Deliverable 5.2

Interactive Decision Support Tool

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Summary sheet

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Abstract	The objective of this document is to describe the methodological background of the implementation of the Decision Support Toolset for planning and management emerging mobility solutions. The specific objectives of this document are; (i) Design the framework and the workflow of the proposed Decision Support Toolset, (ii) Present models and algorithms developed according to the requirements of the Decision Support Toolset, (iii) Setting the Key Performance Indicators to be included in the Decision support tool for the evaluation of the emerging mobility services, according to questions and needs of the city partners proposed in the deliverable D2.2., (iv) Integrate the new modelling approach designed to combine agent-based principles within the strategic four-step approach in the Decision

	Support Toolset, as it was presented in Deliverable 4.1 “Transport Modelling Approaches for Emerging Mobility Solutions: Supply and Demand Models”
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Project partners

Organisation	Country	Abbreviation
EMPRESA MUNICIPAL DE TRANSPORTE DE MADRID SA	Spain	EMT
NOMMON SOLUTIONS AND TECHNOLOGIES SL	Spain	NOMMON
DIMOS THESSALONIKIS	Greece	THESS
ETHNIKO KENTRO EREVNAS KAI TECHNOLOGIKIS ANAPTYXIS	Greece	CERTH
STAD LEUVEN	Belgium	LEUVEN
TRANSPORT & MOBILITY LEUVEN NV	Belgium	TML
STADT REGENSBURG	Germany	REGENSBURG
TECHNISCHE UNIVERSITAET MUENCHEN	Germany	TUM
AIMSUN SL	Spain	AIMSUN SL
POLIS – PROMOTION OF OPERATIONAL LINKS WITH INTEGRATED SERVICES, ASOCIATION INTERNATIONALE	Belgium	POLIS
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Document history

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Issue 1 Draft 1	12/07/2021	CERTH	Initial version	
Issue 1 Draft 2	25/07/2021	CERTH	Comments from reviewers	
Issue 1 Draft 3	29/07/2021	CERTH		

List of acronyms

AI	Artificial Intelligence
BS	Bike sharing
CS	Car-Sharing
CSV	Comma-separated values
DRT	Demand Responsive Transport
DST	Decision Support Toolset
DSS	Decision Support Systems
DARPTW	Dial-a-Ride Problem with Time Windows
EV	Electric Vehicle
FCD	Floating Car Data
JSON	JavaScript Object Notation
KPI	Key Performance Indicator
KM	Kilometre
MAE	Mean Absolute Error
OD	Origin-Destination
OR	Operational Research
PT	Public Transport
RS	Ride Sharing
RMSE	Root Mean Square Error
SS	Scooter Sharing
WP	Work Package

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Executive Summary

The overall goal of the MOMENTUM project is to develop a set of mobility data analysis and exploitation methods, transport models and planning and decision support tools, able to capture the impact of new transport options and ICT-driven behavioural changes on urban mobility. MOMENTUM's aim is to support local authorities in the task of designing the right policy mix to exploit the full potential of emerging mobility solutions.

The objective of this document is to describe the methodological background of the implementation of the Decision Support Toolset for planning and management emerging mobility solutions. The specific objectives of this document are:

- Design the framework and the workflow of the proposed Decision Support Toolset
- Present models and algorithms developed according to the requirements of the Decision Support Toolset
- Setting the Key Pperformance Indicators to be included in the Decision support tool for the evaluation of the emerging mobility services, according to questions and needs of the city partners proposed in the deliverable D2.2.
- Integrate the new modelling approach designed to combine agent-based principles within the strategic four-step approach in the Decision Support Toolset, as it was presented in Deliverable 4.1 "Transport Modelling Approaches for Emerging Mobility Solutions: Supply and Demand Models"

The main outcomes of this document are the following:

- A comprehensive Decision Support Toolset which encompasses various developments with a user friendly environment to test and assess mobility services, with data visualization dashboards, providing an interactive validation of results of testing different mobility services.
- The Decision Support Toolset developed will combine principles of agent-based modelling approach presented in D4.1 "Transport Modelling Approaches for Emerging Mobility Solutions: Supply and Demand Models" alongside with an enhanced transport simulation model developed, as described in Deliverable 5.1. "Enhancement of Transport Simulation Frameworks with Models of Emerging Mobility Solutions"
- Summarize the capabilities of the integrated Decision Support Toolset for cities participating in MOMENTUM project as partners, external cities and mobility stakeholders.

1 Introduction

1.1 Scope and objectives

Decisions on transport policy measures have long-term and important impacts on economy, environment and society. Transport policy measures can lock up capital for decades and cause manifold external effects. In order to allow European policy-makers to evaluate transport polices, the MOMENTUM consortium envisaged a decision support tool that facilitates the evaluation of the economic, environmental and social impacts of the implementation of transport policies.

The objective of the Decision Support Toolset presented in this document is to support the transportation planning and design practices based on an integrated transportation analysis of the examined area, to decide the most applicable combination of mobility services.

This document provides a comprehensive description of the MOMENTUM interactive Decision Support Tool implemented to help cities and decision makers to design their strategy to shape the urban mobility of the future. Questions and needs derived from D2.1 “New Mobility Options and Urban Mobility: Challenges and Opportunities for Transport Planning and Modelling” and D2.2 “Specification of MOMENTUM Test Cases” will be used as a guide to outline the relevant KPIs to each city. The MOMENTUM dashboard is designed to support the formulation, assessment and comparison of different policy alternatives by facilitating the interpretation, analysis and communication of the simulation results.

1.2 Structure of the document

The remainder of this document is divided into the following sections.

- All technical characteristics of Decision Support Toolsets are described in section 2 “Decision tool characteristics”
- In section 3 “Integration of the MOMENTUM Decision Support Tool”, levels developed in the Decision Support Toolset are introduced, along with the performance indicators assigned to each one. These KPIs are based on the research questions outlined for each city in WP2. These sections include for each level, four major parts of testing the tool: (i) input data needed, (ii) theoretical approach developed based on the input data (iii) estimated KPIs (iv) calculated solutions and outcomes
- KPIs based on the questions form city partners are included in the section 4 “Decision criteria”
- In section 5 Connection of the DST with MOMENTUM’s Repository all technical requirements of linking MOMENTUM’s repository to the DST are described
- Added value produced from the implementation of the Decision Support Toolset is described in section 6 “Added value from the Decision Support Toolset”
- Section 7 “Conclusion” summarises the main conclusions along with the key functionalities and lessons learnt from the tool
- In section 8 “References” include all the references used from the literature review
- The last section 9 is the Annex of the document

1.3 Applicable documents

[I] Grant Agreement No 815069 MOMENTUM – Annex 1 Description of the Action.
[II] MOMENTUM Consortium Agreement, Issue 1, April 2019.
[III] MOMENTUM D1.1 Project Plan, June 2019
[IV] MOMENTUM D1.2 Data Management Plan and Open Data Policy, November 2019
[V] MOMENTUM D2.1 "New Mobility Options and Urban Mobility: Challenges and Opportunities for Transport Planning and Modelling
[VI] MOMENTUM D2.2 Specification of MOMENTUM Test Cases, February 2020
[VII] MOMENTUM D3.1 Data Inventory and Quality Assessment, March 2020
[VIII] MOMENTUM D3.2 MOMENTUM Data Repository, June 2020
[IX] MOMENTUM D3.3 Methodologies and Algorithms for Mobility Data Analysis, December 2020
[X] MOMENTUM D4.1 Transport Modelling Approaches for Emerging Mobility Solutions, May 2021
[XI] MOMENTUM D4.2 Open Repository of Demand and Supply Models and Algorithms for Emerging Mobility Solutions
[XII] MOMENTUM D5.1 Enhancement of Transport Simulation Frameworks with Models of Emerging Mobility Solutions

2 Decision tool characteristics

Decisions on transport policy measures have long-term impacts on society. Transport policy measures can lock up capital for decades and cause manifold external effects. In order to allow

Due to the growth in urban population, there has been an increase in demand for mobility and, consequently, an increase in the number of vehicles on the roads. The increased levels of traffic congestion indicate a strong and imminent need for cities to foster sustainable and eco-friendly solutions of urban mobility. Furthermore, the limitation of public budget resources demands an efficient distribution on government's projects. In order to allow

European policy-makers to evaluate transport polices, a decision support tool is required to evaluate economic, environmental and social impacts of the implementation of transport policies. The terms Decision Support Tools or Decision Support Systems (DSS) refer to a wide range of computer-based tools (simulation models, estimation techniques and similar methods) developed to support transport planners in their decisions and participatory processes.

2.1 Objectives of a decision support tool

A decision support system is defined by its ability to accommodate:

- Less well-structured problems that upper-level management faces
- Combination of a variety of techniques and models
- Easy to use and interactive environment for non-proficient users

2.2 Flexible and adaptable structure

In the context of transport planning and management, the aim of a decision support system is to provide decision makers with indicators and predictions to help in the evaluation of mobility interventions with quantitative and qualitative characteristics. Thus, the main goals of the decision support tool are:

- Improving safety of transport means, while increasing the reliability of the transport system.
- Increasing the resilience of the transport network to cope with incidents including collisions, breakdowns, maintenance, and extreme weather events.
- Minimizing the environmental footprint and gas emissions in urban environments.
- Facilitate future economic growth by supporting the goals identified in the Local SUMPS, including the reduction of congestion and related delay

2.3 Scope of a Decision Support Toolset

The scope of the Decision support systems has been changing through the years. Today, with the rampant advancements in information technologies, DSSs are used in a variety of applications across many domains. The ultimate goal of state of art decision support systems is to utilize the available data and implement the necessary models to help users in their decision-making, both at strategic and operational level.

In general, a decision support tool or system consists of the following main components, described in the picture below:

- A **Database Management System (DBMS):** this component holds the available data the DSS acts upon. Nowadays, the large amount of data collected and processed allows us to talk about Big Data.
- **Models**: includes the techniques, algorithms and processes as well as the type of support provided and area of application. The current trend includes techniques derived from the popular Artificial intelligence techniques and algorithms
- **User's interface**: guides and helps the users through the decision-making process by providing a friendly, flexible, simple and interactive interface.

Secondary components include the users themselves and visualization techniques and tools (e.g. Geographic Information Systems (GIS). The user's component includes the individuals or group of people that will use the DST will, such as stakeholders, service providers etc. The visualization component is very important for the user's experience while using the DST. Displaying the information in a compact and interesting way (e.g. through a map) can be beneficial for the overall success of the DST.

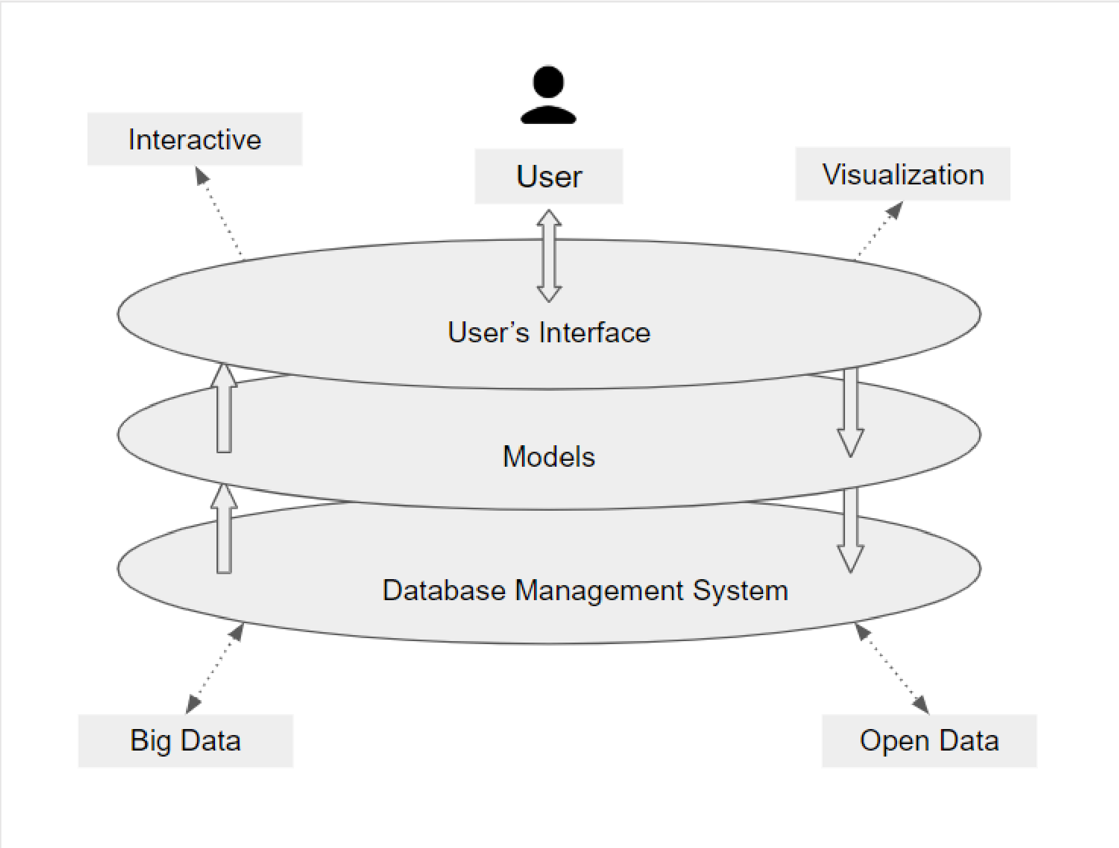

Figure 1: Components of a decision support tool

Based on the main components described above and the descriptions of the previous chapters a high-level architecture diagram can be constructed.

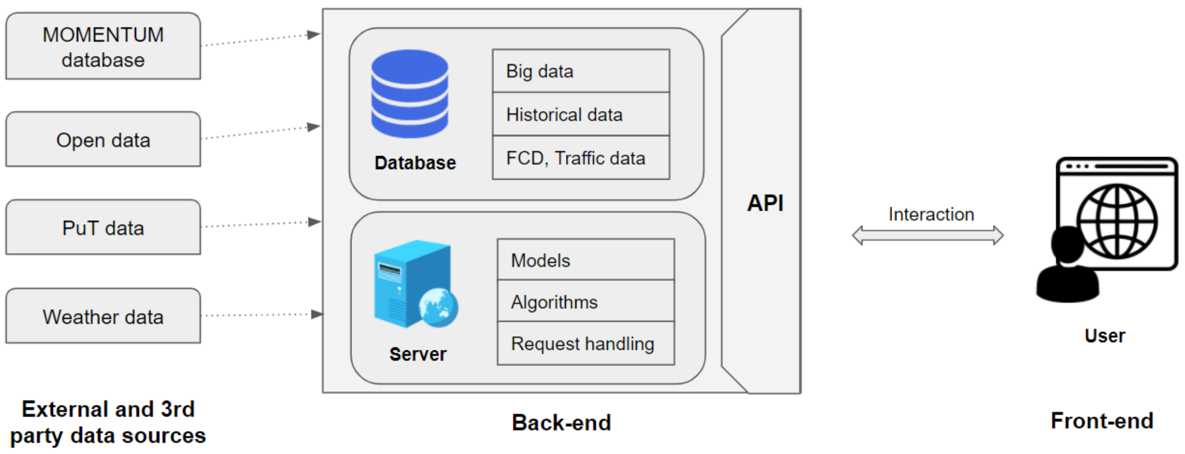

Figure 2: Architecture Diagram of a DST

As can be seen in Figure 2the components of the decision support tool include the following:

- **Front-end**: this component refers to the user's side of the system and includes the web platform, the interface the user interacts with as well as minimal computations on the data retrieved from the server.
- **Back-end**: this component provides the processing power of the decision support tool and includes the API used for the data exchange, the server used for the algorithms' execution and the database used for the storage of the data.
- **External data sources**: this component feeds the back-end with the necessary data for the execution of the algorithms and are provided from external sources such as weather data.

2.4 Categories of Decision Support Toolsets

There are five different types of decision support systems described in literature (Power, 2002 & 2004). The deviation among them is based on the way data have been received. The description of the different DST types can be found below:

1. **Communication-driven decision support systems**: the target group of these decision support systems is the internal teams, which include partners of an organization willing to establish an efficient collaboration, e.g. a successful meeting. A web or client server is the most common technology used to deploy these decision support systems.
2. **Data-driven decision support systems:** these systems are useful for querying a database or data warehouse to seek specific answers for specific purposes. They can be deployed using a mainframe system, client/server link, or via the web.
3. **Document-driven decision support systems:** these systems are used to search web pages and find documents on a specific set of keywords or search terms. They can be implemented via the web or a client/server system.
4. **Knowledge-driven decision support systems:** these cover a broad range of paradigms in artificial intelligence to assist decision makers from different domains. Various data mining techniques, which include neural networks, fuzzy logic, evolutionary algorithm or case-based reasoning. Such techniques can be utilized for developing these systems to provide specialized expertise and information for specific

decision-making problems. They can be deployed using client/server systems, the web, or software running on standalone computers.

5. **Model-driven decision support systems:** these are complex systems developed based on some model (e.g. mathematical and analytical models) to help analyze decisions or choose between different alternatives. They can be deployed via software/hardware in standalone computers, client/server systems, or the web.

2.5 Principal Methods

In this section, the most popular methodologies in the literature are described. These methodologies are integrated in the model base of the systems and are utilized in the transport-oriented decision support tools with the ultimate purpose of solving or aiding in the problems described in the sections above. It is important to mention that a decision support system can utilize a combination of the following methodologies to produce the optimal solution for the corresponding transport problem:

- **Approximate computational procedures –** heuristics and metaheuristics are used more and more frequently due to the complexity of the transport problems, although only near-optimal solutions are assured. Many of the transportation scenarios require real-time solutions which mark the near optimal solutions as acceptable. In this scope, **specialized heuristics** prove to be efficient algorithms but can be deployed for specific decision problems only due to their highly customizable nature. In contrast, **metaheuristics** (Local Search, Tabu Search, Simulating Annealing and Genetic Algorithms) can be constructed as abstract computational models that can be customized to different problems transportation problems or a combination of them such as: vehicle routing and scheduling problem, crew scheduling problem, fleet composition problem, fleet replacement problem, fleet maintenance scheduling problem, etc. To this category belong the **hybrid metaheuristic algorithms: This** are more and more popular and are comprised of a combination of usually two metaheuristic algorithms.
- **Multiple Criteria Decision Making / Aiding (MCDM/A)** addresses the complexity and multidimensionality of the decision problems in transportation. It considers several aspects (economic, social, market orientation, technical, environmental etc.) while being able to cater to the majority of the stakeholders/actors (e.g. service providers, customers) that may have different interests. These features place MCDM/A into one of the preferred methodologies for aiding in decision-making processes in a transport context.
- **Geographic Information Systems (GIS)** provide an ergonomically constructed user interface that facilitates the operation of the decision support tool. For that reason, GIS capabilities are increasingly adopted to provide visualization of the solutions produced by the decision support tools.
- **Online communication / real-time** provides a way of performing real time data analysis for short-term and quick prediction of future and unforeseen events (e.g. traffic jams), aiding in the decision-making processes. The above is made possible with the advancements on Telecommunications that facilitate quick and reliable wireless internet access through the 3G/4G networks with the 5G on the horizon.
- **Web-based Decision Support Systems** are becoming the norm with the rise of the Web 2.0 services. In conjunction with the aforementioned online communication and the standardization of the data exchange (e.g. XML, EDIFACT).
- **Artificial Intelligence tools** usage in decision support systems created the well-known Intelligent Decision Support Systems (IDSS). Taking advantage of the 'self-education' capabilities of the artificial

intelligence methods, IDSS-s can process complex and unknown problems making them one of the most popular solutions. Furthermore, they can be combined with Expert Systems to produce more accurate and rational solutions. The most common AI techniques used in transport-oriented decision support systems are: Artificial Neural Networks (ANN), Fuzzy Logic, Data Mining, Agent-based Systems and others.

- **Interactive character** is one of the most important features of a decision support system. It enabled the end user to iterate through the alternative solutions, to analyze them and in the end to choose the optimal option.
- **Mixed methodologies** are the optimal solution for complex systems and are equipped with a variety of algorithms, methods and models.

2.5.1 Data requirements

Availability of transportation data is a key parameter to a successful decision support tool. They are important, in order to understand all the aspects of the existing transportation systems, propose new ones and validate the produced results. The generic data categories of a decision support systems (DSS) for traffic management are the following:

1. **Historical data:** System inputs consisting of past real-time data stored for specific situations or recurring traffic patterns. System inputs typically consist of data from different types of detectors located in the network (detecting density, capacity, speed), as well as information relative to the day of the week, meteorological conditions, incidents, special events, road works and refurbishment on the road network.
2. **Predictive System:** The system has a module for predicting the state of the road network based on historical data. Predicting the state of the network provides, depending on the methodology used, a complete or partial view of the future status of various variables related to the network.
3. **Strategy analysis:** The system can determine the set of strategies to evaluate the mitigation and anticipation of congestion, using network monitoring of the current state as well as the future state. As a result, a set of indicators is developed for each strategy so that the operator can determine which strategy is best to implement on the streets.

2.5.2 Performance indicators

The performance of urban mobility services in a city is a key parameter towards mobility challenges to a successful system. Policymakers and urban transport professionals depend on the evaluation of a system to have a clear understanding of their operational performance. Thus, it is important to identify key performance indicators (KPIs) that can be used to measure the performance of urban transport mobility systems and the policies applied to them.

Every city is unique and the conditions in every case study differ; from environmental conditions to cities' topography, weather conditions or transportation habits. Nevertheless, there are strategic categories of indicators that provide the guidance to decision makers, in order to understand the level of importance for urban mobility interventions in every city.

1. **Environmental**: includes all the measurement indicators that assess the environmental impact of the systems and the lifecycle carbon footprint of the examined services
2. **Connectivity**: the level of connectivity achieved in the urban environment. for instance, the number of stations to cover existing and forecasting demand

3. **Demand:** includes the alteration of users to services examined – the new mode choice transport model of the travelers who alter their travel habits
4. **Network's performance**: includes all the transportation measures that indicate the performance of a network. For example, travel times, delays, passengers' waiting time
5. **Costs**: the economic cost of implementing and operating the urban mobility service

2.6 Decision Support tools in Transportation

Transport-oriented decision support tools or systems are becoming increasingly popular and new ones are developed every day as the industry becomes bigger. Nowadays, many innovative computer-based decision support tools utilize state of the art techniques and methodology in order to provide updated, safer and more reliable transport services, increase customer satisfaction, reduce costs, maximize profits, improve infrastructure and better match supply and demand.

Similarly, like the majority of the decision support tools, transport-oriented decision support tools are composed of the three main components: database management system, models and user's interface. The tools used today tend to be equipped with a wide range of efficient techniques and methods from different scientific fields: operations research, decision science, decision aiding and artificial intelligence. The selection of the methods and techniques used in the model base design of decision support tool, highly depends on the transportation problem that the solution or decision-making is intended for. Examples of where decision support tools in transport are commonly used for include: fleet assignment, vehicle routing and scheduling, fleet composition, crew assignment and scheduling, fleet replacement, fleet maintenance, service portfolio optimization, infrastructure maintenance and renovation, transportation projects evaluation and others.

2.6.1 Classification of Transport-oriented Decision Support Tools

In the literature, different classification criteria for decision support tools have been proposed. Zak et al. 2010 summarizes the main classification characteristics in his work by applying the rules of generic decision support system's classes in the transport context:

- First, transport-oriented decision support tools can be classified, based on their **modal focus** into airborne, waterborne, road, rail and multimodal transportation decision support systems, as well as the specific category of public transportation.
- Another measure of classification is **the size and the scope** of the decision support tool. This refers to the end user of the product and can be distinguished into: single user (residing in normal personal computers), small network or group (team effort) and centralized or enterprise that are used by multiple organizational units in an organization's hierarchy.
- **Conceptual focus** is an alternative characteristic that stems from the general classification of decision support systems
- An important metric for differentiation of the decision support tools is their **problem-solving approach.** Based on this, the systems are divided into two categories: passive systems that only provide one solution to the user with no capability of calibration and active that allow the user to modify and adjust the solution's metric and parameters in order to generate the most suitable answers.
- **Organizational level** refers to the time frame of the decision-making process. Based on this, the decision support tools are classified as: strategic for long-term objectives, tactical for mid-term planning and control and operational for short-term managerial activities.

- As mentioned, the transport sector requires solutions to a plethora of distinct problems. In that regard, the decision support systems are classified based on the **subject scope and focus**. This category includes, among others, fleet management and replacement systems, vehicle monitoring systems, vehicle routing and scheduling systems, supply chain management systems, freight forwarding systems, fleet accidents management systems, transportation personnel management systems, crew recruiting systems.
- Another characteristic is the **underlying decision-making methodology** used in the decision support system and distinguishes: optimization-based (emphasize on the models and algorithms used to achieve optimal solutions for planning and/or scheduling), simulation-based (the real system of interest is modelled and implemented in simulation software), game theory-based (the outcome depends on the decisions of two or more autonomous players) , data mining -based (analyzing big data and extracting patterns or predicting future behaviors) or hybrid methodologies (the combination of some of the aforementioned categories).
- One of the main components of a decision support system is the data used. In that manner, the **character of the data** is another characteristic and a system can be defined as deterministic (precisely defined parameters) and non-deterministic (stochastic and fuzzy based systems). Furthermore**, time variability of the data** can be used as measure for classification. Data can either be dynamic (time-dependent) and static. Dynamic data are the most popular solution used for the decision-making processes since they are collected in real-time.
- Based on the **internet utilization**, a decision support system can be either online or offline.
- Lastly, the **way of communication with the user** distinguishes the decision support systems into: passive/ single phase (the solution is presented to the user after the data processing) and interactive (the user can modify and reevaluate the solutions).

2.6.2 Problems solved by transport-oriented Decision Support Tools

The transport sector faces various problems that need to be addressed with the utilization of the technological advancements. The proposed decision support systems for transport can either focus on a specific problem or can be more complex and sophisticated, tackling a spectrum of issues. As mentioned before, the overall goal of a decision support system is to help the decision maker in their quest of a short-term or long-term solution of a problem.

Zak in his survey on transport-oriented decision-making system in 2004, constructed the following list of the most common and important problems:

- Forecasting transportation market situation
- Labor force sizing
- Design/ construction of the most desirable portfolio of transportation services
- Managing transportation order fulfillment
- Assignment of vehicles to transportation jobs / routes
- Fleet composition in a transportation company / system
- Vehicle routing and scheduling
- Fleet replacement and maintenance

Other problems found in literature include the following:

- Analysis and evaluation of different transport policies

- Strategic transportation planning
- Sustainable urban land use planning

3 Integration of the MOMENTUM Decision Support Tool

3.1 Introduction

The application of decision support tools in the area of process of urban transport mobility is growing fast. However, the use of DST in transportation has not been well established. There is not yet a widely used framework that is able to set the guidelines.

Nowadays, although data is easily accessible by many sources the problem is rooted in the complex nature of the implementation. The first approach is an oversimplification of the problems. This task is carried out by limiting the number of required input data and using simplified models. However, the results are not usually accurate and reliable enough for industrial decision-making. On the contrary, there are software packages in which transport modellers and planners, can assess and forecast potential investments. This approach itself may lead to several disadvantages such as extensive requirement of input data, lack of user-friendliness or unreasonable analysis time. The use of such software also requires a deep knowledge and expertise in the field.

3.2 Structure of MOMENTUM's Decision Support Toolset

The MOMENTUM DST will follow a multilevel approach. In concrete, a three level system is proposed where each level entails a different degree of complexity, both in the input and in the output data. The proposed three level DST is a scientific and technical procedure aiming to explore the available urban mobility solutions for each examined area, depending on the characteristics (socioeconomic, spatial, existing infrastructure etc.) of each case study. Thus, policy makers, using the outcomes of the multilevel decision tool, can assess each scenario, in order to enhance environmental sustainability and social responsibility. In each stage of the decision support tool, different level of detail is followed depending on the availability of input data. In the first level, low granularity of input data is needed thus the results deriving have a certain level of uncertainty. The input data for the second level of the DST include data driven information from the examined area providing detailed information for the scenarios tested. The last step of the investigation of the DST includes the modelling of the transport scheme of the selected area. The DST is schematised on Figure 3

"Granularity" level	Input Data	Level of Analysis
Level 1 **Preliminary transportation design**	Low	Analytical
Level 2 **Data driven decision system**	Medium	Extensive
Level 3 **Comprehensive Transport planning**	High	Comprehensive

Figure 3: Graphical analysis of different levels of the DST

Based on the information described before, the goal of the DST is to be an accessible and user-friendly tool, for decision makers. On the DST, a user can find a user-friendly environment with explanatory information about the values needed for every step of each level and a manual document describing with examples how an investigation can be done. The available services to be studied in the DST include: bike sharing, ridesharing / taxi sharing, DRT and scooters services in the cities. Furthermore, in order to make the procedure more efficient, the information included in MOMENTUM's data repository (See D3.2 MOMENTUM Data Repository for detail) is automatically used to fill the input forms of the tool. Indicative values are by default filled in value boxes, in order to outline the range of values needed in each case, based on values produced for Thessaloniki.

The structure of the decision support tool, is described in the Figure 4 below.

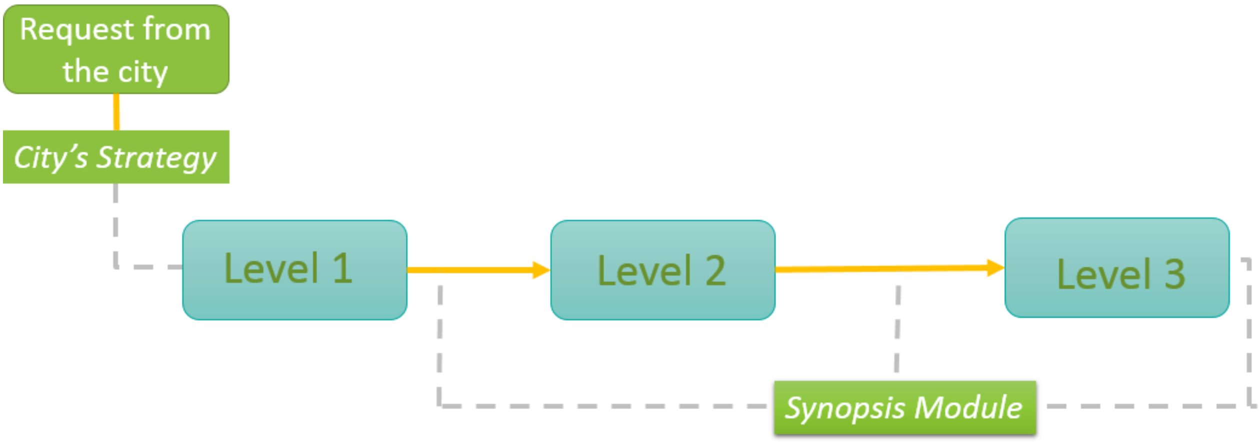

Figure 4: Decision support tool framework

The DST was developed as an online application and is available in the following website (https://momentum.imet.gr/index.html). The interface of the DST is depicted in the Figure 5. More information about the description for the users, presenting snapshots with the steps needed to be followed and associated information, can be found in the user manual available in every level of the DST on the online version.

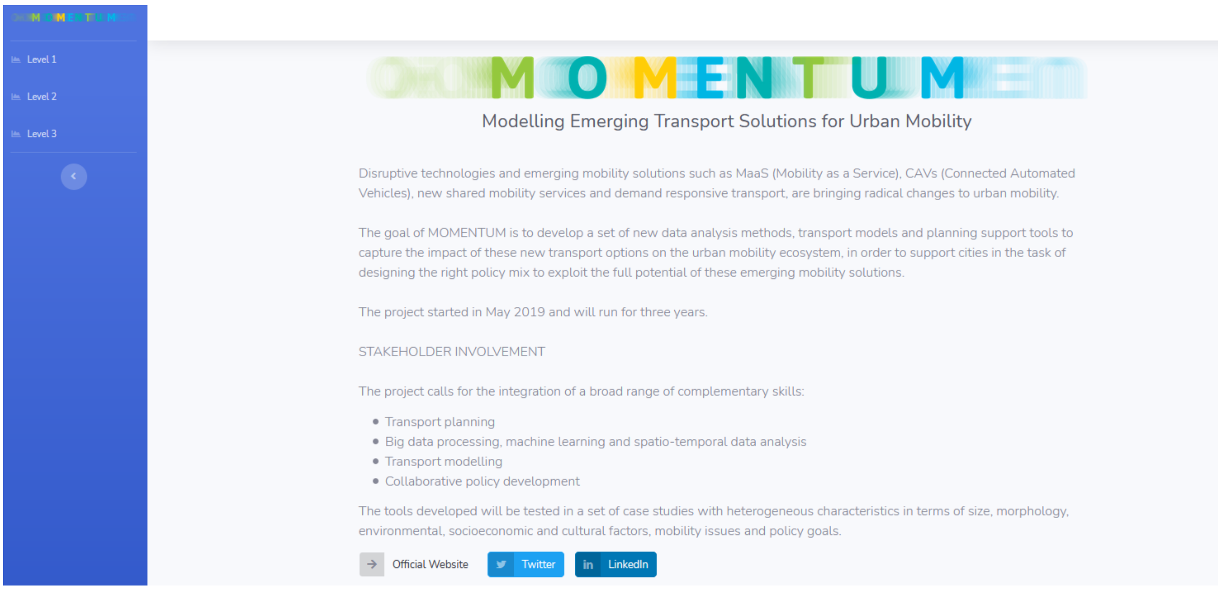

Figure 5: MOMENTUM website interface

3.3 Level 1 - Preliminary transportation design

3.3.1 Introduction

In the first level of the decision tool, an initial investigation of the urban mobility landscape of the city is examined. The preliminary analysis of this step requires a small amount of data such as geospatial socio-economic data about the population of the studied area and the available operating fleets of mobility services. Depending on the applicable urban mobility scheme, the appropriate analytical approach will be implemented. Due to the low granularity of input data, assumptions will be made so that decision makers can receive an initial step of potential urban mobility plans at a very low cost in terms of data.

The main objective of the preliminary analysis is to identify the outlines of potential interventions in the urban mobility characteristics of a city. Key elements of this step are to define city's needs, perform economic and technical analysis for emerging urban mobility in the city. This step demand low granularity of transportation data.

The online version of Level 1 is composed of two different sections. The first section contains general information regarding the examined area, while on the second section specific mobility inputs are needed as input data. Mobility services included in the Level 1 are divided in two major categories based on the methodological analysis followed; Vehicle Sharing and On-demand. Different factors in the methodological function alter the service examined. Thus, the methodological analysis in this deliverable for every service, is divided in the two major categories described before, as input data will have minor differences. All services to be included in Level 1 are:

- Vehicle sharing – bike station
- Vehicle sharing – scooter/floating
- On-demand – taxi or ride sharing
- On-demand – Demand Responsive Transport

First section

In the first part of the Level 1, information about the city or the examined area need to be filled in the tool. If the area of study is not in the default options of the drop-down list (default cities and their values are associated to the cities which participated in the MOMENTUM project), then the users have to manually select the area to investigate and insert its population manually.

Second section

Once the information is filled in, the user needs to select the service to be investigated. The available services include all those which were examined as test beds under European project MOMENTUM, including Vehicle sharing (station-based and floating systems) and On-demand services (ride sharing and DRT).

3.3.2 Vehicle sharing system

For the implementation of the bike sharing, the system assumes that the mobility services will be provided to a certain number of passengers within a geographic region. The examined region is considered as a district within the boundaries of a city.

3.3.2.1 *Input data requirements for Vehicle sharing system*

3.3.2.1.1 Service management modelling of Bike sharing

Operator cost (per km): This parameter is associated with the operational cost of a bicycle per km. This is a value including operational cost of the bicycles (vehicle), such as the repairing cost and depreciation cost per distance travelled.

Operator cost per hour (per dock): Operator cost per hour for every bicycle dock.

Operator cost per hour (per station): Operator cost per hour for each station.

Operator cost per hour (per bicycle): this parameter is associated with the operational cost of a bicycle per km including repairing cost, depreciation per hour usage etc.

Socio-economic and functional variables

Value of time of users: Monetary value of time. It is the amount of money a user would be willing to pay in order to save travel time.

Walking speed: Walking speed of the users.

Bicycles travel speed: Speed of each bicycle.

Mean demand of the area: Number of requested trips per units of time.

Standard deviation of demand of the area: Estimation of the demand of bicycle trips per hour, in the examined area.

Constraints

Maximum waiting time: Maximum waiting time users are willing to spend for a bicycle to become available.

Maximum walking time: Maximum time users are willing to spend walking to reach a bike station.

Decision variables

Number of stations: Minimum and maximum number of stations to be examined.

Number of docks: Minimum and maximum number of docks (per station) to be examined [System has been designed with a fix ratio between bikes and slots equal to 0.5 in order to perform optimally based on literature review]

3.3.2.1.2 Service management modelling of E-scooters

Operator cost (per km): This parameter is associated with the operational cost of a bicycle per km. This is a value including operational cost of the bicycles (vehicle), such as the repairing cost and depreciation cost per distance travelled.

Operator cost per hour (per scooter): This parameter is associated with the operational cost per hour for each mode operating. In this cost, repairing cost, depreciation cost per distance travelled are included

Socio-economic and functional variables

Value of time of users: Monetary value of time. It is the amount of money a user would be willing to pay in order to save travel time.

Users walking speed: Average walking speed of users.

E-scooter travel speed: Average speed of e-scooters

Mean demand of the area: Total number of trips in the area per time interval.

Constraints

Maximum walking time: Maximum time users are willing to walk in order to reach an e-scooter.

Decision variables

Number of e-scooters: Is the size of the fleet of scooters to be deployed.

3.3.2.2 Insights derived from Vehicle sharing system

At this section of the results, the optimal values and KPIs are produced. Based on the values user provided to the tool, the optimal solutions are calculated.

Optimal Cost (BS & E-scooters) = the optimal cost refers to the total cost of the service. It includes the operational and user cost for the service.

Optimal number of Escooters (E-scooters) = Optimal number of the scooters needed for the system, based on the values included in the previous steps.

Total number of Bikes (BS) = Total number of the bicycles needed for the system, based on the values included in the previous steps.

Optimal number of stations (BS) = the optimal number of the stations needed for the system, based on the values included in the previous steps.

Optimal number of docks per station (BS) = the optimal number of the docks needed for the system, based on the values included in the previous steps.

Waiting time (BS) = Waiting time users need to spend to reach a bike of the BSS.

Total Walking time (BS & E-scooters) = Walking time users need to spend to reach a bike of the BSS.

Users walking distance (E-scooters): Distance users of the scooter service will have to walk to reach a unit.

Emissions (E-scooter): Calculated amount of emissions produced by the service, by using the optimal values calculated from the tool

3.3.2.2.1 Visual presentation of the insights derived from Level 1 – Vehicle sharing system

In the last section of the results, charts of the results are presented. The aim of the charts included in the chapter of the results, is for users of the DST to have an overview of the service they want to investigate. In every chart, the optimal solution calculated is provided along with the range of the results of the solutions proposed. Thus, users of the DST are able to easily understand the impact of a different option (than the optimum) or how the cost is split into costs for the user and for the operator side, allocating their actions appropriate.

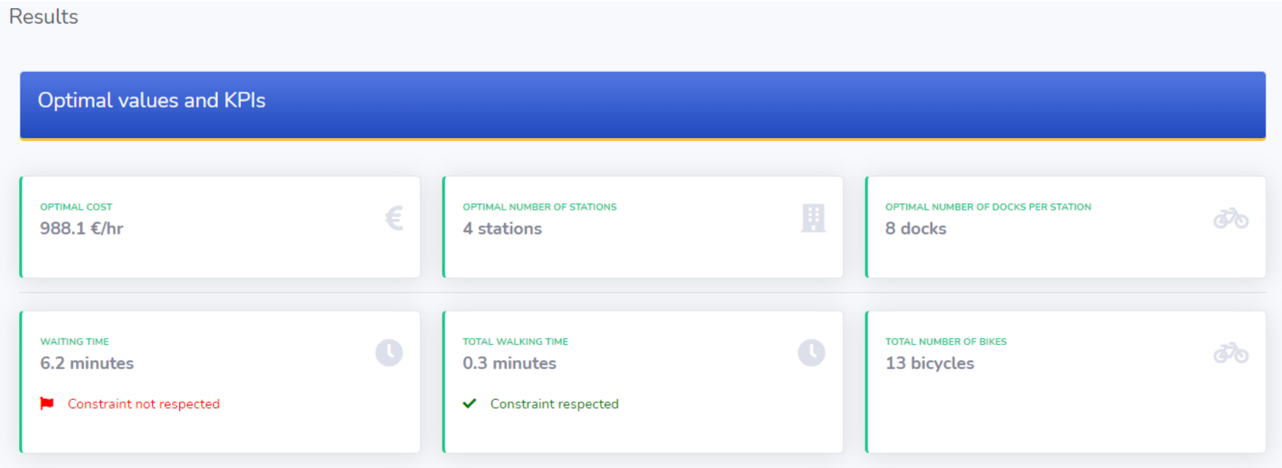

Figure 6:Vehicle sharing (bike sharing) values produced

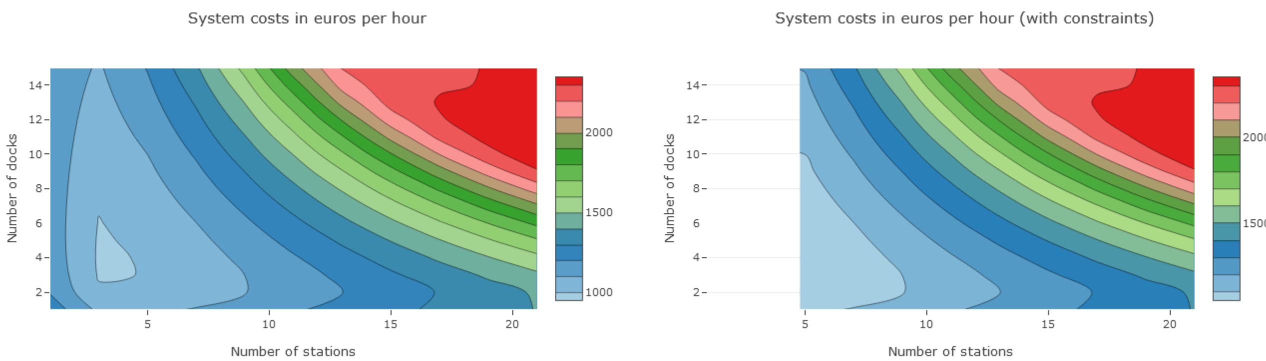

Figure 7: Vehicle sharing (bike sharing) charts produced for system cost with and without constrains

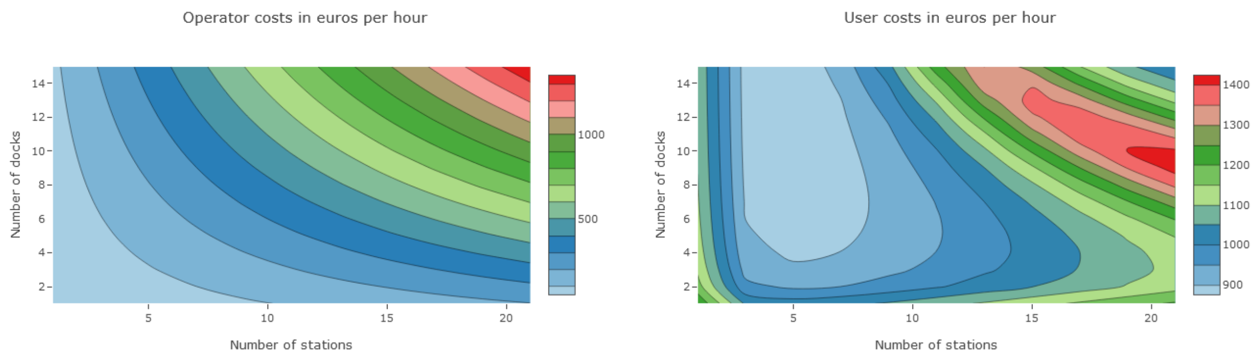

Figure 8: Vehicle sharing (bike sharing) charts produced for operator cost with and without constrains

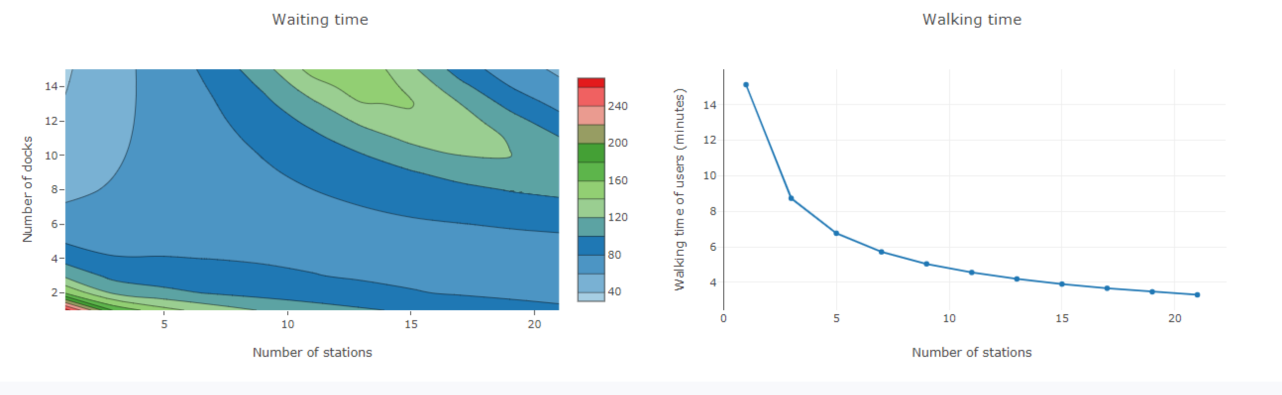

Figure 9: Vehicle sharing (bike sharing) charts produced for waiting and walking time

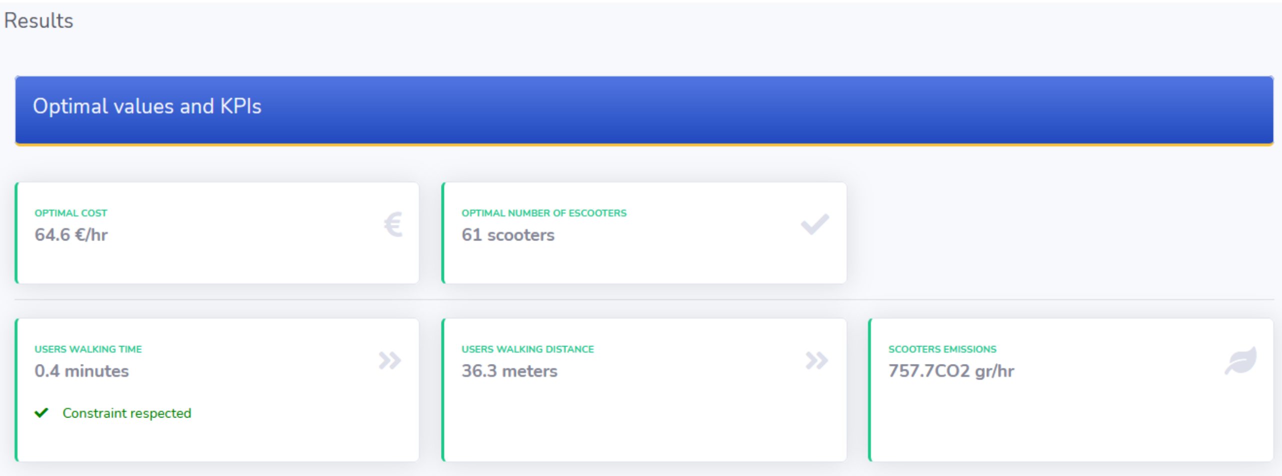

Figure 10: Vehicle sharing (scooters) values produced

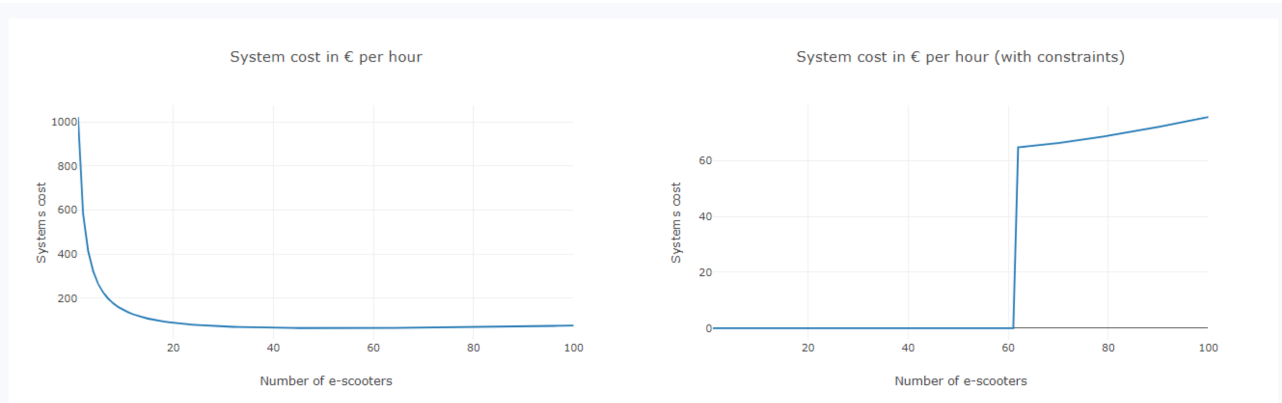

Figure 11: Vehicle sharing (scooters) chart produced for system cost with and without constrains

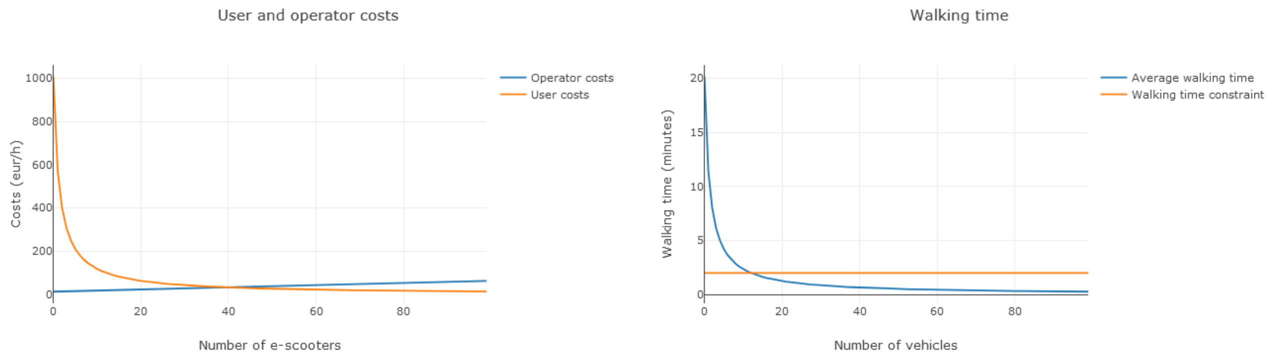

Figure 12: Vehicle sharing (scooters) values produced

3.3.2.3 Decision Support Tool Level 1 - Vehicle sharing system

In this chapter, the theoretical analysis of the Vehicle sharing systems will be described. The examined systems include the bike sharing and E- scooters mathematical procedure followed, to develop the performance indicators for the vehicle sharing system. The aim of the outputs of this analysis is to identify the operational and planning parameters for the tested services.

3.3.2.3.1 Service management modelling of bike sharing systems

The first step of the investigation, is to disaggregate the examined city into smaller districts, based on the data of population and land use. In these districts, smaller areas will be identified and within them, Origin (O) and Destination (D) zones will be further defined.

In each OD pair, each user walks from its origin point to the closest operating origin bike station. If a bicycle is available, the user rents it, otherwise the user waits until a bicycle arrives. After the arrival of the bicycle, the user travels to the destination station closest to the user's final destination point. In this case, and if there is an available slot, the user parks the bicycle, and walks to the final destination point, or waits until a slot is free, and then walks to the final destination. The time between the user's start time from the origin point until their final destination point is defined as one cycle. Moreover, we assume that there are no movements between the stations of the same zone but only between different zones. The distance of the user from the starting station and from the destination station to the user's final destination point depends on the number of stations within a zone and the zone's area.The availability of a bicycle at the station depends on the quantity of bicycles assigned to each station of a zone and the demand for bicycles at the station. This is considered stochastically identical to the demand of all the remaining stations of the same zone. Figure 13 below, illustrates a simplified realization of the different cases mentioned previously.

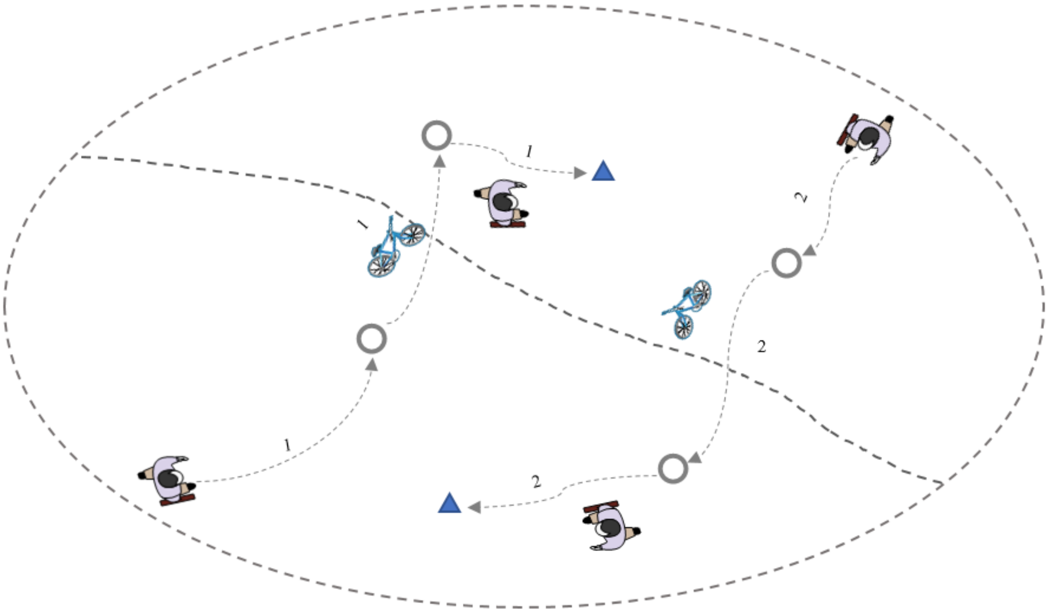

Figure 13: Different scenarios of mobility service

Mobility planners advocate that a higher number of bicycles assigned to a station may reduce the users expected walking and waiting times at the initial station, as this increases the station's service level. On the other side, it may increase the expected waiting times of the users at the final stations, as the probability of finding an empty slot decreases, while also leads to higher bicycle holding and purchase costs. Finally, as the number of stations increase, the walking times of the users to their initial station, and from their destination station to their final destination will be reduced, but the company's fixed station set up costs will increase.

The critical decisions for managing a bike sharing system, involve decisions regarding:

- Number of bicycles assigned to each station within a planning horizon, which further determine the station's capacity
- Number of stations operating within the geographical region in a planning horizon.

The optimization of the system is based on the following key factors.

- The infrastructure cost of the system, involving bicycle's depreciation costs per time unit, the maintenance cost per km and station's rent cost.
- Personnel's salary costs per time unit.
- Passengers' costs which involve the passengers expected value of waiting and travel times.

The first step of the investigation is to disaggregate the examined city into smaller districts, based on the data of population and land use. In these districts, smaller areas will be identified and within them, Origin (O) and Destination (D) zones will be further defined.

For each OD, each user walks from its origin point to the closest operating origin bike station. If a bicycle is available, the user rents it, otherwise the user waits until a bicycle arrives. After the arrival of the bicycle, the user travels to the destination station closest to the user's final destination point. In this case, and if there is an available slot, the user parks the bicycle, and walks to the final destination point, or waits until a slot is free, and then walks to the final destination. The time between the user's start time from the origin point until their final destination point is defined as one cycle. Moreover, we assume that there are no movements between the stations of the same zone but only between different zones. The distance of the user from the starting station and from the destination station to the user's final destination point depends on the number of stations within a zone and the zone's area, while the availability of a bicycle at the station, on the quantity of bicycles assigned to each station of a zone and the demand for bicycles at the station, which is considered stochastically identical with the demand of all the remaining stations of the same zone. Figure 13 below, illustrates a simplified realization of the different cases mentioned previously.

3.3.2.3.2 Service management modelling of E-scooters

In the case of E-Scooters, the general framework of the employed methodology is the same with that of the bike sharing system, with the difference that instead of the number of origin and destination station decision variables s_o, s_d, we now have the number of origin and destination e-scooters denoted by e_o^s, e_d^s. Moreover, the station capacity variables at the origin and destination zones, denoted by $Q_{s_{o,}} Q_{s_{d,}}$, are not included along with the stations fixed cost per planning horizon, which are estimated as functions of the number of bicycles per station. The rest modelling formulations remain the same

3.3.2.4 Bike Sharing System decision making indicators

Based on the findings of the methodology followed in level 1 for the BSS, a summary of the findings will be provided to the decision makers, providing an overview of the results. If the capacity calculated is 1, then a dock-less bike sharing system is a measure with increased chances to be applied in the examined city. Furthermore, in line with the optimization requirements set out in the previous section, the minimized estimated transport cost (EST) of the total interventions will be identified. Thus, policy makers based on the cost and the benefits of the proposed options will recognize the feasibility along with the reasons for the decision of the proposed method.

3.3.2.5 KPIs assessing the Bike Sharing System

The first step of the implementation of the model is to identify the study area. Once the geographical region of interest is determined, then depending on the distribution of trips in this region, pairs of Origin and Destination zones are demarcated. Each zone facilitates a number of bicycle stations, denoted by $s^o \epsilon S^o$and $s^d \epsilon S^d$ respectively. The stations of each zone face a stochastic demand for bicycles which is assumed to be stochastically identical.

To determine the optimum number of bicycles The optimization problem is formulated as a non-linear optimization problem which will try to determine the number of bicycles Q_{s^o} and Q_{s^d}, assigned to the stations of the origin and destination zones respectively, and the number of stations $s^o$and s^d operating within each zone the tool follows a non-linear optimization problem approach.

The objective function is developed and optimized under total bicycle, station and passenger cost minimization objectives per time unit. Bicycle costs involve a fixed bicycle maintenance cost per km (c_o) charged on the kms travelled per route and the routes per time unit, along with a fixed operating cost per time unit denoted by c_f, which involves the bicycle depreciation costs. Regarding user's costs. These costs involve a fixed value of time cost, β_t, charged on the user's walking and travel times per route.

The development of the model initially involves the analytical expression of the passenger's walking times. Thus, for each station of the origin and destination zone we consider a passenger walking time to the station and a passenger walking time from the station to the passenger's final destination. Assuming an average speed v per passenger and an equivalent average walking distance to the origin station, the walking time per route to the origin station per and from the destination station to the user's final destination is equal to $w_o = \frac{\sqrt{\frac{A_O}{s_O \cdot \pi}}}{v}$, and $w_d = \frac{\sqrt{\frac{A_d}{s_d \cdot \pi}}}{v}$ where $A_o$and A_D corresponds to the km service of the origin and destination zones. The total walking times per route can be then estimated through the following Eq. (1)

$$E_w = \frac{\sqrt{\frac{A_o}{s_o \cdot \pi}}}{v} + \frac{\sqrt{\frac{A_d}{s_d \cdot \pi}}}{v}, \qquad Eq. (1)$$

The cycling time between the origin and destination stations also depends on the number of stations operating both at the origin and destination zones. These distances are estimated as an average of the maximum and minimum lengths travelled. The derived function is approximated through Eq. (2).

$$D_c = \frac{\sqrt{A_o + A_d}}{2} \cdot \left(\sqrt{2} - \frac{1}{4} + \frac{1}{\sqrt{s_o + s_d - 1}}\right) \qquad Eq. (2)$$

The geographical region under study is perceived as a rectangle. Thus $A_o + A_d$= ….

Regarding the passenger waiting times, these involve the waiting times at the origin station denoted by t_{s^o} and the waiting times at the destination station denoted by t_{s^d}. The waiting times at the origin station include the time that a user waits to receive a bicycle at the origin station.

The waiting time to receive a bicycle depends on the probability that the station's stochastic demand during the user's walking time $x_{w_o}^{s^o}$ is less than Q_{s_o}, which represents each origin station's bicycle replenishment level per route. This probability is denoted by $\Phi_{x_{w_o}^{s^o}}\left(Q_{s_o}\right) = p(x_{w_o}^{s^o} < Q_{s_o})$. Thus, the probability that a potential user will have to wait for a bicycle arrival is $(1 - \Phi_{x_{w_o}^{s^o}}\left(Q_{s_o}\right))$. Assuming that the bicycles travelling to the origin zone within a geographical region are uniformly distributed, the waiting time of the user at the origin station will then depend on the number of bicycles travelling within the region and onto the origin zone, since more bicycles increase the probability that the bicycle will be closer to the user at the time instance of a bicycle request.

The number of bicycles travelling to the origin stations can be set equal to the expected bicycle stock out level per route at the destination stations. A stock out at the destination station may occur if the users' stochastic demands during their walking times to the station, denoted by $x_{w_d}^{s^d}$ is higher than the station's bicycle quantity Q_{s_d}. Thus, the expected bicycle stock out level per route can be estimated through Eq. (3).

$$E(BO)_d = \sum_{s^d \epsilon S^d} \frac{1}{w_d} \cdot \int_0^{w_d} \int_{Q_{s^d}}^{\infty} \left((x_t^{s^d} - Q_{s^d}) \cdot \varphi\left(x_t^{s^d}\right) \cdot dx_t^{s^d} \right) dt \qquad Eq. (3)$$

Where $\varphi_{x_t^{s^d}}\left(x_t^{s^d}\right)$ represents the probability density function of the station's stochastic bicycle demand per time unit, which is assumed stochastically identical for all stations. The expected number of bicycles destinated to each origin station s^d per route can be then estimated by:

$$B_{s^d} = \frac{E(BO)_d}{\sum_{s^d \epsilon S^d} s^d} , \qquad Eq. (4)$$

Thus, the expected waiting time of the user at the origin station is estimated through Equation (5).

$$E(t_{s^o}) = \frac{\int_0^{\sqrt{\frac{A_o}{\pi \cdot B_{s^d}}}} y_o \cdot B_{s^d} \cdot \left[1 - \frac{{y_o}^2}{\left(\sqrt{\frac{A_o}{\pi \cdot B_{s^d}}}\right)^2}\right]^{B_{s^d} - 1} \cdot \frac{2 y_o}{\left(\sqrt{\frac{A_o}{\pi \cdot B_{s^d}}}\right)^2} \cdot dy_o}{v_b} \cdot \left(1 - \Phi_{x_{w_o}^{s^o}}\left(Q_{s_o}\right)\right), \qquad Eq. (5)$$

Where v_b represents the average bicycle travel speed

Let $X_1, X_2, \dots\dots\dots X_n \dots\dots\dots\dots\dots\dots\dots$

Regarding the waiting times of the bicycle users at the destination stations, these times depend on the probability that each station's demand during the user's walking time to the station plus the waiting time at the origin station plus the travel time between the origin and destination stations are less than Q_{s^d} and thus equal to $\varphi(1) + \varphi(2) + \varphi(3) + \cdots \varphi(Q_{s^d}) = \Phi(Q_{s^d})$. Given that the user will wait for an available slot, the waiting time in turn depends on the user's demand levels for bicycles at the destination zones, which are estimated as:

$$u_d = \frac{1}{(w_d + E(t_{s^o}) + \frac{D_c}{v_b})} \cdot \int_0^{(w_d + E(t_{s^o}) + \frac{D_c}{v_b})} x_t^{s^d} \, dt, \qquad Eq. (6)$$

The expected waiting time of a user at the destination station per route $E(t_{s^d})$ can be then estimated as:

$$E(t_{s^d}) = \frac{\int_0^{\sqrt{\frac{A_d}{\pi \cdot u_d}}} y_d \cdot u_d \cdot \left[1 - \frac{{y_d}^2}{\left(\sqrt{\frac{A_d}{\pi \cdot u_d}}\right)^2} \right]^{B_{s^d} - 1} \cdot \frac{2 y_d}{\left(\sqrt{\frac{A_d}{\pi \cdot u_d}}\right)^2} \cdot dy_d}{v_b} \cdot \Phi_{x_{w_d}^{s^d}}(Q_{s_d}), \qquad Eq. (7)$$

In the tables following the sum of the nomenclature of the model's parameters and variables are listed.

$E_{w_{s^o}}$	Expected walking time to the origin station (time units/route)
$E_{w_{s^d}}$	Expected walking time from the destination station to the final destination (time units/route)
D_c	Bicycle distance travelled per route (km/route)
$E(BO)_d$	Expected bicycle level travelling to the origin stations (bicycles)
u_d	Bicycle demand level at the destination station (bicycles)
$E(t_{s^o})$	Expected waiting time at the origin station (time units /route)

$E(t_{s^d})$	Expected waiting time at the destination station (time units /route)
v_b	Bicycle travel speed
c_o	Bicycle Operating cost per km (€/km)
β_t	User's value of time (€/time unit)
c_f	Bicycle Depreciation cost per time unit (€/time unit)
λ	Expected bicycle demand per time unit (routes/time unit)
c_s	Station fixed costs per planning horizon, expressed as a linear function of the number of bicycles per station

Table 1: Nonmeclature of model parameters

s_o, s_d	Number of stations at the origin and destination zones
$Q_{s_o}, Q_{s_d,}$	Station capacity at the origin and destination zones

Table 2: Nonmeclature of model variables

Consequently, the following objective function is developed for minimizing the total bicycle operators and passengers' costs per time unit.

$$Min\ ETC(s_o, s_d, Q_{s_o}, Q_{s_d}) = \left(c_o D_c + \beta_t \left[E_{w_o} + E_{w_d} + E(t_{s^o}) + E(t_{s^d}) + \frac{D_c}{v_b}\right]\right)\lambda + c_f + c_s, \quad Eq.(8)$$

3.3.3 On Demand system

For the implementation of the ridesharing system, we consider that the mobility services will be provided within a certain geographic region. Number and types of the provided vehicles are determined beforehand and do not change by the end of the investigation.

3.3.3.1 *Input data requirements for on demand systems*

3.3.3.1.1 Taxi / ride sharing

Operator cost (per km): This parameter is associated with the operational cost of a unit per km. In this value repairing cost, depreciation cost per distance travelled are included.

Operator cost per hour (per car): This parameter is associated with the operational cost of a unit per hour. In this value, repairing cost, depreciation cost per distance travelled are included.

Socio-economic and functional variables

Value of time of users: Monetary value of time. It is the amount of money a user would be willing to pay in order to save travel time.

Vehicle speed: Average speed of the vehicles operating in the service.

Mean demand of the area: Total number of trips in the area per time interval.

Constraints

Maximum waiting time: Maximum waiting time, the users are willing to spend for a taxi to become available.

Delay factor: Additional travel time in comparison to the direct trip between origin and destination of the customer (due to the detour to pick up and deliver the co-travellers)

Decision variables

Number of vehicles available for the service: Minimum and maximum number of vehicles to operate.

Number of passengers: Minimum and maximum number of passengers in each vehicle.

3.3.3.1.2 Demand Responsive Transport

Operator cost (per km): This parameter is associated with the operational cost of a unit per km. in this cost, repairing cost, depreciation cost per distance travelled are included.

Operator cost per hour (per unit): This parameter is associated with the operational cost of a unit per hour for each mode operating. In this cost, repairing cost, depreciation cost per distance travelled are included.

Socio-economic and functional variables

Value of time of users: Monetary value of time. It is the amount of money a user would be willing to pay in order to save travel time.

Bus cruise speed: Average circulating speed of the bus operating.

Bus acceleration: Approximate acceleration of the bus operating.

Boarding/alighting time: Approximate time spent for boarding/ alighting of every passenger.

Mean demand of the area Total number of trips in the area per time interval.

Constraints

Maximum "delay" factor: additional travel time percentage in comparison to a normal bus service (due to the detour to pick up and deliver the other passengers). [Example: value 2 refers to 200% increase of travel time]

Maximum waiting time: It is the maximum time users of the service are willing to wait for the service.

Maximum number of buses: Maximum number of buses operating.

Decision variables

Frequency: How regular a bus of DRT service will be available on a station [Example: Frequency value 1 refers to 1 operating car. Frequency value 0.1, refers to 10 operating buses]

3.3.3.2 Insights derived from On Demand system

At this section of the results, the optimal values and KPIs are produced. Based on the values user provided to the tool, the optimal solutions are calculated.

Optimal Cost (TS-RS, DRT) = the optimal cost refers to the total cost of the service. It includes the operational and user cost for the service.

Optimal number of units (TS-RS, DRT) = Optimal number of the units needed for the system, based on the values included in the previous steps.

Optimal frequency (DRT): Regularity of a DRT bus service that will be available on a station. Example - Frequency value 1 refers to 1 operating car. Frequency value 0.1, refers to 10 operating buses

Optimal number of passengers (TS-RS) = the optimal number of the passengers that will use the service, based on the values included in the previous steps.

Waiting Time per Passenger (TS-RS, DRT) = Average time a passenger needs to wait for the transport mode to pick the user.

Delay Factor (TS-RS) Travel time Factor (DRT) = Factor of additional travel time associated with the detour of the taxi/vehicle participating in the service [Example: A value of 100% of this factor indicates that travel time for a user will double, for detouring in order to pick others for this tour satisfying the distance constrains set for the service]

Total Emissions (TS-RS & DRT) = Calculated amount of emissions produced by the service, by using the optimal values calculated from the tool.

Waiting time (DRT) = Waiting time users need to spend to reach a bike of the BSS or a bus of the DRT service.

3.3.3.3 Visual presentation of the insights derived from Level 1 – On Demand Systems

In the last section of the results, charts of the results are presented. The aim of the charts included in the chapter of the results, is for users of the DST to have an overview of the service they want to investigate. In every chart, the optimal solution calculated is provided along with the range of the results of the solutions proposed. Thus, users of the DST are able to easily understand the impact of a different option (than the optimum) or how the cost is split into costs for the user and for the operator side, allocating their actions appropriate.

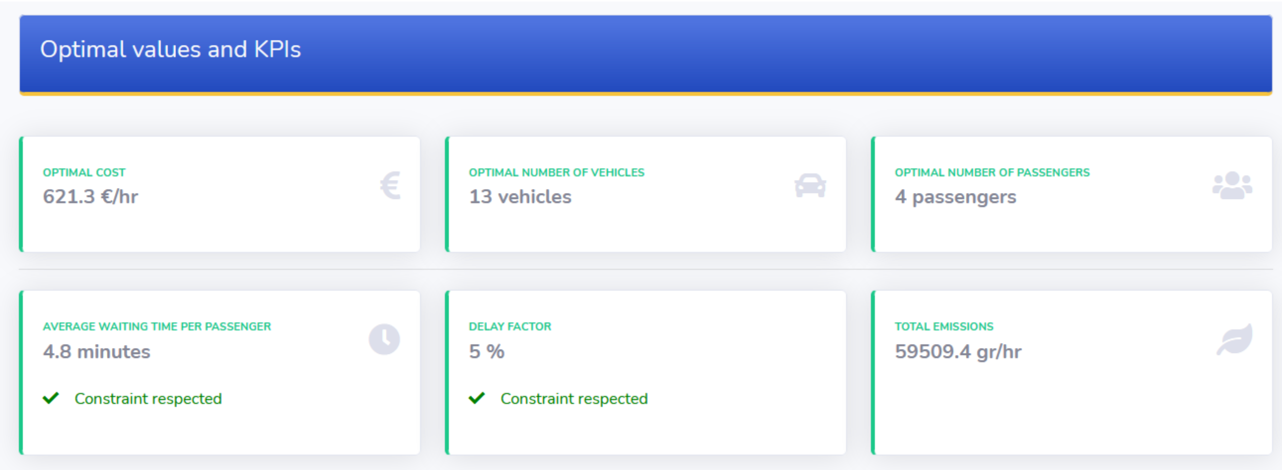

Figure 14: On Demand (taxi ride sharing) values produced

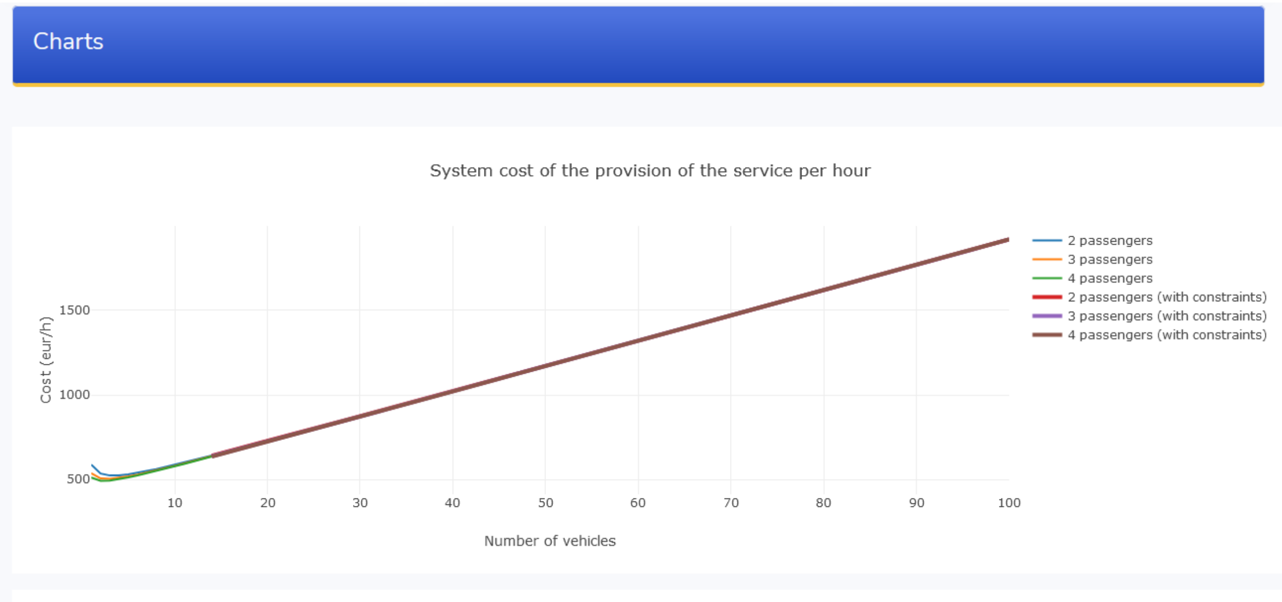

Figure 15: On Demand (taxi ride sharing) chart produced for system cost of the providers of the service

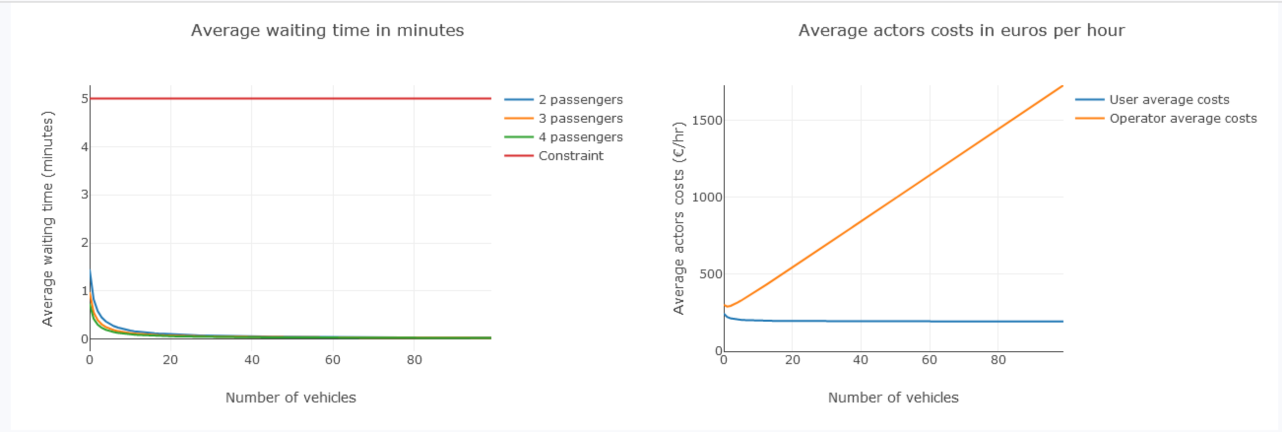

Figure 16: On Demand (taxi ride sharing) chart produced for Average waiting time and average costs

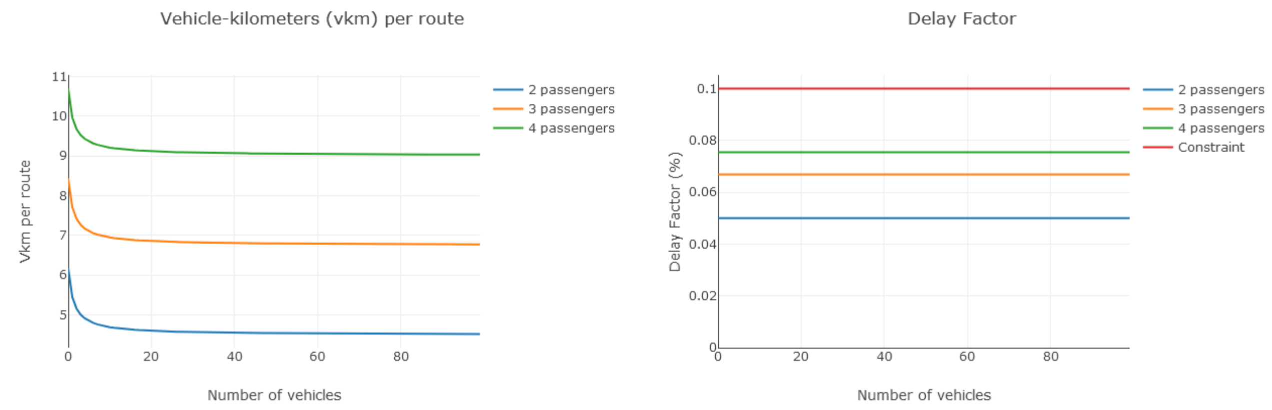

Figure 17: On Demand (taxi ride sharing) chart produced for Vehicle-kilometers per route and delay factor

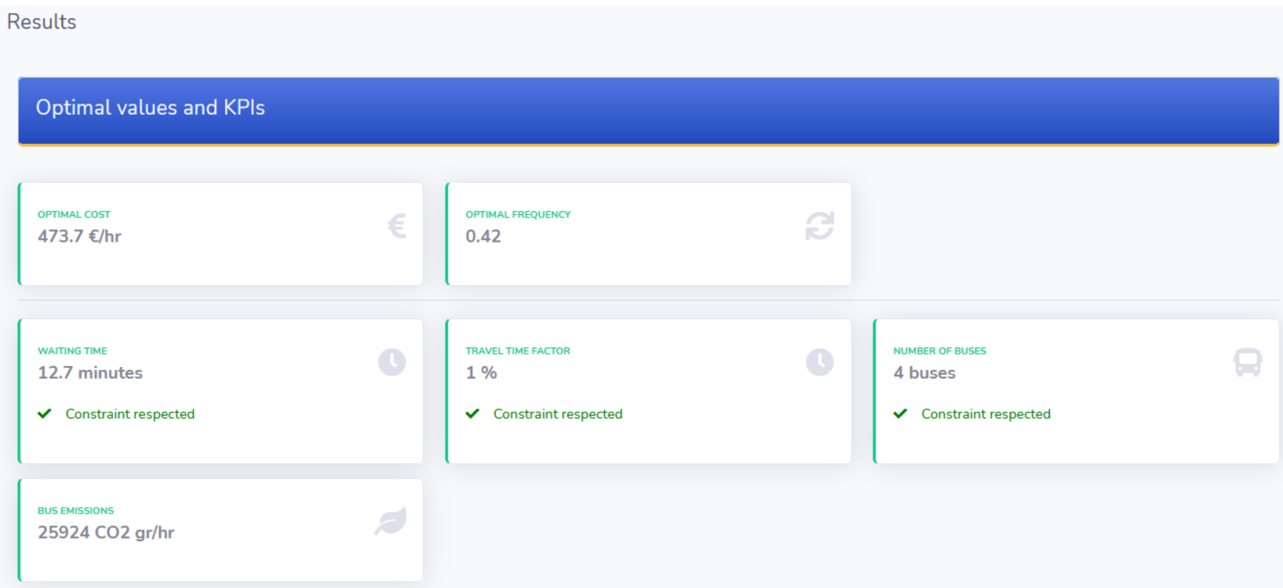

Figure 18: On Demand (Demand Responsive Transport) optimal values

Figure 19: On Demand (Demand Responsive Transport) charts for System Cost and User and operator cost

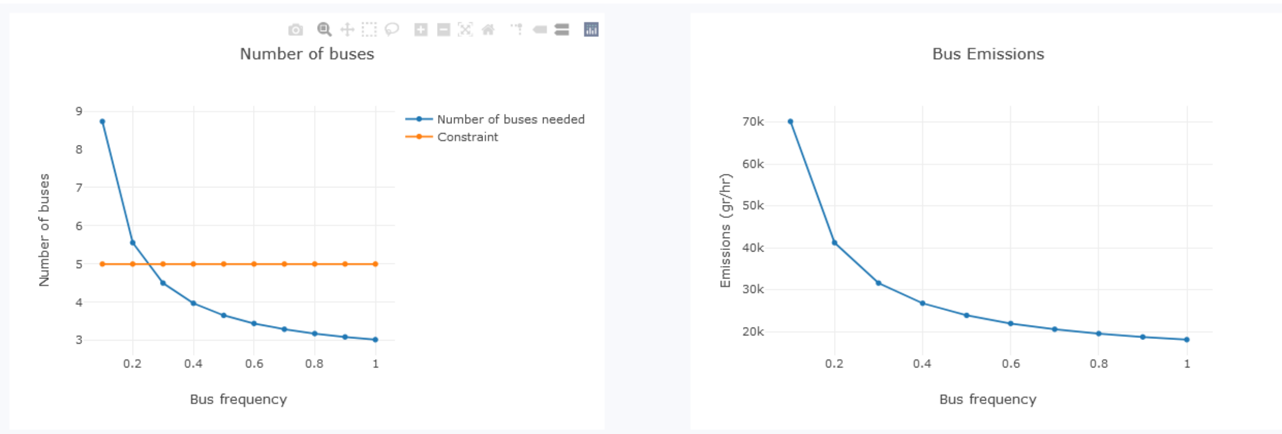

Figure 20: On Demand (Demand Responsive Transport) charts for Number of buses and Bus Emissions

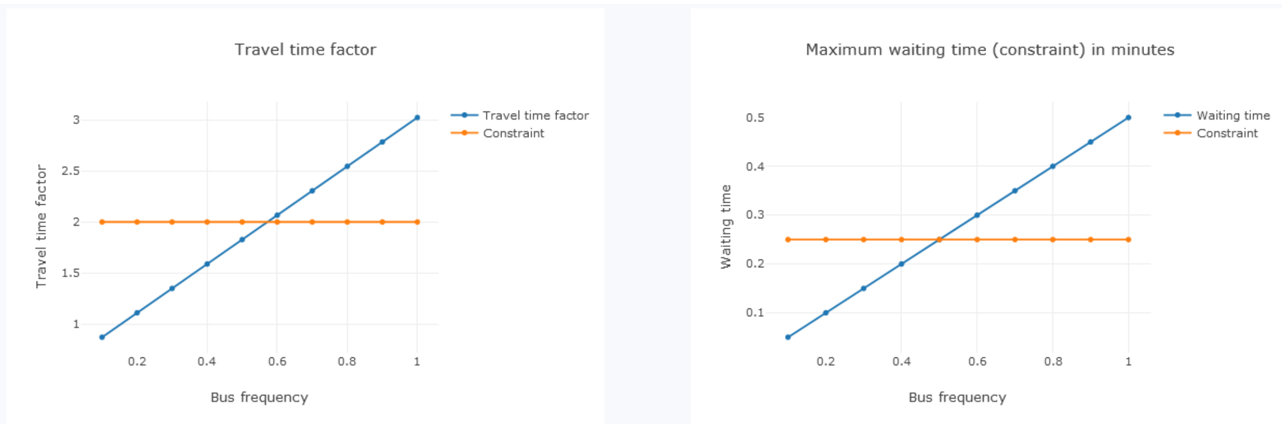

Figure 21: On Demand (Demand Responsive Transport) charts for Travel Time Factor and Maximum waiting time

3.3.3.4 Decision Support Tool Level 1 - On Demand Systems

In this chapter, the theoretical analysis of the On Demand systems will be described. The examined systems include the taxi/ride sharing and DRT will be described. The examined systems include the taxi/ride sharing and DRT mathematical procedure followed, to develop the performance indicators for On Demand system. The aim of the outputs of this analysis is to identify the operational and planning parameters for the tested services.

3.3.3.4.1 Taxi / ride sharing

Once a passenger requests a service for On Demand systems, then a trigger informs the nearest available vehicle, which participates in the system. The vehicle then receives new passenger requests and serves the closest passenger. As the location of the vehicle can be anywhere within a radius, the distance of each vehicle from the user is a stochastic random variable which depends on the number of vehicles operating in the area. Moreover, the distance of the vehicle from the next passenger is also a random variable which depends on the area of the region served and the demand for transportation services within the region.

Mobility planners advocate that a higher number of vehicles operating within a region will lead on the one hand to lower passenger waiting times, but, on the other hand, to higher vehicle operating costs per hour and vice versa. Moreover, and as the number of passengers served per route increases, the vehicle's operating costs per hour will decrease due to economies of scale but also, passenger waiting times will increase. Thus, the number of vehicles operating within the region and the number of passengers that each vehicle will collect are predefined before the ridesharing trip initiation, and determined under total passenger waiting time and vehicle operating costs.

Figure 22 below, illustrates a simplified realization of ridesharing potential cases.

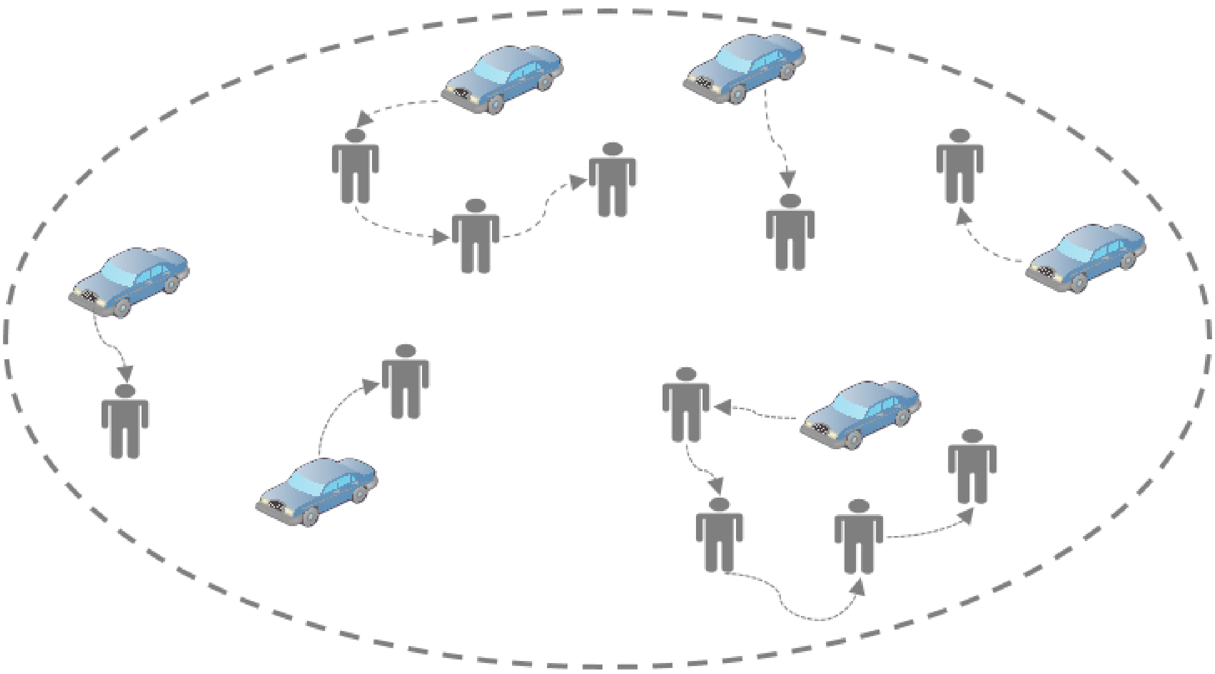

Figure 22: Ride Sharing System

The critical decisions involve decisions regarding:

- The number of passengers that each vehicle will serve in a single route.
- The number of vehicles of a specific type that the ridesharing.

The optimization of the system is based on the following key factors

- The vehicles costs; these costs encompass the vehicle's depreciation, insurance, maintenance, driver's costs per hour etc., and the vehicles operating costs per km.
- The passenger's costs which involve passengers' expected value of waiting and travel times.

3.3.3.4.2 Demand Responsive Transport Modelling

The methodological approach employed for modelling the system is based on the paper of Estrada (Estrada et al. 2020) Estrada presents analytical formulations for estimating the costs of DRT, traditional bus lines and taxi services in a corridor area.

3.3.3.5 Ridesharing decision-making indicators

Based on the findings of the methodology followed in the ridesharing level for the BS system, a summary of the findings will be provided to the decision makers, providing an overview of the results. Furthermore, in line with requirements set out in the previous steps, the minimized estimated transport cost (EST) of the total of interventions will be identified. Thus, policy makers based on the cost and the benefits of the proposed options will recognize the feasibility along with the reasons for the decision of the proposed method.

The developed methodology can be also easily employed for modelling a demand responsive Taxi transportation system, by predefining the number of passengers to P=1 and determining the optimal value of n_m, given that the first and second order conditions of Eqs (21) and (22) respectively are satisfied

3.3.3.6 KPIs assessing Ride sharing system

The problem under study is formulated as a non-linear optimization problem. It decides the number of passengers$p \in P$, that each vehicle should serve in each trip and the number of vehicles$n \in N$ that the ridesharing company should operate within the region. One objective function is developed and optimized under total vehicle and passenger cost minimization objectives per hour. The vehicle costs per hour consists of the vehicle operating costs per km, that includes the km travelled by the vehicle in one hour and the vehicle operating costs per hour which incorporates, the vehicle's depreciation, driver and insurance costs per hour. The passenger's costs per hour involve the perceived value of time per trip multiplied by the trips undertaken in an hour.

The development of the model, initially involves the analytical expression of the passenger's waiting times w_p. Specifically for the first passenger of the ride sharing trip, the waiting time depends on the number of the ridesharing company's operating vehicles (n_m), their average speed v_m and the area of the geographical region served (A), with the expected waiting time being estimated from the following Eq. (1).

$$E(w_1) = \frac{\int_0^{\sqrt{\frac{A}{n_m \cdot \pi}}} y \cdot f_Y(y)dy}{v_m} = \frac{\int_0^{\sqrt{\frac{A}{\pi \cdot n_m}}} y \cdot n \cdot [1 - \frac{y^2}{\left(\sqrt{\frac{A}{n_m \cdot \pi}}\right)^2}]^{n-1} \cdot \frac{2y}{\left(\sqrt{\frac{A}{n_m \cdot \pi}}\right)^2} \cdot dy}{v_m}, Eq. (9)$$

Where $X_1, X_2, \ldots, X_{n_m}$, represent the stochastically identical distances of each n_m from the first passenger of the round sharing trip. Moreover, Y= min ($X_1, X_2, \ldots, X_{n_m}$), with a CDF:

$F_Y(y) = p(Y \leq y) = 1 - p(Y > y)$ Eq. (10)

As Y= min ($X_1, X_2, \ldots, X_n$), the following Eq. (11) is also valid.

$F_Y(y) = p(Y \leq y) = 1 - \prod_{i=1}^{n} p(X_i > y) = 1 - p(X > y)^n = 1 - [(1 - p(X \leq y))^n] = (1 - [1 - F_X(y)]^n$
Eq. (11)

The pdf of Y can be then estimated as: $f_Y(y) = \frac{dF_Y(y)}{dy} = n \cdot [1 - F_X(y)]^{n-1} \cdot \frac{dF_X(y)}{dy} = n \cdot [1 - F_X(y)]^{n-1} \cdot f_X(y)$.

In our case, in order to determine the CDF $F_X(y)$, we assume that all vehicles are uniformly distributed in a geographical area. Thus, each vehicle will be assigned to a specific service area, the radius of which depends on the size of the area and the number of vehicles operating within the area. Thus, the area of the circle assigned to each vehicle can be estimated by the following equation: $\pi \cdot r^2 = \frac{A}{n_m} \Leftrightarrow r_1 = \sqrt{\frac{A}{n_m \cdot \pi}}$. The CDF $F_X(y)$ will represent the probability that one of those vehicles will be located in the area of a circle with a radius y that is concentric to a circle with radius $\sqrt{\frac{A}{n_m \cdot \pi}}$. This probability can be then estimated as the ratio of the areas of the two cycles and will be therefore equal to: $F_Y(y) = \frac{\pi y^2}{\pi\left(\sqrt{\frac{A}{n_m \cdot \pi}}\right)^2} = \frac{y^2}{\left(\sqrt{\frac{A}{n_m \cdot \pi}}\right)^2}$, where $y \epsilon (0, \sqrt{\frac{A}{n_m \cdot \pi}})$. Moreover, $f_Y(y) = \frac{dF_Y(y)}{dy} = \frac{2y}{\left(\sqrt{\frac{A}{n_m \cdot \pi}}\right)^2}$.

Regarding the waiting times of all the remaining passengers, these depend on the number of passengers requesting the service within a specific time horizon (λ). Assuming that each passenger is also uniformly distributed in the same geographical area, the service area assigned to each passenger will have a radius $r = \sqrt{\frac{A}{\lambda \cdot \pi}}$, estimated similarly to the case of the first passenger. Thus, the expected total waiting times of all passengers served will be estimated similarly with Eq. (11), through the following Equation (12).

$$\sum_{p=2}^{P} E(w_p) = \frac{\sum_{p=2}^{P} \int_0^{\sqrt{\frac{A}{\lambda \cdot \pi}}} z \cdot (\lambda - p) \cdot \left[1 - \frac{z^2}{\left(\sqrt{\frac{A}{\lambda \cdot \pi}}\right)^2}\right]^{\lambda - p + 1} \cdot \frac{2z}{\left(\sqrt{\frac{A}{\lambda \cdot \pi}}\right)^2} \cdot dz}{v_m}, \qquad Eq. (12)$$

Where, $Z_1, Z_2, \ldots, Z_\lambda$, represent the stochastically identical distances of the first passenger's location to the passengers requesting the service and K= min($Z_1, Z_2, \ldots, Z_\lambda$).

As the passenger's collected will be transported to final destinations, further leading to higher passenger and vehicle transportation distances, the developed methodology additionally requires the estimation of the total distance as a function of the passengers served. In order to address this issue, we assume that each vehicle's trip consists of three discrete segments. The first segment is the passenger collection zone (D_{CZ}) and is estimated as a sum of the expected distances of the vehicle to the first passenger, and the sum of the expected distances between the passengers. The derived equation is summarized below:

$$D_{CZ} = \left[E(w_1) + \sum_{p=2}^{P} E(w_p)\right] \cdot v_m \quad , \qquad Eq. (13)$$

The second segment involves the main distance D_{main} of the vehicle's trip and encompasses the distance traveled between the route's collection and final destination zones. The Equation employed for estimating the main distance is summarized below.

$$D_{main} = \frac{\sqrt{A}}{2} \ , \qquad Eq.(14)$$

Finally, the passenger destination zone D_{dz} involves the distance between the destination points of P-1 passengers as the first passenger's destination is the endpoint of the main distance. Moreover, we assume that the distances between the P-1 passengers' in the destination zone are mirrors of the P-1 passenger distances in the collection zone. Thus, these distances can be estimated through the following Eq. (15).

$$D_{dz} = \sum_{p=2}^{P} E(w_p) \cdot v_m \ , \qquad Eq.(15)$$

Consequently, the total distance D_{Total}^{P}, travelled by the vehicle is estimated through the following Eq. (16)

$$D_{Total}^{P} = \left[E(w_1) + 2 \cdot \sum_{p=2}^{P} E(w_p)\right] \cdot v_m + \frac{\sqrt{A}}{2} \ , \qquad Eq.(16)$$

Finally, as the collection of multiple passengers will lead to higher total passenger travel and waiting times, these times (T_{Total}^{P}) will be estimated as a function of the passengers served and through the following Equation (17).

$$T_{Total}^{P} = \sum_{p=1}^{P} \frac{p \cdot D_{Total}^{P}}{v_m} - 2 \cdot \sum_{p=1}^{P-1} (P-p) \cdot E(w_p), \qquad \boldsymbol{Eq.(17)}$$

The developed methodology aims to determine the optimal number of operating vehicles of type m within the geographical region (n_m) and the optimal number of passengers P, that each vehicle should serve, under total vehicle and passenger cost minimization objectives and considering the following two constraints: (i) the average waiting time of each should be less than a threshold time T_W^P and (ii) the driver's average net revenue per route should be higher than the average costs per route.

Tables 3 and 4 summarize the model's parameters and decision variables respectively.

$\boldsymbol{c_o^m}$	Operating costs per km for each mode m conventional vehicle and minivan respectively (€/km)
$\boldsymbol{c_f}$	Operating costs per hour for each mode m (€/hr./vehicle)
$\boldsymbol{w_p}$	Waiting time of passenger of $p \in P$ (hrs/passenger)
$\boldsymbol{D_{Total}^{P}}$	Vehicle total transportation distance traveled per route (km/route)

T^P_{Total}	Total waiting and travel time of all passenger's P (hr/route)
T^P_W	Threshold passenger waiting time (hrs)
R	Driver's fee (€/hr)
λ	Passenger trip demands per hour (trips/hour)
A	Area of the geographical region served (km^2)
v_m	Average speed of vehicle m (km/hr)
b_t	Passenger value of time (€/hr)

Table 3: Nonmeclature of model parameters

n_m	Number of vehicles of type m operating within the region
P	Total Passengers served in a single trip

Table 4: Nonmeclature of model variables

Consequently, the following objective function is developed for minimizing the total vehicle and passengers' costs per hour.

$$Min\ ETC(n_m, p) = \frac{\lambda}{p}[c_o^m \cdot D^P_{Total} + b_t \cdot T^P_{Total}] + c_f \cdot n_m, \qquad Eq.(18)$$

Subject to:

$$\frac{E(w_1) + \sum_{p=2}^{P} E(w_p)}{P} \leq T^P_W\ , \qquad Eq.(19)$$

$$c_o^m \cdot D^P_{Total} + c_f \cdot \frac{D^P_{Total}}{v_m} \leq T^P_{Total} \cdot R \qquad Eq.(20)$$

For a given value of P, the optimization process initially involves the determination of the optimal value of n_m that jointly satisfies the first order conditions of Eq. (21) and the inequality of Equation (22). The next step of the optimization process is to examine whether the derived optimal value can satisfy the constraints of Eqs (19) and (20), and if not, to quantitatively determine the subsidy value that should be provided by the government that make the optimal solution sustainable.

$$\left(c_o^m \frac{\lambda}{p} + \frac{b_t}{v_m} - 2 \cdot (P-1)\right) \cdot \left(\int_0^{\sqrt{\frac{A}{n_{m\cdot\pi}}}} \frac{y^2 \cdot \left(1 - \frac{y^2}{\sqrt{\frac{A}{n_{m\cdot\pi}}}}\right)^{n_m}}{\left(\sqrt{\frac{A}{n_{m\cdot\pi}}} - y^2\right)^2} \cdot \left(\begin{array}{l} -\sqrt{\frac{A}{n_{m\cdot\pi}}} \cdot \left(3 + 2 \cdot n_m \cdot Log\left[1 - \frac{y^2}{\sqrt{\frac{A}{n_{m\cdot\pi}}}}\right]\right) \\ + \left(2 + n_m + 2 \cdot n_m \cdot Log\left[1 - \frac{y^2}{\sqrt{\frac{A}{n_{m\cdot\pi}}}}\right]\right) \cdot y^2 \end{array} \right) dy - \frac{A \cdot \left(1 - \frac{A}{n_m \cdot \sqrt{\frac{A}{n_{m\cdot\pi}}} \cdot \pi}\right)^{n_m - 1}}{n_{m\cdot\pi}} \right) + c_f = 0, \qquad Eq.(21)$$

Given that the following inequality is satisfied:

$$
-\left(c_o^m \frac{\lambda}{p} + \frac{b_t}{v_m} - 2 \cdot (P-1)\right) \cdot
$$

$$
\left(\frac{1}{2\left(-\sqrt{\pi}y^2+\sqrt{\frac{A}{n_m}}\right)^3 n_m} \int_0^{\sqrt{\frac{A}{n_m \pi}}} \begin{matrix} \pi^{3/2}y^2\left(1-\frac{\sqrt{\pi}y^2}{\sqrt{\frac{A}{n_m}}}\right)^{n_m} (9A + (4\pi y^4 + 16A\mathrm{Log}[1-\frac{\sqrt{\pi}y^2}{\sqrt{\frac{A}{n_m}}}] \\ -11\sqrt{\pi}y^2\sqrt{\frac{A}{n_m}})n_m \\ +(8\pi y^4 + 4A\mathrm{Log}\left[1-\frac{\sqrt{\pi}y^2}{\sqrt{\frac{A}{n_m}}}\right]^2 - 4\mathrm{Log}[1-\frac{\sqrt{\pi}y^2}{\sqrt{\frac{A}{n_m}}}](-3\pi y^4 \\ +7\sqrt{\pi}y^2\sqrt{\frac{A}{n_m}}) - \\ 11\sqrt{\pi}y^2\sqrt{\frac{A}{n_m}})n_m^2 + \sqrt{\pi}y^2(1+2\mathrm{Log}[1-\frac{\sqrt{\pi}y^2}{\sqrt{\frac{A}{n_m}}}])(\sqrt{\pi}y^2 \\ +\mathrm{Log}[1-\frac{\sqrt{\pi}y^2}{\sqrt{\frac{A}{n_m}}}](2\sqrt{\pi}y^2 - 4\sqrt{\frac{A}{n_m}}))n_m^3) \end{matrix} dy - \frac{1}{2\left(\sqrt{\pi}-\sqrt{\frac{A}{n_m}}\right)^2 n_m} \cdot \right.
$$

$$
A\sqrt{\pi}\left(1-\frac{\sqrt{\frac{A}{n_m}}}{\sqrt{\pi}}\right)^{n_m}\left(-3\sqrt{\pi}+2\sqrt{\frac{A}{n_m}}+\left(2\mathrm{Log}\left[1-\frac{\sqrt{\frac{A}{n_m}}}{\sqrt{\pi}}\right]\left(-\sqrt{\pi}+\sqrt{\frac{A}{n_m}}\right)+\sqrt{\frac{A}{n_m}}\right)n_m\right)-
$$

$$
\left. \frac{A\left(1-\frac{\sqrt{\frac{A}{n_m}}}{\sqrt{\pi}}\right)^{n_m}\left(-2\sqrt{\pi}+\sqrt{\frac{A}{n_m}}+\left(-2\mathrm{Log}\left[1-\frac{\sqrt{\frac{A}{n_m}}}{\sqrt{\pi}}\right]\left(-\sqrt{\pi}+\sqrt{\frac{A}{n_m}}\right)+\sqrt{\frac{A}{n_m}}\right)n_m\right)}{2\sqrt{\pi}\left(\sqrt{\pi}-\sqrt{\frac{A}{n_m}}\right)^2 n_m^2} \right) > 0.
$$

$$
Eq. (22)
$$

3.4 Level 2 - Data driven decision system

3.4.1 Introduction

The aim of this level is to develop an analysis of the planning and evaluation of emerging mobility systems using data driven input data. For the estimation of the supply of the existing demand distribution, different algorithms will be implemented in order to conclude to efficient mobility service options. Through the procedure's steps, information from various sources will be used. The added value of the Level 2 is based on the level of analysis that can be achieved. Granularity of input data lead to develop an in depth analysis of proposed modes of transport.

The higher granularity of input data needed for level 2, increases the level of analysis that can be achieved. Targeted solutions can be developed for each transportation system and area examined, producing reliable results compared to level 1 where, due to the low granularity of the input data, it was needed to take into account assumptions . On the other hand, data driven input required for the level 2 is a complex parameter as information to be used need to be "cleaned" and in the appropriate format. Thus, technical personnel need to work on the preparation of the input data while on level 1, input data can easily be obtained.

Complex integrated DSTs for sustainable urban development typically require a large amount of input data so that they can be effectively used. In some cases, the data required may not be available. When this happens, it becomes a major obstacle to the use of such tools. Therefore, it is very important for a DST to require a reasonable amount of input data which is sufficient for supporting the urban sustainability related decisions.

The second level of the DST is responsible for making more precise decisions compared to Level 1. In that way, the user can have access to a set of results like the actual location of stops of the service, the fleet size needed, and the capacity of stops and vehicles. Indeed, such parameters tend to become critical for the overall performance of the system under various scenarios. The goal of this module is to use real-world data to generate more robust and demand-oriented strategic parameterization for the service. In addition, it produces analytical representations of both the data inputs and the final outputs so that the user gets a more intuitive report about the service.

In level 2 section of the deliverable 5.2, the data input, processing steps and the final outputs will be described.

3.4.2 5.2 Level 2 high level architecture

The planning process aims to embody methods that utilize the spatially distributed data from trips or ODs to perform strategic decisions for the service. The user of the tool should define the desired characteristics of the service to let the algorithm decide the resources needed to fulfil the requirements. In that step the user should tune values like the mean walking distance for a passenger to reach a stop, the maximum waiting time, or the maximum/average trip duration. Based on those criteria the planning module can return the optimal number and location of stops/docks, the capacity of vehicles or stops and similar system parameters. The operational module helps to evaluate each strategic setup based on performance metrics. Those metrics also used in the optimization of planning parameters as they reveal possible surpluses or shortage of resources for the service. Figure 23 shows the relation among the operational and the planning module along their inputs and outputs. Next sections present a detailed demonstration of the algorithms take place across sub-modules. Furthermore, this deliverable describes the connection and interaction across different modules.

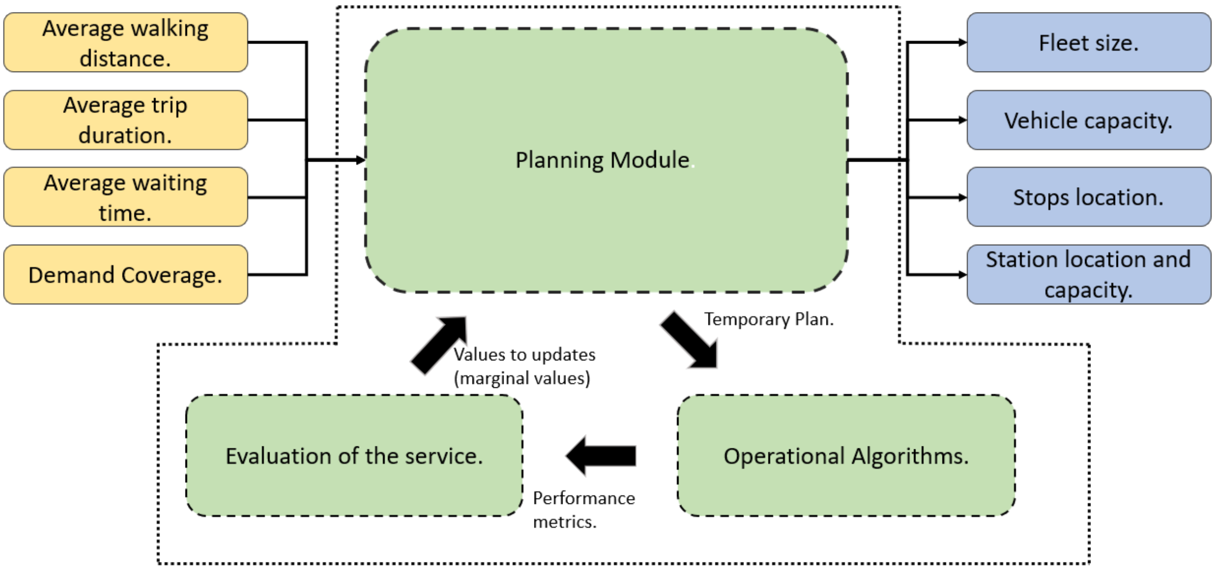

Figure 23: Structure of Level-2

The analysis of different services could be generalized into two categories: those in which users (passengers) share a trip as ride sharing (RS) and demand responsive transport (DRT) and those services in which users share a resource like bike sharing (BS), and scooter sharing (SS).

3.4.3 Input data requirements

The input of the Level-2 mainly tries to leverage trip data along with public transportation and network structure data of the area of interest. Those data are described in Table 5 and the user is responsible for the collection and modification of them. The user has two options: either to insert a set with raw trip data that can describe the spatial distribution of demand or the insertion of a set of OD matrices, in an hourly basis, along with polygon coordinates that correspond to each area Figure 24. The road network file can be used to provide the algorithms with more detailed paths among stations or for the vehicle size decision part, but those values can easily be replaced by Euclidean distance. The Public Transport Network (PTN) data are also optional in case the user wants to integrate the service with the existing PTN.

Data Type	Format	Description
Trip data	csv, json, xlsx.	Data with trips of various transport modes, e.g., taxi, bus, bike sharing, scooter sharing. Must contain basic features like origin-destination coordinates and timestamp.
Origin-Destination matrix.	csv, json, xlsx.	Dataset with OD matrices preferably in hour basis. Along with that dataset the user should also provide the module with the zoning system.

Zoning polygons.	shp, geojson.	A file of coordinates of the polygons of the OD matrices.
Road network	Shp	A file with the road network of the area of interest (where the data are located). It is optional.
Public Transport Network.	shp, geojson.	The stops of bus, metro etc., lines of public transport. It is optional.

Table 5: Technical aspects of input data

Figure 24: Different zones of OD matrices.

In case of the trip data the set must contain for each row (or sub dictionary in case of json) the following features:

- 'trip_start_geog_Long', 'trip_start_geog_Lat': The origin point coordinates.
- 'trip_end_geog_Long', 'trip_end_geog_Lat': The destination point coordinates.
- 'hour_start', 'hour_end': The hour in which the trip started/ended. Values between 0-23.
- 'trip_distance_meters': The distance (in meters) of the trip.
- 'trip_duration_seconds': The duration of the trip (in seconds).
- 'year', 'month', 'day': The year, month, and day the trip took place. Month take values between 1-12 and day 1-31.
- 'min_start', 'min_end': The minutes where the trip starts/ends range between 0-59.

However, features like year, month, day distance and duration are not necessary so that can be inserted as an empty column. The DST provide users with an auxiliary Python Notebook named "jsonify_your_data.ipynb" that contains all the available instructions and functions to manipulate data into the desired format. The same document contains information about the OD matrix formulation, which is simpler, and the format of zones of that matrix.

3.4.4 Insights derived from Level 2

At this section the results from Level 2 are presented. It is important to be mentioned that for further details of Level 2 results we refer the reader to Deliverable 5.3 “Implementation of the decision support toolset in the case study cities”. The results this level contains include:

The distribution of the demand: According to the distribution of the demand the user can decide the most appropriate service for each area. The maps contain distribution of trip distance for each region and distribution of demand across different hours of the day. So, in areas with sparse demand DRT services are more suitable for instance. Similarly, in areas with low trip distances and rich bike network the bike sharing and scooter sharing services have a good chance.

The number and the coordinates of each station: For BS, CS, SS, and DRT this is the most important decision. The location of the service directly affects the overall performance of the system. The user of the tool will be able to get those locations the service will be implemented.

The capacity of each station: For BS, CS, SS the capacity of each station is a crucial parameter with impact on the waiting time, and demand coverage of the service.

The fleet size: The number of vehicles is also an important factor for the overall performance of the services. For DRT services, small fleet leads to higher waiting times, low demand coverage, and longer trip duration. On the other hand, in BS services small fleet can create bottelnecks in redistribution proccess.

The capacity of the vehicles: This parameter is related with the occupancy of the vehicles, the flexibility of the service and the fleet size.

The average trip duration: The average trip duration in DRT and RS services is an important service level factor. Larger trip duration leads to higher headaways and higher waiting time for passengers.

The demand coverage: The number of requests that served by the service out of all the requests the service has. This output depicted for different system parameters (stations, fleet size, fleet capacity, station capacity).

The average rebalancing costs per day: The costs of relocation of resources in case of BS, SS, and SS services.

The average walking time/distance: The distance and time each passenger need to spend to access the service.

The average vehicle occupancy: The number of costumers each vehicle has on average devided by the capacity of the vehicle.

The CO2 per passenger per km: The carbon footprint each passenger spend with the use of that service.

The final form and illustration template of those results will be defined and ready until the first official version of the level 2 on deliverable 5.3.

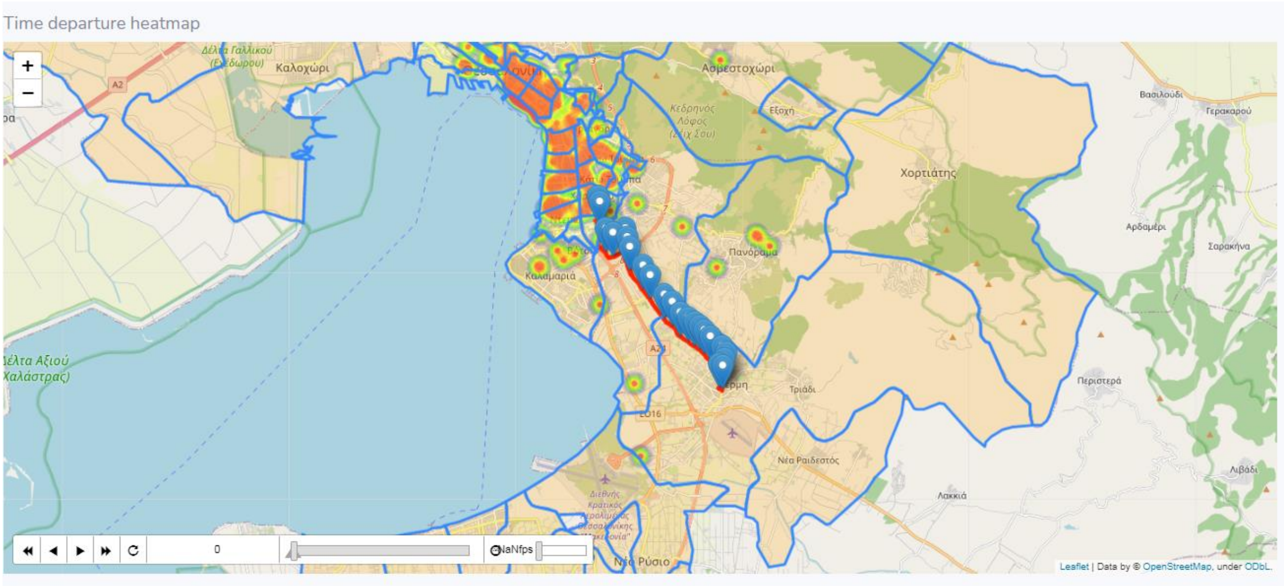

Figure 25: The spatial demand distribution visualizations.

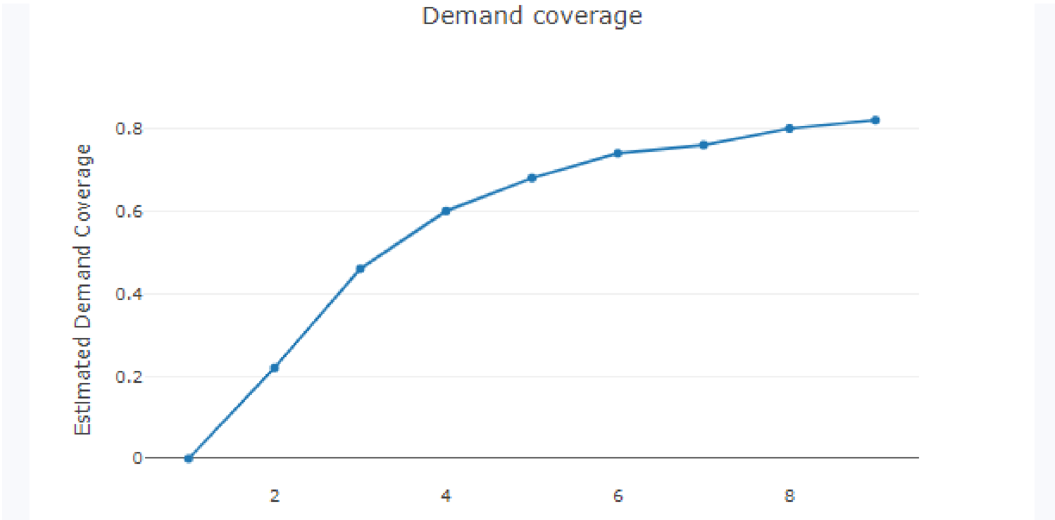

Figure 26: The demand coverage for different fleet sizes.

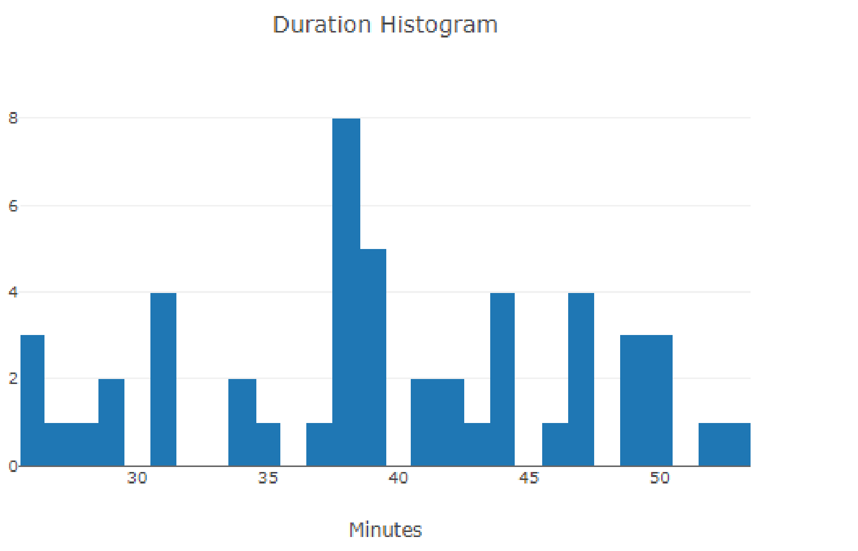

Figure 27: The average route duration for the flexible DRT service.

Figure 28: The final location of stations (blue circles) out of the set of

Candidate stations (red circles) for scooter sharing service.

3.4.5 Decision Support Tool Level 2 models

The theoretical analysis includes both operational and planning modules. The planning step contains the description on how to optimize the location of stations that service will use, the number of vehicles and the according capacity, and the number of shared resources (in case of BS, SS, CS). Those strategic parameters evaluated via the operational algorithms. Each service requires different operational algorithm to be evaluated. More precisely, DRT service evaluated via the Dial-a-Ride problem, BS/SS/CS evaluated with the use of rebalancing programs, while ridesharing performs a matching and routing MIP. As Figure 29 presents the planning process proposes a set of stop and vehicles candidates along with different subsets. The operational algorithms evaluate the robustness of those subsets so that the optimal one to be chosen. Following sections illustrate all those methods extensively. The descriptions also contain the inner algorithmic parameters, requirements, and outputs.

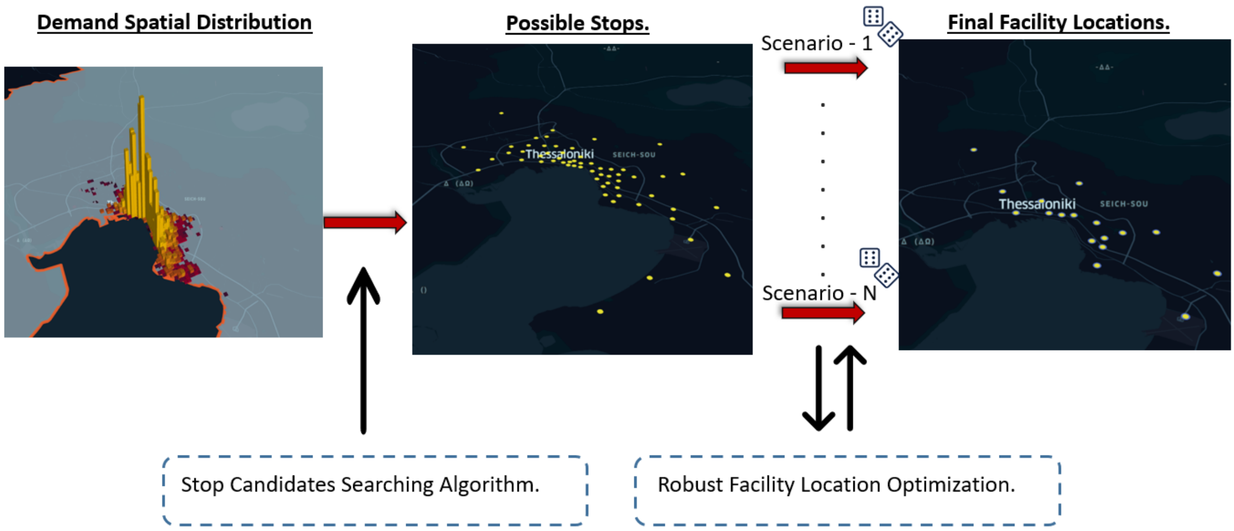

Figure 29: Planning process general flow

3.4.5.1 Planning

As previously mentioned, the purpose of the study is to develop a methodology which uses real-world data to determine the optimal location, number and size of stops that a given service will require for optimal deployment. The process is based on three consecutive steps:

- Extract candidate stops
- Conduct experiments and scenarios based on the actual demand and the set of candidate stops
- Extraction of optimal subset based on mixed-integer program

The first step is to extract candidate stops. The procedure is described in Deliverable 4.1 The origin-destination data of the trips are entered as input. These data reflect the spatial distribution of demand in the area of interest. Then the number of stops to search for, are entered as a decision variable along with the desired mean distance each user need to walk. The goal of the algorithm is to find the optimal number of stops which makes the average walking distance closer to the goal for each stop and user. To create stops, the clustering algorithm of K-means is used, where the centre of each cluster is the station/stop location. This way, starting with a small number of stops (station spaces) and gradually increasing them, the average square error begins to decrease to the point which adding further stations exceeds the original average walking distance target and increases the error. Thus, there is a point where the average distance value of the appropriate number of stops can be identified. The function used for the loss is the root mean squared error (RMSE), which is convex and so it always has a minimum. An example of RMSE and MAE errors for that process illustrated in Figure 30.

Figure 30: RMSE and MAE for different number of stations from desired mean walking distance

Then, as the candidate positions are defined, a methodology is developed to help make use of the actual demand in order to evaluate the contribution of each position so it is possible to select the best subset. For that best and most robust extraction of results the process will be repeated for each hour and in multiple runs of experiments. The goal is to understand the value of each station in the overall system. A key element for the progress of the analysis is the table of origin / destination where it contains the flows of the dataset in the positions where they qualified as candidates. So, for every hour there are pairs that contain the number of trips from position i to j. Thus, the vectors P, D, U ∈ R^N - - are defined for the sum of departures (pick-up), arrivals (drop-off), and unbalancing respectively, where N is the number of candidate stops. These 3 vectors are key elements of the subsequent process. To be precise, they act as a stop selection point. Specifically, the sum of P and D is derived from the cumulative probability density distribution G(x) of visiting each stop that operates as a random sampling roulette. In addition, vector U is derived the probability density distribution F(x) of the imbalance of each position. The higher the imbalance the higher the probability to drop the station. Thus, the stop selection algorithm is developed as follows:

Input:

- Desired coverage range: The percentage of existing demand that should be met.
- Number of experiments: The number of stop samples.
- Maximum cancellation distance: The distance that a user will not walk to reach a stop. The distance that a user will not walk to reach a stop. From that stop and then the user not willing to join the service

Processing:

- For each hour and repetition of the experiment:
- Station selection based on the G(x) distribution.
- Set a random number τ between0-1.
- If for this stop the greater than t of probability F(stop) go to step 4, otherwise return to step 1.
- Remove the stop and distribute the demand to the rest of stops. If a user has a closer stop beyond the maximum cancellation distance remove it from demand.
- Recalculation of the demand covered by the system.

- If the demand covered is less than the target end; otherwise go to step 1.

The process contains two important points. The first is the choice of the stop to be removed. The reason for using roulette and random sampling is that choosing the position with the least demand is not always the best choice. Thus, a possible stop choice can lead to better (lower cost) solutions as it allows the exploration of more possible situations. The second part concerns the use of the imbalance vector. The purpose of the vector is to consider the redistribution needs. The ideal scenario is for all station to converge to a balance situation naturally. Specifically, the inflows should be equal to the outflows. Hence, a position with a high rate of imbalance is more likely to be removed from the algorithm. The aim of this move is to bring the system into physical equilibrium as much as possible by reducing redistribution costs to both fleet size and mileage and, consequently, fuel. In addition, it is considered a limit beyond which a user will not make the effort to join the service. Thus, the removal of a stop would imply the loss of a percentage of demand.

Based on the results of the second step, each stop is characterized by an importance value indicating the number of times this stop is picked in the final setup along with the portion of demand it serves. The final selection of stations is then extracted via a mixed-integer alternative of the p-median problem. The resulting variables of the problem are:

Y_{ij} = $\begin{cases} 1 if demand\ node\ i \in I\ assigned\ to\ facility\ locaetd\ at\ j\ \in J \\ 0, otherwise \end{cases}$

X_j = $\begin{cases} 1\ if\ facility\ \ j\ \in J \\ 0, otherwise \end{cases}$

f_{ij}^{in} = The number of users will destinate instead of node $i \in I$ to facility located at $j\ \in J$ in the case i merged with j

f_{ij}^{out} = The number of users will destinate instead of node $i \in I$ to facility located at $j\ \in J$

$m_j =$ The frequency facility j selected as a final location.

$p_j =$ The percentage of demand facility j covers.

The p-median used here differs from the classical problem as it also involves the imbalanced stations problem and the characteristics each station has according to the experiments of the second step.

$$\min \sum_{i\in I} \sum_{j\in J} d_{ij} Y_{ij} + \sum_{i\in I} \sum_{j\in J} (f_{ij}^{in} - f_{ij}^{out})^2\ Y_{ij}$$

s.t $\quad \sum_{j\in J} Y_{ij} = 1, \forall\ i \in I \qquad (1)$

$$Y_{ij} - X_j \leq 0 , \forall \ i \in I, j \in J \tag{2}$$

$$\sum_{j \in J} X_j = p, \forall \ j \in J \tag{3}$$

$$\sum_{j \in J} m_j X_j \geq z , \forall \ j \in J \tag{4}$$

$$\sum_{j \in J} p_j X_j \geq l , \forall \ j \in J \tag{5}$$

$$X_j \in \{0,1) , \forall \ j \in J \tag{6}$$

$$Y_{ij} \in \forall \ i \in I, \ j \in J \tag{7}$$

The first difference is in the second term of the objective as it tries to match station in a way that the inflow is close to the outflow. The constraints (1)-(3) and (6)-(7) remain the same as the original problem while (4)-(5) allow user to define some features the stations should have.

3.4.5.2 Operational

The operational part aims to evaluate the setup of the stops and vehicles at each iteration of the planning procedure. Indeed, there are some costs and KPIs which are difficult to estimate without the use of operational algorithms and experimentation with multiple instances (simulation). This procedure ensures that the estimated values of the performance of the service will be more accurate and robust, so they will lead to a better optimal solution. For instance, the imbalance term of p-median problem it is not capable of showing the actual cost of rebalancing. Moreover, metrics like average trip distance, duration and acceptance probability of a request are also important aspects that will enhance operational algorithms and simulation.

The following section briefly describes the operational characteristics of the services along with inputs-outputs and the mathematical models used within.

3.4.5.3 Dial – a- Ride. (DRT)

The aim of this section is to describe the software module developed in MOMENTUM Task 5.2 to solve the Dial-a-Ride Problem. To facilitate the understanding of the section, we start by giving some background information about the Dial-a-Ride Problem with Time Windows, optimization algorithms to address this problem and OR-tools, the software library used to build this module. Subsequently, we describe the main characteristics of the module as the input data model, the implementation accomplished, and the output data model.

3.4.5.3.1 The Dial-a-Ride Problem with Time Windows

The Dial-a-Ride problem is a well-known problem in the combinatorial optimisation literature. In this problem, there is a set of customers to be picked up at an origin and dropped off at a destination and a fleet of vehicles to perform this task. The objective consists of finding the optimal routes (sequences of vehicle stops) for each vehicle to transport all customers, but subject to different constraints. Among the most common constraints for this problem, we have the time windows, that is, a time range at which customers must be picked up or drop off. This variant of the problem is known as Dial-a-Ride Problem with Time Windows.

DARPTW has been preceded by a family of pickup and delivery problems, which originates in the problem of the travelling salesman and the Vehicle Routing Problem (VRP). Unlike most vehicle routing problems where goods are transported, in DARPTW it is people who are moved from one location to another. For this reason, the quality of service ,as the time spent on-board by customers or the fulfilment of time window constraints, plays an important role.

More formally, the DARPTW could be defined on a graph $G = (V, A)$, where V is the set of vertices and A is the arc set. DARPTW contains a set of n customers and a set of m vehicles and has a set of transportation requests of clients, each of which is associated with a pickup (denoted by i^+) and delivery (denoted by i_-) location. Each stop, either pick-up or delivery, has a non-negative service time S_i, generally assumed to be similar at corresponding pickups and delivery, and two-time windows: $[l_{i+}, u_{i+}]$ for the pickup and $[l_{i-}, u_{i-}]$ for the delivery. In a pickup location, the demand is positive d_i in contrast to a delivery location where the demand is usually negative $-d_i$. A vehicle k has a maximum capacity q_k, and a maximum route duration t_k (S. Belhaiza, 2018).

In this way, the solution to this problem consists of generating a schedule in which each client is transported by a vehicle, complying with the time windows constraints. Each customer i must be pickup and drop off by the same vehicle within its respective time windows. Each route performed by a vehicle k does not exceed the vehicle load capacity q_k and its total duration does not exceed the maximum duration t_k. The total route duration would be composed of the total travel, waiting and service times. For this module, we have considered a simple scenario of a single depot, where the routes of each vehicle start and end.

3.4.5.3.2 Metaheuristics for the DARPTW

Metaheuristics are widely recognized as efficient approaches for many hard optimization problems (M. Gendreau and J.-Y. Potvin, 2019). They represent a core research field in combinatorial optimization, the field where the VRP variants and the DARPTW in particular, belongs to. Metaheuristics are often more suitable for practical applications than exact algorithms because of their good capabilities to obtain good enough solutions using reasonable time and computing resources. Although there are plenty of metaheuristics proposed for solving the VRP and the DARPT (R. Elshaer and H. Awad, 2020), we will focus here on the algorithm that is considered to be the state-of-the-art in many of their variants, Large Neighbourhood Search (LNS).

LNS is a meta-heuristic in which the neighbourhood of a solution is defined implicitly by destroying and repair operators. A destroying operator destroys part of the current solution while a repair operator rebuilds the destroyed solution. Typically, the destroy method contains some randomness such that different parts of the current solution are modified enabling exploration of the solution search space. This exploration technique enables larger neighbourhoods to be visited in comparison to standard neighbourhoods of classical local search methods. As said above, this property has made this method become the state of the art in many variants of the vehicle routing problem (V. Ghilas et al., 2016), (M. Abdirad, et al. 2020) and that is also why it is the method most commonly implemented in many software libraries and packages related to this field, such as the or-tool library, which we describe below.

3.4.5.3.3 The OR-tool library

To develop this software module, we have used OR-Tools[1]. It is an open-source software suite for optimization, tuned for tackling hard problems in vehicle routing, flows, integer and linear programming, and constraint

[1] https://github.com/google/or-tools

programming. The architecture provides programming language wrappers for operations research tools such as optimisation and constraint solving. OR-Tools was developed in the C ++ language, but also provide wrappers in Python, C#, and Java.

OR-Tools includes a specialized routing library to solve different types of node-routing problems, such as:

- Travelling Salesman Problems (TSP)
- Vehicle Routing Problems (VRP)
- Capacitated Vehicle Routing Problems (CVRP)
- Vehicle Routing Problems with Time Windows (VRPTW)
- Vehicle Routing Problems with Resource Constraints
- Vehicle Routing Problems with Pickup and Delivery (VRPPD)

The route solver that was developed for OR-Tools includes different set-up parametrizations such as the maximum duration, the number of solutions found, the initialization heuristics, or the global solver (e.g., Greedy Descent, Guided Local Search, Simulated Annealing and Tabu Search).

3.4.5.3.4 Input Data Model

In this section, we will describe the input data model designed for the DARPTW software module. In this way, the input data model is composed of the following classes: Input, Depot, JobList, Location, Station, Time Windows and Fleet. The hierarchy and relations among classes are displayed in Figure 31. Below, we describe all the classes:

- *Input* is the main class and contains the principal attributes of the data model: depot, the list of requests or jobs, the vehicle fleet, and the matrix of travel times between locations.
- The *Depot* class has as attributes the station identifier, which must be unique, and the time window that corresponds to this location. This time window attribute indicates the time range in which the vehicles can leave the depot.
- The *Job* class represents a trip request for a group of people from an origin to a destination. To model that information, each job has the following attributes:
    - Origin: represents the origin of the trip. This attribute is an object of the class Location, that in turn has two fields: 1) station, which corresponds to the place where customers should be picked up (given by an identifier); and 2) time window, that represents time range in which the customers must be picked up.
    - Destination: this attribute is analogous to the previous one, but of the destination of the trip request.
    - Demand: integer value that represents the demand for that Job, that is, the number of people that want to travel from the origin to the destination.
- The *Vehicle* class represents a vehicle of the available fleet. The only two fields of this class are the capacity of the vehicle and the maximum travel time of the vehicle.
- The *time matrix* attribute contains the travel times (in minutes) between each pair of locations, so it is a square matrix that has $n * n$ entries, with zeros in the principal diagonal.

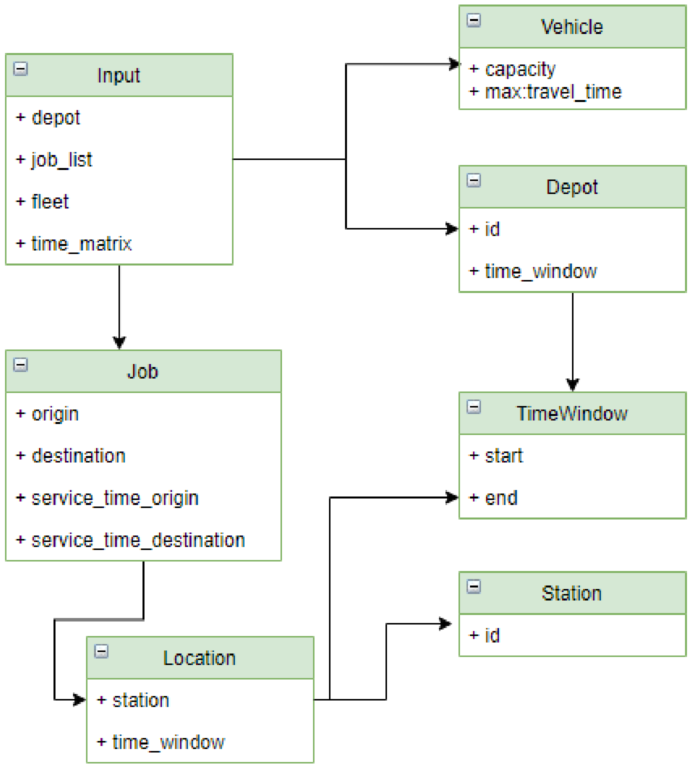

Figure 31 Class diagram for the input data model

3.4.5.3.5 Implementation of the DARPTW solver

In this section, we will describe the most important details of the implementation of the DARPTW solver developed using OR-tools. Concretely, we will first specify how the input data model is transformed to adapt it to the requirements of OR-tools, and then, how to set up the optimization strategy to solve the DARPTW problem.

3.4.5.3.6 Data pre-processing

As mentioned above, to obtain the solution to the problem we use the or-tools library. OR-Tools does not explicitly implement the DARPTW problem model but the VRPTW with Pick-up and Delivery (VRPTWPD). For this reason, we needed to transform the input data model in such a way that it fitted with the data requirements of or-tools for the VRPTWPS. In this sense, the main changes were related to the jobs or trip requests, for which we needed to do the next transformations (see Figure 32 for a toy example with these transformations):

1. Insert each job in the demand array by including a positive demand associated with the pickup and a negative demand associated with the delivery.
2. Insert each job in the pick-up and delivery array to link origins with destinations.
3. Insert origin and destination time windows in the time windows array.
4. Calculate a new time matrix that provides the corresponding travel times of the sequences of pick-ups and deliveries inserted in Step 1. The new time matrix is a square matrix of size $2 * number\ of\ jobs$.

Input Data

$$time\_matrix = \begin{bmatrix} 0 & 2 & 1 \\ 2 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix}$$

$job\ list =$

origin	destination	tw origin	tw destin	demand
1	2	(10,25)	(25,45)	3
1	3	(15, 25)	(30,40)	2

Data Pre-processing

1 $demand = [3, -3, 2, -2]$

3 pickup_deliveries= $[(1,2), (1,3)]$

3 $time\_window = [(10, 25), (35, 45), (15, 25), (30, 40)]$

4

$$time\_matrix = \begin{array}{c} \begin{array}{cccc} 1 & 2 & 1 & 3 \end{array} \\ \begin{bmatrix} 0 & 2 & 0 & 1 \\ 2 & 0 & 2 & 2 \\ 0 & 2 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix} \end{array} \begin{array}{c} \\ 1 \\ 2 \\ 1 \\ 3 \end{array}$$

Figure 32 Example of pre-processing applied to the input data model to fit the needs of or-tools

3.4.5.3.7 Solver configuration

In this section, we will describe how to set up the or-tools library to solve the DRPTW problem. More specifically, we will describe the parametrization of the routing search algorithm. The main parameters that or-tools allows to adjust in the optimisation strategy are the search limits, first solution strategy and local search options.

As for the search limits, we set the time limit parameter to 120 seconds, which restricts the maximum search time to 2 minutes. Continuing with the First Solution Strategy parameter, this sets the heuristic that is used to initialise the local search, i.e., to establish the solution from which the search process starts. In this case, we used the Path Cheapest Arc heuristic. This heuristic constructs a solution by starting a route from an initial node, to which it adds the node not yet assigned that has the shortest travel time to this initial node. Then, it continues this process taking the last added node as a reference. We chose this method because it is a simple and efficient heuristic to build solutions for VRP that usually gives good results.

Finally, the Local Search Options parameter sets the local search algorithm to be used. Among all the available choices, we select the guided local search, since it is the one that corresponds to the Large Neighbourhood Search. As we have said before, this algorithm is usually the one that offers the best results for this type of problem, so that is why we have decided to apply it.

3.4.5.3.8 Output Data Model

This section describes the definition of the data model of the solution that is obtained by the VRP module developed. The output data model is composed of the following elements: Result, a list of objects of class Route and KPIs. The hierarchy and relations among classes are displayed in Figure 33. Below, we describe all the classes:

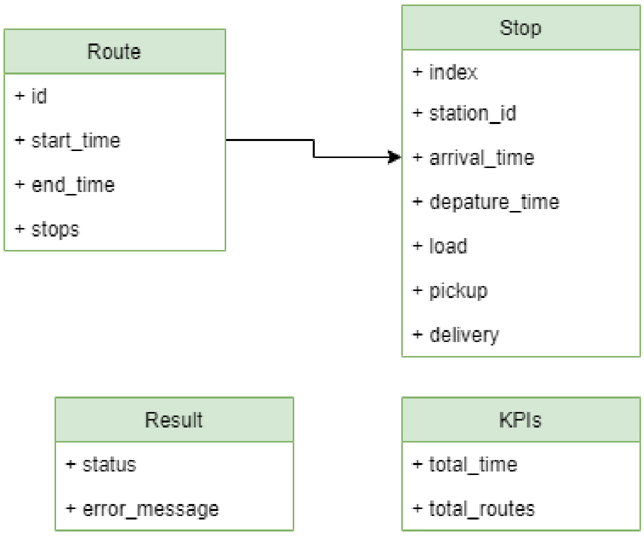

Figure 33 Class diagram for the output data model

- *Result* class whether the search process was successful or not. If a solution was obtained, the status attribute is set to "OK" and otherwise, it is set to "Error". In the latter case, a description of the reason why a solution was not found is included in the attribute error_message (e.g. search time limit has been reached). If the status attribute is set to "Error", Route and KPIs do not contain any value since no solution has been found.
- *Route* class represents the actual solution obtained. More specifically, each Route object corresponds to a vehicle, and it contains the sequence of pickup and deliveries that this vehicle must accomplish, starting and ending at the depot. The Route class has as attributes the route identifier, the start and end minute of the route, and an ordered list of objects of the class "Stop". Each object of the class Stop represents a pick-up or a delivery and it has the following attributes:
    - Index: order of the stop.
    - Station_id: identifier of the station of the stop as given in the input data.
    - Arrival_time: minute of arrival at the station.
    - Depature_time: minute of depart from the station.
    - Load: current number of customers in the vehicle.
    - Pickup: number of people picked up at that location.
    - Delivery: number of people dropped off at that location.
- KPIs class contains different Key Performance Indicators of the obtained solution as the total duration of the routes that compose the solution in minutes and the number of vehicles required to serve the demand.

3.4.5.3.9 Ridesharing taxi sharing

The ridesharing problem refers to the mode in which two or more commuters share a trip. In general, this service can take various forms depending on the model each provider chooses and the customer needs. Figure 34 presents 4 discrete alternatives of ridesharing schemas that can be implemented. In this module the Pattern-3 (Patrial RS) and Pattern-2 (inclusive RS) will be implemented. The matching algorithm and the different operational models of RS extensively described in Deliverable 4.1 in section 4.3. The strategic inputs this algorithm takes are:

- The size and the capacity of available fleet.
- The operational area.
- The demand requests with features:

- The origin and destination coordinates.
- The origin and destination time-window.

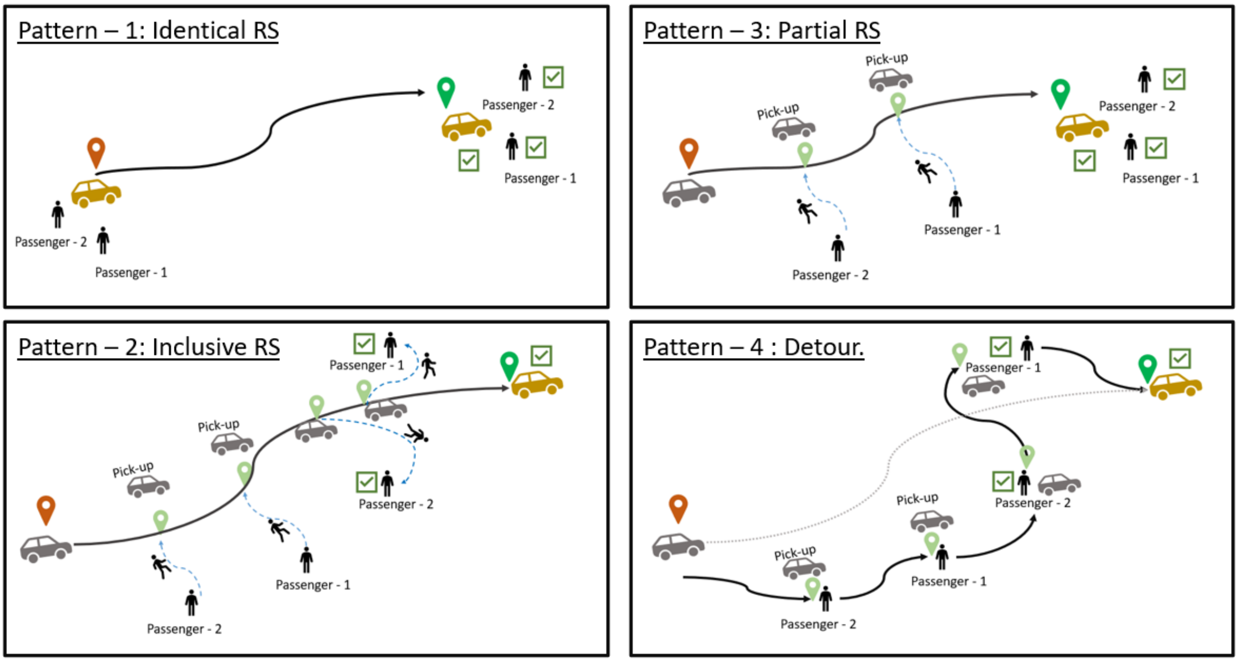

Figure 34: The 4 different Ride sharing patterns

At each simulation iteration the algorithm creates multiple requests, so the matching algorithm generates the shared trips. The aim of this approach is to estimate critical values of the service as:

- The portion of accepted requests.
- The mean distance of each trip divided by the shortest distance.
- The average occupancy of each vehicle.

Those metrics will be used to evaluate the fleet size and occupancy as well as the service area. For example, as the number of vehicles increases, the accepted requests also increases but the average occupancy decreases. The enumeration and experimentation across different strategic parameters provides users of the tool with insightful information to decide about the optimal system parameters.

3.4.5.3.10 Rebalancing bike sharing & scooters

The third operational algorithm supported by the tool solves the rebalancing problem. The rebalancing algorithm used to evaluate the planning of bike sharing and scooter sharing services. As before, this module is used to evaluate some operational characteristics of temporal strategic parameters. More specifically, it is used to evaluate redistribution costs, fleet utilization, and unbalancing related metrics. Table 6 summarizes the metrics extracted along with some comments about their usage. At each iteration of the experiments, a sample based on real world demand generated for each station. Given this generated demand the redistribution algorithm take place to perform the rebalancing and retrieve the performance of that operation.

Metric	Description
Km/Route	The average distance each vehicle spends for a single redistribution.
Bikes/route	The number of bikes each vehicle redistributes in a route.
Unbalancing/step.	The number of unbalanced docks the system has at each time step (e.g., hour)

Table 6: The outputs of rebalancing algorithm

The current development considers the special case of fully dock-based system so that the service users should pick-up/drop-off bikes or scooters only in predefined stations. More details about the system have been extensively discussed in D4.1.

1. Integration of planning and operational modules.

The interaction between planning and operational modules is in the metrics level. For instance, low occupancy of vehicles forces the planning algorithms to reduce the fleet size. In that sense, the two modules are completely independent in terms of software integration. The only interaction is based in the input and output those two stages exchange.

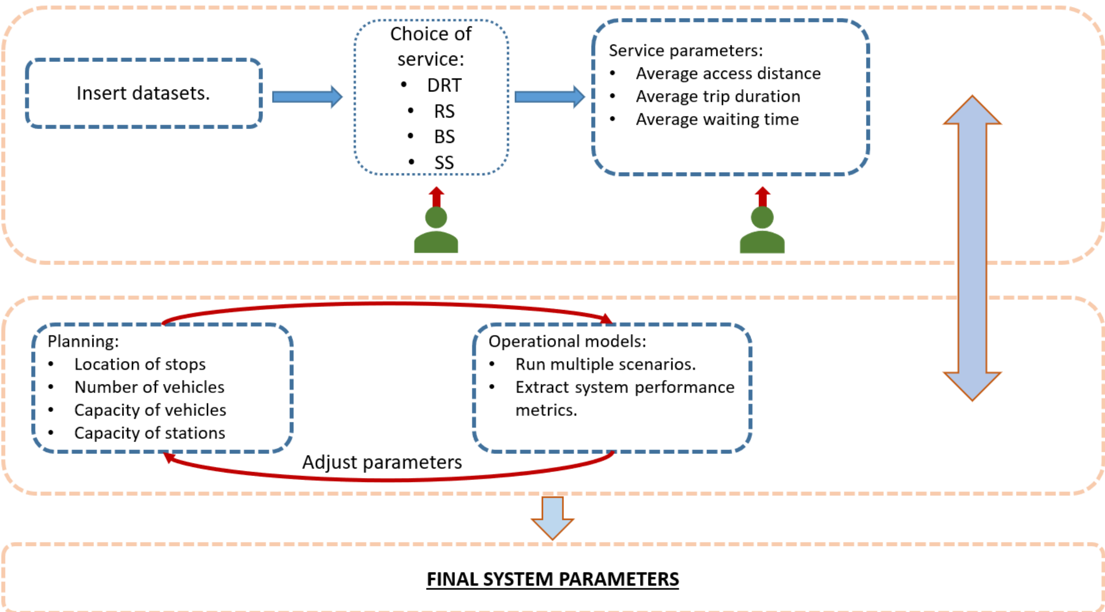

Figure 35: The connection between the modules.

The final outputs contain numerical results with service level metrics as well as visual demonstration about demand analytics or the location/plan of the service. The numerical outputs involve:

- The fleet sizes.
- The location of stations.
- The capacity of stations.

- The average route duration.
- The average route distances.
- The expected demand coverage.
- The average waiting duration.
- The average walking distances.
- The CO2 emissions per hour.

Those results are also illustrated visually along with their values for various strategic planning parameters. The main scope is to give to the user a tool that is easy to handle while providing insightful outcomes. Moreover, it is easy to adjust and manipulate the parameters and make its own decision. Hence, anyone using the tool can adapt, explore and experiment with different solutions.

3.5 Level 3 - Comprehensive Transport planning

3.5.1 Introduction

The last step of the multilevel decision support tool, will involve a comprehensive analysis of the examined district by modelling the transport scheme of the selected city. Modelling can be a powerful tool in understanding the potential traffic impacts of the proposed solutions if used in an appropriate way. It can also enable strategies to be developed, aiming to mitigate environmental impacts.

3.5.2 Input data requirements

The input data used in Level 3, are the outcome of the methodological procedure developed in D4.1 and D5.1. In more detail, the results from the implementation of the modelling schema, consisting of the supply and demand models developed in the project D4.1 is integrated into the transport simulation framework in Task 5.1. Information derive from the transport simulation, will be used as input data to the Level 3 of the decision support tool. In particular, a range of KPIs obtained from the evaluation of different shared mobility services will be provided. Those KPIs are obtained from the different models that are integrated in Task 5.1.

In Task 5.1 the integration of the proposed modelling schema into Aimsun transport simulation framework is presented. The integrated framework provides the capability to model and assess new shared mobility systems in a more comprehensive manner compared to the capabilities of Levels 1 and 2, due to the fact that the input data used for the T5.1 require an extensive analysis of transportation data. More specifically, the disaggregate mode choice model provides the modal splits for each person including the new shared mobility modes as well as the conventional modes as a whole (i.e. private cars, public transport, etc.).

3.5.3 Insights derived

The advantage of Level 3 of the decision support tool is its capability to accurately predict the potential impact of emerging mobility scenarios and optimise the planning of such services. This can be achieved due to the utilisation of adequate methods that can capture multi-disciplinary impacts with respect to the demand and supply for new services, the fleet management effectiveness as well as environmental impacts. The results from the deployment and evaluation of various scenarios in the context of the MOMENTUM project, will be provided to Level 3 of the interactive decision support tool in order to be visualised and support the formulation of policy objectives and impact assessment of alternative policy strategies scenarios across a range of KPIs.

The mobility service simulator further provides KPIs related to the users of each service. These may include, waiting times for each user to be served, travel times to complete their trip. The number of served and unserved requests can be also collected from the simulation. Moreover, the models described in D4.1 and integrated in Task 5.1 provide indicators regarding traffic emissions, car-ownership as well as induced demand due to the introduction of new shared mobility services. For more information regarding the developed models that constitute Level 3 of the decision support tool, we refer the reader to Deliverables 4.1 and 5.1.

Based on the service indicators, the outputs of the Level 3 of the DST are included in the online visualization of the produced KPIS. More specifically, the KPIs that are provided in Level 3 include the kilometres travelled per shared mobility mode, the total travel times as well as the usage of each service fleet and capacities at stations (for station-based sharing systems). An online dashboard will be developed in the DST, so that users of the tool will have the ability to easily understand the effects of the proposed services to the city. Interactive graphs will be used to achieve the optimal solution for the user to present estimated results and understand the added value of the services to the ultimate user of the proposed systems, the people who live and visit the city. The list of KPIs can be extended depending on the needs of a specific case study in terms of the type of impacts to be analysed due to the introduction of shared mobility services in their city.

The proposed integrated modelling framework will be applied in the test bed case of the city of Thessaloniki. Based on the knowledge gained from Thessaloniki, the integrated framework will be tested in to the remaining three city partners (Madrid, Leuven, and Regensburg). More information about level 3 implementation can be found on D5.3

3.5.4 Decision Support Tool Level 3 models

In relation to the planning and evaluation of emerging mobility systems, traffic simulation can be used to model and analyse the feasibility and performance of the transportation system due to the introduction of new shared mobility applications and policies. Simulation of the transportation systems is a valuable means that is being widely used to evaluate various transport planning applications and interventions. The core advantage of simulation is that different scenarios can be designed and analysed in a timely manner and a range of adequate performance indicators can be obtained in order to support cities and authorities in their decision-making process for introducing, for example, a new infrastructure, traffic management strategy, intervention, etc.

In level 3, the fleet operational algorithms developed for each examined service, interact with the shared mobility services simulation platform Aimsun Ride (Aimsun, 2020). This integration allows to execute the requests in a simulation environment according to the optimised trip plans. Various indicators with respect to both the users of the service as well as the service performance are obtained through the simulation. The main advantage of the simulation is the capability to provide more accurate predictions and extended KPIs, which are not available in Level 1 and Level 2 of the decision support tool due to the nature and limitations of the methodologies that they utilise. For a detailed description of the developed models, we refer the reader to D4.1. The proposed modelling schema consists of various models and algorithms that when integrated can provide the necessary functionalities in order to perform more accurate and realistic strategic planning and evaluation of emerging shared mobility services.

The simulation tool provides the flexibility of utilising traffic flows in order to replicate the network traffic phenomena. Concisely, depending on the scope of the analysis and desired level of detail in representing the traffic conditions, the network can be simulated. Hence, with respect to the network performance KPIs, depending on the network model resolution, various network performance indicators can be provided. For instance, in order to obtain realistic network performance indicators on traffic congestion and queues, a more detailed network model representation for the study area of interest would be adequate (e.g. mesoscopic, microscopic or hybrid macroscopic-mesoscopic).

3.6 Additional levels

As part of a holistic approach of the decision support tool, two more levels are suggested to be included. The first one will take place as a pre-analysis step under the name “City’s Strategy” and the second one will follow the last step of the previous three level decision tool (depending on the number of the level decided to be followed) titled as “Synopsis Module”.

3.6.1 City's strategy

This additional level of the DST, included all the preparatory steps to be followed by cities that do not participate as test users under MOMENTUM project. Once a city requests to test urban mobility services, an identification of the needs of the city will take place. Furthermore, available mobility data will need to be identified in order decision makers can have an insight at which level of detail can investigate, based on the provided data. Meetings and workshops need to be implemented under this level, targeting to bring all stakeholders and mobility partners of a city, so that a general strategy for the city can be set. The actions at this level, shall be harmonised with WP6 actions.

3.6.2 Synopsis Module

The Synopsis Module is the final step of the DST. At this level, information about the produced KPIs, visualization charts and insights will be given to the cities as a useful tool to use that information for further consultation. Thus, at every level of the scientific core of the DST (Level 1, Level 2 and Level 3), user will have the ability to extract all the produced results from the tool. As mentioned, that step will follow the last level of investigation of the tool that a city can achieve based on the availability of data provided.

4 Decision criteria

In the development of the DST, different scenarios and transport modes are tested in order to specify system's transport dynamic. Network performance indicators are essential parameters in transport modelling evaluation models. Evaluating the performance

The development of the DST and the research activities in MOMENTUM encompass the development of assessing the impact of new mobility services in test case cities: Thessaloniki, Leuven, Madrid and Regensburg. Questions and needs in urban mobility services in the cities partners were included and described in the D2.2 of the MOMENTUM project. The four cities test cases are:

- Scenarios and policies for each city
- Datasets available in each city
- Novelties and evolutions
- Mobility policy priorities
- Suggested policies to be tested
- Questions to be addressed

Performance measures are necessary for evaluating transport interventions and are considered as a critical tool for reporting successes and opportunities. The ultimate purpose of measuring performance is to improve transportation services for users. Performance measurement is a useful tool that can help decision-makers and authorities to assess the importance of transportation and appropriate investment in transportation investments. Moreover, performance measurement provides both important inputs for setting priorities and critical information that helps decision-makers detect potential problems and make corrections, to meet goals and objectives of the mobility of the future

Considering the mobility policies and questions to be addressed for each study case of the cities, a list of the KPIs was compiled. It is important to mention that due to different level of granularity of input data for each level of the DST, a number of KPIs can be examined and tested. The list below shows the KPIs available in the DST, for each examined Level of the tool.

KPIs	Level 1	Level 2	Level 3
System's cost for each scenario	X	X	X
Travel times	X	X	X
Kilometers Travelled	X	X	X
Number of units needed (vehicles, bicycles etc)	X	X	X
Passengers' waiting time	X	X	X
Demand Coverage		X	X
Accessibility		X	X
Network coverage		X	X
Fleet's management operation - pick up points for DRT, station's locations from BS and micromobilitiy		X	X
Modal split (BS,CS,RS, Conventional Systems)			X
Kilometers Travelled per mode			X
Network's Performance Indicator (Congestion, Traffic flow, delays, travel times, queue lengths)			X
Use of active mobility means			X
Usage rate for each rate (Number of trips, percentage of time use)			X
Car ownership (number of people per 1000 citizens)			X

Table 7: List of KPIs available in each level of Decision Support Toolset

4.1 Visualization of metrics

The comprehensive approach of the DST includes the ability to provide a user friendly environment to test and assess the examined services. Data visualization of the metrics are going to help decision makers to understand the significance of results. In line with that principal objective, the DST will provide interactive dashboards for each Level of the DST. Graphs will be presented after the calculation of the level a user will choose to test. It goes without saying that the KPIs presented will be associated with the indicators described in the Table 7. Granularity of input data needed for each level of the DST, will define the level of detail of the produced KPIs dashboards.

5 Connection of the DST with MOMENTUM's Repository

The aim of this section is to describe how the connection between the DST and the MOMENTUM Data Repository has been made. This repository stores all the datasets and information sources collected and generated in this project. Since this repository is of private use for the project, the main purpose of this connection is to facilitate the use of the DST for the model calibration to be done in Deliverable 5.3 “Implementation of the MOMENTUM Decision Support Toolset in Madrid, Thessaloniki, Leuven and Regensburg” and also for the policy evaluation to be done, since most of the data to be utilized are stored in this repository. Furthermore, this connection would facilitate future integration between the DST and a public data repository that could be accessed by other cities beyond the cities of the consortium.

Based on that, we will first briefly describe the structure, implementation and the tools for accessing the MOMENTUM Data Repository in order to facilitate the understanding of the rest of the subsections. Then, we will explain and justify the approach used to connect the repository to the DST, taking into account the privacy and security aspects of the data. Finally, we will give some brief guidelines on how the repository data can be accessed and used from the DST.

5.1 The MOMENTUM Data Repository

As part of task “Data harmonisation and integration” of the MOMENTUM project, a data repository was developed with the aim of storing the datasets collected and generated in the project, according to the security and privacy levels required by each of them. The description of this repository can be found in deliverable D3.2 "Data Repository". In the root folder, there is a directory for each case study (Madrid, Leuven, Regensburg and Thessaloniki). On the first level within each case study's directory, there is a folder for each of the five data categories considered: Transport Supply, Transport Demand, Maps & Cartography, Socio-Demographic and Travel Times. At the next level, there is a folder for each of the subcategories that were defined within each category. Finally, at the last level of the hierarchy, we can find the folders that contain the datasets.

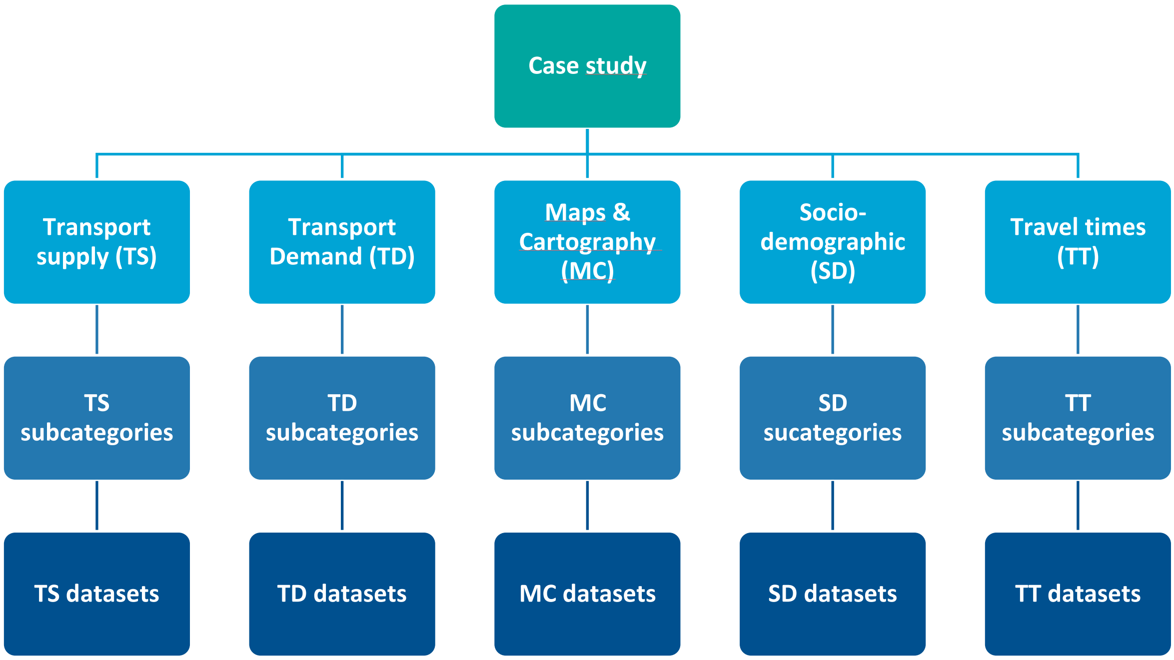

Figure 36: Scheme of the hierarchy of the MOMENTUM Data Repository

The repository was deployed using the Amazon S3[2], a web-based cloud storage service designed for online backup and archiving of data and applications. The main advantages of this service its high availability, scalability and security provided. In addition, it allows easy access and management of data through the use of different tools such as a web interface, a REST API, various SDKs in different programming languages or through third-party applications.

5.2 Available Data for DST

Based on the implementation of the Data Repository, for each of the four case study cities, different datasets were collected to be used for the testing scenarios. Categories of the mobility data stored in the repository include:

- Data from mobile devices (e.g., mobile phone records)
- Sensor data (traffic counts, parking data, etc.)
- Data on the use on new transport services
- Conventional data, such as information coming from mobility surveys

A total of more than 80 data sources are available in MOMENTUM's repository. They are classified into five main categories: transport supply, transport demand, maps & cartography, socio-demographic and travel time. For each of these five main categories, different sub-categories are also identified. Data quality assessment was also performed to each identified data source in terms of reliability, sample size, geographical and temporal scope, geographical and temporal granularity, completeness, validity and accessibility.

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[2] https://docs.aws.amazon.com/s3/index.html

5.3 Connection approach between DST and MOMENTUM Data Repository

For the design of the connection between the DST and the MOMENTUM Data Repository, we have taken into account the user-friendliness, but above all, we have prioritised the security and privacy of the data stored in the repository. Therefore, we ruled out the use of Third-party applications that could result in security breaches and decided to use only the tools provided by Amazon, and specifically the web interface provided by AWS. In this way, the different levels of access and privacy of each dataset defined in the Amazon S3 console will be guaranteed.

More specifically, the approach used for connecting the DST with the data repository is based on a connection link from the DST to the Amazon S3 web interface, mapping the link between those two elements. In this way, the user who is allowed to access the repository, after logging into the Amazon S3 application, can download the files to be used in the DST. The main drawback of this approach is that it involves more manual user interaction with the tool (it requires downloading the file from Amazon S3 and then uploading it to the DST), but, as mentioned above, this approach avoids exposure of the data repository and possible security breaches, given that the DST is public.

Furthermore, the connection between the DST and the MOMENTUM data repository is only required for Level 2 of the tool as for Level 1, input data do not require great storage needs as values need to be inserted manually by the user. For Level 3 due to the fact that input data need to be processed, based on the methodologies reported in D4.1 and D5.1. In the following subsection we explain step by step how to use datasets from the MOMENTUM data repository in the DST.

Finally, for the future exploitation of the benchmarking idea of the use of the DST beyond the MOMENTUM project, the development of a public data repository connected to the DST will be studied and the use of third-party applications such as Filestash[3] will be examined. The purpose is to make possible the use of data sources from a new repository in the DST, in a secure, user-friendly and simpler way for other cities.

5.4 Guidelines for the use of MOMENTUM Data Repository in the DST Level 2

The aim of this section is to briefly describe the steps to follow in order to use the datasets from the MOMENTUM Data Repository in Level 2 of the DST.

First, the user must click on the "Download from Repository" button in the field for which he/she wants to use a dataset from the repository, as shown in Table 2.

[3] https://www.filestash.app/docs/

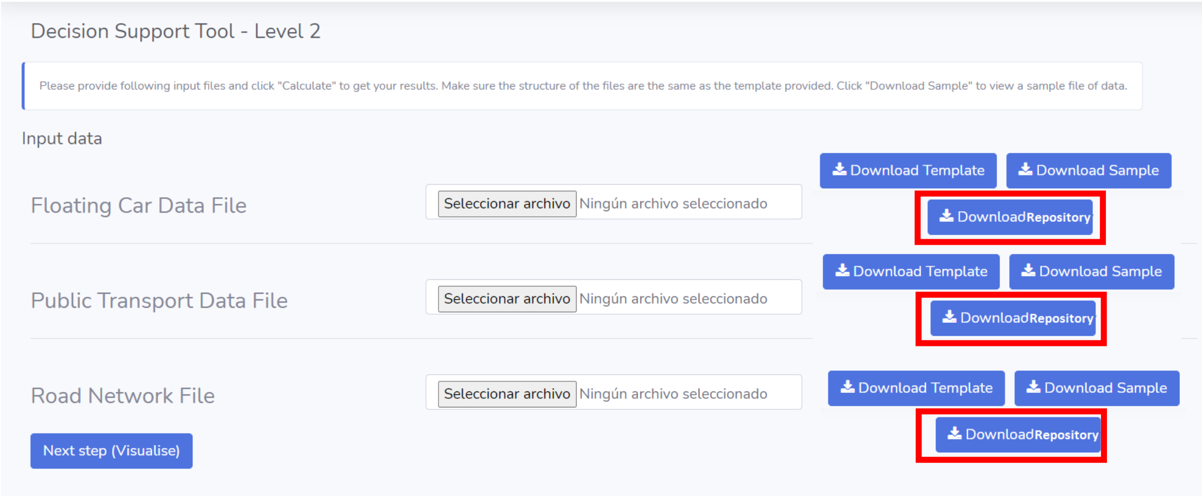

Figure 37: Level 2 DST with the button "Download from Repository" highlighted

This will take user to the login screen for the Amazon S3 web interface, as shown in Figure 38. In that dialogue, user will need to put their credentials to insert to the service.

Figure 38: Snapshot of Login page for Amazon S3 web application

Once inside the Amazon S3 web application, the user must access the corresponding buckets available in the repository and navigate through the hierarchy of folders until he/she reaches the dataset he/she wants to use. The user must then download the file and store it on a local drive, where it can be used later. We do not show snapshots of these steps in the repository for privacy and security reasons.

Finally, the user has to go back to Level 2 of the DST, click on the "Select file" button in the corresponding field (see Figure 39) and then upload the downloaded file of the dataset. Once files are imported, the user will follow the guidelines for testing Level 2 of the DST.

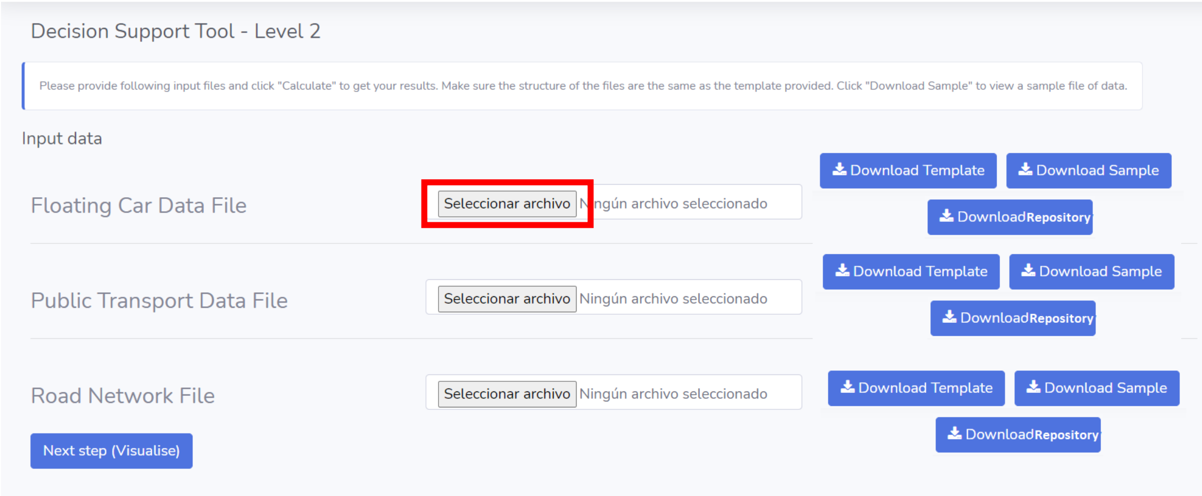

Figure 39: Level 2 interface with connection with the link of repository

6 Added value from the Decision Support Toolset

With emphasis on urban mobility interventions, there is an increasing desire from stakeholders to support implementation of proposed services, with value to business decision makers. Without guidance from an urban mobility roadmap model, transport investments might lead to network discontinuity or insufficient infrastructure for the examined area. Furthermore, based on the limitation of budget resources, an efficient and targeted distribution on invested budget can be

The aim of the multilevel DST described in this deliverable is to create the framework for decision makers to manage and assess urban mobility investments for cities. Depending on the data availability, solutions can be suggested in a centralized and secure manner, from governance and investors approach. Different sources of information affect the reliability of the implemented tool. Research has shown that the type of information provided to managers in support of decision-making, can have a fundamental impact on their contribution to the system.

The overall goal of the MOMENTUM project is to develop a set of mobility data analysis and exploitation methods, to capture the impact of new transport options and ICT-driven behavioural changes on urban mobility. The aim of the project is to support local authorities in the task of designing and adopt the efficient policy mix for each city, to exploit the full potential of emerging mobility solutions in a more sustainable and resilient way. Based on findings from MOMENTUM project and the integration of those methods in the DST, cities and stakeholders can test different mobility scenarios. Thus, the DST can be used as an assisting tool for transport planners and modellers to develop Sustainable Urban Mobility Plans (SUMPs). Existing mobility data, in any level of granularity, can be introduced into the DST to assist policy makers in forming sustainable urban mobility plans, though solutions and KPIs produced by the tool. Furthermore, business stakeholders associated in mobility sector, have the opportunity to easily test and assess the most efficient business plan. In that way, investments can be at some level secure, while following city's transport strategy, based on urban mobility data.

The recent COVID-19 pandemic crisis, changed in many ways the mobility habits of people. Due to the way COVID-19 spreading, travellers tend to avoid services that concentrate great amounts of users in closed spaces, in order to reduce virus spread. DST can provide decision makers information to test different mobility services for targeted solutions. On-demand and shared mobility systems can be an imminent and safe measure to tackle the pandemic crisis and increase city's resilience. Digital mobility tools can incorporate health and safety features by allocating emphasis on urban mobility modes that concentrate to the features decision makers want to target to. Furthermore, resilience provided by the proposed multilevel DST is outlined by the flexibility the tool can provide to cities. Though the procedure followed in each level, the economic assessment of the interventions can be evaluated. Thus, during challenging situations, budgeting can be allocated accordingly.

Conclusively, the multilevel decision support tool for urban mobility will identify the principal strengths and weaknesses while considering a broader issue of how an integrated urban decision support system can be developed using a wide range of criteria and including socio-economic, environmental information and stakeholder participation into the decision making process.

7 Conclusion

This document outlines the role that a targeted decision-support tool can play in facilitating the use of received information in urban mobility decision making. The decision support tool is unique because it concentrates on mobility questions for each studied area meeting the specific needs of district-level decision makers. The DST facilitates the ability to better understand the status of urban mobility in a city. This experience has not only improved data-informed decision making but also provides an important experience of how to identify and meet information needs that can be applied to the development of the mobility of a city.

In cities, sustainable mobility has become promising as it leads to a reduction in city's congestion and pollution, through strategies that remove the single or less occupant personal vehicles on the road. Systems such as bike sharing, car sharing and DRT systems have existed for many years. However, with the advancements in information and communication technologies, the recent advances and developments of disruptive innovations in mobility have become possible at a scale. In addition, these app-based platforms coordinate the on-demand vehicles and pairing to share rides for a long-term efficient transport system. This trend has been benefited by AI technology to improve the customer experience and streamline their businesses. The provided personalized customer experience to the users has become possible with the integration of AI to transportation modes, enhancing the reliability and efficiency of the systems.

The proposed multilevel decision support tool presented in this report consists of five levels. Three levels create the technical core of the decision support tool, investigating the effectiveness of different urban mobility proposed schemes to the examined areas. Each of these levels have a different level of depth of investigation. Thus, a comprehensive analysis is implemented depending on various and specific mobility data.

The aim of the first level of the decision support tool is to identify applicable urban mobility interventions using geospatial data and the cost of their implementation. On the second step of the decision support tool, the goal is to facilitate comprehensive mobility actions by analysing mobility data. Finally, in the last level of the tool an extensive transport planning analysis of the city is undertaken. The remaining two levels enhance the effectiveness and efficiency of the tool. The city's strategy is a preliminary analysis of the existing city infrastructures and the potential identification of new candidate infrastructures. On the other side, the monitoring schedule will be implemented at the end of the last level applied in the decision support tool. The monitoring schedule is an integrated assessment tool of the efficiency of the proposed options from the previous steps..

In conclusion, the proposed interactive Decision support tool is a scientific framework for assessing and evaluating emerging mobility services. The decision support tool, is a standardized methodology for mobility projects depending on each examined district and city's parameters. Furthermore, the extension of the DST depends on a great level, in the availability of transport data in the examined area. The insufficiency of data is not a disincentive parameter in terms of the importance of implementing a DST for urban mobility investments. If local authorities are not able to provide detailed data, then the number of steps of the decision tool that can be implemented, is constrained.

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9 Annex

In this section a selection of recent work found in literature on Decision Support System is presented, describing examples of the implementation of DST in Transport.

- A high-level strategic assessment tool. It is composed of existing tools and new models and is based on the classic transport model for transport demand of passengers and freight. This tool enables the user to define a policy scenario in order to compute the policy assessment (Szimba, E., Mandel, B., Kraft, M., & Ihrig, J. 2017Combined Discrete Choice Models (DCM) with Agent-Based Models (ABM). The aforementioned combination enabled for taking stakeholder's opinion into account to explore shared policy packages. (Le Pira, M., Marcucci, E., Gatta, V., Ignaccolo, M., Inturri, G., & Pluchino, A. 2017)
- A Spatial Decision Support System (SDSS) that aids medical personnel with their crucial and time-dependent decision-making process while using real-time dynamic and static spatial and non-spatial data (Vasilyeva, Y., Widener, M., Ginsberg, Z., & Galvagno, S., 2016)
- Artificial intelligence tools were used in the decision support tool for container transport logistics. Specifically, the tool is equipped with a combination of Artificial Neural Networks (ANN) and Fuzzy Logic, thus creating Fuzzy Cognitive Maps (FCM). FCMs are created based on domain expert knowledge (Tsadiras, A., & Zitopoulos, G. 2017).
- A method based-decision support tool for urban transport system resilience management was implemented that "aims at managing critical infrastructure resilience through a more complex and expressive mode". The model is based on Functional Resonance Analysis Method (FRAM) and exploits smart city data in order to output strategies and recommendations for variability dampening at strategic, tactic and operational stage (Bellini, E., Nesi, P., Pantaleo, G., & Venturi, A. 2016).
- A comprehensive framework was designed, comprised of rough number-based decision-making for sustainable freight transport system evaluation. It is discovered that rough number-based methodologies have advantages over fuzzy or interval-based models (Yazdani, M., Pamucar, D., Chatterjee, P., & Chakraborty, S. 2019)
- A methodology is proposed based on the Analytic Hierarchy Process (AHP) which can utilized for sustainable urban transport planning while taking into consideration the inconsistent and uncertain passengers' and stakeholders' results (Ghorbanzadeh, O., Moslem, S., Blaschke, T., & Duleba, S. 2018)
- A Fuzzy Analytic Hierarchy Process (AHP) and a Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) prioritize effectively the multimodal transportation routes to improve logistics system performance by constructing the possible routes considering transport cost, time, risk, and quality factors. The proposed methodology produces an accurate, practical, and systematic decision support tool (Kaewfak, K., Huynh, V. N., Ammarapala, V., & Charoensiriwath, C. 2019)
- A framework for real-time evacuation planning was developed that combines the results obtained from hydrodynamic modeling and traffic microsimulation. The results from both models were combined to generate a time-lapse animation of emergency evacuation and visualized via Geographic Information System (GIS). (Fahad, M. G. R., Nazari, R., Bhavsar, P., Jalayer, M., & Karimi, M. 2019)

Reference	Characteristics	Methodology
Szimba, E., Mandel, B., Kraft, M., & Ihrig, J. 2017	High-level strategic policy assessment, Multimodal, single user, Data-driven, Strategic, Hybrid, Dynamic and Static	Mixed methodologies (Classic transport model and others)
Le Pira, M., Marcucci, E., Gatta, V., Ignaccolo, M., Inturri, G., & Pluchino, A. 2017	Urban freight transport, Single user, Knowledge-driven, Strategic, Dynamic	Discrete Choice Models (DCM) with Agent-Based Models (ABM)
Vasilyeva, Y., Widener, M., Ginsberg, Z., & Galvagno, S., 2016	Real-time trauma transport, Road, Single user, Data-driven, Operational, Optimization-based, Deterministic, Dynamic and Static Data	Spatial Decision Support System (SDSS)
Tsadiras, A., & Zitopoulos, G. 2017	Container transport logistics, Single user, Data and Knowledge driven, Strategic, Static and Dynamic Data, Interactive	Artificial Neural Networks (ANN) and Fuzzy Logic
Bellini, E., Nesi, P., Pantaleo, G., & Venturi, A. 2016	Urban transport, Group-oriented, Data-Driven, Strategic, Tactical, Operational, Smart City Dynamic and Static Data, Interactive	Functional Resonance Analysis Method (FRAM),
Yazdani, M., Pamucar, D., Chatterjee, P., & Chakraborty, S. 2019	Sustainable freight transport	Rough number-based
Ghorbanzadeh, O., Moslem, S., Blaschke, T., & Duleba, S. 2018	Sustainable urban transport planning, Single user, Data-driven, Strategic, Static Survey Data	Analytic Hierarchy Process (AHP)
Kaewfak, K., Huynh, V. N., Ammarapala, V., & Charoensiriwath, C. 2019	Logistics, Single user, Data-driven, Strategic, Static Data	Fuzzy Analytic Hierarchy Process (AHP) and Fuzzy Technique for Order of

		Preference by Similarity to Ideal Solution (TOPSIS)
Fahad, M. G. R., Nazari, R., Bhavsar, P., Jalayer, M., & Karimi, M. 2019	Real-time evacuation planning, Data-driven, Simulation-based, Real-time, Dynamic and Static Data,	Hydrodynamic modelling and traffic microsimulation

Table 8: Summary table of key characteristics and methodologies of the recent work review