Modeling the Relationships between Home-Work-Home Activity Durations and Travel Times of Workers in Hong Kong

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Abstract: The Activity-based approach has been widely accepted as a more realistic alternative to conventional aggregated trip-based travel demand models with better capability to model individual activity-travel choice behaviors. Attention has recently been given to the relationship between home-work-home activity durations and workers' travel times to develop activity-based models to estimate their activity and travel choices for long-term transport planning. The traditional household interview survey data from the Travel Characteristics Survey (TCS) conducted in Hong Kong in 2011 is used in this paper. With this, we assess the effects of travel times (including departure times to and from work) on the activity durations of workers in Hong Kong. On the basis of these findings, an activity-based model is calibrated to quantify the temporal utility functions of the home-work-home activities of workers. Finally, insightful findings on the data analysis and model results are given in conclusions together with recommendations for further study.

Keywords: activity-based model, activity duration, marginal utility function.

1 INTRODUCTION

Decades have passed since the development and evolution of transportation planning models since the pioneering research in the early 1950s (Mitchell and Rapkin, 1954). As the first generation of transportation planning models, the aggregated trip-based models were adopted and implemented by some transportation departments for travel demand prediction at early stages. These models attempt to represent the aggregated behavior of a group of travelers instead of the behavior of a single individual. Although the aggregated approach can show an entire profile travel behavior at the traffic zone/district level, such models have been severely criticized for their inflexibility and inaccuracy. To meet the need to present detailed individual/household travel behavior, disaggregated approaches have evolved from aggregated approaches, such as VISUM and TRANSIMS. However, despite this movement, trip-based models are still criticized for their limitations: (1) the models ignore that the demand for travel is derived from the demand for activity participation; (2) they focus on individual trips (or tours) and ignore the spatial and temporal relationships between all trips and activities completed by an individual; and (3) they view an individual as a decision maker isolated from the household context.

In response to the need for more realistic models, the activity-based model was proposed to account for travel demands being derived from the desire for activity participation (Hagerstrand, 1970; Kitamura, 1988; Axhausen and Gärling, 1992). Compared with conventional trip-based models, activity-based models have the following advantages: (1) they consider the effects of interactions with household members on the individuals' decision making and (2) travel is no longer considered as isolated trips but as part of an activity pattern with realistic rules and constraints, including activity sequences, the durations of the activities, and the mode contexts.

Although the concept of the activity-based model was proposed not long after the prior research on transport systems, there has been a boom of activity-based models since the 1980s. In the past four decades, various activity-based models have been proposed and implemented (Bowman, 1998, 2000; Recker, 1995; Bhat, 2003; Li *et al*. 2013). The activity-based approach has been widely accepted as a better alternative to overcome the limitations of conventional models because it is better able to model the individual activity-travel choice behaviors in reality. Due to the variety of implemented environments, different methods have been developed for different cities for these models (Rasouli *et al*., 2014; Li *et al*., 2013).

In this paper, the activity-based model belongs to the group of economic models. The theoretical foundation of economic models for the activity-based approach is based on the theory of random utility maximization (Ben-Akiva and Lerman, 1985; Adler and Ben-Akiva, 1979). These models assume that each activity is associated with a specific utility perceived by its participants. Individuals are assumed to be rational. They choose the activities for participation to maximize the total utility he or she gains (Xiong and Lam, 2011).

Various utility functions have been studied and are assumed to be related to activity types and the characteristics of both related activities and individuals (Joh *et al*., 2002; Ettema *et al.*, 2003; Fu *et al.*, 2014, 2015). Individuals adjust their decisions regarding activity participation according to the utility they perceive. Therefore, the definitions and calibration results of the utility functions for activity-based models play important roles in long-term transport planning. A brief overview of the historical development of the travel demand models in this section is given in Table 1.

Table 1. Summary of travel demand models conducted

Travel demand models	Trip-based models	Activity-based models
Aggregated approach	Lowry *et al.* (1964); MUSSA (Martinez, 1996); EMME/2	Li *et al.* (2010); Xiong and Lam (2013); Fu and Lam (2014, 2015)
Disaggregated approach	TRANSIMS; VISUM; Antoniou *et al.* (1997)	BB System (Bowman and Ben-Akiva, 2000); ALBATROSS model (Arentze and Timmermans, 2004); TASHA (Miller and Roorda, 2003)

In this study, in order to examine the profiles of the mechanism by which the utilities of activities affect individuals' activity participation by time of day, we adopted the bell-shaped marginal utility function used in the ALBATROSS model (Joh *et al*., 2002) to calibrate the proposed home-work-home activity model. Using household interview survey data from Hong Kong collected in 2011, this paper aims to calibrate the activity utility functions by time of day for long-term travel demand forecasting, particularly for activity-travel choice behaviors. The estimation performance of the proposed activity-based model is assessed and discussed along with the calibration.

The model calibrated in our paper has the marginal utility functions of home/work activities. It can be used to model the total daily activity-travel utility when disutility of travel from trips are to be incorporated in the activity-based network equilibrium model (Lam and Yin, 2001). With this activity-based approach, changes in activity-travel choice behavior in responds to the transport policies (e.g., reduction or increment in travel times) can then be evaluated using the calibrated function of our paper. People may change their decisions about the duration of activities (longer/shorter), alter the departure times, or even add or cancel the activities to or from their original schedule subject to time availability as a result of transport policy change (Fu and Lam, 2014).

The remainder of the paper is organized as follows. Section 2 introduces the Travel Characteristics Survey (TCS) database and shows the key travel characteristics in Hong Kong with some analytical results from the TCS data. Section 3 gives the formulation of the activity-based model and calibration method. Section 4 presents the numerical calibration results for the utility functions of the proposed home-work-home activity models. Finally, Section 5 concludes the research findings and gives suggestions for further study.

2 PROFILE OF TRAVEL CHARACTERISTICS SURVEY 2011 IN HONG KONG

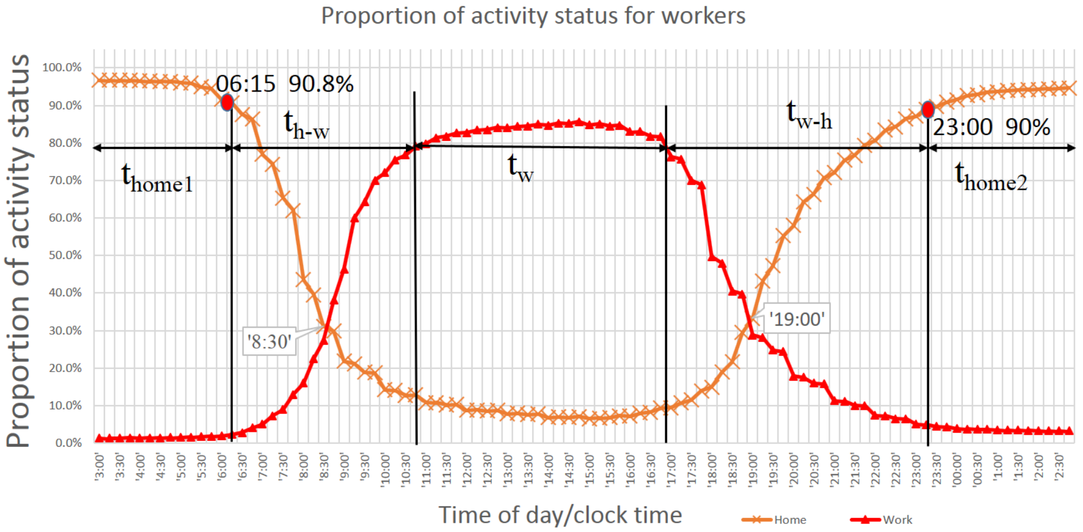
The dataset we used for transportation analysis and calibration of the activity utility function is taken from a household interview survey of the Travel Characteristics Survey conducted in Hong Kong in 2011. Hong Kong is a metropolitan city with a population of 6.88 million at the time of the TCS survey (late 2011 to early 2012). With an area of 1,106 km^2, Hong Kong is mostly covered by mountains. As a result, Hong Kong is a highly dense city because only around 24% of the land is used for urban development, with up to 50,000 persons per square kilometer in most urban areas.

Such a high-density development environment with limited land makes the development of transportation a challenge, but it is important to develop better transportation systems in Hong Kong. To approach this purpose, a comprehensive analysis of the travel characteristics of Hong Kong residents is needed. The Travel Characteristics Survey 2011 aimed to collect up-to-date data on travel characteristics and to develop a database for long-term planning and development. The survey is conducted every 10 years, with the last survey conducted in 2002. The data used for this paper come mainly from one of the three main sub-surveys of TCS Household Interview Survey (HIS). This sub-survey included households' social information, personal and trip data, and information on vehicle availability. Of the 2.36 million households in Hong Kong, 35,401 households responded to the HIS (1.5% sample size).

The remainder of this section includes some statistical analysis of the characteristics of home-work-home workers from the household interview survey. First, an overall profile of these workers' activity participation is presented in Section 2.1. Section 2.2 gives a detailed analysis of the workers' departure time to and from work, and Section 2.3 presents the patterns of work durations by departure time.

2.1 Overall Profile of Daily Activity Patterns for Workers

Among the sampling data, 39,420 residents were reported as workers in the 35,401 households. An average of just more than one person per household worked to provide household financial support. Most of these workers' out-of-home activities consisted of work. Without loss of generality, in this paper, we focus only on workers with a home-work-home activity pattern, which takes up more than 90% of the total activities in the sampling data. Overall, 30,247 workers (77% of the total sample, including full-time and regular part-time workers) had a home-work-home activity pattern. An overall profile of this activity pattern is given in Figure 1.



$t_{h\text{-}w}$: The overall time window of home-work travel

$t_{w\text{-}h}$: The overall time window of work-home travel

t_{home1}: The time stay at home in the morning before work

t_{home2}: The time stay at home in the morning after work

Figure 1. Proportion of activity status for workers.

Under this studied pattern, the daily time allocated to workers can be divided into five components with the following equation:

$$t = t_{home1} + t_{h-w} + t_w + t_{w-h} + t_{home2} \quad (1)$$

where t_{home1}, t_w, and t_{home2} stand for the time spent at home in the morning, the time spent at work, and the time spent back home after work, respectively, and t_{h-w} and t_{w-h} represent the travel time from home to work and from work to home, respectively.

From Figure 1, we can see that in the early morning, most workers are still at home. From around 06:00, the proportion of workers at work begins to increase and the proportion at home begins to decrease. The proportions of those at home and those at work become equal at around 08:30. The proportion of workers at work then continues to increase and reaches a high level at around 10:00, which implies that most workers are required to be at work by 10:00. Little difference is seen in the aggregated status until late afternoon, around 17:00. Most workers reported leaving work and going home by 17:00.

The proportions of workers at work and those who have returned home in the afternoon become equal again around 2 hours later, at 19:00. The same time window in the morning is only around 1.5 hours from around 6:00 to the equal point at 08:30. The time window is longer for most workers' travel to leave work and return home. To some extent, the length of the time window reflects the pressure workers feel from going to work and going home. The narrow time window for going to work implies that some workers may need to hurry to get to work on time due to the constraints of their start time for work. As for going home, the longer time window implies that workers have greater flexibility in their departure times from work to home.

2.2 Departure Time Analysis

An overview of the workers' daily activity pattern is displayed via a profile of activity status in Section 2.1. However, for a more comprehensive understanding of the activity pattern, such as the peak hours for commuting to and from work, more analysis was done regarding the departure times to and from work and is displayed in this section.

In this section, to obtain a more comprehensive distribution of departure times to work, we extend the length of the departure time window from 05:00 to 12:00. The pattern of distribution is displayed in Figure 2.

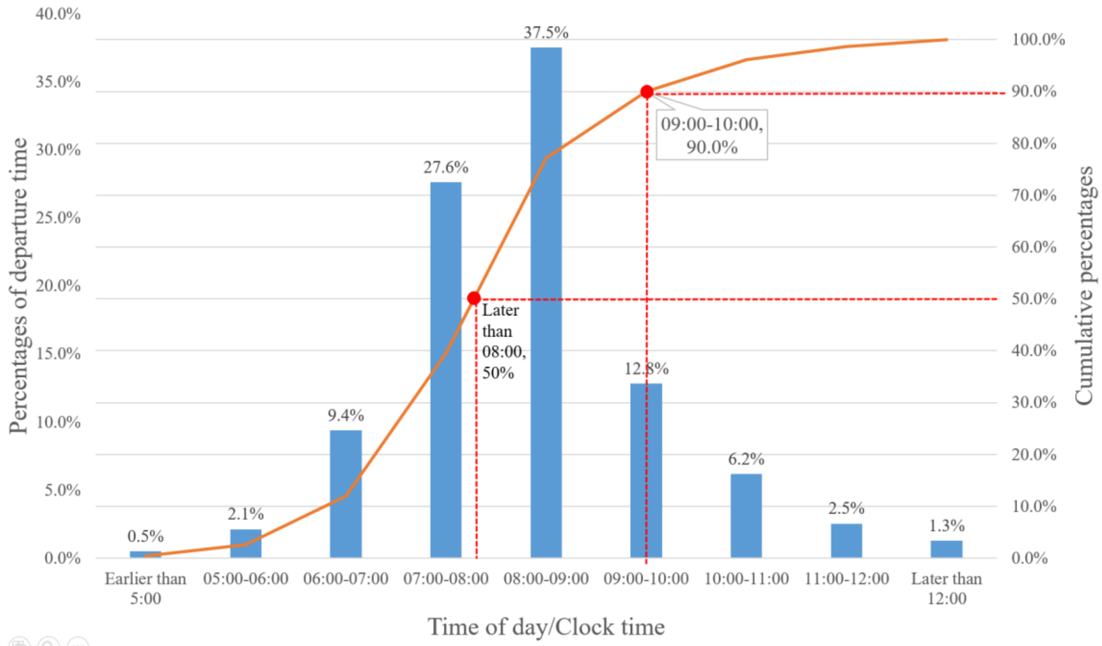


Figure 2. Distribution of departure time to work.

From the result, it is obvious that the peak hour for the home-to-work commute was from 08:00 to 09:00, taking up to 37.5%. It is followed by the hour from 07:00 to 08:00; 50% of trips were made before 08:00, and up to 90% of workers departed from home before 10:00. The departure time from work back home is analyzed in a similar manner in Figure 3.

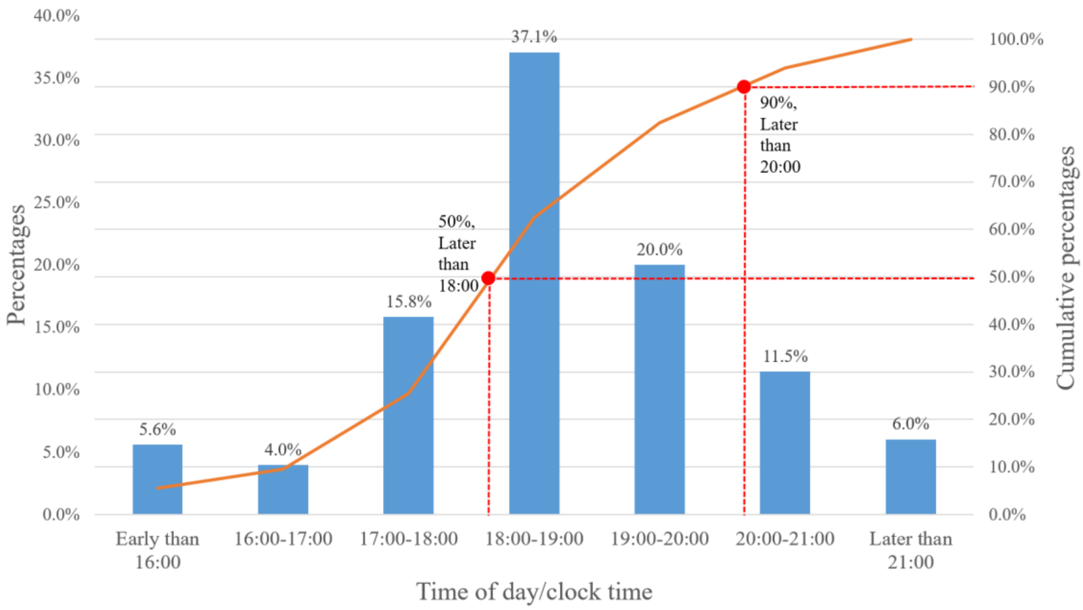


Figure 3. Distribution of departure time from work.

Figure 3 implies that the peak hour for work-to-home travel was 18:00 to 19:00, during which approximately 37.1% of workers left their work for home. Only around 17.5% of workers left for home after 20:00.

When compared with the distribution of the departure time to work in the morning, obvious differences can be found in travel behavior after the peak hours. In Figure 2, the percentages of workers departing for work drops rapidly from nearly 40% to slightly over 10%. However, in Figure 3, the drop is only from 37.1% to 20%. This indicates that unlike hurrying to work in the morning, workers had more freedom to go home from work and showed a tendency to leave later than the scheduled time. The departure time analysis from Figures 2 and 3 is consistent with the result of the profile of the activity status of time spent at home and at work in Figure 1. Workers had greater time elasticity in their choice of departure time from work to home.

2.3 Activity Pattern of Work Duration

Because activity duration is an important characteristic of the activity pattern, in addition to the proportions of activity status and the departure time information, the duration of the activity should be analyzed. The result is presented in Figure 4.

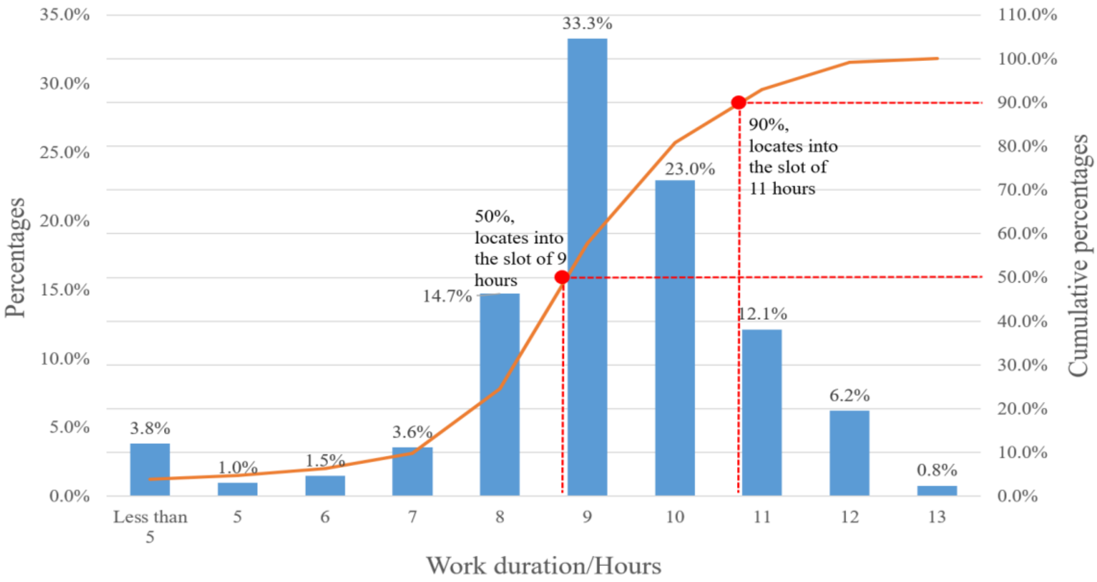


Figure 4. Distribution of work duration.

Figure 4 gives an overall profile of the work duration for Hong Kong workers. The mean work duration was 9.48 hours, and more than 50% of the workers worked for more than 9 hours. This workday is longer than the 8 hours typically required in most places in the world. This finding shows that activity patterns may differ between Hong Kong and other places as a result of longer work hours. A set of utility functions of activity participation for long-term transportation planning should thus be calibrated with the use of the latest travel survey data. Generally speaking, workers in Hong Kong have longer work durations. To determine whether a relationship exists between work duration and departure time, we analyzed the work duration by departure time.

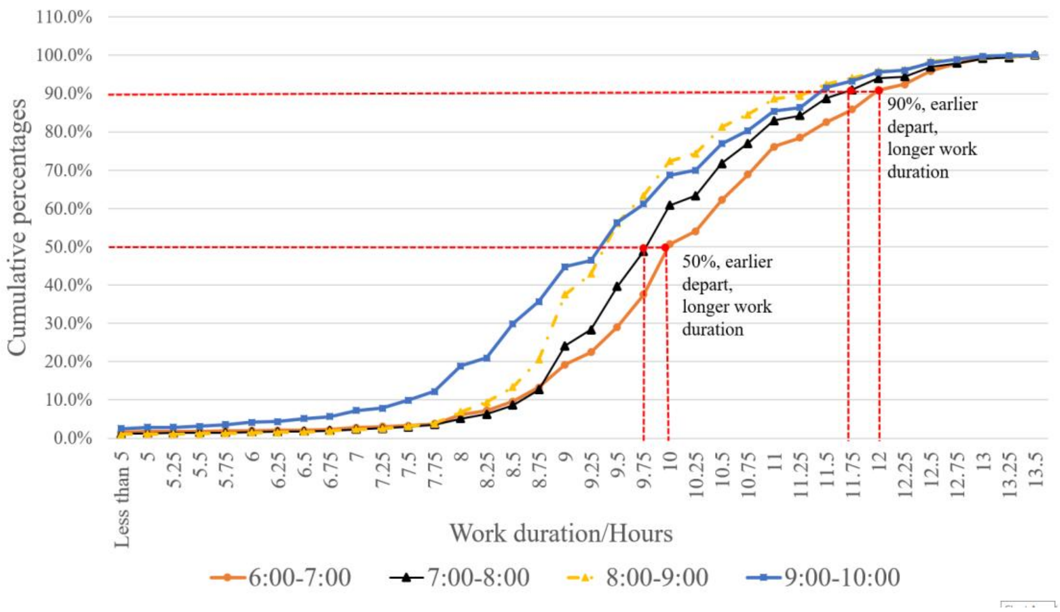


Figure 5. Work duration by departure time.

From the cumulative frequency of work duration by departure time in Figure 5, it is obvious that the earlier the worker departed from home to work, the longer they worked. For example, more than 80% of workers who departed between 06:00 and 07:00 worked for more than 9 hours. The same numbers were around 75%, 60%, and 55% for the departure time periods of 07:00-08:00, 08:00-09:00, and 09:00-10:00, respectively.

2.4 Activity Pattern of Travel Time

Sections 2.1-2.3 display an overview of the daily activity status, the distribution of departure times to and from work, and work duration. Workers reported different patterns of home-to-work travel and work-to-home travel. In this section, we analyze the travel times of the trips under the pattern of home-work-home activities. The results are displayed in Table 2.

Table 2. Travel time and work duration by departure times for workers.

		Travel time			Work duration		
		Overall	Car Owning	Non-car Owning	Overall	Car Owning	Non-car Owning
Departure time to work	06:00-07:00	53.5 (24.2)*	51.6 (26.4)	53.8 (25.90)	10.5 (0.97)	10.5 (0.98)	10.5 (0.83)
	07:00-08:00	**53.6** (21.6)	**50.4** (21.6)	**54.3** (22.78)	9.9 (0.84)	10.0 (0.84)	9.9 (0.72)
	08:00-09:00	43.4 (16.9)	40.9 (17.2)	44.0 (18.24)	9.4 (0.73)	9.5 (0.76)	9.4 (0.68)
	09:00-10:00	38.5 (16.3)	35.0 (16.22)	39.6 (17.86)	8.8 (0.79)	8.8 (0.8)	8.8 (0.78)
	Average	47.2 (20.3)	43.8 (20.0)	48.0 (21.33)	9.6 (0.91)	9.6 (0.93)	9.6 (0.91)
Departure time from work	16:00-17:00	47.3 (22.0)	45.7 (23.6)	47.7 (22.0)	8.4 (0.86)	8.2 (0.98)	8.4 (0.83)
	17:00-18:00	50.7 (21.9)	46.6 (21.8)	51.6 (21.85)	8.9 (0.72)	8.6 (0.71)	8.9 (0.72)
	18:00-19:00	51.4 (21.7)	47.7 (21.4)	52.3 (21.65)	9.5 (0.68)	9.5 (0.67)	9.5 (0.68)
	19:00-20:00	47.6 (19.9)	43.9 (19.6)	48.5 (19.92)	10.4 (0.77)	10.5 (0.72)	10.4 (0.78)
	Average	50.2 (21.3)	46.3 (21.1)	51.1 (21.30)	9.6 (0.91)	9.6 (0.93)	9.6 (0.91)

*Standard deviation in parentheses.

Travel time analysis shows that the more travel time needed, the earlier the workers departed from home to work. However, the travel time of workers who depart to work between 07:00 and 08:00 defies this tendency, perhaps due to heavy traffic conditions during the peak hour of home-work travel. However, travel time increases as the workers put off their departure time until the peak hour. The standard deviations show clear regularity. The larger standard deviations decrease as the departure time to work is postponed. The same thing happens to that of the departure time from work.

The most significant finding in Table 2 is the work duration of workers by two groups of departure times. The results show that the earlier they departed to work, the longer they stayed. In contrast, the workers worked longer if they left work later. This tendency approximately follows the patterns of travel time spent for home-work-home trips.

In summary, this section makes use of the TCS data to give a comprehensive profile of the relationships between activity duration, travel time, and departure time for workers in Hong Kong. Several insightful findings are noted: (1) the time window of travel time to work is longer than that of from work, (2) the peak hours to and from work are compared, (3) the relationship between work duration and departure times to and from work is displayed, and (4) the tendency of travel time to vary by departure time is shown. These findings form the foundation for calibrating activity utility functions under the framework of activity-based models in the next section.

3 METHOD OF MODELING AND CALIBRATION OF THE ACTIVITY UTILITY FUNCTION

3.1 Activity-Based Modeling

As time allocation for activity participation varies by time of day, a temporal utility function would be a better option to model the marginal utility by time of day (Lam and Yin, 2001; Fu and Lam, 2014). The bell-shaped marginal utility function has widely been used in previous papers due to its promising performance for modeling daily activity patterns (Ettema *et al*., 2003, 2004; Li *et al*., 2010; Xiong and Lam, 2011; Fu, 2014, 2015). As such, it is adopted in this paper for calibrating the parameters for utility function. The formulation of a bell-shape utility function is given by:

$$u_i(t) = \frac{\gamma_i \cdot \beta_i \cdot u_i^{\max}}{\exp(\beta_i \cdot (t-\alpha_i)) \cdot (1+\exp(-\beta_i \cdot (t-\alpha_i)))^{\gamma_i+1}} \tag{2}$$

i stands for the index of activity. γ, α, β, and u^{max} are the parameters of the function. Parameter α affects the position of time t so that the marginal function reaches its maximum value. The value of parameter β represents the rate of increasing to the maximum function value and decreasing from that. Parameter γ affects the symmetry of the curve of the utility function. The utility function is symmetric when γ equals 1, whereas the increasing part before the maximum value is greater than the decreasing part when γ is less than 1. u^{max} is the maximum utility of the target activity. γ, α, β, and u^{max} are the parameters needed to be calibrated. Following Ettema *et al*. (2003), the calibration of γ does not result in stable results for the parameters. Therefore, γ is fixed as 1 for better convergence. With the utilities specified for each activity, the daily utility can be calculated with the following equation:

$$\mathrm{U} = \sum_i \int_{t_i^s}^{t_i^e} u_i(t) \tag{3}$$

where t_i^s and t_i^e are the start and end times, respectively, of participating in activity i.

For individual traveler, constant travel times were used for the model development (Ettema *et al.* 2003) and therefore for the simplicity of computation (the choice probability does not change over the alternatives under such simplicity), only the utilities of activities were conducted for calculation. However, further study will consider the utility function of both activities and trips for the evaluation of transport policy.

Based on the findings from the TCS data, the activity duration varies with the departure times. Also, the activity duration differs with different start and end times. Therefore, three models with different considerations of start times and end times into the marginal utility functions are specified and calibrated in this paper.

(1) Model 1: Eq. (2) is set as the marginal utility functions in this model. It is the base model for comparison of the improved models, namely, models 2 and 3.

(2) Model 2: departure time has an obvious effect on activity duration given the way it affects the activity start time. Therefore, in model 2, we explicitly consider the effects of the start time of the activity to the utility. Model 2 replaces the parameter α with $\alpha + t^s \cdot \tau_s$. t^s stands for the start time of the activity, and τ_s is an induced parameter to weight the effects of the start time of the activity to the profile of the utility function. The marginal utility function is updated by:

$$u_i(t) = \frac{\gamma_i \cdot \beta_i \cdot u_i^{\max}}{\exp(\beta_i \cdot (t - (\alpha_i + t^s \cdot \tau_s))) \cdot (1 + \exp(-\beta_i \cdot (t - (\alpha_i + t^s \cdot \tau_s))))^{\gamma_i + 1}} \tag{4}$$

(3) Model 3: similar to Model 2, and corresponding to the analysis of the departure time from work, Model 3 considers the effects of the end time of the activity and replaces the parameter α with $\alpha + t^e \cdot \tau_e$. t^e represents the end time of the activity with τ_e as its impact weighting. The updated marginal utility function is:

$$u_i(t) = \frac{\gamma_i \cdot \beta_i \cdot u_i^{\max}}{\exp(\beta_i \cdot (t - (\alpha_i + t^e \cdot \tau_e))) \cdot (1 + \exp(-\beta_i \cdot (t - (\alpha_i + t^e \cdot \tau_e))))^{\gamma_i + 1}} \tag{5}$$

As the start time and end time of work activity for each individual worker were not available, average values were used in our paper. The start times and end times of the activities were approximated with the mean arrival and departure times of the home-work and work-home travels respectively.

3.2 Calibration Method

Departure times are modeled to be discrete as the choices to maximize the daily utility. A set of departure times are defined. Because the home-work-home pattern is studied in this paper, only two departure times (departure times for home-work travel and work-home travel) are needed for every choice alternative. Based on our analysis of departure time, the departure time choices for home-work travel are 1-hour intervals between 06:00 and 10:00 and between 16:00 and 21:00 for work-home travel. The alternative in the choice set is defined as a combination of two departure times (to and from work): one departure time alternative for home-work travel and another for work-home travel (e.g., 06:00-07:00 and 16:00-17:00 or 06:00-07:00 and 17:00-18:00) were considered simultaneously and modeled as one alternative. The probabilities of departure times follow the logit choice model as:

$$P_{k,n} = \frac{\exp(U_k)}{\sum_{j \in C} \exp(U_j)} \tag{6}$$

where k is the choice of the combination of departure times (departure from home and departure from work) from the choice set C, and n indicates the individual n. U_k is the daily utility in Eq. (3) with the departure time choice k.

The parameters are calibrated using the maximum likelihood estimation method:

$$\log L = \sum_{n \in N} \log(P_{k,n}) \tag{7}$$

As seen in Eqs. (2), (4), and (5), the utility functions for calibration are nonlinear, and a sequential quadratic programming method may be easily stuck in the local maxima. The genetic algorithm is better able to get out of the local maxima. Therefore, in this paper, the genetic algorithm is adopted to calibrate parameters in the marginal utility functions. The crossover method for applying the genetic algorithm is the scattered crossover method. The details of this method are described as follows.

a). A binary random string is generated with the length of the population length.

b). From the two Parents (i.e., Parents 1 and Parents 2) chosen for crossover, choose the value from Parent 1 if the binary string value is 1; otherwise choose the value from Parent 2 to generate the Children for the next generation.

Further details about the key parameter settings are given in Table 3.

Table 3. Parameter settings for genetic algorithm.

Name of parameters	Description	Value for parameter setting
Population size	The number of sets of parameters in each iteration	200
Generations	The maximum number of iteration before algorithm stops	100*No. of variables
Elite-Count	The number of best results that are guaranteed to survive in next iteration	5% of the population size
Crossover fraction	The fraction of the population for crossover operation	0.8
Migration fraction	The fraction of the population for migration operation	0.2
Convergence Torrance	The threshold that the algorithm stops when the average change in the goodness-of-fit is less than that.	10^-6

4 CALIBRATION RESULTS AND DISCUSSION

The calibration results of the three models in Section 3 are displayed in this section.

Table 4. Calibration results.

	Model 1	t-test*	Model 2	t-test	Model 3	t-test
β_{home1}	0.61 (0.003)**	130	0.59 (0.002)	205	0.55 (0.002)	225
β_{work}	0.52 (0.003)	160	0.59 (0.003)	137	0.72 (0.001)	280
β_{home2}	0.85 (0.007)	21.4	0.63 (0.003)	123	0.80 (0.004)	50
α_{home1}	4.43 (0.005)	886	3.69 (0.003)	1230	4.53 (0.003)	1510
α_{work}	13.52 (0.004)	3380	9.60 (0.003)	3200	9.34 (0.002)	4670
α_{home2}	22.14 (0.011)	2012	23.48 (0.016)	1467	22.75 (0.007)	3250
u_{home1}^{max}	30.73 (0.02)	1486	51.44 (0.016)	3152	24.61 (0.008)	2951
u_{work}^{max}	43.91 (0.02)	2146	59.99 (0.026)	2268	60.00 (0.014)	4214
u_{home2}^{max}	20.25 (0.04)	481	32.08 (0.025)	1243	18.17 (0.024)	715
γ_{home1} (fixed)	1	-	1	-	1	-
γ_{work} (fixed)	1	-	1	-	1	-
γ_{home2} (fixed)	1	-	1	-	1	-
τ_s	-	-	0.40 (0.001)	400	-	-
τ_e	-	-	-	-	0.23 (0.0004)	575
Initial Log-likelihood		-34174.90		-34174.90		-34174.90
Final Log-likelihood		-25682.01		-25455.73		-25484.62
ρ^2		0.249		0.255		0.254

* *t*-tests for α and τ are against 0; others are against 1.

** Standard deviation in parentheses.

The calibration results are displayed in the following figures.

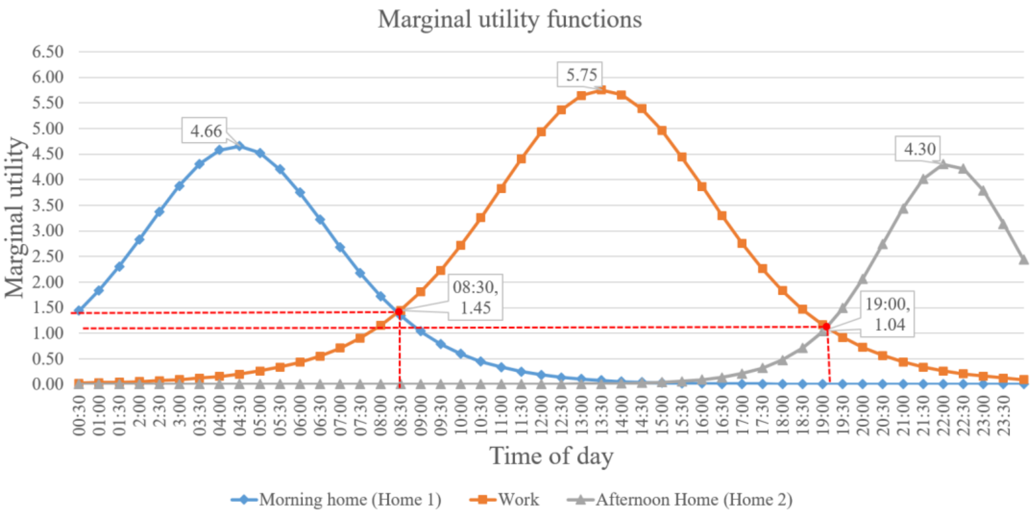


Figure 6. Calibrated marginal utility functions of Model 1.

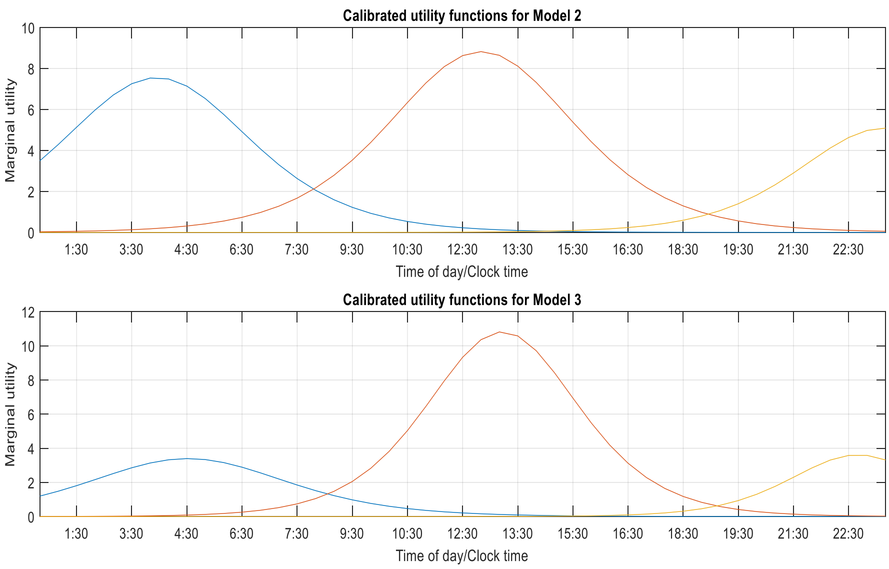


Figure 7. Calibrated marginal utility functions of Model 2 and Model 3

The based model shows a reasonable description for the activity participation of workers under a home-work-home travel pattern. The three activities dominate during different periods. The parameters of α for the three activities indicate the times at which the activities have maximum utility. The maximum marginal utility occurs at 04:26 for home activity in the morning, at 13:32 for work activity, and at 22:08 for home activity in the evening. Without loss of generality, the maximum utility among the three activities belongs to work activity, followed by home activity in the morning. The marginal utilities equalize at around 08:30 and 19:00. To maximize daily activities, people made their trips around these timings for the next activity. These results are also verified by the mean departure times. The lower value of marginal utility for home activity in the afternoon than that in the morning also verifies workers' greater elasticity to decide when to go home, unlike the rush to work in the morning.

Model 2 incorporates the activity start time into the model, and parameter τ_s indicates the effects of the activity start time on the position of the corresponding activity utility function. In our study, the times that matched the maximum utilities of home activity in the morning shift to about 40 minutes earlier. The value of τ_s indicates that the position of the marginal utility curve shifts 0.4 minute in every minute with a change in work start time. The final log-likelihood shows better consistency with the sampling data.

5 CONCLUSIONS

In this study, we used the 2011 Hong Kong TCS data to model home-work-home activity-travel choice patterns. In particular, the relationships between work durations and travel times between home and work were analyzed. Based on the traditional household interview survey TCS data, some statistical analysis is carried out to help us to gain insights from the principal patterns and characteristics of these home-work-home activities. We formulated the proposed activity-based model to quantify the utility functions of home-work-home activities of Hong Kong workers according to the time of day. The proposed model is calibrated with the TCS data, and some statistical tests are shown to report the goodness-of-fit to examine the validity of the calibrated model.

Overall, 30,247 workers, accounting for 77% of the sampled population of workers in the TCS, were found to have the daily home-work-home pattern only during the survey period. Figure 1 shows a significant bell-shape pattern for the daily home-work-home activities. This serves as a justification to choose the bell-shape marginal utility function, Eq. (1), as the decision-making rule for modeling the utility functions of the home-work-home activities of Hong Kong workers according to time of day. We assumed workers were homogenous in activity-travel choice behaviors so that Eq. (1) could be adopted to fit the curves in Figure 1. However, it could easily be extended to cases with heterogeneous workers with different activity-travel choice behaviors, such as workers in car-owning and non-car-owning households.

Second, the TCS data revealed that the departure time obviously affected the travel time between home and work and consequently affected the activity duration of time spent at home and work. In turn, the resultant utility of these two activities was affected. Therefore, the selection of departure time is explicitly modeled in this paper. We expected that workers needed to select departure times from home to work and from work to home and that. And their choices would then determine how much utility they could obtain from these work and home activities. This simplified the model calibration process, as workers made departure decisions rather than making decisions continuously at every time interval throughout the day, saving substantial computation time for model calibration (around 0.5 hour versus 5.3 hours).

Third, we explicitly modeled the start and end times of work activity, τ_s and τ_e, where these two variables determined the exact duration of work activity. The use of τ_s and τ_e involved shifting the position parameter α to infer whether the activity start and end times affected people's activity-travel choice behavior and thus the performance of the transportation network. When the model is applied for transport policy evaluation, adjustment of activities' start or end times, such as a flexible work-hour program, could be applied to evaluate the performance of the transportation network (level of service, such as travel time/congestion level; see Fu and Lam, 2014).

The parameters of the proposed model were estimated using the Hong Kong TCS data. The results indicate that the model parameters are reasonable where the activity patterns are revealed. They illustrate that the marginal utility function of home-work-home activities by time of day can be calibrated satisfactorily with traditional household interview survey data. With these fine-tuned parameters, we could perform a more detailed analysis using activity-based network equilibrium models (e.g., Lam and Yin, 2001; Ouyang *et al*., 2011; Fu and Lam, 2014) for long-term transportation planning.

We also observed that travel times differed significantly across various departure time slots for home-work-home activities. A monotonic trend of work duration was found: those who departed later from home to work had comparatively shorter work durations, whereas those who departed later from work to home had longer work durations. Those who have lower household incomes may live farther from work (e.g., CBD) and therefore need to depart earlier for travel, and those types of work are inclined to include longer work hours (e.g., lower income and longer work duration for labor-intensive job).

For a more comprehensive study on the activity-travel choice behavior using the activity-based approach, some issues remain for further studies. First, because Table 2 reveals differences between the household groups with and without car availability, it would be interesting to determine whether the factor of car ownership is important for activity-travel choice behavior. In fact, to better understand activity-travel choice behavior, further investigation of the effects of socioeconomic variables should be carried out to draw more insightful conclusions. Explicit investigation of these effects would give us more detailed insights into workers' behavior for home-work-home activities, such as examining the effects of different workers (by their household incomes) on their choices of departure times for work and for home (after work) and characteristics such as household size.

Second, although the model proposed in this paper considers the start and end times of activities, a combined model should be explored to analyze the effects of activity start and end times in one model. The proposed model enables us to include these parameters with a high degree of tractability.

Finally, the calibrated model in the paper should be applied for long-term travel demand forecasting and transport policy evaluation using the activity-based network equilibrium approach. With this, we can investigate the change of activity-travel choice behaviors: earlier/later arrival/departure times, longer/shorter activity duration or even stimulating/prohibiting the demand for activities and thus the performance of the transportation networks.

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