Application of Travel Activity Scheduler for Household Agents in a Chinese City

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The travel activity scheduler for household agents (TASHA) is an operational rule-based model that generates activity schedules and travel patterns for a 24-h typical weekday for all persons in a household. This paper reports the application and validation of the model in Changzhou, China. The data cleaning procedure of the traditional household survey and the verification results of the rules used in the TASHA are presented. After the results of the activity generation and scheduling models were analyzed, an iterative approach was applied to inflating the observed activity rates to calibrate the results. The model was shown to replicate observed activity frequency, tour frequency, and trip start time fairly accurately at the regional level. The activity duration of the model was underestimated by 13.1%, but this underestimate did not add much bias to the shape of the duration distribution by start time. The final model results show that the TASHA is an attractive alternative to conventional modeling systems currently used in Changzhou.

Chinese cities have been experiencing unprecedented urbanization and motorization. To solve the subsequent transportation problems, a variety of transportation policies are being examined, discussed, and implemented. Many of these policies such as pricing and alternation hours cannot be fully modeled by using the traditional trip-based model. Activity-based models offer numerous significant advantages in supporting these policies as they model complete travel behavior. Although their advantages have been recognized by a wider community of transportation planning analysts, the data and technical requirements of activity-based models have restricted their application in Chinese cities to date.

In this paper a rule-based model is built for Changzhou, China, by using the travel activity scheduler for household agents (TASHA). The TASHA was developed by the University of Toronto and has been applied primarily in the Greater Toronto Area of Canada (*1*). A key feature of the TASHA is that it can be implemented by using conventional trip diary data, which are used to construct out-of home activity data, thereby making its application feasible in Changzhou where only the conventional travel diary survey has been conducted. Increasingly transportation management policies such as parking pricing and vehicle use restriction, major transportation investments such as bus rapid transit and mass rail transit, and the needs of emission analysis are the incentives for the application of the TASHA in Changzhou.

The rest of this paper is structured as follows. The current state of the activity-based model development and implementation is briefly reviewed, followed by a description of the data source and data cleaning procedure. The modeling process, verification of the modeling rules, and model calibration are presented next. The model outputs such as the activity frequency, start time, and duration are then described, and finally summaries of the paper and the possible improvement of the model are presented.

LITERATURE REVIEW

During the past 20 years interest in the development of activity-based models has increased in transportation research. Different approaches have been used for activity-based models, but most of the models developed follow one of two approaches: utility maximization–based econometric approaches or rule-based computational process model systems (*2, 3*). The utility maximization approach, which usually uses a large nested logit model in which at the higher level an individual chooses a travel pattern and in the lower level tours associated with these activities are selected, is the more commonly used approach in currently operational regional models (*4*). Rule-based models attempt to model the decision-making process itself rather than the outcomes of this process. Although different activity scheduling processes and decision rules are used in several operational models, developing fully verified, generalized decision rules is a challenging task. Research is ongoing on capturing and enumerating all of the decision rules and modeling individuals' daily activity scheduling process by using new data sources, such as scheduling process data (i.e., data to help one understand the sequence of decision making involved in the scheduling process) (*5–8*).

Growing transportation problems in cities such as congestion and pollution stimulate new policies aiming to change people's travel behavior and to form a sustainable urban transportation system. Activity-based modeling is becoming more adept at modeling these issues. Until now, however, the application of activity-based modeling has been concentrated in Europe and the United States. The most well-known examples include Albatross in the Netherlands (*9, 10*) and DaySim and CT-RAMP in the United States (*11, 12*).

Choosing whether to adopt an existing model or to develop a new one is always a concern for model application. Developing a new, well-tested, and debugged model is very costly and time-consuming, while transferring an existing model seems to be an attractive solution for many cases. DaySim and CT-RAMP, which are based on the conventional utility maximization–based discrete choice framework, are two main families of activity-based model systems now being used by large metropolitan planning organizations in the

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Transportation Research Record: Journal of the Transportation Research Board, No. 2429, Transportation Research Board of the National Academies, Washington, D.C., 2014, pp. 121–128.
DOI: 10.3141/2429-13

United States (*12, 13*). Since these activity-based models were developed on the basis of specific cities at first, transferring these models to a new region has become an emerging issue. In most cases, transferring the model means using the same core features of the model system (including software) and introducing additional advanced features or refinements to address specific regional conditions. In some applications, with a relatively small survey sample data and a low budget, the parameters were also transferred to a new model to reduce the amount of time and cost (*13*). Compared with the utility maximization–based econometric approaches, the development and application of a specific rule-based computational process model is usually based on one specific region. For example, so far the transferability of Albatross to other countries has not been investigated, to the authors' knowledge. Compared with conventional utility maximization–based models the study of transferability for the rule-based model seems to be a much more demanding issue.

DATA

Data Description

The model was developed by using data from the *Changzhou Household Travel Survey,* which was initially collected for a conventional trip-based model. Changzhou is located in the Yangtze River Delta area of China. It covers an area of 1,872 km^2 and had a population of 3.124 million in 2008. The city is divided into 438 traffic analysis zones. The sizes of the zones vary by their locations. The average areas are about 0.3, 1.0, 2.5, and 30.0 km^2 for downtown core, downtown, two new developed areas, and rural areas, respectively. The *Changzhou Household Travel Survey* began in October 2008 and ended in May 2009. For the survey 29,589 individuals in 10,238 households were interviewed (approximately a 1% sample rate). The survey collected household characteristics such as car ownership; person characteristics for each household member such as gender, age, and occupation; and a 1-day travel diary for each participant.

Data Cleaning

To support the TASHA model, the observed data, especially the activity location, time, and purpose, were checked and adjusted according to the following rules to ensure that all of the individuals' daily activity decisions were feasible.

The TASHA models individuals' daily activity decisions. The work or school zone of each person is considered to be exogenously known, as with other personal attributes, since it is a long-term decision and does not change on a daily basis. Because work and school locations were not explicitly surveyed as a personal attribute, people's work and school zones were inferred from the observed work and school trip destinations. Farmers' reported work trip locations were invariably their home zones, so home zone locations were also assumed for farmers without reported work trips. This assumption is also justified by the large zonal sizes for farmers' residential locations. For other workers or students without a work or school trip record, several multinomial logit models were estimated by occupation types to generate their work or school zones. Two variables were used in these simple home-based location choice models, Manhattan distance and zonal employment of occupation. For the school model, employment was provided by the survey, which had teacher employment by zone. For school, office, manufacturing, and sales occupations goodness of fit, 0.343, 0.271, 0.295, and 0.315 ρ^2 were obtained. Households of persons making more than one work or school trip to different destinations zones were discarded from the estimation data set (0.77% households of the raw data). Although it is possible that a person has a secondary job at a second location (or has multiple work locations for a single job), since there is no personal attribute about this work status in the survey data, one cannot judge whether or not it is a secondary work episode or just a data error. Households were also removed if their household zone was invalid or if their record contains any trip with an invalid origin or destination zone (i.e., the zone does not exist in the zone system).

The trip start time and purpose should be consistent and meaningful. A household was removed if a person starts his or her first trip before the beginning of the study period (4:00 in the morning) or does not come back home before the end of the day (4:00 a.m. the next day). Since the TASHA models a person's home-based tours only for a weekday, 4:00 is more suitable to be the division of time between 2 days than 0:00, which reduces the number of incompatible persons. The start times of every trip for each person should be in chronological order. The data were also filtered to remove obviously flawed trips, such as a person whose tour involves two return home trips in a row.

Seven full-time occupation types are in the original survey data: manufacturing, attendant or sales, office, self-employed, farmer, and other. Occupation is an important attribute in the TASHA because all occupations have their own distributions for generating activity episodes. For a relatively small sample survey, more occupation types means fewer observed activity episodes available to build the episode distribution for each occupation. Because other category division attributes such as age and number of children are also used to cross classify activity episode generation rates, the distributions can become extremely sparse if too many occupation groups are used. Considering the common ground of these work types, they were grouped into four full-time occupation types: manufacturing (19.6%), farmer (7.9%), sales (9.0%) (which is a general category including service workers or sales and others who are nonsalaried workers), and office (28.3%) (which is also a general category including office workers and self-employed who may have fixed working hours). These people are qualified to engage in work or work-business activity episodes in the model. Among nonworkers, 12.5% are students and 22.7% are neither students nor full-time workers (they may be retirees, homemakers, or "other"). Some of these people are observed to make a work trip or work-business trip in the original survey data. To model these trips, their work status was manually changed to part-time worker. On the basis of this step, the work status of 113 students (0.5%) and 437 others (1.8%) was changed.

There are 10,238 households in the raw data. After data cleaning, 8,385 households remained (81.9% of the raw data). The data were then converted into a set of out-of-home activities with all attributes, such as the trip start time, activity start time, activity duration, and activity location. Two new joint activities are automatically calculated if more than one household member undertake the same activity type at the same time and location.

MODEL SPECIFICATION, RULE VERIFICATION, AND MODEL CALIBRATION

Brief Introduction of TASHA

The TASHA is a large model system that contains a rule-based scheduling model, a tour-based mode choice model, and a location choice model. It was designed to improve on current four-step modeling systems used in the Greater Toronto Area in a number of ways—most important, the behavioral representation of human decision making, the spatial and temporal precision of outputs, and the sensitivity to demand-oriented policies (*14*).

With a two-step process the rule-based scheduling model generates activity schedules and travel patterns for a 24-h typical weekday for all persons in a household. In the first step (episode generation) activity episodes are synthesized by randomly drawing from empirical probability distributions constructed from the household travel survey. For each episode, the nominal start time and duration are generated. These episodes are generated for activities grouped into a set of projects (work, school, individual shopping, individual other, joint shopping, and joint other). In each project the generated episodes are collected into an agenda in which all episodes in each project are feasible (i.e., do not overlap). In the second step (scheduling) a heuristic method is used to assign the episodes from the project agendas to the person's provisional schedule, again ensuring the feasibility of the schedule. In both steps rules are used to adjust episode start times and durations if necessary to ensure feasibility.

Rule Verification

Many rules have been used throughout the model to develop realistic activity patterns. A person's travel behavior changes from city to city and, more obviously, from country to country. Before the model was built, it was necessary to test whether the rules in the TASHA, originally developed for Toronto, were still effective in Changzhou.

Seven different project types have been defined in the TASHA: primary work, secondary work, school, joint other, joint shopping, individual–other, and individual–shopping. The primary work project is the most complicated of all of these projects. It includes one primary work event, zero or one return-home-from-work episode, and any number of work-business episodes. The primary work event is defined as the sequence of work episodes beginning with the first work episode of the day plus any work episodes from subsequent work chains that begin before 3:00 p.m. Return home from work (i.e., lunch) must conclude before 3:00 p.m. and must result in at least 30 min of work before and after returning home. Work–business is defined as work-related episodes that occur at a location other than the usual place of work. These should fall within the primary work event and have durations that are less than the associated primary work events. After the observed activities were checked, the rules for primary work event and return home from work episode were well confirmed. Only 1.1% of return-home-from-work and 2.1% of primary work activity episodes start after 3:00 p.m. For all other projects, only a single episode type is assumed to be included, which is of the same name as the project. In the Changzhou model, since data for secondary work are not available, this project type has not been modeled. Return-home activities are not generated explicitly; rather, they are the default activity that is generated if there are no other out-of-home episodes generated. To make the return-home activity worthwhile, a minimum activity duration threshold of 15 min is set in the model. The assumption conformed to the observed data; only 1.2% of return-home activities were less than 15 min.

All of the rules used in step two can be classified into three categories: priority of activities, conflict-resolving rules, and episode cleanup rules. The priorities for scheduling episodes are, from high to low, primary work, secondary work, school, joint other, joint shopping, individual other, and individual shopping for all people except students, whose highest rank activity is school. The basic idea of conflict-resolving rules is to keep each episode's start time and duration as close as possible to its originally generated values. These two categories of rules are impossible to test directly because of the lack of scheduling process data for Changzhou. These rules can only be verified indirectly by comparing modeled trip start time and activity duration with observed ones (discussed in the next section). If these rules are reasonable and realistic, modeled trip start time and activity duration will be close to the observed ones. The cleanup procedure discards work episodes with less than 30-min durations and rearranges the schedule to remove unrealistically high numbers of short work episodes. The observed data show that only 1.7% of work episodes are less than 30 min. For children (younger than 11 years old), school is the only out-of-home activity generated in the TASHA. Their activities are very random and mostly with their parents and cannot be well modeled. In the survey, school and return home trips account for 97.4% of the total 2,897 trips. Thus, the TASHA assumptions generally appear to be reasonable.

Model Calibration

People always have many activity plans. But because of time constraints, only some of them are realized. The current TASHA implementation, which uses executed activity data from a traditional household travel survey to generate desired activity attributes, is not entirely satisfactory in a behavioral sense (i.e., data on posterior outcomes are used to generate prior plans). Only the executed trips are observed, from which executed activity schedules are derived. If all the desired activities can be executed in the model, the activity frequency would be perfectly replicated. But conflicts are frequently generated during the scheduling process, much as they are in reality. As a result, the total number of modeled episodes is usually less than the observed number. The problem is more obvious in Changzhou where peak hour travel is quite dominant.

In a rule-based model, scheduling-process data help to capture decision procedure, develop decision rules, and finally output more accurate results. As the core of the rule-based model, activity conflict resolution is a complex decision-making process. It is simplified through the use of assumed rule systems and the priority for each activity type in the TASHA. This uniform and fixed scheduling priority has been criticized for ignoring different utility perceptions of episodes by different persons (*5, 6*). Research has shown that these activity type–based priority assumptions often do not hold in actuality. For example, the work by Roorda et al. analyzing conflicts in the Computerized Household Activity Scheduling Elicitor survey data set showed that more than 28.5% of work or school activities were moved to different days or skipped, which would be impossible to represent by current rules (*15*). These situations may lead to inaccuracies in the model results especially the low priority activities. However, the simple and generally reasonable scheduling priorities used in the TASHA are quite suitable for cities that do not have scheduling process data to support advanced priority models. They lower the time and cost for the first model implementation in cities such as Changzhou. An expansion factor is used for each activity type to calibrate the model to fit the observed data. Since high-priority episodes will affect low-priority episodes, all types of activity are intertwined with one another. An iterative approach is then used to calculate the expansion factors for the activities. An expansion factor of 1 (i.e., no expansion) is used in the initial application of the model for all activities. Then the expansion factor is recalculated according to the total number of observed episodes divided by the total number of modeled episodes for each activity. This recalculation is repeated until the generated episodes are close enough to the observed by a user-defined margin.

Table 1 presents results from the initial application of the model in regard to the total number of episodes predicted after the generation and scheduling steps. Generally speaking, the model underestimates the total episodes. The generation model, as expected, reproduces the observed data very well. Because the work activities are combined into a primary work event for each person, and children younger than 11 years old are not included in the travel diary data used to construct the episode generation distributions, the number of predicted and observed work and school episodes do not exactly match. In the absence of empirical data, student episodes for children under 11 years of age are generated with user-defined school start and end times. The observed data also include nonschool out-of-home activities for children younger than the age of 11. Because these trips are very rare, they are not represented in the distribution, nor are they generated in the model.

During agenda formation and scheduling, the conflicts caused by overlapping episodes will result in episodes inserted later in the process having a higher chance of conflict and thus being rejected as being infeasible if the conflict cannot be resolved. To avoid rejecting episodes, the model will first try to regenerate the rejected episode and to insert it up to 10 times. If this process fails to correct the problem, then the episode is finally rejected. Since work and school episodes are scheduled first, they tend to be accurately predicted. Rejections occur more often for shopping and other activities because they are assumed to be low-priority activities that are scheduled later in the process. The priorities of joint shopping and other activities are higher than those of individual shopping and other activities, but the scheduling conflict for any household member that cannot be resolved results in the rejection of joint activity episodes for all other household members. Return home from work is a very constrained activity. The person who does this activity usually works near home or has free time at noon. But the model randomly draws the activity to insert it into a person's schedule. If the person works very far from home or has a limited lunchtime, the activity is very likely to be discarded since it takes a long time to return home and then go to work again.

Given the available data, the only solution to significantly underpredicting episode generation is to manually inflate (calibrate) the generation rates so that more of a larger sample of episodes is available to (it is hoped) generate more successful insertions. After several expansion factors were tested, the following episode generation rate adjustment factors were adopted: work-business (1.2), return home from work (1.6), individual shopping (1.3), individual other (1.5), joint shopping (2.2), and joint other (2.8). Because work and school are primarily the highest-priority activities and return-home activities are not generated directly, they were not expanded. The assumption is that these expansion factors remain fairly stable over time.

TABLE 1 Total Number of Episodes in Each Step

Episode Type	Observed	After Distribution	After Scheduling	Predicted or Observed
Work	15,026	12,286	14,870	0.99
Work–business	2,296	2,290	1,687	0.73
Return home from work	2,540	2,539	1,596	0.63
School	2,381	1,044	2,486	1.04
Individual shopping	5,066	5,060	4,327	0.85
Joint shopping	640	640	274	0.43
Individual other	5,989	5,950	4,608	0.77
Joint other	556	556	168	0.30

MODEL VERIFICATION AND ANALYSIS

Activity and Tour Frequency

Table 2 shows the final frequency of activities generated and successfully scheduled in comparison with the survey data, by activity purposes. The TASHA replicates Changzhou observed data very well, as the total activities are closely simulated (underestimated by 0.35%). The work and school activities are slightly overestimated, whereas individual other and individual shopping are slightly underestimated (all within ±4%). Although joint other and joint shopping are minor activities, they are also well predicted (both within ±10%). Work-business activities and return home from work are underestimated by 14.89% and 16.30%, respectively. Return-home activities are not generated directly, but are rather a by-product of out-of-home activities. The 0.57% overestimated rate shows the good quality of the model. If the total number of return-home activities is compared (including return home from work), the model underestimates it by 1.03%. The activity frequencies of different occupations are also well predicted as Figure 1 shows.

The total number and average size of tours are both well modeled. The total number of tours is predicted by the model to be 26,425, compared with 26,701 observed tours. The average number of trips per tour is predicted to be 2.21 versus the observed value of 2.20 (calculated as the total number of trips divided by the number of return-home trips). As shown in Figure 2, the TASHA also predicts well the distribution of number of trips per tour. The model slightly undersimulates two-trip tours and oversimulates the three-trip tours. Two hundred forty-three different types of tours existed in the observed data; the TASHA generated 186 different types of tours.

TABLE 2 Activity Frequency Comparison by Activity Type

Activity Type	Observed	Modeled	Percentage (±)
Work	15,026	15,490	+3.09
School	2,381	2,476	+3.99
Work–business	2,296	1,954	−14.89
Return home from work	2,540	2,126	−16.30
Individual shopping	5,066	4,880	−3.67
Individual other	5,989	5,961	−0.47
Joint shopping	640	697	+8.91
Joint other	556	564	+1.44
Return home (except from work)	24,161	24,299	+0.57
Total	58,655	58,447	−0.35
Number of tours	26,701	26,425	−1.03
Trips per tour	2.20	2.21	+0.69

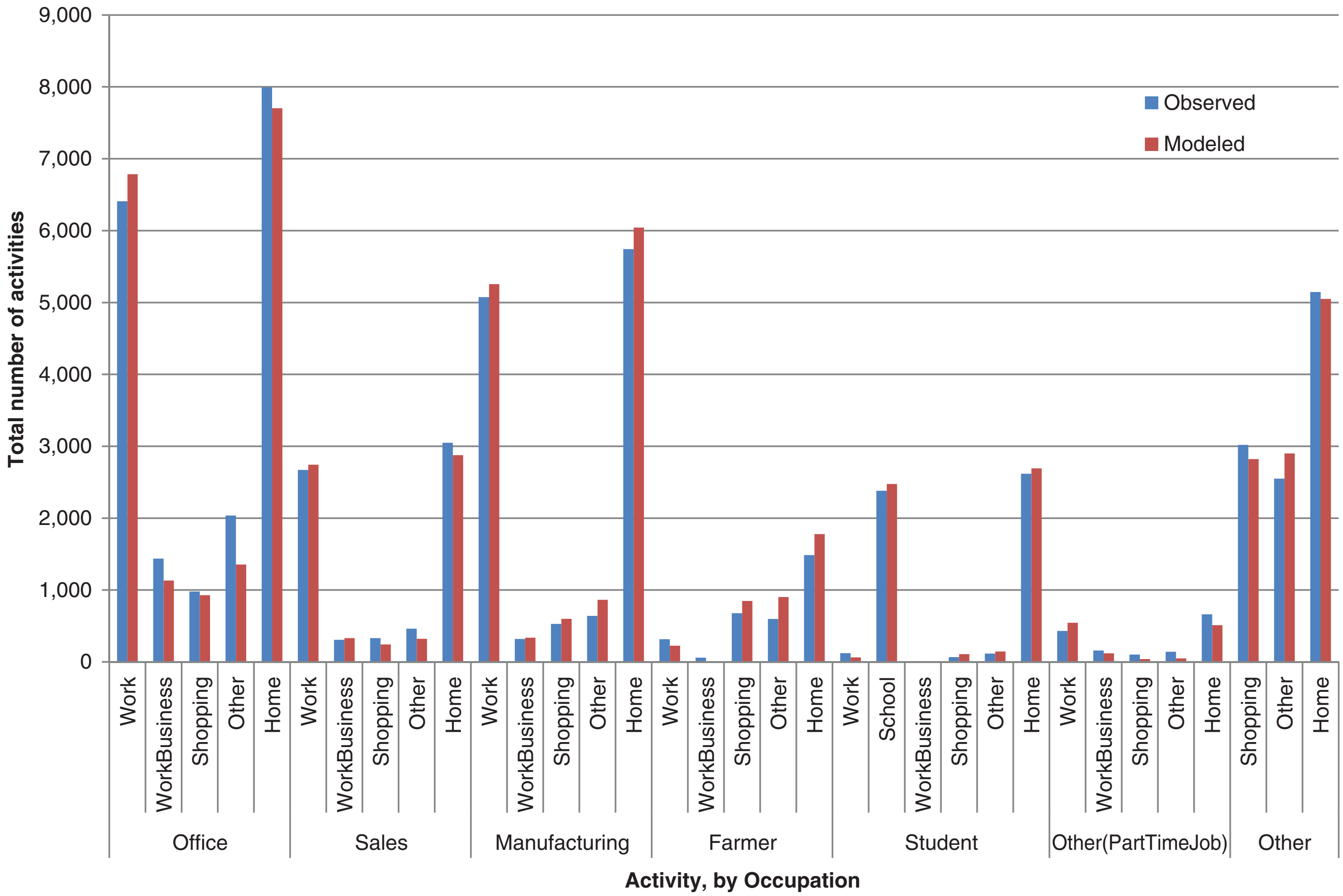

FIGURE 1 Activity frequency comparison by occupation type.

Trip Start Time

Figure 3 shows that activity types are replicated by the TASHA, with the correct distribution over time throughout the day. Total trips in the a.m. peak period (7:00–9:59) is slightly underestimated (–1.9%), while in the p.m. peak period (16:00–18:59) it is significantly underestimated (–18.7%). Figure 4 compares the observed and modeled activity frequency in every 1-h interval for each activity type. Most points fall into the $y = x \pm 5\%$ interval, which also indicates the precision of the model on trip start time. As the labels of the outliers show, the model oversimulates the work activity for 7:00 to 8:00 and undersimulates it for 6:00 to 7:00. Scheduling conflicts occurring in

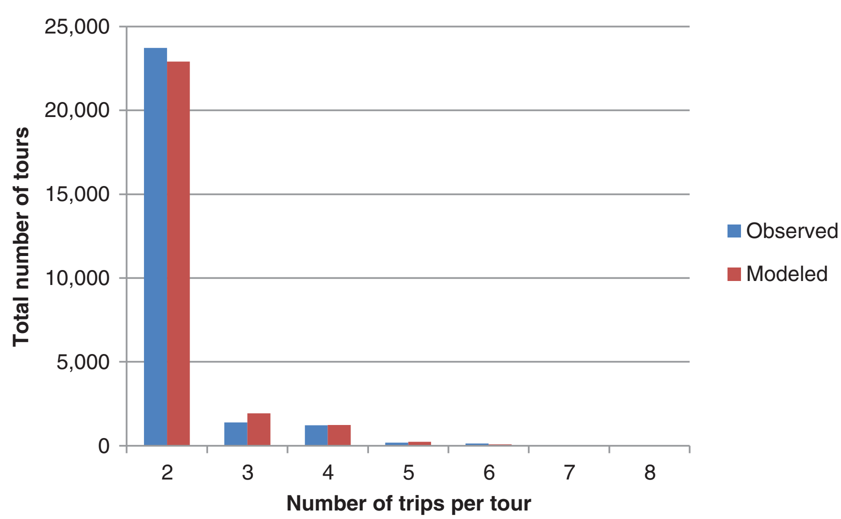

FIGURE 2 Distribution of number of trips per tour.

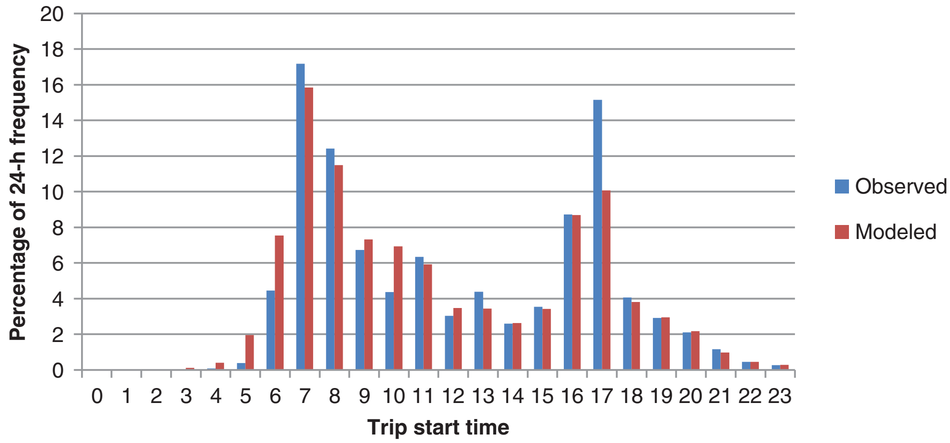

FIGURE 3 Total activity frequency by trip start time.

the model will result in a shift in trip start times out of the desired time period into adjacent time periods. If working frequency in the peak period is computed, the effect will be neutralized to some extent. So will the school activity. The joint shopping activity is the most conflicting activity. The model tends to schedule it in the evening because more high-priority activities such as work and school will compete for morning time. However, as a minor activity that accounts for only 1.1% of the total activities, it will not affect the model results too much. The return-home activity is not generated from an empirical distribution but rather is an emergent by-product of the out-of-home activities. In the TASHA persons are assumed to return home after any out-of-home activity if a sufficient time gap

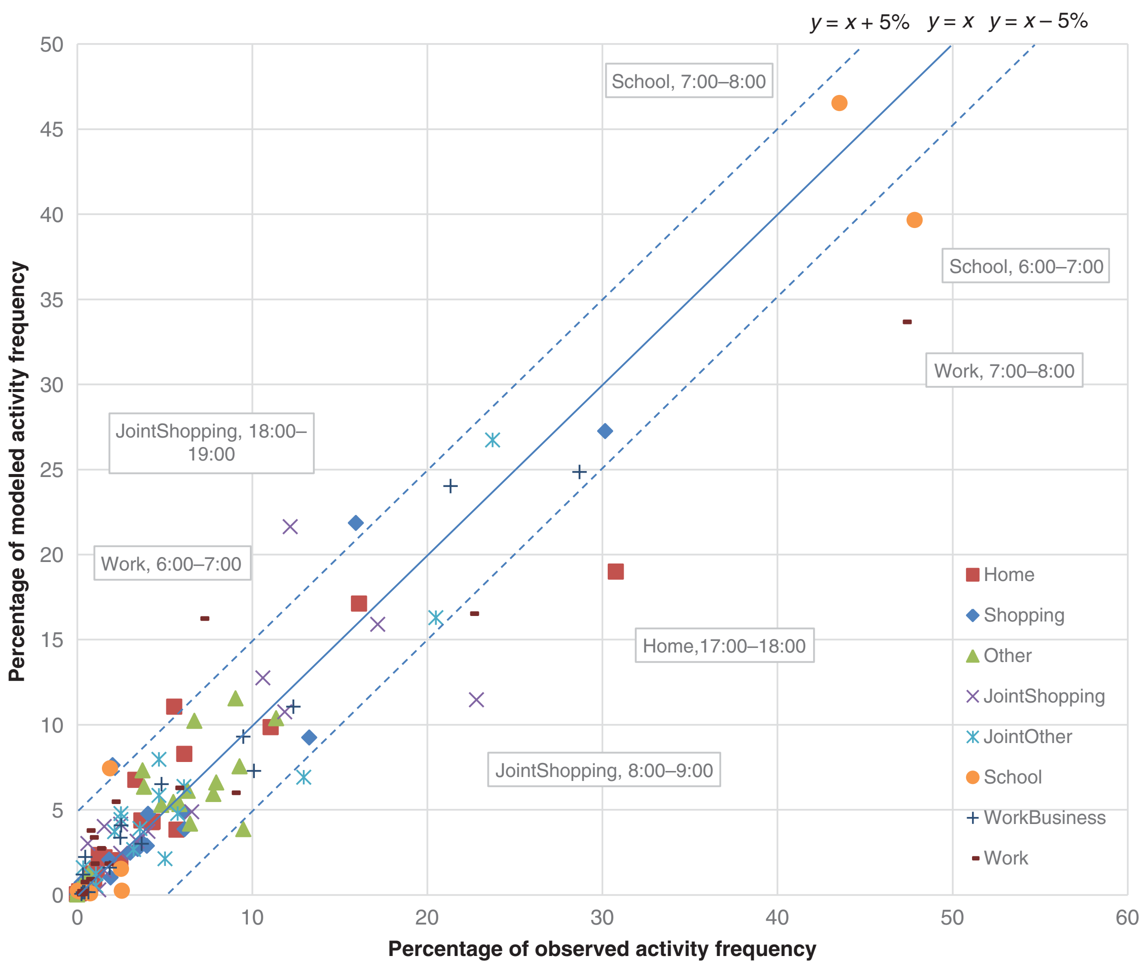

FIGURE 4 Comparison of activity frequency by activity type and trip start time.

exists between subsequent out-of-home episodes to make returning practical or worthwhile. The model significantly underestimates return-home activities for the 17:00 to 18:00 time period, but performs well at other time intervals. Generally speaking, although the episode generation rates for shopping, other, return-home-from-work, and work-business activities were inflated, the start time distributions of these activities are not biased much.

Activity Duration

For all out-of-home activity types, the average activity durations are 291 min for observed activities and 253 min for modeled activities; thus, on average, the model underestimated durations by 13.1%. A box plot of activity duration distributions for each activity type is shown in Figure 5 to provide 0th (lower whisker), 25th (lower hinge), 50th (median), 75th (upper hinge), and 100th (upper whisker) duration percentiles. Extreme cases in the sample are also plotted. The box shapes of modeled durations and observed durations are similar for all activities, with the modeled durations generally being displaced slightly downward (shorter durations). The work activity is generated by randomly inserting work-business and return-home-from-work activity into the primary work event. Because the procedure cannot ensure that the times these two activities happen are the person's optimum choice, some short work activities are generated. For that reason work activity frequency is somewhat overestimated while work activity durations are somewhat underestimated. For work-business, shopping, and other activities, reducing their duration (less than 50%) is the last conflict-resolving strategy in the scheduling model in which a shift in trip start times into adjacent time slots cannot resolve the conflict. Reduction in activity durations occurs more often for joint shopping and other activity because the joint activities need to keep the same state for each of the participants' schedules. The school activities of children younger than 11 years were generated by using unified rules rather than a real distribution; this use of rules led to some overestimation of durations.

As shown in Figure 6, the out-of-home activity duration distribution by trip start time follows a pattern similar to that of the observed data except for the activities that start at or before 7:00 a.m. Because most of the activities that take place at this time are work, underestimation is more obvious for work durations than for other activities.

CONCLUSION

This paper has presented an application of the TASHA to Changzhou, China. Transferring the TASHA to Changzhou radically reduced the amount of time and the cost required to implement an activity-based model. Use of the travel diary as the primary observed data source for developing the model was somewhat challenging given the data completeness and consistency issues and the relatively small sample size. In contrast to the transferring of a utility maximization–based model, in which the core features of the model system are unchanged and specific regional conditions and needs are addressed by adding additional features, the rules—the core of the rule-based model—should be verified and refined if necessary when a rule-based model is transferred. Rule verification shows that the TASHA assumptions generally appear to be reasonable in Changzhou—a different implementation context. After initial application of the model, expansion factors were calculated through an iterative procedure to solve the problem of episode underestimation. The activity frequency, trip start time, and activity duration of the model have been compared against the observed data, and the comparison shows that the model can replicate the observed data well at the regional level. The activity episode durations were underestimated by 13.1%. The authors think that if higher accuracy of duration is required, refining the rules may improve duration predictions for cities that do not have

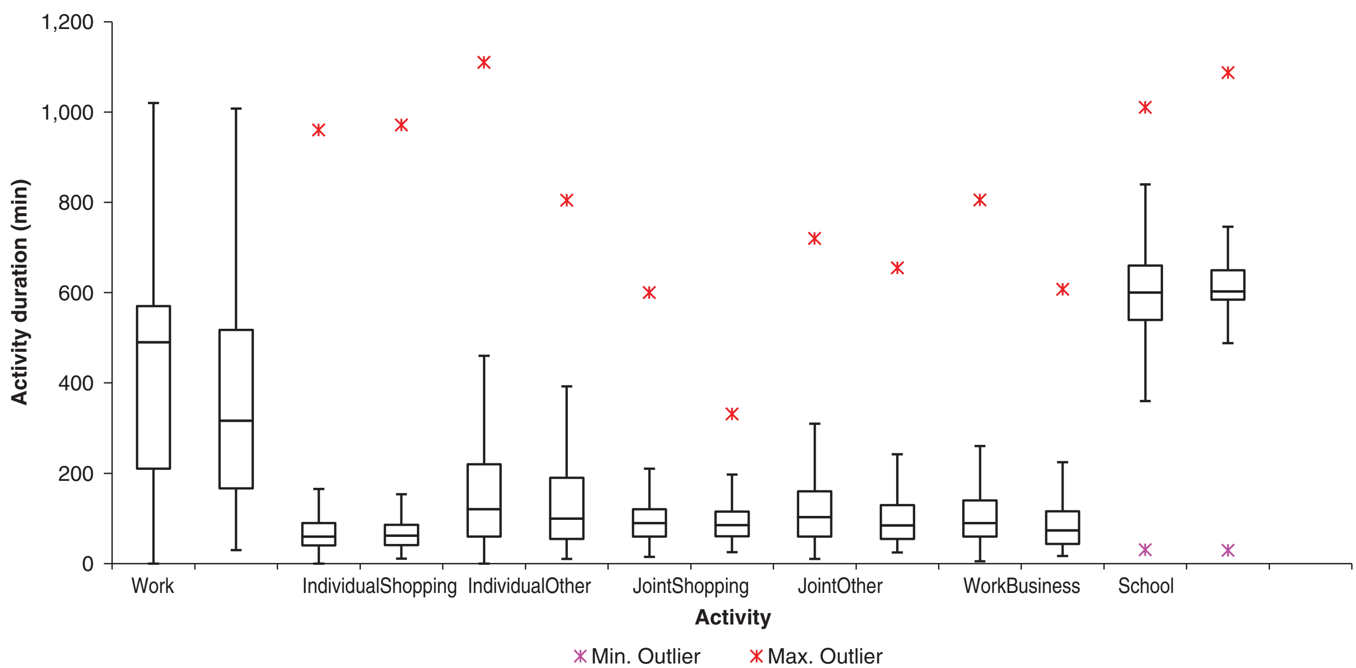

FIGURE 5 Activity duration distributions (for each activity, box on left is observed duration and box on right is modeled duration; min. = minimum; max. = maximum).

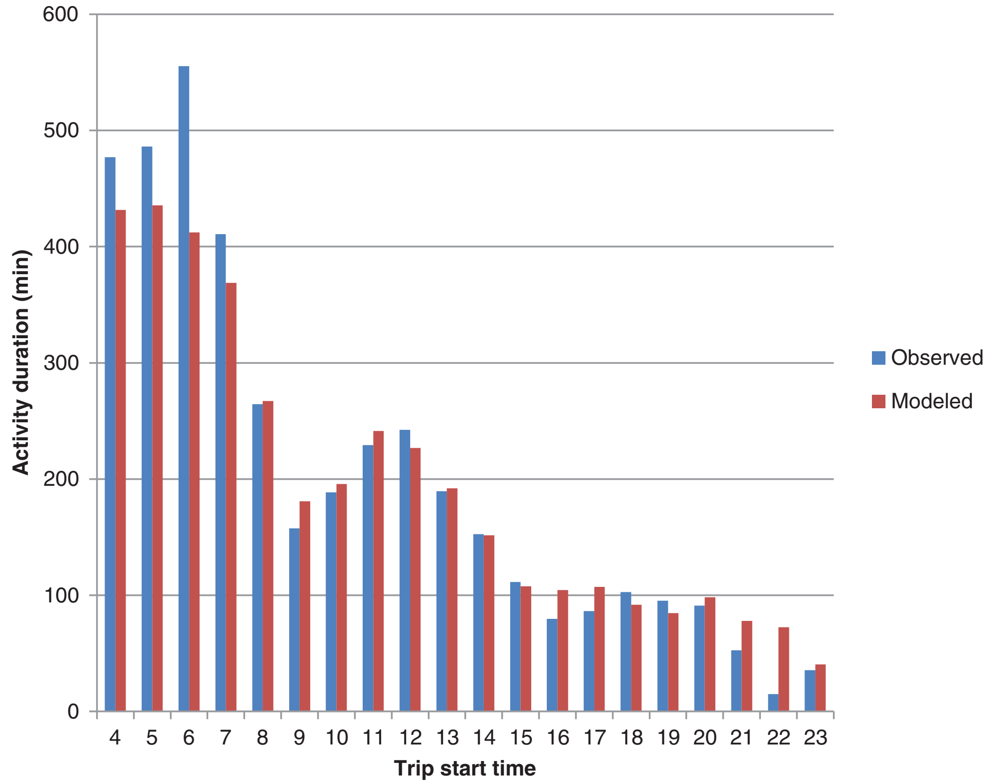

FIGURE 6 Activity duration distribution by trip start time.

scheduling process data: the maximum permitted duration change during conflict resolution could be reduced, the minimum duration threshold for work activities during the cleanup procedure could be increased, or both. Smaller duration-changing thresholds may result in a high rejection possibility when the episodes are scheduled. The expansion factors should be updated iteratively.

The model outputs and rule verification results indicate that the TASHA is a useful activity-based model for application in Chinese cities, where the four-step model framework is still the overwhelming transportation model system. The TASHA has the potential to handle many important transportation planning issues and policies, such as the analysis of transportation infrastructure planning, travel demand management, social equity, and vehicle emissions. This application may provide a possible solution for Chinese cities that have a pressing need to analyze the impact of many emerging policies.

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The Transportation Demand Forecasting Committee peer-reviewed this paper.