



# Using a weight-assessing model to identify route choice criteria and information effects

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## Abstract

Shortest-path (minimum travel time) routing has been adopted over the past few decades. However, many studies have shown that a driver's route and the shortest path differ widely in significant ways, and that most drivers use several criteria in selecting their routes. Since route choice criteria have been the subject of controversy, this study develops an individual behavioral-based mechanism for exploring the crucial criteria affecting drivers' route-selection decisions. On the basis of the weight-assessing model and the habitual domain theory, this study presents the dynamic change of route choice criteria according to their dynamic weights. Furthermore, the effects of information on drivers' route-formulating behaviors are investigated as well in order to provide some valuable suggestions for implementing Advanced Traveler Information Systems (ATIS) in the future. An empirical study in Taipei City was conducted to show the feasibility and applicability of our proposed method and the empirical results indicate excellent performance in practice. © 2001 Elsevier Science Ltd. All rights reserved.

*Keywords:* Route choice; Criterion; Habitual domain; Weight; Information effect

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## 1. Introduction

Drivers' route choice and switching behavior are, in general, the primary issues in Intelligent Transportation Systems (ITS). Since route choice is the basis of traffic assignment, the results of

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choice have a tremendous effect on the traffic volume in a traffic network. Over the last few decades, the most widely used route-selection criterion has been the minimization of travel time that was proposed by Wardrop (1952). Travel time has played an important role in determining route choice because of its simplicity and linkage with traffic assignment models for generating a static equilibrium. However, under the influence of supplying real-time traffic information, this sole criterion cannot clearly grasp the dynamic changes in drivers' route choice behaviors. Additionally, it is difficult for researchers to understand the effects of information on driving behavior and develop new traffic assignment models. Since fastest-path routing is indeed unrealistic in real life and may not match individual driving behavior, how to explore the crucial determinants of route-selection behavior becomes increasingly important for implementing Advanced Traveler Information Systems (ATIS).

A considerable number of empirical studies on route choice behavior indicated that drivers use numerous criteria in formulating a route. These criteria include travel cost, travel time and its reliability, traffic safety, traffic comfort, roadway characteristics, utility, information supply, drivers' habits, drivers' experience, cognitive limits, socio-economic and demographic characteristics, and other behavioral considerations. However, it is impossible for drivers to consider all route-selection criteria. What criteria does drivers' route choice depend on? In addition, do these criteria have the same degree of importance in different situations? Since drivers often consider distinct criteria in specific situations, maybe we should not assume that the degrees of importance for route choice criteria are not dynamically varying. Should the criterion importance vary in some dynamic way, the question then arises as to how to explore the dynamic changes.

In summary, the traditional route-selection criterion has provoked a great deal of controversy, yet the truly important criteria considered by drivers are still open to question. Therefore, the purpose of this study is to develop an individual behavioral-based mechanism for determining the influential criteria for drivers' route choice decision-making. An empirical study determining commuters' route-selection criteria in Taipei City was conducted to show the applicability of the proposed method.

This paper is organized as follows: the related works about route choice criteria are introduced in Section 2. In Section 3, an analytical procedure for specifying the changes in influential criteria is presented. Furthermore, the solution procedure for assessing dynamic criterion weights through the connectivity network is established. Then, in Section 4, an empirical study of commuters' route choice behavior on intracity trips in Taipei City is undertaken to implement this model. Finally, the conclusions are presented in Section 5.

## **2. Related works on route choice**

Exploring route choice criteria is an important issue for implementing ITS. Numerous attempts have been made in the past to study route choices. Wardrop proposed a criterion for minimizing travel time in 1952. Travel time was considered to be the most important criterion affecting road users' route choices as found by Wachs (1967), Huchingson et al. (1977) and Duffell and Kalombaris (1988). Pursula and Talvitie (1992) studied the urban route choice behavior with multinomial logit models. They assumed that drivers' preferences in determining route choice were based on a minimization of generalized costs. This generalized cost is a combination of travel time and travel costs.

The above route choice models applied to conventional traffic assignment procedures are typically based on a single measure of travel impedance, such as travel time or generalized travel cost. Nevertheless, from a behavioral perspective and based on field observations, drivers do not always select the fastest or cheapest path in the real world. Viewed in this light, some researchers investigated the maximization of the utility for route choice, where the utility function is expressed in terms of several criteria for the alternatives (Pursula and Talvitie, 1992; Adler et al., 1993).

In addition, some observations indicated that road users, for regular trips in familiar areas, preferred to choose their usual route instead of selecting the routes with fewest costs or maximum utility (Bonsall and Parry, 1990; Khattak et al., 1991). Users' usual routes are called "habitual routes." Initially, drivers select their desirable route based on minimum cost, maximum utility or other judgment rules. Then, drivers have formed a circuit pattern (Lindsay and Norman, 1972; Bloom et al., 1985; Carlson, 1986) that represents the travel experience of the selected route. If they continue to choose the same route in their daily trip, the circuit pattern about that route will be reinforced and strengthened and a sense of comfort and familiarity will evolve. The stronger the circuit pattern, the easier it can be retrieved and applied (Carlson, 1986; Yu, 1990). Unless extraordinary events arrive, drivers' route-selection behavior will reach some steady state or may even become fixed. Thus, habitual ways of thinking and acting will be manifested most of the time. This is the formation of habitual routes.

Drivers' experiences also produce variations in route selection (Bonsall and Parry, 1990; Iida et al., 1991; Adler et al., 1993; Yang et al., 1993). Many studies concluded that traffic information and drivers' perception of such information are important criteria affecting commuters' behavior in general and route choice in particular (Fricker and Tsay, 1984; Bonsall and Parry, 1990; Bonsall and Joint, 1991; Caplice and Mahmassani, 1992; Adler et al., 1993; Chen and Mahmassani, 1993; Janssen and van-der-Horst, 1993; Khattak et al., 1993; Mahmassani and Shen-Te-Chen, 1993; Uchida et al., 1994).

In fact, the above criteria may exist simultaneously in drivers' minds, but only the criteria with high activation possibilities tend to have significant effects upon drivers' route choice decision process. That is, if a criterion enjoys a strong possibility, it will have a prominent representation in route changing. Thus, the importance of each criterion (i.e., criterion weight) is the key to controlling whether the criterion occurs or not. Note that when the weight of travel time is equal to 1 and other criterion weights are all equal to 0, travel time is the sole criterion (i.e., minimizing travel time), and this is also the route choice criterion proposed by Wardrop (1952). If we can specify the changes in criterion weights, the salient criteria affecting route formulation will correspondingly be found.

On the other hand, in order to draw some useful suggestions for implementing ATIS, this paper investigates as well how information affects drivers' route choice behavior and we explore drivers' responses when faced with an external information stimulus.

### **3. Analytical model for weight-assessing**

Since we intend to use weights to present the changes in route choice criteria, we must focus our efforts on weight-assessing methods. In the following, we illustrate a new method proposed by the authors (Tzeng et al., 1998).

### 3.1. Overview

Trade-offs between criteria significantly influence the decision-making process for route choice. These trade-offs can be computed in terms of the relative ratio of their importance, which can be presented in a “weight” form. From the behavioral viewpoint, the influential factors determining the weight of a criterion include: the difference between the ideal and actual values of the criterion (i.e., level of charge), the diversification and intensification of other ideas which can activate the criterion (i.e., connectivity), the duration of the criterion belonging to the core of habitual domains (i.e., the input frequency of information stimuli), the driver’s personality and social-economic attributes, the intrinsic value of the weight, and the interaction among other criteria. In summary: criterion weights are variable in different situations, including input information, time, learning process, environment, etc. Therefore, it is not easy to clearly delineate the absolute weightings for decision-making criteria.

Most traditional weighting methods (Hwang and Yoon, 1981), such as the eigen-vector method, weighted least-squares method, entropy method, and utility function method, consider only the “interaction among other criteria” and forego consideration of the other factors. Moreover, these methods are based on static analysis, and their results usually reflect only people’s intuition or perception at that time. Even if some newly developed techniques for assessing dynamic weights (Zhang et al., 1992; Saaty, 1980, 1994; Hashiyama et al., 1995) exist, most of them do not take all influential factors into consideration.

On the other hand, the authors’ model treats decision-making as a dynamically adjusting process from the ideal state to the actual state, allowing us to realize the dynamic change of weights depending on different situations. The authors considered simultaneously the influential factors discussed above and utilized the concept of habitual domains, which was proposed by Yu in 1980. Next, we introduce the concept of connectivity and use the connectivities between criteria to establish the network structure.

### 3.2. Establishment of connectivity network

When drivers begin their trips, their first problem is how to choose their routes. For the route choice problem, denoted by  $E$ , there exists a set of goal functions to be achieved for a satisfactory solution. Goal functions can be measured by a collection of elementary criteria,  $\{x_1, x_2, x_3, \dots, x_n\}$ . Let the collection of all elementary criteria be the discussion universe,  $X$ , for the route choice problem  $E$ . For instance, the possible objectives which drivers consider during the route choice process include the minimal travel cost, the fastest driving speed, optimal safety and comfort, the fewest risks, the most familiar route, and the least number of (left) turns and stops. Thus, the discussion universe  $X = \{\text{travel time, delay, driving speed, degree of safety, degree of comfort, degree of risk, familiarity with the route, number of turns, number of stops}\}$ .

Yu (1990) summarized people’s memory and thought processes according to four basic hypotheses. One of them is the analogy and association hypothesis, that is, our brain interprets incoming information using analogy and association with the existing memory. There is a pre-existing code or memory structure that can potentially alter or aid in interpreting an arriving symbol or event. Of course, the premise of this interpretation is that a relationship between the arriving symbol and the pre-existing code must be established. This relation-formulation process

is called analogy and association. Furthermore, the grade of relationship can be measured by a connectivity function (Tzeng et al., 1998).

Let  $(x_i, x_j)$  be an arc that joins criteria  $x_i$  and  $x_j$  (starting from  $x_i$  and arriving at  $x_j$ ). A function  $C_t(x_i, x_j)$  defined on  $X \times X$  at time  $t$  is called a connectivity function on  $X$  if it satisfies the following axioms:

- (i)  $C_t(x_i, x_j) \in [0, 1]$ ;
- (ii)  $C_t(x_i, x_i) = 1 \forall x_i \in X$  (reflexivity).

Because the learning process is usually directed (i.e., the connectivity from  $x_i$  to  $x_j$  is not equal to the connectivity from  $x_j$  to  $x_i$ ),  $C_t$  is not necessarily a symmetric connectivity function. Then, we use the discussion universe  $X$  and the connectivity function  $C_t(x_i, x_j)$  to set up a connectivity network,  $G$ .  $G$  is a fuzzy directed graph (i.e., digraph)  $G(X, C_t)$  consisting of a finite set  $X = \{x_1, x_2, x_3, \dots, x_n\}$  and a fuzzy relation  $C_t$  on  $X$  at time  $t$ .

In order to facilitate our discussion, let us consider the following example. Suppose that a person’s route-selection criteria include travel time ( $x_1$ ), delay ( $x_2$ ), comfort ( $x_3$ ), and familiarity ( $x_4$ ). Thus,  $X = \{x_1, x_2, x_3, x_4\}$ . The connectivity from one criterion to another is given by Table 1. For instance,  $C_t(x_2, x_1) = 0.9$  means the connectivity from  $x_2$  to  $x_1$  at time  $t$  (or stage  $t$ ) is 0.9.

The above information can be more vividly expressed as in Fig. 1. Note that in Fig. 1, the number on each directed arc represents the connectivity starting from a criterion and arriving at another one. Additionally, the dotted lines indicate that it is practically impossible to arrive the column criteria from corresponding row criteria (as in Table 1). Since any criterion is absolutely reachable from itself (i.e., reflexible),  $C_t(x_i, x_i) = 1$ . Observe that this illustration performs a directed graph; that is,  $C_t(x_i, x_j)$  is not necessarily equal to  $C_t(x_j, x_i)$ .

Since the connectivity is measured by a fuzzy relation, we use the max–min operator to calculate the actual degree of connectivity between two criteria. Fig. 1 shows that connecting  $x_2$  from  $x_4$  and  $x_1$  ( $\min[C_t(x_4, x_1), C_t(x_1, x_2)] = \min(0.7, 0.8) = 0.7$ ) is easier than connecting that from  $x_4$  directly ( $C_t(x_4, x_2) = 0.4$ ). Moreover, although there is no arc connecting  $x_3$  directly from  $x_4$ , we can still use the sequence of “starting  $x_4$ , then  $x_2$ , and then  $x_3$ ” to form the directed path.  $x_2$  can be considered as a mediator or intermediate node (Li and Yu, 1994). As mentioned above, we must transfer all connectivities in the original network to “connectivity index,” which is calculated by the max–min composition rule.

Let  $k$  be the length of a path. Let  $C_t^k(x_i, x_j)$  be the maximum connectivity level so that there is a path of length  $k$  starting from  $x_i$  and arriving at  $x_j$ . The connectivity  $C_t^k$ ,  $k \geq 2$  is calculated using the max–min composition rule:

$$C_t^2(x_i, x_j) = \max_{x \in X} \min[C_t(x_i, x), C_t(x, x_j)], \tag{1}$$

Table 1  
Connectivity matrix of the illustration

$C_t(x_i, x_j)$	$x_1$ (travel time)	$x_2$ (delay)	$x_3$ (comfort)	$x_4$ (familiarity)
$x_1$ (travel time)	1	0.8	0.1	0.3
$x_2$ (delay)	0.9	1	0.2	0
$x_3$ (comfort)	0	0	1	0
$x_4$ (familiarity)	0.7	0.4	0	1

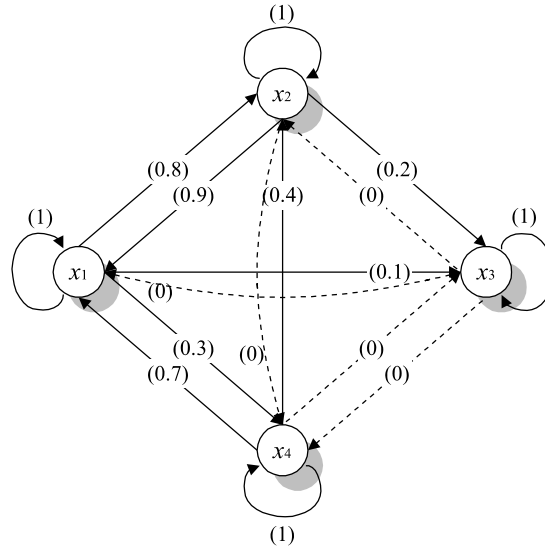


Fig. 1. Connectivity network of the illustration.

$$C_t^k(x_i, x_j) = \max_{x \in X} \min[C_t^{k-1}(x_i, x), C_t(x, x_j)] \quad (3 \leq k \leq n), \tag{2}$$

where  $n$  is the number of criteria in  $G$ .

$C_t^*(x_i, x_j)$  is the maximum level, such that  $x_j$  is reachable from  $x_i$ . We call the connectivity  $C_t^*$  on  $X$  as a connectivity index. The connectivity index is calculated from  $C_t^k$ ,  $k = 1, 2, 3, \dots, n$ , as described in the following proposition:

$$C_t^*(x_i, x_j) = \max\{C_t(x_i, x_j), C_t^2(x_i, x_j), \dots, C_t^k(x_i, x_j), \dots, C_t^n(x_i, x_j)\}. \tag{3}$$

Furthermore, the connectivity index  $C_t^*$  is also given by

$$C_t^*(x_i, x_j) = \max\{\min\{C_t(v, y) \mid (v, y) \in \text{Path}(x_i, x_j)\} \mid \text{Path}(x_i, x_j)\}, \tag{4}$$

where  $\text{Path}(x_i, x_j)$  is a path in  $G$  from  $x_i$  to  $x_j$ .

For instance, in our illustration there are two paths from  $x_1$  to  $x_2$ , as follows:

- (i) When  $k = 1$ ,  $x_1 \xrightarrow{c_t=0.8} x_2$  and  $C_t^1(x_1, x_2) = 0.8$ ;
- (ii) When  $k = 2$ ,  $x_1 \xrightarrow{c_t=0.3} x_4 \xrightarrow{c_t=0.4} x_2$  and  $C_t^2(x_1, x_2) = 0.3$ .

Thus,  $C_t^*(x_1, x_2) = \max\{C_t^1(x_1, x_2), C_t^2(x_1, x_2)\} = 0.8$ .

Similarly, there are three paths from  $x_1$  to  $x_3$ , as follows:

- (i) When  $k = 1$ ,  $x_1 \xrightarrow{c_t=0.1} x_3$  and  $C_t^1(x_1, x_3) = 0.1$ ;
- (ii) When  $k = 2$ ,  $x_1 \xrightarrow{c_t=0.8} x_2 \xrightarrow{c_t=0.2} x_3$  and  $C_t^2(x_1, x_3) = 0.2$ ;
- (iii) When  $k = 3$ ,  $x_1 \xrightarrow{c_t=0.3} x_4 \xrightarrow{c_t=0.4} x_2 \xrightarrow{c_t=0.2} x_3$  and  $C_t^3(x_1, x_3) = 0.2$ .

Table 2  
Connectivity index of the illustration

$C_t^*(x_i, x_j)$	$x_1$ (travel time)	$x_2$ (delay)	$x_3$ (comfort)	$x_4$ (familiarity)
$x_1$ (travel time)	1	0.8	<b>0.2</b>	0.3
$x_2$ (delay)	0.9	1	0.2	<b>0.3</b>
$x_3$ (comfort)	0	0	1	0
$x_4$ (familiarity)	0.7	<b>0.7</b>	<b>0.2</b>	1

Thus,  $C_t^*(x_1, x_3) = \max\{C_t^1(x_1, x_3), C_t^2(x_1, x_3), C_t^3(x_1, x_3)\} = 0.2$ . According to the max–min composition rule, we can acquire the matrix of the connectivity indexes as shown in Table 2.

The bold-type number in Table 2 exhibits the difference between the connectivity index and the connectivity in Table 1. These differences occur in the paths from  $x_1$  to  $x_3$ , from  $x_2$  to  $x_4$ , from  $x_4$  to  $x_2$ , and from  $x_4$  to  $x_3$ .

- (i) The connectivity index from  $x_1$  to  $x_3$  is 0.2, and the practical paths include  $x_1 \rightarrow x_2 \rightarrow x_3$  and  $x_1 \rightarrow x_4 \rightarrow x_2 \rightarrow x_3$ .
- (ii) The connectivity index from  $x_2$  to  $x_4$  is 0.3. The practical path is  $x_2 \rightarrow x_1 \rightarrow x_4$ .
- (iii) The connectivity index from  $x_4$  to  $x_2$  is 0.7. The practical path is  $x_4 \rightarrow x_1 \rightarrow x_2$ .
- (iv) The connectivity index from  $x_4$  to  $x_3$  is 0.2, and the practical paths include  $x_4 \rightarrow x_2 \rightarrow x_3$  and  $x_4 \rightarrow x_1 \rightarrow x_2 \rightarrow x_3$ .

We revised Fig. 1 according to the matrix of connectivity indexes, as presented in Fig. 2. Note that in Fig. 1, it is practically impossible to connect  $x_4$  from  $x_2$  and connect  $x_3$  from  $x_4$  directly. However, through analogy and association,  $x_4$  is reachable from  $x_2$  and  $x_3$  is reachable from  $x_4$ , as shown in Fig. 2.

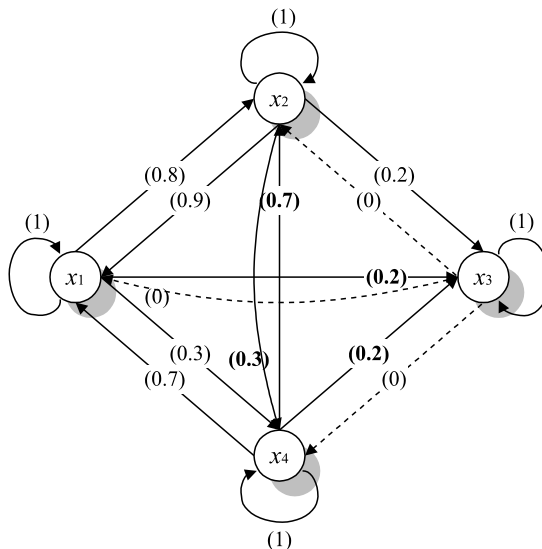


Fig. 2. Revised connectivity network of the illustration.

### 3.3. Formation of generalized current domain

This section describes the formation process of the actual domain and its neighborhood when an information stimulus occurs. Note that each information stimulus is related to a set of goal functions. A goal function can be measured by finite criteria,  $\{x_1, x_2, x_3, \dots, x_n\}$ . There is an ideal state to reach and maintain for each goal function, and this process is called goal setting (Yu, 1980, 1990). The ideal values of the criteria are denoted by  $\mathbf{q}^* = \{q_1^*, q_2^*, q_3^*, \dots, q_n^*\}$ . For the external information stimuli, drivers continuously investigate, measure and attempt to detect any current deviations from their ideal goal states. This process is called state evaluation. The actual values of the criteria are denoted by  $\mathbf{q} = \{q_1, q_2, q_3, \dots, q_n\}$ .

When there is an unfavorable deviation of the perceived value from the ideal, each goal function will produce a corresponding level of charge. The totality of the charge by all goal functions is called the charge structure. The charge structure often changes dynamically since, at any point in time, people's attention will be drawn to the event that has the greatest influence on the charge structure. The difference between the ideal and actual values of each criterion is calculated by  $\|\mathbf{q}^* - \mathbf{q}\|$ . The level of charge, denoted by  $Q_i$ , of  $x_i$ , is measured by the difference between the ideal and actual values:

$$Q_i = \|q_i^* - q_i\| \quad \forall i \in [1, n], \quad (5)$$

where  $\|\cdot\|$  is a meaning norm such that  $0 \leq Q_i \leq 1$  for all  $x_i \in X$ .

Given an external information stimulus  $S_t$  at time  $t$  of the route choice problem  $E$ , we assume that the arriving stimulus can be broken down into several elementary criteria belonging to  $X$ ; that is,  $S_t \subseteq X$ . The corresponding level of charge for each criterion  $x_i$  is denoted by  $Q_i$ . For  $\alpha \in [0, 1]$ , the  $\alpha$ -core of  $S_t$  at time  $t$ , denoted by  $S_t^\alpha$ , is defined as the collection of criteria that can be activated with a level of charge larger than or equal to  $\alpha$ . That is,

$$S_t^\alpha = \{x_i \in S_t \cap X \mid Q_i \geq \alpha\}. \quad (6)$$

$S_t^\alpha$  is the actual domain in a narrow sense at the time  $t$  concerned with an external stimulus  $S_t$ , where the actual domain is a collection of ideas or operators that are actually activated (Yu, 1991).

Taking  $n = 4$  for example, Fig. 3 shows a connectivity network with four criteria ( $X = \{x_1, x_2, x_3, x_4\}$ ) and 12 connectivities. We indicated a low weight by drawing a circle with a thin line. Similarly, a high weight is indicated by a thick line. In this illustration, we assume that the initial weights of all criteria are the same. In addition, the thick arrow represents a strong connection between criteria, and a thin line means a weak connection. We also assumed that the initial connectivity indexes are the same.

When an external information stimulus  $S_t$  arrives at time  $t$ , the criteria that can be activated include  $x_1$  and  $x_2$  since their corresponding levels of charge are larger than the  $\alpha$  value. Thus, the actual domain in a narrow sense at time  $t$ ,  $S_t^\alpha$ , is  $\{x_1, x_2\}$ , as shown in Fig. 4.

Before illustrating the actual domain in a broad sense and the reachable domain, we define the connectivity from the existing domain to a particular criterion. The function,  $\mathcal{C}_t$ , is called a connectivity function of criteria with subsets of  $X$  at time  $t$  if it satisfies the following axioms:

- (i)  $\mathcal{C}_t \geq 0$  (non-negativity);
- (ii)  $\mathcal{C}_t(A_j, x_i) = 1 \quad \forall x_i \in A_j$ ;
- (iii)  $\mathcal{C}_t(A_j, x_i) \leq \mathcal{C}_t(A_k, x_i) \quad \forall x_i \in X$ ; if  $A_j \subseteq A_k$  (monotonicity).



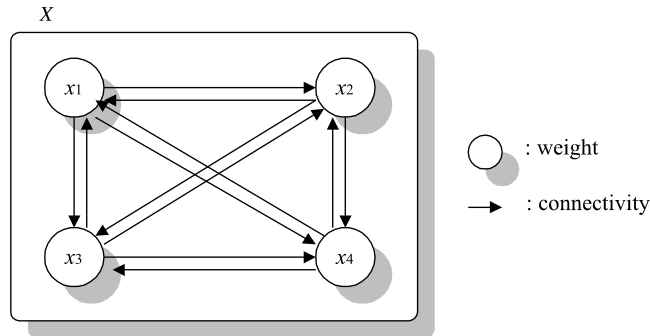


Fig. 3. Initial connectivity network of the illustration.

In the relationship between the connectivity function of a criterion to a criterion and that of a domain to a criterion, the latter can be considered an extension of the former. As mentioned before,  $S_t^\alpha$  is the existing domain which represents a criterion set activated by an external stimulus at time  $t$  for the problem  $E$ . Then, we denote  $\mathcal{C}_t(S_t^\alpha, x_i)$  as the connectivity of a criterion  $x_i$  with the existing domain  $S_t^\alpha$ . When there is no confusion, we treat a connectivity function of criteria with the actual domain as a connectivity function.

According to the analogy and association hypothesis, new things are more easily learned if they are similar to some things that are already known. Additionally, frequently repeated events have a stronger influence on analogy and association. However, those events which pre-exist in weak codes and are stored in remote areas of the brain, will have little impact on the analogy and association process. Thus, we must specify the influential domain from the pre-existing memory through external information stimuli. We restrict the neighborhood of the actual domain in the narrow sense to be the reachable domain, where the reachable domain is a collection of ideas or operators that can be generated from the original idea set and the original operator set (Yu, 1991). To determine the neighborhood of the actual domain in this case, we facilitate our discussion using the connectivity of criteria with the existing domain.

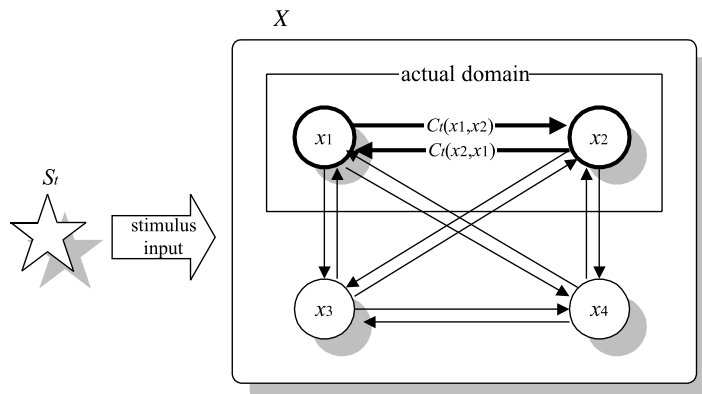


Fig. 4. Formation of the actual domain in a narrow sense.

Given a connectivity network  $G(X, C_t)$  and an external information stimulus  $S_t$  at time  $t$ , the  $\alpha$ -core of  $S_t$  is denoted by  $S_t^\alpha$  and  $\mathcal{C}_t$  is a connectivity function of the criteria with the existing domain. Let  $2^X$  denote the collection of all non-empty subsets of  $X$ . The  $\varepsilon$ -neighborhood of  $S_t^\alpha$  for  $S_t^\alpha \in 2^X$  is defined by  $N_t(S_t^\alpha, \varepsilon)$

$$N_t(S_t^\alpha, \varepsilon) = \{x_j \in X \setminus S_t^\alpha \mid \exists x_i \in S_t^\alpha, \ni \mathcal{C}_t(S_t^\alpha, x_j) \geq \varepsilon\} \quad \forall S_t^\alpha \in 2^X. \tag{7}$$

$S_t^\alpha$  can be considered as the actual domain that contains the set of criteria that are actually activated. Moreover,  $N_t(S_t^\alpha, \varepsilon)$  represents the reachable domain that contains the collection of criteria that are reachable from the existing domain through external information stimuli. Therefore,  $S_t^\alpha \cup N_t(S_t^\alpha, \varepsilon)$  is the actual domain in a broad sense, and we call it the “generalized current domain.”

Continuing our illustration with  $n = 4$ , the formation of the  $\varepsilon$ -neighborhood of the actual domain is presented in Fig. 5. Assume that the connectivity from  $x_2$  to  $x_3$  is stronger than the threshold  $\varepsilon$ . Thus,  $x_3$  has a close connection with the actual domain,  $S_t^\alpha$ , and lies within its  $\varepsilon$ -neighborhood. Thus,  $N_t(S_t^\alpha, \varepsilon) = \{x_3\}$ .

Since  $S_t^\alpha = \{x_1, x_2\}$  and  $N_t(S_t^\alpha, \varepsilon) = \{x_3\}$ , the generalized current domain  $S_t^\alpha \cup N_t(S_t^\alpha, \varepsilon) = \{x_1, x_2, x_3\}$ , as shown in Fig. 6. When external stimuli are repeated, the corresponding circuit patterns will be reinforced and strengthened. Furthermore, the stronger the circuit patterns become, the more easily the corresponding circuit patterns are retrieved in the learning processes. Therefore, it seems reasonable to assume that the connection between a pair of criteria in the actual domain and its  $\varepsilon$ -neighborhood will be reinforced as the learning process progresses. In other words, the connectivity between pairs of criteria in the generalized current domain will increase. Hence, the connectivity function  $C_t$  must be updated after each learning iteration. It can be observed that the connectivities between criteria in  $S_t^\alpha \cup N_t(S_t^\alpha, \varepsilon)$  will be reinforced, including  $C_t(x_1, x_2)$ ,  $C_t(x_2, x_1)$ ,  $C_t(x_2, x_3)$ ,  $C_t(x_3, x_2)$ ,  $C_t(x_1, x_3)$ , and  $C_t(x_3, x_1)$ .

The uncertainty that arises from drivers’ thought processes and the randomness associated with experiments is often confusing. Some of the data obtained in this manner are hybrid; that is, their components are not homogeneous but rather a blend of precise and fuzzy information

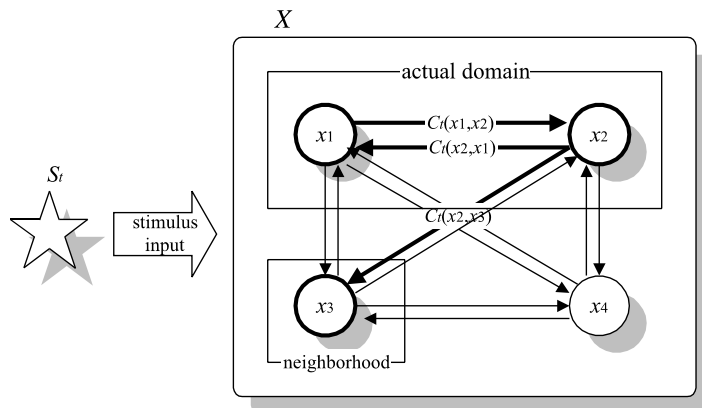


Fig. 5. Formation of the  $\varepsilon$ -neighborhood of the actual domain.

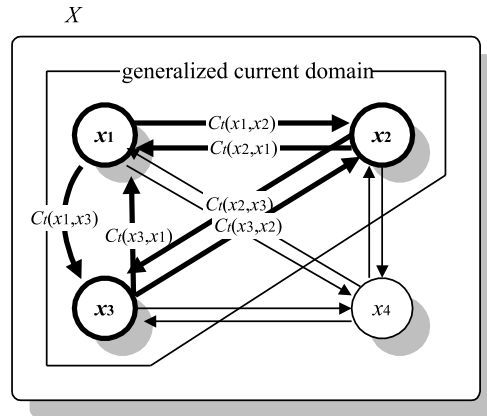


Fig. 6. Formation of the generalized current domain.

(Kaufmann and Gupta, 1991). To simplify matters, we suppose that  $C_t(x_i, x_j)$  is a continuous random variable, uniformly distributed within the interval  $[(\bar{C}(x_i, x_j))^{1/\beta}, (\bar{C}(x_i, x_j))^\beta]$ , where  $\bar{C}(x_i, x_j)$  is the mean of  $C_t(x_i, x_j)$ .  $\beta$  is called the determinate index and its value is in the unit interval  $[0, 1]$ .  $\beta$  characterizes the degree of certainty since the higher the  $\beta$  value, the less change is performed by the connectivity function. Let  $u(0, 1)$  represent a continuous random variable that is uniformly distributed over the interval  $[0, 1]$ . Then we can write

$$C_t(x_i, x_j) = (\bar{C}(x_i, x_j))^{1/\beta} + [(\bar{C}(x_i, x_j))^\beta - (\bar{C}(x_i, x_j))^{1/\beta}] \cdot u(0, 1). \tag{8}$$

To reflect the fact that the connectivity between each pair of criteria is enhanced through the learning processes, we define an index parameter  $I_t(x_i, x_j)$  for each pair  $(x_i, x_j)$  belonging to  $X$  at time  $t$  and a concentration parameter  $\delta$ . The initial values of  $I$  for pairs of criteria are set to zero. If  $x_i$  is activated when  $x_j$  is presented to the input stimuli, the value of  $I$  increases by 1.  $\delta$  represents the change size of the definition domain, and  $0 < \delta < 1$ . Thus, the connectivity function is derived within the adjustment interval  $[(\bar{C}(x_i, x_j) + I_t(x_i, x_j)\delta)^{1/\beta}, (\bar{C}(x_i, x_j) + I_t(x_i, x_j)\delta)^\beta]$  and now  $C_t(x_i, x_j)$  is given by

$$C_t(x_i, x_j) = \min \left\{ 1, (\bar{C}(x_i, x_j) + I_t(x_i, x_j)\delta)^{1/\beta} + [(\bar{C}(x_i, x_j) + I_t(x_i, x_j)\delta)^\beta - (\bar{C}(x_i, x_j) + I_t(x_i, x_j)\delta)^{1/\beta}] \cdot u(0, 1) \right\} \tag{9}$$

To avoid the condition where the connectivity exceeds 1, we use a “min” operator. That is, we use the index parameter,  $I$ , and the concentration parameter,  $\delta$ , to indicate the reinforcement change of circuit patterns.

### 3.4. Weight-assessing procedure

In this section, we propose the weight-assessing procedure according to the connectivity network. The weight-assessing method is based on competitive learning (Grossberg, 1969; Kohonen, 1989). In competitive learning, the output ideas of the network compete among themselves to be

active. Competitive learning begins with a random arrangement of weights and gives all output ideas a chance to compete. It also limits the strength of the weights. Let  $w_i(x_i)$  be the weight of the criterion  $x_i$  from the input information stimulus  $S_t$ . The weights are limited to values between 0 and 1; that is,  $w_i(x_i) \geq 0$  for each  $x_i$ . In addition,  $\sum_{i=1}^n w_i(x_i) = 1$ .

The authors' weight-assessing method performs a generalized winner-take-all competition. That is, the criteria in the generalized current domain are chosen as the winners during the learning process. This is different from the conventional concept of winner-take-all because there is not necessarily only one criterion in the winner group when the competition is completed.

Let  $S_t^z$  denote the actual domain of all winning criteria, and its  $\varepsilon$ -neighborhood be  $N_t(S_t^z, \varepsilon)$ . The output signals of the generalized current domain are set to be equal to one. The output signals of all of the criteria that lose the competition are set to be equal to zero. The output signal is also called the index parameter  $I_t$ . We use the winning set and its neighborhood to update the weights of the network. In the following, we will use a simplified illustration to explain the process of our weight-assessing method.

Fig. 7 is an example that illustrates the weight-updating procedure. For simplicity, we do not show the connectivity links between criteria in the measurable space ( $X$ ). Assume that  $X = \{x_1, x_2, x_3, \dots, x_8\}$ . Suppose that each external information includes only one stimulus in each stage. When the first information stimulus is input,  $S_1^z = \{x_5, x_6\}$  and  $N_1(S_1^z, \varepsilon) = \{x_7\}$ . Thus, the output signals of  $\{x_5, x_6, x_7\}$  are set to be equal to one (i.e., on), and the output signals of other criteria are set to be equal to zero (i.e., off). Correspondingly, the criterion weights of the winning set,  $\{x_5, x_6, x_7\}$  will increase, but the weights of other criteria will decrease. Repeat the above procedure until there are no more information stimuli to be input. At the last stage, we observe that criterion  $x_6$  enjoys the highest weight, the next is  $x_7$ .

A new weight vector can be formed according to a linear combination of the old weight vector and the current input vector. Weight corrections are accumulated over an entire epoch of training patterns (i.e., batch updating). The learning rule of the weight correction is as follows:

$$w_{t+1}(x_i) = w_t(x_i) + \Delta w_t(x_i). \tag{10}$$

We define the adjustment factor  $\varpi_i$  for each criterion  $x_i$  through the level of charge and the connectivity function. For each  $x_i \in N_t(S_t^z, \varepsilon)$ ,  $x_k$  is the precedent criterion of  $x_i$  so that

$$C_t^*(x_k, x_i) = \max \{C_t^*(x_j, x_i) | x_j \in S_t^z\}.$$

The level of charge of  $x_k$  is denoted by  $Q_k$ . The adjustment factor  $\varpi_i$  is computed by

$$\varpi_i = \begin{cases} Q_i & \text{if } x_i \in S_t^z, \\ Q_k \cdot \mathcal{C}_t(S_t^z, x_i) & \text{if } x_i \in N_t(S_t^z, \varepsilon), \\ 0, & \text{o.w.} \end{cases} \tag{11}$$

Assume that the input stimulus contains a set of  $p$  vectors. Let  $\overline{\varpi}_i$  be the average of all  $\varpi_i$ 's during the particular learning iteration; then  $\overline{\varpi}_i$  is

$$\overline{\varpi}_i = \sum_p \varpi_i / p. \tag{12}$$

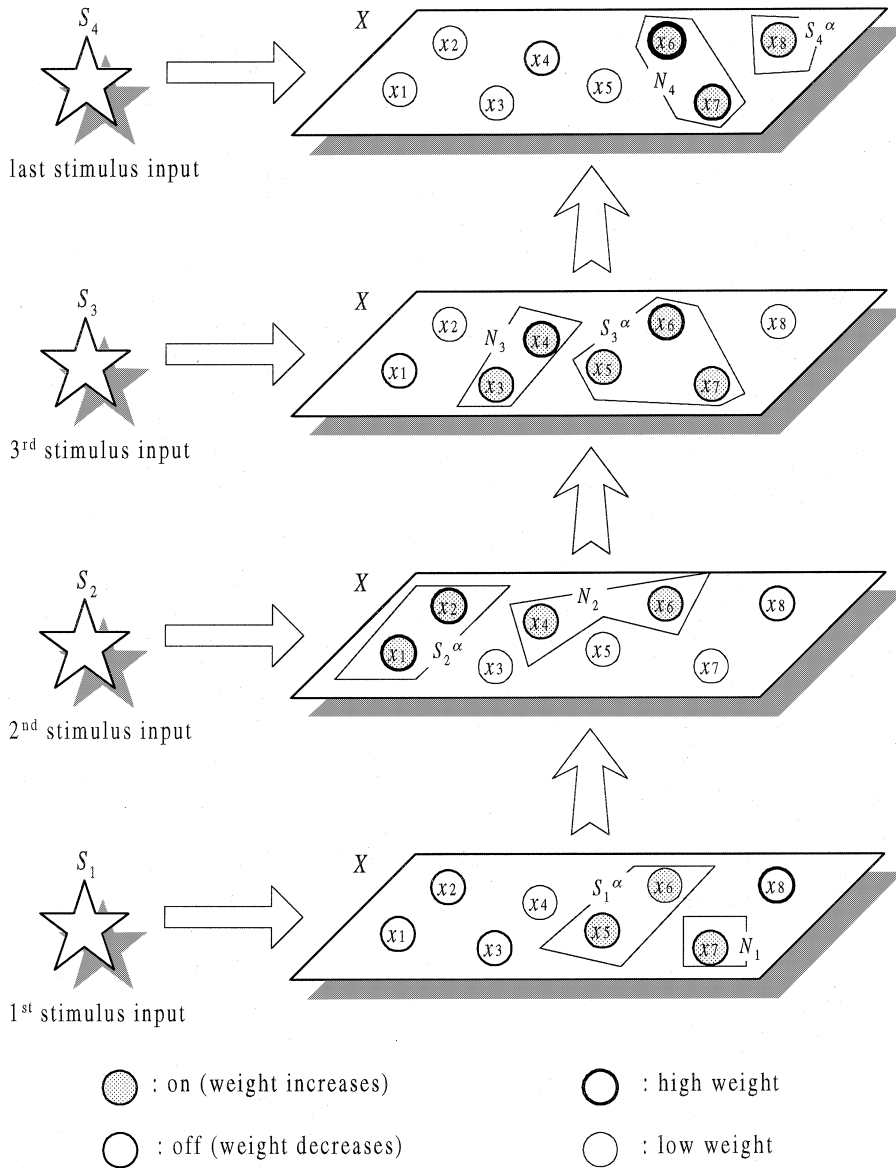


Fig. 7. Simplified illustration of weight assessment.

Using the average adjustment factor, we can obtain the change  $\Delta w_t(x_i)$

$$\Delta w_t(x_i) = \tau_t \times \left[ \left( \frac{\bar{w}_i}{\sum_j \bar{w}_j} \right) - w_t(x_i) \right], \quad (13)$$

where  $\tau_t$  is the learning-rate parameter and its value is chosen by users. Note that the values of  $\tau_t$ 's must be between 0 and 1.

Fig. 8 shows the solution procedure for assessing dynamic weights. We first initialize or survey weights for all of the criteria belonging to  $X$ . Under a situation in which the stopping condition is not satisfied, the connectivity of each criterion with the existing domain is computed for each stimulus vector. Then we can specify the actual domain in the narrow sense and its  $\varepsilon$ -neighborhood. The collection of the actual domain and the neighborhood is the generalized current domain. The connectivities between the criteria within the generalized current domain should be updated until all stimulus vectors have been input. After batch learning, compute the adjustment value for each criterion. Thus, the weights for all criteria within  $X$  can be derived.

According to the procedure indicated in this figure, the authors proposed the algorithm for solving dynamic weights as shown in the previous study (Tzeng et al., 1998). Thus, we omit the

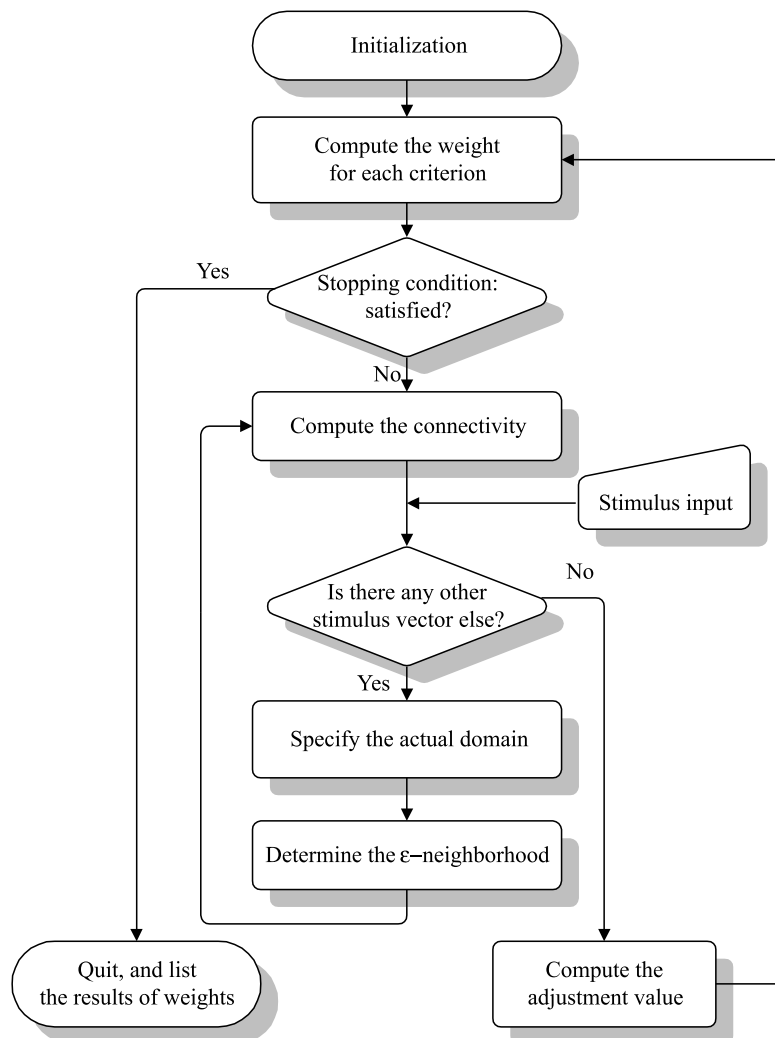


Fig. 8. Solution procedure of dynamic weights.

algorithm in this paper. To show the applicability of the weight-assessing model in the route choice problem, we applied the proposed method to the following empirical case in Taipei City.

#### 4. Empirical study

The purpose of our empirical study was to determine the influential criteria of commuters' route choice in Taipei City. Two-stage questionnaire surveys were conducted to commuters and the empirical results can be used to show the feasibility and applicability of the proposed model.

##### 4.1. Questionnaire design and investigation

When we intend to apply the weight-assessing model, the required input data primarily include the initial criterion weights, the ideal and actual values for each criterion, and the connectivities between criteria. Since it is troublesome to specify the ideal values of all criteria, we decided to adopt a tolerance value for each criterion instead of an ideal value. Therefore, in this study the difference between the tolerance and actual values for each criterion can be used to identify the level of charge.

To design the input information stimuli for each respondent, we conducted two-stage questionnaire investigations. In the first stage, we acquired the initial weights, the tolerance and current values of all criteria, and the connectivities. Then we used the current criterion value of each person to generate the required scenarios for the second-stage questionnaire. Thus, we could observe the effects of these input information stimuli.

##### 4.1.1. First-stage questionnaire

In the first-stage questionnaire, respondents' socio-economic and demographic characteristics include gender, age, marital status, education level, profession, and average monthly income. We determined nine influential criteria related to route choice according to the relevant studies. These criteria include:

- (i) travel time ( $x_1$ ), this refers to the average travel time from the origin (home) to the destination (work location);
- (ii) travel time reliability ( $x_2$ ), this demonstrates the variability of the average travel time;
- (iii) travel expense ( $x_3$ ), this includes the recharging cost, the parking expense, etc.;
- (iv) travel distance ( $x_4$ ), this refers to the total trip length from the origin to the destination;
- (v) drivers' habits ( $x_5$ ), this is used to determine whether habitual routes exist or not;
- (vi) traffic condition ( $x_6$ ), this refers to the traffic volume, directness, number of intersections, traffic signals, driving speed, and other traffic-related factors;
- (vii) traffic safety ( $x_7$ ), this refers to the degree of safety during driving;
- (viii) traffic comfort ( $x_8$ ), this refers to the degree of comfort during driving, and it can reflect indirectly roadway characteristics;
- (ix) drivers' familiarity ( $x_9$ ), this refers to drivers' familiarity with a particular route.

In general, the evaluation criteria must be independent of each other if the traditional analysis methods are used. However, the nine criteria selected by this study are more or less dependent; that is, they are interactive. The interrelation between criteria can be well captured by the connectivity matrix. Thus, even if the nine criteria are not independent of each other, the weight-assessing method can still be applied to identify the importance of route choice criteria.

In summary, we investigated the initial weights, the tolerance and actual values of all nine criteria, as well as the connectivity matrix considered by commuters during their usual route-selection process. Connectivity means the degree of ease from one criterion to another by analogy and association. The mean value of the connectivity  $C(x_i, x_j)$  for all respondents will be denoted as  $\bar{C}(x_i, x_j)$ ; then the connectivity network can be constructed correspondingly. On the other hand, the measurements of criteria  $x_2$ ,  $x_6$ ,  $x_7$ ,  $x_8$ , and  $x_9$  are subjectively judged by respondents on a five-point scale. For example: the tolerance and actual values of traffic comfort are labeled as “very uncomfortable”, “uncomfortable”, “fair”, “comfortable”, and “very comfortable”. As for other criteria, since they are quantitative and crisp, respondents only gave the true value.

The population was the commuters who use private vehicles as their primary mode for intracity trips within Taipei City. A total of 100 questionnaires were sent out and 93 valid copies retrieved. Then the second-stage survey was subsequently conducted. Since we wished to implement experimental design with each respondent, the same persons were interviewed in this stage.

#### *4.1.2. Second-stage questionnaire*

Because ATIS is not available in Taiwan, we used fictitious situations consisting of various scenarios instead of true traffic information. According to the actual values of the criteria obtained in the first-stage survey, we designed the virtual information provided by ATIS person-by-person for the second-stage questionnaire. Then we investigated the criterion weights considered by respondents in the various scenarios. It follows that these scenarios were viewed as the actual criterion values during the learning process of the connectivity network.

In general, there are four types of traveler information in ATIS, including incident information, en-route guidance, pre-trip guidance, and congestion information. For simplicity, we combined en-route and pre-trip guidance as guidance information. First, in our experiment we assumed that the criteria related to congestion information were travel time ( $x_1$ ), travel expense ( $x_3$ ), and traffic condition ( $x_6$ ). Next the criteria related to the incident information included travel time reliability ( $x_2$ ), traffic safety ( $x_7$ ), and traffic comfort ( $x_8$ ). Last, the criteria related to the route guidance information were travel distance ( $x_4$ ), drivers' habits ( $x_5$ ), and drivers' familiarity ( $x_9$ ). In addition, these three information stimuli were classified into six levels: worse-than-current situation amount to 10%, 30%, and 50%; and better-than-current situation amount to 10%, 30% and 50%. We summarized the experimental scenarios in Table 3. There are 18 scenarios in our experiment from Table 3. In the second-stage survey, respondents filled in the criterion weights concerning each scenario.

As mentioned before, we already obtained from the first-stage investigation the tolerance values of nine criteria based on respondents' commuting experiences. Then the tolerance values were compared to the actual values for each scenario to find out what criteria might create a change to the charge structure of drivers. Last, we tested the fitness of our proposed model through a comparison between the predicted weight values and the actual weights as elicited from respondents in the second-stage survey.



Table 3  
Experimental scenarios for the route choice problem

Level	Congestion information	Incident information	Guidance information
Worse scenario High (50%)	<i>Scenario 1</i>	<i>Scenario 7</i>	<i>Scenario 13</i>
	Travel time: +50%	Reliability: –50%	Travel distance: +50%
	Travel expense: +50%	Traffic safety: –50%	Drivers' habits: –50%
Medium (30%)	<i>Scenario 2</i>	<i>Scenario 8</i>	<i>Scenario 14</i>
	Travel time: +30%	Reliability: –30%	Travel distance: +30%
	Travel expense: +30%	Traffic safety: –30%	Drivers' habits: –30%
Low (10%)	<i>Scenario 3</i>	<i>Scenario 9</i>	<i>Scenario 15</i>
	Travel time: +10%	Reliability: –10%	Travel distance: +10%
	Travel expense: +10%	Traffic safety: –10%	Drivers' habits: –10%
Better scenario Low (10%)	<i>Scenario 4</i>	<i>Scenario 10</i>	<i>Scenario 16</i>
	Travel time: –10%	Reliability: +10%	Travel distance: –10%
	Travel expense: –10%	Traffic safety: +10%	Drivers' habits: +10%
Medium (30%)	<i>Scenario 5</i>	<i>Scenario 11</i>	<i>Scenario 17</i>
	Travel time: –30%	Reliability: +30%	Travel distance: –30%
	Travel expense: –30%	Traffic safety: +30%	Drivers' habits: +30%
High (50%)	<i>Scenario 6</i>	<i>Scenario 12</i>	<i>Scenario 18</i>
	Travel time: –50%	Reliability: +50%	Travel distance: –50%
	Travel expense: –50%	Traffic safety: +50%	Drivers' habits: +50%
	Traffic condition: –50%	Traffic comfort: +50%	Familiarity: +50%

#### 4.2. Empirical results for commuters

The statistics of respondents' socio-demographic characteristics are as follows: male respondents comprise 90.3% of the samples, while females comprise 9.7% of the samples; the age group with the highest proportion was 34.4% 40–49 years old, followed by 30–39 years old (28.0%) and 50–59 years old (20.4%). 30.1% of the respondents were unmarried. Most respondents have received high school (49.5%) or college (37.6%) education. The largest proportion of occupations was public servant, followed by service and commercial sectors. Average monthly incomes ranged between 45,000–60,000 NT dollars (26.9%) and 30,000–45,000 NT dollars (20.4%).

The average travel time of respondents, calculated as the difference between the home departure time and the work arrival time, was found to be 32.8 min, with 65.6% of the samples having commuting time of 30 min or less. The average travel expense of respondents was 192.5 NT dollars per trip. The average travel distance for the samples was 13.1 km, and 55.9% of the samples had commuting distance of 10 km or less. Most respondents (80.6%) traveled their habitual routes five or six days a week. 92.5% of the subjects were familiar with their usual routes.

In terms of the current information used by respondents, 80.6% of the samples stated that they listened to traffic reports while en-route and 40.9% indicated that they listened to traffic reports before leaving home. Thus, en-route information was more frequently received by respondents than pre-trip information. Furthermore, 65.6% of the samples were confident of the reliability of traffic information. Even if current traffic information is limited in Taiwan, according to our survey results many drivers still used such information. This finding shows that a great market exists for traffic information and bright prospects for ATIS can be postulated for the future.

Our study intends to establish an individual behavioral-based analytical model for route choice criteria. Hence, we conducted a learning process for the connectivity network person-by-person. The input data included the initial weight of all criteria ( $W$ ), the connectivity matrix of all criteria ( $\bar{C}$ ), the tolerable values for criteria ( $\mathbf{q}^*$ ), and the actual values of the criteria for each input information stimulus ( $\mathbf{q}$ ). It is noteworthy that this data were input for each respondent individually. Suppose the learning rate (geometric decrease) is  $\tau_{t+1} = 0.5\tau_t$ , where  $\tau_0 = 0.6$ . Set the concentration parameter  $\delta = 0.0002$ , the determinate index  $\beta = 0.5$ , and the threshold parameter  $\alpha = 0.6$ . Additionally, suppose the threshold value for an  $\varepsilon$ -neighborhood of  $S_t^z$  is  $\varepsilon = 0.7$ . For the detailed computing procedure, refer to the study of Tzeng et al. (1998).

We obtained the mean values of  $\bar{C}$  for all respondents through the first-stage questionnaire survey as shown in Table 4.

Table 4 indicates the connectivities between criteria of the total samples, and the connectivity stands for the degree of difficulty of being connected from criterion I to criterion II by analogy and association. The connectivity from travel time to traffic condition ranks the highest (0.925), followed by connectivity from traffic condition to travel time (0.860), from travel time reliability to traffic condition (0.849), from traffic safety to traffic condition (0.839), and from drivers' familiarity to drivers' habits (0.839). On the other hand, those of lower connectivity are from the association of drivers' habits to travel expense (0.237), from travel expense to drivers' habits (0.258), from drivers' habits to traffic comfort (0.301), and from traffic comfort to drivers' familiarity (0.301).

Table 4  
Mean values of  $\bar{C}$  in the first-stage survey result

I	II								
	$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$	$x_8$	$x_9$
	Travel time	Time reliability	Travel expense	Travel distance	Drivers' habits	Traffic condition	Traffic safety	Traffic comfort	Drivers' familiarity
$x_1$	<b>1.000</b>	0.559	0.376	0.817	0.430	<b>0.925</b>	0.538	0.516	0.613
$x_2$	0.505	<b>1.000</b>	0.355	0.419	0.366	0.849	0.355	0.398	0.581
$x_3$	0.602	0.387	<b>1.000</b>	0.323	0.258	0.559	0.344	0.548	0.516
$x_4$	0.806	0.634	0.731	<b>1.000</b>	0.581	0.677	0.495	0.441	0.591
$x_5$	0.323	0.462	<b>0.237</b>	0.484	<b>1.000</b>	0.527	0.624	0.301	0.828
$x_6$	0.860	0.828	0.527	0.495	0.441	<b>1.000</b>	0.645	0.570	0.355
$x_7$	0.473	0.419	0.441	0.591	0.613	0.839	<b>1.000</b>	0.602	0.710
$x_8$	0.452	0.344	0.516	0.559	0.452	0.796	0.634	<b>1.000</b>	0.301
$x_9$	0.731	0.645	0.473	0.667	0.839	0.591	0.699	0.559	<b>1.000</b>
Avg.	0.594	0.535	0.457	0.544	0.498	<b>0.720</b>	0.542	0.492	0.562

The average connectivity stands for the degree of difficulty of the specific criterion being associated with other criteria, that is, the degree of ease of other criteria that can activate the specific criterion. From Table 4, we know that traffic condition enjoys the highest average connectivity (0.720); thus, it can be easily activated by other criteria.

The initial weight  $w_i(x_i)$  of each criterion  $x_i$  for all respondents was obtained through the first stage survey, as listed in the following table. Note that  $\sum_{i=1}^9 w_i(x_i) = 1$ . Among the nine influential criteria, the most important criterion is travel time ( $x_1$ ) and its weight is 0.1312; the second is traffic condition ( $x_6$ ) with weight 0.1279. The criterion of least importance is drivers' habits ( $x_5$ ) and its weight is 0.0814; the next is travel distance ( $x_4$ ) with weight 0.0824.

	$x_1$	$x_2$	$x_3$	$x_4$	$x_5$	$x_6$	$x_7$	$x_8$	$x_9$
$W$	<b>0.1312</b>	0.1265	0.1191	0.0824	0.0814	0.1279	0.1252	0.0939	0.1124

According to our design procedure, respondents filled in the criterion weights regarding 18 experimental scenarios in the second-stage survey. After a pre-test, we learned that this was highly infeasible and difficult in practice. Thus, for simplicity we randomly assigned 12 scenarios to respondents. In other words, respondents were required to answer the weights regarding only 12 scenarios.

In order to judge the performance of the weight-assessing results, we used the average error sum of squares between the predicted values and the investigated data of criterion weights under experimental scenarios. Let  $\hat{w}_i^j(x_i)$  and  $w_i^j(x_i)$ , respectively represent the actual value (obtained by second-stage investigation) and the predicted value of the weight by subject  $j$  regarding criterion  $x_i$ . Let  $\mathbb{N}$  be the total number of drivers interviewed (regarding the particular scenario). The average error sum of squares,  $Z$ , for each experimental scenario is defined as

$$Z = \sqrt{\frac{\sum_{x_i \in X} \sum_{j=1}^N [w_i^j(x_i) - \hat{w}_i^j(x_i)]^2}{9 \cdot \mathbb{N}}}. \tag{14}$$

We list the average error sum of squares for weight-assessing results in Table 5. From the table we know that the range of  $Z$  values is [0.0008, 0.0042]. This means that the maximal difference of the estimated and actual values is approximately 5% of the investigated value (0.0042–0.0814  $\cong$  0.05). Thus, the estimated results of criterion weights are very close to the actual data, indicating excellent performance by using the weight-assessing model to solve dynamic weights for route choice criteria.

Fig. 9 shows a comparison of the criterion weights under different scenarios of congestion information. According to our experimental design, the criteria related to congestion information are travel time ( $x_1$ ), travel expense ( $x_3$ ), and traffic condition ( $x_6$ ). Thus, as we expected, the weights of  $x_1$ ,  $x_3$ , and  $x_6$  increase in Scenarios 1–3 under the influence of congestion information. It should be noted that the weights of travel time and traffic condition display rapid growth in Scenarios 1 and 2. The possible reason for this phenomenon is that the original weights for travel time and traffic condition are larger than travel expense. Moreover, the average connectivities of travel time and traffic condition are greater than travel expense, indicating that the degree of ease of travel time and traffic condition activated by other criteria are higher than of travel expense. In

Table 5  
Average error sum of squares ( $Z$ ) for weight-assessing results

Information	Level					
	Worse scenario			Better scenario		
	High (50%)	Medium (30%)	Low (10%)	Low (10%)	Medium (30%)	High (50%)
Congestion information	Scenario 1 0.0011	Scenario 2 0.0013	Scenario 3 0.0008	Scenario 4 0.0010	Scenario 5 0.0015	Scenario 6 0.0012
Incident information	Scenario 7 0.0017	Scenario 8 0.0021	Scenario 9 0.0018	Scenario 10 0.0012	Scenario 11 0.0010	Scenario 12 0.0009
Guidance information	Scenario 13 0.0019	Scenario 14 0.0023	Scenario 15 0.0042	Scenario 16 0.0008	Scenario 17 0.0013	Scenario 18 0.0016

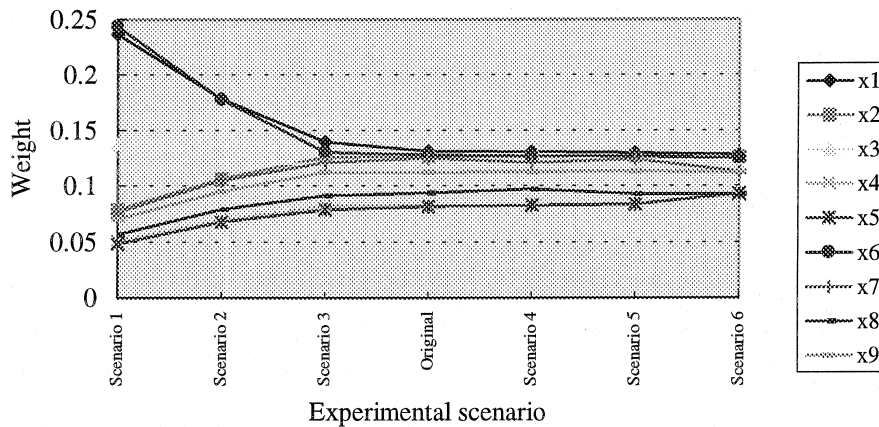


Fig. 9. Comparison of criterion weights under the different scenarios for congestion information.

contrast, the weights of these three criteria do not have the obvious change in the better experimental levels such as Scenarios 4–6.

On the other hand, the weights of other criteria except  $x_1$ ,  $x_3$ , and  $x_6$  are decreasing in Scenarios 1–3 because of the high weight values of  $x_1$ ,  $x_3$ , and  $x_6$ . In addition, the weights of these criteria have only little change in Scenarios 4–6.

From Fig. 9, we know that light traffic information (e.g., Scenarios 4–6) produces a marginal effect on the weight patterns of all criteria. This implies that the criterion weights are not sensitive to traffic improvement information. Furthermore, in Scenario 6 the criteria can be divided into two groups according to their weights:  $x_1$ ,  $x_2$ ,  $x_3$ ,  $x_6$ ,  $x_7$ , and  $x_9$  ( $w_i(x_i) \geq 0.1$ ); and  $x_4$ ,  $x_5$ , and  $x_8$  ( $w_i(x_i) < 0.1$ ). On the contrary, the sensitivity of the criterion weights is very apparent in Scenarios 1–3.

In brief, the congestion information has a prominent effect on the criterion weights only in those scenarios worse than the current situation (Scenarios 1–3). It is difficult to change the weights through the release of traffic congestion, since the weight patterns are stable in Scenarios

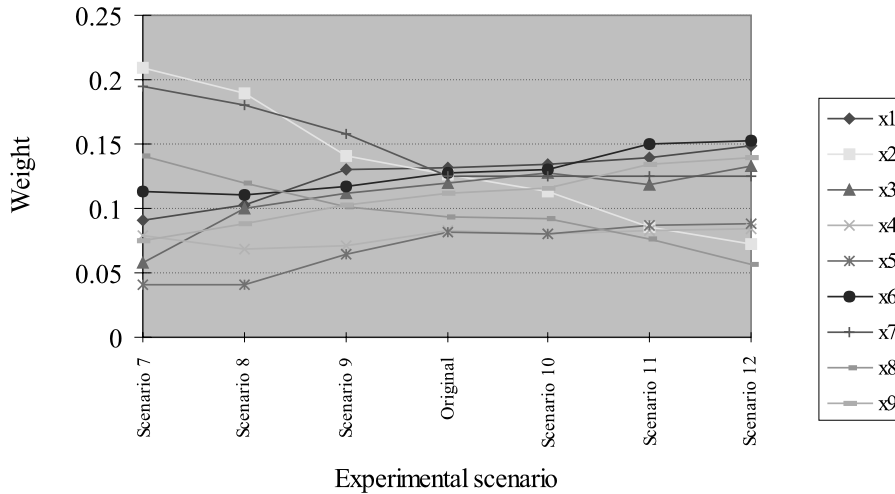


Fig. 10. Comparison of criterion weights under the different scenarios for incident information.

4–6. Thus, the effective influential range of congestion information falls in the level of worse 10–50%.

The dynamic weights of criteria in the different scenarios of incident information are presented in Fig. 10. The weights of the criteria related to incident information ( $x_2$ ,  $x_7$ , and  $x_8$ ) diminish as the scenario condition becomes better. As for the other criteria, the criterion weights increase slowly in the better scenarios except for travel distance ( $x_4$ ). The main cause of this special case is that the influential factors of criterion weights include not only the difference between the ideal (tolerance) and actual values but also the connectivity, random term, and other potential factors.

After the incident rate reduces to Scenario 12, all criteria can be classified into two groups based on the weight values, including  $x_1$ ,  $x_3$ ,  $x_6$ ,  $x_7$ , and  $x_9$  ( $w_i(x_i) \geq 0.1$ ); and  $x_2$ ,  $x_4$ ,  $x_5$ , and  $x_8$  ( $w_i(x_i) < 0.1$ ). We should notice that the criterion weights present the dynamic change in different scenarios, and they do not seem to show a stable tendency. Hence, the influential range is large regarding incident information on drivers' route choice behavior. Furthermore, any incident information may produce an effect on criterion weights.

Fig. 11 depicts the criterion weights under the different scenarios for guidance information. The weights of travel distance ( $x_4$ ), drivers' habits ( $x_5$ ), and drivers' familiarity ( $x_9$ ) related to guidance information decrease from Scenarios 13 to 18. It is not necessary for other criteria to tend to increase in the better scenarios. For example, the weight of traffic safety ( $x_7$ ) is maximal in Scenario 15 among all experimental scenarios.

The criteria of  $x_1$ ,  $x_2$ ,  $x_3$ ,  $x_6$ , and  $x_7$  can be grouped into the same class in Scenario 18 ( $w_i(x_i) \geq 0.12$ ). Moreover, the weights of these criteria show little change in Scenarios 16–18. On the other hand, the weights of  $x_4$ ,  $x_5$ ,  $x_8$ , and  $x_9$  show an obvious change in Scenarios 16, 17, and 18. Thus, we can infer that the route guidance information significantly affects the weights of  $x_4$ ,  $x_5$ ,  $x_8$ , and  $x_9$  in the better scenarios.

Fig. 12 shows the weight comparison for travel time ( $x_1$ ) under all experimental scenarios. Among 19 scenarios (including the original situation), only the weight in Scenario 7 is smaller

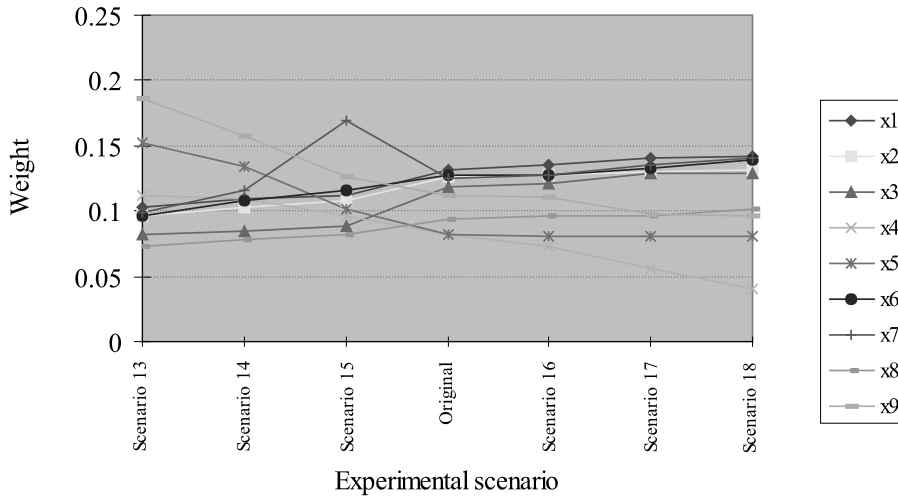


Fig. 11. Comparison of criterion weights under the different scenarios for guidance information.

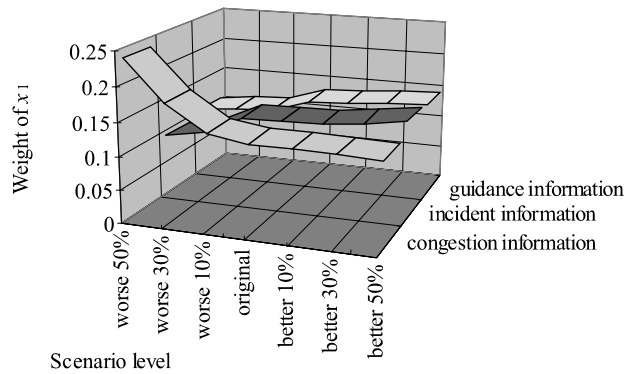


Fig. 12. Weight comparison of travel time ( $x_1$ ) under the experimental scenarios.

than 0.1; thus, the weights for travel time are high on average. On the other hand, the weight of travel time increases in the better scenarios of incident and guidance information. Consequently, we know that drivers attach importance to travel time without incidents or with better route-guidance messages. Finally, the maximum of the weight value is as high as 0.2367 in Scenario 1. In addition, even in the better situations of congestion information (e.g., Scenarios 4–6) the weight does not decrease very much. Thus, drivers are still concerned about travel time even when there are no traffic jams.

The weight comparison of travel time reliability ( $x_2$ ) under all scenarios is indicated in Fig. 13. Since incident information will produce uncertainty in travel time, the weight of travel time reliability has a drastic change from Scenarios 7 to 12. In addition, the weight decreases in the worse scenarios of congestion and guidance information, and stabilizes in the better scenarios.

The weights for travel expense ( $x_3$ ) do not have marked changes, as shown in Fig. 14. Thus, the importance of travel expense considered by drivers does not show great variation in different

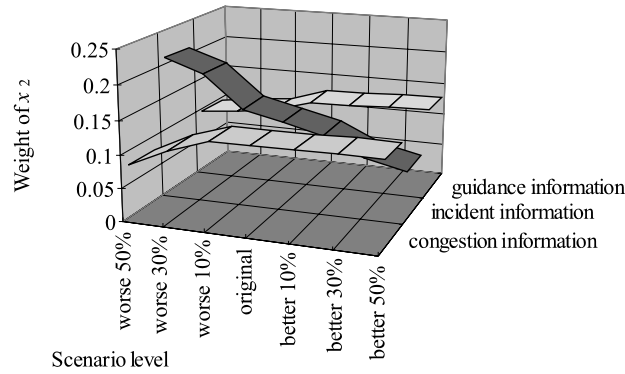


Fig. 13. Weight comparison of travel time reliability ( $x_2$ ) under the experimental scenarios.

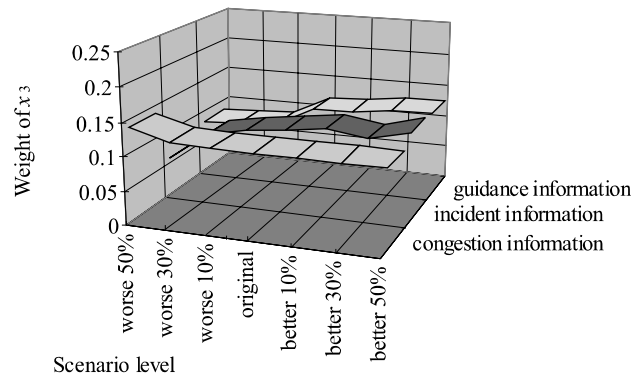


Fig. 14. Weight comparison of travel expense ( $x_3$ ) under the experimental scenarios.

scenarios. The main cause of unvarying importance may include a low sensitivity to travel expense. Additionally, drivers, except for Scenario 1, do not think the different scenarios have different influences on travel expense. Moreover, since the proportion of the parking expense is obviously larger than the recharging cost for many respondents, the saving of recharging costs (resulting from external information) is not critical. Thus, the weight change in travel expense among different scenarios is not clearly apparent.

Fig. 15 indicates that the weights for travel distance ( $x_4$ ) do not significantly vary with the experimental scenarios of congestion and incident information. On the other hand, the weights for travel distance decrease from Scenarios 13 to 18 for guidance information. Unlike  $x_1$ ,  $x_2$ , and  $x_3$ , the weights of  $x_4$  are larger than 0.1 only in two scenarios. Thus, travel distance acquires low importance on average.

From Fig. 16, we know that the weight values for drivers’ habits ( $x_5$ ) are low level under congestion and incident information. Especially, the weights in Scenarios 1, 7, and 8 are smaller than 0.05. It is noted that the weights show a substantial increase in Scenarios 15, 14, and 13 ( $w_i(x_5) > 0.1$ ). Thus, when guidance information significantly deviates from drivers’ habits, more attention will be given

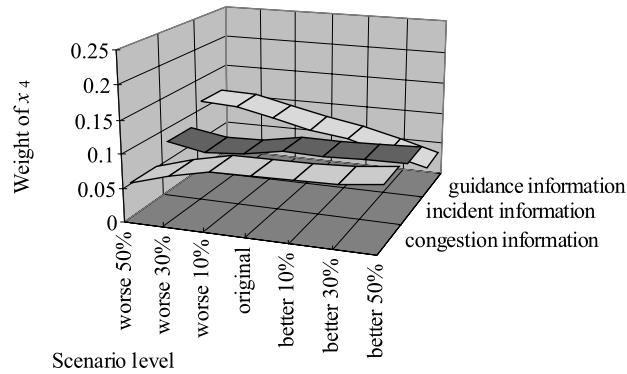


Fig. 15. Weight comparison of travel distance ( $x_4$ ) under the experimental scenarios.

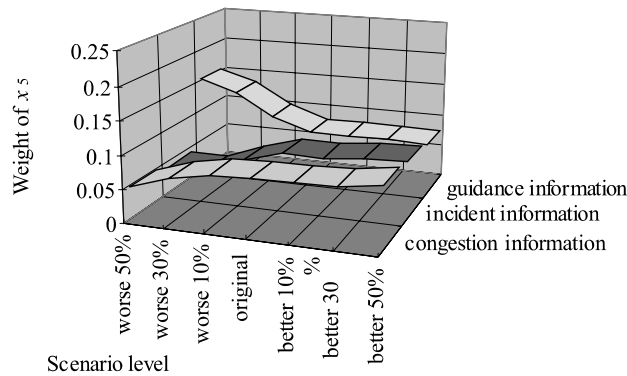


Fig. 16. Weight comparison of drivers' habits ( $x_5$ ) under the experimental scenarios.

to this criterion  $x_5$ . In addition, the weights of drivers' habits make no difference in the better scenarios (from the original to better 50%), and the values are about 0.08.

The weights of traffic condition ( $x_6$ ) in all scenarios are very high, as indicated in Fig. 17. For example: the weights in Scenarios 1 and 2 are, respectively, 0.2435 and 0.1776. Except for Scenario 13, the weights in all scenarios are greater than 0.1. The weights of traffic condition do not obviously decrease even in the better scenarios for congestion information. Furthermore, the importance of traffic condition enhances gradually without the influence of incidents. Finally, the weight patterns are similar under incident and guidance information.

Fig. 18 shows the weight comparison for traffic safety ( $x_7$ ) under the experimental scenarios. Incident information has a great effect on traffic safety, especially in the worse case situations (i.e., Scenarios 7, 8, and 9). When an incident occurs, the difference between the actual and ideal values for traffic safety is enlarged and the weight of traffic safety will increase correspondingly. The weight of traffic safety has a special change in Scenario 15 of guidance information. As for congestion information, the weight change varies little among the experimental scenarios. Since traffic safety is closely related to matters of life and death, the weights for traffic safety are relatively high on average and the weights are larger than 0.12 in many scenarios.



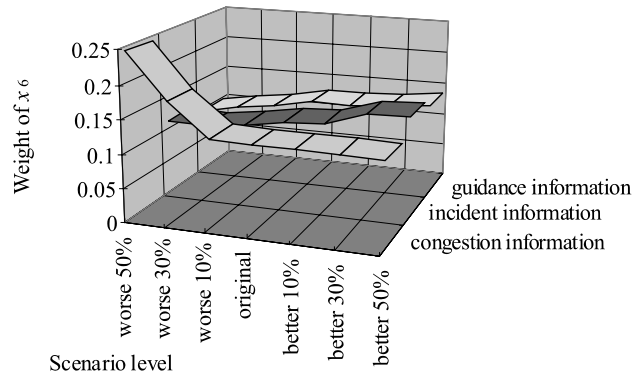


Fig. 17. Weight comparison of traffic condition ( $x_6$ ) under the experimental scenarios.

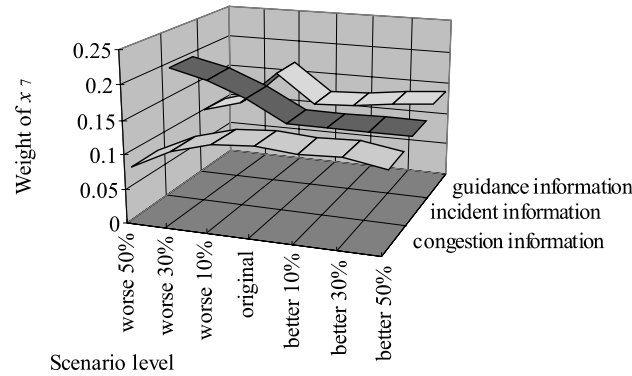


Fig. 18. Weight comparison of traffic safety ( $x_7$ ) under the experimental scenarios.

From Fig. 19, we know that the weight pattern for traffic comfort ( $x_8$ ) is similar to traffic safety under the congestion information. In incident information, the weights increase when the scenario condition becomes worse. Additionally, the weights for the same scenario level are almost equal in

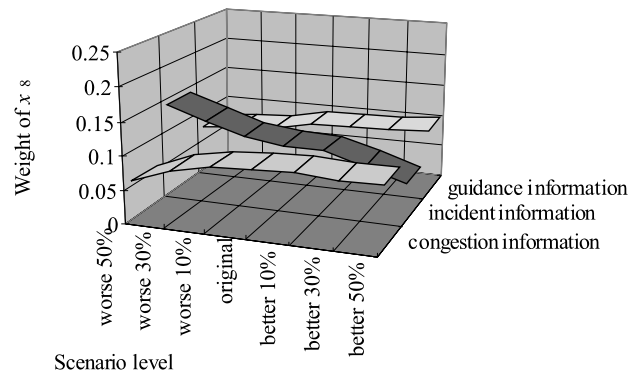


Fig. 19. Weight comparison of traffic comfort ( $x_8$ ) under the experimental scenarios.

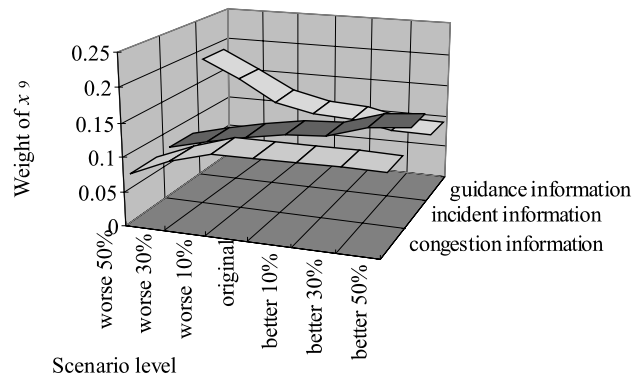


Fig. 20. Weight comparison of drivers' familiarity ( $x_9$ ) under the experimental scenarios.

congestion and guidance information. Since half of the weights in all scenarios are smaller than 0.1, the weights of traffic comfort are medium in our experiment.

As Fig. 20 indicates, the weights of drivers' familiarity ( $x_9$ ) are low in Scenarios 1–3 of congestion information, and there is no apparent change from the original situation to Scenario 6. The weights of drivers' familiarity increase from Scenarios 7 to 12 under incident information. However, the weights of drivers' familiarity decrease under guidance information. When the route guidance message deviates greatly from drivers' familiar routes, the weight of drivers' familiarity will significantly increase.

Based on the aforementioned analysis process, we investigate the information effect on drivers' route choice behavior through the dynamic changes in criterion weights. The empirical results perform well in the average error sum of squares for all 18 experimental scenarios. Furthermore, the prominent criteria can be selected according to their dynamic weights, and these criteria provide the behavioral basis for dynamic traffic assignment. Since traffic assignment must follow the route choice criteria, our dynamic weight-assessing model is, in fact, fundamental for developing the dynamic traffic assignment models. Moreover, the empirical result also demonstrates the outstanding applicability of the proposed model in the route choice problem. Therefore, we suggest that the weight-assessing model can be applied to explore the prominent criteria under the influence of ATIS in the future.

## 5. Conclusions

From a behavioral perspective, the criteria with higher activation possibilities tend to have a prominent effect on drivers' route choice behavior. Since the importance of the criteria is the crucial key to control the influential criteria in formulating a route, we provided a method to assess the criterion weights for determining the route-selection criteria. Our proposed method does not require independence between criteria. Instead, the interrelation between criteria can be truly described through the connectivities. Thus, the proposed method demonstrates more practical flexibility than other weighting methods do.

An empirical study on identifying commuters' route-selection criteria was conducted in Taipei City. According to the experimental results, weights do indeed seem to vary dynamically. Moreover, the results show satisfactory performance by applying the weight-assessing method to derive dynamic criterion weights. Furthermore, we also investigated the information effects of the experimental scenarios on route choice. These information effects can provide some valuable suggestions for the future implementation of ATIS or ITS.

In our empirical study, we fixed the origin and destination as the experiment progressed for simplicity. However, if simulators or ATIS become available, researchers can apply our proposed model as well by adjusting the criterion values according to the variable origin/destination. In other words, researchers only need repeat the weight-assessing procedure to derive the dynamic weights, and then the critical criteria of route choice can be obtained correspondingly. Thus, the effects of ATIS route choice can be easily investigated in practice, and the en-route switching rule can be also specified for ATIS. Another suggestion for future research is that the related criteria for each information type can be redefined according to the actual contents of the information supply. In addition, the correlation analysis of social-economic characteristics and the weight change can be conducted as the basis of market segment.

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