A FIXED-POINT ROUTE CHOICE MODEL FOR ROUTE CORRELATION

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ABSTRACT

In this paper we present a stochastic route choice model for transit networks, which explicitly addresses route correlation due to overlapping in the alternatives. The model is based on a multi-objective mathematical programming problem, which optimality conditions generate an extension to the Multinomial Logit models. The model proposed considers a fixed point problem for treating correlation between routes, which can be solved iteratively. We estimated the new model on the Santiago (Chile) Metro network and compared the results with other route choice models that can be found in literature. The new model has better explanatory and predictive power, correctly capturing the correlation factor.

Keywords: Route Choice, Fixed Point, Route Overlapping, Route Correlation

1. INTRODUCTION

The present study formulates a new route choice model for public transport networks that features significant innovations on existing models. The main enhancement in the proposed model is ability to simultaneously and explicitly integrate the traveler's lack of information (randomness or uncertainty) and the correlation between route alternatives (overlapping). The proposed model is based on a multi-objective mathematical programming problem, and its respective scalarized single-objective problem. The multi-objective problem considers the exogenous cost functions of the network, the entropy of the route choice, and the covariance matrix for the route flows.

From a general perspective, route choice models for transport networks, widely used in urban planning, can be divided into three major groups: deterministic equilibrium models, stochastic route choice models and dynamic route choice models. Our proposed route choice model belongs to the stochastic group.

The deterministic equilibrium group usually state optimality conditions, such as minimizing transport costs or satisfying Wardrop's first principle of traffic equilibrium (Wardrop, 1952). These models assume that travelers have perfect information and seek to unilaterally minimize their travel costs (Beckmann et al., 1956; Dijkstra, 1959; De Cea and Fernández, 1993; De Grange and Muñoz, 2009). Typically, a mathematical programming model is formulated and solved by an iterative algorithm. If applied with care and understanding, a deterministic user-equilibrium model provides a simple but effective method of traffic assignment (Dafermos and Sparrow, 1969; Florian, 1976; Florian, 1977; Dafermos, 1980; Patriksson, 1998; Florian and Hearn, 2001; Boyce et al., 2005).

Stochastic or probabilistic route choice models differ from deterministic formulations in that they incorporate uncertainty, randomness and/or heterogeneity of travelers and alternative routes. Reviews of this class of models are found in Daganzo and Sheffi (1977), Hazelton (1998), Ramming (2001), and Prashker and Bekhor (2004). They are an extension of the deterministic equilibrium group. Among these models, there are some that explicitly consider correlation between alternative routes, such as Cascetta et al., (1996), Ben-Akiva and Ramming (1998), Bekhor and Prashker (1999, 2001), Bovy et al., (2008). A complete review of these studies can be found in Prashker and Bekhor (2004), and Prato (2009). Several of the models presented by the authors were considered for performing a comparison with our new model.

Finally, dynamic assignment models have little relation to the subject of the present article and will not be described here. Extensive references and developments in dynamic transportation network modeling, analysis, and computational methods are given in Ran and Boyce (1996), with further reviews in Boyce et al. (2001) and Szeto and Lo (2006).

In the remainder of this paper, Section 2 contains a brief review of the literature that provides context for understanding the proposed model; Section 3 sets out an analytic derivation of the new formulation; Section 4 applies the model to a medium-sized network (the Santiago Metro), comparing the results with existing models; and finally, Section 5 summarizes the results and presents the main conclusions.

2. LITERATURE REVIEW

The formulation of the route choice or assignment stage in transportation modeling has long followed a paradigm in which users minimize their generalized trip cost on the assumption of perfect knowledge of the transport network. Under this approach, travelers are considered to be homogeneous and each one is fully informed of the cost of each arc on the network at any level of flow (Wardrop, 1952; Beckmann et al., 1956). Clearly, these assumptions are both rather strong even for a small network and the results obtained are often less than satisfactory. Yet thanks to their simplicity and availability many transport planners continue to apply such models, especially with large networks.

Since the perfect information assumption is not totally correct, there is clearly a need for models that represent users who have incomplete or imperfect information on the transport system as regards existing routes and their levels of congestion. Various route choice models in the specialized literature are based on system attributes perceived by travelers and their socioeconomic and demographic characteristics (Dial, 1971; Daganzo and Sheffi, 1977; Bell, 1995; Ramming, 2001; Prashker and Bekhor, 2004). In these models, users behave in accordance with the costs they perceive. The socioeconomic and demographic variable data is usually obtained through user surveys or from network data records, and is easily justified as an integral part of individuals' rational decision-making processes. However, because the modeler lacks information on these processes, the choices as modeled necessarily embody a degree of variability. To explain this variability it would thus be of great interest to incorporate additional information.

Regarding knowledge of routes, it is widely accepted that individual users do not know (or do not perceive/consider) all the route possibilities between a given origin-destination pair (Ben-Akiva et al., 1984; Cascetta et al., 1996; Cascetta et al., 1998; Cascetta et al., 2002; Ben-Akiva and Bierlaire, 2003). This is a reality that should be incorporated into route choice models. Cascetta et al. (2002) propose a Logit-type model of route perception and choice similar to those based on random utility theory. Ben-Akiva et al. (1984) models interurban route choice as a two-stage process in which a set of routes is defined in the first stage and the route choice is made in the second stage.

Correlation between alternative routes can to a certain extent be indirectly addressed, according to Bovy and Hoogendoorn-Lanser (2005), by hierarchical nested Logit and multi-nested GEV models in cases where it arises from overlapping segments and/or nodes. The way in which individuals construct their set of route alternatives and the implications of route similarity for user behavior are analyzed by Prato and Bekhor (2007) and Bekhor et al. (2006). Bliemer and Bovy (2008) study the interdependence of these two aspects.

2.1 Multinomial Logit for Route Choice

The probability of choosing route p to travel between O-D pair w $\left(P_w^p\right)$ can be estimated by discrete choice models in which the cost of a given route as perceived by a user $\left(C_w^p\right)$ is assumed to be given by (1):

$$C_w^p = c_w^p + \varepsilon_w^p \tag{1}$$

The cost is thus perceived as the sum of a deterministic component $\left(C_w^p\right)$ and a random error component $\left(\varepsilon_w^p\right)$. The latter can be interpreted in various ways, one of which is that the error reflects the user's inaccurate perception of route cost due, among other things, to the scarcity of information. In this case, the first term $\left(C_w^p\right)$ represents the real mean cost of the route. The expression for the choice probability $\left(P_w^p\right)$ is a function of the assumed distribution of the error terms and whether or not they are independent. If we assume the errors are i.i.d. Gumbel-distributed with a scale parameter $\theta > 0$, we have a Multinomial Logit (MNL) choice model in which P_w^p is given by (2), where p^w is the set of routes uniting the O-D pair *w*.

$$P_w^p = \frac{\exp\left(-\theta c_w^p\right)}{\sum_{r \in p^w} \exp\left(-\theta c_w^r\right)} \tag{2}$$

An equivalent optimization problem that generates the stochastic assignment model (2) is:

$$\begin{aligned} & \min_{\{h_w^p\}} Z = \sum_w \sum_{p \in p^w} c_w^p h_w^p + \frac{1}{\theta} \sum_w \sum_{p \in p^w} h_w^p \left(\ln h_w^p - 1\right) \\ & s.t. \\ & \sum_{p \in p^w} h_w^p = T_w \qquad \forall w \end{aligned} \tag{3}$$

where T_w is the total number of trips (exogenous demand) between O-D pair w and h_w^p is the flow along route p $\left(P_w^p = h_w^p / T_w\right)$.

In problem (3) the set of routes p^w between each pair *w* must be predefined and maintained invariant during the assignment process. The optimality conditions lead to the assignment criterion given by (2) in which users divide up among the alternative routes according to a Logit model.

It's worth noticing that the objective function on (3) considers two terms: the first term represents the total cost in the network, while the second term represents the negative value of the entropy. The latter is weighted by $1/\theta$ to scale both terms in the objective function. This way, problem (3) can be interpreted as a bi-objective problem that simultaneously minimizes the total cost and maximizes the total entropy (De Cea et al., 2008).

The principal limitation of model (3) is that it does not incorporate a structure for capturing correlation between routes. Possible direct extensions are either extremely simplistic or difficult to apply correctly to real-world scale networks (for example, using a hierarchical Logit model) given that they cannot properly capture the various types of correlation between routes that share arcs with one other in different ways. In urban networks, the routes linking a given O-D pair will typically have many overlaps due to common arcs, with the result that the independent error assumption implicit in Logit-type models such as (2) is unrealistic.

Different extensions of the Multinomial Logit model have been proposed to explicitly capture correlation between alternative routes, some of which are presented bellow. These models are used as a comparative base for our proposed model

2.2 C-Logit Model

In Cascetta et al. (1996) and Cascetta et al. (2002) the authors propose a joint implicit availability/perception (IAP) and route choice (C-Logit) model which also explicitly addresses the correlation issue (i.e., the lack of route independence due to common arcs) and is analytically tractable even for large-scale networks.

The basic idea behind the model is to handle route interdependence via a cost attribute called the "similarity factor" that is added to the cost of the route in a conventional Logit model, instead of dealing with it in terms of error non-independence as does the Probit model. The probability of choosing route p is then given by (4):

$$P_w^p = \frac{\exp\left(-\theta c_w^p + CF_w^p\right)}{\sum_{r \in p^w} \exp\left(-\theta c_w^r + CF_w^r\right)} \quad (4)$$

where CF_w^p is the "similarity factor" for route p joining pair w and is constructed as follows:

$$CF_w^p = \beta \cdot \ln \sum_{a \in p} \left(\frac{l_a}{L_p} \cdot \sum_{r \in p^w} \delta_{ar} \right) \quad (5)$$

where β is a parameter to be calibrated and must be negative, l_a is the length of arc a, L_p is the length of route p, and δ_{ar} is equal to 1 if arc a belongs to some route r joining w but 0 otherwise. Other specifications for CF_w^p may be found in Prato (2009).

2.3 Path-Size Logit Model

Ben-Akiva and Ramming (1998) develop a model denoted Path-Size Logit (PSL) that also aims to correct for routes which have overlaps and are therefore correlated. It attempts to incorporate behavioral theory in Cascetta's C-Logit model. In this case P_w^p is given by (6), where PS_w^p is the correction for route size.

$$P_w^p = \frac{\exp\left(-\theta c_w^p + \beta \cdot \ln PS_w^p\right)}{\sum_{r \in p^w} \exp\left(-\theta c_w^r + \beta \cdot \ln PS_w^r\right)} \quad (6)$$

The correction principle applied in this model is as follows. A route with no arcs overlapping another route needs no correction and is therefore assigned a size of 1. At the other extreme, if there are J duplicate routes (i.e., total overlap), each one has a size of $1/J$. Finally, the length of routes with partial overlap is based on the sizes of the arcs, which are appropriately weighted on some criterion such as the arc's contribution to the total length of the route. Thus, PS_w^p can take the following form:

$$PS_w^p = \sum_{a \in p} \left(\frac{l_a}{L_p} \cdot \frac{1}{\sum_{r \in p^w} \delta_{ar}} \right) \tag{7}$$

where the variables are the same as those employed in (5) to define the similarity factor. Further specifications for PS_w^p may be found in Bovy et al. (2008).

2.4 Paired Combinatorial Logit Model

The Paired Combinatorial Logit Model (PCL) belongs to the family of models that derive from the Generalized Extreme Value (GEV) model (McFaden, 1978). The general PCL model can be derived from the following generation function:

$$G(y_1, y_2, ..., y_n) = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \left(1-\sigma_{kj}\right)\left(y_k^{1/1-\sigma_{kj}} + y_j^{1/1-\sigma_{kj}}\right)^{1-\sigma_{kj}} \tag{8}$$

where:

y_k	characterizes each alternative (in our case, a route between an O-D pair).
σ_{kj}	is a similarity index between alternatives *k* and *j*.
n	is the number of alternatives.

The model was adapted for route choice by Bekhor and Prashker (1999), and in our case we use the expression used by Chen et al. (2003), $y_k = y_w^p = e^{-\theta c_w^p}$. Then, the probability of choosing route *p* when travelling between O-D pair *w* is (9):

$$P_w^p = \frac{\sum_{q \in p^w, q \neq p} e^{\frac{-\theta c_w^p}{1-\sigma_w^{pq}}} \left(1-\sigma_w^{pq}\right)\left(e^{\frac{-\theta c_w^p}{1-\sigma_w^{pq}}} + e^{\frac{-\theta c_w^q}{1-\sigma_w^{pq}}}\right)^{-\sigma_w^{pq}}}{\sum_{r=1}^{p^w-1} \sum_{m=r+1}^{p^w} \left(1-\sigma_w^{rm}\right)\left(e^{\frac{-\theta c_w^r}{1-\sigma_w^{rm}}} + e^{\frac{-\theta c_w^m}{1-\sigma_w^{rm}}}\right)^{1-\sigma_w^{rm}}} \tag{9}$$

In this case for a choice set of pw alternative routes, there are $p^w(p^w-1)/2$ pairs of alternatives. If σ_w^{pq} equals 0 for every pair (*p*,*q*) in *w* of routes, then the PCL model collapses to a MNL model like (2). We use the similarity index proposed by Chen et al. (2003):

$$\sigma_w^{pq} = \frac{L_w^{pq}}{\sqrt{L_w^p \cdot L_w^q}} \tag{10}$$

where L_w^{pq} is the length of overlap between routes p and q, and L_w^p and L_w^q are the respective lengths of routes p and q. It is possible (and convenient) to include an additional degree of freedom in this model, by including a parameter β in (10), as shown in (11). This new parameter must be estimated together with the rest of the model's parameters.

$$\sigma_w^{pq} = \beta \cdot \frac{L_w^{pq}}{\sqrt{L_w^p \cdot L_w^q}} \qquad (11)$$

2.5 Cross-Nested Logit Model

The Cross-Nested Model (CNL) also belongs to the GEV family of models, and was adapted for the route choice context by Prashker and Bekhor (1998), and Vovsha and Bekhor (1998). In that adaptation, the model considers a two-level hierarchical structure. In the upper level are included all the links in the network, and in the lower level are included all the routes that belong to pw. Then, every route is assigned to the nests that represent the links that belong to it.

In this case the probability of choosing route p is given by (12):

$$P_w^p = \frac{e^{-\theta c_w^p} \sum_{m \in M_w^p} \alpha_w^{mp} \left(\sum_{q \in p^w} \alpha_w^{mq} e^{-\theta c_w^q} \right)^{\mu - 1}}{\sum_{m \in M_w^p} \left(\sum_{q \in p^w} \alpha_w^{mq} e^{-\theta c_w^q} \right)^{\mu}} \qquad (12)$$

where:

m	characterizes the links, and therefore the nests.
M_w^p	is the set of links that belong to route p in O-D pair w.
α_w^{mp}	parameters that represent the degree of inclusion of alternative p in nest m.
μ	is the nesting coefficient. If $\mu = 1$ the model collapses to a MNL.

The CNL model is adapted to a route choice context defining the parameters α_w^{mp} as depending of the topology of the network. Prashker and Bekhor (1998) proposed the following expression:

$$\alpha_w^{mp} = \left(\frac{L_w^m}{L_w^p} \right)^{\gamma} \delta_w^{mp} \qquad (13)$$

where L_w^m is the lenght of link m, L_w^p is the lenght of route p, δ_w^{mp} equals 1 if link m belongs to route p, and γ is a parameter that must be calibrated which reflects the percetpion of the travelers regarding the similarity of the alternative routes. For the estimation of the CNL model we use $\gamma = 1$ following Bekhor et al. (2006).

In the following section we develop a new route choice model that simultaneously incorporates (i) users with imperfect knowledge of the network, and (ii) correlation between alternatives (in this case, routes). As noted earlier, the proposed formulation is entropy-based with quadratic constraints.

3. ROUTE CHOICE MODEL WITH CORRELATED ROUTES

3.1 Mathematical formulation of model

The proposed stochastic equilibrium assignment model with capture of route correlation is based on the following multi-objective optimization problem (other applications of multi-objective models in transportation can be found in De Cea et al., 2008, and De Grange et al., 2010):

$$\begin{aligned}
&\min \; F_1 = \sum_{w} \sum_{p \in p^w} c_w^p h_w^p \\
&\min \; F_2 = \sum_{w} \sum_{p \in p^w} h_w^p \left(\ln h_w^p - 1 \right) \\
&\min \; F_3 = \sum_{w} \sum_{p \in p^w} \sum_{\substack{q \in p^w \\ q \neq p}} \left[\eta_w^{pq} \left(h_w^p - t_w \right) \left(h_w^q - t_w \right) \right] \\
&s.t.: \sum_{p \in p^w} h_w^p = T_w, \;\; \forall w \qquad \left(\gamma_w \right)
\end{aligned} \tag{14}$$

Objective F1 relates to the total system cost. Objective F2 attempts to maximize entropy in order to determine the most likely routes; in probabilistic terms, it finds the most feasible route combinations for travelers in equilibrium. Combining F1 and F2 with the flow conservation constraints gives the stochastic assignment model expressed in (3).

Objective F3, the novel element in the proposed model, explicitly incorporates correlation of flows between different routes, whether or not they join the same O-D pair w. The objective is constructed as a weighted sum of the divergences of the flows on the individual defined routes joining w from the average flow on those routes, where $t_w = \dfrac{T_w}{N_w}$ is the average flow, N_w is the number of defined routes (i.e. the cardinality of pw) and T_w is the (fixed) total number of trips between w. Parameters η_w^{pq} are exogenous and determine the degree of correlation (0 to 1) between routes p and q of w. The values of the parameters can be defined in a number of ways (see Cascetta et al., 1996; Yai et al., 1997; Ramming, 2001).

As with F2 , objective F3 is an information criterion (Golan, 2002). If, for example, the flows on all traveled routes were uniform (that is, if $h_w^p = t_w, \forall p$), the value of F3 would be 0 and thus contain no information. F2 also takes its lowest possible value if $h_w^p = t_w, \forall p$.

A substitute optimization problem (Marler and Arora, 2004; De Cea et al., 2008) for (14) that generates the proposed stochastic equilibrium model is the following:

$$\min \;\; F = \sum_w \sum_{p \in p^w} c_w^p h_w^p + \frac{1}{\theta} \sum_w \sum_{p \in p^w} h_w^p \left(\ln h_w^p - 1 \right) + \frac{1}{\rho} \sum_w \sum_{p \in p^w} \sum_{\substack{q \in p^w \\ q \neq p}} \left[\eta_w^{pq} \left(h_w^p - t_w \right) \left(h_w^q - t_w \right) \right] \tag{15}$$

$$s.t.: \sum_{p \in p^w} h_w^p = T_w, \;\; \forall w \qquad \left(\gamma_w \right)$$

The terms $1/\theta$ and $1/\rho$ are the respective relative weights of the two information criteria F2 and F3 with respect to the reference objective F1. θ and ρ are parameters to be estimated.

The first-order conditions for (15) are

$$c_w^p + \frac{1}{\theta} \ln h_w^p + \frac{1}{\rho} \sum_{\substack{q \in p^w \\ q \neq p}} \left[\eta_w^{pq} \left(h_w^q - t_w \right) \right] + \gamma_w = 0 \tag{16}$$

where c_w^p could, for a public transport application, be replaced by $L_w^p = \sum_k \beta_k X_{w,k}^p$ .From (16) we get:

$$h_w^p = \exp \left(-\theta c_w^p - \frac{\theta}{\rho} \sum_{\substack{q \in p^w \\ q \neq p}} \left[\eta_w^{pq} \left(h_w^q - t_w \right) \right] - \theta \gamma_w \right) \tag{17}$$

$$\sum_{p \in p^w} h_w^p = T_w = \exp\left(-\theta \gamma_w \right) \cdot \sum_{p \in p^w} \exp \left(-\theta c_w^p - \frac{\theta}{\rho} \sum_{\substack{q \in p^w \\ q \neq p}} \left[\eta_w^{pq} \left(h_w^q - t_w \right) \right] \right) \tag{18}$$

Dividing (17) and (18) we have:

$$h_p^w = T_w \frac{\exp \left(-\theta c_w^p - \frac{\theta}{\rho} \sum_{\substack{q \in p^w \\ q \neq p}} \left[\eta_w^{pq} \left(h_w^q - t_w \right) \right] \right)}{\sum_{r \in p^w} \exp \left(-\theta c_w^r - \frac{\theta}{\rho} \sum_{\substack{q \in p^w \\ q \neq p}} \left[\eta_w^{rq} \left(h_w^q - t_w \right) \right] \right)} \tag{19}$$

Since η_w^{pq} is an exogenous model parameter (defined by the modeler) and t_w is assumed to be constant (for calibration and modeling purposes), the term $\frac{\theta}{\rho}\sum_{\substack{q\in p^w\\ q\neq p}}\left[\eta_w^{pq}t_w\right]$ is also constant. Letting $\frac{\theta}{\rho}\sum_{\substack{q\in p^w\\ q\neq p}}\left[\eta_w^{pq}t_w\right]=\alpha_w^q$, an intercept or "modal" constant, (19) can then be rewritten as:

$$h_w^p = T_w \frac{\exp\left(\alpha_w^p - \theta c_w^p - \frac{\theta}{\rho}\sum_{\substack{q\in p^w\\ q\neq p}}\left[\eta_w^{pq}h_w^q\right]\right)}{\sum_{r\in p^w}\exp\left(\alpha_w^r - \theta c_w^r - \frac{\theta}{\rho}\sum_{\substack{q\in p^w\\ q\neq p}}\left[\eta_w^{rq}h_w^q\right]\right)} \tag{20}$$

This non-linear expression is similar in structure to the model specified by Ben-Akiva and Ramming (1998), given here as (6). The main difference is that the right-hand side of (20) includes the endogenous variable h_w^q and is therefore a fixed-point function whereas in (6), the right-hand side contains only the model's exogenous variables.

A substitute can be specified for F1 that can model service levels in public transport networks. An example of such a replacement is $\tilde{F}_1=\sum_w\sum_{p\in p^w}L_w^p h_w^p$ where $L_w^p=\sum_k \beta_k X_{w,k}^p$ is a generalized cost given by the weighted sum of attributes or explanatory variables $X_{w,k}^p$ that could represent, for example, the trip time, wait time, cost, etc. of route p between pair w.

We can define $V_w^p=\alpha_w^p-\theta c_w^p-\frac{\theta}{\rho}\sum_{\substack{q\in p^w\\ q\neq p}}\left[\eta_w^{pq}h_w^q\right]$ as the "utility level" of the proposed Logit-based model. By the route choice probability function in (20), the marginal utility of the attribute $X_{w,k}^p$ can be written as:

$$\frac{\partial V_w^p}{\partial X_{w,k}^p}=\beta_k+\frac{\partial V_w^p}{\partial X_{w,k}^p}\cdot\frac{1}{T_w}\cdot\frac{\theta}{\rho}\sum_{\substack{q\in p^w\\ q\neq p}}\eta_w^{pq}\cdot h_w^p\cdot h_w^q \tag{21}$$

Clearing, we get:

$$\frac{\partial V_w^p}{\partial X_{w,k}^p} = \frac{\beta_k}{1 - \frac{1}{T_w} \cdot \frac{\theta}{\rho} \sum_{\substack{q \in p^w \\ q \neq p}} \eta_w^{pq} \cdot h_w^p \cdot h_w^q} \tag{22}$$

Since the denominator of (21) is independent of attribute *k*, the marginal rates of substitution are generic and have the same functional form as traditional discrete choice models.

$$\frac{\partial V_r \big/ \partial X_{w,k_1}^p}{\partial V_r \big/ \partial X_{w,k_2}^p} = \frac{\beta_{k_1}}{\beta_{k_2}} \tag{23}$$

Thus, in the proposed fixed-point model with spatial correlation, the marginal rates of substitution between attributes can be obtained without any additional complexity.

To implement model (20), the parameters $\left(\alpha_w^p, \theta, \rho^*\right)$, where $\rho^* = \frac{\theta}{\rho}$, must first be estimated and the fixed-point equation (20) then solved given that the variable h_w^p appears on both sides of the equation.

However, since the endogenous variable (h_w^p) appears on the right-hand side of the model, the parameters $\left(\alpha_w^p, \theta, \rho^*\right)$ cannot be estimated using maximum likelihood because the presence of the endogenous variable violates the assumption of independent marginal probability functions necessary for defining the likelihood function. To get around this problem, we resort to the use of an instrumental variable to replace h_w^p as explained below.

3.2 Estimation of model parameters

An instrument or instrumental variable, (Greene, 2008) is an exogenous variable that is highly correlated with an explanatory variable exhibiting endogeneity, and can therefore be used as a replacement for the latter without loss of asymptotic properties in the estimated parameters. In our case, a suitable instrument h_w^{p0} to stand in for h_w^p is

$$h_w^{p0} = T_w \frac{\exp\left(-\lambda c_w^p\right)}{\sum_{r \in p^w} \exp\left(-\lambda c_w^r\right)} \tag{24}$$

This formula is a classic MNL model and can be estimated easily. Once this is done, the value of h_w^{p0} is substituted into the right-hand side of (20):

$$h_w^p = T_w \frac{\exp\left(\alpha_w^p - \theta c_w^p - \rho^* \sum_{\substack{q \in p^w \\ q \neq p}} \left[\eta_w^{pq} h_w^{q0}\right]\right)}{\sum_{r \in p^w} \exp\left(\alpha_w^r - \theta c_w^r - \rho^* \sum_{\substack{q \in p^w \\ q \neq p}} \left[\eta_w^{rq} h_w^{q0}\right]\right)} \tag{25}$$

Unlike (20), the parameters $\left(\alpha_w^p, \theta, \rho^*\right)$ in (25) can be estimated directly by maximum likelihood (Raveau et al., 2011) since h_w^{q0} does not exhibit endogeneity. Using these estimates, which we now denote $\left(\alpha_w^{p0}, \theta^0, \rho^{0*}\right)$, we can estimate h_w^{p1} by (26):

$$h_w^{p1} = T_w \frac{\exp\left(\alpha_w^{p0} - \theta^0 c_w^p - \rho^{0*} \sum_{\substack{q \in p^w \\ q \neq p}} \left[\eta_w^{pq} h_w^{q0}\right]\right)}{\sum_{r \in p^w} \exp\left(\alpha_w^{r0} - \theta^0 c_w^r - \rho^{0*} \sum_{\substack{q \in p^w \\ q \neq p}} \left[\eta_w^{rq} h_w^{q0}\right]\right)} \tag{26}$$

The original model (26) is thus estimated iteratively from the following recursive relation (which represents the equilibrium of the fixed-point function):

$$h_w^{p(n+1)} = T_w \frac{\exp\left(\alpha_w^{p(n)} - \theta^{(n)} c_w^p - \rho^{(n)*} \sum_{\substack{q \in p^w \\ q \neq p}} \left[\eta_w^{pq} h_w^{q(n)}\right]\right)}{\sum_{r \in p^w} \exp\left(\alpha_w^{r(n)} - \theta^{(n)} c_w^r - \rho^{(n)*} \sum_{\substack{q \in p^w \\ q \neq p}} \left[\eta_w^{rq} h_w^{q(n)}\right]\right)} \tag{27}$$

The iterative estimation process concludes when convergence in reached; happens when $\left(\alpha_w^{p(n)}, \theta^{(n)}, \rho^{(n)*}\right) \approx \left(\alpha_w^{p(n-1)}, \theta^{(n-1)}, \rho^{(n-1)*}\right)$. If the estimator of parameter $\rho^{(n)*}$ in (27) is statistically different from 0, the null hypothesis of no correlation between route p and any of the other routes joining O-D pair w is rejected.

In analogous fashion to the derivation of (21), upon iteratively solving model (20) the marginal utility of attribute $X_{w,k}^p$ is then

$$\frac{\partial V_w^{p(n+1)}}{\partial X_{w,k}^p} = \beta_k^{(n)} + \frac{\partial V_w^{p(n)}}{\partial X_{w,k}^p} \cdot \frac{1}{T_w} \cdot \rho^{(n)*} \sum_{\substack{q \in p^w \\ q \neq p}} \eta_w^{pq} \cdot h_w^{p(n)} \cdot h_w^{q(n)} \tag{28}$$

This expression generates the marginal utilities recursively in successive iterations. The model converges to the equilibrium of the fixed-point function as follows:

$$\frac{\partial V_w^{p(n+1)}}{\partial X_{w,k}^p} \approx \frac{\partial V_w^{p(n)}}{\partial X_{w,k}^p} \quad \rightarrow \quad \frac{\partial V_r \Big/ \partial X_{w,k_1}^{p(n+1)}}{\partial V_r \Big/ \partial X_{w,k_2}^{p(n+1)}} = \frac{\beta_{k_1}^{(n)}}{\beta_{k_2}^{(n)}} \tag{29}$$

The marginal rates of substitution thus continue to be generic and equal in their functional form to those of the traditional discrete choice models.

4. NUMERICAL RESULTS

Here we present a route choice case study comparing the results of a real application of the proposed model to those generated by a classic MNL model in (2), the C-Logit model in (4), the Path-Size Logit model in (6), the PCL model in (9) and the CNL model in (12) above.

This case study applies the various models to route choice on the Metro rail transport system in the Chilean city of Santiago. Successive transfer points are chosen between origin and destination pairs that in many instances are joined by more than one feasible route (see Figure 1). The analysis focuses on the morning and evening peak periods (7 am to 9 am and 6 pm to 8 pm) when approximately 790,000 trips are taken across the system, 44% of which include transfers.

Trip data was obtained through an O-D survey conducted on the Metro in which 92,800 system users, or about 12% of the total, participated. Since only those trips for which there existed more than one alternative route were retained in the data set, the number of individuals or observations finally employed was 16,029, or about 40% of users who transferred.

When the survey was taken in October 2008, the Santiago Metro consisted of 5 lines and 85 stations, 7 of which were transfer points. Of the 7,140 O-D pairs on the network, 4,985 (70%) of them required making a transfer. The reasonability criterion applied in including a route as a possible alternative for a given pair was that at least one surveyed traveler was observed to have used it. Data on the alternative routes for O-D pairs across the system that had more than one route on this criterion are given in Table 1. Although in the majority of cases there were only two alternatives, some pairs had as many as four. Denser networks than this one would no doubt have a greater proportion of pairs with alternative routes.

For the proposed model (20), the generalized cost of traveling between pair w on route p is defined as $L_w^p = \beta_{time} X_{time,w}^p + \beta_{access} X_{access,w}^p + \beta_{trans} X_{trans,w}^p + \beta_{rr} D_{rr,w}^p + \beta_{old} D_{old,w}^p$, where $X_{time,w}^p$ is total trip time; $X_{access,w}^p$ is the Access time (walking and waiting), $X_{trans,w}^p$ is the number of transfers along the route; $D_{rr,w}^p$ is a binary variable that takes value 1 is route p is reasonable for travelling in w (according to Dial, 1971) and takes value 0 if not; $D^{p}_{old,w}$ is a binary variable that takes value 1 if the rout has less than 10 years old (a proxy of how well known the route is) and takes value 0 if it's older. The number of transfers on a given route alternative is considered as an indicator of the disutility of transferring. Since the Metro uses a flat fare system, the fare is the same regardless of route and can therefore be omitted from the cost function.

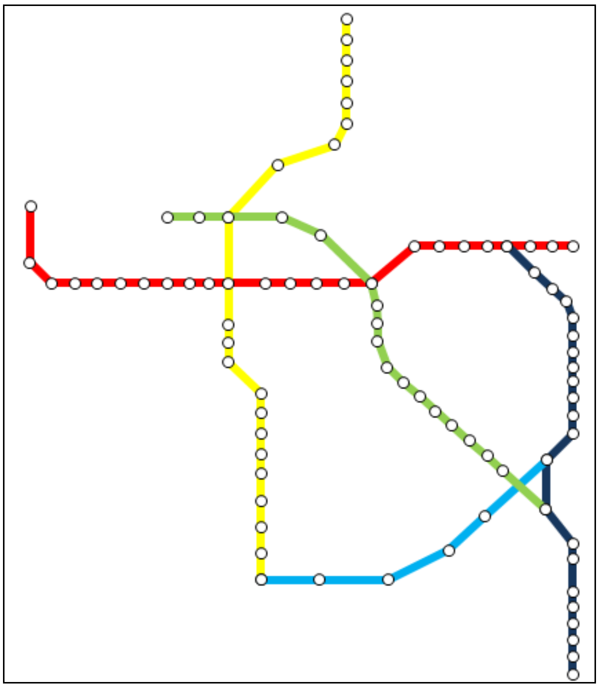

Figure 1 - Santiago Metro in 2008.

Table 1 - Origin-destination pairs and alternative routes, 2008.

No. alternative routes	% of all O-D pairs	% of all trips
2	97 %	93 %
3	3 %	7 %
4	< 1 %	< 1 %

The η^{pq}_{w} term, the spatial correlation factor due to route overlap between routes p and q joining pair w, is defined as suggested by (Yai et al., 1997):

$$\eta^{pq}_{w} = \frac{D^{pq}_{w}}{\sqrt{D^{p}_{w} \cdot D^{q}_{w}}} \qquad (30)$$

where D^{pq}_{w} is the length of overlap between routes p and q, and D^{p}_{w} and D^{q}_{w} are the respective lengths of routes p and q. This expression stems from the traditional definition of the similarity factor in the C-Logit model. As with the parameter β in that model (see (5) above), the parameter $-\rho^{*}$ must be negative, ensuring that ρ^{*} is positive.

The proposed model was compared with a conventional MNL model that included only network service level variables In other words, ρ^* was set to 0. The comparison was performed using statistical tests. Thus, the six route choice models estimated for the Santiago Metro were:

1. Multinomial Logit (MNL). This is the base model since it does not account for correlation and is also used to construct the route choice proxy variables.
2. C-Logit.
3. Path-Size Logit (PSL).
4. PCL.
5. CNL.
6. Fixed Point Model (FPM) with spatial correlation, our proposed model.

The estimation results are set out in Table 2. The proposed FPM converged in only 4 iterations at the 0.01% tolerance level. As can be seen, all explanatory variables had the correct sign and were statistically significant. In the C-logic, PCL, CNL and FPL models the correlation parameter was significant; in the PSL the statistical significance was lower.

The models with better goodness-of-fit (log-likelihood value) were the CNL and our proposed FPL, both very similar. In addition to the log-likelihood function, the following indicators were used to compare the MNL and fixed-point models on goodness of fit (Copas, 1989; Wasserman, 2006):

1. Percent of Correct Predictions (PCP)
2. Residual Sum of Squares (RSS): $S=\sum_i (Y_i - P_i)^2$, where Yi is 1 if alternative i is chosen and 0 otherwise, and Pi is the probability predicted by the model of choosing alternative i.
3. Weighted Residual Sum of Squares (WRSS): $S' = \frac{\sum_i (Y_i - P_i)^2}{P_i(1-P_i)}$.

The results of the three indicators for the estimated models are given in Table 3. The PCP indicator is practically the same for all models, so doesn’t allow any analysis regarding forecasting capability. Regarding RSS and WRSS, once again the best models are the CNL and the FPL.

Table 2 - Route Choice Model Estimation Results

Variable	MNL		C-Logit		PSL		PCL		CNL		FPM	
	Parameter	Test-t	Parameter	Test-t	Parameter	Test-t	Parameter	Test-t	Parameter	Test-t	Parameter	Test-t
Trip time	-0.124	-38.1	-0.126	-37.8	-0.125	-37.5	-0.102	-35.2	-0.407	-11.9	-0.097	-29.2
Walk and waiting time	-0.192	-7.6	-0.212	-8.0	-0.203	-7.7	-0.190	-9.6	-0.518	-7.5	-0.136	-5.5
No. of transfers	-0.853	-13.4	-0.811	-12.3	-0.828	-12.6	-0.588	-11.4	-2.031	-8.9	-0.610	-9.4
Reasonable route	-0.445	-11.1	-0.458	-11.3	-0.454	-11.2	-0.268	-8.2	-0.968	-8.1	-0.239	-5.7
Old route	0.458	10.3	0.448	10.1	0.452	10.2	0.319	9.6	0.979	7.7	0.336	7.2
Spatial correlation	-	-	-0.351	-2.4	0.222	1.5	0.571	19.2	0.306	12.4	-1.980	-17.9
Log-likelihood	-7,225.35		-7,222.51		-7,224.31		-7,117.90		-7,060.65		-7,062.12	
Adjusted rho squared	0.375		0.375		0.375		0.384		0.390		0.389	
Sample Size	16,029		16,029		16,029		16,029		16,029		16,029	

5. CONCLUSIONS

A new transport network route choice model was developed that explicitly incorporates the phenomenon of correlation between routes. The model is applicable to public transport networks. The presence of correlation between route alternatives was contrasted empirically by means of classical econometric techniques.

A multi-objective problem was stated and a substitute problem then formulated whose optimality conditions yielded a Logit specification with an endogenous variable constituting a fixed-point model that is estimated and solved iteratively. The estimation was performed by maximum likelihood and the use of instrumental variables due to the presence of endogeneity in the model's explanatory variables. The functional form of the proposed fixed-point model combined with the utilization of instrumental variables guaranteed both the existence and uniqueness of the solution.

The proposed model was compared with other route choice models reported in the literature in a case study of the Santiago Metro. The results obtained were both satisfactory and superior to the existing formulations. Unlike the latter, the proposed fixed-point model was able to capture the correlation between routes and provided better goodness of fit.

Although the proposed formulation is more complex to estimate due to the iterative process that must be used to obtain the parameters, in practice the iterations converge rapidly. Furthermore, the additional estimation complexity does not complicate the derivation of project evaluation indicators such as marginal rates of substitution, which retain the simple functional form of MNL models.

Finally, future research should address the apparent advantages of the proposed model on larger networks and traffic assignment problems.

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