Performance Models

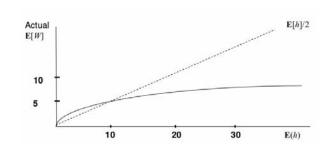
Outline

- 1. Wait time models
- 2. Service variation along route
- 3. Running time models
- 4. Dwell time models

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Passenger Arrival Process

- Individual, group, and bulk passenger arrivals
- Passengers can be classified in terms of arrival process
 - random arrivals
 time arrival to minimized
 - time arrival to minimize E[W]
 arrive with the vehicle, i.e. have W = 0



Wait Time Models

Simple deterministic model

$$\mathbf{E}[W] = \frac{\mathbf{E}[h]}{2}$$

where

- E[W] = expected waiting time
- E[h] = expected headway

Model assumptions

- passenger arrival times are independent of vehicle departure times
- vehicles depart deterministically at equal intervals
- every passenger can board the first vehicle to arrive

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Vehicle Departure Process

Vehicle departures typically not regular and deterministic Wait Time Model refinement:

n(h) = # of passengers arriving in a headway h

- $\overline{w}(h)$ = mean waiting time for passengers arriving in headway h
- g(h) = probability density function of headway

 $E[W] = \frac{\text{Expected Total Passenger Waiting Time per Vehicle Departure}}{\text{Expected Passengers per Vehicle Departure}}$

$$\mathbf{E}[W] = \frac{\int_0^\infty n(h) \cdot \overline{w}(h) \cdot g(h) \cdot dh}{\int_0^\infty n(h) \cdot g(h) \cdot dh}$$

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Vehicle Departure Process

 $n(h) = \lambda h$ where λ is the passenger arrival rate

$$\overline{w}(h) = \frac{h}{2}$$
$$E[W] = \frac{E[h^2]}{2E[h]} = \frac{E[h]}{2} \left[1 + \frac{Var[h]}{(E[h])^2} \right] = \frac{E[h]}{2} \left[1 + c_h^2 \right]$$

where c_h is coefficient of variation of headway

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Vehicle Departure Process Examples

If Var[h] = 0

$$\mathbf{E}[W] = \frac{\mathbf{E}[h]}{2}$$

If vehicle departures are as in a Poisson process

 $Var[h] = (E[h])^2 \qquad E[W] = E[h]$

If the headway sequence is 5, 15, 5, 15, ...

E[h] = 10

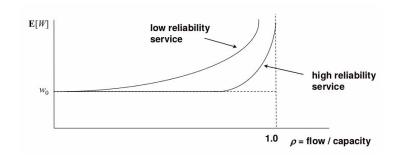
 $E[W] = 2.5 \cdot 0.25 + 7.5 \cdot 0.75 = 6.25$ minutes

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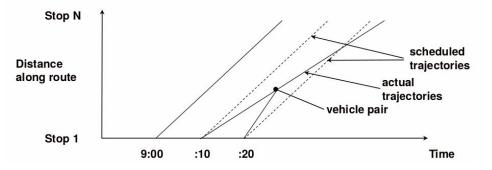
Passenger Loads Approach Vehicle Capacity

• Not all passengers can board the first vehicle to depart:



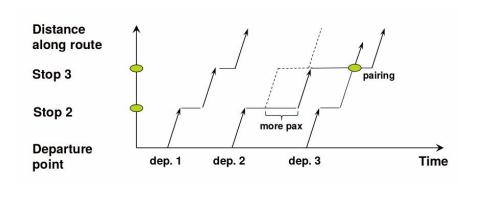
Service Variation Along Route

- Service may vary along route even without capacity becoming binding:
 - the headway distribution can vary along the route, affecting E[W]
 - at the limit vehicles can be paired, or bunched
 - \circ $\;$ this can also result in passenger load variation between vehicles

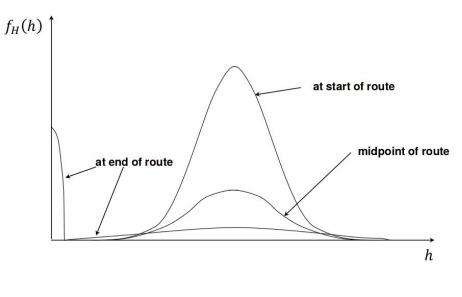


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Service Variation Along Route



Service Variation Along Route



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Factors Affecting Headway Deterioration

- Length of route
- Marginal dwell time per passenger
- Stopping probability
- Scheduled headway
- Driver behavior

Simple model

where

- e_i = headway deviation (actual scheduled) at stop $i\Box$
- $t_i = travel time deviation (actual scheduled) from stop$ *i* 1 to*i*

 $e_i = (e_{i-1} + t_i)(1 + p_{i-1}b)$

- p_i = passenger arrival rate at stop *i*
- b = boarding time per passenger

Mathematical Model for Headway Variance

$$\begin{split} \operatorname{var}(h_{i}) &= \operatorname{var}(h_{i-1}) + \operatorname{var}(\Delta t_{i-1}) + 2p_{i-1}(1-p_{i-1})(c \cdot \overline{q}_{i-1} + \ell)^{2} \\ &+ 2c^{2}\operatorname{var}(q_{i-1}) \Big[1 - \rho_{q} + p_{i-1}\rho_{q} \Big] (1-p_{i+1}) \\ &+ c(1-p_{i-1})^{2} \cdot \operatorname{cov}(\Delta q_{i-1}, h_{i-1}) \end{split}$$

where : $var(h_i)$ = headway variance at stop *i*

c \overline{q}_i

- $var(\Delta t_i)$ = variance of the difference in running time between successive buses between stops i - 1 and i
- p_i = probability bus will skip stop i
 - = marginal dwell time per passenger served at a stop
 - = mean number of passengers per bus served at stop i
 - = the constant term of the dwell time function
- $var(q_i)$ = variance of the number of passengers served per bus at stop i
- ρ_q = correlation coefficient between the passengers served by successive buses at a stop
- $cov(\Delta q_i, h_i) = covariance of the difference in number of$ passengers served by successive buses and theheadway at stop i

* Adebisi, O., "A Mathematical Model for Headway Variance of Fixed Bus Routes." Transportation Research B, Vol. 20B, No. 1, pp 59-70 (1986). Courtesy Elsevier, Inc., https://www.sciencedirect.com. Used with permission.

Vehicle Running Time Models

Vehicle Running Time Models

Different levels of detail

- Very detailed, microscopic simulation
 - o represents vehicle motion and interaction with other vehicles
 - buses operating in mixed traffic
 - train interaction through control system
- Macroscopic
 - o identify factors which might affect running times
 - collect data and estimate model

- Running time includes dwell time, movement time, and delay time
 - dwell time is generally a function of number of passengers boarding and alighting as well as technology characteristics
 - movement time and delay depend on other traffic and control system attributes

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- Typical bus running time breakdown in mixed traffic
 - 50-75% movement time
 - 10-25% stop dwell time
 - 10-25% traffic delays including traffic signals

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Dwell Time Models

- Dwell Time Theory
- Bus Dwell Time Model
 - Milkovits, M.N., "Modeling the Factors Affecting Bus Stop Dwell Time: Use of Automatic Passenger Counting, Automatic Fare Counting, and Automatic Vehicle Location Data." Transportation Research Record: Journal of the Transportation Research Board, pp pp 125-130 (2008).
- Light Rail Dwell Time Model
 - Wilson, N.H.M. and T. Lin, "Dwell-Time Relationships for Light Rail Systems," Transportation Research Record #1361, 1993, pp. 296-304.
- Heavy Rail Dwell Time Model
 - Puong, A., "Dwell Time Model and Analysis for the MBTA Red Line." Internal memo, MIT, March 2000.

Dwell Time Theory

- Vehicle dwell time affects
 - system performance
 - service quality
- A critical element in vehicle bunching resulting in
 - high headway variability
 - high passenger waiting times
 - uneven passenger loads
- Dwell time impact on performance depends on:
 - stop/station spacing
 - mean dwell as proportion of trip time
 - $\circ \quad \text{mean headway} \quad$
 - \circ operations control procedures
- Examples
 - \circ Commuter rail \rightarrow little impact of dwell time on performance
 - \circ $\;$ Long, high-frequency bus route \rightarrow major impact

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Dwell Time Theory

- Dwell time depends on many factors
 - human 0
 - modal 0
 - operating policies & practices 0
 - weather 0
- For a given system we have the following possible models
 - Single door, no congestion and interference 0 DOT = a + b(DONS) + c(DOFFS)
 - Single door with congestion and interference DOT = a + b(DONS) + c(DOFFS) + d(DONS+DOFFS)(STD)
 - Single car with m doors $DT = max(DOT_1, \dots, DOT_m)$
 - Single car with m doors, with balanced flows DT = a + b/m(CONS) + c/m(COFFS) + d/m(CONS+COFFS)(STD)
 - n-car train
 - DT = max(DT1, ..., DTn)
 - n-car train, with balanced flows DT = a + b/nm(TONS) + c/nm(TOFFS) + d/nm(TONS+TOFFS)(STD)

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Objective

- Develop a dwell time model using automatically collected data
- Dwell time factors
 - Boarding and alighting passengers
 - Onboard passengers 0
 - Fare media type
 - Alighting door selection
 - Bus type
- Minimize the unexplained variation in dwell time
- Evaluate impact on dwell time of:
 - fare media type
 - bus design 0
 - enforcement of rear-only alightings

Milkovits (2008)

From Milkovits, M. Modeling the Factors Affecting Bus Stop Dwell Time: Use of Automatic Passenger Counting, Automatic Fare Counting, and Automatic Vehicle Location Data. In Transportation Research Record: Journal of the Transportation Research Board, No. 2072. Copyright, National of Sciences, Washington, D.C., 2008. Reproduced with permission of the Transportation Research Board.

- Limited data on infrequent events
- Crowding
- Do not include latest fare media
- Automatically collected data
 - Does not include fare media information
 - Poor fit of model
- Transit Capacity and Quality of Service Manual
 - Assumes a half-second penalty per passenger for crowding

Milkovits (2008)

From Milkovits, M. Modeling the Factors Affecting Bus Stop Dwell Time: Use of Automatic Passenger Counting, Automatic Fare Counting, and Automatic Vehicle Location Data. In Transportation Research Record: Journal of the Transportation Research Board, No. 2072. Copyright, National of Sciences, Washington, D.C., 2008. Reproduced with permission of the Transportation Research Board.

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Data Set

- Automatically collected data from Chicago Transit Authority bus network
- Non-Timepoint, Far-Side, Known Stops
- Functioning APC counters on all doors
 - Verified by non-zero counts across day
 - Minimum per-passenger dwell time of .5 seconds
- Link-in AFC transactions
 - Fare transactions that take place within the dwell time
- Data from entire month of November 2006
 - o 173,750 Records
 - 2,977 Operators
 - 85 Routes
 - 927 Stops

Milkovits (2008)

From Milkovits, M. Modeling the Factors Affecting Bus Stop Dwell Time: Use of Automatic Passenger Counting, Automatic Fare Counting, and Automatic Vehicle Location Data. In Transportation Research Record: Journal of the Transportation Research Board, No. 2072. Copyright, National of Sciences, Washington, D.C., 2008. Reproduced with permission of the Transportation Research Board. 1 258J 11 541J ESD 226

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Bus Dwell Time: Prior Work

Model Formulation

- Predict dominant door activity
- Segment data and compare by:
 - Bus type
 - Crowding (passengers > number of seats)
- Combine the data and test for significant differences in the estimators

Milkovits (2008)

From Milkovits, M. Modeling the Factors Affecting Bus Stop Dwell Time: Use of Automatic Passenger Counting, Automatic Fare Counting, and Automatic Vehicle Location Data. In Transportation Research Record: Journal of the Transportation Research Board, No. 2072. Copyright, National of Sciences, Washington, D.C., 2008. Reproduced with permission of the Transportation Research Board.

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Dwell Time Estimates – Rear Door

				Adjusted R ² : 0.37
Variable	DUMMY	est	t-stat	Passenger Levels
Intercept		1.42	22.49	
	NABI	2.64	21.26	
ROFF		1.69	40.86	All
	NOVA	0.42	7.47	
	NABI	-0.42	-5.37	
			_	_
ST2_PASS		0.005	5.64	
	NOVA	0.004	2.11	Crowded
	NABI	-0.003	-3.36	[

Milkovits (2008)

From Milkovits, M. Modeling the Factors Affecting Bus Stop Dwell Time: Use of Automatic Passenger Counting, Automatic Fare Counting, and Automatic Vehicle Location Data. In Transportation Research Record: Journal of the Transportation Research Board, No. 2072, Tables 3 and 4, p. 128. Copyright, National of Sciences, Washington, D.C., 2008. Reproduced with permission of the Transportation Research Board.

Dwell Time Estimates – Front Door

				Adjusted R ² : 0.73
Variable	DUMMY	est	t-stat	Passenger Levels
intercept		-1.22	-26.49	
NABI		0.53	7.81	Ι
FON_EX		3.68	154.17	All
	NOVA	0.38	10.51	
	NABI	-0.59	-11.32	
FOFF3UP		1.52	26.22	
CARDS		2.62	10.15	
TICKET		4.88	39.55	1
	NFLYER	-0.58	-3.62	Open
FOFF12		2.83	104.59	
F_SENSOR		4.60	21.55	
		•		•
AFC_TRANS		4.35	15.54	
FOFF12		3.52	22.54	1
	NFLYER	-0.74	-3.71	Crowded
ST2_PASS		0.0011	5.56	1
	NFLYER	0.0017	3.53	

Milkovits (2008)

From Milkovits, M. Modeling the Factors Affecting Bus Stop Dwell Time: Use of Automatic Passenger Counting, Automatic Fare Counting, and Automatic Vehicle Location Data. In Transportation Research Record: Journal of the Transportation Research Board, No. 2072, Tables 3 and 4, p. 128. Copyright, National of Sciences, Washington, D.C., 2008. Reproduced with permission of the Transportation Research Board.

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Bus Dwell Time Model: Key Findings

- Smart media loses benefit in crowded conditions
 Drops from 2 second advantage in non-crowded conditions
- Crowding impact increases exponentially
- Bus attributes impact dwell time
 - Location of magnetic stripe reader (half second difference)
 - Double-wide doors
- Front door alightings may affect dwell time, while rear door alightings will happen in parallel

Milkovits (2008)

From Milkovits, M. Modeling the Factors Affecting Bus Stop Dwell Time: Use of Automatic Passenger Counting, Automatic Fare Counting, and Automatic Vehicle Location Data. In Transportation Research Record: Journal of the Transportation Research Board, No. 2072. Copyright, National of Sciences, Washington, D.C., 2008. Reproduced with permission of the Transportation Research Board.

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MBTA Green Line Analysis

- Branching network of 28 miles (45 km) and 70 stations
- 52-seat ALRVs operate in 1-, 2-, and 3-car trains
 - high floor, low platform configuration
 - 3 doors per car on each side
 - single side boarding/alighting
- Trunk service in central subway:
 - 10 or 14 stations on round-trip
 - 1- to 2-minute headways
 - peak flows ≈10,000 passengers/hour

Wilson and Lin (1993)

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One-car trains

 DT = 12.50 + 0.55*TONS + 0.23*TOFFS + 0.0078*SUMASLS (8.94) (3.76) (2.03) (6.70)
 R² = 0.62

SUMASLS = TOFFS*AS + TONS*LS

Models with Crowding Term

Two-car trains

 DT = 13.93 + 0.27*TONS + 0.36*TOFFS + 0.0008*SUMASLS (7.43) (2.92) (3.79) (2.03)
 R² = 0.70

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Predicted Dwell Times

ONS	LPL	1-Car DT	2-Car DT
0	any #	12.5	13.9
10	< 53	20.3	20.2
10	150	35.6	21.0
20	< 53	28.1	26.5
20	150	58.7	28.1
30	< 53	35.9	32.8
30	150	81.8	35.1

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Findings

- Dwell times for ALRVs are quite sensitive to:
 - Passenger flows
 - Passenger loads
- The crowding effect may well be non-linear.
- Dwell times for multi-car trains are different from those for one-car trains.

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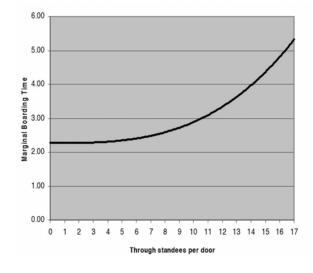
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- The dwell time functions suggest high sensitivity of performance to perturbations
- Effective real-time operations control essential
- Running mixed train lengths dangerous
- Simulation models of high frequency, high ridership light rail lines need to include realistic dwell time functions.

Wilson and Lin (1993)

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Heavy Rail Marginal Boarding Time



Puong (2000)

1.258J 11.541J ESD.226J Lecture 9, Spring 2017 Heavy Rail Dwell Time Function

$$DT = 12.22 + 2.27 \cdot B_d + 1.82 \cdot A_d + 6.2 \ 10^{-4} \cdot TS_d^3 B_d \quad (\bar{R}^2 = 0.89) \quad (9)$$

(12.82) (7.11) (9.07) (4.70)

where

- A_d = alighting passengers *per door*,
- B_d = boarding passengers *per door*, and

 TS_d = through standees per door, i.e., total through standees divided by the number of doors

Puong (2000)

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