Agent-Based Microsimulation Approach for Design and Evaluation of Flexible Work Schedule Policy

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Date: August 1, 2014; November 15, 2014
Word Count: 4,519 words + 8 Figures = 6,519 words

Abstract

The policy of flexible work schedule has been proposed for years in order to stimulate the redistribution of departure time among commuters. However, its potential influence on travelers’ day-to-day traffic dynamics is infrequently seen in existing studies. This paper extends an agent-based positive departure time model to gain perspective on travelers’ dynamic reaction towards the flexible work schedule policy. Unlike most rational behavior models, the positive model emphasizes the bounded rationality in people’s actual behavior, and allows for heterogeneity among travelers. Dynamic traffic assignment (DTA) is integrated with this proposed model to build up the feedback loop between individual choice (demand side) and network performance (supply side). Scenarios of different percentages of population with flexible work schedule are analyzed. It is found that travelers with flexibility in work schedule tend to depart later to avoid peak periods in the morning. The average travel time in the network will decrease by at most 22%, when the policy of flexible work schedule is implemented.

Key words: flexible work schedule; agent-based model; DTA; positive model
1. Introduction

The acceleration of urbanization is witnessed all around the world. Both population and vehicle ownership are rapidly growing, and the induced traffic congestion becomes an increasingly pervasive problem in people’s daily life. In 2011, transportation congestion caused $121 billion economic loss in 498 U.S. urban areas, which was 5 times as that in 1982 (in 2011 dollars) (1). Approximately 63% of total delay occurred during peak periods when the commuting demand was high (1). Working trips play an essential role in the “transportation life of the nation” (2). Therefore, mitigating peak congestions can be a feasible solution to meet the challenge of the urban growth. Various planning policies have been implemented to mitigate urban congestion, e.g., encouraging the use of public transit, and imposing restriction to auto ownership or usage. Although these policies have effectively relieved the pressure of high travel demand, they were not designed specifically to tackle severe congestions during peak periods. The objective of managing commuting demand is very challenging because people should commute to work anyway. As Anthony mentioned (2), traffic congestion would not eventually ameliorate until people changed their daily behaviors.

Rather than these transportation policies, there is an alternative way to gradually inspire redistribution of trips: flexible work schedule. Traditionally, employees should be present at work places during a specific time period (usually from 9 a.m. to 6 p.m.). These traditional work schedules come from several reasons (e.g., human’s common habit of sleeping at night). A consequence of this fixed work schedule is that commuting trips are centralized during peak hours. Compared with the traditional 9 a.m. to 6 p.m. (or 8 a.m. to 5 p.m.) office hours, flexible work schedules (referred as flextime policies hereafter) are becoming increasingly popular, which allow employees to choose their preferred arrival/departure times. For example, employees can arrive at their offices anytime between 8 a.m. to 10 a.m. and leave for home anytime between 4 p.m. to 6 p.m. This policy is believed to be family friendly and productive. However, its impact on urban traffic congestion is rarely seen in existing studies.

The motivation and objective of this paper is to explore potential impacts of this policy on the network performance. In order to capture and characterize how people shift their departure times under different levels of flextime policies, an agent-based positive departure time model (27) is employed in this paper, which simulates travelers’ departure time changes based on their travel experience. The dynamic traffic assignment (DTA) simulator DynusT (3) is integrated with the positive model to obtain traffic condition. Unlike rational behavior models, this study emphasizes the bounded rationality in people’s actual behavior. A real-world application based on an extracted network from the previous Inter County Connector (ICC) model (4) in the State of Maryland is illustrated. Different levels of this flextime policy are tested for
morning commuting trips in the study area. The purpose of this study is to illustrate the capability of integrated agent-based behavior models and DTA for real-world applications; and to investigate empirically the impact of flexible work schedules on network performance. Since this paper only adopts traveler behavior model and traffic assignment model, the direct impact on urban traffic conditions is the only focus, leaving social benefits of this policy for future research.

The article is organized as follows: Section 2 presents a comprehensive literature review on current congestion mitigation policies and the models employed to analyze the effect of those policies. Section 3 briefly introduces the framework of the positive model, as well as the integration of the positive model with a mesoscopic simulation-based DTA simulator. Section 4 presents a real-world case study with scenarios assuming different levels of flextime policies. The discussions and conclusions are drawn in Section 5.

2. Literature Review

Various planning approaches have been proposed to relieve urban traffic congestion. They mitigate traffic congestions by expanding roadway capacity, encouraging public transit, or limiting auto-ownership (i.e., vehicle registrations fees (5)) and auto-usage (i.e., congestion pricing (6)). It is undeniable that these policies have been repeatedly used for congestion management. Although there have been plenty of explorations on these policies, research gap still exists for the analysis of transportation impacts of flexible work schedule policies. Flexible work schedule, as known as flextime policy, is a promising measure that should be effective in mitigating congestion. There are numerous studies underlining potential benefits of this policy. Common conclusions have been drawn: 1) flexible work schedules are expected to “increase employees’ job satisfaction, organizational commitment, productivity, and decrease absenteeism and turnover” (7); and 2) flexible schedules tend to reduce time and role conflicts between work and family non-work responsibilities (such as social activities and children care). Due to these benefits, the implementation of the flextime policy has been increasing rapidly (from 15% of employees with flexible work schedule in 1991 to 27% in 1999) (8). In addition, work schedules in the U.S. seem to be more and more differentiated and flexible (8). Flextime policy receives a high evaluation as a work/life balancing policy. However, there are few studies illustrating its potential value for transportation demand management and peak-hour traffic congestion mitigation.

While flextime related questions are often considered in travel surveys, (e.g., 2009 National Household Travel Survey (9), and Chicago’s Travel Tracker Survey (10)), the questions were simplistic in nature (i.e., simple yes-no questions about whether the survey participant had flexibility in work scheduling). This simplicity makes it difficult to fully understand behavioral changes due to flextime policies. Saleh and Farrell defined the individual’s “level of flexibility” to investigate departure time choice (11). The level of flexibility is determined by traveler’s work schedule
flexibility, personal constraints such as home-responsible activities before work, and socio-economic characteristics. They found that departure time choice could be affected by work/non-work flexibilities and individuals’ socio-economic types. A multinomial Logit model was adapted to investigate the departure time preference for people with flextime. Results showed that flextime increased the probability of post-peak travel and reduced the probability of pre-peak travel (12).

Brewer (13-14) tried to link travel behavior and the flexible work design, and made an assumption of impacts on traffic conditions. A game theoretical method was adopted to model the choice between flexible schedule and non-flexible schedule. No traffic models were used in these studies. Later on, bottleneck models and network equilibrium had been adopted to analyze the economic impact of flextime policy (15-18). The embedded equilibrium condition where no travelers could find better departure time with less cost increased models’ computational burden, especially when user heterogeneity, capacity uncertainty, and behavioral-changing process needed to be captured. This hinders bottleneck models’ application potential in real-world analysis wherein an urban region can easily include thousands of links and tens of millions of heterogeneous commuters.

Considering flexible work schedule policy as a potential attainable alternative to improve traffic condition, this study applies an agent-based departure time choice model to investigate both demand pattern changes and traffic improvement under this policy. Unlike previous models, an agent-based model focuses on actions and interactions of autonomous agents. One of the earliest agent-based models was for segregation (19). With the development of scientific computer, this concept has been widespread to various areas. In transportation research, agent-based studies have already been conducted for studies of demand patterns, such as departure time choice, route choice, traffic diversion, and policy-makers’ investment decisions (20-27). Agent-based models are capable to capture individual-level behavior changes. Individual’s decision and behavior are then aggregated for the traffic demand analysis. This makes agent-based models more powerful over traditional four-step models that ignore the heterogeneity of individuals (28-29).

In terms of the departure time analysis, there used to be extensive research applying rational behavior theory, such as the bottleneck model (16, 30-31), discrete departure time choice models (32-35). Under rational behavior theory, travelers have access to the information of all feasible alternatives and maximize their utility (36). The agent-based departure time choice model in this study is known as a positive model (20). Unlike rational approaches, positive theory assumes that individuals no longer have perfect knowledge to maximize their utilities. The proposed agent-based positive departure time model explicitly simulates the goal, knowledge, learning, and search ability of the travelers in the simulation network (22, 37). The framework of the positive departure time choice model was first developed by Zhang and Xiong (20) under the Search, Information, Learning, and Knowledge (SILK) theory (37). The
model was applied to a large-scale peak spreading study (4) and a numerical study on demand/supply uncertainty (21). This paper would expand Zhang and Xiong’s model in three aspects: 1) improve the calculation of payoff for flextime policy study; 2) consider demand/supply uncertainty to enhance the reality; and 3) adopt a multi-day knowledge updating to obtain traveling agent’s information on travel time reliability. Here “multi-day” means running several rounds of simulation for one demand type, which will be introduced in Section 3.1.

3. Agent-Based Modeling Framework for Flextime Policy

3.1 Behavior Model

Based on previous studies (20-22), the positive departure time model provides a framework for the flextime policy modeling. For each traveler (agent) in the model, he/she is able to acquire traffic information from his/her prior travel experience or other sources (e.g., traveler information systems). Travelers’ knowledge and subjective beliefs about traffic conditions are formed through a perception and learning process. With the explicitly measured knowledge and subjective beliefs, the model can determine personal attitude towards his/her current traffic conditions. That is, how much the person expects to benefit from additional days of searches. Subjective search gain is defined to measure this benefit. It is theorized as the gap between the experienced best situation (the simulation day with best payoff) and the ideal situation (travel on free flow speed, arrive at destination at preferred arrival time (PAT)). Correspondingly, search cost is defined to quantify a person’s perceived loss in each round of search. This may result from a traveler’s searching efforts (e.g., time, monetary, mental efforts, and the risk for worse travel experience). The trade-off between the subjective search gain and the perceived search cost determines the start and the termination of an agent’s searching process.

Once a traveler stops searching, he/she would repeat his/her current departure time for the rest of the simulation days. Otherwise, the traveler would find a new departure time based on current knowledge and a set of search rules. The traveler needs to map his/her spatial knowledge to the traffic conditions of the alternative departure time. Then a binary decision is made based on a set of decision rules about whether or not to switch to the new departure time. After all the agents have made decisions, the individual-level behaviors are aggregated for the traffic modeling of a new day. Refer to (20) for a full-scale view about the search rules and decision rules.

In this research, three major improvements are considered to enhance the robustness of the flexible work schedule modeling. Firstly, as individual-level decisions are made based on current travel experience, it is necessary to build a linkage between work
flexibility and the quantitative attitude towards travel experience. In previous studies, this attitude was modeled following the rational behavior theory:

\[ V(t) = \alpha \cdot T(t) + \beta \cdot SDE(t) + \gamma \cdot SDL(t) \]

\[ SDE(t) = \max(0, (PAT - t - T(t))) \]

\[ SDL(t) = \max(0, (t + T(t) - PAT)) \]

where \( t \) is the departure time, \( V(t) \) is the payoff at \( t \), \( T(t) \) is the travel time associated with \( t \); \( PAT \) is the preferred arrival time to destination, \( SDE/SDL \) represent schedule delay early/late, and \( \alpha, \beta \) and \( \gamma \) are coefficients. In this paper, \( PAT \) is replaced by the preferred arrival time interval (PATI). As illustrated in Figure 1, a traveler arrives earlier than \( PAT \) would gain negative utility due to \( SDE \); however, after he/she has gained flexibility in schedule, the traveler will no longer has \( SDE \) with the same departure time and travel experience (30).

Secondly, uncertainty of both supply and demand sides is simulated in this paper to enhance the authenticity of the scenarios. Due to physical and operational factors, such as the road constructions and maintenance, incidents, and weather, some roadways may lose capacity or be blocked during certain time periods. In order to model supply side uncertainty, the whole 2013 incident data of the study area is obtained from Regional Integrated Transportation Information System (RITIS) (38). Based on RITIS data, we assume the incident frequency follows Poisson distribution with rate 1.74 (times/day). The duration of incidents is assumed to follow Exponential distribution with rate 1/37 (minute\(^{-1}\)). The location of an incident is determined by a link’s failure probability in direct proportion with its volume. Demand, also varies

Figure 1 PATI v.s. PAT

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from day to day following the variation of social activities and events. The demand side uncertainty is introduced by randomness of the total travel demand from day to day. The coefficient of variation (CV, defined as the demand standard deviation divided by the mean travel demand) can be used to measure the demand-side fluctuation. In this study, the day-to-day CV was assumed to have a Uniform distribution from 0 to 0.15.

Thirdly, a multi-day knowledge updating is adopted instead of single-day learning and decision making. It is assumed that travelers will not change their departure times within one week. Before every new week of searching and switching, one week’s (5 simulation work days) travel experience will be simulated. The departure time of each individual remains the same during the week. After the multi-day simulation, the average and standard deviation of travel time for every agent are calculated as a statistical travel experience. There are two purposes for this modification: to avoid simulation noise that may lead to unreasonable behavior change; to capture the impact of travel reliability on departure time choice.

3.2 Integration of Behavior Model with Dynamic Traffic Assignment

In this study, the mesoscopic traffic simulator DynusT (3) is integrated with the positive model to simulate travel experience and model dynamic departure time choice. The integration flowchart is shown in Figure 2. The modeling of departure time shift begins from the static OD estimated via planning models. Multimodal static OD estimation and dynamic OD calibration are then conducted to obtain time-dependent OD tables for study area. Details of these OD estimation approaches can be found in (4). In order to calculate travelers’ current experience, DTA is initially applied to pursue dynamic user equilibrium (DUE), after which travelers’ travel time are collected. Meanwhile, their paths are extracted to calculate free flow travel time (FFTT) as their ideal travel condition. Here FFTT and current travel time are used to initialize their search gain. Heterogeneity is embedded when synthesizing these travelers with socio-demographic variables including: income, gender, flexibility of arrival times, search cost, etc. Under such initialization, dynamic assignment is adopted to simulate weekly traffic knowledge learning process. Travelers’ weekly average and standard deviation of travel time are updated as new information. Then positive model is employed to simulate agents’ travel experience learning, departure time searching, and decision making process. The iterative loops of the departure time modeling would not terminate until only a small percentage of individuals (5%) are still searching for alternative departure times.
4. Flextime Policy Scenario Analysis

In order to demonstrate the capability of the model in analyzing the impact of flextime policies, a real world application is illustrated in this section. The selected study area is shown in Figure 3, which includes Rockville, North Bethesda, and Gaithersburg in Montgomery County of Maryland. Based on Metropolitan Washington Council of Governments (MWCOG) planning model version 2.3 the population in this area is 306,590; and the number of employment is 206,529. Three major roadways (I-495, I-270 and MD355) and other minor/local roadways are coded via DynusT in this study. There are 61 traffic analysis zones, 201 nodes and 1,077 links in total. Already containing AM peak period, the simulation horizon is from 5:00 a.m. to 10:00 a.m. 237,903 vehicles are extracted from the ICC model for the corresponding time period. The demand has already been calibrated and validated in the previous work (4).
There are 11 scenarios designed in this paper, with 0%, 10%, 20% to 100% of the agents randomly assigned with flexible work schedules. Although the flexible schedule percentage in the study area is around 29.1% according to 2007-2008 Transportation Planning Board (TPB) and Baltimore Metropolitan Council (BMC) Household Travel Survey, this paper tries to explore different flextime levels to further understand the impact of this policy. Socio-demographic variables such as gender and income level are generated by the sample distribution in 2007-2008 TPB/BMC Household Travel Survey. In order to reduce the impact of simulation noise, 5 rounds of simulations are performed for each scenario. The 0% scenario is considered as a base case. This base case is assumed to be the original traffic situation, in which everyone has habitual departure time and arrival time provided by dynamic user equilibrium. In these scenarios, people assigned with flexible schedule can arrive any time within their PATI. PATI is assumed to be a two-hour time interval with the current PAT positioned in the center. For example, if a traveler’s PAT is 9:00 a.m., his/her PATI should be from 8:00 a.m. to 10:00 a.m. It takes around 10 weeks (50 simulation days) for each simulation to reach convergence, so there are around 2,750 iterations in total.

After the interaction between departure time change and traffic system performance, only a fraction of travelers (around 5%) are still looking for new departure times. This stable situation among travelers is regarded as behavioral user equilibrium (BUE) (37). The impacts of flext ime policy on the demand pattern are displayed in Figure 4. The curves without dots denote the base case situation, which means no agents have
flexible schedule; the curves with dots denote the scenarios with different percentages of flextime agents. As the percentages of agents with flexible schedules increase, the demand during the peak period (6:00 a.m. to 8:00 a.m.) shifts to later time periods (8:30 a.m. to 10:00 a.m.). A peak spreading is found that the peak period in base case (6:00 a.m. to 9:00 a.m.) has been expanded to a broader time interval. After the percentage of flextime agents increases to 60%, there is no obvious peak period (compared with the base case demand). The demand distributes smoothly from 6:00 a.m. to 10:00 a.m., which is consistent with previous studies (12, 18). The scenario of 100% flextime agents represents the case of most significant peak spreading.
To better understand the demand pattern changes due to the implementation of flexible work schedule policies, Figure 5 illustrates the demand patterns for flextime agents and non-flextime agents separately. Figure 5(a) summarizes the demand pattern change for agents with flextime. The 11 curves from bottom to top correspond to the scenarios with increasing ratios of flex-time agents from 0% to 100%; while in Figure 5(b), the 11 curves from bottom to top correspond to the scenarios with decreasing ratios (100% to 0%). For travelers who have flexible work schedules, even if this ratio is relatively low, there is no significant peak in the demand pattern; while, for travelers without the flextime policy, an obvious peak can be observed between 6:00 a.m. and 9:00 a.m. almost in every scenario. This phenomenon implies that travelers with flexible work schedules tend to depart later to avoid the peak hours. As the percentage of agents with flextime increases, the absolute number of travelers who switch their departure time out of peak hours is also growing. It is found that travelers with flextime have a major contribution to the peak spreading and the demand shifting phenomena as discussed above. On the other hand, this policy has very little impact on the demand pattern of the travelers without flexible work schedules.
Figure 6 indicates the interesting finding that flextime travelers choose to depart later while there is almost no change on the demand pattern of travelers without flexible work schedules. The 70% scenario is selected for analysis because: 1) the total demand is evenly distributed from 7:00 a.m. to 10:00 a.m. (Figure 4); and 2) two groups of agents obtain different changes in their payoff. Figure 6(a) illustrates the payoff changes for the agents with flexible schedules. The horizontal axis represents the original departure time, the vertical axis represents the departure time that agents shift to, and the grey scale represents the payoff change ratio. Obviously, people who used to depart during peak hours benefit the most from the peak spreading effort. That is, the payoff for these travelers increases nearly 50%. There is little change of payoff for travelers who used to depart around 5:00 a.m., because they used to enjoy the FFTT before flextime policy. Figure 6(b) shows how many agents have shifted departure time from/to different time periods (presented as the logarithm of the switching population in grey scale). According to the dark points along the diagonal line, the majority of these travelers still depart at their original time. Travelers who used to depart during AM peak (6:00 a.m. to 9:00 a.m.) period have a much higher
rate to switch their departure time. For those who change behavior, a later departure
time is much more preferred than an earlier one. When some portion of travelers
departs later, traffic congestion is eased and there is less incentive for the rest of
people to change their behavior. This “later-preferred” demand trend also leads to the
peak spreading phenomenon discussed above. Different results are analyzed for
non-flextime agents, as illustrated in Figure 6(c) and 6(d). Before 9:00 a.m.,
non-flextime agents may have minor increase in their payoff (Figure 6c), which is
resulted from the mitigated traffic congestion. Travelers departing after 9:00 a.m. will
suffer a loss of payoff due to the demand increase. Similar to flextime agents, the
majority of non-flextime agents stay unchanged (Figure 6d). What is different is that
the number of agents switching earlier/later is almost identical, which leads to a stable
demand pattern for these agents.

![Figures 6(a)-(d)]

**Figure 6 Payoff Change Under 70% Scenario**

The average travel time diagram (Figure 7) shows the impact of individual behavior
changes on the aggregate network performance. The horizontal axis represents the
departure time, the vertical axis represents the percentage of flextime travelers, and
the grey scale represents the average travel time in minutes. The traffic condition
during the AM peak is improved as the flextime agent percentage increases. For
example, in the base case, there is a “congested departure interval” occurring between 6:40 and 9:00 a.m., which means the average travel time for travelers departing within this time period is over 12 minutes. This “congested interval” gradually disappears after the flextime ratio increases to 50%. However, the relationship between travel time and flextime ratio is not monotonic. Travelers departing after 9:30 a.m. will suffer a small bottleneck when this ratio surpasses 70%. Unlike the traffic congestion during the AM peak in the base case, this bottleneck is resulted from the payoff gain for the agents with flexible work schedule. For the entire simulation horizon, Figure 8 shows the overall average travel time of different policy scenarios. In this case study, scenarios with flextime policy all perform better than the base case; the traffic system with 60% flextime agents reaches the best results in terms of travel time delay, leading to a total travel time saving of 10,785 hours (22.3%).
5. Discussions and Conclusions

This paper attempts to gain perception about travelers’ reaction towards flexible work schedule policy. Unlike previous flextime studies, the research goal in this paper is achieved through further developing the modeling framework of an agent-based positive departure time choice model. Individual knowledge learning and decision making process is specified and empirically modeled to understand the potential influence of this policy on day-to-day traffic dynamics. DTA is integrated with this agent-based positive departure time choice model. One remarkable advantage of this integrated model is its ability to build a feedback between demand-side individual choice and supply-side network performance. The disadvantage (we may also call it our future research opportunity) is that the agent behavior (search rules and decision rules) already built in this study area may be inapplicable for other study areas. Thus, the model requires further calibration before applying to other study areas or scenarios. One alternative calibration method is to apply simulation based optimization to adjust the probability distribution of the new departure time searching (39), which will be explored in future research.

Different scenarios of various percentages of flextime agents are tested in a real world network in Montgomery County, Maryland. It has been found that travelers with schedule flexibility tend to make their travel later, which is the same as (12). This result is in accordance with the purpose of flextime policy, which aims at balancing the conflict between work and family. Travelers’ individual level behavior change may lead to significant improvement on traffic system. As these flextime travelers switch from AM peak to post-peak periods, the congestion during peak hours is alleviated. However, the improvement of traffic condition has few influences on the
demand pattern of agents without flexible schedules. The network with 60% flextime
travelers performs the best. Under such condition, original AM peak in the base case
will spread between 6:00 a.m. and 10:00 a.m.. Compared to the base case, 10,785
hours (22.3%) of traffic delay would be saved. Since the current flextime ratio is
around 30%, the 60% or upper flextime ratio seems unpractical. In addition, results
may not be the same for other areas or networks. This paper holds a theoretical
analysis for prospect of future demand management policies.

In this research, the assumption in terms of flextime policy is strong: the PATI is a
two-hour time window based on travelers’ PAT. This is a shallow attempt to
demonstrate the capability of this integrated agent-based model to capture departure
time change under behavior related policies. Departure time flexibility modeling can
be a complex problem because travelers’ flexibility is determined by a variety of
factors, i.e. travelers’ ability to start work later/earlier, traveler’s house responsibility,
and social-economic characteristics. All these features can be taken into account for
future research. In addition, it will be more interesting and meaningful if monetary
stimulus is considered in flextime policy study. That is, a traveler can get some
monetary reward if he/she switches from peak period to off-peak period. Thus, it
allows us to have perspective view on the monetary cost and welfare gain due to the
introduction of flextime policy. Furthermore, comparisons can be conducted between
traffic demand management and other congestion mitigation methods, such as
roadway capacity extension.

Furthermore, this integrated model is also applicable for studying the impact of other
management policies, demand increase, and even roadway incidents on travel
behavior. Since departure time is the only dependent variable in its current framework,
the model still requests further development to capture travelers’ behavior change in
route choice, mode choice, lane choice, etc. The authors expect to empirically
estimate and embed other behavior rules into this framework for more comprehensive
analysis.

Acknowledgement

This research is financially supported by a National Science Foundation CAREER
Award, “Reliability as an Emergent Property of Transportation Networks”, and the
U.S. Federal Highway Administration Exploratory Advanced Research Program. The
opinions in this paper do not necessarily reflect the official views of NSF or FHWA.
They assume no liability for the content or use of this paper. The authors are
responsible for all statements in this paper.
1. Schrank, D., Eisele, B., Lomax, T., (2012). The Urban Mobility Report. Texas Transportation Institute, College Station, TX.


