Activity-based model for active modes



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An activity-based travel demand model called BRUTUS (Rambøll, 2022) was made for Trondheim on behalf of and funded by the Norwegian Public Roads Administration, Statens Vegvesen. The aim is to explore how a new kind of model can help in evaluating walking and cycling infrastructure investments.

SUMMARY

An activity-based travel demand model is piloted for the region of Trondheim, to understand if these types of models can provide better understanding in evaluation of policy measures regarding active modes and sustainable transport. The pilot model demonstrates capability of capturing the effect of the tested policy measures and illustrates how the effect of several policies on bicycle traffic can be examined.

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INTRODUCTION

Transport models are important tools for evaluating the effect of policy and infrastructure plans. In Norway, the Regional Transportmodell (RTM) is used to analyse car and public transport related questions. The model successfully shows effects of larger scale at an inter-urban level. The model struggles to show impacts of interventions in urban areas, especially related to active modes, due to their relatively small scale. However, active modes are considered crucial in transition to a more sustainable transport system and liveable cities. Therefore, possibility to evaluate related measures are of high importance for the transportation policy makers.

This article presents the results of a pilot project where an activity-based transport model is developed for Trondheim and surrounding municipalities of Malvik, Melhus, and Stjørdal.

The pilot aims to show how such a disaggregated model differs from aggregate four-step models in terms of accuracy, functionality, data requirements and development process, and to demonstrate the benefits of such model in the appraisal of cycling projects. The model is most detailed for cycling and most effort has been put in modelling that mode most accurately. However, the model also includes walking, public transport and private cars.

METHOD

We briefly explain how activity-based models work and thereafter explain the different steps in the model building and using process.

Activity-based models

Activity-based transport models (ABMs) differ from RTM's four-step framework. ABMs generate detailed information of all trips undertaken in a city or region for every single person, instead of modelling aggregate flows of transport between areas (Figure 1). Trips are modelled as connected travel chains, meaning that trips affect each other. This disaggregated approach lets us include people's characteristics like age or gender in modelling how they travel (Zhang & Levinson, 2004; Castiglione, Bradley, & Gliebe, 2015).

These differences matter for modelling active modes for several reasons. Firstly, ABMs can be more detailed spatially because individual activities are modelled (Bastarianto, Hancock, et al., 2023). Simulation time is not primarily influenced by number of zones, but by number of decision makers. A detailed zoning system and network matters, as policies around cycling are more often of smaller scale and cycling traffic is less concentrated than motorized traffic. Secondly, personal preferences and abilities are more important into predicting if someone will use the bike compared to predicting if they use car. Including socio-demographic background variables of decision makers make such prediction more accurate. Thirdly, bicycle trips are often part of more complicated trip chains (Schneider, Daamen, & Hoogendoorn, 2022). The tour-based approach considers this.

Additionally, agent-based models can model policy measures that depend on interactions between agents, such as on-demand transport modes and restriction zones, allowing for the testing of corresponding policy scenarios on traffic and emissions (e.g., Rich, Seshadri, Jomeh and Clausen (2023)).

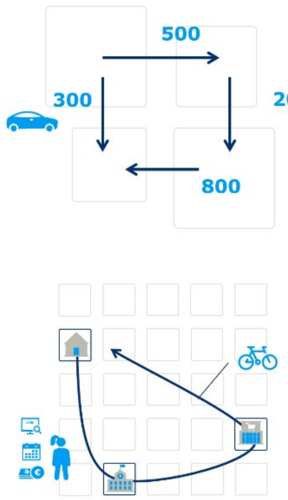

Figure 1: Schematic representation of a four-step model output (above) compared to the output of an activity-based model (below). (Picture: Rambøll)

Input data

The model mainly uses these data types: 1) Spatial land-use data, about where people live and go for various activities (e.g., jobs, stores, schools), 2) Network data, to get travel times between areas and simulate the paths people take, and 2) Travel survey data, to model activity patterns and estimate models for choosing modes and destinations.

The model uses a 250-by-250-meter grid across the model area. The main spatial data sources are

SBB's grid complemented with SBB's ward data for more detailed population data. A base year grid for 2022 and a forecast grid for 2030 were created based on the ADV tool input.

Transport network data is used both from RTM, for car and public transport; and from OpenStreetMap (OpenStreetMap contributors, 2023) for the pedestrian and bicycle networks (Figure 2). The source network contains a lot of information about bicycle infrastructure - and is enriched with elevation data to include slopes.

Figure 2: Close up of the implemented bicycle network for a part of Trondheim's centre. (Picture: Rambøll)

We used survey data from a donor model in Turku, Finland to estimate mode and destination choice model, generate activity schedules and for some input in the population synthesis. Cost related coefficient are adjusted to the Norwegian context and some of the model parameters are calibrated to match mode shares for the Trondheim region. We did not use travel survey data from Norway because of time constraints and the pilot nature of the study.

Model process

Within ABMs modelling steps, first a synthetic population is generated. A synthetic population is a representation of the population in the study area. It contains information on age, employment status, gender, car ownership and household composition, for each person. Activity plans of the decision makers are generated before simulating destination and mode choice. An example of a daily activity plan is home-work-groceries-home and includes durations and approximate departure times.

The destination and mode choice models are multinomial logit models applied sequentially to parts of chains (Doherty & Mohammadian, 2011) consisting of two trips and three endpoints. I.e., a candidate location is always considered in relation to other destinations one should also visit. Destinations are modelled sequentially based on duration of the activity. The mode choice is based on travel time and cost but also on person characteristics such as gender or car ownership.

The trips can thereafter be assigned to the network. Each cycling trip is assigned on one of three best routes using a path-sized logit model, to consider the preferences of different cyclists.

RESULT

The model has been applied to the 2022 base year and the 2030 forecast year. The model has been developed in a six-month period.

Model validation

Model results have been validated against general mode shares and trip length KPIs and OD-matrices derived from the Norwegian national travel survey, RVU, of 2021.

In terms of mode shares, the simulation results are in line with the survey, which is as expected as the mode choice model has been calibrated to the observed modal shares. The model overestimates pedestrian trips in absolute numbers as well as the average walking trip length. For public transport we observe the opposite regarding average trip length. Bicycle and car use volumes align well with mode share, number of trips and trip length KPIs. We consider these results as sufficient, given the use of the donor model for the choice modelling. Further adjustments have been considered out of scope for this pilot.

Scenarios

The model has been applied to three different policy scenarios: (1) A bicycle highway implementation into the base bicycle network between the city centre and a popular shopping and residential area, Lade. (2) A new bicycle bridge between to districts alongside the river, and (3) an increase of 50% cost to drive a car in the whole model area.

Figure 3: Change in cycling volumes between scenario with and without cycling highway. The new cycling highway stands out with the thickest red lines. Red means an increase in cyclists, blue a decrease. (Picture: Rambøll)

When considering mode shift towards cycling explained by the new bicycle highway, a small effect can be observed as the travel time savings are modest. Yet, we observe an increase of 500 daily cyclists. Comfort of the bicycle highway is high and is therefore becoming a popular route (Figure 3).

The new bridge over the Nidelva river attracts almost thousand daily cyclists. The average travel time savings are more substantial than in the first scenario, being up to 8 minutes for travellers departing from areas West from the bridge.

The model shows almost no decrease in car usage if prices go up by 50% in terms of total number of trips and in mode share. This can be because the car users' demand is quite inelastic with respect to out-of-pocket costs. However, the average length of a car ride decreases and so do emissions from cars, by 9.5%.

CONCLUSION

Given the limitations of the scope, we conclude that the model performs reasonably well and captures the effects of various policy measures on travel behaviour and mode choice. More information can be found in the project report, *Brutus model for Trondheim: Pilot project*. (The report is available upon request by Statens Vegvesen.) It is feasible to build a functional ABM in Norway. Bicycle related policies can be modelled in detail and the effects can be illustrated. The approach as described can complement RTM for strategic and cost-benefit analyses by providing more detailed and realistic representation of the transport system and the demand. To further develop the model suitable for decision support, we recommend the use of a local travel survey and calibrate the results further. Having a stated preference survey, tailored to potential policy measures, would allow inclusion of additional relevant variables into the choice models (e.g., comfort level for cyclists).

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