Assessing systemic and wider impacts of cooperative, connected and automated mobility

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New technologies in the transport sector promise to bring about certain benefits, for example related to mobility or safety, but are also expected to cause negative side effects which are in conflict with strategic city objectives. These might be mitigated by appropriate policy interventions that are designed carefully and timely. The Horizon 2020 research project LEVITATE has investigated multiple impacts of connected and automated transport systems, using an integrated multi-method approach, ranging from microscopic and mesoscopic simulations to system dynamics and Delphi panels. In particular, the system dynamics model described in this paper served to assess several systemic and wider impacts that were found difficult or even impossible to assess with the other methods. The main parts of the model are a population sub-model, a simplified traffic demand model distinguishing between three modes of transport, and a model for the use of public space. In order to calibrate the model and get results that are consistent with those of other methods, the input and output data of those simulations have also been incorporated into the system dynamics model. By means of selected example impact variables – modal split, demand for parking space and average commuting distance – the obtained effect of increasing automation as well as of several policy interventions is demonstrated.

Introduction and problem statement

Cooperative, connected and automated mobility (CCAM) is expected to be introduced in increasing numbers over the next decades. Automated vehicles have attracted the public imagination and there are high expectations in terms of safety, mobility, environment and economic growth. With such systems not yet in widespread use, however, there is a lack of data and knowledge about possible impacts.

The impact dimensions for assessment are themselves very wide, and besides positive impacts also several negative side effects may be expected – for instance higher usage of private cars, empty vehicles driving around, or increase of urban sprawl. Stakeholders like urban municipalities are therefore increasingly worried, how far these future developments might be conflicting with their long-term strategic goals (for instance, regarding CO_2 emissions, modal split of traffic and use of public space), and what would be proper policy interventions to make use of the benefits but also prevent negative impacts.

The EU funded (Horizon 2020) project LEVITATE [1] has addressed this by preparing a novel multi-method impact assessment framework to enable policymakers to manage the introduction of connected and automated transport systems, maximise the benefits and utilise the technologies to achieve societal objectives. Three main use cases have been investigated: passenger cars, urban transport systems, and freight transport and logistics, each of them considering a variety of applications, services and policy interventions (which are also referred to as sub-use cases in the following). The impact variables that have been studied have been organised along the dimensions of safety, society, environment and economy – they might also be classified into shorter-term (direct) and longer-term (indirect) impacts. The goal of the LEVITATE approach is to facilitate the quantitative comparison of several scenarios: the status quo (no automation at all), gradually increasing CCAM market penetration rate up to 100%, and finally the application of individual sub-use cases (policy interventions).

While typical transport simulation methods (microscopic, mesoscopic, macroscopic) can give reliable estimates for direct impacts (such as related to travel time or total distance travelled), they are mostly inappropriate for assessing various systemic and wider impacts which are not covered by the simulation model. This gap has been addressed in LEVITATE by means of a simplified system dynamics model that is presented here. This model aims to analyse some of the critical systemic and wider impacts which can strongly impact strategic decisions in transport planning including changes in modal split, demand for parking space, and commuting distances.

The remaining part of this paper is organized as follows: The next section summarizes the LEVITATE approach in some more detail and sets the context and motivation for the research presented here, discussing also previous related work in the system dynamics domain. After that, the used model is described, explaining the structure and main feedback loops, how subscripting has been used to arrive at a more realistic arrayed model, and finally how several possible policy interventions can be represented in this model. This is accompanied by a discussion of used input data, model calibration and validation – explaining how the model is embedded into the LEVITATE multi-method framework. After that, results are presented and discussed for four example impact variables, followed by conclusions and a brief outlook to ongoing and planned further research.

Context and related work

As mentioned in the previous section, forecasting the impacts of automated transport systems is challenging due to lack of data and experience, even more if quantitative results shall be obtained. Combining a set of mature methodologies, however, and including several assumptions that are justified by previous literature and studies, such an assessment has been performed in the LEVITATE project. For each of the investigated impact variables, both the influence of increasing AV market penetration rate (this is considered as baseline scenario, defining an implicit time scale) and the additional impact of certain policy interventions have been studied.

The results of these investigations are being incorporated into web-based policy support tool [2] to enable cities and other authorities to forecast impacts of CCAM on urban areas. Within the toolbox the impact of certain measures can be assessed individually (forecasting), further, a decision support system shall enable users to apply backcasting methods to identify the sequences of CCAM related measures that will result in achieving their desired policy objectives within a specified implementation period (under the precondition that such a pathway of feasible policy interventions exists).

In the following, the applied simulation methods (as far as relevant for the system dynamics model) are briefly described, and related system dynamics approaches are discussed.

Microscopic simulation

Traffic simulation has been widely applied to estimate potential impacts of connected and automated vehicles (CAVs). Many studies have used microsimulation techniques to estimate the potential impacts of connected and automated transport system on traffic performance indicators [3]. It is envisaged that the microsimulation approach can be used to calculate the direct impacts of CAVs. In most cases, a commercially available traffic microsimulation tool (such as AIMSUN, VISSIM, Paramics or SUMO) is used along with an external component. The microsimulation tool is applied to represent the infrastructure and creates the simulated traffic in the predefined road system while the external component aims to simulate the CAVs functionalities.

Within Levitate project, a traffic microsimulation approach is used to model and analyse various impacts on mobility (travel time, congestion, amount of travel), safety (based on vehicular conflicts), and emissions (CO_2, NOx, PM10) due to introduction of CAVs as well as with the implementation of several policy interventions (sub-use cases) including dedicated lanes, parking price policies, parking space regulations, automated ride sharing, and automated urban shuttles. AIMSUN Next microsimulation tool was used to test these policy interventions utilising calibrated and validated city networks including Manchester (UK), Leicester(UK), and Athens (GR). CAV functionalities/behaviours were modelled through adjusting a wide spectrum of parameters in the simulation framework, which are based on various parametric assumptions from the literature review findings as well as discussions with experts conducted as part of the LEVITATE project, as detailed in [4].

Mesoscopic simulation

The mesoscopic simulation approach is residing between microscopic simulations and the system dynamics model presented in this paper, regarding the aggregation level. Simulation of agents and their daily plans of activities is used as a method to estimate the medium-term consequences of several sub-use cases on a variety of defined impacts. The model is based on calibrated choice behaviours of the simulated population, and its methods provide the means to draw direct, data-supported conclusions on the altered choices of agents regarding the use of transport modes under changing circumstances of transportation availability [5].

All investigated scenarios were developed for a model of Vienna and its wider surrounding area, to serve as a prototypical example for a historically grown European city. The segmentation of the city into roughly ring-shaped domains that lie concentric around the city centre was made to enable analyses in accordance with the defined impact requirements. Borders between these domains are formed by major arterial (ring-) roads which are used to circumvent crossing through more densely populated areas towards the city centre. The same segmentation into zones has also been applied to the LEVITATE system dynamics model as will be explained in more detail in the following sections.

System dynamics approaches in the transport domain

There is a long tradition to apply system dynamics for similar problem areas in the transport domain. The following is only a brief collection of essential references relevant for the approach considered in LEVITATE. Land use transport interaction (LUTI) models like MARS [6] are focussing on changes in land use due to certain changes in transport systems or corresponding policies. The MARS model has also been extended and applied to automated mobility scenarios recently [7]. Another very mature and detailed model for transport policy assessment is the ASTRA (ASsessment of TRAnsport Strategies) model [8], which integrates transport with other dimensions including macroeconomic, regional economic and land use, and environment. The underlying approach used in passenger transport part involves conventional four-step travel demand modelling; however, dominated by the time focused perspective of system dynamics modelling. Trip generation is performed using trip rates and population groups classification per defined zoning system. Trip distribution involves several breakdowns of the passenger demand at various defined spatial levels (zones). For determining modal distribution, various elasticities to time and cost changes as well as other influencing factors, have been used.

In the domain of impact assessment of automated vehicles, currently a full exploration of SD modelling approach is lacking in literature. In this regard, an earlier study [9] made an effort for long-term impact assessment of autonomous vehicles based on some perceived scenarios and using an established transportation system dynamics model. This study demonstrated the importance of identifying various interactions within the system for better and holistic understanding of the long-term effects of autonomous vehicles and potential policy directions for achieving desired outcomes.

Recently, Federal Highway Administration (FHWA) report [10] has made some efforts towards developing building blocks for applying system dynamics approach for performing impact assessment of automated vehicles.

The conclusions from initial analysis and literature research in LEVITATE were the following:

- A simple system dynamics model seems to be suitable to attempt bridging certain gaps in the LEVITATE multi-method framework, serving as "glue" model, covering the relationships between impact areas and facilitating the analysis of wider impacts and long-term behaviour.

- In such an approach, many of the assumptions in the simplified SD model can be justified by outputs of microscopic or mesoscopic simulations. Consistency between the models is therefore ensured. Nevertheless, a *validation* of the CCAM related part of the model against historical data remains challenging at present.

- Since the desired SD model has to be quite specific, in terms of impact variables and policy interventions considered as well as regarding interfaces with the detailed simulation models, a direct re-use or adaptation of existing full-blown SD models has not been deemed feasible. The core of the transport part, however, is compatible with the basic design in the ASTRA model.

Description of the LEVITATE SD model

On an abstract level, there are three main stock variables considered in our SD model, which might also be considered as interacting sub-models, due to the underlying structure and dependencies that will be further discussed in this section. A simplified overview of the model structure is depicted in Figure 1; the more detailed stock-flow diagrams are included in the Appendix.

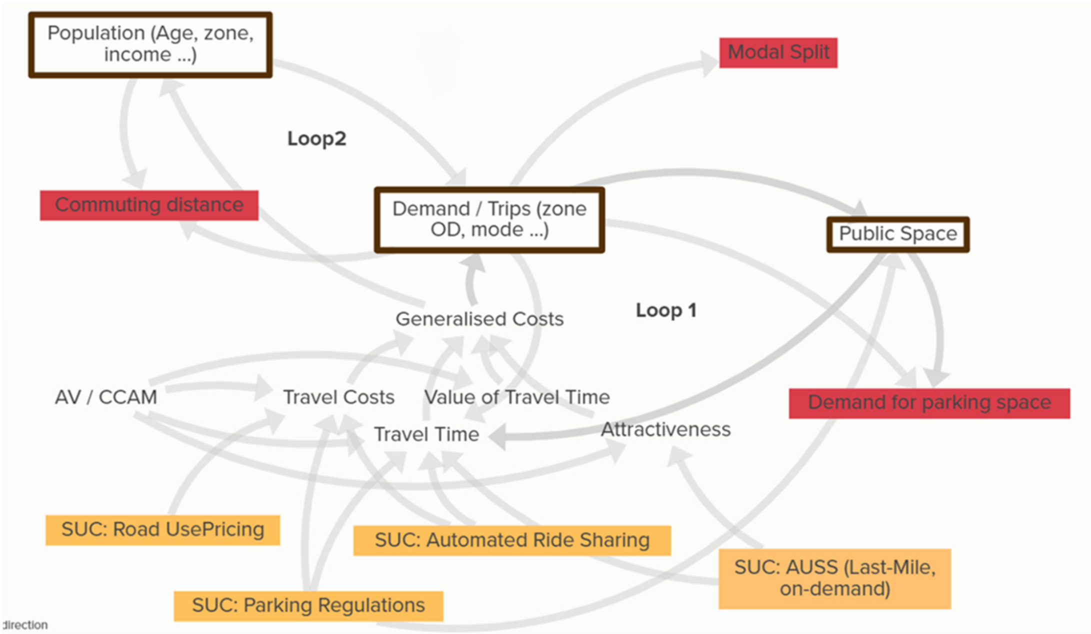

Figure 1: High level overview of the LEVITATE System Dynamics Model, showing main submodules (boxes), calculated impact variables (red) and implemented sub-use cases (yellow)

- At the core, the Transport Model is containing the *travel demand and trips* (based on segmentation of the target area into geographical zones and the mode of transport). Both the change of total demand and the shift between several modes are influenced by the generalized costs, modelled by means of elasticities similar to (ref ASTRA). *Total modal split* is the most important impact variable calculated in this model.
- In order to generate and drive the demand, a detailed *population* model has been implemented (segmentation into age groups, zones, and income groups). This model, allowing people to relocate between zones on longer time scales, is also used to calculate the *average commuting distance* impact variable.
- Finally, the use of *public space* is modelled on zone level, distinguishing between parking space, driving lanes and other purposes. The *relative demand for parking space* (percentage of public space demanded for parking) is calculated in this model.

The generalized costs for travelling are composed by four influencing variables in the following way:

*Generalized Costs = Travel Costs + (Travel Time * Value of Travel Time) − Attractiveness*

Obviously, lower generalized costs might result from changes in any of these four variables, and lead to an increase in corresponding trips. Such changes in the model are caused by:

a) Increasing AV penetration rate: the variable considered as the main parameter in LEVITATE to investigate (implicitly) the development over time,

b) Specific sub-use cases (policy interventions) considered on top of increasing AV penetration rate.

Despite the conceptual simplicity of the described model, certain complex impacts can be assessed in a quantitative way, due to following features of the model:

- The system exhibits multiple (balancing) *feedback loops*, both within the sub-models and between them: a higher share of private car trips, for example, will increase the relative demand for parking space in an area, leading to higher parking search time for non-automated cars (if no parking space extensions occur) and consequently higher generalized costs which result in decreasing demand.
- While residing on much higher level of aggregation than micro-simulation and mesoscopic simulation approaches, the model is segmented with respect to geographic zones, age and income groups. This allows for calculation of more specific dependencies than considering only the average (aggregated) values of all system variables. The segmentation (construction of a multi-arrayed model) has been implemented by means of Vensim's subscripting language.
- Finally, the model has been calibrated against the current behaviour (i.e., the case of no automation), showing the observed modal split values (for the case of Vienna) – this is explained in more detail in the next section.

The following sub-use cases (policy interventions) have been modelled:

- Road Use Pricing: Applying a static city toll when a trip with private car starts or ends in a zone that is part of the target area (inner city, in our model Vienna's zones 1 and 2).
- Parking Price policies: taking over certain parking behaviour patterns from the microsimulation model, associated with parking price and other parameters. Note that with the introduction of fully automated cars, paying for parking might be avoided by driving around, parking outside a specific zone, or even returning home.
- Parking space regulations: Public space available for parking might be reduced (e.g. by 50%) and converted to space for other purposes. In particular, conversion to bike lanes, multi-functional areas and driving lanes has been investigated.
- Automated Ride Sharing: A certain percentage of the total demand is covered by this service, assuming a certain "willingness to share" , influencing both travel costs and travel time.

- Last Mile Shuttles: In a certain target area in the periphery of the city (where spatial and temporal density of public transport is lower than in the centre, in our model zone 3) such a service is introduced as a supplement to the existing public transport system, covering a certain percentage of the total demand.

The integration of sub-use cases into the SD model is highlighted in Figure 2. Note that the specific input parameters are based on assumptions (justified by the literature) as well as outputs from the microscopic simulation as further discussed in the next section.

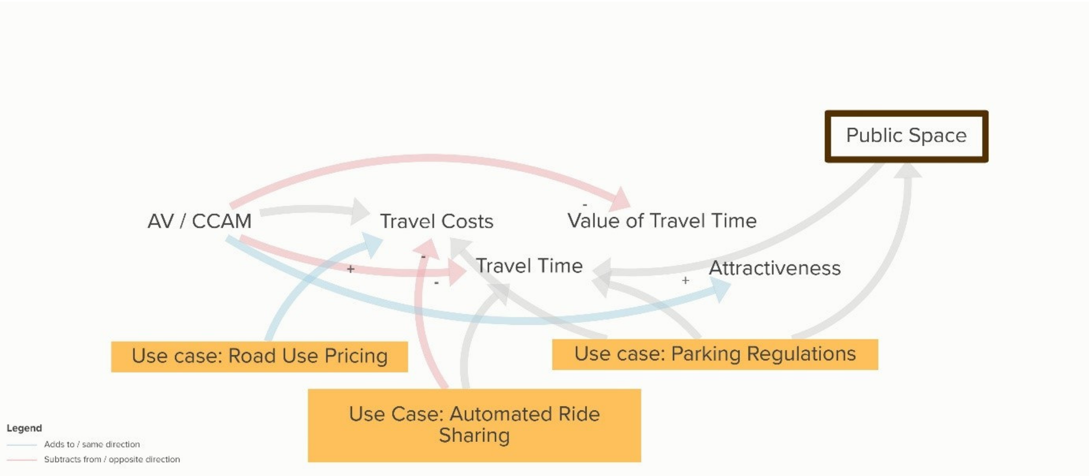

Figure 2: Implementation of sub-use cases in the SD model (red arrows reflect negative polarity, blue arrows positive polarity, and grey arrows unspecified polarity)

Input data, model calibration and validation

The pre-validated population model was then transferred to the region of Vienna (city + surrounding area of approximately 30km out of the city), where the population in each zone and their age structure has been taken from official data sources [11]. Also the rates (birth rate, death rate, migration rate) have been adjusted accordingly. It is important to note that all used parameter values have been aligned with the mesoscopic model outlined earlier in order to ensure a consistent overall modelling approach.

In the next step, the modal split in the status quo scenario (i.e. with no automation taking place) has been used for calibration of the Mode Choice parameters. This means that in the absence of automated vehicles the system should be in (or very close to) an equilibrium state that reproduces the actual current modal split values for each origin – destination pair. It might be argued that there is a diversity of possible sets of parameter values that would reproduce the desired modal split values. Thus, in order to ensure the reliability of the model,

a. The parameters (in particular related to travel costs, travel time, value of travel time) have been taken from statistics data for Vienna, from literature or from other models wherever possible.

b. Sensitivity runs with respect to these parameters have been performed. Results suggest that the impacts (relative changes) due to automation or policy interventions are depending only very weakly on the choice of parameters (as long as the calibration criteria described above are satisfied).

While the SD model has been calibrated in such way for the case of no automation, it was also possible to run consistency checks (or cross-calibrations) against the mesoscopic simulations for increasing automation (but in absence of further interventions; this is considered as the baseline scenario) and, in addition, a few sub-use cases that were modelled both in the mesoscopic and in the SD model – certain variants of road use pricing and last mile shuttles. (Note that there was only a small “overlap” between these methods. Further variants of these sub-use cases, like dynamic city tolls, were too specific to implement in the SD model. On the other hand, several use cases and impacts that could not be covered in the mesoscopic model, were included in the system dynamics approach.)

Finally, briefly discussing one example, the restriction and conversion of a certain amount of parking space, we demonstrate how the input parameters of the SD model have been aligned with the microscopic simulations. Parameters can be included on two levels:

a. Sub-use case specific parameters (characterising the nature and strength of a certain intervention) are directly aligned between the two models, e.g. the *percentage* of public parking space that is restricted, and *how* it is converted (into driving lanes, bicycle lanes, hop-on/hop-off areas or similar).

b. Several output parameters of the microsimulation model, e.g. the (delay in) travel time, that are affected by this sub-use case, are also fed into the SD model as input parameters. In this way the SD model can benefit from the lower-level simulations assessing *direct* impacts that are not modelled in the higher-level simplified SD model.

The results presented in the next section will compare certain impact variables as a function of the AV rate (market penetration rate), which was the standard approach decided in the LEVITATE project across all methods. From a system dynamics perspective, the more natural result is of course the development of these variables as a function of time, over a (longer) time period. To map between these two concepts, the AV rate as a function of time has been assumed as exogeneous data in the SD model. The shape of this function corresponds to certain pre-defined scenarios that users of the policy support tool will be able to select (quick, normal or slow uptake of AVs). For the quick uptake scenario (which was selected for our further simulation runs) the simulation extends over a 40 years’ time range, using time steps of 1 month, with AV rate increasing gradually from 0 to 100% between Year 10 and Year 30. The last 10 years give the system some more time to stabilize in its new equilibrium state – which is expected when studying longer term impact variables.

Results for selected impact variables

In the following, we will discuss the results for four impact variables that are modelled in the SD model:

- The modal split for travels using public transport systems,
- The modal split for travels using active modes (cycling, walking),
- The *relative* demand for parking space, i.e. the percentage of public space demanded for parking,
- The *relative* average commuting distance, i.e. the ratio to the value in case of no automation

This will be shown as a function of AV market penetration rate (from 0 to 100%), for the baseline (i.e. no policy intervention applied), as well as following selected sub-use cases:

- Road use pricing (static city toll of 10 EUR per entry into city centre – zone 1/2)
- Last Mile Shuttle (operating in zone 3)
- Parking pricing – resulting in balanced parking behaviour
- Public parking space restriction by 50%
- Conversion of public parking space to driving lanes
- Automated ride sharing (assuming that 20% of demand can be covered, and full compliance)

Modal split for public transport

The following results (Figure 3) on modal split were obtained for public transport based on distance travelled.

The modal split is determined as share by distance of trips carried out using that transport mode, shown as a fraction of the total distance travelled in any available mode. Percentage of public transport usage is estimated to slowly decrease with increasing rate of AVs with maximum decrease (almost 10%) at full fleet penetration. This can be foreseen as a consequence of increase in access, convenience, and affordability of private automated cars with time and increasing automated fleet.

Implementation of road-use pricing would likely increase modal share in public transport as compared to the baseline curve, in order to avoid paying toll. However, the subsequent decrease in percentage would be observed consistent with the baseline curve due to the aforementioned reasons.

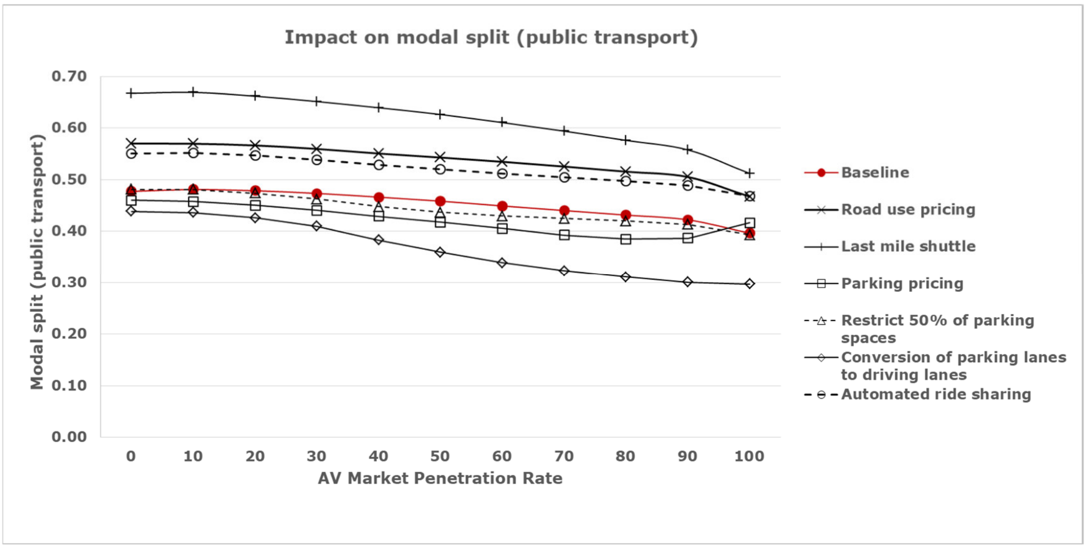

Figure 3: Impact of automation (baseline) and different policy interventions on modal split using public transport

Policy on parking space regulations can have a strong impact on changes in modal split as also found in the SD model results. For example, replacing on-street parking with driving lanes would encourage more vehicles on the roads potentially reducing share of public transport users with increasing MPR; however, becoming almost insensitive at around 80% fleet penetration. Removing 50% on-street parking was found to have a marginal impact on modal shift to public transport.

With regard to parking pricing policies, a balanced strategy (includes proportions of all parking options) was included in the SD model as this was found to be potentially the best strategy in terms of its impacts on traffic operations, as shown by microsimulation analysis. Under balanced parking strategy, a slight reduction in public transport modal split was estimated with increasing AV rate with a slight increase at full automation. This may be attributed to increased congestion at full fleet penetration with such parking policy.

As can be expected, last mile shuttle services (considered as part of public traffic) will significantly increase public transport modal share, as compared to that in baseline condition, due to providing increased access to travel. However, with increasing AV rate, the modal share can potentially decrease due to increase in personal vehicle ownership.

The increased modal share in public transport for Automated ride sharing service is due to the fact that this new mode is also included in public transport. But, similar to other sub-use cases, it can likely decrease at or near full automation due to increased access, convenience, and affordability for private automated passenger cars.

Modal split for active modes

Similarly, the results for active modes are presented through the plot in Figure 4.

With respect to baseline scenario (increasing automation only), active travel is predicted to decrease with increasing rate of AVs in the transport system. This trend was also found to be common under implementation of all sub-use cases (policy interventions). The relative impact compared to the baseline, however, was found to be diverse.

Analysing modal split (active modes) curves under different policy interventions, the results indicated significant increase in active travel due to road use pricing and balanced parking behaviours, as compared to the baseline results. This trend can be expected as such policies involving some sort of price would likely impact motorized travel and influence people to prefer use of active modes. Whereas the parking price policy showed higher increase for medium automation levels, road use pricing showed a higher effect for 100% AV penetration rate.

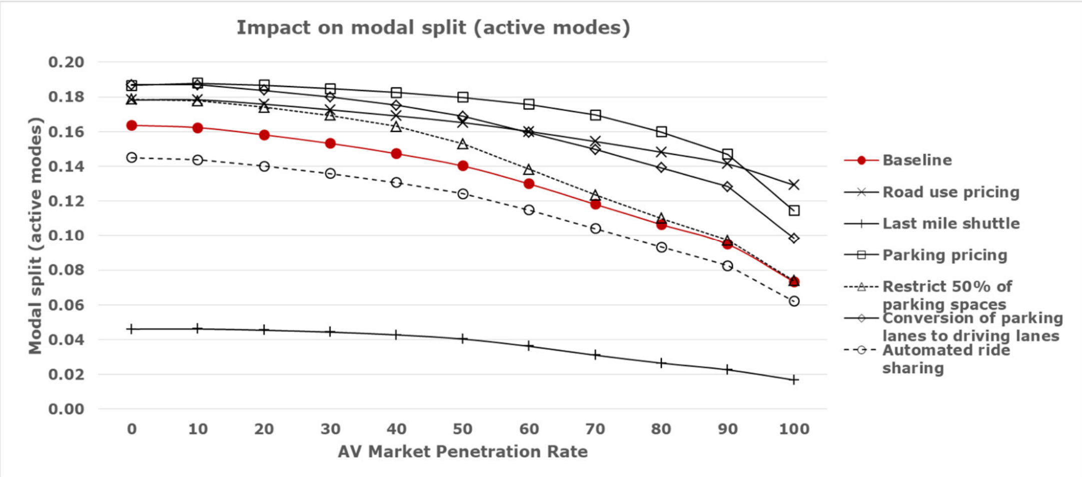

Figure 4: Impact of automation and various policy interventions on modal split using active travel

The results indicated a slight increase in active travel due to replacing on-street parking with driving lanes/cycling lanes, whereas just removing half of the parking spaces was found to increase active travel up to 70% MPR AV penetration rate become insensitive with further increase in the fleet penetration.

Finally, automated ride sharing as well as last mile shuttle services are likely to negatively impact active travel with respect to the baseline due to providing pick-ups and drop-offs closest to the origins and destinations of passengers, where last mile shuttles can potentially have much stronger impact on active travel than automated ride sharing as shown in Figure 4.

Relative demand for parking space

In Figure 5 the impact is presented as relative demand, in percentage of public (street) space within the inner-city area (zone 2). With regard to increasing automation only (baseline), the results indicate an increase in demand for parking with increasing AV rate, reaching more than 40% at full fleet penetration.

Implementation of parking space regulations of 50% on-street parking removal would lower the total demand for parking as compared to baseline condition. Whereas conversion to driving lanes intervention would likely have an increased demand as compared to 50% parking space removal, due to encouraging higher number of vehicles on the road. In comparison with the baseline, this policy will have lesser demand up to 50% fleet penetration and will gradually increase with higher levels of automation.

As expected, the parking price policy providing balanced parking behaviours showed significant impact; the relative demand for parking space stays quite low. Road use pricing implementation was also found to reduce the demand for parking space significantly, very similar to the parking price policy.

Last mile shuttle services would not create any difference on demand for parking as compared to the baseline. Automated ride sharing service was not found to have any added demand for parking as compared to the baseline.

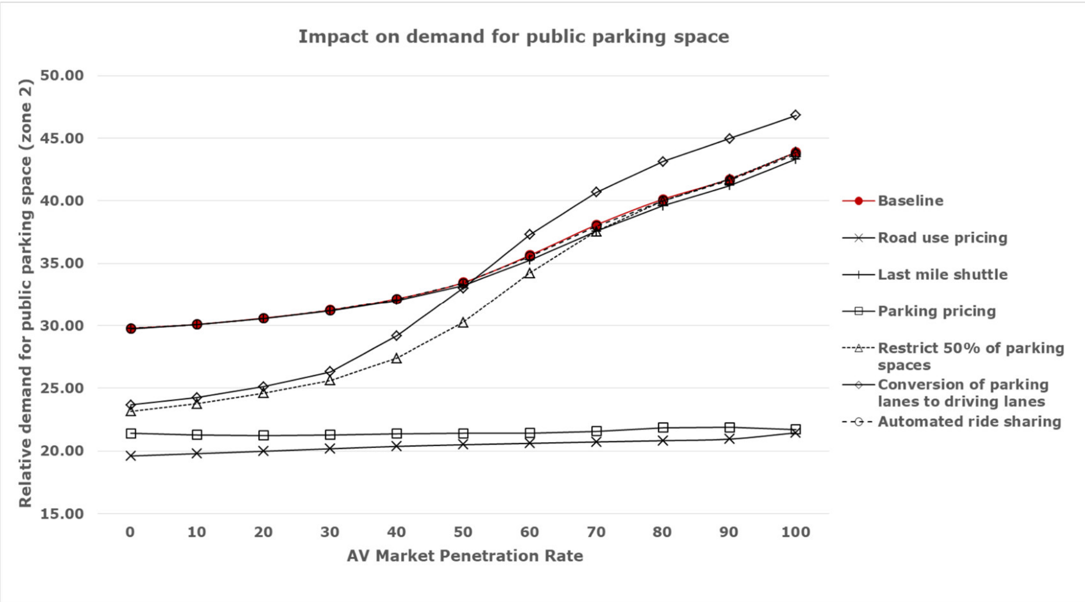

Figure 5: Impact of automation and different policy interventions on demand for public parking space

Average commuting distance

The results are presented in Figure 6. Since the average commuting distance is influenced by many parameters which are not part of the SD model, the figure shows the relative commuting distance - the fraction relative to "no-automation" scenario. (A value of 1.01 indicates an increase of 1% compared to the “no-automation” case.)

Overall, there is a marginal increase in the average commuting distance with increasing automation under the baseline and with the implementation of each policy intervention, reaching maximum value at full penetration of CAVs.

The model results also show larger commuting distances with the implementation of road use pricing. Even if this might seem surprising, it can be explained in the model due to the fact that also inner-city residents would be subject to road use pricing and might therefore decide to relocate to outer zones (which might not happen in reality if they are exempted). And while road use pricing would not help to reduce the commuting distances, it would definitely support a switch to other (non-car) modes.

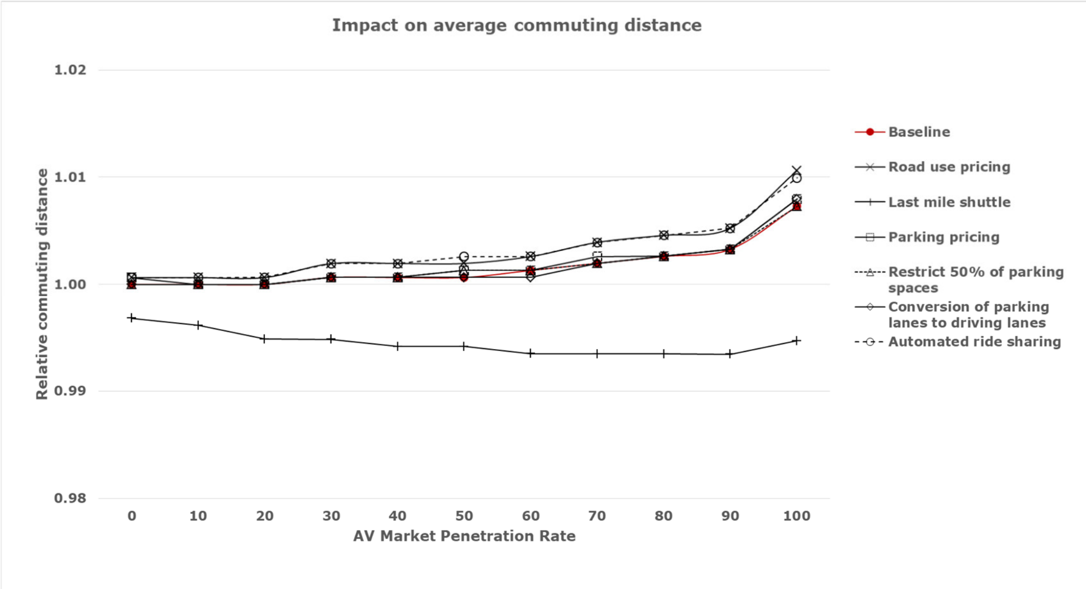

Figure 6: Impact of automation and various policy interventions on average commuting distance

Under automated ride sharing services, the results indicate maximum increase in commuting distances as compared to the baseline and other interventions. This is explainable as such service would provide access and serve customers anywhere to anywhere. However, last-mile shuttle services, operating only in zone 3 and not outside the city boundaries, can significantly reduce commuting distances with comparison to the baseline condition (as shown in Figure 6).

Replacing on-street parking with driving lanes would encourage a greater number of vehicles and potentially increase distance travelled, however, results do not indicate much change in commuting distances due to this policy measure. A similar trend was found under removing 50% of the on-street parking scenario. With regard to parking pricing policy, only a marginal difference in commuting distances with comparison to the baseline was found.

Transferability of results

Besides basic sensitivity analysis (investigating the influence of actual parameter values in the model), it has also been analysed, how far the results presented in this section can be transferred to other regions of the impact parameter space. For this purpose, three settings (that might correspond to different cities / regions) have been evaluated in the SD model for comparison, representing different initial conditions:

1. Lower modal split for public transport (caused by increased value of travel time),
2. Higher modal split for public transport (caused by increased energy costs),
3. Lower demand for public parking space (caused by parking restrictions / pricing).

As a result – with the exception of some "deformations" for extreme values (e.g. where the modal split for public transport gets close to 100%) – the qualitative and quantitative outcomes of the model are quite stable over wide ranges of the parameter space. This increases the confidence of the results that are shown to users of the LEVITATE policy support tool.

Conclusions and Outlook

We have motivated the need for an integrated impact assessment framework that addresses direct as well as longer term systemic and wider impacts of connected and automated mobility, and their interrelationships. A simplified system dynamics model has been developed as part of the multi-method approach applied in the LEVITATE project. Despite its simplicity, this model has yielded valuable insights into the behaviour of the system and quantitative results that are consistent with other simulation methods, and – even more – have been able to cover additional impacts and sub-use cases.

From an analysis point of view, the *problem* statement (reflecting the gap between current state or expected future developments on one hand and the actual stakeholder goals on the other) for this research field is characterized by the following:

- CCAM applications and services will be approaching rapidly, with several benefits being expected – but still a lot of uncertainty.
- On the other hand, other impacts might be negative (opposite to the direction towards desired objectives).
- The main question for stakeholders is how to steer the system in such a way – by means of CCAM related policy interventions – that positive impacts are enforced and negative effects can be mitigated.

Using example results obtained within the SD model, we have shown, (a) how increasing market penetration rate influences the impact variables, and (b) how selected policy interventions can change that behaviour. In most cases such relative changes are observed in both directions. In other words: When one policy intervention helps to bring a specific impact variable closer to the desired objective, it might be different for another impact variable – where a second intervention might do a much better job. Also the timing plays an important role: Some interventions might be good now, but useless in case of full automation.

From a methodological perspective, it is worth to note how this supplementary SD model has been embedded into a multi-method framework. Wherever possible, the model parameters have been aligned with other methods, like the (initial) population data, geographical zones and trip data for the Vienna region with the mesoscopic simulation model. Considering simulation outputs from microscopic simulations (e.g. regarding travel time delay) as (exogeneous) inputs for the SD model ensured to get consistent results. Finally, extensive use of subscripts helped to model complex dependencies while keeping the model conceptionally very simple.

The integration of the results shown here into the overall LEVITATE policy support tool is currently ongoing. This tool will allow stakeholders to assess possible impacts of CCAM and related policy interventions in a holistic way, and will also provide a basic backcasting functionality, answering the question: Which combination and sequence of policy interventions might be most appropriate to exploit the potential of CCAM for reaching desired strategic objectives?

For the system dynamics approach presented here, there are several natural next steps that will be addressed in future research projects. Other impact dimensions can be added into the SD model in a similar manner: health, economic aspects, enhanced behaviour modelling, and emissions & environmental impacts. Most importantly, connecting system dynamics with the backcasting approach that has also been developed in LEVITATE, analysing optimal pathways of interventions directly in a system dynamics model, can be considered as a major future research challenge.

Acknowledgement

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References

[1] LEVITATE (Horizon 2020) project: https://levitate-project.eu/.

[2] LEVITATE Policy Support Tool: https://www.ccam-impacts.eu/pst.

[3] Elvik R, Meyer SF, Hu B, et al. Methods for forecasting the impacts of connected and automated vehicles,Deliverable D3.2. 2020.

[4] Chaudhry A, Sha H, Boghani HC, et al. Behavioural Parameters for Connected and Automated Vehicles within the LEVITATE Project. Working Paper of the Microsimulation Working Group of the H2020 project LEVITATE. 2022.

[5] Müller J, Straub M, Richter G, et al. Integration of different mobility behaviors and intermodal trips in matsim. Sustainability. 2021;14:428.

[6] Pfaffenbichler P, Emberger G, Shepherd S. A system dynamics approach to land use transport interaction modelling: the strategic model MARS and its application. System Dynamics Review. 2010;26:262.

[7] Soteropoulos A, Pfaffenbichler P, Berger M, et al. Scenarios of Automated Mobility in Austria: Implications for Future Transport Policy. Future Transportation. 2021;1:747.

[8] Fiorello D, Fermi F, Bielanska D. The ASTRA model for strategic assessment of transport policies. System Dynamics Review. Wiley Online Library; 2010. p. 283–290.

[9] Gruel W, Stanford JM. Assessing the long-term effects of autonomous vehicles: a speculative approach. Transportation research procedia. Elsevier; 2016. p. 18−29.

[10] Berg I, Rakoff H, Shaw J, et al. System Dynamics Perspective for Automated Vehicle Impact Assessment. 2020.

[11] Statistik Austria. 2022. http://www.statistik.at/web_en/statistics/index.html

Appendix: Stock and flow diagrams

In order to document the assumed dependencies between variables of our model in full detail, the Vensim1 views (stock and flow diagrams) for the main submodules are shown in Figure A.1 – A.3.

These diagrams also show which of the key variables have been modelled as stock variables:

- The *population* (Figure A.1), using the subscripts Age and Zone (income group is implicitly modelled as it is assumed to be a function of the age group),
- The number of *trips* (Figure A.2) as central model variable, using the subscripts Age, Origin Zone, Destination Zone and Mode,
- Three forms of available *Public Space* (Figure A.3) – parking space, lane space and multi-functional / active modes – using the subscript Zone.

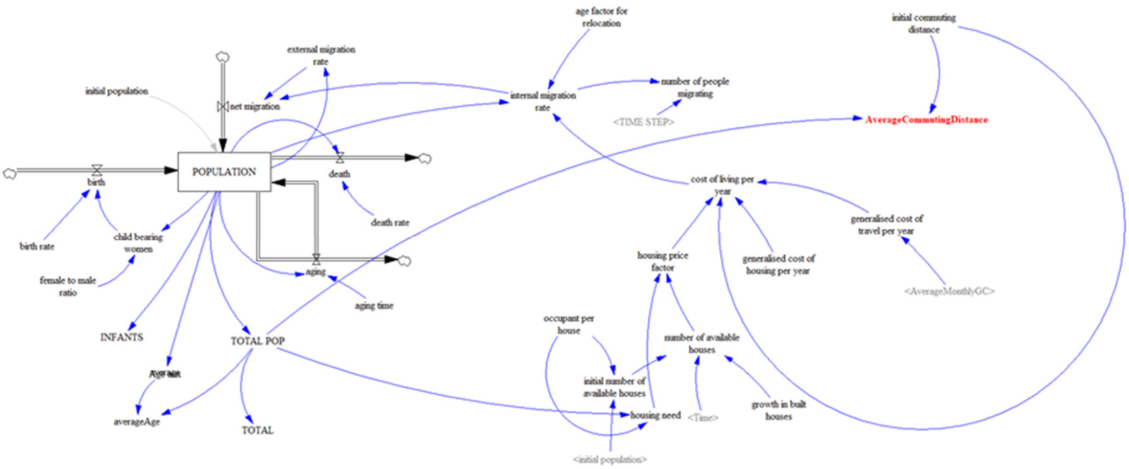

Figure A.1: Detailed Vensim view of the population model

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[1] Vensim from Ventana Systems (https://vensim.com) is the tool that has been used to implement the SD model.

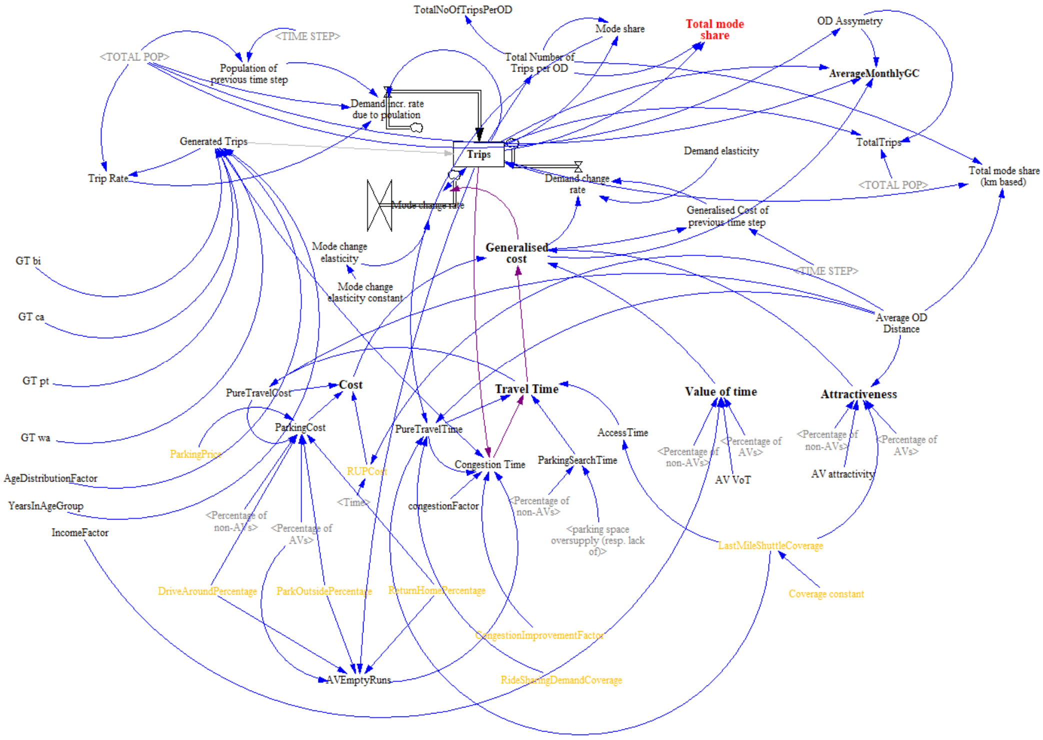

Figure A.2: Detailed Vensim view of the transport model (Demand / Trips)

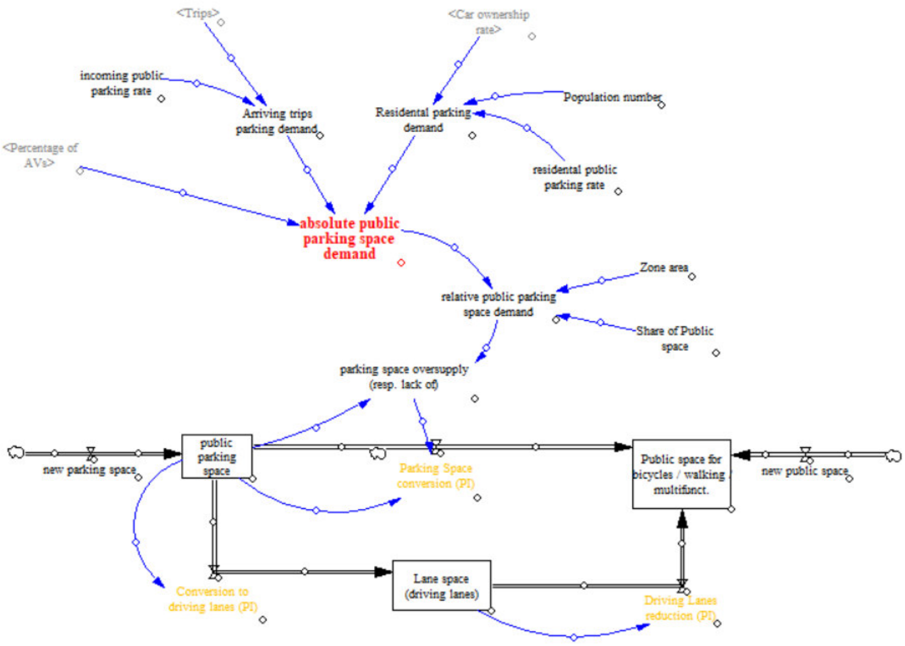

Figure A.3: Detailed Vensim view of the public space model