Large-Scale Transit Schedule Coordination Based on Journey Planner Requests

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ABSTRACT
A two-stage stochastic program that reoptimizes multi-modal transit schedules city-wide is presented. The model works by perturbing or offsetting the schedule such that the expected value of waiting times at all transfer points in the system is minimized. Probabilistic information on transfers is gathered from a prototypical journey planner, a public-facing tool that transit riders query to find optimal paths through a multi-modal network. Aggregating journey plans in this manner provides information on optimal transfers as perceived by the service operator, which are then targeted for improvements. The model is implemented on the large-scale transit network of Washington, D.C., where sampled journey plans representing 9% of the daily transit demand is employed to generate a modified schedule that leads to a reduction in passenger wait times by 26.38%. The results serve to demonstrate how operators can take a user-centric view of their system as a fabric of services, gain insights from user interaction, and achieve no-cost improvements from coordinating services while accounting for uncertainty.
INTRODUCTION
A two-stage stochastic program that reoptimizes multi-modal transit schedules city-wide is presented. The model works by perturbing or offsetting the schedule such that the expected value of waiting times at all transfer points in the system is minimized. Information on transfers is gathered from a prototypical journey planner, a public-facing tool that transit riders query to find optimal paths through a multi-modal network. Transfer volumes of users across space and time are aggregated based on the result of queries that users make to a journey planner and are known only probabilistically.

Aggregating journey plans in this manner provides information on optimal transfers as perceived by the service operator, which are then targeted for improvements. These transfers represent the ‘best-case’ service offerings on part of the operator, or a group of operators. While users may not necessarily follow travel itineraries suggested by the journey planner, a representative sample of journey plans reveal systematic delays that occur at transfer points. The journey planner output, in essence, is the service that operators seek to provide.

The use of a journey planner to assign users to paths in the network can be viewed as being analogous to an all-or-nothing assignment (a procedure where all users are assumed to take the shortest path to their destinations) but has key differences to that and other classical assignment procedures. A collection of journey planning requests constitute revealed or intended demand for travel. A collection of journey results constitute the operator’s best supply offerings. Since journey planners typically account for user preferences only in a very limited manner, heterogeneity in preferences (cost and travel time trade-offs for example) are ignored. Thus the principles of traffic assignment where supply and demand interact are not applied. Rather, the system is viewed entirely from the supply perspective. Given that operators supply journeys to a population of users, what are necessary schedule adjustments to provide optimal service?

Existing transit schedules for large multi-modal transit networks typically evolve over the long term, and operators may lack a high-level snapshot of how interconnected services are employed by the traveling public. Further, for the case of multi-modal networks, where different entities manage modes, the coordination may be hindered by organizational barriers (1). The aim of this work is to serve as a feedback loop within this overall transit planning process (2).

There is considerable literature on schedule generation, schedule coordination and optimization for public transit networks. In a review paper, Guihaire and Hao (3), highlight the need for multi-modal considerations in transit planning and service coordination. For the purposes of this paper we focus on previous work that address the problem of aligning different services to minimize transfer time. Several works that have studied coordination of services (4, 5, 6) aim to coordinate arrivals of services at a single stop. Salzborn (7) presented rules to generate schedules for simple cases and Bookbinder and Désilets (8) considered the problem of minimizing waiting times when travel time between stops is random and services have fixed headways. Given the computational intractability of associated problems, several authors have used meta-heuristic approaches to solve the general problem of transit schedule optimization (9, 10, 11, 12, 13, 14, 15, 16) using methods such as genetic algorithms, tabu search, intelligent agent based optimization, local search, or a combination of approaches (17). Specialized heuristics have been proposed as well, such as Lagrangian-based methods that seeks to optimize one line at a time (18) or generate a joint route and schedule plan (19). Large-scale network design and evaluations have been proposed for Rome (15), Boston (20), London (1), and Miami-Dade County (21). Liebchen (22) presents results from optimizing Berlin’s subways using a periodic event scheduling model where shorter
wait times are achieved using fewer trains.

Some previous works have studied the stochastic nature of the transit optimization and its associated processes. Yan et al. (19) present a joint route-timetable design model that considers stochasticity in demand. Mesa et al. (23) aim to find robust fleet assignments such that frequencies on lines that face high demand are increased in a tactical manner. The model doesn’t consider stochasticity explicitly, but aims to find plans that robust against perturbation in demand. Including variability in problem inputs complicates problem design and solution approaches, given the combinatorial aspect of the decision variables. Liebchen and Stiller (24) seek timetables that are resistant to delays.

The proposed work shares the spirit of work by Guo and Wilson (1) where the cost of transfer inconvenience is evaluated in London using a path choice model and focuses on a set of 303 transfer movements. They highlight the importance of paying attention to transfer penalties that multi-modal transport systems impose on users along with barriers to reducing transfer penalties. There are significant institutional issues, since different portions of the network are managed by different entities, who each may view their role as being limited in correcting asynchronous schedules. The study also points to the gap in tools available to planners in quantifying and assessing the magnitude of transfer penalties, a gap that this paper seeks to address. In previous work by the authors (25), the multimodal connectivity of a transit system was analyzed and a hierarchy of transfers determined for different modal combinations. The paper proposed a deterministic program to optimize a single route, as opposed to a stochastic, system-wide method taken in this paper.

The approach presented herein differs from the previously studied models in the following ways. Using journey planning queries and results, transfer costs city-wide are quantitatively characterized. This characterization leads to a model that determines local changes in schedule, defined by the offset, such that globally there is a decrease in expected waiting time. Key elements that have been the target of previous system optimization efforts such as frequencies, routes, and travel times, are retained from the existing schedule. The model is considered strategic, in that operational issues such as uncertainties in travel times and variability in demand are not considered. The existing schedule is assumed to have adequate slack built in the travel times to absorb these uncertainties. The model keeps these slacks and existing travel time, but only seeks and optimal temporal shift, should one be available. The aim therefore is to remedy particularly egregious transfer delays, as identified by the trip plans. Additionally, any transfers that are currently possible and reflected in the trip planning sample is retained in the modified schedule. The high fidelity of journey plan data is leveraged to tune the schedule in a way that has not previously been feasible.

The paper makes the following contributions. First, it provides a framework to operators to leverage journey planning information to provide a comprehensive view of how services are being offered. Second, it presents a stochastic model to optimize the schedules and suggest trip offsets such that expected waiting time is minimized. Third, it presents a large-scale implementation for Washington, D.C. using the Open Trip Planner (OTP) to generate a modified schedule for a typical Wednesday.

The next section describes the two-stage optimization model in greater detail, followed by which the system in Washington, D.C. is described. The journey planner set up and query samples are presented next followed by an evaluation of the improved schedule.
PROBLEM FORMULATION

To clarify presentation of ideas, we use the following terminology which mirrors the General Transit Feed Specification (GTFS). The term route describes one transit service that serves a series of stops (e.g., Route 86). A route is made up of a collection of trips, where each trip represents one run of the route (e.g., 7:49am service of Route 86). A journey refers to a travel itinerary from the perspective of the user, and involves a set of trips and is the output of a journey planner (e.g. take 7:49am service of Route 86 till Stop b, and walk 10 minutes). A schedule describes the arrival and departure times of each trip at each stop along the route. While the route provides a spatial context, the trip information provides a spatio-temporal sense of the transit network. Transfers of passengers occur on this spatio-temporal network.

Given (a) an existing schedule of a multimodal transit network, (b) a set of routes that need to be coordinated, (c) time headways for each trip for the route, (d) a representative set of user journey plans and (e) a probabilistic estimate of transfer volumes, we seek to find an optimal offset of each transit trip, such that the expected waiting times are minimized. The problem is strategic in nature, and the output is a modified schedule that aims to coordinate trips in a manner that users transferring at various points across the network experience minimal delays.

In determining the optimal offset for each trip, the aim is to seek local improvements in departure time at terminal stations. Existing transfer opportunities are preserved, as are the number of trips for each route, frequency, and travel times between stops. Travel times between stops in the existing schedule are assumed to account for slack, variability in traffic conditions, and incorporate time-of-day and day-of-week effects. For large transit networks, where schedules are periodically modified and evolve to match existing conditions on the ground, planners are cognizant of service performance. The travel time estimates contained in the existing schedule are therefore valuable. As an example see Figure 2 for Washington, D.C. that shows the space-time diagrams for selected routes demonstrating the sensitivity of schedules to day-of-week effects. The model therefore seeks to preserve the travel time estimates.

The model is defined on a general service network defined by a set of nodes \( N \) which represent stops, indexed by \( i \). On this network, there are a set of trips \( Q \) indexed by \( p \). Each trip \( p \) visits a subset of nodes \( N_p \). The service \( p \) arrives at node \( i \) at \( t_{pi} \). Each time a trip \( p \) arrives at stop \( i \), users are presented with a set of transfer opportunities. Users transfer from and to trip \( p \). Denote a set \( Q_{pi}^- \) as a set of trips that users seek to connect to (the minus sign signifies that they deboard trip \( p \)) and a set \( Q_{pi}^+ \) as a set of trips that users seek to connect from (the plus sign signifying that users board trip \( p \)). Each transfer opportunity has an associated volume of passengers that is only known probabilistically denoted by \( C_{pq}^-(\xi) \) and \( C_{pq}^+(\xi) \) depending on if users deboard or board from service \( p \) to service \( q \) at node \( i \). Here, \( \xi \) denotes the uncertainty in second-stage problem input. The service network and associated notation is shown in Figure 1. Define \( \Delta_{pq} \) as the minimum transfer time required to make a successful transfer at node \( i \) from service \( p \) to \( q \), and \( h_p \) as the time headway of trip \( p \). Additionally, define \( a \) and \( b \) as parameters that serve to bound perturbation as a fraction of time headway. For example, for values of \( a = -0.5 \) and \( b = 0.5 \), a trip is bound within one time headway of its existing departure.

There are two sets of decision variables. From the operator perspective, denote \( x_p, p \in Q \) as the time offset for each trip. This offset is determined by waiting times experienced by users, which are uncertain. Denote \( w_{pi}(x_p, \xi) \) as the waiting time in passenger-minutes associated with trip \( p \) at stop \( i \). With these definitions, the network-wide transit coordination problem can be expressed as a two-stage stochastic program as follows.
\[
\min_x \mathbb{E}_{\xi} [Q(x_p, \xi)]
\]
\[
\text{s.t.} \quad ah_p \leq x_p \leq bh_p \quad \forall p \in Q
\]
\[
[(t_{qi} + x_q) - (t_{pi} + x_p)] \geq \Delta_{qpi} \quad \forall p \in Q, q \in Q_{pi}, i \in N_p
\]
\[
[(t_{pi} + x_p) - (t_{qi} + x_q)] \geq \Delta_{pqi} \quad \forall p \in Q, q \in Q_{pi}^+, i \in N_p
\]
\[
x_p \in \mathbb{R} \quad \forall p \in Q
\]

where \( Q(x_p, \xi) \) is the second-stage program defined by

\[
Q(x_p, \xi) = \min_w \sum_{p \in Q} \sum_{i \in N_p} w_{pi}(x_p, \xi)
\]
\[
\text{s.t.} \quad w_{pi}(x_p, \xi) \geq \sum_{q \in Q_{pi}} [(t_{qi} + x_q) - (t_{pi} + x_p)] C_{qpi}^-(\xi) +
\]
\[
\sum_{q \in Q_{pi}^+} [(t_{pi} + x_p) - (t_{qi} + x_q)] C_{pqi}^+(\xi) \quad \forall p \in Q, i \in N_p
\]
\[
w_{pi}(x_p, \xi) \in \mathbb{R}^+ \quad \forall p \in Q, i \in N_p
\]

Equation (1) is the first-stage objective to minimize the expected waiting times of passengers system-wide. Constraints (2) bounds the perturbation for each trip within a fraction of the time headway specified by parameters \( a \) and \( b \). Constraints (3) and (4) serve to preserve transfers that passengers make to deboard and board respectively. Constraints (5) specify the time offset to be real. The second-stage model is defined over the distribution of uncertain transfer volumes \( \xi \). The objective in Equation (6) is to minimize the waiting time system-wide. Constraint (7) specifies the waiting time in passenger-minutes to be the sum of waiting times for passengers to deboard and board. Constraint (8) restricts the wait times at all stops to be non-negative.

The second-stage program is convex and always feasible if the support of the distribution of transfer volumes is finite. If empirical distributions are employed, then this is always the case,
since the transfer volume is always finite. The program is also bounded below, since waiting times are non-negative. This can be exploited in the solution approach, as shown in the next section.

The output schedule of the proposed model could potentially cause routes to have irregular service, since the time headways of the trips that make up a route are not equalized. While the extent of the irregularity can be controlled by changing the parameters $a$ and $b$, there are inherent trade-offs between the costs and benefits of having an irregular schedule. Irregular services are detrimental to users who do not have transfers and arrive at stops without prior knowledge of the schedule. The expected wait times for such users increase on account of service irregularity. This added cost is as a result of aiming to improve services at portions of the network where there is significant transfers and usage. Some of the negative impacts can be ameliorated if changes in the regularity are conveyed to users ahead of time, or via real-time updates. This also places greater import on the way that transfer information is gathered, its accuracy, and distributional assumptions. The model also treats the set of transfers as being known. While there are methods from crowd-sourced data on trips, to numerical transit assignment procedures, that reveal a vast majority of transfers being made, there may be transfers that are not captured. This set of unknown transfers can potentially be worse off when left out of the model. The proposed model also retains any sub-optimal scheduling decisions that were in the existing schedule.

**Solving the Coordination Problem**

The solution technique is briefly described. One method to solve a two-stage stochastic program is to build a discrete set of scenarios that accurately depict the underlying distributions, termed the deterministic equivalent. The deterministic equivalent, has an underlying L-shaped matrix that can be solved using decomposition techniques. Methods such as those proposed by Van Slyke and Wets (26) and Birge and Louveaux (27, 28) can be used to solve the program. To generate the deterministic equivalent, the random vectors in the problem are assumed to be realized at certain values and associated probabilities. The continuous expectation function and the second-stage program can therefore be expressed as a series of linear programs. If the transfer volumes are discretized into a finite set of scenarios $S$, indexed by $s$, that occur with probability $p_s$, then the objective (1) can be written as

$$\min_{x,w} \sum_{s \in S} p_s \sum_{p \in Q} \sum_{i \in N_p} w_{pi}(x_p, \hat{\xi}_s),$$

(9)

where, $\hat{\xi}_s$ is the realization of the random vector in scenario $s$. The value of transfer volumes in constraints (7) can be replaced with the realization $C^{−}_{pqi}(\hat{\xi}_s)$ and $C^{+}_{pqi}(\hat{\xi}_s)$ to yield the deterministic equivalent.

**LARGE-SCALE IMPLEMENTATION**

The major transit operator in the Washington, D.C. region is the Washington Metropolitan Area Transit Authority (WMATA). WMATA operates a multi-modal system consisting of a subway system, called Metrorail, and a bus system, called Metrobus. The system is extensive attracting 1.1 million journeys on a typical workday that are served by 311 routes (not all operated by WMATA), that include 5 major Metrorail lines, serving 11,508 stops across the region. If each run of every route is aggregated, on a typical weekday, the system accounts for 24,390 trips, with a lower number of trips on Saturday (12,964 trips) and Sunday (9,935 trips). The system is a critical component of the urban mobility in the nation’s capital. WMATA has embraced open-data initiatives
by releasing schedule information in the GTFS format, and providing a real-time Application Pro-
gramming Interface (API) that serves information on all aspects of the system. These efforts have
enabled this study.

The existing transit schedule has several service characteristics that are important and need
to be retained though any reoptimization efforts. A critical aspect of service is the sensitivity of
trip travel times to day-of-week effects and time-of-day effects. Since Washington, D.C. ranks
fourth in the nation in traffic congestion, such sensitivity is vital to generate realistic schedules.
Figure 2 graphically demonstrates the day-of-week effects for four sample routes. The slope of the
space-time trajectories represent the speed of the vehicles. The weekend schedules can be clearly
seen to have faster service, on account of traffic conditions. Similar trends are present, albeit less
drastic, for time-of-day effects.

![Sample Space-Time Trajectories of Bus Routes Showing Sensitivity to Traffic Variations](image)

WMATA also operates its own journey planner service on its website, while through its
public data efforts, journey planning is also possible through other widely used tools, such as
Google Maps and Microsoft Bing. For this study, data on journey planning requests made to these
services were not readily available, therefore a representative sample of journeys were sampled based on transit demand for the region and the Open Trip Planner (OTP) employed using Open Street Map (OSM) network data.

FIGURE 3 Spatial Patterns of Transit Demand and 9% Trip Sample

Transit Demand
Demand for transit is estimated by the regional travel demand model maintained by the Metropolitan Washington Council of Governments (MWCOG). The model uses surveys and observed transit ridership numbers to calibrate and estimate mode choice models for the region. For a typical workday, 1.1 million transit journeys are undertaken in the region. Based on this aggregated travel
pattern, a 9% sample, representing roughly 100,000 individual journeys, was constructed.

The aggregate daily transit trips are shown by origin (Figure 3(a)) and destination (Figure 3(b)). The constructed sample, shown in Figures 3(c) and 3(d) show the spatial disaggregation of trips. The sample is spatially representative of overall transit flows.

To derive an accurate temporal representation of usage, a temporal profile was used to distribute the queries across time of day. The temporal profile is based on highway volume data for a typical weekday in the region and follows the typical double-hump observed in a variety of mobility processes. The temporal sample is therefore not representative, but indicative of overall trends.

**Transit Supply**

To represent the transit supply side of the equation, open schedule data from WMATA, and the street network from Open Street Maps (OSM) (29), were used to build a service network using the Open Trip Planner (OTP) (30). Using open tools and data sources allows replication of our proposed work across cities. The network and the journey planning engine available in OTP was set up on an internal server. Using a Python script, OTP planned journeys for the 100,000 sampled journeys.

For multi-modal trips there are several parameters that can be set, including maximum walk time, maximum number of transfers, and restrictions on modal alternatives (e.g., bus-only, etc.). All journeys were set to having the same parameters, i.e. user heterogeneity is ignored. Walk distances are limited to 1/2 mile, maximum number of transfers allowed was set to five, and the quickest path was sought. The trip start time was set based on the temporal profile sampled above. OTP returns several alternate itineraries, and only the fastest journey was considered. Figure 4.2 shows an example journey plan.

![FIGURE 4 An Example Multimodal OTP Query Result Containing Three Modes: Walk, Metrorail and Metrobus](image)

There are some limitations in representing the true transit supply process. A main limitation is the lack of support for journeys that involve a park-&-ride facility, when transit journeys are considered. These facilities play an important role in providing transit access for suburban regions. Secondary access modes such as bicycles and shared-bicycles were also not considered. Cost criteria were not optimized in the travel journeys. Since metrorail is quicker but more expensive for longer journeys than metrobus, journeys that have both options available will favor metrorail.
While these limitations don’t impact the in-system journey plans, they do alter the routes proposed. The limitations can be overcome if the journey planner incorporates these factors. With the a set of synthesized journey requests and a network representation of the transit supply process, transfer costs system-wide can be calculated.

**Estimating Transfers**

The resulting journey plans from OTP are parsed and transfer information recorded for multi-leg journeys. Transfers occur in two modes. Waiting transfers refer to changes from one service to another. Walking transfers involve a change in service and a walk to the next service. Both types of transfers are translated to waiting time, since our purpose is to adjust the schedule. So the walk component of transfers is simply added to $\Delta_{pq}$, the minimum time needed to transfer at stop $i$ between services $p$ and $q$. A detailed characterization of the transfer process is presented in Coffey et al. (25).

A total of 59,344 unique transfer movements were captured from the sample. Each transfer movement represents a service pair at a point in space and time. Two key performance metrics are employed to convey wait times. The basic measure is the wait time in minutes of each transfer, as represented by the journey plan. The second is a volume-weighted waiting time metric in passenger-minutes that is derived by equally apportioning the total travel demand for an origin-destination pair among all journey plans for that pair.

First, an aggregate picture of waiting times is presented. Figure 5 shows the spatial distribution waiting time across the network. Assuming a representative sample, a total of 26,392 passenger-hours of delay was measured for a typical weekday. Assuming a value-of-time (VOT) of $18 per hour, the estimated cost of these wait times is $475,059 daily.

The distribution of wait times by route can be examined to evaluate if there is a high occurrence of particularly extreme waits. Figure 6 show the wait time distribution for selected routes differentiated by mode, showing the higher level of service of metrorail leading to lower wait times.
From a transfer perspective, there is a small proportion of journeys that experience high transfer times that are then optimized. If wait times are aggregated by route, across time and space, route performance can be measured. Figure 7 shows the top twenty routes in terms of daily delay. The major metrorail services that are high volume and frequent, account for significant wait times incurred by passengers. The improvements in wait times based on the modified schedule are also shown.

**FIGURE 6 Distribution of wait Times for Different Services**

**REOPTIMIZATION RESULTS**

The schedule reoptimization model was solved using CPLEX and a modified weekday schedule generated for the entire network. Computational details are omitted for brevity, except to note that 100 scenarios were considered for the second-stage model, where the transfer volumes were assumed to be log-normal, with the mean equal to the transfer volume estimated from the sample.

The wait times for the 9% sample were recomputed, assuming users would have been offered the same journey plans. System-wide waiting time based on the modified schedule were computed at 19,429 passenger-hours (or $349,722 assuming a VOT of $18/hour). This represents a 26.38% improvement in system-wide wait times, achieved by the schedule offset.

The improvements in wait times were disaggregated by route for which passengers wait to board. Figure 7 shows the reduction in wait times as a result of the modified schedule. These are reported for the top 20 routes with largest wait times in passenger-minutes based on the existing schedule.

The schedule modifications for selected routes is plotted in Figure 8. The temporal offset suggested by the model can be ascertained by comparing the existing and modified trajectories. Since the \( a \) and \( b \) parameters were considered as \(-0.5\) and \(0.5\), the offset is limited by one half headway in either temporal direction as shown by Figure 9 which shows the offset distribution for the entire city. This leads to some routes having irregular headways. One method to limit the regularity is to change the \( a \) and \( b \) parameters, or introduce route specific parameters, after the routes have been determined. Ongoing efforts seek to determine the route specific values for these parameters automatically, such that routes are equalized.

Since the model weights the wait times by passenger volumes while seeking the correction,
there are a small proportion of users that see reduced service. The reason this occurs is because the temporal offset optimizes for nodes where transfer volumes are greater, at the expense of nodes at which volumes are low. The distribution of transfer volumes can be compared before and after the schedule update to see what fraction of users see a decreased service as shown in Figure 10. The decreased service is experienced by approximately 15% of users. However the magnitude of the decrease is significantly lower than the magnitude of the improvements seen for the majority of users.

CONCLUSIONS
A stochastic program that computes optimal time offsets for a large-scale transit network is implemented for Washington, D.C. Using output of a journey planner, the transfer penalties, in terms of wait times, that multi-modal networks impose on users is characterized. The high fidelity with which journey plans depict itineraries, coupled with the large volume of queries that agencies or third party providers process, allow a rich characterization of transfers that then drive a system improvement, in this case temporal offsets.

For Washington, D.C. based on a representative sample of queries, users wait a total of 26,392 passenger-hours. Using the proposed model to generate a modified schedule, the waiting times are reduced by an estimated 26.38%. The wait times are also characterized by different routes and distributions, providing vital performance metrics that could also be used to provide system insights.

Extensions of the model that seek to provide equalized headways, include reliability information on routes and uncertainty in travel times, distinguish special event patterns from trip queries would add value for transit operators. This methodology presented leverages information gleaned from contact with users via a journey planner. With time, the set of requests are likely to change to reflect changes in travel patterns. A periodic review of the schedule based on evolving...
FIGURE 8  Comparison of Modified and Existing Schedules for Selected Bus Routes
travel patterns can also provide a closer feedback loop to the design process.

A key concept of the proposed work is to have a representative sample of journey plans. The sample should accurately reflect how transfers are conducted in the system, so that the re-optimized schedule provides efficient mobility for all.

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