Calculation of Transit Performance Measures Using Smartcard Data

Martin Trépanier, Catherine Morency, and Bruno Agard
Ecole Polytechnique de Montréal

Abstract

Smartcard automated fare collection systems (SCAFC) for transit have been considered primarily for their administrative function of controlling access to the service and for revenue management. However, it is likely that data from these systems also can be used to describe both transport supply and demand. This article illustrates the use of smartcard data to estimate various transit performance measures. Combined with well-established evaluation processes, such measures can help operators monitor their networks in greater detail. The performance of the network supply (vehicle-kilometers, vehicle-hours, commercial speed, etc.) and the statistics on passenger service (passenger-kilometers, passenger-hours, average trip length, etc.) can be calculated from these datasets for any spatial or temporal level of resolution, including route and bus stop levels.

Introduction

Smartcard data systems generally are implemented for administrative functions such as controlling access to a service. On a transit network, they help improve the transit user's satisfaction, with simplified ticketing options (single card, security), while enhancing revenue collection for public authorities (reduced fraud, multilevel validation) (Conklin et al. 2004). To do their job, these systems need to record a large amount of information on the daily use of the transit network. Each transaction is recorded, along with spatio-temporal details: time, spatial location,

operational information (line, stop), and card type (fare type and privileges). Even if the resulting dataset was not designed, a priori, for analytical purposes, it can be processed to reveal information on how the network is rendered and used on a continuous basis.

The relevance of smartcard data for monitoring a transit network is validated using a set of continuous data from the Société de transport de l'Outaouais (STO) outputted from the smartcard fare collection system. With these continuous data, daily, weekly, and seasonal activity cycles are identified for various transit card types (regular adults, students, and seniors, for instance) using data mining techniques (Morency et al. 2007). This confirmation of the variability of transit use during these cycles suggests that the supply might not always adequately match the real transit demand.

"Measuring the performance of a transit system is the first step toward efficient and proactive management" (Bertini and El-Geneidy 2003). With this issue in mind, current research is looking into the supply side of the equation and aims to estimate some transit performance indicators using smartcard data. Actually, smartcard data offer a unique opportunity to monitor the use and supply of a transit network simultaneously on any given day. They can be used in an AVL-APC (Automated Vehicle Location, Automated Passenger Counting) system, which has proven to be useful for transportation planning (Furth et al. 2006). Hence, the purpose of the paper is to illustrate the potential of smartcard data to derive operational indicators revealing the service that was truly offered to the users on a specific day (compared with the planned service: vehicle-kilometers for instance), estimate the use of the service on that day (demand: passenger-kilometers, for instance), and observe how these two sides of the transit network evolve over time.

The paper is organized as follows. First, we present work on the use of smartcard data for analytical purposes, followed by some transit performance indicators, keeping in mind that the main purpose of the paper is to evaluate the usability of smartcard data to estimate a number of these classical indicators. Then, the methodology is presented, namely the dataset used for the experiment, some imputation operations, and a description of the transit performance measures. Results of the estimation of indicators from a demonstrative dataset are then presented. A discussion concludes the paper.

Background

Smartcard in Transit

The use of smartcards in transit networks is increasing all over the world. Smartcards are based on a technology patented in 1968 by German researchers Dethloff and Grotrupp (Shelfer and Procaccino 2002). They are used for identification and transaction purposes through the exchange of information with readers installed inside vehicles. Smartcards are useless without a strongly integrated information system which links planned, operational, and user (card) data: the Smartcard Automated Fare Collection (SCAFC) system. The complex fare system that is used by many public transport authorities can be better managed with the help of an SCAFC, because a smartcard can store more than one transport document at a time and because it is validated automatically by the reader. According to Bonneau (2002), the need to integrate fare policies within large metropolitan areas will continue to promote smartcard usage. At the same time, other authors are stressing the important need for privacy, which could retard smartcard implementation. The French Council for Computer and Liberty recommends that care be taken with such data, because they could be used to trace the personal movements of an individual (CNIL 2003). Still, Clarke (2001) recalls that smartcards are no different from other individual data collection systems, like credit cards, road tolls, and police databases.

Bagchi and White (2005) have reported several advantages brought about by the analysis of SCAFC data, like access to larger sets of individual data, continuous data available for long periods of time, and better knowledge about large numbers of transit users. These authors conducted a study on passenger transfer behaviors on the Bradford and Merseyside transit networks in the UK. The absence of alighting location information was identified as the primary issue requiring further analysis.

In the case of the Société de transport de l'Outaouais (STO), Trépanier et al. (2004) have shown the potential of using SCAFC data for public transport network planning with the help of a Transportation Object-Oriented Modelling approach. Furthermore, it has been possible to develop a destination location estimation model for each trip (Trépanier and Chapleau 200; Trépanier et al. 2007). The model, which is based on individual spatial patterns of use, has been applied to the 6.2 million trips of the dataset with a 94 percent success rate (an alighting stop was imputed). Smartcard data also can be useful for travel behavior analysis. Morency et al. (2007) have shown the potential of applying data mining clustering methods

to datasets to observe similar behaviors and also variability in behaviors among the card users. Chu and Chapleau (2008) have discussed imputation and error correction techniques applied to timestamp smartcard data.

Transit Performance Measures

The first edition of the *Transit Capacity and Quality of Service Manual* (TCQSM) was published in 1999 (Kittelson and Associates 1999). This manual recommended the evaluation of transit systems using six performance measures: service frequency, hours of service, service coverage, passenger loading, reliability, and transit vs. automobile travel time. Many examples of transit performance evaluation using the TCQSM can be found in the literature (among others, Perk and Foreman 2003; Caulfield and O'Mahony 2004). These measures generally are estimated using surveys or onboard counts, which provide a snapshot of the service on a particular day. No information is recorded regarding the variability of the service or the validity of the day when the data were collected (is it representative of the other days?). This is where smartcard data become interesting.

Gillen et al. (2001), in their study of the impact of Automated Vehicle Location technology (AVL) on transit firm productivity, observe that the use of such a system "will result in fewer buses used given the number of vehicle miles and number of passenger trips." Cost per mile and annual maintenance hours also are reduced. The acceptance of Intelligent Transportation Systems (ITS) by transit system users has also been investigated. Using an intercept-mail-back survey (approximately 3,000 respondents), Conklin et al. (2004) reported that there is widespread support of such systems among users.

Bertini and El-Geneidy (2003) demonstrate that archived stop-level data can be converted into valuable Transit Performance Measures (TPM). Actually, they argue that many TPM have been proposed in the past but rarely implemented because of data limitations. They confirm that the deployment of ITS to monitor and manage transit networks also enable transport authorities to monitor the performance of the network in real time, or in retrospect. Smartcard data have this potential. In the case of TriMet (Portland, Oregon transit provider), archived data are used to determine various performance measures and compare them from day to day and from route to route.

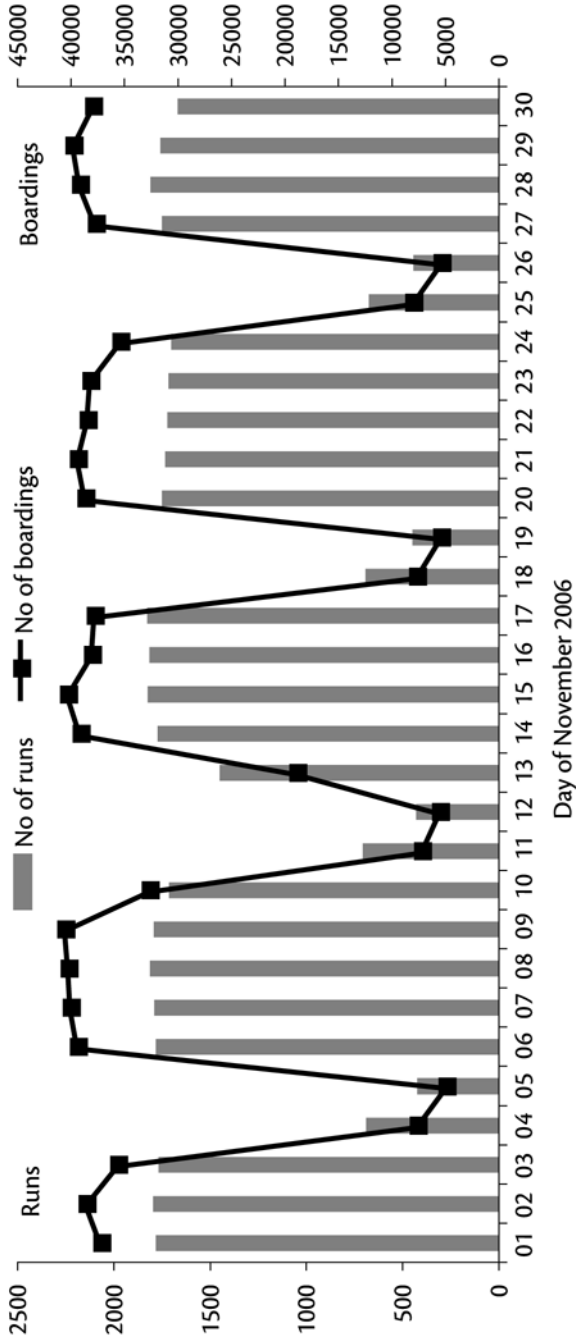## Methodology and Concepts

Dataset

Data from the Société de transport de l'Outaouais (STO) smartcard fare collection system are used for the study. The STO is a medium-sized public transport authority operating 200 buses and servicing 240,000 inhabitants in Gatineau, Quebec. The STO has been operating its smartcard system since 2001. Today, more than 80 percent of all STO passengers living in Quebec have a smartcard. Moreover, every STO bus is equipped with a GPS reader. For each boarding, stop location and bus route are stored in the database, along with a timestamp. Since the STO uses a high-level security procedure to ensure the privacy of the data, smartcard data are completely anonymous. The complete dataset contains about 21 million transactions covering a period from January 2005 to March 2007. The set of data used for this specific experiment relates to November 2006 (917,009 transactions). Table 1 shows the general structure of the information available for each smartcard boarding transaction.

Table 1. Information on Smartcard Transactions in the Dataset

CARD ID	Card number is not related to an individual and is issued only for cross-relating records.
FARE (CARD) TYPE	Fare type related to the card (regular, student, express, etc.).
DATETIME	Date and time of card reading aboard the bus.
ROUTE & DIRECTION ID	Route number and direction on which bus is operating.
BOARDING STOP ID	Stop number of boarding, obtained with help of a GPS device aboard vehicle.
ALIGHTING STOP ID	Estimated stop number of alighting event, obtained by applying Trepanier et al. (2007) algorithm.
VALIDATION RESULT	Indicates whether or not boarding was valid, a transfer, or refused by reader.
OPERATIONAL INFO	Information on run number, vehicle number, and bus driver is also available.

For this study, the dataset has been organized by run number (sequence of stops in a route, single direction). Due to defects in the smartcard system, it is possible that a few runs operated but were not reported. To validate this, Figure 1 illustrates the number of runs that were reported during November 2006. The number of runs is quite stable from one weekday to another (2853 ± 92), as it is for Saturdays (941 ± 6) and Sundays (594 ± 6) (lower bars). There is more variation in the number of boarding transactions, and so it is interesting to analyze this variation through dedicated supply and demand indicators, which we do in subsequent sections of the paper. With only these simple figures, we can easily identify special days of travel. Actually, it is noticeable that a large number of workers had a day off on November 10 and 13, with November 11 (Remembrance Day) falling on a Saturday in that year.

Figure 1. Dataset Characteristics for November 2006

Transit Performance Measures

Transit performance measures are calculated with the help of database queries involving Structured Query Language (SQL) and customized database functions. Two dimensions are examined:

- *Query on transit operation -* This involves linking tables on route geometry, run length, and travel time to those of effected runs (runs operated according to the transaction database). The main results are the number of runs for each route, vehicle-kilometers (veh-kms) and vehicle-hours (veh-hrs).

- *Query on transit use -* This query links the transaction database, the destination location estimation, and the route geometry. Trip duration is estimated from the travel length on the route and the commercial speed (average speed, which takes into account stops), because the exact alighting time is not known, especially at the terminal (recalling that the SCAFC stores the boarding times only, so there is no transaction corresponding to the last stop on the route). The main results are number of passengers, passenger-kilometers, and passenger-hours for each run segment.

Supply-oriented measures

The supply-oriented measures are calculated as follows. The number of vehicle-kilometers D_{ij} of a single run i at day j is equal to the sum of the travel distance Δd_{ijk} between each stop of the run. The same logic is applied for the number of vehicle-hours T_{ij}. Since each measure is disaggregated, the total number of vehicle-kilometers for a route, or for the whole network, is calculated by adding the run numbers. The number of vehicle-kilometers D_{rj} of a route r on a given day j is:

$$D_{rj} = \sum_{i \in r} \sum_{k \in i} \Delta d_{ijk}$$

The same applies for the number of vehicle-hours. Thus, the average commercial speed of a route (C_r) is:

$$C_r = \frac{D_r}{T_r} = \frac{\displaystyle\sum_{i \in r} \sum_j D_{ij}}{\displaystyle\sum_{i \in r} \sum_j T_{ij}}$$

These indicators apply to the operating service only and do not consider the dead time to and from the depot or waiting time during the day. Average length and

duration of runs can then be estimated using vehicle-kilometers, vehicle-hours, and total number of runs operated.

Demand-oriented measures

Similar indicators are obtained for the demand side, where every single trip is put into the calculation. The travel distance in kilometres (d_{iu}) of a user u on a single run i is:

$$d_{iu} = \hat{\partial}_i^{s=a} - \partial_i^{s=b}$$

where $\hat{\partial}_i^{s=a}$ is the total distance on the run at the estimated alighting stop location, and $\partial_i^{s=b}$ is the total distance on the run at the boarding stop. The number of hours (t_{iu}) is estimated with the help of the commercial speed of the run (C_i), because the alighting time is unknown:

$$t_{iu} = \frac{d_{iu}}{C_i}$$

The total number of passenger-kilometers and passenger-hours for a route (a run, or a day) are calculated by adding the kilometers traveled by every boarding passenger. Average length and duration of a trip can be estimated using passenger-kilometers or passenger-hours divided by the number of transit network users.

Performance measures

The combination of supply and demand indicators leads to overall performance measures. In this case, partial measures are calculated because some users do not have a smartcard. A correction coefficient would need to be applied to expand the number of users for each run. This coefficient can be calculated from external passenger count observations. However, this demonstration paper presents statistics on smartcard use only, since adjusted statistics remain confidential to the transit operator.

The average bus occupancy β_{rj} of route r on a given day j is:

$$\beta_{rj} = \frac{\sum_{i \in r} \sum_{u} d_{iju}}{D_{rj}}$$

where d_{iju} is the travel distance of the passenger u on run i and day j, and D_{rj} the number of vehicle-kilometers on run i and day j. The capacity use ratio α_r is then

estimated in a similar fashion, by adding the vehicle capacity V_i on each run to the equation:

$$\alpha_r = \frac{\sum_{i \in r} \sum_u d_{iju}}{D_{rj} V_i}$$

Vehicle capacity is available for each run, because the bus number is recorded at each transaction. The capacity of a regular bus is approximately 75 passengers (41 seats) and 65 passengers for a low-floor bus (38 seats).

The punctuality of the bus service can be evaluated by comparing the scheduled time to the actual time the bus arrives at a stop. This time is supposed to be the time of the first smartcard transaction at each stop, for a given run. A special dataset is built to measure the punctuality of the bus service. It contains the bus stop arrival time for each stop of each run during November 2006.

Results

The list of transit performance measures is quite straightforward and has been a part of the operator's knowledge for a long time now. However, estimating these measures remains a difficult challenge for ill-informed authorities. The following results demonstrate the use of smartcard data to estimate them for very precise elements. Actually, every day of operation, every run, or even every transit stop can be described with respect to supply and demand conditions.

Supply-Oriented Measures

A total of 68,381 runs were offered during the month of observation, resulting in 626,800 veh-kms and 43,600 veh-hrs. The average commercial speed was 14.4 km/h, and the average duration of the runs was 38.2 minutes. These global figures can be segmented according to the type of day to see whether or not the service is equivalent on weekdays and also to measure differences on weekends. From Table 2, we see that the average speed varies between 13.7 and 17.4 km/h and peaks on Sundays, as expected.

These indicators can be obtained for every individual route, on every day, and at all times. For example, Figure 2 illustrates the average commercial speed for route 37 at each hour during weekdays of the month of November 2006. We can see that it is lower during the day, with values as low as 6 km/h around 9:00 a.m. The greatest variability is found at that time (coefficient of variation = 25.2%).

Table 2. Key Facts Regarding Transit Supply During the Four Weeks of November 2006 by Day of Travel

Weekday	Average Speed (km/h)	Average Distance (km)	Average Duration (min.)
Sunday	17.4	11.1	38.3
Monday	14.8	9.1	37.1
Tuesday	14.5	8.8	36.5
Wednesday	14.1	9.1	38.6
Thursday	13.9	9.0	38.9
Friday	13.7	9.0	39.6
Saturday	15.9	10.3	38.8

Demand-Oriented Measures

Figure 3 presents key facts based on demand data. For every day of the month, the number of passenger-kilometers and the average speed of passenger journeys are presented. It is noticeable that:

- There were 917,009 boarding transactions during the month of November 2006; about 93 percent of them occurring on weekdays, for a total of 6.7 millions passenger-kilometers.

- The average in-vehicle speed of journeys is 19.0 km/h, with slight variation during the month (especially on the two last weekends).

- The average length of a journey is about 8.3 km, while the average duration of a trip is 26.3 minutes.

These summary indicators also can be estimated for the main types of smartcards. This segmentation makes it possible to understand the travel patterns of students, seniors, and express-card holders, for instance. A classification of the various card types is used for this purpose. First, the same indicators as presented previously are shown for the main classes of card types (see Table 3). It shows that regular cards for adults account for about 46 percent of passengers boarding during November 2006. The second most important card type is the student card. These figures also reveal some distinctions between the features of trips taken on the transit network by these client groups.

Apparently, interzone cards provide access to more efficient service, since much higher speeds are possible between zones due to the nature of interzone service, which uses a high-capacity road network instead of local streets to link distant

Figure 2. Commercial Speed for All Runs of Route 37 per 1 Hour Time Slice, November 2006 Data, Weekdays Only
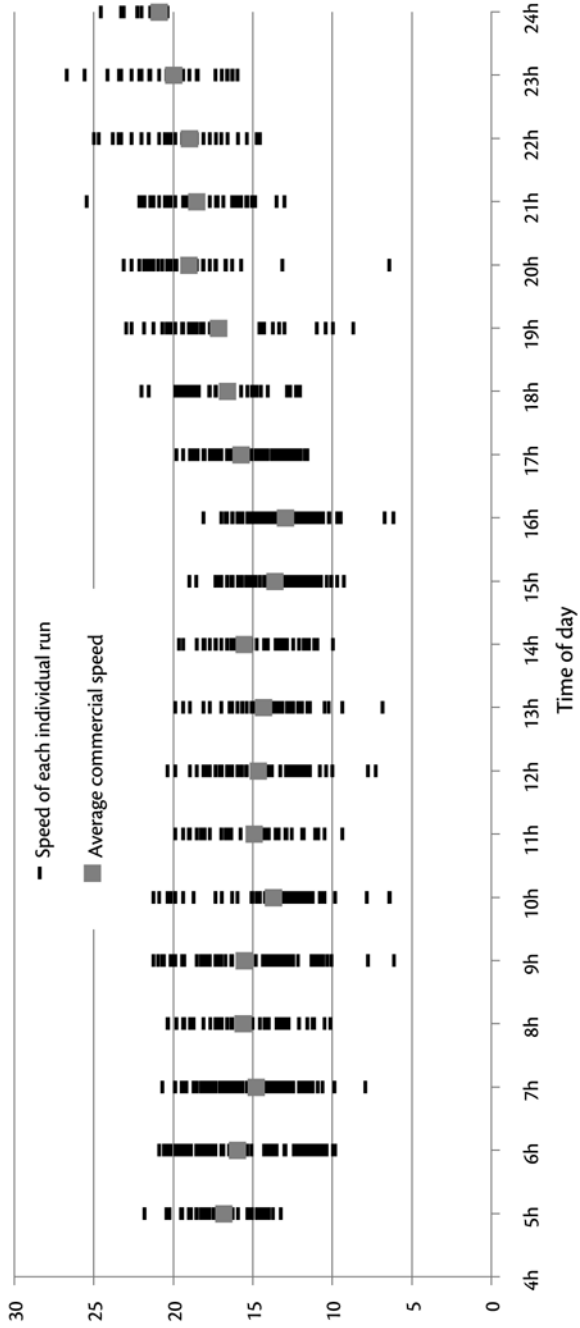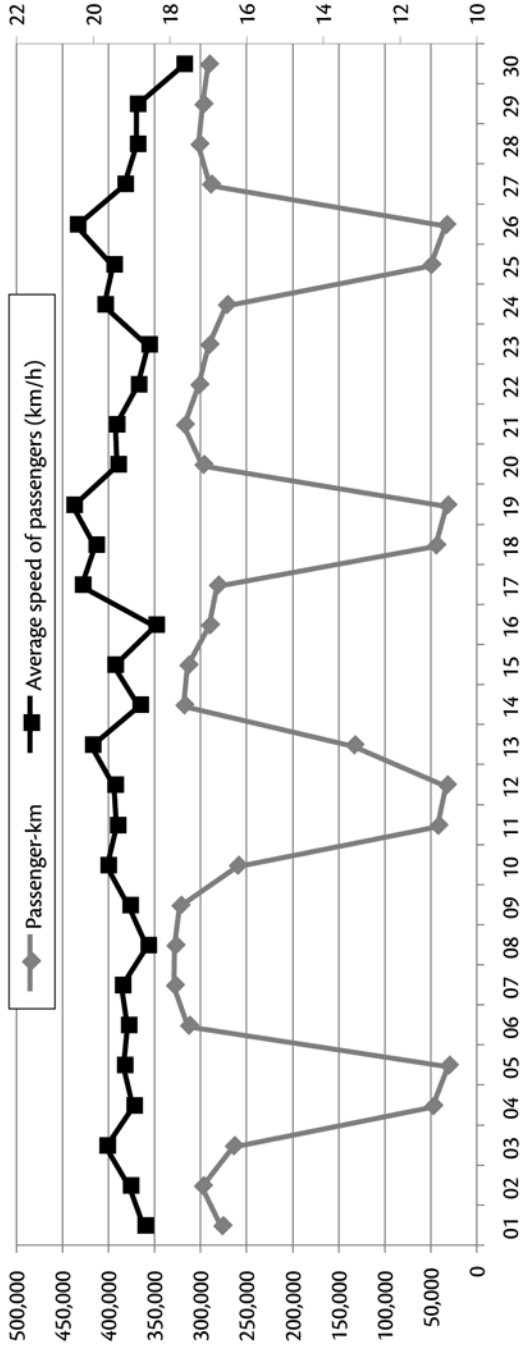
Figure 3. Key Figures for Demand, per Day, November 2006

destinations. Express cards are second in terms of average speed. The average speeds of travel of all other client groups are comparable. The average length and duration of journeys on the transit network reveal similar facts. Interzone cards are used for much longer trips, followed by express cards. Senior cardholders take the shortest trips on the network, followed by students.

Table 3. Key Facts on Demand by Card Type, November 2006

Card type	# Boarding	Pass-km	Pass-hr	Average Speed (km/h)	Average Length (km)	Average Duration (min.)
Adult-Regular	46.2%	38.9%	42.3%	17.5	7.0	24.1
Adult-Express	15.1%	21.8%	20.4%	20.4	12.0	35.3
Adult-Interzone	3.0%	11.5%	8.4%	26.2	31.8	72.9
Student	26.3%	21.0%	21.7%	18.4	6.7	21.7
Senior	3.5%	2.1%	2.3%	17.8	5.1	17.2
Other	6.0%	4.7%	5.0%	17.9	6.6	22.0
Total	100%	100%	100%	19.0	8.3	26.3

Performance Measures

Indicators on supply and demand are combined to calculate the bus occupancy and the number of passengers per run on each route (Figure 4). We must remember that this figure shows only smartcard passengers and thus does not represent the entire clientele. In the figure, the routes are sorted according to smartcard passenger per run. The figure shows that some routes are boarded almost exclusively by smartcard holders, and these users remain on board for the whole distance covered by the run because the ratio between the two indicators is almost one (black circles on the chart).

Schedule adherence is examined for a specific route of the network. Route 37 was selected for the study, as it is the most important route, operating seven days a week. Schedule adherence on Route 37 is examined using a special dataset extracted from the smartcard data. Figure 5 shows the distribution of delays on this route, based on four months of operation between January and April 2005. This representation was inspired by the work of Bertini and El-Geneidy (2003). Perfect schedule adherence occurs for 17.5 percent of the observations (each observation represents the difference between the scheduled time and the arrival time recorded at a specific stop on the route); 18.9 percent of the buses arrived early (avg. 1.6 min), and 63.6 percent were late (avg. 3.0 min). Delays are greater in the inbound direction because the traffic on the roads is more congested during peak hours in the morning in this area.

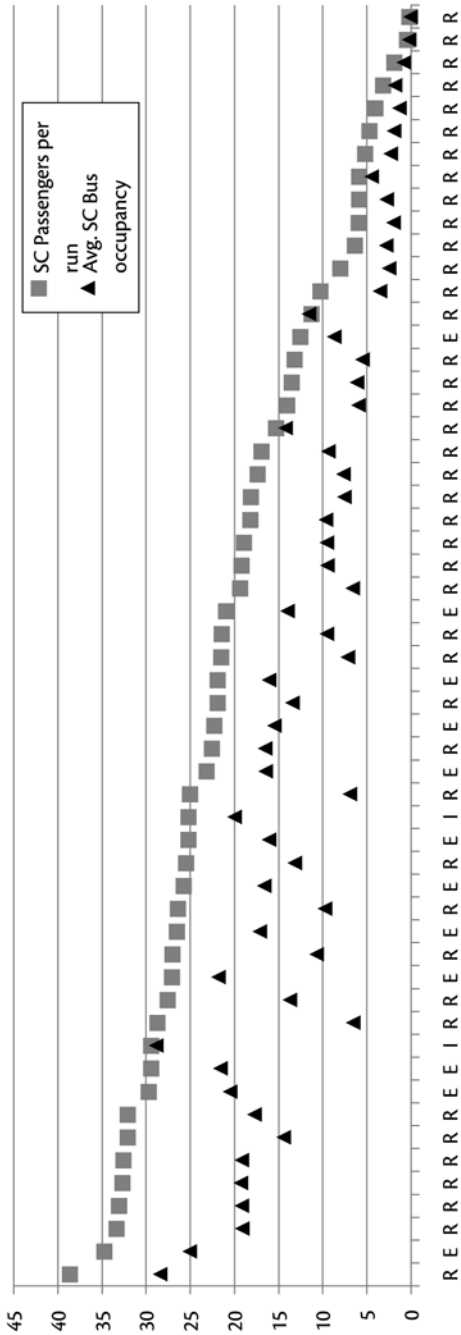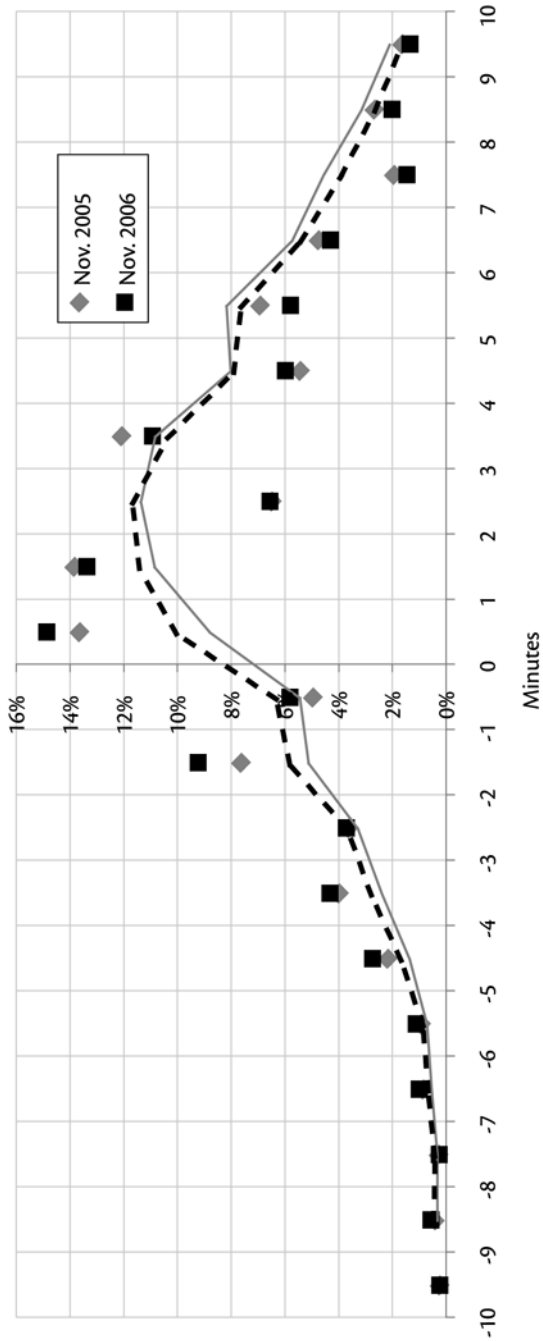**Figure 4. Average Occupancy of Bus Routes, November 2006**

Figure 5. Schedule Adherence on Route 37 based on November 2005 and November 2006 Observations

Discussion and Conclusion

This paper introduces the use of smartcard automated fare collection system data to measure transit supply and demand indicators. With these data, the statistics can be easily compiled if the boarding and alighting locations are available. Planners can obtain these statistics on a daily basis to evaluate the operating service and possibly make corrections on subsequent days. Results show that, while most of the performance measures are stable over time, the approach permits identification and classification of specific characteristics of the operation.

However, the use of smartcard data to obtain transit performance measures has some limitations. First, this approach is very data-intensive, so there is a need to have a strong transit information system to support the analysis. In addition, data must be prevalidated, because there are always a certain number of errors in smartcard systems (missing data, wrong run numbers, equipment malfunctions, etc.). Finally, we should remember that not all transit users have a smartcard. There is a need to compare and balance the statistics from onboard passenger counts to obtain the complete figures. Comparison between synthesized statistics from smartcard data and operational data from the transit authority will help refine the techniques presented.

Further research will focus on disaggregate analysis of both supply and demand. For the demand side, the analysis of individual user behavior will provide additional information to transit planners on the habits of users: departure times, preferred origins and destinations, preferred routes, etc. For the supply side, there is a possibility of finding ways to "optimize" equipment use, looking at operational data and run load information.

Acknowledgments

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About the Authors

MARTIN TRÉPANIER, P. Eng., Ph.D. (*mtrepanier@polymtl.ca*), is associate professor of industrial engineering at the Ecole Polytechnique de Montréal. His research is mainly related to logistics, information systems, object-oriented modelling, public transit management and planning, public transit smartcard data analysis, GIS development and Internet applications in transportation.

CATHERINE MORENCY, P. Eng., Ph.D. (*cmorency@polymtl.ca*), is assistant professor of civil engineering at the Ecole Polytechnique de Montréal. Her research is related to modelling of the interactions between urban travel behavior and spatial dynamics, spatial data analysis methods applied to urban microdata, alternative modes of transportation (ridesharing, carsharing, intermodality, active transportation) and processing of Origin-Destination survey data.

BRUNO AGARD, Ph.D. (*bruno.agard@polymtl.ca*), is associate professor of industrial engineering at the Ecole Polytechnique de Montréal. His main research fields are design methodologies, product families, product diversity, modular design, product delay differentiation, synchronous