

Comparisons of Two Combined Models of Urban Travel Choices: Chicago and Dresden *

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Abstract

Methods for combining the steps of the sequential travel forecasting procedure have gained more and more interest in recent years. A comparison of two state-of-the-art combined models is presented: VISUM/VISEVA by PTV AG and Technical University Dresden, Germany, and CMMC (combined multi-class multi-modal travel choice model) by University of Illinois at Chicago, USA. Each model is tested on large-scale networks used by practitioners at Chicago and Dresden.

*For presentation at the 42nd Congress of the European Regional Science Association at the University of Dortmund, Dortmund, Germany, August 27 – 31, 2002.

Introduction

The basis for most travel choice models is the conventional sequential procedure, which separates prediction of travel choices into trip generation, trip distribution, mode choice and assignment steps. Over the course of several decades, new methods and better algorithms have been developed for each step to improve the computed results. More recently, feedback was introduced into the models in an attempt to achieve an internally consistent prediction, one that takes the results of previous steps into account.

In this paper we compare two state-of-the-art models: first, a combined multi-class, multi-modal travel choice model formulated by Boyce and Bar-Gera (2003). This model combines trip distribution, mode choice and traffic assignment into a single consistent model referred to as CMMC in this paper. Second, a model using VISUM by PTV AG and VISEVA by Lohse et al. (1997) that combines the four steps into one automated solution process. VISEVA is a program for solving trip generation and simultaneous origin-destination and mode choice. VISUM is a program for modeling a network and solving route choice. A macro was used to interrelate the two programs (Lohse 2002). This model is referred to as VIS in the paper.

We applied both models to two large-scale urban road networks. First, the Chicago Regional Model was solved for the *Zone 1995 System and Road Network*. This network includes Chicago and seven surrounding counties. It consists of 1790 zones, 12,982 nodes and 39,018 links, of which 34,484 represent arterials, 976 represent freeways and existing tollways and 3,560 are zone centroid connectors. Second, the Dresden Model was solved for the road network. This network represents the Dresden, Saxony, as well as seven surrounding counties. The zone system and network consist of 688 zones, 8,794 nodes and 21,477 links of which 1,376 links are zone centroid connectors.

Travel Forecasting Models

Most travel forecasting models are based on the concept of a sequential travel forecasting procedure consisting of four steps: trip generation, trip distribution, mode choice, and traffic assignment:

1. In the trip generation step, planners address the problem of where trips begin and end in the network. The planning area is divided into small, homogenous zones;

2. The trip distribution step links origins and destinations together. The result is a trip matrix containing the total number of trips per hour among all origin-destination pairs (OD-pairs).
3. In the mode choice step, trips are allocated among all modes so that one trip matrix now contains all trips among all origin-destination pairs for each specific mode;
4. In the traffic assignment step, flows are assigned to the road and transit networks. The result is flows by each mode on the network links during a specific time period.

Each step is well defined and usually solved independently of every other step. The concept is based on the assumption that travelers make sequential choices in deciding where, when, and how to travel. Because of inherent problems, such as unknown travel times and costs, and the point that travel times on links determined in the last step influence decisions in previous steps, feedback was introduced. Recently, sequences of some steps have been integrated into one model formulation. We present two state-of-the-art travel choice models that solve the travel forecasting problem in different ways.

Formulation of a Multiclass Combined Model of OD, Mode and Route Choice

CMMC integrates the trip distribution, mode choice, and route choice steps into one consistent model formulation. The desired equilibrium solution is determined when generalized costs (a linear combination of travel times and monetary costs) are identical for these three choices. A consistent and explicit formulation of the model interrelates the variables, which can be solved by a convergent algorithm, as described by Boyce and Daskin (1997).

The total demand computed in the trip generation step is fixed and given for each destination and origin. This demand is classified according to classes l . The total flow from origin p to destination q by mode m for class l is d_{pqm}^l . The modes are auto (h) and transit (t), and are independent of each other. P and Q are the sets of all origins and destinations; here $P = Q$. The multi-class model is implemented for the morning peak only, so no choice of departure time is considered. The multi-class combined origin-destination-mode model with user-optimal route choice (following Wardrop's first principle of equal and minimal travel times on all used routes) may be formulated as:

$$\begin{aligned}
\min_{(h,P)} Z(h,P) = & \sum_a \int_0^{v_a} c_a(x) dx + \sum_l \sum_p \sum_q \frac{\gamma_{hOVC}^l}{\eta^l} \cdot d_{pqh}^l \cdot k_{pqh} + \sum_l \sum_p \sum_q \frac{\gamma_{hOVTT}^l}{\eta^l} \cdot d_{pqh}^l \cdot \omega_{pqh}^l \\
& + \sum_l \sum_a \gamma_{hdist}^l \cdot v_a^l \cdot d_a + \sum_l \sum_a \gamma_{htoll}^l \cdot v_a^l \cdot toll_a + \sum_l \sum_p \sum_q \frac{\gamma_{hIVTT}^l}{\eta^l} \cdot d_{pqt}^l \cdot c_{pqt} \\
& + \sum_l \sum_p \sum_q \frac{\gamma_{hOVTT}^l}{\eta^l} \cdot d_{pqt}^l \cdot \omega_{pqt}^l + \sum_l \sum_p \sum_q \frac{\gamma_{hmon}^l}{\eta^l} \cdot d_{pqt}^l \cdot k_{pqt} \\
& + \sum_l \sum_{pq} \sum_m \left[\frac{d_{pqm}^l}{\eta^l \mu^l} \cdot \left(\ln \left(\frac{d_{pqm}^l}{d_{pq}^l} \right) - 1 \right) \right] + \sum_l \sum_{pq} \frac{1}{\eta^l \cdot \beta^l} \cdot d_{pq}^l \cdot (\ln(d_{pq}^l) - 1) \quad (1)
\end{aligned}$$

$$\text{subject to:} \quad \sum_{r \in R_{ij}} h_r^l = \frac{d_{pqh}^l}{\eta^l} \quad \forall p \in O, \forall q \in D \quad (2)$$

$$\sum_p \sum_q d_{pqt}^l = M_t^l \quad l \in L \quad (3)$$

$$\sum_m d_{pqm}^l = d_{pq}^l \quad \forall m \in M, l \in L \quad (4)$$

$$\sum_q d_{pq}^l = O_p^l \quad \forall p \in P, l \in L \quad (5)$$

$$\sum_p d_{pq}^l = D_q^l \quad \forall q \in Q, l \in L \quad (6)$$

$$h_r^l \geq 0 \quad \forall r \in R_{pq}, l \in L \quad (7)$$

$$\text{where:} \quad v_a \equiv \sum_l v_a^l \equiv \sum_l \sum_r \delta_r^a \cdot h_r^l \quad \forall a \in A \quad (8)$$

The solution must satisfy the following constraints: conservation of route flows (2), regional mode choice (3), conservation of mode choices (4), conservation of the total flow from each origin (5) and to each destination (6), non-negativity of route flows (7), and definition of link flow equal to the sum of route flows (8). The toll term in the objective function represents small existing tolls on tollways in the Chicago region.

The variables are defined as follows:

- a any link
- p origin zone
- q destination zone
- l class, defined here to be trip purpose
- m mode of travel (auto h , and transit t)
- r any route
- v_a flow on link a
- h_r^l total vehicle flow on route r in auto equivalent units per hour

δ_r^a	1 if link a belongs to route r , $r \in R$, and 0 otherwise
$c_a(v_a)$	auto in-vehicle travel time as a function of flow on link a
O_p^l	person trips (per hour) starting in p for trip purpose l
D_q^l	person trips (per hour) ending in q for trip purpose l
M_t^l	target person trips (per hour) by transit for trip purpose l
β^l	origin-destination cost sensitivity parameter for trip purpose l
μ^l	mode cost sensitivity parameter for trip purpose l
$toll_a$	toll on link a (cents)
η^l	auto occupancy factor for trip purpose l (persons/vehicle)
c_{pqt}	transit in-vehicle travel time (minutes)
k_{pqh}	auto out-of-vehicle cost like parking fees (cents)
d_a	length of link a (miles)
k_{pqt}	transit fare (cents)
ω_{pqh}^l	auto out-of-vehicle travel time (minutes)
ω_{pqt}^l	transit out-of-vehicle travel time (minutes)
d_{pqh}^l	person trips (per hour) from p to q by auto mode
d_{pqt}^l	person trips (per hour) from p to q by transit mode
d_{pqm}^l	person trips (per hour) from p to q by mode m
γ_{hIVTT}^l	coefficient of auto in-vehicle time for trip purpose l (gcu/minute), which equals 1, and therefore is omitted in the statement of the formulation
γ_{hdist}^l	coefficient of auto distance for trip purpose l (gcu/minute)
γ_{hOVC}^l	coefficient of auto out-of-vehicle cost for trip purpose l (gcu/cent)
γ_{hOVTT}^l	coefficient of auto out-of-vehicle time for trip purpose l (gcu/minute)
γ_{toll}^l	coefficient of auto toll for trip purpose l (gcu/mile)
γ_{IVTT}^l	coefficient of transit in-vehicle time for trip purpose l (gcu/minute)
γ_{IOVTT}^l	coefficient of transit out-of-vehicle time for trip purpose l (gcu/minute)
γ_{ifare}^l	coefficient of transit fare (monetary) for trip purpose l (gcu/cent)

In order to derive the optimality conditions, we form the Lagrangian, take partial derivatives with respect to route flow by class, and origin-destination-mode flow by class, and solve for the flow from origin p to destination q by mode m for class l :

$$d_{pqm}^l = A_p^l \cdot O_p^l \cdot B_q^l \cdot D_q^l \cdot \exp[-\beta^l \cdot \tilde{c}_{pq}^l] \frac{\exp[-\mu^l \cdot \bar{c}_{pqm}^l]}{\sum_m \exp[-\mu^l \cdot \bar{c}_{pqm}^l]} \quad (9)$$

where
$$\exp[-\mu^l \cdot \tilde{c}_{pq}^l] \equiv \sum_m \exp[-\mu^l \cdot \bar{c}_{pqm}^l] \quad (10)$$

Equation (9) is the nested origin-destination-mode travel choice function with endogenous auto travel costs; A_p^l, B_q^l are balancing factors. See Nöth (2001) for details.

The generalized travel costs \bar{c}_{pqm}^l are a weighted linear combination of auto and transit travel times and monetary costs. Auto generalized costs are: in-vehicle travel time, out-of-vehicle travel time, tolls, monetary cost, and distance (to represent the disutility of distance and fuel consumption). In-vehicle travel time on links of the road network are non-negative, increasing, separable functions of total link flows v_a . The Bureau of Public Roads (BPR) travel time function is adopted for representing the relationship between flow v_a and travel time c_a on link a :

$$c_a(v_a) = c_a^0 \cdot \left[1 + \alpha \cdot \left(\frac{v_a}{z_a} \right)^\phi \right] \quad (11)$$

where $c_a(v_a)$ is the travel time on link a with flow v_a , c_a^0 is the free-flow travel time on link a , and z_a is the capacity of link a in vehicles per hour; α and ϕ are parameters to adapt the BPR-function to links with different characteristics (here we use $\alpha = 0.15$ and $\phi = 4$). Average out-of-vehicle travel times include walking times to the car and to the final destination. Costs at destinations, like parking fees, are included in out-of-vehicle costs. Transit costs are in-vehicle travel time, out-of-vehicle travel time, and fares. All costs are represented in the form of the generalized cost unit (gcu), which is equal to auto in-vehicle travel time, by applying money-time conversion factors.

Travelers are assumed to minimize their generalized cost in making their travel choices. Due to lack of information, unmeasured benefits at destinations, individual desires, and behavior about comfort and attractiveness of alternatives, travelers generally do not actually choose the least cost alternative. This dispersion to higher cost alternatives is modeled by including an entropy term. In particular, dispersion to “more expensive” modes and destinations is considered.

Solution Algorithm

The algorithm used for solving the above combined model is a generalization of the Evans (1976) algorithm, which relies on the partial linearization of the objective function. In each iteration the algorithm seeks a feasible direction to decrease the value

of the objective function. A line search is applied to obtain the optimal step size. The algorithm iterates until a specified level of convergence is reached. The model was programmed in C-language at UIC. Because of its *research character*, the program does not offer a graphical interface or other options.

Formulation of VISEVA / VISUM Travel Choice Model

VISUM is a product of PTV AG, a German engineering consulting company, for network manipulation and trip assignment. VISUM has been used in practice for about 20 years. VISEVA is a product of PTV AG and TU Dresden and has been developed over the last seven years. VISEVA offers a characteristic value model (systematic disaggregation of households, person categories and activity pairs; called *Kennwertmodell* in Germany) for trip generation and an algorithm for simultaneous solution of trip distribution and mode choice (four impedance functions are predefined, and additionally a user specified impedance function may be defined; two algorithms are available for balancing the trip tables: MULTI-Model by Lohse (1997) and Furness-Model). Because of their commercial history, both programs offer several additional options and auxiliary functions. In this paper we apply the *EVA-Function* for OD and mode-choice and the *Learning Procedure* for route choice, both developed by Lohse (1997). Because the combined model used does not include trip generation, we used fixed demand for each origin and destination for each trip purpose.

Trip distribution and mode choice are computed simultaneously instead of being computed sequentially. The basis for computing the flow of class l from zone p to q by mode m , d_{pqm}^l , is the user's "evaluation of the costs/impedance/deterrence of this trip"; or in other words, the probability BW (a function of the generalized cost or impedance or *Bewertungswahrscheinlichkeit*) that a user makes this trip from zone p to q by mode m . For trip purpose types 1 and 2 (the origin or destination is either home or work, or otherwise type 3 is used), the flow may be computed as:

$$d_{pqm}^l = A_p^l \cdot O_p^l \cdot B_q^l \cdot D_q^l \cdot C_m^l \cdot BW_{pqm}^l \quad (12)$$

subject to conservation of flow over all origins, destinations, and modes:

$$O_p^l = \sum_q \sum_m d_{pqm}^l \quad (13)$$

$$D_q^l = \sum_p \sum_m d_{pqm}^l \quad (14)$$

$$M_m^l = \sum_p \sum_q d_{pqm}^l \quad (15)$$

A_p^l, B_q^l and C_m^l are balancing factors used for solving for the trip matrices. BW is a combination of costs (like travel time, monetary costs, speed and some more) and is computed with the EVA-Function (Lohse 1997). BW is computed separately for each cost k . Since each cost is regarded as independent of each other, all BW are multiplied to compute a total BW for a flow d_{pqm}^l .

$$BW_{pqm}^l = \prod_k BW_{pqm}^l(k) \quad (16)$$

The EVA-Function is:

$$BW_{pqm}^l(k) = \frac{1}{(1 + k^l_{pqm})^{\frac{E^l}{1 + \exp(F^l - G^l \cdot k^l_{pqm})}}} \quad (17)$$

The EVA-Function also includes an exponential function, like is typically used in a gravity model; but, with its three parameters E, F and G , it is more flexible and easier to adapt in an analysis. Additionally, the EVA-Function shows better properties for short trips, whereas the exponential function decreases too sharply. Figure 1 shows the two functions for $\beta = 0.04, E = 2, F = 5, G = 0.09$:

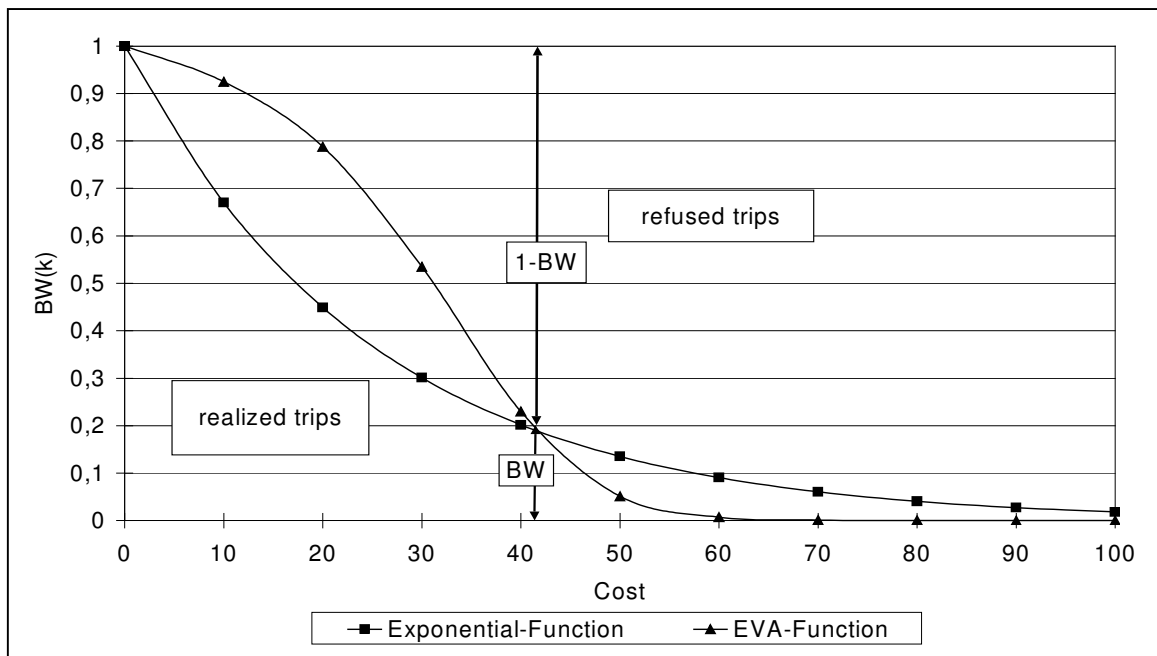


Figure 1: Comparison of Exponential- and EVA-Function

Figure 2 presents the elasticities of the two functions. The exponential-function has a linear decreasing elasticity, while the elasticity of the EVA-function has a lower

elasticity for low and high cost and a higher elasticity for cost in between. This characteristic seems to represent human behavior better, and is similar to a PROBIT-function, which is regarded as best for describing human behavior.

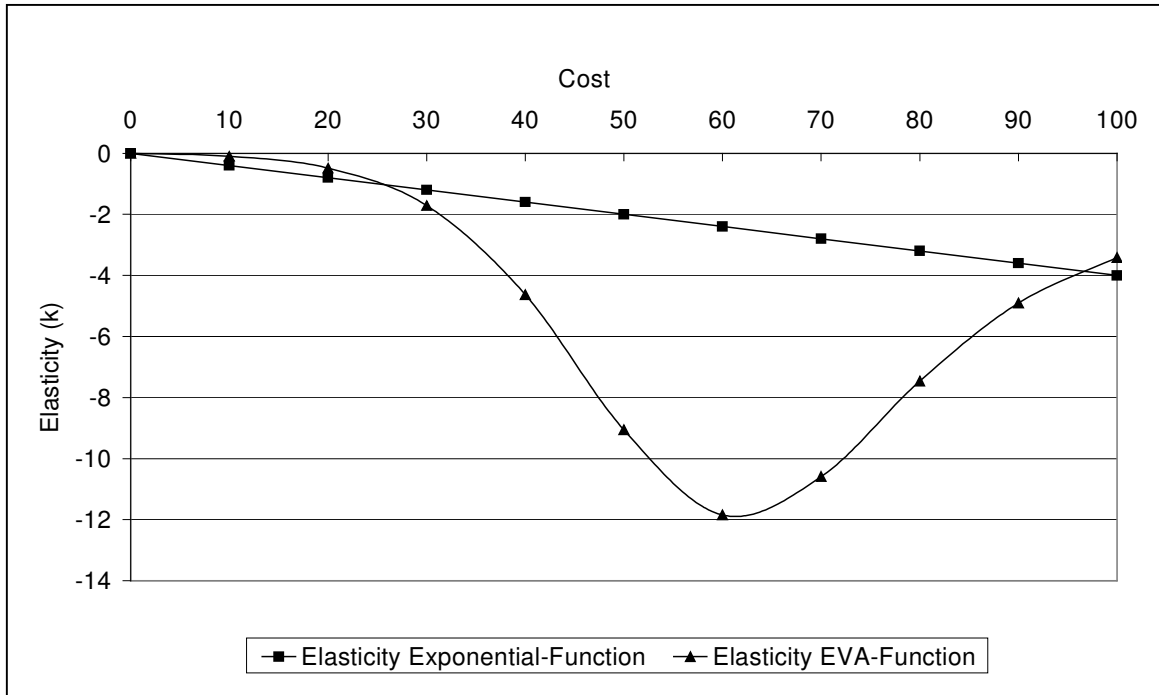


Figure 2: Elasticities of Exponential- and EVA-Function

The three-dimensional routine *Multi-Model* was used for balancing the model. The convergence criterion seeks to minimize the information gain between a probability matrix and the trip matrix. The E , F , and G parameters were obtained from TU Dresden for the Dresden Network, and by applying a calibration tool for the Chicago network. Destination and mode choice had to be computed separately for each trip purpose. Indicator matrices for computing BW were obtained from VISUM, which in turn uses VISEVA trip matrices as an input for trip assignment. In this work we used only travel time (including out-of-vehicle time for walking to and from a car) as generalized cost. All trip matrices by class were summarized to one total trip matrix.

VISUM / Learning Procedure

VISUM offers five different algorithms for auto assignment and three methods for transit assignment. This paper focuses on the *Learning Procedure*, which is an algorithm for auto assignment. This algorithm approaches traffic assignment by modelling the decision making process of a user: before starting a trip from origin p to destination q she compares different routes using estimated travel times on each link.

After choosing the least cost route she learns the real travel time on this route (route travel time is the sum of all link travel times, which are part of this route). Based on this experience she may change the route in the next iteration in case there is a gap between estimated travel time and perceived travel time. If enough iterations ($n > 40$) are performed, a solution is approached in which the realized travel times approximate the estimated travel times for all links. Compared to a Wardrop (1952) equilibrium, however, this solution does not equalize travel times on used routes; indeed, it assigns some flow to routes with higher costs, which is considered to be more realistic.

The *Learning Procedure* is modeled in VISUM with a best-way algorithm and “retrograde calculation” (*Rückrechnung*). VISUM uses the BPR-function for computing link travel times. In each iteration all trips from p to q are assigned to the least cost route, which is found by averaging the estimated and realized impedances (linear combinations of travel time and other defined costs) for each link in the previous iteration using the *Learning Equation*:

$$t_{estimated}(n) = t_{estimated}(n-1) + \Delta \cdot (t_{realized}(n-1) - t_{estimated}(n-1)), \quad 0 \leq \Delta \leq 1 \quad (18)$$

For faster convergence the averaging factor Δ is introduced as variable, which is optimised in each iteration. If the gap between estimated and realized travel times is small enough, the algorithm stops. The gap is computed with a relative-variable measure ϵ . In the retrograde calculation step, all flows on link a are summed up over all iterations and are divided by the number of iterations n . Lohse (1997) presents this algorithm as shown in Figure 3.

For the actual computation of travel forecasts, both programs are either linked by hand or by a VBA-macro. The trip matrix computed with VISEVA is input to an assignment in VISUM. Then, indicator matrices are computed with VISUM for solving a new destination and mode choice with VISEVA. This process is repeated until equilibrium is reached (usually about 5 to 10 iterations are necessary). Figure 4 shows the process.

The convergence criterion seeks to find an equilibrium between demand (trip matrix) and supply (network). The macro used for this study utilizes stability of link flows to check convergence. For computing this stability of link flows between two iterations, the Learning-Procedure criterion is used.

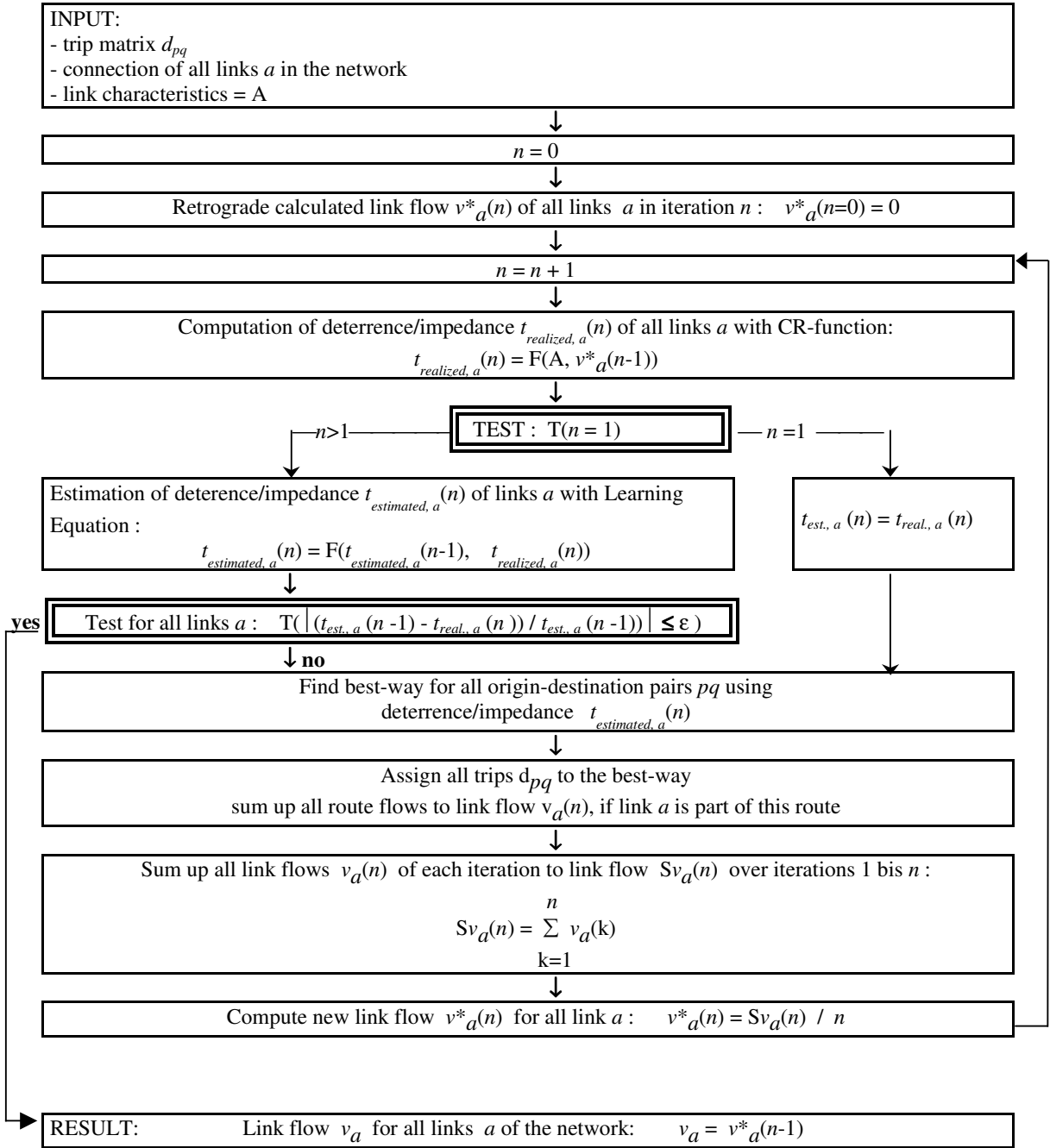


Figure 3: Best-Way-Algorithm with Retrograde Calculation and Learning Procedure

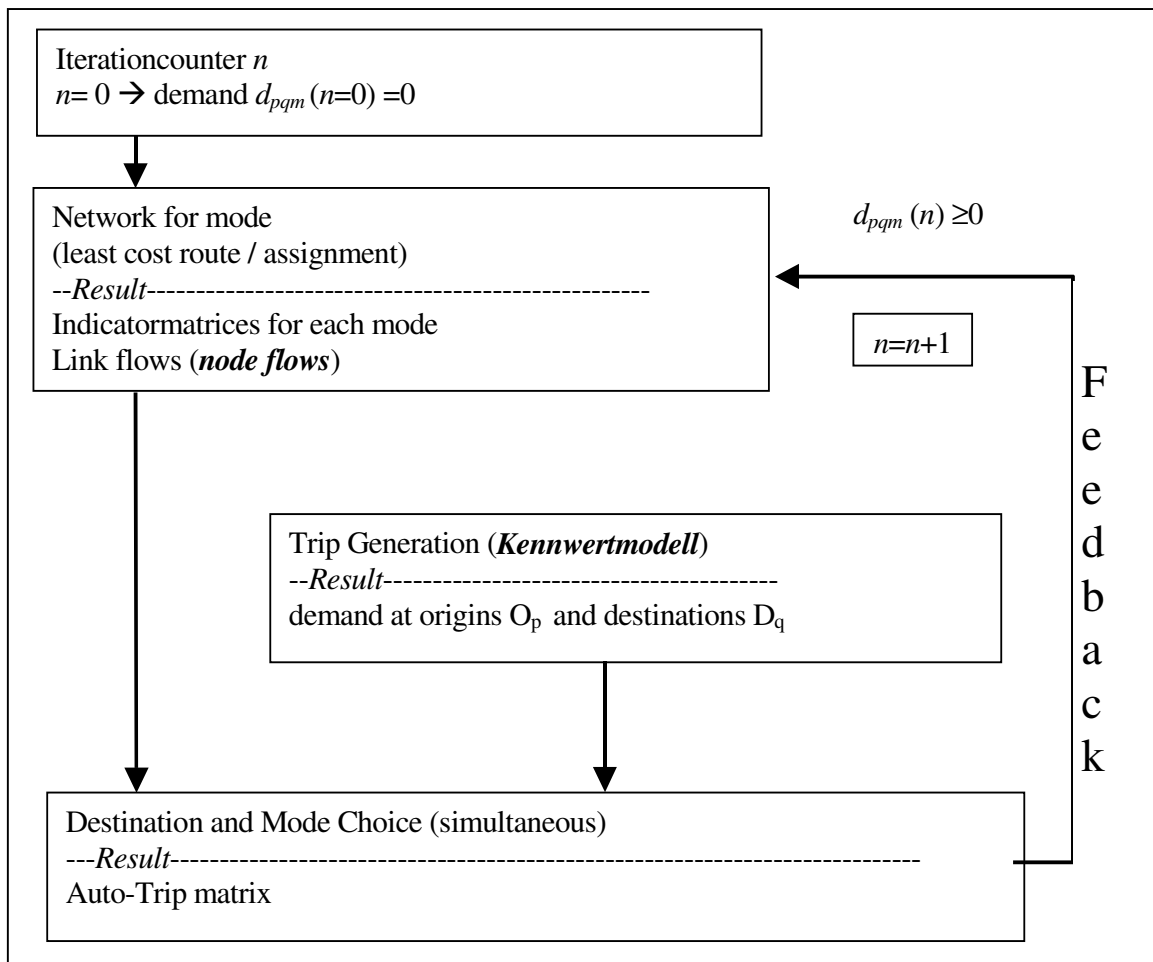


Figure 4: Travel Choice Computation with VISEVA / VISUM

Computational Results

All computations are limited to the morning peak period: 6:30 to 8:30 am for Chicago and 6:00 to 8:00 am for Dresden; the total flow for Chicago is approximately 1.51 million person trips per hour and for Dresden approximately 256,000 person trips per hour. For Chicago total flow is divided into two trip purposes: Home-Work, Home-Nonwork, which also includes all other trips. For Dresden 15 trip purposes are used (see the Appendix). Because of lack of data and different approaches in modeling the transit mode, we excluded transit and therefore mode-choice. This omission also speeds up solution times considerably; solution times are in a range of 10 to 60 hours for the Chicago network. The generalized costs used in both models are based on in-vehicle travel time and out-of-vehicle travel time. Other costs were not included as a result of inconsistencies and lack of data and parameters.

Solution Procedure

In order to compare the models we solved them in the following way:

1. To compare the networks used by planning officials and companies, alter both networks slightly to make them fit both models, CMMC and VIS (e.g., delete elements of modes other than auto, convert the Chicago network to *meters*).
2. Solve the Chicago network with CMMC and the Dresden Network with VIS, using the “original” parameters. These solutions, which are different from the calibrated solutions (e.g. no transit), are our new “correct” solutions.
3. Solve the Chicago network with VIS and the Dresden Network with CMMC.
4. Calibrate them with respect to average travel distance.
5. Compare these solutions to the “correct” ones with the following measures: average travel distance (ATD); average travel time (ATT); average travel speed (ATS); link flows; and integrals of link travel time functions.

Results for the Dresden Network

First, we solved the Dresden network with VIS. Thereafter CMMC was calibrated with respect to ATD. Table 1 presents results for ATD, ATT, ATS and person-trips for the solutions with CMMC and VIS. ATDs are in agreement for all trip purposes. ATTs and ATSS match in particular for trip purposes with a high number of trips. The different characteristics of the exponential function and EVA-function lead to more interzonal travel for VIS:

trip purpose	avg. travel distance in km		avg. travel time in minutes		avg. travel speed in km/h		person-trips (interzonal)	
	CMMC	VIS	CMMC	VIS	CMMC	VIS	CMMC	VIS
HW	16.07	15.97	27.50	26.96	35.08	35.53	148387	153842
HK	6.03	6.01	11.11	14.12	32.58	25.52	8584	10062
HE	15.16	14.31	28.77	24.56	31.62	34.95	13373	14754
HU	14.82	14.80	30.50	25.74	29.16	34.50	4207	4229
HS	8.39	8.45	13.20	17.50	38.13	28.95	10837	12257
HO	11.19	11.20	21.97	21.58	30.57	31.13	20732	22004
WH	16.28	16.32	22.75	26.68	42.94	36.71	435	450
KH	6,132	6.22	8.75	13.98	42.05	26.68	406	468
EH	13.40	13.19	15.57	21.84	51.65	36.24	294	324
UH	15.32	15.34	21.02	24.74	43.72	37.19	23	23
SH	8.59	8.51	12.48	17.42	41.31	29.33	1899	2130
OH	11.36	11.43	16.04	21.03	42.48	32.63	4325	4552
OW	10.86	10.99	16.35	20.64	39.85	31.94	7642	8478
WO	12.09	12.07	20.73	22.41	34.99	32.31	5249	5641
OO	9.33	9.28	16.64	19.33	33.65	28.79	7084	7383
total	14.21	14.01	24.63	24.55	34.62	34.25	233478	246595

Table 1: Average Measures for Dresden

Figure 5 shows the differences in link flows for these solutions. About half of all links have similar flows (± 50 autos/2h). For more than 800 links, differences in link flows are ± 500 autos/2h, which is noticeable. About 3,000 links show a relative difference of $\pm 10\%$ and show similar flows. Nearly the same number of links show a relative difference of $\pm 100\%$, mostly due to links, which get small flows in CMMC and zero flows in VIS.

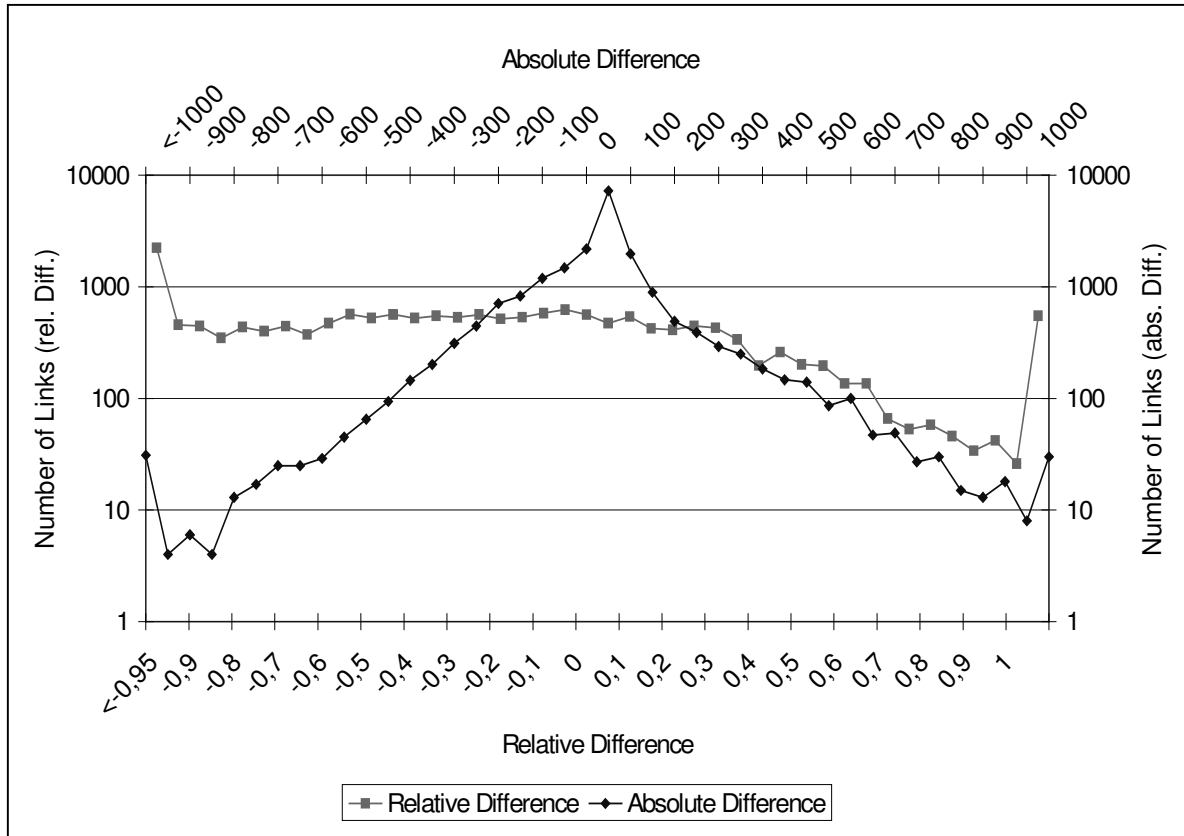


Figure 5: Link Flow Differences between CMMC and VIS for Dresden

However, other reasons for the large differences were identified in rounding errors during the inputting of trip matrices by VISUM, consideration of turning penalties in VISUM and, of course, different models. We solved with VIS a network without turning penalties (referred to as “all turns”) to check this assumption. Additionally, we solved with this modified network a trip matrix multiplied by 1000 to decrease rounding errors (referred to as “1000”, the rounding errors decreased flow by about 20%). VISEVA and VISUM offer various models for solving OD, mode and route choice. We tested an exponential function for OD and mode-choice with the equilibrium assignment in comparison to EVA-function and Learning Procedure. Table 2 shows total results for some measures.

Model	ATD in km	ATT in minutes	ATS in km/h
Exp.-Fct./Equilibrium	16.04	26.5	36.3
Exp.-Fct./Equilibrium "all turns"	13.82	25.7	32.2
Exp.-Fct./Equilibrium "1000"	13.45	26.1	30.9
EVA-Fct./Lernverfahren	13.44	23.7	34.1
EVA.-Fct./Equilibrium "all turns"	12.07	24.0	30.3
EVA.-Fct./Equilibrium "1000"	11.87	24.0	29.6

Table 2: Average Measures for modified VIS Solutions

Figure 6 shows differences in link flows between CMMC and VIS “1000”. In particular fewer links exhibit large absolute and relative differences. Even so, the discrepancies are large. Astonishingly, VIS solutions are in better accordance with each other than with the CMMC, despite the fact that in one VIS formulation an exponential-function and equilibrium assignment have been used.

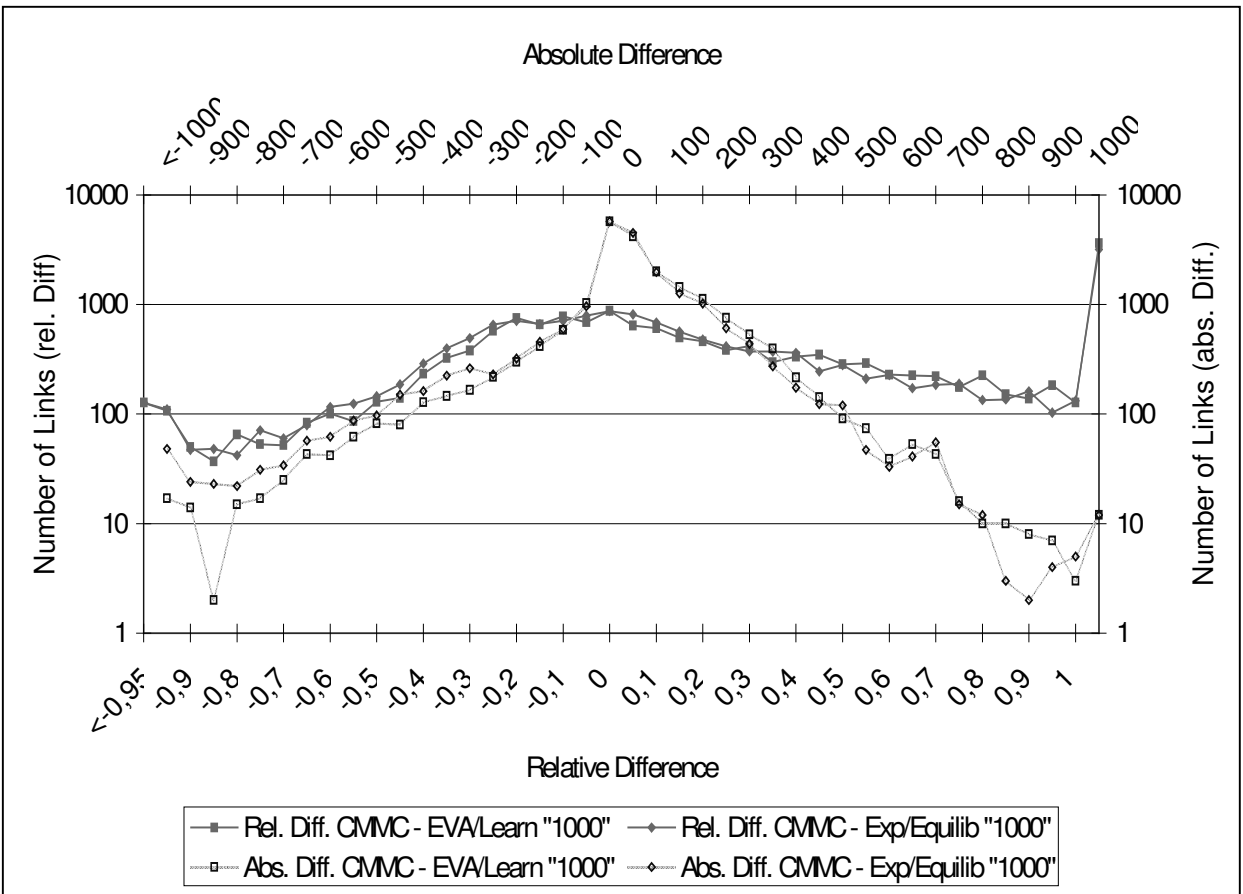


Figure 6: Link Flow Differences between CMMC and Modified VIS for Dresden

These outcomes lead to the question of accuracy. While CMMC solved the assignment to an accuracy (relative gap) of 0.0001 in this study, VISUM uses integers for flows. By increasing the number of trips with a factor of 1000, we addressed this problem in part. Another point concerns when to stop the computations. CMMC uses the integrals of the

link travel time functions in the optimization function to monitor convergence and to define a termination point. Although the VIS convergence criterion seeks to find an equilibrium between demand (trip matrix) and supply (network), the macro also uses stability of link flows to check convergence. In fact, link flows do fluctuate to a small extent. Table 3 shows the number of links with changing flows.

Cumulatigve Number of Links with changing flows	Iteration 1-2	2-3	3-4	4-5	5-6	6-7	7-8	8-9	9-10
± 1%	6822	9900	12243	13891	15113	15558	16202	16318	16397
± 5%	10047	15949	17924	18751	19288	19495	19635	19582	19618
± 10%	13193	18329	19384	19857	19986	20028	20065	20060	20087
Number of all Links	20299	20299	20299	20299	20299	20299	20299	20299	20299

Table 3: Number of Links with Changing Flows between VIS Solutions for Dresden

Table 4 indicates the fluctuation of the sum of link travel time integrals of the VIS solutions. The value for CMMC is 22,494,191 (in CMMC the flow actually assigned to the network is about 20% higher than for these VIS solutions).

Iteration	Exp.-Fct./Equilibrium As.	EVA-Fct./Learning Proc.
1	21,377,568	20,396,703
2	23,772,359	23,074,378
3	22,892,930	22,207,464
4	23,321,581	22,535,061
5	23,078,603	22,368,520
6	23,198,494	22,429,817
7	23,174,430	22,414,096
8	23,212,393	22,407,417
9	23,227,198	22,428,552
10	23,216,013	22,370,515

Table 4: Sum of Link Travel Time Integrals of VIS Solution for Dresden

Results for the Chicago Network

First, we solved the Chicago network with CMMC. Thereafter the three EVA parameters were calibrated with regard to ATD. Table 5 presents results for ATD, ATT, ATS and person-trips for the solutions with CMMC and VIS (after six feedback loops). Clearly, ATD does not match for the two trip purposes, which is also true for ATT and ATS. Only the number of interzonal trips is similar in both solutions.

trip purpose	avg. travel distance in km		avg. travel time in minutes		avg. travel speed in km/h		person-trips (interzonal)	
	CMMC	VIS	CMMC	VIS	CMMC	VIS	CMMC	VIS
HW	19.02	21.50	25.5	30.6	27.8	42.1	929634	932911
HNW	7.70	8.90	10.7	13.5	26.9	39.7	511086	506502
total	15.21	17.07	20.2	24.6	27.7	41.6	1440720	1439413

Table 5: Average Measures for Chicago

Because of the long computation times (roughly one week for six feedback loops), we were not able to re-calibrate the EVA parameters at this time. Furthermore, the Learning Procedure did not converge for the first setting of parameters, so that we had to change Δ after the third iteration; Δ limits the maximum step size of the Learning Equation. Even after the change of Δ , the assignment was terminated after reaching the maximum number of assignment iterations, and did not reach the convergence criterion. From the fifth to the sixth VIS iteration, about 10,000 links show differences in link flow of $\pm 1\%$ and less, but about 6,000 links show differences in link flows of more than $\pm 10\%$. The slow convergence might be a result of the large road network, which is rather congested in some parts, in particular in the Chicago Central Area.

Again we tested an exponential function for OD and mode-choice with the equilibrium assignment in VIS. When using the same β parameter for OD-choice, ATD was about twice as large as in the CMMC solution. We had to increase the exponential-function parameter β substantially to approach the CMMC ATD, which increased the number of intrazonal trips from 60,000 trips to more than 400,000 trips. We are not aware of the reasons for these discrepancies at this time.

Figure 7 presents the actual differences in link flows between the CMMC solution and the VIS solution. About 22,000 links show similar flows for both solutions (± 50 Fz/2h), about 1,400 links show fairly big differences (± 500 Fz/2h).

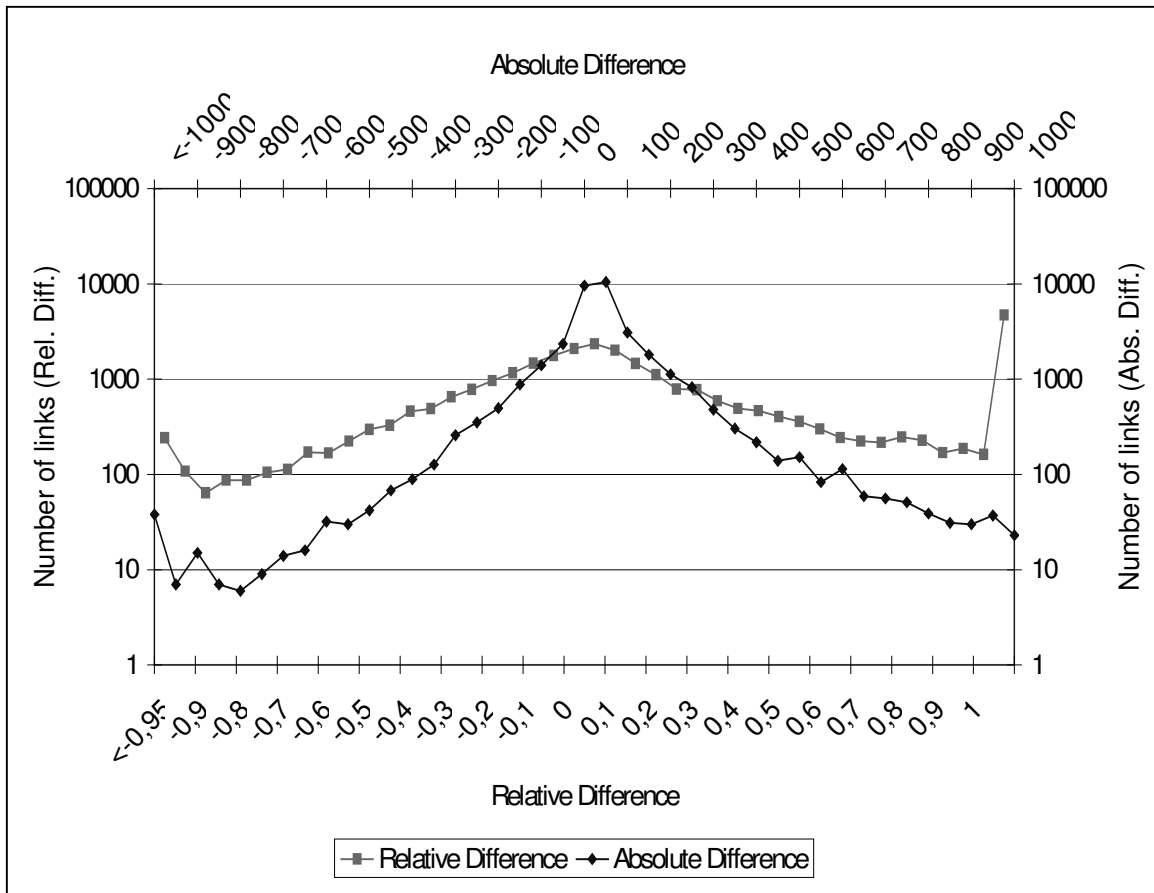


Figure 7: Link Flow Differences between CMMC and VIS Solutions for Chicago

More research testing the convergence characteristics of the Learning Procedure for different parameter settings and very large networks is underway. A new version of the VBA-macro will use *Learning Feedback* (averaging of trip matrices computed in consecutive iterations) to overcome convergence problems and reduce overall computation times.

Conclusions

Solutions of two state-of-the-art multi-class, multi-modal travel forecasting models are presented. In this study both models could be adopted to “foreign” networks with reasonable amount of time and effort leading to good results. The quality of the solutions could have been improved further. CMMC has the advantage of having a well-defined objective function and a clearly defined termination criterion. VIS offers the user various procedures to compute OD, mode and route-choice. Furthermore *EVA-Function* and *Learning Procedure* are probably the better choice, because of their characteristics in reflecting user’s behavior. However, observations in practice show

different states and flows from day to day and during the day, as was true for the various model solutions. Every solution is only one among other likely ones. Using different models might help to emphasize this fact.

Acknowledgements

The study reported in this paper is based in part on network and trip generation data provided by Chicago Area Transportation Study, Chicago, USA, and software provided by PTV AG, Dresden and Karlsruhe. We are grateful to them for the use of these data. Andrew Stryker, Chicago, and Birgit Dugge, Dresden, helped with preparing and processing the input and output data. Frederik Nöth was supported in part by a fellowship from the Friedrich-Ebert-Stiftung, Bonn, Germany.

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Appendix

German		English	
WA	Wohnen-Arbeit	HW	Home-Work
WK	Wohnen-Kindereinrichtung	HK	Home-Nursery School
WB	Wohnen-Bildung	HE	Home-Education
WH	Wohnen-Hochschule	HU	Home-University
WE	Wohnen-Einkaufen	HS	Home-Shopping
WS	Wohnen-Sonstiges	HO	Home-Other
AW	Arbeit-Wohnen	WH	Work-Home
KW	Kindereinrichtung-Wohnen	KH	Nursery School-Home
BW	Bildung-Wohnen	EH	Education-Home
HW	Hochschule-Wohnen	UH	University-Home
EW	Einkaufen-Wohnen	SH	Shopping-Home
SW	Sonstiges-Wohnen	OH	Other-Home
SA	Sonstiges-Arbeit	OW	Other-Work
AS	Arbeit-Sonstiges	WO	Work-Other
SS	Sonstiges-Sonstiges	OO	Other-Other

Table 6: 15 Trip Purposes used for the Dresden Network