Simulation of Urban Rail Operations: Models and Applications

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Abstract SimMETRO is a microscopic, dynamic, stochastic simulator of urban rail operations (METRO), specifically designed for service performance analysis, and evaluation of operations and strategies for real time control of subway systems. SimMETRO employs a detailed representation of the network, rolling stock, signal control, demand, schedule and dispatching. In particular, the various sources of stochasticity in operations are explicitly captured. The paper also presents approaches for calibration of model parameters and input (such as dynamic arrival and alighting rates at stations). A case study, focusing on the Red Line in Boston, MA, is used to illustrate the applicability of the model and the proposed calibration methodology. The results show that calibration, improves the performance of the model. The RMSE of block run times (relative to actual times as reported by the train detection system) is reduced by 60%. The calibrated demand matches well recent counts of arrival rates at the stations, and the model can be used to evaluate alternative operating strategies.

1. Introduction
A number of rail simulation models exist (see for example Nash and Huerlimann, 2000; Bendfeldt, Mohr and Muller, 2000; RAILNET II, 2006; Goodman, Siu and Ho, 1998, Venglar, Fambro, and Bauer, 1995). Many of these models mainly focus on planning and train performance analysis for general rail systems. Heimburger, Herzenberg and Wilson (1999) developed a simulation model to understand the peak hour congestion of MBTA’s Red Line and evaluate alternative schedules. Nash, et al (2006), use the simulation model OpenTrack (Nash and Huerlimann, 2004), to simulate the operations of Zurich’s S-Bahn network, in order to evaluate the reliability of the system and test alternative operating strategies for delay reduction. Their study emphasizes the high sensitivity of service reliability to minor schedule adjustments. Rahbee (2001) discusses the use of simulation of transit rail operations planning and analysis.

Application of rail simulation models requires the calibration of these models so that they accurately replicate observed conditions in the system. However, the literature on calibration and validation of rail simulation models is very limited. Existing approaches for rail model calibration are not very advanced. Most methods are ad hoc and use simple statistics or performance measures to compare the simulator output to field observations while adjusting the model parameters, by trial and error, until the simulated measurements are close to the observed ones (Venglar, Fambro and Bauer, 1995; White, 2005; Tromp, 2004). Such approaches may work satisfactorily in cases where there is little or no uncertainty incorporated in the simulation, or most of the parameters or input data are of good quality and reliability. However, when the number of parameters increases and various sources of randomness are present during system operations, existing methods are unable to calibrate the models in a systematic and consistent way.

Calibration of traffic simulation models on the other hand, has seen a lot of progress in recent years (see for example, Balakrishna, Koutsopoulos, and Ben-Akiva, 2005; Ben-Akiva, Darda, Jha, Koutsopoulos, and Toledo, 2004). These methods are quite general and can be used for the calibration of a number of model parameters and inputs such as dynamic Origin-Destination flows, capacities, etc. Hence, there is the potential to use similar approaches for the calibration of rail simulation models as well.

The paper focuses on simulation of urban heavy rail (METRO) operations and its objective is twofold:

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• introduce a new simulation model, SimMETRO, for mass transit subway systems, particularly its features in representing various sources of randomness that impact operations; and
• discuss general methods for the calibration of the important parameters and necessary inputs of these models using commonly available data, such as track (block) detection data.

The remaining paper is organized as follows. Section 2 introduces SimMETRO and outlines the design characteristics that support the desired functionality. Section 3 details the calibration methodology, and section 4 illustrates the application of SimMETRO and the calibration methodology through a case study of the operations of the Red Line in Boston, MA. Section 5 concludes the paper.

2. The simulation model

SimMETRO is a microscopic, dynamic, stochastic simulator specifically designed for service performance analysis, and evaluation of operations and strategies for real time control of subway systems. The intended applications of SimMETRO include:

• operations planning,
• system performance analysis,
• development and evaluation of real time strategies for operations control,
• capacity analysis,
• training.

In order for SimMETRO to provide the required functionality, the design requirements include the following capabilities:

• dynamic representation of the demand and its impact on train operations (e.g. dwell times at stations),
• representation of all sources of uncertainty including, demand, incidents (such as train malfunctions, station emergencies, control system problems, etc),
• delay propagation through trip chaining and train schedules,
• individual operator performance characteristics,
• train performance and characteristics,
• control system uncertainties,
• flexibility in preparing schedule inputs.

The structure of the simulation model is illustrated in Figure 1.

Figure 1. Architecture of simulation model
The network representation captures merging points and junctions, and all geometric features that impact train performance (e.g. grade and curvature). The network also includes the characteristics of the stations, such as length and platform configuration.

The train control system represents the corresponding block design and associated speed code. Various types of train control can be simulated, including fixed block control.

The schedule can be specified by a number of options, depending on the application. For example, the schedule may be input in the form of departure headways and their time dependent distributions, or as scheduled headways (including the composition of trains and the trips they perform), or as actual headways (to simulate the operations of a specific day). In addition, the schedule includes information not only about headways and/or departure times for the trips, but also trip chains (train schedule) so that delays are propagated accurately as trains perform their sequence of trips.

The rolling stock is represented with all operating characteristics that impact train performance such as, seating capacity, total capacity, door configuration, car composition, and acceleration/deceleration profiles.

Passenger demand can be modeled at various levels of detail, depending on the available data. Under the simplest option (when information about passenger arrival rates or origin-destination flows is not available) the impact of demand is captured by dwell times at stations. These dwell times are station specific and random. If information on passenger arrival/alighting rates is available, a detailed dwell time model is employed that estimates the dwell time as a function of the number of boarding and alighting passengers. The dwell time model is flexible and can accommodate any functional form. In this case the number of arrivals is determined assuming a stochastic process (e.g. Poisson).

Operating strategies include the real-time control of operations aiming at service restoration (in the case of a major disruption), and schedule maintenance including expressing, holding trains at selected stations, or short-turning trains.

The simulator can be used to test and evaluate the operating performance of a system under different schedules, control system configurations and concepts, block designs, rolling stock characteristics, etc. In order to evaluate the system, different scenarios can be generated that represent possible operating conditions. For example, a scenario may represent various levels of demand. Furthermore, a scenario may include incidents. Incidents can be location or vehicle specific. Location specific incidents are used to represent situations such as a medical emergency at a station, or equipment malfunction at a certain block. Train specific incidents are used to represent a disabled train.

In order to evaluate a design or operating policy the simulator outputs a rich set of performance measures both, system and level of service related, such as travel times, headway distribution, passenger waiting times, train passenger loads, number of passengers unable to board the first train, etc.

Through its detailed nature SimMETRO captures the uncertainty in urban rail operations by representing explicitly the various sources of stochasticity in the system. Such sources include, levels of demand, deviations from schedule, propagation of delays through the system, operator variability and its impact on train performance, and train interactions.

3. Calibration methodology

Application of a model such as SimMETRO requires the calibration of model parameters and inputs for the system under study. Important parameters include the dwell time model parameters and the train acceleration/deceleration profiles (if not known). Time dependent (dynamic) arrival/alighting rates at stations are critical inputs that, especially for older systems, may not be available.

Data for calibration may be available from various sources:

- train control and data acquisition system (OCS) data. This data includes activation and deactivation times for each block by the various trains, and hence occupancy times at the stations. These occupancy times are representative of the dwell time, and are a function of the (unknown) arrival and alighting rates,
• prior studies of system performance (e.g. dwell time studies) that provide a-priori estimates of the corresponding model parameters,
• prior passenger surveys and demand counts at various stations.

Depending on the type of data and their source, the above information may provide direct, or indirect measurements of the inputs and parameters of interest at various levels of accuracy. Prior surveys for example provide direct measurements of demand levels at various stations. Dwell times at stations provide indirect measurements of demand, since they are a function of the boarding and alighting passengers.

The train control and data acquisition system (OCS) measures directly the activation and de-activation time of each block in the system due to the passage of a train. Hence, this data, when properly processed can provide valuable information about headways at various locations in the system, travel times, and dwell times at stations.

A general methodology for the estimation of urban rail simulation parameters and inputs from track activation data and other sources is proposed, based on a formulation of the problem as an optimization problem. The objective is to minimize both, errors (difference between simulated and observed values), and deviations of model parameters and inputs from a-priori values.

\[
\begin{align*}
\text{Min} & \quad Z = \sum_{i=1}^{m} w_i (Y_{obs}^i - Y_{sim}^i)^2 + \sum_{j=1}^{n} w_j (P^a - P_j)^2 + \sum_{k=1}^{l} w_k (I^a - I_k)^2 \\
\text{st.} & \quad Y_{sim} = S(P^a, I^a)
\end{align*}
\]

where,
- \(P, P^a\): calibrated and a-priori system parameters, e.g., dwell time model parameters,
- \(I, I^a\): calibrated and a-priori system inputs, e.g. time dependent arrival/alighting rates,
- \(Y_{sim}, Y_{obs}\): simulated and observed measurements, e.g., dwell time at stations,
- \(w_i\): weights capturing the importance and accuracy of each component,
- \(S(P^a, I^a)\): the simulation model that maps the inputs to the corresponding measurements.

The calibration model is a multivariate, stochastic optimization problem. The problem is difficult to solve since it is simulation-based and hence, with no closed form (analytical) objective function (function \(S(.)\) that maps the inputs to the measurements is the simulation model, SimMETRO in this case). Various algorithmic approaches can be used for its solution, such as the SPSA algorithm (Spall, 1998). The SPSA algorithm has demonstrated very good performance in the application reported in this paper.

4. Case Study

The applicability of SimMETRO and the developed calibration methodology is demonstrated through a case study involving the operations of the Red Line of the Massachusetts Bay Transportation Authority (MBTA) in Boston, USA. The line consists of two branches that share a common segment (see Figure 2).
**Current Conditions**

The Red Line is an older system operating under automatic train operations (ATO) control. Operators have some flexibility in their choice of acceleration/deceleration as well as speed (under the received speed command). The line operates with mainly two types of trains, series 1800 and series 1700. The two train types have different acceleration/deceleration capabilities. During the peak hour, typically trains consist of 6 cars with 18 or 24 doors (depending on the train type) and capacity of about 960 passengers (including standees).

The case study focuses on the southbound, afternoon peak period (4-6 pm). The data available for the case study includes OCS data from October of 2004; older count data on arrival and alighting rates at the stations, by time of day, collected in 1997 (but not separated by branch); and dwell time model parameters calibrated from actual data collected at select stations. Since the available OCS data was available from Oct. 2004 the model will be calibrated for that period.

The OCS data can be used to assess the operations of the Red Line for the time period of interest. Based on the activation/deactivation times of each block, departure times at the terminal station, headways at the various stations, travel times, block occupancy times, and dwell times were calculated for each trip in the analysis period. The dwell time at a station calculated from the OCS data is an approximation of the true dwell time. It includes the actual dwell time and the time it takes for the train to enter the station (for more details see Dixon, 2006; Dixon and Koutsopoulos, 2006).

The line is very congested operating, during the afternoon peak, at scheduled headways of mostly 4 min. However, the reliability of the line is rather low. Figure 3 compares the actual departure headways at the southbound terminal (as recorded by the OCS system) to the scheduled headways for the 16:00 – 18:00 time period, and illustrates the high variability in the actual headways.

![Figure 3. Scheduled vs. actual departure headway distribution](image)

Based on the OCS data and the scheduled headways, the distribution of departure headways was developed separately for three sub-periods: 16:00 – 16:40, 16:40 – 17:15 and 17:15 – 18:00. Figure 4 illustrates the empirical distribution of departure headways for the three time periods.
Calibration and Validation

With the above inputs SimMETRO was calibrated. The focus of the calibration was on the station-specific parameters of the dwell time model and the time dependent arrival/alighting rates of passengers at each station by branch. The arrival/alighting rates were estimated for 30 min intervals. The choice of parameters and inputs to calibrate reflects the relative importance of those parameters and inputs, the sensitivity of the results to those values, and the fact that reliable estimates of these parameters were not available from other sources. Hence, these parameters were very critical for the accuracy of the model and presented the greatest opportunity for improvement.

Following the general formulation of the calibration model presented in section 3, the objective function used was the minimization of the (square) error between the simulated and actual dwell time at stops and the (square) difference between arrival/alighting rates and dwell time model parameters and their a-priori values.

The available demand data that served as the a-priori values, was collected in 1997. Clearly, due to economic, demographic, and land use changes since then, the 1997 counts can only provide limited information about the 2004 arrival/alighting rates. Furthermore, the 1997 data represent total counts and not by branch, while the input to the simulation requires time dependent arrival/alighting rates by branch.

The dwell time model used in this case study is based on a model developed in an earlier study (Puong, 2000):

\[ D = C + \beta \cdot B + \alpha \cdot A + \gamma \cdot TS^3 \cdot B \]

where,

- \( C \): constant with calibrated value of 12.22 seconds,
- \( A \): number of alighting passengers per door,
- \( B \): number of boarding passengers per door,
- \( TS \): number of through standees per door,
- \( \alpha, \beta, \gamma \): parameters with calibrated values 2.27 (sec/pax), 1.82 (sec/pax) and 0.00064 respectively.
The model was independently calibrated in 2000, with a relatively small sample collected at two of the Red Line stations (South Station and Kendall/MIT). Hence, the calibrated parameters should capture the dwell time at those stations fairly well. However, the remaining stations have, in some cases, quite different characteristics that impact the dwell time, such as location of passenger accesses, size and number of platforms, and level of platform congestion and passenger distribution on the platform. Since SimMETRO can accommodate different dwell time models for different stations, station-specific parameters were calibrated using the above parameter values as a-priori values.

In order to evaluate the effectiveness of the calibration the estimated passenger arrival rates obtained from the calibration were compared to the actual arrival rates in 2004 at select stations for which such data was available. Note that only the 1997 demand data rates were used for calibration (as a-priori values). The 2004 data was used exclusively for validation purposes after calibration. Therefore, the comparison presents an actual evaluation of the effectiveness of the method to estimate the arrival rates at the stations. Unfortunately, these are the only actual data available for direct comparison.

Figure 5 compares the calibrated arrival rates at the 4 stations for which data from 2004 is available. For each station arrival rates reported correspond to 30 min intervals for the 4–6 pm peak period. The graph illustrates the a-priori values (1997), the actual values (2004), and the calibrated values for the period from 4–6 pm, in 30 min intervals. The results indicate that the calibration estimates the actual arrival rates fairly well, especially for high demand stations. If the 1997 data were used, the corresponding RMSE (over all stations and time periods) is 247 pax/hr. The RMSE of the calibrated demand is 107 pax/hr (a 57% reduction). The comparison is a fair one, since the authority uses the 1997 data for their planning and analysis as the best available information on demand (until the next round of collected data becomes available).

![Graph](image)

Figure 5. Comparison of arrival rates

Table 1 summarizes the calibration error for each station and time period. In general, predictions are better for stations with high levels of demand. This is expected since at these stations the actual time needed for boarding/alighting passengers dominates the dwell time, while at stations with low demand levels the noise in the data is quite high.

<table>
<thead>
<tr>
<th>Time Period</th>
<th>4:00 – 4:30</th>
<th>4:30 – 5:00</th>
<th>5:00 – 5:30</th>
<th>5:30 – 6:00</th>
</tr>
</thead>
<tbody>
<tr>
<td>South Station</td>
<td>-13%</td>
<td>+3</td>
<td>-9</td>
<td>-3</td>
</tr>
<tr>
<td>Downtown Crossing</td>
<td>+1</td>
<td>+5</td>
<td>-8</td>
<td>+2</td>
</tr>
<tr>
<td>Porter</td>
<td>-5</td>
<td>+27</td>
<td>+3</td>
<td>-18</td>
</tr>
<tr>
<td>Davis</td>
<td>-5</td>
<td>+46</td>
<td>+1</td>
<td>-6</td>
</tr>
</tbody>
</table>

Table 1. Calibration error in arrival rates (%)
Table 2 summarizes the calibrated dwell time model parameter values for the various stations and compares them against the original model (independently calibrated with data collected specifically for that purpose at two of the stations). In general, the boarding and alighting times per passenger are slightly adjusted by the calibration, while the constants (representing the dead time at the station) change substantially for some stations. The difference for some stations is caused by station characteristics that are different from the stations where the original model was calibrated. For example, Park station has two platforms that are used for passenger loading and unloading. At this station the operator has to attend to doors on both sides and hence spend more time on door operations. The extra time associated with the operations at Park is captured by the higher value of the constant for that station. In some other cases, the constant may absorb some of the time a train is standing at a station due to congestion which may not be otherwise captured by the simulation model (e g. Charles station).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>C₀ (sec)</th>
<th>α (sec/pax)</th>
<th>β (sec/pax)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a-priori values (Puong model)</td>
<td>12.52</td>
<td>2.27</td>
<td>1.82</td>
</tr>
<tr>
<td>Davis</td>
<td>15.23</td>
<td>2.40</td>
<td>1.89</td>
</tr>
<tr>
<td>Porter</td>
<td>13.61</td>
<td>2.09</td>
<td>1.84</td>
</tr>
<tr>
<td>Harvard</td>
<td>18.12</td>
<td>2.04</td>
<td>1.83</td>
</tr>
<tr>
<td>Central</td>
<td>16.71</td>
<td>2.29</td>
<td>1.77</td>
</tr>
<tr>
<td>Kendall</td>
<td>13.91</td>
<td>2.34</td>
<td>1.83</td>
</tr>
<tr>
<td>Charles</td>
<td>20.04</td>
<td>2.41</td>
<td>1.88</td>
</tr>
<tr>
<td>Park</td>
<td>23.83</td>
<td>2.52</td>
<td>1.89</td>
</tr>
<tr>
<td>Downtown</td>
<td>14.14</td>
<td>2.37</td>
<td>1.87</td>
</tr>
<tr>
<td>South Station</td>
<td>17.40</td>
<td>2.34</td>
<td>1.83</td>
</tr>
</tbody>
</table>

Table 2. Calibrated values for dwell model parameters

In addition, and in order to further evaluate the performance of the calibration approach and the validity of the simulator, a number of goodness of fit statistics were calculated including the Root Mean Square Error (RMSE), and Theil’s U inequality (from more details see Pindyck and Rubinfeld, 1997; Toledo and Koutsopoulos, 2004):

\[ RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (Y_{n}^{\text{sim}} - Y_{n}^{\text{obs}})^2} \]

\[ U = \frac{\frac{1}{N} \sum_{n=1}^{N} (Y_{n}^{\text{sim}} - Y_{n}^{\text{obs}})^2}{\sqrt{\frac{1}{N} \sum_{n=1}^{N} Y_{n}^{\text{sim}}^2} + \sqrt{\frac{1}{N} \sum_{n=1}^{N} Y_{n}^{\text{obs}}^2}} \]

\( Y_{n}^{\text{sim}} \) and \( Y_{n}^{\text{obs}} \) are the simulated and observed measurements respectively (time and location specific).

A Theil’s U value equal to 0 indicates a perfect fit, while \( U = 1 \) corresponds to bad performance. \( U \) can be decomposed into three proportions, \( U^M \) (bias), \( U^S \) (variance), and \( U^C \) (covariance). For a good model, \( U^M \) and \( U^S \) should be as small as possible, while \( U^C \) should be close to 1. Values of \( U^M \) higher than 0.10 indicate high degree of bias in a model.

The calibration improved the performance of the model significantly. Table 3 shows the goodness of fit results with respect to block run times (the time when a block is activated to the time it is deactivated). The RMSE after calibration was reduced by 60%. The values of Theil’s U and its proportions also indicate an overall improved ability to replicate existing conditions. Most importantly, the \( U^M \) value shows a significant reduction in bias.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Before Calibration</th>
<th>After Calibration</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE (sec.)</td>
<td>4.455</td>
<td>1.767</td>
</tr>
<tr>
<td>U (Theil’s statistic)</td>
<td>0.081</td>
<td>0.030</td>
</tr>
<tr>
<td>U^M (bias part)</td>
<td>0.204</td>
<td>0.036</td>
</tr>
<tr>
<td>U^S (variance part)</td>
<td>0.302</td>
<td>0.031</td>
</tr>
<tr>
<td>U^C (covariance part)</td>
<td>0.494</td>
<td>0.933</td>
</tr>
</tbody>
</table>

Table 3. Calibration statistics on block run times
Figure 6 is the scatter plot of average block run times before and after calibration. It shows that before calibration, the runtimes generally have some bias associated, in particular for blocks that experience longer run times, which are mostly blocks with stations (and dwell times contribute the majority of run times), or blocks where serious congestion occurs. After the calibration, significant improvement was gained for those blocks, indicating that the errors in the dwell times and congestion were corrected by the calibration. Most of the points after the calibration lie on the 45° line.

While replication of block run times is an important indication of the simulation model’s ability to represent operations in detail, other aspects are equally important. For example, the distribution of headways over time and across the line is also very critical as it results from interactions among trains and is impacted by the uncertainties in the operations. Headway distribution is a comprehensive indication of whether trains are moving and spaced correctly. Furthermore, headways and their distribution affect the calculation of level of service measures, such as waiting times. Figure 7 shows an example of arrival headway distribution at Park Street station, where one of the highest demands occurs, before (Figure 7a) and after calibration (Figure 7b). The headway distribution replicates well the observed (OCS) headways, while the distribution before calibrations is unable to reproduce the observed behavior.

Finally, the calibrated model is validated against data from a day that was not used in the calibration process. For that day trains are dispatched from the terminal at the actual departure times and sequence as reported by the OCS data for the 4–6 pm time period. Table 4 summarizes the results.
For reference, Table 4 also includes the results from the model using the default values (before calibration).

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Before Calibration</th>
<th>After Calibration</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE (sec)</td>
<td>3.550</td>
<td>2.750</td>
</tr>
<tr>
<td>U (Theil’s statistic)</td>
<td>0.057</td>
<td>0.042</td>
</tr>
<tr>
<td>$U_M$ (bias part)</td>
<td>0.097</td>
<td>0.001</td>
</tr>
<tr>
<td>$U_S$ (variance part)</td>
<td>0.145</td>
<td>0.042</td>
</tr>
<tr>
<td>$U_C$ (covariance part)</td>
<td>0.760</td>
<td>0.957</td>
</tr>
</tbody>
</table>

Table 4. Validation statistics for single day

The after calibration statistics show a good correspondence to observed values and a clear improvement over the before calibration statistics, especially with respect to the bias, which was substantially reduced.

Applications
The calibrated/validated model is used for the evaluation of control strategies to improve the operating efficiency of the line and service reliability. At the Alewife terminal, trains are scheduled at mostly 4-minute headway, with a few pairs of 3-minute headways. However, the actual headways range from around 1.5 minutes to more than 10 minutes (Figure 3). Different real time dispatching strategies are evaluated for their impact on various system performance measures such as average passenger waiting time and travel times, using the calibrated model. The following cases are examined:

- **Ideal case.** Trains are dispatched according to the schedule with no deviations.
- **Base case.** Trains are dispatched from Alewife according to the empirical distributions discussed earlier for each of the three sub-periods.

- **Real time control case** with four strategies:
  - Strategy 1. Holding at Alewife if headway is less than 3 minutes,
  - Strategy 2. Holding at Alewife if headway is less than 4 minutes,
  - Strategy 3. Equalized headways at Alewife when possible.

**Ideal case.** The ideal case aims at providing a bound on the expected system performance when stochasticity with respect to the departure headway is not present, and trains depart from the terminal as scheduled.

**Base case.** It aims at assessing the existing performance of the system.

**Real time control strategies.** This case aims at evaluating the effectiveness of three control strategies. Strategies 1 and 2 apply holding of trains at the terminal (Alewife) for 3 and 4 minutes respectively. These values are consistent with the fact that 3 minutes is the minimum headway that two consecutive trains can be dispatched at, without the following train being delayed by the leading train because of signal control (Figure 6 illustrates the bottleneck at Park station). According to the OCS data 32.9% of the headways are less than 3 min, and 54% less than 4 min.

Strategy 3 is another form of holding. Figure 8 illustrates the relationship between a dispatching headway and the following headway. The graph shows that in several cases short headways are followed by long headways. Therefore, it is possible to hold the first train at Alewife by the time is needed to equalize its headway to the following headway. For example, if the current train is ready to depart at a headway of 2 min while to following train is expected to have a headway of 8 min, the first train’s departure will be delayed by 3 minutes, so both trains will experience 5 min headways. The actual headways at Alewife, as recorded by the OCS data, present a number of opportunities to apply the strategy. For example, of all the headways less than 3 min, 19.2% are followed by headways greater than 4 min, 10.8% by headways greater than 5 min and 3.9% by headways greater than 6 min. The objective of the strategy is to reduce the variability in headways, while maintaining their average value. On the other hand, holding strategies 1 and 2, in addition to reducing variance, will also increase the average headway due to the holding. From an implementation point of view, equalization
of headways is practical in this case, since the central control system can observe, in real time, the position of the trains (also the geometry of the line is favorable).

![Relationship between successive headways (OCS data)](image)

Figure 8. Relationship between successive headways (OCS data)

The above cases were examined using the October 2004 calibrated demand. The destinations of trains follow the scheduled sequence. Table 5 summarizes the results for the 16:00 to 18:00 time period.

<table>
<thead>
<tr>
<th>DISPATCHING STRATEGY</th>
<th>Ideal</th>
<th>Base</th>
<th>Holding, Alewife 3 min</th>
<th>Holding, Alewife 4 min</th>
<th>Equalized</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average trunk headway (min)</td>
<td>3.68</td>
<td>3.95</td>
<td>3.99</td>
<td>4.17</td>
<td>3.92</td>
</tr>
<tr>
<td>Trunk headway standard deviation (min)</td>
<td>0.80</td>
<td>1.78</td>
<td>1.64</td>
<td>1.19</td>
<td>1.24</td>
</tr>
<tr>
<td>Average waiting time (min/pax)</td>
<td>2.76</td>
<td>3.37</td>
<td>3.25</td>
<td>3.22</td>
<td>3.07</td>
</tr>
<tr>
<td>Average travel time to South Station (min)</td>
<td>20.9</td>
<td>22.7</td>
<td>22.2</td>
<td>21.9</td>
<td>21.9</td>
</tr>
<tr>
<td>Max travel time to South Station (min)</td>
<td>24.2</td>
<td>28.1</td>
<td>25.8</td>
<td>26.6</td>
<td>26.5</td>
</tr>
</tbody>
</table>

Table 5. Performance of various dispatching strategies

Table 5 shows that the large variability in dispatching headways impacts the performance of the line both in terms of waiting times for the passengers, and travel times (comparison of base to the ideal case). The various strategies show effectiveness in reducing waiting times and travel times. The equalization of headways seems to be the most effective, resulting in about 9% reduction in average waiting times and 3.5% decrease in average travel time. The maximum travel time was reduced by 5.7%. The reduction also indicates that the congestion in the line must have been reduced. (Note that the waiting time reported is average over all passengers; passengers going to Braintree and Ashmont have longer waiting times, while those using the trunk portion of the line have lower).

The above results should be examined in light of the following:

- The results represent the average values over more than a month of operations. Hence, both “good” and “bad” days are included. During days when the system experiences higher than average variability the benefits are going to by higher as well.
• The strategy of equalizing headways is promising, as it incorporates more intelligence in the decision making. It is a limited, “look-ahead” strategy, compared to holding strategies 1 and 2, which are very myopic. Further analysis is required to evaluate its full potential. Examples of refinements include the use of information of more than one headways upstream; and applying the strategy conditionally so that when a train is delayed, the following train is not subject to any adjustments, in order to maintain the equal headways that were just generated.

• The objective of the case study was to demonstrate the application of the simulation framework, as opposed to studying in detail the various strategies. As such, only a part of the network was simulated with the following implications:
  - The analysis assumed that the application of the holding strategy is always feasible. However, this may not be the case given the capacity restrictions at the Alewife terminal. More detailed simulation of the terminal operations is required to include this effect.
  - The analysis assumed that the departure headways are not affected by the strategy in place. However, one would expect that the strategies will improve the overall reliability of the line, including the distribution of dispatch headways. Again, this effect can only be captured by simulating the operations of the entire line.

5. Conclusion

Urban heavy rail simulation models are useful tools for the analysis of rapid rail transit operations and evaluation of control strategies. SimMETRO is a rapid transit simulation model, specifically designed to simulate such systems at the operational level, capturing important details, such as the uncertainty in operations. Calibration of such models is a very important activity before their actual use. Calibration is facilitated by the availability of extensive data on block activation/deactivation times. A calibration methodology is also presented that takes advantage of the availability of block occupancy data to estimate important model parameters and inputs, such as passenger arrival rates at stations. The results from a case study indicate that the calibration methodology uses the available information effectively to estimate these inputs and parameters (arrival/alighting rates, and dwell model coefficients) and improves the accuracy of the simulation results. The calibrated SimMETRO model is able to replicate observed conditions very accurately, and is capable of evaluating alternative schedules and control strategies.

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6. References


