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Stochastic dynamic switching in fixed and flexible transit services as market entry-exit real options

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Abstract

The first analytical stochastic and dynamic model for optimizing transit service switching is proposed for "smart transit" applications and for operating shared autonomous transit fleets. The model assumes a region that requires many-to-one last mile transit service either with fixed-route buses or flexible-route, on-demand buses. The demand density evolves continuously over time as an Ornstein-Uhlenbeck process. The optimal policy is determined by solving the switching problem as a market entry and exit real options model. Analysis using the model on a benchmark computational example illustrates the presence of a hysteresis effect, an indifference band that is sensitive to transportation system state and demand parameters, as well as the presence of switching thresholds that exhibit asymmetric sensitivities to transportation system conditions. The proposed policy is computationally compared in a 24-hour simulation to a "perfect information" set of decisions and a myopic policy that has been dominant in the flexible transit literature, with results that suggest the proposed policy can reduce by up to 72% of the excess cost in the myopic policy. Computational experiments of the "modular vehicle" policy demonstrate the existence of an option premium for having flexibility to switch between two vehicle sizes.

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Keywords: public transit; market entry and exit real options; stochastic dynamic optimization; flexible transit; last mile problem

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Nomenclature

(subscript c denotes conventional/fixed transit; f denotes flexible transit)
L = length of region (miles)
W = width of region (miles)
J = line haul distance from terminal to the nearest corner of the region (miles)
N_c, N_f = number of routes/zones in region
F_c, F_f = fleet size in region
$S_c(t), S_f(t)$ = vehicle size in region (seats/vehicle)
$h_c(t), h_f(t)$ = headway in region (hours)
V_c, V_f = bus operating speed within the region (miles/hour)
V_x = average passenger access speed (miles/hour)
$C_{sc}(t), C_{sf}(t)$ = total cost accrued from time t to $t + dt$ in region ($)
a = fixed cost of bus operation per unit time ($/hour)
b = variable cost of bus operation per unit time and seat ($/seat·hour)
v_i, v_w, v_x = users' value of time for in-vehicle time (i), wait time (w), and access time (x) ($/passenger hour)
y_c, y_f = ratio of direct line haul non-stop speed over local speed
z_c, z_f = ratio of local non-stop speed over local speed
c_c, c_f = average total cost per trip ($/trip)
ρ = discount rate

Demand parameters
$Q(t)$ = demand density at time t (trips/sq.mile·hour)
μ = mean reversion coefficient for demand process
m = stationary demand density (trips/sq.mile·hour)
σ = process volatility for demand process

Fixed/conventional transit only
r = route spacing for region (miles)
d = bus stop spacing (miles)
D_c = round trip bus distance (miles)

Flexible transit only
D_0 = distance of one flexible bus tour within a service zone (miles)
D_f = equivalent line haul distance for flexible bus (miles)
n = number of passengers in one flexible bus tour
k = constant for a grid network (Daganzo, 1984a) for flexible bus
A = service zone area for flexible bus (sq. miles)
u = average number of passengers per stop for flexible bus

1. Introduction

The potential of optimal timing and control of transit systems under uncertainty continues to grow in today's data-driven environment. There are countless examples of such applications, including: determining when to allow fixed-route services to deviate; optimal holding strategies for buses; adjusting size of vehicle groups (e.g. trains) that are dispatched; positioning idle on-demand vehicles; and determining "price surges". However, there are very few fundamentally general analytical methods available to time decisions under dynamic uncertainty in this domain. In this study, we explore one such timing method based on real options theory, and evaluate its effectiveness in well-studied problems of time-dependent changes between two different transit fleet operating modes.

It has long been known that different demand density levels warrant transit services with different operating policies and degrees of flexibility (Saltzman, 1973; Jacobson, 1980; Adebisi and Hurdle, 1982). Some studies sought to determine thresholds based on demand densities between different transit services, including fixed-route and flexible-route systems (Daganzo, 1984b; Chang and Schonfeld, 1991a; Quadrifoglio and Li, 2009; Qiu et al, 2015). Several studies have examined the problem of integrating fixed-route and flexible-route transit, primarily under the many-to-one service setting which applies either to last mile service design or to monocentric city structures (Chang and Schonfeld, 1991b; Kim and Schonfeld, 2013, 2014). These include joint design of fixed transit lines and feeder services (e.g. Kim and Schonfeld, 2014). With advances in artificial intelligence and autonomous vehicle technologies, as illustrated in Fig. 1, and with planned deployments in Dubai (Spera, 2016) and Singapore