Article

A Game-Theoretic Approach for Mobility Analysis Tools

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Abstract: The mobility ecosystem is rapidly evolving. New forms of mobility offerings start to appear within cities, and new insights into the performance of certain solutions begin to materialize. However, integrating disruptive solutions and assessing their potential socio-economic and environmental impacts within the designs of policy makers remains a challenge. Although there is a big variety of mobility analysis tools available, for the decision-making process it is often necessary to consider competing interests of different stakeholders, and different aspects of key performance indicators (KPIs). In this paper, mobility services are considered as a game, namely a Stackelberg game, where each alternative of solutions receives a score based on weights assigned to different players (or groups of players) and to different aspects, i.e., environmental, economical, and social for selected KPIs. This approach aggregates different aspects into a single solution, and it is illustrated on two use cases, shared-mobility operative area analysis and assessment of traffic management scenarios. Our methodology allows proper decision making on policy instruments given different priorities of the decision maker.

Keywords: game theory, Stackelberg game; Nash bargaining solution; policy instruments for mobility; decision-making on mobility

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1. Introduction

One of the substantial goals of a smart city is the interconnection of various systems and subsystems to provide a better quality of life, energy savings and cleaner environment. For instance, the urban mobility ecosystem is interrelated with other systems, such as energy, urban systems, eGovernment, etc. In a smart city, an electric car could communicate directly with the energy network and reserve a necessary capacity and a charger, or the infrastructure could communicate directly with power plants to optimize energy supplies based on the demand of vehicles [1]. Hence, in addition to datasets and models, mobility analysis tools are required to assess the performance of the mobility ecosystem, as it has implications for the environment, economy, social cohesion, quality of life, and the location and intensity of various activities of citizens.

An improved transportation system may imply the change of a location of people and industry, but also vice versa – a change in land use, such as building of estates, business centres, factories etc., has an influence on travel demand [2]. Therefore, it is useful to consider a smart city as a complex system in the sense of systems theory, more specifically as a cyber-physical system (CPS), and model it as a Multi-Agent System (MAS) [1]. An agent in a MAS can stand not only for a software agent or a robot, but also for a model of a human or some institution or any other entity. MAS can thus be used for the simulation of the actions of various participants in the mobility system. In these agent-based models (ABM), individual travellers and also individual vehicles are treated as autonomous agents with their own goals and behaviours that learn and update their travel patterns iteratively on the basis of defined rules, as they interact among themselves and with the environment [3].

A standard tool for the analysis of agents' interactions and behaviour represents game theory. In general, the concept of a game denotes any decision situation, the result of which depends on decisions of at least two different entities, so-called players, which have at least two different strategies to choose from. These players can be, e.g., various firms in the market, politicians, political parties, shareholders, travellers, users of various networks, creditors of a bankrupted company, or even genes that control the behaviour of their bearers in certain situations.

Furthermore, the mobility ecosystem is rapidly evolving, whereby we see the rise of new stakeholders and services. As new forms of mobility offerings start to appear within cities and regions, new insights into the performance of certain mobility solutions begin to materialize. These insights can highlight the needs of citizens on mobility, reveal new risks, enable new policy instruments, and determine the impacts of mobility services through Key Performance Indicators (KPIs). In [4] we conducted an extensive study on mobility analysis, researching the trends and opportunities, gaps, involved policy instruments, business models including roles of different stakeholders, categories of usable tools, high-level use cases involved, solved challenges, inputs, outputs and KPIs of selected mobility services.

Successfully integrating all these disruptive technologies and solutions within the designs of policy makers remains a challenge, let alone being able to analyse, monitor, and assess mobility solutions and their potential socio-economic and environmental impacts. Therefore, the traditional classification of mobility services and tools, such as in [5], is no longer suitable as it does not take into consideration mobility as a part of a city system, with demands on interdisciplinarity, sharing of resources and various additional topics [4].

To address these shortcomings, the European project nuMIDAS (New Mobility Data & Solutions Toolkit) [6] bridges this (knowledge) gap and creates a tangible and readily available toolkit that can be deployed elsewhere, including a set of transferability guidelines, thereby contributing to the further adoption and exploitation of the project's results. The project nuMIDAS, which is being solved by partners including the authors of this paper, envisions a decision-support toolkit according to the model depicted in Figure 1, previously presented in the conference paper [7].

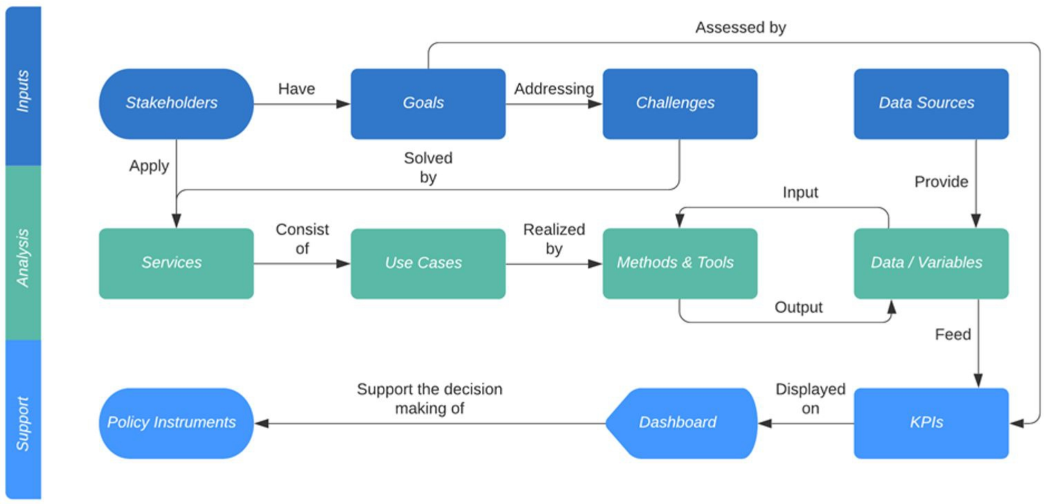

Figure 1. The process of a decision-support toolkit (source: own elaboration)

Figure 1 illustrates that *Stakeholders* (e.g., public transport operators) have certain *Goals* (e.g., environmental sustainability) that are addressing *Challenges* (e.g., estimate and reduce the emissions) within a city or their domain. In order to tackle those Challenges, they apply certain *Services* (e.g., public transport management). The Services can be rather large;

therefore, it may consist of several *Use cases* (e.g., priority management). *Methods and Tools* (e.g., microscopic simulation) can be used to determine the impacts and optimise planning and operations of the service. *Data sources* (e.g., city sensors) may input Data/Variables (e.g., travel demands) in the Methods and Tools, which will generate outputs for *KPIs* (e.g., travel times, queue length, or CO_2 emissions). These KPIs can be incorporated into a *Dashboard* to show, for example, changes in different scenarios. In this way, Stakeholders can decide on the suitable *Policy instruments* (e.g., public transport priority) that focus on multiple goals.

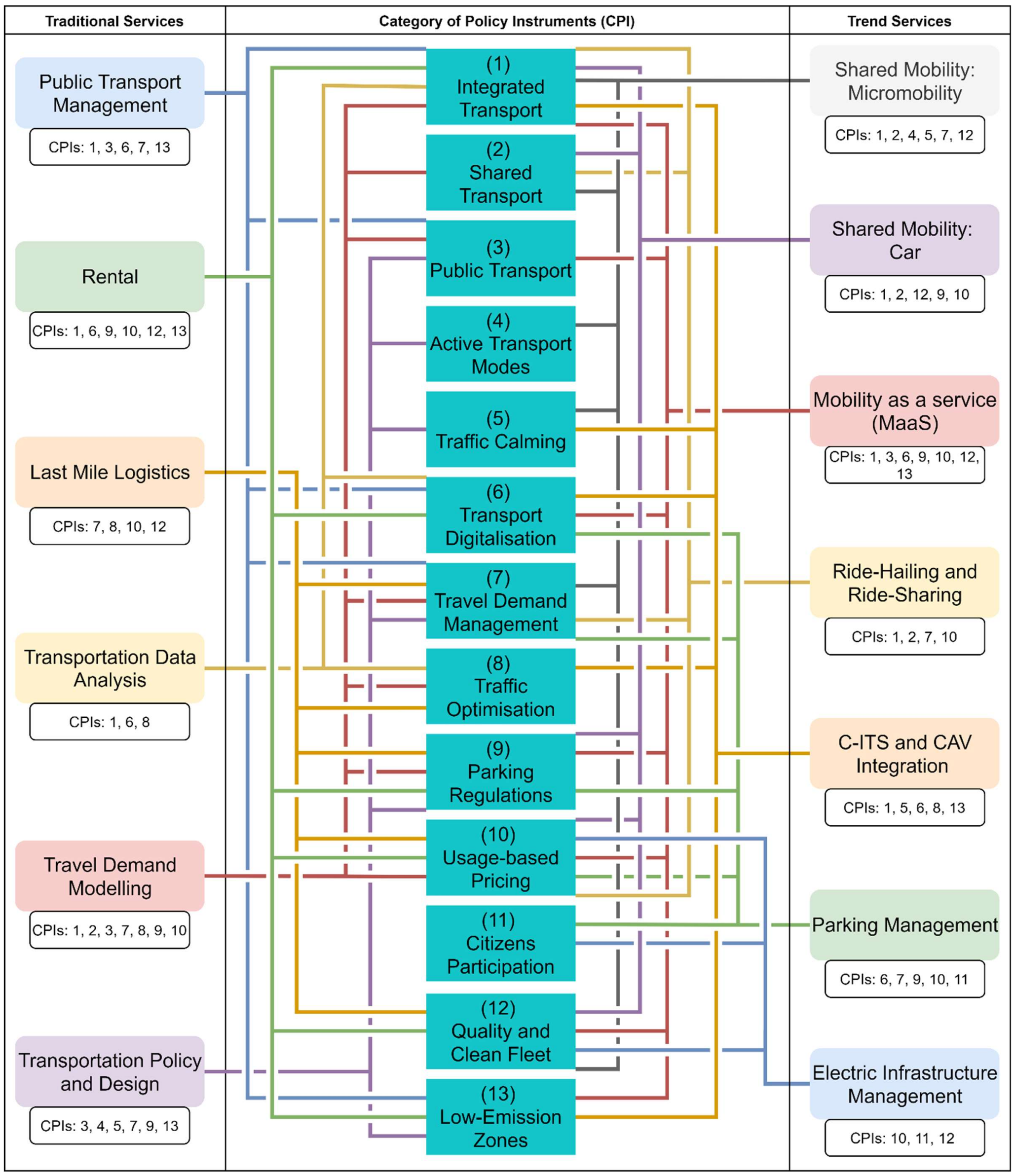

Figure 2. Relation between mobility services and categories of involved policy instruments (source: own elaboration).

In [4], we introduced a relation between mobility services from the perspective of common categories of policy instruments, what is exemplified by the parking management service covering route guidance to available parking places (transport digitisation), reduction of off-street parking spaces to decrease the likelihood of owning one or more cars (travel demand management), parking permits (parking regulations), pricing policy that varies by time of day and by location (usage-based pricing), and shared parking (citizens participation). A graphical overview of these categories is provided in Figure 2, where each Category of Policy Instruments (CPI) is connected to selected traditional (e.g., transportation policy and design) and trend mobility services, such as Cooperative Intelligent Transport Systems (C-ITS) and Connected and Automated Vehicle (CAV).

1.1. Reasoning and Contributions

The enormous amount of gathered data by municipalities, service providers and other related or unrelated parties is the key to the ability to make complex decisions. Integration and smart use of data for the design of the transport system and policy design are important but challenging. It is certainly useful that a huge variety of tools are available in the urban mobility field, allowing simulation of different scenarios, impact evaluation for different policy instruments, solution of various optimisation tasks, enumerating various Key Performance Indicators etc. However, especially at the municipality level it is often necessary to make a decision, taking into account mutual interactions and competing interests of different stakeholders, and different aspects for KPIs evaluation.

The aim of this paper is to provide an aid to decision makers (transport engineers, municipality representatives and other stakeholders) within the changing mobility ecosystem, taking into account the wide range of KPIs from mobility analysis tools, such as those presented in Section 2.1, and various independent stakeholders studied in Section 2.2. Considering the mobility ecosystem as a complex system, as described in Section 2.3, this paper introduces a game-theoretical approach in sections 2.4 and 2.5 to analyse the KPIs stemmed from mobility analysis tools. Mobility services are considered as a game, namely a Stackelberg game, described in Section 2.6. In this game, the municipality acts as a single leader whose payoff function is expressed by a score based on KPIs with certain weights assigned to different players (or groups of players) and to different aspects, i.e., environmental, economic, and social. In section 3.1, we explain how such approach aggregates different aspects into a single solution, allowing proper decision making on policy instruments given different priorities of the decision maker. Nevertheless, this paper, in special Sections 3.2 and 3.3, highlights the usefulness of game theory not only for particular transportation simulations, but also for more efficient, data-driven decision-making in this field.

2. Materials and Methods

2.1. Mobility analysis tools

The relation between mobility services can also be drawn from the perspective of common categories of tools used to solve problems and challenges of various services, which we primarily presented in [7]. Table 1 provides a summary of the tools (i.e., software and methodologies) used for mobility analysis, where each tool is categorised into one of seven categories according to its functionalities.

A. Macroscopic models

Macroscopic models are a classic type of strategic planning tools and the most widely used type of travel demand models. Commonly, the studied area is divided into zones that are represented by their shape and by a single point corresponding to the zone centroid. Centroids represent the origin and destination of all trips from and to the zone, thus matrices with average costs (e.g., time or distance) between zones are calculated based on stages trip distribution and mode.

Example of such tools are: TRIMODE, CUBE, Omnitrans, Emme, TransCAD and SATURN. In addition to the aforementioned, Visum also includes strategic multi-modal transport modelling and environmental-impact assessment. Other proposed methodologies include estimation of the impacts of automated vehicles on the performance of a transport network and travel demand [8], and a method to estimate the impact of automated vehicles on traffic parameters, such as road capacity and saturation [9]. Sonnleitner and Friedrich [10] discuss the possibility of using Visum to demonstrate and evaluate the impacts of automated vehicles on capacity and network performance, perception of automated travel

Table 1. Categories of tools for mobility analysis, examples of usage and software.

Category of Tools	Usage	Software
Macroscopic traffic simulation	Effects of bottlenecks and wave propagation Emerging mobility patterns Recently used also for the implications of Cooperative Intelligent Transport Systems (C-ITS) and Connected and Automated Vehicle (CAV) technologies, as well as to evaluate investments in these technologies and transport infrastructure	TRIMODE, CUBE, Emme, Omnitrans, TransCAD, SATURN, VISUM
Micro-simulation	Estimation of vehicle emission profile by routes/areas/vehicle and public parking Exploring effects of new mobility modes and policies on public transport and the overall transport network performance Impacts of specific C-ITS enabled traffic management scenarios Improvement of charging infrastructure planning Traffic operations assessment Intermodal transport simulation Environmental impact assessment Pedestrian simulation	AIMSUN, VISSIM, SUMO, DIVERT
Agent-based simulation	Assessment and monitoring of demand-responsive transport systems Visualising options with a mix of public/sharing/ public modes of transport related to emissions Providing route options with a mix of transport modes taking emissions into account Estimating the emission vehicle profile by routes/areas/vehicle and public parking Exploring effects of new mobility modes and policies, and external information on public transport and the transport network performance Impacts of specific C-ITS enabled traffic management scenarios Identification of more busy public transport stops, more frequent trips, analysis of service quality Improvement of charging infrastructure planning Modelling of impacts of unforeseen crisis	MATSim, MobiTopp, CityMoS, Immense platform, POLARIS, ALBATROSS, SIMBA, MOBi
Optimisation	Traffic signal optimization Vehicle Routing Problem (VRP) Mobility-service specific problems	LISA+, TRANSYT, VRP Spreadsheet Solver, and other mobility-service specific solutions
Data visualisation and analysis	Data analytics Data mining Online analytical processing Visual analytics Big data analytics Cognitive analytics	MS Excel, Python, MatLab, Statistical Package for Social Sciences (SPSS), Structured Query Language (SQL), R, Microsoft PowerBI, Tableau, ArcGIS, KIBANA – GRA-FANA dashboards, other mobility-service specific tools
Mobility planning	Planning of single-modal and multi-modal trips	Whim, Zipster, WienMobil, Bestmap, CityMapper, CleverShuttle, HQ Rental Software, Moovit, RentSyst, MyRent
Electric infrastructure Management	Energy market analysis Electric vehicle (EV) design Traffic modelling Power network analysis Renewable and/or EV integration in distributed energy systems	V2G-Sim, PSAT, ANSYS Simplorer, MORPHEE tools, Simpow, CANoe, Electric Vehicle Infrastructure Projection Tool

time, ride-matching and vehicle scheduling for high-level automated vehicles that allow unmanned ridesharing or carsharing services.

B. Micro-simulation tools

Microscopic simulation models traffic flow by modelling the behaviour of individual vehicles, in which the representation of travel demand is based on route choice models, while driving behaviour is related to acceleration, lane-changing and gap-acceptance models [11].

There are several micro-simulation tools that model either drivers or automated vehicles behaviour, the most used ones are, according to Vrbanić et al. [12]: AIMSUN, VISSIM and SUMO. Among specific features of micro-simulation tools, Aimsun's simulation platform Aimsun Ride, which is oriented to new demand-responsive transportation services, can model and analyse Mobility as a Service (MaaS) frameworks. This includes: competition between different providers or services, attractiveness levels of different types of service, algorithms for generating different offers, pricing models, target service levels, and rides offered in isolation or combined with public transport as part of a holistic transportation model. Automated vehicles modelling and logistics simulation is present for example in SUMO or VISSIM, while Codecá [13] proposes a parking management framework. Ferreira and d'Orey [14] use the large-scale simulation platform DIVERT for testing new taxi operations, such as sharing trips and new hybrid formats.

C. Agent-based simulation tools

Agent-based models consider individual users and also individual vehicles as agents that make autonomous decisions as they interact with other agents and their environment, which is governed by certain rules. Simulations aim at a user equilibrium of all agents across the whole transport system, given that at each iteration these agents update their travel patterns due to competition for space-time slots [3].

Example of these tools are MATSim, MobiTopp, CityMoS, Immense platform, POLARIS, ALBATROSS and SIMBA MOBi (see [15], [16] and [3]). Other usages of agent-based models are revenue management in public transport [17], examining impacts of mobility-oriented policies [18], leisure trips modelling [19], fleet management and infrastructure operations [20], predicting impacts of urban development [21], electromobility and charging infrastructure simulation [22] and evaluation of district evacuation scenarios [23].

D. Optimisation tools

Optimisation tools for transport systems have the goal of identifying proper strategies and solutions when problems have multiple, often conflicting objectives that should be fulfilled over time. The field is very broad and may be divided into several sub-fields, such as linear, non-linear, dynamic, stochastic, constrained, and unconstrained optimisation [24].

Traffic signal optimisation is a good example of optimisation problem, and the tools LISA+ by Schlothauer and Wauer and TRANSYT by TRL are well established for that purpose. Another very common problem is the Vehicle Routing Problem (VRP). The tool VRP Spreadsheet Solver is used for representing, solving, and visualising the results of more than 64 variants of the VRP, unifying Excel, public Geographic Information System (GIS), and metaheuristics [25]. Alternatives are also tested using a Large-scale Neighbourhood Search (LNS) algorithm in [26]. The VRP optimisation is also explored by Zubin et al. [26], where drones are used for last-mile logistics of medical delivery. Additionally, localization of facilities is also a popular type of problem, which is studied by Iwan et al. [27] for parcel lockers' localization within a city.

Among trend services' problems, resource allocation between transit services and the operation of shared mobility services relying on highly automated (autonomous) vehicles is provided in [28]. Sonneberg et al. [29] introduce a decision support system that provides strategic optimisation of location, number and size of stations for electric vehicles with specific charging infrastructure, station-based car sharing in a two-way mode. Relocation models that maximize profit for providers and customers (or minimize costs) are modelled by means of mixed integer programming models in [30] and [31]. A pricing scenario for Connected and Automated Vehicles is explored in [32]. Esztergár-Kiss and Kerényi [33] propose a methodology for the creation of mobility packages for the MaaS system users that allow to determine the convenient price and specify the modes of transport included in a package (and to which extent).

E. Data visualisation and analysis tools

Data analytics have the purpose to integrate heterogeneous sources of data, establish conclusions, and perform predictions [34]. It includes Machine Learning (ML), which popular methods include regression methods, decision trees, artificial neural networks (ANNs), and support vector machines [35].

There are some well-known tools for general data analysis, such as MS Excel, Python, R, MatLab, Statistical Package for Social Sciences (SPSS), Structured Query Language (SQL), Microsoft PowerBI, Tableau, ArcGIS, and KIBANA – GRAFANA dash-boards. However, data analysis tools are often specific for the application.

Examples of applications for shared mobility include the total number of vehicles per operator, distribution requirements, restricted area rides, infrastructure planning, parking area performance, monitoring of vehicle condition and lifespan, enforcement, and measure accessibility. Bluesystems and Vianova offer real-time data collection, offline data collection, and real-time reaction to anomalies on public transport or irregular parking. The New Urban Mobility Alliance (NUMO) micromobility data analysis tool focuses on trip patterns, modal shift, how to provide safe spaces, equitable access, and the real environmental impacts of micromobility. SharedStreets Mobility Metrics is intended for the analysis of the Mobility Data Specification (MDS) data standard, aggregating useful & privacy-protecting metrics [36]. Remix allows for visualising corridors and trip paths, identifying risk areas and digitizing public policies. City Dive provides a dashboard to monitor fleets, trips and usage patterns such as the number of vehicles available, the density of vehicles available per area, the number of trips, the analysis of trips patterns per hour and per day, origins/destinations. Urban Sharing allows to understand day-to-day user behaviour, propose redistribution of vehicles to meet user-demand, and predict fleet's maintenance needs. Populus manages not only shared mobility vehicles, but also commercial delivery operators, and it supports the management of streets and curbs. Other tools focus only on locating stations, vehicles and possibly displaying some information about them. They include Bike Share Map, City Bikes, Data Flow (Fluctuo), and the Application Programming Interface (API) of Bestmap Bikes.

Public Transport Management includes numerous smaller subsystems, from fleet management tools, traffic management and planning, parking and road safety, real-time vehicle tracking to journey planning applications for end users [37]. The Moovit tool provides a very comprehensive and accurate understanding of travel patterns to and from a region for improving first/last mile access to stations, aligning timetables to improve network connectivity, building access roads or pathways to a station, and assessing the impact of future transit changes on riders and local residents. Vianova allows to control parking of devices, supervise fleet deployments and availability, contributing to the analytical and planning perspective, such as the evolution of fleet sizes, patterns of supply and demand, planning and prioritising access to curb space to prioritise people and goods.

Transport policy and design is assisted by Urbano, which is a Computer-aided Design (CAD) integrated design toolkit designed to help analysing active transport modes and evaluates the accessibility of amenities and public transport. In addition, Urbano gives insight in the under-standing of the implications of urban design choices in very early stages of an urban design process [38]. OSMnx is useful for acquiring, constructing, analysing, and visualising complex street networks. Propensity to Cycle Tool (PCT) is an online open-source interactive map-based web for assessing cycling potential [39].

Advanced tools for Dynamic Traffic Management (DTM) presented in [40] contribute to the incorporation of C-ITS into operational traffic management. Such a system enables the realization of sustainable urban mobility goals and the promotion of cooperation between different actors of the mobility ecosystem based on new business models. The

C-ITS enabled DTM system is developed in the context of the C-MobILE project that accounts for the following aspects: motorway parking availability for trucks, urban parking availability, traffic light priority and green splits, flexible road capacity, in-vehicle signage, mode and time advice, shockwave damping, and metering.

Besides commercial applications for off-street parking, Barone et al. [41] suggest the IPA (Intelligent Parking Assistant) for an architecture of public and off-street parking management based on an Internet of Things (IoT) platform. An already existing example of such a system is the Nice smart parking project [42]. Moreover, an international toolkit focused on on-street parking management can be found in [43].

F. Mobility planning tools

Mobility planning tools involve the planning of trips by mobility service (shared mobility, public transport etc.) users. They can be from private apps that provide a journey with a fleet of vehicles owned by one operator or a Mobility as a Service platform, which features journey planning, optimisation, ticketing, payment, and communication.

Planning of single modal trips can be exemplified by the car rental systems: HQ Rental Software, RentSyst and MyRent. Such tools are designed to automate and control car rental business operations, including fleet management, customer service, bookings, reservations management, driver management, vendor management, accounting, payments, inventory management, rates management, on a common platform. Another example is the Clever-Shuttle service, which is a sharing ride-hailing service used as a complementary service to local public transport [44].

MaaS tools support multi-modal trips and include functionalities of managing user profile & subscription, planning of trips, analysing supply and demand, managing booking, ticketing, and payment, and receiving data reports. Examples of such tools are the following apps: Whim in Helsinki, Zipster in Singapore, and WienMobil in Vienna. Other apps only provide multi-modal route planning, such as Bestmap, CityMapper, and Moovit.

G. Electric infrastructure management tools

Electric infrastructure management tools design, analyse, and control energy management systems. They aim to provide electric power distribution networks with availability and reliability for electric vehicle journeys. Considering the two-way characteristics of Electric Vehicles (EVs), such vehicles not only consume energy but also provide power to grid [45].

There are several relevant tools, for instance: Vehicle-to-Grid Simulator (V2G-Sim), power system analysis toolkit (PSAT), multi-domain systems modelling (ANSYS Simplorer), modelling vehicle integration (MORPHEE tools), power systems simulation tool (Simpow), distributed system design (CANoe) [45]. Current EU projects also concentrate on fast charging (ELECTRIC) and on building fast-charging stations networks (EUROP-E, ULTRA-E, NEXT-E). However, there is a lack of tools for locating charging stations (CS) that would be necessary for municipalities. In Europe, the eCharge4Drivers [46] project aims to provide a tool to guarantee the optimum mix of charging options, while the METIS mathematical model provides analysis of the European energy system for electricity, gas, and heat, though not at a municipality level [47]. In the USA, the Electric Vehicle Infrastructure Projection Tool [48] provides guidance on plug-in electric vehicle (PEV) charging infrastructure to regional/national stakeholders.

2.2. Stakeholder roles and business model analysis

Since there are many stakeholders spread over different mobility services, of which some fulfil similar or overlapping functions, a survey about the stakeholders and a summary of roles is necessary. Primarily, to understand their interests and define what is important to each of them and thus define key performance indicators that measure the performance of alternative solutions and scenarios from mobility analysis tools. Secondarily, to define the priority of each stakeholder according to the desire of the decision maker.

In order to get insights into the involvement of types of stakeholders over mobility services, and to visualize the roles of various stakeholders, it is useful to create a Service Dominant Business Model Radar (SDMB/R) proposed by Turetken and Grefen in [49]. The SDMB/R represents the achievement of shared goals and value co-creation by a group of interacting actors (businesses, firms, government, and customers). A detailed business model analysis including radars is contained in the nuMIDAS project deliverabale [4]. As an example of such business model radar, Figure 3 presents the SDMB/R) for shared micromobility.

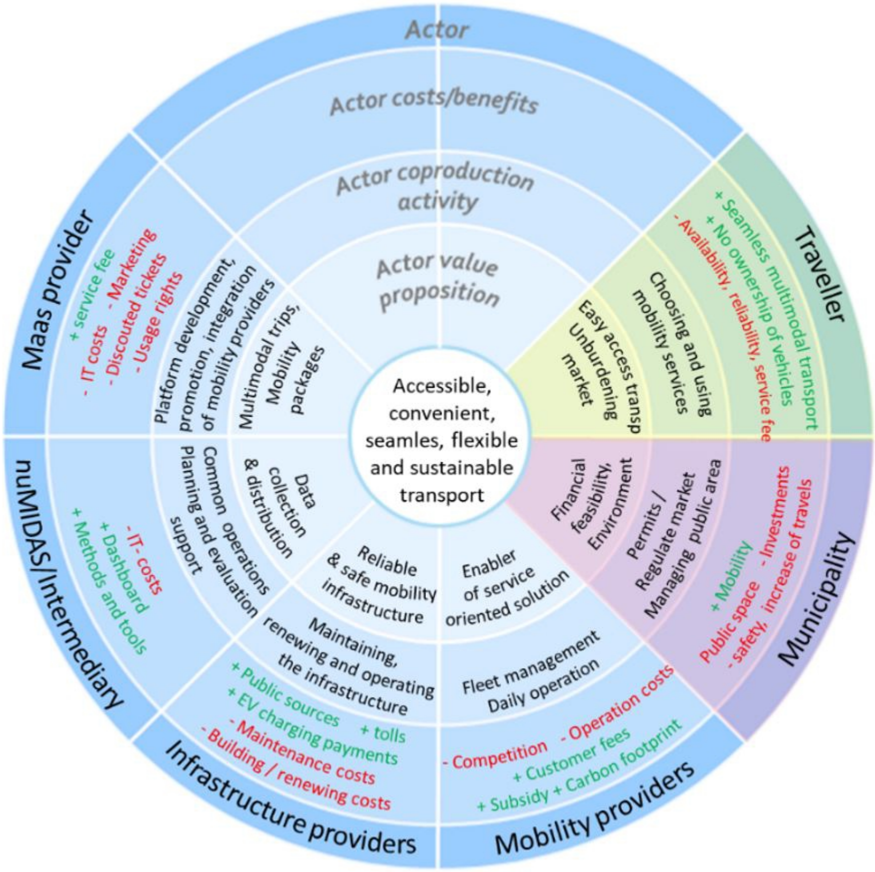

Figure 3. Example of shared micromobility business model radar (source: own elaboration).

In the radar, the value-in-use is the focal point of the service (the inner-most circle in Figure 3), and around it, there are three circles, named and described as:

- *Actor value proposition*, which represents the contribution of the actor to the value-in-use;
- *Actor coproduction activity*, which represents the activities that the actor per-forms in regard to achieving the co-creation of the value-in-use. The effects are observable for the customer;
- *Actor costs and benefits*, which represents the financial and non-financial costs and gains for the co-creating actor.

Each slice of the radar represents one of the co-creating actors and their role in the co-created value-in-use. All actors, including the customer, collaborate in a way that makes it clear what interest they have in the service at hand. The levels of involvement of various stakeholders can be categorised as follows:

- *Focal organisation* is the initiator, and it is responsible for the main activities;
- *Core partner* actively contributes to the essential parts of the service;
- *Customer* is usually the traveller or the stakeholder utilizing the value-in-use;

- *Enriching partner* enhances the value-in-use of a service;
- *Future partner* is expected to find its place in the business model in the near future.

The most common stakeholder categories are listed in the sections 2.2.1 – 2.2.5, as they were identified during the business model analysis and discussed in our previous work [4].

2.2.1. *Municipality*

The municipality can be found in each service as a strategical and tactical stakeholder. A growing mobility market within a city requires a city to increasingly manage, integrate and improve its mobility system. Even though the municipality can be found in each service, it is mentioned as a focal organisation in only the transportation policy and design service. For other services, the municipality is often a core partner, providing permits or subsidies. Municipalities also determine space usage in the city, which is the basis of the mobility system. Municipalities implement policy instruments, which affect the services and influence their opportunities, but they may also challenge them to find new solutions.

2.2.2. *Traveller*

The traveller is usually the customer in the business model. The services are designed to contribute to a more efficient, more integrated, and more sustainable way of travel for the customer. Often, the traveller contributes to the business model by allowing organisations to gather and use data in order to provide the service. In addition, there will also be positive externalities to the society from travellers using these improved and optimised travel modes. Also, all residents of a city will benefit from improved parking spot availability, increases in the liveability of a city, or from the use of electric vehicles, in the form of less noise and environmental pollution.

2.2.3. *(Mobility) service provider*

Often the business models require some sort of mobility service provider. Mostly, the service provider is seen as the focal organisation of a service as the organisation that offers the operational means of travel to the traveller in form of a vehicle, as well as the way to access the service, often through digital platforms. The service providers use these platforms to gather data from their users, which can be sold to interested parties or used to improve their service on both operational and tactical levels. In services where this data from mobility services is used, the service providers are a core partner in the business model. For example, in the Travel Demand Modelling service data from service providers could be used as input for estimation of Origin Destination matrices or travel times.

2.2.4. *Intermediary*

The intermediary organisation can be a future partner. The exact interpretation of activities of the intermediary organisation is still unknown, but it offers opportunities in a mobility ecosystem that is getting increasingly interconnected. Services can often be brought to a higher standard with data sharing between organisations. An independent intermediary organisation will likely contribute to willingness to share data between organisations and can evaluate the functioning of a service objectively. The evaluation may lead to strategical, tactical, and operational advice, depending on the interpretation of the role of this stakeholder.

2.2.5. *Mobility as a Service (MaaS) Provider*

These stakeholders are expected to affect the mobility system as a whole. MaaS providers can be found in the business models of many services, mostly as a future partner. While it is sure that it will affect the system, it is unsure how and what is to be expected in terms of effects on the mobility system, roles of other stakeholders and policy instruments. The MaaS providers are expected to cover strategical, tactical, and operational layers.

2.3. Complex Systems

The concept of a system is understood in the sense of the definition formulated in [50], i.e., as a set of interacting or interdependent component parts forming a complex whole. Every system is delineated by its spatial and temporal boundaries, surrounded and influenced by its environment, described by its structure and purpose, and expressed in its functioning. A system comprising a large number of units where the interaction between the units results in an emergent behaviour is known as a complex system (for a detailed discussion of this concept, see [51]). A Cyber-Physical System (CPS) denotes transformative technologies for managing interconnected systems between its physical assets and computational capabilities [52]. In a CPS, computing elements coordinate and communicate with sensors monitoring physical indicators, and actuators modify the physical environment where they operate [1].

A useful tool used for modelling and simulation of complex systems represent multi-agent systems (MAS), i.e., systems consisting of multiple autonomous entities known as intelligent agents that interact with the shared environment and with other agents. Originally, these systems were used in distributed problem-solving systems, and they were supposed to be benevolent, i.e., to share a common goal. With the rapid development of computer science and the need to deal with more distributed systems, the common goal was replaced by a more realistic assumption that agents are self-interested, following their own individual goals [53]. Nevertheless, a decision-making agent in a multi-agent system corresponds to the concept of a player in a game in the sense of game theory, developed to a great extent even before the advent of computers.

2.4. Games

In general, a game denotes any decision situation, the result of which depends on decisions of at least two different entities, so-called players, that have at least two different strategies to choose from. For the definition of a solution concept and practical use of game theory, it is necessary to characterize a game in a narrower way. Obviously, models are different for different levels of cooperation or communication between players, different organisations of a "game" (e.g., simultaneous or sequential decision-making, one-shot or repeated game), different levels of available information or rationality, etc. For instance, a normal form (or strategic) game denotes a model of interaction of a finite number of players, each selecting a strategy without the knowledge of other players' actions. It is given by the set of players, a strategy set for each player, and a payoff function of each player, representing her/his preferences over all combinations of strategies. In a Stackelberg game, introduced by Heinrich von Stackelberg in his 1934 book [54], one player (called a leader) moves first, and all other players (called followers) move after him, taking the leader's strategy into account, such as the decision-maker deciding on certain policy instrument or applying mobility services and other players being influenced by this decision.

Game theory has already been used for the solution of various problems related to mobility. These problems include behaviour on transportation networks, travel demand management, network reliability, multi-modal competition, supply chain management, pricing, analysis of taxes, tolls and incentives, and analysis of interactions between various actors (travellers, authorities, mobility service providers, infrastructure providers etc.). A detailed survey is contained, for example, in the study [55] and more recent papers [56], [57], and [58]. Zardini et al. [56] provide a game-theoretic framework for the investigation of interactions between stakeholders in a mobility ecosystem, based on the Stackelberg model, and demonstrate its application for the analysis of two case studies.

The present paper points out the suitability of the Stackelberg game for modelling decision-making on various policy instruments and mobility services, reflecting competing interests of involved stakeholders and different societal aspects, employing various kinds of KPIs, and the Nash bargaining solution for cooperative games without side payments (the payoff is not transferable from one player to another one), provided by John F. Nash in [59]. For two players with payoff functions u, v, Nash considered the bargaining problem as an ordered pair $\Psi(P,(u_0,v_0))$, where P denotes the set of all possible payoff pairs, so-called cooperative payoff region, and u_0, v_0 stand for the least guaranteed payoffs of the players. Let us denote the bargaining solution as $\Psi(P,u_0,v_0)) = (u^*,v^*)$. Nash called for the satisfaction of the following conditions that correspond to our intuition about a fair bargaining solution:

Axiom 1 (Individual rationality)

$$u^* \geq u_0, \quad v^* \geq v_0$$

Axiom 2 (Pareto Optimality)

The pair (u^*,v^*) is Pareto optimal, i.e., there does not exist any $(u,v) \in P$, such that $u \geq u_0$, $v \geq v_0$ and at least one inequality is strict.

Axiom 3 (Feasibility)

$$(u^*,v^*) \in P$$

Axiom 4 (Independence of irrelevant alternatives)

If P' is a payoff region contained in P, such that $(u_0,v_0) \in P'$ and $(u^*,v^*) \in P'$, then

$$\Psi(P',(u_0,v_0)) = (u^*,v^*).$$

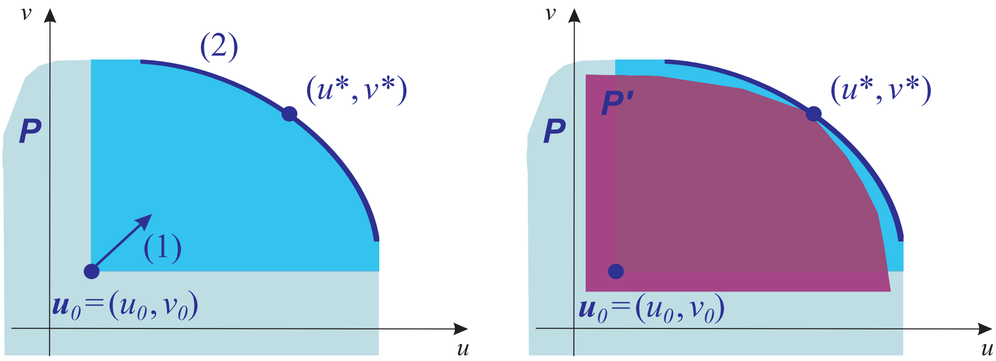

Figure 4. Illustration of Nash bargaining axioms 1-3 **(a)** and 4 **(b)** (source: own elaboration).

Axiom 5 (Independence under Linear Transformations)

Suppose P' is obtained from P by the linear transformation

$$u' = au + b, \qquad v' = cv + d, \qquad \text{where} \quad a, c > 0.$$

Then

$$\Psi(P',(au_0+b, cv_0+d)) = (au^*+b, cv^*+d).$$

Axiom 6 (Symmetry)

Suppose that P is symmetric, i.e., $(u,v) \in P \Leftrightarrow (v,u) \in P$, and $u_0 = v_0$. Then $u^* = v^*$.

In the paper [59], J. F. Nash provided a constructive proof of the following theorem:

Theorem (Nash): There exists a unique arbitration procedure Ψ satisfying axioms 1–6.

For a given bargaining problem $\Psi(P, (u_0, v_0))$, Nash constructed the solution to maximize the product of utility gains

$$(u, v) = (u - u_0)(v - v_0) \tag{1}$$

on the set of feasible and individually rational payoff pairs. Moreover, as formulated in the theorem, he proved the uniqueness of the solution satisfying the conditions 1–6.

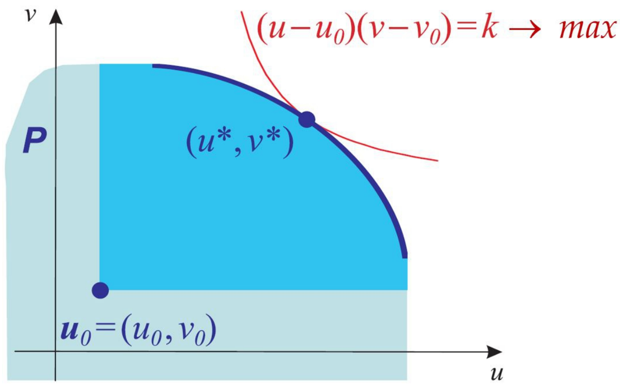

Figure 5. Construction of the Nash bargaining solution (source: own elaboration).

To address different importance of different players, it is possible to omit the symmetry axiom and consider the weighted Nash solution that maximizes the product

$$g(u, v) = (u - u_0)^{w_1}(v - v_0)^{w_2}, \quad \text{where} \quad w_1,\ w_2 \geq 0,\ \ w_1 + w_2 = 1. \tag{2}$$

For more actors/aspects, the weighted Nash solution maximizes the product:

$$g(u_1, \ldots, u_N) = (u_1(x) - u_1(x_0))^{w_1}(u_2(x) - u_2(x_0))^{w_2} \cdots (u_N(x) - u_N(x_0))^{w_N}, \tag{3}$$

where $w_1, w_2, \ldots, w_N \geq 0$, $w_1 + w_2 + \cdots + w_N = 1$, and x stands for a variable that should be optimized. For example, it can be a single-valued variable, representing, e.g., the number of vehicles in a fleet or the number of available parking spaces, a vector representing, e.g., an allocation of some resources, locations of some services etc., or a two- or more dimensional matrix representing certain configuration.

For a coordinate system where $u_i(x_0) = 0$ for all $i = 1, 2, \ldots, N$, the right side of the formula (3) becomes the weighted geometric mean

$$W_N(x) = \prod_{i=1}^{N} [u_i(x)]^{w_i} \tag{4}$$

called also a *Nash social welfare function*. Apparently, payoffs (e.g., utilities) of different players can be of different nature, and they are not necessarily comparable. This is a substantial advantage over the weighted arithmetic mean (utilitarian social welfare function)

$$W_U(x) = \sum_{i=1}^{N} w_i u_i(x) \tag{5}$$

which requires comparable utilities of all actors.

2.5. Performance indicators and their aggregation

Extending the standard approach summarised, e.g., in [60], we propose to utilize the function (4) for the aggregation of performance indicators, allowing the comparison of different scenarios while taking into account different aspects and interests of different actors, where some of them may be more important than others. More specifically, the function (4) is applied to determine a score including non-negative weights $\alpha_1, \alpha_2, \ldots, \alpha_m$ with $\alpha_1 + \alpha_2 + \cdots + \alpha_m = 1$ assigned to different actors (or groups of actors as, for example, travellers, citizens, mobility providers etc.) as players in a corresponding game, and also non-negative weights $w_1,\ w_2,\ w_3$ with $w_1 + w_2 + w_3 = 1$ assigned to different aspects, namely environmental, economical and social. Table 2 illustrates the general form of a scoreboard which is the basis for the score computation.

Table 2. Key performance indicators and the resulting score – a general score board

Player	Player Weight	Key performance indicator	Aspect Weight Environmental w_1	Economical w_2	Social w_3
Player I	α_1	Normalised (aggr.) index 1	S_{11}	S_{12}	S_{13}
Player II	α_2	Normalised (aggr.) index 2	S_{21}	S_{22}	S_{23}
...	...	...	...	...	
Player m	α_m	Normalised (aggr.) index m	S_{m1}	S_{m2}	S_{m3}
		Score:	$S = S_1^{w1} \cdot S_2^{w2} \cdot S_3^{w3}$		

The resulting score is thus computed as the product

$$S = \prod_{j=1}^{3} \prod_{i=1}^{m} S_{ij}^{\alpha_i w_j} = \prod_{j=1}^{3} \left(S_{1j}^{\alpha_1} \cdot S_{2j}^{\alpha_2} \cdots S_{mj}^{\alpha_m} \right)^{w_j} = S_1^{w_1} \cdot S_2^{w_2} \cdot S_3^{w_3}, \tag{6}$$

$$\text{where} \quad S_j = S_{1j}^{\alpha_1} \cdot S_{2j}^{\alpha_2} \cdots S_{mj}^{\alpha_m} \quad \text{for} \quad j \in \{1,\ 2,\ 3\}.$$

For specific use cases, not all aspects are necessarily considered for all players. If an aspect j is not relevant for player i, the value S_{ij} should not affect the product, which is the same as putting $S_{ij} = 1$. In this case, it can simply be omitted from the table.

Since the geometric weighted mean is more sensitive to the change of a smaller term than to the same absolute change of a higher one, it is desirable to normalise all included indexes with respect to their range in all considered scenarios. If a higher value of an index I is preferred to a lower one, the normalised index is computed as

$$S_{ij} = \frac{I - I_{min}}{I_{max} - I_{min}}\,, \tag{7}$$

where I_{max} stands for the maximal value of the considered index I obtained in the best scenario, and I_{min} stands for the minimal value of I obtained in the worst scenario (from the point of view of the index I). This normalisation method can be used for example for utilisation, profit margin, accessibility etc. If, on the other hand, the lower value of an index J is preferred to a higher one (as for example in the case of emissions or travel effort), the normalisation has to transform the index in such a way that 1 will again correspond to the most favourable scenario with $J = J_{min}$, and 0 will correspond to the worst scenario with $J = J_{max}$. The normalised index is therefore computed by the formula

$$S_{ij} = \frac{J_{max} - J}{J_{max} - J_{min}}\,. \tag{8}$$

Table 3. European Air Quality Index (EAQI) – levels for individual pollutants [61]

Pollutant	**Index level (based on pollutant concentrations in mg/m^3)**					
	1 Good	**2 Fair**	**3 Moderate**	**4 Poor**	**5 Very poor**	**6 Extremely poor**
Ozone (O_3)	0 – 50	50 – 100	100 – 130	130 – 240	240 – 380	380 – 800
Nitrogen dioxide (NO_2)	0 – 40	40 – 90	90 – 120	120 – 230	230 – 340	340 – 1000
Sulphur dioxide (SO_2)	0 – 100	100 – 200	200 – 350	350 – 500	500 – 750	750 – 1250
Particles less than 10 mm (PM_{10})	0 – 20	20 – 40	40 – 50	50 – 100	100 – 150	150 – 1200
Particles less than 2.5 mm ($PM_{2.5}$)	0 – 10	10 – 20	20 – 25	25 – 50	50 – 75	75 – 800

Specific indicators depend on the use case to be solved, available information and possibilities of the used tools. Some of the most frequent indicators are mentioned in the following paragraphs.

Environmental indicators

Environmental indicators usually include air quality index and/or emissions of pollutants. For example, EAQI – European Air Quality Index is based on concentrations of the five main pollutants regulated in the European legislation: O_3 (ozone), NO_2 (nitrogen dioxide), SO_2 (sulfur dioxide), $PM_{2.5}$ and PM_{10} (fine particulate matter with a diameter smaller than 2.5 μm and 10 μm, respectively) [61]. As seen in Table 3, for each of these pollutants, an index level ranging from 1 (good) to 6 (extremely poor) is computed separately according to its concentration in the given time interval (hour or day). The EAQI is then defined as the maximal value of indexes for individual pollutants. For more details, see [61].

A methodology proposed by EWI – EcoTransIT World Initiative [62] recommends to consider PEC (primary energy consumption, the main indicator for resource consumption) and emissions of CO_2 (carbon dioxide, the main indicator for greenhouse effect), CO_{2eq} (CO_2-equivalent, indicator for greenhouse gas emissions computed from emissions of CO_2, CH_4 (methane) and N_2O (nitrous oxide) by the formula

$$\mathrm{CO}_{2e} = \mathrm{CO}_2 + 25 \times \mathrm{CH}_4 + 298 \times N_2O\,, \tag{9}$$

and further NO_x (nitrogen oxide emissions, acidification, eutrophication, eco-toxicity, human toxicity, summer smog), SO_2 (sulfur dioxide, acidification, eco-toxicity, human toxicity), NMHC (non-methane hydro carbons, human toxicity, summer smog), and particles $PM_{2.5}$ and PM_{10} (human toxicity, summer smog). For CO_2 and other greenhouse gases emissions, the methodology for the calculation and declaration of energy consumption and Greenhouse Gas (GHG) emissions of transport services (freight and passengers) is formulated in the standard EN16258 [63]. According to this standard, the calculation should consist of two steps, as follows:

1. The final energy consumption (litres of fuel, kWh of electricity) of each part of the transport services, so-called leg, have to be calculated.
2. These energy-consumption values should be transferred into standardized energy consumption (expressed in MJ) and CO_2 equivalent emissions (kg CO_{2e}), namely at the level of both TTW (Tank-to-Wheels) and WTW (Well-to-Wheels).

The concept of TTW relates to the energy consumption and emissions directly caused by the operation of vehicles, while WTW also takes emissions and energy consumption related to the generation of final energy into account. For electricity, the value of WTW factor strongly depends on the energetic mix in the given region, and it should therefore belong to inputs for the computation. For more information on this, refer to [62].

Since the concentration of different pollutants is additive, the total index of pollution reduction can be considered as the sum:

$$I_{EM} = \sum_i w_i \cdot EM_i \,, \tag{10}$$

where EM_i denotes the emitted mass of pollutant i, and the weight w_i is inversely proportional to the threshold limit value for pollutant i. Nevertheless, values of weights can be specified on the basis of further research for each use case of such environmental indicators.

Economical indicators

For service providers, there are several metrics successfully used for the analysis of a business profitability. Useful examples include operating costs (e.g., personnel costs, energy, maintenance costs, fleet redistribution, payment to the municipality), operating profit (the subtraction of all operating expenses, cost of sold goods and depreciation and amortisation from the total revenue), or the operating profit margin, M, computed in its simplest form based on costs and other expenses, C, and revenue, R:

$$M = \frac{R - C}{R} \,, \tag{11}$$

For other players, such as public institutions, measures that can be convertible into financial means or productivity could be also used, for example, time losses or (reduction of) traffic capacity. In the case of service users, the economic aspect could be included in a accessibility index, combining economical, physical and operational accessibility of a considered service. However, such index could be better classified into the social category, discussed as follows.

Social indicators

A typical social indicator is the overall accessibility of a service that takes into account economic, operational and physical aspects (aggregated in a multiplicative way). It includes affordability (e.g., the ratio of the annual cost of a service and the annual income), demand satisfaction (e.g., demand coverage of a service), proximity (e.g., average walking distance to nearest facility). Another important social indicator is safety that can be expressed, for example, by the index of traffic accidents [64] or various statistics [65].

2.6. Stackelberg game

A great variety of problems faced by a policy maker can be viewed as instances of a Stackelberg game with the municipality as a single leader and travellers or also mobility service providers as followers. In this game, the leader moves first and makes a decision on a certain policy, as for example a parking policy, establishment of a low-emission zone, rules for shared mobility providers, policy related to taxes, public transport prices etc. The aim of the municipality is to maximize social welfare expressed as a score based on selected and/or aggregated key performance indicators.

As soon as the rules are given, a simultaneous game among followers proceeds, in which each of them searches a best reply to the action of the leader, and also to the action of other followers. Strategies selected by followers then determine the payoff of the leader, who should consider the best responses of followers to various strategies before the selection of the action.

Example: Decision on policies related to shared mobility

For example, planning of a new shared mobility service may include the computation of a solution (e.g., number of vehicles available for the service) that would be optimal from the perspective of mobility providers (e.g., maximizing their profit margin), and also a solution optimal from the perspective of travellers (e.g., demand coverage). A fair solution then requires a proper conjunction of these different perspectives into a single solution, allowing optimal decision.

Leader: *Municipality*
Strategy to select: rules and conditions for shared mobility (fees, the number of released vehicle licenses and other conditions),
Payoff: score based on KPIs (to be maximized)

Followers: *Mobility service providers*
Strategy to select: fleet design, vehicle types, price structures,. . .
Payoff: profit (to be maximized)

Travellers
Strategy to select: travel mode (shared mobility and its type, walking, public transport, private car)
Payoff: accessibility (economic, operational and physical), user satisfaction, etc.

Mutual influences between players of this game are schematically depicted in Figure 6.

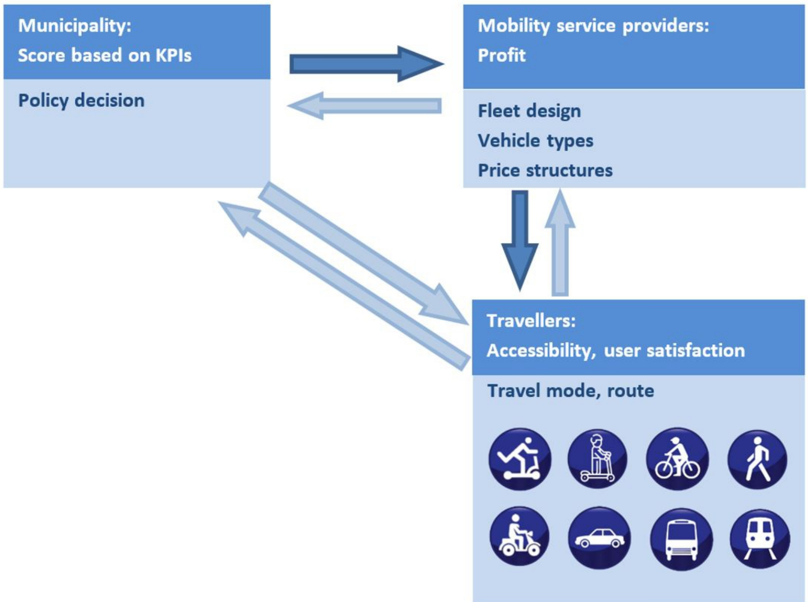

Figure 6. Decisions on policies related to shared mobility as a Stackelberg game (source: own elaboration).

3. Results

3.1. Policy making from the game-theoretical perspective

The improvement of a mobility system requires considering impacts of various decisions from different perspectives, e.g., from the point of view of travellers, society, service providers, and also from the point of view of environment, economy and society. In a game theoretical model, these considerations are included in the analysis of payoff functions of different players. Game theory also provides a solid background for modelling and analysis of various types of interactions that can be one-shot or repeated, proceeded simultaneously or sequentially. There can be various extent of available information, rationality and possible cooperation. According to the business model discussed in Section 2.2, there are different groups of actors (firms, government, customers) whose interests are often competing (costs, benefits), but they also have shared goals and contribute to the value co-creation. Different actors interact with each other, have different strategies to choose from, their “payoffs” depend not only on their own action, but also on the action of other actors, and these interactions should be taken into account in decision processes. The system can therefore be modelled as a game in the sense of game theory.

The municipality can use a great variety of tools showing, for example, the impacts of different measures and results of different scenarios (see Section 2.1). However, its role is usually more ambitious. It can be seen as an arbiter searching for the solution that would be fair for all involved parties and from various perspectives, where some of them may be more important than others. The payoff function of the municipality in the described Stackelberg game can therefore be expressed by a score including non-negative weights $\alpha_1, \alpha_2, \ldots, \alpha_m$ with $\alpha_1 + \alpha_2 + \cdots + \alpha_m = 1$ assigned to different players (or groups of players) and also non-negative weights w_1, w_2, w_3 with $w_1 + w_2 + w_3 = 1$ assigned to different aspects, namely environmental, economic and social (see Table 2). Since payoffs of different types of players are often not comparable (e.g., accessibility vs. profit), and similarly a compensability of indicators representing different aspects is disputable, the weighted geometric mean (i.e., Equation 3) corresponding to the Nash bargaining solution is convenient.

Within the nuMIDAS project [6], solutions for six use cases were tailored, in which a dashboard provides KPIs to estimate or monitor the impacts of applied tools and methods. For the complete description of the methodologies, models, tools, and algorithms in each use case, see [66]. In the remaining of this section, we present the results of the application of the methodology introduced in 2.5 for two use cases. For the complete report of the new concept, variables, and KPIs for all use cases, refer to [66]. Nevertheless, to have a broad diffusion of the toolkit, KPIs have to be transferable, avoiding the calculation of site-specific indicators and/or indexes. As not all municipalities have the same amount of data and the same types of input data, thus the KPIs to be presented in sections 3.2 and 3.3 consider:

1. input data available in the pilot cities of project nuMIDAS,
2. the possibility that these data would be available in many municipalities, and
3. outputs of mobility analysis tools, such as SUMO [67].

3.2. Use Case: Operative area analysis

For the use case related to operative area analysis, the nuMIDAS team developed a data visualisation and analysis tool to assess the extension of current operative area (in which service operators must operate their services) to maximise the level of service for citizens within each zone (sub-area of a municipality), but keeping the service profitable for service operators.

The KPIs outputed by the nuMIDAS tool for each alternative of operative area are provided in Table 4. These KPIs were sorted into categories corresponding to environmental, economical, and social aspect, and also into groups corresponding to different players with competing interests, namely shared-mobility users, shared-mobility providers, and the society as a whole. Although some indicators could be classified into more categories, the most important aspect of each indicator is selected. For example, mobility providers are supposed to consider economic aspects as the most crucial, while indicators related to mobility users are classified as social since they are used to express an overall accessibility of the service.

A step further over the standard key performance indicator to be shown, a KPI is selected (or constructed by an aggregation of some KPIs) as a payoff function representing the interests of each player. For shared mobility providers, the algorithm works with the maximal value of the operating profit and provides other indicators as operating costs or expected revenue. To compare different scenarios, the operating profit margin (e.g., similarly to Equation 11) could be selected as a convenient indicator, since it combines the information on profit and revenue, and it can serve as a guide when considering an acceptable level of profitability. An operating profit margin index, S_M, can be calculated as follows:

Table 4. Performance indicators for the operative area analysis use case

Player	Performance indicator	Analysis tool	Aspect		
			Environ.	Econ.	Social
Shared-mobility user	Proximity	Data visualisation and analysis: nuMIDAS			x
	Ratio of served population				x
	Average waiting time				x
	Average walking time				x
Shared-mobility provider	Fleet size	Data visualisation and analysis: nuMIDAS		x	
	Operating profit			x	
	Operating costs			x	
	Expected revenues			x	
	Operating profit margin			x	
Society	Total number of trips	Data visualisation and analysis: nuMIDAS	x		
	Total distance travelled		x		
	Fleet utilisation		x		

$$S_M = \frac{M - M_{min}}{M_{max} - M_{min}}, \tag{12}$$

where M_{max} stands for the maximal value of profit margin obtained in the best scenario and M_{min} stands for the minimal value of profit margin obtained in the worst scenario (regarding profit) that is to be avoided.

For society, the total distance travelled represent an information for the decision maker, which can be used for statistical purposes and/or for an estimation of fuel or energy consumption (if types of vehicles in a fleet are known). For a distance travelled index, S_D, it is normalised as

$$S_D = \frac{D_{max} - D}{D_{max} - D_{min}}, \tag{13}$$

where D_{max} stands for the maximal value of distance travelled obtained in the worst scenario and D_{min} stands for the minimal value of distance travelled obtained in the best scenario (regarding distance travelled).

However, for shared mobility users, the accessibility index, S_A, can be computed as an aggregation of the proximity, P, and the ratio of served population, R. This can be achieved by a joint maximisation where the geometric weighted mean of both variables can be considered, as it eliminates the mutual compensation (it is not desirable to select an operative area with a high proximity, but a small ratio or served population, or vice versa). Therefore, we maximise the value

$$S_A = N_P^{w_P} \cdot N_R^{w_R}, \tag{14}$$

where the weights of each component of the accessibility are $w_P, w_R \geq 0$, and $w_P + w_R = 1$. N_P and N_R are normalised values for proximity (e.g., average walking distance to nearest facility) and ratio of served population, respectively, i.e.,

$$N_P = \frac{P - P_{min}}{P_{max} - P_{min}}, \quad \text{and} \tag{15}$$

$$N_R = \frac{R - R_{min}}{R_{max} - R_{min}}. \tag{16}$$

The comparison of different scenarios considering different perspectives (by players and aspects) is presented in Table 5. As these KPIs already belong to different categories, it is sufficient to consider weights only for different aspects. Table 6 provide an example on how the selected KPIs for all players could be used for the computation of the overall score for a given scenario.

Table 5. Key performance indicators and the resulting score for the operative area analysis use case

Player	Player Weight	Key performance indicator	Aspect Weight		
			Environmental w_1	Economical w_2	Social w_3
Shared-mobility user	α_1	Normalised accessibility			S_A
Shared-mobility provider	α_2	Normalised profit margin		S_M	
Society	α_3	Normalised distance travelled	S_D		
		Score:	$S = S_D^{w_1} \cdot S_M^{w_2} \cdot S_A^{w_3}$		

Table 6. Example of the score board for the operative area analysis use case

Player	Player Weight	Key performance indicator	Aspect Weight		
			Environmental 0.33	Economical 0.33	Social 0.33
Shared-mobility user	0.33	Normalised accessibility			0.35
Shared-mobility provider	0.33	Normalised profit margin		0.45	
Society	0.33	Normalised distance travelled	0.53		
		Score:	0.44		

3.3. Use Case: Assessment of traffic management scenarios

The aim of this use case is the development of a robust methodology for assessing various traffic management scenarios, which is necessary for an active traffic management system. Considered scenarios may be based on a variety of means, such as the dynamic adjustment of traffic signal control plans, and provision of speed limit information.

Similarly to section 3.2, Table 7 displays the selection of performance indicators for this use case. They are specified according to the outputs of the traffic simulation software SUMO [67]. Additionally, Table 8 presents the key indicators for score evaluation.

For this use case, the player "public administration" can have two key performance indicators: normalised emissions, S_E, and normalised traffic performance, S_T. The former, representing the emission of pollutants (e.g., as a weighted sum such as in Equation 10), can be normalised as

$$S_E = \frac{E_{max} - E}{E_{max} - E_{min}}, \tag{17}$$

where E_{max} corresponds to the values of emissions in the worst scenario and E_{min} stands for the minimum emissions in the best scenario. For the later indicator,

$$S_T = \frac{T_{max} - T}{T_{max} - T_{min}}, \tag{18}$$

where T_{max} is the traffic performance, for instance the sum of time lost, in the worst scenario and T_{min} the lost time in the best scenario. From Table 7, the normalised travel effort, S_F, can be obtained by putting the sum of trip duration into Equation 8, while the

Table 7. Performance indicators for the assessment of traffic management scenarios use case

Player	Performance indicator	Analysis tool	Aspect: Environ.	Aspect: Econ.	Aspect: Social
Traffic Management Center Operator	Traffic capacity	Microscopic simulation: SUMO		x	
	Flow			x	
	Occupancy			x	
	Speed			x	
	Travel time reliability				x
Public administration	Noise pollution	Microscopic simulation: SUMO	x		
	Total driven distance		x		
	Fuel mix		x		
	Emissions		x		
	Time losses			x	
	Queuing time			x	
	Queue length			x	
Society	Energy consumption	Microscopic simulation: SUMO			x
	Trip duration				x
	Waiting time				x
	Stopped time				x

Table 8. Key performance indicators and the resulting score for the assessment of traffic management scenarios use case

Player	Player Weight	Key performance indicator	Aspect Weight: Environmental w_1	Economical w_2	Social w_3
Traffic Management Center Operator	α_1	Normalised traffic capacity		S_C	
Public administration	α_2	Normalised emissions	S_E		
		Normalised traffic performance		S_T	
Society	α_3	Normalised travel effort			S_F
		Score:	$S = S_E^{w_1} \cdot (S_C^{\alpha_1} \cdot S_T^{\alpha_2})^{w_2} \cdot S_F^{w_3}$		

normalised traffic capacity, S_C, can use the traffic capacity and the normalisation given by Equation 7. The final score, seen in Table 8, for the economical aspect requires the product of the normalised traffic capacity and traffic performance, both at the power of the weight of each player, as follows:

$$S_2 = S_C^{\alpha_1} \cdot S_T^{\alpha_2}. \tag{19}$$

4. Discussion

Based on a business model analysis, stakeholders involved in different mobility services can be categorised into different groups of players in the Stackelberg game (e.g., firms, government, customers) that have different interests, often competing (costs, benefits), but they also have shared goals and contribute to the value co-creation. These players also interact with each other and have different strategies to choose from, while their "payoffs" depend not only on their own action, but also on the action of other actors. It is certainly useful that a huge variety of tools are available in the urban mobility field, allowing simulation of different scenarios, impact evaluation for different policy instruments, solution of various optimisation tasks, enumerating various Key Performance Indicators, etc. However, especially at the municipality level it is often necessary to make a decision taking into account mutual interactions and competing interests of different stakeholders, and different aspects of KPIs evaluation.

5. Conclusions

The mobility ecosystem can be viewed as a complex system, as it comprises a large number of elements, where the interaction between them results in an emergent behaviour. A useful tool used for modelling and simulation of complex systems of a distributed nature represent multi-agent systems. Multi-agent systems can therefore be used also for the simulation of the actions of various participants in the mobility system. A standard tool for the analysis of agents' interactions and behaviour represents game theory. In a single-leader Stackelberg game, one agent/player (called a leader) moves first, and all other players (called followers) move after him, taking the leader's strategy into account, such as the decision-maker deciding on certain policy instrument or applying mobility services and other players being influenced by this decision. This paper points out the suitability of the Stackelberg game for modelling decision-making on various policy instruments and mobility services.

The municipality is considered as the single leader and at the same time an arbiter looking for the solution that would be fair for all involved parties and from various perspectives, where some of them may be more important than others. Leader's payoff function is therefore expressed by a score based on KPIs with certain weights assigned to different players (or groups of players) and to different aspects, namely environmental, economical, and social. In general, various tools can be used for the modelling of impacts of different decisions made by the leader, and thus for the enumeration of relevant KPIs (including agent-based models and other tools summarised in Section 2.1, or new ones created for example by the cited nuMIDAS project). The computation of the leader's payoff function is then given by Equation 6, employing the idea of the generalised Nash bargaining solution. Game theory is therefore used as a convenient basis for the support of policymakers, helping them to foresee impacts of various policies and make the decision that is beneficial for the society and acceptable by all sides. The relation between different mobility providers, but also other actors, represents a good example of co-opetition, which denotes the case when competitors find it profitable to cooperate in certain aspect or time period or under certain conditions. For example, at the consumer level (downstream) these actors compete for market share, while at the producer level (upstream) they cooperate in sharing components, costs, knowledge, platforms, networks etc. for mutual benefits.

Finally, the trend of providing anything "as a service" is growing into the mobility field, led by digitalisation [4]. Digital platforms can improve the mobility of anyone within the city by facilitating the flow of information and improving the usage of resources. This may lead to a disruption in traditional services and change of people's behaviour. Cities will have to adjust their policies, affecting business models across all services, in order to build an integrated and efficient urban mobility ecosystem. In addition to adjustments, digitalisation also supports new types of policies, such as smart pricing of services. Mobility services cannot be considered separately anymore, but a customisation to their exact goal within the urban mobility ecosystem of each given city is necessary, including the user experience, which requires a complex decision making. This also covers a better connection between involved stakeholders (including the citizens and travellers). The proposed standard tool for the analysis of players (i.e., stakeholders) helps to aggregate different perspectives into a single solution, allowing optimal decision.

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Appendix A

Table A1. Nomenclature.

Variable	Description
EM_i	Emitted mass of pollutant i
M	Operating profit margin
S_M	Normalised operating profit margin
D	Total distance travelled
S_D	Normalised total distance travelled
A	Accessibility of a service
P	Proximity of a service
R	Ratio or served population
S_A	Normalised accessibility
N_R	Normalised ratio of served population
N_P	Normalised ratio of served population
E	Emissions
S_E	Normalised emissions
T	Traffic performance (e.g., sum of time lost)
S_T	Normalised traffic performance
F	Travel effort (sum of trips duration)
S_F	Normalised travel effort
C	Traffic capacity
S_C	Normalised traffic capacity

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