. The different sizes of the bubbles represent different interval ranges. The smaller the bubble size, the lower the interval range it represents in the corresponding categorization. It is observed that most network stations in 2019 are stable. More specifically, the generator average and the attractor average per station do not differ much from each other. About 56% of the stations have a ratio value belonging to the value interval 0.94-1.08 (value range 0.14), while 82% of the stations gave a ratio value belonging to the value interval 0.89-1.15 (value range 0.26). The year 2018 presents a similar degree of stability with the year 2019, i.e., approximately 86% of the stations have a ratio value belonging to the value interval 0.9-1.21 (value range 0.31). In contrast to the years 2018 and 2019, the year 2020 does not show much station stability. Approximately 70% of the stations have a ratio value on the interval 0.83-1.48 (value range 0.65). The percentage is much lower compared to the other two years, while the value range is almost double. This instability is logically due to the lockdown and the realization of only the essential moves.

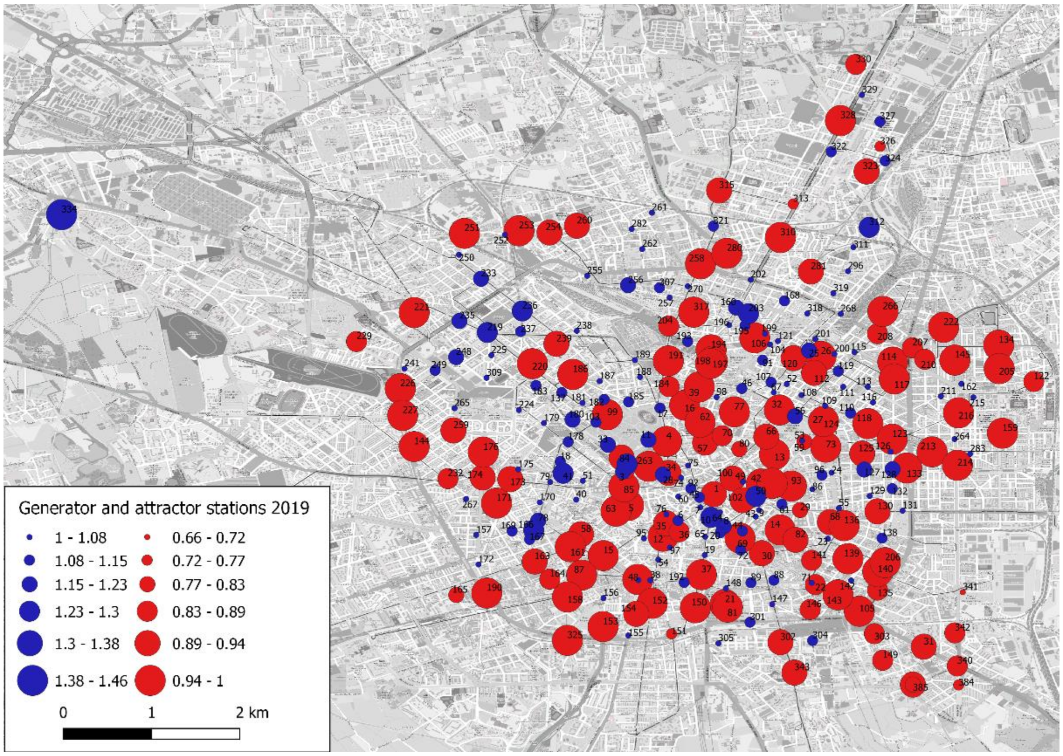

Figure 4-18: Generator and attractor stations of 2019 (scale: 1:38000)

The final analysis performed is related to the travel distance and the frequency of use per vehicle. The main conclusions of these analyzes are as follows. The e-bikes with child seat are introduced in the system in 2019. However, their use is low compared to the other two modes. E-bikes and bikes are used to perform similar travel distances, 0-10 km. The most common traveled distance is 1-2 km. However, bikes have higher rates of use at shorter distances, while e-bikes at longer distances (Table 4-3). This conclusion was expected as existing research (Campbell, Cherry, Ryerson, & Yang, 2016; Shaheen, Guzman, & Zhang, 2010) indicates that the e-bike is more tolerant of long distances. Long distances intervals (6-10 km) have small percentages. Concerning the frequency of use per vehicle, in 2018 the highest percentage of bikes is used 1-3 times a day, while e-bikes 1-4 times. The frequency of use per day of bikes and e-bikes is 1-4 times in 2019 but also the frequencies 5 and 6 show significant percentages. The frequency of use for 2020 is one time for bikes and 1 or 2 times for e-bikes. The smaller number of e-bikes in the system may explain the higher frequency of use per e-bike. It has already been reported that the number of subscriptions in 2019 has decreased slightly compared to 2018 (Figure 4-5). However, the frequency of use per vehicle shows a relative increase in 2019. This is due to the more frequent use of the system by users. This indicates that the system has seen an increase in user preferences.

Table 4-3: Average percentage of the two weeks studied period per travel distance interval (m)

travel distance (m)	Average (%) of the 2 weeks studied period					
	Bike 2018	E-bike 2018	Bike 2019	E-bike 2019	Bike 2020	E-bike 2020
0-500	4.22	4.78	4.22	5.23	14.06	13.03
500-1000	16.26	11.12	17.04	11.97	12.44	7.11
1000 - 2000	40.03	33.86	39.88	34.52	29.91	25.06
2000 - 3000	23.18	25.35	23.28	25.06	21.72	21.96
3000 - 4000	10.24	14.05	9.70	13.50	11.24	14.00
4000 - 5000	3.85	6.41	3.88	5.54	6.02	9.34
5000 - 6000	1.53	2.90	1.38	2.80	2.37	5.14
6000 - 7000	0.46	1.15	0.41	0.88	1.15	3.04
7000 - 8000	0.14	0.29	0.16	0.36	0.73	0.50
8000 - 9000	0.06	0.09	0.03	0.09	0.27	0.79
9000 - 10000	0.01	0.00	0.01	0.04	0.04	0.04

Collectively, some conclusions about the BikeMi system that emerged from its analysis at specific time periods. The use of the system has increased over the years. This may be the reason why the number of stations is constantly increasing. Of course, during the pandemic year (2020) the use of the system fell sharply due to the strict lockdown. Despite this decrease, the number of stations increased again. This may be to better cover some areas. There is no consistent pattern of demand between the years, but during the same year there is a relatively uniformity. As for the demand pattern during a day, it follows the working hours on a weekday, i.e., high demand during the hours of arrival and departure from the workplace. In addition, 4 out 5 users prefer to use a bike over an e-bike. However, in the pandemic year (2020), the use of the e-bike increases, i.e., 2 out of 5 prefer it. Finally, most stations have a balance between the number of rental and return vehicles.

4.3. Scenarios and designs

This chapter presents the designs used to implement the optimization model and the different demand scenarios.

The developed demand scenarios concern the demand of the bike sharing system, which is available for different days, and the unsatisfied demand of the public transport system, which results from the application of the mathematical model of integration of the two systems. The demand for the bike sharing system varies between days and for this reason it is decided to use days with different demand in the creation of the scenarios. Therefore, two days are chosen which are 4/4/2019 and 8/4/2019. On 4/4/2019 the bike sharing system is in low demand while on 8/4/2019 the system is in high demand. As for the demand for the subway system, it remains stable in the developed scenarios as it is the result of generation and not real data.

There are three demand scenarios (SClow, SChigh, SClockdown). SClow is the combination of the unsatisfied demand for public transport system (bike demand: 44715 and e-bike demand: 12685) and the demand for the bike sharing system on 4/4/19 (bike demand: 798 and e-bike demand: 195). SChigh includes the unsatisfied demand for public transport system (bike demand: 44715 and e-bike demand: 12685) and the demand for the bike sharing system on 8/4/19 (bike demand: 3474 and e-bike demand: 540). Regarding SClockdown, it is the demand for the bike sharing system on 8/4/20 (bike demand: 148 and e-bike demand: 91). The bike sharing system during the period of strict lockdown is in low demand all the studied days. The date 8/4/20 is chosen because it is one of the most demanding days in terms of demand for the system during the lockdown period. SClockdown does not include unsatisfied demand from the public transport system as the human movements were very low due to the strict lockdown. Demand in the subway system decreased by 90% and although subway services were reduced to 75% of their normal service, they were sufficient to meet the existing demand. The three different demand scenarios will be used as inputs for the designs. The basic demand scenario that most designs will consider is SClow. SChigh and SClockdown will be used as inputs for a few designs.

The designs are created based on the needs of the bike sharing system. The parameters that differ in the designs are the number of virtual stations and e-bike stations in the bike sharing network, the location of the virtual stations and e-bike stations, the maximum number of bikes per virtual station and the capacity of the e-bike stations. The first categorization of the designs concerns the number of virtual stations and e-bike stations in the bike sharing network, the location of the virtual stations and e-bike stations. Based on these two parameters, 7 basic designs are created. Each design is named with the capital letter D from the word design and the number of stations. These are D225, D245, D238, D241, D236, DM285 and D227. The locations of the new stations are close to subway stations. Then the other two parameters are considered, i.e., the maximum number of bikes per virtual station and the capacity of e-bikes stations. Two main types of designs emerge from this separation, Da and Db. Da has a maximum number of bikes per virtual station at 50 bikes, a minimum number of e-bikes docks at 10 and a maximum number of e-bikes docks at 25. Mb has a maximum number of bikes per virtual station at 80, a minimum number of e-bike docks at 10 and a maximum number of e-bike docks at 40. Design D0 is the design of the bike sharing system in 2019. The size of the stations is between 15 and 39 docks and the system is docked for both modes. Design D0 consists of stations with 30 docks as it is the most common station size. These 30 docks are divided into bike docks and e-bike docks. This means that the maximum number of bike docks per station is 20, the minimum number of e-bike docks is 1 and the maximum number is 10. The specifications of design D0 also apply to D227, which is the network of stations during the lockdown period (2020). The final design that is created is the Mc, in which there is no limit to the maximum number of bikes per station while the maximum and minimum number of e-bike docks are 10 and 200, respectively. Therefore, fifteen designs have been created, which are D225/D0 (current system), D225a, D225b, D245a, D245b, D238a, D238b, D241a, D241b, D236a, D236b, D285a, D285b, D285c and D227. The common features of all designs are the following. The bike sharing system is studied for six hours in the afternoon, 15:00 – 21:00, which include the evening rush hour. The optimization model requires the definition of time periods. In this case the time periods are three, $\tau1$: 15:00-17:00, $\tau2$: 17:00 – 19:00 and $\tau3$: 19:00 – 21:00. Therefore, the demand for the system is divided into these 3-time periods. In addition, the maximum and minimum used capacity percentages are 25% and 75%, respectively. That is, at the beginning of a period each station should have 25% of its capacity filled with e-bikes but also should have 25% of its capacity empty for parking availability. Figure 4-19 shows the above scenarios and designs. The combination of each scenario and design is an independent input into the application step of the optimization model and the order in which each implementation will take place is not particularly important for the next step which is the analysis of the outputs.

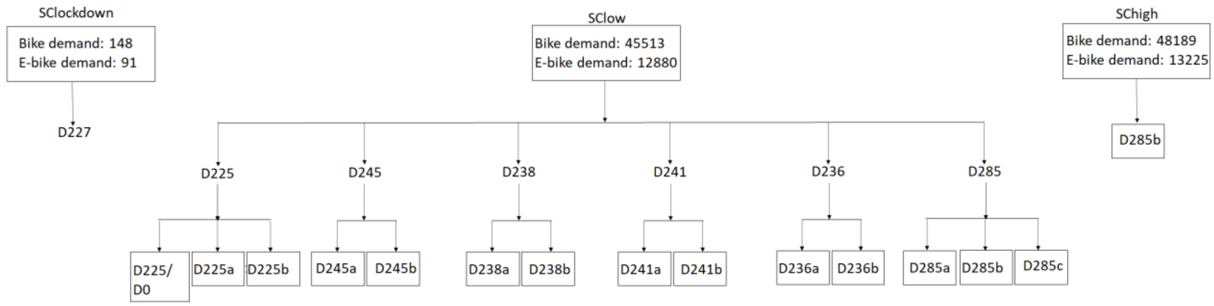

Figure 4-19: Scenarios and designs

The following is an illustration of the bike sharing system network for design D225 (Figure 4-20), which is the bike sharing station network of the city center of Milan for 2019. The Figure 4-21, Figure 4-22, Figure 4-23, Figure 4-24 and Figure 4-25 show the new stations that will be added to the network of 2019 (D225) depending on the study design. That is, design D245 is the network of bike stations of 2019 (D225) and the new stations of the bike sharing system that are placed near the subway stations of the M1 line that have unsatisfied demand. Figure 4-21 shows the new stations of design D245. Figure 4-22 shows the new stations of design D238 located near stations of the subway line M2. Figure 4-23 (design D241) and Figure 4-24 (design D236) show the new stations that are added to the already existing station network of 2019 (D225) and are located near stations of the subway lines M3 and M5 respectively. Design D285 consists of the network of bike stations of 2019 (D225) and the stations that are placed in all subway stations that have unsatisfied demand. Figure 4-25 shows only the new stations that will be added to the existing network of 2019 (D225). Finally, Figure 4-26 represent the network of bike stations of design D227, which is the network of stations during the lockdown period (2020). The station network of 2020 presents small changes and additions in relation to the network of stations of 2019 (D225) and that is why Figure 4-26 shows the whole network.

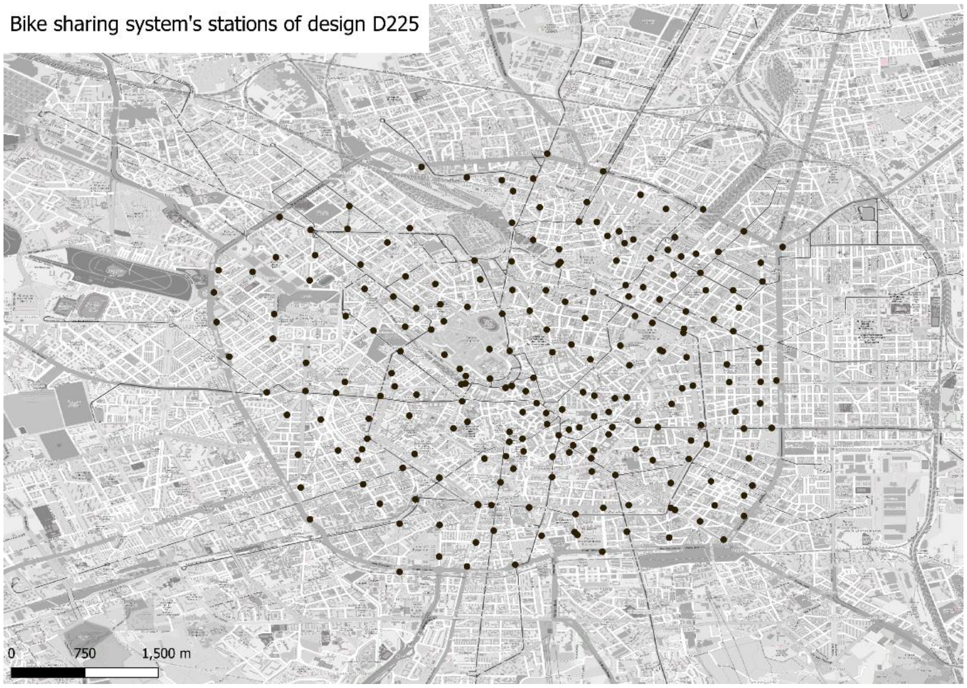

Figure 4-20: Bike sharing system's stations network of design D225 (scale: 1:30000)

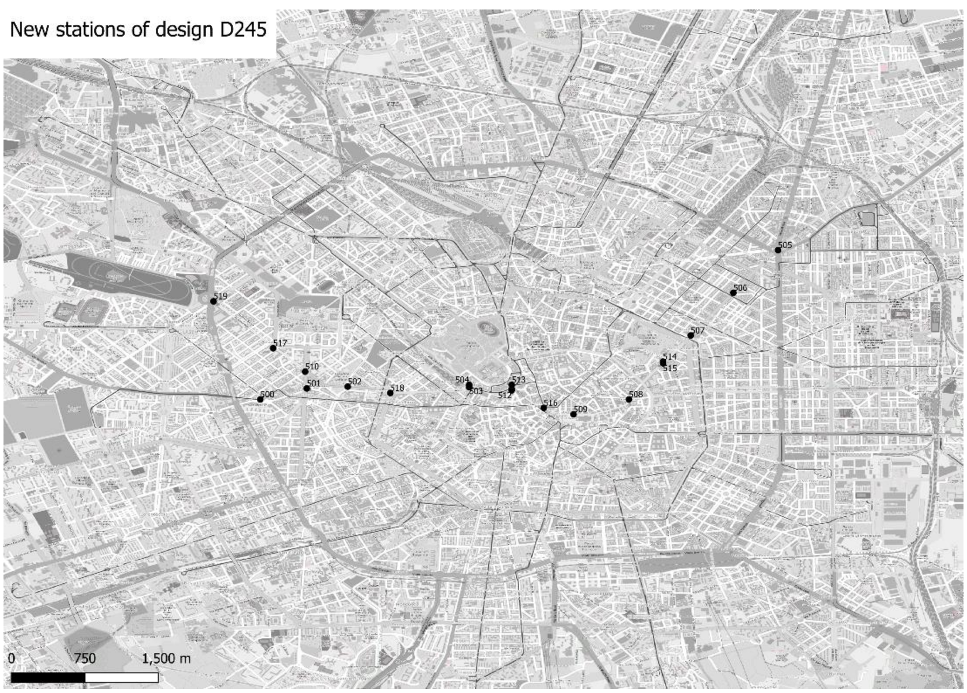

Figure 4-21: New stations of design D245 (scale: 1:30000)

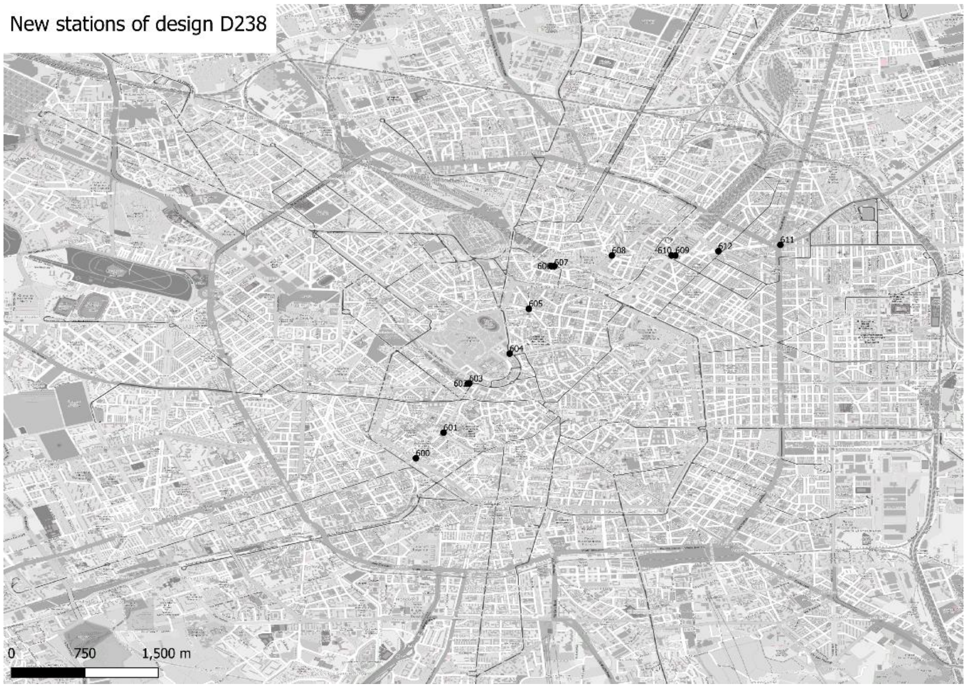

Figure 4-22: New stations of design D238 (scale: 1:30000)

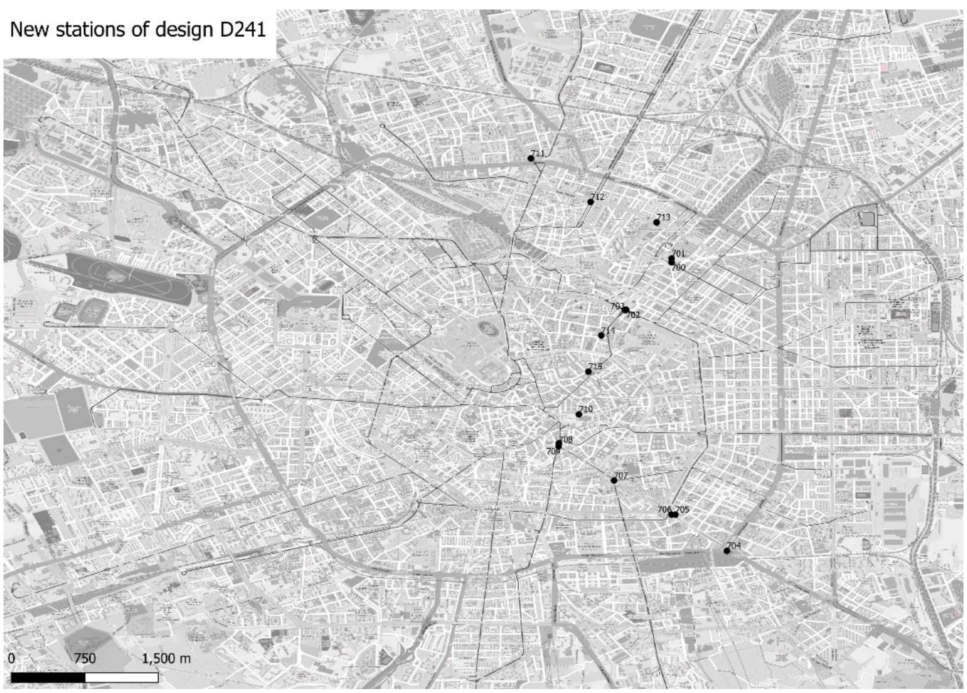

Figure 4-23: New stations of design D241 (scale: 1:30000)

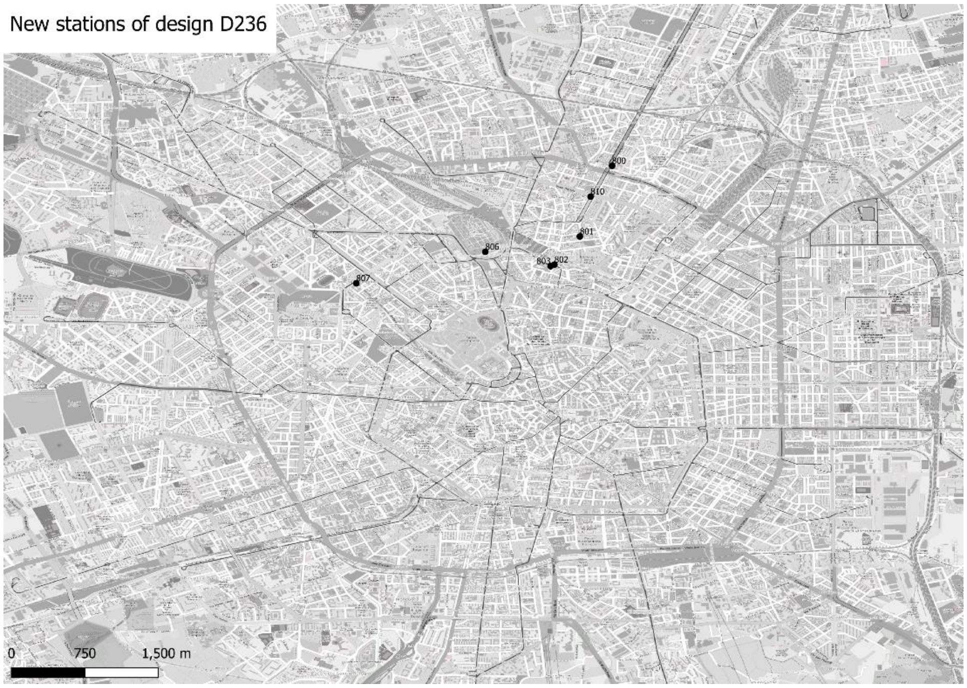

Figure 4-24: New stations of design D236 (scale: 1:30000)

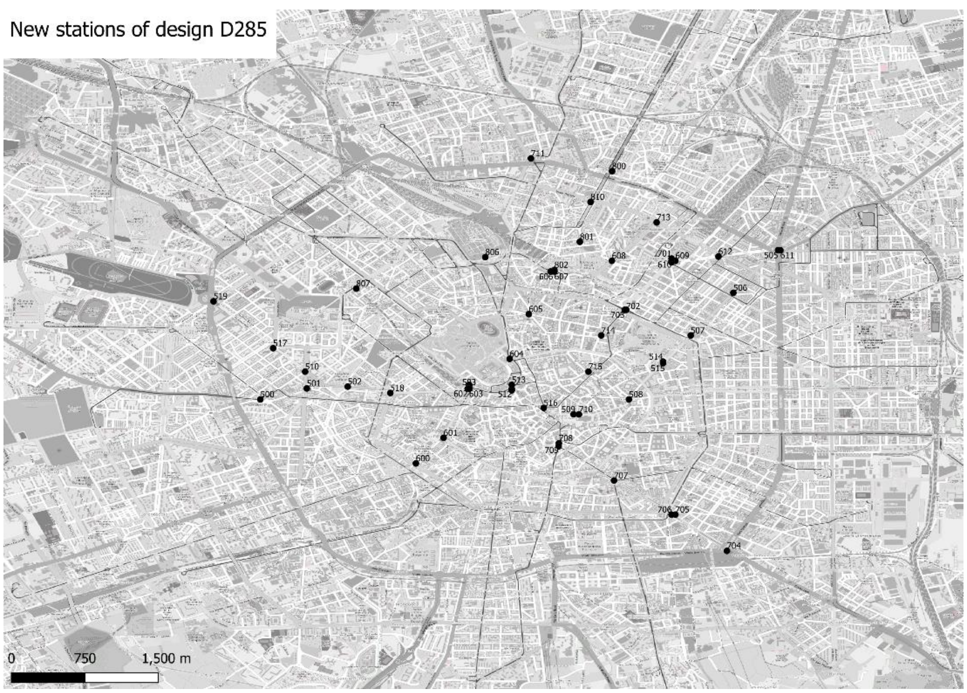

Figure 4-25: New stations of design D285 (scale: 1:30000)

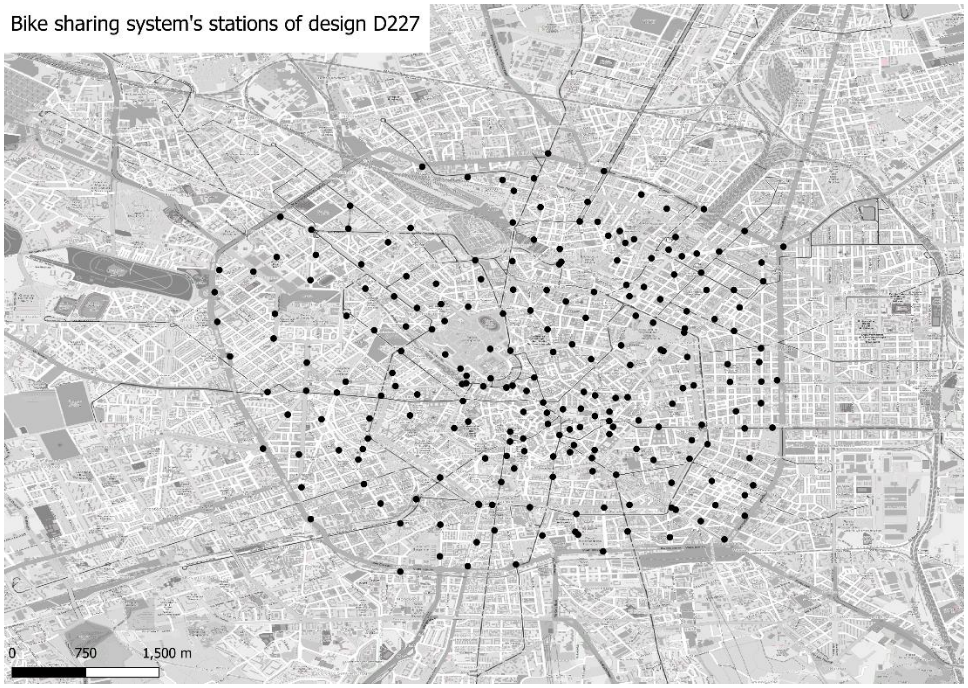

Figure 4-26: Bike sharing system's stations network of design D227 (scale: 1:30000)

4.4. Results and analysis

4.4.1. Bike sharing system demand resulting from the integration of the two systems

The first analysis carried out is related to finding the unsatisfied demand of the public transport system. Unsatisfied demand arises from the use of the mathematical model of integration of the two systems-public transport and bike sharing systems-and the demand of the public transport system. Demand for the public transport system is hourly. It is therefore divided equally among the schedules operated on each direction of subway line per hour. This means that, for example, if there are ten subway schedules taking place within the hour, the hourly demand will be divided equally among all the schedules, i.e., hourly demand/number of schedules within an hour. Unsatisfied public transport system demand due to social distancing constraints is around 30%. It should be noted that there is unsatisfied demand at stations outside the study area which is not included in the analysis. Also, unsatisfied demand for stations in the study area whose destination is outside the study area is not included in the analysis. The unsatisfied demand shown in Figure 4-27 is the total unsatisfied demand of the public transport system for the entire study period (15:00 – 21:00). However, it should be noted that the period 17:00 – 19:00 presents the highest unsatisfied demand, which is logical since it is the central peak hours of the public transport system. About 55% of stations belong to the first demand value interval (8-1150 passengers unable to board), while only 14% belong to the two highest value intervals (3434-5718 passengers unable to board). The stations with the highest unsatisfied demand are located peripherally of the study area and belong to the subway lines M1 and M5. Stations belonging to the other three value intervals are scattered in the study area and belong to all subway lines.

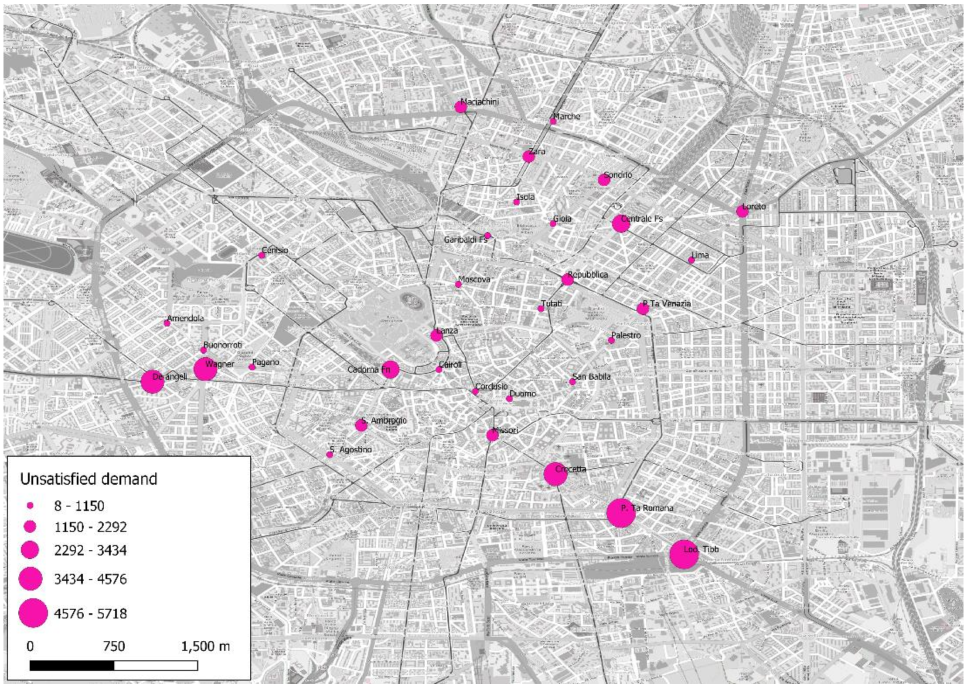

Figure 4-27: Bike sharing system demand resulting from the integration of the two systems

Unsatisfied demand for the public transport system is essentially the demand for the bike sharing system resulting from the integration of the two systems. This demand should be divided into bike and e-bike demand. The distances of the bike network between the subway stations with unsatisfied demand and the percentages of bike and e-bike use for specific travel distances intervals are used to separate the demand between the two modes. The percentages of bike and e-bike use for travel distances intervals are derived from the analysis of the case study and are listed in Appendix C. About 22% of the total demand resulting from the integration of the two systems is the demand for e-bikes and 78% is the demand for bikes. The trends that have been reported to prevail for the total demand of the bike sharing system due to the integration, also prevail in the cases of the demand for bike and e-bike. Figure 4-28 illustrates the bike demand resulting from the integration of the two systems, while Figure 4-29 presents the e-bike demand.

Figure 4-28: Bike demand resulting from the integration of the two systems

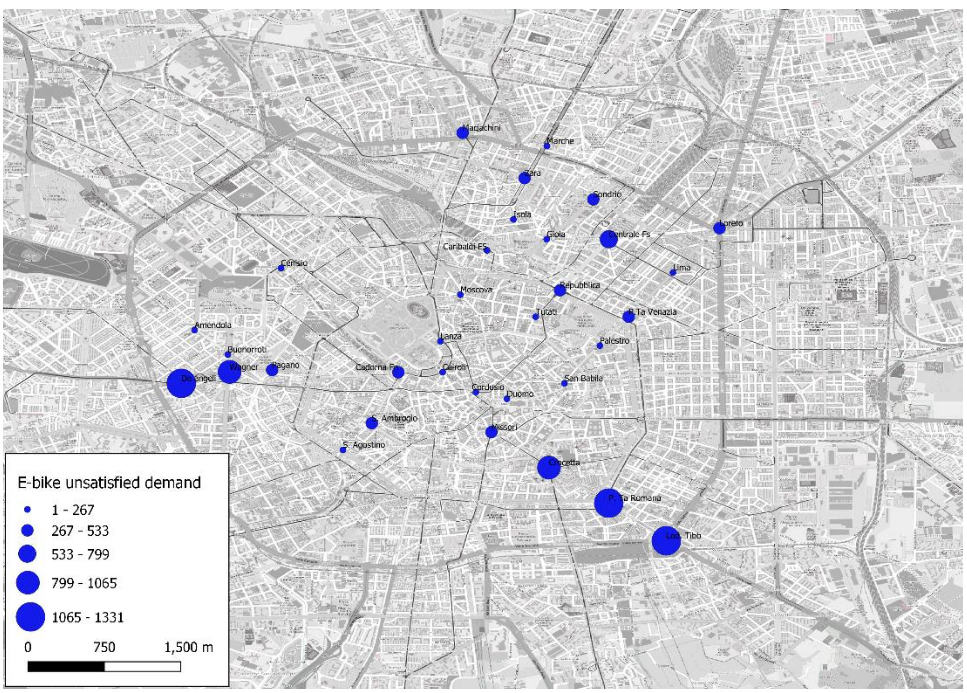

Figure 4-29:E-bike demand resulting from the integration of the two systems

4.4.2. Bike sharing system analysis

The analysis of the bike sharing system considering aspects of the pandemic situation uses the optimization model for a hybrid with mixed-fleet system as well as the various designs developed. The aggregate results of all designs and their inputs are listed in Appendix D. The analysis of the implementation of the optimization model consists of comparing different results such as the covered demand per design, the number of (virtual) stations in relation to the number of bikes or e-bikes, and the number of bikes and e-bikes and their relocation. The analysis follows by category.

- Covered demand per design

This analysis is performed simultaneously for both systems and is shown in Figure 4-30. Covered demand in design D0, current system's design, is just 6% for the bike system and just under 7% for the e-bike system. In all other designs there is at least a doubling of the covered demand rates, i.e., 2.1-2.4 times more covered demand. Only D227 fully meets the demand of both systems, which is logically due to the very low demand that characterizes SClockdown, the input demand scenario. The other design that has full coverage of bike system demand and high coverage of e-bike system demand (almost 70%) is D285c. The large coverage rates in this case are related to the design features of the system, i.e., an unlimited number of bikes per virtual station and a large capacity of the e-stations. In all other designs, it is observed that the covered demand is higher in percentage for the e-bike system. More specifically, the percentage of coverage of the demand for e-bikes in the designs is 2.1-4.4% more than the corresponding percentage of coverage of the demand for bikes. This may be due to the lower demand requirements for the e-bike system. In addition, it is observed that the Da designs, which have lower values in the capacity of their stations, have a lower percentage of covered demand compared to the scenarios Db, which are characterized by higher capacity of the stations. More particularly, an increase of the capacity of the e-stations and the available bikes in virtual stations by 60%, i.e., from 50 to 80 bikes and from 25 to 40 docks, brings about an additional increase of the covered demand by 6.5-7.5%. Demand rates in designs Db show a steady growth rate compared to the corresponding Da designs.

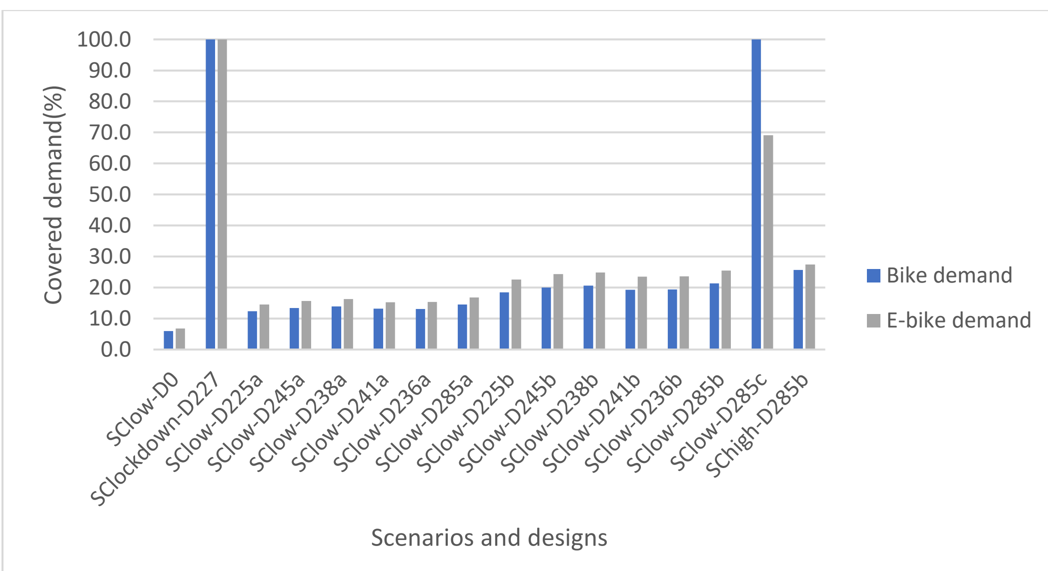

Figure 4-30: Covered demand per design

- Covered demand and fleet size

The analysis that correlates the covered demand with the fleet size is performed separately for the two systems. For the sake of better illustration, the D285c design is not included in the graphs. The general trend in the bike system is that the covered demand increases with the increase of the bike fleet (Figure 4-31). For example, design D241a has covered 5977 trips with 2608 bikes, while design D238a has covered 6333 trips with 2748 bikes. It is also observed that in each design the fleet size is about half in relation to the covered demand. The ratio (covered demand/fleet size) is between 2.13 and 2.36. This observation does not apply only to the D227 design in which the fleet size (137 bikes) and the covered demand (148 trips) are almost in the same size and the D285c design in which the fleet size (30959 bikes) is lower than the covered demand (45513 trips) but not to the trend prevailing in the other designs. In this case the ratio (covered demand/fleet) size is 1.47.

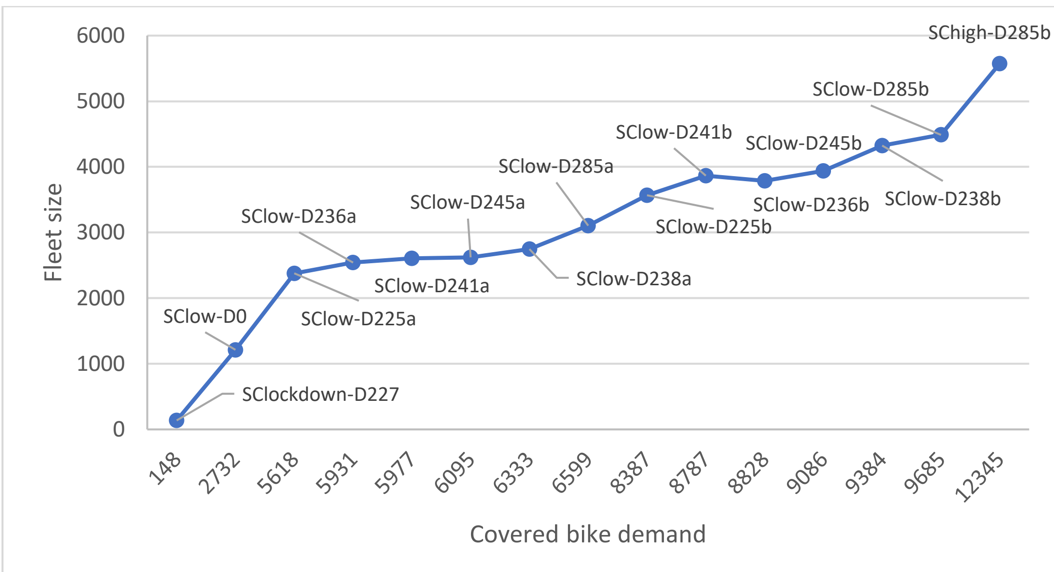

Figure 4-31: Covered bike demand and fleet size

The e-bike system does not show the same trends between the covered demand and the fleet size as the bike system (Figure 4-32). However, there are designs (D241b and D236b) that have a similar fleet size (3027 and 3040 e-bikes respectively) and the covered demand (4599 and 4564 trips respectively) between the designs is quite the same. However, the increase in the fleet in design D236b does not imply an increase in demand compared to design D241b which has a smaller fleet. Also, designs D227 and D285c have a large fleet size (402 and 20445 e-bikes respectively) in relation to covered demand (91 and 8896 trips respectively). The design of the e-bike system in the optimization model contains stricter capacity constraints of the stations and may be this is the reason for this variation between covered demand and fleet size.

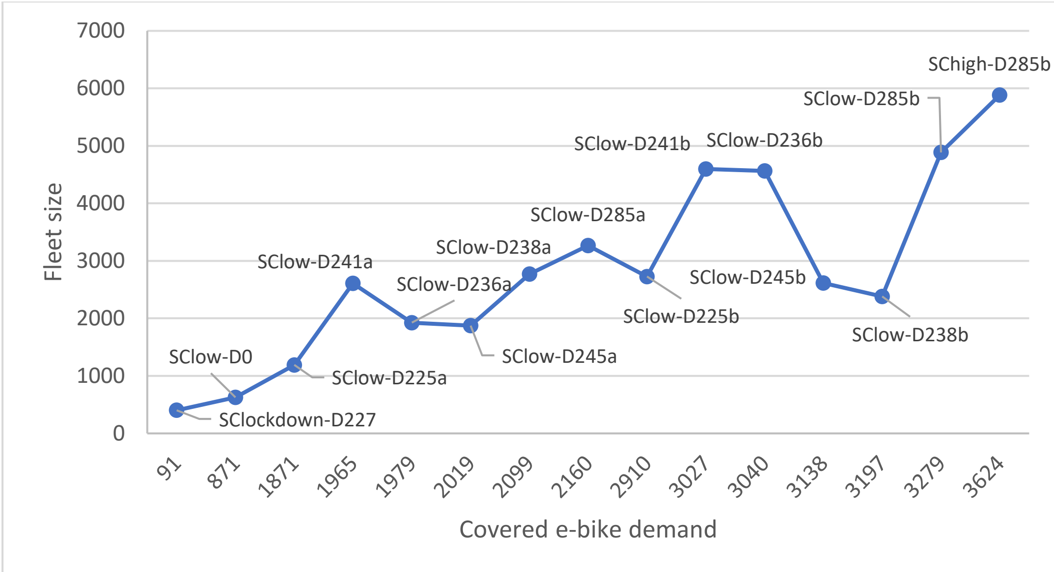

Figure 4-32: Covered e-bike demand and fleet size

The differences for the D227 design, which is in low demand, and D285c design, in which the design specifications of station capacity are large, are observed in both systems-bike and e-bike. These two differences indicate that the bike sharing system based on its design has service specifications, such as the availability of bikes and e-bikes, regardless of the size of its demand.

- Covered demand and number of stations

Then the relation between the covered demand and the number of stations is studied and shown in Figure 4-33, Figure 4-34, and Figure 4-35. This analysis is performed separately for the 2 systems-bike and e-bike. Regarding design D227, in which the SClockdown scenario applies, the demand of both systems is fully covered since the demand requirements are low. Although the demand is low, the size of the station network is relatively large (227 virtual stations and 107 e-stations). This indicates that demand is spread across the study area and wide station coverage is needed even in this case.

For the bike system, the same number of stations can cover more demand in the case of high station capacity specifications (Db designs). For example, designs D238a and D238b have the same number of stations. However, the capacity specifications of the stations in design D238b are increased in relation to designs D238a by 60%. This increase in stations' capacity specifications results in greater demand coverage, i.e., 3051 more trips are covered. Moreover, an increase in the number of stations does not always lead to an increase in covered demand. Namely, design D238b has 7 stations less than design D245b but covers 298 trips more. This observation applies in both cases of station capacities (designs Da and Db). In case the demand scenario, i.e., scenario with higher demand (SChigh), for a specific design (D285b) changes, it is observed that the same number of stations (285) can satisfy more demand. More specifically, design D285b covers 2660 more trips when SChigh is applied than when SClow is applied.

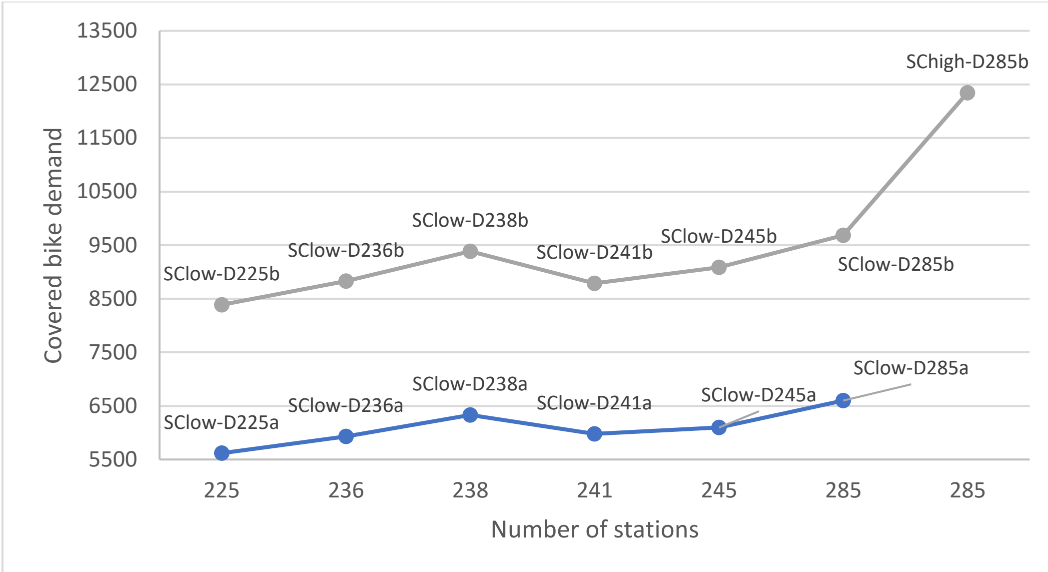

Figure 4-33: Bike covered demand and the number of stations

As far as the e-bike system is concerned, it is observed that the increase of the stations is not in line with the increase of the covered demand in some cases. In the case of designs D245a and D236a it is observed that design D236a has 6 more stations but covers 40 fewer trips than design D245a. Also, there are designs with the same number of stations, such as D236a and D238a with 188 stations and D245b and D238b with 180 stations, but in which the covered demand differs. In the first case there is a difference of 120 covered trips while in the second case this difference is 59 trips. However, this difference in covered demand is

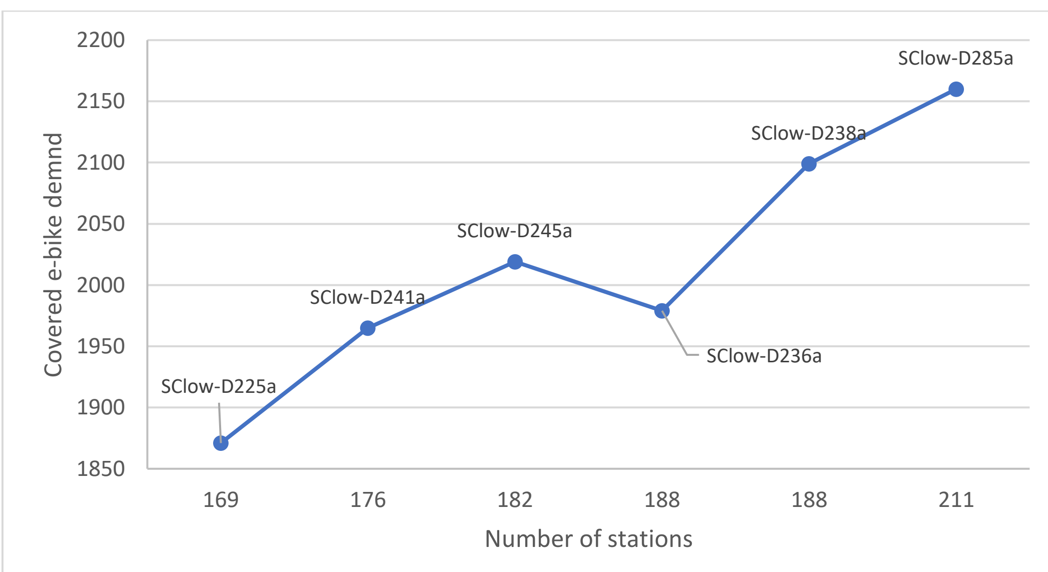

Figure 4-34: E-bike covered demand and the number of stations for Da designs

considered low in comparison to the total demand of the system. The two above-mentioned conclusions concern both cases of capacity specifications of the stations, designs Da and designs Db. The resulting differences between the number of stations and the covered demand may be due to the demand of the selected stations. In cases where the number of selected stations is almost the same such as D236a and D236b, designs with high-capacity specifications (designs Db) satisfy more demand, i.e., 1061 more trips.

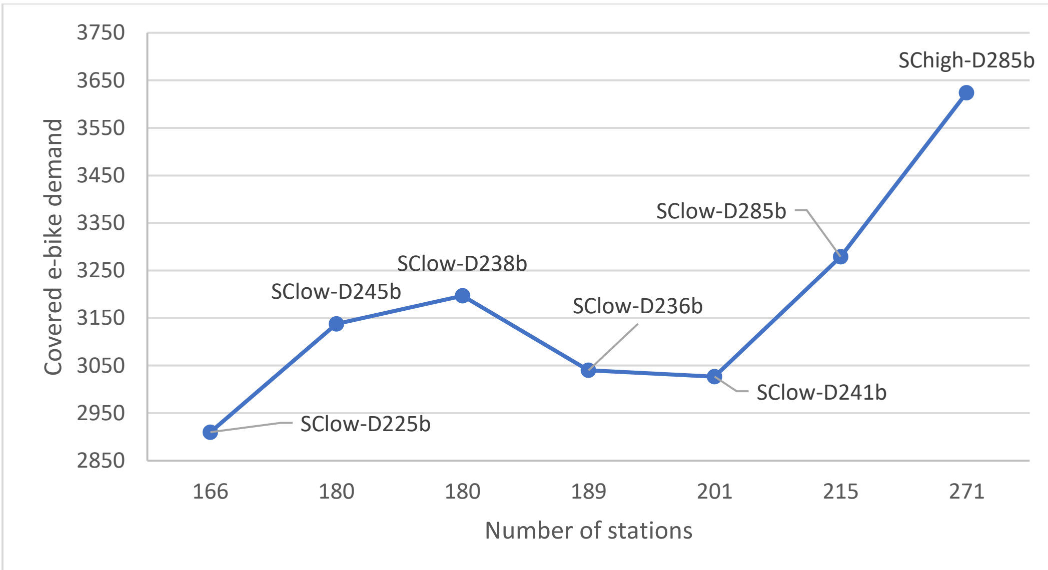

Figure 4-35: E-bike covered demand and the number of stations for Db designs

- Number of stations and fleet size

An interesting analysis is the number of system's stations compared to the size of the fleet. The bike system presents uniformity between the results of designs with low (Da designs) and high (Db designs) capacity specifications. The size of the fleet increases as the number of stations increases. This statement differs only when the number of network stations is 241 (D241a and D241b) and 245 (D245a and D245b). In these two cases it is observed that the bike fleet shows a decrease compared to D238a and D238b designs of which the number of stations is 238, i.e., 3 and 7 stations less respectively. However, this is in line with the demand coverage, i.e., the same fluctuations exist in the designs' covered demand as shown in Figure 4-33. In case the demand of the system increases, different demand scenarios-SClow and SChigh-the same number of stations (285 stations) satisfies more demand.

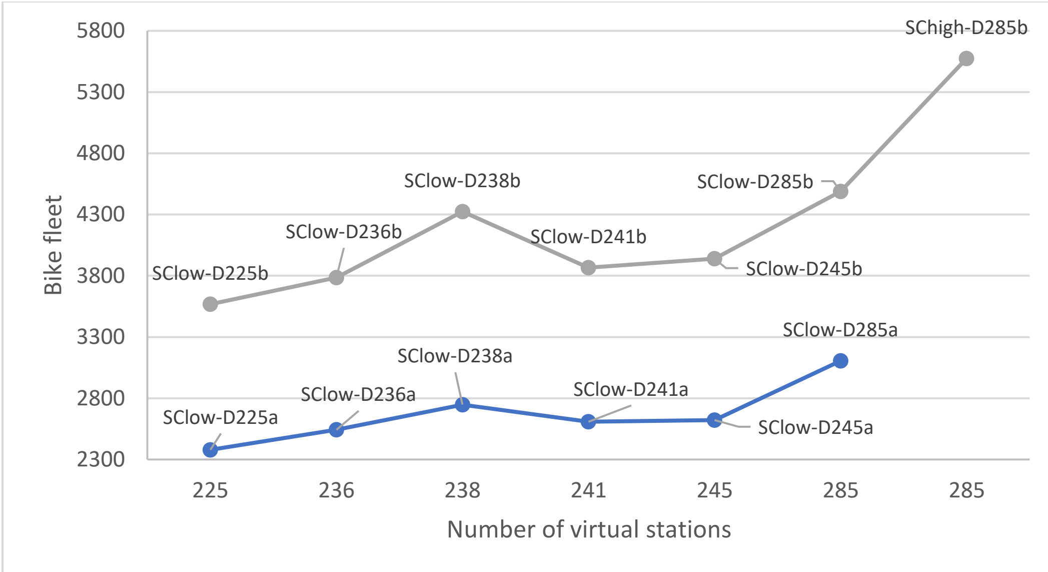

Figure 4-36: Fleet size of bikes and number of virtual stations

Figure 4-37 shows the correlation of the number of stations and the e-bike fleet for the low-capacity specifications designs (Da) in the e-bike system. There can be no clear trend in this case. It is worth noting that the designs D238a and D236a has the same number of stations (188), but they have a relatively large difference in fleet size which is 842 e-bikes. However, there is higher demand coverage in the design with the largest fleet which is the D238a design (Figure 4-34).

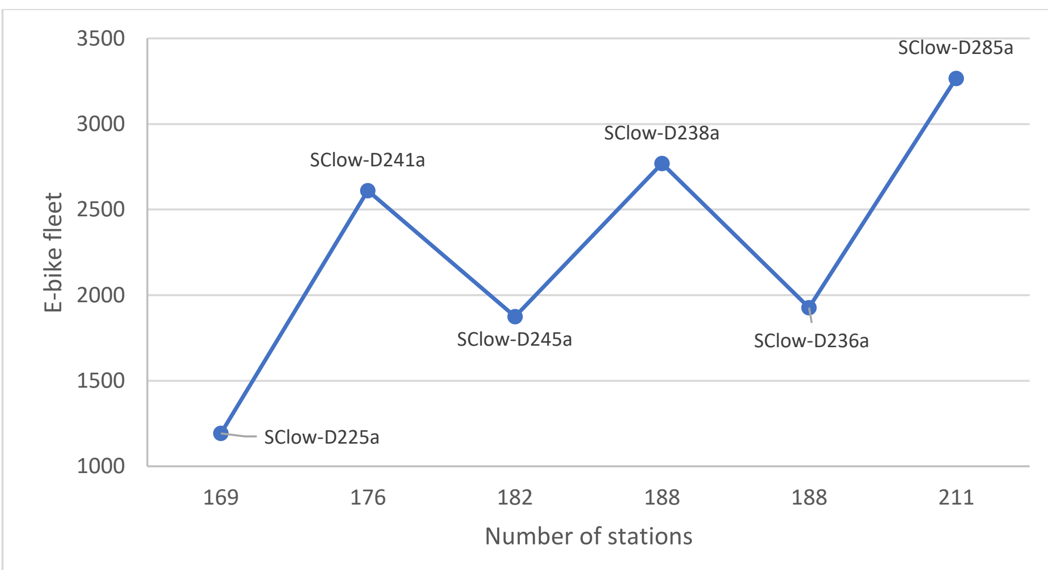

Figure 4-37: Fleet size of e-bikes and number of stations for Da designs

The corresponding analysis for designs with high demand specifications (Db designs) is shown in Figure 4-38. It is observed that the designs D245b and D238b have 180 stations but show a small difference in the size of their fleet which is 232 e-bikes. However, in this case, the D238b, which is the design with the lowest fleet size, satisfies higher demand as shown in Figure 4-35. In addition, the difference in the fleet size between a system with 180 stations and a system with 189 stations is significant, i.e., more than 2000 e-bikes. However, this does not mean an increase in covered demand, but a decrease in covered demand (Figure 4-35). In other cases, as the number of stations increases, so does the number of fleet size as well as the covered demand.

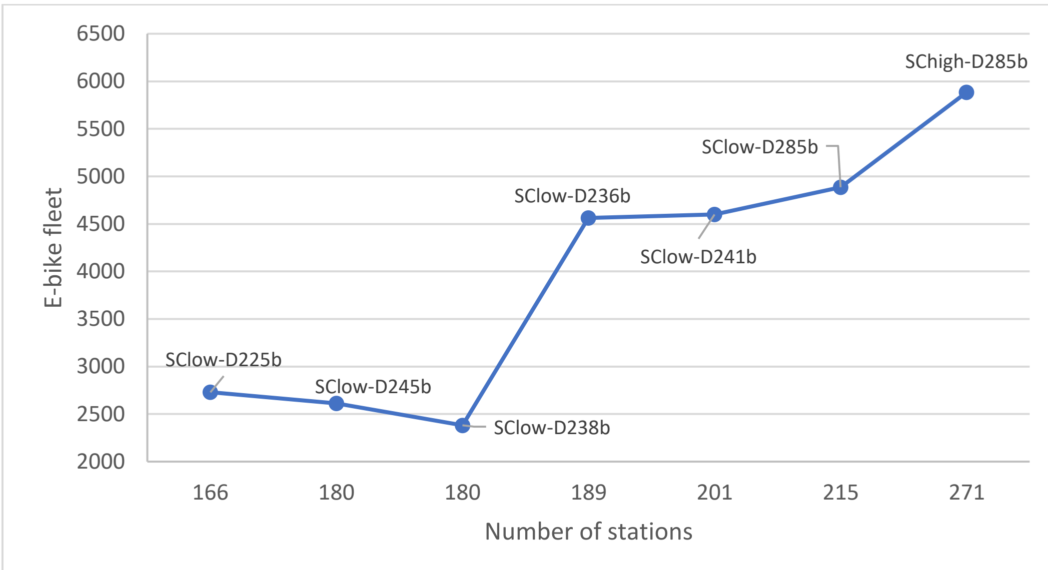

Figure 4-38: Fleet size of e-bikes and number of stations for Db designs

- Fleet size and relocation size

The analysis between the size of the bike fleet and the size of the bike relocation is shown in Figure 4-39. The size of the bike relocation follows an upward trend as the size of the bike fleet increases. For example, the design D238a has 2748 bikes, and the number of the relocated bikes is 2287, while the design D285a has 3105 bikes and 2596 bikes for relocation. In a few cases there is a decrease in the size of bike relocation while there has been an increase in the size of the fleet. These cases are the designs D245a, D245b and D285b under the SClow demand scenario. It is observed that the size of the relocations is always smaller than the size of the fleet. Only the case of design D227 is an exception. This may be due to the large number of stations (227 stations) relative to the small fleet size (137 bikes). It should also be noted that there is no difference in results between designs with low capacity (Da designs) and high capacity (Db designs) specifications on stations.

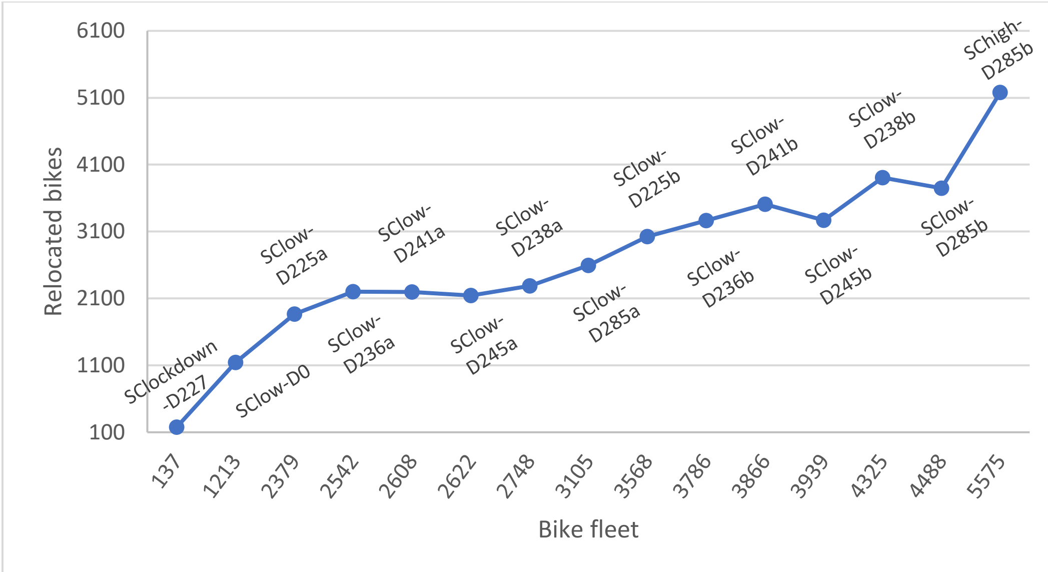

Figure 4-39: Bike fleet size and relocation size

The corresponding analysis for the e-bike system is shown in Figure 4-40. The e-bike system cannot be characterized by stability in the relation between fleet size and relocation size. The size of the fleet is higher than the size of the relocations for all designs beyond the D225a design. In the designs with the high-capacity specifications (Db designs) in their stations, there is a greater number of relocations in relation to the size of the fleet than in the designs with the low-capacity specifications (Da designs).

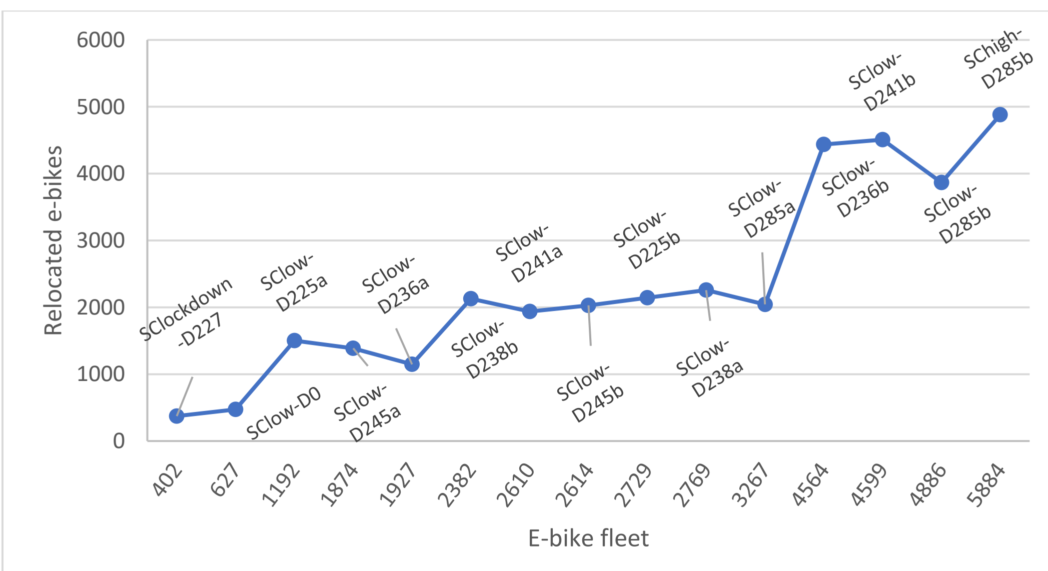

Figure 4-40: E-bike fleet size and relocation size

- Cost analysis

The values used to perform the cost analysis are not related to the case study but are based on the literature. The choice of the price of an e-bike was based on the study of Galatoulas et al. (2018). The e-bike chosen is the Runner model which costs 725€. The study by Ji et al. (2014) states that the e-bike usually has twice the price compared to the conventional bike. Therefore, based on this, the price of the bike is considered equal to 360€. In terms of relocation costs, this is set at 0.2€ per relocated (e-)bike. The results of SClow-D285c are not presented in the graphs for reasons of better representation of the other results.

Figure 4-41 shows the total cost of the designs. The total cost consists of the purchase cost of bikes and e-bikes and the relocation cost of bikes and e-bikes. The cost of buying e-bikes is the highest cost. Designs D227 and D285c show the lowest, which is 891579€, and highest, 25976534€, total costs respectively, which is reasonable given the size of the system of each design. In the first case the fleet consists of 137 bikes and 402 e-bikes while in the second case of 30959 bikes and 20445 e-bikes. Low station capacity designs (Da designs) have lower final costs than higher station capacity designs (Db designs). The only design of category Da that surpasses some designs of category Db is the D285a design. This is due to the large number of e-bikes (3267) that this design has. However, in all cases the Db design have a higher total cost than the corresponding Da design. For example, design D241a has a total cost of 2831957€ while design D241b has a total cost of 4727638€, which is 1895681€ higher than the cost of D241a. The number of e-bikes and bikes explains the variation in the costs of the designs.

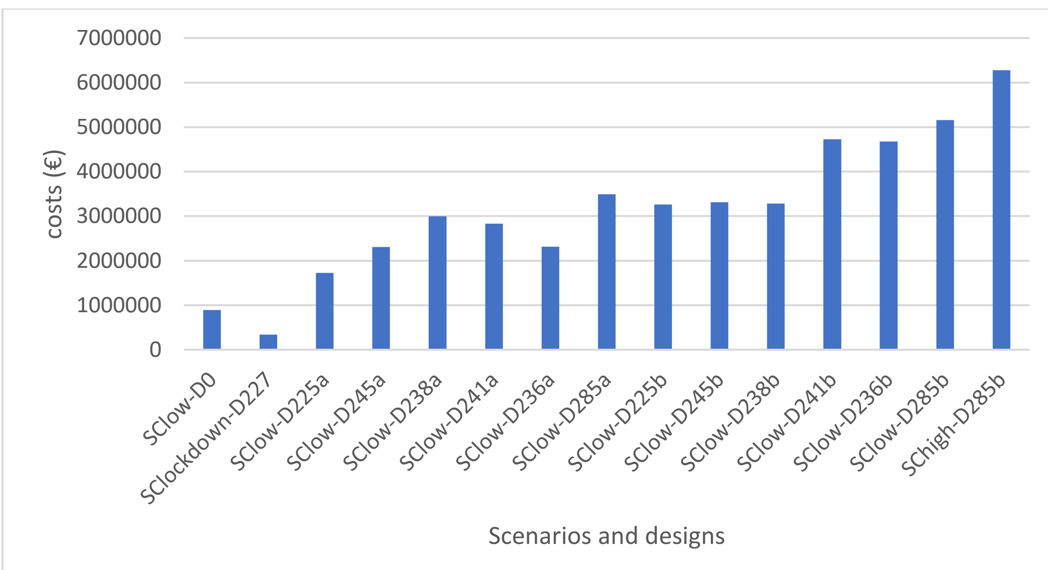

Figure 4-41: Total costs per design

The following analysis relates the bike fleet size of a design and their relocation cost. The cost of relocating bikes is relatively low compared to the purchase costs of the fleet. The lowest relocation cost has designs D227 and D0-current system's design-which have the smallest bike fleet size. Their relocation costs are 36€ and 229€ respectively. While the highest cost, which is 6066€, has design D285c. All designs with low station capacity specifications (Da designs) show lower relocation cost than the corresponding design with high station capacity specifications (Db designs). However, in both categories of designs (Da and Db), an increase in the bike fleet size does not imply an increase in relocation cost. Namely, the fleet size of designs D241b and D245b is 3866 and 3939 bikes respectively while the relocation costs are 702€ and 654€ respectively. Although design D245b has 73 bikes more than design D241b, its relocation cost is 48€ less.

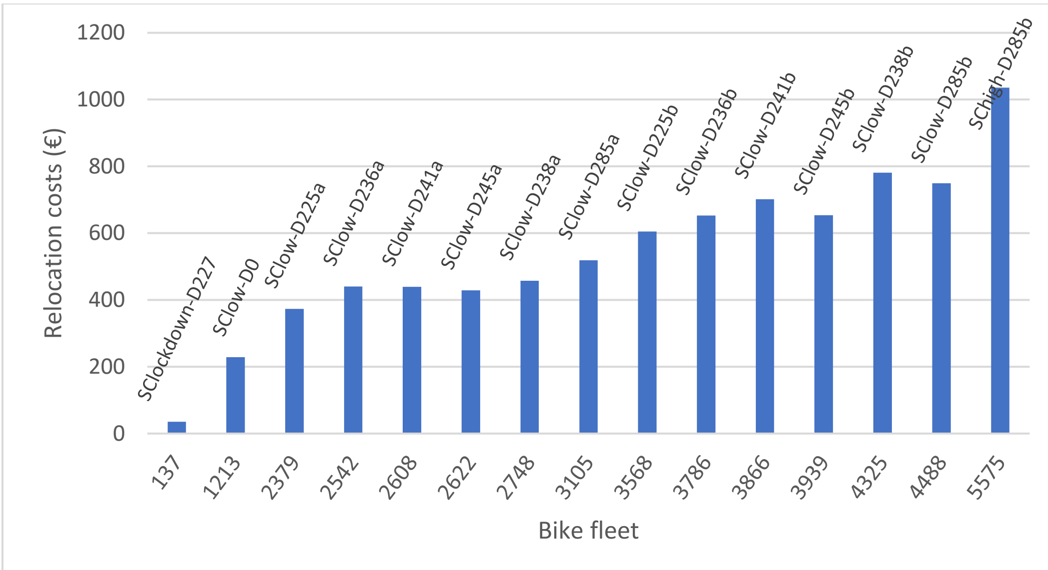

Figure 4-42: Bike fleet size and relocation costs

Figure 4-43 shows the analysis of the size of the e-bikes fleet with their relocation cost. As is the case with the bike system, the D227, D0 and D285c designs have the lowest and highest relocation costs. These costs are 75€, 95€, and 2604€ respectively. It is observed that the relocation costs for e-bikes are about 2.5 times lower than the relocation costs for bikes in designs D0 and D285c. However, this does not apply to design D227 in which the relocation cost for e-bikes is twice the corresponding cost for bikes. This may be because the D227 design has more e-bikes than bikes, something that does not apply to the other designs. In this system, there are designs with the low-capacity specifications in their stations (Da designs) whose relocation cost exceeds the relocation cost of designs with stations of high-capacity specifications (Db designs) such as D238a and D285a. However, in all cases the designs Db exceed in cost the corresponding designs Da. Only in the case of design D238 the opposite happens.

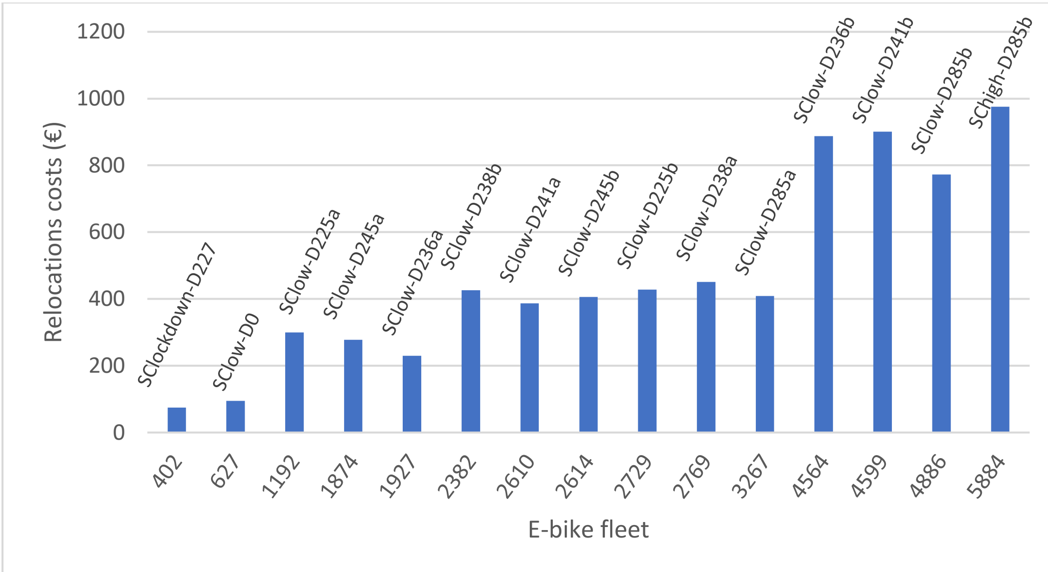

Figure 4-43: E-bike fleet size and relocation costs

The latest cost-related analysis concerns the final cost of each design and the covered demand. The cost ranges from 340880€, which has the design D227, to about 26 million €, which has the design D285c. In both cases the bike demand coverage rate is 100%. However, in the first case the demand of the system is 148 users, while in the second case it is 45513 users. For the e-bike system, the coverage rate is 100% in the case of D227 design and 70% in the case of D285c design. Although the difference in the cost of the two systems is enormous, the cost per user in design D227 is 1426€, while for design D285c is 477€. However, for the rest of the designs there is no specific trend in terms of increasing the covered demand and costs per user. There are designs with relatively low demand coverage (D225a design) that present low cost per user (230€) and there are designs with high demand coverage (D285b design) that present high cost per user (398€). Finally, it is observed that the increase in the covered demand does not imply an increase in costs. For example, design D236b fulfills 11868 trips, and its final cost is 4673400€, while design D245b fulfills 12224 trips, i.e., 356 trips more, with a system cost of 3314250€ which is 1359151€ less.

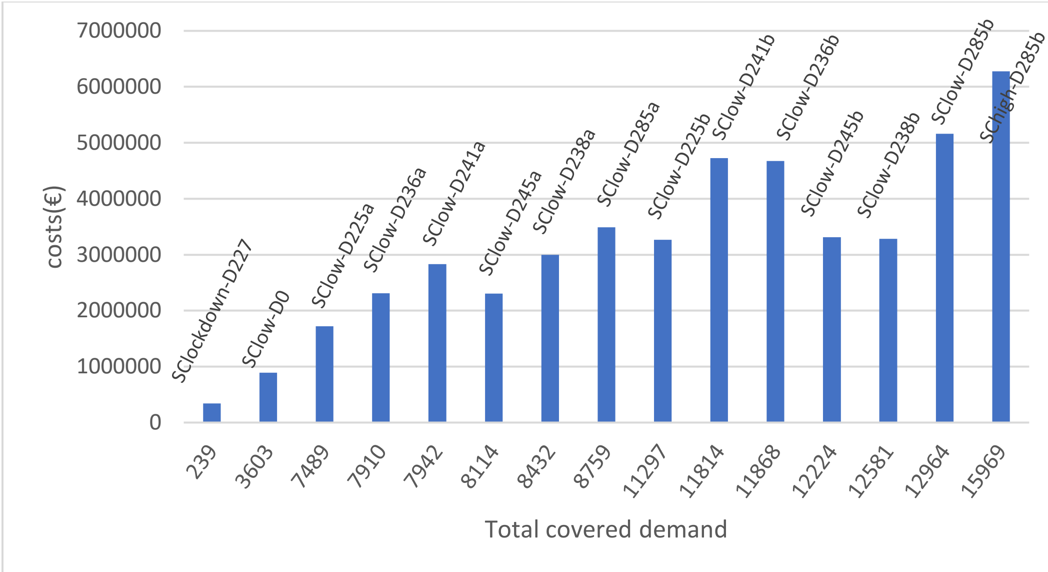

Figure 4-44: Covered demand and total costs

4.5. Conclusion remarks

This chapter summarizes the results of the application of the mathematical model used in the integration of the two systems and the optimization model for the design and operation of a bike sharing system that considers an extreme situation such as a pandemic and the needs arise from this situation. Demand scenarios and designs that reflect the bike sharing system network and its capacity specifications are developed to implement the optimization model.

Initially, the use of the mathematical model for integrating the two systems-subway and bike sharing system-in Milan city results in the fact that about 30% of the demand for the public transport system in the afternoon and evening hours cannot be met. This is due to the social distance measures applied which affect the mobility capacity of the subway system (1.5 meters distance between passengers). Therefore, about a third of users will not be able to travel to their destination with the current public transport system and will look for a transportation alternative. The existence of this unsatisfied demand leads to the need to create a public transport system that will be able to provide mobility capacity for all users during the pandemic. In this study, the bike sharing system will be integrated into the public transport system in an effort to maintain the mobility capacity needs during this extreme and special situation.

The current public bike sharing system of Milan city is docked for both modes-bike and e-bike-and its stations consist of 30 docks of which 20 are for bikes and 10 for e-bikes. This system has very low demand coverage rates. These rates are about 6% for the bike mode and about 7% for the e-bike mode. This means that this system is unable to meet the new mobility needs that arise due to the pandemic situation and the social distancing measures and changes need to be made. The main change that is taking place is the different design approach of the bike system in relation to the e-bike system. The bike system is designed as a free-floating system, while the e-bike system as docked system. This design separation results in a significant increase in meeting system's demand. More specifically, this system's separation increases the covered demand at least twice (2.1-2.4 times). Also, an increase of the capacity of e-stations and the available bikes in virtual station by 60% brings about an additional increase of the covered demand by 6.5-7.5%.

As far as the free-floating bike system is concerned, an increase in fleet size is usually equivalent to an increase in covered demand. It is also observed that there is stability in the ratio of fleet size and covered demand. The ratio (covered demand/fleet size) is between 2.13 and 2.36. This means that in case of known demand for the public bike sharing system in Milan, the fleet size forecast will be quite close to the actual fleet needs of the system. However, this only applies to the bike system. No similar stability is observed in the ratio of fleet size and covered demand in the e-bike system.

The needs of the bike system in terms of the number of stations are higher than those of the e-bike system. This means that in the respective cases of the two systems, the bike system network always consists of more stations than the e-bike system network. Moreover, both systems do not show a clear correlation between the number of stations and the covered demand. This means that an increase in the number of stations does not equate to an increase in covered demand. However, for the bike system, it is observed that the same number of stations can serve more demand when the capacity specifications increase. More specifically, an increase of 60% in the maximum available bikes on virtual stations can lead to an increase of 46.8-49.3% in the covered demand.

Another thing to note is that the needs of the bike sharing system in number of stations and fleet size are high even when the demand for the system is low, i.e., SClockdown where the bike demand is 148 and e-bike demand is 91. The covered demand to fleet size ratio is 1.1 for the bike system and 0.23 for the e-bike system. Also, the network of stations is wide, 107 e-station and 227 virtual stations. Therefore, even in the case of low demand, the system has a spatial range of demand, and it should meet some design requirements (e.g., number of stations and size fleet) to meet the demand. Moreover, to fully meet the bike system demand, it is needed 30959 bikes, while 20445 e-bikes are needed for 70% coverage of e-bikes demand. In this case, there is no limit to the available bikes per station and the maximum number of docks per station is 200.

The e-bike system does not show stability in the relations between the number of stations and the size of the e-bike fleet. However, there is a reference point to the number of stations, which is 180 stations, where beyond that increasing the number of stations equals increasing the size of the fleet. Regarding the bike system, the increase in the number of stations is related to the increase in the size of the fleet. Also, the same number of stations show a higher fleet size in case the capacity specifications increase. More specifically, a 60% increase in the maximum available bikes on virtual stations results in a 48.2%-57.4% increase in bike fleet size.

In the bike system, the size of the fleet and the size of the bike relocation are related. This means that the larger the fleet size, the greater the relocation requirements. It is also observed that the ratio between the size of the fleet and the size of the relocation (bike fleet size/relocation size) does not differ much between the cases of low or high-capacity specifications of the stations. In the case of low-capacity specifications at stations, the ratio varies between 1.1 and 1.3, while in the case of high-capacity specifications it varies between 1.1 and 1.2. For the e-bike system, no clear conclusion can be drawn about the relation between the e-bike fleet size and the relocation of e-bikes. Regarding the ratio (e-bike fleet size/relocation size), in the case of stations with low-capacity specifications it ranges from 0.8-1.7, while in the case of stations with high-capacity specifications it ranges from 1.0-1.3.

Regarding the costs of the bike sharing system, it is noted that it is not the real costs as the used values for the costs are determined by the literature and not at values related in the case study of Milan. The purchase of e-bikes is the most important cost of the system, while the costs for the relocation of bikes and e-bikes are low in relation to the purchase costs. The cost of the bike sharing system increases in case the capacity specifications of the stations increase. This is because in this case the needs of the system in the fleet size increase. In addition, it is observed that there is no clear correlation trend between fleet size-bike or e-bike-and relocation costs. However, the trend is that relocation costs for e-bikes are lower than the corresponding relocation costs for bikes. It is interesting to note that the covered demand does not increase with the increase in costs.

In conclusion, the integrations of public transport system and bike sharing system and the design of a hybrid mixed-fleet bike sharing system can help provide more mobility capacity during an extreme situation such as a pandemic situation and provide better coverage of unsatisfied demand due to distancing constraints. However, the integrated system cannot provide full demand coverage as fleet and station size requirements are high. It is worth noting that the design of the system, i.e., the number of stations and their capacity specifications, affects the provision of mobility capacity. Therefore, the choices when designing the bike sharing system should be very careful. This can be achieved by scrutinizing each case and classifying needs and requirements.

5. Conclusions and recommendations

During the pandemic, many sectors are affected by the governments' measures to reduce the spread of the coronavirus. The transport sector is one of the sectors most affected by this pandemic situation and will continue to be affected in the long run. The mobility capacity of public transport system is reduced by the imposition of the distancing measures. This means that the mobility capacity of the motorized public transport system is reduced, and that part of the existing demand cannot be served especially when life rhythms return to normal, i.e., work from the office, open schools, and market. This leads to the need of creating a new public transport system that can offer mobility capacity to those who need it during the extreme situation of a pandemic. The integration of the bike sharing system and the existing public transport system is this new system proposed in this study. The main goal in the design and operation of the bike sharing system is to meet the needs of the pandemic situation, i.e., the extreme demand that arises due to social distancing measures but also the human prejudice regarding their use. The first need that arises is to provide a solution that can serve all groups of people, i.e., from young to elderly, but also different distances. This need can be met by using a mixed fleet-bikes and e-bikes. The bike can be preferred for shorter distances and by people with better physical condition, while the e-bike can be preferred by people with a health problem but also for longer distances since its use does not require much physical fatigue. The second need that arises due to pandemic is the increased unsatisfied demand for transportation due to the reduced mobility capacity of public transport caused by the distancing measures. The separation of the bike sharing system into a free-floating bike system and docked e-bike system meets this need. This separation results in greater mobility capacity in the bike sharing system. This research seeks to fill the research gap in providing mobility capacity during an extreme situation and disturbances in public transport system such as a pandemic situation and the social distancing measures by integrating public transport and bike sharing systems and design a hybrid mixed-fleet bike sharing system.

To achieve to fill the mentioned gap, a mathematical model that integrates the demand needs of public transport and bike sharing systems is being developed. This mathematical model, which has as inputs the demand of the public transport system, the capacity of the vehicle and the percentage reduction of the capacity due to the social distancing measures, results in the separation of the demand in the two systems. Moreover, a model for optimizing a hybrid mixed-fleet bike sharing system is being developed that does not include cost-related constraints. The non-use of cost-related constraints leads to the development of an optimization model that aims for the best level of service. The objective of the optimization model is to maximize the system's covered demand, i.e., to maximize the mobility capacity of the bike sharing system. The optimization model is used to apply different designs, which concern the bike sharing system network and its design specifications, and demand scenarios in order to identify the prevailing trends for the design and operation of a hybrid mixed-fleet bike sharing system that aims to provide mobility capacity during the pandemic. The city of Milan is used as a case study for the implementation of the developed approach.

The remainder of the chapter has the following structure: Section 5.1 presents the key research findings and answers the research question and the sub-questions. Section 5.2 deals with the implication of the research, while Sections 5.3 and 5.4 refer to the study limitations and the recommendations for future work.

5.1. Key findings

This section presents the answers to the research question and the sub-questions based on the research conducted and the analysis of the results.

RQ: "How can we maintain mobility capacity in public transport under the impacts of social distancing constraints, investigating the case of bike sharing mobility capacity for COVID-19 conditions?"

This research examines the design and operation of the bike sharing system to maintain the mobility capacity of the public transport system under the impacts of social distancing constraints. First, the problem should be identified. The mathematical model developed for the integration of the two systems can help identify the problem of unsatisfied demand. The mathematical model considering the reduced mobility capacity of the public transport system due to the social distancing measures can calculate the demand that could be served by the public transport system and the unsatisfied demand. This will result in finding the areas of the transport network that demand will not be able to meet and therefore finding the areas where mobility capacity is required. The bike sharing system will try to meet the required mobility capacity considering the needs of the pandemic situation. Different groups of people constitute the unsatisfied demand and origin-destination pairs vary in travel distance. These needs arising from the pandemic situation will be met by using two modes in the bike sharing system, the bike, and the e-bike. Also, to try to meet the increased demand resulting from the social distancing measures in public transport system, the bike sharing system will be hybrid. This means that the bike system will be free-floating, while the e-bike system will be docked. This separation increases the capacity of the bike sharing system. A free-floating bike system has more relaxed capacity constraints as there are no stations with docks. Also, the stations, which can also be charging points, will be entirely for the e-bike system so there are more docks available for this system. Based on the needs arising from the pandemic situation, unsatisfied demand should be split into bike demand and e-bike demand. This is done by cycling travel distances between areas of unsatisfied demand and rates of use per mode at various distance intervals. It should be noted that the bike network has expanded due to the pandemic situation, so this is another aspect of the pandemic that is included in the developing approach. The optimization model for the bike sharing system is then developed considering the elements that meet the needs arising from the pandemic situation. As the main goal is to provide as much mobility capacity as possible during the pandemic, the model will not include cost constraints that can significantly reduce the main purpose. Simultaneously with the model, designs are being developed that reflect the needs arising from the pandemic, i.e., the creation of bike stations in areas with unsatisfied demand. The designs also cover cases of different capacity specifications on stations and different station locations. In addition to the designs, demand scenarios are also created. The application of the model is carried out in the combination of demand scenarios and designs, and the analysis of the results provides an insight into how the design parameters affect the mobility capacity.

The developed approach that considers different aspects of the pandemic situation is how we can maintain mobility capacity in the integrated public transport system. Based on the analysis and interpretation of the results obtained from the implementation of the approach, presented in Chapters 4.4.2 and 4.5, some conclusions are drawn. Firstly, the integration of the bike sharing system into the public transport system cannot fully maintain mobility capacity in public transport system during extreme situations such as a pandemic because it is needed high fleet and station size requirements. However, the separation of the bike sharing system into a free-floating bike system and a docked e-bike system and the creation of bike stations near subway stations with unsatisfied demand, increases the covered demand, i.e., provide more mobility capacity, at least twice compared to the current system. Moreover, an increase of the capacity of the e-stations and the available bikes in virtual stations by 60% brings an additional increase of the covered demand by 6.5-7.5%. Therefore, the key elements in providing more mobility capacity are the separation of the bike sharing system into free-floating for bikes and docked for e-bikes as well as the increase in capacity specifications at the e-station and the number of available bikes at the virtual stations.

SQ1: "How are safety measures limiting the mobility capacity in public transport system?"

This sub-question can be answered based on the literature research conducted. All countries have implemented and continue to impose social distancing measures on public transport system, and this of course affects their mobility capacity. The implementation of the general rule of social distancing, i.e., distance between passengers 1-2 meters, can lead to a reduction in metro train capacity of 60%, 80% and 90% for distances of 1, 1.5 and 2 meters, respectively (Krishnakumari & Cats, 2020) and in reducing the capacity of a 48-passenger bus to 11 passengers (ITF-OECD, 2020). However, each country applies its own social distancing measures. There are cases where the general measure of keeping 1-2 meters distance from others applies (Bundesregierung, 2021; COVID-19 Updates, 2021a; Reis alleen als het nodig is , 2021), but there are also cases that have more specific personal distancing measures for public transport system (COVID-19 Updates, 2021b; Coronavirus government response tracker, 2021; Publiction: Level 5, 2021). In some cases, the social distancing measures are stricter, while in other cases the measures are more relaxed. However, in both cases, the mobility capacity of public transport system is reduced. Mobility capacity in public transport system is limited to a range of 25% to 80% (ATM and the COVID-19 emergency: the management of the different phases, 2021; Publiction: Level 5, 2021; Tobing, 2020). Many countries have a capacity reduction rate range and impose different rates depending on the pandemic situation (Covid-19 updates: information for tourists, 2021; Government Gazette search, 2021). In other cases, there is a combination of measures (Diouf, et al., 2020; Tobing, 2020) or different rates of mobility capacity reduction per transport system (Diouf, et al., 2020). There are also extreme cases where for a period there was no public transport at all (COVID-19 Information, 2021). The conclusion is that the mobility capacity of public transport system is drastically reduced even in cases where low-capacity reduction rates are applied.

SQ2: "To what extent can a bike sharing system counterbalance for limited capacity in the public transport system?"

Based on the interpretation of the results, Sections 4.4.2 and Section 4.5, it appears that the current public bike sharing system of Milan city-stations of 30 docks of which 20 are for bikes and 10 for e-bikes-covers a very small percentage of demand, i.e., 6% for the bike mode and about 7% for the e-bike mode. This means that the current system provides a low percentage of mobility capacity. However, following the changes in the bike sharing system resulting from the pandemic aspects, demand coverage is increasing. More specifically, it is observed that the separation of the bike sharing system into a free-floating bike system and a docked e-bike system brings about a significant increase in the satisfaction of the existing demand. This system's separation increases the covered demand at least twice (2.1-2.4 times). It is also observed that an increase of the capacity specifications of the e-stations and the number of available bikes in the virtual station by 60% results in an additional increase of covered demand by 6.5-7.5%, i.e., the percentages of covered demand range from 18.4% to 21.3%. Moreover, the needs of the bike system in terms of the number of stations are higher than those of the e-bike system. This means that in the respective cases of the two systems, the bike system network always consists of more stations than the e-bike system network. However, no specific trend is observed between the number of stations of the two systems. It is observed that the satisfaction of the total demand of bike system and 70% of the total demand of e-bikes system requires great fleet size of bikes (30959) and e-bike (20445) and high-capacity specifications at stations, i.e., no limit to the available bikes per station and the maximum number of docks per station is 200. However, it should be noted that these numbers of fleets are overestimated due to the time specifications set by the optimization model as the two-hour demand of the system is required to be met at a specific point in time. An important factor that should be considered in the design of the bike sharing system is the creation of new bike and e-bike stations near the areas that have unsatisfied demand due to pandemic social distancing measures. In conclusion, a hybrid mixed-fleet bike sharing system can partly compensate for the limited capacity in the public transport system due to the distancing constraints. Moreover, attention should be paid to the required system specifications, system demand needs and the choice of system design parameters such as the capacity specifications of the stations.

SQ3: “How can the selected COVID-19 aspects be adapted to the developed optimization model of bike sharing systems?”

This study deals with the creation of a resilient public transport system that can provide mobility capacity in extreme and special situations and disturbances in public transport system such as the COVID-19 pandemic and the social distancing measures. This system consists of the integration of the bike sharing system in the public transport system. Therefore, one of the main goals is to develop an optimization model for the design and operation of a bike sharing system that considers the needs arising from the COVID-19 pandemic. The transmission of the COVID-19 virus on public transport modes is high. This is because the virus belongs to the category of respiratory viruses and is transmitted through the infectious aerosol which can accumulate over time in an enclosed place (Prather et al, (2020)). This fact affects the mobility capacity of public transport but also the transportation mode choice of commuters. As a result, there is a demand that can no longer be satisfied by public transport system as it used to be. Moreover, in many cases the state has created new bike network to promote bike and e-bike use in order to avoid the use of public transport system. These aspects of the pandemic are the key factors in the new demand that the bike sharing system is trying to provide mobility capacity. This unsatisfied demand due to the COVID-19 virus situation is the main input to the optimization model.

As for the optimization model itself, high demand leads to the design and operation of a bike sharing system to meet transport needs. These needs-high demand, different types of users and different distances-can be met using two different modes-bikes and e-bikes. So, the optimization model aims at the design and operation of these two systems, the bike system, and the e-bike system. Also, the high demand needs result in the design of the bike system as free-floating, and the e-bike system as docked- as this will increase the mobility capacity of the bike sharing system. The above-mentioned features of the bike sharing system that developed to meet the needs of the COVID-19 pandemic situation are applied to the optimization model in the form of constraints, variables, parameters as well as to objective function.

Initially, the objective function consists of two parts, one related to the satisfaction of the demand of the bike system while the other to the satisfaction of the demand of the e-bike system. In addition, the model consists of constraints and variables that affect both systems.

SQ4: “To which extent these findings can be generalized?”

The developed methodology concerns the integration of a bike sharing system in the public transport system and the creation of a public transport system which can provide mobility capacity during the COVID-19 pandemic situation and the social distancing measures. This integrated public transport system can be described as resilient since it can provide mobility capacity in the extreme and special situation of the pandemic. However, the creation of this integration and therefore the existence of a resilient public transport system can be generally useful. Initially it gives an extra transport alternative to the users but offers mobility even in other special situations that affect the existing public transport system as well. Some of these extreme and special situations that affect the mobility capacity of the public transport system are a strike or a possible maintenance of the public transport system or even mass events.

The mathematical model for the integration of the two systems is one of the things developed in this study. In this case it was used for the subway system in Milan, but its use can be extended to other public transport systems. This is because its development was not based on the subway system. The mathematical model is based on parameters such as the initial capacity of the mode, the reduction rate in capacity, system demand, the number of schedules per line. All of these are common features of all public transport modes (e.g., bike, tram, trolley). Therefore, its use can be extended.

The optimization model concerns the design and operation of a hybrid mixed-fleet bike sharing system. The model was not developed based on the specific case study of the bike sharing system in Milan city. It was developed based on the needs of the COVID-19 pandemic situation. However, a bike sharing system with hybrid and mixed fleet characteristics can be exist in a city even in other non-pandemic situations. Moreover, the formulation of the optimization model and the used values can be change easily. It can therefore be applied in any case where a similar bike sharing system is sought.

Regarding the results of the Milan case study, i.e., the specific results from the application of the methodology, a little more attention is needed for their application in other case studies. The conclusions related to the relationship between the covered demand and the separation of the two systems-bike and e-bike-or the different capacity specifications of the stations could be applied in other cases as well. However, results related to, for example, the correlation between fleet size and relocation needs may not be safe to apply to other case studies without further analysis of the other case study.

5.2. Research implications

In this section, the scientific and practical implications of the research outputs are presented.

This research provides theoretical contribution to the literature. Research shows the significant impact on public transport mobility capacity caused by the pandemic situation and the social distancing measures. It also analyzes the results of different designs of a bike sharing system and shows that a bike sharing system can partly counterbalance for the limited capacity in the public transport system if the system is designed based on the aspects of the pandemic and the careful selection of its design parameters.

During the research, an optimization model is developed for the design and operation of a hybrid mixed-fleet bike sharing system. As far as the author is aware, there is no corresponding model in the literature that designs a hybrid mixed-fleet bike system. There are studies that develop models for design and operation of mixed fleet bike sharing systems (Martinez et al, (2012)). However, the combination of mixed fleet, free-floating system for the bike system and docked system for the e-bike system is applied for the first time in an optimization model. Also, this model does not contain cost constraints, so it is based on optimizing the system in terms of the level of service it provides.

In practice, the findings of the study can be used by the stakeholders, i.e., the operators of public transport and bike sharing systems. The main findings and policy implications are summarized subsequently:

- Based on the results, it is observed that 30% of the demand for the evening peak hour of the subway system in Milan cannot be satisfied due to distancing measures. In an effort to maintain mobility capacity in public transport system, it is proposed the integration of the bike sharing into the public transport system. Therefore, it is recommended the cooperation between the operators of the public transport and bike sharing systems.
- The current bike sharing system can only compensate for 6% of the public transport system and its own demand. The proposed advice to bike sharing system operator in order to increase this percentage is to separate the system design. That is, to invest in the creation of e-bike stations and in the free-floating bike system.
- The separation into a free-floating bike system and a docked e-bike system and the creation of bike stations near the subway stations with unsatisfied demand, increases the covered demand at least twice (2.1-2.4 times). It is therefore proposed that the bike sharing system should invest in the construction of stations near subway stations.
- An increase of the capacity of the e-stations and the available bikes in virtual stations by 60% brings about an additional increase of the covered demand by 6.5-7.5%. Based on this, it is consulted to the bike sharing system operator to pay special attention to the capacity specifications of the stations during their design.
- As far as the free-floating bike system is concerned, it is also observed that there is stability in the ratio of covered demand and bike fleet. The ratio (covered demand/fleet size) is between 2.13 and 2.36. It is suggested that the bike sharing system operator take this into account for a rough initial fleet forecast. Based on this, it will provide the necessary mobility but will also make a careful investment.
- The demand for the e-bike system is 22% of the unsatisfied demand and 78% for the bike system. Based on this, the lower station requirements, and the instability of e-bike system results, it is recommended that the bike sharing system operator should carefully invest in the e-bike system and then extend it based on the needs that arise.
- In the study's results, it is observed that the bike sharing system during the lockdown period fully satisfies its low demand, However, the fleet needs in relation to the covered demand are high. The covered demand to fleet size ratio is 1.1 for the bike system and 0.23 for the e-bike system. Also, the network of the stations is wide, 107 e-stations and 227 stations. This shows that the

system has a spatial range of demand. It is consulted to the bike sharing system operator to develop a wide network of stations.

- The results show differences in fleet needs, 137-5575 bikes and 402-5884 e-bikes, and station needs, 107-271 e-stations and 225-285 virtual stations. It is recommended to the bikes sharing system operator to install some stations on mobile trailers to can be easily moved. An additional advice would be that the available fleet on the system should be period-based.

As for the users of the public transport system, their main concern is the ability to move whenever needed. Unfortunately, during the pandemic period due to social distancing measures in public transport system, this is not always possible, or the waiting times are increased. Also, there are people who will prefer a safer alternative than the enclosed public transport modes. The findings of this study can benefit these people as it offers a new integrated and resilient system-public transport and bike sharing systems-that can provide better mobility capacity.

5.3. Research limitations

The scope of the research has narrowed. This is due to the time limitations on performing this research. This section summarizes these limitations.

- The purpose of the research is to design and operate an integrated public transport system that can maintain the needs for mobility capacity in an extreme situation such as a pandemic. The two systems that have been integrated are the public transport and the bike sharing systems. However, this research focuses on the better design and operation of the bike sharing system. There are no changes to the design of the public transport system such as increasing the frequency of services. Simultaneous design of services of both systems may be able to better maintain the mobility of the public transport system.
- The effects of pandemic measures, i.e., distancing constraints, are studied only for the subway system. Other means of public transport such as buses, trams or trolleys are not included in the study. Therefore, the overall problem of the reduced mobility capacity of the city's public transport system is not known. Perhaps the study of each mode and the improvement of its services will offer a better balance in providing mobility in a pandemic situation.
- The origin-destination data of the public transport and bike sharing systems users are between the stations of the respective network. Therefore, the exact origin and the exact destination of the users are not known. If the data related to the users' movements were from the exact origin to the exact destination, the distribution of demand in the systems and the corresponding stations might have been different as users may have been assigned to the other system or other station. This may have changed the need for mobility capacity in the system.
- The only options given to the users are the alternatives of the public transport system and the bike sharing system. In other words, it is assumed that users who will not be able to be served by the public transport system, should be served by the bike sharing system. Other means of transport such as car or private bike are not options in this study. Moreover, the option of choosing other shared transport systems i.e., another bike sharing system or e-scooter sharing system, is not included in this study. In fact, there is no competition from other micromobility systems. Therefore, a single system bears the need for extra mobility capacity which in real life does not happen as users have other mode options or preferences. Thus, for future research it

would be beneficial to include other choices of systems or means of transport based on people's preferences.

- The optimization model concerns the satisfaction of the system's demand and the relocation of the bikes and e-bikes. The first service is continuous while the second takes place at specific times. In this model the use of specific times is selected, i.e., the demand will enter the system at specific times and not continuously. Therefore, mobility needs will be overestimated, and mobility requirements will be increased. However, the optimization model is a good approach to use when installing a bike sharing system.

5.4. Recommendations for future research

This research focuses on creating an integrated public transport system in terms of adequate mobility capacity supply considering the distancing constraints on motorized public transport system due to the pandemic situation and the needs of the pandemic. The goal of the research is achieved with the development of a mathematical model that integrates distancing constraints and seeks to separate the demand of the motorized public transport system into all the alternatives of the integrated public transport system. Also, the development of an optimization model for the design and operation of a hybrid mixed-fleet bike sharing system helps to achieve the research goal. The bike sharing system is chosen to be hybrid and mixed fleet to offer different options to users but also to provide better mobility capacity.

However, there are aspects in the mathematical model but also in the optimization model that can be improved. Initially, the mathematical model based on the distancing constraints on motorized public transport calculates vehicle load by giving priority to people with the longest distances and provides public transport system demand and bike sharing system demand. The approach of the integration of the two systems can be done based on the travel time. The mathematical model will calculate the travel time and suggest the mode with the shortest travel time to the user. This approach can be made more detailed and even more pandemically oriented. This can be achieved by combining this travel time-oriented model and an application that detects the movement of infected people. Therefore, the user will be informed in real time about the chances of coming in contact with an infected person and will choose accordingly the means he desires.

Secondly, there are sections where the optimization model can be extended. The formulation of the developed optimization model refers to the design and operation of a docked e-bike sharing system. The main issue that can arise in e-bikes is their battery level which of course decreases with their use. This can result to the use of an e-bike that is uncharged. This research does not consider the issue of battery level. It is suggested that future research include the choice of whether to use an e-bike based on its battery level. In addition, the developed optimization model relocates bikes and e-bikes. However, it is limited to finding the number of bikes and e-bikes that are relocated from one station to another in each period without considering how the relocation takes place. Therefore, in future research the model could be extended to the design of bike and e-bike repositioning/rebalancing process.

With some attention to adaptation, the optimization model could be used in other sharing systems as well. Of course, each system has its own characteristics and particularities. For example, an e-scooter sharing system has several similarities to a bike sharing system. The procedures for selecting the location of the stations (if any), the fleet and the availability of the e-scooters as well as their relocation are common features. However, the issue of charging e-scooters cannot be omitted. Another example is the car sharing system which is quite different from bike sharing system. Car sharing systems are divided into one-way and round way. The two forms of the system are different in terms of design and operation. The one-way system requires relocation of the fleet, however not as frequent as in the bike sharing system, while the round way system does not require relocation since the user will return it to the station. In addition, in the case of the car sharing system the cost cannot be skipped as it is a high-cost system. Perhaps an approach that jointly determines supply and demand is more efficient in this case. Hence, the adaptation of the bike sharing system optimization model requires more attention in the case of car sharing system.

Finally, this study focuses on providing mobility capacity during the pandemic period by integrating public transport and bike sharing systems. The study's approach is supply oriented. In addition, it gives only two options to the users of public transport and does not deal at all with the real preferences of users. It is suggested in future research that the study of users' preferences regarding the means of transport during the pandemic period precede. From this research will emerge the new modal share and based on this data the study for the provision of mobility capacity will be carried out.

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Appendix A: Scientific paper

Can Shared Mobility Compensate for Public Transport Disruptions? An Analysis of Milan's Bike Sharing and Public Transport System During the COVID-19 Pandemic

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Abstract

The COVID-19 pandemic poses an unprecedented challenge for the public transport systems. The capacity of the transport system has been significantly reduced due to the social distancing measures. Therefore, new avenues to increase the resilience of public urban mobility need to be explored. In this work, we investigate the integration of the bike sharing and public transport systems to compensate for public transport demand under the disruptive impacts of the COVID-19 pandemic. As a first step, we develop a data analysis model to integrate the demand of the two underlying systems. Next, we build an optimization model for the design and operation of a hybrid mixed-fleet bike sharing systems (i.e., free-floating, and station-based bike-sharing with electric and conventional bikes---to consider requirements of elderly passengers). We analyze the case of the subway and public bike sharing systems in Milan to apply the methodology. We find that the bike sharing system (in its current state) can only compensate for a minor share of the public transport capacity, as the needs in fleet and station capacity are very high. However, the resilience of public urban mobility further increases when new design concepts for the bike sharing system are considered. An extension to a hybrid free-floating bike and docked e-bike system at least doubles the covered demand of the system. While an extension of the station capacity of about 60% yields an additional increase of the covered demand by 6.5-7.5%. On the other hand, such a hybrid mixed fleet bike sharing system requires a large number of stations and a relatively large fleet to provide the required mobility even at low demand requirements.

Keywords: Pandemic, COVID-19, Public transport, Bike sharing, Resilience, Linear Programming Model, Milan

Introduction

The global impact of COVID-19 has been established. Due to the high contagiousness of the virus, the outbreak was recognized as a pandemic in March 2020 (WHO, 2020). Measures such quarantine, lockdown, social distancing, travel restrictions, closing of restaurants and schools, and isolation help to reduce the spread of corona-viruses and are followed by many governments (de Haas, Faber, & Hamersma, 2020; De Vos, 2020; Qureshi, Suri, Chu, Suri, & Suri, 2021). The proposed measures for social distancing in closed places have a great impact on the mobility capacity of public transport systems (PTSs) (ITF-OECD, 2020; Krishnakumari & Cats, 2020).

PTSs are mostly closed, overcrowded spaces that increase the chances of transmitting influenza viruses such as COVID-19 virus from infected to uninfected people (Goscé & Jahansson, 2018; Troko, et al., 2011). The aforementioned studies conclude that PTSs are sources of COVID-19 virus transmission. Therefore, social distancing measures have been implemented reducing the mobility capacity of PTSs. The result of the implementation of these measures can be seen, for instance, in the case of the Milan subway in Italy (Figure 1).

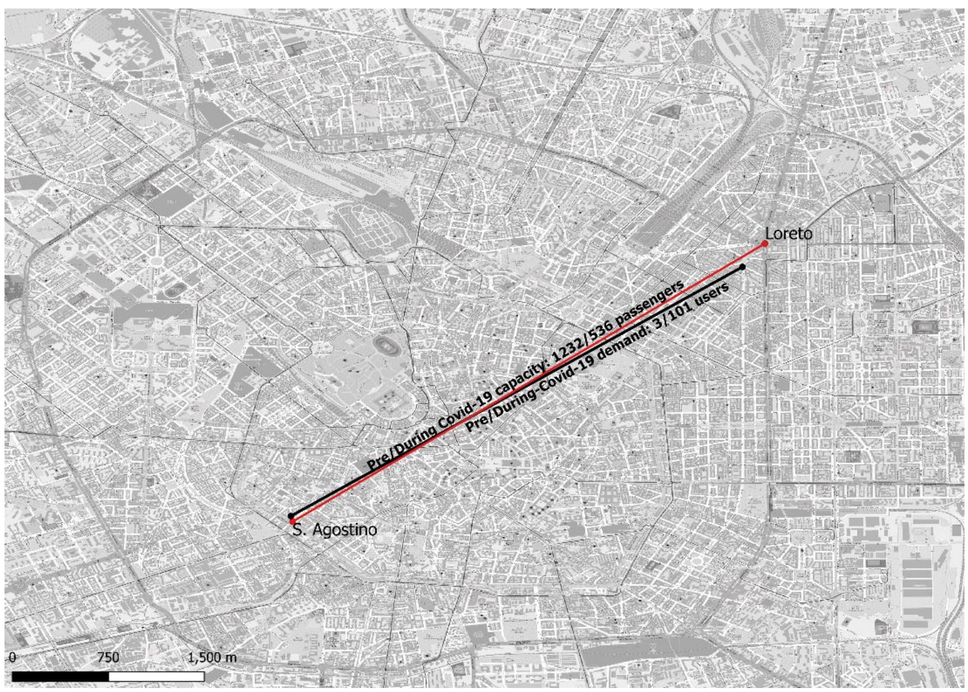

FIGURE 1: Social distancing measures affect the capacity of PTSs. Here, it shows how the implementation of the general rule of social distancing (i.e., 1.5 meters between passengers) affects the capacity of subway trains and the BSS demand in Milan. The red dots represent subway stations, while the black dots represent BSS stations.

The limited capacity of PTSs due to the COVID-19 distancing measures (i.e., mostly 1-2 meters between passengers), the precautionary behavior of people and the gradual return to normal life rhythms leads PTSs in unprecedented states. A main issue is the excessive demand which is not satisfied by the motorized PTSs and pushes for an alternative where people will be able to move in a safe way. There are several alternatives that can be integrated into PTSs to create systems that can accommodate this new situation. However, traffic congestion in most cities and air pollution are prompting the choice of a green alternative that does not burden the network too much. In line with this paradigm, the city of Milan has converted public roads into bicycle lanes during the pandemic.

A recent study on public transit strikes (Saberi et al., (2018)) concludes that integrating bike sharing systems (BSSs) into the PTS increases the system's resilience to disruptive events. Moreover, several studies investigate the interplay of bike sharing and public transport in cities such as Pozna (Radzimski & Dzięcielski, 2021), Oslo (Böcker et al., (2020)), or Vienna (Leth et al., (2017)). Nevertheless, hardly any research considers disruptive events comparable to the COVID-19 pandemic, and, to the best of our knowledge, there is no study on the COVID-19 scenario available. In this work, we propose an alternative to be operationally integrated in terms of demand and mobility capacity, that is, public transport capacity supply and alternative safe way of transportation, with PTSs and BSSs. With this integration and the efficient design and operation of the BSS, a new integrated PTS is created that is suitable to deal with excessive unsatisfied demand due to the social distancing measures or similar capacity-limiting disruptive events.

The main challenge in implementing this integrated alternative is the way of designing and operating the BSS to provide safe mobility for all unsatisfied demand (demand exceeding the capacity implied by the 1.5 meters distance criterion). Distancing measures to combat the COVID-19 pandemic situation have affected PTSs and created a lack of transport. The main purpose of this integrated PTS and the design of the MFHBSS is to ensure the necessary supply. This means that the prospect of approaching the problem is supply oriented. In this work, we focus on the optimal design and operation of a mixed fleet hybrid BSS (MFHBSS) considering the COVID-19 situation and aiming to create an integrated PTS. To this end, we propose a data analysis model to integrate the demand of the two underlying systems and build an optimization mode for the design and operation of a hybrid mixed-fleet bike sharing systems. Such a system integrates free-floating and station-based bike-sharing with electric and conventional bicycles---to consider requirements of elderly passengers. We analyze the case of the subway and public bike sharing systems in Milan to apply the methodology.

Related work

The reduced public transport capacity due to social distancing measures, the increased likelihood of the virus spreading in PTSs, the need for people to keep moving, and the prejudice against PTSs strengthen the need to find a safe alternative to satisfy people mobility. The safe alternative that could be integrated with the current PTSs to maintain mobility capacity is the BSS. This choice is reinforced by the fact that many cities around the world, as they try to deal with social distances measures, become more friendly to pedestrians and cyclists by providing them with more urban space (Broom, 2020; Mobycom, 2020). Moreover, in this moment, there is a surge of people turning to the use of BSSs (Naka, 2020; Schwedhelm, Li, Harms, & Adriazola-Steil, 2020).

The BSSs can complement or substitute the existing PTSs (Campbell & Brakewood, 2017; Leth, Shibayama, & Brezina, 2017; Ma, Yuan, Van Oort, & Hoogendoorn, 2020a; Martin & Shaheen, 2014). Moreover, a BSS can be a solution in the event of a long-term or short-term disruption of the PTS (Fuller, Sahlqvist, Cummins, & Ogilvie, 2012; Saberi, Ghamami, Gu, Shojaei, & Fishman, 2018; Younes, Nasri, Baiocchi, & Zhang, 2019). An element to consider for the efficiency of a BSS is its design and operation. This type of problem can be addressed by optimization models. The main objective categories of these models are the maximization of demand coverage (Çelebi, Yörüsün, & Işık, 2018; Frade & Ribeiro, 2015; Park & Sohn, 2017; Saharidis, Fragkogios, & Zygouri, 2014), the minimization of transportation costs and overall costs

(Caggiani, Camporeale, Dimitrijević, & Vidović, 2020; Lin & Yang, 2011; Yan, Lin, Chen, & Xie, 2017; Yuan, Zhang, Wang, Liang, & Zhang, 2019) or the maximization of profit (Martinez, Caetano, Eiró, & Cruz, 2012; Sayarshad, Tavassoli, & Zhao, 2012). Moreover, there are studies that use different approaches to design and operate a BSS like simulation approach (Fernández, Billhardt, Ossowski, & Sánchez, 2020; Jian, Freund, Wiberg, & Henderson, 2016; Soriguera, Casado, & Jiménez, 2018). Table 1 presents the above studies in summary.

TABLE 1: Analysis of research for BSS Design and Operation

		Objective					
Reference	Problem	MDC	MUD	MP	MC	Method	Case
Caggiani et al. (2020)	Bike station				✓	ILP	AC
Çelebi et al. (2018)	Bike station		✓			MINLP	Istanbul
Fernández et al. (2020)	Bike location					ABS	Madrid
Frade et al. (2015)	Bike station, Bike relocation	✓				MILP	Coimbra
Jian et al. (2016)	Bike allocation Dock allocation		✓			SO	New York
Lin et al. (2011)	Bike station, bikeways				✓	INLP	AC
Martinez et al. (2012)	(E)Bike station, (E)Bike relocation			✓		MILP	Lisbon
Park et al. (2017)	Bike station	✓				BILP	Seoul
Saharidis et al. (2014)	Bike station		✓			PILP	Athens
Sayarshad et al. (2012)	Bike station, Bike relocation			✓		ILP	Tehran
Soriguera et al. (2018)	Bike rebalancing Bike relocation				✓	ABS	Barcelona
Yan et al. (2017)	Bike station, Bike relocation				✓	MILP	New Taipei
Yuan et al. (2019)	Bike station, Bike relocation				✓	MILP	Beijing
This study	Bike virtual station, E-bike station, Bike relocation E-bike relocation	✓				MILP	Milan

Objective: MDC (Maximization of demand coverage), MUD (Minimization of unmet demand), MP (Maximization of profit), MC (Minimization of costs)

Method: ILP (Integer Linear Program), MILP (Mixed-Integer Linear Program), INLP (Integer Non-Linear Program), MINLP (Mixed-Integer Non-Linear Program), BILP (Binary Integer Linear Program), PILP (Pure Integer Linear Program), SO (Simulation – Optimization), ABS (Agent-Based Simulation)

AC: Artificial case

There are many works that study the design and operation of a bike sharing system. The optimization models developed in each study differ in the features, such as the level of service or the costs of the system, that it considers in its formulation. These features are expressed in the objective function and the type of constraints of the models. Most of the reported research include constraints regarding various costs of a bike sharing system or even their objective function refers to the cost or profit of the system. This means that the level of service offered by the bike sharing systems designed by these optimization models is limited by the available budget. It is also observed that the optimization models concern the design and operation of either free-floating systems or docked system whose characteristics differ. The main difference is that the design of the docked system requires the installation of stations, while in the free-floating system there may be no stations. Moreover, it is observed that only one study (Martinez et al., (2012)) approaches the design of a mixed fleet-bike and e-bike-bike sharing system. Therefore, there is no study that simultaneously designs a bike sharing system consisting of a mixed fleet-bike and e-bike- and that the bike system is free-floating, while the e-bike system is docked. Finally, none of the reviewed studies considers extreme situations and disturbances in public transport system such as a pandemic situation and the distancing constraints. In the case that the system costs are not considered, it leads to the development of an optimization model that can provide the design and operation of a bike sharing system designed to provide increased mobility capacity. In addition, a mixed fleet bike sharing system can serve different cases of people such as young people, the elderly, or people with a vulnerable health condition and different distances. A hybrid system can cope with the increased demand that results from the distancing constraints-the reduction in the capacity of public transport systems-as it combines the positives of docked and free-floating systems. To the best of the authors knowledge, this is the first study which considers a pandemic situation and mobility needs arising due to distancing constraints on public transport system and seeks to integrate the public transport system and the bike sharing system in terms of mobility capacity. That is, the study deals with the creation of a resilient public transport system that can provide mobility capacity in extreme and special situations. In addition, it is the first research to develop a bike sharing system optimization model that incorporates the design and operation of a mixed fleet system as well as the different design approach-free floating and docked-of the two modes system. All the above features create an advanced optimization model which optimizes the design and operation of bike and e-bike systems separately but simultaneously.

Modeling approach

In this section, we introduce the applied modeling framework, the data analysis approach to integrate the PTSs and BSSs, and the developed optimization model.

Modeling framework

The modeling framework of the study, which includes the integration of the PTSs and BSSs and the optimization model of the MFHBSS under the impacts of social distancing measures, is shown in Figure 2.

Integration of public transport and bike sharing systems

The objective of the integration of the two systems is to find the demand per system. The approach to achieving this integration is based on the factors of the pandemic, namely the capacity constraints on the PTS and the new bike system network. The first step is to create a mathematical data analysis model that calculates the permissible boarding of demand per station of each public transport vehicle and exports the unsatisfied demand per station. The model gives priority to boarding passengers with the farthest destination. The inputs of the model are the capacity of the vehicle, the percentage of permissible occupancy due to the distancing constraints, the number of schedules and the demand of the PTS. While the outputs of the model are the vehicle load, the demand boarded the vehicle and the destination station

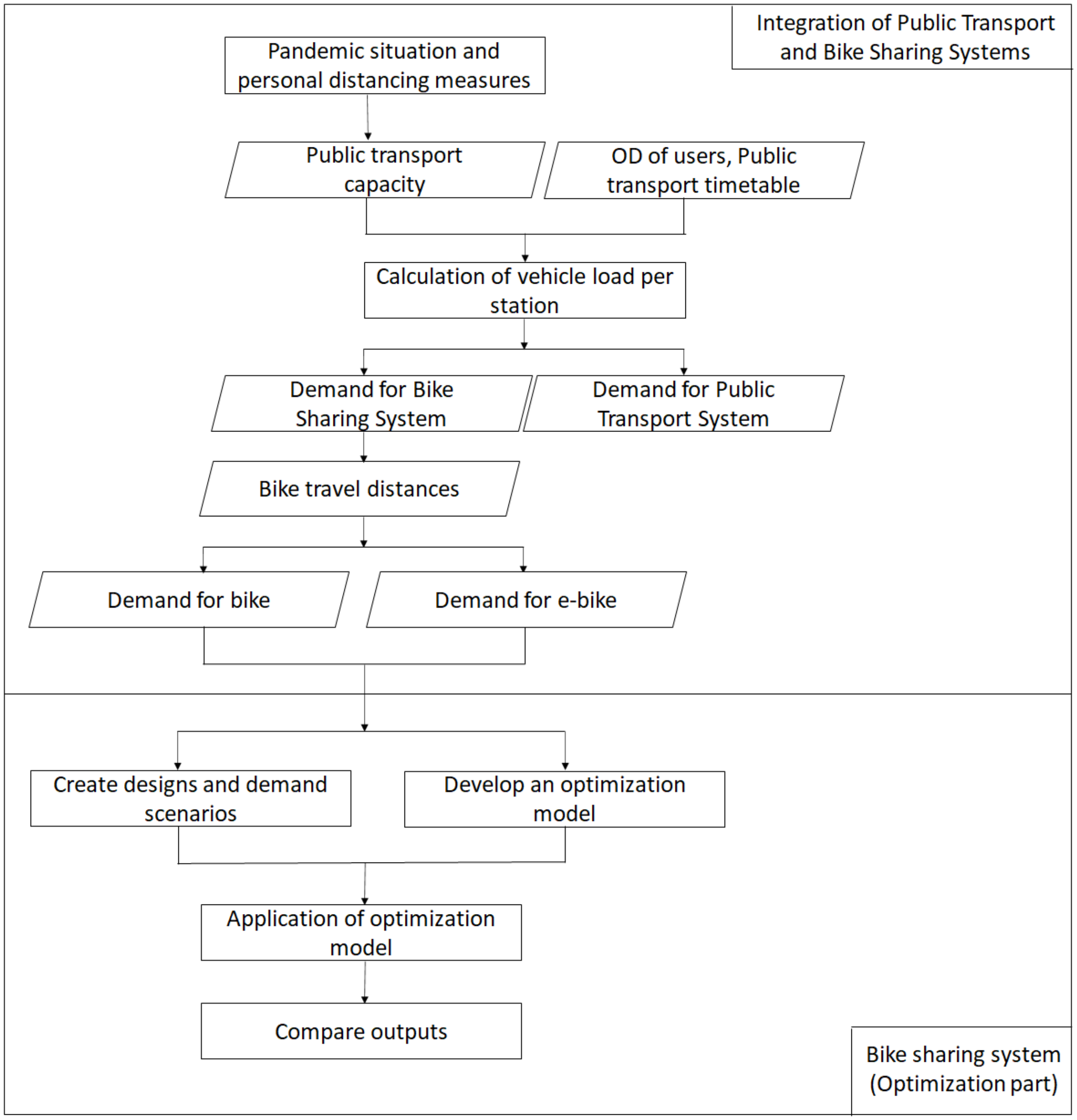

FIGURE 2: This is the modeling framework. It shows the various steps of the process and their sequence. The rectangles represent a process or a state, while parallelograms are used for input or output operation. The arrows connect the symbols and indicate the flow of process and information.

and the unsatisfied demand and the destination station. Therefore, the destination pairs of the unsatisfied demand are known. The result of this model is the distribution of demand in PTSs and BSSs.

P is the set of stations indexed by *i* and *j*, *k* is the index for schedule, ld_{ki} is the load of schedule *k* in station *i*, dem_{kij} is the demand from station *i* to station *j* for schedule *k*, $undem_{kij}$ is the unmet demand from station *i* to station *j* for schedule *k*, *ac* is the allowed capacity on the vehicle, ub_{ki} is the debarcation passengers in station *i* for schedule *k*, b_{ki} are boarding passengers at station *i* for schedule *k*.

Subsequently, the integration approach is described. For the first station of the line, in case the vehicle load is lower than the available vehicle capacity due to the distancing constraints, the following holds:

$$ld_{k\ 1} = \sum_{j\epsilon P} dem_{k\ 1\ j} \tag{1}$$
$$undem_{k\ 1\ j} = 0 \ \ \forall j \in P \tag{2}$$

Equation 1 states that the load of the vehicle schedule *k* at the first station is equal to the sum of the demand of the first station to all the other stations of this line. The unsatisfied demand of the schedule *k* from the first station to any other station is zero (Equation 2).

In case the vehicle load is higher than the available vehicle capacity due to the distancing constraints, the following holds:

$$ld_{k\ 1} = \mathrm{ac} \tag{3}$$
$$undem_{k\ 1\ j} = \sum_{j\epsilon P} dem_{k\ 1\ j} - \mathrm{ac} + dem_{k\ 1\ j} \ \ \forall j \in P \tag{4}$$

The load of the schedule *k* at the first station is equal to the allowed capacity of the vehicle due to the distancing constraints (Equation 3). In this case the unsatisfied demand, Equation 4, of the schedule *k* from the first station to a station *j* is equal to the sum of the demand from the first station to all other stations and the demand from the first station to the station *j* after subtracting the allowed capacity on the vehicle.

For all other stations of the line, in case the vehicle load is lower than the available vehicle capacity due to the distancing constraints, the following holds:

$$ub_{k\ i} = \sum(dem_{k\ 1:i\ i} - undem_{k\ 1:i\ i}) \tag{5}$$
$$b_{k\ i} = \sum dem_{k\ i\ i+1:P} \tag{6}$$
$$ld_{ki} = ld_{k\ i-1} - ub_{k\ i} + b_{k\ i} \tag{7}$$
$$undem_{k\ i\ j} = 0 \ \forall j \in P \tag{8}$$

Equation 5 determines that the passengers who disembark from the schedule *k* in station *i* are equal to the total demand of all the previous stations that have as destination the station *i* if you exclude the unsatisfied demand of all the previous stations that have as destination the station *i*, while passengers boarding the schedule *k* at the station *i* are equal to the total demand from the station *i* to all subsequent stations (Equation 6). The load of the schedule *k* at the station *i* is equal to the load of the schedule *k* at the previous station *(i-1)* and the passengers who want to board at station *i* minus the passengers who want to disembark at the station *i* (Equation 7). Equation 8 states that there is no unsatisfied demand for the schedule *k* from station *i* to any other station *j*.

In case the vehicle load is higher than the available vehicle capacity due to the distancing constraints:

$$ld_{k\ i} = \mathrm{ac} \tag{9}$$
$$undem_{k\ i\ j} = ld_{k\ i-1} - \mathrm{ac} - ub_{k\ i} + dem_{k\ i\ j} \ \forall j \in P \tag{10}$$

Equation 9 specifies that the load of schedule *k* at station *i* is equal to the allowed capacity on the vehicle, while the unsatisfied demand of schedule *k* from station *i* to station *j* is equal to the vehicle load at the previous station *(i-1)* and the demand of station *i* to the station *j* after subtracting the allowed capacity of the vehicle and passengers debarking at station *i* (equation 10).

The second step of the integration approach is to separate BSS demand into bike demand and e-bike demand. This can be achieved based on the travel distances. The data for this step are the unsatisfied demand from the PTS, the travel distances of the bike network, which has been extended due to the pandemic situation, between the stations of the PTS with unsatisfied demand and the rates of use per mode-bike and e-bike-for specific distance clusters. The result of this integration is the separation of the existing demand of the PTS into the demand of the PTS, the demand of bikes and the demand of e-bikes of the BSS.

Optimization model

The optimization model introduced below determines the optimal design and operation of a hybrid mixed fleet bike sharing system to counterbalance for limited capacity in public transport system because of social distancing constraints. This is achieved by maximizing covered demand considering location and relocation constraints. The proposed model follows a maximal covering location paradigm as, for instance, applied by (Frade & Ribeiro, 2015). The notation used to represent the elements of the optimization model is shown in Table 2.

The model has some inputs and outputs. The inputs are a set of stations, the demand of the bike and e-bike systems, the values for the parameters of maximum and minimum capacity, maximum available bikes in a virtual station, and maximum and minimum percentage of used capacity of the e-bike system and the number of time periods. Time periods are essentially the number of periods into which a day is divided. This number can be determined in each case study based on its data. The model satisfies the demand of the system but also relocates bikes and e-bikes, so there should be a balance between them when determining the number of time periods. In addition, the values of maximum and minimum capacity and percentage of used capacity can be determined based on the literature or there can be variation in their range of values. This depends on the requirements of each case study. The parameter for the maximum number of bikes in a virtual station depends on each case of study, that is, the availability of public space. The outputs of the optimization model are the covered demand of the hybrid mixed fleet bike sharing system, the number of stations, the size of the bike and e-bike fleets, the number of bikes and e-bikes at stations in each period, the number of relocated bikes and e-bikes per stations pairs in each time period, the portion of covered demand per stations pairs in each time period, and the number of stations of the e-bike system.

TABLE 2: Optimization model notation

Sets	
J	: set of stations, with indices i and j
T	: set of time period, with index t, T = {1,…,t)
P⊆T	: set of time period, with index t, P = {2,…,t}
Decision variables	
y_i	: is 1 if the bikes virtual station is opened and 0 otherwise
x_{ijt}	: proportion of covered bikes demand from station i to station j in period t
r_{ijt}	: relocated bikes from i to j at period t
υ_{it}	: available bikes in station i at the onset of period t
Tu_t	: total bikes fleet size of the system
h_i	: is 1 if the e-bikes station is opened and 0 otherwise
v_i	: number of e-bikes docks in station i
w_{ijt}	: proportion of covered e-bikes demand from station i to station j in period t
s_{ijt}	: relocated e-bikes from i to j at period t
b_{it}	: available e-bikes in station i at the onset of period t
Te_t	: total e-bikes fleet size of the system
Parameters	
u_{ijt}	: demand of bikes from i to j in period t
e_{ijt}	: demand of e-bikes from i to j in period t
z_{max}	: maximum available bikes in a virtual station
v_{min}	: minimum capacity of e-bikes station
v_{max}	: maximum capacity of e-bikes station
p_{min}	: minimum percentage of used capacity in an e-bike station i at the onset of period t
p_{max}	: maximum percentage of used capacity in an e-bike station i at the onset of period t

In the following the model is presented:

Max Z = $\sum_{i\epsilon J}\sum_{j\epsilon J}\sum_{t\epsilon T}(u_{ijt} \times x_{ijt}) + \sum_{i\epsilon J}\sum_{j\epsilon J}\sum_{t\epsilon T}(e_{ijt} \times w_{ijt})$ (1)

Subject to:

$\upsilon_{it} = \upsilon_{i(t-1)} - \sum_{j\epsilon J} u_{ij(t-1)}x_{ij(t-1)} + \sum_{j\epsilon J} u_{ji(t-1)}x_{ji(t-1)} + \sum_{j\epsilon J} r_{ji(t-1)} - \sum_{j\epsilon J} r_{ij(t-1)}$ (2)
∀i∈J, j∈J, t∈P

$b_{it} = b_{i(t-1)} - \sum_{j\epsilon J} e_{ij(t-1)}w_{ij(t-1)} + \sum_{j\epsilon J} e_{ji(t-1)}w_{ji(t-1)} + \sum_{j\epsilon J} s_{ji(t-1)} - \sum_{j\epsilon J} s_{ij(t-1)}$ (3)
∀i∈J, j∈J, t∈P

$\upsilon_{i,1} = \upsilon_{i,T}$ ∀i∈J (4)

$b_{i,1} = b_{i,T}$ ∀i∈J (5)

$v_i \le v_{max} \times h_i$ ∀i∈J (6)

$v_i \ge v_{min} \times h_i$ ∀i∈J (7)

$\upsilon_{it} \ge \sum_{j\epsilon J}(u_{ijt}x_{ijt})$ ∀i∈J, j∈J, t∈T (8)

$b_{it} \ge \sum_{j\epsilon J}(e_{ijt}w_{ijt})$ ∀i∈J, j∈J, t∈T (9)

$b_{it} \le p_{max}\, v_i$ ∀i∈J, t∈T (10)

$b_{it} \ge p_{min}\, v_i$ ∀i∈J, t∈T (11)

$\upsilon_{it} \le z_{max} * y_i$ ∀i∈J, t∈T (12)

$\sum_{j\epsilon J} r_{ijt} \le \upsilon_{it}$ ∀i∈J, t∈T (13)

$\sum_{j\epsilon J} s_{ijt} \le b_{it}$ ∀i∈J, t∈T (14)

$Tu_t = \sum_{i\epsilon J} \upsilon_{it}$ ∀t∈T (15)

$Te_t = \sum_{i\epsilon J} b_{it}$ ∀t∈T (16)

$x_{ijt} \leq 1$ $\forall$i∈J, j∈J, t∈T (17)
$w_{ijt} \leq 1$ $\forall$i∈J, j∈J, t∈T (18)
$w_{ijt} \leq h_i$ $\forall$i∈J, j∈J, t∈T (19)
$w_{ijt} \leq h_j$ $\forall$i∈J, j∈J, t∈T (20)
$x_{ijt} \leq y_i$ $\forall$i∈J, j∈J, t∈T (21)
$x_{ijt} \leq y_j$ $\forall$i∈J, j∈J, t∈T (22)
$r_{ijt} \geq 0$ $\forall$i∈J, j∈J, t∈T (23)
$s_{ijt} \geq 0$ $\forall$i∈J, j∈J, t∈T (24)
$x_{ijt} \geq 0$ $\forall$i∈J, j∈J, t∈T (25)
$w_{ijt} \geq 0$ $\forall$i∈J, j∈J, t∈T (26)
$h_i \in \{0,1\}$ $\forall$i∈J (27)
v_{it} , b_{it}, v_i, r_{ijt}, s_{ijt}, Tu_t, Te_t ∈ N $\forall$i∈J, j∈J, t∈T (28)

The objective function 1 of this Linear programming model consists of two terms. The first term is the bike covered demand, while the second term is the e-bike covered demand. The objective function maximizes the covered demand by the BSS. Constraint 2 determines the available bikes at virtual station *i* at period *t*. The first term of the constraint refers to the number of available bikes at virtual station *i* in the previous period. The second and third terms refer to the number of bikes that left or arrived at the virtual station *i* respectively in the previous period, while the fourth and fifth terms refer to the bikes transported to or from the virtual station *i* respectively at the previous period. Constraint 3 determines the number of available e-bikes at station *i* at period *t*. Constraints 4 and 5 state that the bike and e-bike fleet of the system remains the same between the first and the last period. The capacity of an e-bike station is limited by the constraints 6 and 7. Constraint 6 specifies the upper capacity limit (number of docks), while constraint 7 specifies the lower capacity limit. The available bikes at the virtual station *i* should meet the demand of the virtual station (constraint 8), and the available e-bikes at the station *i* should meet the demand of the station (constraint 9). Stations should always have available e-bikes as well as available docks for parking. This is achieved by constraints 10 and 11. Constraint 10 specifies that the available e-bikes at the station *i* at period *t* should not exceed a specific number, and there should be a minimum number of e-bikes at the station (constraint 11). Constraints 10 sets a limit on the maximum number of available bikes at a virtual station. The relocated bikes from the virtual station *i* at the period *t* should not exceed the available bikes at the virtual station *i* at that period (constraint 13). The corresponding constraint for e-bike system is constraint 14. Constraints 15 and 16 specify the total bike and e-bike fleet of the BSS, respectively. The portion of covered demand from virtual station *i* to *j* at the period *t* cannot exceed the value 1 (constraint17). The corresponding constraint for the e-bike system is constraint 18. The demand for the bike and e-bike system can only be served by existing (virtual) stations (constraints 19 - 22). Constraints 23 – 28 specify the domain of the decision variables.

Case study and numerical results

In this section, we present the underlying case study, the considered scenarios, and the obtained computational results.

Case study

In this study, the area of investigation is the city center of Milan, and the studied systems are the subway system and the public BSS. Milan is located in northern Italy and is the capital of the administrative region of Lombardy. The Milan subway has 4 lines (M1, M2, M3 and M5) and 106 stations. The public BSS started operating at the end of 2008. At present the system has 4280 bikes and 1150 e-bikes. The number of operational stations is 320. It should be noted that there is no data available on subway demand, so it will be generated.

Scenarios and designs

There are three demand scenarios (SClow, SChigh, SClockdown). SClow and SChigh consist of the unsatisfied demand of the PTS and the demand of different days of the public BSS (4/4/19 and 8/4/19, respectively), while SClockdown consists of the demand of the BSS on 8/4/20. The three different demand scenarios are used as inputs for the designs. The basic demand scenario that most designs consider is SClow. SChigh and SClockdown will be used as inputs for a few designs.

The designs are created based on the needs of the BSS. The parameters that differ in the designs are the number and the location of (virtual) stations in the network, the maximum number of bikes per virtual station and the capacity (number of docks) of the e-bike stations. The first categorization of the designs concerns the number and the location of virtual stations and e-stations. Based on these two parameters, 7 basic designs are created. Each design is named with the capital letter D from the word design and the number of stations. These are D225, D245, D238, D241, D236, D285 and D227. The locations of the new stations are close to subway stops. Then the other two parameters are considered. Two main types of designs emerge from this separation, Da and Db. Da has a maximum number of bikes per virtual station at 50 bikes, a minimum number of e-bikes docks at 10 and a maximum number of e-bike docks at 25, while Mb has 80 bikes, 10 e-bikes docks and 40 e-bikes docks, respectively. Design D0 is the design of the BSS in 2019 with parameters value of 20, 1 and 10, respectively. The specifications of design D0 also apply to D227. The final design that is created is the Mc, in which there is no limit to the maximum number of bikes while the maximum and minimum number of e-bike docks are 10 and 200, respectively. The common features of all designs are the following. The system is studied for six hours, 15:00 – 21:00. The optimization model requires the definition of time periods. In this case the time periods are three, t1: 15:00-17:00, t2: 17:00 – 19:00 and t3: 19:00 – 21:00. Therefore, the demand for the system is divided into these 3 time periods. In addition, the maximum and minimum used capacity percentages on e-stations are 25% and 75%, respectively. Figure 3 shows the scenarios and designs.

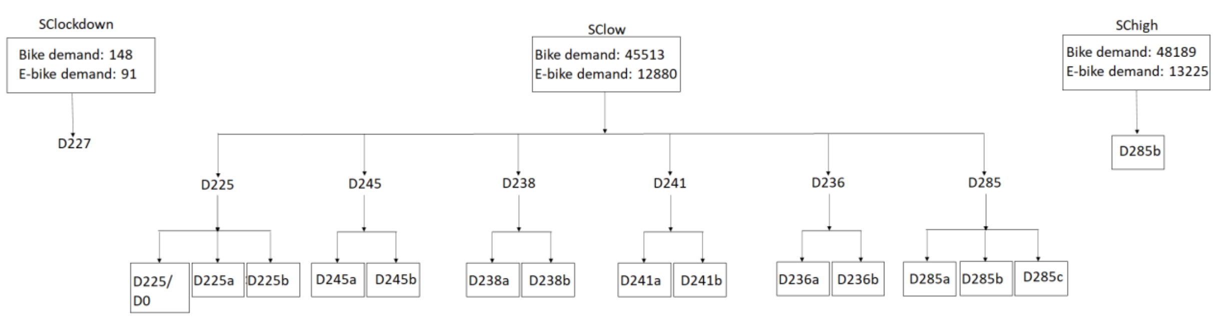

FIGURE 3: These are the developed scenarios and designs for the model application. There are three demand scenarios and 15 designs in which their parameters are differentiated.

Experimental results

The first analysis is related to the unsatisfied demand of the PTS. Unsatisfied demand arises from the use of the mathematical model for the integration of the two systems-PTS and BSS-and the demand of the PTS. Demand for the PTS is hourly. It is therefore divided equally among the schedules operated on each subway line per hour. Unsatisfied PTS demand due to social distancing constraints is around 30%. The unsatisfied demand at stations outside the study area and for stations in the study area whose destination is outside the study area is not included in the analysis. Then, the unsatisfied demand (30%) is divided into bike and e-bike demand based on the bike network travel distances and the rates of bike and e-bike use for specific travel distances intervals. About 22% of the total demand resulting from the integration of the two systems is the demand for e-bikes and 78% is the demand for bikes.

The analysis of the BSS considering aspects of the pandemic situation uses the optimization model for a MFHBSS and the various designs developed. The outputs of the model are the number of stations, the covered demand and the size of the fleets and the relocation. Table 3 shows the outputs of some designs, of which the correlations are analyzed below. The system demand is the same for all designs presented in Table 3.

TABLE 3: Inputs and Outputs of some of the developed designs

	Inputs			
	D0	D285a	D285b	D285c
Number of stations	225	285	285	285
Max number of bikes	20	50	80	unlimited
Max number of docks	10	25	40	200
	Outputs			
	D0	D285a	D285b	D285c
Number of selected stations	169	211	215	210
Number of virtual stations	225	285	285	285
Covered bike demand	2732	6599	9685	45513
Covered e-bike demand	871	2160	3279	8896
Bike fleet	1213	3105	4488	30959
E-bike fleet	627	3267	4886	20445
Relocated bikes	1146	2596	3746	30329
Relocated e-bikes	474	2045	3865	13019

Initially, the covered demand per design is analyzed. Covered demand in design D0 is just 6% for the bike system and just under 7% for the e-bike system. In all other designs there is at least a doubling of the covered demand rates (2.1-2.4 times). Only D227 fully meets the demand of both systems, which is logically due to the low demand of the input SClockdown. The other design that has full coverage of bike system demand and high coverage of e-bike system demand is D285c. The high coverage rates in this case are related to the design features of the system, that is, unlimited number of bikes per virtual station and large capacity of the e-stations. In all other designs, it is observed that the covered demand is higher in percentage for the e-bike system. This may be due to the lower demand requirements for this system. In addition, it is observed that the Da designs, which have lower values in the capacity of their stations, have lower covered demand compared to the scenarios Db, which are characterized by higher stations capacity. Demand rates in designs Db show a steady growth rate compared to the corresponding Da designs.

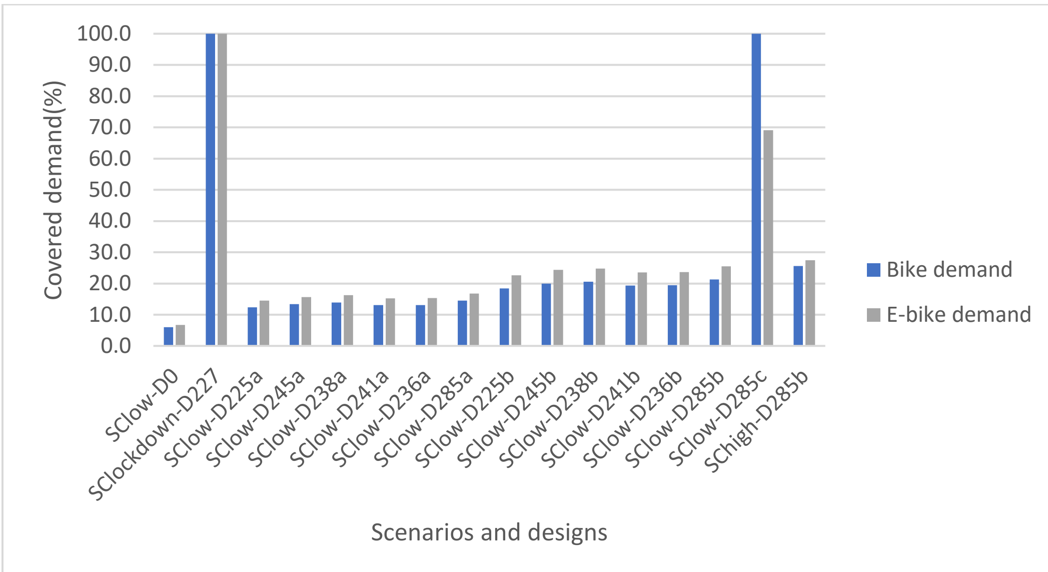

FIGURE 4: Covered demand per design is shown in the figure. For each design the demand of the bike system is presented in blue, while the demand of the e-bike system is presented in gray.

Considering the relation between the covered demand and the fleet size, the general trend in the bike system is that the covered demand increases with the increase of the bike fleet. It is also observed that in each design the fleet size is about half in relation to the covered demand. This observation does not apply only to the D227 design in which the fleet size and the covered demand are almost in the same size and the D285c design in which the fleet size is lower than the covered demand but not to the trend prevailing in the other designs. The e-bike system does not show the same trends between the covered demand and the fleet size as the bike system. Designs D227 (low demand) and D285c (high station capacity specifications) have a large fleet size in relation to covered demand for both systems. This indicate that the BSS based on its design has service specifications, such as the availability of bikes and e-bikes, regardless of the size of its demand.

The analysis of covered demand and the number of stations is performed separately for the 2 system. Regarding design D227, the demand of both system is fully covered. Although the demand is low, the station network is relatively great (227 virtual stations and 107 e-stations). This indicates that demand is spread across the study area and wide station coverage is needed even in this case. For both systems, it is observed that the increase of the stations is not in line with the increase of the covered demand in some cases. In cases where the number of selected stations is the same or almost the same, designs with high-capacity specifications (Db designs) satisfy more demand. For bike system, in case the demand scenario, that is, scenario with higher demand, for a specific design changes, it is observed that the same number of stations can satisfy more demand.

An interesting analysis is the number of stations compared to the size of the fleet (Figure \ref{fig:efleet}). There can be no clear trend for the Da designs of e-bike system. For the Db designs, it is observed that the fleet presents slightly different for the same number of stations (180). However, the design with the lowest fleet size satisfies higher demand. In addition, the difference in the fleet size between a system with 180 stations and a system with 189 stations is significant. However, this does not mean an increase in covered demand. In other cases, as the number of stations increases, so does the number of fleet size as well as the covered demand.

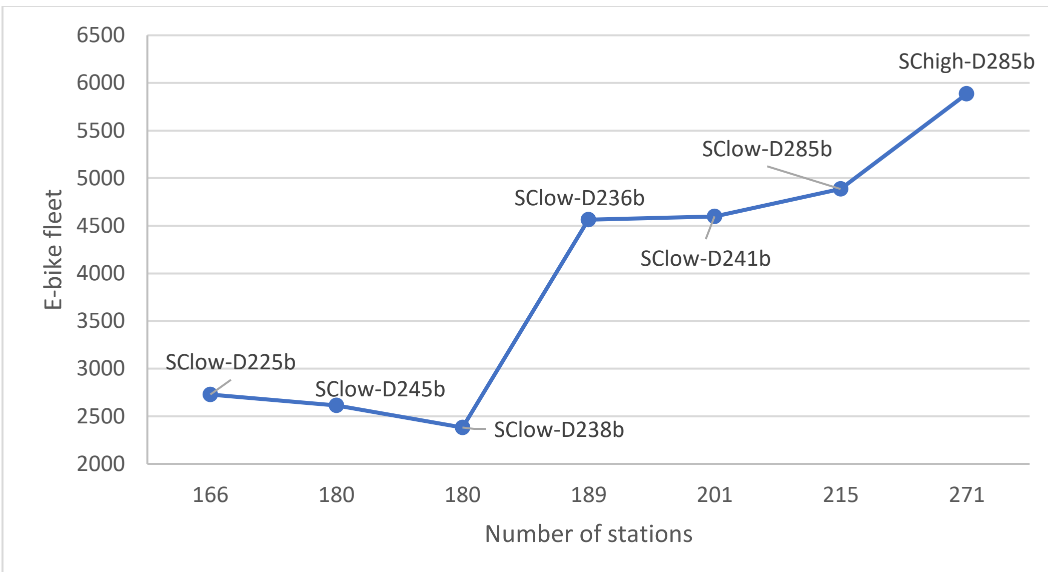

FIGURE 5: For each design, the relationship between the number of stations (x-axis) and the size of the e-bike fleet (y-axis) is presented.

The bike system presents uniformity between the results of designs with low (Da) and high (Db) capacity specifications. The size of the fleet increases as the number of stations increases. This statement differs only when the number of network stations is 241 and 245. In these two cases it is observed that the bike fleet shows a decrease. However, this is in line with the demand coverage. In case the demand of the system increases, the same number of stations satisfies more demand (design D285b under different demand scenarios).

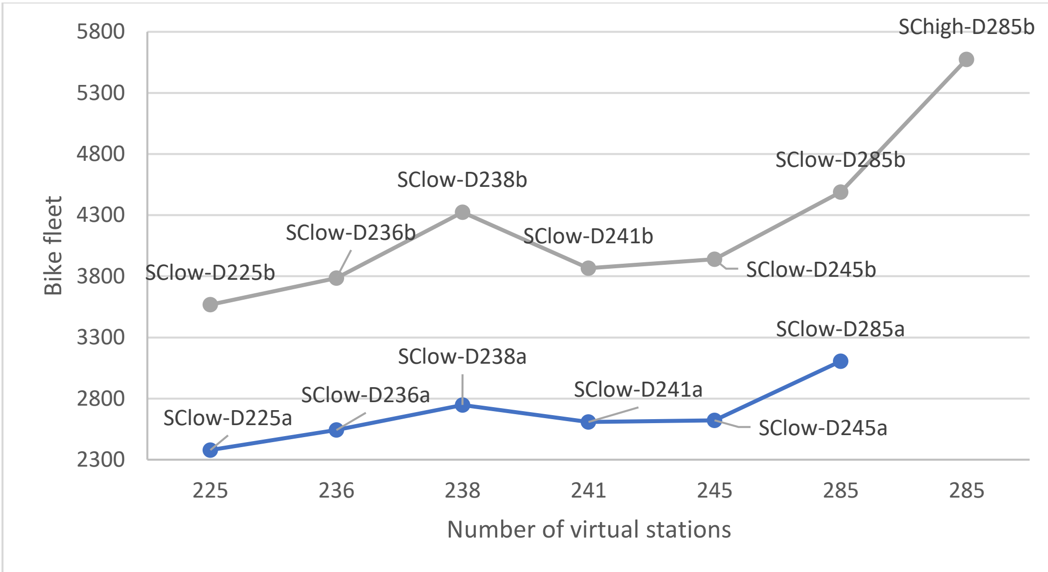

FIGURE 6: For each design, the relationship between the number of stations (x-axis) and the size of the bike fleet (y-axis) is presented. The gray color illustrates the Db designs, while the blue color illustrates the Da designs.

The size of the bike relocation follows an upward trend as the size of the bike fleet increases. In a few cases there is a decrease in the size of bike relocation while there has been an increase in the size of the fleet. The size of the relocation is always smaller than the size of the fleet. Only the case of design D227 is an exception. This may be due to the large number of stations (227 stations) relative to the low fleet size (137 bikes). It should also be noted that there is no difference in results between designs with low capacity (Da) and high capacity (Db) specifications on stations. The e-bike system cannot be characterized by stability in the relation between fleet and relocation size. The size of the fleet is higher than the size of the relocation for all designs beyond one design. In the designs with the stations of high-capacity specifications, there is more relocation in relation to the size of the fleet than in the designs with the low-capacity specifications.

The final analysis concerns the system costs. The total cost consists of the purchase costs and the relocation costs. The cost of buying e-bikes is the highest cost. In most cases, low station capacity designs (Da) have lower final costs than higher station capacity designs (Db). The cost of relocating (e)-bikes is relatively low compared to the purchase costs of the fleet. For both systems, an increase in the fleet size does not imply an increase in relocation cost. Finally, it should be noted that there is no correlation between costs and covered demand.

Conclusions and future work

During the COVID-19 pandemic, many sectors are affected by the government measures to reduce the spread of the virus. The transport sector is one of the sectors most affected by these measures. The mobility capacity of PTSs is reduced by the implementation of the distancing measures. This means that part of the system's capacity can no longer be provided. This leads to the need of finding a new PTS that

TABLE 4: The bike fleet and the relocation sizes per design

Designs	Bike fleet size	Relocation size	E-bike size	Relocation size
SClockdown-D227	137	178	402	373
SClow-D0	1213	1146	627	474
SClow-D225a	2379	1866	1192	1500
SClow-D236a	2542	2200	1927	1147
SClow-D241a	2608	2197	2610	1936
SClow-D245a	2622	2146	1874	1387
SClow-D238a	2748	2287	2769	2257
SClow-D285a	3105	2596	3267	2045
SClow-D225b	3568	3024	2729	2142
SClow-D236b	3786	3264	4564	4438
SClow-D241b	3866	3508	4599	4506
SClow-D245b	3939	3269	2614	2030
SClow-D238b	4325	3907	2382	2130
SClow-D285b	4488	3746	4886	3865
SC2-D285b	5575	5180	5884	4880
SClow-D285c	30959	30329	20445	13019

can offer mobility capacity to those who need it during the pandemic or similar future situations. The integration of the BSS and the existing PTS is one form of such a new system. In this work, the objective has been the design and operation of a BSS to meet the needs of the pandemic situation. The first need that arises is to provide a solution that can serve all groups of people, that is, young and elderly, but also different distances. This need can be met by using a mixed fleet, that is, bikes and e-bikes. The bike can be preferred for shorter distances and by people with better physical condition, while the e-bike can be preferred by people with a health problem but also for longer distances since its use does not require much physical fatigue. The second need that arises due to pandemic is the increased demand for transportation due to the reduced mobility capacity of PTS caused by the distancing measures. The separation of the BSS into a free-floating bike system and docked e-bike system addresses this need. This separation results in greater mobility capacity in the BSS. In this way, this work overcomes a research gap in providing mobility capacity during a pandemic (or similar capacity-limiting events) by integrating PTSs and BSSs and adds to earlier work on the interplay of BSSs and PTSs as presented in case studies different cities (Böcker, Anderson, Uteng, & Throndsen, 2020; Leth, Shibayama, & Brezina, 2017; Radzimski & Dzięcielski, 2021).

To achieve this, a data analysis model that integrates the demand needs of PTSs and BSSs has been developed. Moreover, a model for optimizing a MFHBSS has been proposed that does not include cost-related constraints. The integration method results in the separation of the demand in the two systems, while the optimization model is used to solve different designs and demand scenarios in order to identify the prevailing trends for the design and operation of a MFHBSS that aims to provide mobility capacity during pandemic. The city of Milan is used as a case study for the implementation of the approach. The main findings and policy implications are summarized subsequently:

- Based on our analysis, we see that 30% of the demand for the evening peak hour of the subway system in Milan cannot be satisfied due to distancing measures. In an effort to maintain mobility capacity, we would propose the integration of the BSS into the PTS. Therefore, we recommend the cooperation between the operators of the PTS and BSS.
- The current BSS in Milan can only compensate for 6% of the PTS and its own demand. Our advice to BSS operators in order to increase this percentage is to separate the system design. That is, to invest in the creation of e-bike stations and in the free-floating bike system.
- The separation into a free-floating bike system and a docked e-bike system and the creation of bike stations near the subway stations with unsatisfied demand, increases the covered demand at least twice (2.1-2.4 times). We therefore propose that the BSS should invest in the construction of stations near subway stations.
- An increase of the capacity of the e-stations and the available bikes in virtual stations by about 37\% brings about an additional increase of the covered demand by 6.5-7.5%. Based on this, we would like to advise the BSS operator to pay special attention to the capacity specifications of the stations during their design.
- As far as the free-floating bike system is concerned, it is also observed that there is stability in the ratio of covered demand and bike fleet. The ratio (covered demand/fleet size) is between 2.13 and 2.36. It is suggested that the Milan BSS take this into account for a rough initial fleet forecast. Based on this, it will provide the necessary mobility but will also make a careful investment.
- The demand for the e-bike system is 22% of the unsatisfied demand and 78% for the bike system. Based on this and the instability of e-bike system results, it is recommended that the BSS operator should carefully invest in the e-bike system and then extend it based on the needs that arise.
- In our results, we observe that the system during the lockdown period fully satisfies its low demand. However, the fleet needs in relation to the covered demand are high. The covered demand to fleet size ratio is 1.1 for the bike system and 0.23 for the e-bike system. Also, the network of stations is wide, 107 e-stations and 227 virtual stations. This shows that the system has a spatial range of demand. We would advise the BSS operator to develop a wide network of stations.
- The results show differences in fleet needs, 137-5575 bikes and 402-5884 e-bikes, and station needs, 107-271 e-stations and 225-285 virtual stations. We would advise the BSS operator to install some stations on mobile trailers to can be easily moved. An additional advice would be that the available fleet on the system should be period-based.
- To fully meet the bike system demand, it is needed 30959 bikes, while 20445 e-bikes are needed for 70% coverage of e-bikes demand. In addition, there is no limit to the available bikes per station and the maximum number of docks per stations is 200. It is concluded that the BSS cannot fully counterbalance for limited capacity in the public transport system.
- The BSS may have been designed based on the needs of the pandemic but the use of such a system may be more extensive. The basic criterion for the implementation of a MFHBSS is its ability to satisfy the mobility needs of each case.

Nevertheless, this work also has some limitations that could be addressed in future research. The approach of the systems integration can be done based on the travel time and be more pandemic-oriented with the integration of application that detects the movement of infected people. Therefore, the user will be informed in real time about the chances of meeting an infected person and will choose accordingly the means he desires. Moreover, the formulation of the developed optimization model refers to the design and operation of a docked e-bike sharing system. It is suggested that future research include the choice of whether to use an e-bike based on its battery level or consider the rebalancing processes. Finally, for future research it would be beneficial to include people's preferences regarding the choice of means of transport to travel.

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Appendix B: Subway Analysis

B1: Rush hour per subway line

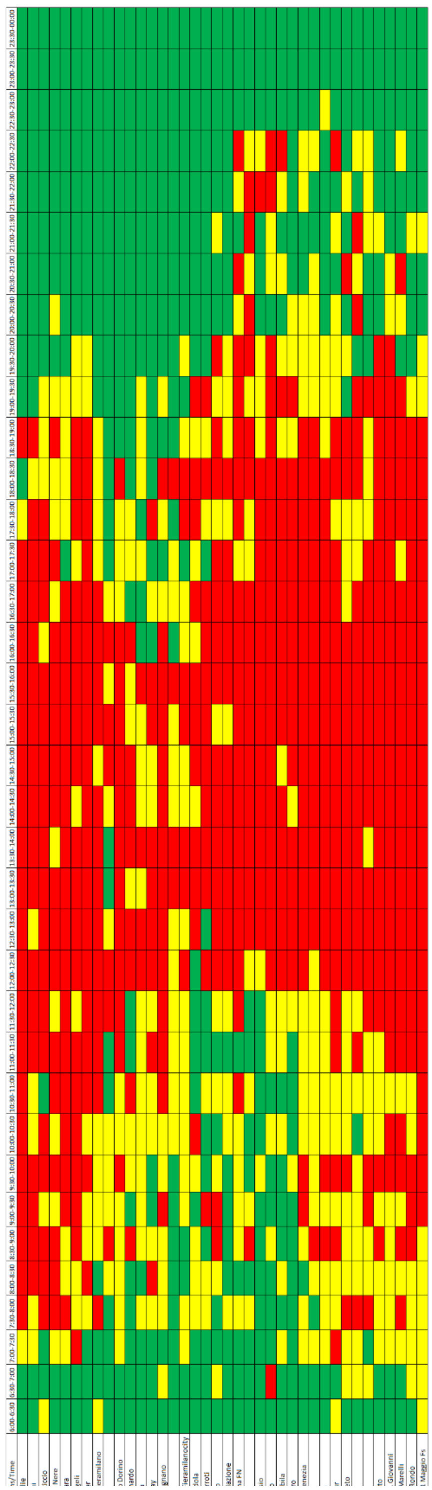

Figure B1-0-1: M1 subway line rush hours during the first week of April (6 a.m. to midnight: data every 30 minutes)

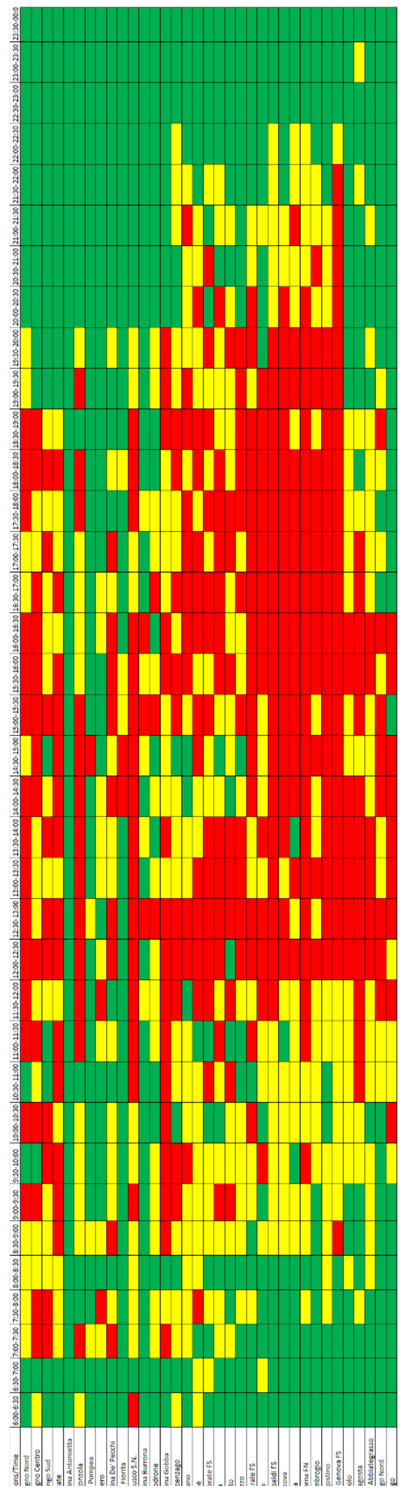

Figure B1-0-2: M2 subway line rush hours during the first week of April (6 a.m. to midnight: data every 30 minutes)

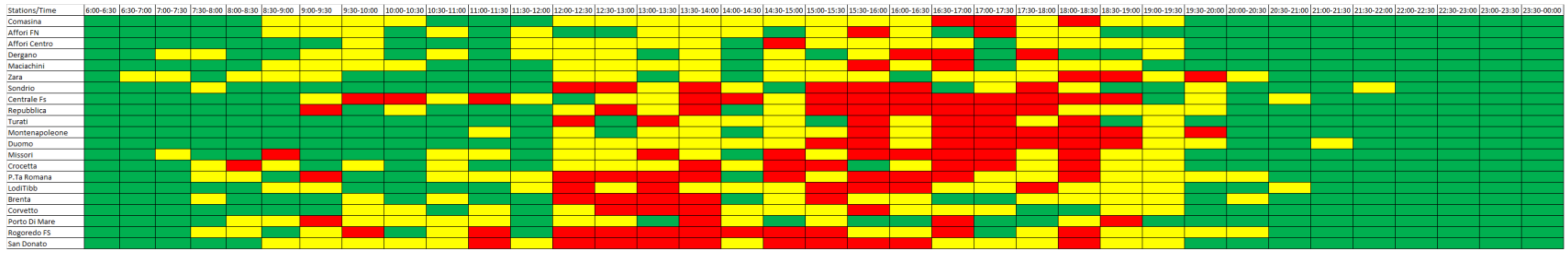

Figure B1-0-3: M3 subway line rush hours during the first week of April (6 a.m. to midnight: data every 30 minutes)

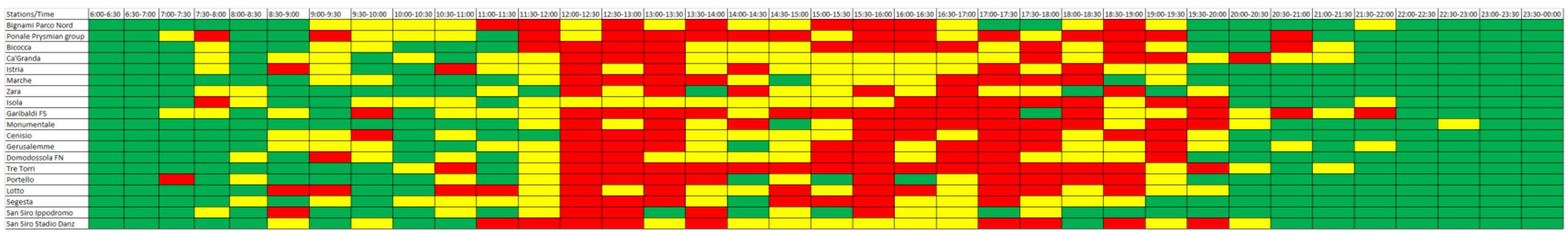

Figure B1-0-4: M5 subway line rush hours during the first week of April (6 a.m. to midnight: data every 30 minutes)

B2: Demand per stop

Table B2-0-1: Demand per subway station for lines M3 and M5

M3 line		M5 line	
Stations	Demand	Stations	Demand
Turati	1328	**San Siro Ippodromo**	563
Affori FN	2614	**Zara**	1123
Sondrio	3913	**Marche**	1698
Affori Centro	5244	**Portello**	2252
Dergano	6530	**Monumentale**	2857
Porto Di Mare	7825	**Segesta**	3439
Montenapoleone	9106	**Domodossola FN**	4051
Maciachini	10508	**Bignami Parco Nord**	4657
Corvetto	11902	**San Siro Stadio Danz**	5253
Brenta	13185	**Cenisio**	5875
Duomo	14546	**Istria**	6482
Repubblica	15935	**Bicocca**	7115
Missori	17283	**Lotto**	7727
Comasina	18683	**Tre Torri**	8319
Zara	20057	**Gerusalemme**	8905
LodiTibb	21418	**Isola**	9490
Crocetta	22797	**Ca'Granda**	10098
Centrale Fs	24187	**Ponale Prysmian group**	10737
P.Ta Romana	25589	**Garibaldi FS**	11360
San Donato	26965		
Rogoredo FS	28387		

Table B2- 0-2: Demand per subway stations for lines M1 and M2

M1 line		M2 line	
Stations	Demand	Stations	Demand
QT8	672	**Cascina Antonietta**	736
Pero	1335	**Villa Pompea**	1476
Bonola	1986	**Villa Fiorita**	2239
S. Leonardo	2651	**Cascina Burrona**	2986
Uruguay	3293	**Bussero**	3740
Lotto Fieramilanocity	3948	**Assago**	4512
Amendola	4601	**Assago Nord**	5257
Conciliazione	5258	**Vimodrone**	6004
Buonarroti	5927	**Romolo**	6744
Cordusio	6635	**Cassina De' Pecchi**	7462
Palestro	7336	**Colongo Sud**	8192
Molino Dorino	8027	**Caiazzo**	8938
Lampugnano	8728	**Famagosta**	9709
RHO Fieramilano	9438	**Gioia**	10452
San Babila	10121	**P.Za Abbiategrasso**	11205
Lima	10794	**Loreto**	11982
Rovereto	11483	**Gorgonzola**	12749
Pagano	12172	**Gessate**	13545
Loreto	12844	**Cologno Nord**	14322
Gorla	13541	**S. Ambrogio**	15100
Cairoli	14218	**Lambrate FS**	15810
Bande Nere	14913	**Cologno Centro**	16573
P.Ta Venezia	15654	**Cascina Gobba**	17376
Gambara	16344	**Centrale FS**	18106
Inganni	17046	**Moscova**	18886
Primaticcio	17744	**Piola**	19640
Wagner	18452	**Lanza**	20389
Duomo	19144	**S. Agostino**	21205
De Angeli	19857	**cimiano**	21993
Cadorna FN	20520	**Crescenzago**	22798
Precotto	21194	**Garibaldi FS**	23606
Sesto Rondo	21886	**Cernusco S.N.**	24418
Turro	22578	**P.Ta Genova FS**	25169
Bisceglie	23303	**Cadorna FN**	25959
Villa S. Giovanni	24021	**Udine**	26723
Sesto Marelli	24727		
Pasteur	25430		
Sesto 1 Maggio Fs	26178		

Appendix C: BikeMi further Analysis

C1: BikeMi users' analysis 2018

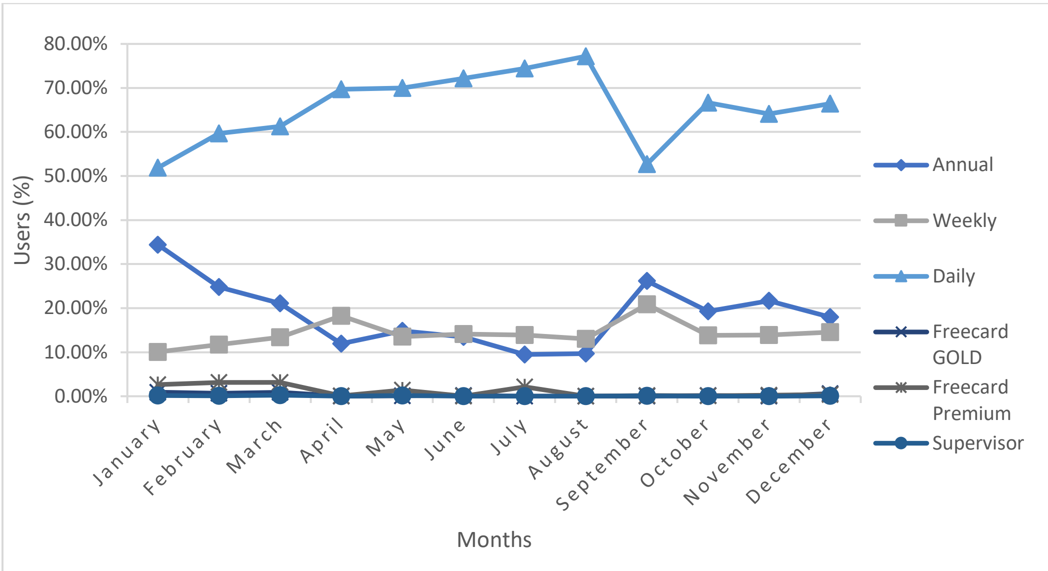

Figure C1-0-1: Subscription types of BikeMi users for the year 2018 (%)

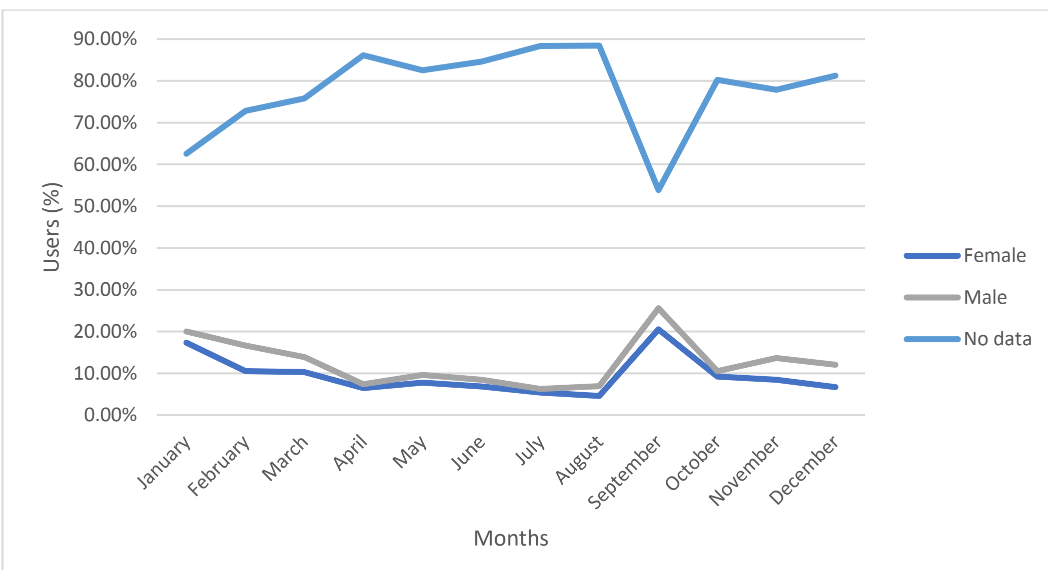

Figure C1-0-2: BikeMi users' gender for the years 2018 (%)

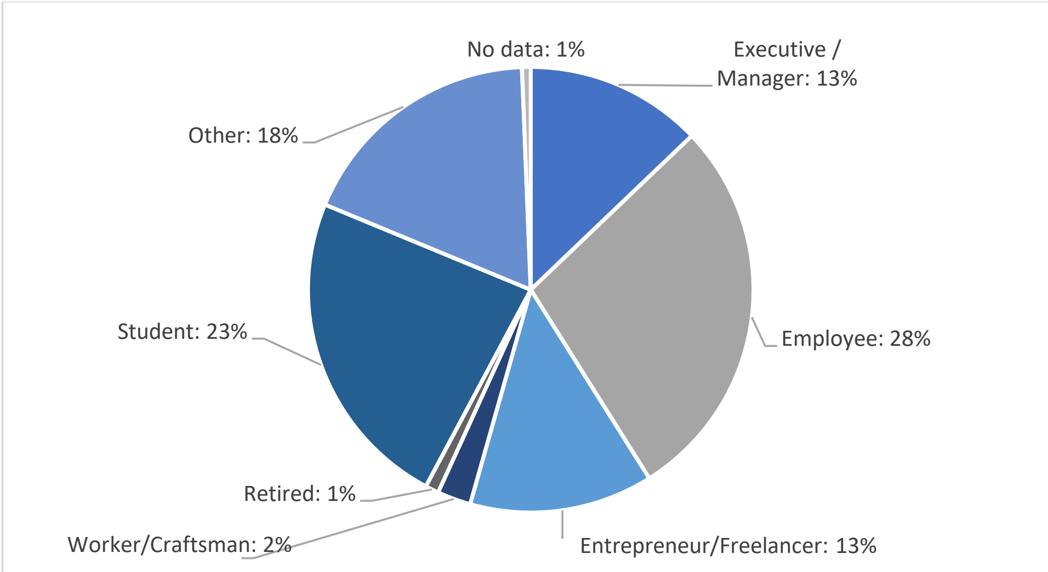

Figure C1-0-3: BikeMi users' profession for the year 2018 (%)

C2: BikeMi daily use per hour and average demand analysis

Hour	01-04-18	02-04-18	03-04-18	04-04-18	05-04-18	06-04-18	07-04-18	08-04-18	09-04-18	10-04-18	11-04-18	12-04-18	13-04-18	14-04-18	15-04-18
00:00- 00:59	no data	58	85	17	32	106	209	301	57	20	90	15	32	216	292
7:00-7:59	19	23	407	355	636	712	142	76	305	703	761	429	561	162	56
8:00-8:59	67	63	1424	894	1852	2073	235	177	1135	2050	2280	1500	1897	298	94
9:00-9:59	87	119	872	223	1076	1283	360	278	289	1164	1270	938	995	387	237
10:00-10:59	188	227	260	131	394	498	488	440	90	452	491	376	318	460	293
11:00-11:59	256	299	246	92	390	419	559	541	51	302	400	349	323	578	328
12:00-12:59	281	315	407	115	623	697	733	608	158	306	477	616	633	708	406
13:00-13:59	206	310	559	259	844	951	581	493	503	186	217	760	839	615	365
14:00-14:59	191	270	477	365	792	822	571	501	591	200	189	745	832	583	387
15:00-15:59	246	356	428	251	564	702	708	577	430	101	77	443	684	649	372
16:00-16:59	314	314	465	194	692	858	721	691	335	188	63	159	789	792	387
17:00-17:59	365	259	794	206	1164	1261	776	667	450	735	109	329	1180	726	455
18:00-18:59	273	275	1085	257	1601	1500	797	675	560	1313	159	546	1426	786	262
19:00-19:59	244	217	408	219	1270	1156	725	603	286	1139	115	477	1078	721	326
20:00-20:59	147	148	92	132	731	668	482	374	128	708	72	374	617	556	237
21:00-21:59	121	158	49	166	415	377	352	186	61	334	20	64	372	362	168
22:00-22:59	77	104	70	102	264	309	320	170	38	244	13	22	273	302	133
23:00- 23:59	71	117	42	91	173	244	272	159	15	175	7	74	264	273	117

Figure C2-0-4: System daily demand per hour in 2018 and demand exceeds the corresponding daily average demand (blue cells)

Hour	01-04-18	02-04-18	03-04-18	04-04-18	05-04-18	06-04-18	07-04-18	08-04-18	09-04-18	10-04-18	11-04-18	12-04-18	13-04-18	14-04-18	15-04-18
00:00- 00:59	no data	58	85	17	32	106	209	301	57	20	90	15	32	216	292
7:00-7:59	19	23	407	355	636	712	142	76	305	703	761	429	561	162	56
8:00-8:59	67	63	1424	894	1852	2073	235	177	1135	2050	2280	1500	1897	298	94
9:00-9:59	87	119	872	223	1076	1283	360	278	289	1164	1270	938	995	387	237
10:00-10:59	188	227	260	131	394	498	488	440	90	452	491	376	318	460	293
11:00-11:59	256	299	246	92	390	419	559	541	51	302	400	349	323	578	328
12:00-12:59	281	315	407	115	623	697	733	608	158	306	477	616	633	708	406
13:00-13:59	206	310	559	259	844	951	581	493	503	186	217	760	839	615	365
14:00-14:59	191	270	477	365	792	822	571	501	591	200	189	745	832	583	387
15:00-15:59	246	356	428	251	564	702	708	577	430	101	77	443	684	649	372
16:00-16:59	314	314	465	194	692	858	721	691	335	188	63	159	789	792	387
17:00-17:59	365	259	794	206	1164	1261	776	667	450	735	109	329	1180	726	455
18:00-18:59	273	275	1085	257	1601	1500	797	675	560	1313	159	546	1426	786	262
19:00-19:59	244	217	408	219	1270	1156	725	603	286	1139	115	477	1078	721	326
20:00-20:59	147	148	92	132	731	668	482	374	128	708	72	374	617	556	237
21:00-21:59	121	158	49	166	415	377	352	186	61	334	20	64	372	362	168
22:00-22:59	77	104	70	102	264	309	320	170	38	244	13	22	273	302	133
23:00- 23:59	71	117	42	91	173	244	272	159	15	175	7	74	264	273	117

Figure C2-0-5: System daily demand per hour in 2018 and demand exceeds the overall average demand per annual period (blue cells)

Hour	31-03-19	01-04-19	02-04-19	03-04-19	04-04-19	05-04-19	06-04-19	07-04-19	08-04-19	09-04-19	10-04-19	11-04-19	12-04-19	13-04-19	14-04-19
00:00- 00:59	155	48	62	66	69	50	152	187	35	86	144	144	28	227	83
7:00-7:59	31	577	633	653	41	498	117	37	533	658	693	244	343	125	22
8:00-8:59	60	1889	1954	2023	556	1593	193	105	1774	2071	2121	531	978	189	44
9:00-9:59	145	1147	1230	1173	458	1014	263	124	1078	1204	1243	389	651	360	79
10:00-10:59	232	418	454	388	223	412	378	201	413	527	548	133	193	461	57
11:00-11:59	334	369	398	111	108	336	437	230	342	433	443	133	242	543	50
12:00-12:59	430	536	606	124	257	641	502	306	503	638	612	253	475	583	52
13:00-13:59	366	719	767	137	276	729	402	225	698	822	805	309	658	554	19
14:00-14:59	341	618	707	160	157	636	397	201	709	749	752	235	674	498	42
15:00-15:59	495	510	543	202	121	543	466	187	538	590	588	107	586	587	65
16:00-16:59	496	633	633	422	180	620	471	212	728	684	625	223	755	602	92
17:00-17:59	491	1026	1013	807	396	1061	511	281	1029	1186	981	384	1136	638	88
18:00-18:59	472	1444	1322	1171	256	1205	468	298	1535	1566	1565	719	1269	633	154
19:00-19:59	513	1149	1070	973	189	912	408	166	1181	1201	1213	305	1089	580	119
20:00-20:59	288	668	617	513	117	594	358	100	694	764	815	246	651	467	49
21:00-21:59	185	279	308	222	132	288	183	36	358	413	349	84	418	234	49
22:00-22:59	162	230	198	157	56	242	181	67	213	345	295	45	275	234	48
23:00- 23:59	146	126	160	145	56	200	183	49	208	289	315	36	266	204	41

Figure C2-0-6: System daily demand per hour in 2019 and demand exceeds the corresponding daily average demand (blue cells)

Hour	31-03-19	01-04-19	02-04-19	03-04-19	04-04-19	05-04-19	06-04-19	07-04-19	08-04-19	09-04-19	10-04-19	11-04-19	12-04-19	13-04-19	14-04-19
00:00- 00:59	155	48	62	66	69	50	152	187	35	86	144	144	28	227	83
7:00-7:59	31	577	633	653	41	498	117	37	533	658	693	244	343	125	22
8:00-8:59	60	1889	1954	2023	556	1593	193	105	1774	2071	2121	531	978	189	44
9:00-9:59	145	1147	1230	1173	458	1014	263	124	1078	1204	1243	389	651	360	79
10:00-10:59	232	418	454	388	223	412	378	201	413	527	548	133	193	461	57
11:00-11:59	334	369	398	111	108	336	437	230	342	433	443	133	242	543	50
12:00-12:59	430	536	606	124	257	641	502	306	503	638	612	253	475	583	52
13:00-13:59	366	719	767	137	276	729	402	225	698	822	805	309	658	554	19
14:00-14:59	341	618	707	160	157	636	397	201	709	749	752	235	674	498	42
15:00-15:59	495	510	543	202	121	543	466	187	538	590	588	107	586	587	65
16:00-16:59	496	633	633	422	180	620	471	212	728	684	625	223	755	602	92
17:00-17:59	491	1026	1013	807	396	1061	511	281	1029	1186	981	384	1136	638	88
18:00-18:59	472	1444	1322	1171	256	1205	468	298	1535	1566	1565	719	1269	633	154
19:00-19:59	513	1149	1070	973	189	912	408	166	1181	1201	1213	305	1089	580	119
20:00-20:59	288	668	617	513	117	594	358	100	694	764	815	246	651	467	49
21:00-21:59	185	279	308	222	132	288	183	36	358	413	349	84	418	234	49
22:00-22:59	162	230	198	157	56	242	181	67	213	345	295	45	275	234	48
23:00- 23:59	146	126	160	145	56	200	183	49	208	289	315	36	266	204	41

Figure C2-0-7: System daily demand per hour in 2019 and demand exceeds the overall average demand per annual period (blue cells)

Hour	29-03-20	30-03-20	31-03-20	01-04-20	02-04-20	03-04-20	04-04-20	05-04-20	06-04-20	07-04-20	08-04-20	09-04-20	10-04-20	11-04-20	12-04-20
6:00-6:59	0	4	4	5	5	4	0	5	12	9	9	7	5	7	4
7:00-7:59	13	42	39	48	47	49	0	7	55	63	59	59	49	25	7
8:00-8:59	11	86	87	73	84	85	22	15	93	97	107	100	105	29	5
9:00-9:59	10	45	46	35	47	48	19	12	61	53	60	61	62	35	10
10:00-10:59	10	40	27	31	36	32	32	18	34	55	33	43	48	46	12
11:00-11:59	18	34	19	18	26	25	54	25	33	25	41	39	48	50	27
12:00-12:59	27	40	36	37	34	42	40	17	32	39	41	37	61	54	29
13:00-13:59	23	46	22	32	45	41	32	21	43	59	55	56	63	43	11
14:00-14:59	22	42	26	37	32	44	41	20	41	49	41	62	60	36	19
15:00-15:59	20	37	32	36	35	44	61	35	39	39	49	54	64	44	22
16:00-16:59	26	19	40	37	49	63	39	19	69	52	59	57	70	65	28
17:00-17:59	24	35	53	50	53	69	32	29	70	87	77	72	81	39	27
18:00-18:59	26	49	51	67	75	57	36	24	64	59	83	84	66	43	22
19:00-19:59	12	30	38	41	51	52	24	20	48	62	72	53	51	46	15
20:00-20:59	12	20	26	27	17	32	13	12	37	30	32	24	34	23	19
21:00-21:59	5	13	16	6	16	15	12	15	11	21	21	19	25	9	10
22:00-22:59	6	6	6	10	7	9	9	6	8	9	7	6	7	6	4
23:00- 23:59	2	1	1	1	4	3	2	3	5	0	1	2	4	4	3

Figure C2-0-8: System daily demand per hour in 2020 and demand exceeds the corresponding daily average demand (blue cells)

Hour	29-03-20	30-03-20	31-03-20	01-04-20	02-04-20	03-04-20	04-04-20	05-04-20	06-04-20	07-04-20	08-04-20	09-04-20	10-04-20	11-04-20	12-04-20
6:00-6:59	0	4	4	5	5	4	0	5	12	9	9	7	5	7	4
7:00-7:59	13	42	39	48	47	49	0	7	55	63	59	59	49	25	7
8:00-8:59	11	86	87	73	84	85	22	15	93	97	107	100	105	29	5
9:00-9:59	10	45	46	35	47	48	19	12	61	53	60	61	62	35	10
10:00-10:59	10	40	27	31	36	32	32	18	34	55	33	43	48	46	12
11:00-11:59	18	34	19	18	26	25	54	25	33	25	41	39	48	50	27
12:00-12:59	27	40	36	37	34	42	40	17	32	39	41	37	61	54	29
13:00-13:59	23	46	22	32	45	41	32	21	43	59	55	56	63	43	11
14:00-14:59	22	42	26	37	32	44	41	20	41	49	41	62	60	36	19
15:00-15:59	20	37	32	36	35	44	61	35	39	39	49	54	64	44	22
16:00-16:59	26	19	40	37	49	63	39	19	69	52	59	57	70	65	28
17:00-17:59	24	35	53	50	53	69	32	29	70	87	77	72	81	39	27
18:00-18:59	26	49	51	67	75	57	36	24	64	59	83	84	66	43	22
19:00-19:59	12	30	38	41	51	52	24	20	48	62	72	53	51	46	15
20:00-20:59	12	20	26	27	17	32	13	12	37	30	32	24	34	23	19
21:00-21:59	5	13	16	6	16	15	12	15	11	21	21	19	25	9	10
22:00-22:59	6	6	6	10	7	9	9	6	8	9	7	6	7	6	4
23:00- 23:59	2	1	1	1	4	3	2	3	5	0	1	2	4	4	3

Figure C2-0-9: System daily demand per hour in 2020 and demand exceeds the overall average demand per annual period (blue cells)

C3: BikeMi station analysis

Table C3-0-1: Stations designated as attractor station and their ratio (picked up bikes average/returned bikes average) in 2018

Attractor stations									
2018									
Stations	Ratio	Stations	Ratio	Stations	Ratio	Stations	Ratio	Stations	Ratio
29	0.700	**250**	0.876	**91**	0.928	**215**	0.953	**102**	0.971
100	0.732	**145**	0.877	**173**	0.930	**254**	0.953	**38**	0.972
59	0.746	**31**	0.881	**65**	0.930	**16**	0.954	**402**	0.976
164	0.769	**311**	0.883	**120**	0.931	**169**	0.954	**67**	0.978
80	0.793	**70**	0.889	**76**	0.936	**207**	0.955	**192**	0.978
28	0.807	**174**	0.891	**14**	0.938	**315**	0.955	**107**	0.979
1	0.807	**81**	0.897	**71**	0.939	**149**	0.956	**105**	0.979
66	0.818	**5**	0.898	**139**	0.940	**12**	0.957	**259**	0.979
251	0.828	**241**	0.899	**221**	0.941	**8**	0.958	**159**	0.980
60	0.837	**232**	0.901	**163**	0.941	**86**	0.959	**108**	0.981
104	0.837	**226**	0.905	**303**	0.941	**115**	0.960	**205**	0.981
153	0.840	**64**	0.911	**304**	0.941	**39**	0.961	**63**	0.982
130	0.845	**208**	0.915	**35**	0.941	**18**	0.963	**98**	0.986
82	0.846	**4**	0.917	**151**	0.943	**27**	0.964	**214**	0.991
34	0.847	**74**	0.917	**258**	0.943	**46**	0.965	**45**	0.991
329	0.856	**13**	0.918	**62**	0.947	**155**	0.966	**325**	0.991
195	0.857	**305**	0.920	**52**	0.947	**57**	0.966	**117**	0.992
101	0.862	**165**	0.920	**204**	0.949	**148**	0.966	**157**	0.993
135	0.865	**77**	0.922	**58**	0.949	**263**	0.966	**211**	0.994
330	0.872	**49**	0.922	**6**	0.950	**131**	0.968	**313**	0.995
190	0.873	**55**	0.923	**227**	0.951	**32**	0.969	**194**	0.995
22	0.875	**321**	0.924	**270**	0.953	**255**	0.971	**168**	0.996
		302	0.926	**68**	0.953	**229**	0.971	**61**	0.997

Table C3-0-2: Stations designated as attractor station and their ratio (picked up bikes average/returned bikes average) in 2019

Attractor stations									
2019									
Stations	Ratio	Stations	Ratio	Stations	Ratio	Stations	Ratio	Stations	Ratio
341	0.663	**70**	0.883	**323**	0.933	**105**	0.965	**62**	0.982
326	0.733	**141**	0.883	**112**	0.933	**206**	0.965	**258**	0.982
384	0.742	**303**	0.886	**34**	0.933	**144**	0.965	**118**	0.982
151	0.771	**36**	0.886	**100**	0.937	**222**	0.966	**161**	0.983
313	0.772	**82**	0.892	**30**	0.938	**159**	0.967	**325**	0.983
29	0.776	**130**	0.892	**260**	0.938	**26**	0.968	**253**	0.983
59	0.788	**57**	0.893	**173**	0.939	**47**	0.970	**152**	0.984
80	0.796	**102**	0.896	**35**	0.939	**93**	0.970	**251**	0.984
165	0.798	**343**	0.897	**58**	0.942	**85**	0.971	**198**	0.984
385	0.803	**163**	0.897	**197**	0.943	**143**	0.971	**317**	0.985
94	0.808	**120**	0.898	**69**	0.944	**14**	0.971	**77**	0.985
22	0.840	**315**	0.900	**266**	0.944	**106**	0.971	**81**	0.986
135	0.846	**1**	0.903	**186**	0.946	**114**	0.972	**158**	0.987
342	0.850	**259**	0.903	**32**	0.946	**13**	0.974	**123**	0.987
229	0.851	**281**	0.907	**99**	0.948	**87**	0.975	**310**	0.988
210	0.855	**302**	0.911	**205**	0.949	**194**	0.975	**171**	0.989
149	0.855	**68**	0.912	**42**	0.950	**117**	0.975	**4**	0.991
146	0.856	**31**	0.913	**190**	0.951	**16**	0.975	**402**	0.991
330	0.857	**101**	0.914	**133**	0.951	**63**	0.976	**136**	0.992
232	0.861	**125**	0.915	**153**	0.951	**263**	0.976	**213**	0.993
184	0.865	**174**	0.921	**176**	0.952	**191**	0.977	**134**	0.993
164	0.875	**383**	0.923	**15**	0.953	**220**	0.977	**216**	0.995
340	0.878	**66**	0.926	**39**	0.955	**328**	0.977	**73**	0.995
207	0.878	**27**	0.928	**21**	0.957	**280**	0.977	**5**	0.996
122	0.878	**254**	0.929	**226**	0.957	**214**	0.979	**145**	0.996
208	0.882	**239**	0.929	**139**	0.959	**221**	0.980	**140**	0.996
204	0.882	**154**	0.931	**124**	0.963	**227**	0.980	**150**	0.998
						12	0.981	**37**	0.998

Table C3-0-3: Stations designated as attractor station and their ratio (picked up bikes average/returned bikes average) in 2020

Attractor stations									
2020									
Stations	Ratio	Stations	Ratio	Stations	Ratio	Stations	Ratio	Stations	Ratio
36	0.000	**342**	0.667	**263**	0.800	**254**	0.867	**66**	0.917
251	0.000	**1**	0.674	**307**	0.800	**15**	0.868	**52**	0.917
385	0.000	**324**	0.688	**341**	0.800	**172**	0.870	**62**	0.917
197	0.200	**49**	0.700	**221**	0.815	**48**	0.871	**109**	0.920
357	0.286	**359**	0.700	**120**	0.818	**241**	0.871	**319**	0.923
358	0.375	**210**	0.700	**215**	0.818	**82**	0.872	**266**	0.926
328	0.455	**7**	0.714	**42**	0.826	**227**	0.872	**383**	0.929
327	0.471	**304**	0.714	**103**	0.826	**143**	0.875	**211**	0.933
13	0.500	**111**	0.714	**340**	0.829	**76**	0.875	**139**	0.937
154	0.500	**301**	0.722	**28**	0.833	**100**	0.875	**127**	0.940
253	0.500	**75**	0.745	**44**	0.833	**370**	0.875	**69**	0.942
70	0.516	**91**	0.750	**361**	0.833	**380**	0.875	**182**	0.944
189	0.533	**40**	0.750	**248**	0.833	**362**	0.879	**23**	0.947
121	0.538	**141**	0.755	**222**	0.838	**151**	0.881	**38**	0.947
119	0.556	**130**	0.762	**41**	0.840	**363**	0.886	**122**	0.947
68	0.560	**131**	0.767	**132**	0.840	**51**	0.889	**8**	0.950
146	0.583	**262**	0.773	**32**	0.842	**164**	0.889	**80**	0.951
78	0.588	**175**	0.776	**73**	0.844	**310**	0.889	**128**	0.951
104	0.600	**140**	0.778	**27**	0.846	**179**	0.891	**57**	0.955
20	0.600	**203**	0.778	**31**	0.850	**22**	0.900	**229**	0.955
190	0.605	**325**	0.778	**354**	0.850	**81**	0.900	**283**	0.956
106	0.611	**72**	0.780	**214**	0.855	**168**	0.900	**64**	0.957
25	0.615	**134**	0.786	**184**	0.857	**196**	0.900	**233**	0.962
191	0.615	**158**	0.786	**202**	0.857	**250**	0.900	**169**	0.964
26	0.625	**107**	0.790	**366**	0.857	**257**	0.900	**187**	0.969
34	0.643	**137**	0.800	**343**	0.860	**17**	0.905	**192**	0.974
114	0.647	**166**	0.800	**77**	0.864	**206**	0.906	**29**	0.979
101	0.667	**201**	0.800	**14**	0.864	**267**	0.909	**313**	0.980
155	0.667	**225**	0.800	**350**	0.865	**381**	0.909	**87**	0.981
5	0.667	**261**	0.800	**226**	0.867	**88**	0.913	**205**	0.982
								10	0.990

Table C3-0-4: Stations designated as generator station and their ratio (picked up bikes average/returned bikes average) in 2018

Generator stations									
2018									
Stations	Ratio	Stations	Ratio	Stations	Ratio	Stations	Ratio	Stations	Ratio
73	1.002	**7**	1.025	**282**	1.041	**161**	1.065	**87**	1.119
152	1.002	**328**	1.026	**238**	1.041	**184**	1.067	**89**	1.120
122	1.003	**283**	1.027	**48**	1.041	**256**	1.067	**141**	1.124
146	1.003	**124**	1.028	**51**	1.042	**17**	1.068	**281**	1.125
134	1.003	**197**	1.028	**54**	1.042	**307**	1.068	**167**	1.128
144	1.004	**265**	1.028	**257**	1.043	**36**	1.069	**137**	1.133
249	1.005	**224**	1.029	**179**	1.043	**21**	1.071	**206**	1.141
264	1.005	**136**	1.029	**327**	1.044	**110**	1.073	**172**	1.145
143	1.007	**126**	1.029	**113**	1.045	**253**	1.075	**23**	1.146
301	1.008	**44**	1.029	**150**	1.045	**133**	1.078	**236**	1.157
26	1.009	**50**	1.030	**19**	1.045	**239**	1.080	**210**	1.158
42	1.009	**111**	1.031	**121**	1.045	**181**	1.082	**323**	1.158
187	1.009	**156**	1.033	**106**	1.046	**183**	1.084	**309**	1.161
322	1.009	**30**	1.033	**158**	1.046	**109**	1.087	**280**	1.165
296	1.010	**99**	1.034	**188**	1.047	**125**	1.089	**318**	1.166
40	1.011	**261**	1.034	**213**	1.048	**178**	1.091	**260**	1.172
72	1.011	**114**	1.035	**191**	1.049	**262**	1.091	**182**	1.177
96	1.014	**69**	1.035	**103**	1.049	**41**	1.092	**219**	1.177
200	1.015	**212**	1.035	**129**	1.049	**324**	1.094	**118**	1.181
199	1.015	**53**	1.035	**142**	1.049	**140**	1.095	**56**	1.214
75	1.018	**170**	1.036	**37**	1.051	**127**	1.097	**203**	1.227
186	1.018	**94**	1.036	**43**	1.053	**310**	1.099	**312**	1.246
47	1.018	**162**	1.036	**33**	1.055	**171**	1.101	**160**	1.255
216	1.018	**138**	1.036	**9**	1.055	**119**	1.105	**3**	1.257
222	1.022	**154**	1.036	**20**	1.055	**252**	1.106	**78**	1.268
116	1.023	**93**	1.038	**88**	1.056	**196**	1.107	**193**	1.270
147	1.023	**225**	1.039	**112**	1.056	**84**	1.107	**233**	1.299
11	1.024	**10**	1.040	**97**	1.058	**185**	1.107	**180**	1.316
201	1.024	**123**	1.040	**132**	1.064	**248**	1.109	**128**	1.322
175	1.024	**317**	1.040	**237**	1.065	**176**	1.111	**25**	1.340
						319	1.117	**334**	1.615

Table C3-0-5: Stations designated as generator station and their ratio (picked up bikes average/returned bikes average) in 2019

Generator stations									
2019									
Stations	Ratio	Stations	Ratio	Stations	Ratio	Stations	Ratio	Stations	Ratio
86	1.002	**113**	1.023	**200**	1.045	**18**	1.085	**168**	1.129
23	1.003	**142**	1.023	**115**	1.046	**324**	1.085	**182**	1.138
179	1.005	**188**	1.023	**162**	1.050	**92**	1.086	**237**	1.143
319	1.005	**109**	1.024	**155**	1.050	**183**	1.089	**167**	1.150
71	1.005	**305**	1.024	**97**	1.051	**45**	1.091	**137**	1.153
7	1.007	**95**	1.024	**199**	1.053	**249**	1.091	**128**	1.159
282	1.008	**40**	1.025	**181**	1.054	**119**	1.092	**127**	1.168
131	1.009	**48**	1.025	**309**	1.054	**327**	1.092	**11**	1.176
255	1.009	**148**	1.027	**189**	1.056	**307**	1.098	**180**	1.178
60	1.010	**211**	1.027	**19**	1.058	**110**	1.099	**8**	1.178
52	1.010	**172**	1.028	**111**	1.059	**107**	1.100	**160**	1.181
55	1.010	**261**	1.028	**267**	1.060	**72**	1.104	**256**	1.181
202	1.011	**38**	1.029	**241**	1.060	**169**	1.105	**248**	1.192
75	1.011	**215**	1.032	**65**	1.060	**185**	1.105	**56**	1.192
76	1.012	**54**	1.032	**126**	1.060	**20**	1.109	**33**	1.194
79	1.013	**43**	1.033	**296**	1.061	**6**	1.110	**25**	1.198
147	1.013	**270**	1.034	**250**	1.062	**304**	1.111	**233**	1.199
257	1.014	**311**	1.035	**129**	1.063	**96**	1.111	**3**	1.201
53	1.014	**238**	1.036	**225**	1.066	**178**	1.111	**28**	1.204
264	1.015	**51**	1.036	**9**	1.067	**132**	1.114	**235**	1.209
196	1.017	**329**	1.036	**170**	1.067	**89**	1.117	**78**	1.219
262	1.017	**175**	1.039	**74**	1.068	**301**	1.119	**84**	1.235
98	1.017	**104**	1.039	**318**	1.069	**322**	1.120	**10**	1.236
157	1.019	**265**	1.040	**121**	1.071	**321**	1.120	**166**	1.238
116	1.019	**64**	1.040	**67**	1.072	**193**	1.120	**236**	1.239
201	1.020	**283**	1.041	**103**	1.078	**91**	1.120	**312**	1.250
268	1.020	**49**	1.041	**17**	1.079	**44**	1.122	**219**	1.261
187	1.022	**156**	1.042	**192**	1.079	**195**	1.123	**203**	1.268
252	1.022	**108**	1.043	**138**	1.080	**61**	1.127	**50**	1.275
224	1.023	**24**	1.044	**46**	1.083	**88**	1.129	**41**	1.293
								334	1.455

Table C3-0-6: Stations designated as generator station and their ratio (picked up bikes average/returned bikes average) in 2020

Generator stations									
2020									
Stations	Ratio	Stations	Ratio	Stations	Ratio	Stations	Ratio	Stations	Ratio
315	1.015	**321**	1.074	**171**	1.135	**16**	1.255	**112**	1.441
259	1.016	**116**	1.075	**133**	1.143	**165**	1.257	**129**	1.455
237	1.022	**113**	1.077	**352**	1.150	**6**	1.261	**264**	1.500
309	1.023	**174**	1.083	**63**	1.155	**4**	1.263	**280**	1.500
220	1.026	**60**	1.087	**176**	1.161	**54**	1.263	**372**	1.500
159	1.027	**303**	1.087	**268**	1.161	**152**	1.269	**258**	1.500
212	1.029	**282**	1.091	**162**	1.167	**236**	1.276	**142**	1.545
232	1.032	**255**	1.094	**200**	1.167	**239**	1.290	**35**	1.600
126	1.034	**183**	1.094	**219**	1.171	**135**	1.292	**97**	1.600
86	1.036	**105**	1.095	**18**	1.174	**79**	1.294	**24**	1.615
281	1.036	**149**	1.095	**265**	1.182	**173**	1.294	**53**	1.636
94	1.040	**181**	1.095	**118**	1.190	**216**	1.300	**312**	1.667
207	1.041	**296**	1.097	**123**	1.190	**323**	1.300	**12**	1.714
39	1.043	**249**	1.098	**110**	1.192	**302**	1.303	**98**	1.742
30	1.054	**193**	1.100	**47**	1.194	**180**	1.304	**326**	1.800
351	1.056	**45**	1.103	**305**	1.200	**144**	1.313	**384**	1.800
157	1.057	**102**	1.105	**163**	1.205	**83**	1.333	**224**	1.833
186	1.060	**85**	1.111	**55**	1.208	**148**	1.346	**156**	1.889
402	1.061	**260**	1.111	**167**	1.208	**67**	1.375	**153**	2.000
311	1.063	**185**	1.117	**318**	1.214	**89**	1.375	**208**	2.000
322	1.063	**71**	1.118	**61**	1.219	**46**	1.382	**3**	2.053
213	1.065	**204**	1.120	**369**	1.222	**65**	1.400	**252**	2.750
194	1.065	**19**	1.121	**256**	1.226	**136**	1.400	**9**	3.000
93	1.067	**74**	1.125	**11**	1.250	**145**	1.405	**329**	3.000
195	1.067	**117**	1.125	**50**	1.250	**95**	1.421	**199**	3.250
178	1.068	**238**	1.129	**108**	1.250	**37**	1.423	**96**	3.833
115	1.068	**138**	1.133	**160**	1.250	**99**	1.429	**33**	generator
124	1.070	**147**	1.135	**198**	1.250	**235**	1.435	**59**	generator

Table C3-0-7: Stations designated as neutral station and their ratio (picked up bikes average/returned bikes average) in 2018

Neutral stations	
2018	
Stations	Ratio
15	1.000
85	1.000
95	1.000

Table C3-0-8: Stations designated as neutral station and their ratio (picked up bikes average/returned bikes average) in 2019

Neutral stations	
2019	
Stations	Ratio
83	1.000
212	1.000

Table C3-0-9: Stations designated as neutral station and their ratio (picked up bikes average/returned bikes average) in 2020

Neutral stations	
2020	
Stations	Ratio
21	1.000
43	1.000
56	1.000
84	1.000
125	1.000
150	1.000
170	1.000
188	1.000
270	1.000
317	1.000
334	1.000

Table C3-0-10: Common attractor stations for the years 2018-2020

Attractor stations		
1	66	151
13	68	164
14	70	205
22	77	214
27	80	226
29	81	227
31	82	229
32	100	251
34	101	254
57	120	263
62	130	313
		325

Table C3-0-11: Common generator stations for the years 2018-2020

Generator stations		
3	126	224
9	138	236
11	147	237
19	156	238
33	160	249
50	162	252
53	178	256
54	181	264
89	183	265
96	185	282
97	193	296
110	199	309
113	200	312
116	219	318
		322

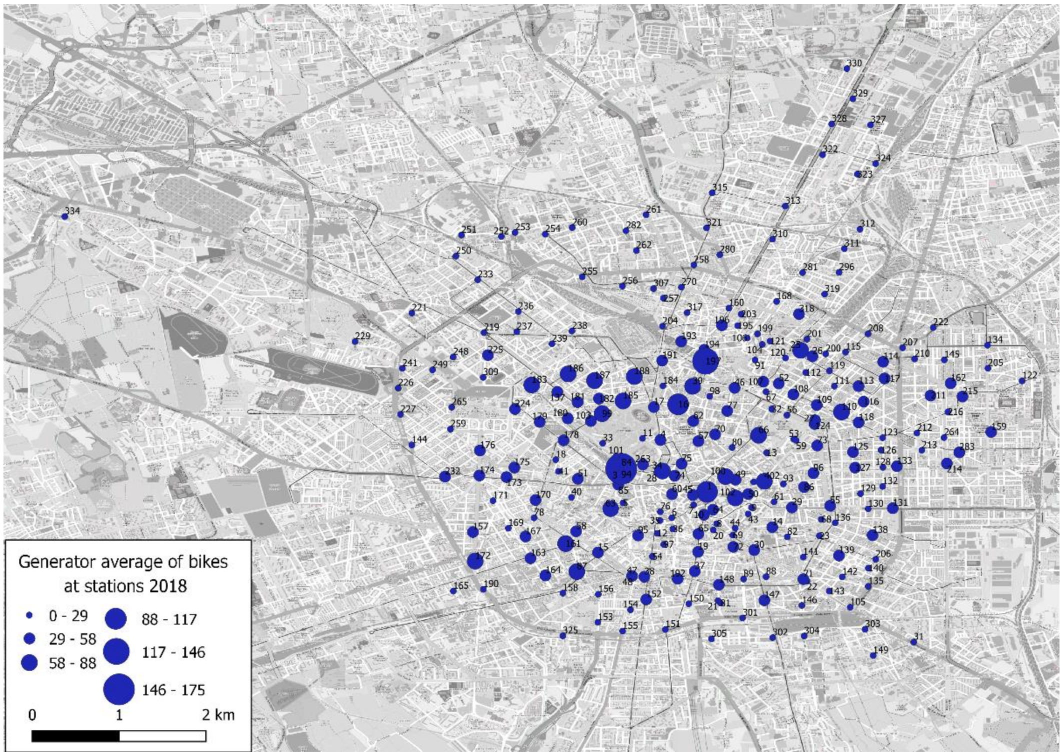

Figure C3-0-10: Generator averages of BikeMi stations 2018 (scale: 1:38000)

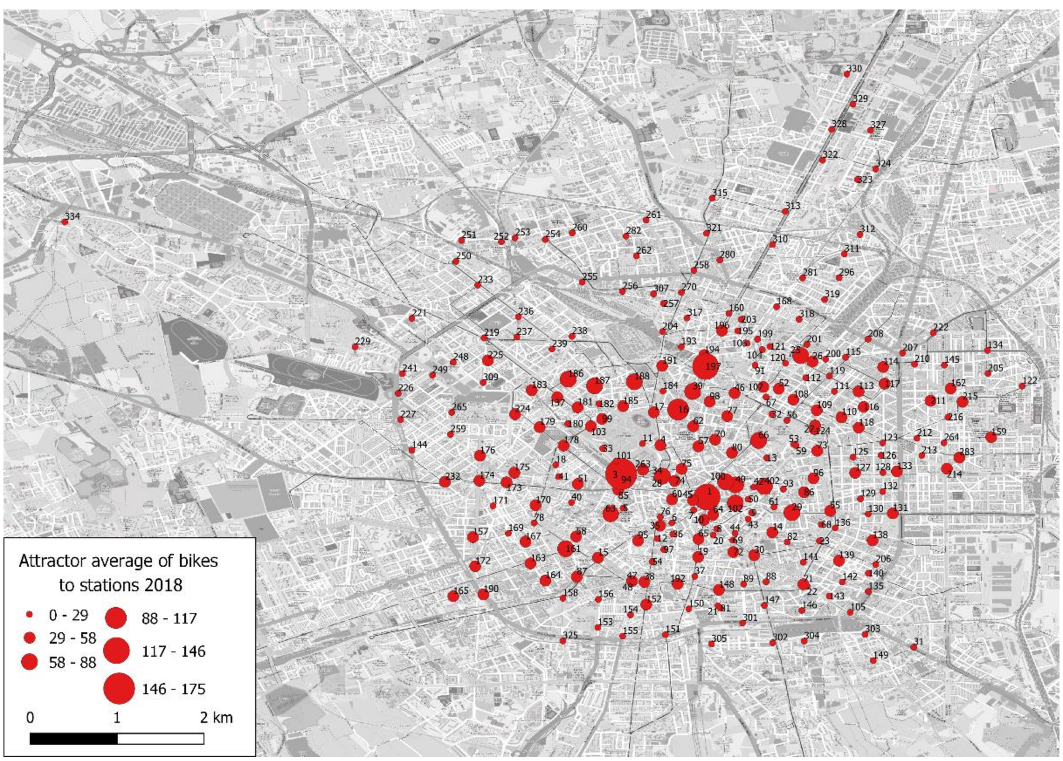

Figure C3-0-11: Attractor averages of BikeMi stations 2018 (scale: 1:38000)

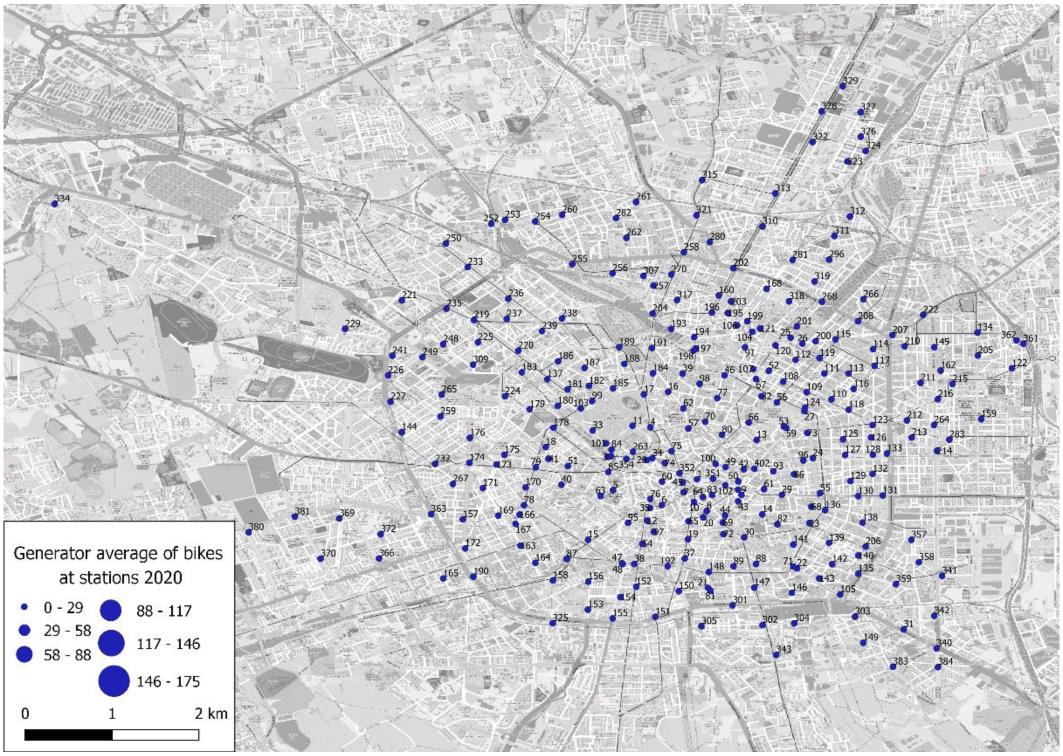

Figure C3-0-12: Generator averages of BikeMi stations 2020 (scale: 1:38000)

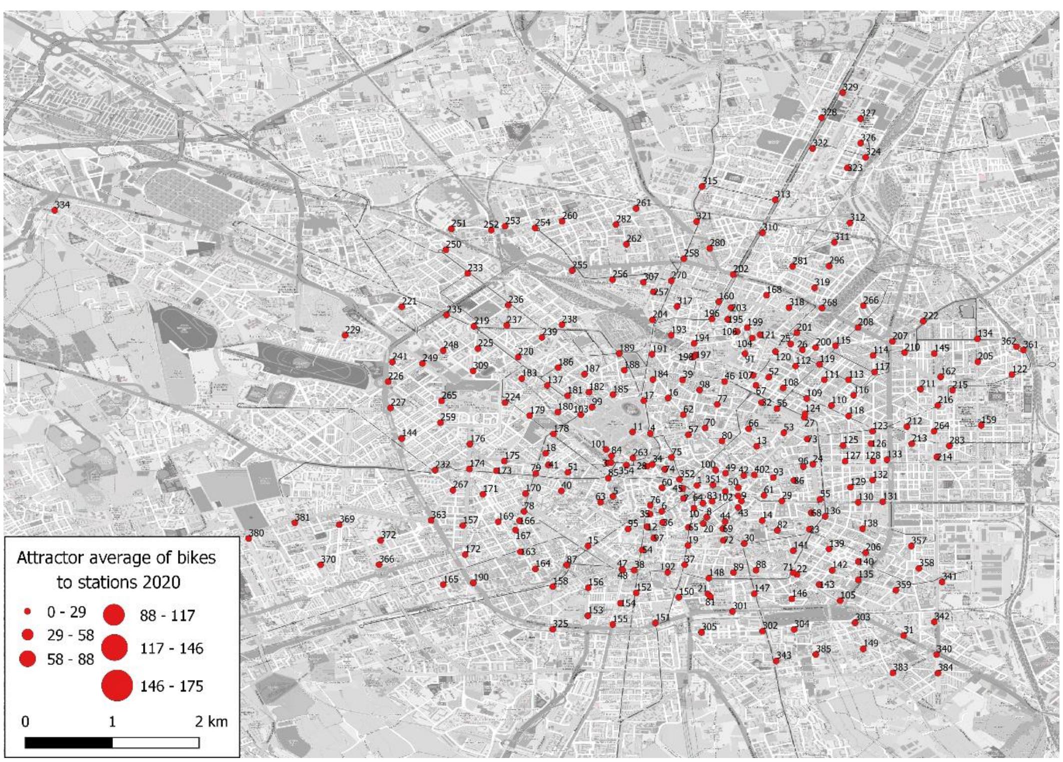

Figure C3-0-13: Attractor averages of BikeMi stations 2020 (scale: 1:38000)

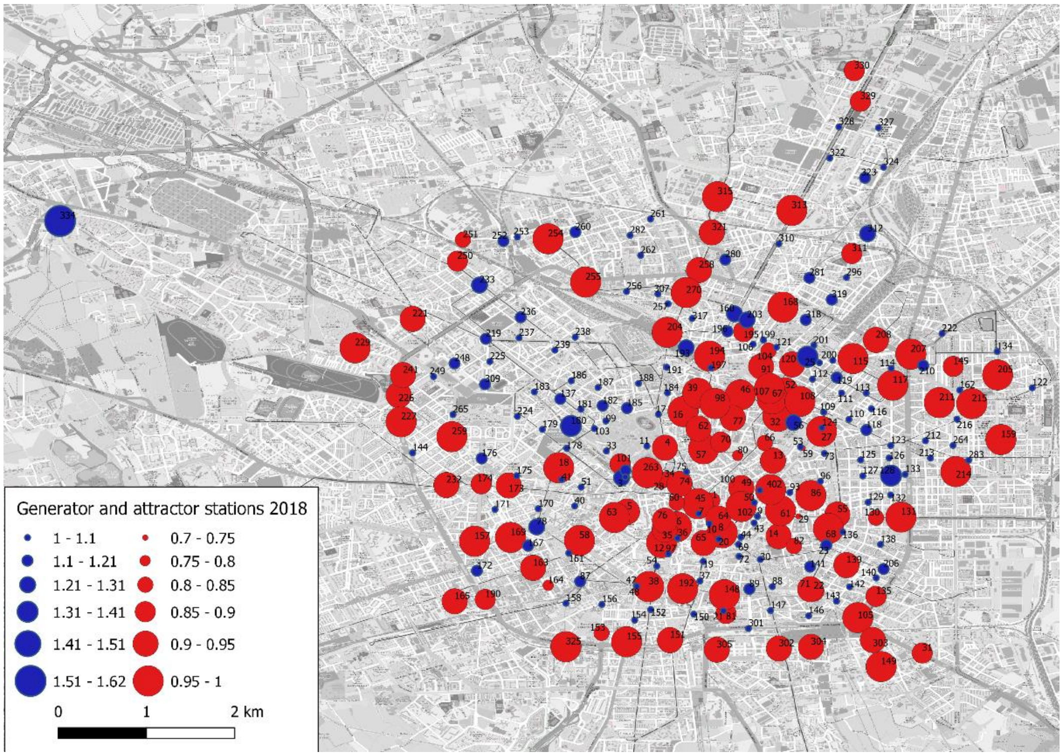

Figure C3-0-14: Generator and attractor stations of 2018 (scale: 1:38000)

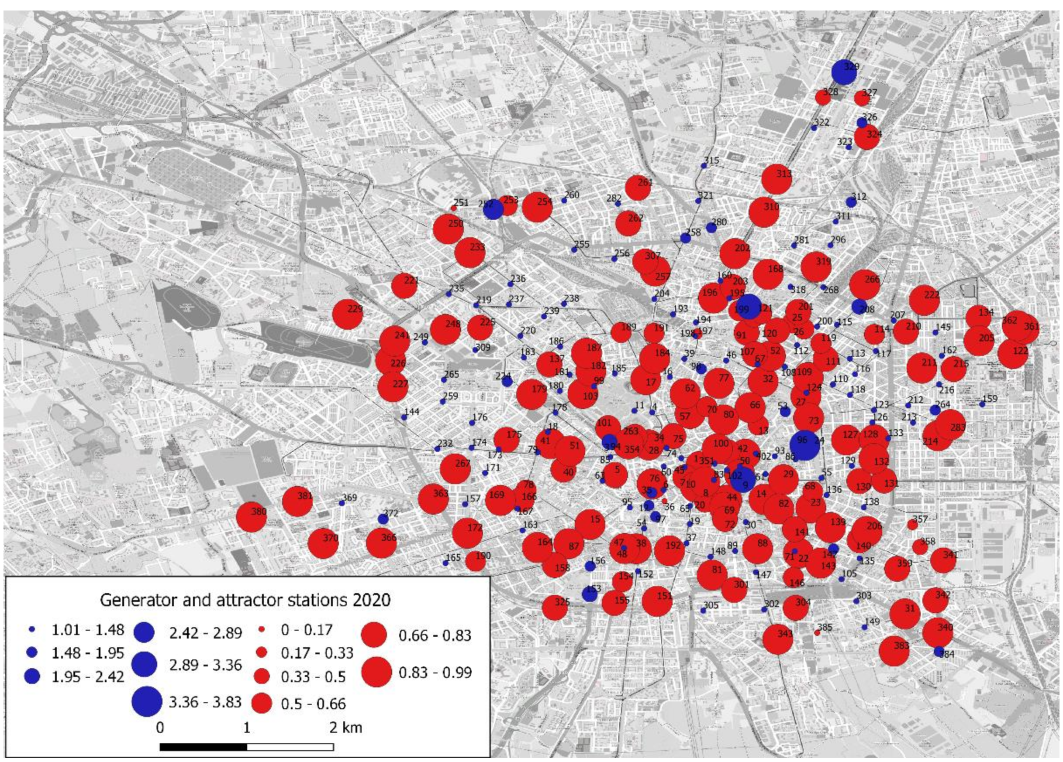

Figure C3-0-15: Generator and attractor stations of 2020 (scale: 1:38000)

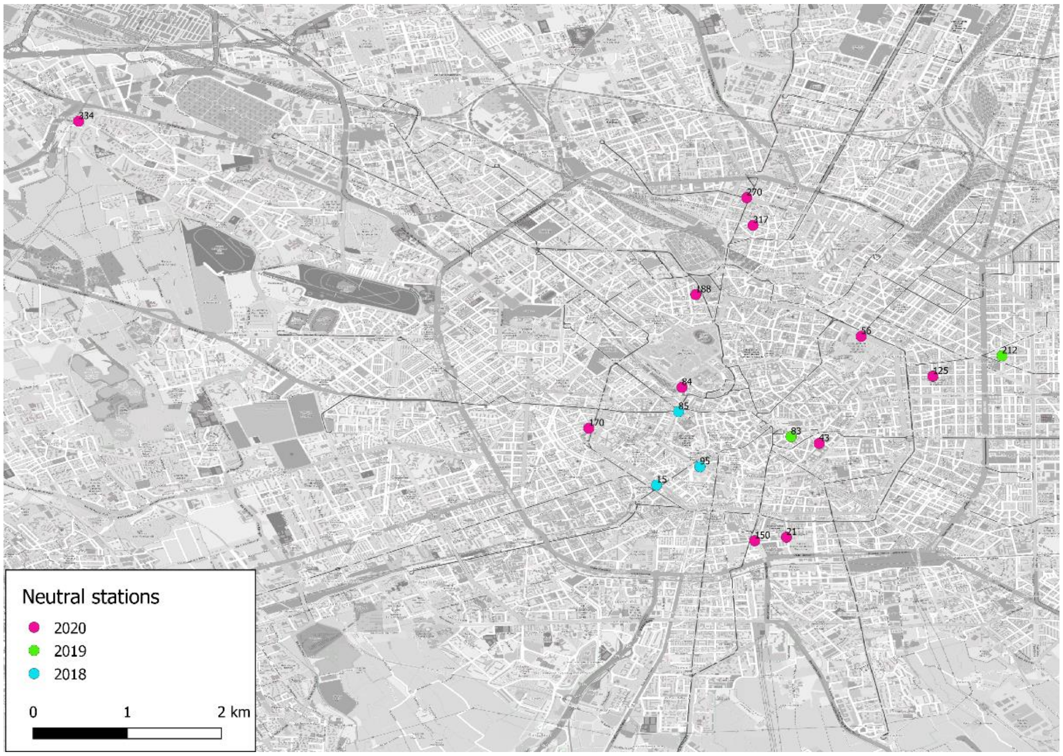

Figure C3-0-16: Neutral stations for the years 2018-2020 (scale 1:38000)

C4: BikeMi travel distance analysis

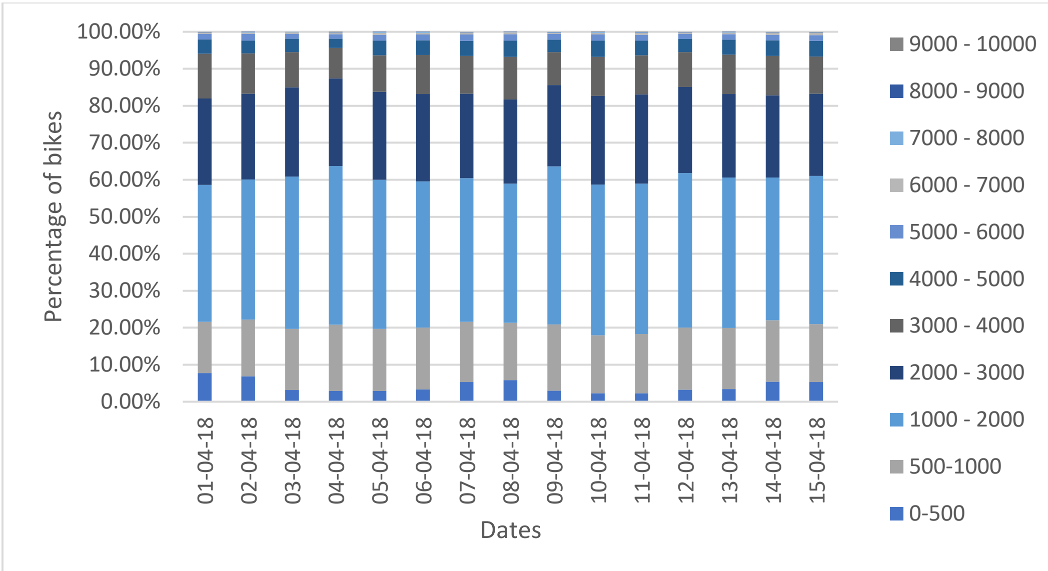

Figure C4-0-17: Travel distance for bikes in 2018

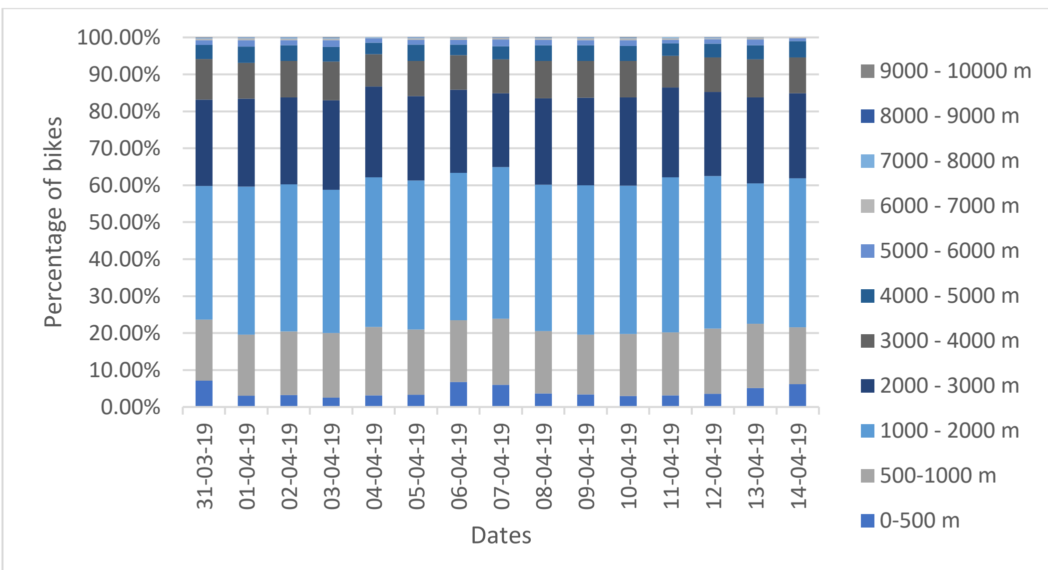

Figure C4-0-18: Travel distance for bikes in 2019

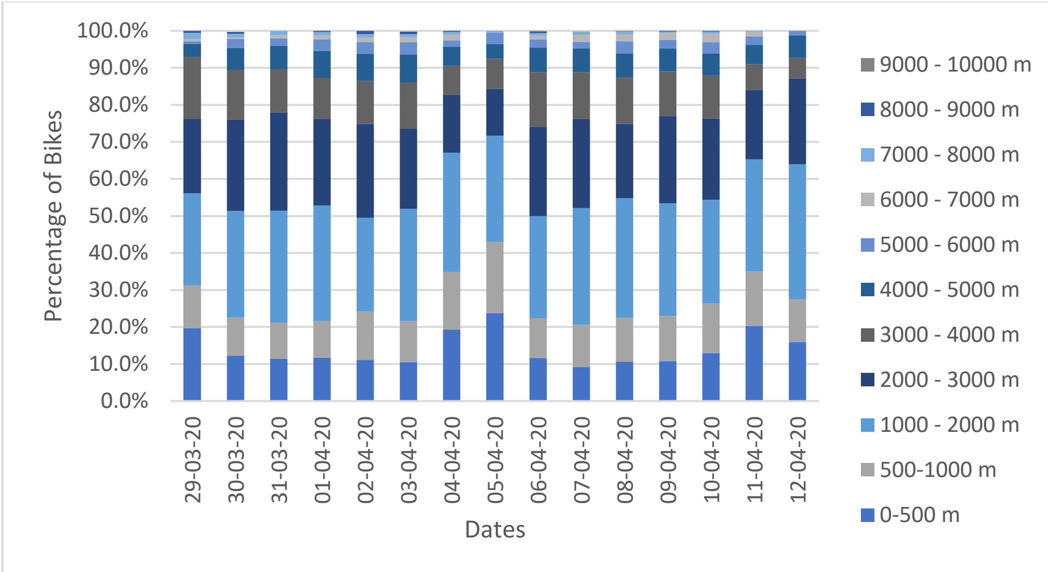

Figure C4-0-19: Travel distance for bikes in 2020

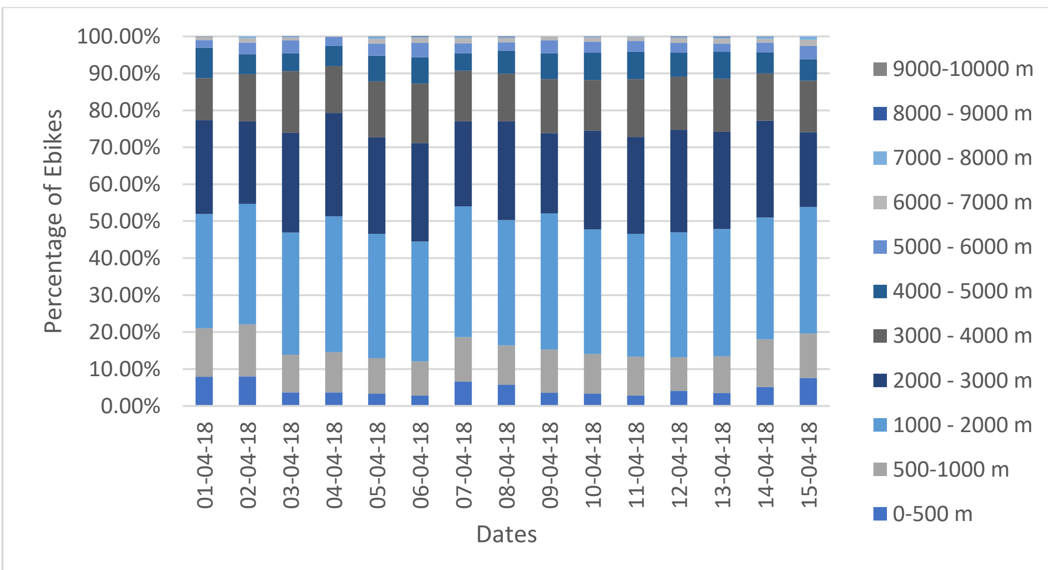

Figure C4-0-20: Travel distance for e-bikes in 2018

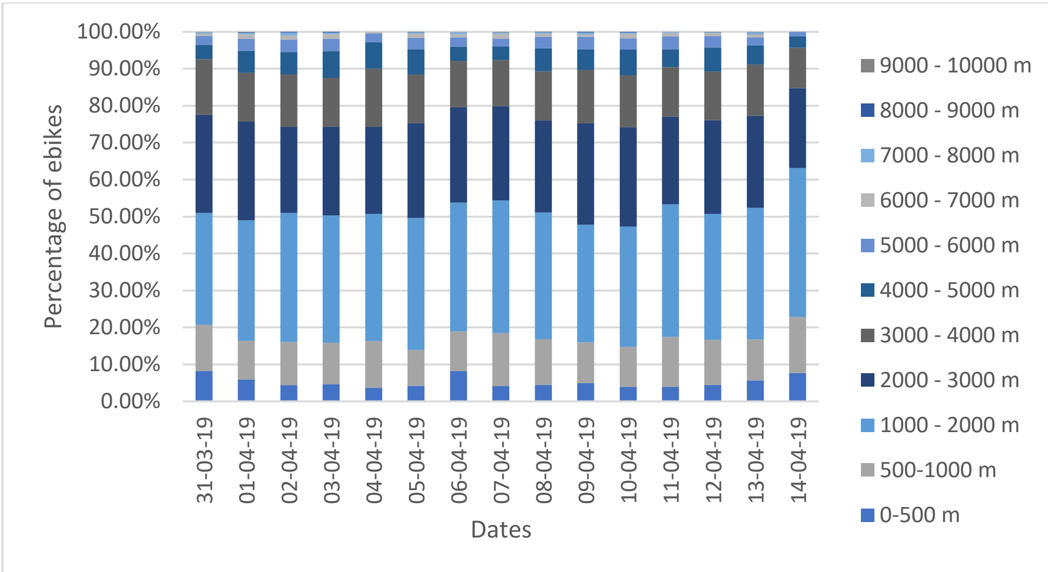

Figure C4-0-21: Travel distance for e-bikes in 2019

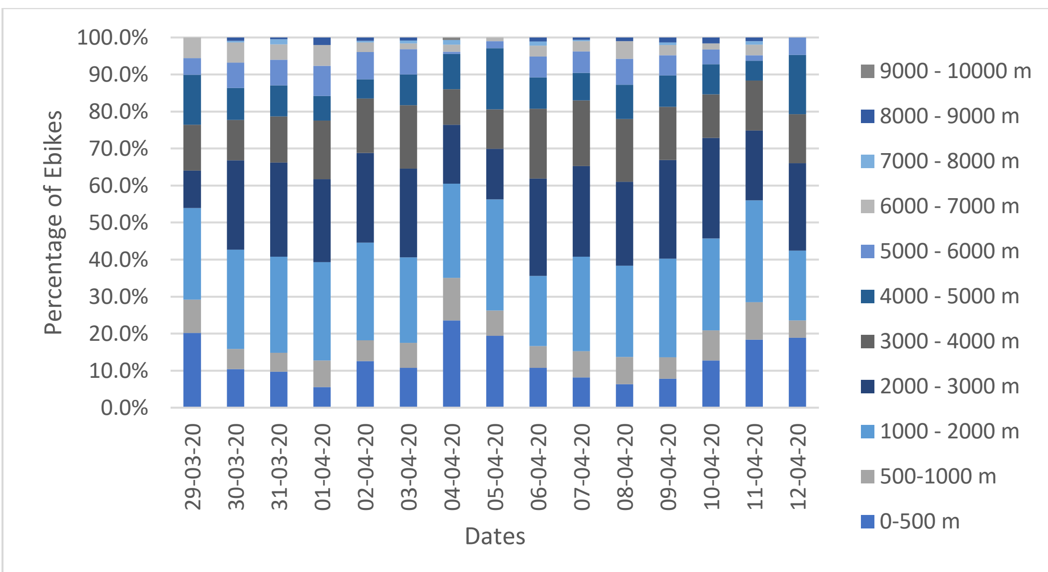

Figure C4-0-22: Travel distance for e-bikes for 2020

Table C4-0-12: Travel distance intervals and used percentage per mode (bike and e-bike)

Travel distance (m)	E-bike (%)	Bike (%)
0-500	19.08	80.92
500-1000	11.80	88.20
1000 - 2000	14.15	85.85
2000 - 3000	17.02	82.98
3000 - 4000	20.96	79.04
4000 - 5000	21.39	78.61
5000 - 6000	27.78	72.22
6000 - 7000	29.00	71.00
7000 - 8000	30.23	69.77
8000 - 9000	39.25	60.75
9000 - 10000	45.43	54.57
10000 - 11000	0.00	100.00
11000 - 12000	100.00	0.00
12000 - 13000	69.71	30.29

Appendix D: Model application and Bike sharing analysis

D1: Model results

Table D1-0-1: Inputs and results of SClow-D0 and SClockdown-D227

Inputs		
	SClow	**SClockdown**
	D0	**D227**
Number of stations	225	227
Time periods	3	
Max number of bikes	20	
Min number of docks	1	
Max number of docks	10	
Bike demand	45513	148
E-Bike demand	12880	91
Total demand	58393	239
Results		
	D0	**D227**
Number of selected stations	169	107
Number of virtual stations	225	227
Covered bike demand	2732	148
Covered e-bike demand	871	91
Covered demand	3603	239
Bike fleet	1213	137
E-bike fleet	627	402
Relocated bikes	1146	178
Relocated e-bikes	474	373

Table D1-0-2: Inputs and results of SClow-D225a, SClow-D245a, SClow-D238a, SClow-D241a, SClow-D236a and SClow-D285a

Inputs						
	SClow					
	D225a	**D245a**	**D238a**	**D241a**	**D236a**	**D285a**
Number of stations	225	245	238	241	236	285
Time periods	3					
Max number of bikes	50					
Min number of docks	10					
Max number of docks	25					
Bike demand	45513					
E-Bike demand	12880					
Total demand	58393					
Results						
	D225a	**D245a**	**D238a**	**D241a**	**D236a**	**D285a**
Number of selected stations	169	182	188	176	188	211
Number of virtual stations	225	245	238	241	236	285
Covered bike demand	5618	6095	6333	5977	5931	6599
Covered e-bike demand	1871	2019	2099	1965	1979	2160
Covered demand	7489	8114	8432	7942	7910	8759
Bike fleet	2379	2622	2748	2608	2542	3105
E-bike fleet	1192	1874	2769	2610	1927	3267
Relocated bikes	1866	2146	2287	2197	2200	2596
Relocated e-bikes	1500	1387	2257	1936	1147	2045

Table D1-0-3: Inputs and results of SClow-D225b, SClow-D245b, SClow-D238b, SClow-D241b, SClow-D236b and SClow-D285b

Inputs						
	SClow					
	D225b	**D245b**	**D238b**	**D241b**	**D236b**	**D285b**
Number of stations	225	245	238	241	236	285
Time periods	3					
Max number of bikes	80					
Min number of docks	10					
Max number of docks	40					
Bike demand	45513					
E-Bike demand	12880					
Total demand	58393					
Results						
	D225b	**D245b**	**D238b**	**D241b**	**D236b**	**D285b**
Number of selected stations	166	180	180	201	189	215
Number of virtual stations	225	245	238	241	236	285
Covered bike demand	8387	9086	9384	8787	8828	9685
Covered e-bike demand	2910	3138	3197	3027	3040	3279
Covered demand	11297	12224	12581	11814	11868	12964
Bike fleet	3568	3939	4325	3866	3786	4488
E-bike fleet	2729	2614	2382	4599	4564	4886
Relocated bikes	3024	3269	3907	3508	3264	3746
Relocated e-bikes	2142	2030	2130	4506	4438	3865

Table D1-0-4: Inputs and results of SC1-DMc and SC2-DMb

Inputs		
	SClow	**SChigh**
	D285c	**D285b**
Number of stations	285	285
Time periods	3	
Max number of bikes	unlimited	80
Min number of docks	10	10
Max number of docks	200	40
Bike demand	45513	48189
E-Bike demand	12880	13225
Total demand	58393	61414
Results		
	D285c	**D285b**
Number of selected stations	210	271
Number of virtual stations	285	285
Covered bike demand	45513	12345
Covered e-bike demand	8896	3624
Covered demand	54409	15969
Bike fleet	30959	5575
E-bike fleet	20445	5884
Relocated bikes	30329	5180
Relocated e-bikes	13019	4880

D2: Cost results

Table D2-0-5: Costs per design (a)

	SClow-D0	SClockdown-D227	SClow-D225a	SClow-D245a	SClow-D238a	SClow-D241a	SClow-D236a	SClow-D285a
Bike fleet cost	436680	49320	856440	943920	989280	938880	915120	1117800
E-bike fleet cost	454575	291450	864200	1358650	2007525	1892250	1397075	2368575
Relocated bikes cost	229.2	35.6	373.2	429.2	457.4	439.4	440	519.2
Relocated e-bikes cost	94.8	74.6	300	277.4	451.4	387.2	229.4	409

Table D2-0-6: Cost per design (b)

	SClow-D225b	SClow-D245b	SClow-D238b	SClow-D241b	SClow-D236b	SClow-D285b	SChigh-D285b	SClow-D285c
Bike fleet cost	1284480	1418040	1557000	1391760	1362960	1615680	2007000	11145240
E-bike fleet cost	1978525	1895150	1726950	3334275	3308900	3542350	4265900	14822625
Relocated bikes cost	604.8	653.8	781.4	701.6	652.8	749.2	1036	6065.8
Relocated e-bikes cost	428.4	406	426	901.2	887.6	773	976	2603.8