Sequential Intermediate Destination Approach to Route Choice Set Generation

Anjilo CARIGMA [a], Mel Francis EDEN [b], John Justine VILLAR [c*], Adrian Roy VALDEZ [d]

[a,c,d] *Scientific Computing Laboratory, Department of Computer Science, University of the Philippines, Quezon City, Philippines*
[a] *E-mail: amcarigma@up.edu.ph*
[c] *E-mail: jsvillar1@up.edu.ph*
[d] *E-mail: alvaldez@up.edu.ph*
[b] *Institute of Civil Engineering, University of the Philippines, Diliman, Quezon City, Philippines*
[b] *E-mail: mseden@up.edu.ph*
[a,b,c,d] *Intelligent Transportation System Laboratory, National Center of Transportation Studies, University of the Philippines, Diliman, Quezon City, Philippines*

Abstract: The problem of route choice set generation have always suffered from the trade-off between accuracy and complexity. Most approaches focused in generating choice sets from a modeler's perspective. These methods search route choices in a large universal set, resulting to increased running time.
This research presents a method of generating route choice sets from the mindset of a traveler. Relevant nodes within an elliptical constraint, called "intermediate destinations", were introduced to mimic traveler's spatial behavior in choosing a route. Intermediate destinations were determined using a hierarchy-based scoring of network nodes. Modified hill-climbing algorithm was used to determine an optimal main branch from the intermediate destinations. A simple graph construction involving the main branch using shortest paths finally generates the route choice set.
Results were verified against network constraints. It was found that the method chooses reasonable routes when applied to a controlled network. Also, the method is reasonably selective even if the number of intermediate destinations chosen was increased indefinitely.

Keywords: route choice, detour factor, road hierarchy, anchor points, hill climbing algorithm

1. INTRODUCTION

Transportation systems are often modified to meet the traffic demand or mitigate the negative effects of the network configurations themselves. These modifications require reasonable evidence and realistic anticipation of the traffic situation which allow effective decision-making on addressing past, present, and future problems and nominating viable solutions accordingly. These solutions, and their possible alternatives, are evaluated to emphasize their strengths and weaknesses when forecasted on the future transportation network (Transport Appraisal and Strategic Modelling Division; 2014).

Transport models provide the tool to quantify the effects of these interventions on a simplified representation of the transportation system. These models can be constructed to satisfy the scale, resolution, and complexity of the analyses but is limited to the assumptions and simplifications made on the system's behavior and observable data (Ortuzár and Willumsen 2011).

*Corresponding author

Route choice models are not exempt to the trade-off between model accuracy and complexity. A perfect replication of the system of interest is desired but even combinations of algorithms and comprehensive models limit their ability to reproduce observed paths at 91% (Ramming 2002, Prato and Bekhor 2006). This constraint is caused by the differences in perception, imperfect information, or simply errors (Ortuzár and Willumsen 2011). Attempts to reach or exceed this limit require models and data as extensive as used by other studies and any further lack of data may lead to inaccuracy not proportional to the deficiency. That is, the use of complex models demand substantial data for localization or calibration for it to reach its intended capacity. Moreover, this complexity of parallel establishment between the algorithm and estimation data is made more difficult by the nature of route choice set being extensive, complex, and continuous such that obtaining stated preference data is difficult. Relying on revealed preference data over a large universal set is also laborious in itself (Bovy and Stern 1990).

For a given rational traveler and its origin and choice destination, a very large set of all paths connecting both exists. This set cannot be explicitly generated due to its size and heterogeneity (Bovy 2008, Frejinger, Bierlaire and Ben-Akiva 2009, Kaplan and Prato 2012). This set includes all possible connections of the origin and destination pair even cyclic, overlapping, and topologically senseless routes. However, all these alternatives are not considered, not even known to be existent, by the traveler as viable options. These are filtered with the traveler's own perception, cognition, and idiosyncracies (Bovy 2008). This general behavioral science aspects of route choice is indefinite and is more or less condensed to a "black box" when the choice process is discretized by literature (Bovy 2008, Bovy and Stern 1990). In the modeler's perspective, this black box is simplified into constraints which attempt to approximate the traveler's propensity towards choosing reasonable routes (Kaplan and Prato 2012). Figure 1 shows the common route choice set generation process. There is a need to model this route choice set generation black box without relying on extensive data and heavy parameter estimation.

Bovy and Stern (1990) defined one fundamental element of route choice reduction to be the spatial restriction and directionality of travel considering the destination. This limits the length and deviation of certain routes which effectively filters the network to a smaller potential path area. The geometric form of this space-time constraint is commonly an ellipse, both geospatially and mathematically, having the origin and destination nodes as its foci (Bovy and Stern 1990). Newsome et al. (1998) first defined the eccentricity and, consequently, the locus of the ellipse as a basis for the willingness or ability of a traveler to deviate from their origin to their destination. Their study incorporated the possibility of trips to be directed away from, even behind, the two foci. This provides a more comprehensive and representative picture of travel behavior even with regards to the elliptical construct being a geometric abstraction. Justen, et al. (2013) introduced the use of empirical detour factor to construct the elliptical constraint and showed that it is negatively correlated to the distance from the traveler's origin to its destination. Their results also revealed that the elliptical detour constraint generates a smaller choice set and with a significantly high rate of inclusion of observed alternatives.

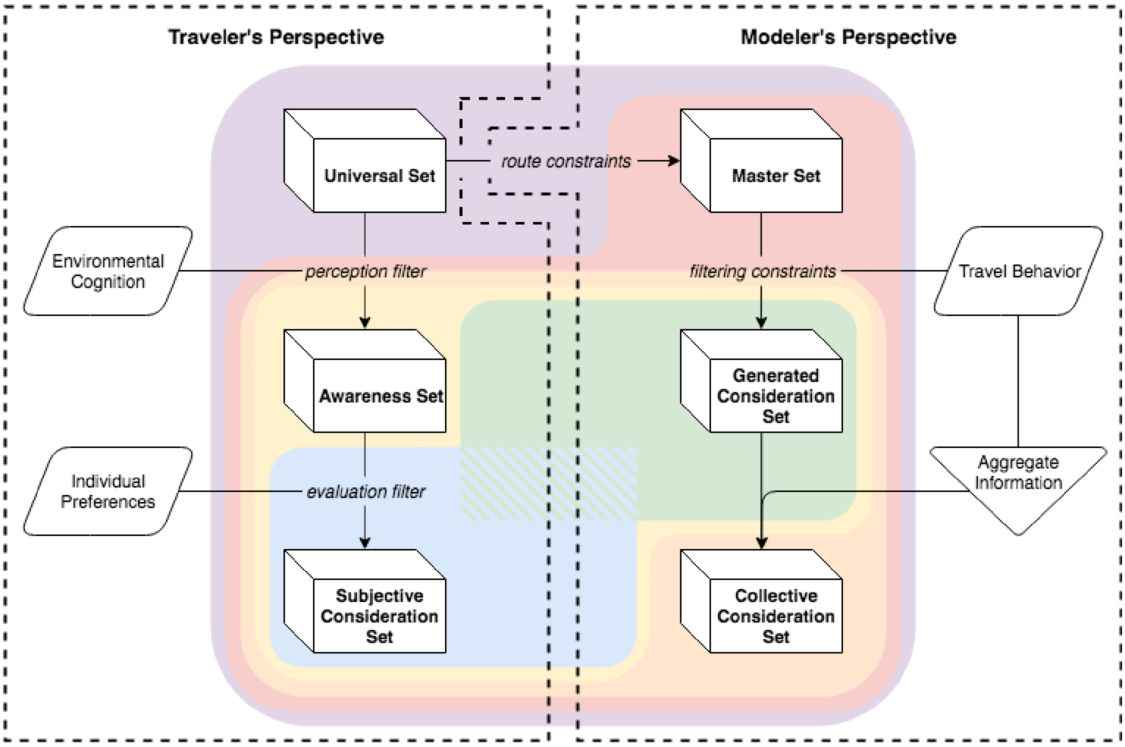

Figure 1. Route choice behavioral framework collated from the definitions and several flowcharts of Bovy *(Bovy 2008, Bovy and Stern 1990)*. Sections are enclosed in boxes to illustrate their sizes relative to the sets mentioned.

An alternative perspective of structuring decisional process of travelers in terms of route choice was examined and implemented by Gentile and Papola (2006) using past studies on behavioral psychology of travel, network cognition, and learning theory. Their study accounted for the spatial behavior of travelers to establish their mental map primarily through the cognitive process of perceiving, storing, and remembering landmarks. These landmarks, referred to as anchor points, are treated as *intermediate destinations* by the traveler and are successively reached until finally arriving to its desired destination. This simplified network of anchor points was found to be a reasonable information a traveler may latently possess in comparison to familiarizing the full extent of the network and its topology. This method of mental network construction was defined by Bovy and Stern (1990) as *sequential choice* with its nature of breaking down the entire route into multiple sub-routes and decision points in which the choices are independent of each other. On the same note, Bierlaire and Frejinger (2005) justified in their study that a traveler does not evaluate their route choice in every link but, rather, for a sequence of links which they referred to as a *subpath*. The same study reasoned that overlapping paths are more attractive to a traveler since these allow switching routes at the intermediate destinations. This was found to be more realistic and comprehensible considering the traveler's route choice behavior.

This paper introduces an alternative approach to route choice set generation by (a) applying the elliptical construct and intermediate destination concept, (b) utilizing observable network characteristics, and (c) applying reasonable constraints over the traveler's route choice set to characterize their route choice behavior. This study is limited to providing *a priori* route choice set alone; route choice and network demand loading is left for models dedicated to congested traffic assignment and equilibrium, segmenting it into a two-stage route selection process. This method allows computational and theoretical advantages such as the exogenous formation of route choice set and the flexibility in choice model types to be adopted (Bliemer and Taale 2006). As such, the route choice set generation is justified as a supply problem in this context. One of the study's minor endeavor is, then, to provide explanatory variables that characterize congestion---a significant factor on the route choice process---from the network properties without directly referencing measures of network congestion themselves.

2. THE MODEL

In the context of the behavioral framework presented above, the approach presented in this paper attempts to create the route choice set in the mindset of the traveler. This study is a deviation from the usual variations from, or augmentations on, shortest path search. Instead, route choice set generation is simplified to a degree similar to how a traveler simplifies its own route choice construction process.

Richardson (1982) enumerated three general ways of reducing the complexity of the route choice process: (a) imposing constraints upon the solution to the choice problem, (b) limiting the number of attributes of each alternative, (c) or limiting the number of alternatives before the choice process itself. The methods provided can be further condensed into simply applying constraints into the different stages of route choice set filtering. This section discusses how various reasonable constraints and logical procedure can be used to approach the function of both the *perception* and *evaluation filters* and potentially construct the route choice set.

The methodology in the succeeding subsections can be summarized as follows. The network in consideration is first reduced by applying a reasonable network filter to characterize detouring. Nodes are highlighted by assigning a score based on the properties of its surrounding links. These are then ranked from the nodes with the highest to the lowest score. Next, an optimal path is searched using a heuristic method with the number of highest-scoring nodes and a controlled objective function as the constraints. Finally, the chosen nodes are connected using a simple shortest path to the origin, destination, and other intermediate destinations to form the route choice set.

2.1 Preliminiaries

Define $G = (V, E)$ to be a directed graph comprised of vertex set V and edge set E. A vertex $n \in V$ correspond to a node and an edge $l \in E$ correspond to a link in the road network. Each edge l has a cost $c(l, j)$ to reflect the penalty of traveling along the link, called *impedance*, implicit to the corresponding road hierarchy j. A shortest path $p(n_a, n_b)$ is a sequence of edges $\{l_1, l_2, l_3, \dots, l_i\}$ connecting vertex n_a and n_b minimizing the total cost $\sum_{k=1}^{i} c(l_k, j)$.

Consider two arbitrary shortest paths connected by a common vertex, say $p(a, b) = \{l_1^{ab}, l_2^{ab}, l_3^{ab}, \dots l_r^{ab}\}$ having r links and $p(b, c) = \{l_1^{bc}, l_2^{bc}, l_3^{bc}, \dots l_s^{bc}\}$ having s links, with b as the connecting vertex.

A *concatenation* $\gamma(a, b, c)$ is a binary operation on $p(a, b)$ and $p(b, c)$ that outputs a path with $r + s$ links. Denote and define the concatenation $\gamma(a, b, c)$ as:

$$\begin{aligned}\gamma(a, b, c) &= p(a, b) \oplus p(b, c) \\ &= \{l_1^{ab}, l_2^{ab}, l_3^{ab}, \dots l_r^{ab}, l_1^{bc}, l_2^{bc}, l_3^{bc}, \dots l_s^{bc}\}\end{aligned}$$

A *track* $\tau = (n_1, n_2, n_3, \dots, n_T)$ is a tuple of nodes, where $n_i \in V$. A track is mapped to an *articulated subroute* by a function ξ, which expresses a track as a series of concatenations $\xi_\tau = \xi(\tau) = p(n_1, n_2) \oplus p(n_2, n_3) \oplus p(n_3, n_3) \oplus \dots \oplus p(n_{T-1}, n_T)$.

2.2 Network Reduction

Initially, the transportation network G is reduced to a reasonable subnetwork using the elliptical construct to implement a limit considering the distance and the directionality of travel. The ellipse was chosen to be a reasonable *potential path area* because of the following justifications:

(a) Most route choice sets for a single origin-destination pair follows a leaf venation pattern which can be tightly enclosed in an ellipse.

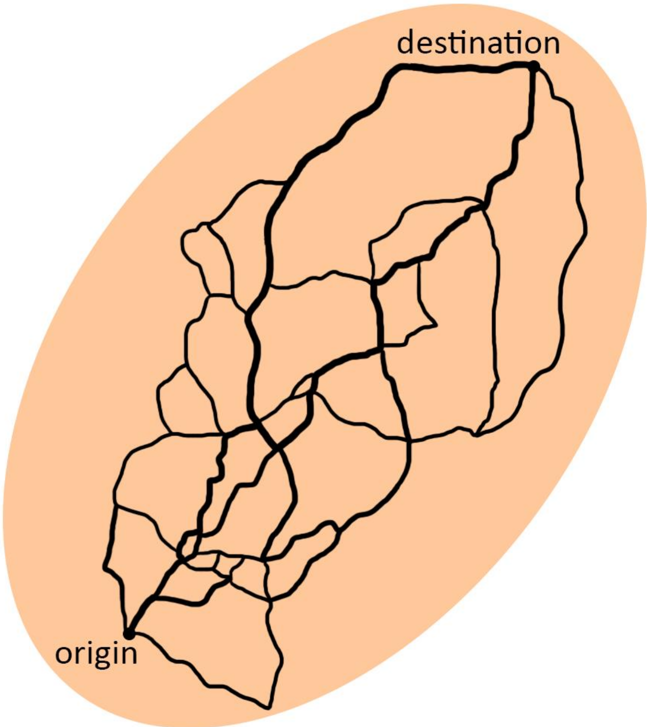

Figure 2. Sample route choice set which shows its venation and elliptical characteristics.

(b) The points along the boundary of the ellipse maintain a constant *detour factor*, which is a measure of deviation from the origin-destination axis. This sets a threshold to limit the traveler from both the origin and the destination.

Ma (2017) used elliptical neighborhoods to constrain route choice sets of discretionary activity locations for use in activity-based demand forecasting. In Figure 1, the detour factor ϕ of an elliptical neighborhood is defined as $\frac{a+b}{c}$. Point A can be any point on the boundary of the ellipse.

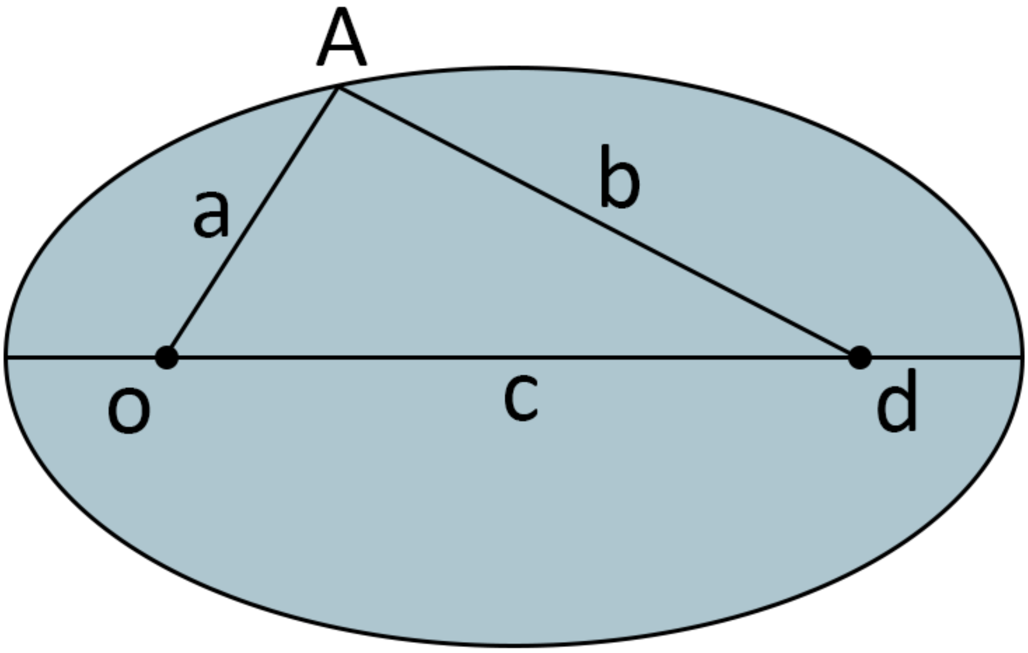

Figure 3. Sample ellipse with origin o and destination d as the foci as defined by Ma (2017). Points on the boundary of the ellipse (e.g. point A) maintain the distance a+b where a=Ao and b=Ad

(c) An elliptical construct allows a traveler to initially travel along any direction, but going against the direction of the destination will limit the space for the route to extend further.

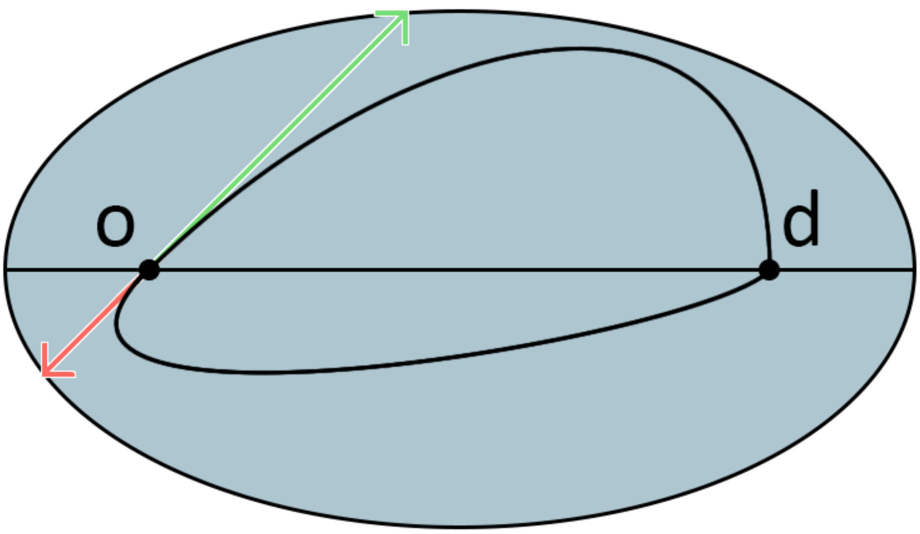

Figure 4. Two routes from origin o to destination d inside an ellipse, with their initial directions (green and red arrows). Initially, following the red arrow will give less space for the route to extend since this direction goes against the destination.

Ma's results show that there is an inverse relationship between the travel time from the origin to the destination and the detour factor ϕ (Ma and Mariante 2017). The longer the travel time for an origin-destination pair, the lesser the willingness of the traveler to deviate from the origin-destination axis. The value for ϕ will be used as the determining quantity for the size of the elliptical neighborhood B_{od} of a traveler for an origin-destination pair (o, d). Furthermore, ϕ is equal to $\frac{1}{e}$ where e is the eccentricity of the ellipse. Thus, for a fixed origin-destination pair, a single ϕ determines a unique B_{od}.

In this study, however, ϕ will be assumed to be an inverse function of the distance l_{od} between the origin and destination, instead of the corresponding travel time. Since route choice set generation for trip assignment was justified earlier as a supply problem, the travel time between two points on a transport network can essentially be substituted by the distance between them, with the two quantities only being related by an assumed maximum speed on the network.

Let $S = S(V_s, E_s)$ be the subnetwork defined by B_{od}, which is the set of all nodes V_s and set of all links E_s inside B_{od} after applying the proposed filtering method. This subnetwork will be used on the subsequent filtering steps.

2.3 Nodal Ranking

From the set of nodes $V_s' = V_s - \{o, d\}$, feasible candidate nodes for intermediate destinations are chosen. Then, nodal affinity score a is defined for all nodes $i \in V_s'$. This is the score attributed to a node based on the hierarchy of the links accessible from it. A node is considered to be more desirable if roads of higher hierarchy are directly accessible since this provides the traveler multiple alternatives to travel along faster corridors (Bovy 2008).

Let L_i be the set of all links $l \in E_s$ that contains node $i \in V_s'$. The nodal affinity score a_i of node i is given by:

$$a_i = \sum_{l \in L_i} a_{i,j}^l , \forall i \in V_s' \qquad (1)$$

where $a_{i,j}^l$ is the score of link l defined by

$$a_{i,j}^l = \begin{cases} a_{i,1}^l + \dfrac{1}{j-1} \displaystyle\sum_{k=1}^{j-1} a_{i,k}^l , & j > 1 \\ c, & j = 1 \end{cases} \qquad \forall i \in V_s' \qquad (2)$$

and j is the rank of hierarchy with the lower ranks representing smaller local roads and the higher ranks representing accessible major roads. The parameter $a_{i,1}^l$ is arbitrarily set to $c > 0$ by the modeler as the rest of the scores scale accordingly. This scaling is set such that

$$4a_{i,j}^l > 4a_{i,j-1}^l \quad \text{and} \quad 2a_{i,j}^l + 2a_{i,j-2}^l < 4a_{i,j-1}^l \qquad (3)$$

which assures that a 4 – approach motorway intersection is incomparable to a 4 – approach trunk intersection, but a 4 – approach trunk intersection is favorable over a motorway – primary road intersection. The reader is referred to Appendix A for the proof of the inequalities 3.

Let V_R be the ordered set of nodes reflecting the scores sorted from highest to lowest. The nodes in V_s' are ranked by nodal affinity and form V_R. In the next section, f is used to define the number of nodes chosen from V_R. V_R is then reduced to form V_f which is a set of f-highest scoring scoring nodes.

2.4 Path Optimization

From V_f, the ordered set of nodes $V_H = (n_1, n_2, n_3, \ldots, v_H)$ that minimizes the objective function ψ is chosen. The objective function is defined by

$$\psi(V) = \alpha T(\xi_V) + (1-\alpha)\frac{T(\xi_V)}{|V|} \tag{4}$$

minimizing a vertex set $V = (n_1, n_2, n_3, \ldots n_v)$ for $n_i \in V_f$ such that

$$V_H = argmin_V\big(\phi(V)\big)$$

where α is varied to reflect the spectrum of the traveler's preference towards T or V, $T(\xi_V)$ is the distance covered by traveling the articulated subroute ξ_V along the network across the ordered nodes in V, and $|V|$ is the cardinality (the number of nodes in the set) of V. The first term exhibits the travelers propensity to minimize the distance traveled while maintaining the intermediate destinations in mind. On the other hand, the second term pulls the objective function towards a solution that minimizes the number of intermediate destinations. From the modelers perspective, the minimization of $|V|$ equates to the tendency of the travelers to select a less complicated route choice set, avoiding loops, similar routes and unreasonable paths. T, which is the length across the network, is not directly comparable to $|V|$ since the former is greater in magnitude so $\frac{1}{|V|}$ was dynamically rescaled by multiplying it with T.

A modified *hill climbing algorithm* is used for finding the set V_H. The modified hill climbing algorithm tests an initial guess if it satisfies the given objective function and incrementally changes it in the direction of the objective to finally arrive at the optimal path (Russell and Norvig 2016). In an iteration, a guess path p is randomly changed under four basic jumps: `add-node`, `remove-node`, `swap-nodes` and `change-node`. The objective function is then evaluated for the result of the jump, p'. The acceptance of p' as the next guess for the solution is based on a scheduled probability function. A p' better than p will have a higher chance of being accepted as a next guess value. This function is selected such that the probability of accepting a worse p' exponentially decreases as the number of iterations progresses. Inclusion of this scheduled function leads to an algorithm that considers objective function values diverging from the optimal value, preventing any estimates to be constrained in a local optimum. The modified hill climbing method used is shown in Algorithm 1.

Algorithm 1 Modified hill climbing optimization

Input V_f,
Initialize $P_0 = (o, n_1, n_2, n_3, \ldots, d)$ where $l_{on_i} > l_{on_j}$, $\forall i > j$
$consistency = 0$
$buffer = [\,]$
Let J_i be the number of possible jumps of type i
$P' = P_0 - \{o, d\}$
$guess \leftarrow P'$
$obj_{guess} \leftarrow \tau(guess, \alpha)$
$threshold = \sum J_i$
$counter = 0$
while $length(jumps\_done) \leq threshold$ **do**
    $dummy = copy(guess)$
    while $jump\_id \in buffer$ **do**
        $jump = random.choice(add, remove, swap, change)$
    end while

$iter \leftarrow jump(dummy)$
$obj_{iter} \leftarrow \tau(iter, \alpha)$
$p = scheduled\_probability(counter)$
if $obj_{iter} < obj_{guess}$
$decision = random.choice([True, False], [1 - p, p])$
else
$decision = random.choice([True, False], [p, 1 - p])$
end if
if $decision\ ==\ True$ **then**
$jumps\_done \leftarrow [\,]$
$guess\ \leftarrow iter$
$obj_{guess} \leftarrow \tau(guess, \alpha)$
$threshold = \sum J_i$
else
$jumps\_done {+}{=}\ jump\_id$
End if
$counter + +$
end while
$V_H \leftarrow guess$
return V_H

The algorithm is applied for all values of α while increasing the size of V_f for each case.

2.4 Route Choice Set Construction

Finally, the route choice set R is constructed from the set of intermediate destinations V_H.

Let $M = \{(x_1, x_2, x_3, \dots, x_n) | x_k \in V_H, \forall x_i = n_r, x_j = n_s, j > i, s > r\}$

1) The shortest paths connecting the origin to each of the intermediate destinations are searched and are collected in a set such that $O = \{\omega | \omega = p(o, n\_i), n\_i \in V\_H\}$
2) The shortest paths connecting each of the intermediate destinations to the destination are searched and are collected in a set such that $D = \{\delta | \delta = p(n\_i, d), n\_i \in V\_H\}$
3) The articulated subroute connecting the intermediate destinations to other intermediate destinations are searched and are collected in a set such that $N = \{\nu | \nu = \xi(z), z \in M\}$
4) A route r in the choice set R is any continuous route concatenating a member in each of the set O, N, and D, in that order.

3. SET UP

For the purpose of the verification, hypothetical networks in the form of grid networks with varying corridor hierarchy, size (number of nodes), and dimension (midblock lengths) are constructed and utilized.

3.1 Detour Constraint

The elliptical constraint is applied to reflect the inclination of the traveler to detour away from the shortest path from o to d. The behavior of this propensity was found to be an inverse relationship with l_{od} as discussed in Section 2.2. and as shown in Table 1.

Table 1. Ma's estimated empirical detour factors. (Ma and Mariante 2017)

Travel Time (min)	Detour Factor
15	2.11
18	1.34
23	1.27
29	1.31
39	1.18
47	1.15
52	1.15

Ma's result was localized to Luxembourg but was used in this study to verify the elliptical constraint as a proof of concept. Ma's dataset was fitted to a negative exponential function of l_{od} with the travel time converted to travel distance using a 100 kph–travel speed, given by

$$\phi = a + be^{-cl_{od}} \tag{5}$$

where $a = 1.209549$, $b = 10896.21$, and $c = 0.626784$.

A network with $size = 100$ and $dimension = 1\ km$ with varying locations of origin and destination along the diagonal is constructed to show the inverse behavior.

3.2 Nodal Affinity

Verifying the effect of the assigned nodal affinity, a network is arranged such that it is enclosed in motorway corridors cascading continuously inwards to quadrants of roads with lower hierarchy. This is illustrated in Figure 5.

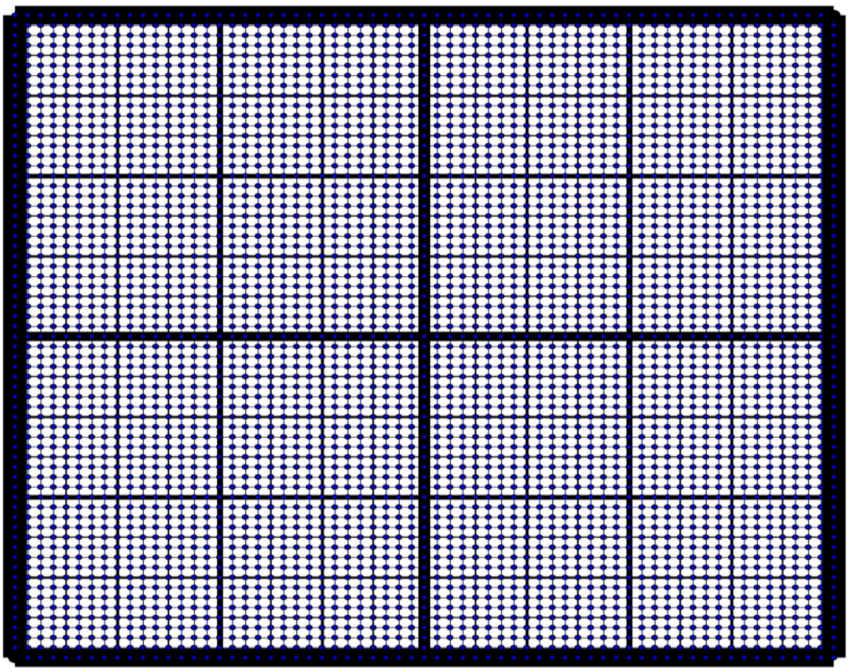

Figure 5. Hierarchical nodal affinity test network.

Moreover, Equation 2 is computed where $a_{i,1}^{l} = 1$. The other scores are shown in Table 2 and are calculated accordingly for Equation 1.

Table 2. Empirical nodal affinity score and speed limit

Hierarchy of l	Nodal Affinity Score	Speed Limit (kph)
Service Road	1.00	40
Residential Road	2.00	50
Tertiary Road	2.50	60
Secondary Road	2.83	70
Primary Road	3.08	80
Trunk	3.28	90
Motorway	3.45	100

3.3 Modified Hill Climbing Algorithm

The objective function considers the traveler's preference towards either traveling along shorter distances or passing by more intermediate destinations by minimizing Equation 4. T is calculated with the cost $c(l_i, j)$, $\forall l_i \in E_s$ and set to the speed limit assigned to the respective road hierarchy j.

There is a need to validate that the choice set generated by the modified hill climbing is in-fact a nearly optimal solution. To do this, filtering saturation points f_{sat} are searched. As f, the number of highest-ranking nodes selected from V_R, is increased, there must exist a point f_{sat} such that increasing f beyond f_{sat} does not further improve the value of the objective function obtained from the generated choice set.

A test network of $size = 50$ with $dimension = 5\ km$ between nodes was used. Network reduction, nodal affinity filtering, and modified hill climbing on the objective function was implemented on the network for increasing values of f. The final values of the objective function for each f were plotted to test the existence of f_{sat}. α was varied from 0 to 1 by increments of 0.1.

The choice set generated from the algorithm must also be reasonable. A test network of $size = 50$ with $dimension = 5\ km$ between nodes was also used. A horizontal corridor with $j = 7$ (*motorway*) was placed in the middle of the network. The hierarchy of links in these regions were randomly assigned, but the maximum hierarchy that can be assigned was varied. To have an equal preference between shortest path and number of intermediate destinations, α was set to 0.5.

As a test of validity, the route choice set generated by the algorithm must use more portion of the horizontal motorway corridor as the maximum hierarchy of links in the two areas is varied decreasingly from $j = 7$ to $j = 1$ (*motorway* to *service*).

4. RESULTS AND DISCUSSION

Shown in Figure 7 is a route choice set generated from a network with links having randomized hierarchy. In this case, $\alpha = 0.5$ for illustration. The red line indicates the path found by the algorithm passing through the chosen intermediate destinations while the blue lines indicate the path connecting all the intermediate destinations to the origin and destination. The black dots are the candidate intermediate destinations not chosen by the optimization. It can be observed that the route choice set resembles an organic leaf-like venation even on a synthetic network.

Aside from the route choice set, the method itself is examined for its validity against expected outcomes. The following are classified into two sections: (1) verification of the imposed network constraints and (2) validation of the route choice set generation.

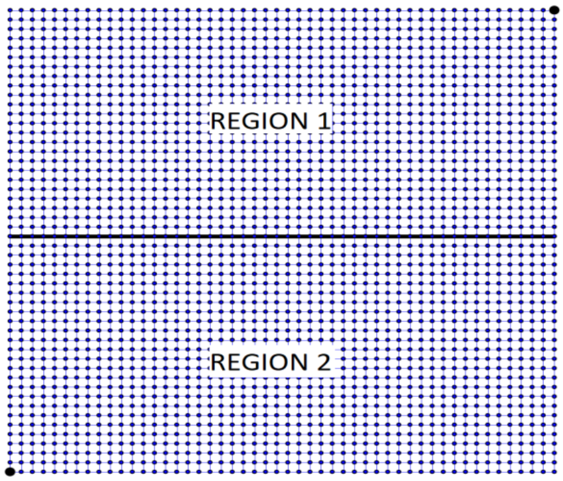

Figure 6. Test grid network with experimental motorway corridor. A varying maximum hierarchy is imposed on Region 1 and Region 2.

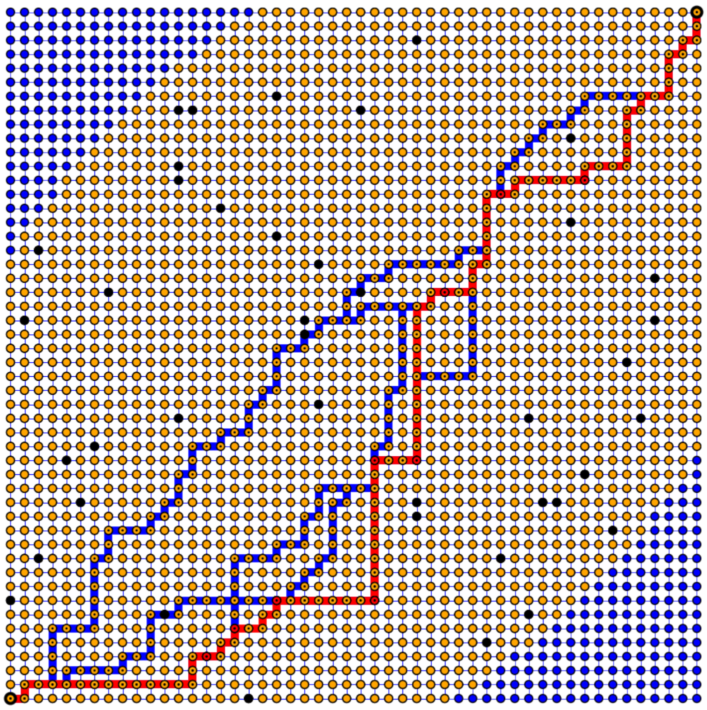

Figure 7. Generated route choice set on a network $size = 50$ and $dimension = 5\ km$

4.1 Detour Factor Behavior

Figure 8 shows how the elliptical constraint changes with varying l_{od}. As the distance gets smaller, the traveler becomes constrained by a region resembling a circle rather than an ellipse (i.e. the ellipse becomes less eccentric). Since the eccentricity of the elliptical constraint is the inverse of ϕ, these results show that a smaller l_{od} leads to a larger ϕ, concurring Ma's results (Ma and Mariante 2017).

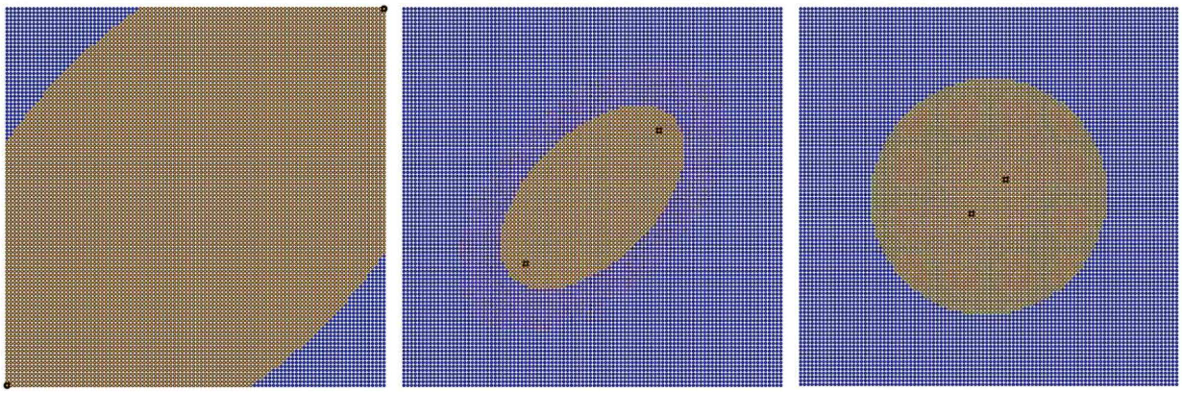

Figure 8. Progression of elliptical constraint with decreasing l_{od}.

4.2 Attraction to Highest-scoring Nodes

With the test network described in Figure 5, a run of nodal affinity scoring and filtering must prefer points lying in the boundaries of outermost quadrants than those that are inside, since these points are intersection of roads with higher hierarchies. The results in Figure 9 show that inner, less relevant nodes in the test network are more likely to be filtered out from the set of candidates for intermediate destinations. It can be observed in this verification step that filtering only considers nodes that are inside the elliptical constraint.

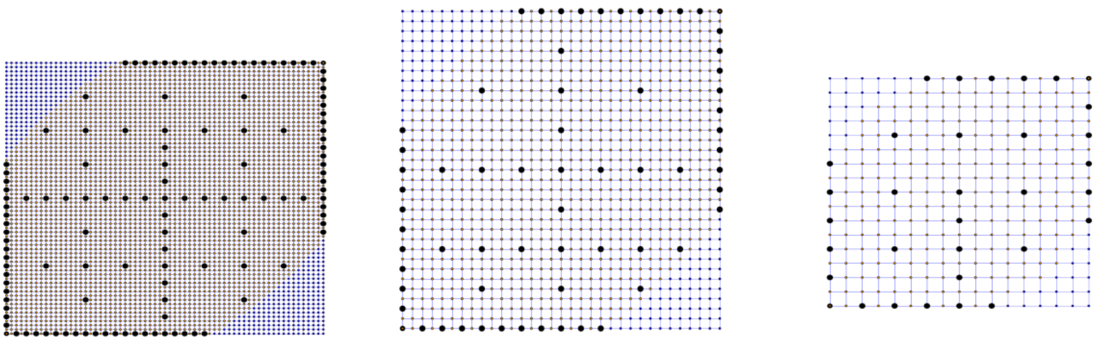

Figure 9. Filtered nodes (shaded black) in the test network after scoring and filtering.

4.3 Existence of Filtering Saturation Points

Figure 10 shows the plots of the objective function values for each value of f for $\alpha = 0, 0.5, 1$. As the value of f increases, points tend to approach a single value, implying that increasing f further will no longer improve the values of the objective function.

Note that for each value of f, the whole process of network reduction, nodal affinity filtering, and objective function, algorithm restarts completely. The proposed algorithm then determines an optimal route choice set that is replicable, even if unnecessary additional points are added to the set of candidate nodes for intermediate destinations. This further reinforces the validity of the route choice set solution obtained by the said algorithm.

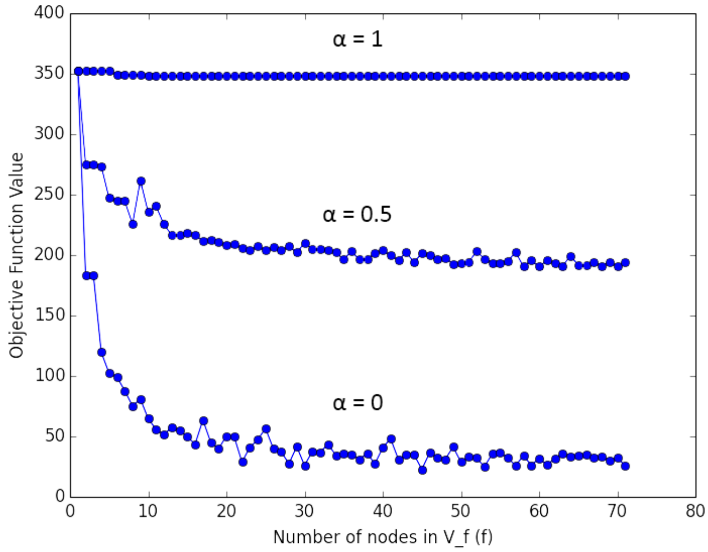

Figure 10. Objective function value (in mins) vs. f plot for $\alpha = 0, 0.5, 1$

It can also be observed that as α approaches 1, the saturation point occurs earlier in the sequence of iterating values of f. Equation 4 reduces to $\psi = T$ when $\alpha = 1$, which is the same as effectively finding the shortest path in a weighted network. Thus, selecting α closer to 1 transforms our method to resemble a shortest path problem, causing the iterations to converge quickly. Figure 4 shows the plot of f_{sat} decreasing as α approaches 1.

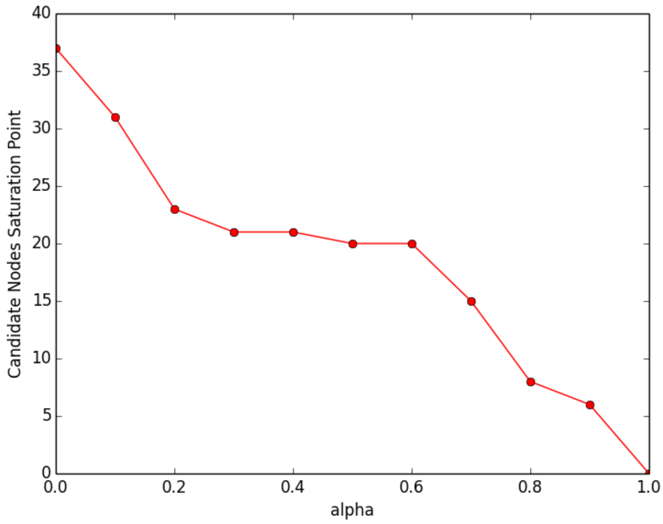

Figure 11. Plot of f_{sat} and their corresponding α

4.4 Faster Corridor Propensity

The test network with an experimental motorway corridor tests the ability of the route choice set generation to recognize significant and faster paths in the network. If the maximum hierarchy in Regions 1 and 2 (see Figure 6) is set close to the hierarchy of the experimental corridor, which separates Regions 1 and 2, the corridor becomes less significant in the network since most of the links will likely have the same cost as the corridor. However, if the maximum hierarchy for the network was decreased, the corridor becomes much less costly than the rest of the network, and travelers will follow routes that take advantage of the said corridor. Figure 5 shows the choice set generated by the method for different maximum hierarchies in Regions 1 and 2 of Figure 6.

The main routes (shown in red) of the choice sets generated by the algorithm passed 19 nodes of the experimental corridor for the network whose maximum hierarchy of the two regions is motorway, 36 nodes for trunk and 50 nodes for service, resulting to the expected trend.

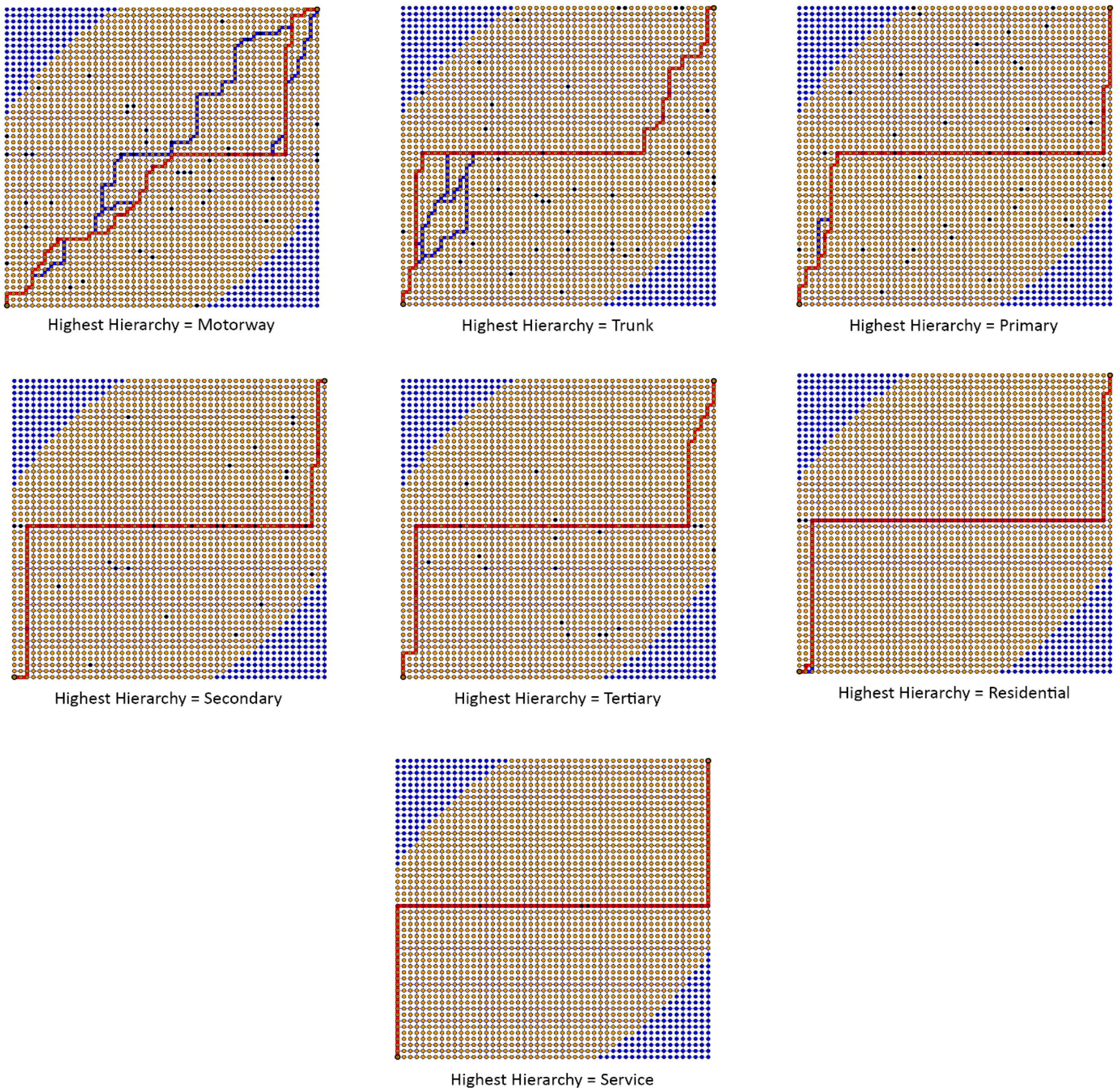

Figure 12. Choice set generated when highest hierarchy is varied

5. SUMMARY AND CONCLUSIONS

Existing route choice set generation methods are incorporated with route choice models themselves. This creates a barrier for the ease of generating the route choice set alone since choice models require substantial data and parameter estimation to capture all possible traveler idiosyncracies. This study attempted to answer the need for a straightforward, yet comprehensive, method of route choice set construction.

This paper focused on the generation of route choice set in the perspective of a rational traveler. Key characteristics of common route choice sets was utilized and implemented as successive constraints to finally minimize the construction to a reasonable route choice set. Allowance for detouring was provided by applying an elliptical filter on the network, affinity towards certain links was applied by scoring them by their respective road hierarchies, and finally, affinity towards certain links was applied by treating them as candidate intermediate destinations and finding an optimal path across the chosen candidate intermediate destinations using a modified hill climbing algorithm. These constraints' impact to the route choice set were verified and validated using hypothetical networks to examine the results. These were compared against their expected trend and were found to behave as such. Consequently, a route choice set with verified reasonability was created.

It has been shown that a route choice set can be generated without relying on latent traveler behavioral framework. Consequently, the need for extensive demographic data and resource-intensive parameter estimation are eliminated for the model construction. %These were substituted instead with reasonable constraints from general route choice behavioral framework and from measurable properties of a road network that are readily obtainable. This results to an efficient alternative approach to route choice modeling by providing a route choice set exogenous from the route choice model itself.

This study's potential improvements are augmentations to the constraints already implemented. Other impedance factors affecting nodal affinity can be added as supplement to the hierarchy score since route choice does not depend entirely on the speed of travel but also other costs of travel.

ACKNOWLEDGEMENTS

This research is supported by the Philippine Council for Industry, Energy, and Emerging Technology Research and Development – Department of Science and Technology through the Cyber-Physical Transportation Studies project.

APPENDIX

Proof of Inequality 3

Given

$$a_{i,j}^{l} = \begin{cases} a_{i,1}^{l} + \dfrac{1}{j-1}\displaystyle\sum_{k=1}^{j-1} a_{i,k}^{l}, & j > 1 \\ c, & j = 1 \end{cases} \qquad \forall i \in V_s'$$

show that

A $\quad a_{i,j}^{l} < a_{i,j+1}^{l} \qquad \forall j > 0$

B $\quad 4\mathrm{a}^{\mathrm{l}}_{\mathrm{i,j}} > 2\mathrm{a}^{\mathrm{l}}_{\mathrm{i,j-1}} + 2\mathrm{a}^{\mathrm{l}}_{\mathrm{i,j+1}} \quad \forall \mathrm{j} > 1$

A

Proof:

For $j = 1$,

$$a^l_{i,j} + a^l_{i,1} = c$$

$$a^l_{i,j+1} = a^l_{i,2} = c + \frac{1}{2-1}\sum_{k=1}^{2-1} a^l_{i,k}$$

$$a^l_{i,j+1} > c = a^l_{i,1}$$

For $j > 1$,

$$\begin{aligned}
a^l_{i,j+1} - a^l_{i,j} &= \left(a^l_{i,1} + \frac{1}{j}\sum_{k=1}^{j} a^l_{i,k}\right) - \left(a^l_{i,1} + \frac{1}{j-1}\sum_{k=1}^{j-1} a^l_{i,k}\right) \\
&= \frac{1}{j}\sum_{k=1}^{j} a^l_{i,k} - \frac{1}{j-1}\sum_{k=1}^{j-1} a^l_{i,k} \\
&= \frac{1}{j}a^l_{i,j} + \frac{1}{j}\sum_{k=1}^{j-1} a^l_{i,k} - \frac{1}{j-1}\sum_{k=1}^{j-1} a^l_{i,k} \\
&= \frac{1}{j}a^l_{i,j} + \left(\frac{1}{j} - \frac{1}{j-1}\right)\sum_{k=1}^{j-1} a^l_{i,k} \\
&= \frac{1}{j}a^l_{i,j} - \frac{1}{j}\left(\frac{1}{j-1}\sum_{k=1}^{j-1} a^l_{i,k}\right) \\
&= \frac{1}{j}a^l_{i,j} - \frac{1}{j}\left(a^l_{i,j} - a^l_{i,1}\right) \\
a^l_{i,j+1} - a^l_{i,j} &= \frac{a^l_{i,1}}{j} = \frac{c}{j} > 0 \\
&\Rightarrow a^l_{i,j} < a^l_{i,j+1}
\end{aligned}$$

B

Proof:

$$\begin{aligned}
4a^l_{i,j} &= 2a^l_{i,j-1} + 2a^l_{i,j+1} \\
&= 2\left(a^l_{i,j-1} + \frac{c}{j-1}\right) + 2\left(a^l_{i,j+1} - \frac{c}{j}\right) \\
&= 2a^l_{i,j-1} + 2a^l_{i,j+1} + \frac{2c}{j-1} - \frac{2c}{j} \\
&= 2a^l_{i,j-1} + 2a^l_{i,j+1} + 2c\left(\frac{1}{j-1} - \frac{1}{j}\right) \\
&= 2a^l_{i,j-1} + 2a^l_{i,j+1} + \frac{2c}{j(j-1)}, \text{ note: } \frac{2c}{j(j-1)} > 0 \\
&\Rightarrow 4a^l_{i,j} > 2a^l_{i,j-1} + 2a^l_{i,j+1}
\end{aligned}$$

REFERENCES

Bierlaire, Michel, and Emma Frejinger. 2005. "Route Choice Models with Subpath Components." *Proceedings of the 5th Swiss Transport Research Conference.* Monte Verità.

Bliemer, Michiel, and Henk Taale. 2006. "Route Generation and Dynamic Traffic Assignment for Large Networks." *Proceedings of the First Internations Symposium on Dynamic Traffic Assignment.* Leeds.

Bovy, Piet H. L. 2008. "On Modelling Route Choice Sets in Transportation Networks: A Synthesis." *Transport Reviews.*

Bovy, Piet H. L., and Eliahu Stern. 1990. *Route Choice: Way Finding in Transport Networks.* Dordrecht: Kluwer Academic.

Frejinger, Emma, Michel Bierlaire, and Moshe Ben-Akiva. 2009. "Sampling of Alternatives for Route Choice Modeling." *Transportation Research Part B* 43.

Gentile, Guido, and Andrea Papola. 2006. "An Alternative Approach to Route Choice Simulation: The Sequential Models." *Proceedings of the European Transport Conference.*

Justen, Andreas, Francisco J. Martínez, and Cristián E. Cortés. 2013. "The Use of Space-Time Constraints for the Selection of DIscretionary Activity Locations." *Journal of Transport Geography.*

Kaplan, Sigal, and Carlo Giacomo Prato. 2012. "Closing the Gap Between Behavior and Models in Route Choice: The Role of Spatiotemporal Constraints and Latent Traits in Choice Set Formation." *Closing the Gap Between Behavior and Models in Route Choice: The Role of Spatiotemporal Constraints and Latent Traits in Choice Set Formation* 15.

Ma, Tai-yu, and Gabriel Leite Mariante. 2017. "Location Choice Modeling Based on Mixed Logit Model and Sampling of Alternative." *Proceedings of BIVEC-GIBET Transport Research Days.* Liège.

Newsome, Tracy H., Wayne A. Walcott, and Paul D. Smith. 1998. "Urban Activity Spaces: Illustrations and Application of a Conceptual Model for Integrating the Time and Space Dimension." *Transportation.*

Ortuzár, Juan de Dios, and Luis G. Willumsen. 2011. *Modelling Transport.* West Sussex: John WIley & Sons Ltd.

Prato, Carlo Giacomo, and Shlomo Bekhor. 2006. "Applying Branch-and-Bound Technique to Route Choice Set Generation." *Transportation Research Journal of the Transportation Research Board.*

Ramming, Michael Scott. 2002. *Network Knowledge and Route Choice.* PhD Thesis, Massachusetts Institute of Technology.

Richardson, Anthony. 1982. "Search Models and Choice Set Generation." *Transportation Research Part A* 16.

Russell, Stuart J., and Peter Norvig. 2016. *Artificial Intelligence; A Modern Approach.* Essex: Pearson Education Ltd.

Transport Appraisal and Strategic Modelling Division;. 2014. *Transport Analysis Guidance Unit M1.* UK: Department.