Methods for Maintaining Transit Service Regularity

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ABSTRACT

Maintaining regular transit service has been a chronic operational problem that affects both travelers and operators. Although many researchers have studied aspects of this problem, major limitations of previous work have resulted in the recommendation of procedures that are neither representative of nor operational in the transit management environment. The development of a method for maintaining service regularity through improved scheduling and real-time control based on models developed and validated from empirical data is described. The method is simple to employ and does not require extensive data from the transit agency considering its implementation. Also included is a case study describing the application of the method to three routes in Los Angeles. The results indicate that the procedure can produce reasonable solutions and demonstrate its potential value to the transit community.

It is generally agreed that maintaining regular transit service intervals is an important operational problem that affects both travelers and operators. Operators rely on minimizing run-time uncertainty in specifying timetables and allocating vehicles to routes. Travelers are affected by the reliability of service, which stems directly from the predictability of vehicle run times. The proper amount of run time and slack to build into a schedule and how to control real-time reliability problems can have a profound effect on service regularity and thus on the productivity and efficiency of transit operations.

Many researchers have studied factors affecting bus running time and what corrective actions should be taken when reliability deteriorates (1-4). In the absence of empirical data because of the high costs associated with direct observation, most studies have been restricted to models that are analytically based. A major limitation of this work has been the assumptions made in order to derive closed-form solutions, which often result in recommendation of procedures that are neither representative of nor operational in the transit management environment.

The primary objective of this research was to make available to transit managers methods for maintaining service regularity through improved scheduling and real-time control based on models developed and validated from empirical data. An interest in developing transferable models and methods that are simple in nature and do not require extensive data from the transit agency was an important motivating factor in the research. The availability of empirically based methods of this kind would alleviate the need to analyze individual problems by manually collecting extensive amounts of data at each agency yet permit the identification of planned and real-time schedule modifications that can be implemented to improve service efficiency and productivity.

RESEARCH METHODOLOGY

The research design consisted of six sequential steps:

1. Determination of mean running time,
2. Determination of running-time variation,
3. Determination of headway variation,
4. Determination of passenger wait time,
5. Identification of optimal control strategy, and
6. Establishment of operator compatibility with the developed methodology.

Steps 1-4 are interdependent problems that, once resolved, serve as inputs to the fifth step. The last step concerns transferring the research results into an environment with which the operator is compatible.

Determining mean running time is the initial step in this process because the schedule and timetable are based on the mean running time. The research emphasis was on the temporal and spatial factors affecting mean running time.

Running-time variation is an important measure in defining unreliable service. The degree to which running-time variation propagates as the vehicle proceeds down the route is of particular interest when real-time control is studied. A priori, one would expect that running-time variation is correlated with mean running time and that delays tend to accumulate once a vehicle falls behind schedule.

It has been proven theoretically and demonstrated empirically that the waiting time of passengers at stops is related to the headway variation. To be able to reduce the headway variation effectively, it is important to know what influences it and how the headway variation propagates along the route. It is also important to understand the relationship between the headway variation before and after the control stop and to what extent a control strategy causes reductions in headway variation.

The effectiveness of both headway-based and scheduled-based strategies was considered in this study. A headway-based strategy is defined here as holding the bus for a certain amount of time (x_0). If the coming headway is less than x_0, the bus is held up to x_0. If the coming headway is greater than x_0, the bus is not held. Headway-based holding is most suitable for routes operating with short, uniform headways. When headways are short and uniform, it is assumed that passengers arrive more randomly at stops and that they are primarily concerned with the headway and not the schedule. Similarly, operators are concerned about keeping vehicles evenly spaced so that vehicle availability remains stable.

Schedule-based holding is considered suitable on routes that have long headways, which means that the schedule is not so tight and the procedure is simple to administer. It may also be appropriate for cases in which headways are uneven and the schedule is designed to meet certain demand requirements. In both cases the passengers' concern is not to miss a certain bus, so the buses should adhere to the schedule. To implement a schedule-based policy, there is a need to construct a reasonable schedule and enforce adherence to it by using proper incentives for drivers and a mechanism for accurate monitoring of their performance.

With either headway- or schedule-based holding, the choice of where to locate a holding point is extremely important. This problem is often solved by determination of minimized passenger wait time. Accordingly, the relationship among scheduled headway, headway variation, and wait time was examined. In this study empirical wait-time models covering a range of headways from 3 to 12 min were estimated and the results were compared with those of theoretical wait-time models and other research findings.

After the first four phases of the research had been completed, an optimization routine was developed to determine (a) the appropriate holding strategy to implement, given the schedule characteristics; (b) the effectiveness of holding on the route; and (c) the location of the control stop and the optimal corresponding holding time, given route and schedule characteristics. For the headway-based strategy the objective was to minimize the total waiting time of passengers, including those delayed on board the vehicle at the holding point. For the schedule-based strategy the objective was to maximize the effectiveness of control; effectiveness is defined in the subsequent discussion.

An important issue to consider is the eventual implementation of the models and methods by the transit operator. Computer software was developed so that the decision methodology could be utilized. The software is designed for a microcomputer system, because many transit operators are now using or considering the use of microcomputers in managing their operations and the program could be used by them without additional cost being incurred.

Mean Running Time

The data used in this analysis were collected in 1978 from Queen City Metro in Cincinnati, Ohio, by General Motors; automated-vehicle-monitoring (AVM) equipment was used. The data consisted of observations on two bus routes, each roughly 10 miles long, that traverse city streets and extend radially from the central business district (CBD) along a traffic corridor. The routes extend into the CBD and return to the suburban origin point. Except for layovers (time spent between the end of the previous run and beginning of the next run) at the CBD and suburban terminals, no other holding points are used on these routes. Peak-period headways are 12 min, increasing to 15 to 20 min during the off-peak period. Additional information on the routes included physical characteristics (length between observation points, number of traffic signals, parking restrictions, stop signs, yields, and unsignalized intersections) as well as dynamic characteristics (average boardings and alightings, average number of stops made, time of travel, and direction of travel). These data were segmented by observation point and operating period (5).

The analysis focused on determining the physical and dynamic factors affecting mean running time. This was accomplished by using linear regression with mean running time as the dependent variable and the route characteristics as the independent variables. Model specification in all phases of this research was guided by a criterion that included consideration of variables that could be justified a priori as explanatory variables of the dependent variable, had the expected coefficient signs, and had statistically significant coefficient estimates (t-statistics). The overall statistical fit of the model (corrected R^2) and potential dependencies among the independent variables were also considered.

The final model for mean running time is as follows:

$$\text{Mean running time (sec)} = \beta_1 + (b_2 * \text{link length}) + (\beta_3 * \text{passengers boarding}) + (\beta_4 * \text{passengers alighting}) + (\beta_5 * \text{percentage off-street parking}) + (\beta_6 * \text{signalized intersections}) + (\beta_7 * \text{daytime off peak}) + (\beta_8 * \text{afternoon peak}) + (\beta_9 * \text{outbound travel}) \quad (1)$$

It was found (Table 1) that mean running time is highly influenced by trip distance, boardings and alightings, and signalized intersections and to a lesser degree by parking restrictions on the route, time of day, and direction of travel. The model results tend to confirm earlier views. The order of importance of the explanatory variables also seems reasonable. The finding that running time is positively related to the number of signalized intersections is consistent with observations made by Welding (6).

TABLE 1 Mean-Running-Time Model

Variable	Coefficient Value	t-Statistic	Variable Mean	Avg Contribution[a]
Constant	-122.04		1.0	-122.04
Link length	216.54	10.89	2.05	443.91
Passengers boarding	6.03	5.74	9.37	56.5
Passengers alighting	3.83	3.83	11.57	44.3
Percentage of on-street parking	114.59	3.15	0.09	10.31
Signalized intersections	8.16	5.13	10.64	86.82
Daytime off-peak period	30.43	2.16	0.25	7.61
Afternoon peak period	41.73	2.78	0.25	10.43
Outbound travel	25.80	1.82	0.5	12.9

Note: Number of observations = 56, F (8, 46) = 76.5, corrected R^2 = 0.92, standard error = 41.9, Durbin-Watson statistic = 1.92.

[a]Coefficient value times variable mean.

It is interesting to note that the value of the constant implies a maximum average running speed of 21 mph. Adding the average number of boardings, alightings, signals, and typical parking restrictions, the average running speed decreases to 14 mph. These values are quite reasonable for bus movement in an urban corridor.

Data from Route 44 in Los Angeles were used to validate the mean-running-time model developed from Cincinnati data. Route 44 has the same characteristics as do the routes in Cincinnati. It is roughly 15 miles long and runs into the CBD and returns to a suburb. Peak-period headways are 5 to 7 min; they increase to 10 to 12 min during the off-peak period. The route was divided into 15 links that ranged from 0.5 to 2 miles long. The day was divided into four time periods as in Cincinnati. For each combination of link, period, and direction, the mean running time was calculated. The mean running time obtained from the model (predicted) and the mean running time observed for each link on Route 44 are plotted in Figure 1. The implication for transferability is encouraging, because most observations fall around the 45 degree line. In fact, a χ^2 goodness-of-fit test suggests that the hypothesis (95 percent confidence level) that the observations are from the same population cannot be rejected.

Running-Time Variation

Separate models for each time period were initially

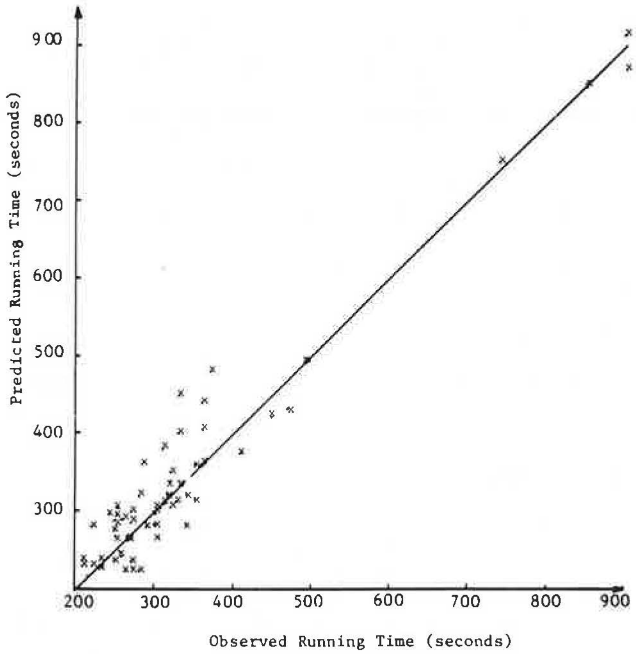

FIGURE 1 Validation of running-time model.

developed by using Cincinnati data. Trip origins and destinations were selected randomly, which resulted in a range of mean running time of only 10 to 47 min. The process of random selection also reduced the degrees of freedom significantly. Data collected in Los Angeles at a later stage provided a basis for both model validation and modification. Separate regression models were subsequently estimated based solely on the Los Angeles data.

For each Cincinnati and Los Angeles regression model, the error sum of squares was calculated. These values were then used to perform an F-test to check whether the Cincinnati and Los Angeles regression lines were significantly different. If the regression lines are not different, they can be pooled to estimate an improved model with more degrees of freedom. The confidence level (α) used in the F-test was 95 percent.

For both the morning and afternoon peak periods, the results suggested that one cannot reject the hypothesis that the two data sets produce the same regression line and therefore that the pooled regression line can be used as the final model. However, for the daytime off-peak period, the two regression lines were significantly different. Because the model estimated in Los Angeles had more degrees of freedom, it was selected as the day off-peak model.

The estimation results are as follows:

A.M. peak (6:00 a.m. to 9:00 a.m.), pooled data

$$\sigma_r = 1.399 + 0.0454U_r \qquad R^2 = 0.82,\ N = 45 \qquad (2)$$

Day off-peak (9:00 a.m. to 3:00 p.m.), Los Angeles

$$\sigma_r = 0.977 + 0.0530U_r \qquad R^2 = 0.90,\ N = 85 \qquad (3)$$

P.M. peak (3:00 p.m. to 6:00 p.m.), pooled data

$$\sigma_r = 0.707 + 0.08197U_r \qquad R^2 = 0.90,\ N = 49 \qquad (4)$$

where

σ_r = running-time deviation (min),
U_r = mean running time (min), and
N = sample size.

The final models cover a range of running time between 10 and 85 min. The highest deviation occurs during the p.m. peak, thus suggesting that service reliability is worse during this time period. This implies that perhaps priority should be given to controlling reliability during the p.m. peak.

Implicit in the model results is the suggestion that running-time deviation at early points on the route propagates as the vehicle proceeds further downstream. This is consistent with observations made by Doras (7) on bus routes in Paris and by Loo (8) in a study of a Minneapolis bus route.

The running-time models can also be used to improve schedules by allowing for the appropriate amount of slack time, so that succeeding runs are less likely to be affected by delays on earlier runs. Assuming a distribution for the running time, the appropriate slack time can be determined for a given confidence level. For example, for a normal distribution of running time, if mean running time from terminus to terminus is 30 min and the standard deviation of running time is 3 min, the operator can be 95 percent confident of having buses begin the next run on time by allowing just under 6 min of slack time in the schedule (union work rules are a separate consideration). This analysis can be extended rather easily to determine the vehicle requirements to operate a route given the desired headway, mean-running-time deviation, and confidence level.

Headway Variation

Headway-variation analyses focused on two issues: (a) deriving a headway-variation model based on scheduled headway and running-time variation and (b) assessing the impact of control on headway variation beyond the control point. The discussion in this and the following section applies only to the headway-based strategy, because the schedule-based strategy does not address regulating headways or the impact of headway variation on system wait time.

The data used to derive a headway-variation model were generated by using Monte Carlo simulation. The inputs to the simulation program included scheduled headway, average running time to each stop, and variation of running time. The scheduled headway was set at 3, 6, and 9 min, and running times were assumed to come from a beta distribution. Stop locations ranged from average running times of 5 to 90 min from the route origin and the coefficient of variation ranged from 0.05 to 0.17. The output of the simulation consisted of headway variation for each combination of scheduled headway, running time, and running-time variation. These results were used as inputs to model estimation by using headway variation as the dependent variable.

The simulation results indicated that the headway variation increases rather quickly near the beginning of the route and then reaches an upper bound. The time it takes to reach the upper bound depends on the scheduled headway and variation in running time. This was borne out by the following model estimation result:

$$v_h = (-12.2 + 6.94\bar{h})[1 - \exp(-0.0447v_t)] \qquad N = 554 \qquad (5)$$

where

v_h = headway variation (min),
$\bar{h}$ = scheduled headway (min), and
v_t = running-time variation (min).

The residual mean square for this model is 4.08, indicating a good statistical fit.

Data from Route 44 in Los Angeles were also available to evaluate the headway-variation model. This validation was performed by comparing the observed headway variation with the predicted headway variation. The predicted headway variation was computed by using the model in Equation 5, where the inputs to the model were derived from the data collected.

Route 44 was divided into links demarcated by the AVM location. For each AVM location, the running-time variation and the headway variation were calculated. Three sequences of scheduled headways were available for calculating the headway variation (6-, 8-, and 11-min headways), with each headway representing a different time period.

Plots of the predicted and observed headway variation appear in Figure 2. The results are generally encouraging, particularly for the 6- and 8-min headways, which are within the 10-min headway range under consideration for headway-based control (see discussion of passenger wait time).

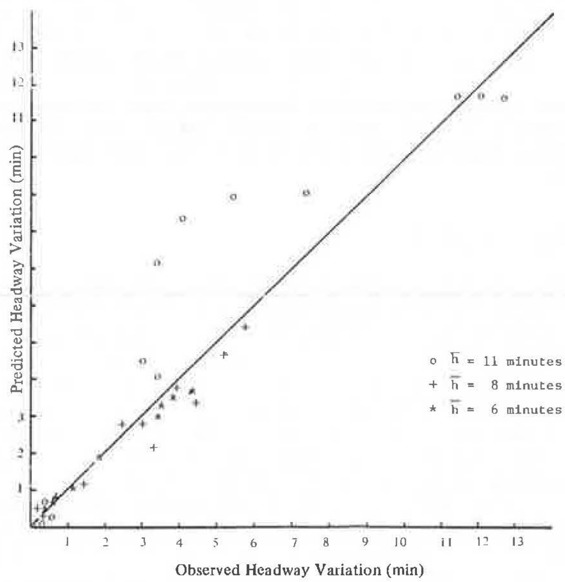

FIGURE 2 Headway model validation results.

The impact of headway-based control on headway variation downstream of the control point was also examined by using simulation, because no transit data on control are now available for model development. Recall that the headway-based approach is to hold to a threshold value (x_0) if the coming headway is less than x_0. The simulation design was to introduce control at stops located 10, 20, 30, and 40 min from the route origin, varying the threshold value in 0.5-min increments from zero to the scheduled headway. Headways of 3, 6, and 9 min were considered. The output measures included headway variation before and after the control stop.

The simulation output provided data for model estimation, which yielded the following:

$$v_a = 0.5448 v_b^{0.713} (\bar{h} - x_0)^{0.734} \qquad \text{corrected } R^2 = 0.94 \qquad (6)$$

where

v_a = departure headway variation at control stop (min),
v_b = incoming headway variation at control stop (min), and
x_0 = threshold value (min).

An interesting implication of this model is that the headway variation reduces to nearly zero when x_0 is equal to the scheduled headway for an extended operating period, independent of the level of variation before control. This does not suggest that it is always better to hold according to a threshold equal to the scheduled headway, because the optimal strategy also depends on the number of passengers on board at the control stop and those waiting downstream.

The model, when combined with Equation 5, implies that the benefits of control are not distributed uniformly to all stops after the control point. Instead it appears that the maximum benefits are felt near the control point; the headway variation begins to increase again downstream until it reaches an upper bound.

Passenger Wait Time

Two types of wait-time models were examined: (a) passenger wait time at stops along the route and (b) delay to on-board passengers when the bus is being held at the control stop.

The analysis of passenger wait time at stops was conducted by using data collected in Los Angeles as part of the evaluation of AVM equipment implemented at the Southern California Rapid Transit District (SCRTD). The data were collected on four routes with headways varying from 3 to 12 min. Checkers were located at specific stops on the routes and noted passenger and vehicle arrival times at stops and the weather conditions at the time of observation. Three days of data were collected on each route in both directions, with the exception of one route for which only one direction was observed. Separate analyses were performed on the 3-min headway route and the other routes (8- to 12-min headways), because there was reason to expect that passenger arrival patterns might be related to the scheduled headway.

The regression estimate for the 3-min route was as follows:

$$\bar{w} = 77.34 + 0.0028 v_h \qquad \text{corrected } R^2 = 0.66 \qquad (7)$$

where $\bar{w}$ is the average passenger waiting time in seconds and v_h is the headway variation in seconds.

It is interesting to note that the wait times were 7 percent lower than would be predicted by using a theoretical model, which assumes random passenger arrivals. Late arrivals running to catch the bus at the last minute might account for this, because they incur no wait time.

The wait-time model for the routes with 8 to 12 min headway was as follows:

$$w = -47.02 + 0.497\bar{h} + 0.00121 v_h \qquad \text{corrected } R^2 = 0.69 \qquad (8)$$

where $\bar{h}$ is the scheduled headway in seconds.

The negative constant and the coefficient for the mean headway, which is less than 0.5, result in lower wait time than that predicted by the theoretical model.

The wait-time analysis results are not unusual and are consistent with findings reported by Holroyd and Scraggs (9), O'Flaherty and Mangan (10), Seddon and Day (11), and Joliffe and Hutchinson (12). If anything, they suggest that the accepted assumption of random passenger arrivals for headways of 12 min or less should be modified to 10 min or less.

The passenger delay at the control stop depends on the headway variation at the control stop as well as on the threshold headway. Simulation was again used to obtain data for the model estimation. Control stops were introduced in the simulation and bus delays were calculated for different threshold values. These data were then used to estimate the following model:

$$d_j(x_0) = \{3.9245 + 0.0755\ \mathrm{var}_j(H)\,[x_0/E(H)]^4\} \qquad R^2 = 0.94 \qquad (9)$$

where

- $d_j(x_0)$ = the average delay (min) at control point j,
- x_0 = the threshold headway (min), and
- $E(H)$ = expected headway (min).

The model is sensitive to x_0 such that when x_0 approaches $E(H)$, the delay increases quickly. This occurs because large values of x_0 are causing many buses to be delayed.

Optimal Control Strategy

The results of the steps described in the previous discussion were used as inputs to the decision process in resolving the following questions:

1. Which kind of control is appropriate?
2. Should the strategy be implemented?
3. Where should the control point be located?
4. For headway-based control, what is the optimal threshold value?

Question 1 is determined outside of the decision algorithm and depends on the length and uniformity of scheduled headways for reasons described previously. The remainder of the questions are addressed within the decision algorithm.

The algorithm developed for headway-based control was to minimize the following objective function:

$$TW = \sum_{i=1}^{j-1} (n_i \times \bar{w}_i) + [b_j \times d_j(x_0)] + \sum_{i=j}^{N} (n_i \times \bar{w}_i) \qquad (10)$$

where

- TW = expected total wait time on route,
- j = the control stop,
- x_0 = threshold value,
- n_i = number of passengers boarding at stop i,
- b_j = number of passengers on board at stop j,
- $\bar{w}_i$ = average wait time at stop i,
- N = total number of stops on route, and
- $d_j(x_0)$ = expected delay at the control stop for the threshold of x_0.

The first term represents the wait time of passengers upstream of the control point. The second term represents the delay caused to passengers on board the bus at the control stop. The final term represents the passenger wait time at stops downstream of the control stop.

The minimum expected total wait time will occur at a specific j and x_0, which will result in the identification of the optimal control point and threshold value. The minimum expected total wait time is then compared with the expected total wait time without control to determine whether control represents an improvement and the magnitude of the benefit provided.

Preliminary evaluation of this algorithm was conducted by using a 30-stop route with five different boarding and alighting profiles. In each scenario, the optimal threshold value and the control point were found and the percentage of reduction in the total wait time was computed (see Figure 3 for a sample of the scenario results).

It was found that the location of the control stop is quite sensitive to the distribution of passengers boarding at stops. Generally the control point occurs just before a group of stops at which many passengers are boarding. Thus, more passengers enjoy a reduction in the wait time, because the headway variation is mainly reduced at stops that are close to the control point. If the number on board is small, it is more likely that the threshold value will be larger. One must remember that the threshold value and the location of the control point are interrelated and that they are dependent on all the input parameters in the algorithm.

The objective for schedule-based control is to find the most effective location for returning service to the original schedule without causing excessive delay to passengers on board the bus at the control point. For this reason desirable locations for enforcing adherence to the schedule should be those points at which the schedule deviation is high and at which few passengers are expected to be on board the bus at the control point.

The algorithm for schedule-based control is to identify the stop that maximizes the following:

$$ER = SD_j(V_r)/\left(b_j/\sum_{i=j}^{N} n_i\right) \qquad (11)$$

where ER is the effective ratio and $SD_j(V_r)$ is the standard deviation of running time at stop j. Thus, the best control stops would be those with high values of ER.

In testing whether ER produces reasonable results, 10 different profiles of passengers boarding and alighting were used. In each case schedule-based and headway-based strategies were compared to see whether the two strategies selected similar con-

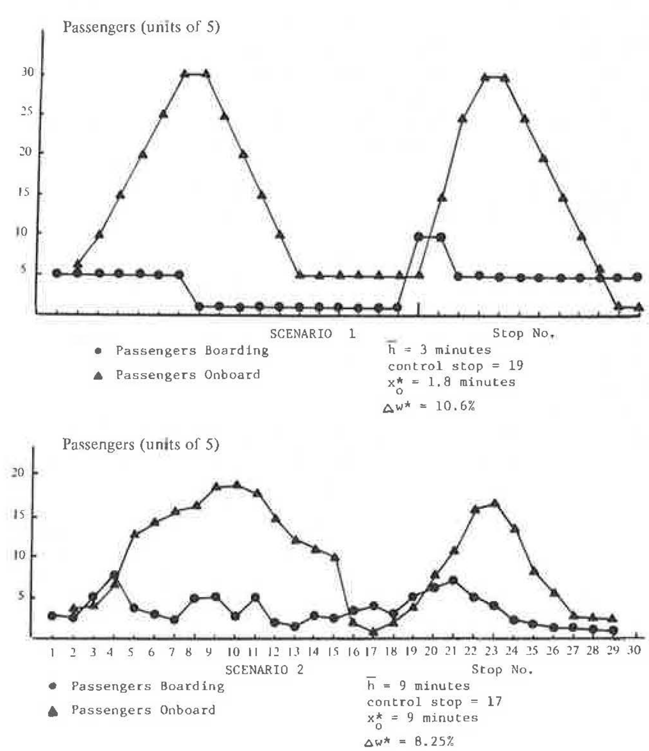

FIGURE 3 Sample evaluation scenarios.

trol stops. In most cases the same or nearly the same stops were selected, which implied that ER is a reasonable selection criterion for the schedule-based holding methodology.

Evaluating the Methodology

Although most of the models developed for the decision methodology were validated individually, there remains a need to test whether the entire methodology produces satisfactory results. A simulation written in the general purpose simulation system (GPSS) was formulated to (a) evaluate whether the control strategy and decision methodology are effective in reducing total passenger wait time on the route and (b) compare the optimal control parameters selected by the decision methodology with those identified by the simulation results.

Introducing the headway-based holding strategy into the simulation reduced passenger wait time on the route by a similar amount as predicted by the decision methodology. This pattern was consistent across different passenger boarding and alighting profiles.

When the optimal control parameters selected by the decision methodology were compared with those of the simulation, the stops chosen by the decision methodology corresponded to those selected by the simulation. In all cases the same stop and the same threshold value were identified or the second-best stop selected by the decision methodology was the first stop selected by the simulation; there were slight differences in the threshold values (1 min and 0.5 min, respectively). Because there is virtually no difference between the decision methodology and the simulation, one can conclude that the decision methodology is feasible for obtaining optimal control parameters.

Another important finding is that the average delay time of buses is small, on the order of 1 to 1.8 min for threshold values of 4 min. This implies that few buses will actually be held for long periods of time and further that the probability of holding more than one bus at the same time is small. This suggests that physical space restrictions are not likely to be a constraining factor in implementing the headway-based strategy.

The previous data used to evaluate the decision methodology were generated by simulation. Data collected in Los Angeles provided an additional opportunity to develop a case study for evaluating whether the decision methodology selects reasonable control parameters.

Routes 16, 30, and 44 were selected to perform the case study. On Route 30, headways are even and short (3 min), and a headway-based strategy was considered. The route follows a westward direction, beginning in the suburbs and passing through the downtown region to another suburb. On Route 16, headways are uneven, so a schedule-based strategy was evaluated. The route begins downtown and moves to the suburbs in a westerly direction. Route 44 represents a route with even but longer headways (5-8 min), which makes it a candidate for the headway-based strategy. The route is U-shaped and passes through the downtown region at its midpoint. Each route of the three routes has approximately 60 stops and data were available for each stop for Routes 16 and 30.

The drawback of using Route 44 in the case study is that the data were only available for AVM locations and not by stop. After consultation with the manager of the SCRTD Planning Department, it was agreed to use the AVM locations as proxies for stops. Thus, the decision methodology could only identify the best AVM location for control, which resulted in potential biases in the results. Data for this route were available for both directions in the morning and afternoon peak periods.

In applying the methodology to Route 30, two adjacent stops were identified as the best stops to control: Broadway and Third Street and Broadway and Fourth Street. Both stops have a threshold value of 1.2 min and are located at the beginning of the downtown region. At these stops there are few passengers on board and many passengers are boarding at stops immediately downstream of the control point. The estimated percentage reduction achieved in passenger wait time was about 3 percent.

For Route 16 a schedule-based strategy was evaluated. In this case the methodology predicted that control would not be effective. An examination of the route substantiates this conclusion, because the route origin is downtown and many people board near that point. In this case the best strategy is to ensure that vehicles depart on time from the route origin rather than detain them en route.

For both the morning and afternoon periods on Route 44, the same AVM location was selected for control; the threshold value in both cases was equal to the scheduled headway. The estimated reduction in passenger wait time was between 11 and 15 percent. The stops chosen are reasonable and are located just before the entrance to the downtown region where many passengers are boarding.

The manager of the SCRTD Planning Department was informed of the results obtained by using the decision methodology and agreed that the recommended strategies for each route were reasonable. It should be noted that the entire analysis was conducted based on data furnished by SCRTD supplemented by additional information that required observation of only a single run on each route.

Operator Compatibility with the Methodology

The decision algorithm has been coded in PASCAL for the Apple II microcomputer. For each stop the user defines the number of boardings and alightings, distance and number of intersections from the previous stop, direction and time period of travel, and, if available, the percentage of on-street parking allowed from the previous stop. Most of this information is available or can be easily collected by the transit agency. This data file serves as an input to the decision algorithm.

The user is prompted to describe the scheduled headway, which determines whether headway-based or schedule-based control will be considered. The input file of stop information is combined with the models previously described to form the inputs to the objective function.

The model output includes a statement of whether control is effective, a priority listing of the most effective control stops, and, for headway-based control, corresponding threshold values and absolute and relative benefits of control over the no-control case. The priority listing is useful in situations where it is impractical to implement control at a particular stop (e.g., traffic conditions) and near-optimal alternatives are worthy of consideration. The absolute and relative benefits provide for a comparison across routes, which is useful when there are constraints on the number of available street supervisors.

Sample output for headway-based control appears in Table 2. To assist transit operators in utilizing the methodology, a user's manual has been written that accompanies the software.

TABLE 2 Sample Output for Headway-Based Control

LIST OF EFFECTIVE CONTROL STOPS BY ORDER

STOP 13,	THRESHOLD 3.75 MIN,	REDUCTION 49.21 MIN,	%REDUCTION 4.98%
STOP 21,	THRESHOLD 3.00 MIN,	REDUCTION 47.15 MIN,	%REDUCTION 4.77%
STOP 20,	THRESHOLD 3.00 MIN,	REDUCTION 46.81 MIN,	%REDUCTION 4.74%
STOP 22,	THRESHOLD 2.75 MIN,	REDUCTION 46.70 MIN,	%REDUCTION 4.73%
STOP 12,	THRESHOLD 4.00 MIN,	REDUCTION 46.36 MIN,	%REDUCTION 4.69%
STOP 11,	THRESHOLD 4.25 MIN,	REDUCTION 42.04 MIN,	%REDUCTION 4.26%

VALUE OF MODELS

The models reported in this paper represent an attempt to use empirical data to establish factors that affect transit route performance and passenger level of service. They should not be interpreted entirely as cause-and-effect models because the collinearity between variables and lack of information on other potentially significant explanatory variables make it difficult to understand the individual contributions of each factor. Other assumptions that were made in conducting this research include independence of routes within the network and on-time vehicle departures from the route origin. Thus, the models should be considered primarily for their value in providing reasonable estimates of performance and service given the availability of information on route characteristics.

CONCLUSIONS

Several findings can be reported from this research activity. Mean running time is strongly influenced by trip distance, passengers boarding and alighting, and signalized intersections; other route characteristics have a lesser effect on this measure. Running-time deviation magnifies and propagates as vehicles proceed downstream. Headway variation is highly correlated with running-time variation; scheduled headway also affects this measure. Headway-based control decreases headway variation, and the magnitude of the change is dependent on the threshold level. Finally models of passenger waiting time that assume random passenger arrivals overestimate observed waiting times, even for short-headway routes.

Beyond the individual model implications, many general contributions can be attributed to this research effort. The research has addressed individually and collectively the issues that affect service regularity, which has resulted in pertinent information on setting timetables and allocating vehicles to routes. These effects are then represented mathematically and utilized in the development of a decision process that can be used to improve service regularity through the implementation of real-time holding strategies. Finally a mechanism is provided by which the operator can apply the methodology directly to address current reliability problems. The research product is based heavily on empirical analysis, which appears to be representative of actual operations.

The research results have direct practical application in metropolitan regions in which conventional transit service is operated. The decision algorithm is economical and does not require special data-collection activities to implement. It has the potential to bring about both cost reductions and increased productivity for public services, which are particularly important in these times of fiscal conservation.

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Do Performance Audits Audit Performance?

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ABSTRACT

The requirements of the state of California for performance audits of publicly funded transit systems are examined. These performance audits are conducted by agencies that distribute state funds to support the operating and capital needs of public transportation systems. The objective of this examination is to discuss the intent of the audit requirement and how audits are conducted in order to determine the purpose of performance audits. The enabling legislation and its implementation are traced into practice and the processes used to conduct audits are critically examined. It is argued that performance audits focus on the management of transit systems at the expense of examining whether they are delivering the service required of them. In conclusion it is argued that performance audits that only evaluate how well systems perform do not fully evaluate transit performance. It is recommended that performance audits first determine whether transit systems are in fact meeting the demand for service. It is argued that performance audits that review the quality of service delivered are more helpful than those that focus solely on the management of the system.

In recent years federal, state, and local governments have become concerned about the rapid escalation in transit operating costs. Although operating costs have risen at rates equal to or greater than the overall rate of inflation, fare revenues have generally been unable to keep pace. Further large deficits in federal as well as state and local budgets have reduced the amount of funding available to support transit. As a consequence, agencies responsible for funding transit have begun to focus attention on evaluating the performance of transit systems. Such evaluations are considered useful in determining whether transit systems can become more efficient and maintain desired levels of service.

Recently several states, including New York, Pennsylvania, and Michigan, either began systematic performance audits of transit systems or were in the process of developing programs to do so. Furthermore, there has long been interest in using the annual reporting system of Section 15 of the Urban Mass Transportation Act of 1964 to conduct performance reviews. However, to date there has been no concerted government effort to do so. This is in large part because of many problems with the reliability of the data base.

Although the states just mentioned are now at the initial stages of their performance audit programs, California has been undertaking such audits for more than 6 years. In 1978, the California legislature passed a law that required all transit systems that receive state sales-tax assistance to have a performance audit conducted triennially. To date, all transit systems that have been in existence since 1979 have undergone at least two such performance audits. What the California performance audit requirement is and how audits have been conducted are examined in this paper. Although performance audits conducted throughout the state are considered, the focus is on those audits conducted for transit systems in the San Francisco Bay Area, which are within the jurisdiction of the Metropolitan Transportation Commission (MTC).

LEGISLATIVE MANDATE

In 1978 California Senate Bill 620 was passed, which amended certain provisions in the Transportation Development Act (TDA) (California Public Utilities Code, Sec. 99200, 1978). The TDA program was started in 1971 and provides sales-tax revenues to support transit systems. It is a multimillion-dollar-a-year program that serves as a major source of both operating and capital assistance to most California public transit systems. The requirement for performance audits is as follows (California Public Utilities Code, Sec. 99246):

> (a) The transportation planning agency shall designate entities other than itself, a county transportation commission, a transit development board, or an operator to make a performance audit of its activities, and those of county transportation commissions and transit development boards located in the area under its jurisdiction, with respect to these funds. The transportation