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Our troubled planet can no longer afford the luxury of pursuits confined to an ivory tower. Scholarship has to prove its worth, not on its own terms, but by service to the nation and the world.

—Oscar Handlin

Comparing the Efficiency of Public Transportation Subunits Using Data Envelopment Analysis

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Abstract

This article discusses the need for a performance measure that compares the efficiencies of subunits within a transportation organization, reflects the diversity of inputs and outputs, and is objective and consistent. The study presents a method for developing such a performance indicator, and illustrates its use with an application to the park-and-ride lots of the Chicago Transit Authority. The proposed method applies Data Envelopment Analysis supplemented by Stochastic Frontier Analysis to estimate efficiency scores for each subunit. The research demonstrates how the scores can provide objective and valid indicators of each subunit's efficiency, while accounting for key goals and values of internal and external stakeholders. The scores can be practically applied by a transit agency to identify subunit inefficiencies, and, as demonstrated by several brief case studies, this information can be used as the basis for changes that will improve both subunit and system performance.

Introduction

Due to shortages of public funds and expanding societal needs, maintaining and improving the performance of public transportation systems are critical for future operations (Kittelsohn et al. 2003; Sulek and Lind 2000). If public transportation

is not as efficient as it could be, it provides less service than desirable or requires taxpayers and riders to pay more than necessary.

Improving the efficiency of a transit system's subunits is one way to increase overall efficiency. Of course, maximizing subunit efficiency does not necessarily maximize system efficiency. However, overall system efficiency can be increased by correctly identifying subunit inefficiencies, and then improving subunit performance with changes that are consistent with system structures, goals, and constraints. For example, the efficiency of subcontracted service providers could be compared, as could the efficiency of individual bus routes, different rail lines, park-and-ride lots, rail stations, garages, and paratransit operations. If some of the subunits performing a given type of activity are identified as relatively inefficient compared with others performing the same activity, then management can take action to improve the least efficient ones, thereby improving overall system performance. The challenge lies in identifying and quantifying objective measures that reflect the multiple outputs and inputs common in public transportation.

This article describes a procedure for comparing subunit efficiency, and demonstrates its application to the Chicago Transit Authority (CTA) park-and-ride lots. Park-and-ride facilities are a strategic component of urban mass transportation systems, effectively extending the service area and attracting riders who may not have otherwise used transit. However, with the high cost of construction, land acquisition, and maintenance of parking facilities, a misplaced or underutilized lot can quickly consume significant resources with little promise for return on investment. The CTA has 17 park-and-ride lots, which not only provide parking for heavy rail passengers but also generate more than \$1 million annually in net operating income. Similarly, the Chicago commuter rail lines (operated by Metra) provide 68 lots, and Metra has been significantly increasing its lots' capacities to attract more riders (Ferguson 2000). Indeed, park-and-ride facilities have become an integral part of almost all medium and large urban transportation systems in North America (Turnbull et al. 2004).

This discussion addresses problems in developing valid efficiency measures that (1) simultaneously incorporate all resource inputs and all desired outputs, (2) adjust for the influences of environmental variables, (3) are objective and can be rationally interpreted, and (4) provide consistent measurements with which to compare subunit performance. We describe an innovative solution to the problems—Data Envelopment Analysis (DEA). We identify the DEA model used, and the inputs and outputs that are most valued by the CTA. Using these inputs and

outputs for the 16 lots for which we have data, we apply DEA. We use Stochastic Frontier Analysis to adjust the lots' DEA efficiency scores for environmental factors. Finally, we present several brief case studies of lots that have been identified as inefficient by DEA.

Problems with Measuring Efficiency of Subunits within a Transit Organization

In economics, efficiency (or more specifically, technical efficiency) is measured by the ratio of output to input (Cooper, Seiford, and Zhu 2004; Färe, Grosskopf, and Lovell 1994). In public transportation, multiple outputs are produced by multiple inputs, so different efficiency rankings may occur depending on the specific output/input ratios chosen for analysis.

For example, although the primary goal of CTA management is to provide parking for heavy rail passengers, the profit derived from these lots also is an important output according to the agency. Thus, the key outputs are (1) number of parked cars, as a proxy for number of passenger trips and (2) parking revenues. Key inputs are (1) number of parking spaces and (2) operating expenses. Of course, other outputs and inputs could be added, but these are key to the CTA and are used to illustrate the process.

Four different efficiency indicators can be constructed from these two outputs and two inputs: cars/expenses, revenue/expenses, revenue/capacity, and cars/capacity. Table 1 shows the actual performance of four CTA lots on these four ratios.

Table 1. Comparative Efficiency of Four CTA Park-and-Ride Lots, First Quarter 2005

Lot	Cars/ Expenses	Revenue/ Expenses	Revenue/ Capacity	Cars/ Capacity
A	3.05	4.25	1.18	0.85
B	2.88	5.70	1.51	0.77
C	0.75	1.80	2.18	0.90
D	1.08	2.14	2.13	1.08

Note that Lot A is the best performer on the first measure, B on the second, C on the third, and D on the fourth. Also, A is the worst performer on the third indicator; B is the worst on the fourth; C is the worst on the first; and D is the next to worst on the second. In short, for this actual data, there are no consistently good or consistently bad performers. Further, which indicators would be considered most important would likely depend on one's function at a transit agency. Land developers would probably prefer to use the third indicator, while those most interested in cash flow would prefer the second. Those concerned in cost control would value the first most heavily, and those trying to maximize transit passenger trips would argue for the fourth. Moreover, at least in Chicago, interest groups for each lot certainly would be involved if the efficiency measures were to be used to make decisions about their lot's fate. It is not hard to imagine which ratios the supporters of each lot would argue were key and which were biased.

Worse, this is a *very simple* situation: there are *only* 4 efficiency measures and *only* 4 lots. Most transit experts could easily identify 4 significant inputs and 4 significant outputs, thereby increasing the potential efficiency measures from 4 to 16. If all CTA lots were compared with all 16 measures, it would make winners and losers even more difficult to identify.

As this example illustrates, even in very simple situations, it often is difficult to compare the *overall* efficiency levels of the subunits performing a given type of activity. What is needed is a single, comprehensive measure of performance that would objectively identify the poorest performers overall, and then use other techniques to determine the reasons for poor performance and to decide on appropriate actions.

To obtain a comprehensive efficiency measure for comparing the lots, we could aggregate each lot's outputs and inputs with some weighting scheme, and then divide the aggregated outputs by the aggregated inputs. That is, for each lot, we could calculate the following indicator:

$$\text{Efficiency} = \frac{\text{OutputWeight}_1 \times \text{Output}_1 + \text{OutputWeight}_2 \times \text{Output}_2}{\text{InputWeight}_1 \times \text{Input}_1 + \text{InputWeight}_2 \times \text{Input}_2} \quad (1)$$

For example, suppose we are most interested in low costs and high revenues. For the outputs we decide to weight revenues at 0.8 and parked cars at 0.2. For the inputs, we choose to weight costs at 0.7 and capacity at 0.3. We use these weights

to calculate the efficiency of each lot. For instance, for Lot A, for the first quarter of 2005 its daily revenue ($Output_1$) was \$519, its daily operating expenses ($Input_1$) were \$122, its average number of parked cars ($Output_2$) was 371, and its capacity ($Input_2$) was 441 spaces:

$$\text{Efficiency (Lot A)} = \frac{0.8 \times 519 + 0.2 \times 371}{0.7 \times 122 + 0.3 \times 441} = 2.25 \quad (2)$$

We perform calculations using the same weights for the inputs and outputs of each lot, and then compare the values. However, it would be difficult to defend definitively the preceding weighting scheme as being optimal, and it would be equally hard to justify assigning equal weights to each input and output (or to each of the four ratios presented earlier). An objective and consistent procedure for assigning weights is necessary to solve the problem.

Data Envelopment Analysis

Data Envelopment Analysis (DEA) offers an innovative approach to the problem of objectively assigning weights to compare the efficiency of the subunits of a transportation organization validly. Since the first papers applying DEA to public transportation were published in 1992, the procedure has become increasingly popular for comparing transit organizations with each other (Brons et al. 2005; De Borger, Kerstens, and Costa 2002). However, DEA has not been used to compare subunits within a given transit organization. Herein, we demonstrate the use of DEA for comparing a set of subunits that each performs the same activity within their parent transportation agency. Similar analyses have been conducted to compare the performance of organizational subunits such as bank branches and retail outlets (Cooper, Seiford, and Zhu 2004; Färe, Grosskopf, and Lovell 1994).

DEA uses linear programming to weight and aggregate outputs divided by inputs in a way that results in a single comprehensive efficiency measure, with efficient units scoring exactly 100 percent. The efficiency of a given subunit (or other unit of analysis), often referred to as a Decision Making Unit (DMU), is expressed as a percentage of the efficiency of its most efficient peers. For the case at hand, each park-and-ride lot is a DMU.

A key feature of DEA is that the weighting for variable aggregation can be different for each DMU. For the target DMU, weights are assigned so it will obtain the high-

est possible efficiency score when it is compared to the other DMUs, when all have been assigned the particular set of weights that is optimal for the target DMU. That is, the procedure is applied to a particular DMU. Then, the entire process is completed for another target DMU, with new weights being assigned to all DMUs that maximize the efficiency of the new target DMU. This process is completed once for each DMU that is in the set being compared. So, if a particular DMU's score is not 100 percent, this tells us that other DMUs are still more efficient even when the weights are set to maximize the score of the given DMU. Once efficiency levels for each DMU have been identified, they can be analyzed to determine why certain DMUs are more efficient than others.

Inputs, Outputs, and DEA Model

For this illustration, the inputs are (1) number of parking spaces and (2) mean daily operating costs. The outputs are (1) the mean number of cars parked in the lot during the workday and (2) mean daily revenue. Because the mean revenue per car that the lots receive varies from \$1.39 to \$3.95, the two output variables reflect different measures of success. All variables are daily averages for the first quarter of 2005. The DEA model is

$$\begin{aligned}
 \max_{u,v} \quad & \theta = \frac{\sum_{m=1}^M u_m y_{mk}}{\sum_{n=1}^N v_n x_{nk}} \tag{3} \\
 \text{subject to} \quad & 1 \geq \frac{\sum_{m=1}^M u_m y_{mj}}{\sum_{n=1}^N v_n x_{nj}} \quad \forall j \\
 & \sum_{n=1}^N v_n x_{nk} = 1 \\
 & u_m, v_n, y_{mj}, x_{nj} > 0 \quad \forall m, n, j
 \end{aligned}$$

In our case there are j DMUs; that is, j lots, to be evaluated ($j=1, \dots, 16$). Each DMU consumes varying amounts of n different inputs ($n = 1, 2$) to produce m different outputs ($m = 1, 2$). Thus, for example, DMU _{j} consumes amount x_{nj} of input

n and produces y_{mj} of output m . For all DMUs, u_m is the weight by which each y_{mj} is multiplied, and v_n is the weight by which each x_{nj} is multiplied. The DMU that is the target of a given evaluation is designated DMU_k , and it is compared to all j of the DMUs including itself. The program (3) maximizes the ratio of weighted outputs to the weighted inputs. The weights u_m and v_n are the variables, and they are changed until the ratio is maximized for the target DMU when those same weights are applied to all DMUs. The value of the ratio, θ , is the efficiency score of DMU_k , where $0 \leq \theta \leq 1$ and a fully efficient DMU receives a score of 1. Again, note that it is the weights that are the variables, with the outputs and inputs being the values actually observed for each lot. The DEAs in this study were conducted with the Efficiency Measurement System (EMS) software developed by Scheel (2003), which converts the fractional program in (3) into a linear program before solving.

Unadjusted DEA Efficiency Scores

The initial efficiency levels of the various lots, unadjusted for any differences in environmental factors, are shown in Table 2. (Frequently, the efficiency score θ is written as a percentage, so an efficient DMU will have a $\theta = 1$ or 100 percent.)

Table 2. Unadjusted DEA Efficiency Scores

Lot	Unadjusted Efficiency ($\theta\%$)
A	100.00
B	100.00
C	100.00
D	100.00
E	94.89
F	91.85
G	89.19
H	85.92
I	76.25
J	76.25
K	70.83
L	62.48
M	58.51
N	54.87
O	43.56
P	20.91

Of the 16 lots, 4 (A, B, C, and D) are efficient with scores of 100 percent; that is, no other lot is more efficient for each of the four lots' optimal mixes of weights. The other lots show varying degrees of inefficiency. Thus, Lot E is 95 percent efficient, and Lot P is only 21 percent efficient. Again, note that these efficiency levels are relative; the most efficient lots receive efficiency scores of 100 percent. A given inefficient lot's score identifies how much less efficient it is than its efficient peers when all lots use the weighting that maximizes the efficiency of the given lot.

Adjusting Efficiency Scores for Environmental Factors

Before analyzing each lot to attempt to determine the reasons for its score, it is informative to adjust the scores for key environmental influences. As typically defined in DEA, environmental factors are influences that are not traditional inputs and outputs, and are not under the control of management (Coelli et al. 2005). Hart (2005) found that the number of cars using each CTA lot was influenced by the distance of the lot from the nearest freeway and from the central business district (CBD). The closer the lot was to the nearest freeway, the higher the demand, and the further the lot was from the CBD, the higher the demand. Many other environment variables could be important (Hart 2005; Spillar 1997), but only a limited number can actually be used given the sample size, so we use those that Hart found optimal for the Chicago lots.

Different methods have been utilized for adjusting efficiency scores to control for environmental factors (Coelli et al. 2005; Ruggiero 2004). The method currently in favor, often called the two-stage method, involves first computing the efficiency scores using *only* true inputs and outputs, as we already have done. In the second stage, environmental influences can be controlled for by regressing the initial efficiency scores on the environmental variables, and then adjusting the initial scores by dividing them by the expected scores.

Ordinary Least Squares (OLS) regression, however, is not a valid method to use when the dependent variable is the DEA efficiency score for several reasons. The dependent variable has an upper limit of 100 percent, and therefore is a censored variable. Using OLS regression when the dependent variable is censored results in biases in parameter estimates (Breen 1996). If such censoring were the only concern, then Tobit regression could be used. But, because we also have to deal with biases caused by inefficiency, as discussed later in this section, Tobit regression is not valid either (Kumbhakar and Lovell 2000).

Another method for dealing with the censoring of DMU efficiency scores is to use superefficiency scores (Andersen and Petersen 1993) as the dependent variable. For inefficient DMUs, efficiency and superefficiency scores are identical. For an efficient DMU, the superefficiency score identifies the proportion by which its current outputs exceed the level necessary to be efficient. Because only four DMUs were found to be efficient in this study, the superefficiency scores will differ from efficiency scores only for these four. The applicable superefficiency scores are lot D (101%), lot A (102%), lot B (117%), and lot C (193%). Because superefficiency scores are not censored, a statistical model adjusting for censored variables is not necessary if they are used as the dependent variable.

However, OLS regression *still* is inappropriate (as is Tobit regression) because of the second problem. Just as most of the lots were inefficient in converting inputs to outputs, it is likely that many of the lots will be inefficient in converting environmental factors to outputs. To account for this possibility, it is necessary to use a statistical model that estimates both normal random fluctuations in the error term and downward biases due to inefficiency, which neither OLS nor Tobit regression do. Therefore, we use Stochastic Frontier Analysis, which adjusts for DMU inefficiency in converting environmental conditions into outputs (Coelli et al. 2005; Kumbhakar and Lovell 2000). (Stochastic Frontier Analysis would be inappropriate if efficiency scores were used as the dependent variable instead of superefficiency scores because, as with OLS, a censored dependent variable will bias estimates.)

The dependent variable, therefore, is the superefficiency score for each parking lot. The environmental variables that influence outputs and thereby the efficiency scores are “distance of the parking lot from the central business district” (relationship expected to be positive) and “distance of the parking lot from the nearest freeway” (relationship expected to be negative).

For DMU_{*j*}, y_j is the superefficiency score; x_{1j} is the distance of the parking lot from the CBD; x_{2j} is the distance of the parking lot from the nearest freeway; v_j is the two-sided noise component of the error term; and u_j is the nonnegative technical inefficiency component of the error term. The noise component v_j is assumed to be normally and independently distributed. The inefficiency component u_j must be greater than or equal to zero, and is assumed to be exponentially and independently distributed. The model is:

$$\ln y_j = \beta_0 + \beta_1 \ln x_{1j} + \beta_2 \ln x_{2j} + v_j - u_j \quad (4)$$

We conducted the analysis with the Frontier Analysis package in Stata 9 (Stata-Corp 2005). The results are shown in the Table 3. Note that this model is estimated using the maximum likelihood method, not the least squares method, so R-Square statistics are not available.

Table 3. Parameter Estimates

Variable	β	Std. Error	P> z
Constant	-0.400	4.54E-06	0.000
x_1 (distance from CBD)	0.195	1.65E-06	0.000
x_2 (distance from freeway)	-0.108	2.82E-07	0.000

Log likelihood = -.102; Wald chi-square (2) = 3.19e+11; Prob > chi-square = 0.000

As expected, the greater the distance of the lot from the CBD (x_1), the higher the efficiency, and the greater the distance of the lot from the nearest freeway (x_2), the lower the efficiency. Thus, it is reasonable to use the expected values predicted by this equation to adjust the uncorrected efficiency scores. The values for adjusted efficiency scores are shown in Table 4.

Table 4. Adjusted Efficiency Scores

Lot	Adjusted Efficiency ($\theta\%$)
B	100.00
C	100.00
E	100.00
H	97.50
F	95.52
G	93.89
D	86.70
I	82.10
J	76.90
L	66.00
M	59.50
N	59.37
K	51.66
A	47.75
O	44.10
P	22.04

Interpreting the Case Study Results

Identification of lot efficiencies, with both original and adjusted scores, is the first step. Next the “red flag” test should be used to identify lots that should receive further attention (Barnum 1987). Low efficiency scores make it easy to identify those lots that need thorough examination. Obvious examples here are lots O and P, which scored at the bottom of both sets of efficiency scores; lot K, which had a significant decrease in efficiency between the unadjusted and adjusted efficiency scores; and lot A which was efficient before adjustment for environmental factors but significantly inefficient after taking its favorable environment into account.

In some cases, uncorrectable factors or other justifiable reasons account for the low scores. In other cases, the low scores may identify lots that can and should be improved. To illustrate the method, we next discuss the examinations of lots A and P that resulted from their flagged efficiency scores.

One of the flagged lots was lot A, whose score dropped from 100 percent to 48 percent after being adjusted for environmental factors. Discussions with CTA personnel uncovered the reasons for this decrease. Lot A competes for business with lot C because they are very close to each other. However, both lots are on the same freeway from the suburbs, with lot C being slightly further from the city. That short stretch of freeway is very congested during rush hour. Hence, even though lots A’s and C’s environmental factors are almost identical, lot C is likely to get many more cars, thus decreasing the adjusted efficiency for lot A.

Of course, lot A is efficient when only the outputs and CTA resource inputs are considered; that is, the unadjusted efficiency. From the viewpoint of the actual inputs and outputs, the lot is performing well when compared to other lots. Further, it is unlikely that the number of lot A parkers could be increased without adversely affecting lot C.

It was suggested that lot A’s revenue output could be increased by raising the rate from \$2 to \$3 for the first 12 hours. The rate at lot C already is \$3, so it is likely that if lot A’s rate were increased, its revenue would increase much more than the number of parkers decreased. This suggested change may be implemented by the CTA.

Also, lot A’s operating expenses are relatively high due to the fact that personnel are on duty to collect parking fees. In lot C and all other lots, parkers deposit their own parking fees. The increase in perceived security provided by parking attendants would attract more parkers to lot A, if not for the fact that even more per-

ceived security is provided at lot C. The suburban police patrol lot C and “maintain an almost constant presence” (Hart 2005, p. 92). CTA resources are not used for this police protection, so lot C’s operating expenses remain low, thereby giving it a big boost in efficiency. Given the recent increase in concerns for security at transit facilities, perhaps the CTA could obtain similar protection for lot A (which is a multistory structure near the airport). This could decrease the CTA’s input costs, thereby increasing the lot’s efficiency.

In a somewhat similar situation, lot P competes with lot K, with not enough parkers to fill both lots. For the unadjusted efficiencies, lot K is the clear winner. But, lot K also enjoys very favorable environmental variables while lot P does not. Thus, it is not surprising that lot K’s efficiency decreases from 71 to 52 percent when we adjust for environmental factors, while lot P’s efficiency increases slightly from 21 to 22 percent.

As seen in Table 4, lot P has the lowest efficiency of all lots for both the unadjusted and the adjusted efficiency scores. This is the result of a relatively large lot with average operating expenses, but with very low occupancy and revenues. These outcomes in turn are likely influenced by the nearby presence of lot K, which has in the past been considered a more desirable place to park. At the time these data were collected, lots K and P were at terminals at the western ends of two branches of the same rapid transit line, and these two branches merged before the line entered the CBD. However, the branch to lot K not only was closer to a freeway, but also it provided more hours of service, and the branch to lot P was impeded because of major upgrades to the tracks and terminals. Recently, however, the branches have been separated into two independent lines, and the frequency of service on each has been doubled. The enhanced service and the readily available parking is expected to increase passengers and parkers for both terminals. If demand does not increase in a reasonable time, however, it might be worth considering the impact of downsizing or closing lot P, since its current demand could be absorbed by lot K. Of course, there may well be factors other than DEA efficiency scores that make such a suggestion infeasible.

Herein we have given only brief analyses of a few lots as examples of the process. Once a lot is flagged as the result of a low efficiency score, a thorough examination of the lot should be made to determine the reasons for the low score. As demonstrated above, sometimes the factors influencing the scores are correctable, and other times they are not.

As was done in this case, flagged subunits should be subjected to joint examinations by transit agency personnel and the DEA analysts, and not be examined by just one group or the other. To best identify and correct problems, both a deep understanding of the transit system and an understanding of the analytical method must be integrated. In the present case, such an examination took place as part of the ongoing partnership between the CTA and the Urban Transportation Center at the University of Illinois at Chicago. This joint analysis provided much of the information in this section.

Conclusions

Data Envelopment Analysis, augmented by Stochastic Frontier Analysis, is a methodology for identifying and comparing the efficiencies of a set of subunits within an organization that recognizes the diversity of inputs and outputs that impact and influence performance, and that provides insights into the differences in performance. Once management has identified the key outputs and inputs of a given type of subunit, then DEA can be applied to identify a comprehensive efficiency score for each subunit of that type. Because this score results in each subunit attaining the maximum reported efficiency when compared to its peers, it is unbiased by particular points of view about the importance of various inputs or outputs, and hence is a much more valid summary measure than typically utilized. This measure can be adjusted to account for differences in environmental factors affecting the subunits, if necessary. Once the original or adjusted measures of efficiency are obtained, then those subunits with low scores can be carefully studied to develop plans of action to improve their efficiencies.

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personnel are combined to produce valuable outputs that would not have been attained by either group alone. Of course, in this research, our ability to interpret correctly what we were told may be lacking, so any errors or misstatements in this article are entirely our own. Likewise, all identifications of lot efficiency are ours alone, and have not been endorsed either by the aforementioned individuals or by the CTA.

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Investment in Mobility by Car as an Explanatory Variable for Market Segmentation

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Abstract

According to the traditional approach, when estimating changes in transportation policies, the household income level (in all its forms) is perceived as the proper explanatory variable for modeling population transportation preferences. However, it is acknowledged that accurate information about this variable is difficult to gather. In contrast, information about household car characteristics is relatively simple to collect. This article presents the hypothesis that a lifestyle variable, such as investment in mobility by car (IMC), is a viable parameter for estimating household members' behavioral tendencies toward transportation, from both practical and conceptual reasons.

This research proposes a simple methodology to infer the IMC using existing data sources, and presents mode choice model estimation results using the IMC both as an explanatory variable and as a segmentation variable. The segmentation of the population in three IMC categories (low, middle, and high) yielded significantly different models of the preference systems for the three segments. These findings show that IMC is a viable variable for market segmentation.

Introduction

It is generally acknowledged that market segmentation is crucial to the modeling process. Disaggregate mode choice models have a particularly vast literature in which the population is segmented in various ways. Examples of different market segmentation approaches in mode choice modeling can be found in Dehghani and Talvitie (1980), Pas and Huber (1992), and more recently Outwater et al. (2004).

This article focuses on the independent variables commonly used in the mode choice modeling process and on the relevance of the variables used for market segmentation. In particular, we consider household variables such as income level and auto ownership. An example of the use of these variables for market segmentation in mode choice modeling can be found in Dehghani and Talvitie (1980).

The motivation for this article is that the number of cars in a household, usually used in travel forecasting methods, is in our opinion too general for market segmentation. A combination of number of cars per household and income level could yield a better indicator. However, data on household income is acknowledged in the literature as problematic to collect. In contrast, data on car characteristics is relatively easy to collect. This enables us to categorize each household according to an estimation of its investment in car mobility. The investment in car mobility is defined as the total market value of the cars in each household. In this article, we explore the possibilities of using this variable for market segmentation.

Determining which type of parameter is preferable for market segmentation can be examined from a practical or from a conceptual aspect. From a practical aspect, we suggest that the investment in mobility by car (IMC) parameter is preferable to income in its different forms, while from the conceptual point of view, it is at least as good as income. While we would have preferred to present a quantitative evaluation of the two parameters, we have to rely on secondhand databases (almost all transportation surveys conducted in Israel did not collect information about household income level), and thus limit our discussion to a qualitative evaluation.

Practical Considerations

In most household travel surveys, it is customary to obtain information about household income. However, we found evidence in the literature about surveys that neither collected nor used this information. For example, Badoe and Miller (1998) used data collected from the very extensive 1986 Transportation Tomor-

row Survey (TTS) for the Greater Toronto Area (GTA). This survey, documented in detail in Data Management Group (1990), included a telephone interview of 4 percent of all households in the area (about 67,000 households) and contained information on household variables, but not household income.

Most travel surveys conducted in Israel, including the National Travel Habits Survey (NTHS) of 1996/7 (Central Bureau of Statistics 1997), which also served as a database for this research, do not include questions about income level. In fact, very few household trip surveys conducted in Israel include data about the income level of respondents. Attempts to use the income variable in modeling estimation were not successful (Taskir 1995).

We believe that this absence of information is not an omission by neglect, but a result of the surveyors' awareness of the unreliability of answers given by respondents to questions involving income. Furthermore, some of the surveyors were concerned that respondents would consider questions about income an illegitimate invasion of privacy, and this would have a damaging effect on the reliability of their answers to the entire questionnaire.

In contrast to the lack of information about income and its inherent unreliability, available surveys in Israel include information about cars possessed by each household. This information enables us to estimate average household investment in mobility by car. Respondents do not have any particular reservations about providing information about the cars they use, simply because it is an obvious fact. The information about car characteristics is also collected in many household surveys found in the literature. For example, the 2001 U.S. NHTS (2004) included information about car make, model, and production year.

Conceptual Considerations

Income level is a physical factor that defines the envelope of the household possibilities to allocate its resources. Salomon and Ben-Akiva (1983) pointed out that "the concept of lifestyle is becoming a major differentiating trait between population groups, substituting for economic and social classes." We do accept the general definition of the lifestyle suggested by the authors, namely that "the lifestyle is defined as a pattern of behavior under constrained resources." The authors showed in their study that lifestyle groups account for taste variations better than other schemes.

Badoe and Miller (1998) proposed a systematic approach to study variations in mode choice behavior. The methodology used was based on the Automatic Interaction Detector (AID) developed by Sonquist et al. (1971), the merits of which were emphasized by Hensher (1976). The authors found that the single most important variable for explaining differences in workers' mode choice behavior was the number of household vehicles. The authors classified this variable as "a socioeconomic factor." We are inclined to define it as a lifestyle variable, even though it is influenced by the socioeconomic status of the household. The number of cars is also an indicator of the household preferences for allocation of its resources between transportation and other uses.

We adopt the notion of lifestyle discussed by Salomon and Ben-Akiva (1983) as a preferable concept for selecting explanatory variables to market segmentation in travel demand modeling. However, we do expect that lifestyle variables that are directly related to transportation behavior, such as the number of vehicles and investment in mobility by car, would be more closely connected to the individual preference system than other lifestyle elements, such as household formation, participation in labor force, orientation toward leisure, and so on.

The assertion that the number of household vehicles is a lifestyle variable supports the claim by Salomon and Ben-Akiva (1983) mentioned above. In addition, the AID application proposed by Badoe and Miller for segmentation and classification is useful for a given set of variables. However, even the best classification system cannot identify and classify variables that are not defined as such. The number of cars in the household itself is not enough to identify lifestyle, as it does not distinguish between different levels of investment by the household in those cars. These levels of investment are believed to be highly correlated with the household preferences concerning choices of transportation alternatives. Therefore, we propose to use another lifestyle variable, complementary to the number of household vehicles, namely IMC.

Our hypothesis is that the behavior presented by the revealed action of IMC is significantly more closely related to population preferences concerning the use of alternative modes of transportation than income level alone. IMC is a behavioral phenomenon that demonstrates the outcome of the choices made by the household concerning its mobility.

The IMC variable could be formulated as a function of the following variables: income level, family size, age and gender composition, transit accessibility mea-

sures, consumption patterns, working patterns, and a preference function concerning the allocation of household resources among household uses.

Most of the above variables are easily observable, and data can be obtained from current practice surveys. However, the preference function concerning allocation of household resources cannot be obtained directly from existing surveys. Surveys generally provide information about the number cars in the household; however, data relating the decision to purchase a car at a given price and at a certain time is not collected. Therefore, at this stage, we limit the investigation to existing data sources, and propose a simple methodology to infer the IMC, presented in the next section.

Methodology

Data Preparation

The database used for model estimation is a subsample from the NTHS, carried out by the Israeli Central Bureau of Statistics in 1996–1997 on behalf of the Ministry of Transport. We confined this study to the Tel Aviv Metropolitan Area (about 1.7 million inhabitants in 1996), since we could reasonably attach a reliable level of service data only for this region.

The survey is a typical revealed preferences (RP) study. About 1 percent of the households were surveyed (5,917 households in the Tel Aviv area). Each person over the age of 14 kept a three-day diary. A total of 29,506 observations, corresponding to trips departing from home, were selected for the analysis. We purposely avoided chained trips, since for more than 95 percent of these cases the chosen mode was identical to the mode used in the trip departing from home.

Travel times for car and transit modes were imported from Emme/2 networks used for modeling a light rail transit project in the Tel Aviv Metropolitan area (Perlstein-Galit Company Ltd. 2001).

The survey collected additional information about the cars in the household. According to information in the questionnaire about the year of production and engine size, we calculated average market values for each car in the household. Table 1 presents average car values (December 1996 prices) according to the price booklet used for car insurance companies (Levi-Itzhak 1996).

Table 1. Average Car Prices for Given Engine Size and Production Year¹

Production Year	Engine Size					
	Up to 1000	1001–1300	1301–1600	1601–1800	1801–2000	2001 & More
Up to 1988	9.5	11.6	14.3	19.8	26.5	38.1
1989	17.6	18.5	27.2	40.2	56.0	72.1
1990	19.3	22.6	32.3	43.8	52.9	77.3
1991	21.8	27.3	37.8	45.1	54.9	75.7
1992	24.6	28.3	42.3	49.2	53.0	88.2
1993	29.1	31.7	45.9	58.8	72.7	98.2
1994	39.0	33.9	50.2	67.3	90.0	113.8
1995	-	38.9	60.8	73.1	93.6	115.7
1996	-	50.8	67.9	84.6	100.2	136.2
1997	-	57.9	78.6	98.5	101.1	187.0

1. December 1996 prices in thousands of NIS (U.S. \$1 = 3.244 NIS).

Model Estimation

This article focuses on the methodological aspects of the population segmentation, rather than model structure and calibration. For this reason, we used the multinomial logit model with the same utility function for all models tested in this study. In this way, we kept the modeling estimation procedure constant throughout, and concentrated on different segments of the population. In addition, the same independent variables were used in all models.

The models were estimated according to two segmentation levels. First, the observations were separated according to car ownership and driver’s license. Three models were estimated at this level:

- *Model A:* The first model was estimated with all the available households (29,506 observations).
- *Model B:* The second model was estimated for persons with a driver’s license and living in households with at least one car (18,975 observations).
- *Model C:* The third model was estimated for the remaining observations (i.e., persons without a driver’s license or living in households without a car; 10,531 observations).

The next segmentation level was formed by further dividing the 18,975 observations related to households with car and persons with a driver's license according to IMC. Three additional models were estimated:

- *Model D*: IMC up to 10,000 NIS (low investment; 3,094 observations);
- *Model E*: IMC between 10,000 and 60,000 NIS (middle range; 8,276 observations); and
- *Model F*: IMC higher than 60,000 NIS (high investment; 7,605 observations).

The thresholds for low, middle, and high IMC used in these models were defined by looking at the IMC distribution in the household sample, as shown in Figure 1. Since 1,834 (31%) of households in the sample do not possess a car, the IMC for these cases is 0. At the value of 10,000 NIS there is a sharp difference in the slope of the cumulative frequency, and for this reason this value was used as a reference for low IMC. There are similar differences around 30,000 and 60,000 NIS, but the 30,000 mark did not yield significant model estimation results. Figure 2 shows the household segmentation for the different models estimated.

Figure 1. Distribution of IMC in the Sample

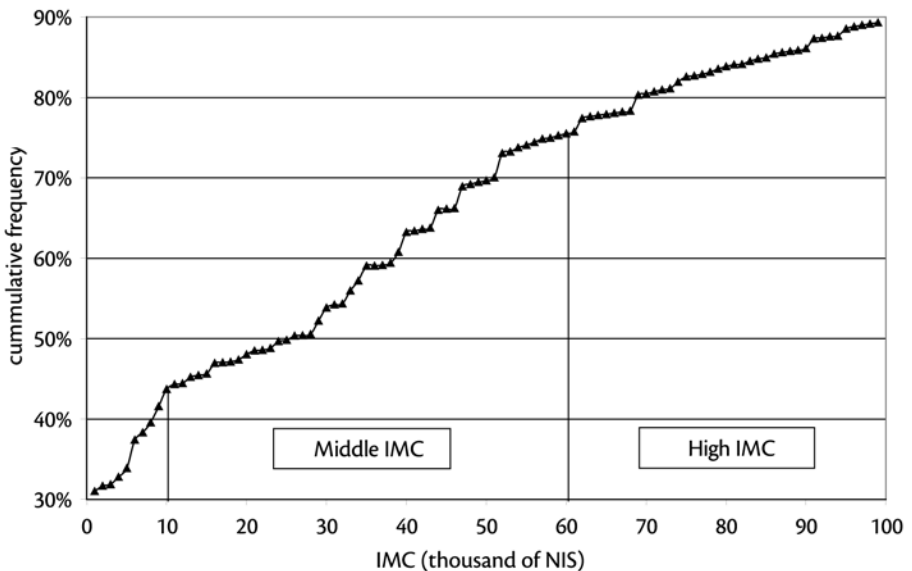
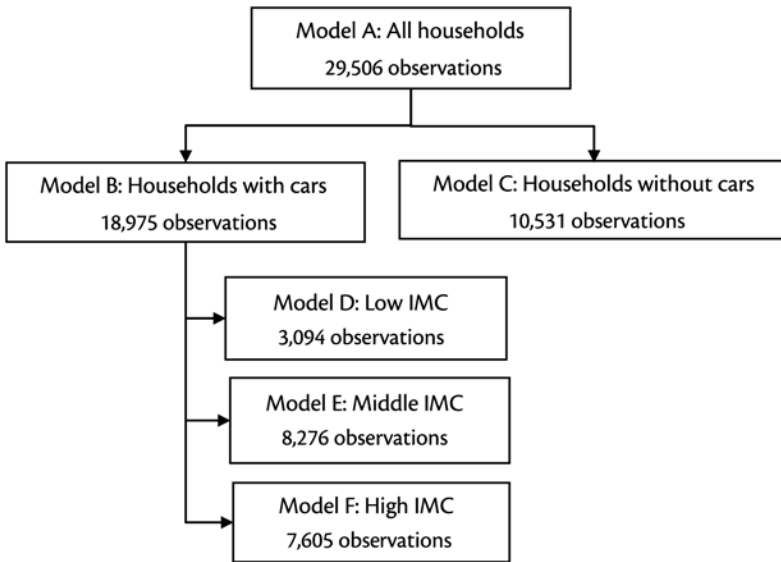


Figure 2. Segmentation Diagram



Since in this study we focus on the influence of IMC variable on mode choice, it is important to verify that transit service is available in all segments. For example, it may be possible that households with high IMC will be located in areas with poor transit service. At least for the data used in this analysis, no significant differences were found in the distribution of the main explanatory variables in each of the IMC groups. Table 2 shows the main statistics (mean and coefficient of variation) for each IMC group.

Apart from the IMC mean value, which is obviously different in each class, all other variables exhibit very similar mean and coefficient of variation values.

Results

Table 3 shows the results obtained from the initial segmentation procedure. The table contains the estimated coefficients and t-values for the first three models described. In addition, overall fit parameters and common level of service ratios are presented, such as values of time (VOT) and ratio between out-of-vehicle and in-vehicle transit times. The third model is related to observations without car

Table 2. Basic Statistics of the Main Explanatory Variables for Each IMC Group

Variable Description	IMC < 10,000 NIS		10,000 < IMC < 60,000 NIS		IMC > 60,000 NIS	
	Mean	CV (%)	Mean	CV (%)	Mean	CV (%)
Number of transfers	1.3	39.9	1.3	40.8	1.3	40.7
Bus wait time (min)	7.6	66.1	7.8	63.9	8.3	64.2
Bus in-vehicle time (min)	24.1	76.7	25.5	78.1	27.3	75.7
Bus walk time (min)	5.8	88.5	5.8	88.3	6.7	89.2
Bus fare (NIS) ¹	6.0	53.8	6.2	55.8	6.5	55.6
Car in-vehicle time (min)	18.2	83.7	19.0	85.2	19.6	81.1
Car cost (NIS) ¹	7.7	62.8	7.9	63.1	8.0	61.5
Park cost (NIS) ¹	2.7	17.0	2.7	17.3	2.7	18.0
Park search time (min)	2.5	96.2	2.5	95.7	2.5	96.9
IMC (thousand NIS) ¹	6.2	37.0	36.6	34.6	104.0	36.3

1. December 1996 prices in NIS (U.S. \$1 = 3.244 NIS).

available, and for this reason the IMC variable in these cases is not relevant for model estimation (since it is equal to 0).

Both IMC and a dummy variable that indicates households with two or more cars are quite significant in the first two models. Although the high *t*-values originate from the large sample size, we may infer that the IMC variable is not just a replacement for the auto ownership variable.

Table 4 presents the results for the segmentation according to IMC. The format of the table is identical to Table 3. Recall that the total number of observations in the three models of Table 4 sum up to the observations for households with car and persons with driver's license, as in the second model of Table 3. The car driver's market share in these cases is quite high, as expected, ranging from 71 percent in the lower third of the IMC to 82 percent in the higher third.

For the two extreme IMC ranges (low or high) the independent variable associated with IMC is not significant. However, in the middle range, the IMC variable is significant, perhaps indicating that at this range the influence of IMC is most pronounced.

Table 3. Estimation Results—Initial Segmentation

Variable Description	Model A		Model B <i>HH with Car and Persons with Driver's License</i>		Model C <i>HH without Car or Persons without Driver's License</i>	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Cd—constant	-1.312	-24.7	1.156	12.0		
Cp—constant	-1.487	-27.0	-0.607	-5.8	-0.706	-11.3
Bus—number of transfers	-0.300	-10.1	-0.284	-5.5	-0.316	-7.6
Bus—wait time (min)	-0.031	-8.4	-0.043	-6.0	-0.045	-9.6
Bus—in-vehicle time (min)	-0.016	-7.9	-0.016	-5.1	-0.024	-8.7
Bus—walk time (min)	-0.022	-5.0	-0.013	-1.7	-0.038	-6.5
Bus—fare (NIS) ¹	-0.169	-22.2	-0.131	-9.8	-0.205	-2.5
Cd—in-vehicle time (min)	-0.025	-7.5	-0.035	-6.8		
Cd—cost (NIS) ¹	-0.029	-3.2	-0.048	-3.6		
Cd—park cost (NIS) ¹	-0.003	-0.3	-0.030	-1.9		
Cd—park search time (min)	-0.012	-1.7	-0.031	-3.2		
Cp—in-vehicle time (min)	-0.030	-8.0	-0.030	-5.0	-0.008	-1.6
Cp—cost (NIS) ¹	-0.041	-4.2	-0.063	-3.9	-0.088	-7.4
Cd—IMC ('000 NIS) ¹	0.018	32.4	0.004	4.4		
Cp—IMC ('000 NIS) ¹	0.013	20.6	0.004	4.5		
Cd—dummy for 2+ cars in hh	0.931	19.5	0.930	12.8		
Cp—dummy for 2+ cars in hh	0.447	8.3	0.486	5.6		
Total number of observations	29506		18975		10531	
Bus riders	7932	27%	1826	10%	6106	58%
Car drivers	14784	50%	14784	78%		
Car passengers	6790	23%	2365	12%	4425	42%
Likelihood (0)	-32415.7		-20846.2		-7299.5	
Likelihood (Constants)	-30612.1		-12889.1		-7164.8	
Likelihood (Final)	-27034.5		-12169.9		-6715.4	
"Rho-Squared" w.r.t. 0	0.17		0.42		0.08	
"Rho-Squared" w.r.t. Const.	0.12		0.06		0.06	

¹ December 1996 prices in NIS (U.S. \$1 = 3.244 NIS).

Table 4. Estimation Results—Segmentation by IMC

Variable Description	IMC<10,000 NIS		10,000<IMC< 60,000 NIS		IMC>60,000 NIS	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Number of transfers	1.3	39.9	1.3	40.8	1.3	40.7
Cd—constant	1.141	5.1	1.206	7.3	0.880	3.8
Cp—constant	-0.333	-1.3	-0.788	-4.0	-0.911	-3.6
Bus—number of transfers	-0.297	-3.7	-0.267	-3.6	-0.218	-2.2
Bus—wait time (min)	-0.023	-1.7	-0.033	-3.2	-0.094	-5.6
Bus—in-vehicle time (min)	-0.022	-1.5	-0.022	-4.7	-0.015	-2.4
Bus—walk time (min)	-0.046	-2.7	-0.011	-1.0	-0.017	-1.1
Bus—fare (NIS) ¹	-0.075	-2.8	-0.118	-6.4	-0.217	-7.6
Cd—in-vehicle time (min)	-0.025	-2.3	-0.038	-5.2	-0.043	-4.2
Cd—cost (NIS) ¹	-0.036	-1.3	-0.048	-2.5	-0.044	-1.7
Cd—park cost (NIS) ¹	0.015	0.4	-0.048	-2.1	-0.026	-1.0
Cd—park search time (min)	-0.090	-3.9	-0.013	-0.9	-0.024	-1.5
Cp—in-vehicle time (min)	-0.014	-1.1	-0.030	-3.5	-0.044	-3.8
Cp—cost (NIS) ¹	-0.086	-2.5	-0.065	-2.8	-0.040	-1.4
Cd—IMC ('000 NIS) ¹	0.027	1.2	0.008	2.8	-0.009	-0.6
Cp—IMC ('000 NIS) ¹	-0.004	-0.2	0.014	3.8	0.005	0.3
Cd—dummy for 2+ cars in hh	0.633	1.9	0.771	8.0	1.237	10.6
Cp—dummy for 2+ cars in hh	0.300	0.7	0.392	3.4	0.718	5.2
Total number of observations	3094		8276		7605	
Bus riders	467	15%	905	11%	454	6%
Car drivers	2208	71%	6316	76%	6260	82%
Car passengers	419	14%	1055	13%	891	12%
Likelihood (0)	-3399.1		-9092.1		-8354.9	
Likelihood (Constants)	-2465.7		-5883.1		-4408.4	
Likelihood (Final)	-2355.0		-5629.7		-4142.4	
“Rho-Squared” w.r.t. 0	0.31		0.38		0.50	
“Rho-Squared” w.r.t. Const.	0.04		0.04		0.06	

¹ December 1996 prices in NIS (U.S. \$1 = 3.244 NIS).

The following analysis is based on the values of time and bus penalties calculated for each of the models. VOT is computed respectively for each mode as the ratio between the in-vehicle time coefficient and the cost coefficient, and the bus penalties are computed by dividing the different out-of-vehicle time coefficients by the in-vehicle bus time coefficient. Table 5 presents the results.

Table 5. Values of Time* and Bus Penalties

	Model A	Model B	Model C	Model D	Model E	Model F
Cd—VOT (NIS/hr)	52.9	43.7		40.3	46.9	57.6
Cp—VOT (NIS/hr)	43.8	28.6	5.1	9.9	27.5	64.8
Bus—VOT (NIS/hr)	5.5	7.5	6.9	17.6	11.0	4.2
Bus walk time penalty	1.4	0.8	1.6	2.1	0.5	1.1
Bus wait time penalty	2.0	2.6	1.9	1.1	1.5	6.1
Bus transfer penalty	19.2	17.3	13.3	13.5	12.4	14.2

* December 1996 prices in NIS (U.S. \$1 = 3.244 NIS).

As expected, car driver VOT is higher in all models than car passenger and bus VOT, with exception of model F, where VOT for car passenger is highest. The comparison across the models shows a general pattern; that is when car VOT increases (both for drivers and passengers), bus VOT decreases. Note also the low VOT for the segment without car (Model C). The last three models, corresponding to the segmentation according to IMC, exhibit a systematic pattern: VOT for car driver and car passenger increases with increasing VOT, and VOT for bus passenger decreases with increasing VOT.

The comparison of the bus penalties shows less consistent results. We expected significantly higher penalties for higher income populations. Since the walk time coefficients in all models segmented by IMC are not significant at the 90 percent level, it is not possible to draw conclusions for the walk time penalty. The wait time penalty can be compared, and the results show that this value is quite high for high IMC (model F), which is consistent with the high VOT found for this segment.

The transfer penalty was found quite similar for each of the models. We also found in the literature similar values for the transfer penalty. Lin et al. (1997) estimated an intermodal transfer penalty of 15 minutes for New York and New Jersey commute corridors, using RP and SP data for car and transit riders. In a study for work

trips in Boston (Central Transportation Planning Staff 1997), the transfer penalty ranges from 12 to 15 minutes of in-vehicle time for urban mode choice modeling. In Israel, the planning agencies are also currently using 12 to 15 minutes of in-vehicle time in transit mode choice and assignment model implementations.

Summary and Conclusions

IMC as an independent variable in the logit model for estimation of the population choice parameters for modal split modeling was proposed in this article as a possible replacement to the income variable for both practical reasons and qualitative conceptual reasons. The ultimate test to verify the most suitable variable is a database that contains both IMC and income; the latter variable was not available in our database.

In the tests presented in this study, we found that segmentation of the population in three categories of IMC yielded significantly different models of the preference systems for the three populations. These findings suggest that the IMC is a viable variable for market segmentation.

The IMC parameter has limitations that need to be acknowledged. First, even if people tend to maintain certain standards of car ownership, they usually keep their cars for two to three years, sometimes even for four years or more. Automobile market value in Israel drops 8 to 20 percent per year (typically 15% per year). Thus, a typical household may be very easily classified 20 to 30 percent above or below the average IMC of the household; that is, the typical household might be classified at a lower or higher category of IMC than to which it actually belongs.

This limitation is inherent to the IMC variable and the proper way to deal with it, using the present data conditions, is to have the segments broad enough to allow the marginal crossover from one IMC category to another.

A more rigorous solution to this problem would be to estimate the average reference year for car possession in the household. This can be done in subsequent surveys by asking respondents how many years they kept their previous car, how many years they have had the present car, and how many years they intend to keep it. Such a procedure would enable the researcher to get a more reliable estimate about the true IMC of the household, and would thus allow for a more refined segmentation of the population.

The second problem with the IMC variable is related to the way the variable was calculated. The available database provided two types of information: car production year and vehicle engine size. This relatively limited information forced us to compute for each combination of these variables an average value for all vehicles belonging to the same category. However, there is a wide variation in the market value of different cars with the same production year and engine size. For example, for production year 1992 and engine size group of 1600 to 1800 cc, the weighted average of the market value for cars in this group in Israel was estimated at 49,200 NIS in 1996 prices (about U.S. \$15,166). However, prices ranged from as low as 33,000 NIS to 80,000 NIS for the same combination of year and engine size.

This problem can be easily solved by adding a simple question in the survey about car make. This information is quite easy to obtain, since most drivers know the make of their car. For example, the 2001 U.S. NHTS (2004) included information about car make, which could be employed in the procedure suggested here.

Finally, the IMC parameter appears to have a rather wide variance when it is derived from questionnaires that have not been designed to minimize this variance. The variance can be minimized to make the IMC a much sharper tool for segmentation purposes.

Reduction of the variance as a result of the market cost of different car makes can be achieved very easily by adding a simple question. However, reduction of the variance due to the tendency of car owners to keep a car more than one year and the difference between car owners as regards the period of car possession calls for a more detailed inquiry. As already pointed out, it would be reasonable to add questions about how many years drivers kept previous cars, how long the present cars were in their possession, and how long they intended to keep these cars until the next car acquisition.

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Are Printed Transit Information Materials a Significant Barrier to Transit Use?

Alasdair Cain, Center for Urban Transportation Research

Abstract

This study investigated the extent to which the lack of ability to use printed transit information materials correctly to plan transit trips is a barrier to transit use. A total of 180 people were asked to undertake two transit trip-planning assignments, each requiring the use of a system map, two route maps, and two schedules.

The study found that only 52.5 percent of the sample, composed of both transit users and nonusers, was able to plan a transit trip successfully using standard printed information materials. The main problems existed at the latter stages of the trip-planning process involving schedule use (55.6% success rate). Although printed information materials were the most popular trip-planning media for transit users, more than half stated that they did not use this method to plan their trips.

Additional questioning suggested that a relationship between transit trip-planning ability and transit use does exist. However, it was also found that while lack of information material comprehension is a problem, it is not a primary barrier to transit use—none of the nontransit users cited lack of transit trip-planning ability as their main reason for not using transit. Furthermore, a wide range of other information resources is available for transit users to choose from if they are uncomfortable with printed media.

Introduction

Printed information materials, such as transit system maps, route maps, and schedules, are the traditional media used by transit agencies to provide service information to customers. Transit providers allocate significant resources in producing such materials and in keeping them up to date with service modifications. There is some concern in the transit industry that public inability to plan transit trips may be a major barrier to transit use. However, relatively little is known about how transit users actually plan their trips, and the extent to which printed information materials are actually used.

This article presents the results of a study completed by the National Center for Transit Research, titled "Design Elements of Effective Transit Information Materials" (Cain 2005). The first objective of the study was to isolate the different design elements that make up printed transit information materials, to determine which design options maximize public trip-planning ability. For more information in relation to this objective, see Cain (2005). The focus of this article is the study's second objective, which was to determine the extent to which transit information materials are a barrier to transit use, by exploring the relationship between transit trip-planning ability and transit usage.

Literature Review

The Transit Cooperative Research Program (TCRP) Report 95 is a series of individual studies assessing how different types of transportation system changes and policy actions affect traveler responses and aggregate travel demand. Chapter 11 assessed how various types of transit information and promotion activities impact ridership. The study stated that the primary goal of transit information and promotion activities is to increase ridership or net revenues, preferably both (Turnbull 2003). Other secondary objectives included retaining existing riders, increasing the frequency of use among current riders, getting nonriders to try the system, and increasing general public awareness of available service options. An understanding of the importance of information and promotion, and the difference between these two terms, is key to this discussion. As noted by Turnbull (2003),

For a person to make use of transit service, and thus become a transit rider, he or she must know of the service and understand how to use it. Moreover, the understanding of how to use the service must be complete enough to overcome the barrier to use posed by unfamiliarity. Transit information activities may thus attract

potential riders to both transit in general and to particular services by informing them about the options available and how to make use of them. Transit promotion seeks to provide that extra nudge for potential riders to make the leap and actually try riding transit, and hopefully become regular users.

Only 55 percent of the U.S. public claims to be familiar with transit (Wirthlin Worldwide and FJCandN 2000).

The TCRP-95 report (Turnbull 2003) referenced the large variety of information sources available, including bus stop signage, telephone information (via call centers—either automated or staffed), Internet resources such as on-line transit trip planners, and oral instruction from transit staff or fellow passengers, as well as printed information materials. The report divided the different information and promotion options into six categories: (1) mass market information, (2) mass market promotions, (3) targeted information, (4) targeted promotions, (5) ongoing customer information services, and (6) real-time transit information (Turnbull 2003). Printed transit information materials appeared in two categories: mass market information, which included brochures, system maps, bus stop signage, telephone information systems, and websites; and targeted information, which included route- or sector-specific maps and schedules.

The report noted that relatively few published examinations of the impacts of transit information and promotion activities on ridership are available. This was attributed to a more general problem associated with evaluating marketing impacts on ridership, caused by many agencies lacking a ridership tracking database. In many cases, rider surveys are used to provide impact assessment data, but the accuracy of these can be questionable as they track stated or intended behavior, not actual behavior, and may also suffer from self-selection bias (Turnbull 2003).

Published research on the impact of mass market information programs, such as door drops of printed transit information material, showed that while such campaigns have proven effective in raising awareness and use of transit service support systems, they have little impact on attracting new riders. Results in relation to increased frequency of use by existing riders have also been mixed. Adding incentives to mass market information programs increases the likelihood of ridership gains, at least in the short term—published results show ridership gains of between 4 and 35 percent (Turnbull 2003). Long-term ridership gains are much more difficult to achieve.

Targeted information programs have been shown to be much more effective than mass market information in generating ridership gains. These can include geographical targeting, such as the campaign conducted by the Niagara Frontier Transportation Authority in Buffalo, New York, that mailed route information materials to more than 20,000 residents living within three quarters of a mile of six bus routes. Targeted information also includes socioeconomic targeting (Turnbull 2003). This was featured in the above campaign, with the targeted areas selected on the basis of population profiles being congruent with those of transit riders. Farebox revenue analysis showed that revenues on these targeted routes had increased 1 to 3 percent on three routes and 11 to 33 percent on the other three routes (TTI 1999). Increases of more than 50 percent have been reported in the short term in relation to other targeted information programs.

Transit information usefulness will also be affected by each potential user's knowledge of local geography, knowledge of the transit system, and ability to process different types of information, including maps and schedules. A study conducted in 1986 found that 64 percent of the U.S. population is thought to have difficulty reading maps of any sort (Streeter and Vitello 1986). Data from the National Adult Literacy Survey found that many people are unable to use a tabular bus schedule successfully. This survey tests adult literacy levels in three separate categories: prose comprehension, document literacy, and quantitative literacy. In the document literacy section, only 37.6 of adults between 21 and 25 years old were able to use a bus schedule successfully to select the correct bus departure time (Kirsch et al. 2001). As such, using a bus schedule was rated at level 4 on a five-point scale, with level 1 being the easiest and level 5 the most difficult.

Despite these difficulties, printed information materials remain the dominant transit trip-planning media. A study titled "Customer Preferences for Transit ATIS" found that "riders prefer traditional forms of paper-based information and traditional wayside signage (e.g., schedules, maps, and fares)" (Cluett et al. 2003), while TCRP Report 45 (Higgins and Koppa 1999) stated that both transit riders and non-riders often mention timetables (schedules) as a potentially useful information aid, which some riders use regularly. The report further stated that many people find timetables difficult to read and understand and recommended that "rather than print and distribute timetables, systems provide departure times or bus headways on bus stops signs, packaging the schedule information into smaller, manageable pieces" (Higgins and Koppa 1999). However, the headway-based approach is limited to situations where service is frequent enough that transit users do not need

to know exactly when their bus will arrive. Research suggests that this “schedule use threshold” lies at around 10 to 15 minutes, with the majority of users being “random arrivals” at bus stops if headways are 10 minutes or less, while at headways of 15 minutes or more, the majority of users are “planned arrivals” requiring schedules (Balcombe and Vance 1998). One study provided anecdotal evidence that appreciable gains in ridership have been made when schedules have been reorganized to a simpler “clockface” format (Webster and Bly 1980). Thus, the level of service complexity is also a factor, with complicated route structures and unstandardized departure times adding to the likelihood of rider confusion and affecting which information provision styles can be used. Considering the fact that transit users are often from low-income, low-education backgrounds, the extent of the challenge in providing understandable trip-planning materials is clear.

Study Objective

The literature review indicated that transit information is crucial to the overall success of a transit service. Although a wide variety of different information media are available, traditional printed information materials remain very popular. However, the review also showed that many transit users, and the public in general, are unable to plan their trips successfully using such materials. Therefore, this study was designed to investigate in more detail the extent to which the general public can successfully use printed information materials to plan a transit trip, and to isolate the aspects of the trip-planning task that cause difficulty. The study then assessed the extent to which transit trip-planning problems affect actual transit usage to determine whether transit information materials are a significant barrier to transit use.

Study Design

A total of 180 people were recruited at three shopping mall sites in the Tampa Bay area in August 2004. Quotas were used to ensure sample variation on age, gender, ethnicity, income level, and transit use (35.6% of the sample used transit at least once a week on average). As the study did not obtain a random sample, the “raw” results could not be used to draw population-wide inferences. To address this, three different weighting factors (a demographic adjustment factor, a travel behavior adjustment factor, and a systematic adjustment factor) were applied to the data to correct for any sample bias. For more detailed information on the

study methodology and data weighting process, see the final project report (Cain 2005).

Each participant was asked to undertake two transit trip-planning assignments. Each assignment involved planning a bus trip that required the use of two bus routes to travel from a specified origin to a specified destination, arriving before a specified time. Thus, each assignment involved one transfer, and required the use of a transit system map, two route maps, and two schedules. Research staff timed and observed participants as they undertook the trip-planning assignments and interviewed them after each assignment. Following the assignments, participants were asked how confident they would be if they had to plan a transit trip using similar materials in “real-life” and whether their participation would have any impact on their future transit usage. Current transit users were also asked to describe the main method they used to plan their transit trips, while nonusers were asked to state the main reason why they did not use transit. A total of 358 test observations resulted from the study.

Assessment of Aggregate Transit Trip-Planning Ability

The trip-planning process was divided into five discrete stages, as shown in Table 1. Stage 1 involved using the system map to identify the trip origin and trip destination. This was a straightforward task for most participants, and the two points were located either by using the street addresses provided, or simply scanning the system map at random until the points were found. Stage 2 involved using the system map to determine which bus routes to use for their trip. This required locating different color-coded routes in close proximity to their trip origin and destination, following the routes through the town, and deciding where to transfer. This was again a simple task for most participants, and Table 1 shows a success rate of 93.6 percent on these first two stages.

Having identified the routes required for their trip, participants were provided with the route maps and schedules for each of these routes, and asked to use them to identify the bus stops and times for boarding and disembarking each bus (if they had not been able to identify the required routes correctly, this was explained to them before they were given the correct route maps and schedules).

The first part of this process (Stage 3) was to identify the four time points (bus stops) required for the trip (first route start point, first route end point, second route start point, and second route end point). In most cases, the points of interest

Table 1. Sample Performance at Each Transit Trip-Planning Stage

<i>Stage</i>	<i>Description</i>	<i>Information Materials Used</i>	<i>Success Rate (%)</i>
1	Locating origin and destination on system map	System map	93.6
2	Selecting bus routes and transfer point	System map	
3	Locating closest time points/transfer time point	System map/route map	73.2
4	Identifying correct section of schedule	Route map/schedule	55.6
5	Using schedule to get bus times	Schedule	
Overall		System map/route map/schedule	52.5

(which included the specified origin and destination points) were not provided on the route maps, so participants had to cross-reference between the system map and the route maps to locate the closest bus stops and the appropriate transfer point. Table 1 shows a relatively high level of success at this stage, with 73.2 percent of assignments successfully completed.

Having identified the boarding and alighting bus stops, participants were then required to begin the task of identifying the times at which they would board and disembark from each bus. The first stage in this process (Stage 4) was to determine which section of the schedule to use. This requires an awareness of (1) the required direction of travel, (2) the required day of travel, and (3) whether the trip is in the morning or afternoon. Each issue affected the determination of which part of the schedule to use, and all three issues were a source of difficulty for study participants. Additional information on these issues can be found in Cain (2005).

The final stage in the trip-planning process (Stage 5) was to use the schedule to identify the correct bus times for boarding and disembarking from each bus (first route boarding time, first route alighting time, second route boarding time, and second route alighting time). Table 1 shows that Stages 4 and 5 caused the most problems for participants, with a success rate of only 55.6 percent. Just under half the sample got at least one bus time wrong, while almost one fifth of the sample

(17.9%) was unable to get any of the times correct. Following the exercise, participants were asked which parts of the assignments were the most difficult. Using the schedule was identified as the most difficult aspect on 162 occasions (almost half of all completed assignments), adding further evidence to the conclusion that schedule use is by far the most difficult aspect of the transit trip-planning task.

Overall, only 52.5 percent of assignments were successfully completed, suggesting that a significant proportion of the general public is unable to successfully plan a bus transit trip from an origin to a destination that involves one transfer. However, in dividing the trip-planning task into a series of five discrete stages, this study suggests that most people are able to complete the first three trip-planning stages successfully, and that the critical problem lies at Stages 4 and 5, where they are required to use a schedule to determine boarding and alighting times. This is consistent with the findings of other research, as discussed in this article's literature review. Therefore, the main conclusion from this part of the study was that there is a critical need to improve the public's ability to understand and utilize the information presented in transit schedules. Having found that a significant portion of the public has difficulty planning a transit trip, the next question to consider was the extent to which this affects public confidence in using transit, and, in aggregate terms, how this affects transit ridership. This topic is addressed in the remainder of this article.

Characteristics of Current Transit Information Material Use

Study participants were asked to indicate, in the post-test self-completion questionnaire, whether they had ever used transit schedules or maps before participating in the study. Their responses are provided in Table 2, stratified by their stated current frequency of transit use.

Table 2 shows that the level of previous experience with transit schedules and maps is different for transit users and nonusers. The majority of transit users (73.2%) had previous experience with transit information materials, while only around half of nontransit users (49.3%) had previous experience. Interestingly, more than one quarter of the sampled transit users (26.8%) did not have previous experience, suggesting that a significant number of transit users do not use maps and schedules to plan their transit trips. This issue was investigated further by asking transit users in the sample to state the main method they used to plan their transit trips. Their responses are provided in Figure 1.

Table 2. Level of Previous Experience with Transit Information Materials by Transit User Status

<i>Whether Participant Has Previous Experience with Transit Information Materials</i>	<i>Transit Users</i>		<i>Nontransit Users</i>	
	<i>N</i>	<i>%</i>	<i>N</i>	<i>%</i>
No previous experience	30	26.8	34	50.7
Previous experience	82	73.2	33	49.3
Total	112	100	67	100

Figure 1. Main Method Used by Transit Users to Plan Transit Trips

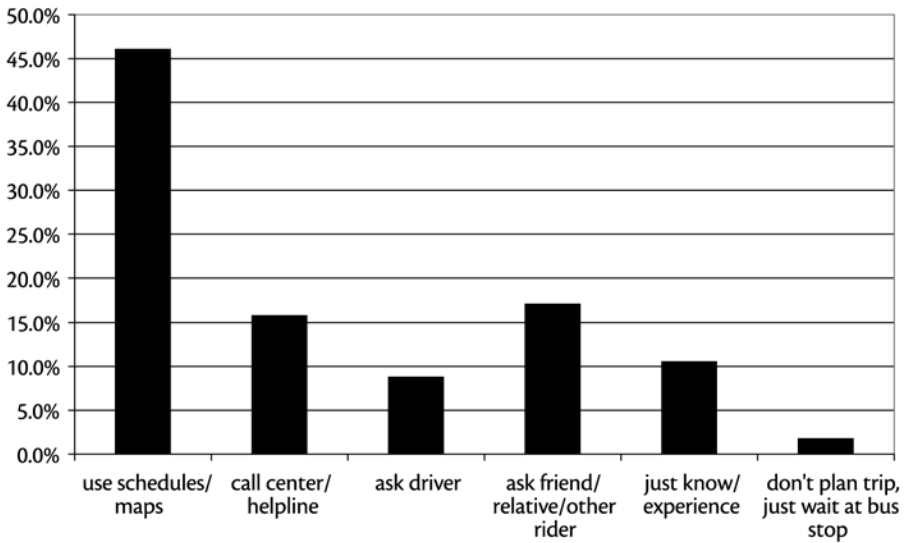


Figure 1 shows that just under half of transit users in this sample used transit schedules and maps to plan their transit trips. Although this was by far the most popular method overall, more than half of the transit users used a different approach. Alternatives included calling a helpline (16%) or asking the bus operator (9%), both of which require transit agency resources. Thus, improving transit user ability to plan their own trips may allow drivers to complete their routes in less

time, and would mean that less staff resources would be spent answering requests for assistance from customers.

Just over 10 percent of transit users stated that they did not need any method to plan their trip as they simply knew from experience where and when the transit services ran. A small proportion of the sample did not employ any trip planning, and simply stood at the bus stop until a bus came. Further analysis was conducted to assess whether there was any variation in trip-planning method used in relation to different frequencies of transit use. Table 3 provides the results of this analysis.

Although the cross-tabulated cell sizes are relatively small, the majority of those who use schedules and maps to plan their transit trips are frequent transit users, with 38.5 percent using the bus four or more times a week and 28.8 percent using the bus one to three days a week. Similar results were observed for people who call a helpline, with again more than half using the bus at least once a week. Frequencies are more evenly spread for people who ask the driver or ask a friend/relative, while almost all those who stated they knew the transit services from experience were also frequent transit users.

Impact of Study Participation on Transit Trip-Planning Confidence

At the end of the exercise, participants were asked whether participation in the exercise had increased their confidence in planning a transit trip. Results are shown in Table 4, stratified by level of previous experience with transit information materials.

Table 4 shows that around two thirds of study participants stated that participation had improved their trip-planning confidence. Furthermore, it appears that whether the participant had previous experience with such materials did not have an effect on this—almost as many participants with previous experience stated a positive impact (66.1%) as those who had never used such materials before (70.3%). This suggests that even people who already use such materials could benefit from further training or instruction. Around one quarter of the participants from each group stated that participation had not increased their confidence.

Further analysis assessed how participants' performance during the exercise varied by their stated level of confidence in transit trip planning following exercise completion. Results of this analysis are shown in Table 5. Inferential statistics were

Table 3. Main Transit Trip-Planning Method by Frequency of Transit Use

Current Frequency of Transit Use	Use Schedules/ Maps		Call Center/ Help-line		Ask Driver		Ask Friend/ Relative		Just Know/ Experience		Don't Plan Trip, Just Wait at Bus Stop	
	N	%	N	%	N	%	N	%	N	%	N	%
Less than once a month	6	11.5	4	22.2	2	20.0	3	17.6	1	8.3	0	0.0
<Once a week; > once a month	11	21.2	3	16.7	3	30.0	7	41.2	1	8.3	1	50.0
1 to 3 days a week	15	28.8	5	27.8	3	30.0	5	29.4	5	41.7	1	50.0
4 or more times a week	20	38.5	6	33.3	2	20.0	2	11.8	5	41.7	0	0.0
Total	52	100.0	18	100.0	10	100.0	17	100.0	12	100.0	2	100.0

Table 4. Impact of Study Participation on Transit Trip-Planning Confidence

“Has your participation today resulted in greater confidence related to planning a trip on the public bus?”	Whether Participant Has Previous Experience with Transit Information Materials			
	No Previous Experience		Previous Experience	
	N	%	N	%
No	15	23.4	29	25.2
Yes	45	70.3	76	66.1
Don't Know	4	6.3	10	8.7
Total	64	100	115	100

used to assess the strength of the relationship between these two variables. Eta is a correlation coefficient that measures the strength of bivariate relationships. An Eta score of 0 means there is no relationship, and the higher the Eta value is, toward a maximum of 1, the greater the strength of the relationship in the sample data. The statistical significance value (Sig.) is used to assess the probability that the relationship observed in the sample, as described by the Eta value, would also exist in the population from which the sample was drawn. A significance value of 0.05 indicates a 95 percent probability that the relationship observed in the sample will also exist in the population.

The statistics computed in Table 5 show that no significant differences exist in the performance of those who were more confident following the survey, and those who were less confident. Indeed, in most cases, the scores of all three groups are very similar, suggesting that actual assignment performance is not related to how confident participants felt after the assignments were completed. Participants who had made mistakes thought they had completed the assignments successfully, stating that they found the assignments “easy” or “very easy.” Overall, this table suggests that many people are unaware of their trip-planning errors, and incorrectly believe that they are successfully planning their trips. This could be a source of customer frustration and complaints against transit services, as such customers would be prone to believing that their services are running late or have been cancelled, when in fact they have actually misread the schedule.

Impact of Study Participation on Stated Future Transit Use

Participants were next asked whether their use of public transit would change in any way following their participation in the study. Table 6 compares participant’s current transit use frequency with their stated future transit use frequency. The information is presented in a matrix format with current frequency in the table rows and future frequency in the table columns. Numbers shown in bold indicate the number of participants who would not change their frequency of transit use.

Summing the numbers in bold indicates that a total of 140 people (77.8%) stated that they would not change their frequency of transit use. Of the remaining 22.2 percent who indicated that their frequency of transit use would change; 8 people (4.4%) stated that they would use transit with less frequency following the survey exercise.

Table 5. Participant Performance by Stated Confidence Level Following Assignment

<i>Post-Test Confidence</i>	<i>Stats.</i>	<i>Overall Performance Score</i>	<i>Time Taken to Complete Assignment</i>	<i>Stated Difficulty: Stages 1 and 2</i>	<i>Stated Difficulty: Stages 3, 4, and 5</i>
Less confident	Mean	8.34	324.8	3.55	3.69
	N	87	87	87	87
More confident	Mean	8.33	327.6	3.26	3.58
	N	243	243	239	238
Don't know	Mean	8.04	308.3	3.57	3.93
	N	28	28	28	28
Total	Mean	8.31	325.4	3.36	3.63
	N	358	358	354	353
Inferential Statistics	Eta	0.036	0.031	0.079	0.058
	Sig.	0.795	0.839	0.334	0.557

Table 6. Impact of Survey Participation on Transit Usage

	Future Transit Usage Frequency					Total
	Never or Almost Never	Less than Once a Month	< Once a Week; > Once a Month	1 to 3 Days a Week	4 or More Days a Week	
Current Transit Usage Freq.						
Never or almost never	53	8	3	3	0	67
Less than once a month	0	16	3	0	0	19
< Once a week; > once a month	0	2	23	2	3	30
1 to 3 days a week	0	0	1	20	10	31
4 or more times a week	0	1	3	1	28	33
Total	53	27	33	26	41	180

The remaining 17.8 percent (32 people) stated that their frequency of transit use would increase. Of the 67 participants who currently never or almost never use transit, 14 stated that they would use transit in future, meaning that 20.9 percent of nontransit users stated they would now use transit having gained experience in using transit information materials. Eight of these stated that they would now use transit less than once a month; 3 stated they would use it between once a month and once a week; and 3 stated they would now use transit one to three days a week. Some participants who currently use transit also stated that they would increase their future use: of the 31 people who currently use transit one to three days a week, 10 stated that they would now use transit four or more times a week. While these results could be viewed as evidence of a relationship between study participation and increased future transit use, it must be noted that stated behavior change does not equate to actual behavior change, and also that the sample size used here is too small to be considered statistically robust.

A further investigation was carried out to determine whether any link existed between participants' performance on the different stages of the assignment and their stated future frequency of transit use. Table 7 compares the performance of three groups: those who stated they would use transit with less frequency than before; those who would not change their transit use; and those who stated they would use transit with greater frequency.

Table 7 shows no significant differences in the performance of the three groups in terms of overall score and total time taken on the assignments. However, significant differences were observed in terms of stated difficulty, for both Stages 1 and 2 and Stages 3, 4, and 5. In each case, the highest stated difficulties were observed among those stating that they would now use transit less, and the lowest stated difficulty among those stating that they would now use transit more. The mean score for people who would now use transit more equated to a difficulty rating of "somewhat easy," while the mean scores for the other two groups equated to a difficulty rating of "neither difficult nor easy." Clearly, participants who found the assignments easier, irrespective of their actual performance, were more likely to state that they would use transit more in future. This suggests a relationship between the perceived difficulty of the transit trip-planning task and the propensity to use transit.

Table 7. Assessment of Participant Performance by Stated Change in Future Transit Frequency

<i>Current versus Future Transit Use</i>		<i>Overall Performance Score</i>	<i>Time Taken to Complete Assignment</i>	<i>Stated Difficulty: Stages 1 and 2</i>	<i>Stated Difficulty: Stages 3, 4, and 5</i>
Lower frequency than current	Mean N	8.44 16	304.9 16	4.38 16	3.81 16
Same frequency as current	Mean N	8.28 279	328.0 279	3.41 275	3.75 275
Higher frequency than current	Mean N	8.44 63	319.2 63	2.89 63	3.08 62
Total	Mean N	8.31 358	325.4 358	3.36 354	3.63 353
Inferential Statistics	Eta Sig.	0.031 0.845	0.034 0.814	0.170 0.006²	0.148 0.021¹

1. Significant at the 95 percent confidence level.

2. Significant at the 99 percent confidence level.

Are Information Materials a Barrier to Transit Use?

Results from the previous sections have suggested that many transit users do not use printed transit information materials to plan their transit trips. Furthermore, while the majority of the sample stated that participation in the exercise had increased their confidence in planning a transit trip, less than one fifth thought that they would now use transit services more often. This suggests that the lack of transit trip-planning ability using transit information materials is not a primary barrier to transit use. To clarify this, nontransit users were asked to state the main reason why they did not use transit. Their responses are provided in Figure 2.

Figure 2. Main Reason Why Nontransit Users Do Not Use Transit

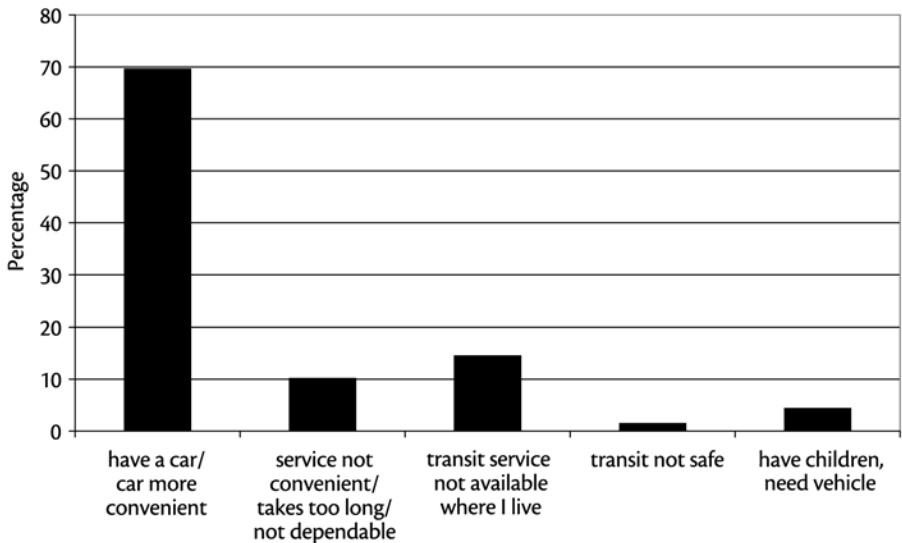


Figure 2 shows that the primary reason for nontransit use among nonusers is that they have access to a private vehicle (70% of nonusers). Other reasons given were that transit services are not convenient, dependable, or quick enough (10%), or that there simply is not a service available for use (15%). In discussions with interviewers following the survey exercise, several transit users stated that while weekday services were adequate, often no service is available on Sundays and public holidays. Complete lack of service is clearly a major barrier to transit use. In reference to this particular investigation, none of the participants cited transit

trip-planning problems as their reason for not using transit. This suggests that lack of transit trip-planning ability is not a significant barrier to transit use.

Conclusions

This study has found that just over half (52.5%) of a sample of transit users and nonusers in the Tampa Bay area was able to plan a transit trip successfully using printed information materials. The main problems existed at the latter stages of the trip-planning process, which involved the use of tabular schedules (55.6% success rate).

Approximately two thirds of the participants stated that their participation had increased their level of confidence in using printed transit information materials; 17.8 percent stated that their frequency of transit use would also increase. Furthermore, 20.9 percent of nontransit users stated that they would now use transit in future. However, these are only statements of future behavior, and should not be used to assume equivalent ridership gains. People who found the assignments easier, irrespective of their actual performance, were more likely to state that they would use transit more in future. This suggests a relationship between the perceived difficulty of the transit trip-planning task and the propensity to use transit.

Overall, this study has shown that a significant portion of the population has difficulty using traditional printed transit information materials, particularly schedules, to plan transit trips, irrespective of whether they use transit. This finding is corroborated by the results of other similar studies [see Streeter and Vitello (1986) and Kirsch et al. (2001)]. Given this fact, the next question to ask is whether these difficulties have an effect on transit usage. The findings of this study suggest that this is unlikely to be a significant problem. None of the nontransit users participating in the study cited lack of transit trip-planning ability as their main reason for not using transit. Also, although printed transit information materials were the most popular method of trip planning for transit users, a wide range of other resources are available, and more than half of the transit users in the study stated that they used these other methods to plan their trips.

Despite difficulties the public has in using schedules, it is still a very popular method for obtaining transit service information. Assuming that this will continue to be the case, serious attention must be given to ways to improve schedule design such that it will be understandable to a higher proportion of the population.

Realistically, there will probably never be a design that every transit user can fully understand, but perhaps some progress can be made to raising the overall proportion. A few options for approaching this include:

- Continue to use the traditional tabular schedule as the design template, but investigate ways of improving its design to raise the overall level of comprehension.
- Investigate the use of alternatives to the tabular schedule, such as the “clock-face” template, or the headway-based approach. However, such designs tend to reduce the completeness of the information that can be presented, and the trade-off between completeness and comprehension would have to be assessed.
- Provide a simplified text-based summary of the schedule information beside the full schedule for people who cannot read the schedule or do not require such accurate information.
- Results from this study showed that exposing the public to trip-planning exercises increased their level of confidence in planning an actual transit trip. Perhaps providing instruction or training in the correct use of the materials would be an effective way to improve trip-planning confidence and overall comprehension.

Another phase of the study is now being undertaken with the objective of investigating further the schedule comprehension issues outlined above. This study aims to develop a design guidelines document that can assist transit agencies in production of their printed information materials. This document will be available in fall 2007.

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Decision and Control Model for Promoting Public Transit via Lottery Incentives

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Abstract

This article reports on a decision model that highlights a reward-based promotional strategy for a bus organization to maintain its market. The market control law is obtained from an optimal solution in the system equations on the basis of the relationship among the transit operator, ticket agent, and government. The article presents a case study for the Taipei bus transit system. Results in this research confirm the effectiveness of the proposed strategy for bus operators as well as for traffic improvement. The proposed model reveals the optimal actions for the agent and bus operators under governmental policy.

Introduction

Public transit ridership in many urban areas is declining. Passenger cars are preferred for travel, subsequently inducing traffic congestion. Although transportation authorities have implemented several encouraging policies, such as tax deductions and exclusive bus system operations, passengers lack interest in traveling by bus because such transportation policies do not directly benefit the customers. In addition, the elasticity of the price of public transportation is extremely low (Lago, Mayworm, and Mcenroe 1981), with an average range of -0.28 ± 0.16 . Such inelastic circumstances imply that reducing the fare price leads to a net loss in revenues.

Indeed, almost all countries have a regulated pricing scheme for public transportation. Applying various pricing strategies to affect transportation markets directly conflicts with such regulations. Therefore, a stimulatory strategy is expected to ensure the survival of bus operators and increase public transit system use.

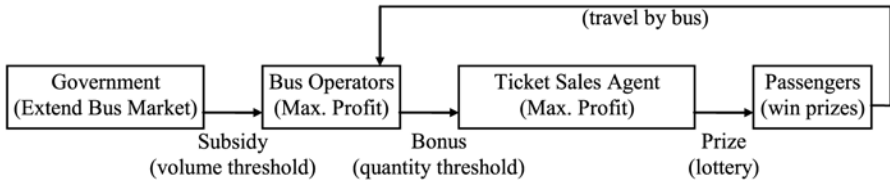
This study presents a novel incentive system to exert control on the transportation market. The proposed system focuses on selling prepaid tickets merged with a lottery to satisfy the operator's expectations, particularly in terms of ridership or revenue. A case study is conducted to verify that such a strategy yields a satisfactory solution for bus operators while also alleviating traffic congestion. As a concrete measure in the proposed strategy, the government is to apply a subsidy policy for bus operators when total passenger loads reach a certain threshold within a specific period. Bus operators can also encourage their ticketing agent to promote the use of prepaid tickets by offering a bonus to the agent when the amount of ticket sales achieves a certain quantity. The agent is also offered several reward grades measured in purchased tickets or mileage for passengers. This incentive strategy subsequently stimulates the market.

Control theory is the basic methodology in the analysis of marketing relationships within the proposed promotional system. The upper level of the strategic goal is to alleviate traffic congestion by encouraging individuals to travel by bus. The primary level is to maximize profits for the ticketing agent and the bus operational organization. The proposed model is constructed with the agent's and the bus operators' profits, respectively, in terms of time. The solution identifies the sensitivity and optimality of the control variables.

Premises for Modeling

Incentive System Structure

Figure 1 depicts the relationships among the ticketing agent, bus operators, and the government in the incentive system. According to these relationships, the ticket sales agent attempts to obtain maximum profit through a promotional strategy for selling a sufficient quantity of tickets. The agent's profit includes the net revenue from selling tickets and a bonus obtained from the bus operators. The bus operators' profit comes from carrying more passengers and possibly from a government subsidy. To obtain the subsidy, the operator must meet a performance threshold of total passengers carried within a period, T . If more

Figure 1. Relations among Sales Agent, Bus Operators, and Government

people travel by bus, traffic congestion is reduced and the quality of life in the city improves. Passengers expect to win an incentive prize from the ticketing agent.

Passenger Incentive Types

Promotional design of the prepaid tickets should be as attractive as possible. To extend the bus transportation market, noncaptive passengers are the targets of the promotional program. According to one survey (Jiang 1998), a lottery is one of the most attractive activities for noncaptive passengers. In this study, a lottery game is designed for the purpose indicated. In the game, both instant and delayed rewards are considered. The quicker an individual purchases a prepaid ticket card the higher the probability of winning an instant reward. After spending the prepaid value of the ticket, the individual has the opportunity to win a grand prize. This strategy encourages individuals not only to purchase prepaid tickets, but also to travel by bus. The structure of the prize layout was arranged as a pyramid with multiple layers and items. The grand prize is generally awarded at the end of a given period, denoted as T .

Passenger Demand Function

During this analysis the passenger demand function is formulated first. Based on the formulated demand function, profits for the ticketing agent and bus operators can then be estimated. Demand is affected by fare and level of transport services such as route, frequency, vehicle-quality (seat, air-conditioned), driver behaviors, and so forth. All routes are assumed to have already been allocated and cannot be changed; the number of existing vehicles is sufficient for any frequency extension (i.e., bus transport capability is far from exhausted and in a depressed period); vehicles are all in the range of usage; and employed drivers are experienced. All people know the fare, route network, schedules, and traffic conditions. The analytical change in price, even through a lottery activity, is relatively small compared to the basic transportation price from the regulated fare. Under these conditions,

the two factors of ticket price and incentive prize are sufficient to determine the demand variation for most road users. Thus, the demand function is assumed to be linear (McConnell and Brue 1993) in terms of the price and the expectation of winning a prize in the incentives:

$$q(t) = ap(t) + bE(M) + c \tag{1}$$

where:

- $q(t)$ denotes the volume of bus trips at time t
- $p(t)$ represents the price of a bus ticket in a unit sale at time t , $t \in [0, T]$
- $E(M)$ is the expectation of winning a prize M
- a, b and c are parameters; a must be negative and b be positive

The expectation of winning a prize, of the given incentives, is defined by

$$E(M) = \sum_j M_j f(M_j) \tag{2}$$

where:

- M_j expresses the prize of j th item of the rewards
- $f(M_j)$ is the probability of winning the reward M_j , $0 \leq f(M_j) \leq 1$

Profit Model for a Ticket Sales Agent

Based on the three premises above, the ticketing agent’s profit can be clarified. The ticket agent’s profit is calculated as the sum of the net profit from selling tickets and the bonus, with the cost of the prizes issued to lottery winners deducted according to the promotional policy. Assume that the basic price of a ticket is C , which the bus consortium (organized by the bus operators in Taipei city) contracts to the agent. The agent sells a unit ticket to a passenger with the price $p(t)$. Thus, the agent’s profit at time t is $[p(t) - C] q(t)$, $p(t) > C$. Obtaining $p(t)$ in Equation (1), the profit can be derived as follows:

$$[p(t) - C] q(t) = \left[\frac{1}{a} (q(t) - bE(M) - c) - C \right] q(t) \tag{3}$$

The gross gain from ticketing in period $[0, T]$ is

$$\int_0^T [\frac{1}{a}(q(t) - bE(M) - c) - C]q(t)(1+i)^{T-t} dt \quad (4)$$

where:

i denotes the interest rate

In addition, supposing that the bus consortium sets the threshold for tickets sold at level H for paying a bonus, and the agent gains the bonus $B(\cdot)$ if the tickets are sold out to the amount of $Q(T)$ in period T :

$$B(Q(T)) \begin{cases} = 0, \text{if } Q(T) < H \\ \geq 0, \text{if } Q(T) = H \\ > 0, \text{if } Q(T) > H \end{cases} \quad (5)$$

Equation (5) indicates that the agent's bonus vanishes if ticket sales do not reach the volume H . The agent will have a bonus of $B(\cdot)$ if the H volume is sold out. In general, $B(\cdot)$ is designed as a linear function with a marginal bonus while the sold quantity is beyond H . However, the expenditure of the agent for the lottery is

$$E(M) = \sum M_j L_j = M_1 L_1 + M_2 L_2 \quad (6)$$

where:

L_j represents the quantity of the reward j

The first item ($j=1$) is the expenditure for the instant reward and the second item ($j=2$) denotes the prize bestowed at the end of the given period of T . In considering the instant reward, the right-hand term in Equation (6) could be replaced by

$$\int_0^T [m_1(t)l_1(t)(1+i)^{T-t} dt + M_2 L_2] \quad (7)$$

where:

$m_1(t)$ denotes the price of an instant reward

$l_1(t)$ represents the quantity of the instant reward

In brief, Equation (7) is used instead of the following form:

$$\int_0^T \hat{M}_1(t)(1+i)^{T-t} dt + \hat{M}_2 \quad (8)$$

By incorporating Equations (4), (5), and (8), the total gain of the agent yields the following:

$$G = \int_0^T \left\{ \left[\frac{1}{a}(q(t) - bE(M) - c) - C \right] q(t) - \hat{M}_1(t) \right\} (1+i)^{T-t} dt \quad (9)$$

$$+ B(Q(T)) - \hat{M}_2$$

With the maximum profit objective, the extreme value from Equation (9) is obtained:

$$G^* = \max \int_0^T \left\{ \left[\frac{1}{a}(q(t) - bE(M) - c) - C \right] q(t) - \hat{M}_1(t) \right\} (1+i)^{T-t} dt \quad (10)$$

$$+ B(Q(T)) - \hat{M}_2$$

While considering the agent’s attitude in referring to Equation (5), three possible types of actions are dealt as follows:

1. The agent may discard obtaining the bonus if the threshold of the sold ticket volume is too high to afford. The proposition is written as

$$\left\{ \begin{array}{l} G_1^* = \max \int_0^T \left\{ \left[\frac{1}{a}(q(t) - bE(M) - c) - C \right] q(t) - \hat{M}_1(t) \right\} (1+i)^{T-t} dt \quad (11) \\ \quad - \hat{M}_2 \\ \text{subject to } q(t) \geq 0, Q(0) = 0, Q(T) < H \\ \quad Q(t) = \int_0^t q(t) dt \quad \text{and} \quad E(M) = \sum_j M_j f(M_j) \end{array} \right.$$

2. For Type II, the agent decides that his task is to reach the threshold for getting a bonus. He is not willing to put forth further sales effort due to the low margin for a bonus. The proposition is written as

$$\left\{ \begin{array}{l} G_2^* = \max \int_0^T \left\{ \left[\frac{1}{a}(q(t) - bE(M) - c) - C \right] q(t) - \hat{M}_1(t) \right\} (1+i)^{T-t} dt \quad (12) \\ \quad + B(Q(T)) - \hat{M}_2 \\ \text{subject to } q(t) \geq 0, Q(0) = 0, Q(T) = H \\ \quad Q(t) = \int_0^t q(t) dt \quad \text{and} \quad E(M) = \sum_j M_j f(M_j) \end{array} \right.$$

3. For Type III, based on the bonus condition in Equation (5) issued by the bus operators, the agent realizes that more profit can be earned by selling more tickets. The proposition is as

$$\left\{ \begin{array}{l} G_3^* = \max \int_0^T \{ [\frac{1}{a}(q(t) - bE(M) - c) - C]q(t) - \hat{M}_1(t) \} (1+i)^{T-t} dt \quad (13) \\ \quad + B(Q(T)) - \hat{M}_2 \\ \text{subject to } q(t) \geq 0, Q(0) = 0, Q(T) > H \\ \quad Q(t) = \int_0^t q(t)dt \quad \text{and} \quad E(M) = \sum_j M_j f(M_j) \end{array} \right.$$

Next, an attempt is made to identify the agent's final decision from the above three propositions. To do so, Equations (11), (12), and (13) must be solved with respect to variable $q(t)$. Since the propositions are dynamic problems depending on time t , the optimal control theory is applied (Chiang, 1992; Kamien and Schwartz 1991). Let $\dot{x} = \dot{x}(t) = q(t)$ and

$$\Omega(x, \dot{x}, t) = \{ \frac{1}{a}(\dot{x})^2 - (\frac{b}{a}E(M) + \frac{c}{a} + C)\dot{x} - \hat{M}_1(t) \} (1+i)^{T-t} \quad (14)$$

According to the Euler equation (Kamien and Schwartz 1991), to find the extreme value from Equations (11), (12), and (13), the following function holds:

$$\frac{\partial \Omega}{\partial x} - \frac{d}{dt} \cdot \frac{\partial \Omega}{\partial \dot{x}} = 0 \quad (15)$$

Substituting Equation (14) into the differential Equation (15) yields, at time t ,

$$\dot{x} = q(t) = \frac{1}{2}(bE(M) + c + aC) + C_0(1+i)^t \quad (16)$$

This is a general solution form. Different constraints in each type lead to different results. Based on the constraint and boundary conditions in Type I, we obtain the following result:

$$\dot{x}_1(t) = q_1(t) = \frac{1}{2}(bE(M) + c + aC) \quad (17)$$

By integration,

$$Q_1^*(T) = \frac{(bE(M) + c + aC)T}{2} \quad (18)$$

Substitute Equations (17) and (18) into (10) yields

$$G_1^* = \frac{(c^2 + 2acC + a^2C^2 + 2bE(M)c + 2abE(M)C + b^2E(M)^2 + 4a\hat{M}_1(t))}{4a \ln(1+i)} \cdot [1 - (1+i)^T] - \hat{M}_2 \quad (19)$$

as well as from Equation (1),

$$p_1^*(t) = \frac{1}{2a} (aC - bE(M) - c) \quad (20)$$

Similarly, for Type II, we have

$$q_2^*(t) = \frac{1}{2} (bE(M) + c + aC) + \frac{\left[H - \frac{1}{2} (bE(M) + c + aC)T \right] \ln(1+i)}{[(1+i)^T - 1]} (1+i)^t \quad (21)$$

$$Q_2^*(T) = H \quad (22)$$

$$G_2^* = \frac{(c^2 + 2acC + a^2C^2 + 2bE(M)c + 2abE(M)C + b^2E(M)^2 + 4a\hat{M}_1(t))}{4a \ln(1+i)} \cdot [1 - (1+i)^T] + \frac{(-2H + aCT + bE(M)T + cT)^2 \ln(1+i)}{4a[(1+i)^T - 1]} (1+i)^T + B(H) - \hat{M}_2 \quad (23)$$

$$p_2^*(t) = \frac{1}{2a} \left\{ aC - bE(M) - c + \frac{[2H - (aC + bE(M) + c)T] \ln(1+i)}{[(1+i)^T - 1]} (1+i)^t \right\} \quad (24)$$

For Type III, the bonus function, described in previous, could be replaced by

$$B(x(t_f)) = B(H) + K[x(t_f) - H] \quad (25)$$

and this implies

$$B'(x(t_f)) = \frac{dB(x(t_f))}{dx(t_f)} = K \quad (26)$$

where:

$x(t_f)$ denotes the total quantity of sales until the termination, $t_f = T$

K is the marginal bonus, the incentive for an extra sale

Consequently,

$$q_3^*(t) = \dot{x}_3(t) = \frac{1}{2}(bE(M) + c + aC) - \frac{a}{2}K(1+i)^{t-T} \quad (27)$$

$$Q_3^*(T) = \frac{(bE(M) + c + aC)T}{2} - \frac{aK}{2} \frac{[1 - (1+i)^{-T}]}{\ln(1+i)} \quad (28)$$

Then, we obtain the following result:

$$G_3^* = \frac{(c^2 + 2acC + a^2C^2 + 2bE(M)c + 2abE(M)C + b^2E(M)^2 + 4a\hat{M}_1(t))}{4a \ln(1+i)} \quad (29)$$

$$\cdot [1 - (1+i)^T] + \frac{aK^2}{4 \ln(1+i)} [1 - (1+i)^{-T}] + B(H) + K[Q_3(T) - H] - \hat{M}_2$$

and corresponding to

$$p_3^*(t) = \frac{1}{2a} \{ aC - bE(M) - c - aK(1+i)^{t-T} \} \quad (30)$$

The optimal action of the agent should be the most profitable one based on the description of the three types under given conditions:

$$G^* = \max \{ G_1^*, G_2^*, G_3^* \} \quad (31)$$

Profit Model of Bus Operators

Bus operators are concerned with the profit they will earn so their goal is also maximum profit. The bus operators' profit function is comprised of the net revenue from their service, the amount of the bonus awarded to their agent, and the governmental subsidy due to their contribution to traffic congestion relief. The governmental subsidy is provided only if the total number of busloads during the fiscal period surpasses the regulated threshold. Net revenue in service is the income from the ticketing agent after deduction of the operating costs shared in the processing of the electronic readers on buses.

While assuming that the operating cost shared in processing one ticket is \hat{f} and the net revenue per ticket is $(C - \hat{f})$, during the period $[0, T]$, the operators' total profit W is calculated by

$$W = \int_0^T [C - \hat{f}]q(t)(1+i)^{T-t} dt - B(Q(T)) + GP(N_b) \tag{32}$$

in which, $GP(N_b)$ represents the governmental subsidy:

$$GP(N_b) \begin{cases} = 0, \text{if } N_b < D \\ \beta(N_b - D) > 0, \text{if } N_b \geq D \end{cases}$$

where:

- N_b denotes the total number of loads carried by the bus operators
- is the unit of subsidy with respect to a load
- D is the threshold for the subsidy

Both β and D are regulated by the government. Therefore, the object function of the bus companies is set to be maximum profit as follows:

$$W^* = \max \int_0^T [C - \hat{f}]q(t)(1+i)^{T-t} dt - B(Q(T)) + GP(N_b) \tag{33}$$

Since three types of agent attitudes have been described, the bus operators also have three respected treatments. Substituting Equations (17) and (18), or (21) and (22), or (27) and (28) into Equation (33) subsequently yields

$$W^* = \max \int_0^T [C - \hat{f}]q_k^*(t)(1+i)^{T-t} dt - B(Q_k^*(T)) + GP(N_b) \tag{34}$$

where:

k indicates the three types, $k=1,2,3$, respectively

As previous shown in Equation (25), the bonus can be expressed using the following general form:

$$B(Q(T)) = B(H) + K[Q(T) - H] \quad (35)$$

The bus operators' profit can then be obtained

$$W^* = \int_0^T [C - f] q_k^*(t) (1+i)^{T-t} dt - \{B(H) + K[Q_k^*(T) - H]\} + GP(N_b) \quad (36)$$

If the ticket agent has made his decision, the bus operators' profit can clearly be confirmed.

Calibration of the Demand Function

A case study is presented for bus operation in Taipei City, where the Taipei Bus Consortium consists of eight bus companies. Passengers pay for bus fare with a prepaid magnetic card. The prepaid ticket cards are sold through a wholesale agent. The agent sells the prepaid ticket cards from ticketing windows distributed throughout Taipei City in convenience stores. To understand the feasibility of implementing the previous model in Taipei City, consumer opinions were investigated using a questionnaire survey. The survey focused largely on understanding demand from and incentives to passengers. The questionnaire was designed to allow travelers to easily state their preferences.

The contents of the questionnaire are: (1) vehicle ownership—motorcycle, passenger car; (2) trip purpose with transportation modal choice and frequencies in the current run; (3) frequency change of riding the bus if the fare varies a Δp ; (4) level of preferences if a lottery is involved in the bus ticketing; and (5) frequency variations of riding the bus corresponding to different prize structures in a ticketing lottery game.

With a 5 percent level of significance in a random sampling of 1,320 Taipei citizens from the phone directory, the statistical results show the following implications:

- The transportation mode distribution for Taipei citizens is one-fifth for buses, and four-fifths for other modes such as motorcycles, passenger vehicles, and

taxi. This indicates that approximately one-fifth of the citizens are classified as captive bus passengers and four-fifths are noncaptive bus passengers.

- On average, the mean and standard deviation for bus use frequency for captive bus passengers are 13.90 and 5.133 trips per week, respectively. The mean and standard deviation for noncaptive bus passengers are 1.31 and 0.58 trips per week, respectively.
- Approximately 70 percent of all citizens consider purchasing promotional tickets merged with a lottery game. Compared to the current one-fifth of the population that travels by bus, the lottery promotion can enhance public transportation ridership.
- For the original captive passengers, if the ticket fare increases a unit, they will reduce their bus usage by an average of 1.16 trips per week. In the noncaptive group, if the ticket fare decreases a unit, these passengers may expand their bus usage by an average of 0.35 trips per week.
- The likelihood of traveling by bus increases as the expectation of winning a prize increases. The analysis of variance shows that with a 5 percent level of significance with our promotional alternatives, there is nearly no difference between captive and noncaptive passengers in terms of bus use frequency. When the total reward (\$5,000,000) is distributed over the structured pyramid proposed for alternative 1, the mean increase in bus use frequency is 6.39 trips per week and the standard deviation is 7.050. If the double incentive in alternative 2 is used, the mean increase in bus use frequencies is 7.43 trips per week. If the expectation value increases a unit, the increase in frequency for all samples is 0.013 trips per week.

Based on the survey, the demand function is calibrated as follows:

For captive passengers

$$\Delta q_b = -1.305\Delta p_b + 0.408\Delta E(M) \quad (37)$$

(-7.473)* (3.813)*

$$R^2 = 0.432^{**} \quad F = 314.415^{***}$$

(* the *t*-value, ** the coefficient of determination, *** the *F*-value)

For noncaptive bus passengers

$$\Delta q_b = -1.181\Delta p_b + 0.495\Delta E(M) \quad (38)$$

(-6.641) (4.547)

$$R^2 = 0.396 \quad F = 307.790$$

For all samples

$$\Delta q_b = -1.240\Delta p_b + 0.454\Delta E(M) \quad (39)$$

(-9.915) (5.936)

$$R^2 = 0.412 \quad F = 618.802$$

where:

Δq_b denotes the quantity variation corresponding to price variation per trip for taking a bus

Δp_b represents the price variation per trip

$\Delta E(M)$ is the expectation variation for winning a prize

Obviously, from Equations (37) and (38), in light of the price variation, captive passengers are more sensitive than noncaptive passengers. Conversely, in considering expectation variation, noncaptive passengers are more sensitive than captive passengers.

To understand the market tendency under the promotional strategy, the demand function in terms of price and the expectation of winning a prize should be clarified. This demand function can be derived from the difference in Equation (39). Next, Equation (39) is transformed into a step function

$$q_b^{n+1} - q_b^n = a_0(p_b^{n+1} - p_b^n) + b_0[E^{n+1}(M) - E^n(M)] \quad (40)$$

where:

$$a_0 = -1.24$$

$$b_0 = 0.454$$

In considering the current mean frequencies for taking the bus transit by captive and noncaptive bus passengers, 13.90 and 1.31 trips per week, weighting with one-fifth of the total trips for captive and four-fifths for noncaptive, the population mean frequency for taking the bus is estimated to be 3.828 trips per week. In Taipei City, the current bus price is uniformly \$15 per trip without promotion. Thus, the boundary state values can be set as $q_b^0 = 3.828$, $p_b^0 = 15$, and $E^0(M) = 0$. By mathematical inductive method (Saber 1996), Equation (40) implies

$$q_b(t) = -1.24p_b(t) + 0.454E(M) + 22.428 \tag{41}$$

Letting $q_b(t)$ be deducted q_b^0 , the induced quantity for taking the bus at time t , $q_b^+(t)$, due to the promotion, is calculated as

$$q_b^+(t) = -1.24p_b(t) + 0.454E(M) + 18.6 \tag{42}$$

Furthermore, if the quantity is expressed by the number of prepaid ticket cards in terms of card price and expectation value, Equation (42) yields

$$q_c^+(t) = \frac{1}{N}[-1.24p_c(t) / N + 0.454E(M) + 18.6] \tag{43}$$

where:

N denotes the number of trips paid using a card

In Taipei City, a ticket card with \$600 can pay for 40 trips (independent of trip distance). By doing so, the demand function is finally realized as follows:

$$q_c^+(t) = -7.75 \times 10^{-4} p_c(t) + 113.5 \times 10^{-4} E(M) + 0.465 \tag{44}$$

Equation (44) represents a person's extra demand trend in unit of card quantity.

Market Analysis

The market effect is primarily evaluated in terms of the sensitivities and tendencies of the bus consortium and the ticketing agent, as well as efficiency in public transportation. As stated in previous sections, obviously the government controls the period length T , subsidy premium $GP(N_b)$, and threshold D for subsidy. The

bus consortium determines basic ticket price C , operating cost f , bonus $B(H)$, threshold loads H for receiving bonus, and its margin K . Game bucks M_1 and M_2 distributed over the structured pyramid layer L_1 and L_2 are provided by the ticket agent. These parameters definitely influence the variations in p^* , Q^* , G^* , W^* , and N_b . These are clarified as follows:

- Governmental Policy and Domination.* Assuming that the government approves and supports the implementation strategy, how much $GP(N_b)$, D , and T should be initially announced by the promotional policy? In the following case study, the periodic activity cycle is normally assumed to encompass one year due to the fiscal system. Based on the records for the past two years, the city government sponsored the city bus consortium with \$300 million annually and with total busloads averaging 650 million trips annually. Therefore, the load subsidy is assumed to be about \$0.5 per trip. In a moderate case, the government can hopefully increase busloads by 36 million trips a year with the proposed incentive strategy. The threshold D can then be set at 686 million loads (= 650 million + 36 million) for paying the extra subsidy. This means that if the annual busloads, N_b , exceed the threshold of 686 million, the bus consortium can obtain an extra \$0.5 subsidy per load, i.e. $GP^+(N_b^+) = 0.5 N_b^+$. $N_b^+ = N_b - 650$ million. Restated, $GP^+(N_b^+)$ denotes the total extra subsidy based on the extra loads N_b^+ over the increased volume $D' = 36$ million.
- Bus Consortium's Proposition.* According to the data from the Taipei City Bus Consortium, their ticketing agent currently receives 4.063 percent of revenue from the selling price. The basic price C issued from the consortium is \$575.62 per ticket card on account of the selling price of \$600. Because the government is to pay an extra subsidy at level of threshold D , the consortium accordingly decides what threshold H' of the extra cards sold for the bonus provision proposed to the agent will maximize their own profit under the consideration of slope K (\$/card sold). $H' = (H - 650 \text{ million}) / 40$ in that each card can pay for 40 trips. However, H' must be equal to or larger than $D' / 40$, which is dominated by the government. Based on Equation (36), the bonus is herein designated by $B(Q(T)) = K \cdot Q(T)$, if $Q(T) \geq H$; otherwise, $B(Q(T)) = 0$. \hat{f} is counted at \$0.76 per card for processing expenditures.
- Ticketing Agent's Plan.* In the case of a promotion for bus passengers, a reward of \$5 million is provided for the game. Of this total, \$2 million is for instant rewards uniformly distributed over the whole year, and \$3 million is for the

delayed prize, the final lottery reward. Referring to Equation (6)~(8), $\hat{M}_2(t)$ is estimated about \$38,462 per week. $\hat{M}_1(t) = \$3$ million.

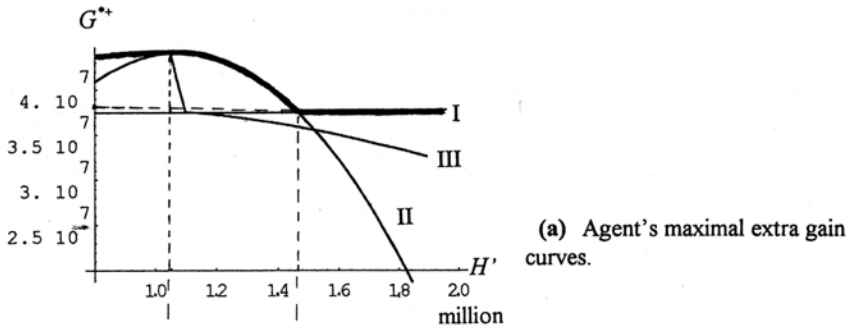
- *Others.* Six percent is taken as a default for the annual interest rate in the following analysis. The expectation $E(M)$ based on M_1 and M_2 and proportional to the market volume is calculated iteratively and finalized by the amount of ticket sold $Q(T)$. Refer to Equation (2), $f(M_j) = L_j / Q(T)$, for all j .

According to official estimates by Taipei, the market has 600,000 attendants. Replacing the personal extra card demand $q_c^+(t)$ with the market volume in Equation (44) and substituting into $q(t)$ of the model described in section 2, the optimal card price p_c^* , the total extra quantity of cards sold $Q_c^{*+}(T)$, total extra gain of the agent G^{*+} , and total extra net revenue of the bus consortium W^{*+} will then be calculated for each type under previous parameters, consciousness, and assumptions. Figure 2(a) illustrates the agent’s maximal extra gain curves G^{*+} with respect to the threshold H' under the condition of marginal bonus $K=\$6$ per card sold. Figure 2(b), (c), and (d) display the relevant plots related to the optimal card price, total extra profit for the bus consortium, and total extra quantity of passengers loaded ($N_b^+ = 40 \cdot Q_c^{*+}(T)$), respectively. According to Figure 2(a), the agent’s reaction is obviously based on what H' was provided by the consortium when calculating the maximal gain from one of three actions: Types I, II, or III.

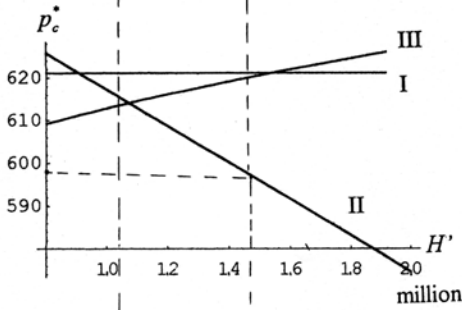
When the threshold of extra cards sold for receiving the bonus from the bus consortium is less than 1.07 million (i.e., $H' < 1.07$ million), the agent’s best action is type III, selling more ticket cards earns him more money. If the threshold is provided between 1.07 million and 1.46 million, the best action is type II, in which the agent’s policy is to sell the ticket cards just to hit the threshold. Otherwise, $H' > 1.46$ million, the best action is type I, not having interest in the bonus provided. Therefore, the decision curve must be the bold envelope line—the linked line that each segment meets along the shapes or tangents to the spheres—indicated in Figure 2(a). Under this circumstance, the corresponding curve in Figure 2(c) for the bus consortium’s profit is also bold.

From the bus consortium’s perspective, however, the maximal profit point occurs at $H'=1.46$ million and the agent’s action should be type II. Because $H'=1.46$ million is the turning point of an agent’s decision for type I or II, the bus consortium should lower the threshold slightly from 1.46 million to ensure the agent’s locking at type II. The final equilibrium point between the bus consortium and the agent leads to the optimal ticket card price of \$598 (Figure 2(b)), with total extra loads being 58.4 million (Figure 2(d)). The extra profit for the bus consortium would be

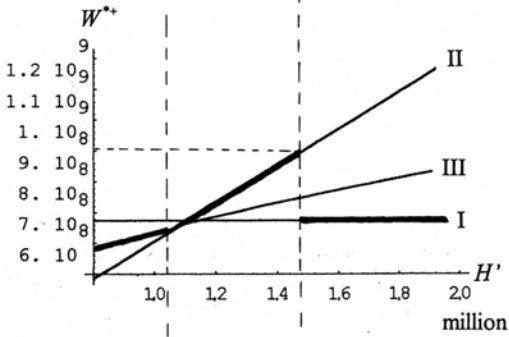
Figure 2. Solution of the Presented Case



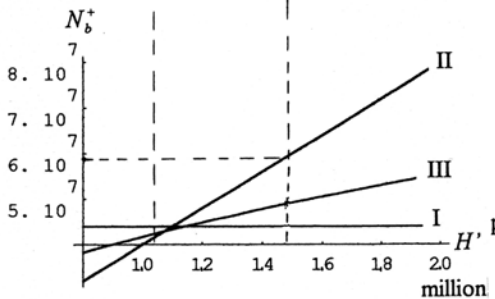
(a) Agent's maximal extra gain curves.



(b) Optimal card price curves.



(c) Total extra revenue curves of the bus consortium.



(d) Total extra quantity curves of passengers loaded or tickets sold.

\$885,299,000 (Figure 2(c)), which includes the subsidy of \$29.2 million from the government, supposing that the threshold of extra loads D' for subsidy receipt is announced at 36 million by the government. The maximal extra gain by the agent at this equilibrium point is \$37,707,100 (Figure 2(a)).

Table 1 summarizes the equilibrium results of the cases: $D'=36$ million, 54 million and 72 million with respect to $K=0, 2, 4, 6, 8,$ and 10 . The table reveals that if the government sets the load threshold at 36 million for bus consortium subsidization, the agent can easily achieve the target only via lottery strategy ($N_b^+ > 36$ million), despite any bus consortium bonus incentive, even $K=0$ (no incentive).

Table 1. Equilibrium Results of the Taipei Case in Presented Model

D' (million trips)	K (\$)	H' (million cards)	W^{**} (\$)	G^{**} (\$)	P_c^* (\$)	N_b^+ (million tickets)
36.0	0	1.09	667,528,000	37,516,000	613	43.6
	2	1.26	769,090,000	37,547,600	606	50.4
	4	1.37	833,477,000	37,585,200	601	54.8
	6	1.46	885,299,000	37,707,100	598	58.4
	8	1.55	936,762,000	37,498,800	594	62.0
	10	1.62	975,819,000	37,828,400	591	64.8
54.0	0	1.09	645,728,000	37,516,000	613	43.6
	2	1.26	743,890,000	37,547,600	606	50.4
	4	1.37	833,477,000	37,585,200	601	54.8
	6	1.46	885,299,000	37,707,100	598	58.4
	8	1.55	936,762,000	37,498,800	594	62.0
	10	1.62	975,819,000	37,828,400	591	64.8
72.0	0	1.09	645,728,000	37,516,000	613	43.6
	2	1.26	743,890,000	37,547,600	606	50.4
	4	1.37	806,077,000	37,585,200	601	54.8
	6	1.46	856,099,000	37,707,100	598	58.4
	8	1.55	905,762,000	37,498,800	594	62.0
	10	1.62	943,419,000	37,828,400	591	64.8

Obviously, the agent will raise the ticket price to earn more profit if K is below \$4. If the government sets the load threshold at 54 million for bus consortium subsidization, the agent meets the target merely on the condition that K is greater than \$4. In addition, if the government sets the load threshold at 72 million, the agent cannot achieve the target if $K \leq \$10$. However, the agent hopes that K is as large as possible while the bus consortium prefers a lower D' . According to Table 1, from the perspectives of the agent and bus consortium, $D' = 54$ million through 36 million is acceptable. Meanwhile, $K = \$10$ is the best solution for their profits, with \$37,828,400 extra gain for the agent and \$975,819,000 for the consortium. Finally, bus trips would be increased by about 64.8 million annually.

Conclusions

This article presented a novel promotion strategy for public transit, with particular emphasis on strategy efficiency through an incentive system between passengers and ticketing agents, ticket agents and bus operators, and bus operators and the government. The mathematical model is formulated with a methodology of optimal control description of the market for this incentive system. This model focuses largely on maximizing the public transit market. Both the ticket agent and bus companies receive their maximal profits in an equilibrium market. Results obtained from this strategy can successfully enhance public transportation.

According to this study, a lottery game for bus passengers is very attractive to the people in Taipei City. Although the captive bus passengers are sensitive to changes in ticket price, both captive and noncaptive passengers reflect the same concerns about rewarding expectations. With the analysis in a previous model, clearly the proposed incentive strategy reveals the efficiency of traffic improvement. While public transport patronage is gradually decreasing, this study's considerations are a useful contribution.

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Parcel-Level Modeling to Analyze Transit Stop Location Changes

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Abstract

Because of how important walk access is for transit travel, service changes that affect walking distance, such as route or stop relocation, call for modeling at a fine enough level to accurately reflect the often arbitrary aspects of the access network and of demand distribution within a zone. Case studies of stop relocation in Boston and Albany demonstrate the feasibility of parcel-level modeling on the unabridged street network using an assessor's database. Parcel-level demand is estimated by allocating observed on/off counts as a function of a parcel's land-use type, size (e.g., gross floor area), and location factors. With actual land-use and street network data, we show how stop service areas can deviate substantially from the simple geometric shapes that follow from assuming airline or rectilinear travel, and demand distribution can be far from uniform within a zone. These factors can significantly favor particular transit stop locations.

Introduction

Travel demand is typically modeled at the level of a traffic analysis zone. With improvements in computing power, zones have been getting smaller over the

years. For automobile travel, zones are generally small enough that errors resulting from aggregating demand to the zonal level are insubstantial. However, for travel by transit, for which the access mode is usually walking, errors from representing an entire zone as having the same walking time can substantially distort an analysis.

We describe a new approach to modeling transit demand using individual land parcels, with walk access along the unbridged street network. This approach, which is roughly synonymous with assigning transit demand to every address, has become possible due to the growing local government use of geographic parcel-level databases for taxation and land-use planning, and the development of geographic information systems (GIS), GIS-based street maps, and GIS program utilities. We demonstrate this approach in stop-spacing case studies in Boston and Albany. Parcel-level modeling should also offer improved analysis for other applications sensitive to walk distance, including mode choice and transit route choice.

Modeling demand at the zone level forces one to assume either that demand is concentrated at a single point (zone centroid), or better yet, is distributed uniformly across the zone. The former is clearly unrealistic, and in many cases, demand is also far from uniform within a zone. Hospitals generate more transit demand than cemeteries, and apartment buildings more than single-family homes. Knowing each parcel's land use and size (not in land area, but in floor area or similar measure related to development intensity) allows one to distribute demand in a zone that naturally recognizes each parcel's trip generation and attraction potential.

GIS-based planning methods that account for land use have been developed for predicting demand along new transit routes (Gan, Liu, and Ubaka 2005) and along existing routes, using on-off count information (Bunner 2005). These approaches use block-level census data, greatly reducing aggregation error. However, they do not use the street network to determine walking paths or stop service areas.

With parcel-level modeling, the issue is not just "stop spacing" but "stop location." With demand distributed over the service area in a way that reflects development intensity, one can readily see the walking distance benefits of locating stops close to major generators and pockets of more intense development.

Zone-level modeling requires assumption of an ideal street network for walk access, which is estimated by such methods as airline distance multiplied by a circuitry factor. However, street networks often have arbitrary barriers and discon-

tinuities, diagonals, curves, and other features that affect walking distance. Modeling demand at the parcel level, using the actual street network for walk access, allows one to determine walk distance without making idealistic assumptions.

With idealistic assumptions about the street network, a transit stop's service area has simple boundaries—each stop's service area borders only those of its neighboring stops, with nice straight shed lines. We show that with realistic networks, service area boundaries can be far more complex, making some stop locations have much larger service areas than others, even if stops are equally spaced. This can affect optimal stop location; for example, adding a stop may have little benefit if that stop has a small service area.

In our application, parcel-level demand estimates are not synthesized directly from parcel attributes; rather, demand estimation begins with on-off counts, with parcel attributes used to distribute demand, mediated by a network analysis that determines which parcels lie in each stop's service area. Naturally, this logic can only be applied along existing routes, and for service changes that are not expected to change demand considerably—which is exactly the case for stop spacing. For such applications, basing demand on historic on-off counts makes the model self-calibrating, a great advantage. For applications to areas currently unserved by transit, or for which service changes are expected to result in large demand changes, parcel-leveling modeling would require the development of parcel-level transit-trip generation models.

Walking Paths and Bus Stop Shed Lines

As a simplification, walking distance to bus stops is often estimated based on airline distance, sometimes multiplied by a circuitry factor. When the access network is a grid, a better assumption is rectilinear travel, meaning the access path consists of segments that are either parallel to or perpendicular to the bus route. In continuum models used in theoretical stop-spacing analyses, the rectilinear approach requires assuming an infinitely dense rectilinear access grid (Wirasinghe and Ghoneim 1981). When stop locations are given, one need not assume an infinitely dense grid; however, one must assume that (1) the route follows a straight line; (2) the streets in the access network form a rectilinear grid; (3) streets perpendicular to the bus route run without interruption across the full width of the service area; and (4) bus stops are all located at four-way intersections. This “ideal” urban layout was the justification for assuming rectilinear travel in our earlier work on stop spacing (Furth and Rahbee 2000).

With idealized access paths, the shed line or service area boundary between adjacent stops is simply the perpendicular bisector of the segment joining the stops. Where the route is straight, or little enough curved so that adjacent shed lines do not intersect within the route's service area, a corollary of using perpendicular bisectors is that a stop's service area will border only that of its immediate upstream and downstream stops.

A more sophisticated way of determining shed lines, presented in Furth and Rahbee (2000), is based on minimizing not just walking time, but a weighted sum of walking and riding time. With this logic a traveler located halfway between two stops will not be indifferent, but will prefer the downstream stop. That shifts shed lines slightly upstream for boardings, and downstream for alightings, by an amount that depends on the ratio of the walking and riding speeds and the ratio of the walking and riding disutilities. Shed lines also vary by direction of travel, as travelers living midway between two stops will walk toward one stop when traveling in one direction, and toward the other when traveling in the other direction.

In practice, streets grids surrounding a bus route often deviate from the ideal conditions described before, and routes can curve or turn. As a result, shed lines are not as simple as (possibly shifted) perpendicular bisectors, and stop service areas can be considerably smaller or larger than one would otherwise expect. These considerations point to the value of using the street network, not simple geometric shapes, to determine stop service areas.

Assigning Parcels to Stops

With parcel-level modeling, a shortest path algorithm is applied on the street network to find the closest stop to each parcel. Shed lines are simply a result of this assignment. To account for the more sophisticated approach of minimizing a sum of walking and riding time, the assignment of parcel k to a stop is found by first finding shortest path walking distances from parcel k to every stop. (In practice, this step can be limited to stops within a certain practical distance of parcel k .) Then, for trips beginning at parcel k , the stop chosen is the one that minimizes, over all stops i ,

$$c_{walk} * d_{ki} / u_{walk} + runTime_i \tag{1}$$

where:

d_{ki} equals (walking) distance from parcel k to stop i

c_{walk} is the cost of a minute of walking time relative to a minute of riding time (commonly given a value between 1 and 2.5)

u_{walk} is walking speed

$runTime_{i\bullet}$ equals running time from stop i to the downstream end of the line

For trips *ending* at parcel k , the stop chosen is the one that minimizes

$$c_{walk} * d_{ki} / u_{walk} + runTime_{i\bullet} \quad (2)$$

where:

$runTime_{i\bullet}$ equals running time from the upstream end of the line to stop i

In general, a parcel has four different assignments to stops, one each for inbound-boarding, inbound-alighting, outbound-boarding, and outbound-alighting; similarly, stops have different service areas for those four combinations. (If inbound and outbound stops are colocated, and if running times in opposite directions are symmetric, the inbound-boarding and outbound-alighting service areas will be identical, as will the opposite pair.)

Service Area Boundaries

To illustrate how in a real network shed lines can differ from the simple shapes one would expect with straight-line travel, observe in Figure 1 the assignment of parcels to stops (stars) on a small section of Boston's B-line, a branch of the Green line light rail, for boarding passengers traveling inbound (in the figure, upward and to the right). The symbol of a parcel centroid is unique to the stop to which it is assigned, allowing one to see stop service areas. Shortest path trees are also shown, which allow one to verify the walking paths determined by the GIS "closest facility" utility used. The service area of Mt. Hood Road (identified as 9 in the figure) is quite unusual—it includes only two parcels on the north side of the transit line, largely because of the absence of an intersecting street on that side of the line. On the south side of Mt. Hood's service area, the shed line is shifted upstream toward Sutherland Road (identified as 10 in the figure).

In Figure 2, applying to outbound (leftward) travel in the same corridor, the difference in a stop's service area for boarding versus alighting can be seen. Stops are shown as stars. Parcel centroids are shown with different symbols according to their outbound alighting stop, while the manually drawn shed lines indicate service areas for outbound boardings. The boarding shed lines are all shifted upstream (toward the right), and alightings shed lines shifted downstream. This analysis emphasizes the need to determine separate service areas for a stop's ons and offs, as well as for each direction of travel.

Figure 1. Optimal Walking Paths for Alightings Near Mt. Hood Road (Outbound)



Figure 2. Stop Service Areas for Boardings versus Alightings (Outbound)

(Manually drawn lines indicate service area for boardings; parcel centroids shown with different symbols indicate service area for alightings.)



Figure 2 indicates how common it is for a stop's service area to border more than just those of its upstream and downstream neighbors. Due to curves in the transit line as well as irregularities in the access network, 9 of the 16 stops have service areas that border those of at least three other stops. The Summit Ave. and Griggs St. stops, located shortly before and after an S-curve, have outbound alightings service areas that border those of 4 other stops. It is also rather startling to see how many shed lines have segments that are more parallel than perpendicular to the transit line, due to discontinuities in the access network.

As this example shows, stop service areas can be influenced considerably by arbitrary aspects of the street network, pointing to the value of modeling demand on a scale smaller than a city block—ideally, a parcel—and modeling walking along the street network itself.

Determining Parcel-Level Demand

The initial goal in parcel-level transit demand modeling is to estimate the current number of trips originating and ending at each parcel. The most reliable approach skips traditional trip-generation and mode split steps, and instead directly uses on/off counts, which, after adjusting for possible passenger transfers, specify the trip generation within the stop's service area. All that remains then is to distribute the demand observed at the stops over each of the parcels in each stop's service area.

Distributing Demand Over Parcels

Reflecting the demand counted at a stop back to the parcels within its service area is a many-to-one trip distribution problem. Productions (trip origins, corresponding to "on" counts at a stop) are distributed separately from attractions (trip destinations, corresponding to "offs"). For productions, the general procedure is to determine for each parcel k in a stop's service area a production strength $onStrength_k$, and to distribute demand in proportion to $onStrength$. A parcel's $onStrength$ depends on two inherent characteristics, its land-use type and a measure of its size, called its *size attribute*, as well as two location characteristics:

$$onStrength_k = xOn(LUC_k) * onCoef(LUC_k) * propensity_k * compFactor_k \quad (3)$$

where:

LUC_k equals parcel k 's land-use code or land-use type

$xOn(LUC_k, k)$ is the value of parcel k 's size attribute (a size attribute is specified for each land-use code)

$onCoef(LUC_k)$ is the coefficient that applies to a particular land-use code's size attribute

The variables $propensity_k$ and $compFactor_k$ are associated with parcel k 's location; they will be explained later.

The size attribute and coefficient are best explained with examples. For each land-use type, a single size attribute is chosen from among the attributes found in the land-use database. For the land-use type "single-family home," the size attribute used in the Boston case study was "living area," and so if LUC_k was "single-family residential," $xOn(LUC_k, k)$ was that parcel's living area, in thousands of square feet. In the Albany case study, however, the land-use database included the population in each residential parcel; therefore, for residential parcels in Albany, $xOn(LUC_k, k)$ was parcel k 's population. For most nonresidential land-uses, $xOn(LUC_k, k)$ was "gross floor area" in the Boston case study, and "number of employees" in the Albany study. Other size attributes could be used if available such as "number of seats" for restaurant parcels.

A parallel procedure applies to distributing off counts. The resulting demand at each parcel may be tiny (a parcel may be allocated 0.06 trip origins and 0.09 trip destinations), but that is entirely appropriate for determining aggregate results such as change in demand or walking impact in response to relocating a stop or a route.

The demand that is distributed over parcels should exclude any transferring passengers, and requires that on-off counts distinguish transferring from nontransferring passengers. Walking impacts to demand arising from transfers is readily calculated based on the distance between the transfer stops.

Estimating Trip-Generation Coefficients

The coefficients $onCoef(LUC)$ and $offCoef(LUC)$ are trip-generation coefficients, reflecting the power of a land-use type to produce and attract transit trips per unit of the size attribute. One of the challenges in proving the practicality of this modeling approach was determining coefficients for different land-use types and size attributes. The Institute of Transportation Engineers (ITE) publication *Trip Generation* (1997) offers a wealth of trip-generation coefficients, mostly based on suburban developments with little or no transit access. ITE trip rates are available by time of day. In general, we used as coefficients the closest possible ITE coef-

ficient, multiplied by “fraction entering” for on coefficients and “fraction exiting” for off coefficients, and by a factor indicating the likely transit share for a land-use type. Transit share data, in the form of mode share by trip purpose and time of day, was obtained from Boston’s regional planning agency. The Boston mode share data showed that in the morning peak, the transit share for trips originating at homes was almost double that of trips originating elsewhere. Therefore, for the morning peak, ITE trip rates for residential parcel types were doubled relative to nonresidential parcel types. Some expert judgment was also used to estimate transit shares; for example, we assigned a high transit share to high schools and a low transit share to elementary schools.

Where land-use codes in a the parcel database encompass several ITE categories, ITE rates in the constituent categories were averaged, weighted by a (subjective) estimate of the relative presence of each category in the area. Where ITE rates used a different size attribute than the parcel data, they were adjusted by the ratio of the means of the size attributes, with mean values found in various demographic or land-use databases. The coefficients used in the Boston study are given in Table 1.

While this method of determining trip-generation coefficients is admittedly crude, we believe that they are adequate for most transit planning applications. Even crude rates accomplish the objective: assigning a stop’s demand to the part of its service area where development is most intense, and away from where there is little development. Incorrect rates might mean, for example, that one block is assigned too much demand and another block in the same stop’s service area is assigned too little. Because the rates are used for trip distribution, not trip generation, they should be transferable to other cities.

Propensity and Competition Factors

A few studies, summarized in Kittleson & Associates et al. (2003), have shown that transit demand decreases at greater distance from a stop. Equation 3 includes the term *propensity_k*, which can be used to indicate a greater or smaller propensity to make a transit trip based on distance from the closest stop. A simple propensity function, often used in gravity models, is exponential:

$$propensity_k = exp(-bd_k)$$

where:

d_k equals distance from parcel k to the nearest stop

b is a calibration parameter

Table 1. Trip Generation Coefficients

<i>Land-Use Code</i>	<i>Size Attribute</i>	<i>Production/Attraction Factors¹</i>					
		<i>AM Peak</i>		<i>PM Peak</i>		<i>Sat Midday</i>	
		<i>On Coef.</i>	<i>Off Coef.</i>	<i>On Coef.</i>	<i>Off Coef.</i>	<i>On Coef.</i>	<i>Off Coef.</i>
R1—Residential 1-family	HH member	0.018	0.008	0.025	0.011	0.016	0.018
	1000 sq. ft. LA	0.036	0.012	0.023	0.041	0.028	0.033
	Unit	0.070	0.023	0.045	0.081	0.054	0.063
R2—Residential 2-family	HH member	0.021	0.009	0.025	0.015	0.017	0.019
	1000 sq. ft. LA	0.038	0.013	0.025	0.043	0.029	0.033
	Unit	0.071	0.024	0.046	0.080	0.053	0.062
R3—Residential 3-family	HH member	0.030	0.012	0.022	0.034	0.018	0.018
	1000 sq. ft. LA	0.042	0.016	0.027	0.043	0.027	0.027
	Unit	0.056	0.022	0.037	0.057	0.036	0.036
R4—Residential 4–6-family	HH member	0.030	0.012	0.022	0.034	0.018	0.018
	1000 sq. ft. LA	0.047	0.018	0.030	0.047	0.030	0.030
	Unit	0.056	0.022	0.037	0.057	0.036	0.036
A—Residential 7+ -family	HH member	0.035	0.013	0.025	0.039	0.021	0.021
	1000 sq. ft. LA	0.054	0.020	0.035	0.055	0.035	0.035
	Unit	0.065	0.025	0.042	0.065	0.042	0.042
CM—Condominium	HH member	0.029	0.006	0.016	0.023	0.018	0.019
	1000 sq. ft. LA	0.051	0.010	0.029	0.040	0.031	0.033
	Unit	0.065	0.014	0.037	0.051	0.039	0.042
Tax exempt land uses	1000 sq. ft GFA	0.097	0.244	0.230	0.108	0.052	0.065
Commercial land uses	1000 sq ft. GFA	0.399	0.483	0.609	0.900	0.552	0.726
Mixed residential-commercial	1000 sq ft. GFA	0.042	0.030	0.052	0.088	0.045	0.056
Industrial land uses	1000 sq ft. GFA	0.013	0.061	0.056	0.020	0.008	0.008
	Acre	0.141	0.539	0.448	0.268	0.125	0.122

¹ LA = living area; GFA = gross floor area.

A value of $b = 0$ means propensity does not fall with distance. In our case studies, we arbitrarily used $b = 0.0037/\text{m}$, for which transit-use propensity is three times greater for a parcel 100 m from a stop than for an otherwise equivalent parcel that is 400 m from a stop.

Traditionally, the phenomenon of decreasing demand with distance is treated as a simple step function: propensity is 1 out to a certain distance from the route (often 0.25 miles in bus route studies), and 0 after that. An exponentially decreasing propensity certainly seems logically superior to such an abrupt change. Of course, as distance from a route increases, one often arrives in the service area of another route, bringing up the issue of route competition.

Competition from other transit routes in part of a stop's service area should logically lead to less demand than otherwise expected for the route of interest coming from that part of the service area. Ideally, the parcel level approach should be extended to include route choice models that account for walking distance as well as other route attributes such as waiting time and speed. For our application, we used a much simpler way of accounting for route competition: simply including in equation 3 a competition factor whose default value is 1, and that can be set to a smaller value in parts of the route's service area to reflect the fraction of transit demand in that part of the service area that is drawn away to other transit lines, based on expert judgment.

Another possible extension would be to assign to each parcel a specific walking speed or unit walking cost. Special values could then be given to elderly housing and hospitals that would have the effect of making such parcels more sensitive to walking distance, giving them more weight in an optimal stop location problem.

An Example

Trip-generation results on a section of Boston's B-line are shown in Figure 3. Symbol size reflects the demand attracted by a parcel for outbound afternoon peak travel. Several items are evident. First, the results are consistent with on/off counts, showing heavy demand around stops with high off counts such as Harvard Ave. and Warren St. Second, they reflect development density. For example, Harvard Ave. has more intense development (apartment buildings) than other nearby streets, and so its parcels are assigned heavy demand relative to other nearby parcels. Third, one can see the effect of the exponential propensity function used, with parcel demand declining as one moves farther from the route.

Application Results

An example application to Boston's B-line is presented in Tables 2 and 3. Table 2 shows impacts by stop and overall for the base case (historical set of stops) for the section of the B-line between Packard's Corner (halfway to downtown) and Boston College (outer end of the line). Table 3 shows the change in impacts when one stop, Mt. Hood, is eliminated. The stop elimination affects only the neighboring stops; overall, walking time went up while riding time and operating cost went down. For the unit costs we used, the net impact was a savings of \$35 per hour, or \$26,500 per year for a three-hour weekday period.

Figure 3. Demand by Parcel, Outbound Alightings (PM Peak)

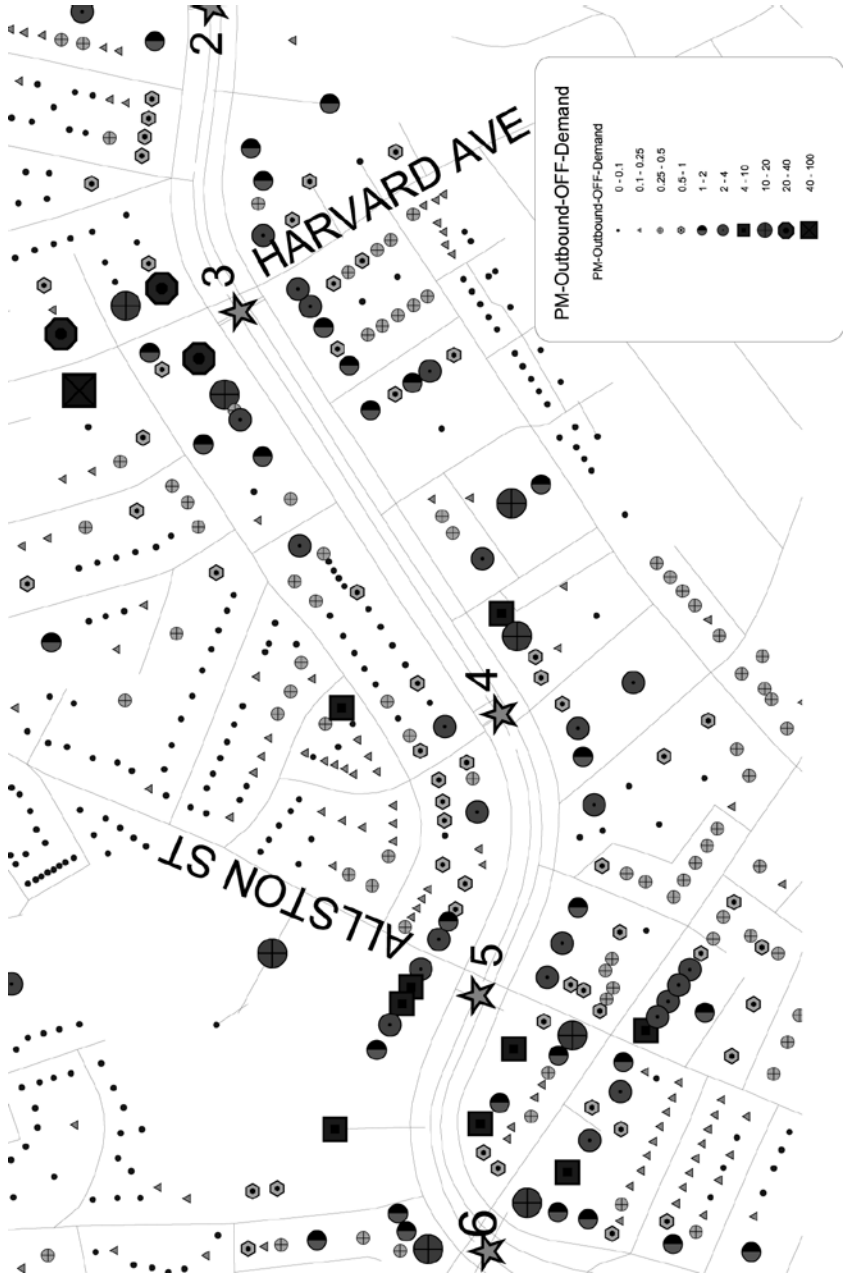


Table 2. Base Case Results, Green Line B (Outbound, PM Peak)

Stop	Stop Description	Ons (pax/ hr)	Offs (pax/ hr)	Dep Vol (pax/ hr)	Un- delayed Run Time (min)	Walk Time On (pax- min/hr)	Walk Time Off (pax- min/hr)	Ride Time (pax- min/hr)	Segment Run Time (min)	Total Cost (\$/hr)
1	PACKARDS CORNER	25	170	1028	1.0	42	350	1746	1.6	453
2	FORDHAM RD	15	74	969	2.1	25	231	1955	2.0	493
3	HARVARD AVE	145	282	832	4.0	410	716	2631	3.1	870
4	GRIGGS ST	22	102	751	6.1	63	308	1820	2.3	542
5	ALLSTON ST	18	123	646	7.6	41	245	1453	2.1	465
6	WARREN ST	24	116	554	9.4	95	325	1066	1.7	409
7	SUMMIT AVE	3	100	457	10.2	7	323	1115	2.3	467
8	WASHINGTON ST	36	144	349	13.1	99	293	1052	2.5	497
9	MT HOOD RD	4	39	314	14.1	9	79	452	1.4	234
10	SUTHERLAND RD	16	71	259	15.2	39	172	402	1.4	257
11	CHISWICK RD	2	76	185	16.0	6	236	366	1.7	302
12	CHESTNUT HILL AVE	20	63	142	17.8	53	200	332	2.0	338
13	SOUTH ST	4	29	117	19.3	13	42	160	1.2	175
14	GREYCLIFF RD	0	4	113	19.5	0	13	106	0.9	130
15	BOSTON COLLEGE	0	113	0	21.0	0	514	107	1.2	262
Total		333	1505			901	4048	14763	27.5	5892

Table 3. Changes Due to Removing Mt. Hood Stop (Outbound, PM Peak)

Stop	Stop Description	Ons (pax/ hr)	Offs (pax/ hr)	Dep Vol (pax/ hr)	Un- delayed Run Time (min)	Walk Time On (pax- min/hr)	Walk Time Off (pax- min/hr)	Ride Time (pax- min/hr)	Segment Run Time (min)	Total Cost (\$/hr)	Annual Cost (\$/year)
8	WASHINGTON ST	1	30	-29	0.0	4.1	113.5	166.0	0.6	114	85,811
9	MT HOOD RD	-4	-39	6	0.0	-8.6	-78.7	-452.5	-1.4	-234	-176,715
10	SUTHERLAND RD	3	9	0	0.0	9.7	29.8	160.1	0.5	85	64,389
	Total	0	0	0		5.2	64.6	-126.4	-0.3	-35	-26,515

An interesting graphic produced in the study is shown in Figure 4, which illuminates the impact of eliminating the Mt. Hood stop. It shows walking paths to the nearest stop for parcels that formerly used Mt. Hood, and indicates how much each parcel's walking time has increased. One can see how small the impact is: eight parcels see their walking time increase by two to three minutes; all others have smaller increases.

Practical Issues

Implementing this new approach to transit demand modeling involves several practical issues.

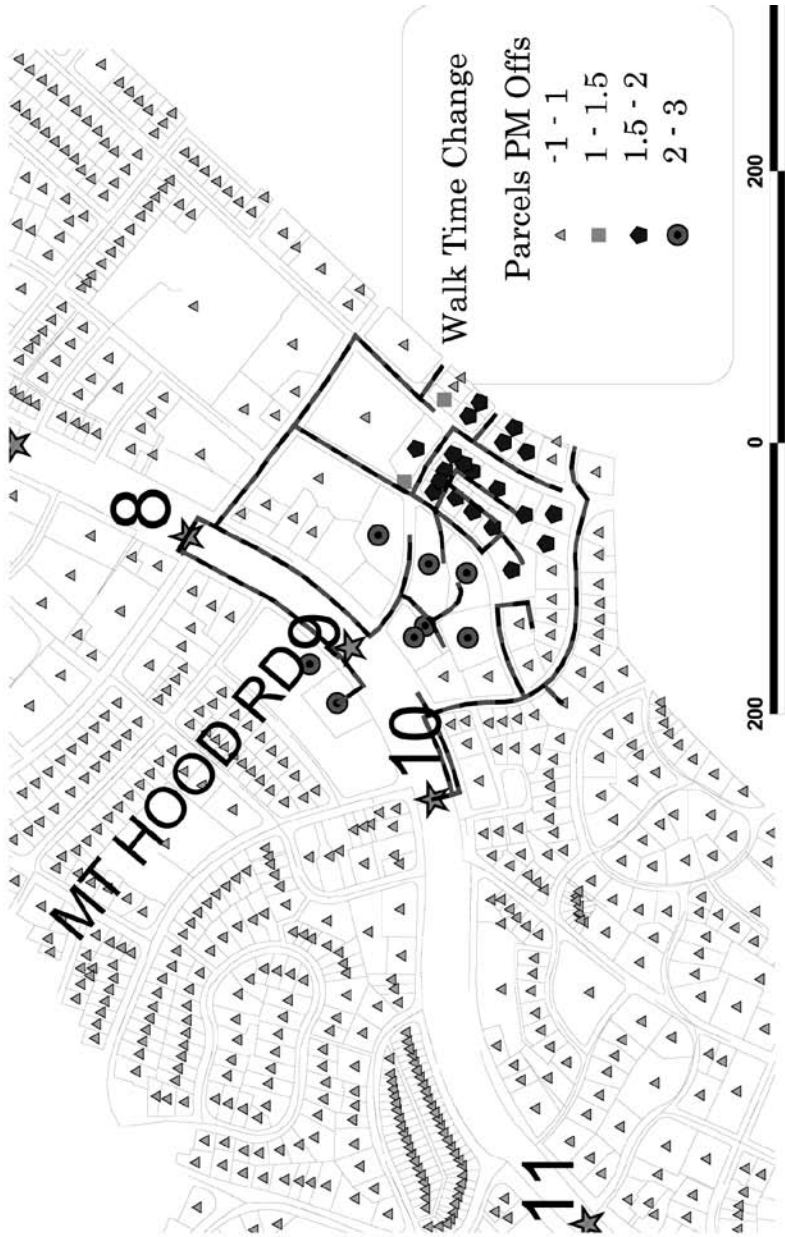
Parcel-level databases are often restricted to a particular political jurisdiction. When a service area touches more than one jurisdiction, problems in securing and coordinating multiple databases arise. Also, some jurisdictions are less willing than others to share parcel data.

We found it necessary to edit street networks manually to ensure that they yielded reasonable walking paths. We had to add a few links to permit pedestrian crossings to some median stations where there are crosswalks that do not appear on the street map. We also deleted some alleys because their inclusion was forcing some parcels to make circuitous walking paths. The latter problem arose because the software utility that connects parcel centroids to the nearest link sometimes connected a parcel to the alleys at its rear rather than to the street at its front. Ideally, centroid connectors should be provided to both the street and the alley, allowing the shortest path routine to choose the better path.

The concept of passengers' walking "cost" can be expanded. Grade could be accounted for if the relevant data is included in the base map file. Other enhancements include accounting for streets segments that lack sidewalks or present safety challenges, and including pedestrian delay at street crossings.

Finally, the automation process was quite complex, involving numerous steps and intermediate databases. As is commonly known, GIS is a data-intensive process and hence processing large amounts of data in an efficient manner is required. Our work was greatly aided by two utilities available on the GIS platform we used: centroid creation and connection (used to convert parcels from polygons to points), and nearest facility (used to find walking paths from parcels to stops).

Figure 4 . Change in Walking Time and New Walking Paths for Parcels Affected by Elimination of Mt. Hood Stop (Outbound Alignments)



Conclusions

Modeling transit demand at the parcel level offers an improved way of accounting for walk access, one of the major user costs involved in transit travel. Using available parcel-level databases and street network data, it is possible to determine walking distance from each parcel to its closest stop in a way that accounts for irregularities and discontinuities in the street network. Using parcel-level data available from tax assessors and regional planning agencies, it is possible to distribute measured demand over the parcels in a stop's service area in a way that reflects differences in land use and intensity. With demand thus assigned to individual parcels, impacts of changing stop location can be determined, as demonstrated in two case studies. We believe that parcel-level modeling also offers promise for other transit planning applications in which walking distance plays an important role.

Acknowledgement

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Metro Station Operating Costs: An Econometric Analysis

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Abstract

This article develops an econometric analysis of metro station operating cost to identify factors that create variation in cost efficiency. Stations operating costs can be classified amongst the semifixed costs that a metro faces in the sense that they do not vary proportionately with metro output. They may therefore be important in determining the degree of returns to density. This article seeks to provide an improved understanding of some of the major factors driving these costs. Empirical results show that strong system-specific influences impact costs but over and above these we detect positive associations from a range of station characteristics, including the length of passageways, number of platforms, peak-level service frequency, interchange demand, and the provision of toilet facilities. In addition, we find that the presence of air-conditioning has a substantial effect in increasing expected station operating cost by as much as 40 percent.

Introduction

The cost structure of the mainline railway industry has received a great deal of attention in the academic literature (e.g., Caves et al. 1980; Caves et al. 1981a, 1981b; Freeman et al. 1985; Caves et al. 1985; Dodgson 1985; McGeehan 1993; Bookbinder and Qu 1993; Oum and Yu 1994; Cowie and Riddington 1996; Wunsch 1996; Tretheway et al. 1997; Oum et al. 1999; Cantos et al. 1999; Cantos et al. 2002). Research has demonstrated the very large variance in cost efficiency, or

productivity, that is often present within a sample of rail firms and has developed cost and production function approaches to analyze the factors underpinning this variance.

A prominent theme in the rail efficiency literature is whether cost structures are subject to returns to scale (RTS) or returns to density (RTD). RTS describe the relationship between all inputs and the overall scale of operations, including both output and network size. RTD describe the relationship between inputs and outputs with the rail network held fixed. Evidence in the literature indicates that RTD are due to the prevalence of fixed costs in the rail industry and to a range of semifixed costs that do not vary proportionally with output. Less consistent evidence is available on the existence of scale economies, though the majority view is that railways operate under constant returns to scale. Few studies have been conducted on the costs structure of urban metros, though Graham et al. (2003) estimates increasing RTD and constant RTS.

Station operations may provide an important source of increasing RTD in metro operations. Stations must remain staffed and functioning, with all the energy and other resources required, throughout the duration of the metro operating hours. Moreover, costs may differ quite substantially from one station to another due to the nature of engineering, the depth of station, its size and dimensions, the technology employed, and so on. So we can conceive of station operating costs as semifixed costs that do not vary proportionately with system throughput and therefore may be instrumental in giving rise to increasing RTD.

In this study we develop an econometric model to analyze variance in station operating costs. An econometric model is essential to determine the effect of a particular characteristic of a metro station on its operating costs while controlling for all other factors affecting the metro station operating cost. The analysis of historical data fails to control for the effects of other factors while estimating the effect of a particular factor. We use data on 83 stations from 13 metro systems from around the world to estimate the main drivers of cost. Model specifications and the data used for estimation are discussed and results are presented.

Model Specification and Data

The data available for our analysis describe the total operating cost of each station and a range of station characteristics collected from a total of 13 metros (Buenos Aires, Dublin, Glasgow, Hong Kong KCR, Hong Kong MTR, Lisbon, London, Montreal, Naples, Sao Paulo, Singapore, Taipei, and Toronto). The analysis we develop

below regresses the total operating costs against these station characteristics to determine their role in influencing variance in costs.

It is important to stress that we do not adopt a conventional cost function approach. We do not have data on factor prices and therefore cannot estimate the cost function. However, another important consideration in this respect is that since the operating costs of any one particular station represents only a small fraction of total metro operating costs, individual stations cannot be regarded as the appropriate units over which cost decisions are made. For instance, metro operators do not demand factor inputs at the station level in accordance with prices but make rational decisions relating to costs and operations for the system as a whole. Furthermore, it would be wrong to ascribe any particular behavioral assumptions to individual stations (e.g., cost minimizing behavior). A metro may not seek to sustain a set level of station efficiency across the system but rather allow for disparities in efficiency to achieve some broader objectives relating to the appropriate level of system output given overall costs.

In this respect, it is mainly how the station *characteristics* serve to influence total cost that is of interest in the present analysis. One important issue, however, relates to the absence of factor price data, because this will certainly be important in determining station costs. To control for these omitted variables, which we cannot observe, we estimate the station operating costs model with a set of dummy variables for the 13 metro systems. We assume that these dummies will capture unobserved system-specific effects including factor prices.

A log linear model is used to identify the factors that influence the operating cost of a metro station. The model can be written as:

$$\ln y_i = \alpha + \beta \ln X_i + \theta D_i + \varepsilon_i \quad (1)$$

where:

- y_i is the total operating cost of a metro station i
- X_i represents a $k \times 1$ vector of continuous explanatory variables describing the characteristics of station i
- D_i denotes a $m \times 1$ vector of dummy explanatory variables relating to metro systems
- ε_i is white noise
- β represents $k \times 1$ vector of parameters to be estimated
- θ is a $m \times 1$ vector of parameters to be estimated

The log linear model is used because it reduces the potential for multicollinearity and provides direct parameter estimates of the elasticities.

The dependent variable is the total cost of operating the station per year. This includes the costs associated with staff, utilities (e.g., electricity, gas, and water), the maintenance of lifts and escalators, and the maintenance of other systems such as CCTV, air-conditioning, ticketing equipment, and building. Two econometric models will be estimated using equation (1). The first model will be estimated without metro-specific dummy variables and the second model will be estimated with metro-specific dummies to control country-specific effects on metro stations' operating cost.

The explanatory variables, which describe the station characteristics, and the hypotheses we seek to test with each variable are described below.

Age of the station. Age of the station is taken as the number of years since the station opened. This figure is averaged if the station was opened in stages. Our hypothesis is that older stations will incur higher maintenance costs than new stations.

Lifts and escalators. The number of lifts and escalators within a station may influence the operating cost because this equipment needs to be in operation on a daily basis and frequently maintained.

Number of ticket machines/ticket offices/ticket sales windows/entry and exit gates. The number of ticket machines includes only those machines used by the public to purchase or validate tickets. The number of ticket offices is the number of areas in the station where ticket-selling takes place. The number of ticket sales windows relates to the number of potentially staffed positions used by the metro staff to sell tickets to passengers. We hypothesize that these factors will influence the staff costs of the station.

Number of opening hours per day. This variable is taken as the average number of metro station opening hours per day. The hypothesis is, of course, that longer operating hours induce higher costs.

Service frequency. Two service frequency variables—peak frequency and off-peak frequency—are considered. Frequency is calculated as the average number of trains per hour (each way) during peak periods (peak frequency) or off-peak periods (off-peak frequency). The inclusion of these variables will allow us to test whether costs are associated with frequency.

Length of trains. This is calculated as the total number of carriages of a train using the station. At stations with multiple lines averages are used.

Platform dimensions. Variables for width, length, and elevation of the platform are used to determine if these factors are important for maintenance and cleaning costs.

Roof length of platforms. For underground stations, this is clearly the same as platform length, but for at-grade and elevated stations only part of platforms may be covered by a canopy, shelter, or overall roof. This variable is included to understand if variation in the maintenance associated with roof lengths affects total station costs.

Length of passageways. This is measured as the total length of passageways, including escalator shafts, estimated by metros as an indicative proxy for the amount of cleaning and building repair that may need to be done. No account is taken of possible variations in passageway width. A better measure might have been the total floor area, but this would not have directly reflected the amount of walls and ceilings that need maintenance and cleaning; this is also discarded as a measure because it is more difficult for metros to estimate easily.

Station demand variables. The two main demand variables considered are entry demand and interchange demand. Station entry demand is the total number of passengers entering the station per year. This includes passengers changing modes at the station, and entering from mainline rail or bus stations, as well as those starting their journeys locally and entering the station on foot. Interchange demand relates only to those passengers changing metro lines at the station concerned. Two secondary variables—peak entry demand and peak interchange demand—are also considered. Peak entry (interchange) demand is calculated as the total number of entry (interchange) passengers for the busiest hour during a standard week, and is designed to test whether peak demand (entry/interchange) drives station capacity and hence costs, or total demand drives staffing levels and hence cost.

Types of metro stations. Dummy variables are used to reflect the overall type of metros in terms of being at-grade, elevated, subsurface (typically constructed by cut and cover, and 5–6m below ground), or deep tube. At-grade and subsurface stations can be managed without lifts or escalators for passengers to travel vertically, whereas elevated and deep tube stations normally need this equipment, which adds significantly to costs (e.g., electricity).

Other variables. Presence of air-conditioning, toilets for public use, platform screen doors, and shops are all included in modeling through a dummy variables. Each is thought to generate costs (electricity, cleaning, maintenance, and management time).

Results

Prior to model fitting, a number of statistical tests were performed to determine the nature of the data. For example, it is possible that the explanatory variables may be correlated with each other (the effect of multicollinearity) or that the data exhibits heteroskedasticity (the effect of nonconstant variance).

Although imperfect multicollinearity does not violate the assumptions of the classical model, if its presence is sufficiently acute, it can lead to biased, inefficient, and even wrongly signed estimates. If the overall goodness of fit, R^2 , is relatively high (say more than 0.8) but only few explanatory variables are significantly different from 0 or there are high pair-wise correlations among the regressors, then it is possible that multicollinearity may be present. Here, we use the variance inflation factor (VIF) proposed by Chatterjee et al. (2000) to determine the presence of multicollinearity. The number of ticket gates at a station, for example, is found to be highly correlated with the entry demand at the station, and the length of the platform at a station is correlated with the length of the longest train passing the station. Based on the VIF test, the highly correlated variables are excluded from the explanatory variables used in the final model. The problem of Omitted Variable Bias (OVB) is addressed in the conventional way by the use of proxy variables and fixed effects to control for unobserved metro-specific variables. We have no evidence that multicollinearity affects the parameter estimates.

Data from London metro stations are not included in the model as operating costs are not obtainable at the station level for the categories which are consistent with the other metros. This reduces the total number of observations to 83. However, we still have to estimate more than 30 parameters which are found to be uncorrelated with each other. Some of the explanatory variables such as entry and interchange demand, lifts, and escalators are then combined to minimize the number of parameters to be estimated. A dummy variable is used to represent the presence of lifts or escalators within a station in the model. This variable takes on a value of 1 if there are any lifts or escalators in a metro station and a value of 0 otherwise. Summary statistics (observations, mean, standard deviation, minimum, and maximum) of the final explanatory variables used in the model are shown in Table 1.

Table 1. Summary Statistics of Explanatory Variables Used in the Model

Variables	Obs	Mean	Std. Dev.	Min	Max
Operating cost (US\$)	83	933731.1	831858.3	148085.7	4347232
Age of station (years)	83	37.265	39.326	1	170
Ticket office (1=Yes, 0=otherwise)	83	0.892	0.313	0	1
Total number of entrances	83	3.434	2.232	1	11
Opening hours per day	83	18.800	0.961	17	21
Presence of escalators or lifts (1=Yes, 0=otherwise)	83	0.928	0.261	0	1
Total passages (m)	83	349	448	0	2808
Total number of platforms	83	2.337	0.994	1	6
The width of the platform (m)	83	8.923	7.684	3	30
The length of the longest train (carriages)	83	6.394	1.848	3	12
Peak frequency (each way train/h)	83	17.845	8.245	4	36
Demand (entry+interchange) (passenger p.a.)	83	14200000	19700000	270000	98900000
Roof length (m)	83	122.024	62.853	0	300
Air-conditioning (1=Yes, 0=otherwise)	83	0.229	0.423	0	1
Presence of toilets (1=Yes, 0=otherwise)	83	0.434	0.499	0	1
Types of metro stations					
At grade	83	0.108	0.313	0	1
Elevated	83	0.265	0.444	0	1
Subsurface	83	0.072	0.261	0	1
Tube	83	0.554	0.500	0	1
Metros 1					
Metro-1	83	0.072	0.261	0	1
Metro-2	83	0.157	0.366	0	1
Metro-3	83	0.072	0.261	0	1
Metro-4	83	0.036	0.188	0	1
Metro-5	83	0.084	0.280	0	1
Metro-6	83	0.084	0.280	0	1
Metro-7	83	0.072	0.261	0	1
Metro-8	83	0.084	0.280	0	1
Metro-9	83	0.084	0.280	0	1
Metro-10	83	0.084	0.280	0	1
Metro-11	83	0.072	0.261	0	1
Metro-12	83	0.096	0.297	0	1

1. Metro names are omitted to preserve confidentiality.

Another important assumption of the classical linear regression model is that the disturbances appearing in the regression function are homoskedastic. The problem of heteroskedasticity is common in cross-sectional analysis because the data usually involves observations from heterogeneous units (i.e., stations from different metros), and therefore heteroskedasticity may be expected if data from small, medium, and large stations are sampled together. In conducting the Park Test (Park 1966), we find that our data are not characterized by heteroskedasticity. This may be due to the use of the log linear model, which reduces the variances among the variables.

Table 2 presents our results. Two models are considered: one without metro dummies and one with metro dummies. The second model includes the metro-specific effects to control for heterogeneous environments. Ramsey's RESET test (an F-test) is used to select the better model (Ramsey 1969) and this shows that the addition of metro station dummies significantly increases the goodness of fit of the model. Therefore, the model with the metro station dummies is used for the interpretation of the results.

The model goodness of fit, the adjusted R^2 , is 0.88, which shows a good degree of explanatory power for a cross-sectional model. The comparison between the observed cost and the predicted cost is shown in Figure 1. The mean prediction error is found to be only 2.3 percent. Note that the names of the metros are omitted to preserve confidentiality.

Figure 1. Observed and Predicted Costs

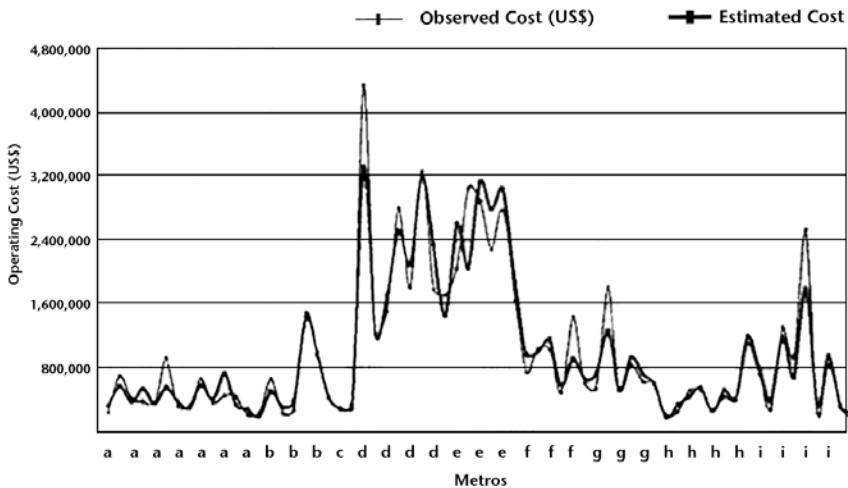


Table 2. Model Estimation Results for the Operating Cost of a Metro Station

Dependent Variable=ln [total operation cost (US\$)]	Log Linear Model					
	Without Metro Dummies			With Metro Dummies		
<i>Explanatory variables</i>	Coeff	t-stat	p-value	Coeff	t-stat	p-value
ln [age of station (years)]	-0.070	-0.90	0.37	-0.100	-1.71	0.09
Ticket office (1=Yes, 0=otherwise)	0.073	0.29	0.77	0.070	0.28	0.78
ln (total number of entrances)	0.064	0.60	0.55	-0.033	-0.40	0.69
ln (opening hours per day)	0.055	0.03	0.97	0.447	0.12	0.90
Presence of Escalators or Lifts (1=Yes, 0=otherwise)	-0.301	-1.13	0.26	-0.229	-1.27	0.21
ln [total passages (m)]	0.093	1.96	0.06	0.142	2.56	0.01
ln (total number of platforms)	0.178	1.04	0.30	0.270	2.25	0.03
ln (width of the platform)	-0.303	-2.39	0.02	-0.113	-0.91	0.37
ln [length of the longest train (vehicles)]	0.258	0.86	0.39	0.423	1.35	0.18
ln [peak frequency (each way train/h)]	0.510	3.01	0.00	0.479	3.63	0.00
ln [demand (entry+interchange) (passenger p.a.)]	0.150	2.11	0.04	0.096	2.08	0.04
ln [roof length (m)]	0.100	1.43	0.16	0.083	1.65	0.10
<i>Types of stations</i>						
At grade (Reference)	-	-	-	-	-	-
Elevated	-0.180	-0.78	0.44	0.093	0.56	0.58
Subsurface	-0.364	-0.96	0.34	0.324	1.12	0.27
Tube	-0.312	-1.25	0.21	0.332	1.54	0.13
Air-conditioning (1=Yes, 0=otherwise)	0.740	3.81	0.00	0.345	2.02	0.05
Presence of toilets (1=Yes, 0=otherwise)	-0.106	-0.86	0.39	0.324	2.85	0.01
<i>Metro-specific dummy 1</i>						
Metro-1 (Reference)	-	-	-	-	-	-
Metro-2				-0.080	-0.21	0.84
Metro-3				1.213	2.72	0.01
Metro-4				0.537	0.93	0.36
Metro-5				0.659	1.89	0.06
Metro-6				0.623	1.69	0.10
Metro-7				0.946	2.45	0.02
Metro-8				-0.360	-0.77	0.44
Metro-9				-0.240	-0.57	0.57
Metro-10				-0.300	-0.71	0.48
Metro-11				0.134	0.47	0.64
Metro-12				0.165	0.61	0.55
Constant	9.051	1.91	0.06	7.27	0.68	0.50
<i>Descriptive statistics</i>						
Number of observations (valid)	83.00			83.00		
R-squared	0.70			0.92		
Adjusted R-squared	0.63			0.88		

1. Metro names are omitted to preserve confidentiality.

Table 2 shows a number of statistically significant effects on metro station operating cost that arise having controlled for unobservable system-specific effects.

The age of the station is found to be negatively associated with the operating cost of a metro station at the 90 percent confidence level. This is surprising as we would expect an older station to require more maintenance and hence be associated with higher costs. The explanation of this counterintuitive finding may be due to the fact that more recent stations (e.g., KCR, Hong Kong) tend to be larger and to have higher quality facilities, which also require a relatively high maintenance treatment.

Length of passageways, total number of platforms, peak-hour service frequency, and entry and interchange demand are found to be statistically significant at the 95 percent confidence level and positively associated with the operating cost. These results confirm our hypotheses. The elasticity associated with the peak-period service frequency is higher compared to others. The result suggests that a 10 percent increase in peak-period service frequency (each way, per hour) is associated with a 4.8 percent increase in the operating cost, and a 10 percent increase in the number of platforms leads to a 2.7 percent increase in the operating cost. The length of the roof is also found to be positively associated with the cost but only at the 90 percent confidence interval.

The effect of air-conditioning is captured by a dummy variable. This variable is found to be positively associated with the operating cost and is statistically significantly different from 0 at the 95 percent confidence level. This is an indication that average operating cost is high in a station with air-conditioning if all other factors remain constant. The coefficient (θ) of the effect of the air-conditioning is 0.35, indicating that the relative effect on the average operating cost due to the presence of air-conditioning is $100 \cdot \{\exp(\theta) - 1\}$, or 41 percent. In other words, air-conditioning has an extremely large impact on costs, increasing the expected operating cost by 41 percent, holding all other factors included in the model constant.

The presence of toilets within a station is also found to be positively associated with the operating cost. This is expected as some costs are associated with the maintenance and staffing of toilets. However, the coefficient of this variable is unexpectedly high, perhaps because this variable represents the effects of some other factors that are not included in the model.

Interestingly, the type of metro station has little effect on operating cost. As explained previously, a categorical variable (grade, subsurface, elevated, and tube) is used to reflect the overall type of metro station. None of the coefficient estimates are statistically significant at the 95 percent confidence level. The tube-type metro station shows a positive coefficient relative to the at-grade-type station but only at the 87 percent confidence level.

The system-specific dummy variables are expressed relative to and intercept for Metro-1. The result suggests that Metro-3, Metro-5, Metro-6, and Metro-7 are costlier compared to Metro-1. The operating cost associated with Metro-5, for instance, is about 93 percent higher relative to Metro-1 if all other factors included in the model remain constant.

The number of ticket offices in a station, total number of entrances, operating hours per day, presence of lifts or escalators, width of platforms, and length of the longest train are found to be statistically insignificant. This is perhaps because the metro-specific dummies included in the model pick up the effects hypothesized from these factors.

The models are reestimated without the statistically insignificant variables (below 90% confidence level) of the models presented in Table 2 (with metro dummies). The results are shown in Table 3. Interestingly, the model goodness of fit remains the same after excluding five insignificant explanatory variables. The age of the station now becomes insignificant. As expected, the metro dummies now pick up most of these effects. The operating cost of Metro-2, Metro-8, Metro-9, and Metro-10 are now lower relative to Metro-1. The effects of all other factors remain invariable.

A limitation of the analysis is that not all of the characteristics associated with cost are readily alterable. For instance, the length of a metro station's roof plays a major role in increasing the station's operating cost.

The standard errors associated with the parameter estimates give us a guide as to how confident we can be in the magnitudes indicated by our results. Of course, econometric models can be revised given better data or new hypotheses to test, but an econometric model should be assessed based on both the "significance" of a variable and "the estimated magnitude of the effects" of the variable as this is one of the fundamental objectives of estimating an econometric model.

Table 3. Reestimated Models with Significant Variables of the Models Shown in Table 2

Dependent Variable=ln [total operation cost (US\$)]	Log Linear Model					
	Without Metro Dummies			With Metro Dummies		
<i>Explanatory variables</i>	Coeff	t -stat	p-value	Coeff	t -stat	p-value
Age of station (years)	0.010	0.16	0.87	-0.059	-1.21	0.23
Total passages (m)	0.123	3.12	0.00	0.090	2.08	0.04
Total number of platforms	0.193	1.15	0.25	0.317	2.89	0.01
Peak frequency (each way train/h)	0.342	2.50	0.02	0.477	3.88	0.00
Demand (entry+interchange) (passenger p.a.)	0.129	2.08	0.04	0.088	2.27	0.03
Roof length (m)	0.122	1.99	0.05	0.115	2.72	0.01
<i>Types of stations</i>						
At grade (reference)	-	-	-	-	-	-
Elevated	-0.446	-2.15	0.04	0.002	0.01	0.99
Subsurface	-0.523	-1.80	0.08	0.203	0.80	0.43
Tube	-0.499	-2.43	0.02	0.209	1.11	0.27
Air-conditioning (1=Yes, 0=otherwise)	0.631	4.25	0.00	0.304	1.95	0.06
Presence of toilets (1=Yes, 0=otherwise)	-0.164	-1.44	0.15	0.280	2.69	0.01
<i>Station-specific dummy 1</i>						
Metro-1 (reference)	-	-	-	-	-	-
Metro-2				-0.374	-2.10	0.04
Metro-3				0.981	3.74	0.00
Metro-4				0.018	0.06	0.95
Metro-5				0.464	1.76	0.08
Metro-6				0.584	1.90	0.06
Metro-7				0.467	2.06	0.04
Metro-8				-0.453	-2.15	0.04
Metro-9				-0.739	-2.54	0.01
Metro-10				-0.475	-1.94	0.06
Metro-11				-0.045	-0.22	0.82
Metro-12				-0.018	-0.09	0.93
Constant	9.481	12.49	0.00	9.388	16.90	0.00
<i>Descriptive statistics</i>						
Number of observations (valid)	83			83		
R-squared	0.69			0.92		
Adjusted R-squared	0.64			0.88		

1. Metro names are omitted to preserve confidentiality.

Conclusions

We have developed an econometric model to investigate variance in metro station operating costs. The model regresses total metro station operating costs on a series of station characteristics and a set of metro systems' specific dummy variables. The results show strong unobserved system-specific effects, confirming the need to differentiate the data in this way. Over and above the system-specific

effects, we have identified some factors that appear to have an important influence on the levels of station costs. These include length of passageways, number of platforms, peak-level service frequency, interchange demand, and the provision of toilet facilities. In addition, we find a very strong effect from the existence of air-conditioning, which raises the expected station operating cost by as much as 40 percent.

Stations operating costs can be classified amongst those semifixed costs that do not vary proportionately with metro output. For this reason, they may be very important in determining the magnitude of RTD on the costs structure and productive efficiency of the firms. This article has provided an improved understanding of some of the major factors driving these costs.

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Design of Feeder Route Network Using Combined Genetic Algorithm and Specialized Repair Heuristic

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Abstract

In metropolitan cities an efficient integrated public transportation system is unavoidable to restrict unsustainable growth of private and intermediate transport modes. Well-designed feeder routes and coordinated schedules to minimize transfer time from the main transit to feeder buses play an important role. Past literature reveals that a heuristic approach had been popular for design of routes and had been applied successfully in a variety of network design problems. Nontraditional optimization techniques, especially genetic algorithms, are also found to be very effective in the generation of optimized feeder routes and schedules. In this research the genetic algorithm first develops feeder routes and then a specialized heuristic algorithm works as a repair algorithm to satisfy the demand of all the nodes. Thus, the advantages of both genetic algorithms and specialized heuristic algorithms are obtained in this method. The developed feeder route structure is found to be better in terms of load factors in buses, satisfaction of demand, and waiting time for feeder buses as compared to existing scenarios and earlier approaches adopted for the same study area.

Introduction

In metropolitan cities of developed and developing countries, suburban railway and public buses are the most common public transport carriers. Commuter dissatisfaction toward public transport stems from increased travel time, poor levels of comfort, uneconomical operations, and higher out-of-vehicle time, especially at transfer points. These problems can be solved by appropriate coordination between major public transport modes. Successful coordination implies

- the traveller's ability to transfer freely and conveniently between modes;
- distinct service areas between each modes, thereby minimizing duplication of services;
- adjustment and interrelationship of schedules; and
- joint fare structure.

A poorly coordinated transfer can require long, irregular waiting for infrequent connecting services. The point of balance between travellers' demand for a direct service and the transit operator's need for economy often lies in the level of attention given to the details of the transfer. Thus, well-designed feeder routes satisfying maximum demand with acceptable travel times are of prime concern. To minimize transfer time, coordinated schedules have to be optimized.

Literature Review and Objective of Study

Many research studies have been conducted of bus route network design problems involving development of routes and schedules. Lampkin and Saalmans (1967), Silman et al. (1974), Dubois et al. (1979), Mandl (1980), and Baaj and Mahmassani (1995) developed bus routes using a heuristic approach. Shrivastava and Dhingra (2001) successfully implemented a heuristic approach for the design of feeder routes for feeder public buses at suburban railway stations. Heuristic algorithms are not theoretically rigorous but have been used successfully for real networks and are capable of providing suboptimal values. Genetic algorithms (GAs), which are robust optimization techniques, have been used successfully for routing and scheduling problems. Pattnaik et al. (1998), Gundaliya et al. (2000), and Tom and Mohan (2003) used GAs for the design of bus route networks. Shrivastava and Dhingra (2002) successfully generated coordinated schedules of public buses for existing schedules of suburban trains on the developed feeder route network using GAs. Chien et al. (2003) presented a model for optimizing service headway and

a bus route serving an area with a commuter (many-to-one) travel pattern. The bus route is optimized by minimizing total system cost, including operator and user costs, while considering diagonal links in the study network. Zhao and Ubaka (2004) presented a mathematical methodology for transit route network optimization. The goal was to develop an effective computational tool for the optimization of large-scale transit route networks. The objectives were to minimize transfers and optimize route directness while maximizing service coverage. Agrawal and Mathew (2004) proposed two parallel genetic algorithm (PGA) models. The first was a global parallel virtual machine (PVM) parallel GA model. The second was a global message passing interface (MPI) parallel GA model. The global PVM model appeared to perform better than the other. Fan and Machemehl (2004) formulated a multiobjective nonlinear mixed integer model for a transit route network design problem (TRNDP). The proposed solution framework consisted of three main components: an Initial Candidate Route Set Generation Procedure (ICRSGP); a network analysis procedure; and a Heuristic Search Procedure (HSP). Five heuristic algorithms—including the GA, local search, simulated annealing, random search, and tabu search—are solution methods for finding an optimal set of routes from the huge solution space. Sensitivity analysis for each algorithm was conducted and model comparisons were performed.

Studies on the development of feeder routes for the same study area using different approaches have been presented. In one study, Shrivastava and O'Mahony (2005) developed feeder routes using a heuristic algorithm that was found to be very effective and the demand at all nodes was satisfied by the developed set of routes. Using a heuristic approach, a set of the routes cannot be guaranteed to be at optimal level; it may yield suboptimal results also. In other research, Shrivastava and O'Mahony (2006) developed feeder routes and schedules simultaneously using GAs for the same study area. While the developed routes and schedules were optimum, the entire demand was not satisfied because in a typical study area some of the nodes did not have good connectivity with other nodes. In view of this, instead of 17 nodes only 16 were selected; the remotest node in the study area was not included. In this article, both approaches are combined and the benefits of both are obtained. The optimal set of feeder routes are first developed by GAs and if any demand remains unsatisfied, it is inserted and/or attached to the best possible route by the specialized heuristic approach, which works as a repair algorithm. Thus, the advantages of both approaches are achieved in this research.

The objective of the proposed research is development of a feeder bus route network and coordinated schedules for public buses for the existing schedules of main transit (suburban train) at the given Dublin (Ireland) Area Rapid Transit (DART) station. To satisfy the entire demand, the routes developed by GAs were modified by a well-designed heuristic approach. The modified routes were used for determination of coordinated schedules. The Dun Laoghaire DART station was selected as the case study. Dun Laoghaire is a rapidly growing suburb of Dublin. Coordination between DART services and Dublin public buses for this DART station is attempted.

Data Collection

DART is a suburban railway system in Dublin running along the coastline of Dublin Bay from Greystones to Howth and Malahide. The existing DART line has 32 stations. Lack of coordination between public buses and DART services has been observed even during peak hours at many stations. Dun Laoghaire is one of the prominent DART stations from where large numbers of trips originate. Dun Laoghaire was selected as the study area due to its land-use pattern, which allows greater scope of feeder bus services from the station. Considerable movement of commuters takes place to many areas from the DART station.

Typical traffic surveys were conducted during the morning peak period (i.e., 7–9AM) on April 28, 2004. Since the maximum number of commuters travel from 8–9AM, this time period is identified as the peak hour. It was confirmed during the surveys that after 9AM commuter traffic starts decreasing and becomes much less after 9.30AM. During the surveys, commuters exiting the DART station were counted manually. Traffic surveyors conducted sample interviews with commuters leaving the DART station. Commuters were asked about their destinations, mode of transport, and travel time to their destinations from the DART station. Commuters not opting for public buses for their further journeys were also asked about their willingness to shift to public buses if buses were coordinated with DART services in future. Of those surveyed, 40 percent work very near the DART station and they only have to walk about 5 minutes. These commuters were not interested in shifting to public buses even if they are well coordinated with DART services. The percentage of commuters willing to move to public buses was added to those who use public buses and a potential demand matrix for public buses was developed. There are 16 destinations (nodes) for which demand exists from the DART station. Table 1 indicates potential demands to various destinations. It

was also observed during the surveys that in the morning peak period the trains toward the city center (northbound trains) contribute about 30 percent of the passengers; the remaining 70 percent were by trains from the city center (southbound trains). There were nine northbound and eight southbound trains during the peak hour of 8–9AM. The schedule coordination for feeder buses is attempted for these trains during the indicated peak hour.

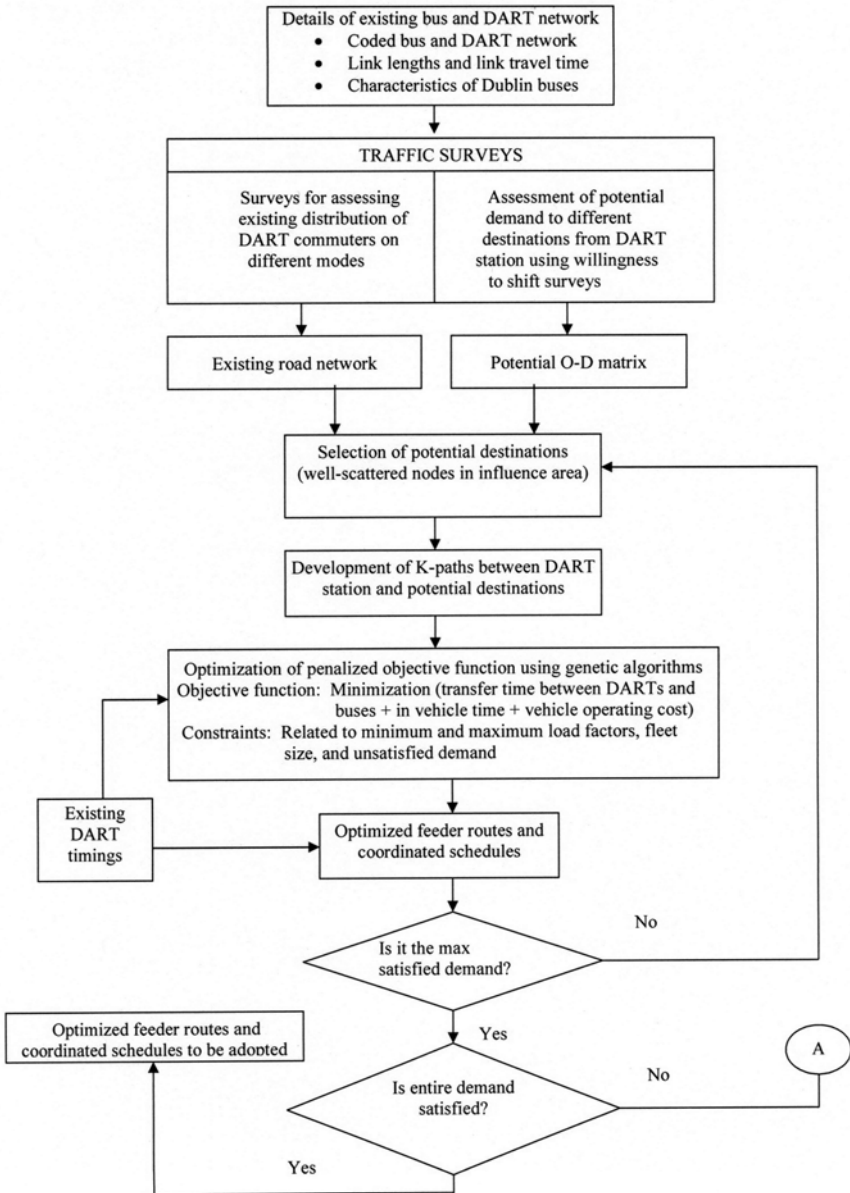
Table 1. Potential Demand to Various Destinations

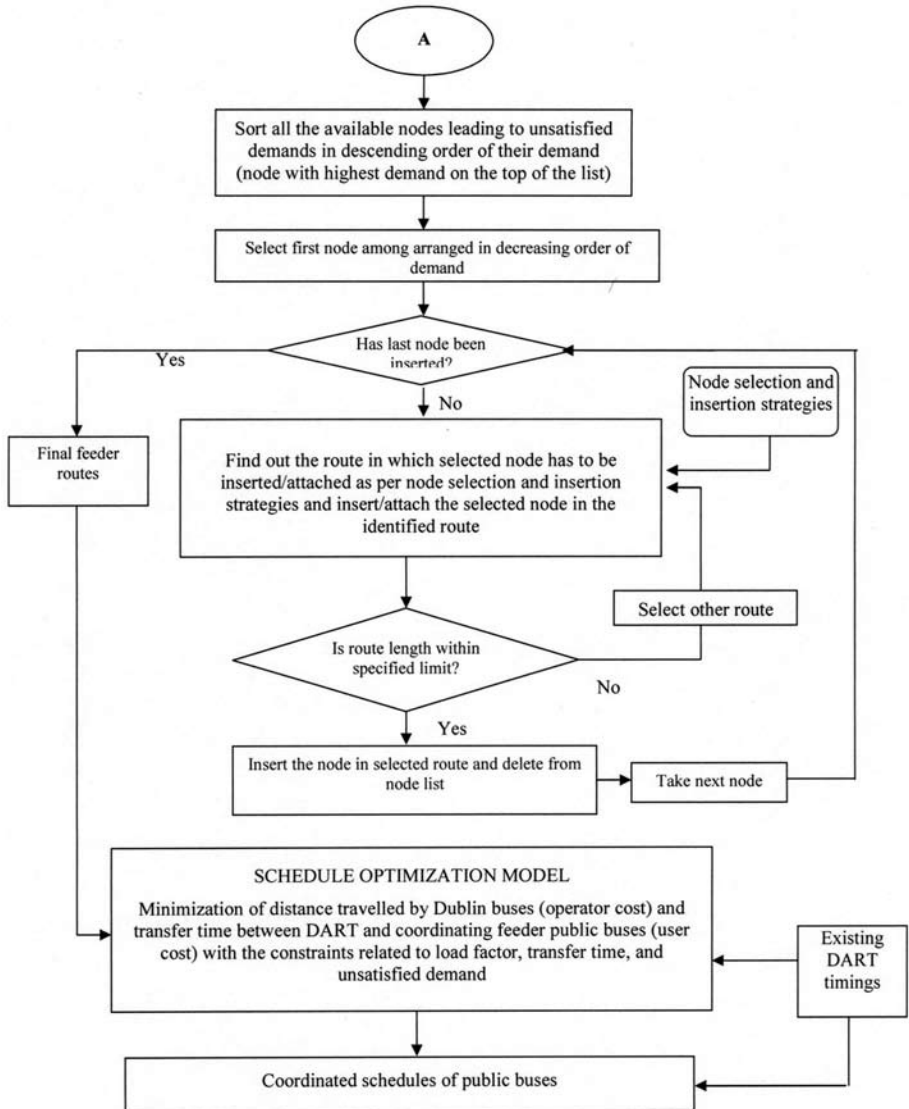
<i>Node No. (code)</i>	<i>Destinations</i>	<i>Potential Demand to Various Destinations</i>		
		<i>7–8AM</i>	<i>8–9 AM</i>	<i>7–9 AM</i>
1	Dun Laoghaire DART Station	00	00	00
2	Dun Laoghaire College	39	202	241
3	Sallynoggin	17	103	120
4	Monks town	10	63	73
5	Deans Grange	16	93	109
6	Temple Hill	02	06	08
7	Black Rock	08	46	54
8	Stillorgan	13	77	90
9	Leopards town	02	08	10
10	Foxrock	02	08	10
11	Maple Manor/Cabinteely	02	04	06
12	Lough Linstown	13	78	91
13	Mount Merrion	02	15	17
14	University College of Dublin	04	23	27
15	Dundrum	06	31	37
16	Sandyford	03	15	18
17	Rouches Town Avenue	02	04	06

Proposed Methodology

The overall methodology for development of feeder routes and coordinated schedules is presented in Figure 1. The methodology is explained in the following steps.

Figure 1. Methodology for Development of Feeder Routes and Coordinated Schedules





Step 1

A potential demand matrix is developed with its origin at a DART station and with destinations as identified in traffic surveys.

Step 2

A travel distance matrix and connectivity details between various nodes were obtained from the Dublin Street Map (2000). The travel distance matrix was converted into a travel time matrix in “minutes,” using an average speed of 15 Km/hr to address the existing congestion level and road geometrics of the influence area (Wilson 2000).

Step 3

Other parameters like capacity of buses, minimum and maximum load factors, maximum fleet size, minimum frequency per hour, minimum and maximum lengths of routes, and multiplying constants, which have been used to convert objective function into monetary values of “euro,” were decided as per practical realities and existing conditions.

Step 4

Using the k-path algorithm (Eppstein 1994), k-shortest paths were developed between the DART station and a set of destinations, which are well scattered and cover the entire influence area. The value of K is adopted as 5 for the case study.

In this research, destinations were based on their locations so that a larger portion of the feeder route network is optimized by GA and the repair heuristic is used only for a few nodes. In view of this, various sets of destinations that were located away from origin and well scattered in the influence area were selected. The set of destinations was selected for which maximum demand is satisfied with the least number of k-paths using GA and few node/nodes are left for the repair heuristic.

With the help of traffic surveys, various locations (nodes) to which demand existed were identified. The selected set of nodes, based on the above criteria for which k-paths were developed, is identified as potential destinations.

K indicates the number of short paths that can be developed between a given origin (DART station) and potential destination. These short paths are developed in the increasing order of their lengths. In this research, the value of k is selected as 5 (i.e., between each origin—DART Station) and potential destination. Five short paths are developed, of which the first is the smallest and the last is largest. Out of

these k-paths the best one is selected after application of GA (corresponding to optimized penalized objective function).

Step 5

The program to calculate a penalized objective function (summation of objective function and penalties due to violation of constraints) is developed in C++ environment. The set of k-paths (5 in the case study for each origin and potential destination) are used with the GA. The coding of a path and its corresponding frequencies are done together in one string only. The binary digit coding to represent routes and schedules together has been adopted. The set of k-paths and frequencies for which the objective function along with penalties is minimum is selected as optimized routes and frequencies. These routes are used for application of specialized heuristics discussed in further steps. The frequencies are used to derive coordinated schedules for the existing DART schedules. Details of the objective function, penalties, and application of GAs are discussed below.

Details of Objective Function, Penalties and Use of GAs. The objective function is adopted as minimization of user and operator costs. User cost is the summation of in-vehicle time cost and transfer time cost between DARTs and buses. Operator cost is associated with vehicle operation cost. Constraints are related to load factor, fleet size, and unsatisfied demand. Mathematically, the objective function and various constraints are as follows:

Objective Function.

Minimize total cost, $Z = \{ \text{Transfer time cost between DARTs and coordinating buses} + \text{travel time cost in buses on selected routes (in-vehicle time cost in buses)} + \text{vehicle operation cost (VOC) of Dublin buses} \}$

Mathematically it can be expressed as

Minimize

$$C_1 \left\{ \sum_j \sum_u \sum_l \text{pass}_j^u (\text{bus}_j^l - \text{dart}^u) \delta_j^{u,l} + \sum_j \sum_u \sum_l \text{pass}_j^v (\text{bus}_j^l - \text{dart}^v) \delta_j^{v,l} \right\} +$$

← Transfer time between nth and sth bound DARTs and buses (first term) →

$$\begin{array}{c}
 \leftarrow \text{In vehicle time} \rightarrow \quad \leftarrow \text{VOC} \rightarrow \\
 \text{in bus (2}^{\text{nd}} \text{ term)} \quad \quad \quad (3^{\text{rd}} \text{ term)} \\
 C_2 \left\{ \sum_j \text{pass}_j \times t_{\text{inv},j} \right\} + C_3 \left\{ \sum_j f_j T l_j \right\} \quad (1)
 \end{array}$$

Constraints.

$$1. \frac{Q_j \text{ max}}{N_j \times CAP} \leq L \text{ max} \quad \text{Maximum load factor constraint} \quad (2)$$

$$2. \frac{Q_j \text{ max}}{N_j \times CAP} \geq L \text{ min} \quad \text{Minimum load factor constraint} \quad (3)$$

$$3. \sum_{j \in SR} NB_j = \sum_{k \in SR} \frac{N_j * (RT)_j}{TP} \leq W \text{ (for all } j \leq SR) \quad \text{Fleet size constraint} \quad (4)$$

$$4. \sum_j d_{\text{unsat}} = 0 \quad \text{Unsatisfied demand constraint} \quad (5)$$

Where:

j is the number of routes available at each station (as per number of potential selected destinations)

l equals the number of buses available for u^{th} northbound DART and v^{th} southbound DART

VOC represents vehicle operating cost for Dublin buses

C_1 is the cost of transfer time in Euro per minute, 11.32 cents/minute for the case study (Steer Davies 1994)

C_2 equals the cost of in-vehicle time in Dublin buses, 0.076 cents/minute for the case study (Steer Davies 1994)

C_3 denotes the cost of operation of Dublin bus per Km., € 3.66 for Dublin buses for the case study (Wilson 2000)

pass_j^u indicates passengers transferring from u^{th} northbound DART to j^{th} route

pass_j^v represents passengers transferring from v^{th} southbound DART to j^{th} route

- $pass_j$ is the total number of passengers transferring to j^{th} route
- bus_j^l is the departure of l^{th} bus on j^{th} route
- $dart^u$ represents arrival of u^{th} northbound DART
- $dart^v$ represents arrival of v^{th} southbound DART
- $\delta_j^{u,l}$ shows whether transfer of passengers is possible. It attains a value of 1 if transfer from u^{th} northbound DART to l^{th} bus on j^{th} route at DART station is feasible; otherwise it attains a value of 0
- $\delta_j^{v,l}$ shows whether transfer of passengers is possible. It attains a value of 1 if transfer from v^{th} southbound DART to l^{th} bus on j^{th} route at DART station is feasible; otherwise it attains a value of 0
- t_{inv-j} denotes in-vehicle time in bus on j^{th} route
- f_j is the frequency of buses on j^{th} route in terms of number of bus trips per hour
- l_j represents length of j^{th} route in kilometers
- T is time period in hours
- $Q_{j,max}$ is the maximum number of passengers on j^{th} route for the given time period
- CAP indicates bus seating capacity; for Dublin buses it is 74 (Wilson 2000)
- L_{max} equals the maximum load factor; it is 1.2 for the case study (Wilson 2000)
- L_{min} equals the minimum load factor; it is 1 for the case study
- d_{unsat} represents unsatisfied demand
- SR equals set of routes
- NB_j is the number of buses required in any route j
- $(RT)_j$ is the round-trip time of the bus on j^{th} route in minutes = $2 t_j$ (in minutes) + layover time (5 minutes for the case study)

- t_j represents total travel time on the route in minutes, including stopping times (journey time)
- TP equals time period in minutes
- N_j is the number of trips per hour times the time period in hours under consideration ($f_j * T$)
- W denotes the maximum number of available buses

The first two terms of the objective function indicate user cost; the third term denotes operator cost. User cost is the summation of costs associated in transferring from DART services (both north and southbound) to coordinating buses (first term) and the cost of traveling time in the buses (second term). Operator cost is in terms of vehicle operating cost, which is proportional to the distance traveled by buses (third term). Constants C_1 , C_2 , and C_3 are used to convert each term of the objective function in monetary unit of Euro (€). The first and second constraints ensure that the load factor lies within a maximum and a minimum value. If the load factor is less than a maximum value, then the crowding level will be less and a better level of service will prevail. The level of service should not be less than a minimum value so as to ascertain availability of a certain minimum number of passengers for economical operations. The maximum load factor is the ratio of crush capacity and normal capacity of Dublin buses. The crush capacity is 88 and normal capacity is 74; thus, the maximum load factor (the ratio of the two capacities) is 1.2 (Wilson 2000). The minimum load factor is 1. The third constraint is associated with fleet size. This constraint puts an upper limit on the maximum number of available buses for operation. The fourth constraint ensures that maximum demand is satisfied and the maximum number of commuters get coordinating buses during the period of analysis. The aim of schedule coordination is to provide coordinating buses to all commuters who transfer from trains to buses. If a large number of commuters are not able to get coordinating buses, the penalty should be higher and it is added to the objective function so that subsequently the GA search for optimal or near optimal values is directed. The penalty corresponding to the fourth constraint is proportional to the ratio of demand unsatisfied to the capacity of buses. This penalty would have played a more realistic role if data collection was done for the whole day (i.e., until the last DART and last available bus).

Because the objective function and constraints in the study pose a constraint optimization problem, the penalty method is adopted for optimization (Deb 1995). Using GAs, the minimum value of the penalized objective function is determined (best fit). Routes and frequencies corresponding to this minimum value are optimal feeder routes and frequencies. These optimal frequencies are used to determine coordinated schedules of feeder buses.

Fitness function = Minimize (Objective Function + Penalties 1 to 4)

Penalty 1: If load factor is more than a maximum value (1.2 for the case study)

Penalty 2: If load factor is less than minimum value (1 for the case study)

Penalty 3: If fleet size exceeds a minimum value (25 for the case study)

Penalty 4: If some demand remains unsatisfied

It is also observed in our typical traffic surveys that it takes about 5 minutes for commuters to reach bus stops located outside the station after arriving from DARTs. Thus, transfer from DART to a bus is feasible if the bus departs only after 5 minutes of scheduled arrival of the DART.

Step 6

Find out the percentage of demand satisfied by increasing/decreasing/changing the destinations as discussed in steps 4 and 5. Initially a few nodes (destinations identified in traffic surveys) that are well scattered and away from the origin are selected. K-paths are developed and it is determined how much the percentage of demand remains unsatisfied after application of GAs. The additional destination is added and again any improvement in satisfaction of percentage demand is determined. The number of destinations for which the maximum demand is satisfied is selected. By gradually augmenting the number of destinations, the maximum possible demand satisfaction is achieved. The minimum number of destinations leading to the maximum satisfaction of demand is selected as potential destinations. If the entire demand is satisfied for a particular combination of potential destinations, then the corresponding feeder routes and frequencies (for determination of coordinated schedules) are optimum. If the entire demand is not satisfied, go to step 7.

Step 7

Find the nodes leading to unsatisfied demand and insert them in the developed feeder routes by a heuristic node selection and insertion process. The node selec-

tion and insertion process acts as repair heuristics by modifying routes. [For a detailed discussion on node selection and insertion process/strategies, see Shrivastava and Dhingra (2001).] Using these repair heuristics, the following innovative ways can be employed for development of feeder routes:

- Determination of the best path among others in which an identified node (destination) can be inserted. The path is selected based on savings in passenger walk time and an increase in bus passenger time due to insertion of a node.
- After selecting the best path, the best way of insertion of node is identified. The best way is the one that gives least delay to destinations following the inserted node.

Step 8

Once all the nodes are inserted, the developed routes are used for determination of frequencies using GAs leading to optimum coordinated schedules for the existing DART schedules.

The objective function for this stage is simpler than the one discussed in step 5. In step 5 both routes and frequencies are determined using GA, whereas in this step only frequencies are determined. Therefore, the objective function involves only the first term (transfer time between DARTs and buses) and third term (vehicle operating cost) along with all the constraints of step 5. In step 5 the routes and frequencies were coded together, whereas in this step only frequencies are coded. Thus, the analysis at this stage is simpler than the one discussed in step 5. In view of this, the details of application of GA are not discussed here. [For a detailed discussion on determination of coordinated schedules on fully developed feeder route network, see Shrivastava and Dhingra (2002)].

Use of GAs for Objective Function and Constraints. GAs are based on exhaustive and random search techniques that are found to be robust for optimizing nonlinear and nonconvex functions (Holland 1992). In this research generational GAs with reproduction, crossover, and mutation operators are used (Goldberg 1989). The penalty method of constrained optimization is adopted (Deb 1995).

The proposed objective function is used with LibGA software of GAs in Linux environments to determine optimal frequencies on the developed feeder route network (Chambers 1995). GA parameters are tuned for the objective function and this type of process and best values of operators are decided. Roulette selection, simple random mutation, and uniform crossover are adopted. With seed

value as 1, pool size 30, crossover probability 0.85, and mutation probability 0.005, the lowest value of penalized objective function (objective function plus penalties) is provided. These values are used for the analysis. A set of frequencies on various routes corresponding to the minimum value of the penalized objective function is used for determining coordinated schedules on various routes.

The decision variables are routes and frequencies of buses during the application of GA. Routes and frequencies are coded together in the same string. The most common coding method is to transform the variables to a binary string. GA performs best when binary coding is adopted (Goldberg 1989). The length of the string is determined as per the desired solution accuracy. In this study, routes and coordinating frequencies of each pair are coded into a single string. Figure 2 indicates typical binary digits coding for routes 5 and 3 with frequencies 6 and 21 per hour. The first four bits show the route and the last six bits show the corresponding frequency in a string.

Figure 2. Binary Digit Coding

Pair No. 1				Pair No. 2											
Route		Frequency				Route		Frequency							
0	1	0	1	0	0	0	1	1	0	0	0	1	1	0	1
Route 5				Frequency 6				Route 3		Frequency 21					

The search space depends on the pool size and smaller pool sizes take less computational time. The case study discussed in this article requires much lower computational time because the size of matrix is very small. In the case of a large network and matrix, the pool size can be appropriately chosen based on convergence criterion. If a smaller pool size is taken, computational time will be lower and values closer to optimal can be obtained. Such values are practically acceptable for this type of problem. However, such smaller pool sizes should be tested with other operators and parameters for a given problem. The heuristic part of the algorithm does not take much computational time because only a few nodes are to be inserted on a fully developed network.

Results and Discussion

As discussed in the methodology, well-scattered minimum destinations satisfying maximum demand are selected as potential destinations. Maximum demand is satisfied when nodes 11, 12, 13, 15, and 16 are selected as potential destinations. Only 2.95 percent of demand remains unsatisfied for which the heuristic node selection and insertion strategy is applied. Table 2 lists the routes developed along with frequencies (for schedules) after application of GAs.

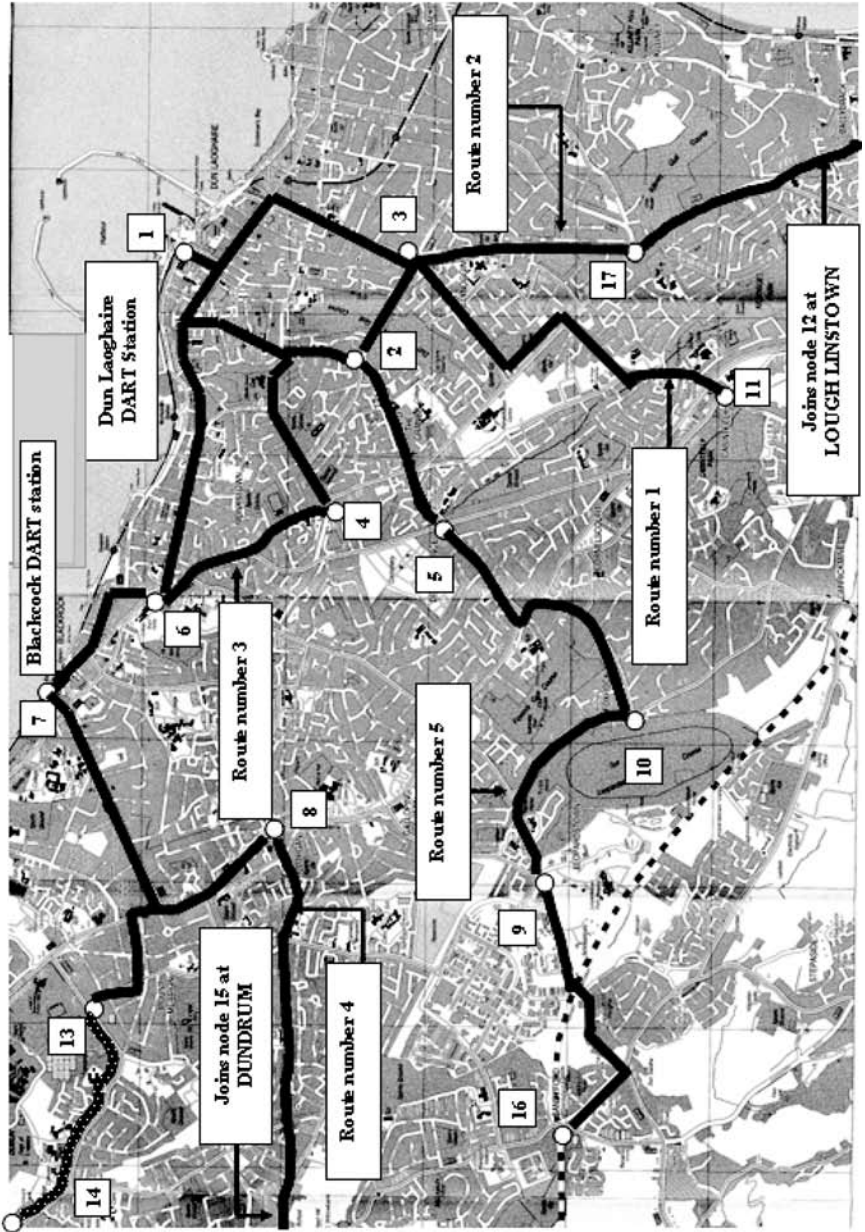
Table 2. Routes and Frequencies after Application of GAs

S. No.	Nodes in Feeder Routes	Length (in km)
1	1 – 3 – 11	4.5
2	1 – 2 – 3 – 17 – 12	6.75
3	1 – 4 – 6 – 7 – 13	8.00
4	1 – 6 – 7 – 8 – 15	10.25
5	1 – 2 – 5 – 10 – 9 – 16	9.00

Since the developed feeder route network does not satisfy 100 percent demand due to the absence of destination node 14 in the structure of feeder routes, the next stage of further modification of feeder routes using node selection and insertion strategies is adopted. Nodes are inserted/attached to developed feeder routes. Frequencies associated with feeder routes in the earlier stage are discarded since fresh frequencies are required to be determined due to modification of routes. After applying a heuristic node selection and insertion process, node 14 is attached with the third route and the length of the third route increases from 8 km to 9.68 km. Figure 3 shows the finally developed five-feeder route. Routes 3 and 4 partially overlap; also node 3 is common to routes 1 and 2. Thus, the overlapping aspects of routes are also successfully attempted in this research. The connectivity between 13 and 14 could be established by repair heuristic. Node 14 was not included in the approach of Shrivastava and O’Mahony (2006) as its demand was not satisfied by the approach adopted and was omitted.

In the development of routes, the origin (DART station) remains the same for all destinations. Therefore, all feeder routes originate from the DART station only. It looks very similar to the spanning tree rooted at DART station (Figure 3). However, the best alternative path out of the selected k-paths for each origin and destina-

Figure 3. Developed Feeder Route Network for Dun Laoghaire DART Station



tion set is developed by a combination of the GA and heuristic approach. In some of the earlier approaches, links on the spanning tree are added/removed to achieve the best network. The approach adopted in this research is quite different.

Table 3 indicates coordinated schedules of feeder buses for the existing schedules of DART and the average load factors on each route. As shown in the table, the load factor varies in the range of 0.33 to 0.83. These load factors will further improve due to local demands at en-route stops. Local demand is not considered because the routes are designed for feeder buses from the DART station. Hence, demand satisfaction generating from the DART station is of prime concern.

The overall load factor attains a value of 0.58—a much improved value against the present scenario in which the load factor remains in the range of 0.2 to 0.3 even during peak hours. Feeder routes and coordinated schedules for the same study area were developed by decomposing the problem in two stages: one for development of feeder routes using the heuristic approach only and another for schedule coordination with GAs (Shrivastava and O'Mahony 2005). Load factors for different routes were in the range of 0.16 to 0.45 with an overall load factor of 0.36. Thus, load factors and the overall load factor by the proposed model have improved values. A comparison between the existing scenario and improvements due to the proposed model is given in Table 4. If all the routes are viewed together, then 42 percent of demand is satisfied within 5 minutes of effective waiting and 29 percent is satisfied between 6 to 10 minutes of waiting. More than 70 percent of demand is satisfied within 10 minutes of effective waiting. The entire demand is satisfied within 20 minutes of effective waiting. In the present scenario, the majority of commuters wait 20 minutes or more for buses and the load factor is also less than 0.3 most of the time even during peak hours. Route details show that on route 2, 62 percent of demand is satisfied within 5 minutes and the entire demand is satisfied within 10 minutes of effective waiting. Route 2 carries about 31 percent of the total trips, making it the maximum trip carrier.

On all routes more than 50 percent of demand is satisfied within 10 minutes of effective waiting. In the developed feeder route structure, route lengths vary between 4.5 km to 10.25 km and 100 percent demand is satisfied without any transfer. If a similar exercise is carried out by identifying influence areas of all stations, shorter feeder routes with better schedules will be developed (Shrivastava and Dhingra 2001). This is due to the fact that one node may be connected to more than one DART station and its connectivity will certainly be better with shorter connecting lengths from one particular station only. As shown in Figure 3,

Table 3. Details of Bus Schedules with Load Factors

S. No.	DART Timings		Bus Timings					Average Load Factors and Number of Buses Required				Overall Load Factor
	Northbound DARTS	Southbound DARTS	Route 1	Route 2	Route 3	Route 4	Route 5	Route Number	Average Load Factor	Number of Buses Required		
1	08.08	08.02	8.07	8.07	8.07	8.07	8.07	8.07	1	0.40	3	Total number of buses needed = 25
2	08.15	08.09	8.27	8.19	8.22	8.27	8.27	8.27	2	0.64	6	
3	08.23	08.20	8.47	8.31	8.37	8.47	8.47	8.47	3	0.33	6	
4	08.29	08.25	Buses to be scheduled after 9AM	8.43	8.52	Buses to be scheduled after 9AM	Buses to be scheduled after 9AM	Buses to be scheduled after 9AM	4	0.70	5	
5	08.33	08.31	Buses to be scheduled after 9AM	8.55	-	Buses to be scheduled after 9AM	Buses to be scheduled after 9AM	Buses to be scheduled after 9AM	5	0.83	5	
6	08.38	08.36		Buses to be scheduled after 9AM								
7	08.43	08.45										
8	08.49	08.53										
9	08.58	-										
10	Trains after 9AM											

Table 4. Comparison between Existing and Proposed Route Network

<i>Property for Comparison</i>	<i>Existing Route Network in Study Area</i>	<i>Proposed Route Network for Study Area</i>
Type of route network	Not a feeder route network	Feeder route network
Average load factor on routes	Less than 0.3	Overall load factor is 0.58 and is greater than 0.3 on all routes
Waiting time/percentage demand satisfaction	Average waiting time is more than 20 minutes	42% of demand is satisfied within 5 minutes, 71% within 10 minutes, and 100% within 20 minutes of effective waiting

destinations like Stillorgan (code 8), Mount Merrion (code 13), University College Dublin (code 14), and Dundrum (code 15) are closer to Blackrock DART station as compared to Dun Laoghaire. Feeder routes for these destinations from Blackrock will be shorter.

The modelling exercise was carried out only for the morning peak hour. The frequency of buses will change during other hours of the day as per the demand. In fact traffic surveys should be conducted for the whole day, covering both peak and off-peak hours. The same methodology can be implemented to determine coordinated schedules of public buses during different periods of the day. A whole day travel pattern will provide more realistic demand to different destinations for development of feeder routes, schedules, and optimum fleet size for different periods of the day.

Conclusions

In the proposed model, well-scattered destinations from the DART station satisfying maximum demand were selected as potential destinations. Feeder routes and frequencies leading to coordinated schedules were developed simultaneously from the DART station to selected potential destinations using GAs. As a low number of potential destinations is found with maximum demand satisfied, the number of generated routes are less. The selection of minimum destinations leads to a low number of routes. If demand at some destinations remains unsatisfied, then with the help of the heuristic algorithm, which works as a repair algorithm, such destinations are inserted/added to the developed feeder route structure. After modification of the route structure, GAs are again applied to determine

modified coordinated schedules. The following conclusions can be derived from the proposed modelling exercise:

1. In the proposed modelling exercise the optimized feeder routes and coordinated schedules are developed together in the first phase. Most of the routes are developed along with the coordinated schedules in this phase only. The coordinated schedules are further checked with a second application of GAs. In the proposed modelling approach, most of the schedules and routes are complementary to each other.
2. The model strikes a balance between user needs and operator requirements. The objective function incorporates user costs in terms of time spent in buses and transfer time between DARTs and buses; operator cost is vehicle operation cost, which is directly proportional to distance travelled by buses. Similarly, constraints are also applied to cover the requirements of users and operators. The load factor constraint is kept within minimum and maximum values so as to maintain a better level of service for users and economic operation to satisfy operators. The fleet size constraint is also a realistic constraint from the operators' point of view. The constraint for unsatisfied demand increases the probability of availability of seats to commuters though it is not very important when the load factor remains less than a minimum value as has been experienced in the study area.
3. The selection of nodes as potential destinations plays a very important role for successful development of feeder routes for typical destinations in the study area network. The network considered for analysis has nodes well scattered in the influence area and destinations having higher demands are closer to the origin (DART station). Some of the destinations away from the DART station have limited connectivity with other nodes. Selection of potential destinations away from the origin and well dispersed in the influence area develops feeder route structures, which satisfy the maximum demand without any transfer.
4. The influence area of each station can be identified and the modelling exercise can be repeated with large-scale data collection for an entire day. Thus, a fully integrated system can be developed in which DARTs can work as a main line haul facility and buses can feed the local areas. The coordinated schedules of buses can be found for each period of the day and hence their requirement can be determined for peak and off-peak periods. The proposed methodology designs feeder routes without any further transfers and the

entire demand is satisfied directly from the DART station. The model takes into account the overlapping aspect of different routes successfully.

5. On average, the developed model satisfies more than 50 percent of demand within 10 minutes of waiting time and the entire demand is satisfied within 20 minutes of waiting time with an overall load factor of more than 50 percent. On some routes, 80 to 90 percent of demand is satisfied within 10 minutes of waiting and many routes have load factors even more than 0.7. In the present scenario (not optimized), the load factor hardly attains a value more than 0.3 and the average waiting time is in the range of 20 minutes or more. Thus, the proposed model judiciously balances waiting time and load factors for feeder buses.
6. The research problem attempted is solely on the development of feeder routes and not a usual network design problem. GA has been successfully implemented for the more usual network design problems where transfer from one route to another is permitted (i.e., passengers are assumed to transfer from one bus to another). In the design of feeder routes, it is not appropriate to incorporate additional transfers on routes because passengers are already subjected to a transfer from train to bus. Therefore, additional transfers will lead to inferior design of the feeder route network. The application of repair heuristics adds to development of feeder routes without additional transfers.

The proposed model can be implemented for the development of feeder routes and coordinated schedules to any other study area if demands to various destinations and network connectivity details are known. Fully optimized feeder routes would be developed if higher demand nodes are well scattered and away from the DART/railway station by the GA itself, otherwise repair heuristics will modify the feeder routes developed by GA. Moreover, feeder routes without additional transfers are desired by planners. Other factors like transfer time, load factors in buses, fleet size, vehicle operating cost, and availability of buses to all commuters are duly taken care both from the users' and operators' point of view. The developed model can be of specific use to service planners working for coordinated operations of public transport modes.

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