VISEM - an Activity Chain based Traffic Demand Model

PTV AG
Stumpfstr. 1
D-76131 Karlsruhe
Tel.: +49-721-9651-0
Fax: +49-721-9651-299
Email: ptv@ptv.de

solutions for traffic.

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M. Fellendorf, T. Haupt, U. Heidl, W. Scherr
PTV AG
76227 Karlsruhe
Germany

ABSTRACT

The shortcomings of the four-stage modelling process in transportation planning are obvious, but most transportation planning systems in practical use are based on it. VISEM is an advanced disaggregate model in this tradition, which estimates and forecasts trip-tables. It has been used in various cities throughout Europe and Asia. Comments on the methods and the data modelling reflecting the planning objective and the available data are made. Our experience in a variety of transportation studies is presented to demonstrate the range of applications already carried out.

VISEM simulates activities; trip chains are computed as a result. Although important dependencies within the trip chain generation and interferences of demand and supply are covered, the system does not require extensive computing power due to the aggregation of individuals to behaviourally homogenous groups. The model is implemented and calibrated with the help of empirical survey data or census data. Revealed and stated preference data can be adopted. The activity-related destination choice within trip chains is modeled by an entropy-maximizing deterrence function. Mode choice is implemented via a multinomial LOGIT model. The number of modes differ from study to study. VISEM is integrated in an urban and regional transportation planning system called VISION, the final objective of which is to estimate mode specific traffic volumes in a more realistic manner than is presently possible using conventional four-stage models.

INTRODUCTION

The presented paper describes a modern activity-based approach to model travel demand which has been developed continuously over the last 10 years and has been used in many practical transportation planning studies. This software, called VISEM, is now implemented for the planning areas of various cities and is used by their administrations to generate demand matrices as a part of the PTV ‘VISION’ system (Visual Information System for Interactive Optimization of Networks). Among the users of VISION are also universities, research institutes and consulting companies. The transportation planning part of VISION consists of two main modules: VISEM, the traffic generation part, and VISUM, the network planning and assignment part.

The PTV company developed VISEM as a tool to estimate and forecast mode specific origin-destination matrices (OD-tables) in a user friendly software system. The two basic ideas of VISEM are the classification of the population into behaviourally homogeneous groups and the generation of trip chains derived from activity chains.

The direct predecessor of this model approach was ORIENT (Sparman 1980). ORIENT itself was derived from a model used in the masterplan of Nürnberg/Fürth (Poeck/Zumkeller 1976). All these predecessors were based on stochastic simulation (like Monte-Carlo simulation). As a further development Schwerdtfeger and Swidersky from the IfV-Institute at the University of Karlsruhe provided the first model using matrix computations and as such the basis of today's VISEM. For further description and references of the „German approach: simulating activity chains" see Axhausen/Herz 1989.

1. MODEL DESCRIPTION

1.1 An Overview of VISEM

VISEM replaces the first three steps of the classic four-stage model in an integrated manner. However the approach can be broken down into three sub-models (See figure 1).

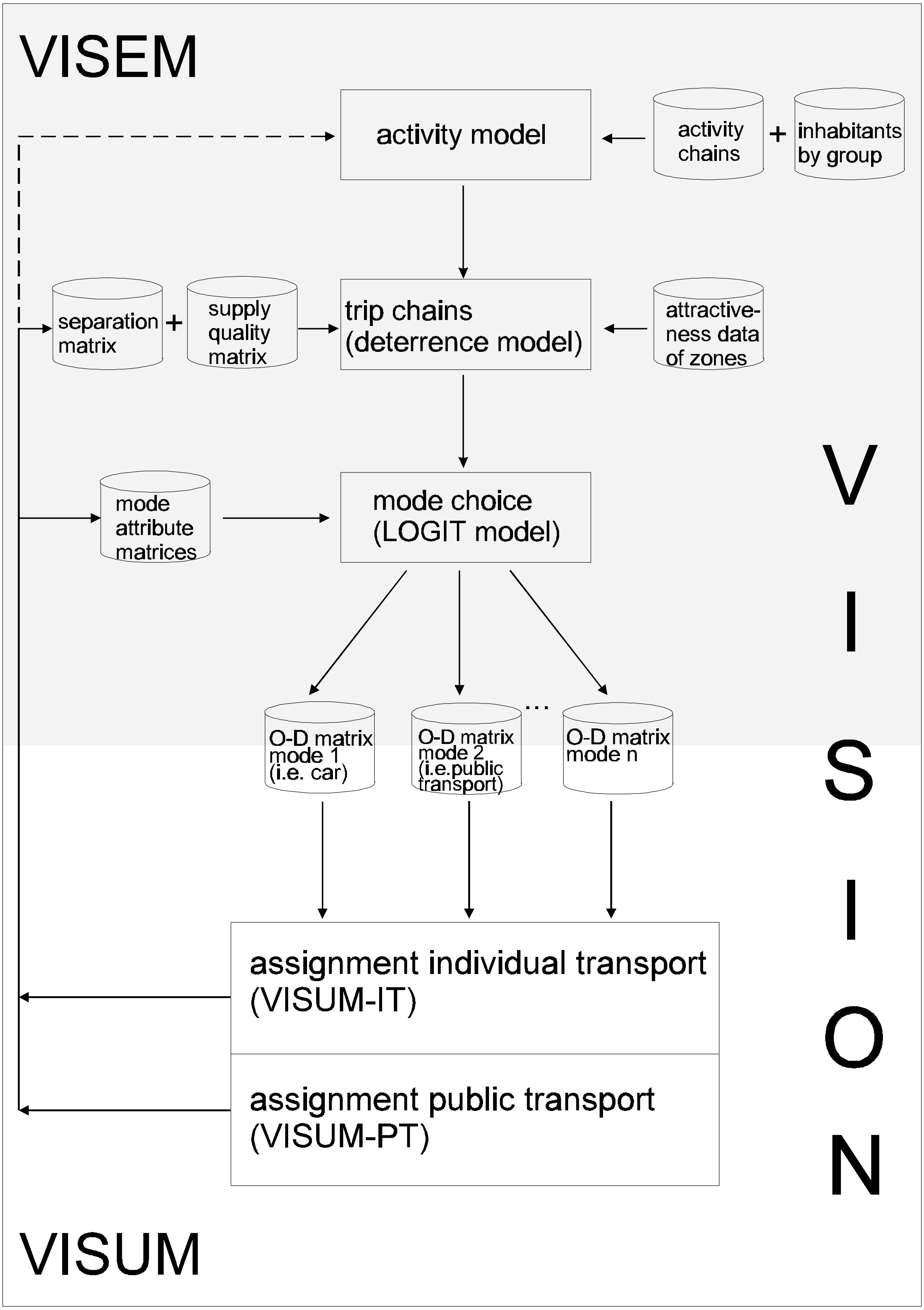
The **activity model** creates mobility derived from activity chains. The result is a set of daily mobility programs, distinguished by the residence zones. Input of this sub-model are activity chains and their probabilities derived from travel diaries, as well as socio-demographic data on a zonal basis that is used to evaluate the relevant number of persons of all population groups.

The second sub-model transfers activity chains into **trip chains**. A trip chain is a consistent sequence of trips between zones. A deterrence model is applied to allocate activities to specific destination zones. The deterrence function is based upon various input data (i.e. activity specific attractiveness for each zone and transport related data like separation and quality of supply for each OD-pair).

The trip chains have to be split into different modes of traffic (**mode choice**), which is done by a multinomial LOGIT model. Mode attributes like travel times, travel cost and travel quality measures are considered.

Mode specific OD-tables are the result of VISEM. These matrices are used by the assignment models, called VISUM-IT and VISUM-PT, to compute route choice and traffic flows. Furthermore VISUM produces various network and spatial data which are directed as input to VISEM. Therefore supply information directly interferes with the demand estimation. Normally modal split variations and destination choice effects are estimated, but induced changings of the activity patterns can be modelled as well.

Fig. 1: Scheme of VISEM and its Interaction with VISUM



Only essential data is shown to present the main modelling techniques, rather than a complete documentation. Whenever the KONTIV is mentioned as source of data, the nationwide transportation survey of Germany is meant. This activity-based travel diary has been carried out in 1976, 1982 and 1989 with a sample size of about 20.000 households including 40.000 persons above 10 years (1989: over 6 years).

1.2 Population Segments: Behaviourally Homogeneous Groups

Whereas previous models such as ORIENT (Sparman 1980) simulate persons as individuals, VISEM uses groups of persons as the primary unit. Using this basis, computation time is reduced and accuracy increases. These groups are person-categories that differ significantly by their specific travel behaviour, whereas members of the same group should show quite identical travel behaviour. VISEM processes each model step separately for each group. The following two tables show a typical classification of the population into groups by employment/education and car availability. 18 years is the minimum age to receive a driver licence in Germany. The parameters listed for each group illustrate the different travel behaviour of the specified groups. The chosen groups are similar to those proposed by Schmiedel (1984).

Tab. 1 : Example of a Group Classification

• Employee having car availability	E+c
• Employee without car availability	E-c
• Not employed having car availability	NE+c
• Not employed without car availability	NE-c
• Students younger than 18 years	St<18
• Apprentices	Appren
• Students 18 years old or older	St.18

Tab. 2: Population Groups and Their Travel Behaviour

Group	Average values by behaviourally homogeneous group			
	Number of trips per day	Trip length per single trip in km	Mainly used mode of transport * (in % of daily trips)	Main activity ** (in % of daily trips)
E+c	3.2	12.8	car (73%)	job (28%)
E-c	2.9	7.5	foot (35%)	job (27%)
NE+c	3.2	8.3	car (60%)	shopping (22%)
NE-c	2.4	4.3	foot (56%)	shopping (26%)
St<18	2.9	4.8	bike (36%)	education (29%)
Appren	3.0	10.6	car (26%)	education (17%)
St.18	3.1	10.6	car (27%)	education (21%)

* : out of 6 possible: foot, bicycle/moped, motorbike, car, car passenger, public transport

** : out of 8 possible (without 'home'): job, business, education, shopping, economic activity, pick up/drop off someone, private purpose/recreation, service

See Tab. 1 for group abbreviations.

Data source: KONTIV '89, Germany, persons ≥ 10 years, monday - friday. Own calculations.

The distribution of the total number of inhabitants of a zone into several behavioural homogeneous groups cannot be determined from the local registration data which are available through local German authorities. But the shares of each group can be estimated from available data elements, e.g. from the year of birth (age structure of a zone), with the help of an allocation of age and group that has to be determined from an empirical survey (e.g. in table 3 from KONTIV ‘89).

Tab. 3: Allocation of Age and Group

Female population							
	Group quota by age group in %						
Age group	E+c	E-c	NE+c	NE-c	Appren	St<18	St.18
10-17		2.1		0.8	11.8	85.4	
18-24	15.3	16.6	2.0	6.8	15.0		44.4
25-59	30.0	27.4	11.9	24.9	0.7		5.0
> 60	0.5	2.0	8.2	89.3			
Male population							
	Group quota by age group in %						
Age group	E+c	E-c	NE+c	NE-c	Appren	St<18	St.18
10-17	1.4			0.5	9.8	88.4	
18-24	19.6	11.8	0.9	2.8	16.3		48.6
25-59	71.7	12.0	3.8	4.1	1.0		7.4
> 60	13.0	1.3	41.2	44.5			

See Tab. 1 for group abbreviations.
Data source: KONTIV ‘89, (towns ≥ 200.000 inhabitants). Own calculations.

Table 3 shows a (4,7)-matrix (age classes, groups) for male respectively female population. If separate age statistics (male respectively female population) of all N zones are available as a (N,4)-matrix (zones, age classes) the zonal number of persons by group results as a (N,7)-matrix from the following matrix multiplication:

(zones, groups) = (zones, age classes) x (age classes, groups).

Unfortunately this formula does not consider detailed information on the degree of motorization of groups. If the number of licensed cars is known for each zone or for macro-zones the (age, group)-matrix can be changed such that in each zone the number of inhabitants E+c and NE+c equals the number of licensed cars in that zone. The calculation procedure is rather simple. For each macro zone a special (age, group)-matrix is generated where the share E+c compared to the share E-c and NE+c compared to NE-c is proportionally adapted according to the ratio of motorization, which already had been obtained by an initial matrix multiplication.

1.3 Trip Generation: Chains of Activities

An activity is defined as an occupation of a person carried out at one location. A chain of activities describes the order of different activities during a person´s run of the day, starting and ending at home, e.g. the chain *Home - Job - shOpping - Home* (*HJOH*). Such an order of activities implies movements from one site to another; e.g. from *HJOH* three trips result: *HJ*, *JO*, *OH*.

In general it is necessary to reduce the huge number of empirical activity chains of a travel diary (as e.g. in table 4) for the model input. On the one hand chains with low reported probability (specially chains of exceeding length) shouldn't be respected. On the other hand the empirical frequencies of activities and their order within chains must be represented in the model. An heuristic procedure is applied to transform the empirical mobility of travel diaries to a reduced set of selected activity chains. Even if VISEM does not limit chain length, computation time is the main reason to drop chains of exceeding length and low probability.

VISEM requires the group specific probability for each activity chain (see table 4). This value states the probabiltity that the activity chain is carried out by a group member at an average day (in %). Note that the probability sum of a column will well exceed 100% since many persons leave home more than once a day.

Tab. 4: Some activity Chains and Their Probabilities

	E+c	E-c	NE+c	NE-c	St<18	Appr	St≥18
HJH	74.30	62.47	8.01	2.69	1.11	31.25	9.52
HVH	0.00	0.00	0.00	0.00	0.00	47.88	0.00
HOH	17.72	24.67	63.35	60.37	12.40	10.56	21.89
HUH	0.00	0.00	0.00	0.00	0.00	0.00	51.08
HPH	27.46	22.65	53.56	37.99	41.05	37.28	36.42
HSH	0.99	2.03	1.13	0.62	79.85	0.00	0.00
HJJH	2.68	0.99	0.28	0.04	0.11	0.43	0.18
HJOH	4.49	6.59	0.85	0.28	0.26	1.77	0.66
HJPH	1.35	0.95	0.19	0.01	0.08	0.98	0.90
...							
HOOH	0.74	0.77	4.71	3.31	0.26	0.34	1.42
HOUH	0.00	0.00	0.00	0.00	0.00	0.00	0.44
HOPH	0.54	0.95	2.60	1.53	0.47	0.62	0.99
...							
HJJJH	2.12	0.59	0.19	0.00	0.00	0.18	0.13
HJJOH	0.10	0.05	0.03	0.00	0.00	0.00	0.04
...							
HJPJPH	0.02	0.07	0.00	0.00	0.00	0.16	0.00
...							

See Tab. 1 for group abbreviations.
Activity abbreviations within chains: H=Home, J=Job, O=shOpping, P=Private, S=School, U=University, V=VocatSchool.
Data source: KONTIV '89, persons ≥ 10 years, monday - friday. The whole sample has about 300 different activity chains.

Each activity chain specifies a frequency of trips per person and their order in the model. The complete set of activity chains determines the mobility per person (i.e. number of trips and number of different activities per head) and the allocation of trips to different trip chains. The total number of trips and of trip chains generated by VISEM depends on the given structure of inhabitants of each zone and on the mobility that is given by the set of activity chains by group.

Example: If zone 1 includes 200 employed persons having car available (E+c), their mobility will be calculated as follows: According to the activity chain distribution listed above they run through the activity chain *HJOH* with 4.49 % probability daily. This means 200 * 4.49 % = 8.98 trips *HJ*, and *JO* and *OH* as well. Thus the 200 E+c in zone 1 generate 3 * 8.98 = 26.9 (rounded 27) trips by this specific activity chain. Considering the probabilities of other activity chains for each group and each zone there can be determined exactly how many trips result from which activities.

1.4 Trip Distribution: Activities + Destination Choice = Trip Chains

Considering the destination activity of each trip VISEM allocates destination zones to the trips. The choice of a destination zone depends on the separation (e.g. distance, travel time) between origin and destination zone and on the sensitivity of each activity to separation. This sensitivity to separation is specified in the parameters of the deterrence function for each activity and each group.

By choosing destinations the destination choice submodel generates numerous trips from each activity chain; thus the results of trip distribution are a complete trip matrix and the total number of trip chains.

Example from 1.3 continued: The mentioned 9 (exactly 8.98) trips of the activity pattern *HJ* have to lead from the origin zone (zone 1) to possible destination zones (with places of work). For these 9 trips VISEM chooses destination zones according to the destination choice model which is described later on. To simplify matters here zone 2 is the destination zone of all trips. Starting from zone 2 after activity *Job* the probability of possible destinations of *JO* (for the destination activity *shOpping*) is calculated (e.g. 40% to zone 3 and 60% to zone 2, which are intra-zonal trips). VISEM multiplies the destination probabilities of possible job and shopping destinations. For the final activity pair within any activity chain (here: *OH*) no destination choice is necessary as the home zone No. 1 is given as the origin zone of the first trip. The example's destination choice can be summarized:
HJ: 100% leaving zone 1 for destination zone 2,
JO: 60% stay within zone 2, and 40 % leaving zone 2 for zone 3,
OH: 100% return to zone 1.

The resulting trip chains and their frequencies are:
1-2-2-1: 8.89 * 100 % * 60 % * 100 % = 3.56
1-2-3-1: 8.89 * 100 % * 40 % * 100 % = 5.33

Thus there have been generated 5 (exactly 5.33) trip chains of the zonal sequence 1-2-3-1 and 4 (exactly 3.56) trip chains 1-2-2-1.

For this choice of destinations within trip chains the model designer must allocate a certain structural quantity (e.g. from land use statistics) to each activity. This quantity represents the attractiveness of zones for trips of that activity.

Tab. 5: Examples of Activities and Correspondent Zonal Attractiveness

Activity	Destination of activity (opportunity)	Numerical attractiveness Z_i can be represented by
Job ('J')	Firms, work places	Number of jobs
shOpping ('O')	Shopping centres ...	Retail floor space
Recreation ('R')	Recreational opportunities	Capacity of recreational areas or: How often a zone has been mentioned as destination of recreational trips in a transportation survey.
School ('S')	School places	Number of students < 18 years, enrolled
University ('U')	Vocational training schools, universities ...	Number of students >18 years, enrolled
Priv. activities ('P')	Private and social opportunities	Number of inhabitants

The deterrence of the destination choice is modelled by the following function. P_{ij} specifies the probability that zone j will be chosen among all destination alternatives as the destination zone for trips originating in zone i, by:

$$P_{ij} = \frac{D_j \cdot f\left(w_{ij}\right)}{\sum_{k=1}^{B}\left(D_k \cdot f\left(w_{ik}\right)\right)}$$

$$F_{ij} = O_i \cdot P_{ij}$$

with

F_{ij} No. of trips from zone *i* to zone *j*

P_{ij} probability for choice of destination *j* for trips originating in zone *i*

O_i originating trips from zone *i*

D_j attractiveness of zone *j*

$f(w_{ij})$ deterrence function with:

$$f\,(w_{ij}) = e^{a w_{ij}} \cdot w_{ij}{}^{b}$$

with

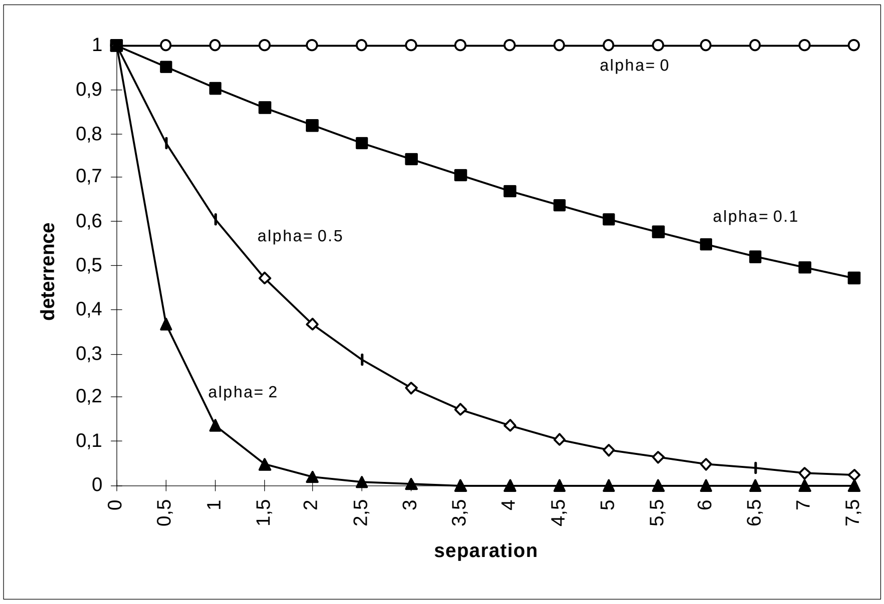
w_{ij} separation from zone *i* to zone *j* (distance, travel time, generalized cost)

a, ˏ parameters (‘alpha-parameter’, ‘beta-parameter’)

B Set of zones (with k=1 as first zonal index)

If ˏ = 0 (what is usually supposed) we get Wilson’s entropy-maximizing deterrence function. Then the specification of parameter a is decisive for the choice of destination zones and describes the sensitivity to separation. If $a = 0$ (and = 0 as well) separation w_{ij} will not influence the destination choice.

Fig. 2: Pattern of the Deterrence Function with Different Alpha-Parameters



VISEM provides specification of alpha-parameters for each combination of *group*, *activity* and *supply quality class*.

Surveys of travel behaviour show that persons with a car available cover longer distances than persons without cars which means that the alpha-parameters of population groups using a car (E+c and NE+c) have to be lower than those specified for groups without cars (E-c or NE-c). Based on empirical evidence the alpha-parameter specified for the activity *Job* has to be lower than that for activity *shOpping*.

Each OD-pair has to be classified according to supply quality. In most VISEM-applications for this classification the public transport service quality is considered (headway and frequency of changings). Using this method VISEM includes transport supply data in the destination choice submodel. Classification-dependent increasing alpha-parameters should be specified for groups without car (e.g. E-c, NE-c or St<18), as the separation sensitivity of these groups declines with increasing service quality. But the alpha-parameters of groups with cars (e.g. E+c and NE+c) do not depend on the PT supply quality.

Tab. 6: Alpha-Parameters of the Deterrence Function (Example)

	Supply quality classes			
	1	2	3	4
group E+c:				
Job	0.15	0.15	0.15	0.15
Shopping	0.34	0.34	0.34	0.34
Private	0.23	0.23	0.23	0.23
group E-c:				
Job	0.18	0.28	0.38	0.48
Shopping	0.38	0.49	0.60	0.71
Private	0.25	0.35	0.45	0.65

See Tab. 1 for group abbreviations.
Four supply quality classes reflect public transport quality in this example (measured in heqadway and number of changes): 1=excellent, 2=good, 3=exceptable, 4=poor.

VISEM can read activity-specific separation matrices. These matrices can be based upon distances, travel times or generalized costs. These basic units of separation can reflect different transport supply situations and as such show destination choice effects of supply variations.

1.5 Choice of Transport Mode: The LOGIT Model

After trip generation and trip distribution total travel demand is available as trip chains with exactly specified origin and destination zones. During the next model step this demand is allocated to the various transport modes. Conventional modal split models subdivide the total demand according to aggregated transport system attributes; such models are hardly able to represent individual choice behaviour. VISEM applies a behaviour-orientated approach which considers three aspects in mode choice:

- the socio-economic situation, specially car availability of the decisive persons (by population group),
- different attributes of the transport mode alternatives (via an utility function),
- choice restraints within a trip chain (as there are defined exchangeable and not-exchangeable modes).

This problem of decision is represented by a multinomial LOGIT model, which states the probability of mode choice for any given trip chain. Therefore the group-specific utility has to be known which depends on transport mode attributes (travel time, access and egress time, fare etc.). For a specified group *g* this model shows the following functionality in VISEM:

$$P_{gij}(m) = \frac{e^{U_{gij}(m)}}{\sum_{k=1}^{M} e^{U_{gij}(k)}}$$

with:

i, j	indices of zones
m	index of mode (M= total number of modes)
$P_{gij}(m)$	group-specific probability to choose transport mode m for the trip from i to j
$U_{gij}(m)$	group-specific utility if transport mode m is chosen to get from i to j

with utility formula:

$$U_{gij}(m) = -p_{1gm} * \boldsymbol{T}_{ij}(m) - p_{2gm} * \boldsymbol{Z}_{ij}(m) + p_{3gm} * log_e(\boldsymbol{D}_{ij} / p_{4gm}) - p_{5gm} * \boldsymbol{C}_{ij}(m) + p_{6gm} + p_{7gm} * \boldsymbol{A}_{ij}(m)$$

with mode attributes:

$\boldsymbol{T}_{ij}(m)$	travel time from *i* to *j* by tranport mode *m*
$\boldsymbol{Z}_{ij}(m)$	sum of access time in *i* and egress time in *j* for transport mode *m*
$\boldsymbol{C}_{ij}(m)$	travel cost from *i* to *j* by transport mode *m*
$\boldsymbol{D}_{ij}$	distance from *i* to *j*
$\boldsymbol{A}_{ij}(m)$	additional supply attribute (e.g. parking facilities) for *m*

and with LOGIT parameters (by group *g* and transport mode *m*):

p_{1gm}	marginal utility of 1 minute travel time
p_{2gm}	marginal utility of 1 minute access or egress time
p_{3gm}	marginal utility of logarithmic relative distance increase (impact of “advantage-distance“)
p_{4gm}	“advantage-distance” of transport mode *m*
p_{5gm}	marginal utility of 1 monetary unit of fare
p_{6gm}	constant utility of transport mode *m*
p_{7gm}	marginal utility of 1 unit of the additional supply attribute

Travel times $\boldsymbol{T}_{ij}(m)$ are given by the network and assignment model VISUM. For public transport it is recommended to use a travel time matrix including the time required for changings and/or delay (but no access and egress time data). If schedules differ in the course of the day a matrix with average values could be used, e.g. from representative peak and off-peak periods. From the calibrated VISUM road network travel time data can be calculated after assignment, such that the modal effects of road capacity restraints can be estimated.

Accessibility of modes of transport at trip origin and at trip destination is considered by access and egress time $\boldsymbol{Z}_{ij}(m)$.

By the mid-eighties costs $\boldsymbol{C}_{ij}(m)$ have rarely been considered in urban traffic demand models, as scientists and professionals agreed upon the indifference of transport costs to the urban modal split. However, fare variations are considered today; thus political and economic changes, e.g. road pricing or increasing parking costs or public transport fares, can be represented by the model. Therefore basic costs (by travel time unit or by distance unit) have to be specified. Usually it is confined to “out-of-pocket” cost.

In addition to costs another attribute of modes $\boldsymbol{A}_{ij}(m)$ can be included in the mode choice model (LOGIT parameter p_7). So if required the user can take frequency of service and/or delays (public transport) or parking costs and/or permitted maximum speed (car) into consideration. As well as travel time or costs this additional attribute must be included as an OD-table.

Parameter p_4 is called "advantage-distance" because it specifies how long (in meters) a trip must be so that distance has a positive impact on utility. In case of distances $D_{ij} > p_4$ the quotient D_{ij} / p_4 will be > 1, and thus the logarithmic term $log_e(D_{ij} / p_4)$ will be a positive value. For this reason the formula $log_e(D_{ij} / p_4)$ has a point of inflexion at $D_{ij} = p_4$ that makes distance utility influence decreasing for $D_{ij} < p_4$ and increasing for $D_{ij} > p_4$.

In VISEM the available modes of transport are subdivided into exchangeable (usually foot, car passenger, public transport) and not exchangeable ones (car, bike). For the first trip of a trip chain VISEM calculates the LOGIT model. So one of the available modes is chosen. If an *exchangeable* mode of transport has been chosen for the first trip the choice of transport mode will be calculated for each following trip of the chain among all exchangeable modes of transport. If a *not exchangeable* mode is chosen for the first trip it will be maintained and no further mode choice will be calculated for the rest of the trip chain.

1.6 Determination of Trips' Day Time

VISEM calculates time-of-day matrices (e.g. a peak hour matrix) based upon time patterns which represent the temporal distribution of activities during the day.

The VISEM format of such time patterns (see table 7) consists of 2 activitiy abbreviations (2 letters) which represent the „change" from the one activity to the other; these two letters are followed by 24 figures, that indicate the probabilities of the specified change of activities over 24 hours.

Tab. 7: Day Time pattern of Activity Pair Home-Job

day time	0	1	2	3	4	5	6	7
probability HJ in %	0.1	0.0	0.1	0.4	1.2	6.9	24.2	33.2
day time	8	9	10	11	12	13	14	15
probability HJ in %	12.2	3.4	1.6	0.8	2.2	4.6	3.5	1.6
day time	16	17	18	19	20	21	22	23
probability HJ in %	0.9	0.9	0.7	0.6	0.3	0.3	0.1	0.1

See Tab. 2 for activity abbreviations.
* Relevant moment: Start of trip to next activity (0 = 00:00 - 00:59 o´clock)
Data source: KONTIV '89, persons ≥ 10 years, monday - friday.

From the pattern *HJ* in table 6 the following information on behaviour can be received: Most of the trips *Home-Job* occur between 6:00 h and 8.59 h: During these 3 hours of the day 24,2% (6:00-6:59 h), 33,2% (7:00-7:59 h) and 12,2% (8:00-8:59 h) of all trips *HJ* are travelled. The importance of trips (employed persons) back home for lunch and back to job again is not significant. Not more than 4,6% and 3,5% of trips *HJ* have been recorded for the periods between 1:00 pm and 1:59 pm respectively 2:00 pm and 2:59 pm, which can be regarded as trips back to the job after a lunch break at home.

1.7 Model Dimensions and Computing Time

Model is processed separately for each group. In middle and large applications (> 100 zones) the computing time is mainly influenced by the number of zones and the number and length of activity chains. Complexity is then $O(n^3)$ with n = number of zones. For the following applications computing time has been measured on a Pentium (90 Mhz):

Tab. 8: Dimensions and Computing Time of Different VISEM Applications

	Model dimension as number of									Computing time in min.		
Study area	zones	groups	acti-vities	modes	(#activity chains * #groups)** l=2*	l=3*	l=4*	l=5*	all*	full calcul.	dest. choice	mode choice
Hannover City	373	8	9	5	31	35	0	0	66	31	18	13
Hannover surroundings	373	8	9	5	29	36	0	0	65	31	17	14
Cologne	222	8	9	5	31	34	0	0	65	6	3	3
St. Gallen	187	7	7	5	22	42	45	42	151	24	20	4
Halle	319	8	8	5	31	73	0	0	104	30	21	9
Leipzig	150	7	9	5	36	87	0	0	123	3	2	1
Prague	198	7	7	5	34	82	0	0	116	7	5	2
Izmit, Turkey	62	8	7	5	28	27	8	0	63	0.5	0.3	0.2

***** l = length of chain (e.g.: HXXH describes three trips, so l=3)
******: Is the number of all activity chains with a probability > 0, summed up over all groups.

2. CALIBRATION OF THE MODEL

2.1 Calibration of Alpha-Parameters and Separation Matrices

The deterrence function described in Chapter 2.1.3 $f(w_{ij}) = e^{-a w_{ij}} * w_{ij}$ weightens the attractiveness of each zone for determination of the specific destination traffic. The alpha-partameters inherent to the function have to be specified by the user for each combination of group, activity and supply quality class. In the calibration of the destination choice model empirical data of real travel demand should be considered. Calibration of alpha-parameters should be based upon a distance distribution of trips or a travel time distribution as well as upon empirical OD-data (e.g. commuters matrices generated from census data). As VISEM's destination choice is activity-based, the calibration should be performed with single consideration on the subset of trips to one specific activity (one by one).

The deterrence function parameters can be evaluated by weighted linear regression based on a travel distance distribution of empirical data. In some VISEM applications separation matrices have been calibrated according to empirical census matrices. This calibration method tries to adaptthe model to grown habits of zomal interaction.

2.2 Calibration of LOGIT Parameters

Seven LOGIT parameters have to be specified in VISEM input data file for each group and each mode of transport. Some of the parameters p_1, p_2, p_3, p_5 can be specified = 0 according to circumstances (if it is assumed that the respective transport mode attribute as e.g. access and egress time or costs is without any influence).

There are two possible methods for LOGIT parameters specification:

1) either using parameter figures from technical literature (see Hautzinger 1978 or Ben-Akiva/Richards 1975) with, if necessary, manual adaption;
2) using a maximum likelihood procedure for analytic estimation of parameters.

The following tables show modal split percentages and relative frequencies of trip length for different modes, both from KONTIV ‘89. Evaluations like these should be used as target values when data are calibrated by hand. VISEM offers tabular and graphical output functions which allow to check intermediate results of individual calibration steps continuously.

Tab. 9: Modal Split of Weekday Traffic

locations . 20.000 inhabitants

in %	E+c	E-c	NE+c	NE-c	St<18	Appren	St.18
foot	9.6	34.9	21.6	54.0	22.6	9.8	9.6
car passenger	5.3	23.8	5.7	16.3	12.4	19.0	12.7
public transport	2.4	16,0	0.7	6.2	28.4	21.1	14.9
car	77.7	3.4	64.8	0.9	0.9	31.1	42.8
bike	5.1	21.9	7.2	22.6	35.7	19.0	19.9

locations 20.000 - 200.000 inhabitants

in %	E+c	E-c	NE+c	NE-c	St<18	Appren	St.18
foot	13.6	37.7	23.8	57.4	30.1	18.2	21.7
car passenger	4.7	17.5	5.0	13.8	10.7	14.8	10.7
public transport	4.4	22.8	3.1	13.8	20.4	15.9	13.1
car	72.7	0.6	62.8	0.7	1.3	31.6	30.5
bike	4.6	21.4	5.2	14.2	37.6	19.5	24.0

locations . 200.000 inhabitants

in %	E+c	E-c	NE+c	NE-c	St<18	Appren	St.18
foot	10.7	30.0	25.6	53.8	30.8	19.5	16.5
car passenger	4.0	13.2	3.8	11.6	9.1	6.1	6.6
public transport	6.0	39.2	4.5	22.6	24.2	32.4	26.7
car	74.8	0.8	59.0	0.3	1.2	26.2	24.8
bike	4.5	16.8	7.0	11.8	34.7	15.8	25.4

Data source: KONTIV ‘89, persons . 10 years, monday - friday. Own calculations.

Tab. 10: Relative Frequency of Distances by Mode of Transport for Group E+c

trip length	relative frequency per transport mode (in %) foot	bike	car	car passenger	public transport	all
0 - 0.5 km	40.0	4.1	1.1	1.2	0.1	5.3
0.6 - 1 km	33.0	18.4	3.2	4.6	0.6	6.9
1.1 - 2 km	13.3	25.0	7.9	7.1	4.1	9.0
2.1 - 5 km	8.8	42.7	27.2	29.7	31.9	27.1
5.1 - 10 km	4.9	5.6	27.9	26.5	33.9	24.8
10.1 - 15 km		3.5	13.1	16.8	14.1	11.4
15.1 - 20 km		0.4	5.8	3.3	4.4	4.8
> 20 km		0.5	12.7	10.7	10.1	10.7
Total	100.0	100.0	100.0	100.0	100.0	100.0

Data source: KONTIV '89, persons . 10 years, monday - friday, locations . 200.000. Own calculations.

These tables show the average modal split of West German municipalities. It is clearly to be seen that the share of public transport increases with increasing number of inhabitants, even in case of groups +c (car available). But studies in several towns also proved that modal split values may differ significantly between locations of the same size. This may be caused by different quality of public transport service and by the different quantity of parking facilities available in the municipal centres or by a different degree of motorization etc. That is why the modal split data listed above should not be used as a basis for VISEM calibration. If possible a specific local survey should be performed.

LOGIT parameters can also be determined by a maximum likelihood estimation. Appropriate software is available. The problem arising from empirical data, resulting from activity-based surveys (according for instance to the German KONTIV standard) is the following: persons who have to indicate the used transport mode will specify the attributes of the used transport mode only but not the attributes of the transport mode alternatives. Thus for a maximum likelihood estimation the attributes of the alternatives which have not been chosen have to be determined additionally. Past experience has shown that the real situation of decision cannot be modelled exactly in most cases. This leads to insufficient estimation results. New survey methods (stated-preference surveys) have been developed which especially focus on the attributes of all alternatives. Thus parameter estimations can be based upon reliable data and the quality of forecasts will increase for situations tested by stated preference surveys.

3. FORECAST AND SCENARIO CALCULATION WITH VISEM

Statements concerning future development of the current transport system are the objective of every traffic forecast. Here the development of transport supply as well as the evolution of traffic demand should be considered. With VISEM demand forecasts can be calculated which result from structural data modifications according to the current trends in reality (called *forecast* in the following). Such modifications of structural data may be caused by increasing motorization or by spatial displacements as well as by demographic shiftings. Furthermore VISEM can generate future mobility which shows the travel demand responding to a modified supply (new transport systems, increased quality, additional relations, improved connections; called *scenario* in the following).

A traffic forecast is based upon the VISEM model, which has been calibrated for the analysis of the current state. According to the objectives of forecasts or scenarios, specific elements of these input data (which originally refered to the current state) are replaced by forecast or scenario data. Then VISEM calculates forecast matrices from the forecast input data.

3.1 The Use of Demographic Forecasts

Local authorities offer statistics and demographic predictions on changes in the number of inhabitants and in the shares of different age classes considering birth- and death rates, the probabilities of future births and deaths as well as rates of immigration and/or migration. Using an approach based upon behaviourally homogeneous groups VISEM is able to model direct effects of demographic shiftings on travel demand and traffic generation.

Tab. 11: Modelling Socio-economic Shiftings

Demographic forecast (No. of inhabitants, age, zones)	→	New group shares derived by zone	→	VISEM: effect modelled in travel demand and traffic generation
Superannuation within certain residential areas respectively zones	→	Relatively increasing number of less-mobile groups	→	VISEM: Decline of the originating traffic
New residential areas	→	Increasing number of inhabitants within these zones	→	VISEM: Increase of originating traffic
Relatively increasing number of 20 - 40-years-old persons in the study area	→	Absolutely increasing number of groups of highest mobility	→	VISEM: Increasing originating traffic from all zones

From this the advantage of the population-group-orientated approach, as it is applied in VISEM, can directly be seen: A demographic forecast (inhabitants by age and zone) performed according to the procedure described in Chapter 1.2 produces data on number of inhabitants by group; from this future distribution of population groups VISEM calculates traffic generation and choice of transport modes.

3.2 Spatial Shifting Resulting from New Land Use Patterns

Based upon new zonal attractiveness (e.g. industrial sites, shopping centres etc.) the future distribution of trip destinations can be forecasted with the help of VISEM.

3.3 Example: Scenario „Ecological Traffic Policy”

A description of some general ideas for scenario calculation with VISEM follows. The following scenario approach listed in the table does not much modify behavioural parameters such as alpha-parameters or LOGIT parameters; such modifications would be caused by real changes of population behaviour but can hardly be predicted in a serious maner. On the contrary, the question posed: What travel demand modifications can be caused by optional measures in the field of transport supply in the case of constant traffic behaviour, as it has been stated in the parameters of the current model.

Tab. 12: Modelling the Demand Effects of Modified Supply

Mode of transport	Change in transport supply	Modelling the supply changes within VISEM
Public transport	Improved accessibility of stops in/from specified zones	Reduce access and egress time of from/to these zones
Public transport	Acceleration (bus lanes, priorities), additional lines, e.g. tangential lines on OD-pairs which are demanded most	Reduced public transport travel time, either obtained from a future VISUM-PT network model (lines and/or scedule) or obtained by processing current travel time matrix)
Motorized individual traffic	Limitation of parking facilities in and car-accessability to the downtown area	Increase access and egress times of the respective central zones
Motorized individual traffic	Speed limits (30 km/h) in residential areas	Increase travel time for intrazonal trips in zones which are residential areas
Bike	Offer sufficient parking facilities for bikes within the downtown area	Reduce access and egress times of the zones concerned
Bike	Increase attractivity by improved safety measurements on all roads	Increase LOGIT parameter p_6.
Foot, Bike	Abolish hindrances, Priority at junctions	Increase basic speed or reduce travel time required by OD-pair and transport mode

ACKNOWLEDGEMENTS

This paper evolves from the work carried out in Germany by various institutions over the past two decades. A literature review is given by Axhausen/Herz 1989. The authors are grateful for the substantial work and the ideas brought by our collegues.

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