### □ 論 文 □

# 個別 로짓 모형을 利用한 非就業者의 1日 通行行態에 關한 硏究

A MODEL SYSTEM FOR NON-WORKER'S DAILY TRAVEL DEMAND BASED ON DISAGGREGATE BEHAVIOURAL MODEL

# 裵 永 錫

((株) 建益 技術研究團)

# 金大雄

(嶺南大學校 都市工學科)

- 目

- I. INTRODUCTION
- II. PRIOR WORK
- III. THE ANALYSIS ON ACTUAL DATA OF NON-WORKER'S DAILY TRAVEL

IV. THE STRUCTURE OF THE MODEL SYSTEM

V. FORMULATION OF THE MODEL

VI. EMPIRICAL TESTS OF THE MODEL

VII. CONCLUSION

── 〈국문초록〉 —

本 研究에서는 個別模型(disaggregate model)을 利用한 都市圈의 交通需要豫測 模型體系의 構築을 最終自的으로 하며, 그때 個人이 1日 中에 行하는 復數의 트립에 관한 意思決定間의 相互關係를 적절히 고려함에 의해, 되도록 個人의 交通行動을 論理的으로 說明함과 동시에 模型의취급이 容易하도록 論理性과 實用性이 잘 조화된 模型의 構築을 시도하였다. 模型의 체계는 非就業者와 就業者 各各의 1日의 通行行態類型의 選擇에 관한 2個의 Sub-model로 構成되어져 있다.

本 論文은 그 Sub-model中의 하나인 非就業者의 1日의 通行行態類型(트립發生, 各 트립의 目 的地와 交通手段)의 選擇에 관한 個別模型의 開發을 행한 것이다.

本 模型의 특징은 tour別 效用最大化行動假說에 기초를 두어 個人이 1日 中에 行하는 각 트립의 選擇行動은 該當트립의 前後에 행해지는 트립들의 選擇行動의 영향을 고려하여 意思決定을하는 것으로 假說을 설정하여 트립간의 상호관련성을 표현하였다.

模型의 構造로서는, 模型의 취급이 보다 容易하도록 tour에 效用最大化를 트립單位의 段階型模型으로 表現하는 nested logit model型의 遂次同時效用最大化 模型을 構築하였다.

實際의 都市圈에 대한 實證的 檢討를 行한 結果,本 硏究에서 開發한 個別模型의 有效性이 確認되었다.

#### I . INTRODUCTION

A main component of transportation planning and policy analysis is the prediction of the future performances and impacts on the transportation system for each of the available plans or policy alternatives.

Disaggregate models which have advantages over traditional approaches based on aggregate models have been developed for the travel demand prediction. In the modeling of travel demand, disaggregate models allow us to consider the individual's attributes that influence on the travel behaviour and to make more efficient use of available individual data. However, applications of those models to transportation planning are limited: they are usually applied to the local and short-term transportation planning, or used in the frames of traditional 4-step travel demand forecasting models by replacing some of those steps. That is, there have been few attempts to develop and apply disaggregate travel demand model systems for predicting travel demand in metropolitan areas.

This paper develops a disaggregate model system in a metropolitan area. And its empirical tests have been done for Nagoya metropolitan area. In formulating the model, we attempt to develop the model that can logically represent individual travel behaviour and is also an operational model, as much as possible.

The model developed in this paper incorpo rates trip generation choice, destination choice and mode choice for non-woker travel into a utility maximizing framework by using the concept of travel tours under the assumption that the decisions of a trip in a tour depend on the decisions of trips conducted theretofore

and the decisions of trips planned thereafter, as well as on the current trip conditions.

#### II . PRIOR WORK

Travel demand forecasting is an essential element in the analysis of transportation system. Significant advances have been made in developing and applying disaggregate behavioural demand models to many aspects of urban travels.

As a study against to traditional approaches for the metropolitan transportation planning, MTC model based on disaggregate travel demand modeling approach has been developed (Ruiter and Ben-Akiva, 1978). The components of the MTC model system are largely classified according to the aspect of time(long-run, short-run) and the level of trip-making decision(developer, household, individual). Then, the modeling system of travel decisions deals separately with home-based and non-home-based trips. This simplifies the representation of trip chains. However, MTC model system can not completely consider interrelationships among trips.

On the other hand, it has been assumed that there are interrelationships among trips made by an individual. Accordingly, some studies are performed by explicitly considering the trip chaining behaviour.

Adler and Ben-Akiva(1979) described a utility maximizing model for a household's choice of a daily travel patterns which are described by the number and characteristics of destinations chosen for non-work activities, the mode used to travel to those destination, and by the number of tours used to travel to the set of destinations during the day. However, a household has, in principle, infinite

possible patterns which are the alternatives. From this reason, in this model, the household's alternative set for estimation was constructed by using the chosen travel patterns of other households.

Lerman(1979) tried to synthesize two different analysis methodologies, disaggregate choice models and semi-Markov process, to develop an operational, policy sensitive model of non-work trip chaining. The model permits multi-destination travel but treats choices of travel frequency out side of the utility maximizing behavioural framework. Moreover, this model requires the simplifying assumption that current travel decisions are independent of past travel decisions or future travel plans.

Horowitz(1979, 1980) developed a structural model of demand for multi-destination non-work travel, which is based on the principle of utility maximization. The model incorporates travel frequency, destination choice and mode choice for both single and multi-destination and incorporates the concept that current travel decisions may depend on past travel decisions and future travel plans. The model estimates firstly, the expected value of total daily person trips to non-work destinations other than home by defining a timeintegrated utility of travel from i to j by mode m. Then, travel frequency and destination choices are carried out within that bounds. In the model, the effects of past travel decisions and future travel plans, for making current decisions, are represented as considering the bounds which are the expected trip numbers of total daily person trips. However, the model does not thoroughly consider the direct effects of the trips before and after on current trip.

Kitamura (1984) developed a model of destination choice employing "prospective utility of a destination zone as its attraction measure. The prospective utility accounts for future dependency of destination choice and makes possible relevant treatment of interdependent choices in a trip chain. However, the model treats only destination choice.

Recently, travel demand modelers have attempted to derive models of travel demand from an underlying theory of activity scheduling behaviour which consider the interrelationships between activities and travels. This approach treats travel as a derived demand and analyzes the interrelationships between activities and travels under the temporal and spatial constraints.

Damm and Lerman(1981), Damm(1984) formulated a theory of activity scheduling for urban workers. This model conducts the choice of each worker that whether or not to participate in an out-of-home, non-work activity in each of five blocks of time defined around their obligatory trip to work, moreover, the chosen duration of participation is analyzed, conditional on the decision to participate in any particular time. However, there are still no operational model that directly links choice of activities with trip making.

### III. THE ANALYSIS ON ACTUAL DATAS OF NON-WORKER'S DAILY TRAVEL

In this study the data of non-workers who live in Nagoya City, which is obtained from the person trip survey in 1981 for the Chukyo Metropolitan Area of Japan. Let us see the actual datas of non-worker's daily travel before we examine the models. Table 1 gives the aggregated results at present for trips and tours in a day. It will be known from this table that the percentage of the people have

trips number	(A)persons	(B)persons	trips	(B)/(A)
per day	number	number	number	(%)
0	8130(39.0)	_		_
1	101( 0.5)	-	101( 0.3)	_
2	7734(37.1)	7703(61.5)	15468(41.0)	99.6
3	1010( 4.8)	995(7.9)	3030(8.0)	98.5
4	2227(10.7)	2211(17.7)	8908(23.6)	99.3
5	529( 2.5)	521(4.2)	2645( 7.0)	98.5
6	641(3.1)	635(5.1)	3846(10.2)	99.1
7	202( 1.0)	200( 1.6)	1414( 3.7)	99.0
more than 8	283( 1.4)	251( 2.0)	2348( 6.2)	88.7
total	20857(100.)	12516(100.)	37760(100.)	98.3

Table 1. The aggregated results of trips and tours in a day for non-workers

(Note)

(A): The number of persons including trip-maker who do not make any tour

(B): The number of persons making tours

no trip is 39.0%, and 37.1% of the total have two trips in a day. Among the people who have at least one trip during a day, 98.3% of them make tours, and the people who did not make any tour are not over 1.7%. Table 2 illustrates the percentage using same mode in a tour. From this Table, it will be known that the percentage of the tours with the same mode in a tour is 94.4% of the total tours. From the aggregated results of Table 1 and Table 2, it will be known in case of excluding the people who have no trip, the average number of trips one person made in day is 2. 97, and the average number of tours is 1.35. Furthermore the average number of trips in a tour is 2.20.

In Figure 1, the percentage of tours with same mode in a tour are shown by different modes and the number of trips in a tour. From this Figure it can be known that the percentage of tours with same mode is generally as smaller as the number of trips in a tour gets more. By the travel mode, it is found that in cases of walking, two-wheeled vehicle(bicycle and motorcycle), transit and taxi, same

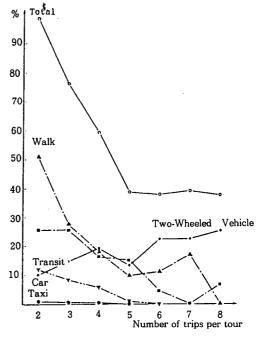


Figure 1 The percentage of tours with same mode in a tour by different modes and the mumber of trips per tour

with the total case, there is a tendency that the percentage of tours by same mode is get ting as smaller as the trips number in a tour gets more, whereas in case of car, is oppositely getting bigger.

Next, from Figure 2, the ten sequential order aggregated result for travel tour pattern of trip ma ker, it is known that the persons making the piston tour pattern is 61.5% of all persons making tours, and the other patterns are also combined by the tours with 2 or 3 trips.

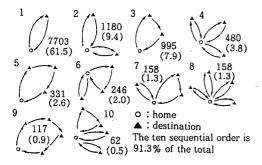


Figure 2 The tour patterns of non-worker's trip in a day

#### IV. THE STRUCTURE OF THE MODEL SYSTEM

Disaggregate models have been formulated from the concept of random utility, which assume that individuals' decisions about available alternatives are determined by selecting the alternative that has the highest utility. In this study, we assume that individual behaviour can be explained by using the utility maximizing theory. Accordingly, for formulating the metropolitan travel demand forecasting model, we apply disaggregate behavioural model.

Generally, in individual travel patterns during a day, there are two different types: non-worker's pattern and worker's pattern(see Figure 3). Non-worker's case only consists of home-based tours which have one or more destination, while worker's case consists of home-based tours and work-based tours.

Most non-worker trips differ from worker trips in several aspects. Firstly, they are characterized by a large degree of substitutability among alternatives. Secondly, the non-worker trip pattern is substantially more complex than that of worker trips. Finally, trip frequency is far more likely to be responsive to changes in the level of service provided by the transportation system than that of worker trips.

In this paper, we focus on non-worker whose daily travel pattern largely varies from the degree of substitutability. We assume that an individual does not independently make

Table 2. The present states for non-workers using the same mode in a tour(%)

(A)trips number         (B)tours number         (C)tours number         (D)total number           2         14,322         208         14,540           (98.6)         (1.4)         (100.)           (89.5)         (22.0)         (85.8)           3         1,291         402         1,693           (76.3)         (23.7)         (100.)           (8.1)         (42.6)         (10.0)           4         290         201         491           (59.1)         (40.9)         (100.)           (1.8)         (21.3)         (2.9)           5         56         89         145           (38.6)         (61.4)         (100.)           (0.4)         (9.4)         (0.9)           6         17         28         45           (37.8)         (62.2)         (100.)           (0.1)         (3.0)         (0.3)           7         7         111         18           (38.9)         (61.1)         (100.)           (0.0)         (1.2)         (0.1)           8         3         5         8           (37.5)         (62.5)         (100.) <td< th=""><th></th><th></th><th>,</th><th></th></td<>			,	
2		(B)tours	(C)tours	(D)total
(98.6) (1.4) (100.) (89.5) (22.0) (85.8)  3 1,291 402 1,693 (76.3) (23.7) (100.) (8.1) (42.6) (10.0)  4 290 201 491 (59.1) (40.9) (100.) (1.8) (21.3) (2.9)  5 56 89 145 (38.6) (61.4) (100.) (0.4) (9.4) (0.9)  6 17 28 45 (37.8) (62.2) (100.) (0.1) (3.0) (0.3)  7 7 111 18 (38.9) (61.1) (100.) (0.0) (1.2) (0.1)  8 3 5 8 (37.5) (62.5) (100.) (0.0) (0.5) (0.1)  total 15,996 994 16,940 (99.4) (5.6) (100.) (100.) (100.)		number	number	number
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	2	14,322	208	14,540
3       1,291       402       1,693         (76.3)       (23.7)       (100.)         (8.1)       (42.6)       (10.0)         4       290       201       491         (59.1)       (40.9)       (100.)         (1.8)       (21.3)       (2.9)         5       56       89       145         (38.6)       (61.4)       (100.)         (0.4)       (9.4)       (0.9)         6       17       28       45         (37.8)       (62.2)       (100.)         (0.1)       (3.0)       (0.3)         7       7       111       18         (38.9)       (61.1)       (100.)         (0.0)       (1.2)       (0.1)         8       3       5       8         (37.5)       (62.5)       (100.)         (0.0)       (0.5)       (0.1)         total       15,996       994       16,940         (99.4)       (5.6)       (100.)         (100.)       (100.)       (100.)		(98.6)	(1.4)	(100.)
(76.3) (23.7) (100.) (8.1) (42.6) (10.0) 4 290 201 491 (59.1) (40.9) (100.) (1.8) (21.3) (2.9) 5 56 89 145 (38.6) (61.4) (100.) (0.4) (9.4) (0.9) 6 17 28 45 (37.8) (62.2) (100.) (0.1) (3.0) (0.3) 7 7 111 18 (38.9) (61.1) (100.) (0.0) (1.2) (0.1) 8 3 5 8 (37.5) (62.5) (100.) (0.0) (0.5) (0.1) total 15,996 994 16,940 (99.4) (5.6) (100.) (100.) (100.)		(89.5)	(22.0)	(85.8)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	3	1,291	402	1,693
4 290 201 491 (59.1) (40.9) (100.) (1.8) (21.3) (2.9) 5 56 89 145 (38.6) (61.4) (100.) (0.4) (9.4) (0.9) 6 17 28 45 (37.8) (62.2) (100.) (0.1) (3.0) (0.3) 7 7 111 18 (38.9) (61.1) (100.) (0.0) (1.2) (0.1) 8 3 5 8 (37.5) (62.5) (100.) (0.0) (0.5) (0.1) total 15,996 994 16,940 (99.4) (5.6) (100.) (100.) (100.)		(76.3)	(23.7)	(100.)
(59.1) (40.9) (100.) (1.8) (21.3) (2.9) 5 56 89 145 (38.6) (61.4) (100.) (0.4) (9.4) (0.9) 6 17 28 45 (37.8) (62.2) (100.) (0.1) (3.0) (0.3) 7 7 111 18 (38.9) (61.1) (100.) (0.0) (1.2) (0.1) 8 3 5 8 (37.5) (62.5) (100.) (0.0) (0.5) (0.1) total 15,996 994 16,940 (99.4) (5.6) (100.) (100.) (100.)		(8.1)	(42.6)	(10.0)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	4	290	201	491
5		(59.1)	(40.9)	(100.)
(38.6) (61.4) (100.) (0.4) (9.4) (0.9) 6 17 28 45 (37.8) (62.2) (100.) (0.1) (3.0) (0.3) 7 7 111 18 (38.9) (61.1) (100.) (0.0) (1.2) (0.1) 8 3 5 8 (37.5) (62.5) (100.) (0.0) (0.5) (0.1) total 15,996 994 16,940 (99.4) (5.6) (100.) (100.) (100.)		( 1.8)	(21.3)	(2.9)
6 17 28 45 (37.8) (62.2) (100.) (0.1) (3.0) (0.3) 7 7 111 18 (38.9) (61.1) (100.) (0.0) (1.2) (0.1) 8 3 5 8 (37.5) (62.5) (100.) (0.0) (0.5) (0.1) total 15,996 994 16,940 (99.4) (5.6) (100.) (100.) (100.) (100.)	5	56	89	145
6 17 28 45 (37.8) (62.2) (100.) (0.1) (3.0) (0.3) 7 7 111 18 (38.9) (61.1) (100.) (0.0) (1.2) (0.1) 8 3 5 8 (37.5) (62.5) (100.) (0.0) (0.5) (0.1) total 15,996 994 16,940 (99.4) (5.6) (100.) (100.) (100.) (100.)		(38.6)	(61.4)	(100.)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		( 0.4)	(9.4)	(0.9)
7	6	17	28	45
7 7 111 18 (38.9) (61.1) (100.) ( 0.0) ( 1.2) ( 0.1) 8 3 5 8 (37.5) (62.5) (100.) ( 0.0) ( 0.5) ( 0.1)  total 15,996 994 16,940 (99.4) ( 5.6) (100.) ( 100.) (100.) (100.)		(37.8)	(62.2)	(100.)
(38.9) (61.1) (100.) ( 0.0) ( 1.2) ( 0.1) 8 3 5 8 (37.5) (62.5) (100.) ( 0.0) ( 0.5) ( 0.1) total 15,996 994 16,940 (99.4) ( 5.6) (100.) ( 100.) (100.) (100.)		( 0.1)	(3.0)	(0.3)
8 3 5 8 (37.5) (62.5) (100.) (0.0) (0.5) (0.1) total 15,996 994 16,940 (99.4) (5.6) (100.) (100.) (100.) (100.)	7	7	111	18
8 3 5 8 (37.5) (62.5) (100.) (0.0) (0.5) (0.1) total 15,996 994 16,940 (99.4) (5.6) (100.) (100.) (100.) (100.)		(38.9)	(61.1)	(100.)
(37.5) (62.5) (100.) (0.0) (0.5) (0.1) total 15,996 994 16,940 (99.4) (5.6) (100.) (100.) (100.) (100.)	1	( 0.0 )	(1.2)	(0.1)
total (0.0) (0.5) (0.1) 15,996 994 16,940 (99.4) (5.6) (100.) (100.) (100.) (100.)	8	3	5	8
total 15,996 994 16,940 (99.4) (5.6) (100.) (100.) (100.)		(37.5)	(62.5)	(100.)
(99.4) (5.6) (100.) (100.) (100.) (100.)		( 0.0 )	( 0.5)	(0.1)
(100.) (100.) (100.)	total	15,996	994	
		' '	(5.6)	(100.)
		(100.)	(100.)	(100.)

(Note)

- (A): The number of trips made during a day
- (B): The number of tours using the same mode in a tour
- (C): The number of tours using the different mode in a tour
- (D): The total number of tours

trip decisions without considering the interrelationships that may exist among choices made by an individual for a series of trips but does trip decision-making with considering the interrelationships. Therefore, for applying disaggregate behavioural model, we should define the concept for decision-making in individual daily travel behaviour.

There may be three alternative hyptheses:

. Hypothesis -1: a utility maximizing framework over daily travel behaviour.

Hypothesis -2: a utility maximizing framework for each tour.

Hypothesis -3: a utility maximizing framework for each trip which makes a tour.

The first hypothesis assumes that trip maker maximizes his utility for whole a day and there are interrelationships among trips. The second one assumes that when an individual does decision-making, he takes utility maximizing for each tour and there are no interrelationships but sequence among tours, and the tour which has the higher degree of importance will be determined prior to other tours. The result of this behaviour will be one of the conditions for the utility maximizing of next tours. The third one assumes that an individual maximizes his utility for each trip and there are no interrelationships among trips. But it is just like hypothesis-2 that there exists a sequence characteristic. That is, the trip which is considered to be important is decided firstly, then considering it as one of the conditions, a traveler will maximize his utility for the next trip.

Which of the three hypotheses mentioned above are reasonable as the decision-making principle of individuals' travel behaviour depends on how many future trips will be considered and how much information for the alternatives of future trips will be obtained in making travel behaviour. Hypothesis—1 is overestimating individuals' planning ability for daily travel behaviour. On the contrary, hypothesis—3 is underestimating it.

Therefore, in this study, we adopt hyothesis -2 which is the utility maximizing for each tour. As the structure of the model, nested logit model is used to avoid a simultaneous model's complexity caused by a large number of alternatives that a traveler faces in making his travel decision, while the model represents simultaneous decision-making process. From this, the model incorporates the concept that decisions of a trip in tours depend on decisions of the trips conducted theretofore and decisions of the trips planned thereafter, as well as on current trip conditions.

For doing decision-making of the trip departing from home in a tour, we can not assume that individual takes account of all trips which make a tour, so we amend an individual behavioural hypothesis as follows:

A traveler maximizes his utility by each trip in a tour, conditional on the trips conducted theretofore, by considering the conditions of trip chains returning his home which consist of L trips at most.

While we can set any value for the value of L, by considering the actual state of using data and the practical aspect of model we will adopt the value as 2 in this study. Figure 4 illustrates the structure of decision tree in a tour used in this model. The model presented here incorporates trip frequency, destination choice and mode choice. We assume that travelers do not change the modes during tours, so that the mode used in a tour is same during the tour.

#### V. FORMULATION OF THE MODEL

# 1. General formulation of disaggregate model

Most disaggregate models have been formulated from the concept of random utility which assumes that an individual always selects the alternative with the highest utility. However, it has also been explicitly recognized that all the important components of utility

O:home

• : work

△: destination

I : home-based tour(before work)

(a) Non-Worker

function cannot be observed or measured, so that in practice the utility function (U) of alternative i is typically represented by a deterministic portion (V) and a random portion  $(\varepsilon)$  and the deterministic portion is specified as linear-in-parameter function of the explanatory variables. That is,

$$U_{in} = V_{in} + \epsilon_{in}$$

$$= \sum_{K} \beta_{K} X_{inK} + \epsilon_{in}$$
(1)

II: home-to-work trip chaining

II : work-based tour

IV: work-to-home trip chainingV: home-based tour(after work)

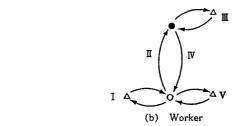


Figure 3 The typical travel behavioural patterns

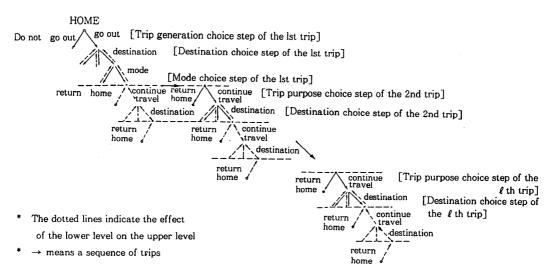


Figure 4 The structure of decision tree in a tour

where  $X_{int}$  is kth characteristic of alternative i for individual n

#### $\beta_k$ is kth unknown parameter

The probability that any element i in the feasible choices is chosen by decision maker n is given by

$$P_{in} = pr \left[ U_{in} > U_{jn}, \text{ for an } j \neq i \right] \cdots (2)$$

From the assumption that the random component of the utility function is independently and identically distributed by means of the negative reciprocal exponential distribution, we can derive the multionomial logit model as follows:

$$P_{in} = \frac{\exp(\lambda V_{in})}{\sum_{i} \exp(\lambda V_{in})} \quad \dots \tag{3}$$

where  $P_{in}$  is probability that a decision maker n will choose alternative i from the set of feasible alternatives and  $\lambda$  is a positive scale parameter.

# The formulation of the nested logit model

In this study, nested logit model are used to formulate the models relating the decision-making for each trip represented by the tree of Figure 4. The following are going to show simply the basic concept of the nested logit model<sup>9</sup>.

Now, considering a decision-making tree with two levels, the choices of which are denoted by i, j respectively, then the utility U(i, j) can be written as:

$$U(i, j) = U_i + U_{jli} \quad \cdots \qquad (4)$$

where  $U_i$ : the utility of the choice i at the upper level

 $U_{ji}$ : the utility of the choice j at the lower level conditional on having the choice i

at the upper level

Here we think  $U_{i}$ ,  $U_{ji}$  are independently distributed with the expected values  $V_{i}$ ,  $U_{ji}$  and variances  $\delta_{i}^{2}$ ,  $\delta_{ji}^{2}$ , so equation(4) can presented:

$$U(i, j) = V_i + V_{jli} + \varepsilon_i + \varepsilon_{jli} \quad \cdots \qquad (5)$$

where  $\varepsilon_{ii}$   $\varepsilon_{jli}$  are the random portions of the utilities  $U_{ii}$   $U_{jli}$  scparately and are assumed to be independently Gumbel distributed.

According to the assumption of the utility maximization, the joint probability of choosing both choice i and choice j should be the probability when maximizing the utility U(i, j). In the case of nested logit model, the joint probability could be expressed as follows:

$$P(i, j) = P(i) P(jli) \qquad \dots \qquad (6)$$

Firstly, with the condition of having chosen the alternative i at the upper level, the conditional probability  $P_{ji}$  of choosing j at the lower level becomes:

$$P_{jii} = pr[V_{jii} + \varepsilon_{jii} \ge V_{jii} + \varepsilon_{jii}, \text{ for all } j \ge i]$$

$$= \frac{exp(\lambda_j V_{jii})}{\sum_{i}, \exp(\lambda V_{jii})} \qquad (7)$$

where  $\lambda_1$  is the seale parameter of  $\varepsilon_{fli}(\lambda_1^2 = \pi^2/6\delta_{fli}^2)$ .

Then, the marginal probability  $P_i$  of choosing i at the upper level can be presented as equation(7) with an additional term  $U_i$ \*, which is the maximum utility of the lower level conditional on the result of choosing at the upper level, added to the utility of only the upper level.

$$P_{i} = prob \left[ V_{i} + \varepsilon_{i} + U_{i} * \geq V_{i'} + \varepsilon_{i'} + U_{i'} *, \right.$$

$$for all j \approx i \right] \dots (8)$$

where 
$$U_{i*} = \max(V_{jli} + \epsilon_{jli})$$
  
=  $V_{i*} + \epsilon_{i*}$  .....(9)

Since  $\varepsilon_{ji}$  is by assumption Gumbel distributed with parameter  $\lambda_1$ ,  $U_i$  \* is also Gumbel distributed with the expected value  $1/\lambda_1 \ln \frac{\Sigma}{j}$   $\exp(\lambda_1 V_{ji})$  and variance  $\delta_{ii}$ ?.

Now, by instituting equation(8), the factors of equation(7) are written as follows:

$$V_i + \varepsilon_i + U_i *= V_i + V_i * + \varepsilon_i + \varepsilon_i *$$

$$= V_i + V_i * + \tau_i \quad \dots \qquad (10)$$

where  $V_{i*} = 1/\lambda_i \ln \frac{\Sigma}{i} \exp(\lambda V_{ji})$ 

$$\tau_i = \varepsilon_I + \varepsilon_{I^*} \quad \dots \qquad (11)$$

Next, supposed  $\tau_i$  is the Gumbel distribution with the expected value value o and variance  $\delta *^2$ , the following equation can be obtained:

$$P_{i} = \frac{\exp[\lambda_{2}(V_{i} + V_{i}*)]}{\sum_{i} exp[\lambda_{2}(V_{i} + V_{i}*)]} \quad \cdots \qquad (12)$$

where  $\lambda_2$  is the scale parameter of  $\tau_i[\lambda_2^2 = \pi^2/6]$   $(\delta_2^2 + \pi^2/6\lambda_1^2)^{-1}$ .

Furthermore, as the necessary condition that the estimated nested logit model is consistent with the utility maximizing theory,  $0, < \lambda_2/\lambda_1 \le 1$  should be satisfied. In other words, the variance of the random utility is the smallest at the lowest level of the tree, and it cannot decrease as we move from a low to a higher level.

As showed above, the nested logit model is represented by the choice probabilities at the sepa-rated two levels. Also, the nested logit model can simirally be extended for the cases of the tree levels. In this study, the nested logit model described above are used to the multi-level choice problem so that we can, avoid a simultaneous model's complexity caused by a large number of alternatives that a traveler faces in making his travel decision.

According to the concept of the model em-

ployed in this study, the utility of the lower level is included into the upper level model as an explanatory variable in the form of the expected maximum utility. In addition, although the effects of the decisions of the upper levels are not clearly expressed in the above formulation, they are contained in the utility of the current level.

The estimation method of the parameters

As the choices of the destination, 16 zone in Nagoya Metropolitan Area are used, and at mode choice level, car and transit are considered as two choices.

Since these models consider 4 or 5 levels for a decision-making of one trip, it is difficult to estimate all parameters simultaneously. Therefore we use the easier method, sequential estimation. In the decision tree illustrated Figure 4, the sequential estimation procedure for home-based trip(the 1st trip) consists of the following steps:

Step 1: Firstly, the parameters  $\beta_{d(l+1)+d(l),m}$  at the lowest level, which are the destination choice of the trip followed by the trip returning home, are estimated in terms of the maximum likehood estimation method. It should noted that it is necessary to estimate for car and transit se-parately.

Step 2: The estimated parameters at step 1 are computed to be the expected maximum utility variable and used as the utility of continuing trip. Then the parameters  $\beta_{N(l+1)+d(l),m}$   $\beta_{h(l+1)+d(l),m}$  for binary logit model of yeturning home or continuing trip are to be estimated. Of course same as the step 1, the estimation should be made for transit and car separately.

Step 3: The parameters  $\beta_{m+h,d(1)}$  for the binary logit model of the choice between car

and transit are estimated. Then, the utility of the lower level is included into the mode choice level model as an explanatory variable in the form of the expected maximum utility.

Step 4: At this step, the parameters  $\beta_{d(1)+h}$  for the destination choice model of home-based trip are estimated. By using the estimated result at the step 3, the utilities of mode choice for the different destinations are represented as the expected maximum utility expression in this model.

Step 5: At this step, the parameters  $\beta_{N(1)+h}$ ,  $\beta_{H(1)+h}$  for the binary logit model of the choice going out or not are estimated. Then the estimated parameters at step 4 are used to be as the expected maximum utility for the choice of go out.

Non-home-based trips can be treated with the same process of the 1st trip(home-based trip) described above, only step 3 is omitted.

### VI. EMPIRICAL TESTS OF THE MODEL

Disaggregate behavioural model proposed in this study was examined for Nagoya metropolitan area. In the following, the estimated results are presented for each level of the decision tree(see Figure 4).

## Destination choice level of non-homebased trip

Now we are going to estimate the parameters of destination choice model of non-home-based trip. The alternatives are 16 zones in Nagoya metropolltan area.

Three variables are used in the destination choice model, which are the natural logarithm of the daytime population at non-home potential destination, travel time and the expected maximum utility of the following trips(mentioned at chap 4). Table 3 presents the estimation result of the destination choice model for both car and transit. All of the parameters have the expected signs and are statistically significant at 0.01 level. Particularly, the statistical significance of the expected maximum utility variable means the validity of the assumption of this study that a traveler makes his decision with considering that he will return home after 2 trips. And since the coefficient of the expected maximum utility variable has the value between 0 and 1, this model satisfies the utility maximizing theory.

Although the value of 9<sup>2</sup> and hit-ratio for this model are not so high, they seem to be good results considering we use two explanatory variables for the choice of 16

Table 3. Parameter estimates for destination choice model of non-home-based trip

Variable	Tran	nsit	Car	
variable	Coefficient	t-value	Coefficient	t-value
ln(daytime population)	1.479	6.43	1.140	5.89
travel time	-0.1096	-9.24	-0.1426	-16.04
expected maximum utility*	0.960	3.53	0.719	13.37
$\rho^2$	0.336		0.4	78
hit-ratio	37.4	4	55.6	
no. of observations	187		432	2

expected maximum utility of the following trips.

alternatives here. At this step, in order to obtain the model having the better results, there

is a need to develop improved sets of explanatory variables for destination choice model.

# 2. Frequency choice level of non-home-based trip

There are two alternatives which are returning home or continuing travel for both car and transit. Table 4 presents the estimated results.

When the alternative is continuing travel, we use the expected maximum utility for the lower level as an explanatory variable. Its t value is statistically singificant at 0.10 level and its coefficient has the value between 0 and 1. Therefore it can be said that this model satisfies the utility maximizing theory.

On the other hand, when the alternative is returning home, car ownership, travel time, trips number are used as the explanatory variables. According to the estimated results, it can be found out that non-worker tends to continue travel as the travel time from a non-home-based destination to his home gets longer. Here the trips number which have been made by the traveler prior to the current trip in a day is used to find out the effects on the current trip from the trips made before. The t value of that coefficient is statistically significant at 0.10 level. Then it can be also known that non-worker using transit tends to continue travel, but in the case of using car, he tends to return home as the trips number become more.

The t values of the expected maximum utility and the trips number variables are not so high, but their use can make it clear that when a traveler does decision-making of a trip, his decision of the current trip is affected by decisions of the trips before and after.

Table 4. Parameter estimates for frequency choice model of non-home-based trip

Alternative	Variable	Transit		Car	
	variable	Coefficient	t-value	Coefficient	t-value
continue travel	expected maximum utility	0.221	1.71	0.399	2.17
	constant	41.030	1.83	12.973	2.40
return	if have no car	0.864	1.96	0.919	1.83
home	travel time	-0.0087	-1.08	-0.0396	-3.08
	trips number	-1.511	-2.07	0.309	1.67
$ ho^2$		0.5	542	0.1	35
hit-ratio		90.3		70.8	
no. of observations		1922		1480	

#### 3. Mode choice level of home-based trip

The estimated results of the mode choice is shown in Tabele 5. There are two alternatives which are transit or car.

The expected maximum utility and travel time are used as a common variable for two alternatives. They are statistically significant at 0.01 level and since the coefficient of the expected maximum utility variable has the value between 0 and 1, this model satisfies the utility maximizing theory.

On the other hand, when the alternative is car, we use sex and license as the explanatory variables. They are statistically significant at 0.01 level.

All of the coefficients of the variables are statistically significant at 0.01 level and  $\rho^2$ ,

Alternative	Variable	Cofficient	t-value
transit, car	expected maximum utility	0.667	9.70
	travel time	-0.0915	-5.36
car	constant	92.130	9.38
	if male	-1.403	-14.91
	if have license	4.080	19.43
$\rho^2$	1	0.5	29
hit-ratio		87.1	
no. of observations		1671	

Table 5. Parameter estimates for mode choice model of home-based trip

hit-ratio have fully high values.

Destination choice level of home-based trip

At this step, the alternatives and the explanatory variables are same as that used at destination choice level of non-home-based trip. The coefficients are fully significant, par-

ticularly the expected maximum utility variable for the lower level has considerably large t value(Table 6). From this result, it can be confirmed that there are the interrelationships among trips. However, similar to 2, it is necessary to adopt other available variables in order to obtain the model having the better results.

Table 6. Parameter estimates for destination choice model of home-based trip

Variable	Coefficient	t-value
ln(daytime population)	1.679	20.82
expected maximum utility	0.909	42.15
$ ho^2$		0.325
hit-ratio		42.3
no. of observations		1671

### Trip generation choice level of homebased trip

The estimated results for trip generation choice model is shown in Table 7. There are two alternatives which are going out or not going out from home. When the alternative is going out from home, the expected maximum utility for the lower level is used as an explanatory variable. It is statistically significant at 0.01 level and its coefficient has the value between 0 and 1, so this model satisfies the utility maximizing theory.

On the other hand, for the case that the alternative is not going out from home, we use sex, occupation and car ownership as the explanatory variables, here to examine the influence of the numbers of car ownership on trip generation choice, car ownership variable is divided into three cases, having no car, having 1 car and having more 2 cars. According to the estimated results, the more cars the person has, the easier he(she) tends to go out from home. And all used variables have the expected sings and except the car ownership having 1 car the variables are statistically sig-

Alternative	Variable	Cofficient	t-value
go out	expected maximum utility	0.564	10.84
do not	constant	67.170	10.85
go out	if male	-0.449	-3.22
	if housewife	-0.907	-8.49
	if have no car	1.630	9.97
	if have 1 car	0.305	2.10
$ ho^2$		0.09	98
hit-ratio		63.0	6
no. of observations		231	15

Table 7. Parameter estimates for generation choice model of home-based trip

nificant at 0.01 level.

From the above results of 1-5, we can confirm the assumption that when a traveler makes a trip during a tour, the trip decision-making of each level depends on not only the decisions of the upper level but also the lower level, as well as on the decisions of the current level. And the coefficients of the expected maximum utility have the value 0 and 1. Therefore it can be said that these models satisfy the utility maximizing theory.

#### VII. CONCLUSION

In this paper, a disaggregate model system for the travel demand of non-worker's trip in a metropolitan area has been developed, and empirical tests of the model has been done.

The model in this paper incorporates trip generation choice, destination choice and mode choice for home-based trip, and destination choice and mode choice for non-home-based trip of non-worker into a utility maximizing framework, which uses the concept of travel tours. And the model incorporates the concept that the decisions of a trip in tours depend on the decisions of trip conducted theretofore and the decisions of trips planned thereafter, as well as on the current trip conditions in order

to represent the interrelationships among trips made during a day. Then we adopt the assumption that a traveler makes successively utility maximizing with considering the following 2 trips that will be made after.

Empirical tests of the model for Nagoya metropolitan area show encouraging results and prove the validity of the assumption of this model.

The issues in the future research are as follows:

- 1) we propose the assumption that when a traveler does decision-making for a trip during a tour, he will consider the following 2 trips that will be made after. However, it must be necessary to examine the validity of the assumption by testing for the other numbers of the following trips.
- 2) The model system in this study is developed for predicting travel demand in a metropolitan area. Accordingly, it is necessary to be test the validity of the model system in the prediction by applying it to the travel demand prediction.

#### REFERENCES

Adler, T. J. and Ben-Akiva, M. E., (1979),
 A Theoretical and Empirical model of

- Trip Chaining Behavior", Transpn. Res., 13B, pp. 243-257.
- Damm, D. and Lerman, S. R., (1981), "A
   Theory of Activity Scheduling Behavior",
   Environment and Planning A, Vol. 13, pp. 703-718.
- Damm, D.,(1984), "The Integration of Activity and Transportation Analysis for Use in Public Decision-Making", Transpn. Policy Decision Making 2, pp. 249-269.
- Horowitz, J.,(1979), "Disaggregate Demand Model for Non-Work Travel",
   Transpn. Res. Rec., No. 673, pp. 65-71.
- Horowitz, J., (1980), "A Utility Maximizing Model of the Demand for Multi-Destination Non-Work Travel", Transpn. Res., 14B, pp. 369-386.

- Kitamura, R., (1984), "Incorporating Trip Chaining into Analysis of Destination Choice", Transpn. Res., 18B, pp. 67-81.
- Lerman, S. R., (1979), "The Use of Disaggregate Choice Model in Semi-Markov Process Models of Trip Chaining Behavior", Transpn. Sci., 13, pp. 273-291.
- 8. Ruiter, E. R. and Ben-Akiva, M. E., (1978), "Disaggregate Travel Demand Models for the San Francisco Bay Area", Transpn. Res. Rec., No. 673, pp. 121-128.
- Williams, H. C. W. L.,(1977), "On the Formation of Travel Demand Models and Economic Evaluation Measures of User Benefit", Environment and Planning A, Vol. 9, pp. 285-344.