

Origin-Destination Table Disaggregation Using Fratar Biproportional Least Squares Estimation

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Abstract: This paper describes a group of techniques for disaggregating origin-destination tables for travel forecasting that makes explicit use of observed traffic on a network. Five models within the group are presented, each of which uses nonlinear least-squares estimation to obtain row and column factors for splitting trip totals from and to larger geographical areas into smaller ones. The techniques are philosophically similar to Fratar factoring, although the solution method is quite different. The techniques are tested on a full-sized network for Northfield, MN and are found to work effectively.

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INTRODUCTION AND PREVIOUS WORK

It is often desirable to obtain a highly detailed origin-destination (OD) table for vehicles or commodities, when only a much more aggregated table is available. These situations typically arise when survey data are organized into fairly large districts (zip codes, cities, counties or states) in order to preserve confidentiality or simply to provide meaningful flow comparisons when the number of data samples is limited. Commercial vehicle and freight data, in particular, are prone to this type of spatial aggregation. This subject has gotten recent attention in the professional literature with the release of the Freight Analysis Framework 2 (FAF²) and subsequent interest expressed by many planners in disaggregating commodity flows from the 114 domestic regions to smaller zones, such as counties.

In a paper that directly address the FAF² disaggregation problem, Ruan and Lin (1) identified two prevailing methods of OD table disaggregation and present their own statistical method of using economic data. Ruan and Lin observed that the “proportional weighting” method is most often chosen by planners. Examples of the proportional weighting method in the freight planning literature abound, for example studies by Fisher, Ang-Olson and La (2), Sorratini and Smith (3), Viswanathan, et al. (4), and Rowinski, Opie and Spasovic (5). These studies principally use economic data, with an occasional use of aggregated traffic statistics, to create the disaggregation factors.

For the purposes of this discussion, the aggregated OD table will be said to contain trip data between “districts”, while the disaggregated OD table will be said to contain trip data between “zones”. Traditional application of the proportional weighting method has been to disaggregate a district-level origin-destination table by factoring it along its rows and columns, simultaneously. That is:

$$T_{ij} = A_i B_j \tau_{kl} \quad (1)$$

where:

i = an origin (row) in the disaggregated (zonal) table and where i is an element in the set of zones I ;

j = a destination (column) in the disaggregated (zonal) table and where j is also an element in the set of zones I

k = an origin (row) in the aggregated (district-level) table and k is an element in the set of districts K ;

l = a destination (column) in the aggregated (district-level) table and l is also an element in the set of districts K ;

T_{ij} = the disaggregated origin-destination table, zone-to-zone;

A_i = a row split factor for each zonal table origin;

B_j = a column split factor for each zonal table destination;

τ_{kl} = the aggregated origin-destination table, district-to-district.

The sets of splits, A_i and B_j , have the effect of spreading a large number of trips between an origin and a destination into smaller numbers of trips between, perhaps, many origins and many destinations. Each i and each j is associated with one and only one k or l , respectively. So for notation purposes, it is necessary to define two further sets, L_k^A and L_l^B , which keep track of the structural relationship between the two tables. That is,

L_k^A = the set of i rows that are associated with row k in the aggregated district table;

L_l^B = the set of j columns that are associated with column l in the aggregated district table.

Zones nest into districts and no zone may occur in multiple districts. Each district table index can be computed as a function of a given zonal table index. This is, when i is known, then k can be found by referencing the set, L_k^A .

It should be recognized that this traditional practice ignores the possibility that there are special zone-to-zone interactions that are hidden in the aggregation at the district-to-district level. For example, a large factory might ship to a large warehouse, creating a particularly large OD flow between two zones that might not be apparent by just looking at the flow between the two respective districts.

Origin-destination tables are often thought to be nearly symmetric over a 24-hour period for passenger travel; however, commodity flow tables cannot be assumed to be symmetric and vehicle flow tables, both passenger and freight, are rarely symmetric for periods of time shorter than a day.

Although the term “origin-to-destination” is used in this discussion, the procedures developed herein are equally applicable to “production-to-attraction” flows for passenger travel and “production-to-consumption” flows for commodities.

The amount of data available to determine A_i and B_j varies considerably depending upon the planning problem. Very often planners will calculate the splits from socioeconomic data or by applying trip generation equations, as they might have been prepared for a travel forecasting model. Another possible method is to determine the splits by observing the amount of travel in each disaggregated zone, such as the zone’s VMT (vehicle miles of travel), as illustrated by Rowinski, Opie and Spasovic (5) and Battelle (6). Battelle (6) used zonal VMT to create the FAF² traffic assignments. Rowinski, Opie and Spasovic (5) concluded that zonal VMT was helpful in creating a disaggregated truck OD matrix in New Jersey.

The use of zonal VMT data to supplement socioeconomic information is a good idea, but it is also problematical. To cite an extreme example, a zone with a large interstate highway could have a huge VMT even though the zone is otherwise desolate. A potentially richer data source is traffic counts on individual links, which would be needed anyway to calculate zonal VMT. However, individual traffic counts are difficult to use directly for determining the splits because any one count is not usually associated with any specific zone. Indeed, the relationship between a traffic count and the number of trips that are generated in a nearby zone is quite complex. However, to properly include traffic counts in creating row and column factors, there is a need to pull certain key concepts from the field of estimating synthetic OD tables using ground counts. The earliest methods date from the late 1970s and many improvements have been proposed since. A very complete review of the literature as it relates to static methods through 1998 has been written by Abrahamsson (7). Several such methods are derived from the concept of least-squares estimation, which is the stepping-off point for the work presented here.

Some recent work on estimation of origin-destination tables from traffic counts by Horowitz (8) has direct implications for the OD table disaggregation problem. One technique in particular, Fratar biproportional least-squares estimation, can be suitably modified to create needed row and column splits. In particular, Fratar biproportional estimation seeks the solution of this nonlinear, least-squares minimization problem to obtain sets of row and column factors to refine a rough (or “seed”) table at the same level of aggregation:

$$\min P = \sum_{\forall a \in A} w^a \left(C^a - s \sum_{\forall i \in I} \sum_{\forall j \in I} p_{ij}^a x_i y_j T_{ij}^* \right)^2 + z \sum_{\forall i \in I} \sum_{\forall j \in I} T_{ij}^{*2} (1 - x_i y_j)^2 \quad (2)$$

where

x_i = row (origin) factor for zone i ;

y_j = column (destination) factor for zone j ;

C^a = ground count for link direction a , with each direction on two-way links tabulated separately, and a is an element in the set of all counted directions A ;

T_{ij} = number of trips between origin i and destination j to be estimated;

T_{ij}^* = seed trip table;

p_{ij}^a = estimated proportion of trips between zones i and j that use link direction a (as determined by an equilibrium traffic assignment);

I = set of zones, $i = 1$ to N or $j = 1$ to N ;

A = set of link directions;

w^a = link weight for link direction a ;

z = the trip table weight; and

s = a scale factor that is either set to 1 or selected automatically to scale the trip table to produce the correct average traffic count before optimization.

This technique was later extended to dynamic OD tables by Horowitz and Dajani (9).

For example, this equation might be useful for approximating a peak-hour origin-destination table, zone-to-zone, from peak-hour traffic counts and from a 24-hour origin-destination table, also zone-to-zone. Seed tables are often built from survey data, behavioral travel theory or expert judgment. The estimation finds the best compromise set of origin and destination factors that gives good agreement with traffic counts and does not deviate hugely from the seed table. It is also mathematically necessary to constrain the factors to be greater than zero, and it is quite desirable in most circumstances to keep them within reasonable bounds, say no smaller than 0.2 and no larger than 5.

If an aggregated, district-level OD table is perfect, then the following relationship must hold:

$$\tau_{kl} = \sum_{\forall i \in L_k^A} \sum_{\forall i \in L_l^B} T_{ij} \quad (3)$$

However, it is entirely possible that the district-level OD table is less than perfect, because it too is subject to various data collection errors or inadequacies in theory. In such cases, it may be appropriate to avoid using Equation 3 as a strict constraint.

Previous research and practice suggests that a planner should be able to find some socioeconomic data to suggest how the district-level OD table might be disaggregated, justifying the use of splits, A_i and B_j , at least tentatively. However, traffic counts might suggest that different splits are better for the purpose. Therefore, Equation 1 should be modified to include the information coming from all sources:

$$T_{ij} = sx_i A_i y_j B_j \tau_{kl} \quad (4)$$

where x_i and y_j are empirical modifiers, somehow derived from traffic counts, of A_i and B_j . Thus, s , x_i and y_j have similar purposes to the same variables in Equation 2.

In many planning situations socioeconomic data and traffic data would be to some extent redundant with each other, so a well constructed disaggregation should find x 's and y 's that are close to 1. Placing tight bounds on the x 's and y 's would tend to strengthen the contribution of the socioeconomic data to the computed zonal OD table.

There are limits as to how many x 's and y 's can be estimated, given the amount of data available to the problem from the district-level OD table and from the traffic counts. It is also entirely possible that a given zone's traffic (origins or destinations) might not travel on any of the counted links; in such cases the x 's and y 's must default to 1.0, with all the factoring carried by the predetermined s , A 's and B 's.

The strength of the solution depends upon how much traffic data are available and the sizes of the two OD tables. There are $2N$ variables, where N is the number of zones in the zonal OD table. For example, if the district-level OD table has 12 districts and if there are 400 traffic counts, then there are 544 data items in the estimation ($12^2 + 400$). This means that the estimation can reliably expand this table to at most 272 zones, i.e., half the number of data items, but probably somewhat less. The locations of the 400 traffic counts matter. More splits can be estimated when the traffic counts are spread evenly throughout the region and where the counting stations are located on major roads.

There are a number of different ways to formulate the estimation methodology, and five of these ways are discussed in this paper.

Model I: District-level OD table is approximate

Model II: District-level OD table is perfect

Model III: District-level OD table is approximate, OD's are affected by trip utility

Model IV: District-level OD table is perfect, OD's are affected by trip utility

Model V: District-level OD table is approximate, some zone-to-zone flows are special

MODEL FORMULATIONS

Model I: District-Level OD Table Is Approximate

Model I is consistent with past practice in OD table estimation from ground counts, where the seed table is considered to be, at best, a rough approximation of reality. Assuming that the district-level OD table is approximate provides some flexibility to the estimation and recognizes

that there may be serious inconsistencies between the ground count data and the survey data that were used to build the district-level OD table.

$$\min P = \sum_{\forall a \in A} w^a \left(C^a - s \sum_{\forall i \in I} \sum_{\forall j \in I} p_{ij}^a x_i A_i y_j B_j \tau_{kl} \right)^2 + z \sum_{\forall k \in K} \sum_{\forall l \in K} \left(\tau_{kl} - s \sum_{\forall i \in L_k^A} \sum_{\forall j \in L_l^B} x_i A_i y_j B_j \tau_{kl} \right)^2 \quad (5)$$

$$x_i \geq 0, \quad \forall i \in I$$

$$y_j \geq 0, \quad \forall j \in I$$

or as a possible user option to lend strength to any socioeconomic data,

$$x_{\min} \leq x_i \leq x_{\max}, \quad \forall i \in I$$

$$y_{\min} \leq y_i \leq y_{\max}, \quad \forall i \in I$$

where both x_{\min} and y_{\min} are greater than zero.

Again, k and l are functions of i and j . Judgment as to which are most accurate, either ground counts or aggregated OD flows, is expressed by the set of link-direction weights, w^a , and by the sole table weight, z . The actual effects of these weights are not obvious beforehand, so the effects are best evaluated after a trial optimization has been completed.

The scale factor, s , has been retained from Equation 2. A scale factor can help eliminate systematic errors in data collection or adjust for different sets of units. For example, it is conceivable, though not recommended, that an aggregated freight OD table can be given in units of tons of while the link volumes can be given in units of trucks. At the surface, s appears to be entirely redundant. However, upper and lower bound constraints placed on x 's and y 's can make it desirable to keep them close to 1, and a value of $s \neq 1$ allows this to happen more readily.

Model II: District-Level OD Table Is Perfect

The least squares estimation for this model tries to match ground counts while fitting the district-level OD table exactly.

$$\min P = \sum_{\forall a \in A} w^a \left(C^a - s \sum_{\forall i \in I} \sum_{\forall j \in I} p_{ij}^a x_i A_i y_j B_j \tau_{kl} \right)^2 \quad (6a)$$

where k and l are taken to be functions of i and j , respectively. These constraints must hold.

$$\tau_{kl} = s \sum_{\forall i \in L_k^A} \sum_{\forall i \in L_l^B} x_i A_i y_j B_j \tau_{kl}, \quad \forall k \in K, \forall l \in K \quad (6b)$$

$$x_i \geq 0, \quad \forall i \in I$$

$$y_j \geq 0, \forall j \in I$$

This method can be implemented within the mathematics of Model I, if a suitably large value of z (see Equation 2 and previous section) is selected to assure that the first constraint is satisfied.

External Stations in Models I and II

As a practical matter, all of the models must account for the presence of external stations on the network. There can be no “intrazonal” trips within external stations. This is perhaps a minor detail, but it can be handled by introducing another factor G_{ij} (near where A_i and B_j appear in all expressions) which applies to all zones within the set E of external stations, where $E \subset I$. Thus,

$$G_{ij} = 0, \text{ if } i = j \text{ and } i \in E \quad (7a)$$

$$G_{ij} = 1, \text{ otherwise} \quad (7b)$$

This same variable should be introduced in the implementation of any of the models described here.

Models III and IV: OD's Are Affected by Trip Utility

Model IV (perfect district-level table) can be treated as a special case of Model III (approximate district-level table). Both models introduce the idea from a gravity model of trip distribution or a logit model of destination choice that there is less likelihood of a trip between a pair of zones if there is considerable spatial separation between them. Spatial separation is measured by a traveler's “utility”, which is almost always increasingly more negative or less positive as trip distance increases. Most travel forecasting models calculate a value of utility primarily from the travel time between the two zones. Define:

U_{ij} = utility of travel from zone i to zone j ; and

V_{kl} = utility of travel from district k to district l .

Utility in these cases are deterministic and can be obtained directly from the traffic network. The district-to-district utility of travel may be approximated by taking a weighted average of all zone-to-zone utilities. Thus,

$$V_{kl} = \frac{\sum_{\forall i \in L_k^A} \sum_{\forall j \in L_l^B} x_i A_i y_j B_j U_{ij}}{\sum_{\forall i \in L_k^A} \sum_{\forall j \in L_l^B} x_i A_i y_j B_j} \quad (8)$$

which would need to be recomputed repeatedly as the set of x 's and y 's become better known. If the A 's and B 's are known fairly well, then initially, $x_i = 1$ and $y_j = 1$.

Assuming a logit or maximum-entropy relationship for destination choice, then the following correction, F_{ij} , might be needed for zone pairs from particularly large districts:

$$F_{ij} = e^{U_{ij}} / e^{V_{kl}}, \quad (9)$$

and k and l are functions of i and j .

Model III's objective function can be obtained by slightly enhancing Model I:

$$\min P = \sum_{\forall a \in A} w^a \left(C^a - s \sum_{\forall i \in I} \sum_{\forall j \in I} p_{ij}^a x_i A_i y_j B_j F_{ij} \tau_{kl} \right)^2 + z \sum_{\forall k \in K} \sum_{\forall l \in K} \left(\tau_{kl} - s \sum_{\forall i \in L_k^A} \sum_{\forall j \in L_l^B} x_i A_i y_j B_j F_{ij} \tau_{kl} \right)^2 \quad (10)$$

Parameters of U_{ij} could be adopted from a trip distribution model for the region, or it could be obtained directly through the optimization process.

Model IV could be implemented by setting z to a large number. Both Models III and IV are mild departures from the proportional weighting paradigm, as they include information above and beyond what can be gotten from simply looking at origin zones by themselves or destination zones by themselves. One would surmise that Models III and IV would work best when zones are large (for example, counties) relative to average trips lengths.

Model V: District-Level OD Table Is Approximate, Some Zone-to-Zone Flows Are Special

In some circumstances it might be necessary to account for known high interactions between specific pairs of zones. Model V represents a major departure from the proportional weighting paradigm. The number of such zone pairs must be kept to just a few so as not to overwhelm the estimation process. Therefore, it is assumed that these zone pairs can be identified in advance, even if the actual level of interaction is unknown. Such interactions can be incorporated into the model by defining a mask H_{ij} for special zone pairs:

$$H_{ij} = 1, \text{ if the interaction between } i \text{ and } j \text{ is special, and} \quad (11a)$$

$$H_{ij} = 0, \text{ otherwise.} \quad (11b)$$

The additive adjustment for special trips between an OD pair, M_{ij} , can then be inserted into any of the previous models. For example, for Model I the objective function becomes:

$$\min P = \sum_{\forall a \in A} w^a \left(C^a - s \sum_{\forall i \in I} \sum_{\forall j \in I} p_{ij}^a A_i B_j (x_i y_j + H_{ij} M_{ij}) \tau_{kl} \right)^2 + z \sum_{\forall k \in K} \sum_{\forall l \in K} \left(\tau_{kl} - s \sum_{\forall i \in L_k^A} \sum_{\forall j \in L_l^B} A_i B_j (x_i y_j + H_{ij} M_{ij}) \tau_{kl} \right)^2 \quad (12)$$

and,

$$x_i y_j + H_{ij} M_{ij} \geq 0,$$

which allows M_{ij} to be either positive or negative. It is difficult to imagine how special zonal interactions could otherwise be discerned from the traditional approach (that is with zonal

socioeconomic and/or VMT data) without considerable local knowledge, special surveys or traffic counts.

Bilevel Solution Algorithm

The OD disaggregation problem, any model, is solved by embedding it within a travel forecasting framework, as illustrated in Figure 1. Two separate input OD tables must be provided: the district-to-district OD table and an initial zone-to-zone OD table. The sole reason for the initial zone-to-zone table is to obtain a traffic assignment that can be used to compute the p_{ij}^a array and to obtain an initial set of delays on links and at intersections. A good source of an initial zone-to-zone OD table is Equation 1. The initial zone-to-zone OD table does not directly contribute to the creation of origin and destination factors, but the initial table is retained in the method of successive averages (MSA) process and can slightly influence assigned volumes, depending upon the number of MSA iterations.

Bilevel algorithms similar to Figure 1 must be used when the OD table has not been fully determined at the point of initial traffic assignment and congestion is present on the network (10,11). An accurate traffic assignment needs accurate link delays that require the correct loadings, which can only be found for congested networks after a sizable number of MSA iterations.

The algorithm selected for the solution of the lower-level minimization problem is the gradient projection method with PARTAN. Searches in the gradient projected direction are stopped when the step size, η , decreases beyond:

$$\eta < \theta\sqrt{2N} \quad (13)$$

where θ is a suitably small number and $2N$ is the number of zones. The optimization is terminated when the relative change in the objective function between PARTAN steps is smaller than another small arbitrary number, determined through a trial and error process. Trials on big networks revealed that speed of convergence could be an issue because a rather large optimization problem is solved at each MSA iteration. Therefore, care was taken to fine-tune the optimization step by implementing analytical differentiation and parallel processing.

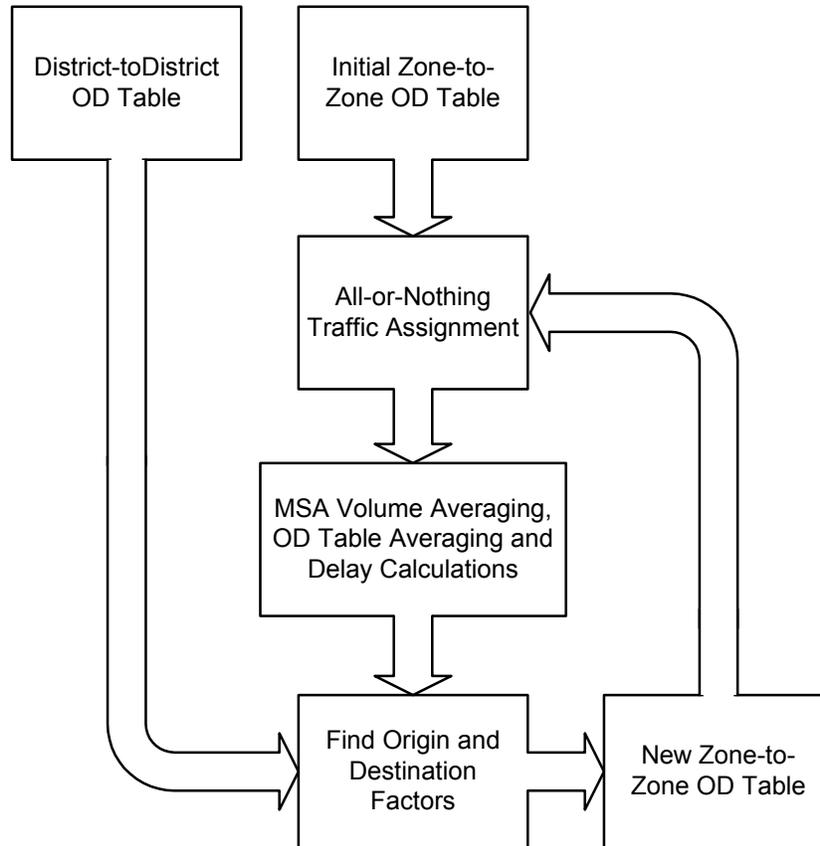


FIGURE 1 Bilevel Algorithm for Solving the OD Table Disaggregation Problem

COMPUTATIONAL TESTS, ALL VEHICLE OD TABLE ESTIMATION IN NORTHFIELD

The Northfield, MN network was selected for testing the computational properties of OD table disaggregation. Northfield was the smallest of three networks tested in the earlier study by Horowitz (8). The network is just 4.7 miles across (east-west) for its longest dimension. Northfield has a population of about 17,000 people. These current tests involved passenger, commercial and freight vehicles in a single-class traffic assignment. The Northfield network is shown in Figure 1. It has 29 zones and 12 external stations, which were organized into 11 districts. External stations were treated similarly to zones in the tests. Because all streets were included in the network, there were 819 links, but just 60 link directions had traffic counts. The number of ground counts is undesirably less than the number of variables. In Figure 1, district boundaries are included as thick blue lines while zonal centroids and external stations are shown as large green dots. Districting for external stations, which do not have logical polygons, is shown by thick black lines.

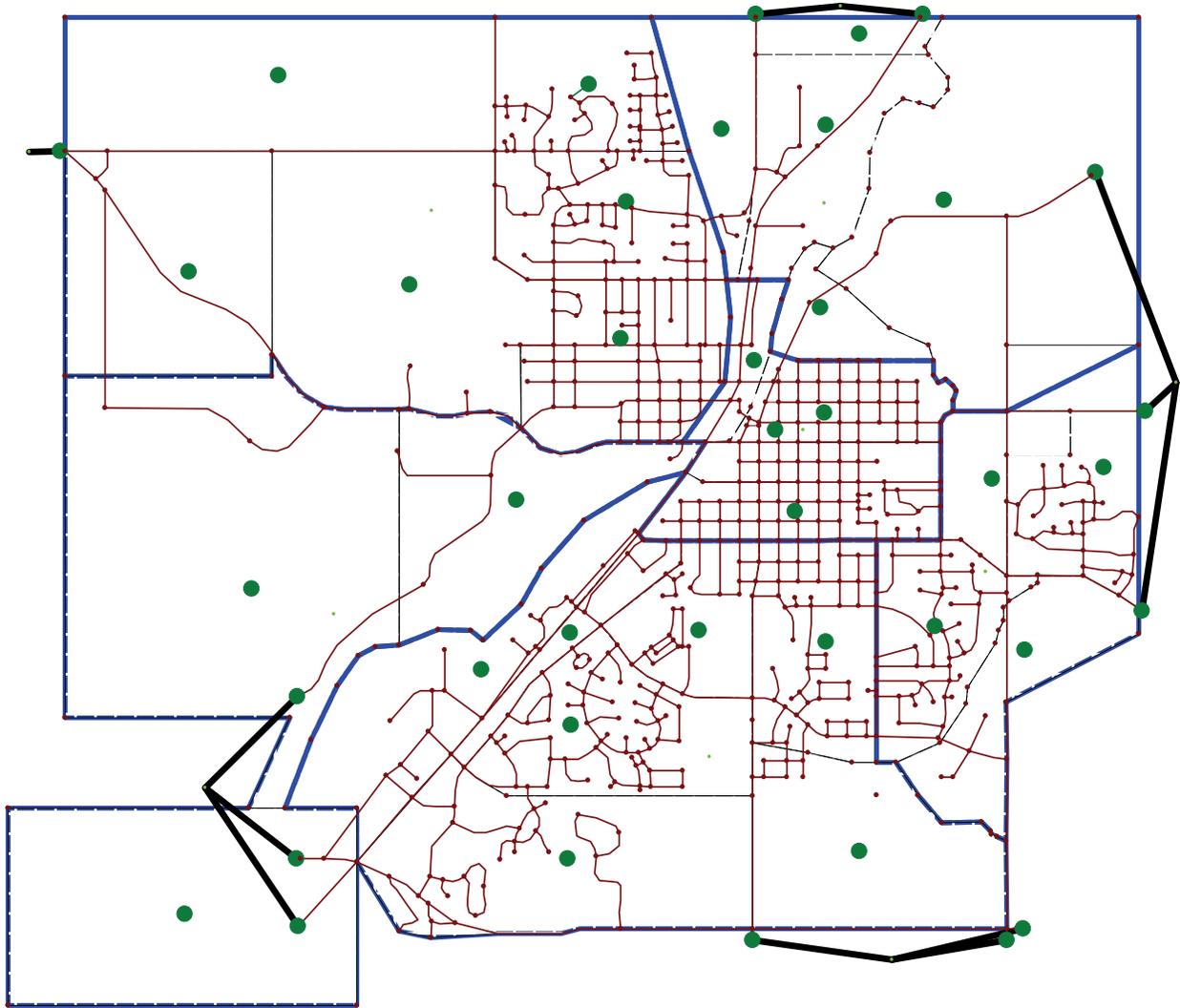


FIGURE 2 Northfield Test Network and Internal Districting

The aggregated OD table was created by a gravity model at the zone-to-zone level with home-based-work, home-based-nonwork, and nonhome-based trip purposes for passengers, then aggregated to the district level. The zone-to-zone OD table was retained for comparison purposes. All parameters were taken from NCHRP Report #365 for passenger travel (12). Because the aggregated OD table omitted any consideration of freight or commercial vehicles, substantial disagreement with the ground counts was anticipated. So not only would the model be expected to disaggregate the OD table, but it would also be expected to correct for errors inherent in the aggregated OD table caused by omitting many trucks.

Zonal characteristics were available that could have permitted the creation of fairly good sets of zone splits, A_i and B_j , but there was a particular interest in seeing what a cruder set of zone splits would accomplish. So for these tests all A_i 's and B_j 's were set to the reciprocal of the number of zones in their respective districts.

Models I through IV apply to the Northfield case. Optimization parameters were set as follows:

- All link weights, w^a , were set to 1;
- The OD table weight, z , was set to 100 for Models II and IV and 10,000 for Models I and III;
- There was prior scaling of the OD table, i.e., $s \neq 1$, to at least account for the omission of trucks from the district-to-district OD table;
- Equation 9 for Models III and IV set $U_{ij} = -0.1t_{ij}$, where t_{ij} is the congested interzonal travel time.
- All x 's and y 's were constrained to be between 0.2 and 5.

All simulations and optimizations used “area spread” equilibrium traffic assignment (13), which loads traffic at almost all intersections and dispenses with centroid connectors, which are common devices in travel forecasting networks. This assignment method is able to assign the vast majority of intrazonal trips to the network and is highly multipath, properties which are beneficial to the process of estimating row and column factors. Equilibrium was achieved by running 40 iterations of the method of successive averages (MSA), which is more than in most travel forecasting applications, but not sufficient to reduce convergence error to a negligible amount, as will be seen later. Link delays were calculated using operational analysis methods from the 2000 Highway Capacity Manual for both signalized and unsignalized intersections. The time period of the simulations was a full 24-hours, assigned statically.

Computational results were obtained for the first four models (I through IV) and the fifth model (some special flows) was checked for reasonableness. A statistical summary of the first four models and an ordinary simulation are shown on Table 1. Data are given for the 60 link directions with ground counts.

TABLE 1 Summary of Computational Tests, Inexact Input Data

Model	Average Ground Count	Average Assigned Link Volume	RMS Difference in Volumes	RMS Difference in Aggregate OD Table
I	3840	3814	1008	6.9
II	3840	3781	1152	0.3
III	3840	3862	1013	9.2
IV	3840	3851	1385	1.6
Simulation	3840	2594	2238	0.0

The RMS difference in the OD table for the simulation was zero because the original zone-to-zone OD table was not changed during the simulation and the district OD table was built by aggregating the original zone-to-zone OD table. The average aggregated OD flow was 554 vehicles.

The ordinary simulation performed very poorly in matching ground counts in relation to Models I to IV, even though it had the advantage of being provided a zone-to-zone (41 by 41) OD table instead of a district-to-district (11 by 11) OD table. A major contributor to the error of the simulation was an average of approximately 1200-vehicle systematic underestimate of all ground counts; presumably many of these were trucks. Another possibility for the underestimate is that the simulation does not have enough congestion to create diversion due to equilibrium effects and traffic is unrealistically being kept on some routes with slight advantages in free travel time and were not among those counted.

Models III and IV did slightly worse than Models I and II, which was unexpected given that the district-to-district OD table was created with a gravity model and Model III differs from Model I by making gravity-type adjustments. Table 1 shows that Model II preserves the district-to-district OD tables (to within one-half of a trip), with only a slight increase in the RMS difference between the forecast and the ground counts over Model I. Even the 9.2 trip error in the aggregated OD table for Model III is not large. It is likely that Northfield is too small a city to show that zonal-level, gravity-type adjustment are significant over and above the gravity model assumptions already embedded in the district-to-district OD table. The zonal-level gravity model effects are simply too subtle given the need to limit the number of MSA iterations, the need to set optimization convergence criteria, errors inherent within the traffic counts and deviations in the traffic counts from theory.

As an example, Figure 3 shows a map of the computed destination factors from Model I. These destination factors have been multiplied by the scale factor, s . Darker red hatching indicates zones that have destination factors between 0.2 and 0.4 and the darker green hatching signifies destination factors between 3.2 and 4. Brown zones are neutral. A zone could have a large destination factor because it has more activity, overall, than its companion zones or because it has activities that generate a disproportionate amount of travel not accounted for in the NCHRP Report #365 parameters, such as truck travel. The map confirms intuition by having about as many green zones as red zones in each district. The results for origin factors and for Model I were similar. It is difficult to further interpret Figure 3 without considerable local knowledge. A visual comparison of link counts to assigned volumes did not provide any additional insights as to how the models could be further improved.

The scale factor, s , was selected by the algorithm to be between 1.12 and 1.17, depending upon the model. The 1996 Quick Response Freight Manual (14) states that commercial vehicles make up 10.5% of traffic on urban principal arterials, so these scale factors are a bit greater than what would be expected if they were only accounting for the absence of trucks in the district-to-district OD table. The reason for the larger scale factors than expected is not entirely obvious, but might be attributable to parameters from NCHRP Report #365 not being exactly appropriate for Northfield.

All of the factors changed from their original values of x_i and y_j of 1.0, and all of the factors fell easily within the constraints of being between 0.2 and 5.0. These initial tests of Models I to IV demonstrate that they can give plausible results, but these tests do not necessarily demonstrate that the results are accurate.

Model V was not tested as fully as the other four models because it was not possible to identify sets of zone pairs *a priori* that needed special attention in Northfield. When random zone pairs were selected for Model V, both the fit to ground counts and to the district-level OD table improved in each case, but not to an interesting degree. Letting the algorithm select the zone pairs is not computationally feasible.

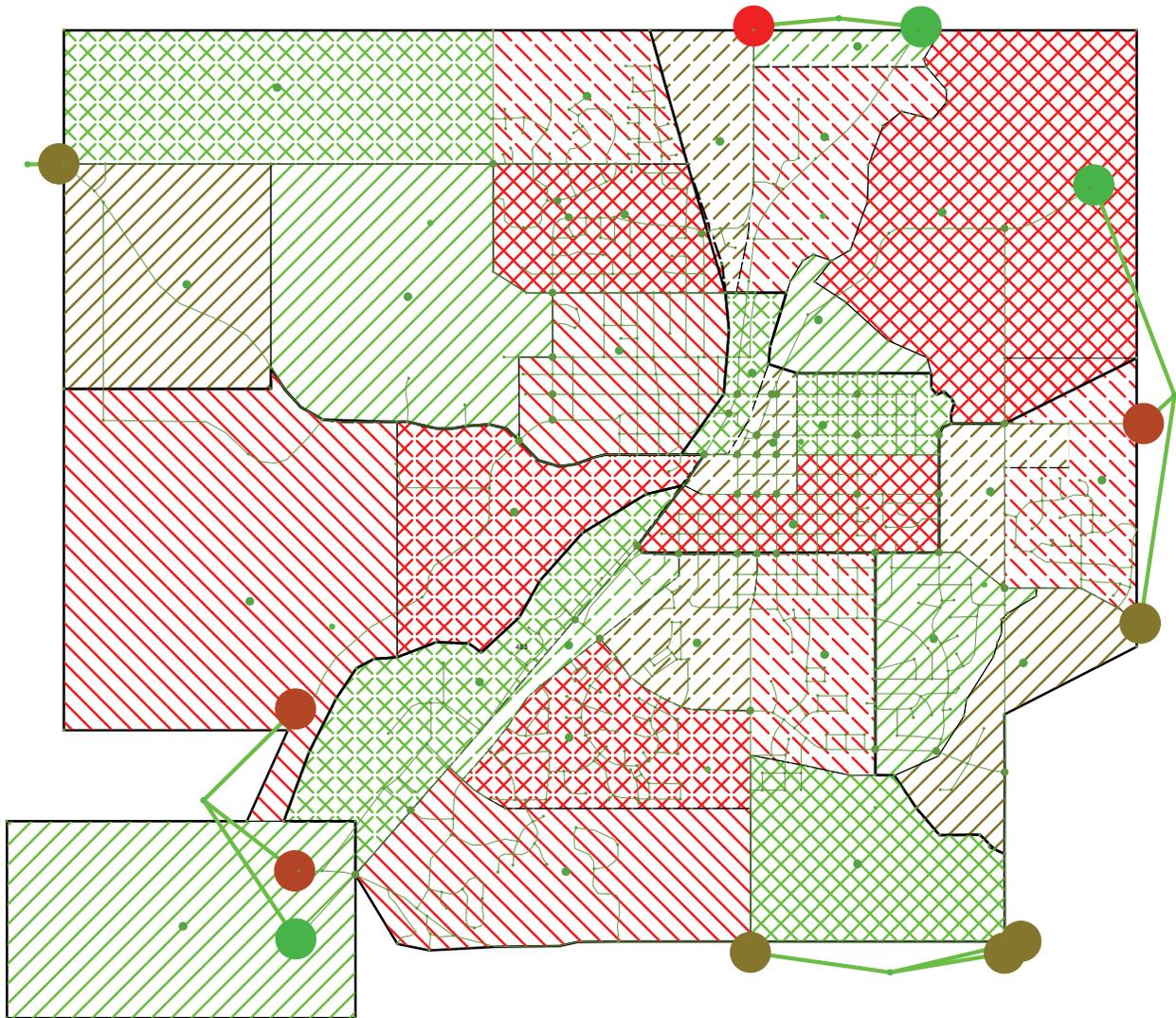


FIGURE 3 Destination Factors for Model I at Zones (Shaded Areas) and at External Stations (Dots) (Darker Green Indicates Larger Factors, Darker Red Indicates Smaller Factors and Brown is Neutral)

To better gauge the accuracy of the models in reconstructing an underlying zone-to-zone OD table, these steps were performed:

1. Create a reasonable zone-to-zone OD table for Northfield, in this case by adopting the output table from the last iteration of Model I of the previous tests. Retain the origin and destination factors.
2. Build a district OD table from the zone-to-zone OD table by simply adding up zone pairs.
3. Assign the zone-to-zone OD table to the network and obtain assigned link volumes.
4. Set the “ground count” on all arterial links equal to the assigned link volumes, artificially.
5. Using the district-to-district OD table and the artificial “ground counts”, compute a new zone-to-zone OD table.

6. Compare the original and new origin and destination factors.

This procedure resulted in 527 “ground counts” on the network that were perfectly consistent with the zone-to-zone OD table. For these tests, the OD table weight, z , was left at 100, even though there were a greater number of ground counts than the earlier tests. It should be noted that the input zone-to-zone table was computed from Equation 4, so the relationship between the zonal and district-level OD tables perfectly adheres to the theory. Table 2 shows that the optimization, as expected, is finding a solution that is very close to an exact fit to both the district-to-district OD table and the “ground counts”. The average OD flow in the district-to-district table was 623 vehicles, so the errors in matching the aggregated OD table is just 1% and the error in matching ground counts is less than 3%. The remaining small differences between assigned volumes and “ground counts” in the OD table are attributed mainly to convergence error of the equilibrium traffic assignment algorithm. The test was repeated by eliminating the bounds on x 's and y 's (0.2 to 5.0) to determine if these bounds were inhibiting the estimation process. The results in Table 2 for the less-constrained optimization, although barely improved, indicate that the constraints were not a serious issue in finding origin and destination factors.

TABLE 2 Summary of Computational Tests, Artificial Input Data

Model	Average Ground Count	Average Assigned Link Volume	RMS Difference in Volumes	RMS Difference in Aggregate OD Table
I Constrained	2138	2103	59	6.5
I Unbounded	2138	2104	53	5.7

The most interesting outputs of these tests are shown in the scatter charts of Figures 4 and 5, which compare the results of the optimization with the known origin and destination factors. The original and computed sets of factors compare very well to each other.

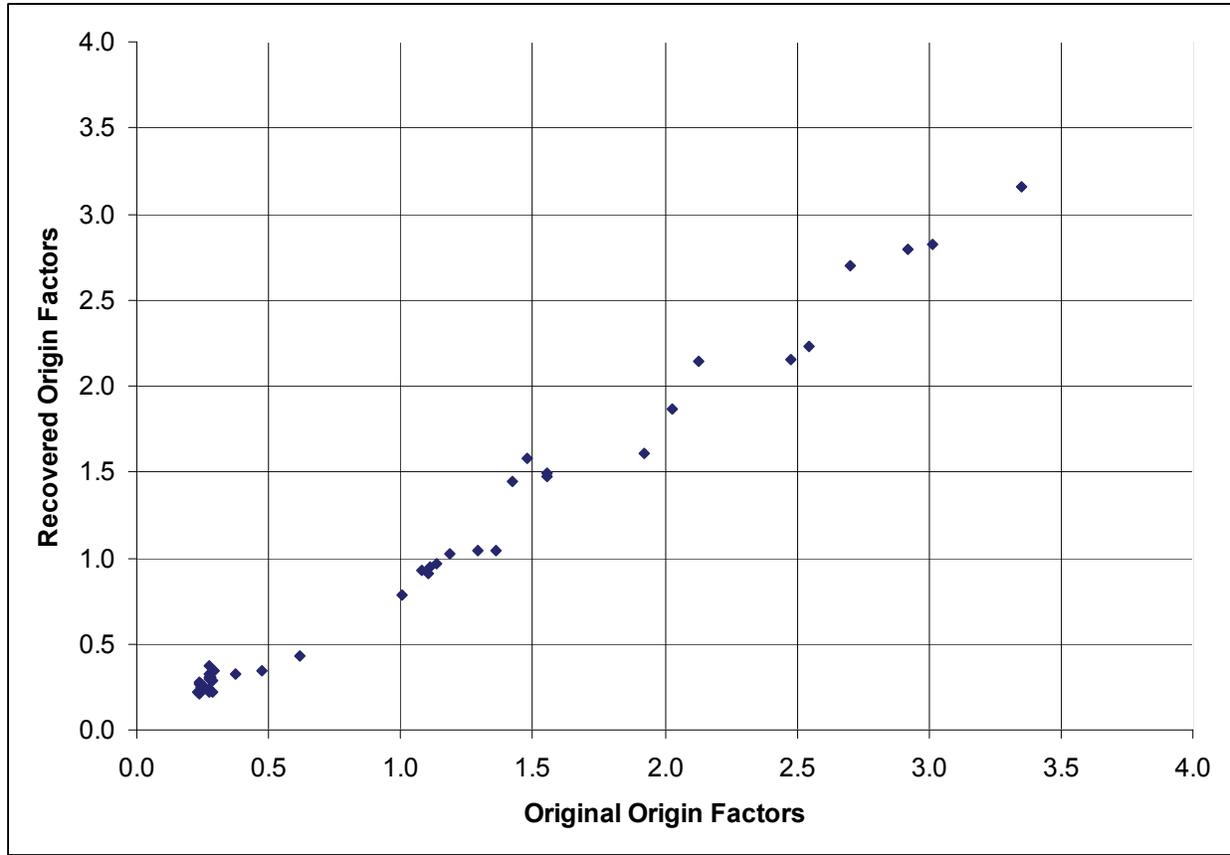


FIGURE 4 Scatter Chart Showing the Computed Origin Factors Against the Known Origin Factors

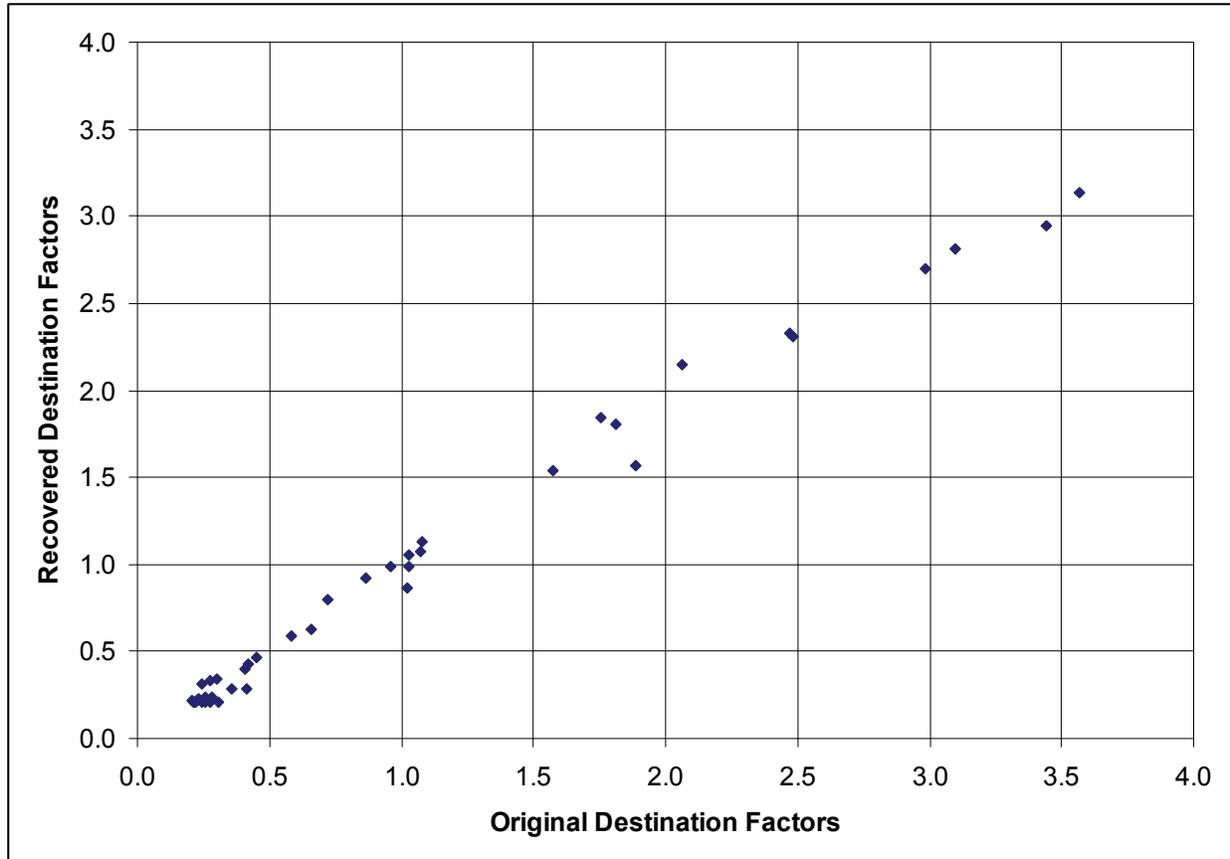


FIGURE 5 Scatter Chart Showing the Computed Destination Factors Against the Known Destination Factors

The tests of Table 2 and Figures 4 and 5 were idealized so that they could be readily interpreted. They do not represent the sternest test of the models and solution algorithm. However, these tests indicate that if the data fit the theory of the model, if there is consistency between the aggregated OD table and ground counts and if there are sufficient number of ground counts, a least squares optimization can do very well in estimating origin and destination factors.

It is likely that more MSA iterations or tighter optimization convergence criteria would straighten the scatter charts even more. Of course, there is always a tradeoff between computational precision and the need for manageable execution times while recognizing the amount of error inherent in the source data.

CONCLUSIONS

This paper outlines several optimization models that can disaggregate origin destination tables by using information from ground counts. Four of the optimization models were tested on real data from Northfield, MN and were found to work effectively.

One of these optimizations models was tested on realistic, but artificial data, on the same Northfield network and was found to be able to accurately reproduce known underlying origin and destination factors in ground counts.

These methods developed in this paper are primarily intended for commercial vehicle or freight forecasts because origin-destination data for these flows are often aggregated to a level where they are no longer useful for detailed planning purposes.

The methods make effective use of traffic count data for disaggregating OD tables without resorting to creating zonal VMT statistics, which can distort the relationship between a zone's level of activity and traffic within that zone.

The choice among the set of models largely rests on the needs of the study, but the simplest model (I) worked well for Northfield. It gave assigned volumes that were respectably close to traffic counts and did not seriously distort the district-level OD table. Models III and IV, which included gravity-type assumptions failed to improve upon Models I and II.

The tests presented here mainly dealt with passenger travel, but the most interest in OD table disaggregation in recent years relates to freight. Therefore, additional tests are needed on full-scale freight networks.

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