IMPROVED REPRESENTATION OF HOUSEHOLD DECISIONS IN THE ALBATROSS MODEL SYSTEM: TESTS OF VALIDITY AND SENSITIVITY

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ABSTRACT

The authors have completed re-designed the Albatross model system to better represent household decisions. In this paper, this new version and the previous version are compared in terms of a set of validity measures and in terms of a sensitivity analysis, based on a scenario of increased participation of women in the workforce. Results suggest that there is not much difference between the two models in terms of validity. However, the new model shows much higher sensitivity to the scenario.

Keywords: recreation, travel behavior, dynamics

INTRODUCTION

Although it has been realized since decades that decisions such as car allocation, task allocation and joint activity participation can be best represented as *household* decisions, comprehensive activity-based models of transport demand typically rely on *individual* decisions and choice behavior. The existing literature on household travel behavior is limited to some analytical studies and a few modeling attempts, often confined to just a few facets of activity-travel choice (e.g. Zhang et al., 2005; Gliebe and Koppelman, 2005). Comprehensive activity based models such as DAM, FAMOS, CEMDEP and TASHA are based on assumptions of individual choice behavior; household characteristics are only included as explanatory variables. An exception is ALBATROSS (Arentze and Timmermans, 2004), which takes the

scheduling decisions of the spouse into account in a sequential consideration of the various choice facets. Because this is a limited representation, the authors have recently extended and re-estimated the model using an explicit representation of household choices.

Partial results of this project have been reported in previous publications (Anggraini *et al*, 2008, 2009). In this paper, we will discuss the results of the comprehensive, integrated model. In particular, we will compare the performance and sensitivity of the household version and the previous version of ALBATROSS, using a large data set (MON) collected for the Netherlands. Performance will be examined by comparing how sensitive the integrated model is for impacts of changes in household settings on activity-travel patterns at the activity, tour and schedule level. Moreover, the new and old version of the model will be compared in terms of some performance indicators that the model generates. Sensitivity will be examined by formulating a scenario about the future participation of women in the workforce and comparing differences in simulated impact by the two versions of the model.

We expect that differences in goodness-of-fit will be small because both models use the same data, variables and tree induction method. However, because the scenario is expected to have a substantial impact on task allocation and therefore on individual activity-travel patterns of both household heads, we anticipate that the latest version of Albatross based on explicit household decisions, will be more sensitive to this (and related) scenarios than the older version.

MODEL DIFFERENCES

ALBATROSS (A Learning-Based Transportation Oriented Simulation Systems) predicts for each household in a studied population the schedule of activities and trips of each household head for a particular day. The activity scheduling process consists of four major components: (1) work activity generation (including timing, duration, location and transport mode choice for each work trip), (2) other fixed activity generation (including timing, duration and location), (3) flexible activity generation (including timing, duration and location), and (4) trip-chaining decisions and transport mode choice for each tour. In the existing ALBATROSS model, interactions between persons are represented only in a limited manner. Scheduling steps are made alternately between the household heads whereby the condition of the schedule after each decision step of one person is used as condition information in the next decision step of the other person, and vice versa. Some aspects, such as activity allocation, car allocation, and joint participation in activities and traveling, however, require joint decisions of the two household heads (Anggraini et al., 2007). In a series of recent studies, the Albatross model was extended and restructured to represent explicitly joint decision making of the members of a household regarding joint activity participation, task allocation and car allocation. The resulting new version of the model uses the same methodology of decision trees to model decisions and was estimated on the same national travel survey data (called the MON) as the old

version. Furthermore, both the old and new version take into account.a full set of space-time constraints

As the above-mentioned phases suggests, the activity types distinguished are grouped into *fixed activities* and *flexible activities*. A fixed activity can be considered as an activity that has to be done within a particular time horizon on a regular basis, due to longer term commitments made by the individual. A flexible activity is an activity that can be done freely at any time. Examples of fixed activities are work and escorting a child to school, while most non-work activities are considered flexible activities. In order to identify household-level decision making in activity scheduling and taking into account available activity data, we cluster activities into 10 activity categories as displayed in Table 1. These activities are similar to the classification used in the current ALBATROSS model. Nevertheless, to distinguish person (P) and household (HH) level activity-participation decisions, we subdivide each non-task activity category into independent and joint activities.

No	Activity	Clustered Activity	Personal (P) or Household (HH) Level	Scope of Activities
1	Work	Work	Р	Full-time and part-time
2	Business	Work-	Р	Work-related
3	Other	related	Р	Other mandatory activity (school, etc)
4	Bring/get person		НН	Drop-off/pick-up children/spouse to a certain location
5	Shop-1-store	Task	НН	Shopping, 1 store
6	Shop-n-store	activity	НН	Shopping, multiple stores
7	Service-related		HH	Renting movie, getting (fast) food, institutional purposes (bank, post office, etc)
8	Social-independent		Р	Meeting friends, relatives, etc
	Social-joint	Non-task	НН	
9	Leisure- independent	activity	Р	Sports, café/bar, eating out, movie, museum, library, etc.
	Leisure-joint		НН	

Table 1 -. Activity Classification in a Household

10	Touring- independent	Ρ	Making a tour by car, bike, or foot (eg., letting out the dog, etc)
	Touring-joint	HH	

A task activity refers to a household task. Bring/get person, shop-1-store, shop-nstore, and service-related activities (see Table 1) are considered task activities. A non-task activity just as a task activity can be conducted anytime by any person in the household either independently or jointly. Social, leisure and touring activities (see Table 1) are considered non-task discretionary activities. As said, also task activities possibly can be done jointly. Joint participation is a choice within a next allocation decision.

Thus, note that joint participation is a possible outcome for both task and non-task activities, but the processes are different. In case of a task activity it is the result of two decisions, namely to include the activity and next to conduct the activity jointly. On the other hand, in case of a non-task activity it is the result of a one-step decision, namely to include a joint activity in the schedule of both household heads.

Timing of task and non-task activities takes place in the next stage. It defines the duration and start time of activity categories both at the household level and person level. Having defined the timing, trip-chaining choices are made, the last two components include the car allocation and transport mode choice, particularly for each non-work tour. The latter choices are conducted at either household or person level depending on whether the tour includes a joint activity or not. It is noteworthy that, each decision in this process model is modeled by a decision tree whereby the results of earlier decisions are used as conditions for each next decision. Decisions made are transformed in operations on an evolving schedule. The process results in a complete schedule for each person.

For joint activities, the duration, start time and location decisions are all made jointly by the household heads of the household in the model. This means that the sum of the constraints across the two (evolving) schedules of the two household heads determines the constraints on the decision concerned. The space-time prism determining the feasible locations for a joint activity, for example, is defined as the overlapping area of the space-time prisms of the two individual persons. In decision trees for joint activity participation, in general, the most limiting of the conditions across the two persons is taken as indicative for the decision, such as for example the longest work hours in determining the available time window for the activity. For task allocation decisions (e.g., who escorts the child to day care?), on the other hand, the least restrictive of conditions across the two household heads is taken as indicative for activity participation decisions, e.g. the longest time available across the schedules of the households determines the time window.

DATA

The data used for deriving the decision trees originates from the Dutch National Travel Survey (MON = Mobiliteit Onderzoek Netherlands) collected in 2004 covering all of the Netherlands. The survey is conducted on a regular basis to obtain travel and activity information of residents in the Netherlands. It is a household survey where data is collected of all household members for the diary day as well as general information about household and individual attributes such as, gender, age, vehicle ownership and driving license ownership, home location, individual income, occupation, number of working hours per week, etc. Respondents were also requested to give information about all trips made on a designated day as well as on the activities conducted on trip destinations. Information for each trip includes start time, trip purpose, destination, activity type at the destination, and transport mode. Situational variables are reported as well. All in all, this survey provides a comprehensive data source to analyze activity-travel behavior of Dutch residents. In the data collection, 29221 households filled out a one-day travel/activity diary and 28600 of these households fit the criteria for being considered in ALBATROSS. The data were transformed to an activity-diary data format for the current estimation purpose. In this study, we focus on two-heads household, i.e. households consisting of a single head are not included in the analysis. Then, there are 18037 households used for deriving the envisioned decision tree.

Data about land-use are available at the level of postcode areas and involve employment by sector. These data are used by the scheduler to determine feasibility and attractiveness of locations for conducting certain activities. Data on the transport system describe fastest-path distances and travel times by slow mode and car mode under free-floating traffic conditions under morning peak and afternoon peak conditions. Furthermore, travel times and travel costs data for train and Bus/Tram/Metro are available. Finally, the scheduler uses data on parking facilities and opening hours.

TESTS OF VALIDITY

In order to test the performance of the comprehensive ALBATROSS model system, we first compare the goodness-of-fit of the predictions of the old and new version of the integrated model on the Dutch National Travel dataset (MON). As explained, the old version uses individual-based decisions and the new version uses household-based decisions where appropriate. We test the extent to which predicted activity patterns correspond to observed activity patterns in the MON data in terms of frequencies of choice facets involved and indicators of resulting travel demands. We expect that the result of the new version is not really different from the old version on this level. Both models should be able to reproduce the aggregate distributions that are found in the MON data. In this section, we compare test this hypothesis.

Frequencies

To examine the validity of the model, the discrepancy between observed and predicted data of the old version and new version of ALBATROSS system is analyzed. The Chi-square (χ_i^2) measure can be used as a measure of difference between an observed and predicted frequency distribution. Table 2 displays the results of a frequency analysis of activity patterns generated by ALBATROSS model for the MON sample for both the individual-based (old version) and household-based (new version) decisions. The table illustrates the observed frequencies in the MON data and predicted frequencies by the old version and new version of ALBATROSS in terms of some variables. The variables shown here represent the most relevant facets at the *activity-level, tour-level*, and *schedule-level*.

Activity-level facets refer mainly to all main activity attributes. The frequency distribution across activity types is fairly accurate. The discrepancy stays within a range from 0-2 percent points. The only clear tendency in both models is that the frequency of work activities is somewhat underpredicted. This is a known bias that is due to the fact that ALBATROSS imposes the restriction of maximally two work episodes per person. The Chi-square value that measures the discrepancy between observed data and prediction of the new version (χ_3^2 = 145.32) proves a low dissimilarity (given the large sample size we have), meaning that the new version model predicts the activity type distribution accurately. Furthermore, the accuracy is somewhat better than the old version (χ_3^2 = 145.3 versus χ_1^2 = 232.8). The time-ofday distribution displays a relatively high dissimilarity which is caused by a shift from day-time time slots to evening. Also, this bias is known and has been reported before. The temporal constraints imposed on schedules cannot be fully accounted for in the decision trees so that during scheduling a certain proportion of activities are shifted from blocked to open time slots where open time slots are more likely to occur in the evening. The old version and new version show similar predictions on this aggregate level, as indicated by a relatively low Chi-square value (χ^2_2 = 526.06). The bias is slightly stronger in the new version as indicated by the higher value of the Chisquare. The explanation for this is that joint activities have a higher probability to find an only feasible time slot in the evening compared to independent activities, as they have to meet temporal constraints of both persons at the same time, resulting in a somewhat larger shift.

In terms of trip-chaining, both models predict the frequencies of the so-called After stops and Before stops rather accurately but underpredict the Between-stops somewhat. The underprediction is slightly bigger in case of the new model. Also, this can be understood in terms of the increased difficulty of finding a feasible in-between time slot due to additional constraints that joint activities bring along.

Activity Type	Observed Data (%)	Predict Old Version	ed Data (%) New Version
Work	20.47	18.8	38 18.39
Business	5.80	6.4	13 5.79
Bring-Get	7.96	8.3	30 8.65
Shop-1 store	20.92	22.5	53 21.61
Shop-n store	4.07	4.4	46 3.97
Service	5.28	5.6	5.08
Social	13.17	11.6	67 13.86
Leisure	12.90	12.5	51 12.92
Tour	8.04	8.1	16 8.27
Other	1.39	1.4	1.47
Total	82584	7684	42 78812
$\chi_1^2 = 232.83; \ \chi_2^2 = 2$	250.29; $\chi_3^2 = 145$.	32	

Table 2 - Some Releva	nt Variahlas	at the Anaroaste	
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Activity	Observed		Predicted Data	(%)
Time of Day	Data (%)	Old Version	New Version	
10			05 70	
<=10 am		29.03	25.79	24.69
10-12 am		16.71	13.99	12.88
12-2 pm		15.23	12.93	11.96
2-4 pm		15.63	16.72	15.01
4-6 pm		9.84	11.84	12.29
> 6 pm		13.55	18.73	23.16
Total		82584	76842	78812
$\chi_1^2 = 1334.11;$	$\chi_2^2 = 526.06$; $\chi_3^2 = 3267.36$		

Table 2 ((cont.)
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Trip-Chain	Observed	Predic	Predicted Data (%)		
Pattern	Data (%)	Old Version	New Ve	ersion	
Sinale-stop	63.6	61 63	3.25	69.45	
After-stop	13.4	4 15	5.54	13.06	
Before-stop	13.4	4 15	5.54	13.06	
In-between stop	9.5	52 5	5.67	4.43	
Total	82584	76842		78812	
$\chi_1^2 = 1015.18; \ \chi_2^2 =$	678.59; $\chi_3^2 = 1$	700.95			

Activity	Observed	Predicted	Data (%)
Location	Data (%)	Old Version Nev	v Version
Home Zone Home	30.059	32.107	36.251
Municipality Municipality	29.475	25.797	25.043
order1 Municipality	14.876	16.300	14.867
order2 Municipality	9.094 5.843	10.367 6.195	9.288 5.834

order3 Municipality			
order4	3.816	4.110	3.700
Municipality			
order5	5.054	5.125	4.582
MISSING	1.784	0.000	0.435
Total	82584	76842	78812
$\chi_1^2 = 1754.39;$	$\chi_2^2 = 684.59; \ \chi_3^2 = 1430.83$		

First Tour	Observed	Predicted Data (%)		
Mode	Data (%)	Old Version	New Version	
Car	43.31	47.31	44.55	
Slow	42.86	38.09	40.23	
Public	3.10	3.15	3.14	
Car Passenger	10.73	10.66	11.31	
Unknown	0.00	0.80	0.78	
Total	63627	60544	65027	
$\chi_1^2 = 791.33; \ \chi_2^2 = 1$	01.02; $\chi_3^2 = 568.02$			

Number of Act	Observed	Predicted Data (%)		
in a Tour	Data (%)	Old Version Nev	v Version	
1	82.56	80.27	84.17	
2	10.19	14.55	12.07	
3	4.55	3.71	2.66	
4	1.48	1.03	0.73	
> 4	1.22	0.43	0.38	
Total	63627	60544	65027	
$\chi_1^2 = 831.31; \ \chi_2^2 = 3$	48.20; $\chi_3^2 = 887$.54		

Tab	le	21	(cont.)	
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Number of Tour	Observed	Predicted Da	ta (%)
in a Schedule	Data (%)	Old Version	New Version
0	18.10	21.81	19.04
1	45.41	42.18	42.85
2	24.38	24.48	24.38
3	8.52	8.34	9.19
> 3	3.59	3.18	4.55
Total	46876	46593	46593
$\chi_1^2 = 229.46; \ \chi_2^2 = 22$	21.47; $\chi_3^2 = 109.83$		

Number of N Work Act (Se	lon- Obser chedule)	ved Data (%)	Predicted Data Old Version	(%)	New Version
0	31.5	3	34 94	31.90	
1	30.69	9	28.60	32.17	
2	19.24	4	17.99	17.75	
3	9.9 [.]	1	9.88	9.43	
4	4.84	4	5.16	4.75	
> 4	3.74	4	3.42	3.99	

Total	46876	46593	46593
$\chi_1^2 = 144.63;$	χ_2^2 = 195.79; χ_3^2 = 54.84		

The last variable that is taken into account in this class is activity location. The activity location that is the same as the home zone (Home Zone) is slightly overpredicted by both models and a little more so by the new model. The frequency of other location types (outside the home zone and within own municipality and outside the home municipality in municipalities of different order) are predicted accurately. Again, this slight difference between the old version and new version can be attributed to increased constraints that joint activities must meet compared to independent activities. All in all, the new version predicts location type frequencies slightly better than the old version ($\chi_3^2 = 1430.83$ versus $\chi_1^2 = 1754.39$).

At the *tour-level*, a first variable considered is the transport mode of the first link of the tour. Here, the old version and new version show a similar prediction as indicated by a low value of the Chi-square measure ($\chi_2^2 = 101.02$). However, the prediction of the new version seems somewhat better than the prediction of the old version as indicated by a lower Chi-square value ($\chi_3^2 = 568.0$ versus $\chi_2^2 = 791.3$). In terms of number of activities in a tour, the two models perform approximately equally ($\chi_3^2 = 887.5$ versus $\chi_2^2 = 831.3$). In both cases there is a slight underprediction of the multiple-activities tours that might be related to the (imposed) underprediction of work activity episodes.

At the *schedule-level*, the prediction of the new model in terms of the number of tours in a schedule shows a satisfying result ($\chi_3^2 = 109.83$). It accurately predicts the frequency distributions of schedules across numbers of tours on a day. Compared to the old model the prediction is even more accurate. Finally, regarding the number of activities in a schedule, the new model also shows an improvement in accuracy of the prediction as indicated by the lower Chi-square value ($\chi_3^2 = 54.8$ versus $\chi_2^2 = 144.6$). In overall, the new model shows equal or better predictions in the frequency distributions of the relevant variables, than the old model, except for time of day and trip-chaining.

Indicators

In addition to frequency distributions of relevant choice facets of activity-travel patterns, we also calculated a set of relevant mobility indicators to examine the validity of the model. Again, we use the MON sample and evaluate the dissimilarity between observed and predicted data of the old version and new version of ALBATROSS. We consider the system total as well as the mean across schedules, standard deviation, difference in means and *t*-value of differences in means for each indicator. The significance of differences between means is based on a two-sided independent samples *t*-value. The *t*-value is defined as follows:

$$t = \frac{\overline{X}_{1} - \overline{X}_{2}}{\sqrt{\frac{S_{1}^{2}}{n_{1}} + \frac{S_{2}^{2}}{n_{2}}}}$$
(2)

where

 X_1 is the mean of sample 1;

 \overline{X} is the mean of sample 2;

 S_1^2 is variance of sample 1,

 S_2^2 is the variance of sample 2;

 n_1 = size of sample 1;

 n_2 = size of sample 2.

Similar to what we did in case of frequency analysis, there are three aspects that we want to compare. The three *t*-values are used to identify the differences between: (i) observed and predicted data of the old version (*t*-value₁), (ii) predicted data of the old and new versions (*t*-value₂), and (iii) observed and predicted data of the new version (*t*-value₃). As for (i) and (iii), smaller differences indicate better performance of the model. Analysis (ii), on the other hand, indicates a difference between the two models.

Table 3 displays the observed values in the MON data and predictions of the old and new version of ALBATROSS for the same sample in terms of a number of indicators that are generally of interests. In terms of total travel time, the old and new model show small differences in prediction, as signified by a low *t*-value (*t*-value₂ = -2.1). Although both models show an underprediction of average travel times (which is known to the developers), the new model seems somewhat better than the old model (*t*-value₃ = 41.3 and *t*-value₁ = 42.3). In terms of travel time for each mode, the new version of ALBATROSS shows a better prediction than the old version for all transport modes, except car driver. The prediction of number of tours and number of trips by the new model are also more accurate than the old model. In terms of distance traveled by each transport mode, the new model's predictions are good for every long slow mode travel times in the MON data). Only in terms of total distance, the prediction of the old version is slightly better than the old model.

TESTS OF SENSITIVITY

Another and perhaps more interesting test is whether the potentially improved decision mechanism at the household level make the model more sensitive to

evaluate policy scenarios that should be expected to influence household decision making. The results of such a test are described below

Synthetic population

ALBATROSS has been developed to analyze the impacts of possible scenarios on activity patterns and related travel demand. To that end, first a synthetic population needs to be constructed for the whole Netherlands. The synthesis agent uses two sets of data, namely national population statistics by zone (1308 zones) and a national sample of households. The population statistics define the marginals and the sample data the initial proportions of a multiway household attribute table that is generated and fitted using an iterative proportional fitting method (IPF). Generated populations by zone (1308 zones) are then allocated to the post code areas (3987 areas) within the zone proportional to the known population sizes in postcode areas (Arentze and Timmermans, 2005).

The results of the population synthesis procedure replace existing observed schedules. The new set of observed schedules specifies for each case the day of the week, an empty schedule for each person-day and household and person level data.

Scenario

In order to evaluate the sensitivity of the new ALBATROSS model, we develop a scenario on the level of the synthetic population. The scenario considered here involves an increase of female household head participation in the labor force of 41 % overall (labor scenario) assuming the year 2000 as the base year. This is a relatively strong increase, but it should be noted that, in the scenario, the labor participation rate of women is still substantially less than that of men. The ratio of part-time workers was not changed in the scenario meaning that a much larger proportion of working women are part-time workers compared to men. Due to correlations, the scenario population will also display differences in other sociodemographic characteristics. Table 4 shows the differences between the baseline and labor scenario for household composition, presence and age of children, car possession, age of person, and work status of person. As side effects, there are shifts towards higher income levels, no children in the household and an increase in car possession. There are no noticeable differences in age distribution as age is a variable that is constrained by population data in the synthesis. The differences between populations will be discussed in more detail below.

Table 3 - Observed and Predicted of the Old and New Versions

		OBSEF	RVED		PREDIC	TED (OL	D VER	SIONS)	PREDIC	TED (NE	N VERS	IONS)		t	t
INDICATORS	Total	N	Mean	Stdev	Total	N	Mea n	Stdev	Total	N	Mean	Stdev	<i>t</i> -value₁	value ₂	value₃
Total travel time	2997661	46876	63.9	71.0	2128941	46593	45.7	60.8	2167099	46593	46.5	57.4	42.3	-2.1	41.3
Travel time car driver	1466223	46876	31.3	54.8	1085816	46593	23.3	40.7	1051020	46593	22.6	38.8	25.3	2.9	28.1
Travel time public	249738	46876	5.3	30.8	210930	46593	4.5	28.1	215128	46593	4.6	27.4	4.2	-0.5	3.7
Travel time slow	873736	46876	18.6	39.5	601229	46593	12.9	38.6	633901	46593	13.6	35.1	22.4	-2.9	20.6
Travel time car passenger	407964	46876	8.7	31.0	216631	46593	4.6	17.4	254214	46593	5.5	19.1	24.7	-6.7	19.3
Number of tours	63585	46876	1.4	1.0	60521	46593	1.3	1.0	65027	46593	1.4	1.1	8.3	-13.7	-5.7
Number of trips	146115	46876	3.1	2.4	137145	46593	2.9	2.4	143839	46593	3.1	2.5	11.1	-8.9	1.9
Ratio trips-tours	2.29795				2.26607				2.21199						
Ratio single stop tours - all tours	0.82559				0.80441				0.84167						
Total travel distance	1812815	46876	38.7	82.4	1632628	46593	35.0	64.6	1622956	46593	34.8	61.8	7.5	0.5	8.1
Distance car driver	1115245	46876	23.8	62.7	1200032	46593	25.8	57.0	1138415	46593	24.4	53.6	-5.0	3.7	-1.7
Distance car passenger	331312	46876	7.1	35.4	226063	46593	4.9	23.3	277702	46593	6.0	26.1	11.3	-6.9	5.5
Distance slow	223210	46876	4.8	34.3	79349	46593	1.7	6.9	80604	46593	1.7	6.5	18.9	-0.6	18.8
Distance public	143048	46876	3.1	24.2	127184	46593	2.7	24.1	126235	46593	2.7	22.5	2.0	0.1	2.2

To identify predicted effects, we compare the prediction under the scenario with the prediction of the baseline for each of the two model versions. The results are displayed in Table 5 and Table 6 for the old and new version respectively. Comparison with the baseline reveals the effects of the scenario that each model predicts. In turn, comparison of predicted effects between models reveals the extent to which the models differ. An increase of sensitivity of the new model would emerge as a difference in predicted effects. This means that a difference in predicted effects is evidence for an improved sensitivity of the model (and a better prediction). We use the same set of attributes and indicators as before for this analysis. Furthermore, we use a standard functionality of ALBATROSS to reveal the variance of stochastic variation in predictions. For each prediction, ALBATROSS calculates the mean and standard deviation between subsets of the set of predicted schedules. The subsets are determined based on a random partitioning of the set (in three subsets). Each table shows information about the mean across subsets of the base-scenario (m_0) , difference in means between base-scenario and labor-scenario as a percentage of m₀ (m₁-m₀%) and the *t*-value of differences in means for each variable/indicator. The significance of the differences between means is based on a two-sided, independent samples *t*-test.

Household Composition	m _o	m ₁ -m ₀ (%)	sign	<i>t</i> -value	df	
Single, 0-worker	52134	-11.81	**	-31.889	4	•
Single, 1-worker	42460	14.32	**	88.292	3	
Double, 1-worker	39852	-27.73	**	-104.422	3	
Double, 2-worker	60545	32.67	**	62.848	3	
Double, 0-worker	32931	-26.2	**	-96.458	3	
Total	227922	0.01		0.07	4	

Table 4 - Comparison between Base-line and Scenario on Socio-Demographic Characteristics

Household SEC	m _o	m₁-m₀ (%)	sign	<i>t</i> -value	df
Minimum	61086	-7.45	**	-18.438	3
Low	55251	-2.7	**	-8.345	3
Medium	48576	3.15	**	5.778	4
High	63009	7.19	**	95.832	3
Total	227922	0.01		0.07	3

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Presence and Age of Children	mo	m₁-m₀ (%)	sign	<i>t</i> -value	df
No Child	164326	0.74	**	6.743	4
< 6 yr	29190	-3.54	**	-5.845	4
6-<12 yr	17936	-1.58	**	-10.251	3
12-<17 yr	16470	0.71		1.013	2
Total	227922	0.01		0.07	3

N Cars	m _o	m ₁ -m ₀ (%)	sign	<i>t</i> -value	df	
No car	46327	-5.26	**	-9.764	4	
One car	127312	-0.74	*	-2.355	3	
2 or more	54283	6.27	**	20.098	3	
Total	227922	0.01		0.07	3	

Age of Person	m ₀	m ₁ -m ₀ (%)	sign	<i>t</i> -value	df
< 35 yr	83562	-0.32		-0.697	2
35-<55 yr	156184	0.58	*	2.662	4
55-<65 yr	51397	1.56	**	5.622	4
65-<75 yr	38943	-1.14	**	-12.128	4
75+ yr	31164	-2.8	**	-16.872	4
Total	361250	0.03		0.22	4

Person Work Status	m ₀	m ₁ -m ₀ (%)	sign	<i>t</i> -value	df
Non-Worker	157847	-21.83	**	-196.857	3
Part Time Worker	53665	35.71	**	89.985	2

Full Time Worker	149738	10.3	**	28.384	3
Total	361250	0.03		0.22	4

Table 4 illustrates the comparison between baseline and labor scenario in terms of socio-demographic variables. As expected, with the increasing labor participation of women, single-1-worker and double-2-worker households increase significantly with 14.32% and 32.67% respectively. With regard to household SEC (income), medium and high income households increase with 3.15% and 7.19%, respectively. As for the presence and age of children, household composition changes only slightly. It indicates that households with children aged under 12 years decreases with 1.58% (6-11 years) and 3.54% (<6 years). As opposed to that, households with children over 12 years of age do not change significantly and no-child households show a small increase of 0.74%. These results indicate that with the increasing labor participation of women, the tendency of having children decreases, and hence, no-child households increases.

In terms of car ownership, the prediction concludes that the possession of 2 or more cars increase with 6.27%, whereas the number of households with no cars decreases about 5.26%. In connection with person age, there are no noticeable changes as we would expect since this variable is constrained by zonal population data in the synthesis. In terms of work status of the person, as expected, the number of non-workers among household heads decreases strongly (21.83%). On the other hand, the number of part time workers increases significantly with 35.71%. Also the number of full-time workers increases, all be it less substantial, with 10.3%. This reflects the fact that in the baseline a relatively large proportion of women workers are part time workers and this is maintained in the scenario.

Activity Type	m ₀	m₁-m₀ (%)	sign	<i>t</i> -value	df	
Work	114791	13.15	**	30.473	2	—
Business	37685	9.89	**	11.649	3	
Bring-Get	50647	-4.98	**	-7.255	4	
Shop-1-store	132147	-5.58	**	-12.04	2	
Shop-n-store	26508	-6.54	**	-7.476	3	
Service	30773	-1.33		-1.472	2	
Social	72570	-0.66		-1.52	2	

Table 5 - Predicted Scenario Effects on Some Variables/Indicators: Old Model Version

Leisure	76844	1.76	**	3.99	4
Tour	47565	0.33		0.496	4
Other	9112	-6.84	**	-5.922	2
Total	598643	1.2		2.538	2

Activity Start Time	m ₀	m₁-m₀ (%)	sign	<i>t</i> -value	df	
<= 10 am	154755	6.67	**	12.981	2	
10-12 am	81568	-4.39	**	-9.219	4	
12-2 pm	78170	-3.08	**	-4.892	2	
2-4 pm	97964	-2.69	**	-4.742	2	
4-6 pm	72187	2.1	*	2.759	3	
> 6 pm	113998	3.48	**	7.455	3	
Total	598643	1.2		2.538	2	
Activity Trip Pattern	m.	mm. (%)	sian	<i>t</i> -value	df	
	110	1111 1110 (70)	eign	t value	u	
Single-stop	378913	1.16	*	2.996	2	
Single-stop After-stop	378913 92716	1.16 0.9	*	2.996 1.371	2 3	
Single-stop After-stop Before-stop	378913 92716 92716	1.16 0.9 0.9	*	2.996 1.371 1.371	2 3 3	
Single-stop After-stop Before-stop In-between stop	378913 92716 92716 34298	1.16 0.9 0.9 3.28	*	2.996 1.371 1.371 4.549	2 3 3 2	
Single-stop After-stop Before-stop In-between stop Total	378913 92716 92716 34298 598643	1.16 0.9 0.9 3.28 1.2	*	2.996 1.371 1.371 4.549 2.538	2 3 3 2 2	

Activity Location	m ₀	m₁-m₀ (%)	sign	<i>t</i> -value	df
Home Zone	180365	-1.65		-2.86	2
Home Municipality	172704	1.7	**	4.371	4
Municipality order1	92733	2.24	*	3.354	2
Municipality order2	55633	2.84	**	11.294	2

Municipality order3	38707	3.55	**	4.583	2
Municipality order4	26996	2.16		1.861	3
Municipality order5	31505	5.13	**	9.554	3
Total	598643	1.2		2.538	2

First Tour Mode	m _o	m₁-m₀ (%)	sign	t-value	df
Car	219422	3.43	**	6.726	2
Slow	184496	-1.34	**	-3.972	3
Public	17397	2.68	**	5.748	4
CarPass	49528	-0.61		-1.05	4
Unknown	787	2.2		1.078	3
Total	471629	1.11		2.565	2

# Activity in a Tour	m _o	m₁-m₀ (%)	sign	<i>t</i> -value	df
1	378913	1.16	*	2.996	2
2	68348	0.29		0.429	4
3	17259	1.91		1.845	2
4	4908	3.02	**	8.55	2
> 4	2201	7.25	**	6.347	2
Total	471629	1.11		2.565	2

# Tours in a Schedule	m ₀	m₁-m₀ (%)	sign	<i>t</i> -value	df
0	77177	-4.09	**	-12.867	2
1	153575	0.26		0.81	3
2	89193	3.41	**	8.073	2

3	29699	0.97		1.699	4
> 3	11607	-3.82	**	-3.043	4
Total	361250	0.03		0.104	3

INDICATORS	m _o	m₁-m₀ (%)	sign	t-value	df
Total travel time	17379946	-3.89		-0.625	2
Travel time car driver	7940591	4.56	**	7.313	2
Travel time public	2867975	-36.74		-0.938	2
Travel time slow	4961321	0.15		0.352	3
Travel time car passenger	1588751	0.45		0.545	4
Number of tours	471629	1.11		2.565	2
Number of trips	1070272	1.16		2.55	2
Ratio trips-tours	2.269	0.05		1.864	3
Total travel distance	11586597	4.09	**	7.014	2
Distance car driver	8409780	4.73	**	6.799	2
Distance car passenger	1587591	1.01		1.046	3
Distance slow	672783	1.11	*	2.457	4
Distance public	916444	5.79	**	7.887	3
Distance car driver	8409780	4.73	**	6.799	2

Activity Type	m _o	m₁-m₀ (%)	sign	<i>t</i> -value	df
Work	115089	12.79	**	32.421	3
Business	35932	10.78	**	17.52	4
Bring-Get	53238	2.6	**	6.752	4
Shop-1-store	133379	-3.15	**	-4.387	4
Shop-n-store	25328	-3.81	**	-6.136	3
Service	30111	2.2	**	9.94	3
Social	89070	-1.21	**	-6.987	4
Leisure	81842	-0.69		-1.12	2
Tour	49668	-3.53	**	-6.355	3
Other	9506	-3.15	*	-2.143	4
Total	623163	1.89	**	7.448	2
Activity Time of Day	m _o	m₁-m₀ (%)	sign	<i>t</i> -value	df
Activity Time of Day	m ₀ 152278	m₁-m₀ (%) 6.87	sign **	<i>t</i> -value 42.423	df 2
Activity Time of Day <= 10 am 10-12 am	m₀ 152278 78937	m₁-m₀ (%) 6.87 -3.38	sign ** **	<i>t</i> -value 42.423 -9.712	df 2 4
Activity Time of Day <= 10 am 10-12 am 12-2 pm	m₀ 152278 78937 74125	m₁-m₀ (%) 6.87 -3.38 -1.4	sign ** ** **	<i>t</i> -value 42.423 -9.712 -3.819	df 2 4 4
Activity Time of Day <= 10 am 10-12 am 12-2 pm 2-4 pm	m₀ 152278 78937 74125 94292	m₁-m₀ (%) 6.87 -3.38 -1.4 -1.83	sign ** ** **	<i>t</i> -value 42.423 -9.712 -3.819 -3.021	df 2 4 4 3
Activity Time of Day <= 10 am 10-12 am 12-2 pm 2-4 pm 4-6 pm	m₀ 152278 78937 74125 94292 76311	m ₁ -m ₀ (%) 6.87 -3.38 -1.4 -1.83 3.14	sign ** ** ** *	t-value 42.423 -9.712 -3.819 -3.021 7.582	df 2 4 4 3 4
Activity Time of Day <= 10 am 10-12 am 12-2 pm 2-4 pm 4-6 pm > 6 pm	m₀ 152278 78937 74125 94292 76311 147220	m₁-m₀ (%) 6.87 -3.38 -1.4 -1.83 3.14 2.95	sign ** ** ** ** **	t-value 42.423 -9.712 -3.819 -3.021 7.582 10.241	df 2 4 4 3 4 3
Activity Time of Day <= 10 am 10-12 am 12-2 pm 2-4 pm 4-6 pm > 6 pm Total	m₀ 152278 78937 74125 94292 76311 147220 623163	<pre>m₁-m₀ (%) 6.87 -3.38 -1.4 -1.83 3.14 2.95 1.89</pre>	sign ** ** ** ** **	t-value 42.423 -9.712 -3.819 -3.021 7.582 10.241 7.448	df 2 4 3 4 3 2
Activity Time of Day <= 10 am	m₀ 152278 78937 74125 94292 76311 147220 623163 m₀	<pre>m₁-m₀ (%) 6.87 -3.38 -1.4 -1.83 3.14 2.95 1.89 m₁-m₀ (%)</pre>	sign ** ** ** ** ** ** **	 <i>t</i>-value 42.423 -9.712 -3.819 -3.021 7.582 10.241 7.448 <i>t</i>-value 	df 2 4 3 4 3 2 df
Activity Time of Day <= 10 am 10-12 am 12-2 pm 2-4 pm 4-6 pm > 6 pm Total Activity Trip-Chain Pattern Single-stop	 m₀ 152278 78937 74125 94292 76311 147220 623163 m₀ 428113 	m1-m0 (%) 6.87 -3.38 -1.4 -1.83 3.14 2.95 1.89 m1-m0 (%) 0.94	sign ** ** ** ** ** sign	t-value 42.423 -9.712 -3.819 -3.021 7.582 10.241 7.448 t-value 4.287	df 2 4 4 3 4 3 2 df 2
Activity Time of Day <= 10 am 10-12 am 12-2 pm 2-4 pm 4-6 pm > 6 pm Total Activity Trip-Chain Pattern Single-stop After-stop	<pre>m₀ 152278 78937 74125 94292 76311 147220 623163 m₀ 428113 83041</pre>	m1-m0 (%) 6.87 -3.38 -1.4 -1.83 3.14 2.95 1.89 m1-m0 (%) 0.94 3.31	sign ** ** ** ** ** sign * *	t-value 42.423 -9.712 -3.819 -3.021 7.582 10.241 7.448 t-value 4.287 8.936	df 2 4 4 3 4 3 2 df 2 4 2 4

Table 6 - Predicted Scenario Effects on Some Variables/Indicators: New Model Version

In-between stop	28969	7.82	**	8.038	4
Total	623163	1.89	**	7.448	2
Activity Location	m ₀	m₁-m₀ (%)	sign	t-value	df
Home Zone	208622	-0.4		-0.912	4
Home Municipality	176818	2.31	**	5.825	4
Municipality order1	89258	3.19	**	6.588	4
Municipality order2	53451	3.06	**	7.408	3
Municipality order3	37198	3.55	**	9.142	4
Municipality order4	25510	4.59	**	6.679	2
Municipality order5	30073	5.06	**	14.281	3
Total	623163	1.89	**	7.448	2
First Tour Mode	m ₀	m₁-m₀ (%)	sign	t-value	df
Car	225592	4.28	**	13.694	3
Slow	207409	-1.31	**	-5.519	4
Public	18526	1.4		1.946	4
CarPass	57839	-0.78	*	-2.483	4
Total	511154	1.32	**	6.051	2
# Activity in a Tour	m ₀	m₁-m₀ (%)	sign	t-value	df
1	428113	0.94	*	4.287	2
2	62941	2.12	**	10.25	4
3	14011	5.8	**	5.137	4
4	4074	9.56	**	8.777	3
> 4	2014	10.66	**	4.806	2
Total	511154	1.32	**	6.051	2

# Tours in a Schedule	m _o	m ₁ -m ₀ (%)	sign	<i>t</i> -value	df
0	64541	-6.46	**	-28.859	3
1	156377	1.24	**	7.4	2
2	90293	2.12	**	5.146	3
3	33563	1.53	**	3.333	4
> 3	16475	-0.5		-0.832	4
Total	361250	0.03		0.22	4
INDICATORS	m ₀	m₁-m₀ (%)	sign	<i>t</i> -value	df
Total travel time	18044438	-3.38		-0.526	2
Travel time car driver	7820339	5.08	**	21.663	4
Travel time public	2917420	-36.33		-0.944	2
Travel time slow	5320978	0.94		2.71	2
Travel time car passenger	1922107	0.2		0.387	3
Number of tours	511154	1.32	**	8.975	2
Number of trips	1134317	1.63	**	11.374	2
Ratio trips-tours	2.219	0.31	**	7.856	3
Total travel distance	11872101	4	**	12.347	4
Distance car driver	8203993	4.93	**	17.335	4
Distance car passenger	2036742	0.36		0.536	3
Distance slow	708375	2.03	**	4.718	3
Distance public	922991	5.2	**	6.485	2

Table 5 and Table 6 illustrate the comparison between the baseline and labor scenario for the old version and new version respectively. Concerning the a*ctivity-level* facets, both versions predict considerable shifts in frequency distributions as consequences of the scenario. However, we are interested here in the differences in prediction made by the old version (Table 5) and the new version (Table 6). In

predicting the number of work activities, both versions predict similar effects as we would expect. However, in terms of household tasks activities (bring-get, service, shop-1-store, and shop-n-store), the predictions of both versions are quite different. The old version predicts a decrease of activities for all household task activities. The new version predicts a slight increase in bring-get and service activities of 2.6% and 2.2% and smaller decreases of the other household activities compared to the old version. The explanation might be that by making explicit allocation decisions considering both schedules of the spouses, the new model might be better able to find a time slot in either one of the two schedules for including a task activity. Since the old version does not consider schedules of the spouses in combination it may fail to find a time slot in the schedule of the person that is primary responsible for the task and omit rather than re-allocate the activity.

On the other hand, for non-task discretionary activities, social, leisure and touring, the two model versions also predict rather different effects. Note that non-task discretionary activities are relatively often performed jointly in the baseline. When labor participation of women increases according to the scenario, the models predict opposite effects. The old version predicts no change or an increase depending on the specific type of discretionary activity. The new version in contrast predicts a decrease at least for the social and touring activity (the decrease of the leisure activity is not significant). Also this difference can probably be attributed to a specific strength of the new model. With increasing work time of the female, there will be fewer opportunities to find a time slot where the activities can be conducted jointly. Given a preference to conduct them jointly, a decrease in opportunities will lead to a decrease in these activities. This effect is predicted by the new model. The old model treating activities independently does not impose the requirement of finding a common time slot of (a subset of) the activities across the schedules and, therefore, finds in more cases opportunities to schedule the activities.

In terms of time of day, there are no significant differences in predictions between the old version and the new version. Both models predict an increase of activities with a start time before 10 am of around 6-7%. This is an expected effect of an increase in work activities, given that work activities tend to start at early time moments of a day. In terms of trip-chaining, the new version predicts a stronger increase of activities on an in-between stop (7.82% versus 3.48%). This result is consistent with the prediction of the new model that more household-task activities are maintained in the scenario and a tendency that these activities are combined with work activities. For example, females tend to make multiple stops from home to work and stop by at school.

Regarding locations of activities, both versions again show similar results. The number of activities conducted in the same postcode area where the person lives decreases as a consequence of the scenario, whereas the choice of destinations outside the own municipality slightly increases. Thus, the prediction points out that people tend to travel longer from home when labor participation of women increases.

Regarding transport mode choice for tours, the two models predict more or less the same effects. There are only slight differences which may not be significant. The new version predicts a slightly stronger increase in car driver mode (4.28% versus 3.43%), whereas the old version predicts a slightly stronger increase in public transport mode than the new version do (2.68% versus 1.4%). These predictions are plausible, given the increase in income, car possession, work activities and distance to destinations. Furthermore, both models predict an increase of tours where multiple activities are combined (more than 4). The new version predicts a slightly stronger increase of such complex tours, which is consistent with the earlier finding that this model predicts a stronger increase of activities conducted on in-between stops.

In terms of the prediction of indicator variables, the old and new versions give similar results but at the same time display some notable differences. Total travel time decreases about 3 - 4%. Percentage-wise, the models predict a small increase in travel time for car driver (5.08% and 4.56%) and a strong decrease of travel time by public transport (36 - 37%). The models predict different effects regarding the number of trips, number of tours and ratio trips-tours. The old version predicts that there are no effects on these variables. In contrast, the new version predicts a small but significant increase in each of these variables. This difference reflects the differences that we saw in terms of number of activities, trip-chaining and number of activities per tour. Hence, the specific sensitivity of the new model is visible even at the level of aggregate mobility indicators. As for distance traveled across all modes, the two models both predict an increase of around 4 %. Based on the increase of work activities alone, one may have expected a stronger increase in mobility. We should realize, however, that the increase takes place primarily in the part time worker segment which is characterized by relatively short home-work distances. Furthermore, it should be noted that non-work activities decrease in this scenario. Distance traveled by public transport increases 5 - 6%, and travel distance by car driver increases 4 - 5%. According to those predictions, there is a tendency of people traveling longer distances by car and public transport. Finally, the model predicts different mobility effects for the weekend days and weekdays (not shown) that can be interpreted too as a result of an increased sensitivity of the new model.

CONCLUSIONS AND DISCUSSION

This paper discussed the validity and sensitivity of the full ALBATROSS model by comparing the performance of the old version and the new version. A validity test on the basis of the MON data set established that the new version is able to predict choice-facet frequency distributions and mobility indicators observed in the MON data as accurately as the old version. The goodness-of-fit of the new version for most choice facets appeared to be either equivalent or slightly better than the goodness-of-fit of the old version. The only exceptions are time of day and trip-chaining. For these facets the old model produced better results. The bias in time-of-day predictions in the new version is probably due to the inclusion of joint activities. Joint activities might be more feasible to do in the evening compared to independent

activities, as a consequence of coupling constraints, resulting in a fairly larger shift towards evening hours. In relation to trip-chaining, the new model underpredicted the in-between stops. This can be understood in terms of the increased difficulty of finding a feasible in-between time slot due to additional constraints that joint activities bring along.

With regard to performance indicators, the new version of ALBATROSS shows better predictions than the old version, for all transport modes, except car driver, in terms of travel time for each mode. The prediction of the number of tours and number of trips by the new model are also more accurate than the old model. In terms of distance traveled by each transport mode, the new model's predictions are better for every transport mode except slow modes. Only in terms of total distance, the prediction of the old version is slightly better than the new version.

Subsequently, to test the sensitivity of the new model, we considered an application of the model to a particular scenario of change in the Dutch population. The scenario assumed an increase of 41 % in labor participation of women (labor scenario) assuming the year 2000 as the base year. A fraction of 10% of the year 2000 population of the Netherlands was generated using the synthesis module of ALBATROSS for the baseline and the labor scenario. Due to correlations the scenario population also demonstrates dissimilarity on various other socio-demographic characteristics. Both the new and old model versions were then used to predict for the base line and the scenario the activity patterns of the population. The effects predicted by each model regarding an essential group of attribute and indicator variables were compared to assess the specific sensitivity of the new model. Given the fact that the new model takes into account within-household interactions, it was expected that the new model predicts to some extent different effects.

In terms of a test of sensitivity, the new model proved to be more sensitive to the impacts on situational and decision dimensions of activities, such as activity type, start time, trip-chaining, location, etc. The scenario involved an increase in work activity load in women's schedules and the new model predicted somewhat different responses that could be interpreted in terms of better representing opportunities and requirements related to task allocation and joint activity participation. In sum, by considering decisions of household heads on these dimensions in interaction, the system is able to predict with increased sensitivity processes of activity re-scheduling in response to a change. The results showed that this can lead to differences in prediction of activity generation and travel choices that have an impact on aggregate mobility indicators (e.g., number of trips, shifts in timing and transport mode) that are relevant for planning and policy making. Other scenarios could be considered as well, but this case served our purpose to evaluate the working of the new model.

Thus, this study provides evidence that incorporating mechanisms of joint decision making and coupling constraints in activity scheduling models of travel demands has significant effects on predictions even on the level of travel demand

indicators for a studied population. We suggest as a topic for future research to further extend activity-based models to consider interactions between individuals in the broader context of social networks where task allocation, joint activity participation and even car allocation take place as well.

REFERENCES

- Anggraini, R., T.A Arentze and H.J.P. Timmermans (2007), Refining Albatross: Modeling household activity generation and allocation decisions using decision tree induction. In: Proceedings WCTR Conference,. Berkeley (CD-Rom: 21 pp.).
- Angrainni, R., T.A. Arentze and H.J.P. Timmermans (2008), Car allocation between household heads in car deficient households: A decision model, European Journal of Transport and Infrastructure Research, 8, 301-109.
- Angrainni, R., T.A. Arentze and H.J.P. Timmermans (2009), Continuous choice model of timing and duration of joint activities, Transportation Research Record, 2135, 17-24.
- Arentze, T.A. and H.J.P. Timmermans (2005), Parameterized action decision trees: Incorporating continuous attribute variables into rule-based models of activitytravel behavior. In: Proceedings of the 84th Annual Meeting of the Transportation Research Board, Washington D.C., USA (CD-Rom: 15 pp.).
- Arentze, T. and H.J.P. Timmermans (2004), *Albatross 2.0: A Learning Based Transport* Oriented Simulation System, EIRASS, Eindhoven, 394 pp.
- Gliebe, J.P. and F.S. Koppelman (2005), Modeling household activity-travel interactions as parallel constrained choices, *Transportation*, 32, pp. 449-471.
- Zhang, J., H.J.P. Timmermans and A.W.J. Borgers (2005), A model of household task allocation and time use, *Transportation Research B*, 38, 81-95.