A Method for Estimating Long-Term Changes in Time-of-Day Travel Demand

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One of the desired features of a travel demand model is an ability to estimate not only 24-hr traffic volumes but also their distributions during the day. In this paper, usefulness of the recently proposed person-category trip generation model to address this issue is examined. A method to estimate time-of-day productions and attractions is proposed. The time-of-day travel profiles of homogeneous groups of persons from Lodz, Poland, and Baltimore, Maryland, are examined. Category-specific, time-of-day travel patterns appear consistent for different subareas within a given metropolitan area, whereas the differences in travel profiles among person-categories are high. This modeling approach provides insight into long-term changes in time-of-day travel distribution as a result of such trends as increase in female employment, increase in average age of the population, increase in automobile availability level, and so on. Forecast and policy implications are also discussed.

Time-of-day variations in daily traffic are of particular interest to transportation planners and engineers. Most of the transportation problems in urban areas are strongly correlated with the magnitude of the peak traffic and could be significantly alleviated if there were a way to distribute traffic more evenly during the day. For obvious reasons, peaking in travel demand is unavoidable, and traffic volumes during the morning and afternoon peak constitute criteria for the geometric design of the transportation network.

Several studies have been performed in different metropolitan areas around the world to examine and better understand peaking phenomenon in daily traffic. A typical result of such studies could be an hourly histogram of daily traffic similar to Figure 1, which presents time-of-day traffic variations in Melbourne, Australia (1, 2). The traffic profiles in other cities show regularities similar to that from Melbourne, although the shapes of actual distributions vary from city to city. For example in Lodz, Poland, the morning peak hour between 7:00 and 8:00 a.m. accounted for 10.3 percent of daily traffic and the afternoon peak hour between 4:00 and 5:00 p.m. accounted for 10.8 percent of daily traffic (3). Because the morning traffic revealed less directional variability, the morning rather than the afternoon peak volumes were used to determine road geometry in Polish cities (3).

In earlier studies, time-of-day travel profiles were often complemented by additional profiles for different trip purposes or profiles differentiated by the transportation mode used for a given trip. In recent approaches using disaggregate choice modeling methodology, time of day may be included as an

additional element of a choice facing Individual i. For example, probability of Individual i's choosing to travel to Activity (trip purpose) p by Mode m and during Time Period t can be described as a product of respective conditional probabilities.

$$P_i(p, m, t) = P_i(p)P_i(m/p)P_i(t/m, p) \tag{1}$$

where

$$\begin{aligned}
P_i(p) &= \text{probability that Individual } i \text{ travels} \\
&\quad \text{during the day to Purpose } p, \\
P_i(m/p) &= \text{probability that Individual } i \text{ chooses} \\
&\quad \text{Mode } m \text{ for Purpose } p, \text{ and} \\
P_i(t/m, p) &= \text{probability that Individual } i \text{ travels} \\
&\quad \text{during the specified Time Period } t \text{ for} \\
&\quad \text{Purpose } p \text{ on Mode } m.
\end{aligned}$$

High heterogeneity of the urban population is the reason why the probabilities vary from person to person, thus making practical applications difficult, particularly in a context of forecasting the peak-period and off-peak traffic volumes. Therefore, it seems reasonable to link time-of-day travel modeling with modeling of trip generation. An extended trip generation model able to estimate travel demand not only for a 24-hr period, but for any peak or off-peak period as well, could be sought. One such model could be a zonal regression model with the coefficients recalibrated for time of day instead of the 24-hr period. However, well-known criticism directed toward this class of models (estimating generations, not attractions) would apply as well.

Another candidate technique could be category analysis. A representative example in this class of models is the 108-household-category model developed by Wooton and Pick in 1967 (4). However, any household-based model will face an unavoidable basic problem of a high heterogeneity of the household. Detecting regularities among categories of households treated as a whole in their trip-making behavior with respect to trip purpose, mode, or time of day is difficult if not practically unfeasible. The large variety of households types, sizes, and structures will always primarily influence all these joint characteristics.

A person-based category model appears a logical candidate for this analysis of the time-of-day travel because of a clear link between individuals' outside-home activities and resulting travel. Kutter's idea of constructing hourly histograms of travel (5) is a successful attempt to prove that different segments of the population have distinctly different patterns of their activities and travel.
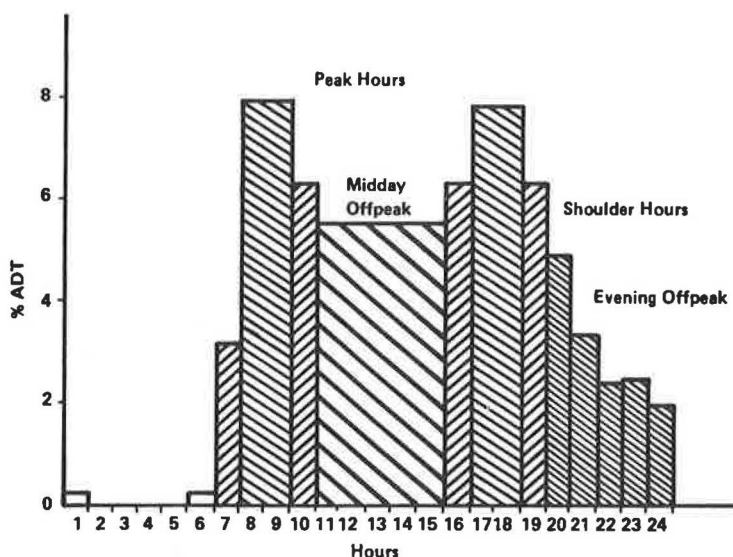
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FIGURE 1 Typical hourly traffic pattern—weekday *(1, 2).*

In this paper the suitability of the person-category modeling approach to analyze time-of-day regularities in travel behavior of homogeneous groups of individuals is examined. The model is an extension of the 15-category trip generation model developed by Supernak for Polish cities in 1979 *(6)* as well as the 8-category trip generation model developed by Supernak et al. for American cities in 1983 *(7).* The main objectives of this paper are

1. To investigate consistency of time-of-day travel patterns related to homogeneous categories of individuals,

2. To analyze the potential for using these patterns to estimate peak-period and off-peak trip generation and distribution, and

3. To discuss regularities in time-of-day travel patterns in the context of the utility maximization principle.

APPROACH AND DATA

The major difference between the person-based modeling approach and other approaches is the fact that grouping of the individuals (potential or real travelers) into groups of similar behavior is based on revealed differences in trip-making behavior (in terms of mobility, mode choice, time-of-day preferences, etc.) rather than on those individuals' automatic affiliation to the same geographic area (zonal level) or the same family (household level). Generalization of the observed behavior of any disaggregate analysis unit (household or person) is unavoidable in any application context, and can be accomplished much more easily and more adequately if (a) a proper market segmentation takes place, and (b) market segments are identifiable and predictable *(8).*

The advantages of the person-based travel demand approach over the household approach were discussed elsewhere *(7, 9).* They include better behavioral background (same analysis unit over all modeling stages), easier forecasts (prediction of population segments is independent of the changes in family formations), and significant reduction of data needed (and consequently lower cost of travel surveys). In the specific context of

this paper, the major advantage of the person-based approach is its fundamental ability to analyze and interpret time-of-day travel patterns at all. Similar patterns applied to such heterogeneous clusters as household would not have much merit or use.

Two data sets were used for the analysis reported in this paper. The first set was gathered in 1973 in Lodz, the second largest agglomeration in Poland (about 1 million inhabitants), and the second one in 1977 in the Baltimore, Maryland, metropolitan area (with population also about 1 million). The sizes of the data sets were different—about 40,000 persons in Lodz versus about 1,800 persons in Baltimore. The relatively small size of the Baltimore data set was the reason why some aspects of the analysis reported in this paper could be performed only on Lodz data. Both surveys used home interviews as a data-gathering technique.

The methodology of creating homogeneous person-categories was also similar in both studies. Both models were developed in stages (two in the Lodz case, three in the Baltimore case) in order to gradually reduce the number of person-categories by eliminating variables that revealed least explanatory power at each stage. Cluster analysis and analysis of variance were used as statistical techniques to accomplish this goal. The analysis resulted in relatively small numbers of person-categories—15 in the case of Lodz and 8 in the case of Baltimore. The procedure of developing person-categories is described in more detail in Supernak et al. *(7).*

The final categories in the Lodz study were defined as follows:

Category	Description
1	Primary school children
2	High school students
3	College students
4	Youth, nonstudents, and nonemployed
5	Housewives
6	Retired and pensioners
7	Male employees, family with a car
8	Male white collar workers, no car
9	Male blue collar workers, no car

Category	Description
10	Male service workers, no car
11	Female employees, family with a car
12	Female white collar workers, no car
13	Female blue collar workers, no car
14	Female service workers, no car
15	Preschool children

For Baltimore the categories were defined as follows:

Category	Description
1	Persons <18 years of age
2	Employed, age 18 to 65, car never available
3	Employed, age 18 to 65, car sometimes available
4	Employed, age 18 to 65, car always available
5	Nonemployed, age 18 to 65, car never available
6	Nonemployed, age 18 to 65, car sometimes available
7	Nonemployed, age 18 to 65, car always available
8	Persons >65 years of age

The most significant variables explaining differences in travel behavior were

Lodz (Poland)	Baltimore, Maryland
Age	Age
Employment status	Employment status
Automobile ownership	Automobile availability
Sex	
Type of employment	

The criteria for homogeneity of old categories to be combined into a new category were different in both studies. For the Lodz study, two Categories i and j were considered similar only if their 35-element vectors of partial trip rates differentiated by (a) base (home-based origin, home-based destination, non-home-based); (b) trip purpose (work, education, other purposes); and (c) time of day (midnight to 5:30 a.m.; 5:30 a.m. to 8:30 a.m.; 8:30 a.m. to 2:00 p.m.; 2:00 p.m. to 5:00 p.m.; 5:00 p.m. to midnight) satisfied the following criteria of similarity:

1. Correlation coefficient $r_{ij} \geq 0.900$,
2. Slope $0.75 \leq b_{ij} \leq 1.25$, and
3. Intercept $|a_{ij}| \leq 0.10$.

In the Baltimore study, each category was represented by a 15-element vector of partial trip rates differentiated by (a) base (home-based origin, home-based destination, non-home-based), and (b) trip purpose (work, education, shopping, personal business, social, recreation). Thus, the time-of-day criterion was not introduced as a criterion of similarity of travel patterns in Baltimore. This lack was mainly due to scarcity of the Baltimore data. Introducing this criterion in the Lodz study was probably responsible for the significance of the variable employment type (white collar workers, blue collar workers, service employees) because of differences in working hours between white and blue collar workers (mostly 8:00 a.m. to 4:00 p.m. for office employees versus 6:00 a.m. to 2:00 p.m. for factory workers in Poland).

For this paper, the Lodz study was more meaningful than the Baltimore one because (a) time of day was a primary criterion of category definition, and (b) the data set was much larger.

RESULTS OF THE STUDY

The results of both studies are presented in Figures 2–4. Figure 2 shows hourly trip histograms for a sample of 9 out of 15 person-categories in Lodz. There are separate profiles for (a) trips originated at home (HO), (b) ended at home (HD), and non-home-based (NHB). If the data set is large enough, this separation may help with directional analysis of traffic volumes generated by each category, for example, toward the central business district (CBD), away from CBD, and non-CBD-oriented. Figure 3 shows a sample of joint hourly trip histograms for just three categories in Lodz representing three fundamentally different activity and trip patterns for (a) preemployment, (b) employment, and (c) postemployment segments of the urban population. Figure 3 shows joint hourly trip histograms during the 24-hr period between 4:00 a.m. and 4:00 a.m. the next day. (This presentation should probably be recommended instead of the period between midnight and next midnight because of late returns home from such activities as entertainment or personal visits.) The four geographic areas within Lodz are rings differentiated by the transit travel time to the CBD: Zone 1, <15 min; Zone 2, 15 to 30 min; Zone 3, 30 to 45 min; and Zone 4, >45 min. Figure 4 shows a joint trip histogram of Categories 1–8 in Baltimore.

The basic objective of this analysis is to answer two questions: (a) are there significant differences among person-categories in terms of their time-of-day travel patterns? and (b) are the category-based time-of-day trip characteristics consistent geographically? Visual inspection of Figures 2–4 suggests positive answers to both questions. Hourly trip histograms are indeed category-specific in both geographic contexts (in Lodz, Poland, and Baltimore, Maryland). Note that person-categories with no obligatory activities (e.g., work, education) try to plan their discretionary activities (shopping, personal business, recreation, etc.) during off-peak periods, more convenient for travel. This applies to Category 6 in Lodz (Figures 2 and 3) and to Categories 5–8 in Baltimore (Figure 4). Hourly trip histograms from both cities could be approximated by smooth, continuous functions.

A brief comment on the findings presented in Figures 2–4 can be made in terms of the utility maximization principle, commonly applied in disaggregate travel demand methodology. Persons participating in discretionary activities try to minimize disutility associated with travel (time expenditure, discomfort, etc.) by traveling during the off-peak periods. Moreover, several discretionary activities (shopping, park recreation, etc.) have their highest utility also during the off-peak period (e.g., quicker service at stores, more sunshine during the middle of the day). Thus, persons who select the off-peak period for their activity and associated travel are acting rationally because they are trying to maximize their overall utility of the activities while at the same time minimizing their disutility of travel.

For employed persons and students, the choice scenarios are greatly limited. The utility of being at work (or, to a lesser degree, at school) is commonly perceived as high but is normally restricted to a specific period during the day. The high utility of the activity is commonly able to offset even the highest disutility of travel during peak periods. (Changing the job or relocating will not be seen as the person's immediate reaction to the congestion problems experienced during travel to work.)
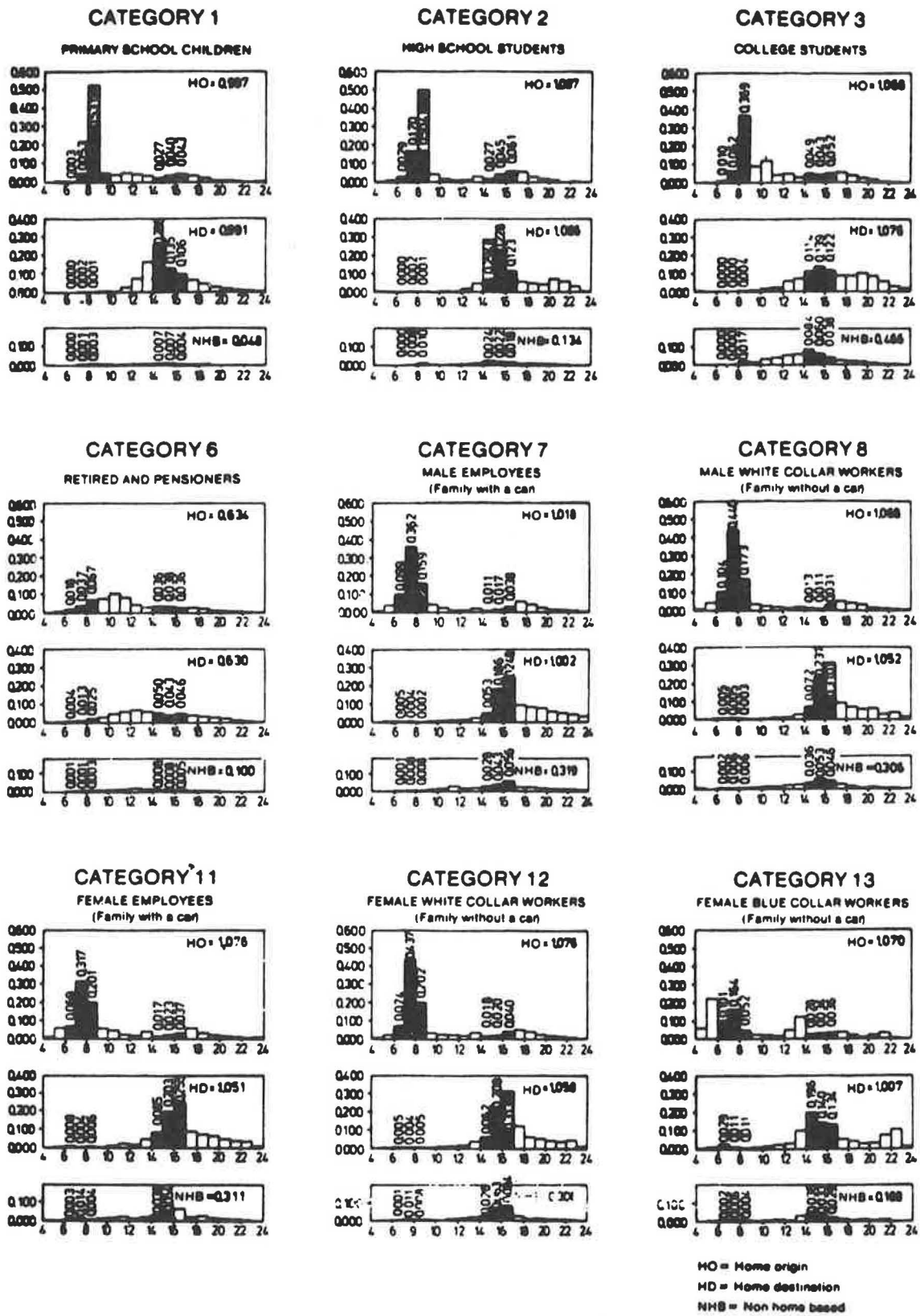
FIGURE 2   Hourly trip histograms of 9 out of 15 person-categories in Lodz, Poland. Total of *HO* + *HD* + *NHB* constitutes the daily trip rate for Category *i*.
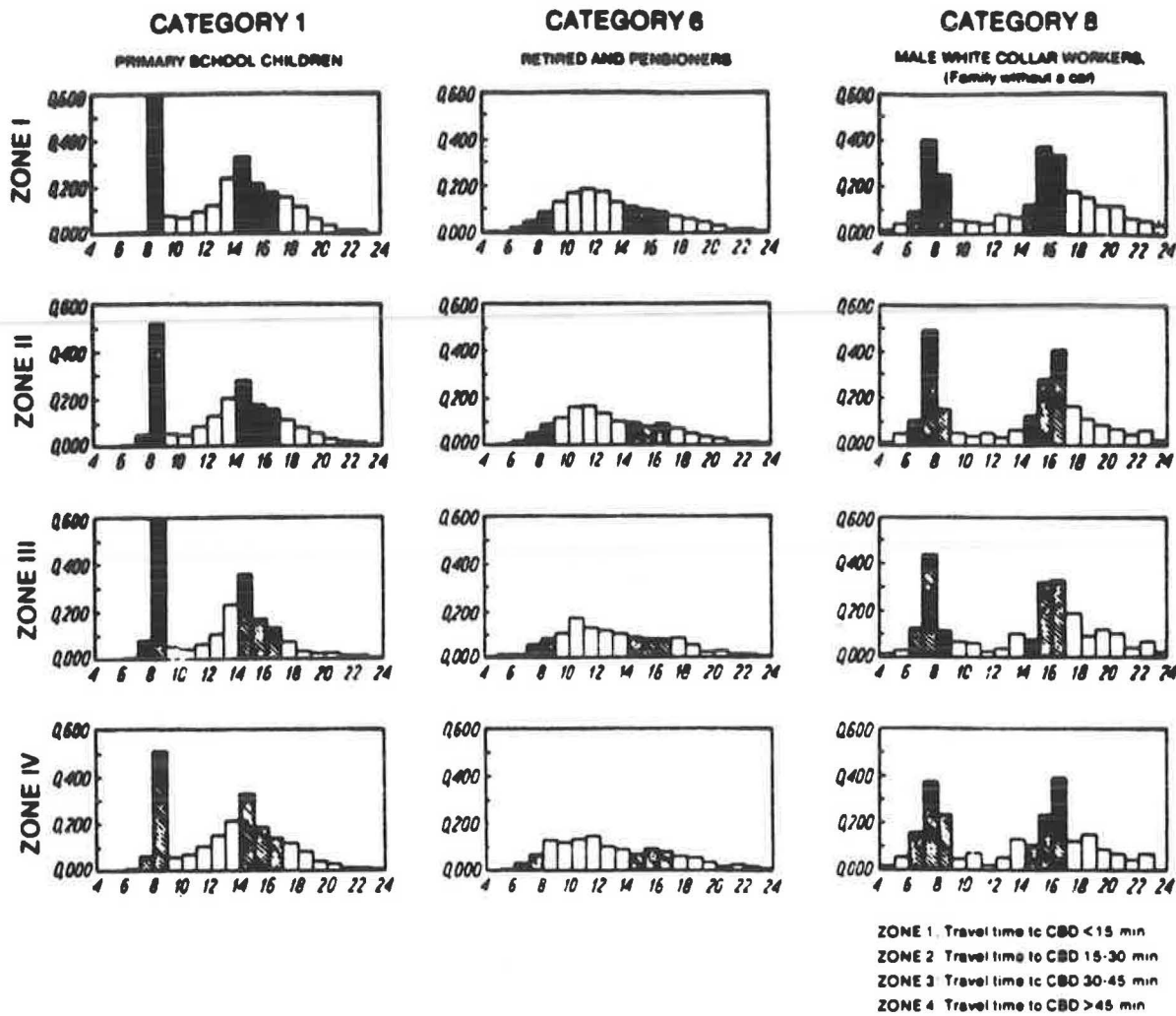
FIGURE 3   Hourly trip histograms of three representative person-categories from four zones of Lodz, Poland. Total of hourly rates amounts to daily trip rate N_i.
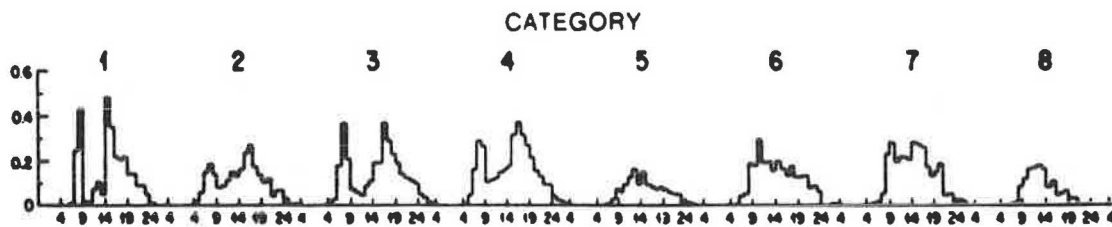

FIGURE 4   Hourly trip histograms of eight person-categories from Baltimore, Maryland. Total of hourly rates amounts to daily trip rate N_i.

Results of the statistical analyses presented in Tables 1 and 2 are in agreement with the previous impression about the observed regularities in category-based time-of-day travel patterns (Figures 2–4). For the purpose of this analysis, all hourly histograms from Figure 3 had to be standardized, that is, each hourly value represented the revealed probability of travel during a given period similar to Figure 1 (with a total of 1 for the 24-hr period).

Table 1 confirms the hypothesis that there are significant differences in hourly trip histograms among person-categories.

Time-of-day trip distributions of Category 1 (primary school children), Category 6 (retired persons), and Category 8 (male white collar workers) are significantly different from the expected population distribution in all cases analyzed ($\alpha = 0.01$).

Table 2 shows that area differences in category-specific time-of-day trip profiles are significant only in 2 out of 12 cases analyzed ($\alpha = 0.01$). The geographic stability of travel profiles within homogeneous categories is an interesting finding considering the dramatically different geographic contexts analyzed (central city versus suburbs in Lodz). Similar analysis for

TABLE 1 RESULTS OF THE KOLMOGOROV-SMIRNOV TEST FOR GOODNESS OF FIT OF TIME-OF-DAY DISTRIBUTION FOR CATEGORIES 1, 6, AND 8 TO EXPECTED CATEGORY TIME-OF-DAY TRIP DISTRIBUTION (DATA FROM LODZ, POLAND)

Zone	Characteristic	Category 1	Category 6	Category 8
1	n	1422	1913	878
	D_{max}	0.114	0.136	0.179
	D_{crit}	0.042	0.037	0.055
2	n	4357	4108	2024
	D_{max}	0.115	0.155	0.194
	D_{crit}	0.025	0.024	0.036
3	n	618	646	187
	D_{max}	0.127	0.134	0.257
	D_{crit}	0.066	0.066	0.119
4	n	1747	979	370
	D_{max}	0.068	0.127	0.210
	D_{crit}	0.039	0.052	0.085

n = sample size (number of trips); $D_{max} = \underset{i=1}{\overset{24}{Max}} |F_i - S_i|$; $\alpha = 0.01$

Baltimore could not be performed because of the limitations of the size of the data set. It is not clear, therefore, to what extent the travel pattern regularities from Lodz could be generalized for West European or American cities.

APPLICATION OF THE TIME-OF-DAY TRAVEL PROFILES TO TRIP GENERATION AND DISTRIBUTION

The trip interchange $T_{ij}(t_1, t_2)$ between Zones i and j during a specified Time Period $t_2 - t_1$ can be described as follows:

$$T_{ij}(t_1, t_2) = f_1[P_i(t_1, t_2), A_j(t_1, t_2), C_{ij}(t_1, t_2)] \tag{2}$$

where

$P_i(t_1, t_2)$ = production of Zone i during Period $(t_2 - t_1)$,

$A_j(t_1, t_2)$ = attraction of Zone j during Period $(t_2 - t_1)$, and

$C_{ij}(t_1, t_2)$ = generalized cost of travel between Zones i and j during Period $(t_2 - t_1)$.

The attractions $A_j(t_1, t_2)$ can be known from empirical studies of the time profiles of arrivals at major employment places and schools, and to a lesser degree at other potential attraction points (parks, banks, etc.). If it is assumed that for each trip purpose p the corresponding shares $S_p(t_1, t_2)$ or arrival probability functions $g_p(t_1, t_2)$ are known, then

$$A_j(t_1, t_2) = \sum_P A_{jp}(t_1, t_2) \tag{3}$$

$$A_{jp}(t_1, t_2) = A_{jp}S_p(t_1, t_2) \tag{4}$$

or

$$A_{jp}(t_1, t_2) = A_{jp} \int_{t_1}^{t_2} g_p(t)\,dt \tag{5}$$

where A_{jp} is the total daily attraction of Zone j for Purpose p.

Productions $P_i^{HB}(t_1, t_2)$, on the other hand, do not depend on area characteristics but rather on characteristics of trip makers who try to satisfy their outside-home activities at some time during the day. The category-specific hourly trip histograms can now be useful for estimations of $P_i^{HB}(t)$, which otherwise could be rather difficult to estimate.

$$P_i(t_1, t_2) = P_i^{HB}(t_1, t_2) + P_i^{NHB}(t_1, t_2) \tag{6}$$

The home-based production of Zone i, $P_i^{HB}(t_1, t_2)$, can be estimated as

$$P_i^{HB}(t_1, t_2) = L_i \sum_{k=1}^{n}\left[\alpha_k\left(\sum_{t=t_1}^{t_2} H_{kt}^{HB}\right)\right] \tag{7}$$

summed over the hourly histogram, or, if normalized travel profiles are used,

$$P_i^{HB}(t_1, t_2) = L_i \sum_{k=1}^{n}\left[\alpha_{ik}N_k^{HB}\left(\sum_{t=t_1}^{t_2} h_{kt}^{HB}\right)\right] \tag{8}$$

where

L_i = population of Zone i,

α_{ik} = share of Category k in Zone i,

N_k^{HB} = home-based daily trip rate of Category k,

H_{kt}^{HB} = hourly histogram of daily trip rate of Category k, and

h_{kt}^{HB} = normalized histogram of daily trip rate of Category k.

The h_{kt} satisfy the normalization condition

$$\sum_{t=0}^{24} h_{kt} = 1$$

If histograms h_{kt} could be substituted by a probability function $h_k(t)$ such that

$$\int_0^{24} h_k^{HB}(t)\,dt = 1,$$

then Equation 8 becomes

$$P_i^{HB}(t_1, t_2) = L_i \sum_{k=1}^n \left[\alpha_{ik} N_k^{HB} \int_{t_1}^{t_2} h_k^{HB}(t)\,dt \right] \qquad (9)$$

$$P_i^{NHB}(t_1, t_2) = f_2[A_i(t_1, t_2)] \qquad (10)$$

During the 24-hr period, the following balancing condition has to hold (if trips crossing the cordon of the study area are ignored):

$$P = A = Y \qquad (11)$$

where

P = total daily trip production (generation) in the city (sum of all zonal productions, both HB and NHB);

A = total daily trip attraction in the city; and

Y = total daily number of trips made (anywhere) by inhabitants of all zones.

Thus non-home-based production will be

$$P^{NHB} = A - P^{HB} \qquad (12)$$

Trip total Y will amount to

$$Y = L \sum_{k=1}^n (\alpha_k N_k) \qquad (13)$$

where L, α_k, N_k are as before but for the entire city. It could be reasonable to assume that

$$P \Big|_{t_1}^{t_2} = A \Big|_{t_1 + \Delta t}^{t_2 + \Delta t} = Y \Big|_{t_1}^{t_2} \qquad (14)$$

where $\Delta t = \bar{t}_{ij}(t_1, t_2)$ = the average travel time between a pair of zones during the analyzed period $t_2 - t_1$ for the entire city.

Thus, balancing conditions for period $t_2 - t_1$ for the entire city are

$$L \sum_{k=1}^n \left[\alpha_k N_k^{HB} \int_{t_1}^{t_2} h_k^{HB}(t)\,dt \right] + f_2[A(t_1, t_2)]$$
$$= \sum_{p=1}^m A_p \int_{t_1 + \Delta t}^{t_2 + \Delta t} g_p(t)\,dt \qquad (15)$$

or

$$L \sum_{k=1}^n \left[\alpha_k N_k \int_{t_1}^{t_2} h_k(t)\,dt \right] = \sum_{p=1}^m A_p \int_{t_1 + \Delta t}^{t_2 + \Delta t} g_p(t)\,dt \qquad (16)$$

This equation can be used to adjust f_2 and $g_p(t)$.

TABLE 2   RESULTS OF THE KOLMOGOROV-SMIRNOV TEST FOR GOODNESS OF FIT OF TIME-OF-DAY DISTRIBUTION FOR ZONES 1–4 TO EXPECTED ZONE TIME-OF-DAY TRIP DISTRIBUTION (DATA FROM LODZ, POLAND)

Category	Characteristic	Zone			
		1	2	3	4
1	n	1422	4357	618	1747
	D_{max}	0.024	0.013	0.063	0.024
	D_{crit}	0.043	0.025	0.066	0.039
6	n	1913	4108	646	979
	D_{max}	0.051[a]	0.018	0.059	0.106[a]
	D_{crit}	0.037	0.024	0.066	0.052
8	n	878	2024	187	370
	D_{max}	0.043	0.019	0.018	0.071
	D_{crit}	0.055	0.036	0.119	0.085

[a])Difference significant at $\alpha = 1\%$ level

The time-of-day travel forecasts can be made by introducing corresponding forecast variables L', α'_k and adjusting functions f'_2 and $g'_p(t)$. This procedure should give a modeler an approximate idea about the expected changes in traffic volumes not only during the 24-hr period but during any peak or off-peak period as well.

It is clear that such changes as increasing female employment, increasing automobile availability, and gradual aging of the society and changes in family structures have had a profound effect on changes in both overall daily volumes and time-of-day distribution of the daily traffic during the recent decade or two. This process continues, and will influence, among other traffic characteristics, time-of-day travel profiles. The person-category method is able to account for these long-range changes, and thus provide useful information about the scale of the desired changes in time-of-day traffic distribution in the future. It will be up to the transportation policy makers to decide to what extent the expected demand should be satisfied, or the anticipated peak-hour behavior modified [by, for example, some specific transportation systems management (TSM) actions].

The complete equilibration process is, of course, much more complicated than the theoretical considerations from this paper (e.g., than Equations 15 and 16) would suggest. The basic category analysis assumption is that travel characteristics of homogeneous categories of individuals will remain unchanged over time. This assumption seems reasonable for the off-peak traffic when the system functions below its capacity. In the case of peak-period traffic, the situation may often be quite complex. First, the model coefficients calibrated for existing conditions may already reflect some modifications in travel patterns resulting from some degree of the oversaturation of the transportation network in some places. Second, even if it is not the case (which would not be a realistic assumption for most North American and European cities), the forecast year may indicate deterioration of the currently satisfactory travel conditions in several areas. In that case, the forecast made by using person-category travel profiles would represent desired volumes rather than real ones. Traffic assignment forecast would have to reduce these volumes to the level determined by the equilibrium conditions on the specific elements of the network. For the travelers it will mean either (a) necessarily eliminating some noncompulsory travel during peak period; (b) searching for a more convenient route or mode of traveling (e.g., abandoning a car in favor of transit if it enjoys preferential treatment), or (c) accepting increased delays and consequently also increasing length of peak periods.

It is felt that, in spite of its simplification, the person-category time-of-day volume estimation would be useful not only for an assessment of likely changes of traffic volumes in the future but also for policy analyses of possible counter-measures (such as different TSM strategies, among them flexible work hours) to be applied in situations where the traffic situation is expected to deteriorate. Today, in most western cities and probably in several cities elsewhere a significant part of the vital elements of transportation systems operates under saturated or oversaturated conditions during peak periods. Therefore, peak-period travel profiles for specific person-categories may represent an unnegotiable need for travel, independent of its inconvenience. It will be unrealistic to assume that many of these trips would disappear if the travel conditions deteriorate even more. Rather, a mode switch consideration or acceptance of longer delays and longer peak periods would be more likely options. Therefore, category-specific time-of-day profiles may appear more stable over time than the complexity of the phenomenon [influence from (a) traveler, (b) network, and (c) traffic] would indicate. Previous studies about actual responses in time-of-day travel to specific policies *(11, 12)* will be helpful for any extended application of the approach proposed in this paper.

CONCLUSIONS

1. Extension of the person-category trip generation model by using category-specific time-of-day travel patterns appears a useful approach to estimate peak and off-peak traffic volumes in metropolitan areas. Time-of-day travel patterns are found to be significantly differentiated among person-categories and relatively stable for representatives of the same person-category residing in different subareas of the metropolitan area studied.

2. Time-of-day regularities in travel represent a rational behavior of groups of persons who try to maximize their utility of outside-home activities and minimize the disutility of associated travel. The resulting time-of-day travel patterns are strongly related to the time-of-day changes in both utilities of activities and disutilities of travel. These patterns illustrate a fundamental difference between highly constrained behavior of employed persons and students, and a relatively unconstrained behavior of persons involved in discretionary outside-home activities only.

3. Person-category time-of-day travel analysis can provide a better insight into the peaking phenomenon, useful in travel studies and forecasts. Category-specific travel patterns can provide a base for estimation of the scale of the potential long-range changes in traffic volumes for any time-of-day period. By estimating potential demand for additional traffic volumes during peak periods, this approach can help develop appropriate solutions to best handle the network oversaturation problems by adequate TSM strategies or protransit policies.

ACKNOWLEDGMENTS

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