EU Smart Cities: Towards a New Framework of Urban Digital Transformation

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The URBANITE H2020 project aims to address urban mobility challenges caused by growth and new transportation methods. It develops a decision support system for policymakers, incorporating simulation, evaluation of key performance indicators, a recommendation/decision support system, and machine learning capabilities. The system helps identify and improve key performance indicators, proposes effective policies, and enhances urban digital transformation for sustainable and efficient mobility.

Povzetek: Podan je pregled novih storitev, razvitih v H2020 projektu pametnih mest Urbanite.

1 Introduction

Rapid urbanisation and population growth [1] pose significant challenges for modern cities. Smart cities (SC) have emerged as a solution for sustainable development, leveraging technology and data to enhance citizens' quality of life [2, 3, 4, 5]. In the context of the European Union (EU), the concept of SC has been a focal point of urban development and digital transformation initiatives. Several studies and research papers have explored various aspects of EU smart cities and their journey towards a new framework of urban digital transformation. Neirotti et al. analysed European SC by exploring their potential for innovation and sustainability [6]. Kitchin et al. examined the enabling and success factors in the development of SC in Europe [7]. Hollands conducted a systematic analysis of SC initiatives in Europe, highlighting diverse approaches and strategies [8]. Deakin et al. explored the role of policy in shaping smart urban futures in Europe [9]. These studies shed light on technology, governance, citizen engagement, and policy frameworks in the transformation of EU SC. Four cities were selected for this study: Bilbao, Amsterdam, Helsinki, and Messina. Each city is actively addressing specific transportation challenges. Bilbao, in Spain's Basque Country, has implemented measures to reduce pollution and congestion by closing city centre streets to private vehicles. Amsterdam, the capital of the Netherlands, focuses on cyclist safety and promoting a cyclist-friendly environment. Helsinki, the capital of Finland, plans to construct a tunnel near the port to enhance mobility and reduce congestion. Messina, in Italy, aims to improve its public transport network by introducing new lines for better accessibility and connectivity. These four cities serve as valuable case studies, illustrating different approaches and initiatives in urban digital transformation. By analysing the experiences and strategies of Bilbao, Amsterdam, Helsinki, and Messina, valuable insights can be gained towards developing a new framework for urban digital transformation in the context of EU SC. In that context, Urbanite strives to create more liveable, inclusive, and resilient cities that leverage technology and innovation to address urban challenges, improve sustainability, and enhance the quality of life for citizens. By fostering collaboration and knowledge exchange, the project aims to accelerate the transformation of European cities into smart and future-ready urban centres.

In this paper, we propose a novel approach within the Urbanite project, addressing the specific challenges faced by each city through the utilisation of multiple modules. These modules include a simulation tool, subjective key performance indicators (KPIs) tailored to each city, a recommendation engine, and machine learning (ML) techniques. In the following sections, we provide a concise overview of the general schema and discuss each module individually, highlighting their functionalities and contributions to the overall framework.

2 Urbanite architecture

In this section, we introduce a new framework developed within the Urbanite project [10], aimed at implementing SC solutions throughout Europe. Urbanite aims to enhance the quality of life for urban residents by leveraging innovative technologies and sustainable practices. The project brings together multiple stakeholders, including municipalities, research institutions, and industry partners, to collaborate on creating smarter and more efficient cities. One of the key objectives of Urbanite is to foster the integration of various SC components, such as smart mobility, en-

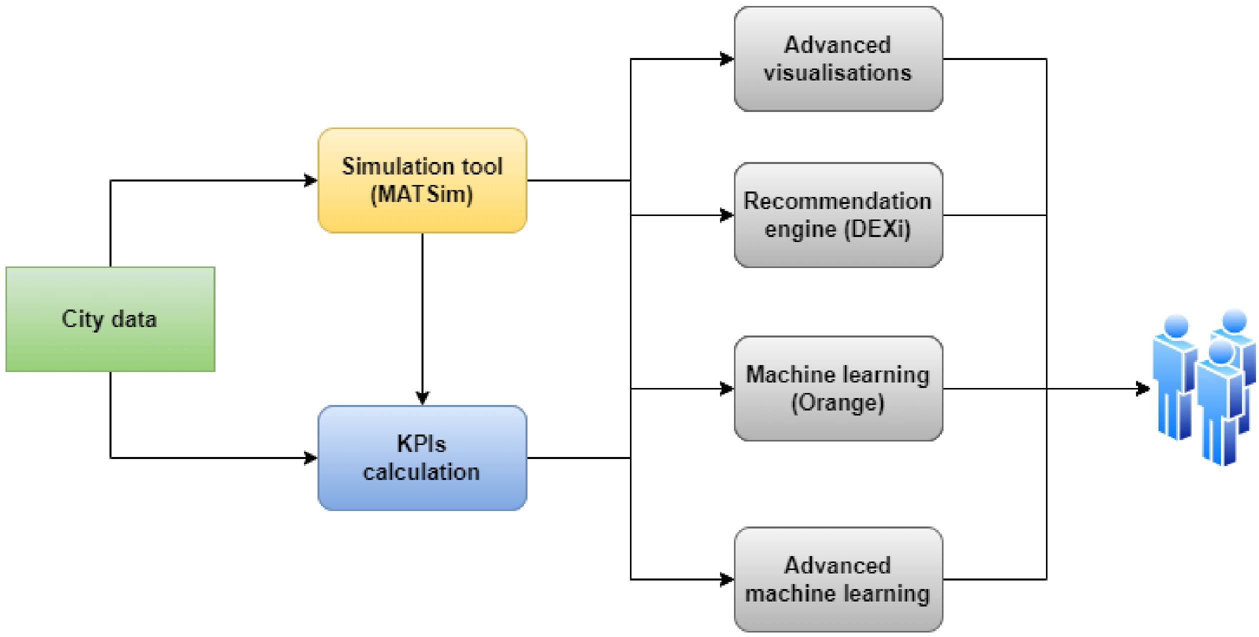

Figure 1: General schema of the software framework.

ergy management, and digital infrastructure. By harnessing data and technology, the project seeks to optimise urban services and resources, improve environmental sustainability, and enhance the overall urban experience. Urbanite promotes the concept of citizen-centric SC, where the needs and well-being of residents are at the core of urban development. It emphasises citizen engagement and participation in decision-making processes, encouraging the active involvement of communities in shaping the future of their cities. The project also focuses on promoting cross-sector collaboration and knowledge sharing among cities. Through pilot initiatives and best practice exchanges, Urbanite aims to facilitate the replication and scalability of successful SC solutions across different urban environments in Europe. A lot of research has been done on Urbanite presented in the following papers [11, 12, 13, 14].

The proposed software framework adheres to a general schema, as depicted in Figure 1. It begins by fetching data from a data platform and employing a microscopic traffic simulator to simulate a variety of scenarios. Following the completion of the simulations, specific KPIs defined by users are computed. These simulations, alongside the KPIs, are subsequently utilised by a range of modules, encompassing advanced visualisations, a recommendation system, and ML modules. Collectively, these modules provide policy recommendations and aid decision-makers in making well-informed choices.

The usage of microscopic traffic simulations has gained prominence as a cost-effective approach for testing, implementing, and evaluating mobility policies and urban changes, circumventing the expenses associated with real-world experiments. The simulator relies on city-related data such as population statistics, network maps, and public transit schedules to operate effectively. Once executed, the simulator enables the calculation of city-specific subjective KPIs related to factors such as air pollution, congestion, cyclist safety, and more. The resulting simulation output, coupled with the calculated KPIs, is then leveraged by other models integrated within the framework.

The recommendation system, implemented with the Dexi tool [15], compares two scenarios and selects the preferable option based on subjective preferences, such as lower CO_2 or NOx emissions.

The ML module, implemented using Orange [16], serves the purpose of evaluating the quality of mobility policies through microscopic traffic simulations. The user-friendly nature of Orange makes it accessible to users without a programming background.

Additionally, an advanced version of the ML module is utilised to propose mobility policies based on a previously simulated finite set of scenarios, further enhancing the framework's capabilities.

Overall, the proposed software framework incorporates multiple modules and techniques to facilitate the testing, evaluation, and recommendation of mobility policies, ultimately contributing to more informed decision-making processes in urban planning.

3 Simulation

The novelty of our study revolves around four distinct cities, each with its own unique set of demands and challenges. In order to address these challenges, we used MTASim (Multi-Agent Transport Simulation) simulation tool. In addition to MTASim, we evaluated several other state-of-the-art simulation methods to address the challenges faced by the four cities in our study. These methods included SUMO (Simulation of Urban Mobility) and PT VISsum.

SUMO is a widely used microscopic traffic simulation tool capable of simulating large-scale transportation networks. It offers detailed modeling of individual vehicles, their interactions, and traffic dynamics. SUMO considers factors such as lane-changing, traffic lights, and road infrastructure to provide realistic simulations of urban traffic scenarios.

PT VISsum, on the other hand, focuses on public transport simulation. It enables the modeling of various aspects of public transport systems, such as schedules, routes, and passenger behavior. PT VISsum allows for the evaluation of public transport performance and the analysis of potential improvements in terms of efficiency, reliability, and passenger satisfaction.

With the successful identification of MTASim as the optimal approach, we proceeded to apply it to each of the four cities under study. By implementing MTASim, we aimed to tailor the solution to the specific demands and characteristics of each city, taking into account their individual requirements and objectives.

MATSim is a powerful simulation framework designed to model complex transportation systems. It employs an agent-based approach, simulating the behaviour and interactions of individual travellers within a network. MATSim operates by simulating the daily activities of each traveller, including their commuting patterns, mode choice decisions, and route selections. By capturing the heterogeneity of traveller behaviour, MATSim enables a detailed understanding of transportation dynamics and their implications for urban mobility. The simulation process begins with an initial demand, which is then simulated in the mobsim module and evaluated in the scoring module. The scoring module assesses transportation options and scenarios based on criteria like travel time, cost, environmental impact, and user preferences. Through iterative iterations, the simulation dynamically adapts and optimises system performance, responding to changing conditions and policy interventions via the replanning module. This cyclic process is illustrated in Figure 2.

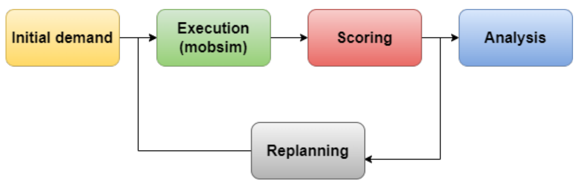

Figure 2: MATSim cycle.

To run the simulator, several input files are required. First, the network is generated from OpenStreetMap (OSM) data [17]. This network serves as the foundation for the simulation, capturing the road and transportation infrastructure of the studied area.

Next, travel plans are generated to simulate individual behaviour within the network. These travel plans dictate the movements and activities of simulated travellers, allowing the simulator to capture their interactions and decision-making processes.

In addition to the network and travel plans, other files are needed, including public transport schedules, descriptions of vehicles, and a configuration file that acts as a bridge between the user and the simulation tool. The configuration file allows users to fine-tune various parameters of the simulator according to their specific requirements and objectives.

Once the simulation is completed, several output files are generated. The most important of these is the event file, which contains a detailed description of people's movements and activities within the network. This file serves as a valuable resource for analysing and evaluating the simulated scenarios. Utilizing the event file, KPIs can be calculated to assess the efficiency, effectiveness, and other relevant metrics of the simulated transportation system.

4 Key performance indicators

4.1 Bike infrastructure

The KPI for bike infrastructure measures the extent and quality of the infrastructure available to support bicycle transportation. This includes factors such as the number of bike lanes, bike parking facilities, and the quality of road surfaces. The information taken into account is freely available from OSM. Based on the reported properties of the road a number of points is assigned to each road segment. Higher numbers are better, where 0 is a motorway (inappropriate and illegal to bike) to 10 (a bike-only road).

4.2 Bike speed limit

The KPI for bike speed limit refers to the maximum speed limit for bicycles on specific roads or bike lanes. This KPI is important for ensuring the safety of cyclists and other road users and promoting sustainable mobility by encouraging more people to cycle. The information taken into account is freely available from OSM. Based on the speed limit, each road segment is assigned a different number of points from 0 to 10.

4.3 Bikeability

The KPI for bikeability is a comprehensive metric that assesses the overall quality of the cycling environment. This KPI takes into account the bike infrastructure KPI and the bike speed limit KPI.

4.4 Bike intensity

The KPI for bike intensity measures the volume of bike traffic on a specific road or bike lane. This KPI is essential for understanding the usage and popularity of cycling as a mode of transportation and can help identify areas where improvements are needed to support increased bike traffic. The KPI is calculated by counting simulated bikes moving on each road segment.

4.5 Bike congestion

The KPI for bike congestion measures the level of traffic congestion experienced by cyclists on specific roads or bike lanes. This KPI is important for understanding the quality of the cycling experience and identifying areas where infrastructure improvements or traffic management strategies may be necessary to reduce congestion and improve safety for cyclists. The bike congestion KPI is calculated by first calculating the traffic flow on bikeable road segments and detecting low speeds with a high volume of bikes.

4.6 Share of bikes

This KPI measures the proportion of trips made by bicycle of all trips made. This allows the user to see where there are bikes and cars competing for the road surface, which can be dangerous, as well as identify areas where cycling should be encouraged either via infrastructure improvements, informing the public or other interventions. This KPI is complementary to the share of cars and the share of public transport.

4.7 Share of cars

This KPI measures the proportion of trips made by cars in a given area. It provides insights into the prevalence and effectiveness of car use as a mode of transportation, which can have significant impacts on urban mobility, air quality, and congestion. This KPI is complementary to the share of bikes and the share of public transport.

4.8 Share of public transport

This KPI measures the proportion of trips made by public transport vehicles, such as buses, trains, and trams, in a given area. It provides insights into the prevalence and effectiveness of public transport as a mode of transportation, which can have significant impacts on urban mobility, accessibility, and air quality. This KPI is complementary to the share of bikes and share of cars.

4.9 Acoustic pollution

This KPI measures the level of noise pollution in a given area, which can have significant impacts on public health, quality of life, and urban mobility. High levels of noise pollution can contribute to stress, sleep disturbance, and hearing loss. The acoustic pollution calculation is based on the simulated vehicle movements and geometry of buildings along the roads.

4.10 CO_2, PM_{10}, NOx

These KPIs measure the levels of carbon dioxide, particulate matter, and nitrogen oxides in a given area, which can have significant impacts on air quality, public health, and climate change. High levels of these pollutants can contribute to respiratory problems, cardiovascular disease, and other health issues. The amounts of air pollutants emitted are calculated based on the simulated vehicle movements and emission factors from the Handbook of Emission Factors (HBEFA).

4.11 Average pedestrian trip time

This KPI measures the average time it takes for pedestrians to complete a trip in a given area. It provides insights into the accessibility and quality of the pedestrian infrastructure, which can have significant impacts on urban mobility, safety, and public health. Due to limitations of the traffic simulation used the pedestrian trips do not take into account the infrastructure, only the distance between the source and destination. Therefore, this KPI is an estimation and not an exact value.

4.12 Congestions and bottlenecks

Congestions and bottlenecks are key performance indicators that help evaluate the efficiency of the urban mobility system. High levels of congestion can result in increased travel times, decreased accessibility, and reduced economic productivity. By monitoring and analysing the levels of congestion and bottlenecks, decision-makers can identify areas where traffic management interventions, such as lane restrictions or public transportation improvements, may be necessary. The congestions and bottlenecks KPI is implemented by calculating the traffic flow on each road segment and identifying segments with high volume but low speed.

4.13 Harbour area traffic flow

Harbour area traffic flow is a critical KPI in evaluating the efficiency of cargo transportation in urban areas. High levels of traffic flow can result in congestion and bottlenecks in the harbour area, leading to increased travel times and reduced economic productivity. This KPI is implemented by adding virtual traffic sensors to the relevant road segments of the simulation.

4.14 Public transport usage

This KPI measures the number of passengers using public transport services in a specific period. It is a critical metric for urban mobility decision-makers as it provides insights into the demand for public transport services and helps identify potential opportunities to improve service quality and coverage to meet the needs of the public.

4.15 Average speed of public transport

This KPI represents the average speed of public transport vehicles in a given area or route. It provides insight into the efficiency and reliability of public transport services, as well as the effectiveness of traffic management policies. Improving the average speed of public transport can reduce travel time and encourage more people to use public transport.

4.16 Number of bike trips

This KPI measures the number of trips made by bicycles in a specific period. It is a critical metric for urban mobility decision-makers who aim to promote sustainable and healthy transportation alternatives. By encouraging more people to use bicycles, cities can reduce traffic congestion, improve air quality, and promote physical activity.

5 Decision Support System

Dexi is a decision tool that assists individuals and organisations in making informed choices by leveraging data and analytics. It is designed to simplify complex decision-making processes and provide actionable insights.

The tool offers a user-friendly interface that allows users to define decision criteria, set up models, and conduct scenario analyses. Dexi provides visualisation features to present the results in intuitive and understandable formats, such as charts, graphs, and dashboards. This helps users grasp the implications of different options and assess the potential outcomes of their decisions.

Dexi supports both strategic and operational decision-making processes across different domains. It can be applied to various use cases, such as financial planning, risk assessment, marketing campaign optimisation, supply chain management, and resource allocation. By leveraging advanced analytics, Dexi empowers users to make data-driven decisions that align with their goals and objectives.

Overall, Dexi is a versatile decision tool that combines data integration, analysis, and visualisation capabilities. It supports evidence-based decision-making, empowers users with actionable insights, and enhances efficiency in decision processes across various domains.

In the system, we utilise the output of Dexi in two ways. The first one is creating a textual suggestion which will inform the decision maker about which mobility policy is better in subjective terms with regards to another policy. The second way is visually by the usage of a chart.

6 Machine Learning

The purpose of the ML module in the Urbanite framework is to estimate the quality of a proposed policy without previously simulating it. The main concept centres around employing a single simulation run as a training example. Various groups of parameters associated with the simulation's input and output serve as the features, while the KPIs represent the target variables. To illustrate this approach, the city of Bilbao is selected as a practical case study. Our analysis focuses on the potential impact of closing Moyua Square in the city centre and altering the number of cyclists on air pollution, particularly by estimating CO_2 emissions. Multiple ML algorithms are tested, and the findings indicate that closing the main square in the city centre and promoting cycling has a positive effect on reducing CO_2 emissions.

To implement the idea in a user-friendly manner, Orange was used. Orange is a powerful machine learning (ML) tool developed by the research group at the Faculty of Computer and Information Science (FRI) and Jozef Stefan Institute (JSI) in Slovenia. It is open-source software that provides a user-friendly interface for data analysis, visualisation, and ML modelling. Orange is designed to make ML accessible to users without extensive programming knowledge. It offers a visual programming environment where users can create ML workflows by connecting pre-built components called "widgets." These widgets represent various data processing, analysis, and modelling techniques, allowing users to construct complex ML pipelines intuitively. With Orange, users can perform a wide range of tasks, including data preprocessing, feature selection, clustering, classification, regression, text mining, and more. It supports data visualisation and integration with other popular ML libraries and tools. The open-source nature of Orange encourages community involvement and contributions. Users can access the source code, contribute to its development, and create custom widgets tailored to their specific needs. The tool has an active user community, which provides support, shares resources, and promotes collaboration.

In this context, in Figure 3, the outcomes of the implemented policy using Orange visualisation widgets are illustrated. It depicts the correlation between the number of cyclists and the level of co_2 emissions. The x-axis represents the number of cyclists near the square, while the y-axis represents the number of cyclists in the centre. The varying colours indicate the number of co_2 emissions as the target variable, with the baseline scenario marked by an orange circle. The figure demonstrates that closing the main square to private traffic and decreasing the number of private vehicles in its vicinity leads to a reduction in co_2 emissions.

7 Advanced Machine Learning

Unlike the standard ML module, the advanced ML module leverages more sophisticated tools to tackle intricate problems. The key novelty of this module lies in its utilisation of multiclass-multioutput ML models, enabling the simul-

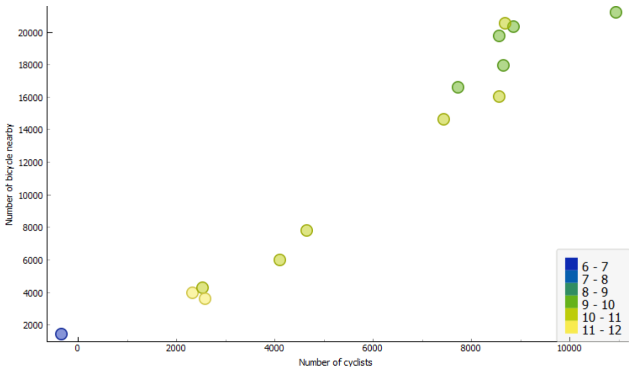

Figure 3: CO_2 emissions in the Moyua square (baseline scenario is marked with an orange circle).

taneous prediction of multiple outcomes using a diverse set of input variables. The primary goal of the ML module is to assist decision-makers in defining potential city scenarios and utility functions, allowing the ML model to identify policies that best align with given constraints and preferences. Notably, the module offers significant improvements in policy testing speed, with performance gains of several orders of magnitude. The system underwent testing in Bilbao's Moyua area, successfully achieving a predefined reduction in emissions and other KPIs. Furthermore, it provided valuable insights into optimal policies for closing specific districts to private traffic and determining the ideal timing for these closures based on data from simulated and learned scenarios.

The complexity of the problem lies in predicting multiple target variables which are discrete and continuous. The policy we want to predict is related to the start hour and duration of closing and what part of the city centre to close. Therefore the problem was split into classification (area of closure) and regression (start hour and duration of closure) tasks. Several ML algorithms that support multiclass-multioutput problems were tested.

Overall, the multiclass-multioutput module in the Urbanite project explains complex relationships between factors like traffic patterns and travel behaviour. It provides insights and recommendations to city planners, aiding informed decisions. This study is the first to address policy testing in a real city using multiclass-multioutput ML. Additionally, the ML module significantly speeds up simulations by several orders of magnitude, transforming time-demanding simulations into nearly interactive ML modules. The ML module reduces simulation time from 3 hours to just 10 seconds per simulation on a PC. While learning the ML module took 23 days for 192 simulations, running a total of 1452 simulations would take approximately 6 months. Experimental results demonstrate a high similarity between ML-simulated city performance and actual simulations.

8 Conclusion

In this paper, we tried to present the main software framework of the Urbanite H2020 project, which aims to address urban mobility challenges in the context of smart cities. The project develops a decision support system that incorporates simulation, evaluation of KPIs, recommendation/decision support, and ML capabilities. The goal is to identify and improve KPIs, propose effective policies, and enhance urban digital transformation for sustainable and efficient mobility.

The paper introduces the concept of smart cities and highlights their significance in addressing challenges posed by rapid urbanisation and population growth. It references several studies and research papers that have explored various aspects of smart cities in Europe, including innovation, sustainability, governance, citizen engagement, and policy frameworks. The Urbanite project builds upon this knowledge to create smarter and more efficient cities that prioritise the well-being of residents.

The paper focuses on four cities: Bilbao, Amsterdam, Helsinki, and Messina, which serve as case studies for understanding different approaches and initiatives in urban digital transformation. Each city faces specific transportation challenges, and the Urbanite project aims to tailor solutions to their unique requirements. By analysing the experiences and strategies of these cities, the project aims to develop a new framework for urban digital transformation in EU smart cities.

The proposed software framework consists of multiple modules, including a simulation tool, subjective KPIs, a recommendation engine, and ML techniques. The simulation tool, based on the MTASim approach, replicates various traffic situations within the network, enabling the evaluation of mobility policies and city changes. Subjective KPIs are calculated to assess factors such as air pollution, congestion, and cyclist safety. The recommendation engine, implemented using Dexi, helps decision-makers choose the most suitable policy based on subjective preferences. ML techniques, implemented using Orange, evaluate policy quality and propose mobility policies based on previously simulated scenarios.

Overall, the Urbanite project contributes to the development of smarter and more sustainable cities by leveraging technology, data, and citizen engagement. The proposed software framework enhances decision-making processes in urban planning, allowing for the testing, evaluation, and recommendation of mobility policies. By addressing the specific challenges faced by each city and fostering collaboration among stakeholders, the project aims to accelerate the transformation of European cities into smart and future-ready urban centres.

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