Two-Level, Dynamic, Week-Long Work Episode Scheduling Model

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The two-level dynamic model presented in this paper was developed for scheduling work episodes within a 1-week planning period. The week-long time frame captures day-to-day variability in an individual's work participation within a typical week. Two types of work episodes are modeled: those planned before the week (preplanned) and those scheduled during the week (unplanned). The first level of the model schedules preplanned work episodes, considering workers' total time awake as their time budget. After the schedule of the preplanned episodes is known, the second level schedules unplanned work episodes. In this level the duration of preplanned episodes is subtracted from the first level's time budget to define the individual's time constraint. In each level of the framework, discrete-continuous econometric models are used to model jointly the decision of working on each day with the associated episode duration and start time. Results indicate that not only do work episodes have different attributes based on the time when they are added to the schedule but also there are interdependencies between preplanned and unplanned work episode scheduling. Working on previous days of the week increases the probability of scheduling work episodes on the following days; this setup is representative of the routine nature of much work activity. Workers with a fixed place of work schedule more preplanned work episodes, whereas they engage in fewer unplanned episodes. Flexible work duration increases time expenditure on preplanned episodes. Both models are estimated with computerized household activity scheduling survey data collected in Toronto, Ontario, Canada.

Work is a primary activity in a worker's schedule, attributes of which impose constraints on the rest of the schedule. It is arguable that all work episodes in a person's weekly schedule are interrelated from a scheduling perspective. It is also arguable that work episodes are generally scheduled before other activities, given the high priority, level of prior commitment, and relative regularity of work. One can think in terms of a work project as a container of the information and rules or processes that generate all weekly work episodes for a worker, including a representation of the interdependencies that exist in the scheduling of these episodes (*1*). The attributes of work episodes exhibit relatively lower levels of flexibility compared with nonwork activities because of the fact that work episodes are either part of an ongoing contract or a one-time commitment with an external agent (i.e., the employer or job) (*1*). Therefore, their attributes are generally determined by the external agent and the individual becomes committed to them by accepting the contract (*1*). The routine nature of work activities and the fact that they consume significant portions of a person's time budget make them pegs for the individual's schedule around which nonwork activities can then be planned (*1*). Accurate prediction of the attributes of the skeleton schedule, defined by scheduled work activities, is critical to the prediction of nonwork and school (NWS) activities (*1*). The same comment holds for school activity episodes for students. This study, however, focuses on workers and the scheduling of their work activities.

Several studies modeled different attributes of commuting trips such as work trip departure time and mode. The main purpose of these studies usually was to predict peak-hour demand for analysis of traffic congestion. Ettema and Timmermans modeled start time and duration of work episodes considering that all other schedule components and their attributes are known (*2*). Nurul Habib jointly modeled work trip mode choice, work start time, and duration for one day by using a trivariate discrete-continuous-continuous model to capture peak spreading (*3*). Nurul Habib et al. jointly modeled morning work start time and mode choice by using joint multinomial logit and hazard econometric models (*4*). In another study, Nurul Habib modeled work trip departure time and mode choice by applying a discrete-continuous random utility maximization (RUM) approach; this work did not model work duration (*5*). In a separate study, Nurul Habib and Miller focused on scheduling the workers' daily activity schedule (*6*). In this work, each day of a week was divided into before-work gap, work, after-work gap, and night sleep. Duration of each of these components was found by using multilevel linear models and continuous-time hazard models. The sequential choice of duration for consecutive components determined their start time. Ettema et al. modeled work start time and duration jointly as a function of time of day (*7*). The schedule delay component was added to the utility function in this model to capture the penalty of deviating from the desired start time. The final utility to be maximized was the sum of the utilities of all the undertaken activities without consideration of priority for work episodes. Generation of work activities was not part of the work in any of the stated studies.

Unlike the different modeling frameworks proposed for NWS activities, there are few models that focus on generation and scheduling of work activities. The travel activity schedule for household agents (TASHA) considers work as a project that generates work episodes of various types for a single day, categorized by an individual's number of jobs and usual place of work (i.e., home or out-of-home) (*8*). TASHA generates different types of work episodes in the work project based on the observed frequencies for different occupation types and employment status. Start time and duration of these episodes are then randomly drawn from the observed joint distributions. The generated work episodes in the work project are then scheduled within a rule-based process with a predefined priority order. ALBATROSS finds the number of work episodes longer than 1 h with a maximum frequency of 2 with their associated start time and duration within its rule-based decision tree framework (*9*). Work episodes with shorter duration than 1 h are planned in the next model step under the category of secondary fixed activities along with

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other activity types. The Florida activity mobility simulator (FAMOS) uses a fixed activity generator that also applies observed distributions to generate work start time and duration probabilistically (*10*). The applied data-driven approach in TASHA, ALBATROSS, and FAMOS is not policy sensitive and depends on the conditioning variables and their relationship with the decision variables (*7*). In PCATS the start and end times of work episodes are based on typical working hours, starting at 8:00 a.m. until noon, a 1-h break, and then from 1:00 to 5:00 p.m. (*11*). An arbitrary time is assigned in this model to the start time of the before-work gap and the end time of the after-work gap. However, in subsequent versions of the model a stochastic frontier concept is used to generate unobserved vertices of the time–space prisms. The agent-based dynamic activity planning and travel scheduling (ADAPTS) model generates routine activities in a separate framework from the nonroutine activities using a competing hazard model (*12*). Despite consideration of the planning order for scheduling nonroutine activities, all the attributes of the work activity are planned jointly in ADAPTS. Finally, start time and duration of work episodes are randomly drawn from observed distributions. The comprehensive econometric microsimulator for daily activity-travel patterns (CEMDEP) also fixes work and school as the temporal pegs of the schedule and applies a combination of econometric models to schedule work activities by using discrete time intervals (*13*). Ordóñez-Medina extracts weekly patterns of fixed activities including number of working days, their start time, and duration from Singapore transit smart card data using the DBSCAN clustering algorithm (*14*). Clusters are recognized in the absence of socioeconomic characteristics such as individuals' work attributes. Fixing work as the schedule skeleton, Ordóñez-Medina extends the multiagent transport simulation (MATSIM) structure to model multiday activity chains (*15*). CUSTOM (*16*) and C-TAP (*17*) schedule all activity types of an individual simultaneously without considering scheduling priority for work. Hence, CUSTOM and C-TAP do not consider work as a qualitatively different activity compared with nonwork activities. CUSTOM applies a discrete-continuous RUM-based choice model to jointly generate episode types with their chosen destination and duration. C-TAP applies heuristics to schedule episodes, considering future opportunities at each decision point within an open planning horizon.

With the exception of a few of the stated models, all of the models discussed generate and schedule work activity within a single weekday, which does not capture potential day-to-day scheduling dynamics or variations in work episode attributes. Despite the relatively fixed attributes of many work episodes, stochastic elements in daily life exist that can cause changes in their attributes from day to day (*1*). Therefore, intraperson variability exists between different working days; this variability indicates the need for developing week-long activity-based models. Prior work episode participation and the attributes of these prior episodes, as well as future opportunities (i.e., remaining days of the week) to fulfill work requirements, influence work scheduling at each decision point on each day. Moreover, as with any other type of activity, individuals probably consider a week-long time frame in scheduling their work episodes. Assuming that all working days of a person are the same can lead to inaccurate time budget predictions for scheduling NWS episodes.

Although most existing activity-based models give higher priority to work episodes compared with other episode types in their scheduling process, they should also prioritize among different work episode types. Priority in planning different work episodes in a week can be captured by taking into account the time they are added to the individual's schedule.

The purpose of this study is to address the stated deficiencies of the work activity scheduling within existing activity-based models. A two-level model is applied to schedule work episodes of an individual for a period of 1 week. This model is part of a comprehensive activity-based model currently under development for scheduling all activity types of individuals. In the NWS scheduling component of the model system, work episodes are assumed to be a component of a predetermined skeleton schedule that constrains the scheduling of NWS episodes.

In general, a person's weekly work episodes can be divided into those that are generated and scheduled before the start of the week because of their fixed nature (e.g., regular work, in-office work); those generated before the start of the week but not scheduled, either because they need to be coordinated with others or have more flexible attributes (e.g., meetings, visiting clients); and those both generated and scheduled during the week (e.g., service calls by a plumber). Given the available data set for this study, however, the latter two categories must be combined into a single category, and so the work project in this study consists of work episodes scheduled before the week (preplanned) and those scheduled during the week (unplanned). This categorization is important because attributes of work episodes vary based on their planning horizon. Moreover, attributes of the unplanned work episodes are influenced by those of the preplanned work episodes. In the first level of the model, preplanned work episodes are generated and scheduled as a joint decision of working or not on a given day together with choices of work duration and start time (in the case of working). When the schedule of the preplanned work episodes is known, in the second level unplanned work episodes are scheduled. Locations of an individual's work and home are exogenous to the model. Scheduling work episodes is assumed to be independent of and before the rest of the activities in the schedule. The week-long time frame of the model captures the routine nature of work scheduling as well as the intraperson variability in work episodes on different days of the week.

METHOD

The proposed two-level model applies a sequence of discrete-continuous econometric choice models to schedule work episodes over an entire week. The first level of the framework schedules all the preplanned work episodes in an individual's week. The scheduling process starts on Monday with a binary decision of working or not on that day and, if working, for how long and at what point of time in the day the episode starts. The joint choice of all the attributes of work activity captures the interrelationship between them. To capture the effect of future opportunities to fulfill work requirements on the decision at the current point in time, a nested logit model is applied in which each level represents one future day of the week. Scheduling all the work episodes within the same planning horizon in a nested structure allows interdependencies between episodes to be captured. Figure 1 shows the weekly scheduling process and feedback between different choices on each level of the developed model.

The utility function of choice of working on day k is as follows:

$$u(w_k|\text{number of working days})$$
$$= \alpha + \sum_{i=1}^{6} \beta_i (\text{day of week alternative specific})$$
$$+ \sum_j \lambda_j x_j + \mu_{k+1} \ln\left(\sum_{k+1}^{7} e^{\mu_k u(w_k|\text{number of working days})} \right) \tag{1}$$

$$u(nw_k) = \frac{1}{\mu_{k+1}} \ln\left(\sum_{k+1}^{7} e^{\mu_k u(w_k|\text{number of working days})} \right) \tag{2}$$

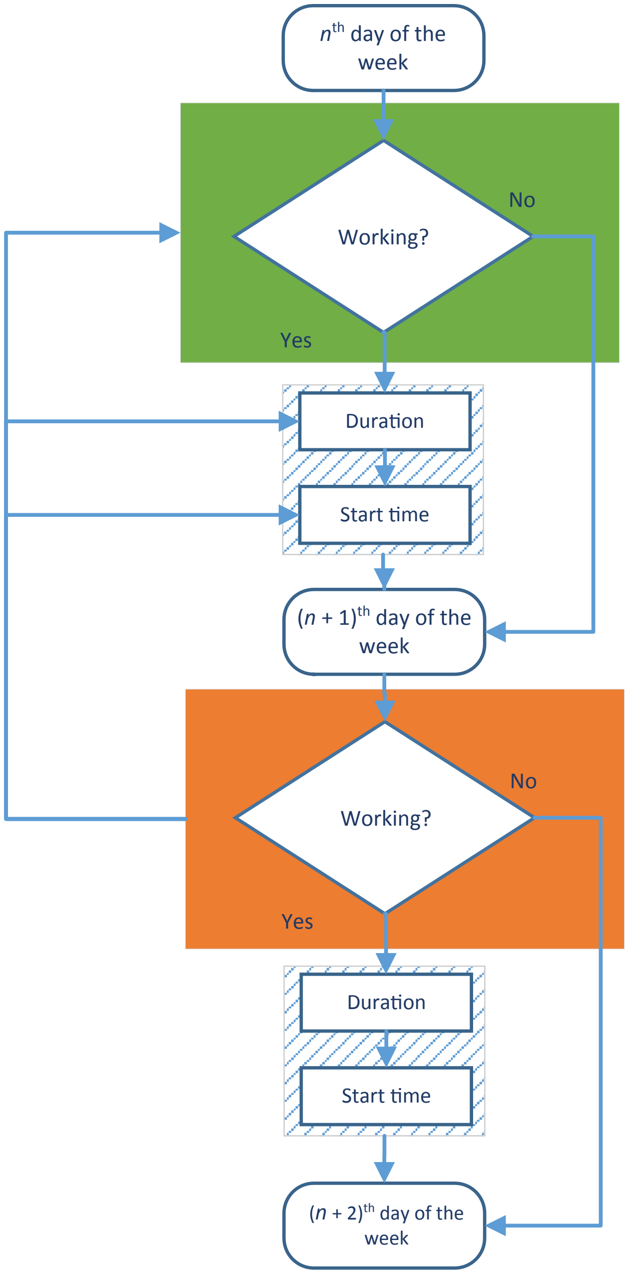


FIGURE 1 Scheduling process in each level of framework.

$$\mu_{k+1} = \mu_k + \exp(\sigma A) \tag{3}$$

where

x = set of explanatory variables describing socioeconomic and job attributes of individual,
α = alternative-specific constant,
β = set of coefficients for day-of-week alternative-specific variables,
λ = set of coefficients for rest of explanatory variables,
i = days of week (as described in the above equation),
j = explanatory variables, and
μ_k = choice scale factor on day k.

The last term is the maximum expected value of choice of working or not on the following days of the week from the lower nest levels. The choice scale factor on day k is μ_k, defined as shown in Equation 3, where A is a set of explanatory variables and σ is their associated coefficients. Equation 3 ensures satisfaction of the assumed nested logit hierarchy. The scale factor captures the correlation between alternatives on different days of week. For the first day (Monday) the scale factor is normalized to 1.

Work episode duration for each day is modeled by using a continuous RUM time expenditure choice model. The random component in this approach captures the effect of the behavioral unobserved factors influencing the choice. This approach finds duration of each work episode against the composite activity, which includes all the unplanned activities in the schedule (*18*). Composite activity represents the effect of the time pressure of the rest of the unplanned episodes in the individual's schedule on the duration of the current episode (*18*). Thus, the model captures trade-offs in time expenditure between the work project and other activities in the schedule under a time constraint while keeping the continuous nature of time expenditure. The total duration of an episode is a function of marginal utility and satiation. The satiation parameter captures changes in marginal utility gained by an increase in the time spent on the activity (*19*), which is essential in modeling duration for long episodes such as work (*7*). Finally, the probability (pr) of spending t unit of time on the generated work episode on day k is found by using Equations 4 through 9 (*16*).

$$v_k = (\alpha_k - 1)\ln(t_k) + \gamma_k z_k + \varphi \frac{\mu_k}{\mu_{k+1}} \ln\left(\sum_{k+1}^{7} e^{\mu_k u(w_k|\text{number of working days})}\right) \tag{4}$$

$$v_c = (\alpha_c - 1)\ln(T - t_k) \tag{5}$$

$$v_k = (\alpha_k - 1)\ln(t_k) + \gamma_k z_k + \phi \frac{1}{\mu_{k+1}} \ln\left(\sum_{k+1}^{7} e^{\mu_k u(w_k)}\right) \tag{6}$$

$$\alpha_k = 1 - \exp(\rho_k p_k) \tag{7}$$

$$\mu_{t_k} = \exp(\gamma_k' x_k') \tag{8}$$

$$t_k + t_c = T \tag{9}$$

where

v_k, v_c = marginal utility of time assigned to scheduled work episode and composite activity, respectively;
α_k = satiation parameter;
t_k = work episode duration on day k;
t_c = time remaining for composite activity;
z = variables to explain duration baseline utility function;
y = vector of coefficients of z;
φ = coefficient of maximum expectation from utility of work schedule;
p = variables to explain exponential function of satiation parameter;
ρ = set of parameters of p;
μ_{t_k} = scale parameter for time expenditure on day k, which is inverse of choice variance;
x' = set of explanatory variables; and
γ' = corresponding parameters.

For preplanned work episodes, T (time budget) is the duration of time the individual is awake. Maximum expectation from the utility of the work schedule for the rest of the week is added to the duration baseline utility function to capture its effect on the termination of the current work episode.

Finally, a proportional hazard model is used to model work episode start time. In this model, the hazard at time t for individual i is calculated by multiplying an exponential function of covariates in a baseline hazard function as follows (*20*):

$$\lambda_i(t|x_i) = \lambda_0(t)\exp(x_i\beta) \tag{10}$$

where $\lambda_0(t)$ is the baseline hazard function, which represents the risk when $x = 0$. The baseline hazard function is the reference risk and the exponential part is the relative risk, which captures changes in the value of the reference risk based on the covariates (*20*). The value of the relative risk is assumed to be independent of time. The survival function finds the probability that the event of interest has not occurred by time t and is defined as follows:

$$S(t) = \mathrm{pr}(T \geq t) = 1 - F(t) = \int_t^{\infty} f(t)\,dt = \exp\left(-\int_0^t \lambda_i(t)\,dt\right) \tag{11}$$

where F is the cumulative hazard function and dt is incremental changes in t.

A Weibull distribution is considered for the baseline hazard function because it shows a better fit compared with other tested statistical distributions. Equation 10 can be rewritten as

$$\lambda_i(t|x_i) = \gamma t^{\gamma-1}\exp\left(x_i\beta + \theta\frac{1}{\mu_{k+1}}\ln\left(\sum_{k+1}^{7} e^{\mu_k u(w_k)}\right)\right) \tag{12}$$

where γ is the shape parameter of the Weibull distribution. The scale parameter of the Weibull distribution is fixed to 1. To capture the effect of the rest of the week's work schedule on work start time at the current decision point, the maximum expectation from the lower levels of the nesting structure is added to the rest of the covariates with weight θ.

The likelihood of failure at time t is calculated as

$$L_i(t) = \lambda_i(t)S_i(t) \tag{13}$$

where S_i is the survival function.

Finally, the overall model's likelihood over the course of 1 week is

$$L = \prod_{i=1}^{I}\prod_{k=1}^{7}\left(\mathrm{pr}(t_k)\right) * \left(\mathrm{pr}(w_{ik})\right)^{\delta} * \left(\mathrm{pr}(nw_{ik})\right)^{1-\delta} * L_{ik}(t) \tag{14}$$

where

- $\mathrm{pr}(w_{ik})$ = probability of scheduling a preplanned work episode on day k for individual i,
- $\mathrm{pr}(nw_{ik})$ = probability of not scheduling a preplanned work episode,
- δ = 1 if a preplanned work episode is scheduled on day k and 0 otherwise,
- $\mathrm{pr}(t_k)$ = probability of duration t_k for generated work episode on day k, and
- L_{ik} = work start time probability at time t in the case of working.

The likelihood function of the model is closed form and can be estimated by using the Broyden–Fletcher–Goldfarb–Shanno gradient search algorithm in the Gauss software (*21*).

The same mathematical framework is applied to schedule unplanned work episodes starting from Monday. Inputting results of the first level of the framework into the second level captures the interdependency between preplanned and unplanned work episode schedules, with the unplanned work time budget being calculated by subtracting time assigned to the preplanned work episode on each day from the awake time of the individual.

EMPIRICAL MODEL AND VALIDATION

The data set used to estimate the proposed framework is the computerized household activity scheduling (CHASE) data set, collected in Toronto, Ontario, Canada, in 2002 to 2003 (*22, 23*). The CHASE data include an activity-travel diary for one full week for 416 individuals from 262 households, including the planning process for activities such as the planning horizon or timing when activities are added to the schedule or subsequently modified. The data set also includes self-reported flexibility of the activities in time, space, mode, and participants. Based on previous analyses conducted on CHASE data, it is clear that intraperson variability exists between individuals' working days in a week.

The CHASE data set consists of 53% men and 46% women. Workers make up 74% of the individuals, of whom 7% are teleworkers and 4% have second jobs. There is no great variety in terms of the employment status in the data set because 84% of the CHASE workers are full-time workers.

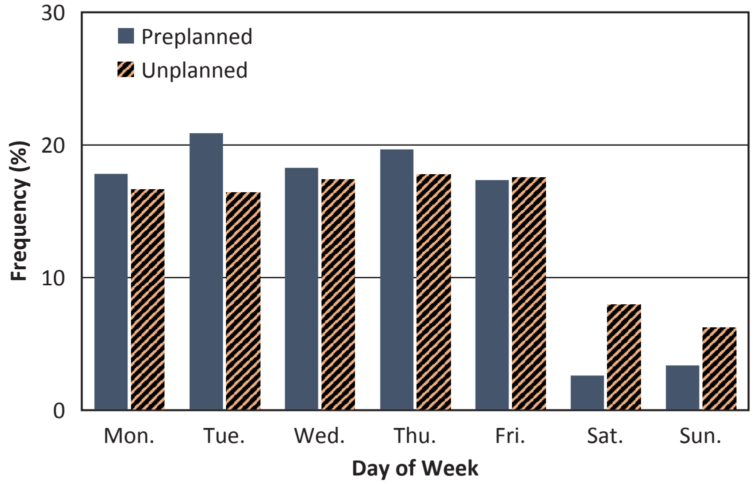
Differences in the attributes of preplanned and unplanned work episodes are shown in Figures 2 and 3. Unplanned work episodes are shorter in duration and start later in the day. For both preplanned and unplanned work episodes, weekend episodes start later and are shorter in duration. As shown in Figure 2*a*, except on Friday, the number of preplanned work episodes on all weekdays is greater than unplanned ones, and there are more unplanned work episodes on the weekend. Workers in service jobs have the highest percentage of unplanned work episodes, as shown in Figure 2*b*.

As discussed earlier, work episodes in TASHA are scheduled by using the concept of the project. The work project in TASHA consists of different types of work episodes as well as return-home episodes from work (e.g., for lunch) (*8*). In this study, which is one component of a comprehensive framework for scheduling all activities of an individual for a course of 1 week, return-home is modeled within the NWS scheduling component, and so the work project consists of only preplanned and unplanned work episodes. Scheduling is done within the work project independently from the other activities or projects in the individual's schedule, given the assumed higher priority of the work project.

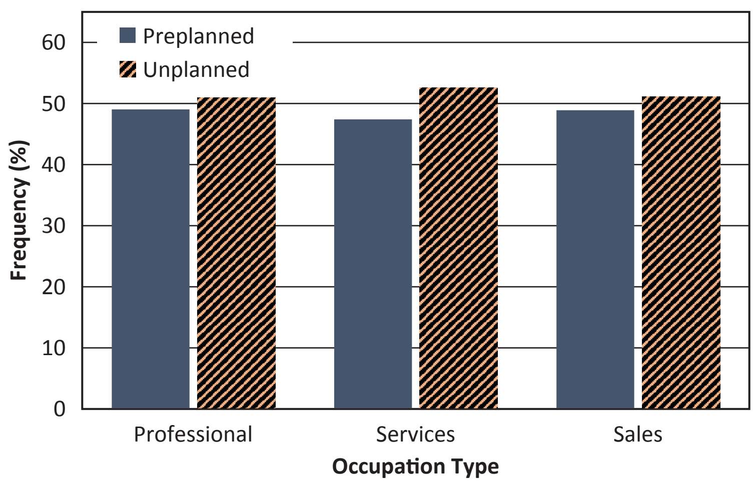
The estimation results of the first level and second level of the framework are shown in Table 1 and are discussed in detail next.

Work Episode Generation

Results show that the decision to work on different days of the week has a joint nature rather than a nesting structure for both preplanned and unplanned work episodes. The probability of scheduling either a preplanned or an unplanned work episode on every day of week is more than on the weekend. Full-time workers have more work episodes scheduled in the week compared with part-time workers. Working on the previous days of the week increases the probability of scheduling work episodes on the posterior days; this factor represents the routine nature of the work activity. Also, 84% of the CHASE data set are full-time workers who have a regular work schedule. However, the probability of having an unplanned work episode decreases with an increase in the number of the scheduled preplanned work episodes; this finding is due to the limited time budget assigned to the work project weekly. Moreover, it represents the pressure from other activity types in the schedule on work project scheduling. Fixity of work duration and location reduces the probability of having unplanned work episodes, whereas fixity of work



(a)



(b)

FIGURE 2 Distribution of preplanned and unplanned work episodes in CHASE (*a*) by day of the week and (*b*) by occupation type.

location increases the probability of scheduling preplanned work episodes. People with professional occupations are more likely to schedule unplanned work episodes than those in sales and services. Workers who live farther from their workplace are more likely to have preplanned work episodes, whereas they are less likely to participate in unplanned work episodes. Workers with an income greater than $75,000 (high income level) have fewer preplanned work episodes in their week than the rest of the income groups. However, workers with medium income have the least number of unplanned work episodes. Women schedule fewer preplanned work episodes, although they engage in more unplanned work episodes. Those with a longer duration of being employed in their current job are less likely to schedule preplanned work episodes.

Work Episode Duration

For both preplanned and unplanned work episodes, the variance of time expenditure decreases as the week progresses because people have to fulfill their work requirement by the end of week. Individuals attach greater utility to spending more time on preplanned work episodes compared with the composite activity on every weekday; however, on weekends individuals tend to spend more time on the composite activity. For unplanned work episodes there is always higher utility for spending more time on the composite activity. Workers with low (less than $35,000) and medium levels of income have longer preplanned work episodes than those with a high income level. Flexible working duration increases the preference to spend time on preplanned work episodes, which may be the result of the hourly salary in this case. Increase in the expectation from the rest of the week's schedule of preplanned work episodes increases the work duration at the current decision point. This finding represents the pressure on individuals to fulfill work requirements at the current decision point instead of postponing them for the following days. However, individuals terminate their unplanned work episodes earlier if the expectation from the rest of the week's schedule of unplanned work episodes is larger. Also, an increase in the number of preplanned work episodes during the week decreases the duration of unplanned work episodes. The last two points indicate that limits exist in the time budget that is assigned to the work project during

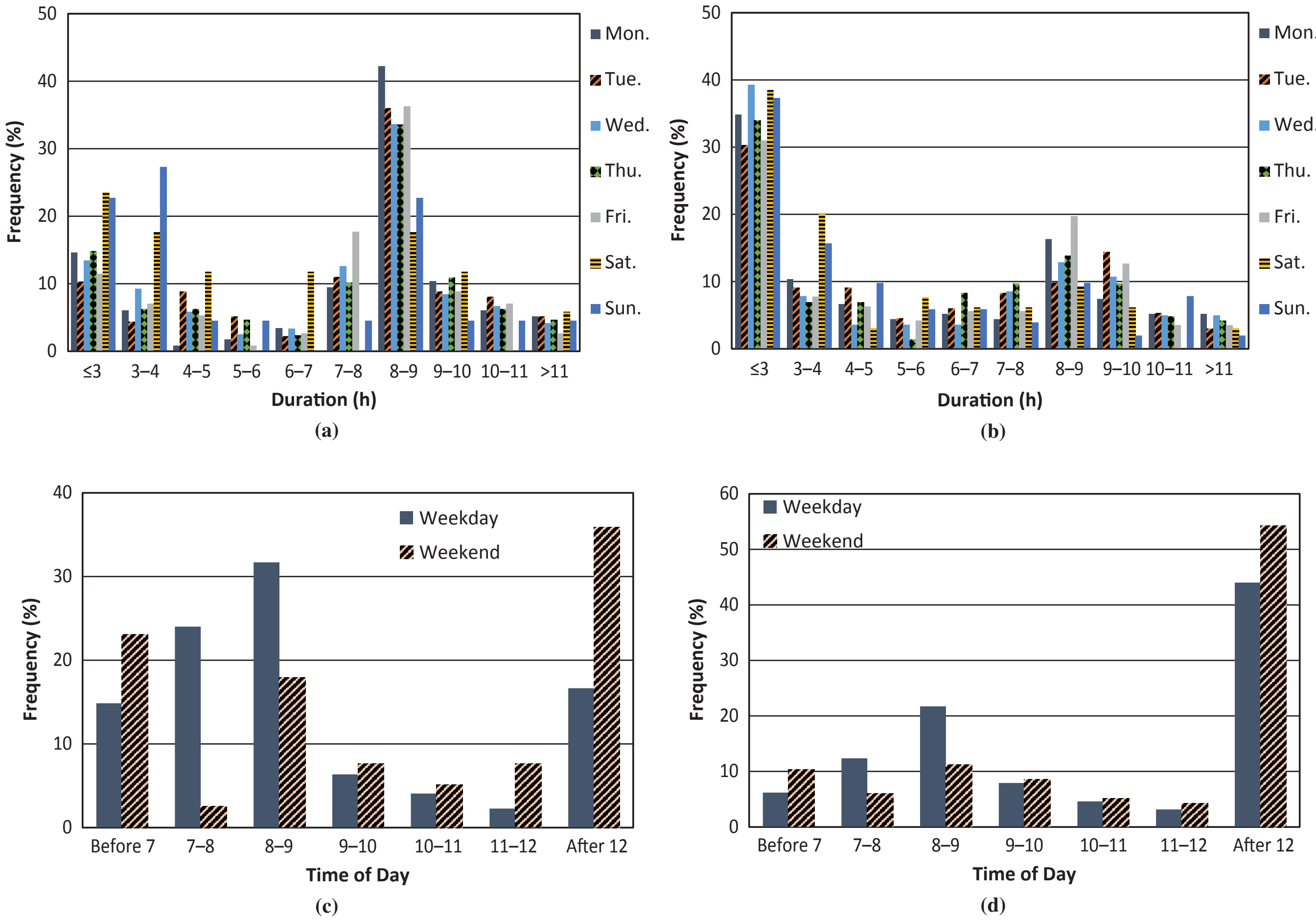


FIGURE 3 Observed duration and start time frequency in preplanned and unplanned work episodes in CHASE data: (*a*) duration of preplanned work episodes, (*b*) duration of unplanned work episodes, (*c*) start time of preplanned work episodes, and (*d*) start time of unplanned work episodes.

the week, and the model is capturing the trade-off between time expenditure on the work project and the rest of the activities in the schedule.

The total duration of work episodes is a function of both marginal utility and satiation effects. For preplanned work episodes, satiation is defined as a function of the day alternative-specific constant and job attributes of the person for weekdays. For weekends satiation is defined only by the job attributes. For all weekdays, satiation is negative for people in the CHASE sample; this finding means that workers do not tend to spend additional time on work episodes. However, depending on the job characteristics of the person, weekend satiation can be positive. For all days of the week, full-time workers, longer work–home distances, low and high income, and those in professional and service occupations have a greater tendency to spend additional time on their preplanned work episodes. Because unplanned work episodes do not have a totally regular nature, their satiation on every weekday except Monday is just defined by job attributes. Full-time workers, those with a fixed work location, flexible work duration, longer employment duration in their current job, longer place of work and home distance, and in-service occupations are more inclined to extend the duration of their unplanned work episode.

Work Episode Start Time

Preplanned and unplanned work episodes with longer duration tend to start earlier in the day. Weekend preplanned and unplanned work episodes start later than on weekdays, although there is no significant difference in start times among different weekdays. Both preplanned and unplanned work episodes with larger expectations from the work schedule in subsequent days tend to start earlier, presumably capturing the effect of the individual's work load. For full-time workers unplanned work episodes start later in the day as a result of the scheduled preplanned work episodes earlier in the day. Those with longer duration of employment in their current job start preplanned work episodes earlier, and their unplanned work episodes start later. Those with high income levels start preplanned work episodes earlier than those with a medium income level, whereas lower-income individuals start later than medium-income workers. Workers with a medium-level income start their unplanned work episodes earlier than the other two income groups. Part of these differences may be explained by the different status of the workers in the workplace. Younger workers and those in households with more adults start their unplanned work episodes later. Individuals with professional occupations start their unplanned work episodes

TABLE 1 Estimation Results of Preplanned and Unplanned Work Scheduling Models

Variable	Coefficient	*t*-Stat.	Coefficient	*t*-Stat.
Choice of working	Preplanned		Unplanned	
Constant	−0.46	−1.69	−2.24	−8.03
Full-time worker	0.19	1.36	0.24	1.79
Monday	−0.45	−1.80	1.58	8.11
Tuesday	—	—	1.45	6.66
Wednesday	−0.37	−1.36	1.64	8.28
Thursday	−0.18	−0.72	1.64	8.28
Friday	−0.55	−2.06	1.74	9.13
Weekend	−2.99	−11.52	—	—
Female	−0.09	−1.19	1.71	9.45
Professional	−0.12	−1.24	—	—
Services	—	—	−0.04	−0.39
Sales	—	—	−0.06	−0.41
(Number of days worked so far)/7	3.01	5.84	2.42	5.88
Number of preplanned working days/7	—	—	−1.34	−3.62
Job experience	−0.004	−0.79	—	—
Distance to work (km)	0.004	0.97	−0.01	−1.18
High income level	−0.10	−0.90	0.05	0.48
Low income level	—	—	0.02	0.15
Age younger than 35	−0.16	−1.49	—	—
Age 35–45	−0.18	−1.65	—	—
Flexible work location	−0.05	−0.61	—	—
Fixed place of work	—	—	−0.17	−1.80
Fixed work duration	—	—	−0.14	−1.39
Duration baseline utility function				
Monday	8.95	5.33	−5.92	−11.16
Tuesday	5.72	4.37	−5.98	−26.80
Wednesday	2.39	1.51	−6.04	−48.38
Friday	2.64	1.31	−6.13	−80.66
Weekend	−1.39	−7.98	−6.27	−146.74
Expectation from choice of work on the next days	0.48	2.87	−0.08	−1.94
Number of preplanned working days/7	—	—	−0.42	−2.98
Low income level	0.46	−0.94	—	—
Medium income level	0.81	1.56	—	—
Flexible working duration	0.19	2.57	—	—
Satiation parameter				
Monday	1.08	−10.02	1.08	−0.71
Tuesday	0.86	−8.26	—	—
Wednesday	0.56	−3.32	—	—
Thursday	0.25	−1.60	—	—
Friday	0.49	−2.27	—	—
Distance to work (km)	−0.001	2.55	−5.96	0.24
Full-time worker	−0.07	5.19	−4.21	8.16
Services	−0.01	1.91	−5.59	0.43
Professional	−0.03	2.45	1.88	−1.29
Low income level	−0.02	1.13	—	—
Medium income level	0.06	−1.37	—	—
Fixed place of work	—	—	−2.22	2.01
Fixed work duration	—	—	2.53	−3.39
Job experience	—	—	−0.11	3.03
Duration scale factor: logarithm of the sequence of day in week (1 = Monday)	0.50	9.40	1.03	56.96
Start time hazard covariates				
Constant	−12.04	17.52	−8.60	−15.03
Monday	—	—	0.27	1.68
Tuesday	−0.11	0.33	0.27	1.68
Wednesday	−0.10	0.22	0.27	1.68
Thursday	−0.21	0.40	0.27	1.68
Friday	−0.17	0.21	0.27	1.68
Weekend	−0.26	0.39	—	—
Part-time worker	−0.10	0.59	—	—
Full-time worker	—	—	−0.13	−1.24
Services	−0.14	1.33	−0.13	−1.31
Professionals	—	—	1.88	−1.29
Shape parameter	1.85	46.36	2.70	59.03
Work episode duration	0.17	−9.49	0.28	31.36
Job experience	0.02	−2.90	−0.01	−2.13
High income level	0.13	−0.90	−0.40	−4.95
Low income level	−0.06	0.40	−0.45	−5.94
Expectation from choice of work on the next days	0.03	−1.18	0.05	1.03
Number of preplanned working days	—	—	0.60	1.26
ln(age)	—	—	0.47	3.45
HH adults	—	—	−0.05	−2.90

NOTE: — = insignificant, reference variable, or not applicable; HH = household.

earlier than those in sales and those in services start later than workers in sales.

The *R*-square is .221 for the preplanned work scheduling model (with 222 individuals) and .25 for the unplanned work scheduling model (with 244 individuals), which are typical for goodness of fit for models of this type.

Because of the small sample size, variables with *t*-statistics smaller than the threshold for the 95% confidence interval are kept in the model for the sake of discussion. The validation results for work episode generation on each day are shown in Figure 4 and the duration and start time validation results are shown in Figure 5. The developed model overpredicts the number of preplanned work episodes with duration between 5 and 9 h; this finding is due to the high percentage of full-time workers in the CHASE data. The models, however, capture the time expenditure pattern very well. Start time and duration validation results show a better fit for unplanned work episodes. The tighter time budget while scheduling unplanned work episodes improves the model performance. Moreover, unplanned work episodes do not have a routine pattern as do preplanned work episodes and can be better captured by the applied explanatory variables. However, attributes of the preplanned work episodes are more determined by external agents (i.e., employers). Figure 6 presents weekly work patterns of individuals after scheduling conflicts with their sleeping hours have been resolved in the microsimulation process. Figure 6 shows the number of microsimulated working episodes versus observed working episodes in each 15 min of each day of the week. The patterns represent the models' fit on the number of generated work episodes as well as their associated start time and duration.

CONCLUSION

A two-level dynamic model is developed to generate and schedule an individual's work activity episodes for a full week. Work episode types within a work project are categorized into those scheduled before the start of the week (preplanned) and those scheduled during the week (unplanned). The first level of the model schedules preplanned work episodes, considering the non-night-sleep time during each day as the time budget for each individual. In the second level, unplanned work episodes are scheduled. The preplanned weekly work schedule is the input of the unplanned work episode scheduling level in order to capture the interdependency between their scheduling processes. For unplanned activities, the duration of the preplanned work episodes is deducted from the available time budget in the first level to dynamically keep track of each individual's time budget. The week-long time frame of the model captures the intraperson variability in the weekly work schedule of a person, in spite of the nominally routine nature of the work activity. It also captures differences in the effects of attributes of the working episodes with different planning horizons.

Preplanned work episodes are longer in duration compared with unplanned ones and start earlier in the day. An increase in the num-

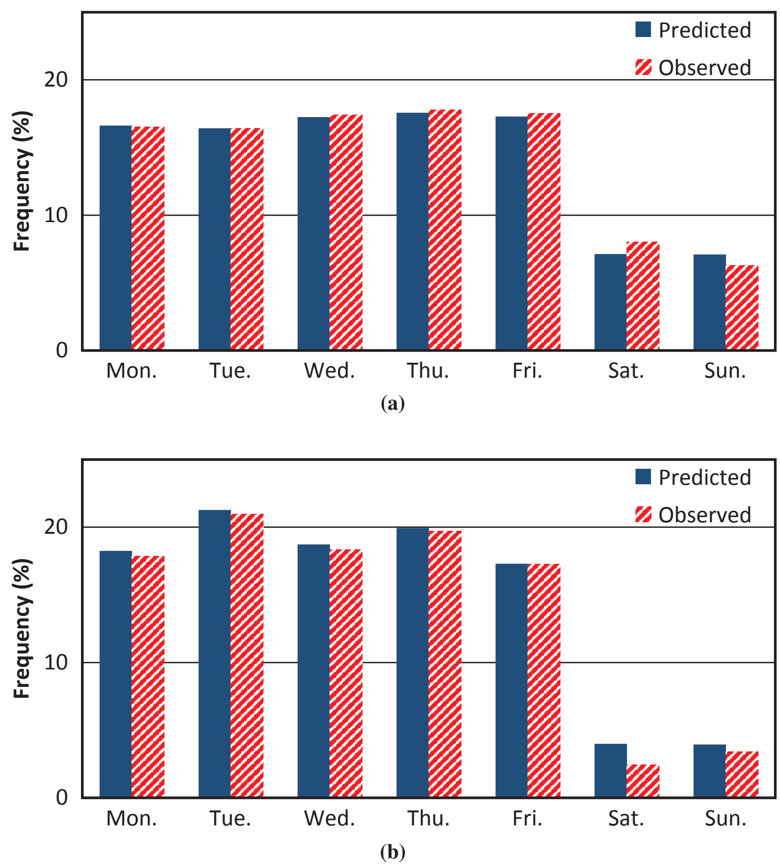


FIGURE 4 Validation results of work episode generation on each day: (*a*) preplanned work episode generation model and (*b*) unplanned work episode generation model.

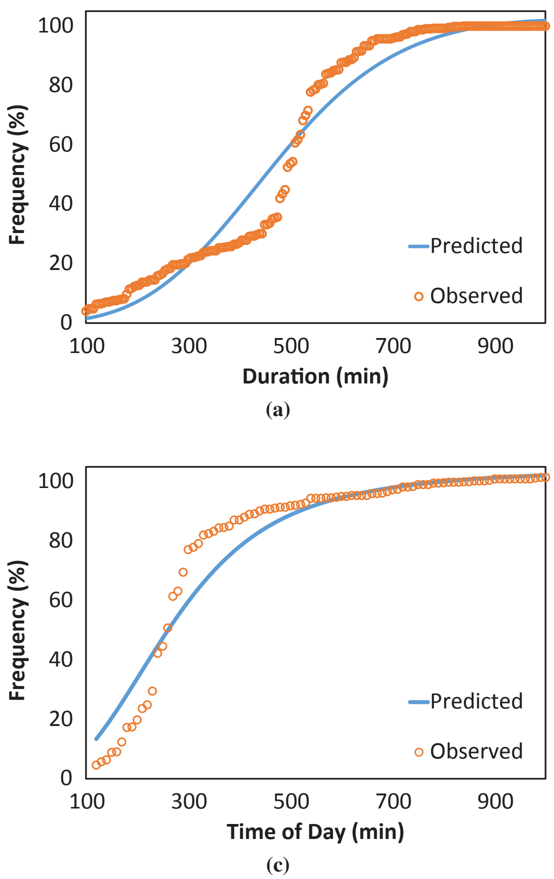


FIGURE 5 Start time and duration validation results: duration validation of (*a*) preplanned work episodes and (*b*) unplanned work episodes and start time validation of (*c*) preplanned work episodes and (*d*) unplanned work episodes.

ber of preplanned work episodes scheduled in a week decreases the probability of scheduling unplanned work episodes and results in shorter unplanned episodes when they do exist. Because of the regular nature of work activity, previous participation in the work episodes increases the probability of scheduling them in the remaining days of the week. Increases in the maximum expectation from the rest of the week of the preplanned work schedule increase the duration of the current preplanned work episode; this finding indicates that the existing work load on the following days prevents individuals from postponing their current work to the future. However, more expectation from the unplanned work schedule of the following days decreases the current unplanned episode's duration; this finding shows the limited time budget assigned to the work project during a week and captures the pressure from the rest of the activity types in

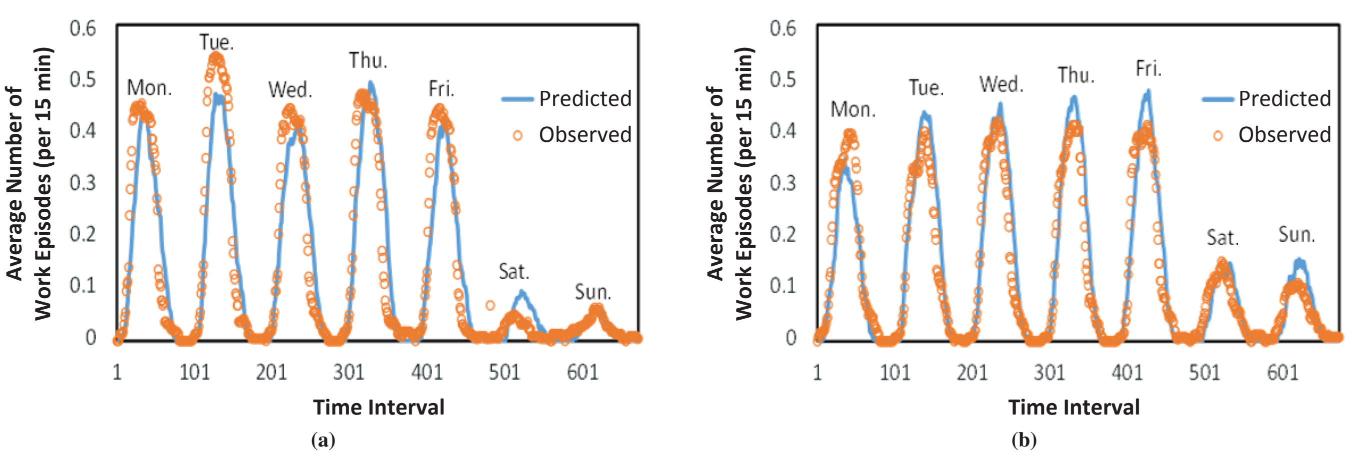


FIGURE 6 Weekly skeleton pattern prediction: (*a*) average number of preplanned work episodes every 15 min, and (*b*) average number of unplanned work episodes every 15 min.

the schedule on work project scheduling. Larger expectations from the rest of the week's work schedule result in an earlier start time for both types of work episode. Flexibility of the individual's place of work decreases the probability of scheduling preplanned work episodes; however, it increases individuals' engagement in unplanned work episodes. Individuals with flexible work duration have longer preplanned work episodes.

A richer and more up-to-date data set including more information on job attributes and more variation in occupation and industry types as well as more recent developments in the labor market would improve work pattern prediction. The model presented here will be combined with a previously developed week-long NWS activity scheduling model, which takes work and school episodes as a prior skeleton schedule defining constraints on feasible time gaps within which NWS activity episodes can be scheduled. The predictive ability of the combined work and NWS models will be compared with an all-activities scheduling model similar to the NWS that generates and schedules work and school along with all NWS activities without giving priority to work and school episodes. This comparison will provide a strong test of the hypothesis that work and school activities should be given priority over NWS activities in the scheduling process. However, future work will allow for a feedback between work and NWS scheduling models to resolve a possible conflict of an urgent NWS episode such as a medical activity with a scheduled work episode.

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