Optimization of Spacing of Transit Stops on a Realistic Street Network

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A discrete model of bus stop location in which candidate stops are either selected or not has several practical advantages over classical continuum models. An evaluation method for stop sets that uses parcels as units of demand and the street network to model walking paths between transit stops and parcels has been proved effective and realistic. In this framework, the on–off counts at existing stops are used to allocate demand to the parcels in each stop's service area in proportion to the stops' trip-generating ability. The result is a demand distribution that matches existing counts and reflects variations in land use. However, with demand modeled on the street network, the placement of service boundaries midway between neighboring stops becomes invalid because of irregularities in the network of access streets and curves in the transit route. The dependence of a stop on more than its immediate neighbors for determination of its service area complicates the process of optimization of stop locations by use of dynamic programming. The proposed solution expands the state space so that a stop's service area is dependent on the two prior and the two succeeding stops. The resulting dynamic programming model was tested on two bus routes and found solutions that were better than the existing stop set and the stop sets proposed by consultants by use of simple yet state-of-the-art models. This paper describes a method for optimization of stop locations on an existing route that includes realistic and localized estimates of its impacts on walking and riding times and operating cost.

A common complaint about bus service is that it is too slow because buses make too many stops. A rule of thumb in the industry is that about 30% of the running time on a typical bus route is lost at stops. Although the loss of time required for passengers to board and alight is expected, other losses, such as those due to deceleration, acceleration, and opening and closing of doors, or roughly 8 to 15 s per stop, could be reduced by consolidation of stops. This reduction was shown by Reilly, who noted the greater stop spacing found on European transit routes and the correspondingly speedier service (*1*). In the last few years, several U.S. transit agencies have applied or considered the use of stop consolidation to make their services more efficient and competitive.

Until now, the methods used to make and analyze decisions about stop spacing have been extremely simplistic. This paper describes a method for optimization of stop location on an existing route that includes realistic and localized estimates of its impacts on walking time, riding time, and operating cost. Application to two routes in the Boston, Massachusetts, area indicates that it finds a solution better than both the existing stop set and that derived by experts using simplistic yet state-of-the-art methods.

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IMPACTS OF CHANGES TO STOP LOCATION

Changes to stop locations on existing routes (which stops to keep, drop, or insert) have three main impacts: walking time, riding time, and operating cost. As stops become farther apart, walking time increases, whereas riding time and operating cost decrease. These countervailing impacts create a trade-off whose optimum depends on the relative weights given to each impact.

A fourth possible impact that this analysis ignores is that demand may change. Demand response can be divided into two kinds. One is an elastic response to service in which service becomes slightly slower or faster and walking distances become slightly longer or shorter. Although impacts will be amplified when this effect is accounted for, it is unlikely to change the optimal decision because the best way to attract new passengers is to offer good service to existing passengers.

The second type of demand response is a loss of riders if stops become spaced so far apart that some riders consider the stop to be no longer accessible. This kind of demand change can be important if long distances between stops are considered. For this analysis, it is assumed that transit agencies are under a mandate not to space stops so far apart that they become inaccessible; when this constraint is accounted for by use of a maximum stop spacing, this second type of demand response can also be ignored.

CONTINUUM MODELS

A general formulation for determination of the optimal spacing between stops can be derived by use of a continuum model; good treatments are given by Wirasinghe and Ghoneim (*2*) and by Van Nes and Bovy (*3*). The street network is assumed to be rectilinear and infinitely dense, so walking paths to a stop can be divided into a component transverse to the transit line (which can be ignored) and a component parallel to the transit line. This assumption, in effect, places all demand along a single line. In addition, demand density is assumed to vary slowly along a line, so that one can meaningfully consider the demand density in a neighborhood to be a point. In those models, as in the one described here, the service area of a transit line is assumed to be an area within a fixed distance (e.g., 0.25 mi) of the transit line.

With demand collapsed to a single dimension, the service area boundary for a stop simply becomes the midpoint to neighboring stops, adjusted to account for the fact that the cost-minimizing passenger will walk a bit farther downstream than upstream to take advantage of riding time savings (*4, 5*). As a result, service area boundaries shift upstream for boarding passengers and downstream for alighting passengers. Therefore, a stop's service area boundaries for boarding passengers traveling in one direction will differ from the boundaries for alighting passengers traveling in the same direction and for boarding passengers traveling in the opposite direction.

With the continuum approach, optimal stop spacing can be derived by the use of calculus. Although this approach is useful for establishment of a general guideline for stop spacing, it has three main weaknesses. First, demand often does not vary slowly. Significant punctuations in demand can occur because of different land uses (compare, for example, a hospital versus a cemetery), and stop locations should be sensitive to the origins of the demand. Second, the street network is often not ideal; turns on the transit route and irregularities in the street network influence people's walking paths and can make certain stop locations more favorable. Third, the result of such an optimization is hard to apply because stops should normally be located at intersections (both for shorter walk access and for proximity to crosswalks) and the optimal stop spacing may not be a convenient multiple of block length. For example, suppose intersections are 200 m apart and the optimal stop spacing is 300 m; should stops be located at every stop, every other stop, or somewhere in between?

DYNAMIC PROGRAMMING WITH DISCRETE MODEL

Furth and Rahbee were the first to propose a discrete model for optimization of stop spacing for an existing route (*5*). It treats each intersection along the route as a candidate stop and then selects the optimal set of stops from that list. To model punctuations in demand density, they allowed an analyst to assign different levels of density (1, 2, 3, etc.) to each intersecting street and to the longitudinal streets between each intersection. For the existing set of stops, the demand at a stop [the numbers of on- and off-loadings (referred to here as ons and offs) per hour] is reflected back to the block faces in the stop's service area by allocation of demand in proportion to a block's strength, that is, its length multiplied by its demand density. When new combinations of stop locations are considered, the number of ons and offs at a stop can simply be determined by aggregation over the blocks in its service area. Walking distance can likewise be modeled as a sum of the transverse and longitudinal distances from the center of each block face.

In the discrete model, the impact of a candidate stop on riding time is a fixed loss that accounts for deceleration, acceleration, and opening and closing of doors multiplied by the probability of stopping, which is based on a Poisson model of passenger arrivals. Both arriving and departing passengers contribute to the probability that a stop will be requested; passenger demand, in turn, is based on the demand in the stop's service area multiplied by one headway. The discrete modeling framework is not designed to make fine-level decisions about where at an intersection a stop should be placed (e.g., on the near side or the far side); analysts are expected to make those choices on the basis of local factors. One paper has analyzed the effects of stop placement to recommend various values of time lost because of stopping (*6*).

The model of Furth and Rahbee still makes significant approximations by use of an assumption of a regular, rectilinear grid (*5*). This conveniently reduces the demand profile to a single dimension, equivalent to a combination of point demands and uniformly distributed demands along a line, like loads on a structural beam.

With demand thus reduced to a single dimension, the optimal stop location problem can easily be solved by use of dynamic programming (DP). The impacts are additive, and a stop's service area depends only on which candidate stops are selected to be a stop j for inclusion in the service area. The impact of the decision over what should be the next stop after stop j is independent of the stops that were chosen upstream of the stop at the starting point for all stops except the previous one, since that decision affects the probability that a bus would have to stop at the stop that comprises the starting point.

Let stops be numbered consecutively from the start to the end of the line, and consider three successive stops, i, j, and k. With demand along a line, this (i, j, k) triplet defines the service area of stop j and allows one to define stop-specific demand as ons(j; i, k) and offs(j; i, k (ons and offs per hour)), where (j; i, k) represents the demands at stop j when its predecessor is i and its successor is j.

All of the impacts associated with stop j can then be determined by use of the defined model of walking routes, the probability of stopping, and delay because of stopping. These impacts are as follows:

walk(j; i, k) = walking cost for all passengers walking to or from stop j when its predecessor is i and its successor is j,
ride(j; i, k) = riding cost for all passengers between j and k when stop j's predecessor is i and its successor is j, and
oper(j; i, k) = operating cost between j and k when stop j's predecessor is i and its successor is j.

These cost functions include unit costs applied to walking time, riding time, and running time. The riding time and operating cost functions include dwell time and acceleration delay at stop j and deceleration delay at stop k.

The backward recursive DP formulation is

$$f(j;i) = \min_{\min S(j)\le k\le \max S(j)} \{\text{walk}(j{:}\, i,k) + \text{ride}(j;i,k) + \text{oper}(j;i,k) + f(j;k)\} \qquad \text{for } \min P(j) \le i \le \max P(j) \tag{1}$$

where $f(j; i)$, the optimal return function, is the cost required to serve the route from stop j to the end, given that the stop before j is stop i. A maximum and a minimum permitted stop spacing are accounted for by definition of minimum (min) $P(j)$ and maximum (max) $P(j)$ to be the farthest and the closest predecessors of each stop j, respectively, and min $S(j)$ and max $S(j)$ to be the closest and the farthest successor of each stop j, respectively. In the DP algorithm, the stage variable is j, and the algorithm has only one state variable, i. The algorithm begins with j as the final stop and initializes $f(j; i)$ at 0 for all legal values of i; it then proceeds backwards, with j being reduced by 1 and Equation 1 used to solve for $f(j; i)$ at 0 for all legal values of i. The algorithm thus proceeds until j is equal to 1. When stop 0 is allowed to be a dummy start stop, the value of $f(1; 0)$, again found by the use of Equation 1, is the optimal solution for the route.

DISCRETE MODELING ON REAL STREET NETWORK

Unlike continuum modeling, discrete modeling does not give a formula for optimal stop spacing; it gives a list of optimal stop locations selected from a set of candidate stop locations, which makes the results directly applicable. However, although Furth and Rahbee proved the value of discrete modeling, the subjective assignment of demand intensity level required made it impractical, and its assumption of a regular, rectilinear network made it too idealistic for many situations (*5*).

The first model of demand for the stop location problem that went beyond a single dimension was developed in two previously published papers (*7, 8*). The unit of demand is a land parcel which is located on the real street network. Passengers use shortest paths along the street network between their parcel and their stop. Existing geographic information system databases of parcels, streets, and transit stops make such an analysis feasible. For consistency, passengers are assumed to minimize their combined travel time (walking time plus riding time from the stop that they walk to, with the same weights used in the global optimization), which creates the same offset in service area boundaries mentioned earlier.

With demand originating at parcels on the street network, service area boundaries for each stop are no longer defined by one-dimensional constructs such as the perpendicular bisector of a line segment. Service areas are not modeled explicitly; rather, they simply fall out as an outcome of each passenger selecting the stop that minimizes that passenger's weighted walking plus riding time from the stop that they walk to in a process that can be considered a Voronoi diagram on a network. The walking distance along the street network from each parcel to each stop is directly measured.

To assign demand to a parcel, service areas for the historic stop set are first determined by the shortest-path or Voronoi process. Then, for each historic stop, historic boarding demand (an input) is allocated over all parcels in the service area in proportion to a parcel's production strength. A parcel's production strength is the product of its size variable (e.g., gross floor area) and a production coefficient reflecting the parcel's land use (e.g., single-family residential, multifamily residential, and commercial). Production coefficients were based on production factors found in the ITE handbook *Trip Generation* (*9*). Likewise, historic alighting demand is allocated over parcels in proportion to each parcel's attraction strength. Additional factors account for diminishing demand as one gets farther from a stop and for competition with other transit routes.

With the use of allocation logic rather than direct estimation of demand for each parcel, demand along the route is completely consistent with existing counts. However, when parcel attributes (land use type and size) are used to allocate demand, the spatial distribution of the parcel within each stop's service area reflects the variations in land use within the service areas of historic stops. When demand is related to parcel attributes, candidate stop locations closer to parcels with a higher propensity for transit use are rewarded relative to locations farther from likely demand concentrations.

Multiple Stops Influencing Service Area Boundaries

As pointed out previously, when demand points are distributed spatially and passengers use the real street network to access transit stops, a stop's service area can be affected by more than the location of its neighboring stops (*8*). Real street networks often have diagonal or curving streets and discontinuities (streets that do not continue uninterrupted within the route's influence area), and transit lines often include curves and turns, which together make it possible for a stop's service area to have boundaries with more than one upstream or downstream stop. Figure 1 shows an analysis of a service area for a transit stop in which one stop, Stop 11, has inbound service boundaries not only with Stops 10 and 12 but also with Stops 13 and 14 and even a small boundary with Stop 7.

This finding, called the "curve effect," makes a model in which demand is distributed on the real street network violate a key assumption of prior optimization models, including the model of Furth and Rahbee (*5*), as well as the continuum models. This assumption is that the demand at a stop—and, therefore, the impacts associated with a stop—depends only on the location of its neighboring stops. Because of the curve effect, it is impossible to define impacts on the basis of (i, j, k) triplets. The demand at stop j—and, therefore, the walking cost and other impacts associated with j—also depends on which stops precede i and which ones follow k.

The curve effect is accounted for when the discrete model is used to do an evaluation, that is, when the costs associated with a particular stop set are evaluated, as shown by previous examples involving a streetcar line in Boston and a bus route in the Albany, New York, area (*5, 6*). However, it was not accounted for by DP by use of Equation 1, which will give spurious results, depending on which stops before i and after k were assumed when the impact for triplet (i, j, k) is evaluated.

Optimization by Use of Expanded State Space

A goal of this research was to develop an optimization method by use of the realistic model of parcel-level demand located on the street network. The approach ultimately chosen to overcome the curve effect was to expand the DP state space to three variables with the assumption that a stop's service area is defined by its previous two stops and its following two stops, which creates the paradigm of a quintuplet (i, j, k, l, m) for which impacts associated with stop k can be determined. This is an assumption that can be violated in theory but that is unlikely to be violated in most practical problems. Its violation would mean, for example, that Stop 10 has a service area boundary not only with Stop 9 and Stop 8 but also with Stop 7 and that people along the last boundary would choose either Stop 7 or Stop 10, skipping Stops 8 and 9.

The formulation based on quintuplets has the following recursion formula:

$$f(k; i, j, l) = \min_{\min S(k) \le m \le \max S(k)} \{\text{walk}(k; i, j, l, m) + \text{ride}(k; i, j, l, m) + \text{oper}(k; i, j, l, m) + f(l; j, k, m)\} \tag{2}$$

where all of the variables are as defined previously and k is the stop whose impacts are being evaluated when the previous two stops are i and j and the succeeding two stops are l and m.

To check whether the assumption of dependence on stops outside the quintuplet is violated, one can track the demand (ons and offs) associated with each quintuplet in the optimal solution and check it against the given total demand. A violation of the assumption would mean that in the solution some parcels are doubly counted or not counted at all. Given that the method seeks

FIGURE 1 Service area boundaries on curved route with irregular street pattern (7).

to minimize cost and that walking cost will be underestimated if some passengers are not accounted for, it is likely to lean toward solutions in which some slivers of demand are unaccounted for, if, indeed, such solutions exist.

Boston, unlike most American cities, has a street network that is not at all rectilinear or regular. Nevertheless, the applications done on Boston bus and streetcar routes have had no violations or (as in the case in Figure 1) the amount of demand unaccounted for was small enough (no more than 1%) that it would not appreciably affect the optimal solution and would be readily detectable.

The state space expansion greatly increased the algorithm's computational burden. Because of space limitations, those computational issues and their solutions will not be discussed here. In the end, the algorithms that were coded are efficient and solved the problems reported in the examples section in less than 10 s on a standard desktop personal computer.

Accounting for Multiple Periods and Both Directions

As a practical matter, transit demand changes across the day, as do running times; however, it is impractical for stops to vary across the day. Multiple periods can easily be accounted for by summation of the impacts over all periods in Equation 2. For example, a variable such as walk(k; i, j, l, m) should be a sum of the impacts of walking cost associated with stop k over all the periods of the day for a stop set including the quintuplet (i, j, k, l, m).

If it is permissible to have different stop sets in the two directions of a route, each direction can be optimized separately. However, if policy is such that a route should have the same stops in each direction, then each of the terms within Equation 2 should include a sum over both directions.

EXAMPLE APPLICATIONS

The Massachusetts Bay Transportation Authority (MBTA) has shown an interest in stop consolidation on its bus and streetcar routes for several years. Recently, it has embarked on the Key Routes program to improve the service quality and image of its 15 most heavily used routes. Part of the Key Routes program considers stop consolidation to be one of several ways to increase service speed and reliability. Routes 1 and 57 were recently studied as part of this program.

Route 1

Route 1 is a cross-town route in Boston and Cambridge that runs between two major transfer points (Harvard Square and Dudley Square); crosses three rapid transit lines; and serves such destinations as the Prudential Center, Boston Medical Center, and numerous colleges and universities. Figure 2 depicts the three essential geographic data sets (street network, parcels represented by dots, and bus stops). The service area was assumed to extend 0.25 mi to either side of the route.

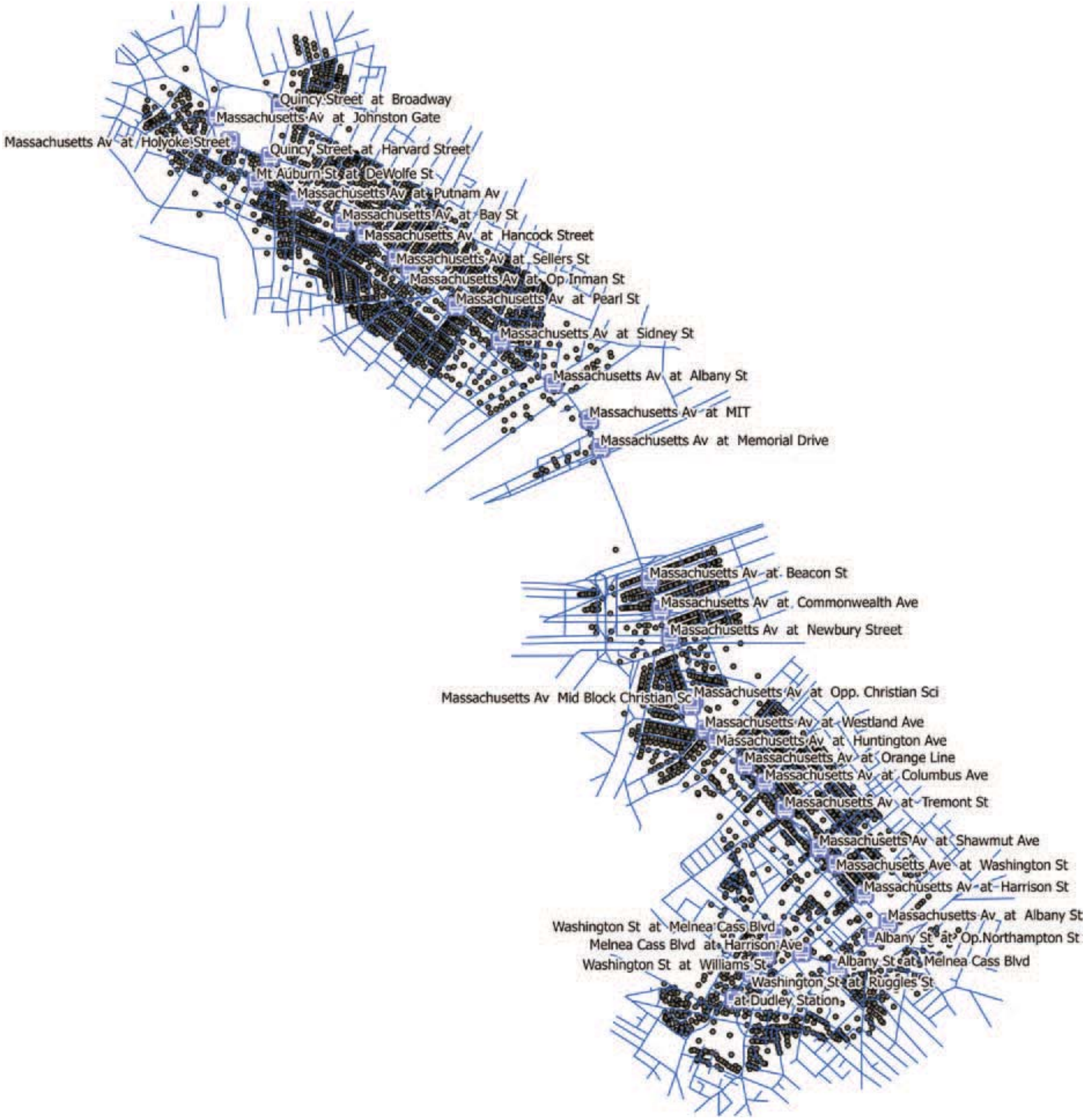

FIGURE 2 Streets, parcels, and southbound bus stops along Route 1.

Available demand data included on and off volumes by direction in the a.m. and p.m. peak hours. For the purpose of this example, a representative "day" is treated as 5 h of a.m. peak service and 5 h of p.m. peak service. The two directions were optimized separately, consistent with MBTA policy that allows different stops by direction.

The parameters used in the cost function were as follows:

walking speed = 1.2 m/s (4 ft/s),
unit walking cost = \$12 per passenger hour,
unit riding cost = \$6 per passenger hour,
unit operating cost = \$143 per vehicle hour,
unit boarding time = 2 s per passenger,
unit alighting time = 2 s per passenger,
lost time per stop = 8.5 s, and
headway = 8.75 min.

Parcel data were obtained from the city assessor's offices. Relevant land uses and their production and attraction coefficients for the a.m. period are shown in Table 1. For the p.m. period, production and attraction coefficients are reversed.

Analysis Results

Stop-level results for the a.m. peak southbound are shown in Table 2 for three scenarios: the historic stop set (which existed in spring 2011), the consultant's tentative recommendation posted on MBTA's website announcing a public hearing, and the optimal solution found by the use of quintuplet-based DP. The consultant's recommendation was based on the kind of simple rule of thumb

TABLE 1 Land Use Parameter Data for a.m. Period

Description	Code	Attraction Coefficient	Production Coefficient
Residential–commercial	RC	0.05226	0.08774
Single family	R1	0.0233	0.04141
Residential condo	CD	0.0233	0.04141
Mobile home	R1	0.0233	0.04141
Two-family dwelling	R2	0.02479	0.04308
Three-family dwelling	R3	0.02745	0.04293

NOTE: Measure of size is based on living area.

that represents the state of the art, which recommends that stops be eliminated if their demand is low and the resulting distance between stops would not exceed a threshold. This rule of thumb does not account for differential impacts to riding time (stop elimination is the most beneficial on those parts of the route with high through volumes), nor does it recognize that stop consolidation is the most beneficial at an intermediate level of demand in which about one person gets on or off per stop per bus, at which level the bus is still likely to have to stop but the number of people affected by consolidation is small. With higher demands, the impact on walking becomes large, and with low demand, the benefit of consolidation becomes small because stops with low demands are often skipped anyway.

The historic stop set has 35 stops in the southbound direction. Stop 20 was added at the suggestion of the consultant. The consultant recommended that the number of stops be reduced to 29; the optimization model recommends a reduction to 20 stops. A more judicious choice of stops for elimination results in an optimal solution with a slightly less average walking time than that from the consultant's recommendation, despite elimination of more stops, and therefore has a better total cost.

Impacts of Results

Results at a daily level are shown in Table 3. The two directions were optimized separately by consideration of the impacts on the two periods combined. Results for the two directions are summed. The number of stops recommended for the two directions combined falls from 71 for the historic case to 55 for the consultant recommendation and 45 for the DP optimum. Compared with the historic case, the other two recommendations involve a little more walking, on average, and a little less riding time. For round-trip running time, the consultant recommendation saves 1.1 min and the DP optimum saves 2.4 min.

Despite a large difference in number of stops, the difference in overall impact is small, which indicates that the curve for total cost is rather flat near its optimum. Compared with the historic stop set, the optimal solution has a net societal savings of $130 per day, which is 0.66% of the total walking, riding, and operating cost. Nevertheless, the value of an optimization method can be seen by comparison of the results obtained by that method with the consultant's recommendation, which actually has a negative overall effect for the set of unit costs used. Its main weakness is that its changes to stop locations increase the average walking time quite a bit, by 0.3 min, without comparable savings in riding time or operating cost.

Route 57 Results

A second case study is MBTA Bus Route 57, which runs from Kenmore Station to the Watertown Yard running through Boston, Newton, and Watertown and whose service area also includes parts of Brookline and Cambridge, as shown in Figure 3. It has 45 inbound and 43 outbound stops and runs every 8 min during the a.m. peak and every 10 min midday. The analysis for Route 57 was similar to that for Route 1, except that the Route 57 analysis involved five inbound periods and six outbound periods. Table 4 shows the results for the inbound direction.

Stop spacing may sometimes be longer than the normal walking distance (U.S. customary spacing) of 0.125 mi. The optimal arrangement shows spacings of 0.4, 0.46, and 0.26 mi between Stops 1 and 3, 3 and 6, and 6 and 8, respectively, for Route 57. The reason for such a result is that Stops 1 and 3 are in the sparsely populated section of the route, whereas Stops 3 and 6 have an interchange for a highway between them and the route geometry turns around, which makes the real spacing look longer than that which can be seen from a map. The interaction of walking path and route geometry is complex and may be captured only in the world of spatial analysis, which makes the decision for a stop to be included interesting.

Comparison of Results for Routes 1 and 57

The overall impacts are greater on Route 57 than on Route 1, with the DP optimum indicating a daily savings of $920, which comes from savings in running and riding times, offset by small increases in walking time. In comparison with the DP optimum, the consultant recommendation, which eliminates a nearly identical number of stops and achieves a similar running time savings, is not as judicious in its choice of stops to be eliminated and ends up increasing societal cost overall, at least for the parameter set chosen.

A check on total demand for all of the Route 57 and Route 1 results shows that no demand was unaccounted for in any of the solutions, which supports the practicality of the quintuplet-based DP approach.

CONCLUSION

This paper introduces a method for optimization of stop spacing that is realistic. Demand is modeled at the parcel level and is sensitive to both parcel attributes and historic on–off patterns. Walking distance to stops takes place along the actual street network, with passengers choosing shortest paths. The curve effect, which causes service areas for stops to be sometimes bordered by the service area of more than one upstream or downstream stop and which renders single-state variable DP unusable, was overcome, at least for typical routes, by use of a three-state formulation in which a stop's service area and impacts depend only on the two prior and two succeeding stops. All of the necessary data from geographic databases were readily available.

Case studies of two Boston area bus routes revealed that on one route, the trade-offs involved in stop spacing appeared to be so flat that gains in speed were often countered by similar losses in walking times. On the other route, significant positive impacts were predicted from use of an optimal solution with 32 instead of 45 stops. In both cases, it was found that a consultant, using state-of-the-art logic, recommended similar cuts in the optimal number of stops

TABLE 2 Stop-Level Results for a.m. Period Southbound

Stop	Distance from Start (mi)	Departing Volume (pax/h)	Ons + Offs (pax/h)			Avg. Walking Time (min)			Total Cost ($/pd)		
			H	R	O	H	R	O	H	R	O
1	0	41	41	41.0	58.6	3.3	3.3	2.4	97	97	190
2	0.08	56	15	15.0		4.9	4.9		147	147	
3	0.4	63	9	9.0	3.2	2.0	2.0	3.0	149	149	234
4	0.58	68	5	5.0		2.8	2.8		95	95	
5	0.7	73	5	5.0		3.0	3.0		90	90	
6	0.86	84	13	13.0	30.4	4.9	4.9	5.6	134	133	293
7	1.03	94	14	14.0		3.9	4.0		114	115	
8	1.12	100	8	8.4	18.3	2.1	2.2	3.4	87	107	182
9	1.26	101	5			2.3			75		
10	1.32	105	12	16.6	16.6	3.5	3.7	3.7	103	158	158
11	1.52	148	75	75.0	75.0	2.4	2.4	2.4	238	239	237
12	1.72	161	23	23.0	25.5	3.3	3.4	3.5	212	214	280
13	1.96	164	13	13.0		5.7	5.7		204	204	
14	2.14	173	39	41.0	51.5	2.8	2.7	3.5	184	384	507
15	2.24	175	2			0.8			249		
16	2.73	162	17	22.0	22.0	2.5	2.9	2.9	272	355	353
17	2.84	154	12			2.5			92		
18	2.94	123	81	89.1	88.0	3.6	3.5	3.4	286	343	334
19	3.18	120	15		15.0	2.2		2.2	110		140
20	3.2	120		32.7			4.1			208	
21	3.29	113	29		29.0	2.7		2.7	97		104
22	3.34	116	21	31.1	21.0	1.6	2.4	1.6	81	133	81
23	3.47	133	47	47.0	47.0	2.5	2.5	2.5	149	149	149
24	3.57	132	7	7.0	7.0	3.2	3.2	3.2	94	94	93
25	3.68	125	11	14.5	21.7	3.6	4.0	4.3	132	167	217
26	3.86	118	9			3.5			113		
27	3.94	110	16	21.1		3.7	3.7		101	174	
28	4.09	86	78	78.1	112.3	4.8	4.8	4.7	288	289	525
29	4.22	81	21	13.0		4.7	5.7		120	204	
30	4.28	80	3			4.1			83		
31	4.45	74	6	8.0	9.7	5.5	5.2	5.7	113	142	238
32	4.59	72	2	2.0		2.8	2.8		81	82	
33	4.7	70	2	2.4		4.7	5.1		65	67	
34	4.79	65	5	5.0	9.4	1.1	1.1	2.1	53	54	173
35	4.86	61	4	4.0		2.0	2.0		67	67	
36	5.03	0	61	61.0	60.0	0.0	1.8	1.9	116	116	141
Total			726	717.1	721.1	3.0	3.3	3.3	4,693	4,775	4,631

NOTE: Pax = passengers; H = historic; R = recommended; O = optimal; avg. = average; pd = period (in hours).

TABLE 3 Results for Both Periods and Both Directions Combined for Route 1

Scenario	Number of Total Two-Way Stops	Average Time (min)			Change in Cost ($/day)			
		Walking	Riding	Two-Way Running	Walking	Riding	Operating	Total
Historic	71	3.46	36.4	88.5	0	0	0	0
Analyst recommendation	55	3.77	35.7	87.4	705	−267	−113	326
DP optimum	45	3.57	35.5	86.1	243	−218	−156	−132

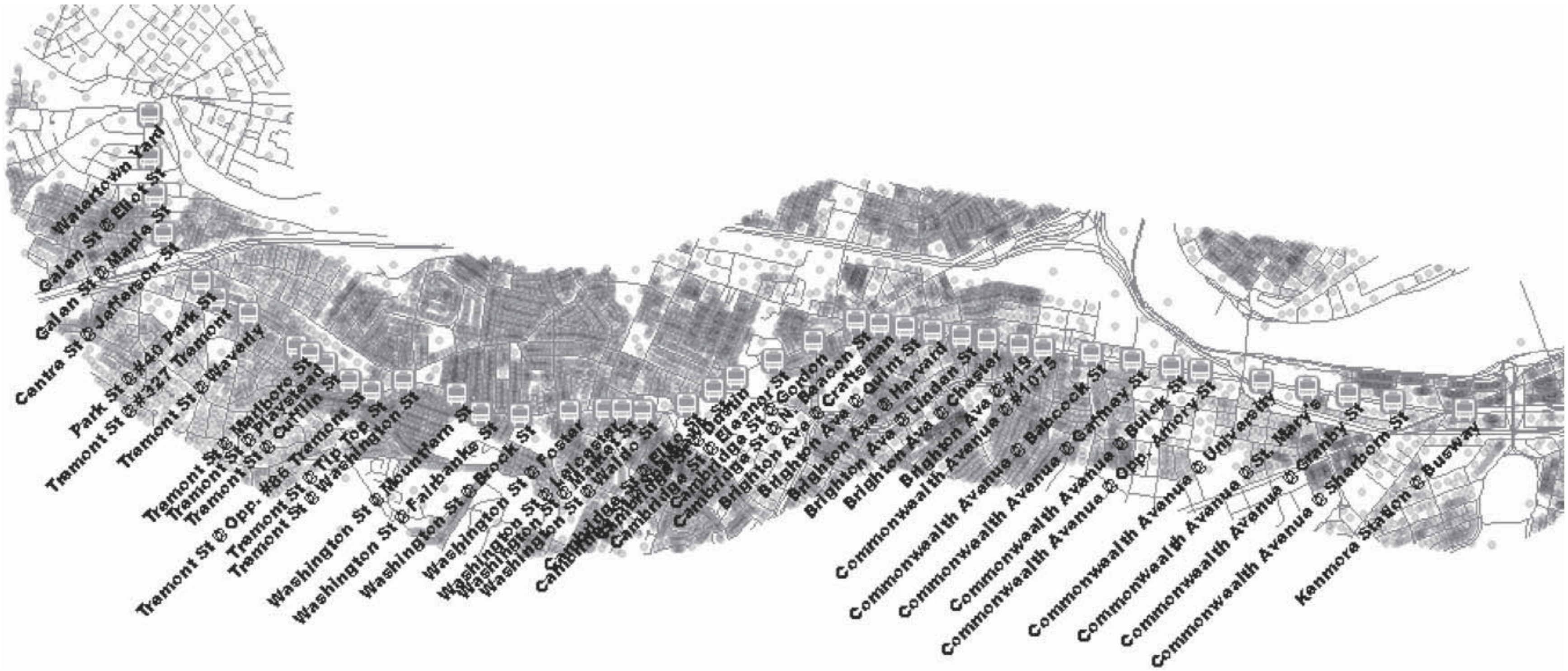

FIGURE 3 Streets, parcels, and westbound bus stops along Route 57.

TABLE 4 Inbound Results for Route 57

Scenario	Number of Stops	Change in Walking Time (pax-min/day)	Change in Running Time (min)	Change in Cost ($/day)			
				Walking	Riding	Operating	Total
Existing	45	na	na	na	na	na	na
Consultant recommendation	31	7,669	–1.9	3,672	–2,509	–488	674
DP optimum	32	3,955	–1.8	1,761	–2,211	–469	–920

NOTE: na = not applicable.

as DP but was unable to select them in a way that minimized the net impact. This result highlights the underlying complexity that makes trade-offs in stop spacing difficult to do by hand or use of rule of thumb.

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