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Audit and update of Swiss national LCV model

Update of June 2nd, 2023

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Version	Date	Description
0.1	8-12-22	First working version
0.2	20-12-22	Updates December 2022
0.3	14-2-22	Updates February 2022
0.4	13-4-23	Draft report
1.0	28-4-23	Final version, delivered at the end of the project
1.1	2-6-23	Updated version, including Appendix A

Table of contents

Glossary

Term	Definition
AMG	The aggregated freight demand model of Switzerland
LCV	Light Commercial Vehicle
LCV data	The data collected with the Light Commercial Vehicle survey
NPVM zones	Zones of the national passenger transport model of Switzerland
Original LCV model	Version of the LCV model that was developed prior to this project
PLZ zones	The zones related to the postal codes
Revised LCV model	Version of the LCV model after all the improvements made in this project are implemented

Summary

The aim of this project is to carry out a critical review of the new national model for the estimation of light commercial vehicles (LCV) for Switzerland, to propose and test potential improvements and to ensure quality control for this model. The project consists of 4 work packages:

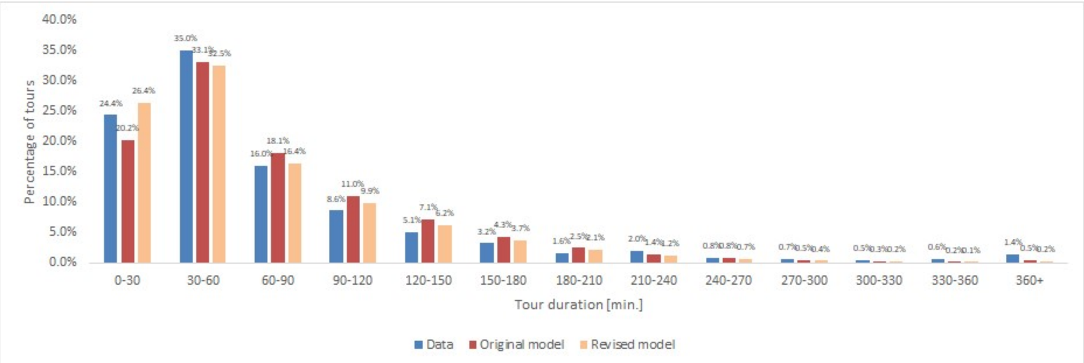
- WP1: Critical review and suggestions for improvement;
- WP2: Implementation of potential improvements;
- WP3: General quality tests and visualizations;
- WP4: Synthesis & Reports.

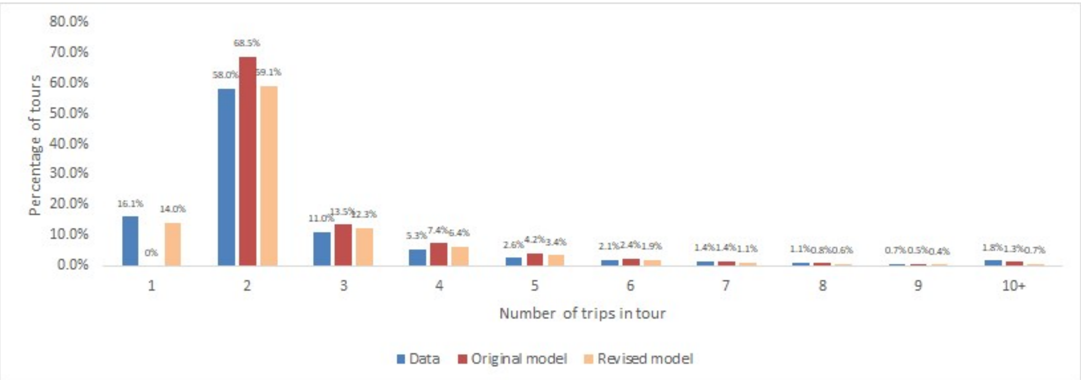
Based on the literature a number of improvements were identified and discussed with the client, the Swiss federal office for Spatial Development (ARE). Based on this discussion, the following improvements are worked out in this project:

1. Re-estimation of the Next Stop Location model using generalized travel cost instead of travel time.
2. Test approaches for improved intuitiveness and efficiency of the tour patterns in the Next Stop Location module.
3. Implement a decision rule for whether the tour should make a return trip to the home base at the end of the tour.
4. Implement a maximum tour duration parameter.
5. Implementation of a separate module for parcel deliveries

The outputs of the original and revised LCV model were assessed in terms of: tour characteristics, intuitiveness, parcel demand and simulation variance. The tour characteristics show a clear improved match to the observed survey data. The parcel delivery tours have a similar, but slightly shorter average tour length as reported by Universität St. Gallen (2017). The recommended setting for granularity is 0.1 which in effect means the results are an average of 10 times the number of tours. The indicators used in the quality assessment also provide a good basis for a validation framework for future model updates. The analyses and data preparations that have been done in the study are registered in Python scripts and available through the GitHub page of the model.

The following figures show the evaluation of the match of tour duration and number of trips per tour. These indicators show a better match with the data after (*Revised model*) the model updates compared to before (*Original model*).





The model improvements are implemented in the existing Python software implementation. Additionally, several improvements have been made in terms of code quality: the calculation time is reduced strongly, settings and model dimensions are stored centrally, tours are exported as shapefiles (for validation) and the code quality was improved (according to PEP-8 guidelines).

The overall assessment is that the model provides a good basis for implementation in the national transport model. Some observations can be made on the application of the model. Next to the model assessment, the results from the analyses also provide relevant insight for further improvement or tuning of the approach.

1. Introduction

This report describes an audit and update of the light commercial vehicle (LCV) model for Switzerland. In the project, a critical review of the developed model was carried out, and improvements were proposed and tested to ensure quality control for this model. The project consisted of 4 work packages that are described in this report.

1.1 Project background

ARE has developed a new national model for the traffic estimation of light commercial vehicles (LCV). This model describes all LCVs, regardless of whether they are used to transport goods or to provide services. In contrast to the Aggregated Freight Demand model (AMG), the focus of this "LCV model" is not on the weight of the transported goods, but on the journeys, regardless of whether they are used to deliver goods or to provide a service.

The aim of this project is to carry out a critical review of the developed model, to propose and test potential improvements and to ensure quality control for this model. The project consists of 4 work packages:

- WP1: Critical review and suggestions for improvement;
- WP2: Implementation of potential improvements;
- WP3: General quality tests and visualizations;
- WP4: Synthesis & Reports.

1.2 Current LCV model

The original LCV model consists of the following processes:

- Vehicle Generation
  - Calculates the number of LCVs per zone
- Vehicle Purpose
  - Assigns a purpose to every vehicle (goods, service, other or idle)
- Number of Tours
  - Sets the number of tours made by every non-idle vehicle
- Correction
  - Corrects for the difference in daily traveled distance between tours with few stops (part of estimation data) and tours with many stops (only summary data available)
- Next Stop Location
  - Chooses the next stop zone of a tour
- End Tour
  - Decides whether to end the tour or continue adding stop zones to the tour

Throughout these processes, the following key dimensions are used:

- Branches: according to the first level of the NOGA classification
- Vehicle types: light (≤2 tons), heavy (>2 tons)
- Purposes: goods, service, other
- Zones: NPVM zoning system (7965 zones in Switzerland)

Throughout the report, we will refer to this existing model as the “original LCV model”. The version that includes all implemented improvements made within this project will be referred to as the “revised LCV model”.

1.3 Report outline

This working document follows a logical structure based on the work packages of the project. Chapter 2 first describes the review of the current model and relevant literature and makes recommendations for the model improvement. Chapter 3 reports the analyses on the outcomes of the current model with respect to different indicators. Chapter 4 describes the implementation of model improvements, and the analyses of model outcomes. Chapter 5 discusses the software implementation and gives an overview of scripts developed for the additional analyses. Finally, the conclusions and recommendations are described in the final Chapter.

2. Critical review and suggestions for improvement

2.1 Literature overview of LCV models

Table 1 presents an overview of several relevant papers for modelling LCVs. From this list of papers, we can deduce three main modelling approaches:

- An aggregate approach with a gravity model and/or trip matrix calibration.
- A disaggregate tour-based approach with a tour generation model and a tour formation algorithm.
- A disaggregate shipment- and tour-based approach with a shipment demand module and a tour formation algorithm.

These different approaches each have their pros and cons, mostly in terms of data requirements, behavioral realism and predictive power, as shown in Table 2. The most suitable approach depends on which segment is modelled and what data is available. In terms of behavioral realism, a disaggregate shipment-based approach is the preferred option, but its higher data needs often require a step back to a tour-based or aggregate trip-based approach.

For the parcel segment a shipment-based approach is chosen most often (de Bok et al., 2022; Sakai et al., 2022; Llorca & Moeckel, 2021, Reiffer et al., 2021). The decision context of the parcel segment is very much one that involves decisions related to the consolidation of shipments, so a shipment-based approach is key for behavioral realism. Usually it is feasible to find aggregate (or even disaggregate) data based on which demand for parcel deliveries can be calculated.

The goods and service market, however, are much more diffuse and heterogeneous. For this reason, modeling the underlying demand (i.e., shipments or service appointments) of these segments requires an extensive trip diary or survey data collection including information about this underlying demand. Therefore, for these segments, we find more often tour-based approaches (Ellison et al., 2017; Hunt & Stefan, 2007) and aggregate trip-based approaches (Tolouei et al., 2022; Steinmeyer & Wagener, 2006).

Table 1 – Overview of relevant LCV modelling papers.

Reference	**LCV segments**	**Area**	**Approach**
De Bok et al. (2022) *Impact assessment of freight transport decarbonization using the HARMONY Tactical Freight Simulator*	▪ Goods ▪ Parcel ▪ Service ▪ Construction	Netherlands	▪ Goods LCVs are modelled together with trucks with a shipment-based and tour-based simulation approach. ▪ Parcel LCVs have dedicated module with an explicit representation of parcel couriers and their depots. The number of B2B and B2C parcels are calculated with an ordered logit model estimated on a household survey and using aggregate parcel market statistics. These parcels are assigned to the courier's depots and grouped into tours using simple tour formation heuristics. ▪ Service and construction LCVs are modelled with a classical trip-based gravity model.
Sakai et al. (2022) *Household-based e-commerce demand modeling for an agent-based urban transportation simulation platform*	▪ Parcel	(prototype city)	▪ Orders per household are calculated with the following steps: determine adoption of e-commerce, the total e-commerce expenditure per month, the purchase amount per transaction, and home delivery vs. pickup. ▪ The orders are then converted to package with a weight and assigned to a parcel depot, after which tours are formed.

Tolouei et al. (2022) *A novel approach to developing LGV trip matrices for the second generation of regional traffic models*	▪ Goods / parcel ▪ Service ▪ Personal travel	England	▪ A base year matrix of LCV trips is calibrated using GPS OD data, traffic counts and aggregate mileage statistics. ▪ The matrix is split into travel purposes with a statistical model with trip distance and departure time as key explanatory variables.
Llorca & Moeckel (2021) *Assessment of the potential of cargo bikes and electrification for last-mile parcel delivery by means of simulation of urban freight flows*	▪ Parcel	Munich, Germany	▪ Commodity flows from a strategic freight model are disaggregated into individual parcels using a parcel weight distribution that is calibrated to reproduce the observed total number of parcels in the area. ▪ Tours are formed using MATSim.
Reiffer et al. (2021) *Integrating urban last-mile package deliveries into an agent-based travel demand model*	▪ Parcel	Karlruhe, Germany	▪ An MNL for parcel demand per person based on age, gender and job type; based on collected survey data. ▪ Tours are formed using simple tour formation heuristics.
Ellison et al. (2017) *Modelling Sydney's light commercial service vehicles*	▪ Service	Sydney, Australia	▪ An MNL model for tour type, predicting the probability that a service worker makes a tour with a specific number of stops. ▪ A NL model for stop location using travel cost, population and employment sector as explanatory variables. ▪ A Vehicle Routing optimization for choosing the order of visiting the stops.
Hunt & Stefan (2007) *Tour-based microsimulation of urban commercial movements*	▪ Goods ▪ Service	Calgary, Canada	▪ A regression equation determines the number of tours originating in each zone. ▪ Each tour is grown iteratively using Monte Carlo simulation, by modelling the following decisions: tour purpose, tour departure time, next stop purpose, next stop location, stop duration.
Steinmeyer & Wagener (2006) *Using national behavioral data on commercial traffic for local and regional applications*	▪ Goods ▪ Service	Berlin, Germany	▪ The number of vans and trucks are estimated based on the number of employees by business group. ▪ A trip matrix (regardless of trip purpose/segment) is created using the average number of trips and vehicle-km traveled per day from a survey on commercial traffic.

Table 2 – Overview of main approaches in modelling LCV traffic.

Approach	**Data needs**	**Behavioral realism and predictive power**

<u>Aggregate</u> approach with a gravity model and/or trip matrix calibration	Limited
	▪ Employment and/or vehicle registration data
		▪ Lack of behavioral realism
		  – Disregards tour patterns
		  – No real decisions modeled, only using averages
		▪ Predictive power
		  – Growth of employment
		  – Changes in travel costs
		    ○ On trip distance

<u>Disaggregate tour-based</u> approach with a tour generation model and a tour formation algorithm.	More extensive
	▪ Employment and/or vehicle registration data
	▪ Trip diary survey
		▪ More behavioral realism
		  – Considers tour patterns
		  – Some real decisions modeled
		  – Does not consider travel as derived demand from need for goods or services
		▪ Predictive power
		  – Growth of employment

		– Changes in travel costs ○ On trip distance ○ On tour patterns
Disaggregate shipment/order- and tour-based approach with a shipment demand module and a tour formation algorithm	Most extensive ▪ Employment and/or vehicle registration data ▪ Trip diary survey ▪ Shipment demand data ▪ Locations of warehouses (but for modeling the parcel market usually aggregate statistics and openly available data suffice)	▪ Most behavioral realism, in particular for parcel and goods – Considers tour patterns – Many real decisions modeled – Considers travel as derived demand from need for goods or services ▪ Predictive power – Growth of employment – Changes in travel costs ○ On trip distance ○ On tour patterns ○ On ordering behavior – Logistic developments ○ Growth of e-commerce ○ Economies of scale ○ Locations of warehouses

2.2 Strengths and weaknesses of the original version of the LCV model - from a theoretical perspective

In this Section the original version of the LCV model is reviewed from a theoretical perspective. In Paragraph §2.2.1 and §2.2.2 we discuss the strengths and weaknesses respectively, based on which the improvements for this project are proposed in the next Section (§2.3).

2.2.1 Strengths

The original version of the model, as described in Section §1.2, consists of the following steps: Vehicle Generation, Vehicle Purpose, Number of Tours, Correction, and an iterative tour construction consisting of the steps Next Stop Location and End Tour.

The core strengths of this original model are as follows:
- The model features an explicit representation of tours, following the well-established trip-chaining approach of Hunt & Stefan (2007).
- The tour construction part of the model has a strong empirical basis, using the national LCV survey to estimate the Next Stop Location and End Tour choice models. The processing steps taken to prepare this data for estimation are valid.
- A granularity parameter to model multiple days instead of one average day is an effective method to reduce the simulation variance by relying on the law of large numbers.
- In absence of sufficient data that allows direct estimation of a trip or tour generation model, the model for vehicle generation with a subsequent tour generation step is an apt solution. Such a vehicle generation step is found more often, for example in Steinmeyer & Wagener (2006).

Several other positive observations can be made about some specific model steps:
- Vehicle Generation model:
  - Using rates per sector more or less solves the issue of vehicles being registered at headquarters of a company.
  - It is a good decision to exclude negative coefficients during estimation process.
- Vehicle Purpose model:
  - It was requested to get the number of vehicles that did not travel on a day by branch, otherwise an overestimation of the number of active vehicles on a day would take place.
- Next Stop Location:
  - A separate travel time parameter is included for first trip and later trips in a tour. This allows to model more realistic tours, in which the first trip tends to be longer on average.
  - A term is added to the utility function that takes the natural logarithm of the probability of sampling an alternative in the choice data generation. This is based on the theoretical properties of the MNL. The theory of sampling for discrete choice models was originally only

developed for MNL (McFadden, 1978; Manski and McFadden, 1981). Since then, there has been theoretical and empirical work also for multivariate extreme value distributions (such as nested logit and CNL) and mixed logit, including EC (Guevara and Ben-Akiva, 2013a,b). The experiences with sampling of alternatives described in these papers are usually favorable.

- Sampling 300 alternatives in the choice data generation is a good strategy to enable an extensive model specification search in estimation (without very long run times, or reaching software limitations), that theoretically leads to consistent coefficient estimates for the full choice set; and on the other hand do a full-scale application (which of course is preferable for application). This strategy is used more often.
- The panel nature of the data is taken into account during estimation. The "repeated measurement problem" is prevented in Apollo by specifying the survey identifier (OID) as the unit of observation for clustering the standard errors and calculating the robust t-ratios. For a more detailed discussion on panel data in discrete choice models we refer to Appendix A.

2.2.2 Weaknesses

While the assessment of the model from a theoretical perspective is positive in general, there is room for improvement. Below follows a list of identified weaknesses. In the next Section (§2.3) the suggested improvements for this project are listed; between bold brackets we refer to the improvements that aim at improving each weakness.

Four key weaknesses of the current approach are identified:

- **(5)** The same approach is used for three very distinct segments: goods, service, parcels.
  - The type 2 survey is used to estimate the Next Stop Location and End Tour model but is probably not representative for service transports, as this type of survey requires that vehicles carried at least 50 kg of goods that day.
  - The parcel segment is growing a lot faster than the others and has unique tour patterns and spatial distribution (far more stops per tour and tours originating from specific depots).
- **(5)** There is no explicit representation of the underlying demand (i.e., shipments or service appointments). Modelling the underlying demand allows incorporating more behaviorally realistic decisions in the model but also increases data collection needs and model complexity.
- **(1)** The Next Stop Location and End Tour choice models are not sensitive to generalized cost (consisting of travel time and distance costs), but only to travel times. Impacts of increased costs (e.g., fuel prices, road charges) on destination choices can therefore not be modelled.
- **(-)** The LCV model is independent from the national freight model, so no modal shift between vans and trucks can be modelled.
  - Improvements on this aspect are not picked up in this project because it requires changes to the conceptual model architecture that are too large for the scope of this project.

At a finer level of detail, some specific steps could be improved too:

- **(-)** No random seed is fixed nor specific simulation variance reduction techniques are applied. In some microsimulation models the random seed is fixed at a fine level of detail in order to get more logical and stable impacts of scenarios. For example, for the *x*th tour starting from zone *i* for purpose *p*, the same error term would be drawn for the utility calculation for one of the modelled decisions across different scenarios.
    - Improvements on this aspect are not picked up in this project because it is not clear yet if it will be necessary. This will depend on the types of scenarios that are used and the level of detail at which indicators are derived.
- **(-)** Vehicle Generation model:
  - In Table 4 of the technical document we see quite a large deviation from the observed distribution of vehicles between branches.
    - Link the vehicle registration data with business data to improve branch-specific rates and match with observed distribution of vehicles between branches (in accordance with existing plans).
    - Segments with a low statistical significance could have been combined during estimation.
    - Improvements on this aspect are not picked up in this project because the newly linked data becomes available only after the end of the project.
- **(5)** Correction:
  - We might be able to remove this module by adding a separate model for parcel deliveries, as probably most of the tours with many stops (which are not used for the Number Of Tours model) are in the parcel segment, especially if they fall under the segment Goods. But we would need to be careful with potential double counting.
- Next Stop Location:

- **(2)** The trip-chaining approach might lead to unintuitive and inefficient tour patterns with many internal crossings in the case of tours of many stops.
  - In a paper from Poot et al. (2002), for example, we find that clients of their tour planning software tend to find such "visual attractiveness" of their tours quite important, so this is a consideration we actually observe in real-world tour planning.
  - Possible solutions:
    - Estimate a parameter for "angle from tour starting point to next stop" like Hunt & Stefan did.
    - Estimate a parameter with a "penalty for next stop locations that would cause the tour to cross itself".
    - Estimate a parameter for "savings", similar to the TB-Freight module of PTV Visum.
    - Do a posterior optimization of tour sequences with a swapping algorithm.
- **(1)** Having a dummy for intrazonal alternatives, rather than using an intrazonal travel time, is problematic given that the zoning system applied in the model is different from the zoning system used during estimation. The definition of what constitutes as an intrazonal trip is different between application and estimation, so different intrazonal travel times should be used in application and estimation.

- End Tour:
  - **(3)** Not all tours in the processed LCV data return to their home base, yet in model application not all tours return to their start location, which is inconsistent.
  - **(4)** There is no maximum tour duration constraint, this could lead to outliers with unrealistically long tour durations.
  - **(-)** An alternative approach would have been to integrate the End Tour decision in the Number Of Tours model. You could calculate the number of tours by number of stops for each zone, and let this deterministically set when the tour has to be ended.
    - This removes some simulation variance and allows using the information of the total number of stops in the tour in the Next Stop Location decision (e.g., tours with many stops might drive shorter distances between stops).
    - It could also make outcomes more easily interpretable. Right now, some complex interactions between the Next Stop Location and End Tour model can take place. For example, if travel times increase in the network, shorter trips will be made in the tour due to the Next Stop Location decision, but it might also impact the End Tour decision and actually lead to longer tours and more vehicle kilometers.
    - This way, the choice of a next stop location could also depend on stop location choices for subsequent stops, using the expected utility (logsum) of those subsequent stops.
    - Improvements on this aspect are not picked up in this project because it requires changes to the conceptual model architecture that are too large for the scope of this project, while it is uncertain to what extent the model outcomes improve.

2.3 Suggestions for improvement

Based on the literature a number of improvements were identified and discussed. Based on this discussion, the following improvements are worked out in this project:

1. Re-estimate the Next Stop Location model using generalized travel cost instead of travel time. This makes the model sensitive to road charges and other cost developments, and allows considering both travel time and travel distance.
2. Test approaches for improved intuitiveness and efficiency of the tour patterns in the Next Stop Location module.
3. Implement a decision rule for whether the tour should make a return trip to the home base at the end of the tour.
4. Implement a maximum tour duration parameter.
5. Implement a separate module for parcel deliveries, using publicly available data.
   The delivery of parcels to households is a dedicated segment in (micro) freight transport with typical tour patterns and it is expected to grow more rapidly compared to the other mobility segments. The suggested simulation approach is a pragmatic simulation procedure using publicly available data, and consists of the following steps:
   - Model the number of parcels per zone based on employment and population, using ordering rates deduced from aggregate parcel market statistics of Switzerland.
   - Assign parcels to couriers based on their observed market shares.
   - Assign parcels to nearest depot of courier; collect depot locations from OpenStreetMap and Google Maps.
   - Form tours using simple optimization heuristics.

Another suggestion, outside of the scope of this project, is to continue working on a data fusion linking the vehicle registration with business data to improve the branch-specific rates of the Vehicle Generation model (this is in accordance with existing plans).

3. Analyses of the current outcomes

In this Chapter we report the analyses on the outcomes of the original LCV model with respect to efficiency and intuitiveness (§3.1), number of trips per tour (§3.2) and distance and duration (§3.3). Note that in the subsequent Chapter some of these analyses will be repeated after implementation of model improvements (§4.2).

3.1 Efficiency and intuitiveness

Below we see a sample of modeled tours originating from one specific zone. What we observe is that the tours with 2-4 stops follow a sensible sequence. The tour that goes to the southwest in the figure has more than 4 stops, and we see that in this case the sequence of visiting the stops is not as sensible. This tour has many path crossings and, therefore, looks rather inefficient and unintuitive.

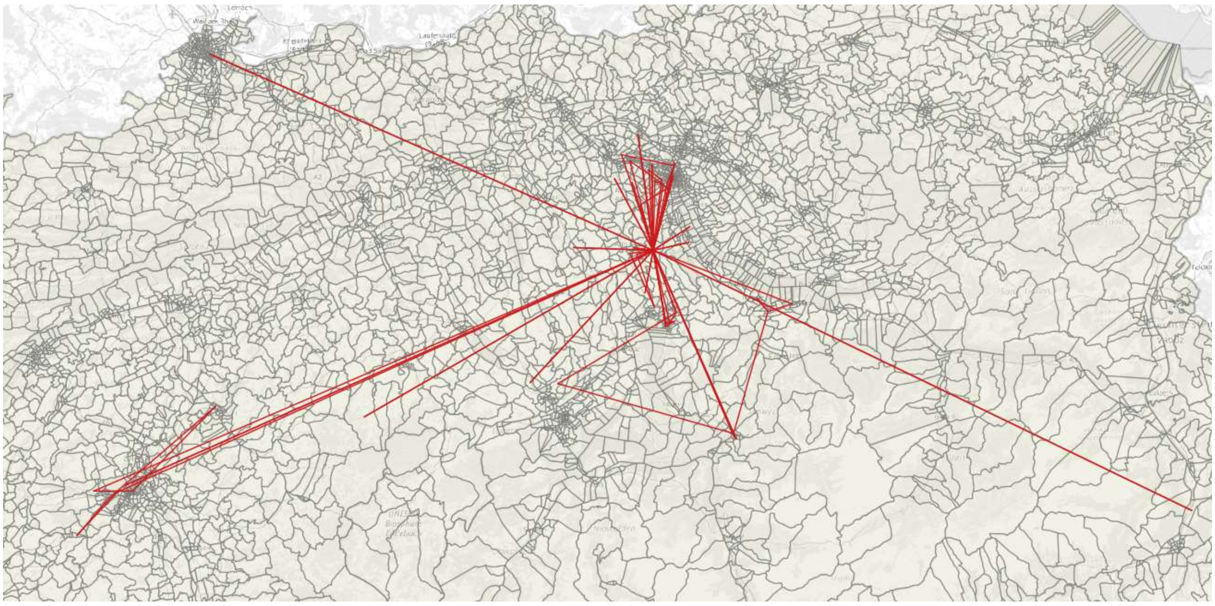


Figure 1 – An example of a few modelled tours from one origin zone.

To determine if improvements to this are needed, we compare the modeled tours to the observed tours with two metrics:

- The number of crossings per tour. We define a crossing in the geometric sense, i.e. two lines, which represent the trips, intersecting.
- The tour distance reduction potential, i.e., how much could the tour distance be reduced by swapping the order of visiting the stops (sometimes referred to as the 2-opt algorithm).

In Figure 2, we see that the modeled tours tend to have more crossings than the observed tours, especially for the tours that consist of many trips. For tours with many stops, tour planners will try to construct an efficient sequence in order to save travel costs, while in the model there is no such consideration present in the decision steps.

When we look at Figure 3, we see a similar trend. For tours with many trips there is quite some distance reduction possible through optimization compared to the observed tours. For tours with few stops, the model results actually show even more efficient sequences than the observed data. For these short tours there might more often be unobserved constraints, like time windows, influencing the sequence of the observed tours, while for the longer tours it gets more important to optimize the sequence to reduce travel costs.

Overall, we can conclude that there is no major difference in efficiency or intuitiveness between the modeled and observed tours. Only for the small minority of tours with 8+ stops, the tours in the LCV data are quite noticeably more efficient and intuitive in terms of distance and crossings.

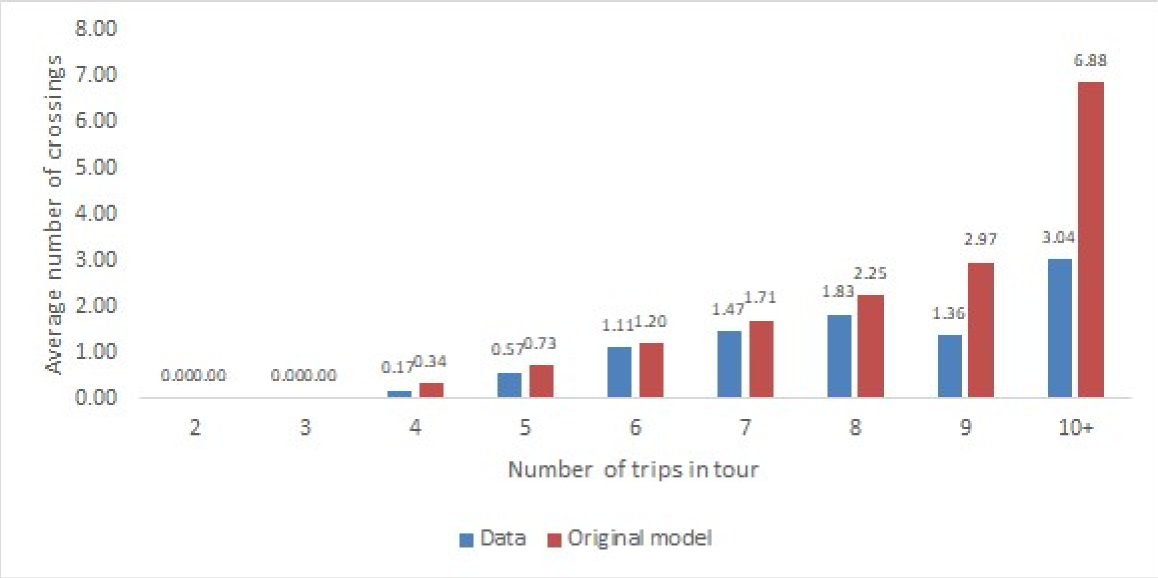


Figure 2 – The average number of tour crossings, by number of trips in the tour.

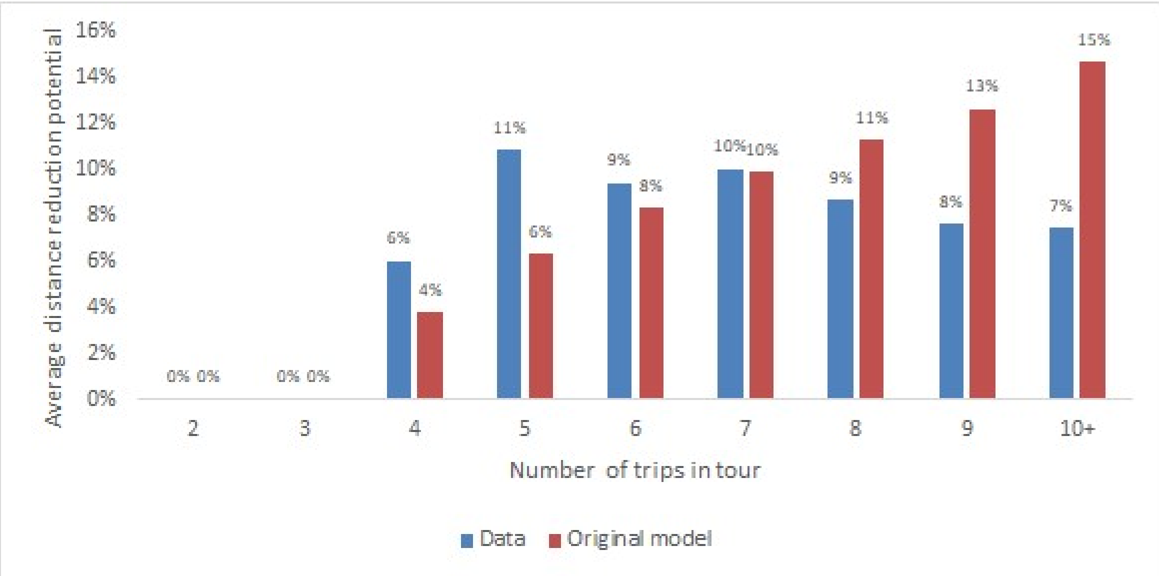


Figure 3 – The average tour distance reduction potential, by number of trips in the tour.

When comparing Figure 2 with Figure 3, it is striking that for tours with few stops the LCV data has fewer crossings than the model, while also having a lower reduction potential. This might be due to the substantial number of tours in the LCV data that is structured as shown in Figure 4. Given zones A, B and C, the tour sequence is A-B-C-B-A, which the swapping algorithm will improve to A-B-B-C-A. This reduces the tour distance, while no reduction in the number of crossings is realized.

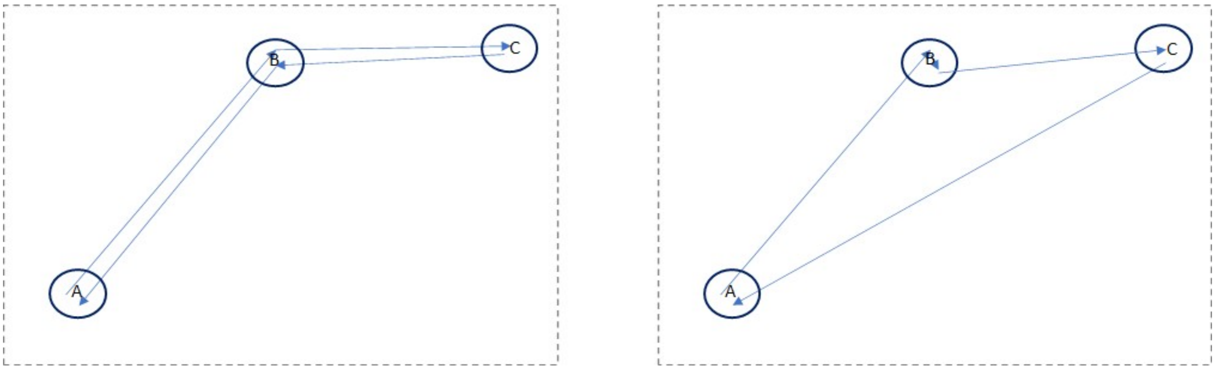


Figure 4 – A hypothetical tour visiting zones A, B and C. Left, the order as it is often found in the LCV data. Right, how the order is adapted by the swapping algorithm.

3.2 Number of trips in tour

The number of trips per tour is analyzed, to verify whether the model predicts valid tour patterns. Figure 5 shows the observed frequency distribution of number of trips per tour in the data and for the model. The patterns are comparable, with the large majority of tours being direct tours.

We observe the largest deviation between 1 and 2 trips per tour, which exists mainly because in the model always a return trip is made, while in the data this is not always the case. In Section §4.2.3 we will see how these outcomes change if a return trip probability is implemented.

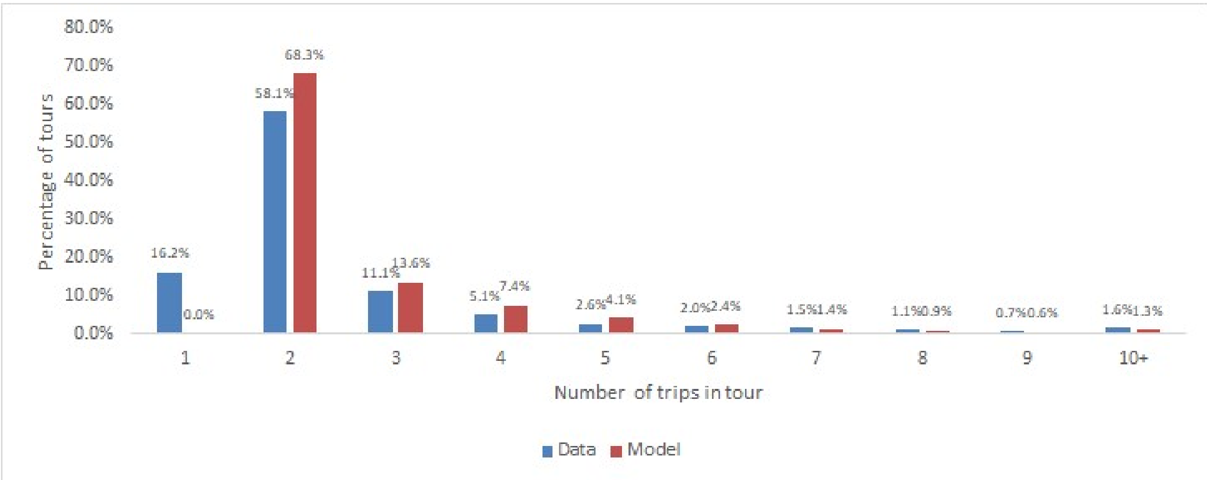


Figure 5 – The percentage of tours, by number of trips in tour.

3.3 Distance and duration

In this Section we analyze the duration and distance at the level of trips and tours. For these analyses we use the travel times and distances from the model for passenger traffic (NPVM), both for the LCV data and the model outcomes. This ensures that the measurement of duration is not affected by other time components that are not modelled (non-logistic breaks such as refueling, resting or other unplanned breaks). Note that we use the postal codes (PLZ) as zones for the LCV data, while we use the model zones for the model outcomes; the skims for both zoning systems are deduced from the same road network (including congestion) though.

3.3.1 Tour duration

The distribution of tour duration is visualized in Figure 6. We observe the largest difference between observed and modelled duration for short tours (0-30 minutes). The deviation here likely arises mainly because in the model always a return trip is made (see Section §3.2). Section §4.2.3 shows how these outcomes change when a return trip probability is implemented.

Note that tour duration is measured as the sum of travel times of the trips inside the tour, excluding dwelling times at stops.

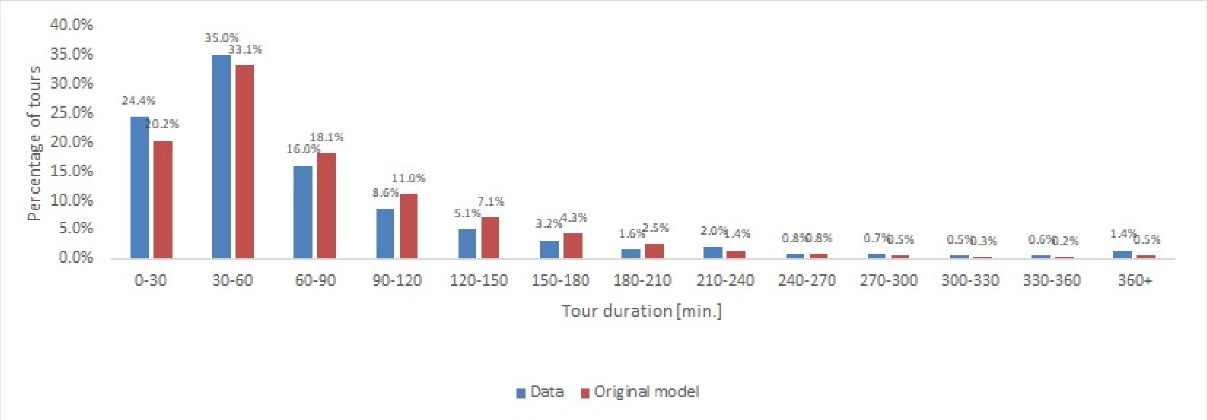


Figure 6 – The distribution of tour durations.

3.3.2 Trip duration

In Figure 7 we see that the overall average trip duration is in the same order of magnitude in the estimation data and the model outcomes (29.4 min. vs. 26.9 min.). The deviation is most notable for the intermediate trips of a tour. It is hard to say why exactly this occurs. A test model application on the PLZ zones ruled out the hypothesis that the difference in zoning system between estimation and application is the cause. This deviation might be a consequence of a different composition of the different segments (i.e., combination of branch, purpose and vehicle type) in the LCV data and the model application. Another possible explanation is that there is a correlation between the *b_cost* and *b_cost_to_target* components of the utility function, which could both make nearby alternatives more attractive.

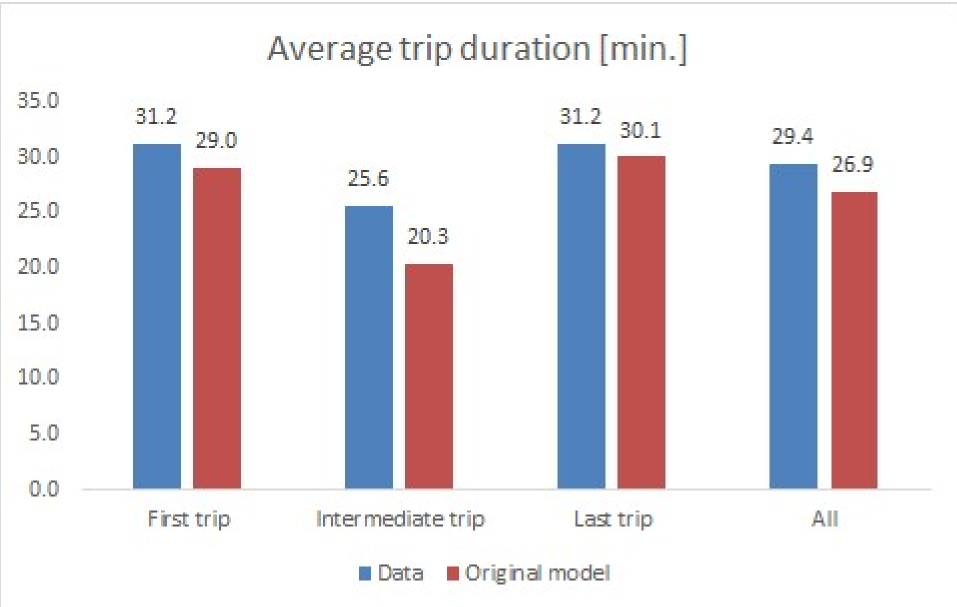


Figure 7 – The average trip duration.

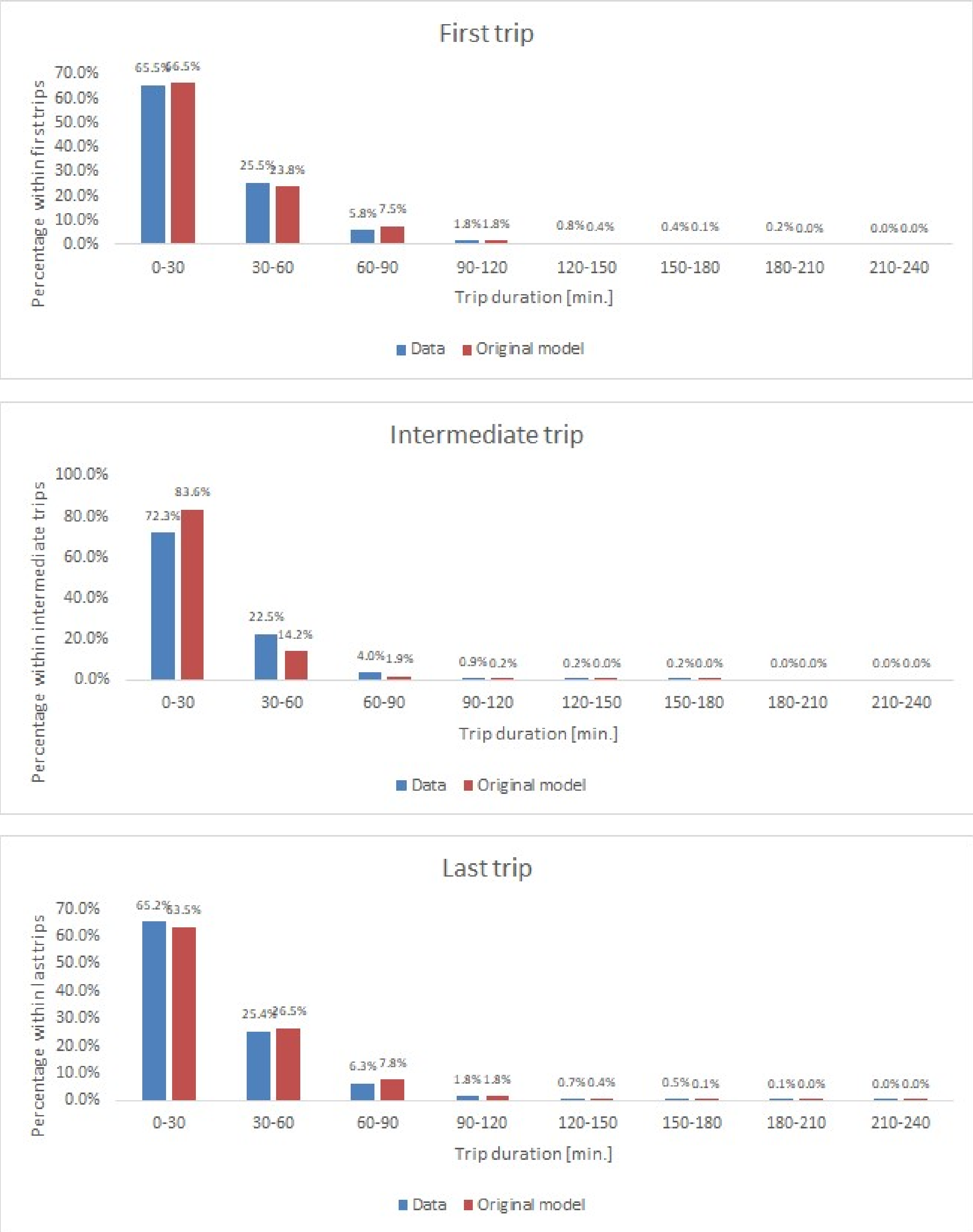


Figure 8 – The distribution of trip durations.

3.3.3 Trip distance

The results are very similar for trip distances and trip durations. For trip distances, we also see a similar order of magnitude for the overall average trip distance, but a more striking underestimation of the trip distance for the intermediate trips.

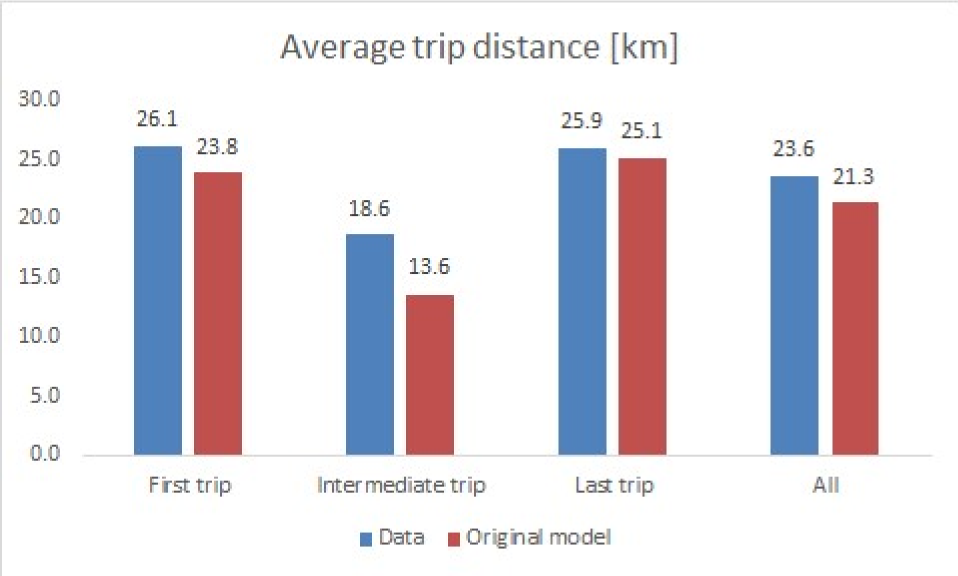


Figure 9 – The average trip distance.

4. Improvements to the model

This section describes the implemented improvements in more detail in §4.1 and subsequently shows the impacts of these improvements in isolation on the model outcomes in §4.2. Finally all improvements are combined to analyze their impact on the model outcomes together in §4.3.

4.1 Implementation of improvements

4.1.1 Implementation of improvement 1: Generalized travel cost

Cost figures
The official cost figures for vans for cost-benefit analysis (REGnorm, 2019) are used in model estimation and application. The values for 2016 are 0.5553 CHF/km and 48.90 CHF/hour. To account for cost developments between 2013 (estimation data) and 2021 (model application), we use the producer price index for goods transport by road, as reported by the Federal Statistical Office (2023). The producer price index for the years 2013, 2016 and 2021 are 100.3, 95.7 and 99.7.

The cost figures used during estimation (with data from 2013) are 0.5820 CHF/km and 51.25 CHF/hour and those used in model application (for the year 2021) are 0.5785 CHF/km and 50.94 CHF/hour.

Re-estimation of Next Stop Location choice model

As a first step for the re-estimation, new skims with travel times and distances were generated in VISUM to improve consistency between the model skims (NPVM zone level) and estimation skims (PLZ zone level). The existing models were re-estimated using these skims, after which a series of models were estimated in which (1) the intrazonal dummy was replaced by intrazonal skim values, (2) time coefficients were replaced by cost coefficients, and (3) the optimal piece-wise linear relation between utility and generalized cost was specified. The choice for the final specification was based on the loglikelihood of the model, the significance of its coefficients and the interpretability of its coefficients.

The utility function for choosing zone j as the next stop zone is as presented below. During estimation we correct for the probability of sampling zone j for the choice set, hence the term $log(probability\_sampling_j)$. During model application no sampling of zones is applied, so this term is not applied there.

$$
\begin{gathered}
U_j = \\
b\_LowDen * (LandUse_i = \mathrm{L}) + b\_Res * (LandUse_i = \mathrm{R}) + \\
b\_Inter * (LandUse_i = \mathrm{I}) + b\_EmpNode * (LandUse_i = \mathrm{C}) + \\
(b\_cost\_0 \; + \; d\_cost\_0\_first \; * \; (n\_stops\_since\_base = 0)) * cost_j + \\
d\_cost\_50 * \left(cost_j \; > \; 50\right) * \left(cost_j - 50\right) + \\
b\_cost\_target\_to\_base * (n\_stops\_since\_base \; > 0) * cost\_to\_base_j + \\
b\_size * \log\left(b\_jobs * \left(1 + jobs_j\right) + b\_pop * \left(1 + pop_j\right)\right) + \\
\log(probability\_sampling_j)
\end{gathered}
$$

In Table 3 we see the estimated coefficients for the purposes goods, service and other. The land use coefficients show similar impacts as in the existing specification. The contribution of the generalized cost term to the utility function is plotted in Figure 10. It shows a sort of distance decay function, in which the marginal utility contribution decreases for longer distances (or rather, higher generalized costs). For the goods purpose, we find that the generalized cost is more important for the later trips of a tour compared to the first trip. This is what we also saw in Figure 7 and Figure 9; the average duration and distance is shorter for later trips than for first trips of a tour.

The size term shows a positive contribution to the utility for zones with more jobs and a higher population. For goods, service and other, the contribution of one job is larger than the contribution of one inhabitant to the probability of selecting a zone as the next stop. While the *b_jobs* coefficient is not significant at the 95% reliability interval for service and other, it was decided to leave it in the specification, as a value much larger than 1.0 was found repeatedly during cross-validations.

Table 3 – The coefficients of the final specification for the Next Stop Location choice model. Between brackets the robust t-ratio is presented.

Parameter	Goods	Service	Other
b_EmpNode	0.0 (-)	0.0 (-)	0.0 (-)
b_Inter	0.4993 (4.91)	0.5833 (3.41)	1.9434 (2.85)
b_Res	0.5515 (4.89)	0.7104 (3.28)	2.2321 (3.01)
b_LowDen	1.2299 (8.19)	1.1810 (4.51)	2.5784 (2.94)
b_cost_0	-0.0932 (31.32)	-0.0863 (23.97)	-0.0971 (7.18)
d_cost_0_first	0.0089 (3.39)	0.0 (-)	0.0 (-)
d_cost_50	0.0540 (14.15)	0.0505 (9.68)	0.0667 (3.62)
b_cost_target_to_base	-0.0092 (4.76)	-0.0297 (7.23)	-0.0245 (2.55)
b_jobs	14.4227 (2.09)	4.5483 (1.18)	49.7528 (0.59)
b_pop	1.0 (-)	1.0 (-)	1.0 (-)
b_size	0.7369 (29.23)	0.7455 (15.63)	0.6631 (5.26)
N	3583	945	147
LL (0)	-17328.03	-6587.83	-758.54
LL (final)	-11713.52	-4498.61	-507.42

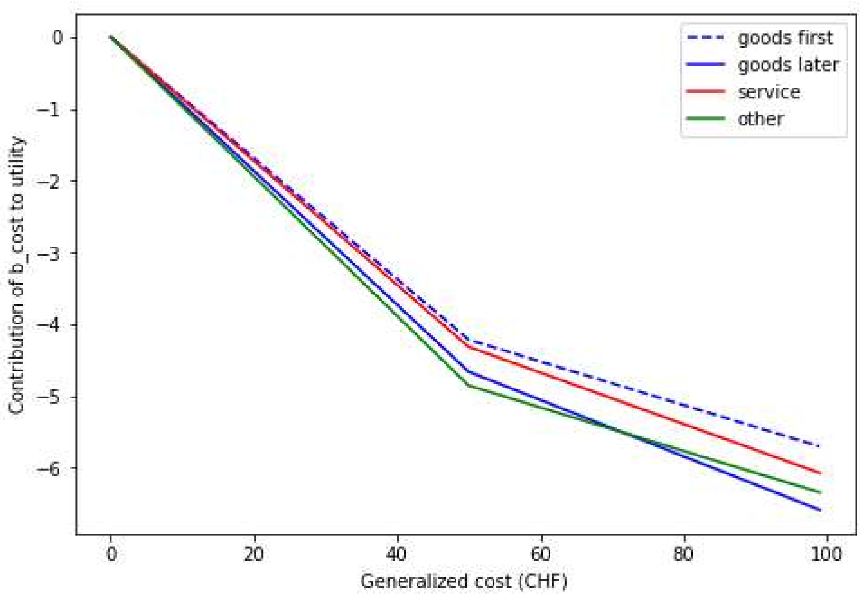


Figure 10 – The contribution of the generalized cost to the utility function.

Re-estimation of End Tour choice model

The End Tour choice model was also re-estimated to include a *b_cost_return* component instead of a *b_time_return* component and to use the newly generated skims which are more consistent between the model application (NPVM zones) and estimation (PLZ zones). The results are very similar to the existing model specification.

Table 4 - The coefficients of the final specification for the End Tour choice model. Between brackets the robust t-ratio is presented.

Parameter	Goods	Service	Other
ASC	-0.7228 (-2.65)	-0.0093 (-0.06)	0.2169 (0.67)
BSC_branch7	0.7516 (5.58)	0.6454 (4.80)	0.0 (-)
BSC_branch8	0.7669 (4.12)	0.0 (-)	0.0 (-)
BSC_branch14	0.4074 (1.52)	0.0 (-)	0.0 (-)
BSC_branch100	0.2830 (2.35)	0.0 (-)	0.0 (-)
cons_2stops	-1.0694 (-6.22)	-0.8659 (-8.31)	-1.0367 (-2.08)
large_curb_weight	0.3997 (3.65)	0.0 (-)	0.0 (-)
b_ln_stops	0.2981 (2.07)	0.0 (-)	0.0 (-)

Parameter	Goods	Service	Other
b_cost_return	0.0046 (3.93)	0.0 (-)	0.0 (-)
b_accessibility	0.2252 (2.10)	0.2302 (1.94)	0.0 (-)

4.1.2 Implementation of improvement 2: Intuitiveness / efficiency of tours

We implement the swapping algorithm for tours with 8 or more stops. For these tours, the distance reduction potential and number of crossings is quite high compared to the LCV data (Figure 2 and Figure 3), while there is limited impact on the trip distance distribution, as this is about 2% of all the modelled tours.

4.1.3 Implementation of improvement 3: Return trips

Probability of making a return trip

79.9% of the tours in the LCV data return at the end of the tour to the starting point. No clear relationship was found between making a return trip and other variables (number of stops, goods vs. service, travel time / distance of (hypothetical) return trip. This indicates that there are no specific types of tours for which more often no return trip is made. Hence, we implemented a generic parameter, set at 0.799, which is used in the End Tour model to draw the decision (using Monte Carlo simulation) to make a return trip back to the tour origin zone or not. For the sake of flexibility, the parameter is added to the CSV file with the End Tour parameters and thus adaptable per segment.

Maintaining vehicle conservation

Since some tours do not return to their origin anymore, vehicle conservation is not guaranteed anymore, i.e. the number of trips entering a zone can differ from the number of trips exiting. In order to maintain vehicle conservation, another step is built in to symmetrize the trip matrix before exporting it. This comes down to the equation below, where M^t denotes the transpose of M.

$$\text{SymmetrizedTripMatrix} = \frac{OriginalTripMatrix + OriginalTripMatrix^t}{2}$$

4.1.4 Implementation of improvement 4: Maximum tour duration

For the implementation of a maximum tour duration we make a slight modification to the End Tour module. If the total travel time of the tour, including a return trip to the tour origin zone, would last more than *max_tour_duration* hours, then we always end the tour, i.e., we override the previously drawn “End Tour” decision.

Based on analyses on the LCV data, a value of 8 hours seems to be a reasonable value for the *max_tour_duration* parameter. The largest calculated tour duration in the LCV data (based on a travel time matrix of the passenger model and excluding dwell times) is 9 hours, and the 99%-percentile is at 5 hours.

Note that it is still possible to construct a tour slightly longer than 8 hours in the model, as the tour is only forced to finish after a trip that causes the tour duration to exceed 8 hours has already been added.

4.1.5 Implementation of improvement 5: A new Parcel Delivery module

The Parcel Delivery module follows the approach developed for the Tactical Freight Simulator in the project HARMONY for the European Commission (de Bok et al., 2022b; Eggers et al., 2022). It has since been implemented in several other model systems, including the Flemish national freight model (Thoen & de Bok, 2020), the Dutch national freight model (Significance, 2022) and the Amsterdam traffic model (de Bok et al., 2020). Within this project it is implemented for Switzerland.

Scope

The Parcel Delivery module focuses on the last leg of parcel deliveries in the B2C (business to consumer) and B2B (business to business) segments, i.e., we model the trips made with vans coming from the parcel depots going to the end receivers. Here, we only model the parcel deliveries and not the post / letters. Due to data availability, we only model parcel deliveries of Swiss Post (La Poste), DHL, DPD and FedEx.

Model inputs

The module uses the following inputs:

- Demand parameters
  - Average number of parcels per person per day (B2C segment)
  - Average number of parcels per job per day (B2B segment)
- Average number of delivery attempts
- Scheduling parameters
  - Maximum number of parcels per van
  - Maximum tour duration
- Parcel courier market shares (in terms of volume, i.e., number of parcels)
- Depots for parcel delivery
- Travel distance matrix
- Socio-economic data (number of jobs and persons in each zone)

Below, an overview is presented of the minimal and optimal data requirements. In green, we show which data we managed to collect and use in the module.

Data type	Minimal	Better	Optimal
Demand	Total number of parcels delivered	Total number of parcels delivered (✓), for B2B and B2C separately **(separation B2B/B2C only for Germany)**	Household survey data on number of ordered parcels
Number of delivery attempts	One average for the number of delivery attempts (✓)	The average number of delivery attempts, for B2B and B2C separately	
Depots	All (or most) depots	All (or most) depots, by courier (✓)	
Couriers	No explicit couriers	Couriers, market shares in terms of number of delivered parcels (✓)	Market shares in terms of number of delivered parcels, by region
Vehicle types	Maximum number of parcels per van (✓)		Explicit vehicle types (short and long van) market shares and average number of parcels per vehicle

The parcel demand parameters were calculated as follows.

$$n\_parcels\_per\_job \;= n\_parcels\_total \,*\, perc\_b2b \,/\, n\_jobs\_total \,/\, year\_factor$$

$$n\_parcels\_per\_person \;= n\_parcels\_total \,*\, perc\_b2c \,/\, n\_persons\_total \,/\, year\_factor$$

The total number of delivered parcels in Switzerland in 2021 is approximately 250 million, based on Swiss Post (2023) and PostCom (2022). The percentage of B2B and B2C deliveries could not be obtained for Switzerland, so percentages from Germany were used instead, based on BIEK (2022), resulting in 23% B2B deliveries and 77% B2C (+C2C) deliveries. The total number of jobs and persons in Switzerland are taken from socio-economic zonal data that is input to the model. Finally, to convert the annual rates to average daily rates, we use a year factor of 6/7*365=313 (no deliveries on Sundays). This gives us 0.0752 parcel per person per day and 0.0471 parcels per job per day.

The average number of delivery attempts is deduced from Universität St. Gallen (2017). They present the percentage of successful deliveries at the first, second and third attempt for urban, suburban and rural environments respectively. Based on the reported percentages, the average number of delivery attempts ranges between 1.18 and 1.28 depending on the environment, so we set the overall average number of delivery attempts at 1.23. No data was obtained that reports delivery success rates separately for B2B and B2C deliveries, so for both types of deliveries the same number of delivery attempts is used in the model.

The maximum number of parcels per van is set at 160, based on the study of Universität St. Gallen (2017), which reports an average of 152.3, 160.9 and 122.7 parcels per tour for urban, suburban and rural environments respectively.

In Figure 11 we see the 76 parcel depots that were identified for the four modelled couriers. This collection was based on OpenStreetMap and Google Maps searches and the depots listed by La Poste (2023a). For all four couriers a network of depots distributed over most of the country was found; this is important to prevent unrealistically long tours in the module.

The market shares of the four modelled couriers, in terms of number of delivered parcels, is deduced as follows. The market share of La Poste is approximately 80%, based on La Poste (2023b) and PostCom (2022). The market shares of the other couriers is based on the number of identified depots, giving us 7.5%, 7.5% and 5% for DHL, DPD and FedEx respectively.

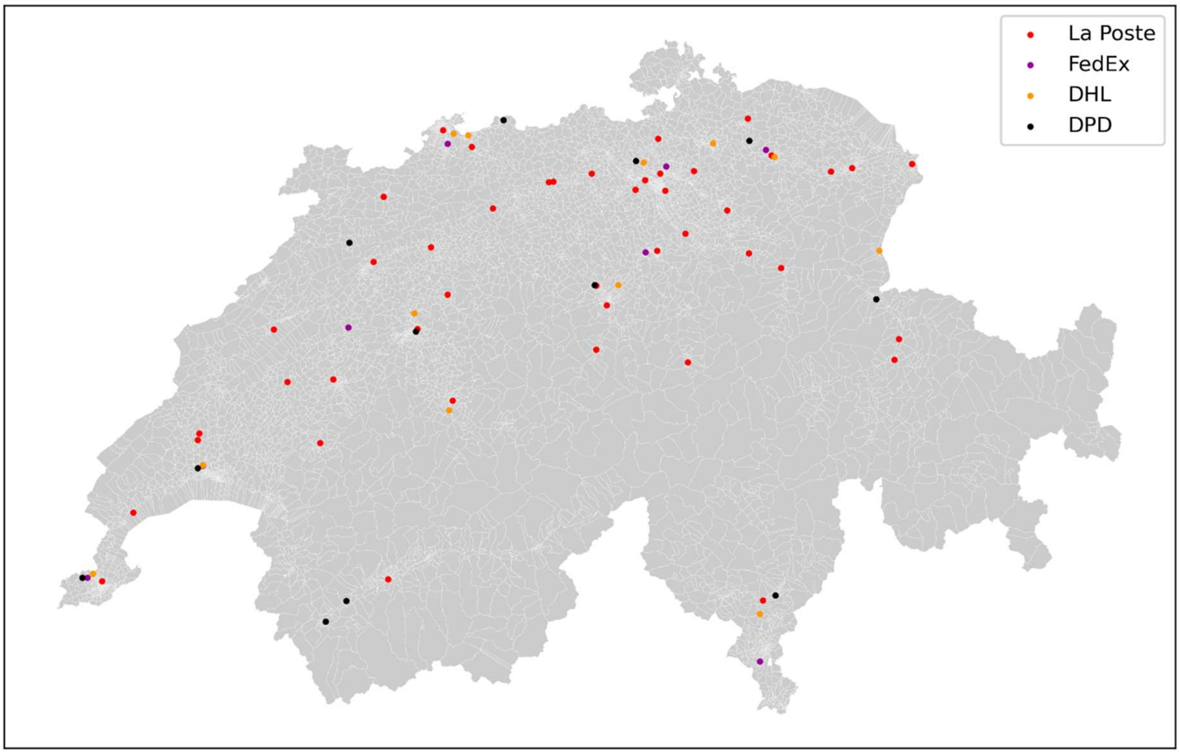


Figure 11 – The parcel depots used in Parcel Delivery module.

Model steps

Below follows a technical description of the steps of the parcel module.

- **Parcel generation:** calculate the number of parcels in every zone i:

$$n_{parcels_i} = (n\_jobs_i * parcels\_per\_job * average\_n\_attempts\_b2b + population_i * parcels\_per\_person * average\_n\_attempts\_b2c)$$

- **Distribution of parcels among couriers:** Distribute the number of parcels in each zone i between the couriers C based on their respective market shares. Round these numbers to the nearest integer, so we have a set of discrete parcels for every combination of zone i and courier c.

- **Assignment of parcels to a depot:** Assign the parcels of every zone i and courier c to the nearest depot d of courier c. If zone i is isolated for depot d (i.e., no path back to the depot can be made through the other zones assigned to depot d), consider the second or third nearest depot if this resolves the isolation of zone i.

- **Clustering of parcels for tour construction:** For each depot *d*, group the parcels into clusters of parcels that will be delivered within the same tour, using the following iterative procedure:
  a) Select the parcel assigned to depot *d* and not yet assigned to a cluster that is the furthest from depot *d* and assign it to a new cluster *k*
  b) Keep adding parcels to cluster *k* from the zones that are the nearest to the first delivery zone assigned to cluster *k* and still have parcels not yet assigned to a cluster.
  c) If cluster *k* has *max_parcels_per_van* parcels or would lead to a tour longer than *max_parcel_tour_duration* hours, then the cluster is full. Save it, increase *k* by 1 and go back to step a to start creating a new cluster.
  d) If depot *d* has no parcels left to assign to a cluster, save the current cluster, increase *d* by 1 (i.e. move to the next depot), increase *k* by 1 and go back to step a to start creating a new cluster. Stop if this was the last depot.

- **Tour construction:** All the parcels belonging to the cluster and that need to be delivered in the same zone are assumed to be delivered successively. The order in which the various delivery zones are visited is then defined using a nearest neighbor search and a swapping algorithm. The swapping algorithm swaps every combination of two stops in the tour and accepts the swap if it reduces the global tour distance.

There is a large body of literature dedicated to Vehicle Routing Problem (VRP), which seeks to find the optimal set of delivery tours, given a set of depots and clients to serve and numerous constraints. For several reasons, it was decided to apply the more pragmatic heuristics presented above.

- Firstly, optimization approaches to solve the VRP rely heavily on properly set constraints to define an appropriate solution space, such as a vehicle fleet size, the number of available drivers, and delivery time windows. Given that our model is of a strategic and descriptive nature, rather than an operational planning model, we will never be able to set all constraints properly. In the absence of such constraints, a VRP approach would lead to "too optimal" tours.
- Secondly, VRP optimization solutions tend to be quite complex and might feel like a "black box" to those unfamiliar with this field of research. The implemented "common sense" heuristics make the parcel module more easily understandable and, therefore, more transparent and reproducible.
- Finally, depending on the exact chosen methodology and its parameter values, a VRP optimization solution is computationally heavy and not applicable at a national scale. The more pragmatic heuristics applied here allow the parcel module to be finished with its calculations in about 2 minutes.

Additional corrections step

The original version of the LCV model predicts the tours in Switzerland for all LCV segments. To prevent double counting of kilometers in the parcel segment, we need to correct the LCV model for the kilometers made in the dedicated parcel module. The objective is to keep the total vehicle kilometers in the base year the same after inserting the parcel module, while still allowing a larger growth of the parcel segment to further increase the total vehicle kilometers in a forecast year.

In order to achieve this, we build in a factor (*correction_factor_parcel*) that reduces the number of tours (*n_tours_init*) calculated initially by the model for the vehicles registered in the branch H (transportation and storage), the branch that parcel couriers are attributed to, as well for vehicles of the segment "other".

In order to set this factor, a base year run with the model without such corrections is needed, such that $vkm\_init_{H+other}$ can be derived.

$$n\_tours_{H+ot} \quad = n\_tours\_init_{H+oth} \quad * correction\_factor\_parcel$$

$$correction\_factor\_parcel \ = \frac{\left(vkm\_init_{H+ot} \quad - \ vkm_{parcel}\right)}{vkm\_init_{H+oth}}$$

Where:

$n\_tours\_init_{H+oth}$ = The initial number of tours modelled for the segments relating to branch H and the segment "other"
vkm_{H+oth} = The modelled vehicle kilometers of the segments relating to branch H and to the segment "other"
vkm_{parcel} = The modelled vehicle kilometers of the parcel module

Based on current model outputs, the factor needs to be set at 0.851. This same factor needs to be applied in base year and forecast year run.

4.2 Analyses of improved model outcomes

In this Section we analyze the outcomes of the model after implementation of the improvements. The first five sub sections will look at each of the five improvements in isolation, while the last sub section combines all improvements in one model run.

4.2.1 Analyses of improvement 1: Generalized travel cost

In Figure 12 to Figure 15 we see that the impact of the generalized cost specification has a limited impact on model outcomes such as trip distance, trip duration, tour duration and number of stops per tour. This is as expected; the utility functions are changed only minimally.

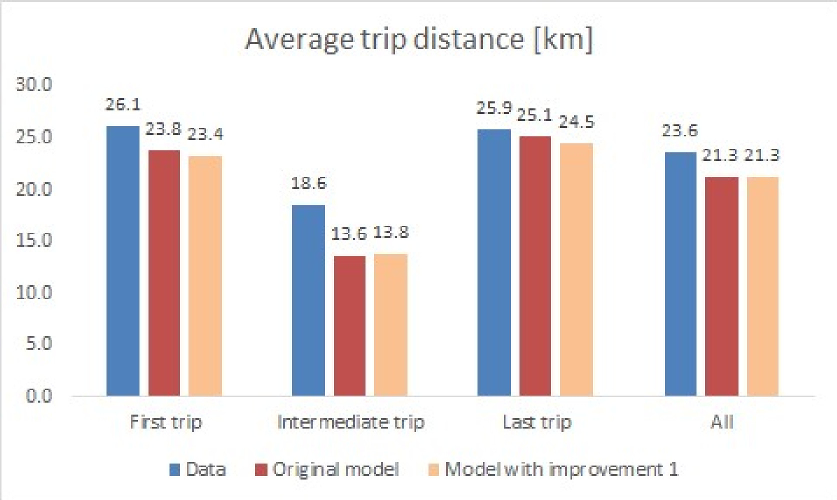


Figure 12 - The average trip distance, before and after implementation of the generalized travel cost models.

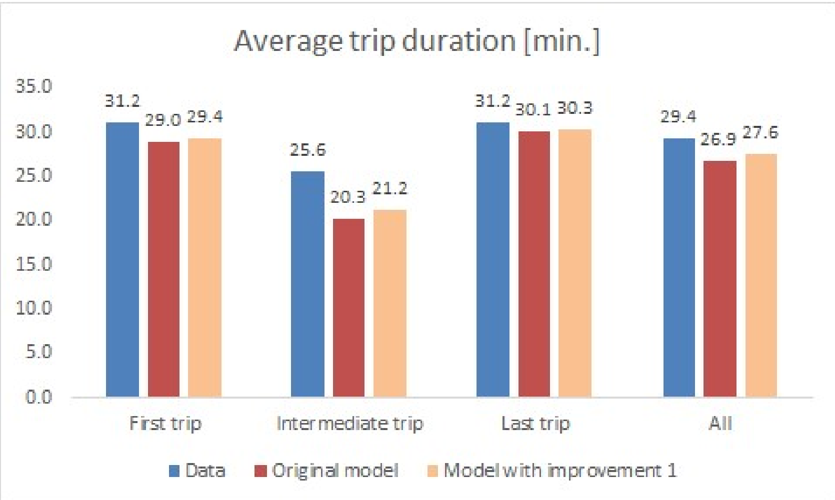


Figure 13 - The average trip duration, before and after implementation of the generalized travel cost models.

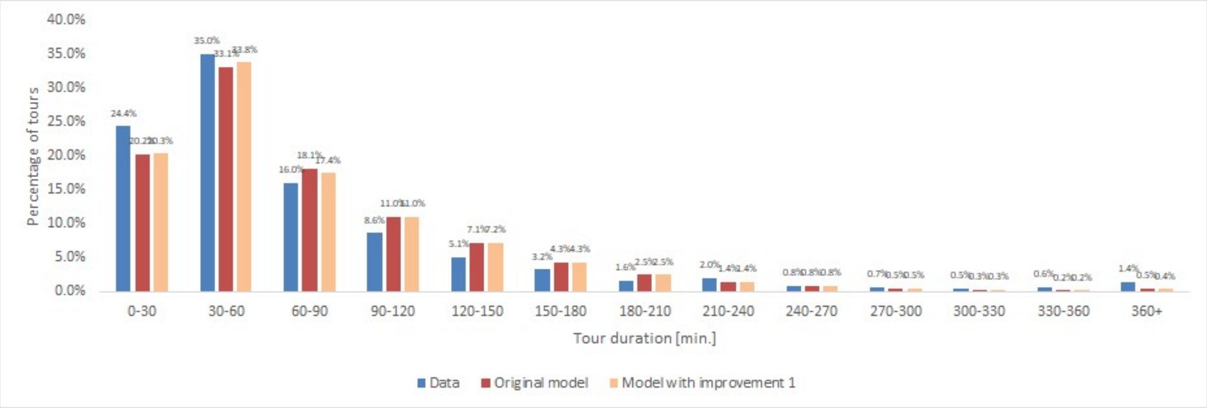


Figure 14 - The distribution of tour durations, before and after implementation of the generalized travel cost models.

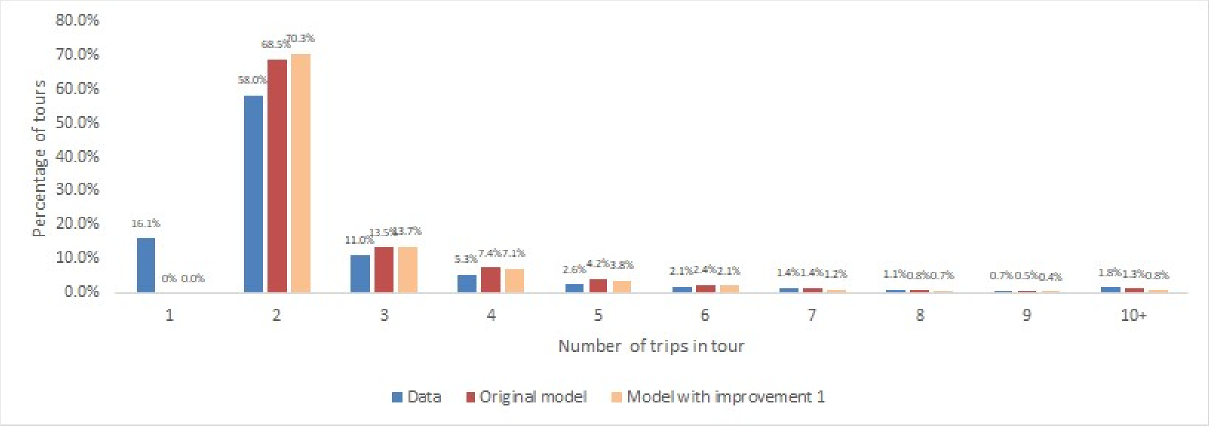


Figure 15 - The distribution of number of trips per tour, before and after implementation of the generalized travel cost models.

To test the cost sensitivity of the model, we did a run in which the distance costs were increased with 0.10 CHF/km. This is an increase of 17.3% in distance costs. The resulting vehicle kilometers were reduced by 7.5% in this run compared to the reference run. This means that the elasticity for distance costs in the destination choice is 0.43.

In the trip-based module for service and construction vans of the Dutch national freight model such a scenario with 17.3% increased distance costs gives an elasticity of 0.22. The cost sensitivity of 0.43 of the Swiss LCV model is therefore considered reasonable in order of magnitude, although possibly a bit on the high side. The difference between the trip-based vs. tour-based approach, however, makes the comparison difficult; in the tour-based approach not only the destination choice but also the end tour choice is impacted, while in the trip-based approach the impacts are purely destination choice impacts.

4.2.2 Analyses of improvement 2: Intuitiveness / efficiency of tours

Implementing the 2-opt algorithm for tours with 8 or more stops has the following impacts as shown in Figure 16 to Figure 18.

- Naturally, the distance reduction potential is almost 0% for tours with 8 or more stops. It is not exactly 0%, as the 2-opt algorithm is run with only 1 iteration of the tour stop locations, while it could still find further improvements after multiple iterations (Figure 16).
- The number of crossings is also reduced substantially for tours with 8 or more stops. Especially for tours with 10 or more stops we see crossings in a similar order of magnitude as in the observed LCV data (Figure 17).
- The overall average trip distance is impacted minimally, although the reduction of 13.6 km to 13.2 km for intermediate trips is notable (Figure 18).

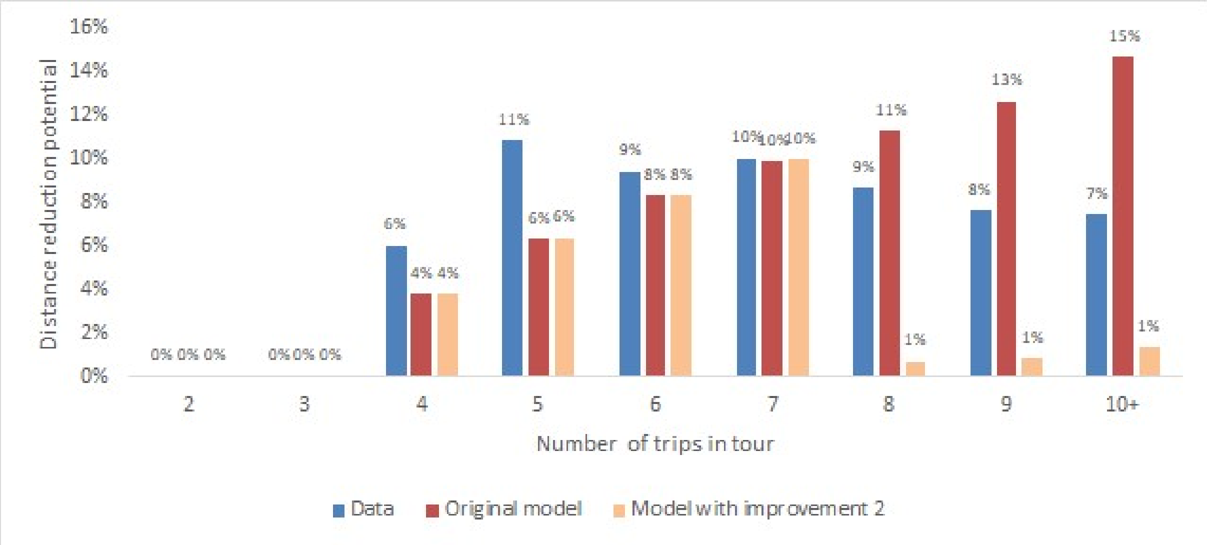


Figure 16 – The distance reduction potential, by number of trips in the tour, before and after implementation of the swapping algorithm for tours with 8+ stops.

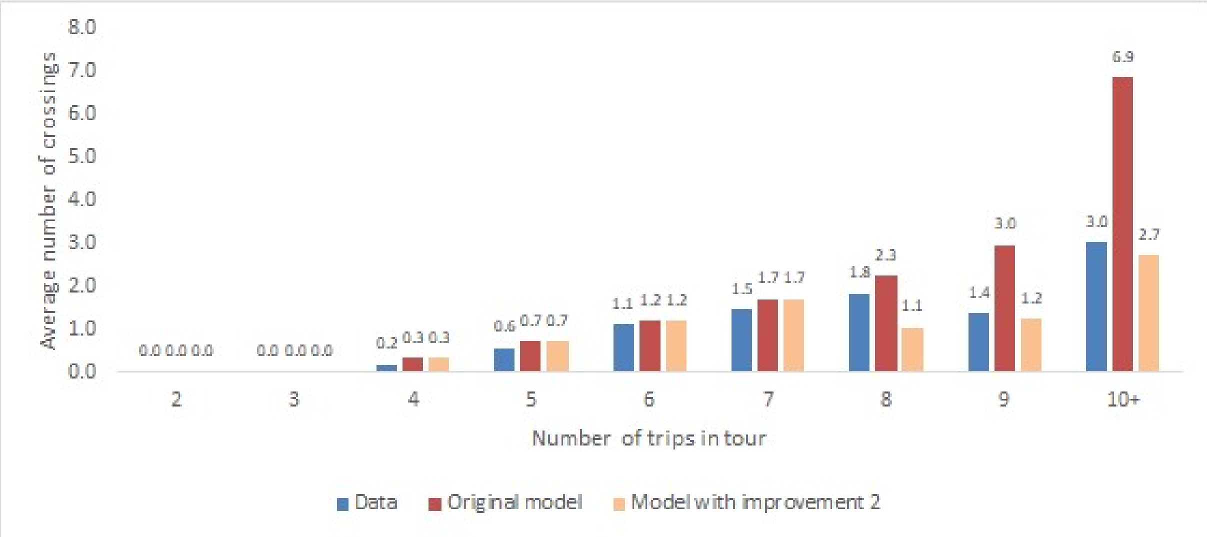


Figure 17 - The average number of crossings, by number of trips in the tour, before and after implementation of the swapping algorithm for tours with 8+ stops.

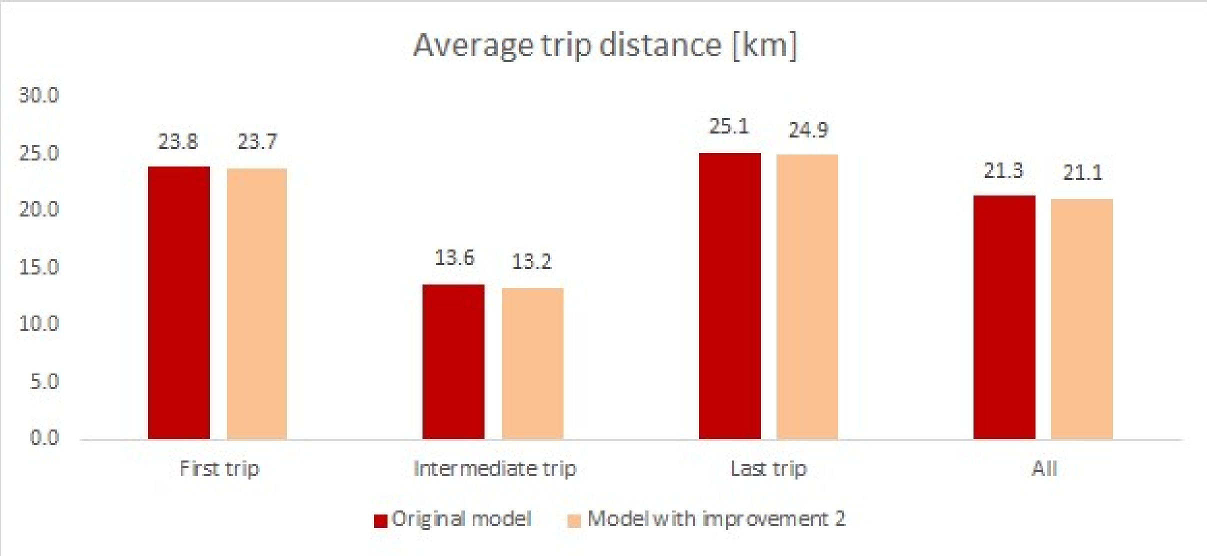


Figure 18 - The average trip distance, before and after implementation of the swapping algorithm for tours with 8+ stops.

4.2.3 Analyses of improvement 3: Return trips

In Figure 19 we see that the match with the LCV data with respect to the number of trips per tour improves substantially with the implementation of the return trip probability in the model. This can be attributed to the fact that the definition of a tour is more consistent now between the LCV data and the model, i.e., a tour does not have to be closed by definition. Figure 20 shows that the match with respect to the also tour durations improves somewhat.

The total vehicle kilometers decrease with 8.4% after the implementation of the return trip probability.

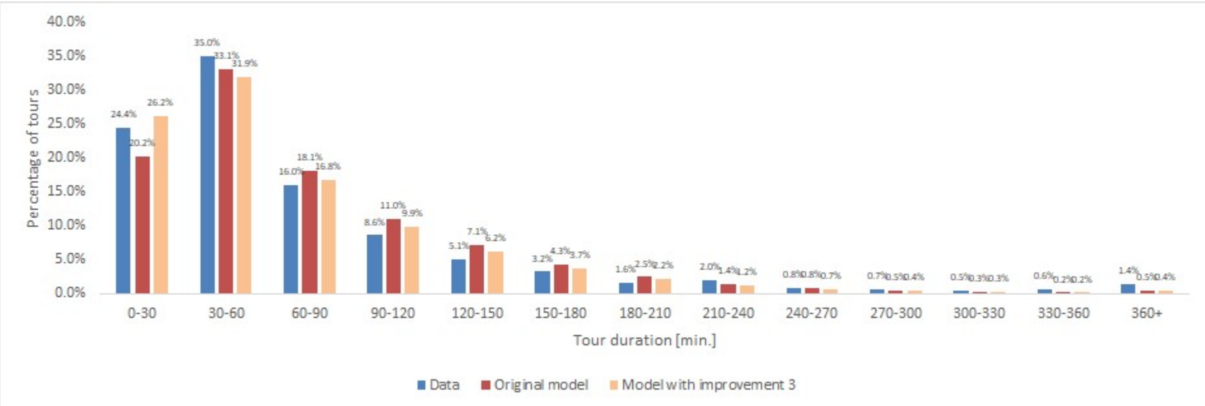


Figure 19 – The percentage of tours, by number of trips in the tour, before and after implementation of the return trip probability.

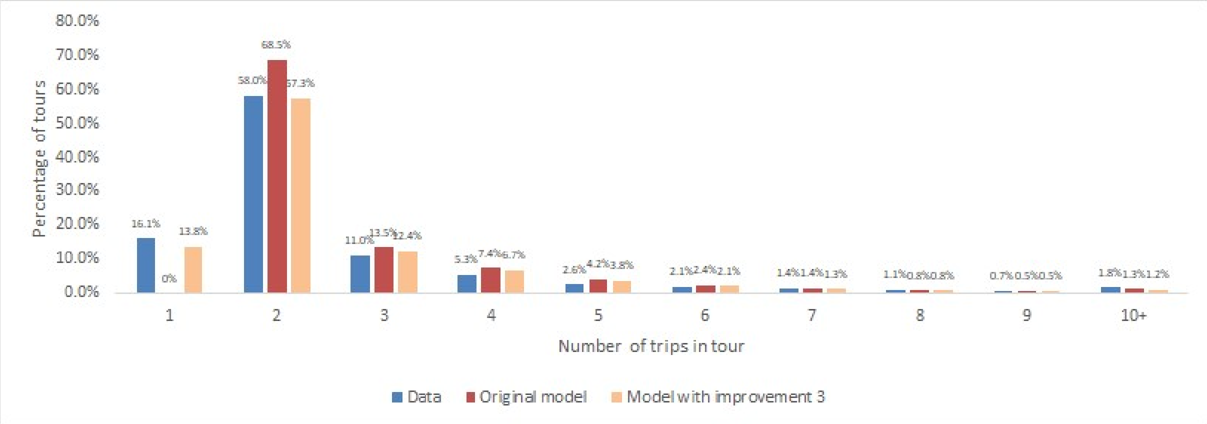


Figure 20 – The distribution of tour durations, after implementation of the return trip probability.

4.2.4 Analyses of improvement 4: Maximum tour duration

The purpose of this improvement was to prevent the model from generating unrealistic outliers, with extremely long tour durations. As expected, the total vehicle kilometers do not change noticeably[1] after implementation of the maximum tour duration, and the realized maximum tour duration decreases from 24+ hours to 10 hours.

4.2.5 Analyses of improvement 5: A new Parcel Delivery module

The four maps in Figure 21 and Figure 22 illustrate the outcomes of the Parcel Delivery module for two of the modelled couriers. Figure 21 shows to which depot each zone is assigned, which indicates that the depot assignment based on network distance, with additional “isolated zone” improvements, works as intended. In Figure 22 we see the tours that are formed to deliver these parcels from the depots of these couriers.

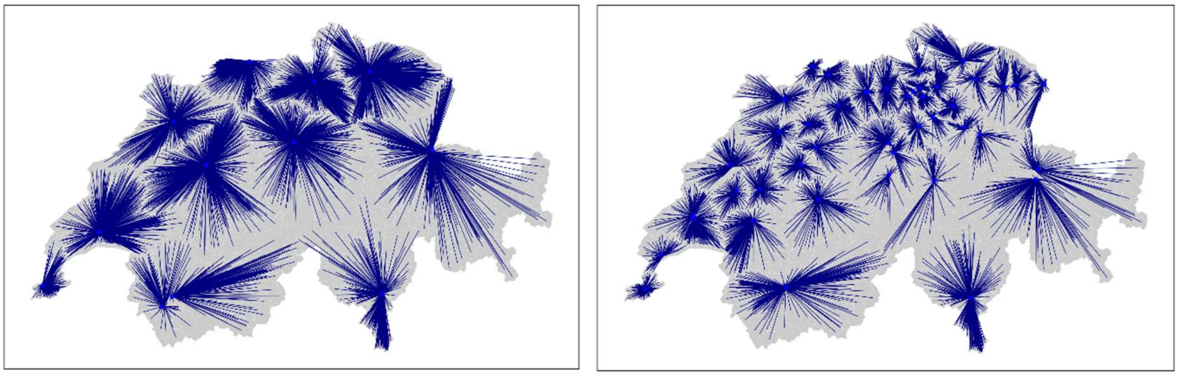


Figure 21 – A map of the parcel demand assigned to depots for two of the couriers. Each line represents one flow of parcels originating at a depot and ending at a delivery zone.

[1] I.e., the simulation variance in this run was larger than a potential decrease in vehicle kilometers caused by the introduction of a maximum tour duration.

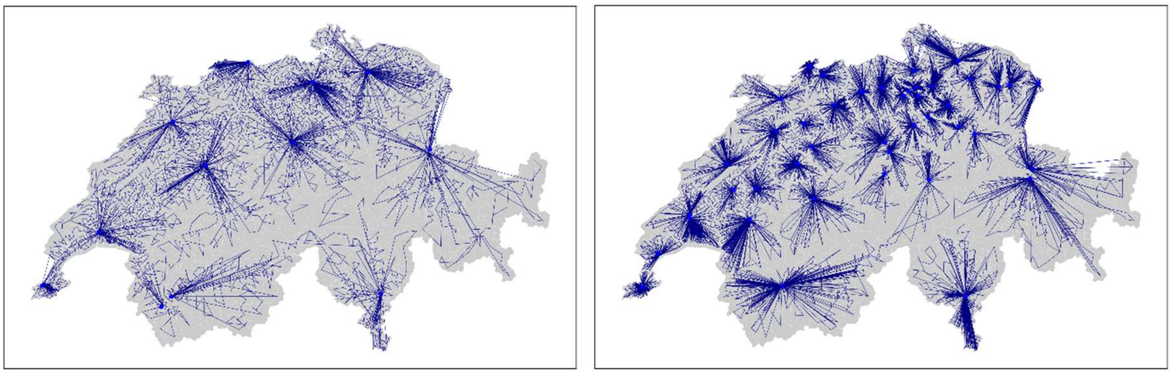


Figure 22 - A map of the parcel schedules for two of the couriers. Each line represents one trip from an origin zone to a destination zone.

Some key output indicators of the Parcel Delivery module are listed hereafter:

- Average tour duration: 100 minutes
- Average tour distance: 53 km
- Total vehicle kilometers: 328106 km
- Total number of parcels: 977574 parcels
- Total number of tours: 6195 tours
- Total number of trips between different zones: 44130 trips
- Average number of parcels per tour: 158 parcels
- Average number of parcels delivered in a zone during a trip: 26 parcels

Figure 23 shows the distribution of tour durations of the parcel tours (excluding dwell times). The majority of tours lasts less than 2 hours, while the maximum tour duration is 8 hours. This large tour duration (which still does not account for dwell times and trips inside a zone) is certainly the result of assuming a unique number of parcels per tour. In practice, this number of parcels per tour is likely to depend on demand density (couriers with a small market share are likely to deliver fewer parcels per tour, because they need to travel longer distances between customers).

The average tour distance of 53 km is similar in order of magnitude to what we find in Universität St. Gallen (2017), who report 60.6 km, 73.4 km and 67.6 km for urban, suburban and rural delivery tours respectively. The fact that the modeled tour distance is somewhat shorter might relate to kilometers caused by intrazonal trips, which would need to be added to the modeled parcel tours.

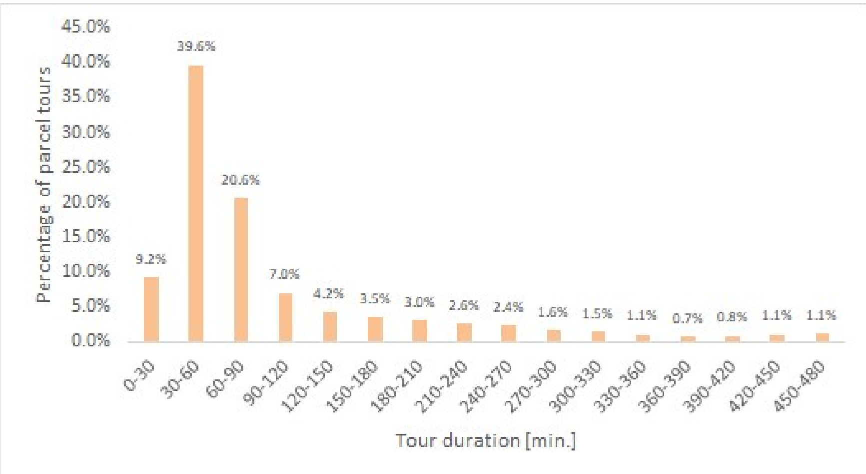


Figure 23 – The percentage of parcel tours by tour duration.

4.3 Analyses of final module with all improvements combined

Figure 24 to Figure 26 show statistics regarding the trip distance, trip duration, tour duration, and number of trips per tour for a model run with all improvements implemented, excluding the parcel deliveries. Just like in §4.2.1, we see a minimal impact on the average trip distance and trip duration Figure 24. Mainly due to the improvement related to the return trips (§4.2.3), we see a substantial improvement for the tour duration and number of trips per tour in Figure 25 and Figure 26.

The total vehicle kilometers generated by the model (including for parcel deliveries) is reduced by 14.9% after implementation of the five improvements. This is mainly due to the return trips, which are not added to all tours anymore. The generalized cost specification and improved efficiency of tours with 8+ stops cause some additional reductions in the total vehicle kilometers.

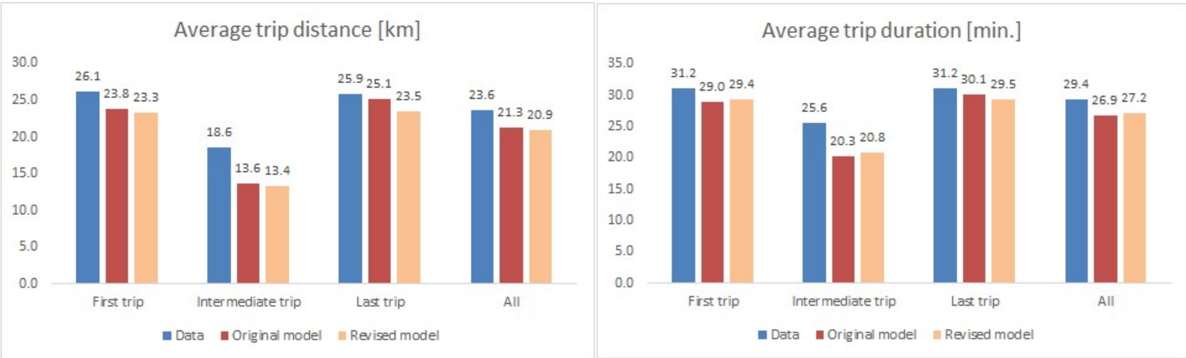


Figure 24 – The average trip distance and trip duration in the LCV data, the existing model, and the model with all five improvements combined.

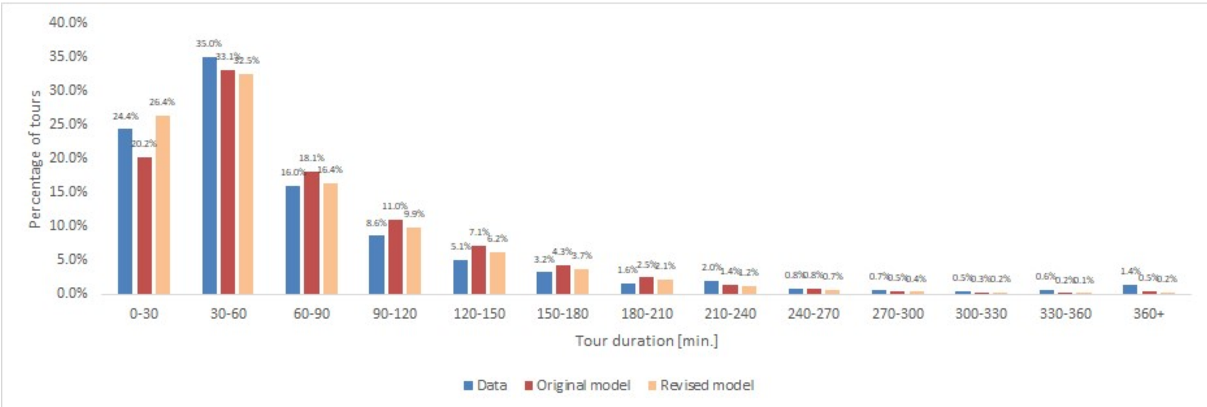


Figure 25 – The distribution of tours durations in the LCV data, the existing model, and the model with all five improvements combined.

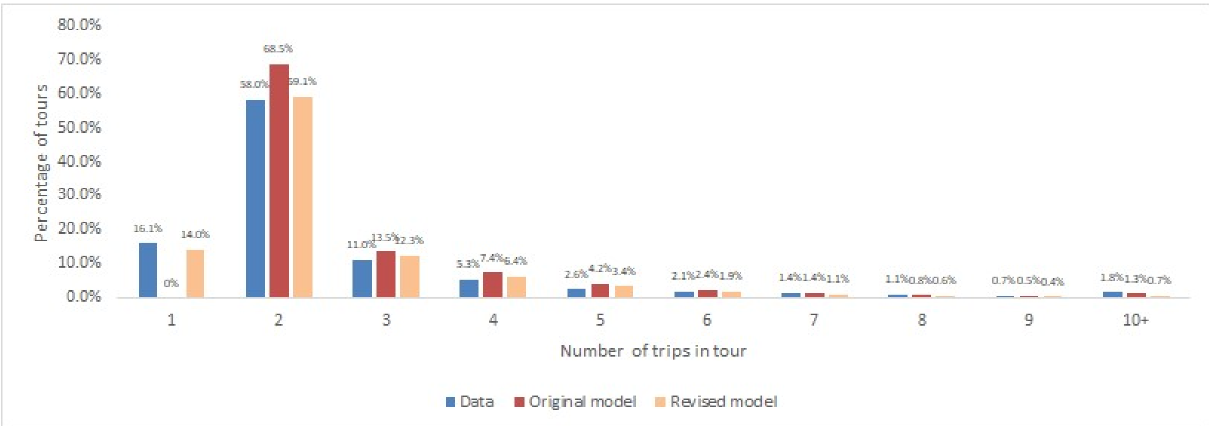


Figure 26 – The distribution of tours by number of trips in the tour; in the LCV data, the existing model, and the model with all five improvements combined.

4.4 Simulation variance

A microsimulation approach inherently comes with simulation variance. To form discrete tours, discrete choices need to be sampled from probabilities calculated with logit models. In this section, we analyze the extent to which this simulation variance causes deviations from expected zonal productions and link intensities.

For the analysis we use three different settings for the *granularity* parameter: 1.0, 0.5 and 0.1. This means we model 1x, 2x or 10x the intended number of tours. By modelling a larger number of tours we can increasingly rely on the law of large numbers to arrive at “average” model outcomes. In this section the parcel deliveries are included in the analysis.

Trip productions

In the three graphs below, we see scatter plots for the different granularity settings in which each dot represents one zone. As the simulation variance reduces, the Root Mean Square Error (RMSE) decreases and the trip productions of one run (y-axis) tend more towards that of the average of five runs (x-axis), which we take as the expected value here.

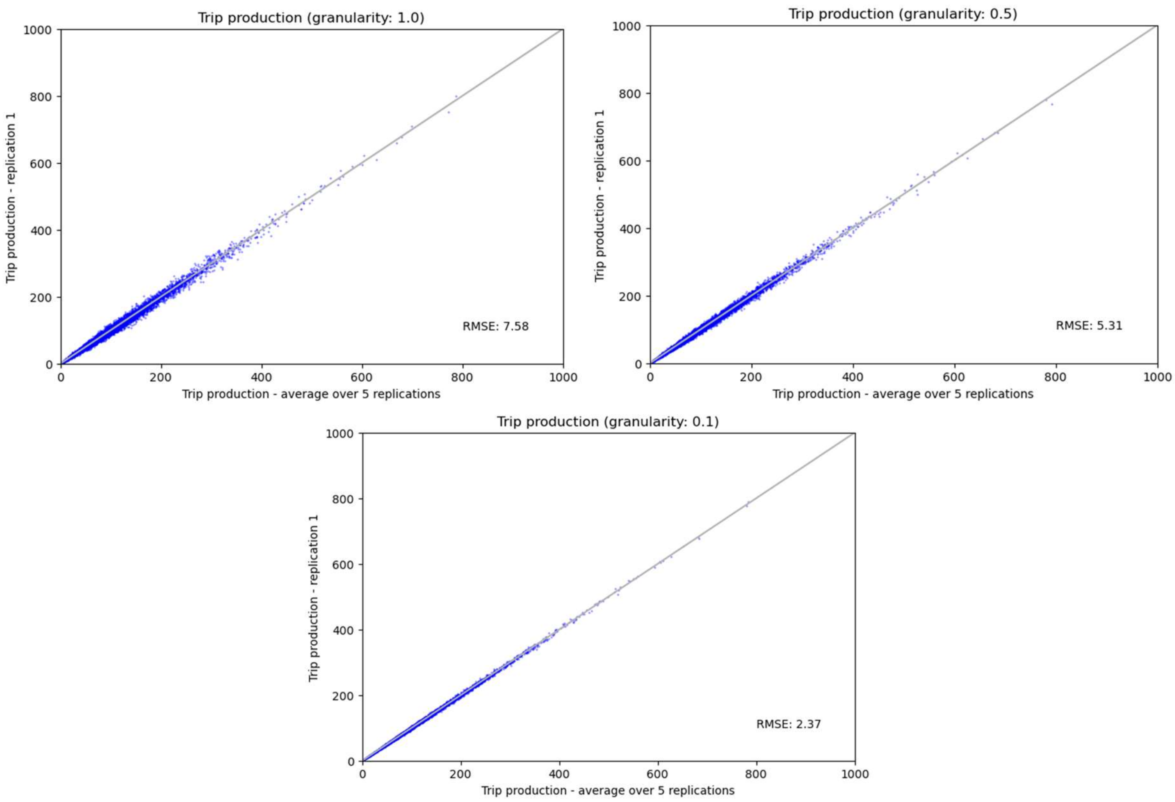


Figure 27 – The zonal trip productions; the results of one run set out against the average of 5 runs.

Link intensities

The trip matrices resulting from these runs were assigned to the road network in VISUM. In the three graphs below, we see how the link intensities for one run relate to the averaged link intensity over five runs (i.e., the expected value). On the x-axis we see the average intensity over five runs, on this y-axis we see the relative deviation from this average, i.e.: $abs(intensity_{run1}/\ intensity_{avg})\ /intensity_{avg}$.

With a granularity setting of 0.1 (the third figure), the deviation would rarely be more than 1% for any link with 4000 veh./day or more. A link with an expected intensity of 4000 veh./day would get intensities between approximately 3950 and 4050 veh./day depending on the random seed used in the tour construction process. If we use a lower granularity of 1.0 or 0.5, the simulation variance would get more problematic; such a link could get intensities between 3800 and 4200 veh./day.

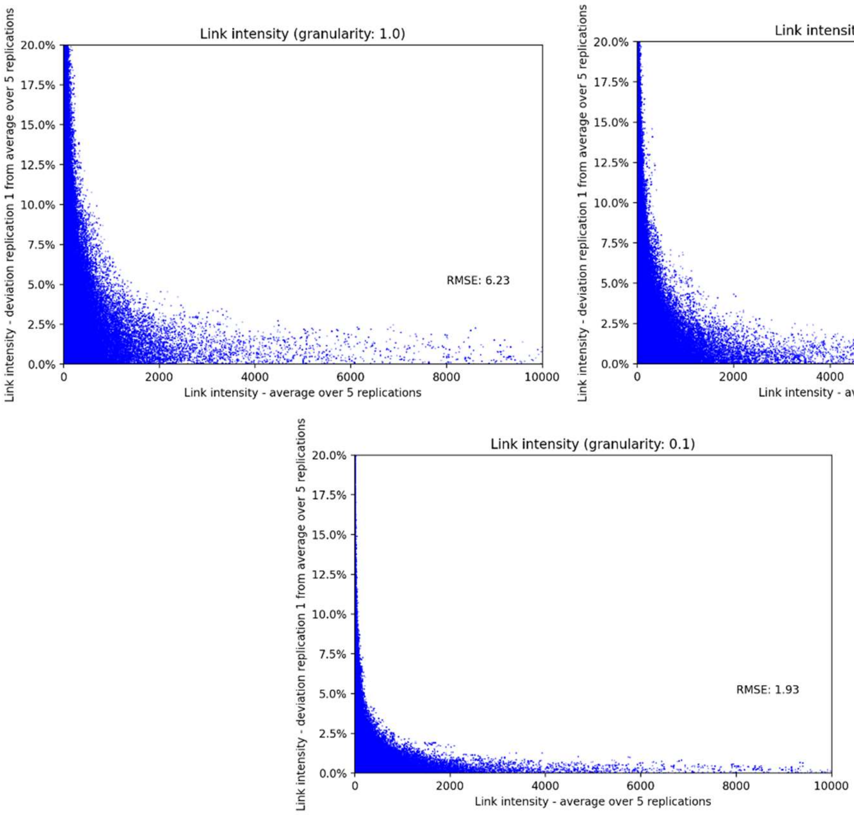


Figure 28 – The link intensities; the results of one run set out against the average of 5 runs.

Recommended granularity setting

We recommend a granularity value of 0.1, or less. In Figure 27 and Figure 28 we see that stability of the outcomes is acceptable for the link intensities and zonal trip productions.

Whether the granularity should be further reduced, depends on the relative importance of calculation times. With a granularity of 0.1, the calculation time is approximately 60 minutes on a PC with an i7 processor using 7 cores, and 30 minutes on a PC with an i9 processor using 10 cores. The calculation time increases more or less linearly with 1/granularity. According to the law of large numbers, we expect the RMSE to be proportional to the square root of the granularity. Based on this intuition, Figure 29 shows an extrapolation of the RMSE with a granularity of 0.05 and 0.01.

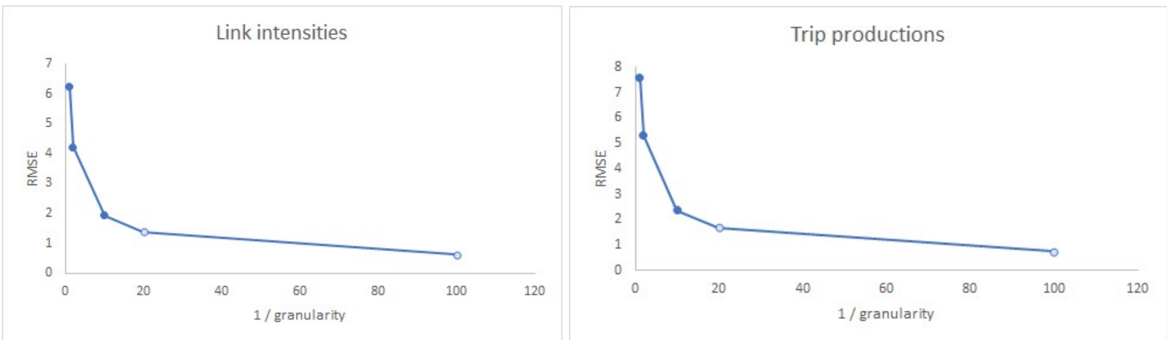


Figure 29 – The relation between the granularity and the RMSE.

5. Software architecture

5.1 Model implementation

Improvements

The existing Python software implementation has been adapted to include the model improvements described in the previous chapter. Additionally, several improvements have been made in terms of code quality. Several concrete examples are the following:

- Configuration settings are stored centrally in a file called *config.yaml* instead of hard-coded in the script.
- Model dimensions are stored centrally in a file called *config.yaml* instead of being spread over different files or hard-coded.
- The expected headers of each input file are stored centrally in a file called *config.yaml*, in order to be able to provide warnings about missing headers instead of just getting a cryptic automated Python error message.
- A logging file is written to the output folder. This allows checking the settings of a completed run and finding the error message related to a crashed run.
- The calculation time is reduced substantially by implementing a more efficient function for drawing a choice from a series of probabilities (function: *draw_choice*) and by implementing parallelization of processes in the tour construction procedure (input parameter: *n_cpu*). The calculation time used to be several hours when using a granularity parameter of 0.1, while it is now 30 minutes (on a PC with an i9 processor using 10 cores).
- The code follows more consistently the guidelines of PEP-8[2], e.g. variable names using underscores.
- Data types of variables are specified using Python's *typing* library, for easier understanding of blocks of code.
- The different sub modules and processes are divided into functions, for easier understanding of the overall program flow.
- The constructed tours are not only exported a trip matrix but also as a shapefile of trips, allowing for more in-depth analyses of model outcomes and visual validations.

General overview

The key components that form the model are found on the GitHub repository under the folder *src*.

- ***main.py***
  - This the central script that needs to be run.
- ***config.yaml***
  - This file contains the configuration settings, model dimensions and expected file headers. It follow the YAML language conventions. This file is read by *main.py* before the start of its calculations.
  - Under *settings* we specify the following configuration settings:

Parameter	Type	Description
granularity	Float	the vehicle equivalent for the tours we model[3]
max_tour_duration	Float	a tour is ended if it lasts more than this number of hours
min_n_stops_for_2_opt	Integer	for tours with this number of stops or more we apply the 2-opt algorithm to improve the order of visiting its stops
n_cpu	Integer	the number of cores over which the tour construction procedure is parallelized; if it is left empty, it is set to the number of available cores minus 1

[2] https://peps.python.org/pep-0008/

[3] A granularity of 0.1 means that if in reality 100 tours are generated from a zone on a representative day, then 100/0.1= 1000 tours are generated in the simulation, each of them counting for 0.1 vehicle equivalent. The smaller the granularity, the longer the computational time and the smaller the simulation variance.

Parameter	Type	Description
n_external_zones	Integer	the number of external zones in the skim matrices
sep	String	the separation character that is used in input and output CSV files
write_omx	Boolean	a Boolean specifying whether the trip matrix is written in OMX format or not
write_csv	Boolean	a Boolean specifying whether the trip matrix, tours, parcel demand and parcel schedules are written in CSV format or not
write_shp	Boolean	a Boolean specifying whether the tours, parcel demand and parcel schedules are written in shapefile format or not

- Under *paths* we specify the paths of the input and output files. Within this segment, it is possible to refer to other paths, e.g., by writing '${param_folder}NextStopLocation.csv', to refer to the path specified for *param_folder*.

- ***parcel_demand_synthesis.py***
  - The *main* function of this script is used by *main.py* to execute the calculations for parcel demand.
- ***parcel_delivery_scheduling.py***
  - The *main* function of this script is used by *main.py* to execute the calculations for construction parcel tours.
- ***support.py***
  - This script contains several general functions used by the other scripts, for example reading the *config.yaml* file or writing shapefiles.

The following input files are to be specified in the *config.yaml* file:

Input	Description
centroids	The X and Y coordinates of every zone centroid, to be used for writing tours and parcels to shapefile
params_correction	Model parameters for correcting the number of tours for filtering out the “simplified tours” during estimation.
params_correction_parcel	Model parameters for correcting the number of tours for vehicle kilometers now generated in the parcel module.
params_end_tour	Model parameters for the End Tour step.
params_next_stop	Model parameters for the Next Stop Location step.
params_n_tours	Model parameters for the Number Of Tours step.
params_parcel_couriers	The set of couriers for parcel delivery, including their market share.
params_parcel_demand	Model parameters for the Parcel Demand Synthesis step.
params_parcel_depots	The set of depots for parcel delivery.
params_parcel_scheduling	Model parameters for the Parcel Scheduling step: the maximum number of parcels per van and the maximum tour duration in hours.
params_share_active	Model parameters for the Vehicle Purpose step.
params_vehicle_generation	Model parameters for the Vehicle Generation step.
params_vehicle_purpose	Model parameters for the Vehicle Purpose step.
tt_matrix	The skim matrix with travel times between NPVM zones.
dist_matrix	The skim matrix with travel distances between NPVM zones.
zone_neighbors	The set of NPVM zone combinations that are neighbors, used during the assignment of zones to parcel depots.

Input	Description
zone_stats	The socio-economic data of the NPVM zones.

Instructions and recommendations

The current code is written for Python 3.7 and requires the following libraries (above the Python standard library):

- numba (version 0.53.0)
- numpy (version 1.19.1)
- openmatrix (version 0.3.3)
- pandas (version 1.3.5)
- pyshp (version 2.1.0)
- PyYAML (version 5.3.1)
- xarray (version 0.18.2)

For future applications of the model, either the script *main.py* under *src* needs to be called from a Python environment with the above listed required libraries installed, or it could be compiled into an executable using the *pyinstaller* Python library. In addition, it is required that the *config.yaml* file is located in the working directory.

Given that Python is integrated in PTV Visum, it might be possible to call *main.py* directly from Visum. In that case, some of the settings might also be specified within Visum, and then written to the *config.yaml* file which is passed onto *main.py*.

Note that running the code from Spyder is only possible when *n_cpu* is set to 1, as Spyder does not cooperate with the *multiprocessing* Python standard library which is used for parallelization of processes.

Some ideas for further software improvements:

- The current setup expects a file *config.yaml* in the working directory, but it might be more practical to pass the exact location of *config.yaml* when calling Python or a compiled version of the code. For this purpose the attribute *argv* could be called from the Python standard library *sys*.
- Unit tests could be added to verify the working of small blocks of code and to make sure changes to code that should not impact model results do indeed not impact model results.
- Some parameters are placed under the settings in *config.yaml* while some are found within CSV files in the folder *parameters*. This could be made a bit more consistent.

5.2 Analysis and preparation scripts

Throughout the project many data preparations and analyses have been done using Python scripts. These can be found on the GitHub page under “analysis scripts”. The table below presents an overview of these scripts and their functionalities.

Python script name	Description
analyze_lcv_tours	Creates a set of summary tables (as Dataframes in memory) of the shipments, tours and trips constructed by *construct_tours_from_lcv_data*.
compare_stochasticity_runs	Generates plots to compare stochasticity runs with different granularity settings, like Figure 27 and Figure 28.
construct_tours_from_lcv_data	Replaces the old VBA script that generates a database of shipments, tours and trips, from which the estimation data can be generated.
create_estimation_data_ for_next_stop_location	Replaces the old VBA script that generates the choice data for estimation of the Next Stop Location model.
create_neighboring_zones_file	Creates the file *neighborsNPVM.csv* based on *zonesNPVM.shp*. It contains the zone pairs that are neighbors of each other.
create_parcel_demand_parameters	Determines the parcel demand parameters.
create_prodattr_plots	Creates an interactive HTML map of the productions and attractions per model zone based on the trip matrix CSV.

Python script name	Description
create_summary_tours	Creates an Excel sheet with a large number of tables summarizing the tours, parcel demand and parcel schedules of a model run.
plot_cross_validation	Plots the resulting coefficients of several replications of model estimations with different holdout sets in the estimation data.
plot_marginal_utility_cost	Plots the contribution of the cost term to the utility function of the Next Stop Location model, like Figure 10.
plot_parcel_depots	Plots a map of the parcel depots, like Figure 11.
plot_parcel_tours	Plots a map of the parcel demand and parcel schedules, like Figure 21 and Figure 22.
plot_perc_chosen_next_stop_location	Plots the percentage of chosen alternatives per distance band in the Next Stop Location estimation data.
summarize_estimated_coefficients	Summarizes a batch of Apollo estimation files into one table in Excel.
verify_parcel_outputs	Performs a series of checks on the outputs of the Parcel Delivery module. It checks the market shares of the couriers, the consistency of the number of parcels per depot and zone between the parcel demand and the parcel schedules, and the number of parcels delivered in each zone. Possible warnings are printed to the console.

No Python script was created to generate the data required for the estimation of the End Tour module (the re-estimation of this module was done by the ARE).

6. Conclusions and discussion

6.1 Conclusions

The existing LCV model proved to provide already a sound theoretical and empirical basis for simulation of national demand matrices for LCVs in Switzerland. The model was well reported and implemented in a structured Python code. Based on a critical review, a number of improvements were identified with the aim to further improve the quality and use of the simulation outputs. Strong points in the existing LCV model are the use of a dedicated LCV survey and a sound theoretical model: the incremental logit approach by Hunt and Stefan (2007). The improvements that were made are aimed to improve the consistency of the approach (re-estimation), the validity of the outcomes (tour sequence optimization, return trip and tour duration modelling), or the functional use of the model (use of generalized costs, parcel deliveries).

The outputs of the original and revised LCV model were assessed in terms of: tour characteristics, intuitiveness, parcel demand and simulation variance. The tour characteristics show a clear improved match to the observed survey data. The parcel delivery tours have a similar, but slightly shorter average tour length as reported in Universität St. Gallen (2017). The recommended setting for granularity is 0.1 which in effect means the results are a factored average of 10 times the number of tours. The indicators used in the quality assessment also provide a good basis for a validation framework for future model updates. The analyses and data preparations that have been done in the study are registered in Python scripts and available through the GitHub page of the model.

The model improvements are implemented in the existing Python software implementation. Additionally, several improvements have been made in terms of code quality: the calculation time is reduced strongly, settings and model dimensions are stored centrally, tours are exported as shapefiles (for validation) and the code quality was improved (PEP-8).

6.2 Discussion and recommendations

In the project a number of adaptations were made to improve the existing LCV model. The over-all assessment is that the model provides a good basis for implementation in the national transport model. Some observations can be made on the application of the model. Next to the model improvements, the results from the analyses also provide relevant insight for further improvement or tuning of the approach. The updated LCV model is still estimated on the available vehicle-based survey from 2013: it is expected that the model will be updated when an updated survey will become available.

Recommendations for future updates of the LCV model:

- Perform a data fusion linking the vehicle registration with business data, in order to improve the branch specific rates of the Vehicle Generation model.
- Experiment with exclusion of branches 531 (Postal activities under universal service obligation) and 532 (Other postal and courier activities) from the estimation data for the Vehicle Generation model. This will avoid the need for a correction on the total vehicle kilometers due to the Parcel Delivery module.
  - In order to check the assumption that the Parcel Delivery module covers all kilometers generated by these two branches, we recommend to compare two runs with coefficients estimated on the Vehicle Generation with and without these segments. If the reduction of kilometers in the run with coefficients estimated on data excluding these branches is roughly similar or even smaller than the Parcel Delivery module kilometers, it is not problematic. But if this reduction is much larger, it would be problematic, and the current correction approach might need to remain.

- One of the evaluation criteria that was difficult to improve was the underestimation of trip distances and durations. This could be further analyzed in future updates. A more fundamental analysis could focus on the evaluation of the tour typology. The existing approach already distinguishes the configuration of first, versus last or intermediate legs. A direction of research could be to identify if it is possible to develop on the observations a tour typology based on sparse deliveries vs. dense cluster deliveries.

Recommendations for application/implementation:

- If traffic counts for vans are available, either a classical trip-based calibration of the trip matrix could be done, or a tour-based calibration of the tours. In the latter approach, each tour is assigned a weight, and deeper analyses on which tours get a lower or higher weight can aid in identifying which types of tours are underestimated or overestimated, giving the modeler hints at which model parts should be corrected or improved. This has been applied successfully in the Flemish agent-based passenger transport model (van Houwe et al., 2020).

- More stability of scenario impacts could be reached if simulation variance reduction techniques are implemented. Two specific suggestions for this, are to (1) set the random seeds at the level of individual tours and decisions instead of once at the start of the module and (2) simulate choices by explicitly drawing an error term and choosing the alternative with maximum utility rather than using Monte Carlo simulation based on cumulative probabilities. In that case, the same choice is made in a scenario for cases where the utilities of the alternatives do not change compared to the reference run, and switches to other alternatives are only made if the utilities of those alternatives increase compared to the reference run.

- To develop a reference forecast scenario for the parcel market.

  - We have currently set the parcel demand parameters (and courier shares / depot locations) for the base situation. But in the future it is highly likely that more parcels are ordered per person and job. Either the trend of the past years could be extrapolated (although this could lead to unrealistically large parcel ordering rates in the long term) or reports and other literature forecasting e-commerce growth could be investigated.

  - More depots could be assumed in the forecast scenario too if the demand increases. It is recommended to keep the strategy for identifying these future depots simple and, where possible, in line with existing land use scenario assumptions. For example, potential locations for new depots could be chosen based on existing forecasts of industry employment per zone. Note that the relation between demand and number depots is probably not linear, couriers could also increase the efficiency or size of existing depots.

- Consider adding intrazonal trips to the parcel schedules. In Section §4.2.5 we observed a small underestimation of the average tour distance in the parcel module, which could be resolved by adding intrazonal trips for zones where multiple parcels are delivered. How many intrazonal trips should be added is up to debate and requires further analyses.

- Assessment of consistency with national freight model (AGM). Currently no integration exists between the freight model for heavy good vehicles (HGV) and the LCV model. This could be desirable to simulate vehicle shift impacts from specific changes in HGV charges. Other potential inconsistencies can also be relevant to evaluate. These can include differences in theoretical models, segmentations, aggregation in implementation (aggregate vs microsimulation), and different calibration and validation targets.

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Appendix A: Panel data in discrete choice models

Gerard de Jong, Significance, 5 May 2023

If the data contain multiple units (e.g. persons, firms, vehicles), each of which (or only some of which) are observed multiple times, standard discrete choice model estimation runs into problems. This is called the 'repeated measurement' problem or 'panel data' problem (because the data then form a panel). This problem is caused by the fact that the observations for the same unit will be correlated, since there will be unobserved factors that they have in common. The standard estimation methods (and standard calculation of standard errors and t-ratios) assume that all observations are independent (part of the so-called 'i.i.d.' assumption of the standard MNL model), so repeated measurements constitute a violation of this basic assumption

In regression analysis (continuous endogenous variables), there are relatively simple ways to deal with these problems (e.g. taking first differences in time), but these do not carry over to models with discrete endogenous variables.

In discrete choice models, it is often found that the impact of the repeated measurements on the estimated coefficients is limited: often the standard estimation method yields similar coefficients relative to methods that take the panel nature of the data into account (see below for those methods).

However, the t-ratios of the standard estimation will have an upward bias: the standard t-ratios are too optimistic. In reality, some seemingly significant coefficients should not be significant.

The earliest ways of dealing with this problem kept the original coefficients, but deflated the t-ratios, for instance using the square root of the number of repetitions per unit.

Recent discrete choice estimation software such as Apollo has more explicit ways of correcting the t-ratios. It not only produces the standard t-ratios, but also robust t-ratios, by clustering the standard errors at the level of the unit of observation (e.g. individual, vehicle). A relatively simple method to determine the variance-covariance matrix of the estimates (and thus the standard errors and t-ratios) that is used here is called the sandwich estimator (Daly and Hess, 2010).

A group of methods that has also been used to correct for panel effects uses the idea of repeated sampling of observations using the sample at hand and estimating the model using standard methods for each of the samples obtained. This is followed by averaging the results over all the estimations carried out. The two best-known resampling methods are the Jackknife and the Bootstrap (see for instance Cirillo et al., 2000). These methods can correct for other data problems than just repeated measurements, but they are very time-consuming, since they require hundreds or thousands of estimation runs.

There is a version of the mixed logit model, that explicitly accounts for the panel nature of the data. This is the random coefficients model, where coefficients of the model (possibly only the alternative specific constants, but potentially also coefficients like time coefficients) not only depend on observed variables, but also vary randomly across the population. If one then makes sure that the random variation only refers to differences between different units (i.e. using the same draws for each unit in estimation), one obtains a panel mixed logit model (Revelt and Train, 1998). This will produce coefficients and t-ratios that take the panel nature of the data into account. The mixed logit model is estimated by taking draws from a stochastic distribution for the random parameters and therefore also requires the analyst to do hundreds or thousands of estimation runs (Train, 2009), leading to long estimation run times.

In the panel mixed logit model, the distribution function for the random coefficient(s) is continuous. One could also assume that a coefficient/parameter can take several discrete values. This is the latent class model. For this model, a panel version exists as well, the panel latent class model (see for instance Kouwenhoven et al., 2014). An advantage of this model over the mixed logit model is that its estimation does not require simulation.

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