OPTIMIZING DAILY TRAVEL SEQUENCES AND TIME-USE PATTERNS OF INDIVIDUALS

Naznin Sultana Daisy, Dalhousie University
Lei Liu, Dalhousie University
Hugh Millward, Saint Mary's University
Proceedings of the 52nd Annual Conference
Canadian Transportation Research Forum

Introduction

Activity-based models aim for a better understanding of people's desires for, restraints on, and likelihoods to perform activities. They emphasize travelers' participation in out-of-home activities, because people mostly travel to perform particular activities at different geographic places, rather than traveling just for the sake of travelling. Thus, travel demand is a by-product of the desire or need to participate in different activities. Since activities may take place at different geographic locations, traveling is required. Therefore, analyzing different people's daily activity patterns in different localities will assist modeling of urban transportation demands. The notion of travel as an induced demand has been well established and accepted by researchers through the work of Oi and Shuldiner (1962), which suggests that one should study travelers' participation in out-of-home activities first, before studying travel demand per se, as activities generate travel demand (Meyer and Miller, 2001).

The set of activities performed by individuals each day is influenced by the choices and preferences of the individual as well as those of their household members, or social groups. Thus, agent-based models such as MATSim aim to obtain the optimal daily schedules so that existing activity travel behavior can be replicated, and future travel patterns can be predicted according to changes in activity timing or location. Construction of satisficing schedules that integrate the resources available for choices are the goal of optimal daily activity schedules. However, these models face challenges such as name and type of activities, sequence of activities, start and duration of activities, composition of the group participating etc. (Axhausen, 2011). Feil et al. (2010) developed a *tabu-search* based optimizer for the number and sequence of activities and proposed a recycling approach to overcome the computing time problems. Subsequently, Mahdieh (2017) proposed a bi-level optimization model where accuracy of the predicted model has been optimized in the upper level model and utility of participating in each activity has been optimized in the lower level model.

Despite all the progress made in activity-based models, there are few studies that emphasize optimization of individual daily activity patterns. Thus, the aim of this study is to design and implement a prototype optimization model that efficiently optimizes a schedule, including the number, type, companionship, location, and sequence of its activities.

Data and Empirical Analysis

The analysis is based on the STAR (Space-Time Activity Research) travel survey, conducted in Halifax Regional Municipality from 2007 to 2008. Two days or 2880 minutes in the lives of 1,971 Primary Respondents of each households were collected using GPS-assisted prompted recall computer assisted telephone interviews. This translates into 3,919 diary days of information, comprised of 108,529 episodes of time diary information. For each of these minutes the data collector retrieved: (i) what was being done, (ii) what else was being done at the same time, (iii) where it was done, (iv) how long it was done for, (v) who it was done with, and (vi) purpose/for whom it was done. The survey also contains 4,663 diary days of out-of-home activity diary information collected from 4,663 eligible secondary respondents (all other household members aged 5 and older) about the out-of-home activities they engage in for the same two-day reporting period.

The STAR data include socio-demographic information, household size, accommodation type, motor vehicles and modes of transportation, parking availability and type, household energy usage, residential locations, education status, employment statistics (e.g. number of working adults in the household, occupation type, work hours, location, etc.), commitment (family, work, etc.), travel behavior (purpose of trip, duration etc.), spatial information on activities (latitude, longitude, address, municipality information, frequency of visit, etc.), routing information, distance of trip, and trip accompaniment. Full descriptions of the survey design and the socio-demographic characteristics of respondents can be found in TURP, 2008; Millward and Spinney, 2011; Millward et al. 2013; Spinney and Millward, 2011.

Hafezi et al. 2017 developed a pattern recognition framework and applied it to the STAR survey data. Using a fine-tuned fuzzy c-mean clustering technique, they obtained twelve unique clusters comprising individuals with homogenous activity patterns. Our empirical analysis showed that the proposed optimization algorithm performed better when we use clusters as input instead of entire sample populations. The finer results may be because of obtaining more precise temporal information and activity sequences. We compared our optimized individual activity patterns with the representative activity patterns in each cluster.

Mathematical Model

A bi-level optimization model has been designed and implemented to obtain the optimized activity timing and activity sequences. Temporal and spatial information related to activity, such as activity types, activity start time, activity duration, activity location and activity sequences, are model inputs. The upper level of the model maximizes the accuracy of the model whereas the lower level model maximizes the utility maximization. In this paper, utility maximization refers to activity timing and activity sequences. The authors of this paper are currently undertaking work to extend the proposed optimization model to include activity participation, location choice, and mode choice decision variables. Lower level model outputs are activity sequence, start time, duration, and end time. From the observed sequence, we found the highest number of times ($\mathbb{R}$) any activity occurred per cluster. Thus, for obtaining better sequences, it is assumed that any activity has the probability to be repeated $\mathcal{R}$ times maximum in a given day. There are some implicit assumptions in this paper, notably the idea that all individual Daily Activity Patterns (DAPs) should be as close as possible to the central (representative) DAPs for their cluster. Our argument of selecting DAPs within a cluster as target is that the dataset sample is representative; if the model results can replicate the representative DAPs for their cluster, it means that the model could replicate reality. The flowchart in figure 1 illustrates the optimization procedure.

Upper level:

$$\boldsymbol{Z^c = Max(AC|QU, ST, DU, L, A)}$$

$S.t.$:

$$Z^c = Max\ \ F(QU, ST, DU, L, A)\left|\left\{P_i^1, \ldots, P_I^{N_c}\right|\Delta^c, \Theta^c\right\}$$

where:
QU is the activity sequences
ST is the activity start time
DU is the activity duration
AC is the activity clusterΔ is a matrix of the mean values of start and duration of each activity episode, by activity type for all activity episodes in cluster c
Θ is a matrix of the variance values of start and duration of each activity episode, by activity type for all activity episodes in cluster c
c is the cluster number
L is the location of the activity
A is the companionship
$i = 1, \ldots, I$ is the activity type
N_c is the total number of individuals in the cluster c $\forall N_c \in \{1, \ldots, N_c\}$

Decision variables:

1. $K = \begin{bmatrix} k_{0,0} & \cdots & k_{0,2n+1} \\ \vdots & k_{n,i} & \vdots \\ k_{2n+1,0} & \cdots & k_{2n+1,2n+1} \end{bmatrix}$

is a binary matrix, value of 1 means that activity i is followed by the next activity $i+1$ and value 0 means that activity i is visit from a location i to itself

2. $ST^{N_c} = \left[ST_1^{N_c}, ST_2^{N_c}, \dots, ST_{2n+1}^{N_c}\right]$

is a vector indicating arrival time of activity i to activity locations i

3. $\Delta_{ST^{N_c}} = \begin{bmatrix} \Delta_{ST}{}_1^1 \\ \vdots \\ \Delta_{ST}{}_n^1 \end{bmatrix}$

$\Delta_{ST^{N_c}}$ is a matrix of the start time mean values

4. $\Delta_{DU^{N_c}} = \begin{bmatrix} \Delta_{DU}{}_1^1 \\ \vdots \\ \Delta_{DU}{}_n^1 \end{bmatrix}$

$\Delta_{DU^{N_c}}$ is a matrix of the duration mean values

5. $\Theta_{ST^{N_c}} = \begin{bmatrix} \Theta_{ST}{}_1^1 \\ \vdots \\ \Theta_{ST}{}_n^1 \end{bmatrix}$

$\Theta_{ST^{N_c}}$ is a matrix of the start time variance values

6. $\Theta_{DU^{N_c}} = \begin{bmatrix} \Theta_{DU}{}_1^1 \\ \vdots \\ \Theta_{DU}{}_n^1 \end{bmatrix}$

$\Theta_{DU^{N_c}}$ is a matrix of the duration variance values

Lower level Model:

$\boldsymbol{Z_i^c = Max\ \ f_i\ \ (QU, ST, DU, L, A)\big|\{P_i^1, \dots, P_I^{N_c}\big|\Delta, \Theta\}}$

The terms of the objective function are:

1. Minimizing disutility of late or early arrival time to activity location, compared to the mode of the arrival time distribution to that activity
2. Minimizing disutility of deviation of the activity duration from the mode value of activity duration
3. Maximizing the utility of activity participation from the initialized values

Minimization of the deviation of start time of activity

(1) $\boldsymbol{Min\ \ \sum_1^{N_c}\left|ST_i^{N_c} - ms_i^{N_c}\right| \ = \ Min\ \ \sum_1^{N_c} {ST_i^{N_c}}^{+} + \sum_1^{N_c} {ST_i^{N_c}}^{-}}$

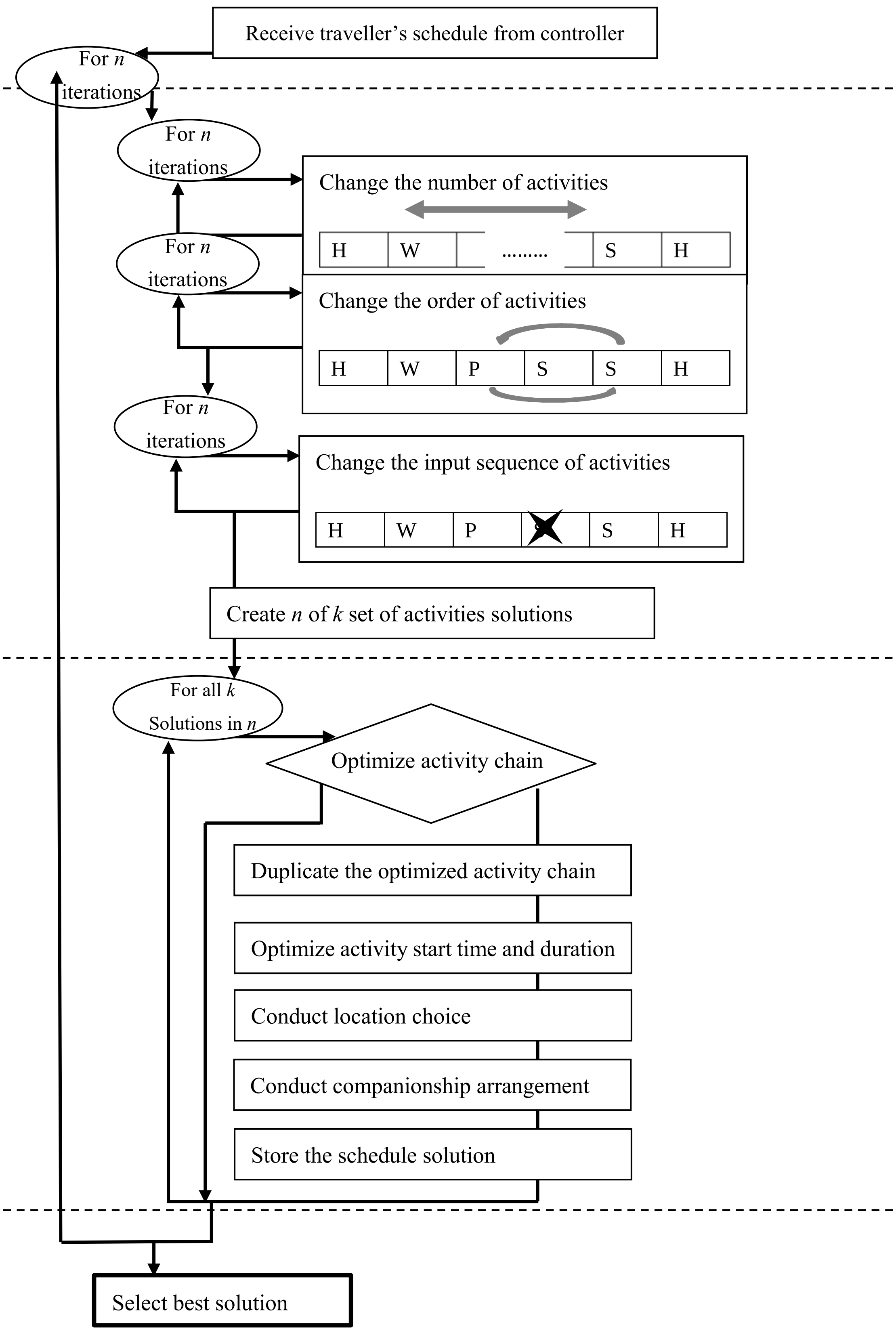


Figure 1 Optimization model procedure

$S.t.$:

$ST_i^{N_c^+} \geq ST_i^{N_c} - ms_i^{N_c}$

$ST_i^{N_c^-} \geq ms_i^{N_c} - ST_i^{N_c}$

where:

$ST_i^{N_c}$ is the arrival time of individual n in cluster c to activity location i

$ms_i^{N_c}$ is the mode of the arrival time of individuals in cluster c to activity location i

$\left|ST_i^{N_c} - md_i^{N_c}\right|$ is the absolute deviation of arrival time to activity location i

Minimization of the deviation of activity duration

(2) $\boldsymbol{Min} \;\; \sum_{\mathbf{1}}^{N_c} \left|\boldsymbol{DU_i^{N_c}} - \boldsymbol{md_i^{N_c}}\right| \; = \; \boldsymbol{Min} \;\; \sum_{\mathbf{1}}^{N_c} \boldsymbol{DU_i^{N_c^+}} + \sum_{\mathbf{1}}^{N_c} \boldsymbol{DU_i^{N_c^-}}$

$S.t.$:

$DU_i^{N_c^+} \geq DU_i^{N_c} - md_i^{N_c}$

$DU_i^{N_c^-} \geq md_i^{N_c} - DU_i^{N_c}$

where:

$DU_i^{N_c}$ is the duration of activity i belongs to the individual n in cluster c

$md_i^{N_c}$ is the mode of the duration of activity i belongs to individuals in cluster c

$\left|DU_i^{N_c} - DU_i^{N_c}\right|$ is the absolute deviation of duration to activity location i

Minimizing deviation utility gained from the participation in different activities

(3) $\boldsymbol{Min} \;\; \sum_{\boldsymbol{i \in I}} \boldsymbol{k_{n,i}}$

$S.t.$:

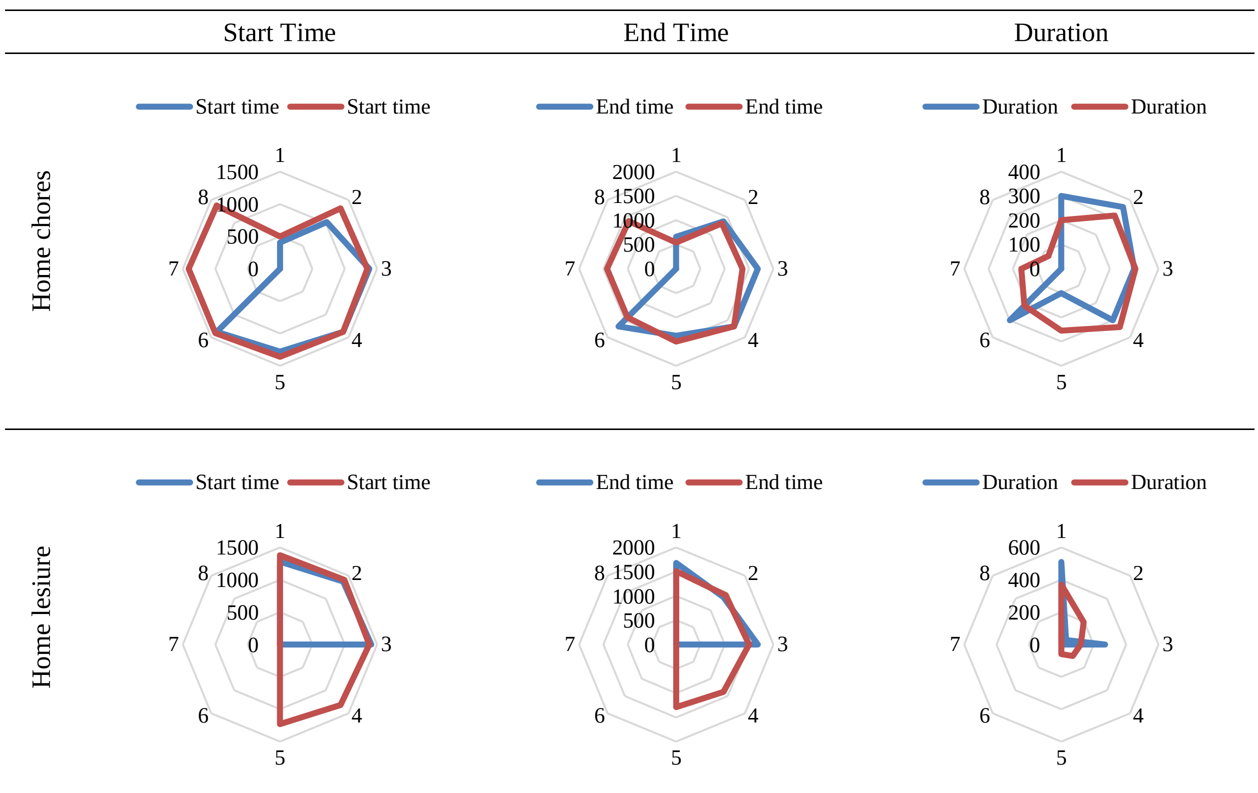
$$k_{n,i} \begin{cases} 1 & if \;\; individual \;\; n \;\; in \;\; cluster \;\; c \;\; participate \;\; in \;\; activity \;\; i \\ 0 & if \;\; individual \;\; n \;\; in \;\; cluster \;\; c \;\; do \;\; not \;\; participate \;\; in \;\; activity \;\; i \end{cases}$$

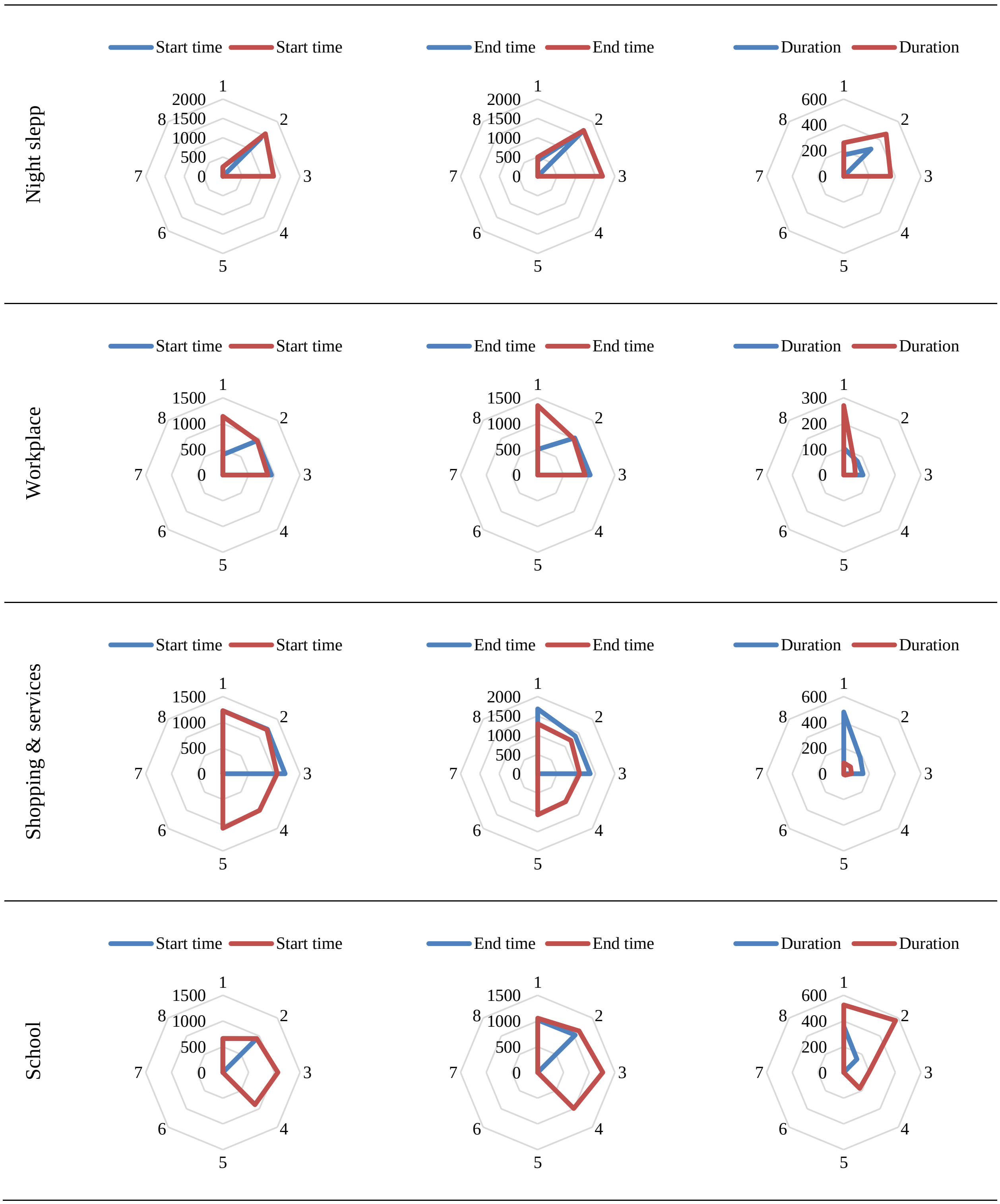
Model formulation for the lower level model:

$$Min\ \ Z_i^c = \left(\sum_{1}^{N_c} ST_i^{N_c^+} + \sum_{1}^{N_c} ST_i^{N_c^-} + \sum_{1}^{N_c} DU_i^{N_c^+} + \sum_{1}^{N_c} DU_i^{N_c^-}\right) + \sum_{n \in N} \sum_{i \in I} k_{n,i}$$

Results

In the current paper, we presented results of a prototype optimization model where we obtained the optimized activity sequences, activity start time, activity end time, and activity duration. The observed and predicted start time, end time and duration of 9 activity types for cluster one (student group) are presented in Figure 2. For better sequence, we assumed that each activity can be repeated a maximum of 8 times. Thus, the graph shows the start time, end time, and duration for the probable 8 repeated times for any activity. For all the activities, the goal is under-achieved rather than over-achieved. Discretionary activities, including entertainment, shopping, and organizational and voluntary activities, are better represented in the current model in comparison to other activities. Work and school activities show that current model needs further weighting on mandatory activities for higher accuracy. In-home activities, including home chores, home leisure, and night sleep, show less deviation than observed. However, according to the existing constraints that particularly control for activity timing and number of activity episodes, the optimization model results are within the acceptable range. Further work will include adding more constraints, such as activity participation and location choices, to the proposed optimization model




Night slepp
Workplace
Shopping & services
School
Start time
Start time
End time
End time
Duration
Duration
1
2
3
4
5
6
7
8
0
500
1000
1500
2000
100
200
300
400
600

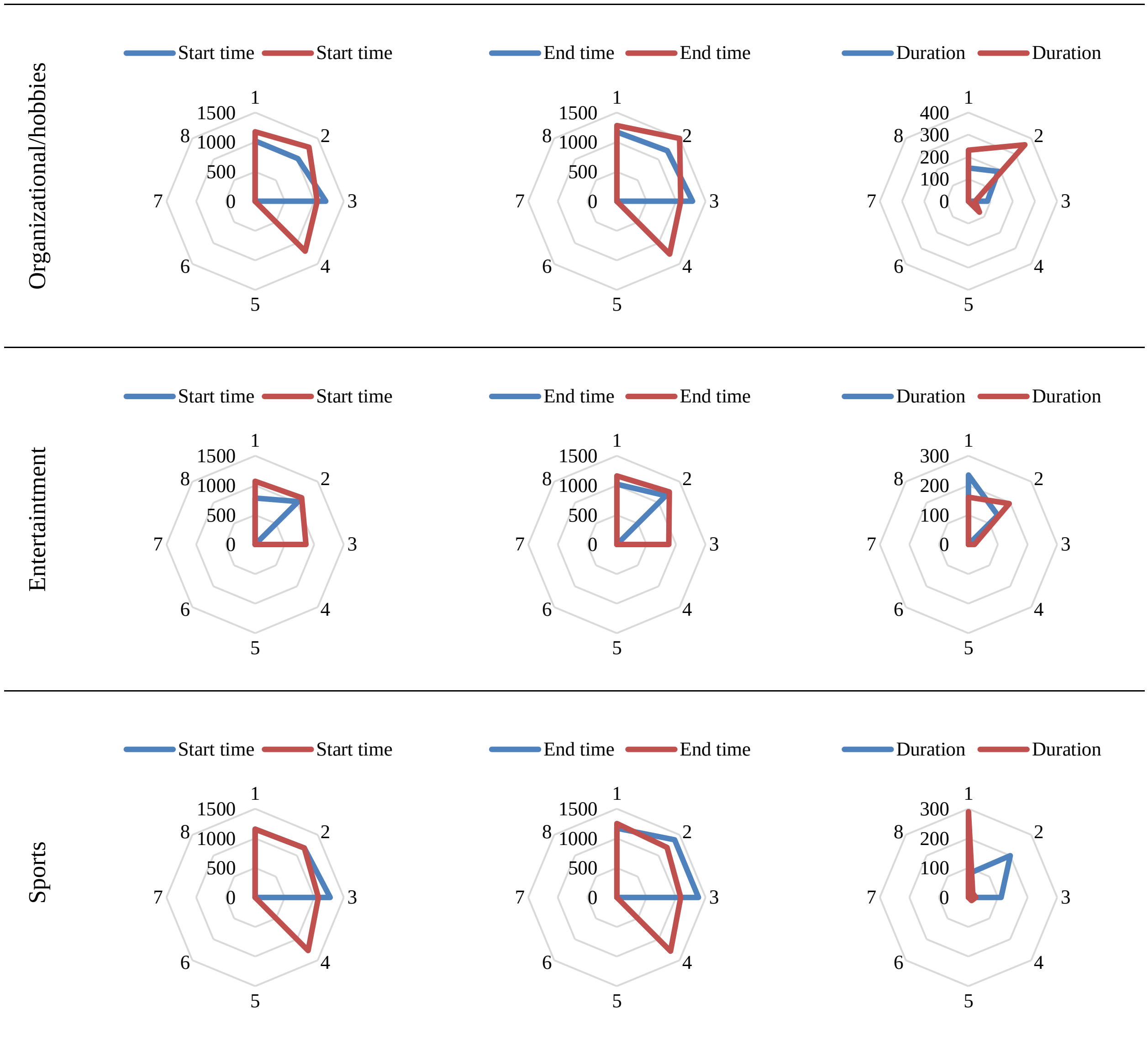


Figure 2 Comparison between observed and model results for activity timing and activity episodes

Conclusion

In daily life, individuals try to optimize their daily activity patterns so that they can participate in all of their scheduled activities. This issue is more important when individuals experience longer travel or longer activity duration than expected: then they have less time to participate in other scheduled activities. Hence, they try to find an optimal schedule for the remaining time of the day to maximize their activity participation. This paper contributes to the literature on activity-based models by developing a prototype model to optimize individual daily activity patterns. In this paper, we defined a set of constraints to control for activity timing (i.e. start time, end time, and duration) and activity sequences. Subsequently, a bi-level optimization model was developed to maximize the utility of activity participation from the initialized values, minimize disutility of late or early arrival time to activity location, and minimize disutility of deviation of the activity duration from the mode value of activity duration. We intend to extend the optimization model to include more decision variables, such as activity participation and activity location choices.

Acknowledgments

This research was supported, in part, by grants from Dalhousie University. Their support is gratefully acknowledged. The authors would also like to thank the Natural Sciences and Engineering Research Council (NSERC) for their contribution in supporting the research. Special thanks to Mohammad Hesam Hafezi and Bing Wang for their help in executing the model in LINGO. We would also like to thank the Dalhousie Transportation and Environmental Simulation Studies (TESS) group members for their valuable suggestions. Data for this research were provided by the Halifax STAR Project, supported through the Atlantic Innovation Fund from the Atlantic Canada Opportunities Agency, Project No.181930.

References

Allahviranloo, M. and, K. Axhausen (2017). Estimation of Utility Distribution Parameters for Joint and Solo Activities. Presented in the 96th Annual meeting of Transportation Research Board (TRB), Janaury 8-12, 2017, Washington DC, USA.

Axhausen, K. (2011). Computational Challenges for integrated micro-simulation models, *Travel behaviour Research for and Evolving World*.

Feil, M., Balmer, M., & Axhausen, K. W. (2009). *New approaches to generating comprehensive all-day activity-travel schedules*. ETH, Eidgenössische Technische Hochschule Zürich, IVT, Institut für Verkehrsplanung und Transportsysteme.

Hafezi, M. H., Liu. L. and, H. Millward (2017). Identification of representative time-use activity patterns using fuzzy c-means clustering. *Transportation Research Record: Journal of the Transportation Research Board*. In press.

Meyer, M. D. and E. J. Miller (2001). Urban Transportation Planning, 2. edn., McGraw-Hill,

Millward, H. and J. E. Spinney. (2011). Time use, travel behavior, and the rural–urban continuum: results from the Halifax STAR project. *Journal of Transport Geography*. 19(1), pp. 51-58.

Millward, H., J. E. Spinney, and D. Scott. (2013). Active-transport walking behavior: destinations, durations, distances. *Journal of Transport Geography*. 28(1), pp. 101-110.

Oi, W. Y. and, P. W. Shuldiner (1962). An Analysis of Urban Travel Demands, Northwestern Singapore.

Spinney, J. E. and H. Millward. (2011). Weather impacts on leisure activities in Halifax, Nova Scotia. *International Journal of Biometeorology*. 55(2), pp. 133-145.

TURP. (2008). *TURP (Time Use Research Program)*. Retrieved from Halifax regional space time activity research (STAR) survey: A GPS-assisted household time-use survey, survey methods. Halifax: Saint Mary’s University. University Press, Evanston.