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ACTIVITY-BASED APPROACHES TO TRAVEL ANALYSIS

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PERGAMON

3

PTV VISION: ACTIVITY BASED DEMAND FORECASTING IN DAILY PRACTICE

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INTRODUCTION

An activity-based approach to travel demand modelling is continuously applied in various German and some European transportation planning studies. The model is implemented in a software system called VISEM. VISEM is part of the urban and regional transportation planning system PTV VISION (Visual Information System for Interactive Optimisation of Networks). PTV VISION has been developed to assist transportation planners in finding solutions by testing networks with quick response methods and to estimate mode specific traffic volumes in a more realistic manner than presently done using conventional four step models. VISEM estimates and forecasts mode specific origin-destination matrices (OD-Tables). The two basic ideas of VISEM are the classification of the population into behaviourally homogeneous groups (person categories) and the generation of trip chains derived from activity chains. Disaggregated household survey data is classified into clusters of behaviourally homogeneous groups to eliminate computational burdens and to ease calibration. VISEM includes a set of models in one system. The most important ones are (i) *daily mobility patterns* derived from activity chains distinguished by residence zones and behaviourally homogenous group; (ii) *trip chains* derived from the mobility patterns and a deterrence model to allocate activities to specific destination zones; (iii) nested *logit mode choice* to split the trip chains into specific modes taking into account exchangeable and non-exchangeable modes. Whereas activity chains and their advantages for transport planners are well documented in the scientific literature, there are no other models known to the authors applying these techniques for practitioners. VISEM tries to fill this gap.

MODEL DESCRIPTION

Rather than a complete documentation, only essential data are shown to present the main modelling techniques. Whenever the KONTIV is mentioned as a source of data, the nation-wide transportation survey of Germany is meant. This activity-based travel diary has been carried out in 1976, 1982 and 1989 with a sample size in 1989 of about 20.000 households, 40.000 persons and 120.000 trips.

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.

Table 1
Population Groups and their Travel Behaviour

Group		Average values by behaviourally homogeneous group					
		trips per day	Mean of trip length in km	Mainly used mode of transport * (in % of daily trips)		Main destination activity ** (in % of daily trips)	
E+c	employee with car availability	3.2	12.9	car	(73%)	job	(50%)
E-c	employee without car availability	3.1	7.6	foot	(30%)	job	(47%)
NE+c	non-employee with car availability	3.1	9.1	car	(56%)	shopping	(50%)
NE-c	non-employee without car availability	2.6	4.5	foot	(53%)	shopping	(59%)
Appr	Apprentices •	3.2	10.7	car	(31%)	education private	(32%) (32%))
Stud	students on high schools	3.2	12.2	car	(32%)	education private	(34%) (35%)
Pupil	pupils, 10 to 19 years	3.0	5.3	bike	(34%)	education	(55%)

* : out of 5 possible: foot, bicycle/moped, car/motorbike, car passenger, public transport
** : without trips back home, out of 5 possible activities:
job, business, education, shopping, private purpose/recreation
Data source: KONTIV '89, Germany, persons ≥ 10 years, Monday - Friday.
Own calculations based on data weights by DIW (1993).

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 modelling step separately for each group. Table 1 shows a typical classification of the population into groups by employment/education and car availability. 18 years is the minimum age to receive a driver license 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).

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. However, the shares of each group can be estimated from available data elements as illustrated in Table 2 for the age structure of a zone.

Table 2
Allocation of Age and Group

	Group quota by age class in % (male population)						
age class	E+c	E-c	NE+c	NE-c	Appr	Stud	Pupil
-17	0,2	0,2	0,0	0,7	6,9	1,3	90,7
-24	22,1	12,7	1,6	2,3	16,3	31,1	13,9
-34	54,6	12,5	1,6	2,8	2,1	26,4	0,0
-54	83,0	10,8	2,0	3,6	0,1	0,5	0,0
-64	47,8	5,9	29,2	16,9	0,0	0,3	0,0
+	2,8	0,3	47,8	48,2	0,1	0,7	0,0
	Group quota by age class in % (female population)						
age class	**E+c**	**E-c**	**NE+c**	**NE-c**	**Appr**	**Stud**	**Pupil**
-17	0,0	0,4	0,0	1,5	7,5	1,1	89,4
-24	12,6	20,8	2,2	8,7	11,5	33,1	11,1
-34	25,9	24,3	9,5	21,2	1,7	14,4	0,0
-54	24,2	30,5	8,6	36,1	0,1	0,5	0,0
-64	7,0	12,9	11,1	68,7	0,3	0,0	0,0
+	0,8	1,7	5,5	91,9	0,0	0,2	0,0

See Table 1 for group abbreviations.
Data source: KONTIV '89, Germany, persons ≥ 10 years, Monday - Friday.
Own calculations based on data weights by DIW (1993).

Table 2 depicts a (6,7)-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,6)-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 motorisation of zones. 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 motorisation, which already had been obtained by an initial matrix multiplication.

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, such as for example 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 for model input. On the one hand, chains with low reported probability (specially chains of exceeding length) should not be included. On the other hand, the empirical frequencies of activities and their order within chains must be represented in the model. A 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 3). This value states the probability 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.

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. For 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 * 4.59 % = 9.18 trips *HJ*, and *JO* and *OH* as well. Thus the 200 E+c in zone 1 generate 3 * 9.18 = 27.54 (rounded 28) trips by this specific activity chain. Considering the probabilities of other

activity chains for each group and each zone, one can determine exactly how many trips result from which activities.

Table 3
Some Activity Chains and Their Probabilities

	E+c	E-c	NE+c	NE-c	Appr	Stud	Pupil
HJH	74.54	62.45	8.16	2.82	33.52	10.80	1.88
HVH	0.00	0.00	0.00	0.00	47.62	0.00	0.00
HOH	17.55	25.82	60.55	62.93	12.32	23.76	12.98
HUH	0.00	0.00	0.00	0.00	0.00	45.09	0.00
HPH	26.81	25.52	52.19	39.76	37.69	37.57	40.27
HSH	0.89	1.81	0.96	0.47	0.00	0.00	80.41
HJJH	2.68	0.78	0.13	0.06	0.52	0.16	0.11
HJOH	4.59	7.01	0.96	0.33	1.79	0.80	0.37
HJPH	1.54	1.43	0.18	0.02	0.86	1.56	0.09
...							
HJPJPH	0.03	0.06	0.00	0.00	0.28	0.00	0.00
...							

Activities: H=Home, J=Job, O=shOpping, P=Private, S=School, U=University, V=VocatSchool.
Data source: KONTIV '89, persons ≥ 10 years, Monday - Friday.
Own calculations based on data weights by DIW (1993).
The whole sample has about 300 different activity chains.

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 4) consists of 2 activity abbreviations (2 letters) which represent the change from one activity to another; these two letters are followed by 24 Figures, that indicate the probabilities of the specified change of activities over 24 hours.

From the pattern *HJ* in Table 4 the following information on behaviour can be received: most of the trips *Home-Job* occur between 6:00 hr and 8.59 hr: During these 3 hours of the day 23.9% (6:00-6:59 hr), 32.7% (7:00-7:59 hr) and 12.5% (8:00-8:59 hr) of all trips *HJ* are made.

The importance of trips (employed persons) back home for lunch and back to job again is not significant. Not more than 4.6% and 3.6% of trips *HJ* are recorded for the periods between 1:00 p.m. and 1:59 p.m. respectively 2:00 p.m. and 2:59 p.m., which can be regarded as trips back to the job after a lunch break at home.

Table 4

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	0.3	1.2	6.9	23.9	32.7
day time	8	9	10	11	12	13	14	15
probability HJ in %	12.5	3.6	1.7	0.9	2.2	4.6	3.6	1.7
day time	16	17	18	19	20	21	22	23
probability HJ in %	1.0	0.9	0.7	0.6	0.2	0.4	0.1	0.1

* Relevant moment: Start of trip to next activity (0 = 00:00 - 00:59 o'clock)

Data source: KONTIV '89, persons ≥ 10 years, Monday - Friday. Own calculations based on data weights by DIW (1993).

Trip distribution: activities + destination choice = trip chains

To determine 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, to continue our example, the results of trip distribution are a complete trip matrix and the total number of trip chains.

To continue our example, for these 9.18 trips of the *HJ* activity pattern, VISEM chooses destination zones according to a 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 inner 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 as *HJ* (100% leaving zone 1 for destination zone 2); *JO* (60% stay within zone 2, and 40 % leaving zone 2 for zone 3), and *OH* (100% return to zone 1). The resulting trip chains and their frequencies are 1-2-2-1 (9.18 * 100 % * 60 % * 100 % = 5.51); 1-2-3-1 (9.18 * 100 % * 40 % * 100 % = 3.67). Thus 5.51 trip chains of the zonal sequence 1-2-3-1 and 3.67 trip chains 1-2-2-1 are generated. For this choice of destinations within trip chains, the model designer must allocate a certain structural quantity (e.g., statistical data from land use studies) to each activity. Number of jobs, retail floor space, recreational attractiveness and student enrolment are typical factors to quantify zone attractiveness (see Table 5 for

examples). 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:

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

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

where,

F_{ij}	is the number of trips from zone i to zone j;
P_{ij}	is probability for choice of destination j for trips originating in zone i;
O_i	is the number of trips originating from zone i;
D_j	is the attractiveness of zone j;
$f(w_{ij})$	is the deterrence function, where:

$$f(w_{ij}) = e^{\alpha w_{ij}} \cdot w_{ij}^{\beta}$$

where,

w_{ij}	separation from zone i to zone j (distance, travel time, generalized cost);
α, β	deterrence parameters ('alpha-parameter', 'beta-parameter');
B	set of zones (with $k=1$ as first zonal index).

If $\beta = 0$ (what is usually assumed) the result is Wilson's entropy-maximising deterrence function. Then the specification of parameter α is decisive for the choice of destination zones and describes the sensitivity to separation. If $\alpha = 0$ (and $\beta = 0$ as well) separation w_{ij} will not influence the destination choice.

A specific of deterrence parameters for each combination of group, activity and supply quality class is used by VISEM. Surveys of travel behaviour show that persons with a car available cover longer distances than persons without cars which means that the α-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 applications, the public transport service quality is considered (headway and frequency of changing).

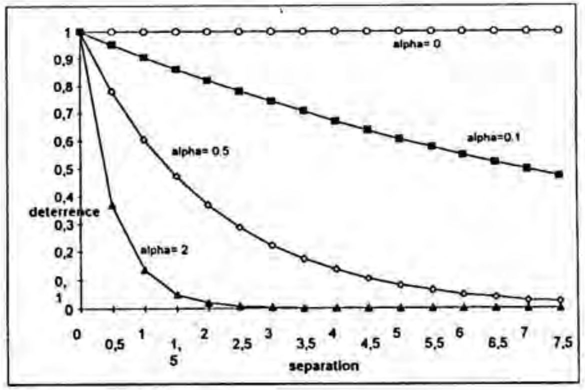

Figure 1
Deterrence Function with Different Alpha-Parameters

Using this method transport supply data are included in the destination choice submodel. Classification-dependent increasing alpha-parameters should be specified for groups without car (e.g., E-c, NE-c or Pupil), 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 public transport supply quality.

Table 5
Alpha-parameters of the deterrence function (example)

	Public transport 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

Four supply quality classes reflect public transport quality in this example (measured in headway and number of changing): 1=excellent, 2=good, 3= acccpTable, 4=poor.

The calibration of the destination choice model, requires empirical data of real travel demand. 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). 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 trip length distribution of empirical data. This calibration is an iterative procedure and is similar to FHWA (1977). The OD-values of the separation matrix are classified into K intervals. For each class k an average deterrence value f_k is computed with an average separation value of each class.

$$f_k(n) = f_k(n-1) \cdot \frac{F_k}{\sum_k F_{ij}(k)}$$

where,

$f_k(n)$	is the value of the deterrence function in iteration n;
F_k	is the number of trips in class k (empirical distribution);
$\sum_k F_{ij}(k)$	is sum of all trips in class k (computed distribution).

Using linear regression over all separation classes, the best fitting α- and β-values of the deterrence function are computed.

Activity-specific separation matrices are used by the model. These matrices can be based upon distances, travel times or generalised costs. These basic units of separation reflect different transport supply situations and as such show destination choice effects of supply variations. In some applications, separation matrices have been calibrated according to empirical census matrices. This calibration method tries to adapt the model to grown habits of zone interaction.

Mode choice: the LOGIT model

After trip generation and trip distribution, the 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 behavior. VISEM applies a behaviour-orientated approach which considers: the socio-economic situation, especially car availability of the decisive persons (by population group); different attributes of the transport mode alternatives (via utility function), and choice constraints within a trip chain (as there are defined exchangeable and not-exchangeable modes).

This decision problem is represented by a multinomial LOGIT model, which predicts 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 has the following functionality:

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

where,

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

with utility formula:

$$U_{gij}(m) = -p_{1gm} * T_{ij}(m) - p_{2gm} * Z_{ij}(m) + p_{3gm} * \log_e(D_{ij} / p_{4gm}) - p_{5gm} * C_{ij}(m) + p_{6gm} + p_{7gm} * A_{ij}(m)$$

with mode attributes:

$T_{ij}(m)$	is the travel time from i to j by transport mode m;
$Z_{ij}(m)$	is the sum of access time in i and egress time in j for transport mode m;
$C_{ij}(m)$	are the travel cost from i to j by transport mode m;
D_{ij}	is the distance from i to j;
$A_{ij}(m)$	is the additional supply attribute (e.g., parking facilities) for m and with LOGIT parameters (by group g and transport mode m);
p_{1gm}	is the marginal utility of 1 minute travel time;
p_{2gm}	is the marginal utility of 1 minute access or egress time;
p_{3gm}	is the marginal utility of logarithmic relative distance increase (impact of "advantage-distance")
p_{4gm}	is the "advantage-distance" of transport mode m;
p_{5gm}	is the marginal utility of 1 monetary unit of fare;
p_{6gm}	is the constant utility of transport mode m;
p_{7gm}	is the marginal utility of 1 unit of the additional supply attribute.

All mode specific matrices are given by the network and assignment model of PTV VISION, called VISUM. Normally we distinguish 5 modes: pedestrians, cyclists, car drivers, car passengers and public transport. 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 constraints can be estimated.

Accessibility of modes of transport at trip origin and at trip destination is considered by access and egress time $Z_{ij}(m)$. By the mid-eighties, costs $C_{ij}(m)$ 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 $A_{ij}(m)$ can be included in the mode choice model (LOGIT parameter $p7$). So, if required, frequency of service and/or delays (public transport) or parking costs can be taken into consideration. This additional attribute is presented 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 inflection at $D_{ij} = p_4$ that makes distance utility influence decreasing for $D_{ij} < p_4$ and increasing for $D_{ij} > p_4$.

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 the LOGIT model is applied, and 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. The LOGIT parameters can be derived from values given in the technical literature (e.g., Hautzinger, 1978 or Ben-Akiva and Richards, 1975) with, if necessary, manual adaptation. LOGIT parameters can also be estimated 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 that 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. Nation-wide surveys can hardly be used as calibration basis, because model choice behaviour differs significantly between different locations. This is caused by the specific PT service quality, by the parking situation or by traditionally caused behaviour. So if available, local survey data should be used.

INTEGRATION IN THE PLANNING PROCESS AND EXAMPLES

Travel diaries providing behavioural data

All behavioural data are gathered by activity based travel surveys that are carried out nation-wide or with a local household sample. The minimum sample size is about 500 households or 1000 persons. Larger samples can provide more detailed calibration data. To classify each member of the household to one of the behavioural homogeneous groups general demographic data are required for each household member. All members of the household members are asked to report all their trips for one specific day.

Structure data for each zone

The number of persons in each population group has to be determined. Other available structure data is used to describe the zonal opportunities for activities. Table 5 shows the relation between trip purpose (activity) and the used structural data to measure the opportunities in each zone. The relation between activity and structure (describing the opportunities) is set by the user. This modelling approach enables to test the results of land use scenarios directly on their impact to the transportation system.

Examples and complexity of computation

Modelling activity chains based on Monte-Carlo simulation (Sparmann, 1980) requires vast computing power and produces uncertainty concerning results and calibration methods. When using behavioural groups and matrix operations this disadvantage does no longer exist.

Table 6
Examples of Activities and Correspondent Zone 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
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

In middle and large applications (> 200 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) with VISEM Version 3.7. Models which involve more than 500 zones are considered less attractive in terms of computing time (≥ 1 hr). In this case, the aggregation level of zones should be discussed. It is useful to keep disaggregate zonal data in the database and to produce the model data at a more aggregate level. Afterwards the disaggregate database can be used to split the matrices into the level of disaggregation one intends to have.

Network modelling and interdependencies

VISEM as a part of the transport planning package PTV VISION replaces the first three steps of the classical four-stage model in an integrated manner. The approach can be broken down into three sub-models that have been described above: the *activity model* creates mobility derived from activity chains and their frequencies in the origin zones. The second sub-model transfers activity chains into *trip chains*. A deterrence model is applied to allocate activities to specific destination zones. The trip chains are split into different modes of traffic (*mode choice*), which is done by a multinomial LOGIT model.

Mode specific OD-Tables are the result of the above procedure. These matrices are used by the network models VISUM-IT (individual transport) and VISUM-PT (public transport) to compute route choice and loading with different assignment procedures.

Table 7
Dimensions and Computing Time of Different VISEM Applications

City region			Model dimensions as number of								
Name	inhabitants in 1000	surface area in km²	ones	groups	activities	activity chains** l=2*	=3*	l=4*	l=5*	tot.*	computing time in min.
Hannover	1.090	2.290	373	8	9	31	35	0	0	66	12
Köln	960	410	222	8	9	31	34	0	0	65	3
Munich	2.400	5.500	559	9	9	39	86	0	0	125	75
Leipzig	640	770	397	10	10	50	69	0	0	119	20
Neckar	830	3.700	256	11	9	46	114	0	0	160	8
St. Gallen	280	680	187	7	7	22	42	45	42	151	9
Halle	300	140	319	8	8	31	73	0	0	104	12
Prag	1.750	4.130	198	7	7	34	82	0	0	116	3
Izmit	270	90	62	8	7	28	27	8	0	63	0.2
Zürich	1.760	2.300	574	8	6	36	62	14	0	112	80

* l = length of activity-chain (HXXH describes three trips, so l=3)
**: activity-chains per group with probability>0, summarized over all groups
Number of modes for all applications is five.

VISUM network models provide matrix input data for the submodel VISEM like separation and supply quality in the deterrence model and mode attributes (travel times, travel cost, mode accessibility, distance, PT-headway) in the mode choice submodel. Therefore network supply quality indicators explicitly interfere with the demand modelling.

Applications: modelling the present state and future scenarios

In the first step, the model is used to evaluate the present state of the transport system. This involves graphical presentation of networks and traffic flows; network performance indicators (travel times, level of service, etc.) and network saturation indicators.

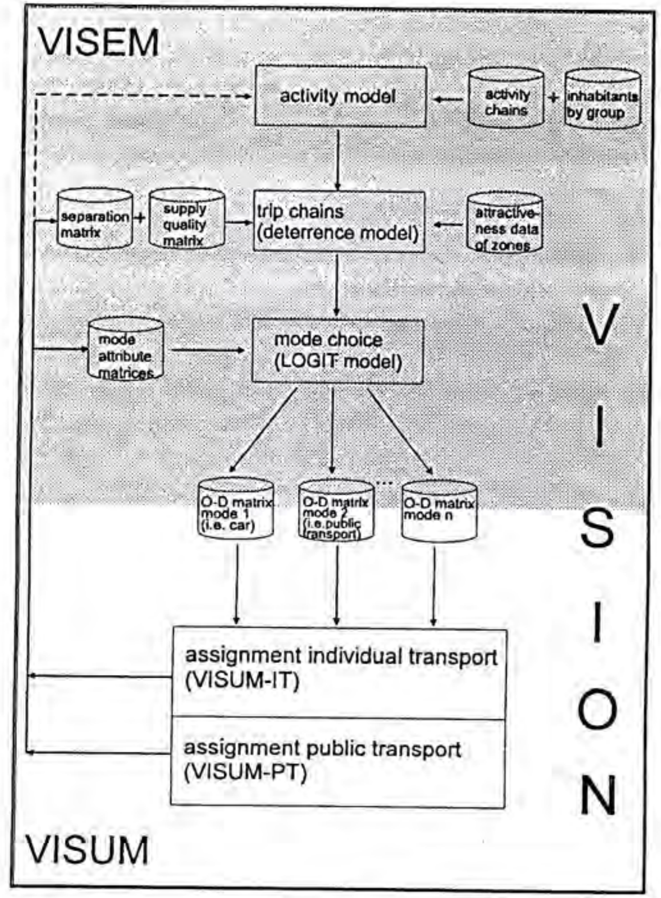

Figure 2
Scheme of VISEM and VISUM

To identify this present state analysis helps deficiencies and problems in the transport system. Next, measure for a future state can be modelled as a part of VISION. The model enables the transport planner to forecast the impact of future measures by modelling possible developments in a scenario approach. Future scenarios must consider development of transport infrastructure as well as the evolution of the socio-economic factors to estimate future transport demand.

The forecast of the socio-economic situation contains the evolution of motorisation, a shifting in the demographic composition of inhabitants, employment rate, suggestions about travel behaviour (for instance changed activity patterns), and changes in land use (for instance new residential and/or commercial areas). Ideas of the transport system are described by network models that enable the planner to evaluate changes in the public transport system (schedule, access times, fares), the future situation of the automobile system (limitation in parking facilities, travel speed, cost), and changes in the non-motorised individual transport facilities (pedestrian zones, bike lanes).

A scenario is the result of combining one structural forecast and one network concept. The result of each scenario is a set of demand matrices and a transport system loading. A set of scenarios shows the range of future developments. For example optimistic and pessimistic forecasts can be modelled. To see the impact of detailed measures (for instance, where exactly the new metro line shall have it's stations) we define different versions within one network concept and test them with the same scenario-matrix. Figure 3 describes this approach.

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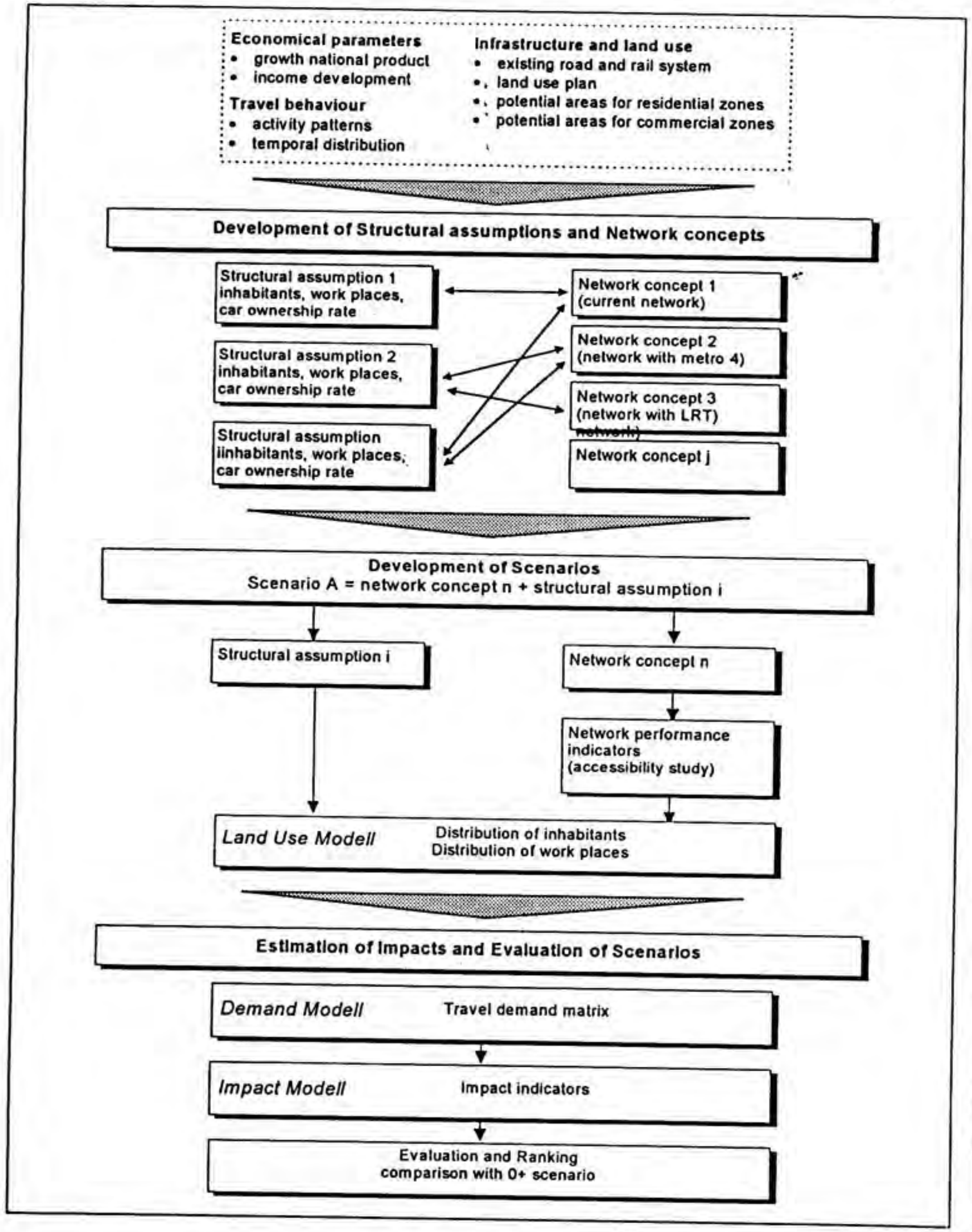

Figure 3
Analysing a Future State of the Transport System by Modelling Scenarios