

A ROUTE-CHOICE MODEL CONSIDERING TOPOLOGICAL ASPECTS OF A ROAD NETWORK

Yasuo ASAKURA
 Professor
 Dept. of Civil and Environ. Eng.
 Ehime University
 Matsuyama 790-8577
 Japan
 Fax: +81-89-927-9843
 E-mail: asakura@en1.ehime-u.ac.jp

Toshimichi YAMAUCHI
 Graduate Student
 Graduate School of Civil and Environ. Eng.
 Ehime University
 Matsuyama 790-8577
 Japan
 Fax: +81-89-927-9843
 E-mail: Nasaka001@aol.com

Eiji HATO
 Research Associate
 Dept. of Civil and Environ. Eng.
 Ehime University
 Matsuyama 790-8577
 Japan
 Fax: +81-89-927-9843
 E-mail: hato@en2.ehime-u.ac.jp

Masuo KASHIWADANI
 Professor
 Dept. of Civil and Environ. Eng.
 Ehime University
 Matsuyama 790-8577
 Japan
 Fax: +81-89-927-9843
 E-mail: kashiwa1@en1.ehime-u.ac.jp

Abstract: This paper proposes a drivers' route-choice behaviour model that considers the topological aspects of a road network. The model consists of two stages. The first is the route-selection phase, which generates a set of alternative routes between an origin and a destination. The configuration of intersections and the degree of a mixture of functional hierarchy of road links along the path represent topological aspects of a road network. These aspects are considered in an EBA (elimination by aspects) process at the route-selection stage. The second stage is a route-choice process. The model was verified using driver's route-choice data observed for an actual road network in Matsuyama.

Key Words: behavioural analysis, route choice, network topology, elimination by aspects.

1. BACKGROUND AND OBJECTIVES

Modelling an individual's route-choice behaviour in a transport network is essential for describing flow in the network. Traditional traffic assignment models, such as the deterministic user equilibrium (UE) model, employ a simple mechanism for a driver's choice of route in a network: the driver is generally assumed to choose the minimum cost path between an origin and destination pair. This assumption seems valid, if the driver has perfect travel information, such as travel time and costs, and makes a rational choice.

The deterministic route-choice rule can be extended to the probabilistic case. Probabilistic route-choice models assume imperfect travel information, and a driver is assumed to choose the minimum cost path based on his perceived travel costs in the network. A variety of probabilistic route-choice models applying random utility theory has been proposed and used in stochastic network assignment processes.

The probabilistic network assignment model with fixed link travel costs was first formulated by Dial (1971). Dial's method has been widely used as a "loading rule" for probabilistic traffic assignment. Daganzo and Sheffi (1977) introduced the concept of stochastic user equilibrium (SUE), and formulated an SUE assignment model with a probit-based route-choice model. A logit-based SUE model was formulated by Fisk (1980). In addition to simple logit- and probit-based route-choice models, advanced probabilistic models have been developed and used in traffic assignment models within the SUE framework. Asakura et al. (1999b) proposed a NLSUE (nested-logit-based SUE) model, which considers the driver's trip-generating behaviour as well as his route-choice behaviour. Bekhor and Prashker (1999) formulated CNL (cross-nested logit) and PCL (paired combinatorial logit) models, both suitable for studying the problems of overlapping routes in a network.

The route-choice rules used in traffic assignment are designed to be as simple as possible, so that assignment models can be mathematically formulated and systematically calculated for larger networks. Analytical convenience in traffic assignment requires simple route-choice models, such as one that considers travel time as a route-choice variable and then applies the shortest path rule. When several variables are considered, they are combined linearly as a generalised cost function. However, travel cost variables are not always additive in a linear manner. It is over-simplified route-choice assumptions that have led to the criticism that the route models used in traffic assignment do not describe the actual route-choice behaviour of drivers.

Theoretical dynamic traffic assignment models for general networks are incomplete, and have not been implemented for practical use. Network-wide dynamic traffic simulation models are expected to be powerful tools for describing and evaluating flow and the performance of a network. A large number of dynamic network simulation models that include driver's route-choice behaviour have been developed. However, in spite of their detailed descriptions of traffic flow, network traffic simulation models assume overly simple route-choice mechanisms. Either the predetermined shortest path or the minimum travel time path for a time interval is generally employed, and, as with static traffic assignment models, criticism of the assumed choice of route by the drivers in these traffic simulation models may be inevitable.

On the other hand, some theoretical studies have included uncertainty in drivers' route-choice behaviour. Mirchandani and Soroush (1987) formulated a general network equilibrium model that considers the probability distribution of actual link travel costs, as well as the probability distribution of drivers' perceptions. They considered drivers' attitude towards risk in a network. Kobayashi (1994) also focused on the uncertainty of drivers' route-choice behaviour and travel costs. He applied the concept of rational expectation (RE) theory from economics to describe drivers' day-to-day route switching behaviour, under an information provision system. These studies are categorised as risk models of route choice. In contrast with detailed formulations, the size of the networks handled in risk models is limited, often to a network with one OD pair and two links.

The laboratory approach has been used to describe day-to-day perception and behaviour in route choice; Mahmassani and Chang (1986) specified a dynamic route-choice model using behavioural data. Although the experimental approach is useful for obtaining travel data at little cost, the travel environment is very different from real experience. In particular, route choice in a hypothetical network with one OD and two links seems quite unrealistic. Bonsall et al. (1997) developed a route-choice simulator, called VLADIMIR, to obtain behavioural data of drivers 'travelling' in hyperspace using CG (computer graphics) technology. In comparison

with traditional laboratory experiments, computer simulation appears more effective for collecting data on driver's route-choice behaviour, in a more realistic travel environment. However, there are still major differences between simulated and real networks, and the time and space recognition bias of laboratory experiments should be considered when investigating route-choice behaviour.

One important problem is that the route-choice models used in traffic assignment, traffic simulation, and laboratory experiments have not been sufficiently validated in actual transport networks. Furthermore, the cost variables in these models were not examined, perhaps partly because collecting data on drivers' route-choice behaviour in an actual network was not an easy task.

A few studies have observed drivers' route-choice behaviour using travel data for a real network. Itoh et al. (1995) applied a 'stated preference' approach to identify the key variables in drivers' route choices for given choice alternatives. Iwasaki et al. (1995) investigated sequential route switching behaviour in an actual road network. As well as drivers' socio-economic variables, their models considered several variables representing the networks' configuration. The results of the analyses were then used in network simulation models. These experimental studies were restricted by the data collection methods at the time. Recently, mobile communication technology has made it possible to obtain precise travel records for drivers (Asakura et al., 1999a; Murakami and Wegner, 1999). Thus, using ITS technology, it is now possible to study route-choice behaviour using actual route-choice data for individuals.

In addition to these studies, architects and urban planners have investigated pedestrians' route-choice behaviour empirically when designing walkways and passages in residential areas and shopping zones. Watanabe and Mori (1992) reported several studies on pedestrians' route choice. The results of these studies will be considered when we discuss the elements of route recognition and individual way-finding behaviour.

Bovy and Stern (1990) published a book on drivers' route-choice behaviour. They discussed a wide variety of topics related to route choice. In addition to conceptual modelling, the analysis of route-choice behaviour was investigated. One important result of their work was the model proposed, of a hierarchical series of alternative choice sets. They defined a series of alternatives, as shown in Figure 1. Existing opportunities are all of the possible routes between a particular origin and destination in a given network. Known alternatives are the subset of existing alternatives known to the traveller. Available alternatives constitute a subset of the known alternatives that can potentially satisfy the traveller's needs. Feasible alternatives are a subset of the competing available alternatives. The used alternative is the actual route(s) chosen.

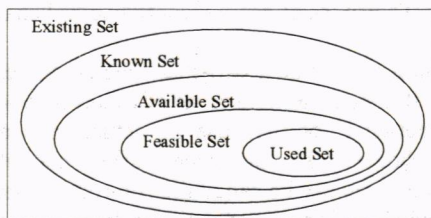


Figure 1. A hierarchical series of choice alternatives (page 46, Bovy and Stern, 1990)

It has not yet been proven that drivers' choice mechanisms are consistent with the hierarchical series of alternatives, and such a detailed order of alternative sets may not be necessary for practical purposes. However, the concept of a hierarchical choice set seems important, and it is useful for describing drivers' route-choice behaviour in an actual network. This process can be divided into at least two stages. The first generates or selects a set of alternative routes from an existing set, which is the full network. The second is the process of choosing one route from the set of alternatives.

This paper proposes a descriptive route-choice model that is potentially applicable for quantitative network analysis, such as in traffic assignment. We introduce the reality of drivers' route-choice behaviour into a simple route-choice model. Using the hierarchical framework of the choice process proposed by Bovy and Stern (1990), we present a two-stage route-choice model. The first stage is the route-selection phase, which generates a set of alternative routes between an origin and a destination. The topological aspects of the road network are considered as variables that are related to route selection. The second stage is the route-choice process. The model was verified using observed drivers' route-choice data in an actual road network in Matsuyama.

2. MODEL FRAMEWORK

2.1 Dynamics of Route Choice

The assumption of a hierarchical series of alternatives does not explain the dynamics of drivers' route-choice behaviour. Assuming that a driver is travelling between a particular origin and destination pair in a network, we can identify the double dynamics of route choice as shown in Figure 2. The outer dynamics are the day-to-day dynamics, and the inner dynamics are the intra-trip dynamics.

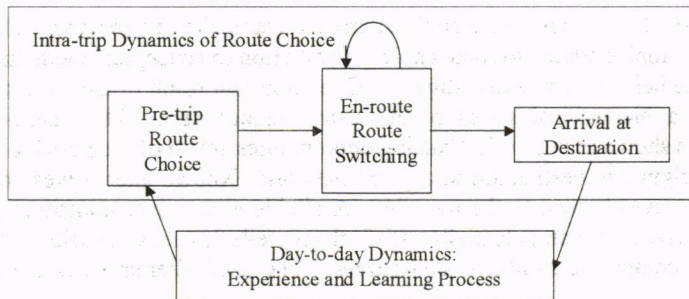


Figure 2. Dynamics of drivers' route-choice behaviour

For network travel, it is natural to assume a two-stage choice process. The first stage is the pre-trip choice of a route. In this stage, a route or set of routes is roughly determined. Drivers choose routes based on experience, or may use an actual road map. The second stage corresponds to the en-route choice of a route, since a driver may change the predetermined route for various reasons. This stage can be called the "en-route switching" or "adaptive route choice" process. En-route switching is repeated until the driver arrives at the destination. The intra-trip dynamics correspond to these dynamics of route choice within one day. Previous experience of a trip may affect behaviour on subsequent days, and day-to-day dynamics are

concerned with such learning processes by drivers. Laboratory experiments and CG simulator-based studies have investigated the characteristics of en-route switching behaviour to formulate simplified models of the day-to-day dynamics of route choice.

In actual networks, however, various factors related to the route-choice process make it difficult to formulate the day-to-day dynamics. Thus, we investigated the pre-trip choice process within a day, and day-to-day dynamics, such as the effect of the learning process on route choice, were not considered in this study. En-route switching was also not considered. Although our model remains a “static” choice model, it could be integrated with a probabilistic assignment process as a “realistic” loading tool.

2.2 Model Framework

We developed a pre-trip route-choice model for drivers using the concept of a hierarchical series of choice sets. As mentioned above, Bovy and Stern (1990) assumed that choice sets are subsumed in the order: existing, known, available, feasible, and used sets. However, it is not easy to distinguish a series of alternatives in such detail. Thus, we assume the simplest hierarchy, which consists of two stages of choice, as shown in Figure 3. The first stage is the route-selection process, in which a set of alternative routes between an OD pair in a network is generated. This corresponds to the process of generating a feasible set from an existing set. The second stage is the route determination process, in which one route is chosen from the set of alternative routes. Random utility theory is applied to give a choice probability to each route in the set of given routes. Variables representing network topology are involved at both the route-selection and route-choice stages. Details of these variables are explained below.

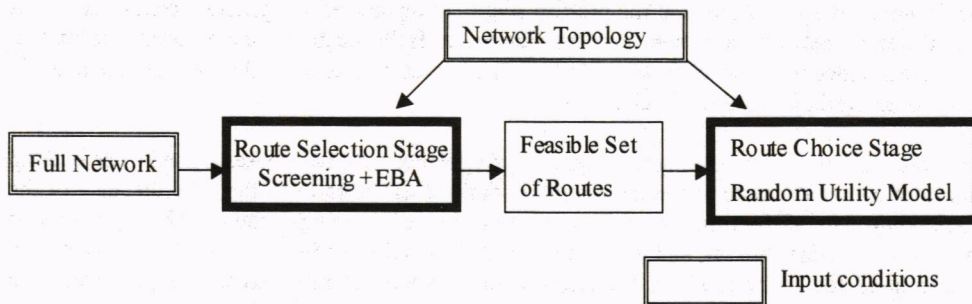


Figure 3. Route selection and choice processes

A two-stage route-choice model framework was implicit in previous traffic assignment route-choice models. Dial (1971) proposed the effective path concept. Dial's algorithm generates a subset of a network from the entire network. A link in the subset satisfies the condition that the path using the link must get closer to the destination. When a path heads back towards the origin, the link is eliminated from the subset. Effective path generation corresponds to the route-selection process. Although Dial's algorithm is popularly used in stochastic assignment, the algorithm may not always be appropriate, since it eliminates too many possible paths. Ben-Akiva et al. (1984) presented a choice-set generation model using a labelling approach. A link impedance function is calculated using travel time, distance, and other quantitative attributes. A path is involved in the choice set when the impedance value for the path satisfies given conditions. The conditions were determined such that the generated path set covered the observed paths of travellers in an actual network. Recently, D'Este (1997)

presented a hybrid route-choice procedure. His algorithm combines the k-th shortest path algorithm and the elimination process. Consequently, a set of paths that can satisfy multiple attributes is generated. D'Este's approach seems attractive, since it is possible to consider multiple path-oriented attributes, which may not always be additive or decomposable into links.

The model used at the route-choice stage in this paper is a traditional logit-type model. Except for including variables representing network topology, the model-formulation process of the route-choice model is familiar. Thus, we will focus on the route-selection process. When formulating the route-selection process in a full network, two points should be considered. One is to avoid enumerating candidate routes, since route enumeration becomes impractical in a large network, and the other is to involve multiple route-choice variables. As well as traditional variables, such as travel time, we considered route-oriented variables representing the topological aspects of the route. Thus, we apply an EBA (elimination by aspects) model in combination with a screening process. The idea is very simple. A candidate route is generated within the complete network. The distance between the OD pair is the principle attribute of the pre-trip route choice. Thus, the k-th shortest path algorithm is applied to find the candidate route. The attributes of the generated route are then examined to determine whether it is acceptable. When one of the attributes of the route is judged unacceptable, the route is eliminated and the next shortest route is generated. In order to avoid enumerating all the routes in a network, an upper limit to travel distance is imposed.

As mentioned above, D'Este (1997) applied the EBA concept to transport network models. He eliminated the nodes and links from an entire network, and constructed a sub network of acceptable nodes and links; the routes in the sub network were allowed to overlap markedly. This feature does not seem appropriate for the pre-trip route-selection process, since the routes should not overlap very much at the pre-trip stage. In this paper, we generate candidate routes from the entire network, and then examine each route. If the attributes of a route are acceptable, the route is added to the set of feasible routes. The degree of overlap of the routes in the feasible set is considered one attribute in elimination.

A simple measure for evaluating the degree of overlap between two routes is used. The overlap ratio of a candidate route to the base route is defined as the ratio of the total distance of the overlapping part of the route to the total route distance of the base route. The base route is contained in the feasible set, and is therefore shorter than the candidate route. The overlap ratio is calculated for every route in the feasible set. When the ratio exceeds a predetermined criterion, the candidate route is considered to overlap at least one route in the feasible set, and is eliminated.

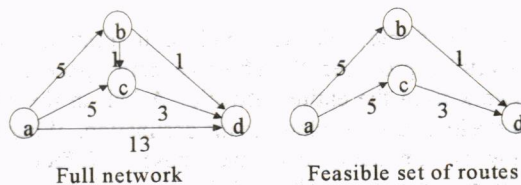


Figure 4. A simple example of route selection

Figure 4 shows an example using EBA plus the screening algorithm. The only attribute used for the EBA is the overlap ratio. When the overlap ratio exceeds a threshold value, we eliminate the route from the feasible set. In this example, we assume the threshold value as $3/5$. The algorithm terminates if a route length becomes sufficiently long. We also assume that the

threshold is twice of the length of the shortest route. The second shortest path (via nodes a, c, and d) does not overlap the shortest path (a, b, d), and it is added to the feasible set. The third shortest path (a, b, c, d) overlaps the first and second routes, with respective overlap ratios of $5/6$ and $3/8$. The maximum ratio $5/6$ exceeds $3/5$ and the third route is eliminated. The distance of the fourth route (a, d) is double that of the shortest path, so the algorithm is terminated.

Tversky (1972) presented the EBA concept for studying the psychological features of the choice mechanism. It is natural to assume that a consumer eliminates an alternative when one of the attributes of the alternative is unacceptable. For example, one does not use a route if the out of pocket cost along the route is extremely high. In other words, the feasible set consists of the alternatives with acceptable attributes. Non-compensatory aspects can be considered in the EBA model, since it is not necessary to compose a compensatory additive function, such as the conventional generalised cost function. The variables that represent network topology are route-oriented and may not always be additive. The values of topological variables cannot be defined unless the route is determined. Furthermore, topological variables cannot always be decomposed into link-based variables. As we mention later, a variable representing the functional hierarchy can be calculated when the complete route is generated. Such variables can be managed within the EBA process, as well as decomposable variables, like distance or travel time.

3. MODEL FORMULATION

3.1 Route-choice data

In 1997, we surveyed the route-choice behaviour of local drivers in the central part of Matsuyama City, population 450,000. A driver joining the survey was requested to drive between a given origin and destination pair. When unfamiliar with their destination, drivers may get lost. Therefore, the OD pairs were designed so that the destinations were very familiar, and the drivers were expected to have visited them. The travel distances were limited to between 2 and 5 kilometres to collect route data effectively. An observer in the vehicle monitored the route taken and travel times along the route during the trip.

Before starting each trip and after arriving at the destination, drivers were asked the questions listed in Table 1. Although the results of actual runs are not used in this paper, the questions for actual runs and en-route switching are also listed in the table. Drivers were only requested to give the names of streets or landmarks along the route, and not asked about the planned or alternative routes in detail before starting the trip, since a driver who has been asked to describe a planned route in detail may become very conscious of their answer and then not drive as they would normally. After arrival at the destination, the details of the planned and alternative routes were confirmed on a map.

We collected 85 sets of pre-trip route-choice data. The GIS-aided network of the central area of Matsuyama City is depicted in Figure 5. The network has 913 nodes and 1,402 links, and the total link length is 177.3 km. Each link was classified into one of four categories of the functional hierarchy of roads. The proportion of links involved in each category was 12.7, 8.0, 27.4, and 51.9% for the highest, second highest, third highest, and lowest hierarchies (Levels 1, 2, 3, and 4), respectively. Each intersection was characterised by its topological configuration. As depicted in Figure 6, eleven shapes of intersection were considered. These were used as one of the attributes of pre-trip route choice.

Table 1. Questions that drivers were asked before and after a trip

| Timing of question | Question |
|--------------------|---|
| Before starting | 1. The number of previous visits to the destination. |
| | 2. The date of the most recent visit to the destination. |
| | 3. The planned route to the destination. |
| | 4. Reasons for the planned route. |
| | 5. The expected travel time to the destination. |
| | 6. Alternative routes to the destination, if any. |
| After arriving | 1. Confirmation of the planned and alternative routes. |
| | 2. Whether route switching occurred. |
| | 3. Reasons for not switching, for those who did not change their route. |
| | 4. Reasons for switching, for those who did change their route. |
| | 5. Planned route after switching, for those who changed their route. |
| | 6. Reasons for the planned route after switching. |

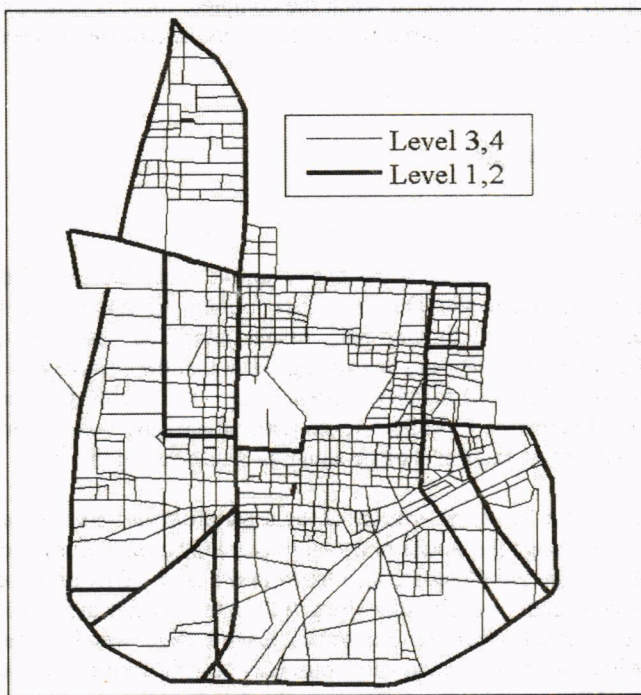


Figure 5. Street network in central Matsuyama City

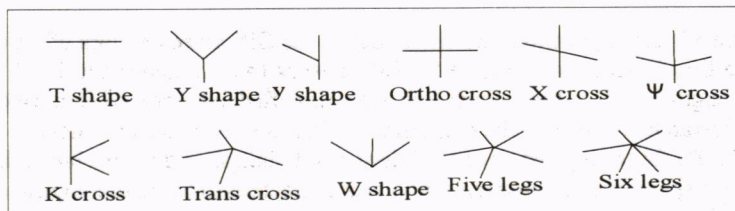


Figure 6. Type of intersection according to shape

Table 2. Reasons for the route chosen before starting a trip

| Item | Details (sample answers) | Number of answers* |
|-------------------------------|--|--------------------|
| 1. Distance | The shortest distance. | 27 (31.8%) |
| 2. Travel time and congestion | Expected travel time seems the shortest. Little traffic. To avoid congestion. | 8 (9.4%) |
| 3. Network topology | Easy to understand. Simple route. Few turns. Wide street. | 31 (36.5%) |
| 4. Others | Experienced and familiar route. Safety. To avoid traffic control. | 29 (34.1%) |
| Total | | 95 |

* Multiple answers, the percentage is calculated for 85 samples.

3.2 Reasons for the Pre-Trip Route Choice

The reasons for the pre-trip route choice are shown in Table 2. These were obtained from question number 4, which asked about the planned route before starting the trip. Distance and travel time were the principle reasons for pre-trip route choices. In addition, the topological conditions of the routes were important in the decision. Drivers prefer easier and simpler routes without many turns; for example, drivers do not use a zigzag route when travelling between a diagonal OD pair in a grid network. The reasoning behind the planned routes suggests that variables representing network topology or the simplicity of a route are involved in the pre-trip route-selection process.

3.3 Variables Representing Network Topology

We evaluated the simplicity of routes from a topological perspective. Various definitions are possible for topological variables in a network. It is generally assumed that the number, variety, and arrangement of components determine simplicity. In other words, a route with a small number of links and nodes is simple. A route is also simple when the attributes of links and nodes are uniform, and links and nodes are connected regularly.

We considered some variables to evaluate the simplicity of a route. One was the number of turns along a route, and another was the functional hierarchy of sections of road, which may affect simplicity. We considered the ratio of the length of higher hierarchy roads to the total route length. The degree of disarrangement of the functional hierarchy of a route was also evaluated by counting the number of irregular changes in the hierarchical levels. Assume that the functional hierarchy of a road section changes as shown in Figure 7.

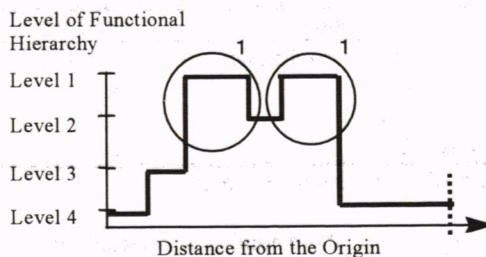


Figure 7. Measuring disarrangement of the functional hierarchy in a route

In order, the route changes from level 4 to level 3 to level 1, down to level 2, back up to level 1, and finally to level 4. Two convexities of hierarchy level can be identified in the diagram. The number of convexities represents the degree of disarrangement, and in this example it is two.

Another variable in measuring the simplicity of a route is the number of intersections of complex-shape along the route. As depicted in Figure 6, eleven types of intersection were identified. The Y-shaped, W-shaped, trans-cross, five-leg, and six-leg intersections were defined as complex intersections.

3.4 Route Selection using the Overlap Ratio

First, we applied a route-choice model using the overlap ratio in the elimination process at the route-selection stage. The k-th shortest paths were generated one after another, and then it was determined whether the overlap ratio of the generated route to the routes in the set of existing routes exceeded 50%. Path generation was repeated until 10 routes were included in the set of routes or the number of the shortest path search reaches 10,000. Consequently, the number of selected routes between OD pairs was from 2 to 10.

The planned and alternative routes were added to the set of selected routes, and a logit-type route-choice model was calculated. The explanatory variables were the distance, number of turns, ratio of higher hierarchy roads, number of convexities (the degree of mixture of functional hierarchy), and number of complex intersections. However, we found that the results of the parameter estimation were not verified, since inappropriate signs for the parameters had been estimated for some of the variables. An elimination process that uses only the overlap ratio may not always remove unrealistic routes, such as a short route with many turns. Furthermore, the route first added to the path set generally remains superior to a route generated later, even if the latter is more realistic.

3.5 Route Selection using Topological Variables

Topological variables representing the simplicity of a route were then considered in the EBA process of selecting a route. The level of acceptability of each variable is determined from the distribution of attribute values for the planned and alternative routes. We examine two levels of acceptability in Table 3. In one, 80% of the routes are satisfactory, and in the other it is 90%. The percentage means the ratio of the cumulative frequency to the total frequency of each variable. When the percentage of a variable is set higher, a route with the higher value of the variable is not eliminated. For example, if we assume 90% value for distance, a route with 1.5 times longer than the shortest route is not eliminated by distance.

Table 3. Acceptable Levels for Attributes in EBA

| Variables | 80% value | 90% value |
|---------------------------------|--------------------------------|--------------------------------|
| Distance | Minimum distance \times 1.33 | Minimum distance \times 1.57 |
| Number of turns | 4 | 5 |
| Number of convexities* | 1.0 | 1.5 |
| Number of complex intersections | 2 | 3 |

* The degree of disarrangement of the functional hierarchy

Figure 8 shows the frequency distribution of the number of selected routes between an OD pair. The average number of selected routes for the OD pair is 16 routes at the 80% level, and 85 routes at 90%. Eighty percent would seem appropriate, in terms of the number of routes

selected, since less routes are selected; however, the number of routes decreases to zero for 6 OD pairs at the 80% level, which means that all of the routes may be eliminated when this criterion is applied. Therefore, 90% is considered an appropriate level of acceptability for elimination.

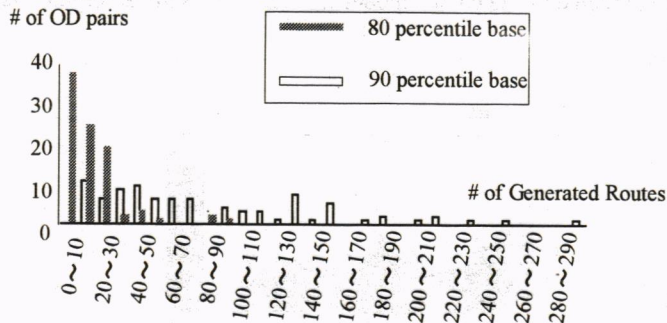


Figure 8. Frequency distribution of the number of routes generated between each OD pair

We then determined whether the set of routes selected included the planned route. Of the 85 OD pairs, 58 included the planned route in the set of selected routes. When a selected route was plotted on the city map, the route was considered sufficiently similar to the planned route when more than 70% of the route overlapped the planned route. When we defined a route with an overlap of 70% or more as a similar route, 71 of the 85 OD pairs included a route similar to the planned route in the set of routes selected. These results seem satisfactory as the output of a route-selection model in an actual network.

3.6 Route Choice for a Given Set

A multinomial logit-type route-choice model was then calibrated for the set of routes selected. The sample data were limited to the 58 OD pairs for which the set of selected routes included the planned route. The results of parameter estimation are shown in Table 4. All of the parameter signs are valid, and the values of the t-statistics are significant, except for the number of complex intersections. The likelihood ratio is sufficiently high. Thus, the model has been validated internally.

Table 4. Estimated parameters of the route-choice model

| Variables | Estimated parameter | t-statistic |
|----------------------------------|---------------------|-------------|
| Distance | -7.477 | -4.98 |
| Number of turns | -0.776 | -4.83 |
| Percentage of higher level roads | 0.059 | 6.61 |
| Number of convexities | -1.759 | -4.24 |
| Number of complex intersections | -0.231 | -0.81 |
| Likelihood ratio: 0.34 | | |
| Proportion of hits: 19/58 | | |

The choice probability of each route was then calculated using the estimated logit function. The routes in a choice set were sorted in order of higher probability. The average rank of a planned route was 10.2 out of 94 routes in a choice set. The route with the highest choice probability was compared with the planned route. Figure 9 depicts the distribution of the overlap ratio of these routes. For 20 of 85 samples, there was perfect (100%) overlap between

the planned route and the route with the highest choice probability. If we assume that an overlap ratio of 70% or more indicates similar routes, the route with the highest choice probability was similar to the planned route in 32 of the 85 samples. The percentage of samples with good fit was 25-40% (20-32 of 85 samples), which is not very high. However, considering that these results were obtained using an actual road network with an extremely large number of alternative routes, the outcome of the choice model was felt to be satisfactory at this trial stage of model application.

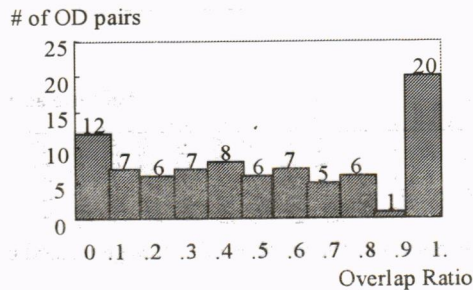


Figure 9. Overlap ratio between the route with the highest choice probability and the planned route

4. CONCLUSIONS

We developed a pre-trip route-choice model and examined its performance using route-choice data for an actual road network. Summarising this model:

- (1) A two-stage route-choice model framework is proposed, based on the previous study by Bovy and Stern (1990). The first stage is the route-selection phase, which generates a set of alternative routes between an origin and destination pair. The second stage is the route-choice process for a given set of routes.
- (2) The screening method used in the route-selection stage uses the EBA (elimination by aspects) procedure originally proposed by D'Este (1997). Instead of a sub network, a set of selected routes is generated such that mutual overlap of routes is avoided where possible.
- (3) Topological aspects of the road network are considered at both the route-selection and route-choice stages. The topological complexity of intersections and changes in the functional hierarchy of links along a route are evaluated and involved in the model.

The model was verified using pre-trip route-choice data for an actual road network in Matsuyama. Using only the overlap ratio of routes in the EBA process was inadequate, so variables representing topological aspects of routes were added to the process. The performance of the model was found satisfactory for an actual network, at both the route-selection and route-choice stages.

We concluded that the model development process and the application test were both successful. However, the proposed model remains at a primitive stage and there is room for improvement. For example, we applied the multiple logit model in the second stage of the model. Even if the

choice set of alternative routes is well-examined in the first stage, the IIA (independent from irrelevant alternatives) property of the logit formulation was not solved. The overloading to the overlapped links still remains in the model though overlapped routes are eliminated in the first stage.

The ultimate goal of this study is to introduce the reality of drivers' route-choice behaviour into a quantitative route-choice model that is also applicable for network traffic assignment. The model developed in this paper could be used in static path-flow-based network assignment algorithms. One possibility is to combine the model with the column generation phase of the simplistic decomposition algorithm (Patriksson, 1994), in which the set of candidate routes is up-dated in the column generation phase, which corresponds to the pre-trip route generation process studied in this paper. The screening method using EBA can be designed so that extremely similar routes are removed. This procedure can be applied to various types of network assignment. Details are now under consideration and will be presented elsewhere.

Another point for discussion is the validation test of the proposed method in actual networks. Although the data used in this paper were collected in an actual route-choice environment, the sample size was small and limited, so the model should be validated with a large number of samples. The variables representing network topology may need to be more sophisticated. In particular, the variable representing the changes in functional hierarchy along a route could be improved.

As shown in the reasons given for route choice, drivers' experience affects pre-trip route-choice behaviour. The route-learning process may be taken into consideration in the model. In addition to theoretical model development, the day-to-day dynamics of route-choice behaviour should be observed in actual networks. It should be possible to apply advanced technology, such as mobile communication devices, to detailed route-choice data collection. The authors are developing a mobile phone-based travel data collection system and expect to use such data to analyse route-choice behaviour.

ACKNOWLEDGEMENTS

The authors would like to express their sincere appreciation to Mr. Kohtaro Munesada and Mr. Yasuhisa Maura, M.Sc., graduates of Ehime University, for their collaboration in data collection and model application. The Ministry of Education provided financial support in the form of Grants-in-Aid for Scientific Research (#10650529 and #12450207).

REFERENCES

- Asakura, Y., Hato, E., Nishibe, Y., Daito, T., Tanabe, J. and Koshima, H. (1999a) Monitoring travel behaviour using PHS-based location-positioning service system. *Proc. the 6th ITS World Congress* in Toronto, in CD-ROM.
- Asakura, Y., Hato E. and Kashiwadani, M. (1999b) Flow model and performability of a road network under degraded conditions. *Transportation and Traffic Theory (Proc. the 14th ISTTT)*, Ceder A. (ed.), Pergamon, pp. 257-282.
- Ben-Akiva, M., Bergman, M.J., Daly, A.J. and Ramasway, R. (1984) Modeling inter-urban route-choice behaviour. *Proc. the 9th ISTTT*, Volmuller, J. and Hamerslag, R. (eds.), VNU Press, pp. 299-330.
- Bekhor, S. and Prashker, J. (1999) Formulations of Extended Logit Stochastic User Equilibrium

- Assignments. *Transportation and Traffic Theory (Proc. the 14th ISTTT)*, Ceder A. (ed.), pp. 351-372.
- Bonsall, P., Firmin, P., Anderson, M., Palmer, I. and Balmforth, P. (1997) Validating the results of a route choice simulator. *Transportation Research C*, Vol. 5, No. 6, pp. 371-387.
- Bovy, P.H.L. and Stern, E. (1990) *Route Choice: Wayfinding in Transport Networks*. Kluwer Academic Publishers.
- Daganzo, C. and Sheffi, Y. (1977) On stochastic models of traffic assignment. *Transportation Science*, Vol. 11, pp. 253-274.
- D'Este, G. (1997) Hybrid Route Choice Procedures in a Transport Network Context. *Journal of EASTS*, Vol. 2, No. 3, pp. 737-752.
- Dial, R.B. (1971) A probabilistic multipath traffic assignment algorithm that obviates path enumeration. *Transportation Research*, Vol. 5, pp. 83-111.
- Fisk, C. (1980) Some developments in equilibrium traffic assignment. *Transportation Research*, Vol. 14B, pp. 243-255.
- Itoh, Y., Ikenoue, K., Yasui, K. (1995) Modelling drivers' route-choice behaviour in an urban area. *Infrastructure Planning Review*, No. 12, pp. 485-491 (in Japanese).
- Iwasaki, N., Kubota, T., Sakamoto, K. and Takahashi, N. (1995) A route-choice model focusing on the possibility of route change at intersections. *Proc. Infrastructure Planning*, No. 18(2), pp. 509-512 (in Japanese).
- Kobayashi, K. (1994) Information, rational expectation and network equilibria. *The Annals of Regional Science*, Vol. 28, pp. 396-393.
- Mahmassani, H.S. and Chang, G. (1986) Experiments with departure time dynamics of urban commuters. *Transportation Research*, Vol. 20B, pp. 297-320.
- Mirchandani, P. and Soroush, H. (1987) Generalized traffic equilibrium with probabilistic travel times and perception. *Transportation Science*, Vol. 21, No. 3, pp. 133-152.
- Murakami, E. and Wagner, D.P. (1999) Can using global positioning system (GPS) improve trip reporting? *Transportation Research C*, Vol. 7, pp. 149-165.
- Patriksson, M. (1994) *The Traffic Assignment Problem: Models and Methods*. VSP, Utrecht.
- Tversky, A. (1972) Elimination by Aspects, a Theory of Choice. *Psychological Review*, 79, pp. 281-299.
- Watanabe, A. and Mori, K. (1992) Route-choice models. *Models and Analytical Methods for Architecture and Urban Planning*. Japan Society of Architects (ed.), pp. 71-84 (in Japanese).