# A PIVOT POINT PROCEDURE IN THE COMPASS ACTIVITY-BASED MODEL FOR COPENHAGEN

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## 1. INTRODUCTION

Copenhagen is the capital of Denmark and the largest city in Scandinavia. It is located in the extreme east of the country, with suburbs spreading to the north, west and south, and a road and rail connection across the Øresund strait to Malmö in Sweden. In the conurbation there are extensive public transport networks, deploying several modes, while cycle use has increased, so that about one third of vehicular trips are now made by bike. Road congestion is quite severe on specific corridors at peak times.

To improve travel opportunities and to address issues of infrastructure and network management, planners in the Greater Copenhagen Area (GCA) use cost-benefit analysis (CBA) to appraise alternative planning scenarios, each of which requires forecasts of travel demand, while forecasts are also needed to support the design of new infrastructure. Models predicting travel demand are therefore required. In the last 25 years the OTM model (Jovicic and Hansen, 2003) has been used, generating confidence among users because of its accuracy with respect to base-year flows in traffic assignments, resulting from a careful validation (Vuk and Overgaard, 2006).

An important contribution to the accuracy of OTM is the use of pivoting, i.e. the use of the forecasting model to predict *changes* relative to an accurately-measured base situation. Pivoting is a procedure that has been used in travel demand forecasting for some time (e.g. Daly et al., 2005, 2011, which refer to earlier studies on pivoting) and is recommended by the UK government for studies carried out in Britain (DfT, 2014). It would not be acceptable in future model developments for the GCA to retreat from the accuracy offered by OTM.

However, the range of policy issues to be considered in the GCA has become considerably wider, so that the ability of OTM to respond to the new developments and policy levers has come into question. Among the policy issues under consideration in the next few months and years will be:

- extensive street management plans;
- extensions of the metro;
- the Grand Départ of the Tour de France (2022) requiring many road closures and reroutings;
- road pricing, with prices specific to road and vehicle type, time of day;
- far-reaching cycle priorities with ‘bike & ride’ facilities;
- new parking policies and strategies;
- a new comprehensive Mobility Plan;
- prioritising electric cars and car-sharing.

A proper approach to some of these issues requires consideration of the travel patterns of individuals and their households over a whole day or longer. The current OTM is a tour model, i.e. a model in which the basic unit of travel is a tour by an individual from home to one or more destinations before returning home. Multi-tour and household interactions can be covered only approximately in a tour-based model. Moreover, the OTM is not the most sophisticated of the tour models currently in operation, particularly in the way it segments the population. In the context of the GCA, we can see transport choices as involving 'life-style' choices between car, public transport and cycling as primary modes of transport, quite likely applying to all movements by an individual and to several household members.

For these reasons a new activity-based model (ABM) was developed, which was given the name COMPASS. Activity-based models represent the daily pattern of out-of-home activity by a household and their travel is then derived from these predicted activities (see e.g., Ben-Akiva, Bowman and Gopinath, 1996, Bowman, 1995, Bowman and Ben-Akiva, 2001 and Bradley, Bowman and Griesenbeck, 2010). COMPASS is believed to be the first fully featured operational ABM in Europe (i.e. a model simulating travel demand under time restrictions through to assigning traffic to networks), although such models are in operation in the US and in Israel. Academic projects in Europe have investigated ABM potential and produced partial models. One such project, ACTUM (ACTUM, 2011-2016), showed the possibilities for Copenhagen in the specific context of Danish data, developing model components and a basis for the planning of COMPASS development. An ABM offers a more complete and therefore in principle a more realistic representation of travel than a tour-based model, providing that accuracy can be maintained.

The accuracy and credibility that had been achieved with OTM depend on the use of pivoting. However, pivoting has not been a feature of the ABMs that have been developed to date. The work described in this paper was therefore undertaken to implement pivoting for COMPASS. The base 'pivot point' relative to which the modelled changes are applied is a trip matrix, which is easier to relate to a tour-based model than to the day schedules and household travel patterns that are predicted and output by an ABM; the issue of pivoting from a trip matrix for an ABM is one we address in the paper.

The following section of the paper presents the details of the general approach to pivoting, using OTM as an example. Section 3 describes the COMPASS model itself and section 4 the way in which pivoting has been implemented. Then we present the validation of the procedure and the base-year accuracy that has been achieved. A final section gives our conclusions.

## 2. PIVOT IN A TOUR-BASED MODEL

Pivoting for the COMPASS ABM has been developed from the pivoting process used for tour-based (and trip-based) models. As an example, we take the OTM, which covers the GCA and which uses the '8-case' pivoting method specified by Daly et. al (2011).

In the GCA, the base information on traffic flows is available as trip matrices, i.e. movements from a specific origin zone to a specific destination zone. It is relatively straightforward to apply a tour-based model to produce trip forecasts. Specifically, a tour from i to j yields trips from i to j and j to i, with adjustments for non-home-based trips to obtain a 'synthetic' forecast of total trips.

The basic concept of pivoting is that the trip forecast is equal to the base matrix multiplied by the ratio of synthetic trips in the forecast and base situations. That is:

(1) $$M_{ijmpt} = B_{ijmpt}\frac{S_{F,ijmpt}}{S_{B,ijmpt}} = S_{F,ijmpt}\frac{B_{ijmpt}}{S_{B,ijmpt}}$$

where $S_B$ = modelled trips, i.e. synthetic trips, in base year
$S_F$ = synthetic trips for a future year/scenario
M = predicted trips for a future year/scenario
B = observed trips from base year matrix
i,j = origin and destination zones
m, p, t = mode (m), travel purpose (p) and time-of-day (t)

We can define the growth factor $G=S_F/S_B$ and the correction factor $C=B/S_B$ (omitting other subscripts for clarity). The final term in equation (1) points to the possibility of using a more aggregate approach for C:

(2) $$M_{ijmpt} = S_{F,ijmpt}\frac{B_{a(ijmpt)}}{S_{B,a(ijmpt)}}$$

Here the subscript a(ijmpt) represents an aggregation over the dimensions of geography, mode, purpose and time. For example, aggregations in these dimensions can be used when the base matrix is not specified in as much detail as the synthetic forecasts, or when the base matrix is not reliable at detailed level because (for example) of sampling issues. Note that it remains possible in equation (2) to obtain forecasts at detailed level even if the correction factors are defined at a coarser level.

Any combination of the three components of the calculation in equations (1 – 2) can be zero, making the calculation impossible or at least questionable. The '8 case' approach specifies formulae to be used in each case arising when the terms in the equation are zero or non-zero. The calculations used for OTM are set out in Table 1.

It may be noted that when $S_F = S_B$, the output forecast will always be equal to the base matrix B.

Table 1: The 8-case pivoting method as applied in OTM

| Case | Base (B) | Synthetic Base | Synthetic Future | Predicted trips (M) |
|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | >0 | $S_F$ |
| 3 | 0 | >0 | 0 | 0 |
| 4 | 0 | >0 | >0 | Normal 0<br>Extreme* $S_F - k\,S_B$ |
| 5 | >0 | 0 | 0 | B |
| 6 | >0 | 0 | >0 | $B + S_F$ |
| 7 | >0 | >0 | 0 | 0 |
| 8 | >0 | >0 | >0 | Normal $B\,S_F / S_B$<br>Extreme* $k\,B + (S_F - k\,S_B)$ |

* The 'extreme growth' formulae are applied when $S_F > k\,S_B$, i.e. the growth in trips exceeds a pre-defined ratio. In practice, the assumption k=5 has proved to be satisfactory.

An important issue in classifying cells in the matrix into one of the 8 cases is how 'zero' is defined. A value is taken to be zero when less than a given Z. The specification of Z depends on how the base and synthetic matrices are calculated: for example, for OTM the value Z = 0.005 is used, but for COMPASS this has been reduced to Z = 0.001, because of sampling issues in the base matrix and in the simulation procedure that produces the synthetic matrices.

Only the case where all of the components of the formula are positive, i.e. case 8, uses the calculation as originally specified. It is also found by experience that case 8 gives the most satisfactory results, for example that the final forecasts are most consistent with the synthetic predictions of the model. The forecasting can be improved by a suitable choice of aggregation to reduce ‘sparsity’, i.e. to reduce the fraction of zeroes in the matrices and thus to increase the fraction of matrix cells that fall into case 8. A suitable choice of Z can also help here.

When working with a tour-based model, an issue arises because the pivoting is done at trip level, to match the information in the base trip matrix, so that i-j pivoting may work out differently from j-i pivoting, particularly when separate pivots are calculated for separate time periods. Inconsistencies can be reduced by a process called ‘normalisation’, in which row totals in the matrix are corrected. Daly et al. (2011) discuss how normalisation can be applied, also in nested models. They also show that the pivoted model remains consistent with a utility maximisation paradigm, so that the model will behave in intuitive ways.

## 3. THE COMPASS MODEL

The COMPASS model (**Co**penhagen Greater Area **M**odel for **Pass**enger Transport) has been built for the Copenhagen Municipality and covers the GCA, an area of 60 sq. km. The model’s base year is 2017, and forecasts are produced for an average workday.

The existing traffic tour-based model for the GCA, the OTM model, has been in use since 1995 with seven major updates. Considerable research on ABMs had already been completed at the Danish Technical University (DTU), for example in the ACTUM project funded by the Danish Transport Research Council (ACTUM 2011-2016), preceding the proposal for an ABM for the GCA in 2018. Given a synthetic population and detailed information about the region, such as employment, school enrolments, transport network, and parking supply, the demand model, running in DaySim[1], operates iteratively with the network assignment models to generate predictions of the mode-specific traffic volumes. Within DaySim, an interconnected set of 26 choice models predicts (a) long-term choices, such as work location and car ownership, (b) day-level choices that define the overall pattern of activities, tours and trips for each household and its members, (c) choices of the tours made by the members of the household, including purpose, destination, mode and timing, and (d) choices of any additional stops made on those tours, including their purpose, location, travel mode and timing. COMPASS integrates the representation of activities and travel conducted by a household and its members over the course of an entire workday. About two million people in the GCA generate about ten million trips by all modes in an average workday in 2017, including trips crossing the area boundary.

Innovative features in the COMPASS demand model include (a) detailed modelling of slow modes, including route choice models, (b) the introduction of family in-home quality time (Vuk et al, 2016), (c) a car ownership model including electric cars, autonomous vehicles and car sharing, (d) park-and-ride, ‘kiss-and-ride’, ‘bike & ride’, and taking bicycles onto the train or metro, and (e)

a detailed model of parking in the Copenhagen city. Values of travel time are based on a large SC survey for the Copenhagen area in 2017 (Lu et al., 2021). COMPASS includes five assignment models. The car assignment includes static and dynamic (DTA) versions. Another advanced feature is a mixed use of schedule and frequency-based services in a public transport assignment (Eltved et al., 2017*)* that includes capacity restrictions. For example, waiting for an overcrowded metro or bus will cause the passenger to wait for the next departure or to make a new decision (e.g. change mode or route). Also, additional disutility is calculated for standing passengers.
Copenhagen is known for its bicycle infrastructure, transport policies that support cycling, and a large share of bicycle trips within the city. COMPASS integrates a detailed bicycle assignment model with 'bike & ride' facilities at stations and the option of taking the cycle onto the train. As a further innovative feature, in COMPASS bicycle traffic causes extra delays for cars at street crossings. Finally, the walk assignment model, similar in structure to the bicycle model but without capacity restrictions, includes access and egress trips to public transport which make up 2/3 of all walk trips in the GCA, giving more accurate flows.
COMPASS also includes an environmental model. This model deals with pollution, accidents, noise and changes in travel time, all of which can be applied in the feasibility analysis of planning projects. Being a fully disaggregated model COMPASS allows for CBA calculations separately for different social groups, which is considered to have a large potential for future users of the model because of the increasing gaps between social groups.
An extensive demand model calibration was completed prior to undertaking the pivoting, most importantly related to the numbers of trips by mode and purpose. The target values for this calibration are summed from the 2017 base matrices, trip lengths and car ownership data. Here distance calibration is essential, and mode-specific piecewise linear distance terms were introduced (other options were also tested).
The run time of the ABM to simulate one day of travel for a 100% population sample is 5 hours on a standard pc, but only 75 minutes on the high-performance computers used for COMPASS. More approximate results can be obtained more quickly with smaller population samples.
Running the COMPASS model, updating the networks, and showing model results is performed via the COMPASS User Interface (Israelsen, 2020), which is based on ArcGIS Enterprise[2] and Traffic Analyst[3]. The key tables and figures as well as result maps are produced automatically after each run and can be accessed in the Traffic Analyst web site included in Compass. Examples of results available in the web site are: traffic volumes, capacity utilisation, queue lengths etc. Scenario inputs, like networks, are prepared in ArcMap with extensions from Traffic Analyst.

## 4. PIVOTING IN COMPASS

The ABM simulates a list of trips for each household and person. A straightforward approach would be to aggregate the output and conduct the pivoting as described above before assigning the trips to the networks. However, the approach has major disadvantages. First, detailed information is lost e.g., the linkage of persons and activities to travel. Second, the disaggregate trips are not available for route choice modelling which would increase computing time and complicate the use of DTA. The computing time for route choice models depends on the number of elements in the segmentation of trips by travel purposes, zones etc. In OTM, the multi-dimensional trip matrix includes several hundred million cells while the ABM produces only about 3 million records with car trips. Therefore, the method should attach a pivot factor to each simulated trip, which the DTA then uses as a weight when it assigns trips.

The implemented method includes three elements: i) calculation of adjustment factors, ii) added trips, and iii) a weighting procedure. Adjustment factors are calculated using the 8-case approach of Table 1. The ABM simulates travel for the residents of the GCA whereas the base matrix is developed from observed trips, count data etc. and includes all trips within the area. Instead of expanding trips from the ABM to approximate non-resident trips, they are added as part of the pivot procedure. A weighting procedure is used to maintain consistency in the output from the ABM, for example, that the number of out-bound trips is equal to the number of home-bound trips.

Table 1 indicates that the adjustment factors given in Equation (1) are relevant only when $S_F > 0$, so that, when using these factors, and depending on the values of B and $S_B$, the pivot table can be reduced to the four cases shown in Table 2, using the correction factor C and growth factor G. Given the simulation of synthetic trips, the value of $S_F$ is either zero (because there are no trip records in the cell) or equal to or larger than 1. Hence, the acceptance level Z is only relevant for base year trips (B). A suitable value of Z = 0.001 has been determined. The value of k = 5 is adopted from OTM.

Table 2: Adjustment factors applied to output $S_F$ from the ABM

| Case | Base (B) | Synthetic Base | Condition | Adjustment factor |
|---|---|---|---|---|
| 2 | 0 | 0 | $S_F > L$ | $(S_F – L) / S_F$ |
| 4 | 0 | >0 | $G > k$ | $1 – k / G$ |
| 6 | >0 | 0 | $S_F > B$ | $(S_F – B) / S_F$ |
| 8 | >0 | >0 | $G \leq k$ | C |
| | | | $G > k$ | $1 + (C – 1) k / G$ |

In case 2, B and $S_B$ are zero whereas $S_F > 0$, which usually indicates green-field developments. However, for the ABM it also includes random noise from simulation. A minimum value (L) is introduced to reduce inconsistency compared to the base year. Tests have shown that results are relatively insensitive to values between 5 and 10. Here, a value of L = 5 is used. In case 6, only when trip sums are larger than observed in the base year should records from the activity-based model be adjusted, to avoid double counting of trips in the added trip matrix.

If trips are observed without any synthetic trips (case 5 in Table 1), for example, bicycle trips made by tourists in downtown Copenhagen which are not modelled by the ABM, adjustment factors cannot be applied. Hence, the observed base year trips (B) should be segmented into non-resident trips and resident trips where the former is used as added trips and the latter for pivoting. Since information is not available for splitting the trip matrix into the two categories, it

is assumed that 5-10% of all trips (depending on travel mode) within GCA are made by non-residents. Then, the added trips are estimated as the difference between observed base year and pivoted synthetic base year trips. Due to the added trips and weighting procedure explained below the observed base year matrix B is not exactly reproduced when $S_B = S_F$.
Finally, a 'normalisation' procedure applies row-normalisation factors at cell level to ensure the origin totals remain consistent with expectation.
The ABM simulates tours and joint tours among household members. Tours are made by a single person of the household. Fully joint or partial joint tours occur when two or more persons from the household travel together on the full tour or part of the tour e.g., one person may travel with another person from the same household on the outbound half of the tour and with a different household member on the home-bound half of the tour. COMPASS predicts more than 80% of all trips to be part of single person tours.
If public transport is used on a tour, it will most likely be the main mode with the longest travel distance of the tour. If car is used on the tour, it is more likely to be the main mode rather than bike or walk. Therefore, we define the main tour mode (public transport, car driver, car passenger, bike, and walk) by the following simple rules. The tour mode is:

1. public transport if used, otherwise
2. car, if a car is driven, otherwise
3. car passenger if it occurs, otherwise
4. bike if used.

Walk forecasts are not considered for pivoting because data do not support development of a base matrix. The adjustment factor is therefore set to 1 and the weight to 0 if other modes are used on the tour.
The travel purposes are identified for trips where the trip mode is equal to the tour mode. Tests of different weighting of travel purposes e.g., higher weight to commute trips than to leisure trips, have been made without improving the trip length distribution or traffic flows compared to counts. Therefore, all travel purposes made by the main mode on the tour are assigned a weight of 1. All other trip modes and purposes are assigned a weight of 0 for calculation of the matrices for pivoting. (When the pivoting is carried out, all trips within the tour receive the factor corresponding to the main tour purpose and mode.)
Adjustment factors are assigned to trips and multiplied by a weight factor of 1 or 0 as calculated above. Then factors are averaged over tours, joint tours and households. This is done for factors at cell-level, at row-level, and after row-normalisation.
The implemented method ensures the same adjustment factor across all trips within tours, joint tours, and households in which partial joint tours are made.

## 5. VALIDATION OF THE METHOD

### 5.1 Aggregation of dimensions for pivoting

It is possible to calculate adjustment factors aggregated over dimensions as shown in equation (2), as a balance between reliability and accuracy. Aggregation improves reliability because sampling effects are reduced and pivot case 8 (all values > 0) happens more frequently, but it may worsen accuracy, for example in the trip length distribution. Extensive tests have been

conducted to find a suitable aggregation of zones, modes, purposes, and time periods.
The base year trip matrices for car and cycle use 4059 zones, whereas those for public transport represent trips between 3292 terminals. Running pivoting without any geographic aggregation was immediately rejected because of the sparsity of the synthetic matrix (recall that the ABM uses simulation and therefore many cells are not sampled in a given run). Two levels of aggregation using the zonal systems of the Danish National Model (LTM) were analysed: simply many-to-one aggregations of zones in COMPASS to the two systems of 266 LTM-zones and 1003 LTM-zones. Public transport terminals were mapped to the LTM-zones for pivoting.
The advantage of using an aggregation to 266 zones is a less sparse synthetic trip matrix, i.e., a low share of trips where $B > 0$ and $S_B = 0$. However, the disadvantages compared to the less aggregate 1003 zones were a less accurate trip length distribution and significantly lower flow accuracy, so that it was decided to use 1003 zones in the pivot point procedure.
Base year matrices are developed from travel survey data and passive data (e.g., National Travel Survey, smart card data, and GPS data) and count data for cycle, single occupancy vehicles (SOV), high occupancy vehicle drivers (HOV), car passengers, and public transport. Since the estimated split between SOV and HOV in the base year matrices at OD level is less accurate, adjustment factors are differentiated by the following four modes:

1. Cycle
2. Car driver
3. Car passenger
4. Public transport

The base year trip matrices are segmented into 6 travel purposes (as listed in Table 3). In pivoting, aggregation of travel purposes changes the split of trips by purpose which complicates the analysis of the model predictions by purpose. For example, work and education trips by car have completely different travel patterns and the aggregate is dominated by work trips giving a wrong travel pattern for educational trips. It was considered more important to allow the user to analyse results by purpose than reduce sparsity.
The base year trip matrices are split into 10 time periods. The assignment of trips to time periods is somewhat arbitrary due to the matrix adjustment procedures (Nielsen, 1998; Nielsen et al., 2006; and Bagger, 2020) where the trip pattern is adjusted to match counts. Therefore, the mapping between the ABM and trip matrices is not exact with respect to time periods. An aggregation of all time periods was tried but gave incorrect peak flows because the ABM was not able to predict the variation of departure times across the GCA sufficiently accurately. The most accurate flows were achieved with an aggregation into 6 periods differentiating between peak hour and peak hour shoulders in the morning period.
The above aggregation gives matrix dimensions: 1003 zones, 4 modes, 6 purposes and 6 periods, in total 1003 x 1003 x 4 x 6 x 6 = 144,865,296 cells.

### 5.2 Analyses of sparsity

COMPASS is run multiple times with different seed values to improve coverage of the dimensions described above. Tests showed significant improvement in coverage with 10 runs compared to 2 and 5 runs. Computing time for 10

executions with a 100% population is about 12 hours on the COMPASS computer. The same sequence of seed values is used to avoid spurious differences caused by 'chatter'. Consistency with respect to sampling is particularly important for the effectiveness of pivoting.
Table 3 shows the proportion of trips that are in the standard pivot case where $B > 0$ and $S_B > 0$ (case 8) by mode and travel purpose. Case 8 occurs for 79% of all trips. The lowest shares are for educational and business trips, while car passenger and public transport have lower shares than cycle and car driver.

Table 3: Trip shares in normal case where $B > 0$ and $S_B > 0$ (case 8)

| Purpose | Cycle | Car driver | Car passenger | Transit | Total |
|---|---|---|---|---|---|
| Home-Work | 80% | 74% | 23% | 80% | 75% |
| Home-Education | 76% | 25% | 41% | 69% | 62% |
| Home-Shopping | 90% | 85% | 79% | 83% | 84% |
| Home-Leisure | 90% | 93% | 88% | 80% | 89% |
| Other leisure trips | 87% | 79% | 67% | 81% | 78% |
| Business | 63% | 61% | 19% | 54% | 57% |
| Total | 84% | 80% | 73% | 78% | 79% |

Further analysis shows that the majority (16%) of the cells that do not fall in case 8 are cases where $B > 0$ and $S_B = 0$ (case 6). That is, sparsity of the synthetic trip matrix is the main cause of the loss of coverage in Table 3, since only 100% - 79% - 16% = 5% of these trips are due to sparsity in the observed base year matrix (case 4). In particular, there is a discrepancy between the observed and synthetic matrices for education and business, and for car passenger trips, making pivoting less reliable than for other modes and purposes. For example, a high share for case 6 is observed for educational trips by car which means that their improvement in accuracy by pivoting is questionable. Fortunately, there are few educational trips by car within the GCA (2.4% of all car trips).

### 5.3 Analyses of trip length

The impact of pivoting on the mean and distribution of trip length was analysed, because trip length is important for the sensitivity of the model and flow accuracy. Synthetic output from the ABM was compared with trip lengths from the observed base year matrices based on straight line distances between 4059 zones.
In Figure 1, the orange columns show the trip length distribution after pivoting home-work trips by car. The x and y axes represent distance intervals in km and the share of total trips. It shows a good fit with only a small underestimation of long trips and an overestimation of very short trips. In contrast, the result before pivoting showed a significant underestimation of trips with lengths of 1 to 7 km and an overestimation of trips with lengths of 13 to 37 km.
Table 4 shows the differences in average trip lengths after pivoting compared to observed data. In total, the table shows that the predicted trip length is 5% less than observed: a distance of 300 metres. The largest relative divergence is observed for home-based leisure trips. The divergence across all modes is 18% for home-leisure trips.

Figure 1: Trip length distribution after pivoting home-work trips by car compared to observed data

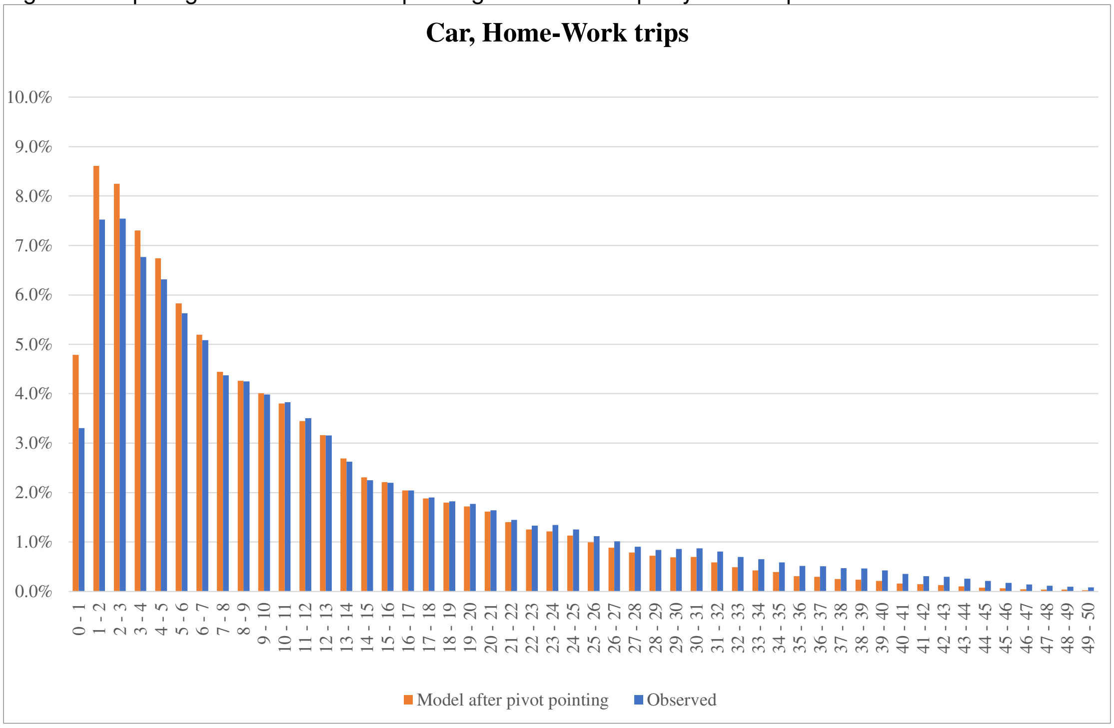


Table 4: Relative difference in average trip length between observed data and result after pivoting

| Purpose | Cycle | Car driver | Car passenger | Transit | Total |
|---|---|---|---|---|---|
| Home-Work | -27% | -11% | -33% | -1% | -12% |
| Home-Education | -18% | -14% | -19% | -14% | -12% |
| Home-Shopping | 0% | -12% | -17% | -11% | -11% |
| Home-Leisure | 30% | 25% | 16% | -11% | 18% |
| Other leisure trips | 34% | -8% | -20% | -15% | -10% |
| Business | 29% | -1% | -1% | 19% | 1% |
| Total | 1% | -6% | -11% | -7% | -5% |

## 5.4 Sensitivity analyses

Pivoting changes the elasticities compared to the synthetic output due to corrections of mode shares and adding of fixed trips. The impact of pivoting was tested for three scenarios: i) public transport fare increased by 20%, ii) public travel time reduced by 10%, and iii) car driving costs increased by 20%.
Adding fixed trips naturally damps elasticities compared to the synthetic results. Therefore, Table 5 includes elasticities before adding ('Cor.') and after adding fixed trips ('Cor.+ add trips') in comparison to the synthetic elasticities.
In the fare scenario, the differences between the synthetic elasticities and the corrected results are marginal, and the fixed added trips explain the differences between the synthetic and resulting elasticities after pivoting. In the driving cost scenario, the pivot corrections reduce the shift from SOV to HOV marginally.
The sensitivity is as expected higher for travel times than costs. The transit elasticity changes from -0.673 to -0.749 after pivot corrections, most likely due to an increase in long trips not supported by observed trips (case 4). After adding external trips, the difference is reduced.

It is observed that walk and cycle trips increase when transit fare or travel time is reduced. Walk and cycle trips are positively correlated with public transport trips because of access and egress trips to public transport.

Table 5: Elasticities before and after pivot correction

| Purpose | Transit fare | | | Transit travel time | | | Car driving costs | | |
|---|---|---|---|---|---|---|---|---|---|
| | Synth | Corrected | Cor.+ add trips | Synth | Corrected | Cor.+ add trips | Synth | Corrected | Cor.+ add trips |
| Walk | -0.063 | -0.061 | -0.061 | -0.256 | -0.174 | -0.174 | 0.035 | 0.030 | 0.030 |
| Cycle | -0.003 | -0.007 | -0.007 | -0.006 | 0.003 | -0.003 | 0.069 | 0.065 | 0.060 |
| SOV | 0.036 | 0.035 | 0.031 | 0.120 | 0.118 | 0.106 | -0.107 | -0.099 | -0.089 |
| HOV | 0.033 | 0.030 | 0.024 | 0.098 | 0.089 | 0.072 | -0.026 | -0.042 | -0.034 |
| Car pas. | 0.039 | 0.036 | 0.029 | 0.190 | 0.172 | 0.141 | -0.068 | -0.064 | -0.052 |
| Transit | -0.180 | -0.181 | -0.170 | -0.673 | -0.749 | -0.702 | 0.126 | 0.115 | 0.108 |
| Total | -0.030 | -0.029 | -0.027 | -0.121 | -0.092 | -0.086 | 0.004 | 0.002 | 0.002 |

## 6. BASE YEAR ACCURACY

### 6.1 Estimates of accuracy for car flows

Car flow accuracy is assessed by comparing DTA with observed traffic volume on 2,553 network links.

Given a link i with observed traffic $x_i$ and estimated traffic $y_i$, the vehicle km is the product of volume and link length $l_i$. Assuming that the network is stratified into H strata e.g., by link type or volume, the ratio estimate (Cochran, 1977) is:

$$\bar{R} = \frac{1}{Q}\sum_{h=1}^{H} Q_h \frac{\bar{q}_{yh}}{\bar{q}_{xh}} = \frac{1}{Q}\sum_{h=1}^{H} Q_h \frac{\sum_{i\in h} l_i y_i}{\sum_{i\in h} l_i x_i} \qquad (3)$$

Where Q is population kilometrage. Approximating the population kilometrage by estimated vehicle km we get a ratio estimate $\bar{R} = 1.00$, i.e., there is no overall bias between modelled and observed traffic. There is an overestimation of traffic on roads with less than 1,000 vehicles per day by 30%. Overestimation on minor roads is inevitable because the model includes only a sample of these and traffic is usually loaded onto local roads located close to the zone centroid. Also, many traffic counts on minor roads are one-day manual counts from 8 a.m. to 6 p.m., giving quite large sampling errors (Tolouei et al., 2016). Roads with more than 1,000 vehicles show no bias at 95% confidence limits (for calculation of confidence limits see Cochran, 1977).

The Percent Root Mean Square Error (%RMSE) is often used (Vuk and Hansen, 2006) to evaluate accuracy at link level. Given a sample of n links it is:

$$\%RMSE = \frac{1}{\bar{\bar{X}}}\sqrt{\frac{\sum_{i=1}^{n}(Y_i - X_i)^2}{n-1}} \qquad (4)$$

The overall estimated average accuracy is %RMSE = 17.8%. In comparison, the accuracy achieved for OTM7, delivered in August 2018, was 20%.

Validation of OTM (Vuk and Hansen, 2006) only provides accuracy estimates for morning and afternoon peak periods, based on much smaller samples of counts, 38% and 47%, respectively. In COMPASS, the corresponding values are 29% and 23%, again more accurate than OTM.

The UK Department for Transport (DfT, 2013) provides advice on validation and acceptability for assignment models. The WebTAG criteria are shown in Table 6 factored to 24-hour flows. The last column shows that COMPASS comfortably meets these criteria.

Table 6: Comparisons with WebTAG individual link validation criteria

| Daily flow (vehicles) | Allowed divergence | Acceptability guideline | COMPASS |
|---|---|---|---|
| 0 – 16,800 | 2,400 vehicles | >85% | 92% |
| 16,800 – 64,800 | 15% of counted flows | >85% | 92% |
| Over 64,800 | 9,600 vehicles | >85% | 100% |

### 6.2. Estimates of accuracy for public transport passengers

Table 7 shows statistics on public transport boarding passengers by mode for a working day in 2017. There is no bias in estimated train passengers whereas bus passengers are slightly overestimated.

The relative accuracy is given by %RMSE. Metro and S-Train are the most accurately modelled. Bus has as expected the lowest relative accuracy because it is difficult to estimate bus passengers at individual bus stops accurately. A comparison to OTM 7 reveals higher accuracy for COMPASS. For example, OTM 7 achieves a %RMSE-value of 23% for S-train whereas COMPASS achieves 15%.

Table 7: Statistics for estimated and observed passengers on a working day in 2017

| Mode | No. of stations/stops | Average volume Obs. | Average volume Model | Divergence | %RMSE |
|---|---|---|---|---|---|
| Bus | 8,020 | 75 | 77 | 3.9% | 107.4% |
| Metro | 22 | 9,082 | 9,132 | 0.6% | 8.3% |
| S-Train | 84 | 5,428 | 5,395 | -0.6% | 15.0% |
| Regional train | 32 | 4,917 | 4,779 | -2.8% | 34.3% |
| Local train | 75 | 296 | 314 | 6.1% | 43.6% |

## 7. SUMMARY AND CONLUSIONS

Planners in the GCA wish to consider a broad range of policy options, which include several options that could have impacts on the travel patterns of individuals and households over the whole day. For this reason they chose to develop an ABM, COMPASS, to make the travel demand forecasts required for the appraisal of infrastructure and policy scenarios.

COMPASS must achieve similar levels of accuracy as the existing transport model OTM. Therefore, pivoting was also required for COMPASS, requiring new methods, because pivoting has not been a standard part of ABM systems; indeed, we are not aware of other ABMs using pivoting. This paper describes a successful implementation of pivoting in COMPASS giving satisfactory results, in the sense that the match to observed flows is within the confidence limits, for both car and public transport. Moreover, the fit is somewhat better than for OTM. Other criteria, such as those used in the UK, are also comfortably met.

We conclude that the introduction of pivoting to COMPASS makes the model thoroughly acceptable for use in the GCA.

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## NOTES

[1] DaySim is an activity-based travel demand model system proposed in 1994 by Ben-Akiva et al. (1996), demonstrated as a prototype for the Boston metropolitan area (Bowman, 1995; Bowman and Ben-Akiva, 2001), implemented operationally for Sacramento, California (Bradley et al., 2010) and subsequently enhanced and used in many United States locations in collaboration with RSG, Inc.

[2] See www.esri.com.

[3] See www.rapidis.com.