Microsimulation for Commuters' Mode and Discretionary Activities by Using Neural Networks

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Abstract

This research aims to develop an activity-based travel demand model and its microsimulation model for commuters' work-tour mode and their discretionary activities & travel by using neural networks. The model system is designed as a series of hierarchical submodels. At the highest level is a given condition of primary travel pattern of employees between home and workplace, which constrains their behavior whether and how to make discretionary tours. At lower levels of the system are the choice of discretionary travel generation and subsequently the choice of their destination, travel mode and activity duration time.

The study employed the person-trip survey data for the metropolitan area of Nagaoka, Niigata conducted by the national government in November 1999. The empirical estimation by neural networks revealed that an activity & tour were not independent but closely interrelated among a daily activity pattern. Next it simulated an individual discretionary travel pattern under a number of conditions assuming the introduction TDM measures such as flexible work times or staggered work hours. The microsimulation showed its practical capability to predict the impacts of TDM measures on daily travel patterns.

Introduction

Travel demand management (TDM) policy such as the introduction of flexible work hours and park & ride systems become more important and necessary to decrease traffic congestion during the peak period and improve living environment in the society of automobile dependency. Therefore most of travel analyses have focused on commuters' behavior. To evaluate the effectiveness of such a policy, travel should be taken into account as induced demand of personal activities; this has been called as an activity-based approach (Kitamura,1996).

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Many researchers have tackled an activity-based approach to analyze and model an individual travel behavior in both a static and dynamic manner. Conventional statistical techniques such as the discrete choice model and the structural equation model have been usually applied to an activity-based approach. Microsimulation models have also been developed to simulate individuals' daily activities or time use on the time axis (Fujii et al., 1997).

Recently soft computing techniques such as neural networks are expected to be a new promising tool to apply to an activity-based approach (Shimazaki & Yasuda, 1994). Shmueli et al. (1996) evaluated various directions in analyzing complex travel data with neural networks. Subba Rao et al. (1998) found that performance of neural networks is much superior to the multinomial logit model both in calibration and prediction due to its highly nonlinear internal relationships. But most studies so far have applied neural networks to a simple travel behavior not to an activity-based model system.

The study aims to develop an activity-based travel demand model and its microsimulation model for commuters' work-tour mode and their discretionary activities & travel before and after work by using neural networks. The model system is designed as a series of hierarchical submodels. At the highest level is a given condition of primary travel pattern of employees between home and workplace, which constraints their behavior whether and how to make discretionary tours. At lower levels of the system are the choice of discretionary travel generation before and after work, and subsequently the choice of their destination, mode and activity duration time. Next it simulates an individual discretionary travel pattern under a number of conditions assuming the introduction TDM measures such as flexible work times or staggered work hours.

Hierarchical process of decision making

The study focuses on mode-choice decision of commuters' work-tour, where their works are subsidiary activity and their work hours (precisely beginning-time and ending-time of their works) are supposedly predetermined. Here the additional unique assumption of study is that commuters' mode choice is interrelated with their discretionary activities & trips before and after work. Their 'trips before work' are usually conducted as an intermediate stop from home to workplace, and their 'trips after work' as an intermediate stop from workplace to home or a home-based secondary tour after returning home.

The study develops a microsimulation model that estimates work-tour mode and attributes of discretionary activities & trips before and after work for commuters under the constraint of work hour. Figure 1 shows the decision-making process of microsimulation consisting of three models and a number of submodels. All of submodels are calibrated by using neural networks.

Work-tour mode can be specified as a primary and customary factor for a commuter, which influences his/her work activity and daily travel. So that, variables of individual attributes and household attributes including the location of home and workplace and work hour are input into the work-tour mode choice model. Then determined work-tour mode is input into the two models of discretionary activity & trips before and after work. The travel mode choice model for work-tour and discretionary trips is two-staged such that the first step is the choice of car use or not, and the second step is the choice of transit, two-wheel or walk & others.

The two models of discretionary activities before and after work estimate trip generation (a trip is generated or not), destination, mode and activity duration sequentially. Here we assume that decision making of the two models are dependent and interrelated each other. When microsimulation proceeds, estimated results of the two models of discretionary activities are feedbacked into each of the two models and iterated until a kind of equilibrium could be reached.

Data used

The study employed the person-trip survey data for the metropolitan area of Nagaoka, Niigata conducted by the national government in November 1999. Nagaoka is the second biggest local core city with population of 200,000 in Niigata prefecture, Japan. The study was intended to get statistical data of daily personal travel behavior for a weekday to predict travel demand for the

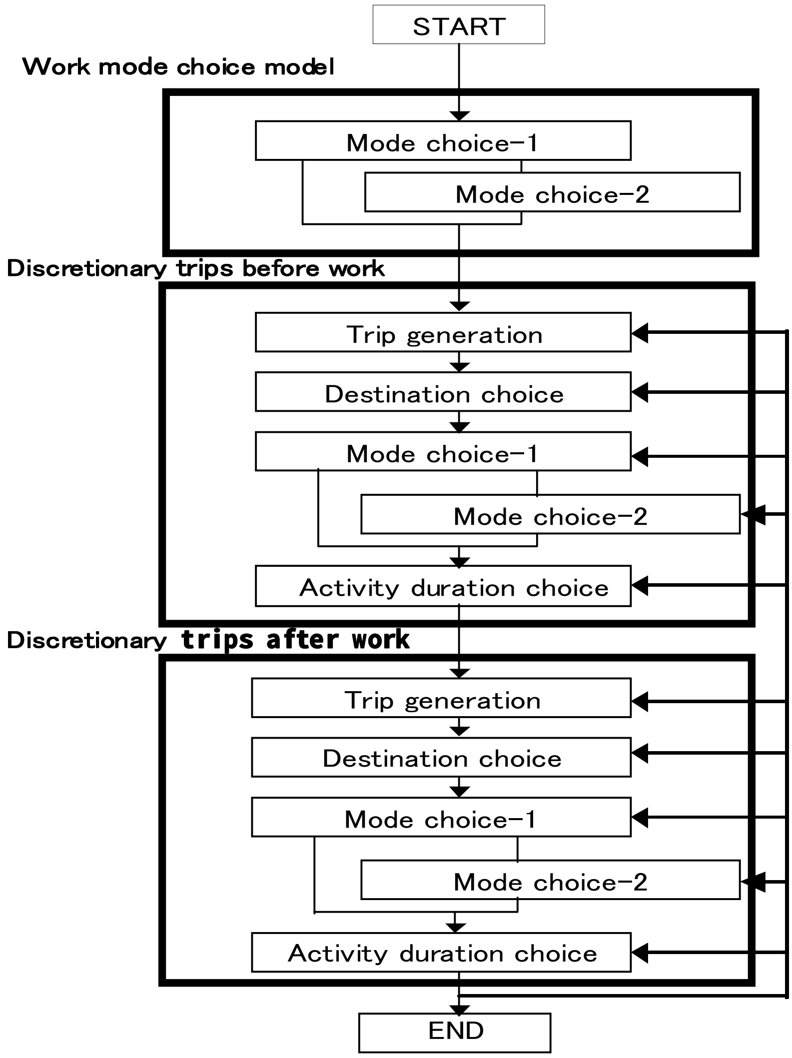

Figure1. Framework of microsimulation model

year 2025, with the study area of nine local governments around the city of Nagaoka. The area has the population of 350,000, and the sample size of the survey is 8,752 households and 24,291 individuals.

This study uses their sampling data of 5,205 individuals who make commuting trips on the day. The actual case of Table 4 in the subsequent section shows characteristics of the sampling individuals. Modal share of work-tour are: 84.4% for car, 0.0% for transit, 1.7% for two-wheel, and 13.9% for walk & others. Persons of 1.5% (76 samples) make discretionary trips before work, and their mode share is: 80.3% for car, 0.0% for transit, 7.9% for two-wheel, and 11.8% for walk & others. Persons of 10.7% (555 samples) make discretionary trips after work, and their mode share is: 71.4% for car, 0.0% for transit, 15.5% for two-wheel, and 13.1% for walk & others.

Estimation of Submodels

All of the submodels shown in Figure 1 are estimated by using neural networks. The architecture of our neural network consists of three layers of interconnected neurodes: an input layer, a hidden layer and an output layer. Currently there is no rule for determining the optical number of neurodes in the hidden layer or the number of hidden layers. A single hidden layer is usually satisfactory, including this study. The number of neurodes in the hidden layer is decided to be half of those in the input layer through experimentation. The most commonly used learning system, and the one adopted in this study, is the back-propagation model. Table 1 shows independent variables and their categories of an individual and household including his/her beginning and ending time of work.

Table 1. Independent variables for submodels.

Variables	Categories	No. of Nurons
Sex	1.Male 2.Female	2
Age	1 .～29 2 .30～39 3. 40～49 4. 50～	4
Driver License	1. Holding 2. Not holding	2
Available private car	1.Yes 2. No	2
Occupation	1. Farmer 2. Mining 3. Manufacture 4. Sales 5.Service 6. Transport & communication 7. Security 8.Office clerk 9. Technical & Professional 10 .Management	10
Household size	1. 1 2. 2 3. 3～4 4. 5	4
Family member	1. Householder 2. Spouse 3. Child 4. Parent 5. Others	5
No. of Cars owned	1. ～2 2. 3～ (per household)	2
Childrens under age 5	1. Yes 2. No	2
Elderly person	1. Yes 2. No	2
Place of house	1. City center 2. South 3. North 4. West 5. Out of City of Nagaoka	5
Place of work	1. City center 2. South 3. North 4. West 5. Out of City of Nagaoka	5
Beginning time of work	1. ～7:30 2 .7:30～8:00 3. 8:00～8:30 4. 8:30～9:00 5. 9:00～9:30 6. 9:30～	6
Ending time of work	1. ～ 17:30 2. 17:30 ～ 18:00 3. 18:00 ～ 18:30 4. 18:30～19:00 5. 19:00～19:30 6.19:30～	6

Table 2. Estimation of submodels and microsimulation.

	Submodel	Estimation		Simulation	
		Samples	Hit Ratio(%)	Samples	Hit Ratio(%)
Work tour	Mode-1	5,205	86.47	5,205	86.47
	Mode-2	813	95.20	1,389	61.38
Discretionary activity before work	Trip generation	5,205	97.41	5,205	49.82
	Destination	76	100.00	87	49.72
	Mode-1	76	100.00	87	49.72
	Mode-2	14	100.00	19	49.50
	Activity Duration	76	93.42	85	49.01
Discretionary activity after work	Trip generation	5,205	89.47	5,205	40.65
	Destination	555	90.99	1,028	40.40
	Mode-1	555	98.92	1,028	40.40
	Mode-2	159	98.74	592	40.38
	Activity Duration	555	87.21	1,028	40.36

Table 2 shows the estimated results of submodels. All of the hit ratio of submodels (ratio of correctly hit samples among the all samples) are more than 85%, extremely high enough to reveal good fitness of neural networks. Particularly the hit ratios of before-work submodels are nearly 100%.

Neural networks have been criticized for failing to provide a basis for describing a set of causal factors. For each input variable we computed an indicator 'range' which was the overall differences of output values generated by changes of the input variable. Computed ranges are equally big enough for all of the submodels, which reveal that all of the relevant independent variables are effective enough to influence on an outcome. But, ranges cannot describe the way in detail how an input variable influence upon an outcome. Subba Rao et al. (1998) presented the relative influence of each input variable which involves partitioning the hidden-output layer connection weights of each hidden neuron into components associated with the input neuron.

We present a simple method to describe the relative significance of an input variable influencing on a particular output variable. For each input neuron i, and hidden neuron j, multiply the absolute value of the input-hidden layer connection weight by the absolute value of hidden-output layer connection weight. This is done for an output variable k (precisely for all of categories of an output variable) to obtain the products P_{ijk}. For an output variable k, compute the difference between the maximum and minimum of P_{ijk} and take the mean of the differences (difference per category) associated with the output variable k and each input variable. The computed mean shows the relative significance of an input variable influencing on the output variable k.

Table 3 shows the relative significance of input variables influencing on the choices of discretionary activities before and after work. Doing discretionary activities before and after work are much influenced by individual attributes such as age, occupation and family member, and both of work beginning and ending time. Further, discretionary activities before work are

Table 3. Relative influence of input variables on discretionary activities

Input variables		Discretionary actiivty before work		Discretionary activity after work	
		Trip generation	Duration time	Trip generation	Duration time
Socio economic attributes	Sex	0.80	3.50	1.14	3.60
	Age	0.97	2.51	1.72	5.33
	Driver licence	0.85	2.04	1.06	4.32
	Available car	1.05	2.91	1.20	4.67
	Occupation	1.10	2.38	1.43	5.23
	Household size	1.02	2.56	1.35	4.74
	Family member	1.09	2.93	1.55	5.87
	No. of cars	1.01	2.39	1.17	3.56
	Children under age	1.03	2.04	1.43	3.04
	Eldrely person	0.78	2.93	1.19	5.12
Work tour	Home place	0.99	2.87	1.27	5.17
	Work place	1.03	2.47	1.32	4.56
	Work beginning time	1.13	3.36	1.49	5.26
	Work ending time	1.14	2.98	1.38	5.56
	Distance b/w home and work	1.02	2.80	1.27	5.03
	Commuting mode	1.03	2.99	1.45	4.51
Discretionary trips before work	Destination	--	2.43	1.61	3.21
	Mode		2.37	1.85	3.05
	Duration time	--	--	2.16	5.11
Discretionary trips after work	Destination	1.03	2.87	--	4.56
	Mode	1.14	2.97	--	4.49
	Duration time	1.09	3.30	--	--

influenced by discretionary activities after work and vice versa. Duration time of discretionary activity before and after work are much influenced by individual attributes such as sex, age, occupation and family member, elderly people and residential place, and both of work beginning and ending time. The result clearly shows that duration time of activity before work are influenced and interrelated by duration time of activity after work, and vice versa.

Microsimulation and its application

An individual was enumerated and simulated following the process of Figure 1 for the entire samples (5,205 persons). Table 2 also shows the hit ratio for each of submodels when microsimulation proceed from the first submodel and ends at the final submodel with feedback iterations. Work-tour mode choice model (car or others) reveals a very high hit ratio of 86%, then the hit ratios decrease step by step until the final hit ratio of 40%. As simulation proceeds from top to bottom, prediction errors in the proceeding steps seem to influence on the prediction of the next step even though the two models of discretionary activity are simulated interrelatedly. Number of samples of which all of submodel outputs were correctly hit are 2,101 persons, 40.36% of all samples.

Case 1 of Table 4 shows the predicted number of samples for each submodel under

Table 4. Microsimulation for TDM alternatives.

		Actual		Case 1		Case 2		Case 3	
		Before work	After work	Before work	After work	Before work	After work	Before work	After work
Commuting mode	Car	4,392		3,816		3,471		2,885	
	Transit	1		27		189		509	
	Two-wheels	87		542		811		1,939	
	others	725		820		734		172	
	Total	5,205		5,205		5,205		5,205	
Discretionary activity	Trip generation	76	555	87	1,028	78	824	95	795
Destination of discretionary trip	City center	28	183	6	40	17	228	10	34
	South of City	4	56	43	284	30	270	55	354
	North of City	0	0	3	68	8	45	2	40
	West of City	31	192	33	548	21	244	26	315
	Outside of City	13	124	2	88	2	37	2	52
Mode of discretionary trip	Car	61	396	66	436	54	404	53	420
	Transit	0	0	4	30	4	46	8	82
	Two-wheels	6	86	8	362	6	224	13	183
	others	9	73	7	200	14	150	17	110
Duration time of discretionary activity	～20 min	38	169	7	59	7	72	15	71
	20～40 min	9	128	16	369	16	190	36	519
	40～60 min	10	68	4	470	47	536	33	156
	60 min～	19	190	58	130	8	26	9	49
Total		631		1,115		902		890	

the null condition assuming the actual case. As the hit ratios of each submodel in the estimation of table 2 suggest for themselves, simulated results can classify the actual choices of the submodel almost correctly. But when it comes to the sequential simulation of all submodels, it is true that the simulated results cannot fully reproduce the actual choices of a submodel. More studies are needed to analyze how to train and calibrate neural networks.

Case 2 &3 of Table 4 show simulated impacts for the cases when TDM policy such as flexible work hours are introduced; Case 2 assumes that work hour only ends by 30 minutes later than Case 1 (work beginning time is the same as Case 1), and Case 3 assumes that work hour begins as well as ends by 30 minutes later than Case1.

In Case 2 and 3, by comparing with Case 1, commuters shift their commuting modes from car and other modes (i.e. mainly walking) into transit and two-wheels. In Case 2, 'later ending time' shifts 10% of car use and walking, and in Case 3 'later beginning & ending time' shift more 15% of car and more 70% of walking into transit and two-wheels. The main changes in Case 3 supposedly stem from the increase of their idle time before work begins.

'Later ending time' in Case 2 induces to decrease trip generation of discretionary activity before as well as after work, because commuters have to spend 30 minutes longer than usual at office. In Case 3, 'later beginning & ending time' make increase discretionary trips before work, but decrease those after work. Duration times of discretionary activity tend to become shorter in Case 2 and 3. These changes of trip generation and duration time can be assessed almost justifiable. But there are supposedly unreasonable and unstable changes in the choice of modes and destinations of discretionary activity. In particular, it is difficult to justify mode changes that commuting mode and mode of discretionary activity do not have the same tendency to shift.

Conclusions

The study developed a microsimulation model that estimated work-tour mode and attributes of discretionary activities & trips before and after work for commuters under the constraint of work hour. Neural networks were employed to calibrate all of the submodels which yielded very high hit ratios. We presented a simple method to describe the relative significance of input variables influencing on a particular output variable. The estimated results demonstrated our assumption that decision making of the two models of discretionary activities (before and after work) are interrelated or feedbacked each other.

A microsimulation was carried out from the top submodel to the final submodel with feedback iterations, resulting in 40% of the overall hit ratio. For cases when TDM policy such as flexible work hours was introduced, microsimulation could estimate possible impacts on travel behavior of commuters. When it comes to overall microsimulation of sequential submodels with feedback iterations, however, simulated results are not sufficient enough to reproduce actual choices of submodels. More studies are needed how to train and calibrate neural networks by applying indicators of relative significance of an input variable.

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