Supporting Decision-Making in the Urban Mobility Policy Making

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ABSTRACT

City mobility is changing rapidly due to population growth and disruptive technologies. To efficiently handle these changes, policymakers need advanced tools based on AI, including simulation, prediction, decision making, and visualization. In the URBANITE H2020 project, we are developing a decision support system (DSS) that is based on DEXi and enables the decision-makers to combine low-level mobility data obtained with simulation, into high-level attributes suitable for decision making and comparison of mobility scenarios. By providing the user preferences in advance, DSS can be also used in combination with machine-learning models to search for the best mobility policies automatically.

KEYWORDS

decision making, mobility, urban transformation

1 INTRODUCTION

The mobility in cities is changing rapidly. On one hand, the population in cities is growing which results in increased congestion and pollution. On the other hand, new and disrupting mobility modes are being introduced, such as vehicle sharing, hop on/off bikes, etc. The city policymakers thus face a very complex problem: how to improve mobility under growing congestion pressures, while considering new mobility modes [1]. Advanced tools that include artificial intelligence (AI) approaches can significantly help policymakers to select the most appropriate actions [4].

AI-based tools for city mobility typically include the city models and traffic simulation, which enables the users to simulate various traffic situations [3]. We are developing a system that will, besides city models and traffic simulation, include also a decision support system (DSS) [2] and a machine learning module. The decision support system will support the user, either human or algorithm, in selecting the best policy, while the machine learning module will aim at replacing human decision-makers with algorithmic ones. In this paper, we focus on the DSS of the URBANITE H2020 project [5].

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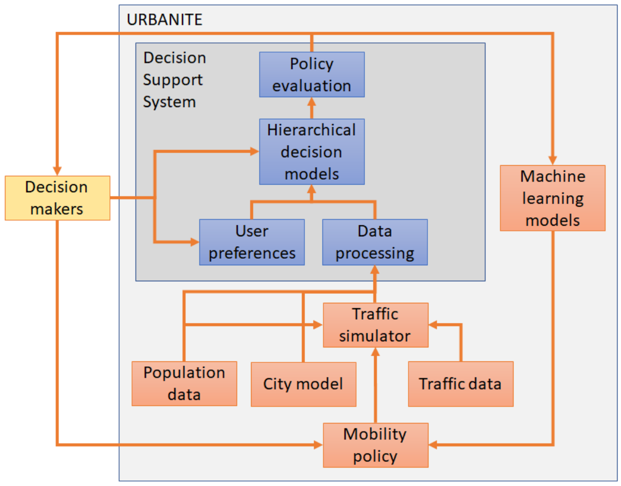

Figure 1: The architecture of the URBANITE system.

The developed DSS aims to enable the users to select the most appropriate policy actions based on data from simulations, population data, current and predicted traffic data, and user (citizen, decision-makers) preferences. By defining the user preferences in advance, it weights and hierarchically aggregates the basic data to obtain one or a few objectives, based on which the evaluated policies are compared and ranked. The policy ranking represents the key information for the final decision regarding which policy should be applied.

The rest of the paper is organized as follows. Section 2 presents the URBANITE system. The decision support system within URBANITE is described in Section 3. Finally, Section 4 concludes the paper with a summary and ideas for future work.

2 OVERVIEW OF THE URBANITE SYSTEM

The URBANITE system consists of several modules such as tools for the involvement of various types of stakeholders, including the general public. However, from the point of view of the presented decision support system, only the modules relevant for DSS are presented in Figure 1.

There are two main inputs to DSS. The first one consists of the expert knowledge, provided by the decision-makers. This knowledge is of key importance when building hierarchical decision models, as well as when defining user preferences (see Section 3 for details).

The second input consists of raw data including city models, population data, and evaluation results from the traffic simulator. Population data include the number of people in the urban area as well as their distribution between the districts. The city model consists of a map of roads, districts, public areas, etc. Finally, traffic simulation results are trip traces that include all the relevant data such as the (vehicle) positions, time, and pollution. These results are obtained by evaluating a mobility policy with the traffic simulator. To this end, the simulator processes the population data, the city model, and the past traffic data to emulate the characteristics of real-life traffic as much as possible.

The mobility policy consists of a set of actions to be applied within the urban area (such as closing a specific road for cars) and can be proposed either by decision-makers or by machine-learning models. Both take into account the policy evaluation, computed by the DSS. The main difference between the two approaches is the fact that decision-makers rely on expert knowledge and define the mobility policies by hand, while machine-learning models apply pattern-recognition approaches, process a possibly huge amount of data, and select mobility policies automatically.

Finally, the decision support system consists of several components that are described in Section 3.

3 DECISION SUPPORT SYSTEM (DSS)

Our DSS aims to evaluate mobility policies, i.e., for each policy produce one or a limited set of objectives that are easily interpretable and handled by the experts. Note that a baseline mobility policy is evaluated by the traffic simulator, but the evaluation provided by a standard simulator is very difficult to process by experts due to a large amount of data since the evaluation consists of traces of all the trips within the city. Therefore, the DSS aggregates evaluation data into meaningful high-level attributes to enable efficient and effective decision-making.

3.1 Components of the URBANITE DSS

The main component of the DSS is the hierarchical decision model (see Figure 1). A hierarchical decision model is defined by the experts/decision-makers based on their expert knowledge. It starts with the evaluation values, provided by the traffic simulator, and iteratively combines semantically similar attributes into higher-level attributes until only one attribute remains. This results in a tree structure in which the root represents the final evaluation of the policy. However, it is not required to always use the final evaluation during the decision-making process. In some cases, it is more appropriate to use several high-level attributes (e.g., pollution and congestion) to compare the policies in all the aspects that the decision-makers are interested in. In this case, the selected attributes are inner nodes of the tree structure.

To create the hierarchical decision model and to select the relevant attributes, user preferences have to be obtained. They are included in the module by experts/decision-makers. When creating the decision model, the preferences are used to weigh the attributes within the tree structure. More precisely, when combining attributes into a higher-level node/attribute within the tree structure, a utility function needs to be defined, which specifies how each combination of lower-level attributes transforms into the higher-level attribute. This is a preference-based process and typically involves combining qualitative attributes of various types.

Hierarchical decision models are not able to directly handle the city model data or the raw data obtained from the traffic simulator. Therefore, the baseline data need to be preprocessed and, if appropriate, aggregated. For example, if the city pollution is required as an input to the hierarchical decision model, it has to be calculated from all the trips within the city.

Finally, policy evaluation has to be executed. This is done by applying the preprocessed traffic simulator data within the hierarchical decision model. The resulting values of the high-level attributes, selected based on user preferences, are then sent to decision-makers or machine-learning models (see Figure 1). The hierarchical decision models, including their definition and execution, were implemented with DEXi [2].

3.2 Hierarchical Decision Model for Mobility Policy Evaluation

A new hierarchical decision model was developed by focusing on the needs and preferences of the URBANITE project [5], based on the user experience of four major EU cities. The model shown in Figure 2 was developed based on mobility policies that include building new roads, closing parts of the city like squares, setting up new lines of public transport including ferries, and other potential modifications of the city mobility. For a policy, three areas within the city were identified as relevant:

- Target area where the policy action is applied
- Nearby area that surrounds the target area and which is directly influenced by the applied policy
- The entire city

The attributes were divided into three categories:

- Road network
  These attributes measure the size of the city area where the policy action has a direct influence. They also consider the capacity of the affected roads and take into account both target and nearby areas.
- Population-related attributes including the type of the area and public transport data.
  Area type is defined with the position within the city (e.g., center, periphery), the district type (e.g. residential, commercial), and the population number. Public transport counts the available bus and underground stops, and the lanes of public transport. All these attributes are measured in both target and nearby areas.
- Policy impact
  It measures the change with respect to the baseline scenario when no policy action is applied. The following aspects are taken into account:
  - Change in air pollution
  - Change in the number of used private vehicles
  - Change in the number of used bicycles
  - Change in the number of used public transport
  - Change in the number of pedestrians

  In addition, it also takes into account congestion change. All the attributes are measured in both target and nearby areas, as well as in the entire city.

The developed model is intended to be used for both comparing the effects of applying a policy with the baseline as well as comparing the effects of various policies between themselves. As

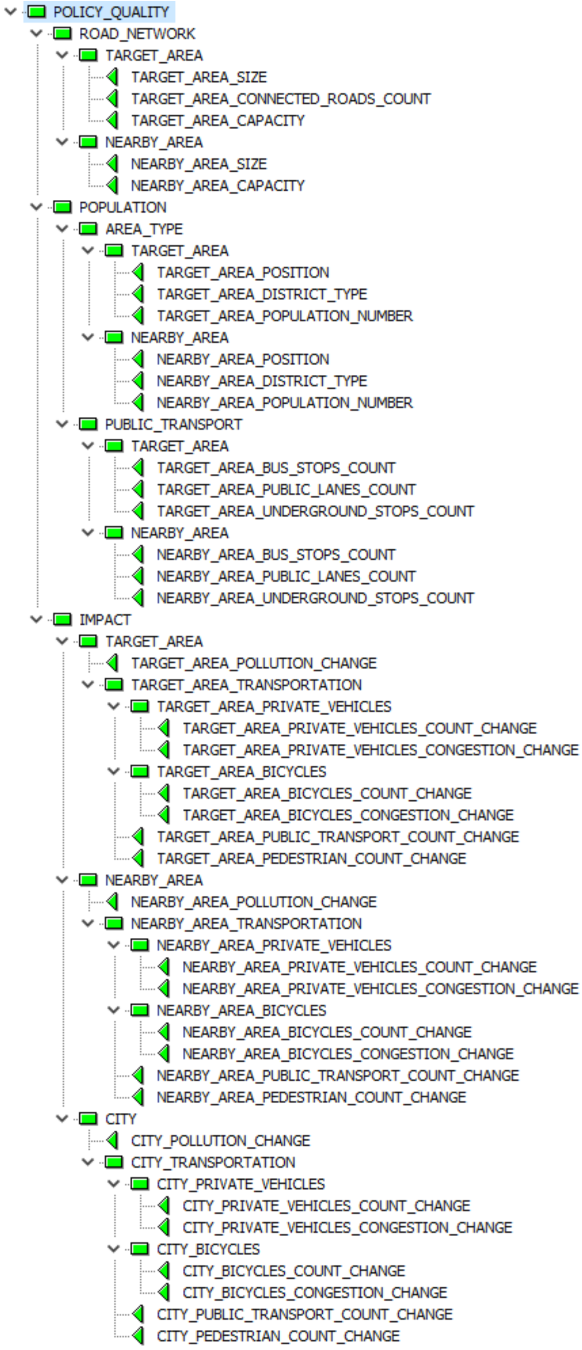

Figure 2: A hierarchical decision model for mobility policy evaluation.

a consequence, some attributes focus on comparison with baseline, while others focus on differences among various policies.

Selection of the attributes and their organization into the tree structure is only the first step when building the hierarchical model. The second step consists of defining the functions that aggregate the lower-level attributes into higher-level ones, i.e., utility functions. All the attributes in the inner nodes of the tree were defined as categorical from 1 to 5, which facilitated the utility function definition. The default scale defined the higher the better, except for the pollution where the the-lower-the-better scale was applied. An example of the utility function is shown in

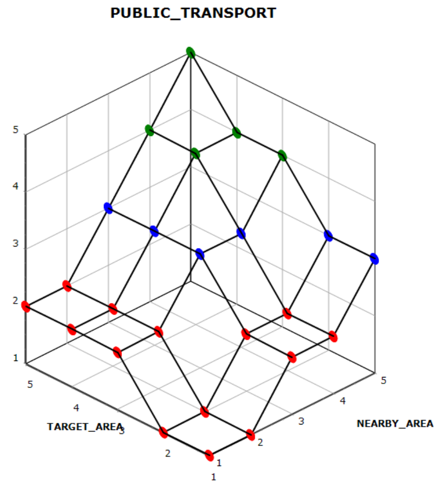

Figure 3: An example of the utility function for the selected attributes.

Option	WITHOUT_INTERVENTIONS	CLOSED_SQUARE
TARGET_AREA_SIZE	2	2
TARGET_AREA_CONNECTED_ROADS_COUNT	2	1
TARGET_AREA_CAPACITY	2	1
NEARBY_AREA_SIZE	2	2
NEARBY_AREA_CAPACITY	2	2
TARGET_AREA_POSITION	center	center
TARGET_AREA_DISTRICT_TYPE	residential	residential
TARGET_AREA_POPULATION_NUMBER	1	1
NEARBY_AREA_POSITION	center +districts	center +districts
NEARBY_AREA_DISTRICT_TYPE	residential	residential
NEARBY_AREA_POPULATION_NUMBER	2	2
TARGET_AREA_BUS_STOPS_COUNT	3-6	3-6
TARGET_AREA_PUBLIC_LANES_COUNT	3-6	3-6
TARGET_AREA_UNDERGROUND_STOPS_COUNT	1-2	1-2
NEARBY_AREA_BUS_STOPS_COUNT	7+	7+
NEARBY_AREA_PUBLIC_LANES_COUNT	7+	7+
NEARBY_AREA_UNDERGROUND_STOPS_COUNT	3-6	3-6
TARGET_AREA_POLLUTION_CHANGE	5% decrease - 5% increase	+20% decrease
TARGET_AREA_PRIVATE_VEHICLES_COUNT_CHANGE	5% decrease - 5% increase	+20% decrease
TARGET_AREA_PRIVATE_VEHICLES_CONGESTION_CHANGE	5% decrease - 5% increase	+20% decrease
TARGET_AREA_BICYCLES_COUNT_CHANGE	5% decrease - 5% increase	+20% increase
TARGET_AREA_BICYCLES_CONGESTION_CHANGE	5% decrease - 5% increase	+20% decrease
TARGET_AREA_PUBLIC_TRANSPORT_COUNT_CHANGE	5% decrease - 5% increase	5-20% increase
TARGET_AREA_PEDESTRIAN_COUNT_CHANGE	5% decrease - 5% increase	+20% increase
NEARBY_AREA_POLLUTION_CHANGE	5% decrease - 5% increase	5-20% increase
NEARBY_AREA_PRIVATE_VEHICLES_COUNT_CHANGE	5% decrease - 5% increase	5-20% increase
NEARBY_AREA_PRIVATE_VEHICLES_CONGESTION_CHANGE	5% decrease - 5% increase	5-20% increase
NEARBY_AREA_BICYCLES_COUNT_CHANGE	5% decrease - 5% increase	5-20% increase
NEARBY_AREA_BICYCLES_CONGESTION_CHANGE	5% decrease - 5% increase	5-20% increase
NEARBY_AREA_PUBLIC_TRANSPORT_COUNT_CHANGE	5% decrease - 5% increase	5-20% increase
NEARBY_AREA_PEDESTRIAN_COUNT_CHANGE	5% decrease - 5% increase	5-20% increase
CITY_POLLUTION_CHANGE	5% decrease - 5% increase	5-20% decrease
CITY_PRIVATE_VEHICLES_COUNT_CHANGE	5% decrease - 5% increase	5-20% decrease
CITY_PRIVATE_VEHICLES_CONGESTION_CHANGE	5% decrease - 5% increase	5-20% increase
CITY_BICYCLES_COUNT_CHANGE	5% decrease - 5% increase	5-20% increase
CITY_BICYCLES_CONGESTION_CHANGE	5% decrease - 5% increase	5-20% increase
CITY_PUBLIC_TRANSPORT_COUNT_CHANGE	5% decrease - 5% increase	5-20% increase
CITY_PEDESTRIAN_COUNT_CHANGE	5% decrease - 5% increase	5-20% increase

Figure 4: Definition of two test scenarios.

Figure 3 that shows how the Target area attribute and the Nearby area attribute are combined into the Public transport attribute.

3.3 Evaluation of Mobility Policies

The hierarchical decision model, described in Section 3.2, was used to evaluate a test policy that prescribed that the main square of a test city should be closed. The effects of this policy were compared to the baseline, where no actions were taken.

First, both scenarios (no intervention and closed square) were simulated and the obtained results were preprocessed. Second, the data were inserted in DEXi as shown in Figure 4, where each column represents one scenario and colors represent the evaluation of single attributes (green: good, black: neutral, red:

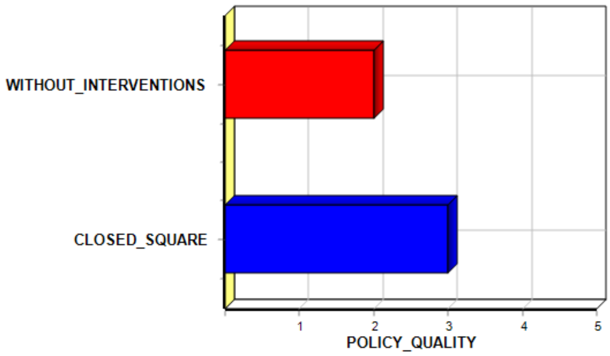

Figure 5: Comparison of the overall quality of the test scenarios.

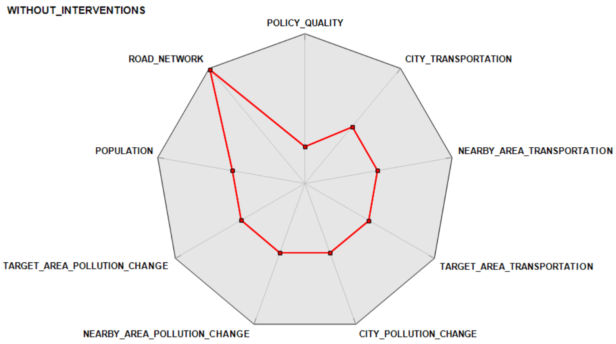

Figure 6: Evaluation of the scenario without interventions.

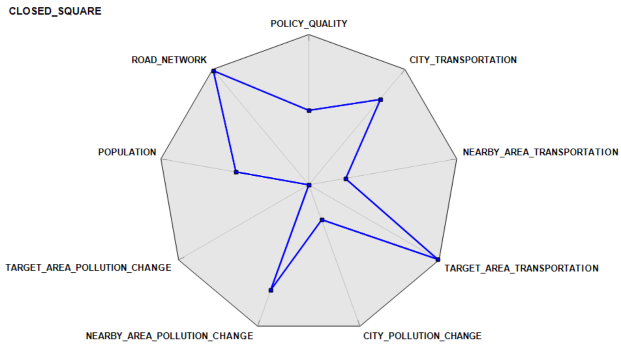

Figure 7: Evaluation of the scenario with closed square.

bad). This figure shows that the differences between the scenarios are in the target area roads and the impact attributes. The impact is negative only in a minority of attributes: in the nearby area and the congestion when observing the entire city (see the color change from black to red). On the other hand, there is a positive change in the majority of the impact attributes (black color to green).

The selected scenarios were evaluated both based on the overall quality and based on a set of the most relevant high-level attributes, i.e., inner nodes of the tree. The overall quality comparison is presented in Figure 5, while the comparison on the selected attributes can be found in Figures 6–7. These figures show that the overall quality of the closed-square scenario is higher in comparison to no interventions. As noted previously, for the pollution change in Figures 6–7, lower, i.e., near the center of the graph is better, while for other attributes, higher, i.e., near the edge of the graph is better. In these figures, we can observe a similar trend as in Figure 4. The difference is that in Figure 4 we compare the scenarios on basic attributes (leafs of the tree), while in Figures 6–7 we compare scenarios on the higher-level attributes (inner nodes of the tree). Finally, Figure 5 shows the comparison on the top-level attribute, i.e., the root of the tree.

4 CONCLUSION

Selection of the best mobility policy for a city is typically a complex task since the policy can influence a large variety of mobility aspects. In addition, simulation tools typically produce a large amount of data that needs to be appropriately preprocessed and aggregated. Consequently, a suitable approach for hierarchical aggregation of mobility attributes needs to be defined to get a low number of higher-level attributes that make the decision-making process feasible.

In this paper, we proposed to aggregate the mobility attributes with DEXi. DEXi applies hierarchical decision models that are defined based on expert/decision-maker knowledge. We developed a new hierarchical decision model that was then used for basic and multiobjective comparison of mobility scenarios.

This paper also presented a basic graphical interface for comparing the scenario outputs, while additional and more advanced GUIs are still under development. The evaluation of the developed decision model on a variety of mobility policies is ongoing and aims at determining whether the model is suitable for all the relevant scenarios. In case of discovered deficiencies, we will upgrade the model with additional attributes and/or attribute rearrangement.

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