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 traditional aggregated trip-based models with better capability to model the activity-travel choice behaviors of individuals. Recently, attention has been given to the relationship between activity durations and travel times. Activity-based models are studied to estimate individuals' activity and travel choices for the purpose of 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 home-work-home (HWH) pattern workers in Hong Kong. An activity-based model is calibrated to quantify the temporal utility functions of the HWH activities of workers by time of day. 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 times. These models attempt to represent the behavior of a group of travelers in an aggregated way instead of the behavior of one single individual. Although the aggregated approach can provide an overview of travel behavior at the traffic zone/district level, such models have been severely criticized for their inflexibility and inaccuracy. To meet the needs of presenting detailed individual/household travel behavior for travel demand modeling, 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 the fact that the demand for travel is derived from the desire for activity participation; (2) traditional trip-based models only focus on aggregated number of trips (or tours) between two traffic zones and ignore the spatial and temporal relationships between trips and activities completed by the same individual; and (3) those models view individuals as decision makers isolated from the household context.

In response to the need for more realistic models, the activity-based model was proposed to account for the fact that travel demands are derived from the desire for activity participation (Hagerstrand, 1970; Kitamura, 1988; Axhausen and Gärling, 1992). Compared with traditional trip-based models, activity-based models have following advantages: (1) The models consider the effects of interactions between household members on the individuals' decision makings and (2) travels are no longer considered as isolated trips but as parts of activity patterns with realistic rules and constraints, including activity sequences, the durations of the activities, and the travel modes.

One example is illustrated as follow for explaining the advantages of the activity-based model compared with the trip-based model. In a household with children that needed to be escorted to school in earlier morning, the employed parent may first conduct a trip to drive his/her children to school first and then drive from the school to his/her work place. Under this situation, the traditional trip-based model may generate two origin-destination attractions, i.e. home to school attraction for the children and home to work location for the employed parent. However, under the context of household interaction, the travel from home to work place for the employed parent is replaced with two consequent trips, i.e. one escorting trip from home to the children's school following by the other one from children's school to the parent's work place. From the example, we can see that the traditional trip-based model might mispresent the trip makings and unable to present the escort travel behavior accurately. In contrast to the trip-based models, activity-based approach considers the interactions between individuals (i.e. household interaction in this sample) and the relationship between activities and trips (i.e. the home-school travel followed by the school-work travel). Therefore, the activity-based model can better present the activity-travel realism and is more accurate for the purposes of long-term transport planning and evaluation of transport policy.

Although there were pioneering researches in earlier 1950s (Mitchell and Rapkin, 1954) it was not until the 1980s that a boom of studies on activity-based models was witnessed. In the past four decades, various activity-based models have been proposed and implemented (Bowman, 1998; Bowman and Ben-Akiva, 2000; Recker, 1995; Bhat and Koppelman, 2003; Li *et al*. 2013). Due to the variety of implemented environments, different methods for these models have been developed for different cities (Rasouli and Timmermans, 2014; Li *et al*., 2013).

In this paper, the activity-based model falls into the category of economic models. The theoretical foundation of economic models for the activity-based approach is the theory of random utility maximization (McFadden *et al.*, 1973; Ben-Akiva and Lerman, 1985; Adler and Ben-Akiva, 1979). These models assume that each activity is associated with a specific utility perceived by the participants. Individuals are assumed to perform rational behavior. They choose activities for participation to maximize the total utility he or she gains (Xiong and Lam, 2011).

Various utility functions have been proposed (Joh *et al*., 2002; Ettema *et al*., 2004; Fu and Lam, 2014; Fu *et al.*, 2015). Individuals adjust their decisions on activity participations regarding the utility they perceive. Therefore, the definitions and calibration results of the utility functions for activity-based models play important roles in travel demand prediction. A brief overview of the historical development of the travel demand models in this section was given in Table 1.

Table 1. Summary of travel demand models conducted

Travel demand models	Trip-based models	Activity-based models
Aggregated approach	Lowry (1964); MUSSA (Martinez, 1996); EMME	Li *et al.* (2010); Xiong and Lam (2011); Fu and Lam (2014); Fu *et al.* (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 how 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 activity-based model for HWH pattern of workers. Using household interview survey data from Hong Kong collected in 2011, this paper aims to calibrate the marginal utility functions of activities 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 will be assessed and discussed.

The model calibrated in our paper uses the marginal utility functions of work/home activities. It can be used to model the daily activity-travel utility when the disutility of travels being 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 be evaluated using the calibrated functions in this paper. People may change their decisions on the durations of activities (longer/shorter), alter the departure times, or even add/ cancel the activities to/from their original schedules 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 presents some key travel characteristics in Hong Kong with analytical discussions. Section 3 introduces the formulation of the activity-based model and calibration method. Section 4 presents the calibration results for the marginal utility functions of the proposed models for HWH pattern workers. 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 the analysis and calibration of the activity utility function is taken from the 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 surveying period (late 2011 to early 2012). With an area of 1,110 km^2, Hong Kong is mostly covered by mountains. As a result, Hong Kong is a highly dense city as only around 24% of the land is used for urban development, with the population density of up to 50,000 persons per square kilometer in most urban areas.

Such a high-density environment with limited land use makes the development of transportation a challenge. However, it is important to develop better transportation systems to meet the requirements of urban development. Thus, 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 is mainly from one of the three main sub-surveys of TCS, i.e. Household Interview Survey (HIS). This survey included households' and personal information, trip data, and information on vehicle availability. Firstly, the quarters or area segments were randomly selected by the Census and Statistics Department (C&SD) of the Hong Kong Government. Then all the households were interviewed within the selected quarters or area segments. All household members over 2 years old were asked for their daily trips records. Among the 2.36 million households in Hong Kong, 35,401 households responded to the HIS (1.5% sample size for both household size and individual population).

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

2.1 Overall Profile of Daily Activity Patterns for Workers

Among the sampled data, 39,420 residents were reported as workers from 35,401 households. An average of just more than one person per household was found employed workers. Most of these workers' conducted only one out-of-home activities, i.e. work activity. Without loss of generality, in this paper, we focused only on workers conducting HWH activity pattern. 30,247 workers (77% of the total sample, including full-time and regular part-time workers) performed the HWH activity-travel pattern. An overall profile of this activity pattern was given in Figure 1.

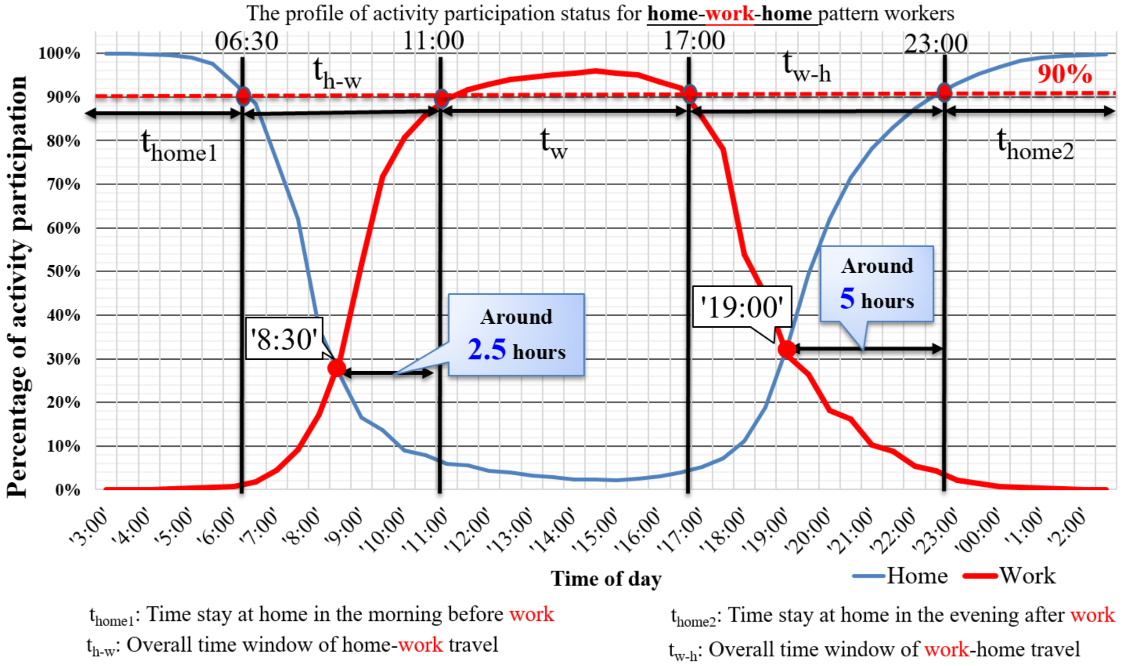

Figure 1. Proportion of activity status for workers

Under this studied pattern, the daily time period for workers was 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 at home after work, respectively. t_{h-w} and t_{w-h} are the travel times from home to work and from work to home, respectively.

In Figure 1, we can see that in the early morning, most workers were still at home. Two timings indicating workers changing their activity participation were shown in the figure, i.e. 8:30 and 19:00. After 8:30 in the morning, more workers had been at work than at home while after 19:00, more workers arrived at home. On the other hand, a time window of 2.5 hours was recorded from the intersection point (8:30) to the timing of 90% cumulative frequency at work (11:00) and that of home arrival was 5 hours (from 19:00 to 23:00). Such statistics indicated the AM peak demand was higher and the variation was smaller for home-work travel than work-home travel. The constraints of on-time arrival for work activity were stronger than home arrival. Thus, workers might need to hurry to get to work in the morning and resulted in shorter travel time window.

2.2 Departure Time Analysis

An overview of the workers' daily activity pattern was displayed by 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 traveling to and from work, more analysis had been carried out regarding the departure times to and from work and was displayed in this section.

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

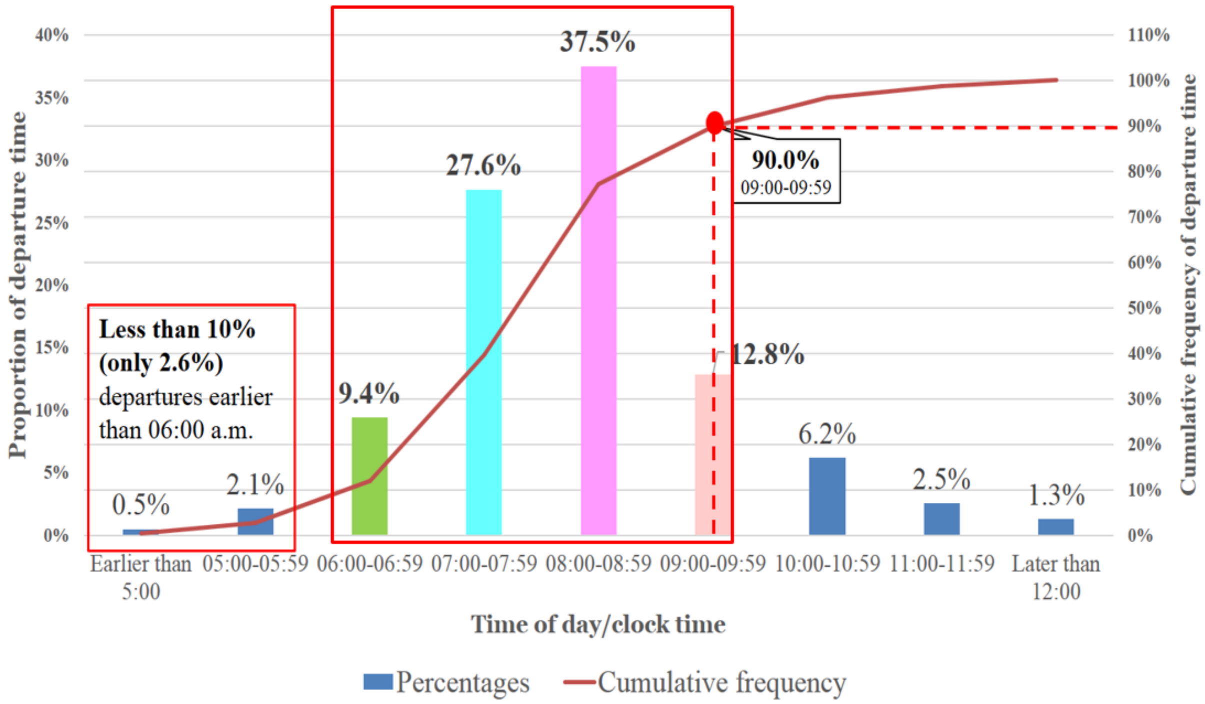

Figure 2. Distribution of departure time to work

From the results shown in Figure 2, it was obvious that the peak hour for the home-work travel was from 08:00 to 09:00, taking up to 37.5%. It was followed by the hour from 07:00 to 08:00. Up to 90% of workers departed from home before 10:00. Four major time intervals (from 06:59 to 09:59 a.m.) took up 87% of the samples of HWH patterns, which provided implications for choice set generation in Section 3. The distribution of departure time from work back home was analyzed in a similar manner in Figure 3.

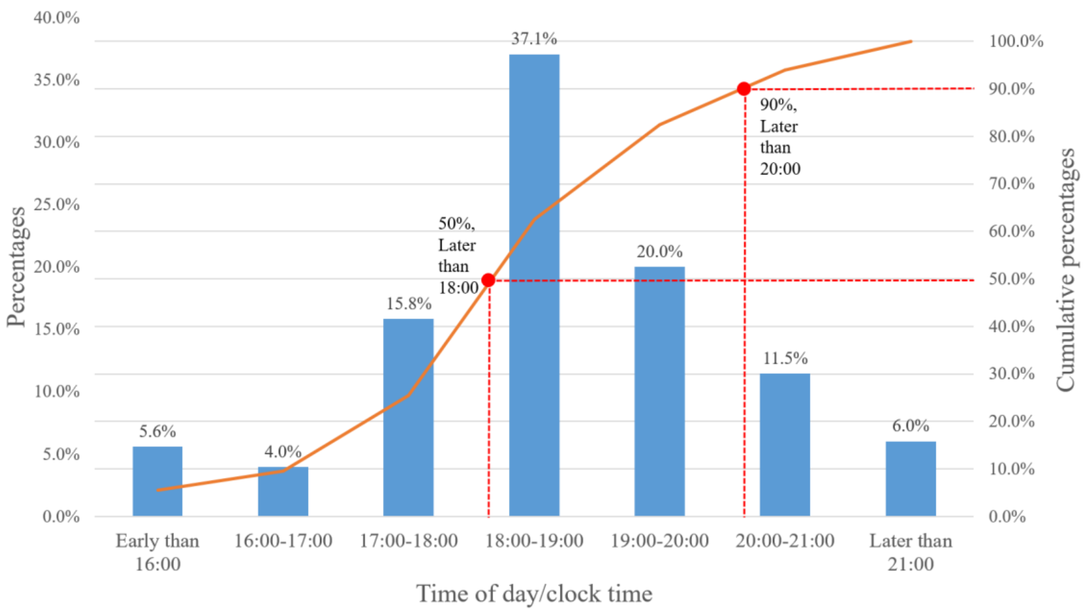

Figure 3. Distribution of departure time from work

Figure 3 implied that the peak hour for work-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 departed for home after 20:00.

When compared with the distribution of the departure time to and from work, obvious differences could be found in travel behavior after the peak hours. In Figure 2, the percentages of workers departing for work dropped rapidly from nearly 40% to slightly over 10%. However, in Figure 3, the drop was only from 37.1% to 20%. This indicated that unlike hurrying to work in the morning, workers had more freedom to decide when to go home and showed a tendency to leave later than the scheduled time. The departure time analysis from Figures 2 and 3 was consistent with the result of the profile of the activity status in Figure 1. Larger variation for the travel time of work-home travel was inferred and workers had greater time elasticity in their choice of departure time from work back 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 distributions, the duration of the activity should be analyzed. The result was presented in Figure 4.

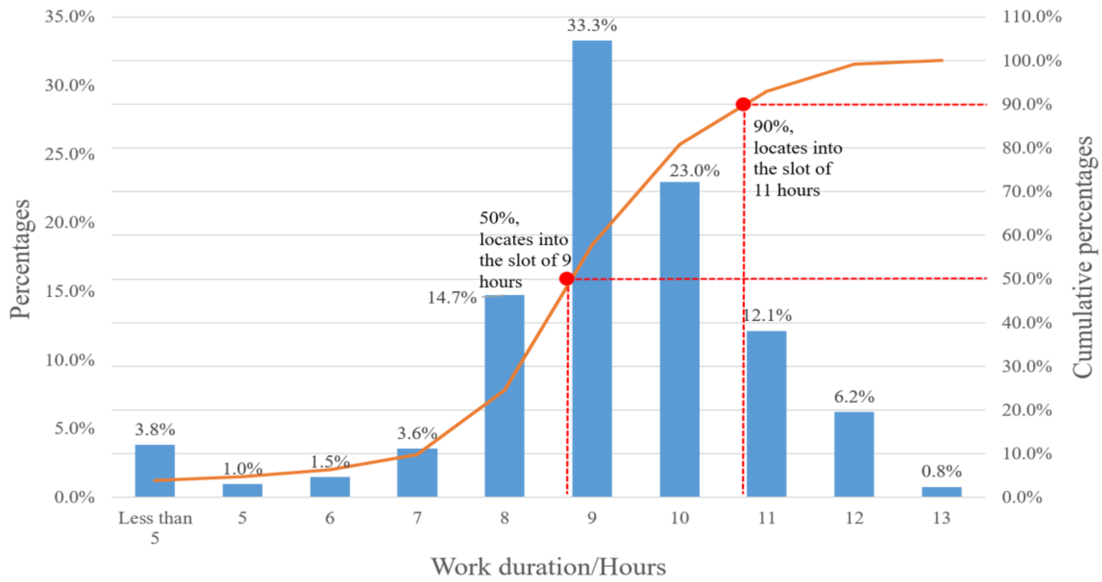

Figure 4. Distribution of work duration

Figure 4 gave an overall profile of the work duration for Hong Kong workers. The mean work duration was 9.6 hours (including lunch), and more than 50% of the workers worked for more than 9 hours. The daily work duration was longer than typical work duration, i.e. 8 hours, in most places in the world. This finding showed that activity-travel patterns in Hong Kong might differ from other cities in the world. A set of utility functions of activity participation should be calibrated with the use of the latest travel survey data for long-term transportation planning purpose in Hong Kong. To determine whether a relationship exists between work duration and departure time, we analyzed the work durations by departure times in Figure 5.

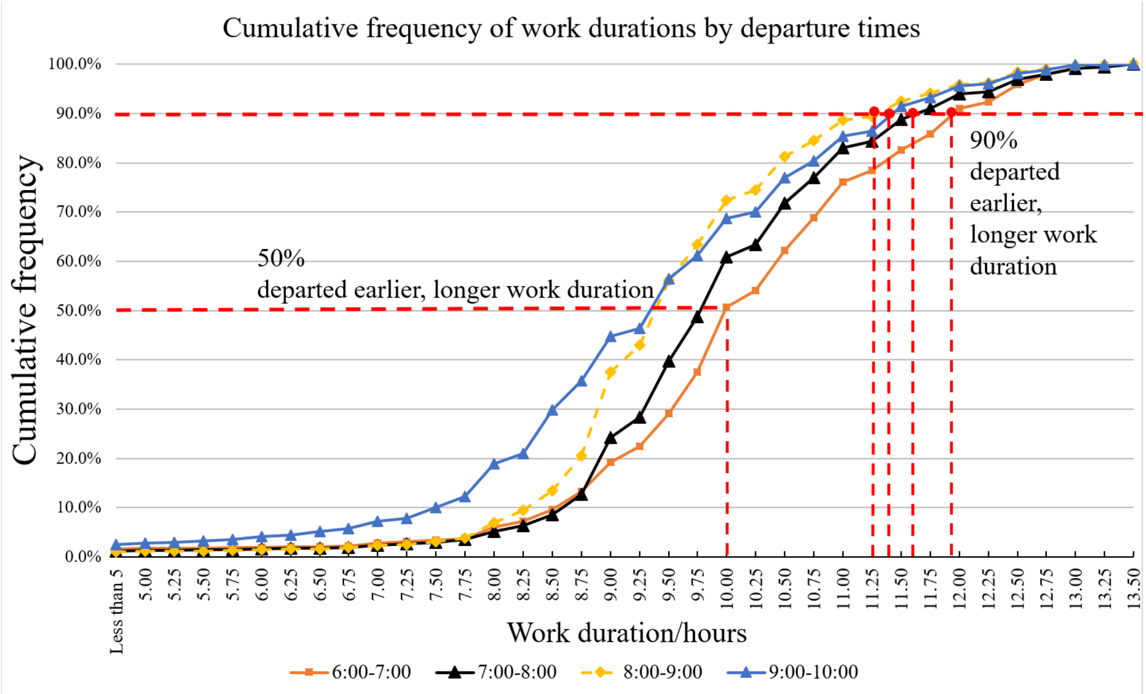

Figure 5. Work durations by departures time

From the cumulative frequency of work durations by departure times shown in Figure 5, it was found that the earlier the worker departed from home to work, the longer they worked. For example, looking at 90% cumulative frequency, the work duration for those workers departed between 06:00 and 07:00 a.m. was nearly up to 12 hours. Similar work durations of 11.60, 11.40 and 11.25 hours were found for workers with departure time periods of 07:00-08:00, 08:00-09:00, and 09:00-10:00, respectively. The results were also similar for work duration at 50% cumulative frequency level.

2.4 Activity Pattern of Travel Time

Sections 2.1-2.3 gave an overview of the daily activity participation status, the distribution of departure times to and from work as well as work duration. In this section, we analyzed the travel times of the trips of HWH activity-travel pattern. The results were displayed in Table 2.

The analysis of travel time showed that the more travel time required, 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 defied this tendency, perhaps due to heavy traffic conditions during the peak hour of home-work travel. However, travel time decreased as the workers put off their departure time for home-work travel until the peak hour. The standard deviation decreased as the departure time to work was postponed. The same was found on the departure time from work back home. On the other hand, the mean travel time (home-work and work –home travel) summed up to be around 1.6 hour (47.2 min+50.2 min). This value would be used for the calculation of work duration to compare with the estimated value to validate the model performance in Section 4.

Table 2. Travel times and work durations 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

One another significant finding in Table 2 was the work duration of workers by two groups of departure times. The results showed that the earlier they departed to work, the longer they stayed at work. In contrast, the workers worked longer if they left work later.

In summary, this section made 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 were noted: (1) the time window of travel time to work was shorter than that of from work, (2) the peak hours to and from work were compared, (3) the relationship between work duration and departure times to and from work was displayed, and (4) the tendency of travel times by departure times was shown. These findings formed the foundation for calibrating activity utility functions in line of activity-based approach 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, the temporal utility function tends to 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-travel patterns (Ettema and Timmermans, 2003; Ettema *et al.*, 2004; Li *et al.*, 2010; Xiong and Lam, 2011; Fu and Lam, 2014; Fu *et al.*, 2015). As such, it was adopted in this paper for calibrating the parameters of marginal utility function. The formulation of a bell-shape marginal utility function was 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 the function along the time axis on when the marginal utility function reaches its maximum value. The value of parameter β affects the rate of increasing to the maximum value and decreasing from that. Parameter γ affects the symmetry of the marginal utility function. The 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, serving as the scaling parameter in the function. γ, α, β, and u^{max} are the parameters needed to be calibrated. Following Ettema *et al.* (2004), γ is fixed as 1 for better convergence as the calibration of γ does not result in stable results for the parameters. 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.

Constant travel times were used for the calibration of the model (Ettema *et al.*, 2004) 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 considered in this paper for the calculation. However, further study will consider the utility functions of both activities and trips for the evaluation of transport policy.

Based on the findings from the TCS data, the activity durations varied with the departure times. Also, the activity durations varied by different start and end times. Therefore, three models with different considerations of start times and end times into the marginal utility functions were introduced 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, Model 2 and Model 3.

(2) Model 2: departure time has an obvious effect on activity. Therefore, in Model 2, we explicitly considered the effects of the start time of the activity on 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 the

induced parameter to assess the effects of the start time of the. The marginal utility function is updated as:

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

(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 is the end time of the activity with τ_e as weighting parameter. 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 times and end times 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 were modeled as discrete choices for workers' choosing to maximize their daily utilities. Because the HWH pattern was studied in this paper, only two departure times (departure times for home-work travel and work-home travel) were required for each choice alternative. Based on our analysis above, the departure time choices were 1-hour intervals between 06:00 and 10:00 for home-work travel and between 16:00 and 21:00 for work-home travel. The alternatives in the choice set were defined as the combination of two departure times (to and from work). Each choice alternative was considered as the combination of 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). The probability of departure time choice 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 were 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 the sequential quadratic programming method may be easily stuck in the local maxima as the objective function is neither convex nor concave. The genetic algorithm is able to get out of the local maxima. Therefore, in this paper, the genetic algorithm was adopted to calibrate parameters of the marginal utility functions. The crossover method for applying the genetic algorithm is the scattered crossover method. The details of this method were described as follows.

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

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

Further details about the key parameter settings were 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 tolerance	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 were displayed in Table 4 and Figures 6 and 7. In Table 4, the calibration results showed that the parameters were in good performance under significance test (all t-test scores were larger than two for 95% confidence level). The base model showed that the calibrated results of the parameters positioned the locations of marginal utility functions in a reasonable way. The largest value (43.91 compared to 30.73 and 20.25) of scaling parameters u^{max} belonged to the marginal utility function of work activity. The results accounted for the workers activity changing behavior, which would be discussed later. For Model 2 and Model 3, which aimed at investigating the impacts of the start time and end time of work activities. Higher impact of work start time than work end time could be inferred from the values of corresponding parameters of τ (0.40 compared with 0.23). However, the activity start time and end time should be incorporated into one integrated model for studying their impacts to the activity travel behavior together and will be carried out for future study.

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.

As shown in Figure 6, the marginal utilities in the base model equalized at around 08:30 and 19:00. These two values indicated that the base model well captured the timings of activity changing behavior, i.e. changing from staying at home to work and from work back home. To maximize daily activity utilities, workers made their trips around these timings for the next activity. More workers had been at work than at home after 8:30 in the morning and more workers had arrived at home than stayed at work after 19:00 in the afternoon. The mean duration of work activity calculated from these two values was 8.9 hours (excluding the total travel time of 1.6 hour), with an 8% error from observed 9.6 hour (TCS statistics).

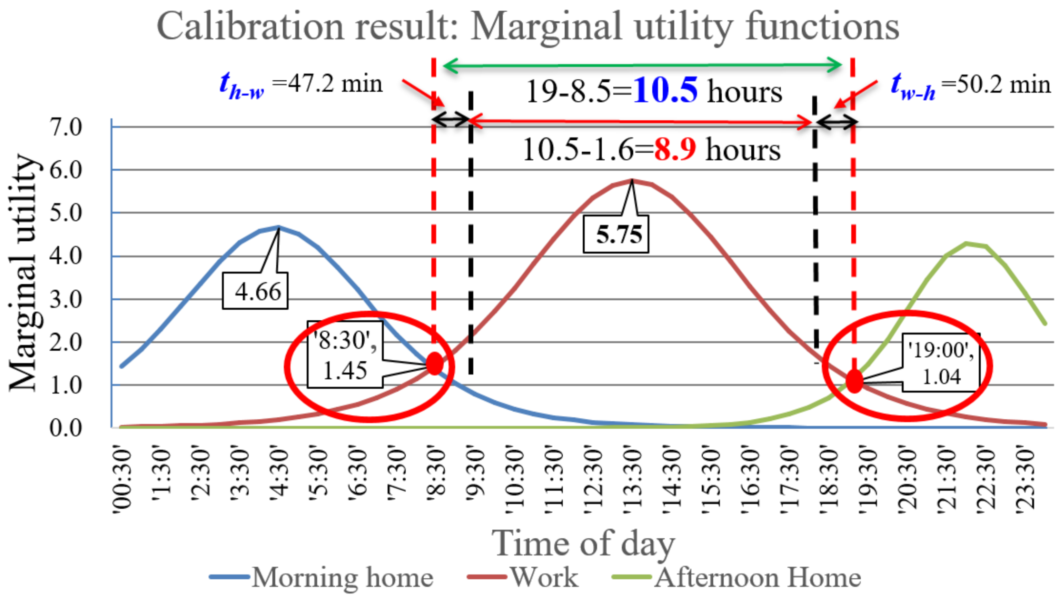

Figure 6. Calibrated marginal utility functions of Model 1

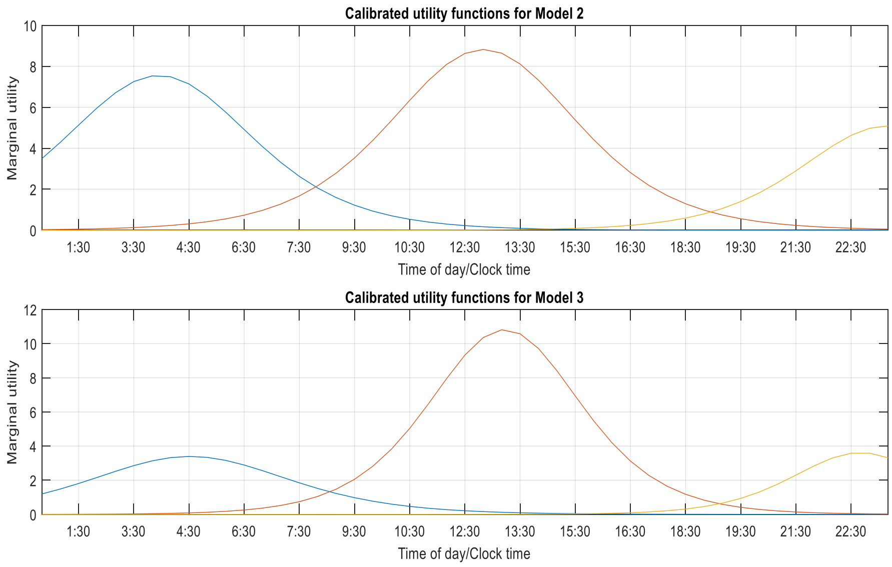

Figure 7. Calibrated marginal utility functions of Model 2 and Model 3

Model 2 and Model 3 incorporated the activity start time and end time into the model, and parameter τ indicated the effects of these timings on the position of the corresponding marginal activity utility functions. In our study, the times that matched the maximum utilities of home activity in the morning shifted about 40 minutes earlier. The value of τ_s indicated that the position of the marginal utility function shifted 0.4 minute in every minute change in work start time. The final log-likelihood showed better consistency with the sampling data.

The validation result was shown in Figure 8. The value of R^2 between the estimated probability and the observed probability was 0.9181. This result showed the good performance of predicting the departure time choice behavior of HWH workers.

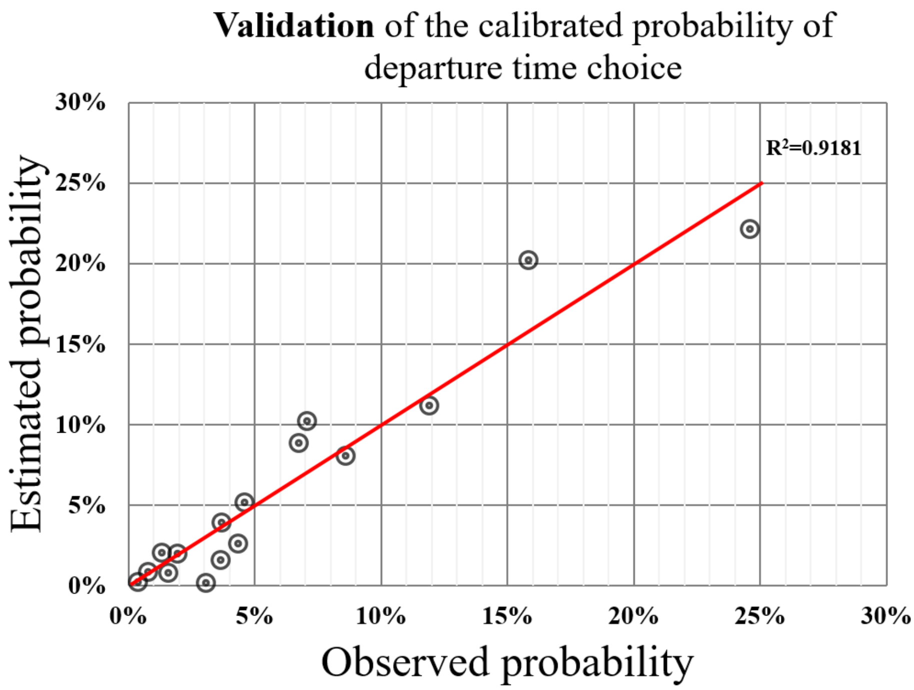

Figure 8. The validation of the calibrated probability of departure time choice

5 CONCLUSIONS

In this study, we used the data of TCS 2011 in Hong Kong to model the choice behavior of HWH activity-travel patterns. In particular, the relationships between work durations and travel times between home and work were analyzed. Based on the traditional household interview survey data, some statistical analysis was carried out to study the characteristics of these HWH activities. We formulated an activity-based model to quantify the marginal utility functions of work/home activities of HWH pattern workers. Some statistical tests were shown to report the goodness-of-fit to examine the performance of the calibrated model.

Overall, 30,247 workers, up to 77% of the sampled population of workers from the TCS data, were found to have the daily HWH pattern. Figure 1 shows a significant bell-shape pattern for the daily HWH activities. This served as a justification to choose the bell-shape marginal utility function, i.e. Eq. (1), for modeling the utility functions of the HWH activities. 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 the 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 travel time to and from work obviously affected the departure time and consequently affected the duration of work. Departure time choice was explicitly modeled in this paper. We assumed that workers select departure times to and from work so as to maximize their daily utilities. Their choices determined how much utility they could obtain from these work and home activities. This simplified the calibration process of the model, 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 time and end time 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 time and end time affected people's activity-travel choice behavior. 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 calibration results indicated that the model parameters were statistically significant. The validation results showed the R^2 of 0.9181 between the estimated probability and observed probability of departure time choice behavior of HWH activity-travel pattern. An 8% error of mean duration of work activity was estimated. The marginal utility functions can well capture the timings of activity changing behavior (i.e. 08:30 and 19:00) from home to work and from work to home. These results illustrated that the marginal utility function of HWH activities by time of day can be calibrated satisfactorily with traditional household interview survey data (TCS). 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 HWH 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 had lower household incomes may live farther from work (e.g., CBD) and therefore needed to depart earlier for travel, and those types of work were 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 revealed differences between the household groups with and without private cars, it would be interesting to quantify the impacts of car ownership on activity-travel choice behavior. In fact, in order to better understand the 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 HWH activities, such as examining the impacts of different workers (by their household incomes, as well as other characteristics such as household size) on their choices of departure times to and from work.

Second, although the model proposed in this paper considered the start time and end time of activities, an integrated model should be explored to analyze the joint impacts of activity start time and end time within 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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