Exploring the effectiveness of bus rapid transit - a prototype agent-based model of commuting behavior

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A B S T R A C T

The introduction of Bus Rapid Transit (BRT), typically involving the use of exclusive bus lanes and related bus priority measures, is increasingly advocated as a flexible and cost-effective way of improving the attractiveness of public transit in congested urban areas by reducing travel times and variability. These schemes typically involve the reallocation of road space for exclusive use by buses, presenting commuters with potentially competing incentives: buses on BRT routes can run faster and more efficiently than buses running in general traffic, potentially attracting commuters to public transit and reducing congestion through modal shift from cars. However, a secondary impact may also exist; remaining car users may be presented with less congested road space, improving their journey times and simultaneously acting as an incentive for some bus-users to revert to the car. To investigate the potential for these primary and secondary impacts, we develop a prototype agent-based model to investigate the nature of these interactions and how they play out into system-wide patterns of modal share and travel times. The model allows us to test the effects of multiple assumptions about the behaviors of individual agents as they respond to different incentives introduced by BRT policy changes, such as the implementation of exclusive bus lanes, increased bus frequency, pre-boarding ticket machines and express stops, separately and together. We find that, under our assumptions, these policies can result in significant improvements in terms of individual journey times, modal shift, and length of rush hour. We see that the addition of an exclusive bus lane results in significant improvements for both car users and bus riders. Informed with appropriate empirical data relating to the behavior of individual agents, the geography and the specific policy interventions, the model has the potential to aid policymakers in examining the effectiveness of different BRT schemes, applied to broader environments.

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1. Introduction

Bus Rapid Transit (BRT) consists of road-based policy measures that aim to increase priority and, therefore, the performance of bus services. BRT comes in many forms but typically includes exclusive bus lanes, higher frequency services and express-only stops (Vuvhic, 2005). Together, these are intended to increase the attractiveness of bus transport and affect modal shift. BRT generally uses existing infrastructure, either through the reallocation of road space from moving or parking lanes or addition of previously unused space (for instance, hard shoulders). Accordingly, implementation is often cheaper and quicker than for other public transport investments, particularly rail (for more see Levinson et al., 2003; Hensher, 2007). However, because of its relative flexibility in implementation, no clear standard definition of what actually constitutes BRT has emerged nor what characteristics are required to justify the moniker of BRT (Kantor et al., 2006). There is also little understanding as to what individual measures or combination of measures policymakers should focus on when implementing BRT when considering the performance of BRT in any given locality. Accordingly, critics argue that the “brand” of BRT is weaker than alternative transport modes such as light rail.

BRT is increasingly being used by policymakers to tackle congestion and other externalities arising out of the common good nature of urban road space. If policymakers intervene to allocate some of that road space exclusively for use by buses, it is likely that the bus service will become more attractive to bus users and potential users. In addition, any modal shift from car to bus may result in a set of rebound secondary effects. In cases where bus lanes are using previously open lanes, the remaining...
car users are presented with less space on that route. Where lanes are new or used space previous restricted to moving cars (e.g. parking lanes or shoulders), remaining car users may be presented with less congested road space as buses are removed from traffic and the bus modal share potentially improves (this ignores the impact that removing parking will have on car users looking to store their cars at the end of their journey). This may result in improved journey times for the remaining car users, offering renewed incentives for potential car users (see, Litman, 2001; Grüttner Consulting, 2006). In contrast, increasing the modal share of the bus without increasing capacity may result in additional congestion for bus users (existing and new) which may trigger its own set of reactions. Despite these competing influences on urban road space, little focus has centered on the impacts of these micro-level interactions on the success or otherwise of such schemes.

In this paper, we present a model to explore the primary and subsequent impacts of changing the incentives faced by individual agents, in this case commuters on an arterial road to the CBD. Although many BRT schemes have been developed around the world, the simultaneous incentives and disincentives arising from their implementation on existing road users has largely escaped research focus. It is of particular interest because existing road users are presented with potentially large and little understood disincentives arising from micro-level interactions (e.g., congestion in the car lanes, crowding in buses). This research aims to build upon existing research. We explore how these interactions impact transport choice, to generate insights into the aggregate effects of individual decision-making in the face of this new environment, something that has gained currency amongst researchers (Webster et al., 1998; BTE, 1998; Stern and Richardson, 2005) but has largely been overlooked in relation to BRT. In addition, while there is a rich and growing literature relating to modeling long term transportation patterns (e.g. between transport and land use; see for instance: Kitamura, 1994; Southworth, 1995; Wegener, 2004), our research is focused on examining the shorter term behavioral impacts of introducing new transportation infrastructure. Short-term behavior can be thought of as the response of commuters to changes in system characteristics, given that long-term decisions, such as residential and employment locations, are fixed.

The next section outlines the literature and methodology, and presents the agent-based model of a BRT scheme in a hypothetical urban corridor. Section 3 includes preliminary tests of our prototype model. The policy scenarios and analysis are described in Section 4, followed by the policy implications.

2. Mode choice and BRT: theory and methods

Our research is focused on identifying emergent patterns arising from individual actions. There is a very wide range of research aimed at predicting transportation patterns at an aggregate and disaggregate level. Researchers and policymakers generally utilize three methods to do this: asking people if they would change their behavior if certain factors changed (stated preference; see for example, Spencer and Andong, 1996; Currie, 2005; McDonnell et al., 2009); drawing inferences from observed behavior under different conditions (revealed preference), and simulation methods derived from models aimed at forecasting and optimization (Stern and Richardson, 2005; Wegener, 2004; FHWA, 2004), which tend to be data-driven. Rather than using data to derive relationships and decision rules, we developed a stylized agent-based model based, in part, on existing mode-choice modeling approaches, but that additionally attempts to recreate the decision-making process of choosing a mode. Our research thus aims to complement the more established simulation techniques, and be flexible enough to be informed by data from both the first and second methods.

Analysis of modal share and modal split is perhaps the most explored topic in transportation research. Within that area, discrete choice analysis dominates. Such analysis models the choice of a decision maker among a set of finite, mutually exclusive alternatives. Each alternative is comprised of a set of attributes that describe that alternative, and the decision maker derives a level of utility from that alternative based upon those characteristics and the characteristics of the decision maker. This leads to the concept of utility maximizing behavior; an individual will choose an alternative if and only if the utility associated with that alternative is greater than any other alternative on offer (Train, 2003). This is operationalized in the modeling structure by making the choice a function of both the alternative attributes and the characteristics of the decision maker. In reality, modelers can only observe part of the utility, the observed part, leaving an unobserved part. By having an unobserved element, it means that the deterministic choice structure is now defined as probabilistic. Thus, a random utility model (RUM) is adopted, meaning that the alternative with the highest observed utility has the highest probability of being chosen by the decision maker (Louviere et al., 2004). Various forms of logit and probit models are most frequently used to estimate the probabilities (see, Train, 2003; for a complete discussion).

Analysis of existing BRT and bus systems in general are well developed in many areas (Azar et al., 1994; Levinson et al., 2003; Vuvhic, 2005; McDonnell et al., 2006). For instance, microscopic simulation techniques are used extensively in the realms of traffic flow simulation and performance analysis of new infrastructure such as intelligent transport systems (ITS) (for more see: Yang et al., 2000); For a detailed review of best practices in micro simulation models see Sbayti and Roden (2010). Similarly, microscopic techniques have tested the impacts of Bus Rapid Transit schemes on local traffic flows and travel times; for instance, SmartBRT (2004) and, more recently, an analysis of BRT in the Chicago Loop by Jiang and Murga (2010). The latter study, using microscopic traffic simulation techniques and data about the traffic network, signaling and bus service levels focuses on three performance criteria: bus travel speed, car travel speed and bus travel time and reliability. However, the study does not explore the primary and subsequent impacts that the very existence of a BRT route may have on mode choice and how that relationship subsequently affects travel times.

Beyond simulation, research focus in relation to BRT has generally been on aggregate modal choice as a by-product of policy interventions (see Levinson et al., 2003). Investigations into potential behavioral patterns and mode decision-making by individual agents faced with new (as yet, unimplemented) BRT-related policies and the subsequent system-wide impacts is less common. In a wider context, researchers have described the tendency to overlook choice rules and focus instead on the relationship between input and output variables as “black box” modeling (Boyé and Stern, 1990). The individual choice rules about mode and congestion response strategies are often not explicitly modeled. Artificial neural network models and rule based models, in contrast, can enable adjustments to improve performance (Stern and Richardson, 2005). Similarly, “fuzzy set theory” is a framework that assumes that decision-making is based on a number of simple rules rather than maximizing some utility function; in other words, a series of “IF, THEN” rules. See (Stern and Richardson, 2005) for a discussion on behavioral modeling in road transportation. However, as far as the authors are aware, very little of this behavioral modeling research has focused on how road users respond to investments related to BRT.
and how each measure or combination of measures induce behavioral change.

The goal of our research is to begin to address this gap and understand the potential impacts of increased bus priority measures (separately and together) on commuter choice and road performance in an urban corridor. We are interested in developing generalized insights about how actions by individual agents result in system-wide impacts and the mechanisms involved in those interactions. Unlike much of the discrete choice modeling literature, we are not concerned in forecasting outcomes as an end, but rather how and why outcomes may emerge. As such, we are complementing the existing literature by presenting a simple model of how individual actions create system-level patterns through interactions with each other and their environment. We do this through the use of agent-based modeling, which allows for the creation of a simulated environment in which autonomous individual agents with defined decision-making structures interact with each other. The decision structures are defined by the modeler, can accommodate existing behavioral data or new untested assumptions, and can simulate a population of agents with homogeneous or heterogeneous preferences in the face of defined incentives, all operating concurrently. From these agent-level interactions, large-scale outcomes and patterns emerge. ABM is thus a powerful tool for exploring how such local interactions, using multiple decision assumptions, can determine system-wide outcomes (Epstein, 2006; Tesfatsion, 2006; Grimm et al., 2006; Miller and Page (2007)). Such models are important in both the theoretical and management spheres because they allow for the consideration of aspects usually difficult to explore in other analytical approaches (Grimm et al., 2006; Axelrod and Tesfatsion, 2006).

Agent-based models have been used in the analysis of a wide array of transportation and urban systems related phenomena (see for instance: Zhang and Levinson (2004), Arentze and Timmermans (2004), Batty (2005) for a more complete review), and particularly in the realm of traffic simulation models for congested urban areas (Wilensky, 1997; Wilensky, 1998; Dresner and Stone, 2004). ABM's have also been used to explore decision-making processes related to infrastructure users and operators (Zhang et al., 2007), route choice (Dia, 2002) and real time information (Wahle et al., 2002). More recently, Lu et al. (2008) have investigated how land-use policy interventions affect travel mode choice behavior. However, analysis of mode choice as an emergent pattern in the face of the imposition of a system of BRT remains largely unexplored.

Our research explores the effect of different BRT policy interventions on the commuting behavior of household agents. In our agent-based model, we represent an urban corridor in which agents move from diverse origins (representing homes in the catchment area of a road) to a single destination using a single arterial road. The agents’ choices for this journey are limited to the length of time for all road users to reach a destination and (b) modal share, to investigate the impact of BRT-related policies. Our environment was intended to represent one generic route. Since we are not focused on using the model as a prediction tool, we focus on developing a synthetic simplified environment where our agents are limited to a simple decision making structure, informed or calibrated with data within reasonable ranges, i.e. within the same order of magnitude as the observed system. In constructing the environment and the scenarios we draw upon context from existing sources, particularly from the City of Chicago, where the City government and the Chicago Transit Authority (CTA) were awarded, then lost out on, over $150 million from the US Department of Transport to tackle congestion. Currently, a BRT analysis is being undertaken by coalition of the CTA the Chicago Department of Transportation (CDOT) and the Chicago Metropolitan Planning Council (Metropolitan Planning Council, 2010). In addition, Chicago, in common with many cities in the US and beyond has a well-developed grid of city streets on which the existing bus network is largely based. As such, developing a model that draws upon this generic environment can provide policymakers, in Chicago and elsewhere, with a framework to explore more fully the dynamics of bus priority provision on a congested urban system. Instead of relying on traditional ex-post aggregated analyses of BRT scheme implementations, our methodology allows for the simulation of hypothetical scenarios to analyze individual agent behavior change and emergent patterns.

The goal of this paper is to present this stylized version as a prototype to build upon. In future work, we will expand the model to include more geographically correct representations of specific neighborhoods, to accommodate the possibility of route shifting, the presence of additional modes and the lack of a car choice for certain households.

3. Our model

Following the structured suggested by Grimm et al. (2006), we present our model in three sections: purpose and overview, design concepts, including the state variables and scales and finally, the process overview and scheduling.

3.1. Purpose and overview

We test the hypothesis that the behavior of interacting individual agents, in terms of their modal choice, will alter significantly as a result of the introduction of measures related to BRT. In addition, we test the proposition that mean journey times will be reduced as a result of these policy interventions. Finally, we investigate the emergent system-wide properties by analyzing the length of the rush hour (i.e. the time taken for all commuters to reach the destination).

We constructed our spatial simulations in Netlogo, a multi-agent programmable modeling environment used across a wide range of disciplines, authored by Uri Wilenski and developed by the Center for Connected Learning (CCL) and Computer-Based Model and Northwestern University. Janota et al., (2005) gives a brief outline of the potential for traffic simulation models in Netlogo. The model environment represents a generic single-direction 5-km road running to a destination representing a central business district (CBD). The road has a number of entrances and bus stops along its route, intended to represent the grid structure in Chicago, although it is not geographically linked to any particular road section; our focus is on gaining insights into the emergent properties of the modeled system. Future work will employ real street characteristics to adapt it for policy exploration in specific corridors. In addition, the road has two lanes: one in which all cars and buses can use collectively, and one that is left empty. The latter represents a parking/loading lane if there is no BRT and is designated for the sole use by buses if there is BRT in operation. This is in contrast to other models of the impact of converting a lane of general traffic to a lane used exclusively by public transit (Currie et al., 2007). This dichotomy will form the basis of our policy scenarios. Our road runs through a catchment area within which all our residents live. The commuters move from their unique origin to the common destination.

We implement six types of agents (or “breeds” in Netlogo language): households, which represent the origin of all commuters and are fixed according to the initial density set by the modeler. Each household produces either bus riders or cars.
accordance to the modal choice of the household. Buses transport
the bus riders (riders must wait for a bus, households using cars
have a one seat journey). Depending on the mode choice, the
commuter initially moves to its nearest car entrance or bus stop.
From there, they move along the road to the destination. Travel
time is computed by each household taking note of both the
departure time and the arrival time at the destination for the
commuter associated with it.

Mode choice is represented as a decision to switch from bus to
car or vice-versa when the travel time for a specific day exceeds
the travel time for the previous day. Mode choice is a learning
process, a function of the agents' own experience and habit
formation as they explore the available options to complete their
daily commute (Bannister, 1978), rather than a comparison
between average journey travel times for each mode, a knowl-
edge to which individuals may not have access. Modal switch is
an important determinant of our model. It occurs as a result of
lengthening commutes, as individual travel times are impacted
both by the agents' own behavior and by the presence and scale of
negative externalities (i.e. time costs associated with congestion).
In current scenarios, users of each mode have a "tolerance" to
lengthening commutes. If their commute exceeds their tolerance
level (set relative to the previous day's commute), they will
switch modes. The tolerance is designed to represent the reluc-
tance of users of one mode to switch to another; particularly
evident amongst car users (Hensher and Reyes, 2000). In initial
testing, we examine the impact of different tolerance levels to
assess the importance of this attribute to modal shift. Future
model development will involve the inclusion of presumed com-
muting times in alternative modes in the agents' mode-choice
mechanisms and heterogeneous tolerance levels.

The current scenarios run for 20 days during which the
commuters make their experience-based choices of transporta-
tion. The focus of our model is on short-term travel behavior;
initial testing of the models tended to show stable patterns
emerging within the first 10 days. We also run several simula-
tions for each scenario to gain a sense of the variability generated
by stochastic mechanisms in the model. At the end of each day
and at the end of each run, the model computes the variables for
time of travel, modal share and length of the rush hour.

3.2. Design concepts

In this section we describe the components of the model in
more detail. Table 1 outlines the main parameters and ranges
used in our base model to design the environment and the agents.

3.2.1. Model environment

Our environment, 5 km in length and just over 1 km in width,
is represented by a world that is 126 cells (or "patches" in Netlogo
language) long and 33 cells wide. Each patch thus represents
40 m in length and width (1600 m²/approximately 0.28 acres).
Timing in the model is determined by the maximum speed
allowed in urban areas. The speed limit in urban Illinois areas is
30 miles per h (48.27 km per h)—translating as 1 km approxi-
mately every 75 s (Downs, 1992). Our commuters can travel a
maximum of 25 patches per 75 s. The Netlogo platform records
time progression as ticks (each time step), thus in our model
every 20 ticks represents 1 min. When all commuters reach the
destination, we define this as the end of the rush hour or "day".

3.2.2. Road

The road is a two-lane, single direction route with a sidewalk
cutting across the length of the environment. At intervals
specified by a parameter, there are entrances and bus stops on
the sidewalk where cars and bus riders wait for a space on the
road and an oncoming bus, respectively. This represents a typical
grid structure in Chicago in which large streets are at 1/2 mile
intervals and small one way streets are 200 m (1/8 of a mile)
apart. Car entrance and bus stop are typically at 400-m or
x-disentrance and x-diststop. Each road and an oncoming bus,
respectively. This represents a typical grid structure in Chicago in
which large streets are at 1/2 mile intervals and small one way
streets are 200 m (1/8 of a mile) apart. Car entrance and bus
stop are typically at 400-m or
x-diststop (false), all
parameters, respectively. Without the BRT lane (BRT? is false),
all commuters travel on the single lane to the common destination;

Table 1
Parameters in BRT base model.

<table>
<thead>
<tr>
<th>Level of parameter</th>
<th>Parameter</th>
<th>Description</th>
<th>Base value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global</td>
<td>x-Distentrance</td>
<td>Distance between entrances</td>
<td>400 m</td>
</tr>
<tr>
<td></td>
<td>x-Diststop</td>
<td>Distance between bus stops</td>
<td>400 m</td>
</tr>
<tr>
<td></td>
<td>Residents</td>
<td>Number of residents in residential patches</td>
<td>3000</td>
</tr>
<tr>
<td></td>
<td>Probability-of-bususer</td>
<td>Initial proportion of bus users</td>
<td>10%</td>
</tr>
<tr>
<td></td>
<td>BRT?</td>
<td>Determines if the buses are in general traffic or on a separate lane</td>
<td>False</td>
</tr>
<tr>
<td></td>
<td>Minute</td>
<td>Timing parameter</td>
<td>20 ticks</td>
</tr>
<tr>
<td>Turtle</td>
<td>Bus riders</td>
<td>Tolerance threshold</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>Cars</td>
<td>Speed-min</td>
<td>0 mph</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Speed-limit</td>
<td>30 mph</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Acceleration</td>
<td>0.225 (3 m/s²)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Deceleration</td>
<td>0.337 (4.5 m/s²)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Tolerance threshold</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>Buses</td>
<td>Speed-min</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Speed-limit</td>
<td>30 mph</td>
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<tr>
<td></td>
<td></td>
<td>Deceleration</td>
<td>0.337 (4.5 m/s²)</td>
</tr>
<tr>
<td></td>
<td>Frequency</td>
<td>How often a bus runs on the route</td>
<td>10 min</td>
</tr>
<tr>
<td></td>
<td>Bus load</td>
<td>How many bus riders are on the bus</td>
<td>0 bus riders</td>
</tr>
<tr>
<td></td>
<td>Bus-capacity</td>
<td>How many bus riders can access the bus</td>
<td>100 bus riders</td>
</tr>
<tr>
<td></td>
<td>Boarder-per-min</td>
<td>How many bus riders can board per min</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>Car entrances</td>
<td>Number of cars waiting at the car entrance</td>
<td>0 cars</td>
</tr>
<tr>
<td></td>
<td>Car-counter</td>
<td>Number of bus riders waiting at the bus stop</td>
<td>0 bus riders</td>
</tr>
<tr>
<td></td>
<td>Bus stops</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Rider-counter</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
with the BRT lane, buses have the exclusive use of this additional lane. Currently, there is no passing of vehicles allowed. As a result, when a vehicle is stopped (because of congestion or because it is at a bus stop to pick up riders in the case of a bus), it imposes a time delay on the following vehicles. This simulates a single lane road where it is difficult for vehicles to overtake other vehicles, especially in congested conditions.

3.2.3. Residential cells and households

The catchment area where residents live extends almost 600 m on either side of the road so that the total area is 1160 m (almost 3/4 of a mile), a conservative estimate based on empirical studies (McDonnell et al., 2006). Every residential patch (each patch that is not part of the road) has the capacity to contain a household who sends a single commuter to the destination. This implies a population density maximum of about 4 commuters per acre. In our model, the variable residents defines the number of households within the catchment area, which is set at 3000 (approximately 3 commuters per acre). The Chicago population density is approximately 19.9 persons per acre (Cyber Drive Illinois, 2010). However, not all of these would be road users, whose interactions are the focus of our model.

The households are situated randomly on the residential patches catchment area (see Fig. 1). The households either take the form of a car-using household (indicated by a red color) or a bus-using household (indicated by a green color) according to the initially defined probability of bus use (probability-of-bus-user). Each household records the distance to the nearest bus stop and car entrance in preparation for sending their agents to the road.

3.2.4. Cars and bus riders

Car-using households produce a car agent and bus-using households produce a bus-rider. All households do not send commuters to the road simultaneously. Instead, we simulate a rush hour in which commuters leave their household over a three hour period. For these scenarios we create a normal distribution of departure times, meaning that the population of departing commuters increases to a peak 90 min after the start of the rush

![Model environmental and decision-tree for household, bus and commuter agents.](image-url)
Each household records the time the commuter leaves it. All cars move to their nearest car entrance and are assigned a sequential queue number. The queue number must be higher than for the cars that preceded its movement from the household. This ensures that cars leaving the households get onto the road in the order they arrived at the car entrances. When their turn comes to be first in line, each car must wait until there is a free space on the road immediately in front of it to move in. Once on the road, the car travels towards the destination as fast as the prevailing traffic allows. Bus riders move to their nearest bus stop in a similar way. There, they wait for a bus in the order in which they arrived. Future versions of the model will represent these movements using local street networks in addition to the main route of interest.

3.2.5. Buses

Each bus leaves from the bus depot situated at the furthest point of the route from the destination at intervals defined by the parameter frequency, which is initially set to one bus every 10 min (120 ticks), although this frequency may be high for many urban areas, all of Chicago’s 9 busiest routes, each carrying more than 7 million passengers in 2009 (Gibson, 1998), run at headways of 10 min and less during peak time (CTA, 2009a, 2009b).

As each bus approaches the next bus stop, they search for any bus riders waiting there. If bus riders are present and the bus is not at capacity (bus-capacity, set to 100), the bus stops and the riders board the bus. If the bus reaches capacity, riders with a higher queue number must wait for the next available bus. The time spent at each bus stop (load-time) will be determined by the number of riders waiting at the stop and the average boarding time per rider (boarders-per-min), initially defined as 8 per minute. Hounsell (2004) notes that average boarding times range from 3 to 9 s depending on the provision of certain facilities such as pre-boarding tickets, in this research we assume a cash only system for our base model so that boarding times are likely to be longer, allowing for fewer passengers to board per minute. Once all bus riders are collected or the bus reaches capacity, the bus starts moving again and repeats the procedure at each bus stop. If the bus is full, it does not stop until it reaches its destination. The bus riders are now associated with the bus that stopped for them.

3.2.6. Bus and car speeds

Bus and car speeds range between 0 and 30 mph (Illinois urban speed limit) and are defined by the speed-min and speed-limit parameters. Acceleration and deceleration parameters determine the reaction times of the cars and buses to increased flow or increased congestion, respectively (adapted from the Netlogo traffic basic model by Wilensky (1997)). These parameters are determined by data from the FHWA (2004) and translate approximately as 0.225 patches and 0.337 patches per tick in our model.

3.2.7. Reporting travel times

When the commuting agent reaches the destination, it reports the travel time to its household and its travel time can be computed as the time it took from leaving the household to reaching the destination. Thus, journey times are determined by the characteristics of the commuters’ mode of travel and also characteristics of the road and the other road users. In the example of bus riders, journey times will depend on their own characteristics (time of departure), the characteristics of the bus (speed, acceleration, deceleration, etc.), the number and boarding times of bus riders at each of the stops and the speed of other buses preceding them (if applicable). If there is no BRT, the buses travel in general traffic and journey times will also be determined by congestion. By stopping, the bus will impose a time delay on any cars or buses behind it. The journey times will determine the mode choice for the following day depending of the tolerance to longer commute times for each user (see next section).

4. Preliminary testing: understanding the model

When the model is initialized, a day begins and commuters are produced for each household as determined by the probability-of-bususer parameter, initially determined by the modeler.

After initialization, commuters move to the bus stop or car entrances. Commuter departure times are normally distributed over a 3 h period (see Section 3.2.4). Once the car users are at the road and it is their turn to move onto the road, they must check the road patch directly in front of them. If there is a car or bus there, they wait until a space becomes free. Once it does, they move onto the road and start moving towards the destination as per their speed, acceleration and deceleration parameters. Bus riders need to wait for the bus. Buses start departing from the bus depot as per the frequency parameter, riding along their exclusive lane (BRT? is true) or sharing the road with cars (BRT? is false). Every bus departs the depot empty. As they approach each stop they check for the presence of bus riders and their capacity; if both conditions are met, the bus stops and boards riders in the order in which the riders arrived. When the bus reaches capacity, it stops boarding riders and moves on again. Each bus rider will become associated with that bus and is removed from the bus stop, the bus rider with the lowest subsequent queue number will then become the next bus rider to board. If the bus is already at capacity, it does not stop at any more bus stops. If there is little traffic on the road, the agents move at speeds approaching the stated speed limit. However, as the road becomes congested, agents (in this case, cars or buses) must respond to the presence of other agents on the road and reduce their speed accordingly.

When each commuter reaches the destination, it reports its journey time to its household. When all commuters reach the destination, the rush hour ends. The final modal share, mean journey times and the length of rush hour are all computed. The next day immediately starts and commuters are created and initialized according to the household initial mode choice. Only at the end of the second day, each household is able to compare the most recent journey time of its commuter with that of the previous day, and this becomes the basis for mode choice for all the remaining days until the end of the run, 20 days long, as influenced by their tolerance or reluctance to switch mode. In subsequent scenarios, we tested higher tolerance levels to allow for more realistic inertia levels in modal switch (outlined below). Prior research has indicated a reluctance of users of one mode, especially the car, to switch modes (Hensher and Reyes, 2000). The decision-making framework is outlined in Fig. 1.
impact on its performance but further reduces journey times for cars. We subsequently restrict our scenario analysis to an environment with 3000 households. Given that the population density is still relatively low by Chicago standards, this remains a conservative assumption. We aim to design and test the basic mechanisms of the model first, to later build on this prototype and explore higher-density scenarios with the consequent computational expense.

We analyzed the impact of initial modal share on continuing modal share to investigate behavioral adaptation. Our hypothesis was that, no matter the initial modal share, behavioral adaptation would lead to similar proportions of bus users and car users at the end of each run. With differing levels of initial bus modal share (10%, 25%, 50% and 75%), we find the resultant means after 20 days to be approximately similar, and that stable patterns are established by the third or fourth simulated day, after initial large switches in modal share. However, further analysis shows that the means are statistically different below the 10% level, indicating that initial modal share has some influence on results. At the extremes, there may be substitution for the more popular mode resulting from a “congestion penalty”, a crowding effect resulting in modal shift that dissipates as modal share becomes less lopsided. In addition, we find that, with BRT, car users are more likely to be situated closer to the destination, while bus users dominate the catchment area more than 2.5 km away. This suggests that the bus may not be able to compete with the car at closer distances, maybe a mirror of the “first mile last mile” problem found in the literature (Kopp et al., 2006).

To investigate the bias regarding modal shift in the first iterations, we test the model with different tolerance levels, allowing modal shift to occur if most recent journey times were longer than the previous day. These levels range from no tolerance of longer model shift to tolerance of journey times doubling. Without BRT and with an initial mode share of 10% of the bus, we see the bus modal share rise to about 28% if the tolerance levels are set at zero; 45% if there is BRT. This might suggest that the process of getting onto the road is more efficient for bus riders than for cars, i.e. cars must wait longer at the entrances than bus riders need to wait for a bus. When we increase the tolerance to longer journey times to 100% for car drivers (i.e. journey times doubling before car-using households switch), bus modal share remains at around 13% without BRT. However, with BRT, the bus share still rises to 43%. This suggests that the model is more sensitive to the inclusion of the BRT route and to the inertia of car drivers. If the bus tolerance is doubled while car-using households have a zero tolerance for longer journey times, the bus modal share rises to 47% without BRT and 58% with BRT.

5. Simulations and results: assessing the effects of BRT

Our scenarios focus on the difference between the environments with and without BRT and the ancillary policies (separately and together), to investigate the impact on average journey times for each population of road users, modal share and the length of time it takes for all users to reach the destination. A priori, we would expect that the addition of a BRT lane to the existing road will reduce journey times for bus riders and increase the modal share of buses. We would also expect that the length of rush hour, our measure of efficiency, will be reduced since the addition of a lane should induce better road performance. However, journey times for cars may also decrease as there will be fewer cars and no buses on the road, thus reducing congestion and attracting car drivers—a rebound effect. Therefore it is difficult to anticipate the final outcome. The current version of our model does not account for switching routes or times of day (Downs 1992; Stern and Richardson, 2005); we only focus here on mode choice to keep the representation of competing incentives simple and the interactions tractable. As a result, initial journey times are likely to be longer as road users are restricted from changing route, even in the face of extreme congestion.

In each of the reported scenarios, we set the tolerance levels for the car at 40%, meaning that if journey times for the car are 40% longer than in the day before, car users will switch modes. For bus riders, we set a lower tolerance of 25%. This is designed to

| Table 2 |
|-----------------|---------------|-------------|
| **Scenarios**   | **Parameter** | **Value**   |
| 1. Baseline, no exclusive bus lane or ancillary measures | BRT? | False |
|                 | Frequency     | Every 10 min (200 ticks) |
|                 | x-Diststop    | 400 m (10 patches) |
|                 | Boarders-per-min | 8 per minute |
| 2. Exclusive bus lane introduced | BRT? | True |
|                 | Frequency     | Every 10 min (200 ticks) |
|                 | x-Diststop    | 400 m (10 patches) |
|                 | Boarders-per-min | 8 per minute |
| 3. Off-board ticketing introduced | BRT? | True |
|                 | Frequency     | Every 10 min (200 ticks) |
|                 | x-Diststop    | 400 m (10 patches) |
|                 | Boarders-per-min | 12 per minute |
| 4. Express bus stops introduced | BRT? | True |
|                 | Frequency     | Every 10 min (200 ticks) |
|                 | x-Diststop    | 800 m (20 patches) |
|                 | Boarders-per-min | 8 per minute |
| 5. More frequent buses introduced | BRT? | True |
|                 | Frequency     | Every 5 min (100 ticks) |
|                 | x-Diststop    | 800 m (20 patches) |
|                 | Boarders-per-min | 8 per minute |
| 6. All measures introduced | BRT? | True |
|                 | Frequency     | Every 5 min (100 ticks) |
|                 | x-Diststop    | 800 m (20 patches) |
|                 | Boarders-per-min | 12 per minute |
represent the higher inertia effects outlined in recent research amongst car users (Hensher and Reyes, 2000). We chose these thresholds after initial testing in which we tested tolerance levels from 0% to 100% (outlined above).

We developed a base case scenario and five implementation scenarios (see Table 2). The base case has no exclusive bus lane (Scenario 1). In Scenario 2, the exclusive bus lane is added to the environment. In Scenario 3, we extend the policy environment towards a consolidated BRT policy agenda by also reducing the interval between buses from one every 10 min to one every 5 min. In contrast, Scenario 4 explores the introduction of express stops on the route so that buses stop once every 800 m (1/2 a mile) on the exclusive bus lane, designed to reduce journey times through a reduction in stops the bus has to make. Average boarding times per passenger can vary considerably based upon a number of characteristics (Hounsell, 2004). In Scenario 5, we simulate a modest decrease in passenger boarding times associated with the introduction of pre-boarding ticket machines; 12 passengers board per minute instead of 8. Scenario 6 hypothesizes the introduction of all three ancillary measures in tandem with the exclusive bus lane.

In all scenarios, the initial modal share is 10% for the bus. This figure is conservative for Chicago, which has a modal share for the bus of about 14% (RTAMS, 2008). After initial testing showed some stability after approximately 20 days, we run all our simulations for this period. Each scenario is run 25 times after which the mean and standard deviation of the modal share, travel times and length of rush hour are computed. Table 3 shows these results for each scenario. Given the purpose and stylized nature of our model, these results are only meant to be meaningful in relative terms, i.e. in relation to each other, not as accurate predictions.

Scenario 1: Baseline, no exclusive bus lane or ancillary measures

In the base case, we see a switch in bus modal share in the first day of comparison from the initial starting point of 10% to approximately 25% after the first day of comparison. Bus modal share declines immediately after that, and a stable pattern emerges in which mean modal share is 21% within a small range of variance. On the first day of comparison, about 15% of households initially using the car switch to the bus, somewhat compensated by a move from bus-using households. After 6 days about 40% of the population who started as car users had used the bus at least once. In general, about 30% of initial car users switched to the bus each day; however, most of these were repeat users, moving back and forth between the bus and the car.

Household travel times from origin to destination average almost 89 min (with a standard deviation of less than 3 min). This is a long journey time; however, as we note, we are using this model to focus on the relative changes, not as a prediction tool. Perhaps surprisingly, bus travel times are significantly shorter than for the car, again indicating that there seems to be greater efficiency for bus riders accessing the road. The longer journey times for car users are partially driven by the fact that they wait to gain entrance to the road, especially pronounced in highly congested conditions. Bus riders must only wait for a bus with capacity to stop at their bus stop. In some respects, the barriers to entering the road are higher for car users when there are frequent buses in a highly congested environment. However, the longer journey times by car are not long enough to affect any large scale modal shift. Even in the face of significant congestion and much longer journey times, car-using households in our baseline scenario show significant reluctance to switch modes. This suggests that a lower tolerance would be needed to see significant moves from our baseline (even if we reduce car tolerance for longer journey times to 25%, the bus modal share only increases to approximately 25%).

In all runs, the mean modal shares and journey times settle into a quick pattern. Bus riders experience a journey time of about an hour, car-using households have longer journey times. This despite the fact that car-using households are concentrated nearer to the destination. Bus riders must wait for a bus but, once it arrives, they can board at the rate of eight per minute until there are not more bus riders waiting or the bus reaches capacity. However, car-using households must wait in the order they arrived at the entrance until there is a clear space on the road. In these scenarios and without traffic lights, we expect that in grossly congestion conditions, car users will have to wait significant periods of time until there is a space on the road. Accordingly, the longer journey times are not that surprising. Under these conditions, it takes approximately 367 min for all road users to reach the destination, showing a chronic level of congestion in both entering the road and traveling on it for all users. This length of the rush hour is only meant as a baseline for comparison rather than for forecasting purposes, since vehicles are not allowed to take alternate routes and cannot overtake stopped buses. However, the estimates, while high, may not be unreasonable as narrow urban single carriageways typically have a capacity of between 750 and 900 vehicles per direction per hour (Highways Agency, 1999). In addition, buses stopping in general traffic are also likely to impose significant costs.

Scenario 2: Exclusive bus lane introduced

The addition of the exclusive bus lane and the subsequent removal of buses from general traffic results in a much improved performance for all indicators. The bus modal share quickly jumps to over one third of all users. Travel times for all users fall from about an hour and a half on average to just over 50 min, representing an approximate 40% decline. Although the bus mode remains the quickest, the removal of buses from general traffic has significant positive benefits for the remaining car users. Modal share varies quite strongly; the bus share ranges from a low of about 29% to a high of over 41% over the 25 runs. The mean of modal share in this scenario is statistically different from that of Scenario 1 at the five percent level (all significance testing in

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Bus Share (%)</th>
<th>Household travel time (min)</th>
<th>Bus travel time (min)</th>
<th>Car travel time (min)</th>
<th>Length of rush hour (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean Standard deviation</td>
<td>Mean Standard deviation</td>
<td>Mean Standard deviation</td>
<td>Mean Standard deviation</td>
<td></td>
</tr>
<tr>
<td>1. Baseline</td>
<td>20.71 2.62</td>
<td>89.09 2.81</td>
<td>64.74 5.62</td>
<td>95.37 3.73</td>
<td>367.20 4.73</td>
</tr>
<tr>
<td>2. Exclusive lane</td>
<td>34.90 2.93</td>
<td>51.92 2.78</td>
<td>40.24 6.58</td>
<td>57.83 5.50</td>
<td>260.65 9.13</td>
</tr>
<tr>
<td>3. Ticket machines</td>
<td>41.60 3.16</td>
<td>39.78 2.29</td>
<td>29.42 4.87</td>
<td>46.77 4.45</td>
<td>234.47 10.82</td>
</tr>
<tr>
<td>4. Express stops</td>
<td>33.34 4.00</td>
<td>54.27 3.90</td>
<td>40.81 6.04</td>
<td>60.44 6.92</td>
<td>261.45 10.37</td>
</tr>
<tr>
<td>5. Improved frequency</td>
<td>39.42 3.17</td>
<td>42.71 2.77</td>
<td>31.81 3.87</td>
<td>49.54 4.51</td>
<td>243.19 7.99</td>
</tr>
<tr>
<td>6. All measures</td>
<td>49.85 2.85</td>
<td>27.10 1.89</td>
<td>21.90 2.67</td>
<td>32.02 4.43</td>
<td>209.51 9.07</td>
</tr>
</tbody>
</table>
this research is at the 5% level). Perhaps unsurprisingly, the quickest bus journey times were achieved when it had the lowest modal share, and the quickest average car times occurred in the scenario run with the lowest car modal share.

Overall, the addition of the exclusive bus lane results in an environment with much less congestion and quicker journey times. The time it takes to clear all households wishing to travel to the destination falls from over 6 h to just over 4 h.

**Scenario 3: Off-boarding ticket machines**

Pre-boarding payment of fares are often cited by policymakers and academics as an efficient way to reduce journey times by reducing the dwell times at bus stops (Wright and Fulton, 2005; Vuvhic, 2005; McDonnell et al., 2009). In this scenario, we increase the number of passenger boarding the bus from 8 to 12 per minute.

Bus modal share increase to almost 42% (significantly different from Scenarios 1 and 2). Average journey times fall by 23% over exclusive bus lanes alone, bus and car journey times are reduced by 27% and 19%, respectively. The disproportionate impact on bus journey times suggests the more targeted nature of improving boarding facilities on bus users. Once again, bus commuting households are more likely to be situated further away from the destination. The length of rush hour also declines to under 4 h; once again pointing to the potential importance of reduced boarding times for reducing journey times for all, but particularly bus users, and increasing the efficiency of the route.

**Scenario 4: Express bus stops**

Express bus stops are designed to aid bus operations by reducing the number of stops a bus has to make; however, this may be at the expense of longer stopping periods (because of more bus riders at each stop) and longer walking distances for those bus riders, potentially acting as a deterrent (Levinson et al., 2003; Vuvhic, 2005). We test a doubling of the interval between stops from 400 to 800 m. What we find is that the addition of this measure actually reduces bus modal by about 1.5% over Scenario 2 (the difference in means is statistically significant). Average journey times also increase slightly, although bus journey times decline marginally. The results are comparable (but significantly different) to Scenario 2 in terms of its positive impacts and show a clear improvement on Scenario 1. Once again, car users are more likely to be situated closer to the destination. The length of rush hour increases marginally in comparison to Scenario 2, but it is still considerably lower than in Scenario 1.

**Scenario 5: Improved bus frequency**

One of the main ancillary measures associated with a BRT package is the reduction of headways between buses. This potentially reduces the average wait times for users and produces less congestion. However, it is also expensive for operators to provide, unless passenger numbers justify it. Our base case scenario, we hypothesize a 10 min headway between buses. The increase in bus frequency to one every 5 min results in a 5% increase in the bus share over scenario 2. However, the modal share is lower than in scenario 3 (significantly different). General practice in BRT calls for a frequency of at least one bus every 10 min (Levinson et al., 2003; Vuvhic, 2005), the increase to 5 min has only a marginal impact both on the efficiency of the bus and on the attractiveness of the mode.

**Scenario 6: All ancillary measures introduced**

The aim of BRT is to introduce a number of related policies in tandem to maximize the efficiency of the bus as a mode (Levinson et al., 2003). Research has found that such policies should be introduced in tandem as their collective impact is likely to be greater than individually (Wright and Fulton, 2005; Vuvhic, 2005; McDonnell et al., 2009). Here, we explore if and how this is the case. As expected, the introduction of all measures together results in significant improvements in our output variables. We see that bus modal share increases to almost 50%, fully 29% higher than without the exclusive bus lane and 15% higher than with the exclusive lane alone. Even addition of ticket machines or increasing bus frequencies along with the exclusive lane results in a modal share that are 8% and 10% below our results for scenario 6 alone. The length of rush hour is approximately half of what it was without the lane and is 19% lower than on Scenario 2.

Travel times also continue to decline with the addition of all ancillary measures to the exclusive lane. Household travel times are now 48% quicker than in Scenario 2 and 32% quicker than with pre-boarding ticket machines, the best performing ancillary measure alone. In fact, travel times are now a fraction of what they were when buses ran in general traffic. Remaining car users are, once again, disproportionately situated close to the destination; therefore, we might expect their journey times to be lower.

However, what we find is that, in all scenarios, car travel times are longer than bus travel times. This suggests that, despite the falls in car travel times, congestion on the road still acts as a barrier to entry under our current model framework. This, however, is likely an artifact of the model as cars are not allowed to overtake buses or seek alternate routes. Future versions will adjust this by allowing for limited overtaking and/or bus bays at stops. However, it is interesting to see that, with the exception of increased bus frequency, the effectiveness of BRT policies only begin to become apparent with longer commuting distances.

### 6. Policy implications and conclusions

In summary, under our model structure and not surprisingly, the addition of an exclusive bus lane improves efficiency of a route by increasing mode share and reducing travel time for bus users. A large proportion of this is undoubtedly as a result of the addition of a new lane, but what is worth noting is that additional improvements can be attained with ancillary policies, and with some more than with others. The addition of pre-boarding ticket machines is the most effective followed by the introduction of higher bus frequencies. On the other hand, express stops offer relatively little marginal benefit over the addition of an exclusive bus lane in our model and may, in fact, be detrimental. While the impact of individual ancillary measures beyond that of the exclusive bus lane is modest, they seem to reinforce each other when applied together, achieving further modal shift, reducing travel times and reducing the length of the rush hour. Further, journey times for all users, not just bus users, are significantly improved by the addition of this set of BRT measures, an important result of increased accessibility (Grengs et al., 2010).

Improving the efficiency of bus boarding times should thus be an important aim for policymakers as the time a bus is stopped to collect passengers can often amount to 20% of a total journey (Vuvhic, 2005). In addition, while increasing the frequency of the bus from 10 to 5 min has significant positive impacts on our output variables, the impact is smaller than for pre-boarding ticket machines. The latter point is also relevant in discussing the very nature of BRT, the addition of a number of policy measures together which are meant to improve the efficiency and attractiveness of the mode more than if the measures were implemented individually. This reinforces previous findings (Wright and Fulton, 2005; Vuvhic, 2005; McDonnell et al., 2009).

This model is focused on garnering insights into the system-wide patterns that can emerge from individual-level decisions in the face of changing incentives and environments. As such, its focus is on highlighting the existence of these patterns. Future work will develop this methodology but it will also focus on developing more nuanced and realistic environments. For instance, we plan to develop a grid-based version of this model.
to assess the potential impacts of network effects of changes on one single route. We will also develop heterogeneous decision-making structures to represent both the availability of travel options for commuters (e.g., car ownership) to the socio-economic characteristics of those commuters. In addition, we will incorporate measures of generalized cost (Ortuzar and Willamson, 2001) for a more accurate assessment of the disutility associated with each element of the journey for bus riders and car users alike; and assess the environmental impacts of these modal shifts in terms of local and global pollutants.

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References


