Analysis of Downtown People Mover Systems by Using the DPM Simulation Model

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Downtown people movers (DPMs), a class of automated transit system that operates on exclusive guideways, are being considered by many cities as a possible solution to their circulation and distribution problems. This paper describes how a discrete event-simulation model developed by the Transportation Systems Center can be used in the planning and design of DPM systems. The paper identifies the variables that can be studied and that affect system ridership, cost, and performance by the model. The key inputs, the modeling functions, and outputs of the model are discussed in the context of an example, the 1990 Los Angeles DPM system. Use of the model to determine the feasible combinations of fleet size, vehicle capacity, and operating headway to meet the Los Angeles DPM system performance goals for the year 2000 is discussed. Finally, the use of the model to examine the effects of a vehicle failure on passenger service and system operation and to evaluate three algorithms for system recovery is illustrated.

Downtown people mover (DPM) systems are a subset of automated guideway transit (AGT) systems, a class of transportation system that is characterized by unmanned vehicles operated on fixed exclusive guideways. The first generation of DPMs will consist largely of elevated systems in which proven technologies are deployed in central business districts (CBDs) and adjacent areas of larger U.S. cities.

As part of its program for transportation planning support to urban areas, the Urban Mass Transportation Administration (UMTA) has sponsored the development of special demand and supply analysis techniques. The Downtown People Mover Simulation (DPMS) model was developed to provide a tool for planners and designers:

1. To determine the sensitivity of system performance to the range of AGT design parameters (such as capacity, speed, and safe headway) and to variations in the magnitude and spatial distribution of demand;
2. To determine potential system bottlenecks created by the dynamic interaction of demand and service;
3. To examine the impact on service of infrastructure decisions that affect system operation, such as station size or guideway curvature;
4. To determine the effect of anomalies such as demand surges or equipment failures on passenger service; and
5. To examine a variety of system operating strategies.

THE DPM PLANNING AND DESIGN PROCESS

The planning process examines the feasibility of DPM in comparison with other modes by determining the ridership of alternative route alignments, station locations, and intermodal concepts together with the trip-making characteristics of the deployment area.

The DPMS model provides a tool for the linking of the planning process and the design process. Figure 1 illustrates this concept. The design process defines the detailed system characteristics that will provide the level of service that was assumed in the demand estimation and planning process. Hence, the system designer takes the guideway layout, which includes station locations and the distances between stations, and the baseline station-to-station demand matrix as given. System service characteristics used in the planning process, such as headways and travel times, represent constraints.

The system designer incorporates network constraints and demand profile assumptions into the scenario representation. Sets of system operating and hardware characteristics that affect the baseline service characteristics are defined. Table 1 lists the scenario and design variables that can be manipulated by the DPMS and the corresponding service characteristic variables that are model outputs or can be derived from model outputs. Sensitivity analysis should be performed in the areas shown in Figure 1. These include network constraints, demand projections, alternative system characteristics, and anomaly analysis. The final products of the design process include the sensitivity of service characteristics to system variables, the cost impacts of system variables, and the performance specifications. The variables addressed by the DPMS that affect cost and performance specifications are also shown in Table 1. The design variables used as model inputs will be discussed later in the context of the Los Angeles DPM example.

By use of the simulation input variables defined in Table 1, the system designer conducts a series of simulation experiments. The simulation model represents the movement of the vehicles on the guideway. Safe headway separation is maintained according to defined vehicle control strategies. Vehicles travel along predefined routes. The vehicles are dispatched from the stations according to the route headways and dispatch algorithms specified. Passengers arrive at their origin station at the time defined in the trip list and enter a boarding queue. When the simulated vehicle arrives, passengers deboard if the particular station is their destination and board if the vehicle has sufficient space and is headed toward their destination station. The model records the time at which individual passengers deboard and board all vehicles. The model keeps track of the current occupancy and time integral of occupancy for all passengers at each station and on each vehicle and for all vehicles at each station, on each link, and on each route of the network.

At user-specified intervals, samples are collected on passenger- and vehicle-related statistics. These sample statistics are reported at periodic intervals during the simulation process and stored for analysis during the output processing stage. The model also records statistics on each completed trip. During the output processing phase, the statistics of interest are displayed in a variety of ways, depending on user requirements. Three major types of reports can be generated: (a) a standard summary report; (b) time-series plots, histograms, summaries, or lists of sample values of key variables; or (c) station-to-station matrices for key travel time statistics.

A complete description of the model is provided in the DPMS program writeup (1). A computer-animated film has also been developed to illustrate the model's key features. Both of these documentation sources are available from the Transportation Systems Center (TSC) of the U.S. Department of Transportation.

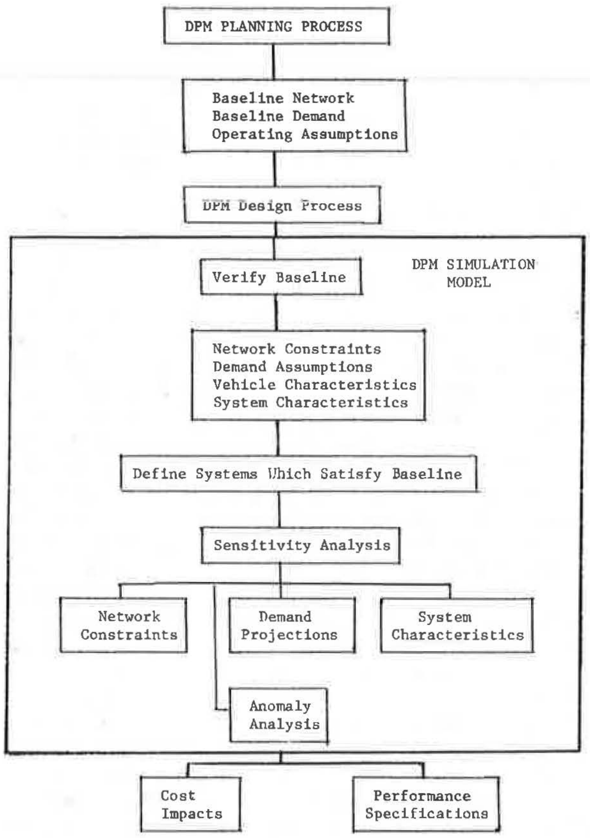


Figure 1. DPM planning and design process.

THE DPM MODELING PROCESS: THE LOS ANGELES DPM EXAMPLE

This section describes the modeling of the baseline Los Angeles DPM system. Variables that describe the Los Angeles DPM were supplied by the Los Angeles Community Redevelopment Agency. The variables were converted by TSC to DPMS inputs to model the Los Angeles baseline design. The Los Angeles DPM case studies are included in this paper to illustrate the use of the model.

Network Modeling

Network connectivity is modeled in the DPMS by a set of unidirectional links that are defined by in-nodes and out-nodes. The nodes are numbered, and contiguous links are defined by common node numbers. Since DPMS represents the actual movement of vehicles through defined physical areas, stations are also represented by unidirectional links. Figure 2 shows the DPMS representation of the Los Angeles DPM network.

In addition to the connectivity, the guideway links are defined by the following parameters: length (m), capacity (vehicles), average speed (m/s), nominal travel time (s), and minimum safe headway (s). The two most important variables for simulation are the nominal travel time and the minimum safe headway. These variables are used to schedule the completion of events in a vehicle's traversal of the guideway link. The minimum safe headway defines the time during which no other trains may enter a link. The nominal travel time defines the time required to complete the link travel event. If a train cannot enter a link due to capacity, headway, or failure conditions, the train is queued until the condition is cleared. The list below shows the Los Angeles network parameters.

Los Angeles DPM Baseline

1. Demand—evening peak period = 2 h, peak hour demand = 9200 passengers/h, and 4600 passengers are carried during the peak 20 min;

Table 1. Simulation variables related to ridership, cost, or performance specifications.

DPMS Variable	Ridership Variable	Cost Variable	Performance Specification
Input			
Station-to-station demand rate by time interval	In-vehicle and wait times		
Guideway speed limits	In-vehicle time		
Station configurations	In-vehicle time	Capital cost	
Station-to-station distance	In-vehicle time	Capital cost	
Vehicle speed	In-vehicle time	Vehicle cost	
Vehicle capacity	Wait time	Vehicle cost, guideway cost	Square meters per passenger, standee-seated ratio
Vehicle loading rates	Wait time		Deboard and board rate
Vehicles per train	Wait time	Station cost	
Minimum safe headway	Wait time	Vehicle cost	
Route headway	Wait time		
Transfer points	Transfer time		
Minimum and maximum door open times	Wait and in-vehicle times		Time to unload vehicle
Failure conditions	Wait and in-vehicle times	System cost	Maximum delay times
Output			
Wait-time distribution	Wait time reliability		Maximum wait
In-vehicle time distribution	In-vehicle time reliability		
Maximum station queue		Station cost	Platform size
Load factors	Fare		
Vehicle kilometers	Fare	Operating and maintenance cost	
Passengers served	Fare		
Peak vehicles	Fare	Capital cost, operating and maintenance cost	

Figure 2. Los Angeles DPM network.

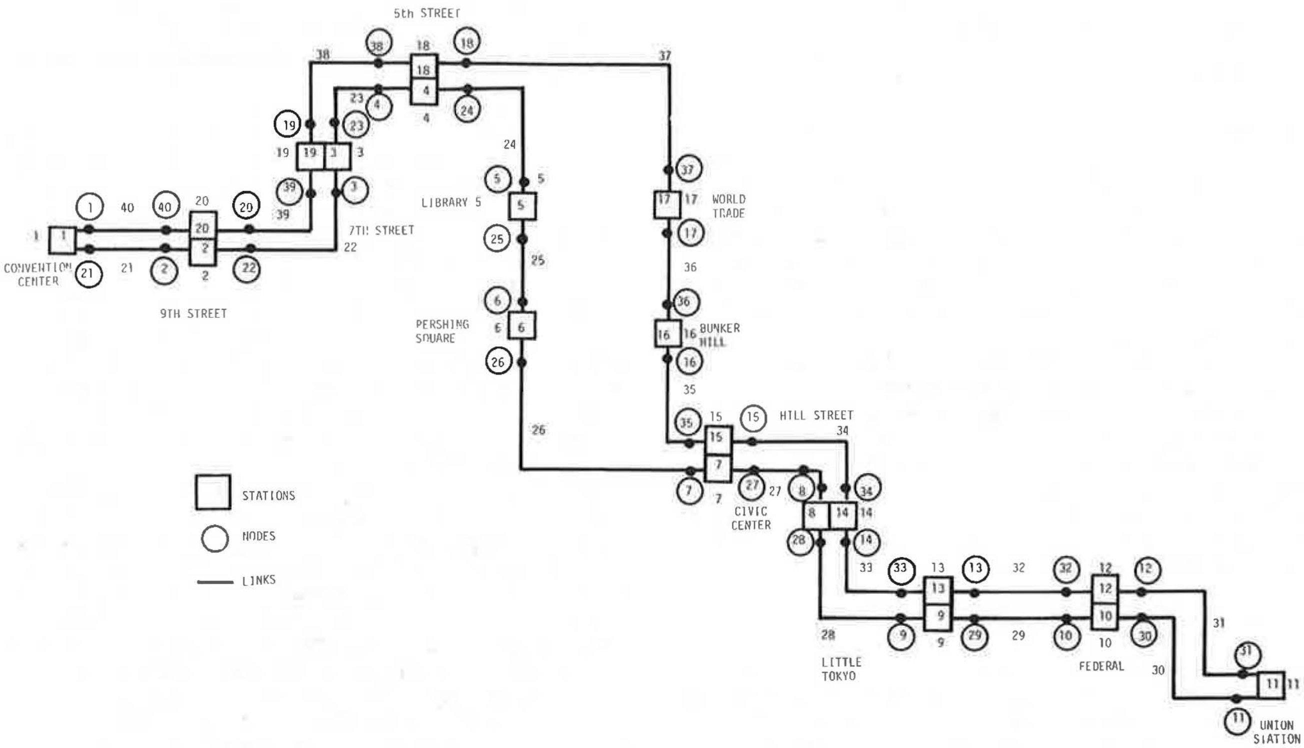
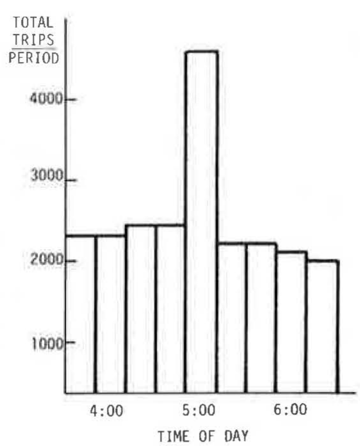


Figure 3. Los Angeles DPM 1990 evening peak profile.



2. Network—average speed on guideway including station input ramps and crossovers = 8.76 m/s, station configurations (all on line) are two end-of-line stations with inbound crossovers, four single-side one-way stations, and seven split-platform stations; average station-to-station distance = 436 m, network connectivity is closed loop, and door is open a minimum of 5 s and a maximum of 55 s;

3. Vehicle characteristics—vehicle speed = 8.76 m/s average, vehicle capacity = 41, number of seats per vehicle = 17, passenger loading rate per vehicle = 0.8 s/passenger, vehicle length = 8 m, and vehicle dispatch = midpoint; and

4. System characteristics—one route that stops at all stations, route headway = 106 s, vehicles per train = 4, transfer points = 2 (one at 10 s and one at 108 s), and average dwell time = 24.5 s (15 s with door closed + 5 s minimum + 4.5 s expected variable).

Station Modeling

In the DPMS, stations are modeled as a set of links and a set of events that occur on each link. Events include headway and travel times, which are similar to the guideway link events. In addition, deboard, board, and launch events can be specified. The deboard event removes passengers from vehicles and computes the time to deboard each vehicle in a train. The board event places trips from the station boarding queue in vehicles that have sufficient capacity and go to their destination and computes the time to board all passengers on each vehicle. Deboarding and boarding times may be constant or may vary between a minimum and maximum, depending on the number of passengers. The launch event is used to determine the time the vehicle is dispatched as a function of the current time and the dispatching algorithm in use. The modeling of the Los Angeles DPM stations was summarized in the above list.

Trip-List Generation

The DPMS generates a time-ordered sequence of passenger arrivals, called a trip list. The trip list contains the time of arrival and the origin and destination times of each trip. The trip list is generated from a station-to-station demand matrix and a set of scale and interval values. The model uses this information to determine an average arrival rate for each station pair. The trip list is generated as a series of Poisson arrivals based on these rates and a specified random number. Figure 3 shows the Los Angeles evening peak demand profile as a set of 20-min intervals with varying demand magnitudes.

Vehicle Characteristics

The vehicle characteristics that are specified include capacity, length, speed, number of seats, and load and unload rates. The above list shows these variable values for the Los Angeles DPM baseline.

Network Operations

The final step in modeling the baseline Los Angeles DPM system is to specify the system operating conditions. These include a definition of the route (set of station stops), the operating headway on the route, the definition of which routes passengers board at each station for each destination, the points at which passengers transfer, the time it takes to transfer at each transfer point, the dispatching policy used, and the number of vehicles per train.

The model can calculate the desired route headway from the number of trains or vice versa based on the nominal round-trip time. Since the designer works within the constraints of the planned system, the route headway is usually input. If a given train capacity is known, the model can calculate the route headway and the fleet size based on a specified demand interval, such as the peak 20 min. The above list shows these variable values for the Los Angeles DPM baseline.

Los Angeles Baseline Results

Figure 4 shows one of the system summary printouts from the model, and the "base" column in Table 2 shows the significant statistics of this run. Passenger waiting times and trip times are key performance measures. The trip time is defined by the network speed constraints; the wait time is a measure of the service provided. The worst-case station (number 6, Pershing Square) had a maximum wait of 184 s. Figure 5 shows a time-series plot of maximum wait times at Pershing Square. This plot shows stable service with a slight degradation during the peak period. This plot also shows that vehicles are being dispatched from this station evenly, since each asterisk at a point greater than zero represents a dispatch in that 60-s sampling interval. We can also verify this stability from the minimum and maximum dispatch times shown in Table 2.

Other key statistics from Figure 4 include the system average load factor (0.315) and the maximum load factor on any link (1.00). The worst-case link is after the worst-case station. The queuing at station 6 is caused by a combination of high demand and trains that arrive at near capacity. The vehicle speed in the network and the ratio of planned to actual travel time vary due to the effects of variable dwell times.

Other key statistics shown in Table 2 include the 95 percent wait time, which is derived from a sort of the log of all completed trips; the standard deviation of trip time, which is derived from the trip log for each pair of stations and indicates predictability of service; the maximum door-open time, which indicates station dwells and affects minimum route headways; and the maximum number of waiting passengers at the worst-case station, which can be used to evaluate station platform capacity.

This simulation indicates that the system design described in the preceding list performs almost as ex-

Figure 4. System summary statistics.

DPMS STANDARD REPORT 2----SYSTEM SUMMARY STATISTICS

SYSTEM-WIDE MEASUREMENTS

	TOTAL	AVERAGE	MINIMUM	MAXIMUM
VEHICLE FLEET SIZE	-	56.000	56.000	56.000
SEAT CAPACITY	-	952.000	952.000	952.000
SEAT AVAILABILITY	-	335.753	101.832	450.340
VEHICLE METERS TRAVELLED	2365500.00	-	11116.000	26096.000
VEHICLE LOAD FACTOR	-	0.315	0.0	1.000
NUMBER OF PASSENGERS IN SYSTEM	-	879.233	606.000	1679.000
PASSENGER METERS TRAVELLED	29887632.0	-	108705.000	579067.000
PASSENGER WAIT TIME (SEC)	-	57.016	0.0	183.900
NUMBER OF PASSENGERS WAITING	-	112.165	37.000	324.000
PERCENT COMPLETED TRANSFERS	17.717	-	2.857	41.860
NOMINAL TRAVEL TIME / ACTUAL TRAVEL TIME	0.951	-	0.553	1.116
VEHICLE SPEED IN NETWORK--INCLUDING STATION TIME (M/SEC)	6.299	-	4.484	8.257
VEHICLE SPEED ON GUIDEWAY--EXCLUDING STATION TIME (M/SEC)	9.753	-	8.515	10.675

STATION MEASUREMENTS (BY STATION)

	TOTAL	AVERAGE	MINIMUM	MAXIMUM
--STATION 1--				
NUMBER OF VEHICLES	-	2.099	0.0	4.000
NUMBER OF VEHICLES QUEUED:				
INPUT RAMP	-	0.0	0.0	0.0
INPUT QUEUES	-	0.0	0.0	0.0
DOCKS	-	0.0	0.0	0.0
OUTPUT QUEUES	-	0.0	0.0	0.0
OUTPUT RAMP	-	0.0	0.0	0.0
STORAGE	-	0.0	0.0	0.0
VEHICLE TIME IN STATION (SEC)	-	55.669	51.500	69.400
NUMBER OF PASSENGERS:				
ENTERING	1424.000	-	4.000	30.000
EXITING	3515.000	-	0.0	100.000
TRANSFERRING	0.0	-	0.0	0.0
WAITING	-	10.223	0.0	47.000
PASSENGER WAIT TIME	-	53.960	0.0	112.900
VEHICLE LOAD FACTOR--IN	-	0.315	0.140	0.610
VEHICLE LOAD FACTOR--OUT	-	0.128	0.024	0.323
--STATION 2--				
NUMBER OF VEHICLES	-	0.829	0.0	4.000
NUMBER OF VEHICLES QUEUED:				
INPUT RAMP	-	0.0	0.0	0.0

Table 2. Los Angeles DPM year-2000 sensitivity analysis.

Characteristic	Base	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6
System							
Headway (s)	106	106	106	88	75	59	45
Train capacity	164	180	240	180	160	120	90
Number of trains	14	15	15	18	21	27	35
Evening peak demand	15 321	21 891	21 891	21 891	21 891	21 891	21 891
Evening peak time (h)	2	2	2	2	2	2	2
Throughput (places/h)	5570	6113	8151	7361	7680	7322	7200
Performance							
System maximum wait (s)	184	558	153	164	150	167	169
Station 6, 95 percent wait[a] (s)	129	404	122	114	95.2	99.7	103
System 95 percent wait[a] (s)	120	201	121	104	89.1	75.4	66
Trip time							
Mean (s)	400	433	423	413	409	399	394
Maximum SD[b]			38.7	57.8	25.8	29	37
Dispatch time							
Minimum	94	94	87	78	64	52	41
Maximum	119	119	125	102	87	67	51
Maximum door open, station 11	37	45	49.5	40.6	36.6	39	22
Maximum waiting passengers, station 6	77		102	103	95	100	116

[a]95 percent wait = 95 percent of trips wait less than this time.
[b]Maximum standard deviation of travel time between any pair of stations.

pected. However, it is significant to note that station 6 did experience some queuing. This potential problem would not have been predicted without the DPMS. The static peak link-load analysis indicated that a train capacity of 154 would be sufficient. Even though the simulation experiment was run by using a train capacity of 164 (a 7 percent increase), some passengers were forced to wait for another train.

One run of the simulation experiment, as discussed here, is not sufficient to base design conclusions. Since many random events interact with one another in the simulation, several experiments that use different random number seeds should be run to obtain the desired level of confidence. The experiments discussed in this paper are illustrative of the type of information available from the model.

LOS ANGELES BASELINE SENSITIVITY ANALYSIS

Once the baseline system has been modeled, the DPMS can be used to explore a range of demand and system characteristics and possible system anomalies. This section shows how the model was used to determine the combinations of route headway and vehicle capacity that would meet the baseline wait-time goals for an estimated demand of 100 000 persons/day in the year 2000 versus 72 000 persons/day in the baseline year.

In the absence of other information, we assumed that the spatial distribution in the evening peak would be the same in the year 2000 as in the baseline year, 1990. The increase in demand will be modeled by a change in the scale factor in the demand profile. The scale factor for each interval was multiplied by 1.38 to generate the trip list for the year-2000 case. This was derived from an increase from 72 000 to 100 000 persons/day.

The only other changes made to the baseline case were the removal of the switchback constraint at the end stations and an increase in the expected door-open time at the stations from an average of 10 s to an average of 15 s because of the higher demand. This change resulted in a total nominal travel time around the network of 1593 s, an increase of 109 s from the baseline case.

The simulation experiments examined system operation at the following nominal headways: 45, 59, 75, 88, and 106 s. Train capacities ranged from 80 to 240 passengers. To evaluate the performance of these various combinations of throughput, several measures of passenger wait time were calculated. These measures include the average, maximum, and 95 percent wait times. These measures were computed for the entire system and for each station from the station-to-station matrices, which were derived from the log of trips completed during the evening peak.

Results of Year-2000 Demand Study

Table 2 presents the results of a set of simulation runs for the demand in the year 2000. The left-hand column lists the key system and performance characteristics. The base run lists the statistics of the baseline (1990 demand) scenario discussed previously. Run 1 shows the results of using essentially the baseline system to try to serve the year-2000 demand. Even with an increase in train capacity from 164 to 180, the system is clearly saturated. Run 2 shows the results of a simulation experiment that uses a train capacity of 240 and a headway of 106 s. The statistics for this run indicate service comparable to the baseline case. The next four columns (runs 3, 4, 5, and 6) show the results of simulation experiments that use different headways and train capacities that offer comparable levels of service. In all cases the system average wait time was equal to one-half of the headway, and the average wait time at the worst-case station was slightly higher.

The performance characteristics for runs 2-6 are approximately equivalent in terms of the worst-case station (and system) maximum and 95 percent wait times. The system 95 percent wait time (as well as the system average wait time) decreases with decreasing headway. The next two lines show the average trip times for each run and the maximum of standard deviations for the station-to-station trip times. Trip time is measured from time of arrival at a station to time of completion. The average trip time is not affected significantly by the headway changes. In fact, the change shown is approximately one-half the headway change, as would be expected. The worst-case standard deviation of trip time is a measure of the predictability of service. In all cases shown here, this number is low. However, a decrease in the headway does not guarantee an improvement of this statistic. The average dispatch time between vehicles was equal to the planned headway in all cases. The range of dispatch times is shown here. These ranges indicate that the dispatching algorithm used by the model worked well. The maximum door-open time statistic at the end station can be used to evaluate the feasibility of using switchbacks at lower operating headways. The maximum number of waiting passengers can be used to evaluate the station design capacity.

Figure 6 shows the train capacities and headway com-

Figure 5. Time-series plot of maximum wait time at station 6.

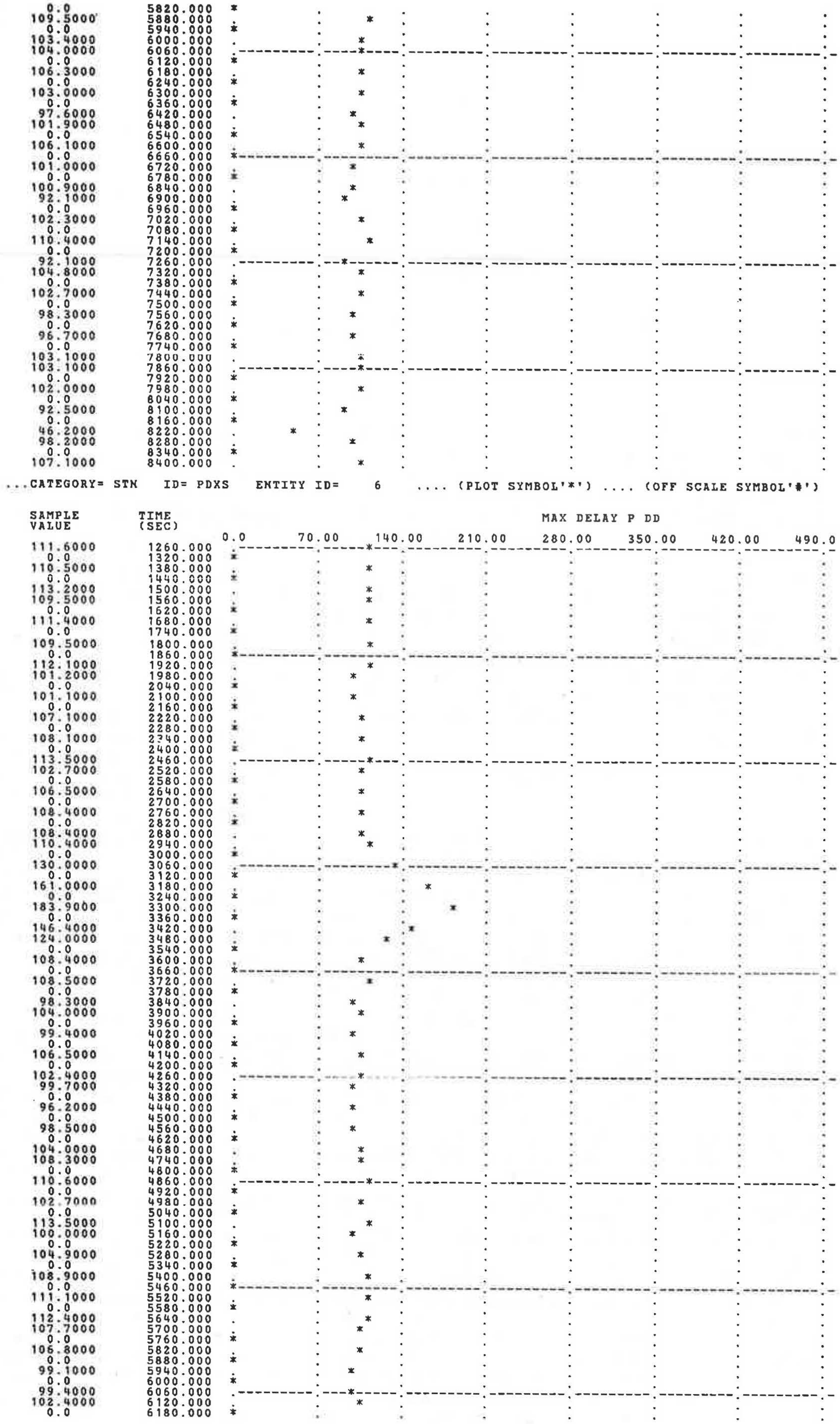


Figure 5. Continued.

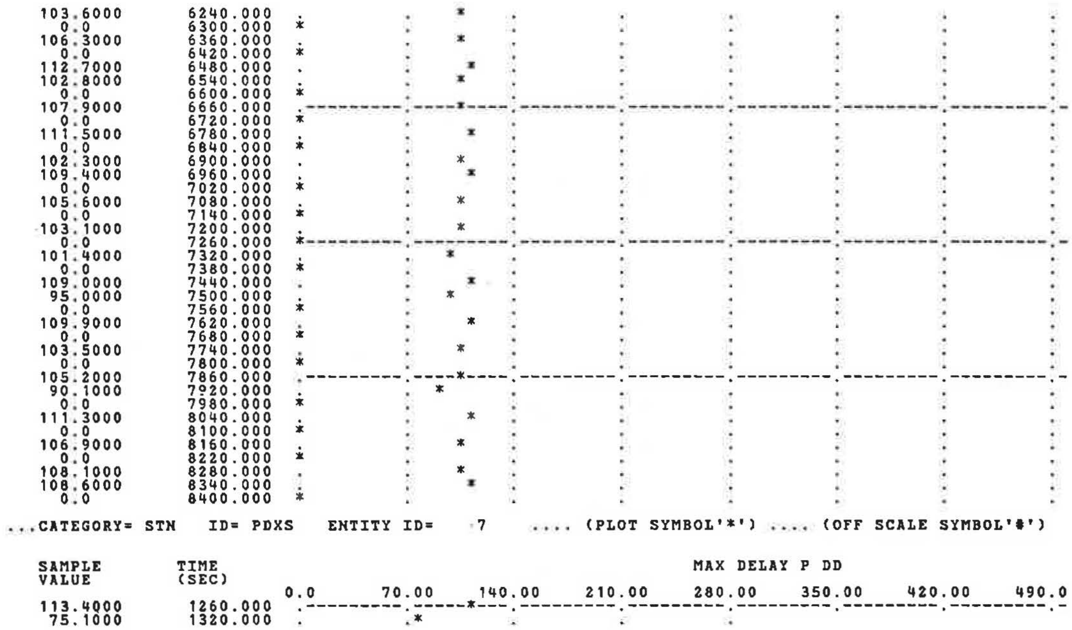
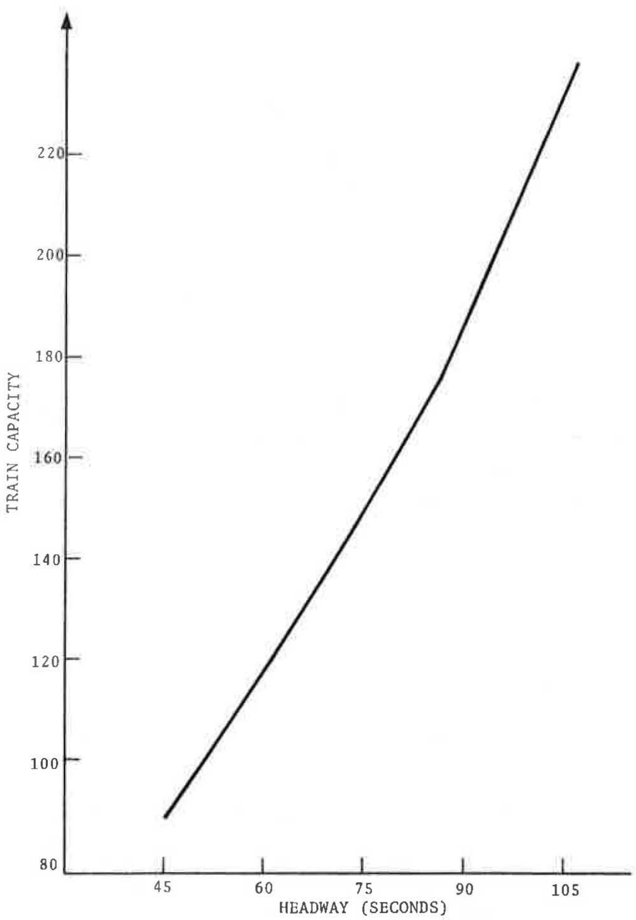


Figure 6. Headways and capacities needed to produce 95 percent wait time of 2 min at station 6 on the Los Angeles DPM in the year 2000.



binations needed to meet the 95 percent wait-time goal (2 min) at the worst-case station. These results were derived from a series of simulation runs.

Modeling System Anomalies

The DPMS was used to model system response to a vehicle stoppage on the link between stations 5 and 6 by inputting the location and time of the failure and recovery events. The failure is assumed to occur at the beginning of the peak 20 min and last for 5 min.

A vehicle stoppage is represented in the DPMS by a failure of a link exit, which then prohibits vehicles from leaving the specified link. The first vehicle that reaches the end of the defined link queues, as do all following vehicles. When the failure is removed, the guideway link model within the DPMS prompts the queued vehicles to start moving again. All passengers remain in the system and the failed vehicle is considered operational once the failure is removed.

Three failure experiments were conducted by using the same failure scenario and different dispatching algorithms. The dispatching algorithms affect the time the system takes to recover from the failure. The first algorithm dispatches vehicles as fast as they are loaded if they are far behind schedule. The second algorithm dispatches vehicles one predetermined headway behind the preceding vehicle. The third algorithm dispatches vehicles midway between the predetermined headway and the time vehicles are ready to be launched.

Analysis of the Failure Scenario

Table 3 presents the results of the simulation experiments. The system and performance characteristics shown are similar to those shown in Table 2. The first column shows the baseline results. The second column shows the results of the baseline system by using the as-soon-as-possible dispatching scheme. The increase in system maximum and system 95 percent wait times are dramatic, as expected. The average wait time over the 2-h peak period increases by only 15 s. The station that has the worst average and 95 percent wait times is now station 17. The range of dispatch times indicates the possibility of bunching.

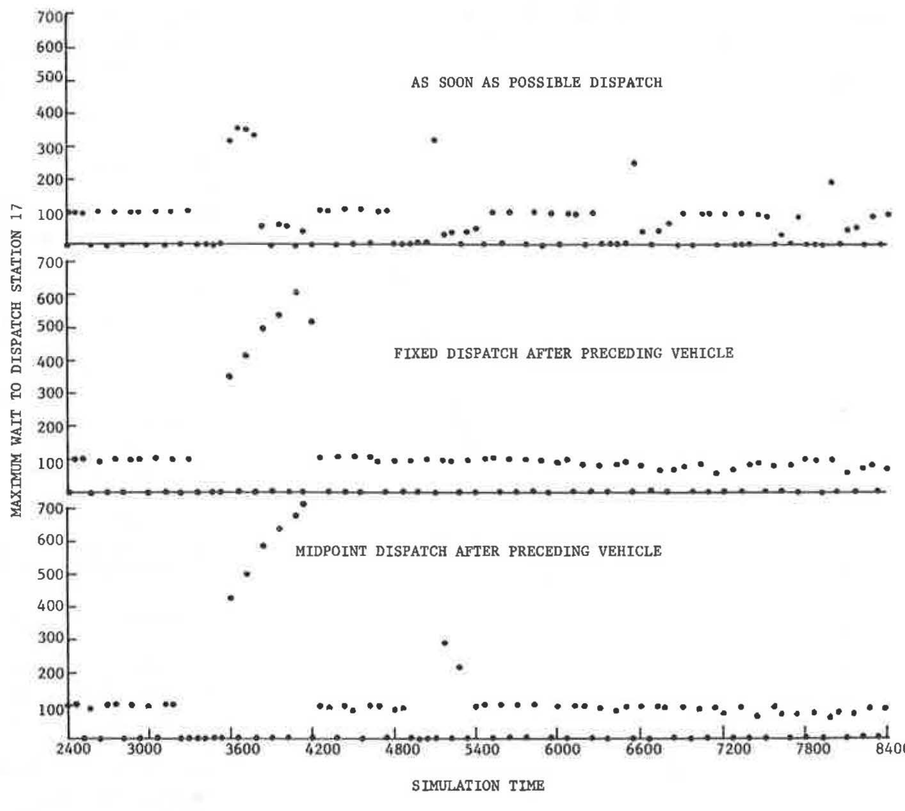
The results of the alternative dispatch algorithms can be explained by looking at Figure 7. This figure is a reproduction of the time-series plots of passenger maximum wait time at station 17. Samples have been taken every 60 s. A zero wait time means that no passengers were dispatched; a positive time indicates that at least one vehicle was dispatched in that interval.

The first algorithm works best in this case, because it moves vehicles to the stations downstream of the fail-

Table 3. Los Angeles DPM failure scenario analysis.

Characteristic	Baseline	Dispatch: As Soon As Possible	Dispatch: Fixed After Preceding Vehicle	Dispatch: Midpoint After Preceding Vehicle
System				
Headway	106	106	106	106
Train capacity	164	164	164	164
Number of trains	14	14	14	14
Evening peak demand	15 321	15 321	15 321	15 321
Evening peak time (h)	2	2	2	2
Failure location		Link 25	Link 25	Link 25
Failure time (s)		300	300	300
Performance				
System average wait (s)	57	72	76	86
System maximum wait (s)	183	395	615	734
System 95 percent wait (s)	121	194	208	275
Worst station	6	17	17	17
Worst station average wait (s)	62	92	112	141
Worst station 95 percent wait (s)	128	256	403	509
Dispatch time				
Average	106	106	108	110
Minimum	94	20	106	63
Maximum	119	332	367	462
Passengers with excess travel time of				
300-600 s	0	37	288	351
More than 600 s	0	0	47	53

Figure 7. Los Angeles DPM baseline to 5-min failure on link 25.



ure quickly, which is important when the failure occurs in the peak hour. The effects of bunching are seen in the periodic peaking of the wait times later in the simulation. The second plot shows that the vehicles are spaced nicely but that they provide insufficient throughput to handle the large queues during the peak. This algorithm might be more effective for off-peak stoppages. The third algorithm moves the vehicles downstream only slightly faster (the sixth vehicle arrives sooner). Its poor performance results mainly from the fact that the initial gap between dispatches after the failure was 420 s, rather than 300 s for the first two alternatives. Another set of failure runs was made by using the same failure scenario (time and place) but a different random number. They showed that the midpoint dispatching algorithm was slightly more effective than the fixed-interval algorithm, but both were inferior to the first algorithm. From this result, we can conclude that the best algorithm for this failure scenario is the one that dispatches vehicles as fast as possible and that bunching is a secondary effect.

SUMMARY

The results presented illustrate the capability of the model to represent a variety of demand, network, system operation, and system event scenarios. The modeling of these changes from the baseline case is quite simple and the model provides the analyst with the information necessary to understand the results.

ACKNOWLEDGMENT

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REFERENCE

1. Systems Operation Studies for Automated Guideway Transit Systems, Downtown People Mover Simulation (DPMS) Program Write-Up. General Motors Transportation Systems Division, Warren, MI, Rept. EP-79020, Feb. 1979.

Publication of this paper sponsored by Committee on Transportation Systems Design.

Generating Alternatives for Alternatives Analysis

William S. Herald

Alternatives analysis is the planning process mandated by the Urban Mass Transportation Administration for the assessment of major transit investments. The alternatives analysis process is a means of ensuring comparability between rapid transit planning studies across the nation. Up to now, the focus of attention has been on the results or products of the process. Interest has centered on the selection of a recommended alternative and its costs and impacts. This paper examines an earlier stage in the planning process that has critical importance in the validity of alternatives analysis studies. The basic concern is with the ways that alternatives are derived and described. If alternatives are the central feature of the process, we should know more about what they are and where they come from. The investigation reviews a group of alternatives analysis reports to establish the state of the art in generating alternatives for major transit studies. Ten potential imputs to alternatives generation are identified. In addition, the paper assesses the use of specific techniques or methodologies for the generation of alternatives. Specifications for alternatives and the properties of alternative sets are reviewed. The paper includes an examination of the ways that transportation system management and baseline alternatives have been defined and used in past studies. Conclusions on the state of the art in alternatives generation and its expression in alternatives analysis studies are presented as the results of the investigation.

Alternatives analysis is the process mandated by the Urban Mass Transportation Administration (UMTA) for planning major rapid transit facilities. As the name implies, the central feature of this planning process is the comparative assessment of the costs and impacts of a set of alternative configurations of technologies and services. Paradoxically, although alternatives occupy a central position in this planning process, little attention has been focused on the alternatives themselves. The major focus of methodological interest has been on techniques to predict the impacts of alternatives on the urban transportation system and the environment.

This paper is concerned with such issues as where alternatives come from and what makes up an alternative. The review of the transportation literature for this investigation suggests that these basic issues are seldom articulated and that alternatives development may be an activity characterized by pervasive assumptions and a lack of structural approach. The purpose of this paper is to examine the state of the art in the identification of alternatives. We are interested in the answers to a number of questions:

1. When are alternatives generated in the planning process?
2. What are the inputs to alternatives generation?
3. What techniques are used to identify alternatives?
4. What characteristics have been used to define and describe alternatives? and
5. How have baseline and transportation system management (TSM) alternatives been considered?

To assess the actual experience of the alternatives analysis process with respect to the generation of alternatives, 15 sources were read and evaluated (1-15). These sources were a mixed collection of complete alternatives analysis final reports, single volumes from a series of rapid transit engineering studies, supplementary reports submitted in response to UMTA questions, and draft reports. Altogether the group of documents reviewed represents 11 alternatives analysis efforts. This represents roughly a 30 percent sample of the universe of 35-40 alternatives analysis studies identified in this investigation. Although this is not a random sample, it is assumed that the reviewed studies are reasonably typical of past and current alternatives analysis experience.

Some important limits on the analysis must be noted. The first of these is the evolutionary nature of the alternatives analysis process. Because the process has developed over time, each application has been treated somewhat differently. Thus, all the studies cannot be expected to be similar. Also important is the fact that the alternatives analysis process was imposed on several rapid transit planning efforts in midstream. It can be expected that these studies show significant differ-