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Microsimulation of Organized Car Sharing: Description of the Models and Their Calibration

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This report is one of a series that report the methodology and findings of an investigation of the likely impact of organized car-sharing schemes. This volume summarizes the structure of a microsimulation model of organized car sharing. It includes a description of the model itself, the preparation of the necessary data base, and the calibration of the choice models by using data from a special survey. Microsimulation is a technique of computerized modeling within which the decision-making process is replicated for each individual in the system. Monte Carlo sampling of probability distributions is used to generate all the individual decision makers, each of whom is uniquely identified within the model. The model consists of three stages: In the first stage it considers each eligible trip maker and predicts whether or not he or she will apply to join an organized car-sharing scheme; in the second stage all these applications are processed to produce match lists of potential traveling companions; in the final stage the model considers the decision by each applicant of whether to form a car-sharing arrangement with anyone on his or her match lists. The model was successfully calibrated and its predictions accord well with empirical evidence of the performance of car-sharing schemes.

This report is one of a series (1-3) that emanates from a study of organized car sharing. Readers interested primarily in the likely effects of car-sharing schemes will find the relevant results of the modeling exercise elsewhere (3); those who have an interest in the surveys on which calibration of the models is based should see another report (2).

The objective of the study was to provide guidance for policymakers who are contemplating the implementation of car-sharing schemes, by estimating the relationships that exist between the performance of schemes, the policy environment in which they operate, and the nature of the schemes themselves, and so predict the likely impact of schemes that operate under a variety of conditions.

Although field trials must obviously constitute the final test of the performance of car-sharing schemes, it was decided to base the current investigation on calibrated models. The models allowed us to experiment with a wider range of options than would have been possible in field trials and enabled us to gauge the likely scale of impact on public transport (a desirable preliminary since this impact could be very important).

Several studies have suggested that organized work-journey car sharing has the potential to have a large effect on the transport system (4,5). Given this potential impact, the problem is how to estimate the likely impact. Valuable work in the United States (6,7) has treated car sharing as a separate mode and has estimated demand by simple extension of existing modeling techniques. However, these techniques cannot produce accurate estimates since they do not consider the compatibility of carpool members (compatibility of location, journey time, and personality). Other work has concentrated on attitudes toward car sharing (8-12). It has provided useful insights into the likely behavior and compatibility of individuals but it is, in itself, not readily adapted for predictive purposes because it is concerned with individuals rather than populations and cannot consider the likelihood that the compatibility constraints will be met.

This project was intended to bridge the gap between theoretical modeling and attitudinal investigation by developing a model that, although based on the attitudes and consequential decisions of individuals, could take into account the availability, characteristics, and compatibility of potential partners and could thus predict not only the demand for car-sharing arrangements but also whether they were likely to be established. The form of model best suited to this task is considered to be microsimulation.

MICROSIMULATION

Microsimulation is a technique of computerized modeling within which the decision-making process is replicated for each individual decision maker within the modeled system. These decision makers effectively become actors who are each uniquely identified. The decision-making processes are driven by Monte Carlo-type sampling, according to probabilities that are determined previously, depending on the many different attributes of the actors, their environment, and the proposed scheme.

The simulation suite itself has three stages, each of which represents a distinct process in the establishment of an organized car-sharing scheme. The first stage is concerned with the scope and intensity of the scheme being simulated and the decisions by members of the public to be associated with it. The second stage deals with the mechanics of attempting to match up potential partners, and the third stage deals with the reactions of the participants in the scheme to their proposed partners.

The model has been designed so that a variety of car-sharing schemes can be tested in a variety of policy environments. The complete list of control parameters and coefficients includes (a) descriptions of the actors in the system (inhabitants of the area); (b) parameters to define the scope and operational details of the scheme to be tested (for example, Which workers or residents are to be exposed to publicity for the scheme? How intense will be the publicity and how many people will be included on each match list?); and (c) coefficients that govern the decision to apply to join a car-sharing scheme and the decision to match with a given person (each decision is calibrated by special survey). Other parameters allow the user to test changes in the operating environment, such as changes in gasoline prices, changes in public transport fares, or the provision of reserved parking for carpoolers.

The model predictions are fed into an analysis package that provides for a range of descriptions and performance indicators that include some graphical display. The list of indicators includes profiles of the applicants and participants, operational characteristics of the scheme, and effects on selected components of the transport system such as vehicle distance traveled, car occupancies, and abstraction of public transport patronage.

Synthesis of the Population Base

A fundamental input to a microsimulation model is a unique description of each of the actors in the system of interest. These individual descriptions cannot be replaced by collective probability matrices because microsimulation involves strict accounting procedures: As each individual passes through the system, records must be kept on his or her progress. This is particularly important in the present case because it is a fundamental feature of car sharing that there be absolute equality between supply and demand (each lift is given once and once only).

Ideally, of course, the population of actors would be taken from a 100 percent household census, but since this is not feasible a synthetic population has to be generated. (In some microsimulation models a sample population would suffice, but in the case of car sharing it is not possible to properly represent the spatial relationships of potential partners unless the total population is included.) This synthetic population must be more sophisticated than that which would be produced by a simple factoring-up procedure because simple factoring would have produced a population of sets of identical people whose mutual interactions would therefore have been quite different from those of the true population. The method of synthesis used in the current project is described below; however, it should be stressed that the population synthesis is not a part of the microsimulation technique, but merely a device that prepares data for it.

Structure of the Synthesis Suite

A full description of the method of synthesis is given in a background working paper (13). In summary, the method is based on the probability with which one characteristic of an individual or household will depend on other characteristics, as revealed in a household survey. Monte Carlo sampling of the various probability distributions is then used to generate individuals within control totals derived from published census material. For each individual in the population, the following attributes were synthesized:

1. Home geocode--precise locations are specified because, in a model that addresses the interaction between neighbors, the use of zone centroids or density functions would have been unacceptably crude;
2. Workplace geocode--precise locations are specified for the same reason as that given for the preceding attribute;
3. Sex;
4. Age--under 30, 30-50, or over 50;
5. Whether head of household;
6. Driving license tenure;
7. Employment category--manual or shop floor, technical or clerical, or professional or managerial;
8. Whether car is needed at work for business use;
9. Current mode of travel to work--i.e., prior to the introduction of car-sharing scheme (possible modes are 1 = solo car driver, 2 = car driver with one passenger, 3 = car driver with two passengers, 4 = car driver with three or more passengers, 5 = car passenger, 6 = public transport, and 7 = any other mode; since the evening mode is not constrained to equal the morning mode, there are 49 possible modal combinations);
10. Normal time of arrival at work;
11. Normal time of departure from work;
12. Number of cars available in the household;
13. Number of licensed drivers in the household;
14. Total number of people in the household; and
15. Household telephone availability.

In addition to these 15 attributes, each individual is allocated a reference number that indicates the household to which he or she belongs and his or her unique identity within that household. Each individual is also allocated a random number with which to seed the Monte Carlo sampling. The 15 attributes were chosen as having a strong bearing on an individual's reaction to and performance within organized car-sharing schemes. Clearly, there are many other attributes (e.g., smoking habits and preferences, education, income, and variability of work hours) not mentioned above that might be expected to have equal or greater influence on car-sharing schemes. Unfortunately, however, only those attributes whose distribution in the population was known and observed in the calibration surveys could be included in the modeling.

The synthesis suite has three distinct stages concerned with synthesis (a) of population, (b) of mode choice, and (c) of location within zones.

Synthesis of Population

The first model begins the synthesis by considering, in turn, every zone within the study area. For each household within the zone, it synthesizes the characteristics of each household member in turn. The synthesis proceeds within a framework of exogenously defined control totals of households per zone, but the core of the synthesis is concerned with building up an individual's characteristics, one by one, according to observed probabilities. The synthesis of each new characteristic is governed by random selection according to probabilities based on some of the previously synthesized characteristics.

The random selection is governed by cumulative probability tables disaggregated according to the different values of the data items (and combinations thereof) on which the selection is based. Thus, for example, characteristic A will be governed by a probability matrix P(A|B,C,D) in which the distribution of A will depend on the other characteristics B, C, and D. To select a value of A when B = 1, C = 2, and D = 3, a random number R is chosen from a rectangular distribution between 0 and 1. Then A is assumed to take the value at which the cumulative probability for A exceeds the value of R, subject to the maximum allowable value n. That is,

$$A = \min \left\{ n : \left[\sum_{i=1}^{n} P(A=i|B=1,C=2,D=3) \right] \geq R \right\} \quad (1)$$

The cumulative probability tables, which are the basis of the model, come from two submodels that deal with individual characteristics and trip distributions, respectively. The cumulative probabilities for individual characteristics are simply derived by appropriate summation within the household interview data. The distribution model, however, is a doubly constrained entropy-gravity model for two sexes, two person types (office and nonoffice), and 11 categories of industry. Thus, the predicted number of trips between residence zone i and work zone j (P_{ij}) is given by

$$P_{ij}^{snfk} = A_i^{snf} B_j^{snf} \exp(-\beta^s c_{ij}^k + \delta^{sk}) \quad (2)$$

where

- s = sex,
- n = person type (1 = office, 2 = nonoffice),
- f = industrial category,
- k = mode (1 = car or motorcycle, 2 = all others including walk),
- A = balancing factor associated with residence (calibrated),
- B = balancing factor associated with work place (calibrated),
- c = generalized cost of travel in generalized tenths of minutes (generalized cost here includes in-vehicle time, excess times, and out-of-pocket costs),
- β = deterrence factor (calibrated), and
- δ = calibrated modal penalty for persons who have cars available.

The values of A and B are calibrated to satisfy the following constraints:

$$\text{for all isnf} \quad \sum_{jk} P_{ij}^{snfk} = O_i^{snf} \quad (3)$$

$$\text{and for all jsnf} \quad \sum_{ik} P_{ij}^{snfk} = D_j^{snf} \quad (4)$$

where O_i = observed number of work-trip origins in zone i (from 1971 census) and D_j = observed number of work-trip destinations in zone j (from 1971 census).

The values of β and δ^{s1} are calibrated to satisfy the following constraints:

$$\text{for all s} \quad \sum_{ijk} c_{ij}^k \left(T_{ij}^{ks} - \sum_{fn} P_{ij}^{snfk}\right) = 0 \quad (5)$$

$$\text{and for all s} \quad \sum_{ij} \left(T_{ij}^{1s} - \sum_{fn} P_{ij}^{snf1}\right) = 0 \quad (6)$$

where T_{ij}^{ks} = observed number of trips from i to j by mode k by person of sex s (from 1971 census).

Synthesis of Mode Choice

The second synthesis model deals with the normal mode of travel to work adopted by each member of the population synthesized in the first model. The synthesis of mode is treated as a separate operation in order that the influence of short-term transport policies can be included in the overall simulation suite. A postdistribution modal-split model can be used here because modal choices are more responsive than are distributional choices to the policy changes that are to be tested.

The model uses the observed mode of persons who have a given combination of characteristics to create a mode-choice probability matrix. The probability matrices were derived by simple summation within the household-interview data. The synthesis model then proceeds by random selection governed by these matrices, in a manner parallel to that described in Equation 1 for the first synthesis model.

Synthesis of Location Within Zones

The final synthesis model ensures that each member of our population is located at a precise point in space both at home and at work. The model uses a random number generator to generate, for each synthesized individual, one set of 0.1-km grid coordinates within his or her residence zone and another set within his or her work zone. Those coordinates are then taken to be actual locations of the home and work place, respectively. The distribution of such locations is facilitated by the assumption that all zones are circular, centered around the zone centroid, and of an area that corresponds to the zone's actual area. The distribution of activity within these circular zones is represented by a set of concentric rings centered on the zone's activity centroid, each ring of which has a known width and a known proportion of the zone's total population or employment. These data were estimated approximately by inspection of ordnance survey maps.

Performance of the Synthesis Suite

The synthesis models are based on observed probabilities and, if the explanatory variables have been correctly identified, the models are therefore constrained to give good results. However, testing of the models was required in order to validate the choice of explanatory variables and to investigate whether or not the sequential nature of the models has allowed the propagation of errors.

Ideally, the models would have been validated by testing the goodness of fit between the synthesized population and an independent description of the actual population that it represents. However, insufficient data were available to allow part of it to be held back for model testing. Any goodness-of-fit tests, therefore, have to involve the testing of characteristics of the synthesized population against characteristics of the population sample on which they themselves were based. Such tests are perhaps of questionable validity, but no better alternative was available. This problem of statistical verification is compounded by the use of two data sets that refer to the same phenomena, which makes it difficult to define the number of independent observations and thus the degrees of freedom. In the absence of a single satisfactory statistical test of these models, a range of measures was produced.

The simplest test was of households drawn at random from the synthesized population. These households were subjected to close examination in order to discover whether they had any counterintuitive attributes or internal inconsistencies. In fact, none of the households sampled showed anything untoward.

The next test was a comparison of the observed and synthesized populations with respect to the aggregate occurrences of particular characteristics or combinations of characteristics. Once again there appeared to be no serious cause to doubt the accuracy of the synthesis. Other tests sought to examine the accuracy of the distribution submodel and to search for significant biases within the results. Again, there was no reason to doubt the efficacy of the synthesis. A full account of these tests is given elsewhere (13).

The computational cost of the synthesis suite were somewhat less than 1 p (US $0.02) (at notional commercial rates set by the University of Leeds in 1979) per synthesized individual. To provide a comprehensive population base for the microsimulation model of organized car sharing, 180 000 individuals were synthesized.

THE MICROSIMULATION MODEL

Model of the Decision to Join a Car-Sharing Scheme

The assumption is made that each member of the target population will receive promotional material and an application form for an organized car-sharing scheme. The model then determines, for each member of the population, whether he or she will fill out the application form and, if so, what type of application he or she will make. There are seven types of application:

1. To carpool--alternate driving and riding,
2. To give lifts mornings and evenings,
3. To give lifts mornings only,
4. To give lifts evenings only,
5. To receive lifts mornings and evenings,
6. To receive lifts mornings only, and
7. To receive lifts evenings only.

The likelihood of an individual's making any of the various types of application is deemed to be a function of certain characteristics--length of journey to work, previous mode of travel, age, sex, economic status, work hours, driving license tenure, household license tenure, car availability, and telephone availability.

Table 1. Calibrated coefficients of decision to apply.

		Application								
			Lift Giving			Lift Receiving			Passengers	
No.	Characteristic and Values[a]	Pooling	Morning and Evening	Morning Only	Evening Only	Morning and Evening	Morning Only	Evening Only	Allow More Than One	Allow More Than Two
0	Dummy (1)	-3.53	-2.96	-4.06	-0.77	-2.62	-3.24	-1.89	0.82	0.51
1	Length of journey to work (km)	0.16	0.13	0.11	-0.09	0.09	0.00	-0.14	-0.04	-0.02
	Normal morning mode									
2	Solo driver (0-1)	0.48	0.60	0.09	-0.57	-0.20	0.81	-0.60	0.25	0.35
3	Accompanied driver (0-1)	0.09	0.30	-0.27	0.20				-0.30	0.27
4	Passenger (0-1)	-0.86	-0.18	-0.56	-0.07	-0.48	-0.77	0.14	0.16	0.26
5	Public transport (0-1)	0.64	0.02	-0.31	-0.06	-0.06	-0.23	-0.30	0.07	0.23
	Normal evening mode									
6	Solo driver (0-1)	-0.36	-0.00	0.08	-0.69	-0.40	-1.04	-0.61	0.57	0.25
7	Accompanied driver (0-1)	1.03	0.94	-0.00	0.39				0.70	0.38
8	Passenger (0-1)	0.34	0.32	-0.36	-0.13	0.11	0.09	0.07	-0.43	-0.11
9	Public transport (0-1)	-0.43	-0.40	-0.60	-0.08	0.51	0.60	0.74	0.00	0.32
10	Less than 30 years old (0-1)	-0.44	-0.18	-0.50	-0.37	0.29	-0.56	-0.17	-0.15	0.64
11	More than 50 years old (0-1)	-0.64	-0.24	-0.72	0.24	-0.08	-0.71	-0.96	0.20	-0.50
12	Household cars available (0-4)	0.21	-0.43	-0.16	-1.26	-0.69	0.14	-0.09	-0.41	-0.02
13	Full car driving license (0-1)					-0.19	-0.05	-0.53		
14	Factory or manual worker (0-1)	-1.67	-1.39	-1.77	-0.61	-1.22	-0.15	-0.76	0.14	-0.24
15	Professional or managerial worker (0-1)	-0.74	-0.35	-0.13	-0.57	-0.19	-0.12	-1.28	0.63	0.12
16	Female (0-1)	-0.36	-0.32	-0.19	-0.44	-0.19	0.67	-0.45	0.05	-0.06
17	Number of licensed drivers in household (0-8)	-0.02	-0.09	0.19	-1.31	0.17	-0.48	-0.33	0.22	0.21
18	Number of nondrivers in household (0-8)	-0.44	-0.46	-0.49	-1.31	-0.31	-0.48	-0.89	0.37	0.02
19	Morning journey driving off peak (0-1)				-0.63			-0.51	0.44	-0.10
20	Evening journey driving off peak (0-1)			0.29			-0.58		0.04	0.09
21	Household has telephone (0-1)	1.35	0.63	0.65	-0.05	0.31	0.23	0.26	0.17	-0.68

[a]Where the characteristic takes only the values 0 or 1, 1 = an affirmative answer to the question asked and 0 = a negative answer.

In order to establish the importance of these characteristics, a series of binary logit models was calibrated based on the results of a field survey. The survey, which is described in a companion report (2), simulated the distribution of car-sharing promotional material among a population of known characteristics and then analyzed the characteristics of the resulting applicants.

The logit models used were regression transformations of the form:

$$P_j = \exp\left(\sum_{i=0}^{21} a_{ij}x_i\right) \Big/ 1 + \exp\left(\sum_{i=0}^{21} a_{ij}x_i\right) \tag{7}$$

where

P_j = the probability of making an application of type j,
x_i = the value of the ith characteristic of the individual being considered (21 characteristics were considered in total), and
a_{ij} = the calibrated coefficient.

Application of this logit model for each individual in the population produces a probability of the individual's making each type of application to join a car-sharing scheme. In order to represent the stochastic element of choice, this probability is then compared with a random number drawn from a rectangular distribution between 0 and 1. If the probability exceeds this random number, then an application is deemed made; in this way the probabilities are transformed into binary choices.

The calibration process involved evaluation of binary logit models of the form shown above in order to give values of a_{ij} that would reproduce the results of the survey (i.e., that would produce the same number of applicants that have the same average characteristics from a synthesized population designed to replicate the population surveyed). Table 1 shows the resulting values of a_{ij}. The dummy characteristic (numbered 0) corresponds to the basic decision, aggregated across the entire population, of whether or not to apply. This probability is then modified cumulatively according to the coefficients of the various characteristics.

The mechanism by which the microsimulation model uses these calibrated coefficients can perhaps be appreciated by considering the example of one individual chosen from the synthesized population base. This individual has the following characteristics:

1. Location of home is GR 847 237 and location of work is GR 295 299; therefore, the length of the journey to work is 8.09 km;
2. Normal mode of travel to work is solo driver;
3. Normal mode of travel from work is solo driver;
4. Age is 30-50;
5. One car in household;

Table 2. Regression coefficients: components of match utilities.

Value Coefficient (a_n)	Number of Observations	Transformation Used (y =)[a]	R^2	Residual (e_n)	Characteristics of Individuals (p_m) (p/week): Constant	Female	No Phone	Age: <30	Age: >50
For prospective passengers, the value of									
1. Standard driver	68	$\sqrt{x}$	0.34	2.46	11.68	-1.56	0.04	-0.73	-0.81
2. Driver female	68	$\sqrt{-x+51}$	0.27	1.70	8.10	-0.57	-0.41	-0.07	0.41
3. Early departure in morning (min)	67	$\sqrt{-x+7}$	0.13	0.54	2.53	0.01	0.13	0.10	0.13
4. Late return in evening (min)	55	log (-x + 2)	0.33	0.63	0.21	-0.04	-0.05	-0.07	0.39
5. Driver has no phone	67	log (-x + 21)	0.26	0.77	3.06	-0.05	-0.05	-0.29	0.29
6. Work separation (mile)	55	$\sqrt{-x+51}$	0.36	4.40	11.38	-1.97	-3.00	-0.25	1.00
7. Home separation (mile)	67	$\sqrt{-x+68}$	0.25	3.39	8.87	-1.05	-1.34	-0.06	1.73
8. Driver >50	42	$\sqrt{-x+46}$	0.21	1.68	7.46	-0.08	-0.29	0.68	-0.59
For driver offering lifts, the value of									
9. Standard passenger	51	$\sqrt{x-401}$	0.21	4.82	19.33	1.76	-1.18	-1.01	0.03
10. Passenger female	51	$\sqrt{x-26}$	0.15	1.47	5.15	0.60	0.08	-0.13	-0.65
11. 1 min early morning	41	log (-x + 1)	0.54	0.95	0.52	1.46	0.36	0.66	-0.26
12. 1 min late evening	30	log (-x + 1)	0.62	1.04	1.15	1.49	-0.09	-0.52	0.72
13. Passenger has no phone	46	$\sqrt{-x+101}$	0.32	2.16	9.46	2.19	0.96	0.91	0.63
14. Work separation (miles)	33	$\sqrt{-x+1}$	0.62	3.68	10.63	3.63	-1.83	4.80	-3.65
15. Home separation (miles)	15	log (-x + 1)	0.90	1.32	4.64	0.00	0.36	0.88	-1.49
16. Passenger >50	33	$\sqrt{-x+51}$	0.54	1.57	5.66	3.07	-0.92	2.13	-0.38
17. Diversion (miles)	46	log (-x + 1)	0.40	1.52	3.91	1.19	-0.54	1.33	-0.63
18. Passenger is not the first	46	x	0.32	70.67	27.62	-16.94	0.70	48.96	-32.05
For prospective poolers, the value of									
19. Standard pooler	63	$\sqrt{x-301}$	0.21	5.33	20.20	1.18	1.40	-2.36	-0.95
20. Copooler female	62	x	0.21	17.91	-10.06	2.70	18.37	5.66	2.02
21. 1 min early morning as passenger	34	x	0.50	29.46	-41.41	18.88	4.63	4.18	-25.25
22. 1 min late evening as passenger	23	x	0.53	28.50	14.89	-5.5	-0.23	-10.96	-11.30
23. 1 min early morning as driver	63	x	0.11	29.46	2.72	-1.71	-11.67	1.79	-2.85
24. 1 min late evening as driver	36	log (-x + 1)	0.40	1.77	3.32	0.75	0.66	0.48	1.55
25. Copooler having no phone	61	$\sqrt{-x+101}$	0.18	5.58	17.84	0.91	0.24	-1.35	1.36
26. Work separation (miles)	37	$\sqrt{-x+101}$	0.40	4.89	12.82	4.02	-4.40	-3.66	-3.23
27. Home separation (miles)	20	$\sqrt{-x+134}$	0.40	7.47	21.07	3.91	3.75	-5.16	3.35
28. Copooler >50	37	x	0.32	145.45	59.17	-149.22	7.85	2.94	131.94
29. Diversion (miles)	58	$\sqrt{-x+1}$	0.17	7.97	14.18	1.43	-1.96	0.30	1.43
30. Partner is not the first	55	x	0.34	150.09	-155.83	56.14	-61.91	122.43	-84.61

[a]Transformation converts observed distribution of utilities to approximate normal shape.

6. Driving license held;
7. Professional worker;
8. Male;
9. Two licensed drivers in household;
10. Two nonlicensed members in household;
11. Work hours are 8:00 a.m.-5:00 p.m.; and
12. Household has a telephone.

With these characteristics, his likelihood of making each of the seven types of applications is achieved by substituting in Equation 7 the elements from the following rows of Table 1: 0,1 (length = 8.09), 2, 6, 12, 13, 15, 17 (number = 2), 18 (number = 2), and 21. The other rows are not applicable to this individual. Thus, the probability (P_1) of applying to pool will be

$$P_1 = \exp(x)/1 + \exp(x) \tag{8}$$

where, by using the first column of Table 1 (for carpoolers),

$$x = -3.53 + (0.16 \times 8.0) + 0.48 - 0.36 + 0.21 - 0.74 - (0.02 \times 2) - (0.44 \times 2) + 1.35 = -2.216.$$

Therefore $P_i = 0.098$.

For the other six applications, the P values will be 0.07, 0.037, 0.000 05, 0.028, 0.005, and 0.0002, respectively. Seven random numbers between 0 and 1 are then chosen. In this example they are 0.03, 0.84, 0.62, 0.85, 0.08, 0.46, and 0.19. The seven P values are then compared with these seven random numbers to estimate the likelihood of an individual's applying. Only for the application of type 1 (pooling) does the P value exceed the random number and, therefore, the individual is deemed to apply for pooling but for nothing else.

Modeling the Matching of Applicants

This submodel is a direct representation of the matching process that is fundamental to organized car-sharing schemes. As such, it accepts a file of applicants and, as far as is possible, produces for each applicant a list of people whose journey-to-work characteristics and expressed interest in car sharing make them feasible traveling companions. Within the simulation suite the submodel will therefore consider all those individuals deemed to have applied in the preceding model and will attempt to find potential traveling companions for each of them from among their fellow applicants. The matching programs used in this project are similar to ones used in real schemes. They are described in more detail elsewhere (14).

Modeling the Acceptance of Matches

This part of the simulation suite is the most ambitious and is closest to the ideal of microsimulation. It represents the consideration,

Manual	Professional	Distance (km)	Previously an Accompanied Driver	Previously Nondriver	More Licenses Than Cars in Household	One-Way Journey
-0.89	-0.97	0.3	NA	0.47	0.20	-0.72
-0.27	-0.25	0.1	NA	-0.81	-0.75	-0.25
-0.26	-0.08	0.0	NA	0.14	0.20	0.09
-0.56	-0.09	0.0	NA	0.91	0.09	0.03
-0.45	0.17	0.0	NA	0.49	-0.23	-0.41
-4.40	-3.33	0.2	NA	1.51	2.11	-0.93
-2.33	-1.81	0.1	NA	1.90	0.66	-0.28
-0.41	-1.24	0.0	NA	-0.69	0.70	-0.18
3.74	0.67	-0.2	-1.77	2.47	-1.02	-0.57
0.23	0.66	-0.0	-0.17	0.09	0.11	0.07
0.72	0.53	-0.0	-0.78	1.28	0.22	0.54
0.84	0.58	-0.0	-1.09	2.43	-0.55	0.05
-1.80	0.99	0.1	-0.90	-1.02	0.21	-0.49
-3.56	-4.25	-0.2	0.94	-0.77	0.73	2.14
2.69	1.65	-0.1	-2.72	-1.14	-2.09	-0.28
0.74	-0.29	0.1	-0.52	0.38	0.33	0.16
0.54	0.50	-0.1	0.00	1.18	-0.82	0.51
-5.92	3.31	4.4	-23.04	-118.86	-2.62	-24.37
-0.17	-0.25	0.3	0.89	-0.08	-2.35	NA
-1.00	8.71	-0.2	2.93	6.95	1.29	NA
16.94	-11.75	0.4	39.07	4.84	28.95	NA
-7.22	-25.92	-0.0	-11.48	-53.94	31.45	NA
-5.22	5.64	-0.9	-10.57	-2.24	6.04	NA
-1.82	0.27	-0.1	-0.77	-0.87	-1.22	NA
-2.18	1.00	-0.2	-3.54	-4.59	-0.18	NA
6.95	2.23	0.0	0.38	-2.49	1.01	NA
-4.96	-0.45	-0.3	0.20	-1.13	-3.89	NA
-83.77	72.17	-8.3	-38.05	-12.63	-27.69	NA
-2.90	-1.08	-0.3	0.01	4.81	1.86	NA
13.29	6.19	-8.6	76.06	84.33	34.41	NA

by each applicant, of the list of potential traveling companions sent by the organizers of car-sharing schemes. This consideration is assumed to involve an evaluation by the applicant of the net expected utility associated with each possible arrangement presented by the individual's list of potential partners. This evaluation is made on the basis of the known and expected characteristics of the arrangement postulated. If an arrangement has a positive net expected utility to all participants within it and has a higher utility than any other arrangement to at least one of them, then it is deemed a successful car-sharing arrangement. All participants in that arrangement are then withdrawn from the system.

The model is thus based on utility maximization subject to a satisficing constraint. The utility to a given person (P) of a given arrangement (A) is a function of the personal characteristics of the person P, of the personal characteristics of his or her partners in arrangement A, and of the operational consequences of the arrangement (e.g., delays or diversions) on the participants. These utilities can be represented as

$$U_{AP} = \sum_{n=1}^{N} \sum_{m=1}^{M} a_n p_m x_{nm} + e_{nP} + \text{fee paid} \qquad (9)$$

where

U_{AP} = utility of the arrangement A to person P;

$a_1 \ldots a_n$ = attributes of the arrangement A, including a description of the would-be partners and the consequences that the arrangement would have for the respondent;

$x_{11} \ldots x_{nm}$ = components of utility associated with any person who has characteristic m engaging in an arrangement that has attributes n;

$e_i \ldots e_{nP}$ = stochastic elements associated with the utility to person P of an arrangement that has attributes n; and

fee paid = the net sum of money, if any, that passes to this person in respect of participation in the scheme.

The calibration of the components x was on the basis of data from the special field survey (2). Within the survey, respondents were asked to put values on arrangements that have given attributes. By comparing a respondent's evaluation of arrangements with differing attributes, utilities could then be imputed to each attribute. The distributions of utilities assigned by the various respondents were analyzed by using regression techniques to relate them to the characteristics of the respondents. Since may of these distributions were very skewed, they were transformed prior to the regression in order to bring them closer to a normal distribution.

The residual term from the regression was used in the model to impart a stochastic element (e_{nP} in Equation 9) to the individual decisions. This was done by random sampling from a normal distribution with mean zero and standard deviation equal to the standard error of the residual.

Table 2 contains the resulting regression coefficients and residuals. The mechanisms by which the microsimulation model uses these coefficients may be appreciated if the same individual as in the example above is considered.

Given this individual's characteristics, it can be seen that, in considering the utility to him of a pooling arrangement, a linear combination is required of the values of the constant, professional, and distance columns of Table 2 (length = 8.09) and whether the household has more drivers' licenses than cars. These combinations are then supplemented by the stochastic element obtained by multiplying each residual by a standard unit normal random number. This process is completed by retransformation of the resulting values. Values are required for the pooling rows from Table 2. They are as follows: 477, 24, -16.81, 0, -13.1, -138, -59, -219, 152, -41, and -284 (the derivation of these values from the coefficients given in Table 2 is tedious to follow; space restrictions have precluded inclusion of the workings in this paper). Having derived these values for the individual in this example, the model then uses them as determined by the characteristics of the carpooling arrangements he is to consider. Thus, for example, suppose he is to consider pooling with a female who causes him, when he is the passenger, to set out 1 min early and to arrive home 2 min late and, when he is the driver, to set out 5 min early and to arrive home 5 min late. Suppose also that the proposed partner has a household telephone, works at the same place as he does but lives 1.6 km away from him, is less than 50 years of age, and will cause him to drive 1.6 km out of his way each day in order to pick her up. The utility would be 477 + 24 - (16.81 x 1) + (0 x 2) - (25.86 x 5) - (13.1 x 5) - (219 x 1) - (41 x 1) = 23.39 p/week (US $0.53).

If the woman in question also puts a positive value on the arrangement, and if this arrangement appears to our individual to be the best on his list, then the arrangement is deemed made. Note that if the woman had had no telephone at home then the utility of the arrangement would have been reduced by 138 p/week (US $3.10) and, since the net value of the arrangement would have been negative (-108.61), it is assumed that it would not come into operation.

If the utility of an arrangement to give lifts (as opposed to alternating driving) had been under consideration, then any deficit in the individual's utility might have been made up from a surplus utility that accrued to his potential passenger. This transfer of utility might be by means of cash (a fare paid) or through some other medium (e.g., periodic gifts). The model will calculate the magnitude of any such transfers of utility and will assume that they take place. However, it does not have to consider how they would be effected.

In early runs of the model, a small minority of individuals in the system seemed to behave in a peculiar manner (for example, by showing an eagerness to get up very early in the morning or to make considerable detours in order to give someone a lift to work). (One of the strengths of microsimulation is that such strange behavior is readily detectable rather than being lost in a formula that represents aggregate behavior.) Apparently, some of the utility formulations were given counterintuitive values for certain match attributes, but subsequent investigation of this phenomenon showed this to be due primarily to the occasional addition of an unusually large stochastic element. Sometimes, however, this behavior was due to the coincidence of a set of attributes and characteristics each of which, when taken separately, militate against a strongly intuitive valuation. For example, if young people, manual workers, and women tend to dislike getting up early in the morning less strongly than do other people, then young female manual workers might be predicted

Table 3. Comparison of observed applicants with simulation model predictions.

Category	Observed	Prediction[a] Average	SD (σ_n)
Applicants for carpooling			
Number	129	126.9	6.98
Number as a percentage of theoretical total[b]	5.8	5.74	0.32
Length of journey to work (km)	8.49	8.88	0.50
Percentage previously public transport users	6.2	7.00	2.61
Percentage previously solo drivers	61.2	59.20	5.23
Percentage previously accompanied drivers	27.9	25.33	3.00
Percentage female	20.2	19.18	4.17
Percentage having a home telephone	90.7	86.54	2.65
Percentage professional workers	45.7	44.83	3.60
Percentage <30 years of age	28.7	28.70	3.93
Applicants to give lifts			
Number	162	168.1	11.07
Number as a percentage of theoretical total[b]	5.28	5.48	0.36
Percentage offering morning and evening lifts	69.1	68.70	4.21
Percentage offering morning lifts only	30.9	33.57	3.89
Mean length of journey to work (km)	8.23	8.41	0.20
Percentage previously public transport users	1.9	2.02	0.94
Percentage previously solo drivers	70.4	65.23	2.69
Percentage previously accompanied drivers	25.3	25.35	2.45
Percentage female	22.2	23.20	2.75
Percentage having a home telephone	84.6	79.33	2.98
Percentage professional workers	54.9	50.49	4.01
Percentage <30 years of age	29.0	27.99	2.80
Applicants to receive lifts			
Number	184	173.9	26.94
Number as a percentage of theoretical total[b]	3.9	3.87	0.85
Percentage wanting morning and evening lifts	77.2	73.82	2.79
Percentage wanting morning lifts only	20.1	21.83	3.53
Mean length of journey to work (km)	6.45	6.43	0.45
Percentage previously public transport users	60.3	65.07	3.64
Percentage previously solo drivers	13.0	16.52	2.74
Percentage previously car passengers	17.4	6.56	1.77
Percentage female	53.8	53.03	1.46
Percentage having a home telephone	72.3	69.72	2.70
Percentage professional workers	26.6	27.33	2.60
Percentage <30 years of age	39.7	36.17	3.97
Percentage having no household car	53.8	52.92	3.00
Percentage having no driving license	60.9	63.06	3.46

[a] Due to the stochastic element in the simulation model it was decided to run the model 10 times and to present here the mean value and its standard deviation.
[b] The theoretical total number of applications assumes one application from each eligible member of the population (i.e., after taking account of items such as license tenure, car availability, and work hours). These theoretical totals are 2212 for pooling, 3067 for lift giving, and 4703 for receiving lifts.

to actually enjoy getting up early in the morning. After several solutions to this problem were considered (14), it was decided to impose a constraint that any valuation that was clearly counterintuitive should be set to zero.

Performance of the Microsimulation Model

In order to test the first stage of the microsimulation suite, the model was run by using the calibrated coefficients and acting on a synthesized population that represents the sample subjected to the car-sharing survey.

Table 3 shows a comparison of the applicants predicted by this model with applicants observed in the field survey. Clearly, the simulation model has reproduced the observed applicants with a fair degree of accuracy. The only discrepancy of any significance is a 10 percent underprediction (6.56 percent instead of 7.4 percent) of the proportion of requesters who previously traveled as car passengers, but this will result in an extremely marginal overprediction of the net effectiveness of a car-sharing scheme. When the model is run several times with different sets of random numbers, the standard deviations of the model predictions are generally low. This indicates that, overall, the model is not highly sensitive to changes in the stochastic element.

Investigation of the performance of the matching routines and the decision-to-match model are best carried out in the context of a full run of the model. For this purpose a possible car-sharing scheme was defined based on the central business district (CBD) of Leeds (an area somewhat less than 1 km^2 that has a workforce of 21 000). The results of running the model for this scheme are presented in Table 4. Full discussion and analysis of these predictions is included in a companion report (3). For the purposes of this paper, it suffices to say that the predictions are well in line with empirical observations of organized car-sharing schemes in Britain [see, for example, Bonsall (15)] and the United States (16).

Table 4. Summary of the results of a full run of the microsimulation suite on the Leeds CBD.

Category	Value
Target population	
Number of eligible work trippers	21 235
Modal split as a percentage of public transport	47.83
Peak-period work-trip vehicle use (km/week)	453 896
Peak-period work-trip public transport use (passenger-km/week)	600 750
Work-trip parking space requirement (spaces/day)	6981
Applicants	
Number	1688
Percentage of target population	8.0
Percentage that are for true pooling	30
Percentage that are for lift giving	32
Percentage that are for lift receiving	38
Percentage that previously drove solo	40.4
Percentage that previously used public transport	35.07
Matching system	
Number of persons for whom a match list was created	1586
Percentage of total applicants	94
Arrangements actually formed[a]	
Number of participants	327
Participants as a percentage of applicants	19
Participants as a percentage of target population	1.5
Percentage of participants engaged in true carpooling	15
Percentage of participants previously solo drivers	37
Percentage of participants previously public transport users	41
System effects[a]	
Net reduction in peak-period work-trip vehicle use (km/week)	1423
Percentage of before situation	0.31
Net reduction in peak-period work-trip public transport use (passenger-km/week)	10 708
Percentage of before situation	1.78
Net reduction in car-park space requirement (spaces/day)	24
Percentage of before situation	0.34

[a] These values are averages derived from 12 separate runs of the model (the stochastic elements in the choice process being the source of variation between runs). Confidence limits for these predictions are included in the background working paper (14).

The computational costs of the microsimulation (at notional commercial rates set by the University of Leeds) are approximately £4 (US $9.00) each time that a new scheme location or intensity is to be tested plus 1 p/applicant (US $0.02) each time that new match lists are to be created and 6 p/applicant (US $0.14) each time that matching decisions are to be made. These costs are clearly very reasonable.

CRITIQUE OF THE SYNTHESIS MODELS

With the wisdom of hindsight, it is possible to point to a number of shortcomings in the synthesis models and to suggest how they might be remedied. These points are discussed in some depth in the background working paper (13), but it is appropriate to summarize them here:

1. Isolation of significant variables in the synthesis process should perhaps have involved analysis of variance in addition to inspection and intuition, and
2. When synthesizing the characteristics of the journey to work, a serious problem, and one that would benefit from a substantial research effort, is the difference between behavior observed on a

particular day (i.e., the usual household interview snapshot) and habitual behavior. In our synthesis we have had to use the former as if it were the latter.

CRITIQUE OF THE MICROSIMUATION MODELS

I will here summarize recommendations discussed more fully in a background paper (14).

1. It must be admitted that the amount of data obtained from the calibration surveys is less than I would have wished and that this has put severe strain on the calibration procedures. This deficiency is, however, one of judgment rather than methodology: The survey cost less than £2400 (US $5500) to mount and, in retrospect, the volume of data could have been increased substantially at little extra cost.

2. The model was designed to simulate organized car-sharing schemes, but it has since become apparent (16) that increasing ad hoc car sharing can be just as important an element in a car-sharing promotional strategy. It would have been wise to have pressed for an extension of the original project brief in order that the model framework could have been extended to deal with ad hoc car sharing (this would clearly have involved a major change in the survey technique).

3. The model predicts the initial acceptability and establishment of car-sharing arrangements; more research is required to study their long-term survival.

4. More rigorous sensitivity analysis of the decision algorithm in the decision to match is required.

5. An attempt should have been made to obtain more data in order that additional important variables (e.g., smoking habits) could have been included in the model.

CONCLUSION

Even with the deficiencies noted above, I believe that the microsimulation model presented in this report is the best model yet developed for the prediction of the performance of organized car-sharing schemes and that its methodology also represents a contribution to the development of improved travel demand models. In particular

1. The synthesis of a realistic population base to provide actors for a microsimulation model has proved possible and tolerably efficient.

2. The model predictions, briefly presented in Table 4 but discussed elsewhere (3), suggest that the model accords well with empirical evidence of the performance of organized car-sharing schemes.

3. The unconventional calibration base (from the field-simulation survey) has proved to be a very useful device.

4. The fact that the model deals with individual decision makers rather than populations has allowed the predictions to be closely scrutinized and verified in a manner that is impossible with conventional models.

5. In short, a microsimulation model calibrated on stated-intention data has proved an attractive device that can be at once behaviorally based and yet computationally tractable. One of its particular attractions is its treatment of system constraints (in this case the compatibility of potential carpool partners). It is this treatment of constraints, rather than any sophistication in the decision models, that is responsible for the close correspondence between model predictions and empirical evidence.

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Estimating Behavioral Response to Peak-Period Pricing

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The concept of applying peak-period pricing policies to highways and other urban transportation facilities has been proposed as one means of reducing rush-hour congestion and compensating for the social costs of travel. This research was designed to assess the potential impacts of rush-hour pricing on the six toll bridges and tunnels between New York City and New Jersey that are operated by the Port Authority of New York and New Jersey. Elasticity coefficients were computed by using data obtained from 943 respondents to detailed telephone attitude surveys. Peak-period crossing patrons, categorized by market segment, were asked to give their likely behavioral responses to off-peak discounts or peak-period surcharges. Several options were identified, including ridesharing, transit, and time-of-day shift. Approximately 16 percent of all passenger-car motorists would change travel time to avoid a $1.00 toll surcharge, but less than 20 percent of these would be willing to shift time by more than one hour. Work trips were found to be less sensitive to toll changes than were nonwork trips, and a substantial cost disincentive was found to be somewhat more effective in removing vehicles than was an off-peak incentive. To avoid higher toll charges, the average motorist would react in the following order of preference: (a) switch to another crossing, (b) switch time of travel, (c) switch to transit, (d) travel less often or not at all, and (e) join a carpool.

This paper summarizes the results of a behavioral research study conducted in 1978 to determine the feasibility and impacts of adjusting toll rates during peak periods (1,2). Elasticity and cross-elasticity coefficients are developed from a detailed telephone attitude survey of motorists by using the six Port Authority vehicular crossings between New York and New Jersey for (a) peak-period toll surcharges, (b) off-peak-period toll discounts, and (c) differential tolls between vehicular crossings.

The Port Authority of New York and New Jersey operates six vehicular crossings between New York and New Jersey. These facilities include three crossings of the Hudson River into Manhattan [the George Washington Bridge (I-95), the Lincoln Tunnel (I-495), and the Holland Tunnel (I-78)] and three bridges between Staten Island and New Jersey. Together, the six facilities accommodate approximately 400 000 automobiles and 50 000 trucks and buses daily.

The eastbound traffic pattern at each crossing is similar and differs only in magnitude. Traffic starts to build up about 6:30 a.m., reaches a peak between 8:00 and 9:00 a.m., and then reduces to midday levels. At the three Hudson River crossings, demand exceeds capacity, which results in queues by 7:00 a.m. that may persist beyond 10:00 a.m. A similar pattern exists during the evening peak period.

In May 1975, the passenger-car cash toll, collected in only one direction on all six vehicular crossings, was raised from $1.00 to $1.50, and various changes were introduced relative to the reduced-rate ticket books. On November 7, 1977, the Federal Highway Administration affirmed a previous ruling that the revised toll structure was acceptable pending recommendations of a further Port Authority study. These investigations were to include an evaluation of the economic feasibility, traffic management and environmental effects, and impact on mass transit of various alternative rate structures of commuter and carpool discounts and of peak-period pricing.

PEAK-PERIOD PRICING

The concept of applying peak-period pricing policies to highways and other urban transportation facilities has been suggested as one means of reducing rush-hour congestion and compensating for the social costs of travel.

Peak-period pricing assumes that, as more vehicles use a roadway system during a given period, each additional vehicle will interfere with the free flow of others in the stream, which will cause them to reduce speed and lead to congestion. As additional vehicles try to enter the system, they further congest the total flow and impose additional costs and loss of time on vehicles that are already in the system. The total additional delay and discomfort forced on all vehicles generally exceeds the delay and discomfort to those marginal vehicles that enter a system that is approaching capacity.

In economic terms, drivers who enter a congested traffic stream do not realize the total cost to society generated by their trips because they pay only the average cost of the trip. If these drivers actually paid the true cost, each would face an economic decision as to whether or not to make the trip at that time. A driver who values traveling during a peak period sufficiently would theoretically pay for these additional costs through a surcharge or, in the case of this study, a higher toll during the congested periods. A driver who did not so value his or her travel would change travel time or mode. In theory, the surcharge or toll should vary directly in proportion to the degree of congestion.

Although there have been several instances of peak-period pricing in the transit industry, experience in highway applications is limited. The most notable example is the Singapore traffic-restraint scheme, which requires special payment to legally operate vehicles in the designated central zone during peak periods (3). This lack of precedents made it necessary to derive elasticity